Caught in the Act:
Investigating Crime by Agent-Based Simulation
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Caught in the Act: Investigating Crime by Agent-Based Simulation

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Part I –
Introduction

1. Background

Deviant behaviour or behaviour that violates social norms is an aspect of everyday life that has been important since the beginning of mankind. One could say that eating the forbidden fruit from the tree of knowledge of good and evil by Adam and Eva [16] was the first ‘deviant’ act performed by mankind. Since then, the world has changed in almost every possible way and the content of deviant behaviour has changed accordingly. In this thesis we focus on the legal aspect of deviant behaviour commonly know as crime. Crime can be defined as the violation of rules that, according to criminal law, would lead to conviction.

With time came also a changed interpretation of deviant behaviour. Countries were formed, the population increased and also the number of types of ‘criminal’ acts expanded and changed over time. This resulted in changes in (criminal) law, which could mean that acts that were punishable before suddenly were not punishable anymore, for example adultery. In addition, also acts that were not punishable earlier became punishable, like for instance insider trading. An important thing to note here is that crime is something that is socially constituted and can differ between different countries. Something that is prohibited is one country (for instance bigamy) is considered a normal way of life in other countries.

The reaction on crime has also changed over time. The era of burning witches or torture of thieves is luckily long gone in most parts of the world. After a period in which these brutal methods were normal (not only to punish but also as means to get a statement or a confession), an era started in which the investigation and treatment of different causes of crime became more prominent. There was a period when Lombroso [18] defended his theory that criminality is caused by someone’s biological makeup and that this was visible in someone appearance (e.g. large nose, thick eyebrows). In response to this, others like Lacassagne instead claimed that the social environment was the main factor to contribute to criminal behaviour [30].

Nowadays it is more accepted that anyone can be an offender, and that crime may have biological, psychological, and social causes. It is important to note here that crime is usually the result of an interaction of the different aspects. Someone may temporarily have a high level of testosterone which can cause aggressive behaviour (biological component), however there also has to be an opportunity to act (social component). Or a person can have a desire for material needs (a psychological component) but will only act on this desire (by for instance stealing) when after weighing the pros and cons (s)he has an opportunity that is too good to pass on (social component). Thus, to be able to understand, explain and possibly predict deviant behaviour, one needs to gain more insight in both biological, psychological, and social aspects of human behaviour.

Fortunately, over the last decades, there have been rapid developments in various scientific disciplines related to these human aspects. For instance, the area of neurological research has quickly developed during the last couple of years. The possibility to perform brain scans and observe what happens in the brain under different circumstances and the possibility to acknowledge deviations in the brain are part of recent accomplishments, and may be useful in understanding (deviant) behaviour.
Another example is the development of DNA databases. This is an area under development which can be very beneficial while identifying offenders.

In line with these developments, in this thesis we will also make use of new scientific research methods to help gain greater insights in crimes and offenders. Increasing the insight in why and when certain crimes are performed by certain people is very important to help develop approaches and measurements to prevent criminal actions. Instead of using more traditional research methods we are applying techniques from the area of Artificial Intelligence (AI) to realise this goal. The last couple of years there has been a growing interest in the question how social processes (such as crime) can be studied by means of computational methods, as for instance from AI. In my thesis we will use such techniques (like mathematical modelling, agent-based and population-based modelling, simulation and formal verification) and we will show that applying them to study criminological theories may be very beneficial to the understanding of the occurrence and dynamics of crime and how crime in some cases can be predicted, prevented or decreased.

This introduction is organised as follows. First, in Section 2, we will briefly introduce the research goal of this thesis. Next, in Section 3, we will discuss the areas within Artificial Intelligence that were important in my research. In Section 4 the methodology will be discussed, and the modelling approach will be presented in Section 5. Finally in Section 6 a short overview of the chapters to come is provided.

2. Research Goal

The main research goal of this thesis is to explore whether techniques from the area of Artificial Intelligence can increase insight into different aspects within the field of Criminology. Thus, the main research question of this thesis is defined as follows:

*How can techniques from the area of Artificial Intelligence enhance the understanding of criminological phenomena?*

Obviously, in criminology, already many theories exist about various (biological, psychological, and social) aspects of deviant behaviour. However, such theories in the criminological domain are often informal, i.e., not in a computational format. This is not a problem when one wants to understand what is happening on an abstract level. However, when detailed dynamics are studied, it is important to take the influence of all aspects (and their interaction) involved into account. This can still be done using an informal theory, but when the number of aspects increases it will be more difficult to oversee all dynamical patterns that result from the interaction between these aspects. Thus, when the numbers increase, it can be very helpful to represent the theories in a computational format, in such a way that they can be used to perform simulation. This will make it possible to perform automated (pseudo-)experiments, in order to gain more insight in a phenomenon, and possibly refine the original theory. This is exactly what is meant with enhancing the insight as mentioned in the main research question. This approach leads to another research (sub-)question namely:

*How can theories from criminology be represented as computational models?*
Using such computational models, the researcher can investigate different dynamical aspects of the process without changing anything in the real world. Moreover, when something changes in the real world (for instance when a new railway station is opened providing opportunity for offenders, or a new drug comes on the market that changes biological states within a person), one can easily alter the model accordingly. It should be noted that these models usually are not a representation of the entire world but only of relevant aspects. We do not suggest that the models are complete and 100% correct. The main goal (at least of the models presented in this thesis) is to help researchers within the criminological area to gain more insight in different phenomena.

More specifically, for this thesis three domains have been chosen as case studies, namely 1) biologically determined violent behaviour, 2) social learning of delinquent behaviour during adolescence, and 3) spatio-temporal dynamics of crime. For these three case studies (which are addressed, respectively, in Part II, III, and IV), relevant criminological theories have been identified and formalised as computational models. For more information about these theories, see the introductions of the respective parts.

3. Artificial Intelligence

Artificial Intelligence (AI) is a very broad research area, which aims to create intelligence by means of computational methods [26]. Within AI, a large number of different techniques are applied for this purpose. In this thesis the scope is on techniques related to modelling and simulation. The relevant concepts are explained in some more detail below.

Modelling and Simulation

A model could be defined as a representation of an object, system, or idea in some form other than that of the entity itself [27]. Furthermore, a model is a simplified version of reality. A model can be static (e.g. a model of a building) or dynamic (e.g. the model of a process). To make a model of a certain process, one represents the most important elements that occur within that process and their relations. This way, the modeller is not distracted by elements with only a small or even no contribution. One of the things one can do with a model is to study the modelled process by simulation. Simulation of a process is the imitation of that process over time within an artificial environment.

When developing a simulation model of a process, the modeller usually starts with an informal theory. This theory is assumed to describe the process in an informal, but correct manner. The next step in the modelling process is to formalise the theory. This is usually done by identifying relevant concepts in the theory, as well as relationships between them, and formalising these concepts and relationships in some modelling environment. There are multiple modelling environments available (e.g., programming languages like C++ or Java, numerical modelling toolkits like MatLab or Excel, or dedicated simulation environments like LEADSTO) in which one can formalise a theory. When the theory is formalised in enough detail to perform simulation experiments with it, the experimental results of these simulations can offer new insights, that go beyond the insights one had on the basis of the theory only. For example, when a model predicts roughly the behaviour described by the theory, however with some small deviations, then these predictions can be used to create a refined theory.
In addition to the fact that computers can process the consequences of a theory much easier than human beings, there are several other reasons for studying a model instead of the real thing. For instance, sometimes such a reason is that it is too dangerous to test something in real life. Within the criminological domain, one can think of a situation with a paedophile. Can you really let him alone in a classroom full of toddlers, to investigate his behaviour? In this case it would be better to investigate the existing literature in order to make a correct model of the paedophile, the toddlers and classroom, and simulate their behaviour to see what happens. Another example is when one wants to investigate which strategy would be best to use for a police officer in order to prevent crime. The researcher can have police officers perform each type of strategy in the real world, and then evaluate these afterwards, but this is both time and money consuming. In this case a model of a city and guardians set with different parameters could do the trick. Note that, when making a model, certain choices have to be made. Since it is not feasible to model all aspects of a certain process in detail, usually only the most relevant aspects are taken.

**Social Simulation**

Within the general area of social simulation, two perspectives can be distinguished, namely population-based simulation and agent-based simulation.

The classical approaches to simulation of processes in which groups of larger numbers of agents and their interaction are involved are population-based: a number of groups are distinguished (populations) and each of these populations is represented by a numerical variable indicating their number or density (within a given area or location) at a certain time point. Such a simulation model takes the form of a system of difference or differential equations expressing temporal relationships for the dynamics of these variables. An example of population-based modelling is presented in Chapter IV.3, which focuses on the spatio-temporal dynamics of crime in a city. In the model presented in that chapter, three groups are distinguished (guardians, passers by and offenders) that are represented by a number that indicates the amount of agents in the group. When simulating the behaviour of these agents, each time step a percentage of each group moves. In the case of a population-based model the number of agents that move does not have to be discrete, since they are modelled as a density instead of as individuals. The model has the form of differential equations. An example of such an equation for the moving of agents from one location to another is the following:

\[
g(L, t + \Delta t) = g(L, t) + \eta \cdot \left( \left( \frac{c(L, t)}{c} \right) \cdot g \cdot g(L, t) \right) \Delta t
\]

This formula expresses that the number of guardians present at a location \( L \) at time point \( t + \Delta t \) is equal to the number of guardians at that location before \( g(L, t) \) plus the number of agents that move \( \eta \cdot \left( \left( \frac{g(L, t)}{g} \right) \cdot p \cdot p(L, t) \right) \). This movement is based on the attractiveness of that location for the type of agents (in this case, guardians). The attractiveness for guardians is dependent (in this simple case) on the offenders present at that location \( c(L, t) \).

In contrast, in the last decades there has been a growing interest in the area of Agent Based Social Simulation (ABSS). In ABSS, which integrates approaches from agent-based computing, computer simulation, and the social sciences, researchers try to exploit agent-based simulation to gain a deeper understanding of social phenomena [1, 12]. ABSS makes use of the agent-based modelling paradigm [29]. According to this
4. Methodology

Theories used in Criminology are often informal and multi-interpretable. There are usually many relevant contributors to behaviour which makes it difficult to use a theory for anything else than as a guideline. Investigating dynamics or making predictions is not possible solely based on an informal theory. Our contribution to the solution of this problem is the formalisation of these theories. We have combined and formalised different theories from all sides of the criminological spectrum. The main AI goals we had in mind while doing this are to analyse and combine existing theories, to predict future behaviour and to perform a meta-analysis of the theory.

The methodologies used in the different parts of this thesis differ. In part II we analysed criminal behaviour on both a biological and a cognitive level. First we formalised existing informal domain knowledge, then we combined this into a simulation model and analysed the behaviour of this model. Based on this model we were able to obtain a more clear insight in the different aspects of the behaviour of certain types of violent offenders.

In part III we use a different methodology. In this part we first explored existing theories, in order to develop a model of learning of criminal behaviour during adolescence. After our model was able to simulate behaviour according to the theory we started collaboration with Dr. Frank Weerman, an empirical researcher from the NSCR (Netherlands Institute for the Study of Crime and Law Enforcement), who could provide us with real world data. He and his colleagues had performed a large longitudinal study on juvenile delinquency, and had gathered a lot of empirical data, which we were allowed to use. We used part of the data as a training set, to fine-tune the formulae in our model. After we distinguished a number of interesting variants of the model, we tested (by simulation) these models on the remaining data. Based on these simulations we could evaluate the models.
Part IV again started with an exploration of existing work and theories. In this research we started working from the beginning with Prof. dr. Henk Elffers (from both the department of Criminology of the VU University Amsterdam and from the NSCR), who is an expert in (Environmental) Criminology. In this part, we focused on the development of a model that could function as an analysis tool for researchers. We developed a model that simulates behaviour according to the relevant theory. Based on that model, we adjusted certain parameters to see what would happen if one changed a policy. The main reason for abstracting from real world details in this part is that we do not look at the entire picture. It is almost impossible to simulate the dynamics of crime movement according to reality because the numbers of relevant contributors are endless. Thus, we can not predict the exact outcome of a changed policy. However, we can show the influence of a certain alteration in policy on an abstract level. Therefore, part III explores the effects of such alterations.

In principle, the research presented in all parts has the same goal, namely to develop an analytical tool to gain better insight in the processes described in these parts. However in Part II and IV a different methodology has been used than in Part III. In Part II and IV a theory was taken and formalised, and the process was simulated according to the theory. The methodology used in Part III is different. Here, the formal model is not only based on a theory but also on empirical data. Future behaviour was then simulated based on the model. The results of these simulations were artificially generated data. We then compared the artificially generated data with another set of empirical data that was available, in order to validate the model. Note that the data we used to develop the model was a different subset of the empirical data than the data we used to compare the results.

5. Modelling Approach

In the different research projects we performed throughout the thesis we used a couple of existing modelling languages and environments. These modelling languages and environments will be explained in this section.

TTL

To model different aspects of crime, an expressive modelling language is needed. There are qualitative aspects that need to be addressed, such as physical aspects (e.g. brain deviations), observations, beliefs, decisions to perform a certain action and some aspects of the environment such as the presence of certain agents. But there are also quantitative aspects that need to be modelled, e.g. the reputation of locations or, when taking a physiological perspective, the level of hormones and neurotransmitters. These quantitative aspects can best be represented by real numbers and mathematical formulae.

Another requirement of the modelling language to be chosen is its suitability to express the basic mechanisms of crime-related processes on the one hand (for the purpose of simulation), and on the other hand more global properties (for the purpose of logical analysis and verification). For example, basic mechanisms of movement of crime involve decision functions for individual agents, whereas global properties are the types of statements like “the location of hot spots changes over time”.

The predicate-logical Temporal Trace Language (TTL) fulfils all of these requirements [4]. It integrates qualitative, logical aspects and quantitative, numerical aspects. This integration allows the modeller to exploit both logical and numerical
The TTL language is based on the assumption that dynamics can be described as an evolution of states over time. The notion of state as used here is characterised on the basis of an ontology defining a set of physical and/or mental (state) properties that do or do not hold at a certain point in time. These properties are often called state properties to distinguish them from dynamic properties that relate different states over time. A specific state is characterised by dividing the set of state properties into those that hold, and those that do not hold in the state. Examples of state properties are ‘agent 1 has a high level of testosterone’, ‘agent 1 is risk seeking’, ‘agent 1 performs an assault on agent 2’, or ‘there are 5 guardian agents at location A’. Real value assignments to variables are also considered as possible state property descriptions.

To formalise state properties, ontologies are specified in a (many-sorted) first order logical format: an ontology is specified as a finite set of sorts, constants within these sorts, and relations and functions over these sorts (sometimes also called signatures). The examples mentioned above then can be formalised by n-ary predicates (or proposition symbols), such as, for example, performed or number_of_guardians, which can be used to define more complex atoms like performed(assault_at(a1,a2)) or number_of_guardians(loca, 5). Such atoms are called state ground atoms (or atomic state properties). For a given ontology Ont, the propositional language signature consisting of all ground atoms based on Ont is denoted by APROP(Ont). One step further, the state properties based on a certain ontology Ont are formalised by the propositions that can be made (using conjunction, negation, disjunction, implication) from the ground atoms. Thus, an example of a formalised state property is number_of_guardians(loca, 5) & number_of_guardians(locb, 3). Moreover, a state S is an indication of which atomic state properties are true and which are false, i.e., a mapping S: APROP(Ont) → {true, false}. The set of all possible states for ontology Ont is denoted by STATES(Ont).

To describe dynamic properties of crime-related processes (such as the biological and psychological processes inside a person, or the learning of (criminal) behaviour), explicit reference is made to time and to traces. A fixed time frame \( T \) is assumed which is linearly ordered. Depending on the application, it may be dense (e.g., the real numbers) or discrete (e.g., the set of integers or natural numbers or a finite initial segment of the natural numbers). Dynamic properties can be formulated that relate a state at one point in time to a state at another point in time. A simple example is the following (informally stated) dynamic property about the number of guardians at a certain location:

For all traces \( \gamma \),
there is a time point t such that
at location A, there are at least x guardian agents.

A trace \( \gamma \) over an ontology Ont and time frame \( T \) is a mapping \( \gamma: T → STATES(Ont) \), i.e., a sequence of states \( \gamma(t) ∈ T \) in STATES(Ont). The temporal trace language TTL is built on atoms referring to, e.g., traces, time and state properties. For example, ‘in trace \( \gamma \) at time t property p holds’ is formalised by \( \text{state}(\gamma, t) |= p \). Here \( |= \) is a predicate symbol in the language, usually used in infix notation, which is comparable to the Holds-predicate in situation calculus. Dynamic properties are expressed by temporal
statements built using the usual first-order logical connectives (such as \( \neg, \land, \lor, \rightarrow \)) and quantification (\( \forall \) and \( \exists \); for example, over traces, time and state properties). For example, the informally stated dynamic property introduced above is formally expressed as follows:

\[
\forall \gamma: \text{TRACES} \exists t: \text{TIME} \exists i: \text{INTEGER} \\
\text{state}(\gamma, t) = \text{number\_of\_guardian}(\text{locA}, i) \land i \leq x
\]

In addition, language abstractions by introducing new predicates as abbreviations for complex expressions are supported. For more details of TTL, see [4].

**LEADSTO**

To be able to perform (pseudo-)experiments, only part of the expressivity of TTL is needed. To this end, the executable LEADSTO language [5] has been defined as a sublanguage of TTL, with the specific purpose to develop simulation models in a declarative manner. In LEADSTO, direct temporal dependencies between two state properties in successive states are modelled by *executable dynamic properties*. The LEADSTO format is defined as follows. Let \( \alpha \) and \( \beta \) be state properties as defined above. Then, the notation \( \alpha \xrightarrow{e,f,g,h} \beta \) means:

- If state property \( \alpha \) holds for a certain time interval with duration \( g \),
- then after some delay between \( e \) and \( f \)
- state property \( \beta \) will hold for a certain time interval with duration \( h \).

As an example, the following executable dynamic property states that “if an agent \( a \) goes to a location \( l \) during 1 time unit, then (after a delay between 0 and 0.5 time units) this agent will be at that location for 5 time units”:

\[
\forall a: \text{AGENT} \forall l: \text{LOCATION} \\
\text{performed}(a, \text{go\_to\_location}(l)) \xrightarrow{0, 0.5, 1, 5} \text{is\_at\_location}(a, l)
\]

Based on TTL and LEADSTO, two dedicated pieces of software have been developed [4, 5]. First, the LEADSTO Simulation Environment takes a specification of executable dynamic properties as input, and uses this to generate simulation traces. Second, to automatically analyse the resulting simulation traces, the TTL Checker tool has been developed. This tool takes as input a formula expressed in TTL and a set of traces, and verifies automatically whether the formula holds for the traces. In case the formula does not hold, the checker provides a counter example, i.e., a combination of variable instances for which the check fails.

**Matlab**

Matlab is a numerical computing environment maintained by The MathWorks [32]. This environment allows easy matrix manipulation, plotting of functions and data, implementation of algorithms, creation of user interfaces and interfacing with programs in other languages. In the current thesis, Matlab has mainly been used for simulation purposes. Matlab has as advantage over the earlier mentioned TTL and LEADSTO environments that it has a higher computational efficiency, which allows the modeller to run very large simulations in a short amount of time. For example, in the research project concerning the spatio-temporal dynamics of crime (see Part IV) we performed

8
simulations with a large number of locations and over a long period. Matlab was the appropriate environment for these simulations. Further, we wanted to visualise the results of the simulations in terms of animations in a two-dimensional space. Matlab also provides good facilities for this.

**Microsoft Office Excel**
In the research project concerning social learning (Part III in the thesis) we performed simulations in the Microsoft Office Excel environment. This environment features calculation, graphing tools, pivot tables and a macro programming language. Although this software originally was not designed for simulation experiments, it fitted our requirements very well. First, it can easily import and handle the large set of numbers that resulted from the empirical study used in Part III. As explained in that part, we were working with empirical data from a large network of students, which were all (possibly) connected to each other, and were already available in terms of Comma Separated Values (CSV) files. A second motivation to use Excel for this project was the fact that it could adequately perform the mathematical operations that were required by the model, including operations such as searches and lookups in different data sheets.

**6. Overview**
To illustrate the contribution of the interdisciplinary research between AI and Criminology in three different domains, this thesis consists of three parts. These parts are dedicated to different domains within criminology and for each of these domains it is illustrated how AI techniques can be beneficial in understanding, analysing or predicting criminal behaviour. Each of the parts starts with an elaborate introduction. Below you will find a short description of the contents of each of the parts.

Part II focuses on the biological and cognitive aspects of criminal behaviour. Certain types of violent criminal behaviour can best be explained by taking a combination of biological, psychological and social aspects into account [23, 24]. Dynamical modelling methods developed in recent years often address biological, psychological, or social dynamical systems separately. This research makes the first step in the development of an agent-based modelling approach for criminal behaviour in which these aspects are integrated in one dynamical system. Based on existing literature on violent offenders, the approach provides the analyst more insight in how certain types of violent behaviour may result from an interaction between biological factors (e.g., certain brain deviations, testosterone levels and serotonin levels), cognitive and emotional factors (e.g., aggressiveness and impulsiveness) and social factors (e.g., the presence or absence of certain other agents). The approach consists of one generic model for the behaviour of violent offenders with parameters that can be set to obtain simulation traces for three known types of offenders. This enables the analyst to find out whether an offender of a certain type may show certain behaviour under given circumstances, but also (in the opposite direction) to determine what kind of scenario or circumstances could lead to certain given behaviour.

Part III addresses development and validation of a dynamic agent-based approach to simulate the dynamics of delinquent behaviour among adolescents [9, 22]. More specifically, a model has been developed that can simulate the development of youth delinquency in a classroom. The approach has been used to perform simulation experiments in which the delinquency of 250 pupils was dynamically calculated over a couple of years. This expected delinquency is based on personal characteristics on the
one hand and the delinquency of peers on the other hand. A second dataset has been used to validate the model, using a specifically developed accuracy measure. The validation shows that the model predicts delinquency substantially better than a baseline model that only uses the delinquency of the previous year. Next the same model is used to perform so-called “what-if simulations”, or computer-supported thought experiments. An interesting question is, for example, “what would happen if we placed one bad child in a classroom full of teacher’s pets”? The answers to these questions may be very useful for policy making. Since these what-if simulations make use of the (validated) model developed earlier, which was tested against several datasets, the outcomes also are expected to have some validity. However it is not guaranteed that they have the same level of validity as the outcomes from the original simulations, because each new scenario in principle may introduce new factors that can influence the results.

Part IV focuses on the spatio-temporal dynamics of crime. Within the routine activity paradigm, it is argued that crime takes place when a motivated offender finds an insufficiently guarded attractive target [11, 15]. Although this theory has as advantage that it is very clear and understandable at an abstract level [14], this simplicity seems to vanish as one zooms in towards concrete questions on underlying processes. For example, what governs whether a motivated offender will find an attractive target? This research proposes to use social simulation techniques to answer these types of questions. As such, simulation should be seen as an analytical tool that makes it possible to investigate what is happening, given a set of rules whose mutual interactions are too complex to see through by analytical methods. Simulation is -in such an application- not an empirical, but a theoretical method, which uses computer generated instances of realisations of processes. In the current research, this approach is used to investigate various aspects of spatio-temporal dynamics of crime, including situations in which the targets are static as well as dynamic, and where different strategies for guardianship are used.

This thesis ends with a concluding chapter in which will be explained what has been done. We will discuss the research presented in the different parts in relation to the research goal mentioned in this introduction to draw conclusions about the usefulness of research between AI and Criminology for both research areas. Further we will discuss possible future directions for this research area.

Some discussion may exist about the terminology used and the assumptions made throughout the chapters of this thesis. Obviously, informal theories are often multi-interpretable. While formalising such theories certain choices need to be made, as was also the case in this thesis. For example, we used the word ‘displacement’ to indicate the spatio-temporal dynamics of crime throughout this thesis. In addition, while we used the word ‘criminal’ to indicate a person who commits a certain delinquent act, in the field of criminology the more correct word ‘offender’ is used. The latter term emphasises the fact that every person could in principle be someone who breaks the rules, without stigmatising people for life. We agree with this view; however we sometimes used the word ‘criminal’ to make a strict distinction between the three types of agents used in our computational models, namely criminals, passers by and guardians. We also acknowledge that passers by may well become criminals if the opportunity arises and the same can be said about guardians; they also can break the rules if the opportunity outweighs the consequences. Similarly, passers by can count as guardians when they prevent a crime from happening, and insufficient guardians can be seen as passers by. Thus, to conclude, in practice the distinction between these three
types of agents is not so clear at all, but for the sake of simplicity we made the distinction when building our simulation models.

References
16. Genesis 2:16-17


Part II –
Modelling Biological and Cognitive Aspects of Violent Behaviour

In the current part, the main focus is on the biological and psychological aspects of aggressive behaviour and how different factors from these domains interact.

In recent years, there is growing consensus that it is impossible to separate biological and psychological factors, and that behaviour rather is the outcome of the interaction of both types of factors [1, 3, 4, 5, 6]. In this part we make this assumption as well. We present a dynamic model for certain types of aggressive behaviour that incorporates both biological and psychological aspects. In some cases these aspects can be roughly mapped onto each other, for instance, for the case of aggressive behaviour. Aggression is a cognitive state but has a rather direct biological contributor, namely the hormone testosterone [5].

Although aggressive behaviour does not always lead to breaking the law, it is an interesting type of behaviour to study, because much literature about the underlying mechanisms exists. Based on such existing literature on violent behaviour and violent offenders, the approach presented in this part provides the analyst more insight in how certain types of violent behaviour may result from an interaction between biological factors (e.g., certain brain deviations, testosterone levels and serotonin levels), cognitive and emotional factors (e.g., aggressiveness and impulsiveness) and social factors (e.g., the presence or absence of certain other agents).

In this part we present five chapters. Chapter II.1 describes the initial step in the development of an agent-based modelling approach for aggressive behaviour. In this paper we present a model that integrates all relevant aspects (i.e., biological, psychological as well as social aspects) in one dynamical system. We introduce three types of violent offenders (namely the violent psychopath, people with an antisocial personality disorder, and people with an intermittent explosive disorder) and show how within a certain social context, biological factors affect cognitive and emotional functioning in such a way that aggressive behaviour is performed.

Chapter II.2 explores the behaviour of persons with an intermittent explosive disorder in some more detail. This paper specifically applies the model presented in the first chapter to these types of persons. Since interaction with other persons plays a central role here, an important focus is on the social aspect. Moreover, to analyse the model in more detail, a number of dynamic properties are formalised in a logical language, and are automatically verified against a large set of simulated traces. These dynamic properties, both of logical and probabilistic type, comprise not only behavioural and internal properties of the agents involved, but also properties that address the society as a whole.

Whereas the papers presented so far integrate cognitive and biological factors and their relationships within one model, the next chapter (II.3) presented in this part attempts to separate the two types of factors in different models and to represent their relationships as a mapping between both models. Hence, this chapter discusses how a cognitive modelling approach for criminal behaviour can be related to a biological modelling approach. A cognitive model is discussed that shows the behaviour of the three types of offenders mentioned earlier depending on the characteristics set and input.
from the environment. Next, it is shown how the model can be related to a biological grounding by a formal interpretation mapping.

Chapter II.4 makes use of the research presented in the three chapters mentioned earlier. This chapter illustrates how the model can be used to determine which types of violent offenders may have committed a given crime. For example, imagine a certain crime has happened, two suspects are available, and the characteristics of the crime are known. Then, by verification of behavioural properties against the scenarios, one is able to find out which of the two suspects is most likely to be the offender. Note that this perspective differs from the approach taken so far, since that approach took the behaviour as a basis, in order to derive possible scenarios.

In the last chapter (II.5) of this part we shift focus. The model that is presented in the chapters mentioned so far is used but instead of investigating interaction of aspects for disorders we focus on decisions. The model of biological and psychological aspects is combined with a rational choice model. The Rational Choice Theory by Cornish and Clarke [2] is the basis for this chapter. The main idea behind the Rational Choice Theory is that humans are rational beings and make rational choices. In most cases they think before they act and weigh the pros and cons of each action. In the domain of Criminology, this implies that offenders seek advantage by their criminal behaviour. This advantage can for instance be money, goods or a better reputation among peers. Weighing the pros and cons entails making decisions among alternatives. Which action will lead best to the fulfilment of my desire? These decisions are rational within the constraints of time, ability and the availability of relevant information. In Chapter II.5 the model presented in the first four chapters of this part is extended with a rational choice model. Why does an offender choose to commit an assault on person A and not on person B? And how does his biological/psychological makeup influence this decision? We present a modelling approach for decision making which integrates the Rational Choice Theory with the personal psychological and biological aspects from the original model. To study the behaviour of the model, it has been applied to a case of street robbery, for which various scenarios have been simulated. In addition, the model is incorporated into a virtual storytelling application. A user study has been performed, in which the generated simulation traces were converted into virtual storylines, which were read by 20 participants. The study confirmed our hypothesis that the model enhances realism of (deviant) virtual characters. This means that the model helps to make the characters act more human like according to the participants.

The chapters presented in this part are based on the following publications:

Chapter II.1 appeared as:


This work is also based on:

Chapter II.2 will appear as:


This work is also based on:


Chapter II.3 appeared as:


Chapter II.4 appeared as:


Chapter II.5 will appear as:


This work is also based on:


References


Towards Integration of Biological, Psychological, and Social Aspects in Agent-Based Simulation of Violent Offenders

Tibor Bosse, Charlotte Gerritsen, and Jan Treur

Abstract. In the analysis of criminal behaviour, a combination of biological, psychological and social aspects may be taken into account. Dynamical modelling methods developed in recent years often address biological, psychological, or social dynamical systems separately. This paper makes the first step in the development of an agent-based modelling approach for criminal behaviour in which these aspects are integrated in one dynamical system. It is shown how within a certain (multi-agent) social context, biological factors such as certain brain deviations, testosterone levels and serotonin levels, affect cognitive and emotional functioning in such a way that a crime is committed when the perceived opportunity is there. The paper presents one generic model for the behaviour of violent offenders with parameters that can be set to obtain simulation traces for three known types of offenders.

1. Introduction
Within Criminology, the analysis of criminal behaviour is a central issue. Such an analysis involves different types of aspects, such as biological, psychological, and social aspects and their mutual interactions; e.g., [5, 15, 30, 33, 36, 37]. Usually such analyses are made by criminologist researchers or practitioners in a nonexact manner, without using any formalisation or computer support. The interplay between the various aspects involved may be complex and dynamic. Therefore such a task requires a rare combination of expertise in different knowledge domains. But even if such a combination of expertise is available, often it is not straightforward and in certain cases may be quite difficult indeed. Therefore computer support is more than welcome, both concerning the expertise in the different knowledge domains and the complexity of the dynamical aspects of the integrated process. Due to the difficulty to address this area within Criminology, the few contributions made to the literature often address only one or some of these types of aspects, for example, social and environmental aspects, as in [3].

In recent years much progress has been made in biological, cognitive, and social complex dynamical systems modelling within areas such as Artificial Intelligence, Computational Biology/Artificial Life, Cognitive Science, and Computational Social Science/Organisation Theory. The methods developed in these areas usually address one of the disciplines separately. For example, in social simulation the agents usually are assumed to show simple behaviours, and their internal cognitive systems are not taken into account. Similarly, in cognitive modelling often biological factors are not addressed [23].

However, when an integrated modelling approach is applied, this opens the perspective to address the analysis of criminal behaviour in more exact, formalised and computer supported manners. Thus, the way is paved to a more solid basis and
computer support for simulation and analysis in the area of Criminology. The research discussed here explores this potential. It identifies on the one hand useful knowledge from the literature in Criminology and the different disciplines underlying it (e.g., [9, 17, 30, 33, 36], and on the other hand it exploits dedicated agent-based modelling techniques [9]. The aim is, by combining these, to develop an integrated computer-supported method to criminal behaviour analysis and management. The work reported here has been performed in close collaboration with a team of scientists from different disciplines, among whom outstanding criminologists and psychologists. They consider the approach explored here as having a high potential to develop support for both policy makers and practitioners in management of crime in society.

As part of this enterprise, agent-based dynamical models for different types of criminal behaviour are being developed. These models may incorporate behavioural agent models from an external perspective, as well as models for internal dynamics. Behaviour models from an external perspective may involve rather complex temporal relationships between (1) external factors in the criminal’s social context that occur as stimuli and (2) his or her actions, mediated by his or her characteristics. Models of internal dynamics usually can be expressed by direct temporal/causal relationships between stimuli and internal states, between different internal states, and between internal states and actions. The internal states may involve, for example, cognitive, decision, reasoning, normative/ethical, attentional, emotional, and personality aspects. In addition, they may involve underlying biological aspects such as specific types of brain deviations, levels of hormones or neurotransmitters. Example of aspects related to the wider social context are the observed level of social or organised security control, expectations about acceptance of certain actions within society or within a peer group, and social dynamics within groups. Such dynamical models are being collected in a model library. Moreover, relationships between such models are to be established, for example the fact that one model M₂ refines another model M₁, or that a model M₁ from an internal perspective generates the behaviour of a model M₂ from an external perspective.

As a first step in that direction, this paper presents one generic simulation model for the behaviour of violent criminals. As input, certain parameters can be set with respect to biological and cognitive characteristics of a type of criminal, and social and environmental aspects of its environment. As output, simulation traces are generated that show the behaviour over time of such a type of criminal under these circumstances.

In comparison to existing work in the analysis of criminal behaviour, an important distinction is that the agent-based modelling approach presented here focuses on the dynamical aspect of criminal behaviour. Most approaches to the analysis of criminal behaviour that have been proposed are basically static and usually based on profiling, i.e., they assume a number of fixed criminal profiles, whose behaviour depends in a deterministic way of certain personality characteristics, thereby ignoring the fact that these characteristics often are quite context-sensitive and may change over time; e.g., [1]. In contrast, the proposed approach (1) takes the dynamical systems perspective on behaviour as a point of departure, which considers behaviour as emerging from a dynamic interplay of various components and aspects, and (2) provides an integrated approach to model such complex dynamical systems incorporating biological, psychological and social aspects.

In this paper, Section 2 discusses three specific types of criminals used as a case study: the violent psychopath, someone with an antisocial personality disorder and someone diagnosed with an intermittent explosive disorder. In Section 3 the proposed
methodology is discussed. In Section 4 the simulation model is presented and in Section 5 the settings for the model are discussed. Section 6 discusses some of the simulation results. Section 7 presents the validation of the simulation model. Finally, Section 8 is a discussion about the approach and its possible applications.

2. Three Types of Violent Criminals

Criminals are found in a large variety of types. One classification is to divide criminals into violent offenders and non-violent offenders. The case study made in this paper is taken from the group of violent offenders.

When considering violent offenders different aspects need to be addressed that play an important role in their violent behaviour namely cognitive and behavioral aspects (such as low arousal, impulsiveness), socially related aspects (such as feeling guilt, remorse, having a theory of mind, empathy), and biological aspects (such as brain deviations, hormone levels, neurotransmitter levels).

When a closer look at the group of violent offenders is taken, a wide variety of types can be distinguished e.g. schizophrenics, serial killers, violent rapists, psychopaths. This paper focuses on three types of violent offenders for which these biological, cognitive and social aspects have extensively been studied in the literature: the violent psychopath, the offender with an antisocial personality disorder (APD), and the offender who suffers from an intermittent explosive disorder (IED) (e.g., [5], [14], [24], [25], [30], pp. 123-183, [32], [33], [37], pp. 193-207). In this section, these types of criminals are briefly introduced. Section 2.1 discusses the violent psychopath. In Section 2.2 the person with APD is described, and the person with IED is discussed in Section 2.3. Finally, in Section 2.4, these aspects are summarised and compared from a modelling perspective, i.e., some characteristics are introduced that are useful to consider when modelling criminal behaviour, and it is explained to what extent these characteristics hold for the three types of violent criminals.

2.1 The Violent Psychopath

Cognitive and Behavioural Aspects

Psychopaths do not show feelings like the rest of us. They lack the normal mechanisms of anxiety arousal, which ring alarm bells of fear in most people. Confronted with trial and danger, even their skin does not sweat and becomes clammy like the skin of normal people ([30], p.157, [33], pp. 159-165). Violent psychopaths, who are almost always males, can be described as predators and are usually proud of it. They lack the usual type of more impulsive aggressive behaviour, i.e., violence accompanied by an emotional discharge (usually anger of fear) and an excitement arousal (in the sympathetic nervous system). Instead, their kind of violence is similar to predatory aggression, that is accompanied by minimal or no sympathetic arousal and is planned, purposeful, and without emotion. This is correlated with a sense of superiority; they like to exert power and have unrestricted dominance over others, ignoring their needs and justifying the use of whatever they feel compelling to achieve their goals and avoid adverse consequences for their acts. As it happens with predators, psychopaths are capable of having extremely heightened attention in certain situations. An important trigger for psychopathic violent behaviour is the use of drugs and/or alcohol. They are more likely to turn to alcohol and drugs and their brain reacts in a different way to the
effects of drugs and alcohol. For a psychopath, using drugs or alcohol can become a compulsion and, through a genetic and neurological mechanism, result in violent behaviour ([30], p.201, [33], p.98).

Social Aspects
Psychopaths are characterised by a disregard for social obligation and a lack of concern for the feelings of others. They display pathological egocentricity, shallow emotions, lack of insight, poor control of beings and remorse, anxiety or guilt in relation to their antisocial behaviour. They are usually callous, manipulative individuals, incapable of lasting friendship and of love. They use charm, manipulation, intimidation and violence to control others and to satisfy their own selfish needs. Lacking in conscience and in feelings for others, they violate social norms and expectations without the slightest sense of guilt or regret ([30], p.150, [33], p.8).

Biological Aspects
Psychopaths have a specific deviation in the brain: the frontal lobes are disconnected from the limbic area. The frontal lobes are the area of the brain that is concerned with conscience, guilt and remorse and is the residence of our morality ([33], pp. 109-113). The limbic area generates feelings ([30], p.157, [33], p.115). Because of the disconnection, psychopaths cannot express their emotions in terms of feeling. They know the difference between right and wrong, but the difference does not matter to them. It is hard for a psychopath to understand or imagine the pain of other people ([30], p.158, [33], pp. 7-8). Furthermore, violent psychopaths have a high level of testosterone, which makes them more aggressive in their behaviour, and low levels of serotonin, which makes them easily bored, and stimulates them to seek sensation. Once they reach adulthood, their condition is incurable. However, only a fraction of psychopaths develops into violent criminals ([30], p. 267).

2.2 Antisocial Personality Disorder

Cognitive and Behavioural Aspects
Persons with an Antisocial Personality Disorder seem to have a cluster of traits that make them prone to show violent behaviour. They have a low emotional boiling point, which can lead to inappropriate and aggressive reactions to minor provocations. They are sparked into a violent act, losing control of themselves ([30], p.163). In contrast to the emptiness of feeling of the psychopath, someone with APD shows emotion in the form of an outburst or anger, but hardly emotions other than these.

APD types usually have abnormally low levels of arousal and they soon become habituated to stimuli and are often bored ([17], p.100, [30], pp. 74-80, 173-174, [33], pp. 222-224, [35], p.38). This explains how some of them can initiate violent acts: they are only stimulated when engaged in actions providing strong stimuli. Therefore, they often seek risk and use drugs in the search for stronger stimuli. Risk-seeking behaviour and substance abuse can be seen as attempts to escape feeling empty or emotionally void.
Social Aspects

Central to understanding individuals diagnosed with APD is that, in social context, they cannot experience emotions associated with either empathy or suffering of others. They tend to be more hostile, less affiliative, and have problems with moral understanding ([2], p.706, [30], p.178, [33], p.7, [35], p.40). The APD usually comes to attention because of a gross disparity between behaviour and the prevailing norms, and is characterised by at least: callous unconcern for the feelings of others; gross and persistent attitude of irresponsibility and disregard for social norms, rules and obligations; incapacity to maintain enduring relationships; very low tolerance to frustration in social contacts; a low threshold for discharge of aggression, including violence towards others; incapacity to experience guilt and to profit from experience, particularly punishment.

APD offenders have a serious lack of feelings of guilt and remorse in comparison to the non-violent population, but most of them are still capable of having feelings of guilt and remorse ([2], p.706, [30], p.164, [35], p.40). In line with what is stated above, this disorder is characterised by a long standing pattern of a disregard for other people’s rights, often even violating these rights. This pattern of behaviour usually has occurred since the age of 15, and consists of failure to conform to social norms, deceitfulness, impulsivity, irritability and aggressiveness, a reckless disregard, a consistent irresponsibility and often lack of remorse.

Biological Aspects

The aggressive behaviour of the violent APD offender is likely to be related to low serotonin levels and an inadequate control mechanism due to brain damage ([30], p.177, [33], p.85). Brain damage in the frontal lobes, the limbic system or both results in a brain deficient in the normal control systems – the brakes on behaviour are faulty. The violent APD offender has been shown to have this sort of abnormality. Although all criminals discussed in this paper have damage in the frontal or temporal lobes or in the limbic system in some combination ([30], p.180, [33], pp.109-115), within the person with APD in particular, the brain mechanism that generates feelings is connected to the frontal cortex (the area which is involved in learning from the consequences of our behaviour). This explains why the APD type is capable of remorse sometimes ([30], p.180, [33], pp.109-115).

The anxiety associated with certain types of Antisocial Personality Disorder may represent the limit of emotions experienced, or there may be physiological responses without analogy to emotions experienced by others.

Low levels of serotonin in the violent offender with APD do not produce aggression per se, but it increases the tendency to respond aggressively to provocation ([2], p.706, [30], p.177, [33], p.85, [35], p.40). Also the hormone of aggression is involved in the person with APD: (s)he has a high rate of testosterone, which is associated with a lack of inhibition, and more aggressiveness.

2.3 Intermittent Explosive Disorder

Cognitive and Behavioural Aspects

There is a class of violent offenders who are capable of acts just as savage as the psychopath’s but who nevertheless retain full ability to show remorse and regret. This
type of disorder is called Intermittent Explosive Disorder (IED) ([2], pp.663-667, [30], p.184). An Intermittent Explosive Disorder is a disorder of impulse control characterised by several episodes in which aggressive impulses are released and expressed in serious assault or destruction of property although no such impulsiveness or aggressiveness is shown between episodes.

Social Aspects

Offences by persons with IED are almost always associated with an unprompted outburst, a disproportionate reaction and consequent injury, usually to an acquaintance or family member. After the episode the offender has no recollection of his actions and has feelings of remorse.

Biological Aspects

What seems to be happening is that the brain itself generates a form of miniature epileptic fit. An electrical storm in the rage areas spreads to the rest of the brain. A defect in various areas of the limbic system can have a similar outcome; the affected patient has the sensation of feelings that occur in a vacuum – there is no reason or cause for them, but they have been generated internally by this glitch in the system. The mechanism for processing emotions has produced a rogue emotion of its own and it cannot control its own creation. This causes a sudden and inexplicable alteration in mood. It only takes a mild trigger to produce this abnormal electrical discharge, e.g. the meeting of someone with negative, provoking behaviour ([2], pp. 663-667, [30], p.187).

2.4 Comparison

When comparing the three types of violent offenders described above, it turns out that they can be distinguished by taking a number of basic characteristics into account (see Table 1 for an overview):

**Anxiety Threshold:** this is the threshold that needs to be passed by certain stimuli, in order to make a person anxious. Thus, when a person’s anxiety threshold is high, it is very difficult for this person to become anxious (and as a result, (s)he hardly knows any fear). This seems to be the case for the violent psychopath: in these persons, a notion of fear is almost completely not showing. In contrast, persons with APD and IED have a medium anxiety threshold. Nevertheless, in some special circumstances (i.e., during the short episodes of aggressiveness described above) the anxiety threshold of a person with IED suddenly becomes much higher.

**Excitement Threshold:** this is the threshold that needs to be passed by certain stimuli, in order to make a person excited. Thus, when a person’s excitement threshold is high, it is very difficult for this person to become excited (and as a result, (s)he is often bored). This is the case for the violent psychopath and for persons with APD. These persons are very hard to excite and are very often bored. This can be related to their low serotonin level (e.g., [32, 33]). Persons with IED have a medium excitement threshold. But under certain circumstances (during aggressive rage) their excitement threshold is low, and they get excited very easily.

**Theory of mind:** The notion of theory of mind (e.g., [4, 18, 27]) covers two concepts: 1) having the understanding that others (also) have minds, which can be described by different and separate mental concepts, such as the person’s own beliefs, desires, and intentions, and 2) being able to form theories as to how those mental
concepts such as the person’s own beliefs, desires, and intentions play a role in his or her behaviour. The violent psychopath has a limited theory of mind, which is however highly developed in a very specific sense. He or she can make the distinction between himself and another person, and is able to form theories about another person’s beliefs, desires and intentions, in particular, as far as this is of use to achieve his or her own goals, for example, by manipulating the other person, in case of self interest. A person with APD has a less developed theory of mind and is not able to make the distinction between him and someone else. Persons who are diagnosed with IED normally have a medium theory of mind and can make the distinction between themselves and others, but when they have an aggressive episode, their theory of mind decreases and they are not able to distinguish between themselves and others anymore.

**Positive and negative emotional attitude towards others:** these concepts express the extent to which a person may have positive or negative feelings with respect to other persons. For the violent psychopath, both attitudes are low: these persons hardly show any emotion concerning other persons, so for them, both the positive and the negative emotional attitude towards others is low. For the offender with APD, the situation is slightly different. Like the violent psychopaths, these persons do not have much positive feelings towards others, but they may have some negative feelings towards others. Finally, offenders with IED usually have a normal (medium) positive and negative emotional attitude towards others, but during the episodes of discontrol, all their positive feelings disappear, and quite substantial additional negative feelings arise.

**Aggressiveness:** since the case study focuses on violent offenders, by definition this considered type of criminal is aggressive, which can be related to a high level of testosterone; e.g., ([17], p.65, p.68, pp.83-85, p.112). However, the criminals with IED only become highly aggressive during a short period, whereas the other two types are always aggressive.

**Impulsiveness:** when someone acts impulsive, this means that the action was not planned. Many types of violent criminals are impulsive, but they differ in the type of impulsive action they perform. While the APD offender may lash out in disproportionate overreaction, the psychopath, with his emotional detachment, will impulsively take whatever course of action will supply him with the necessary gratification. ([26], ([30], p.176, [38]). Persons with IED normally have a medium impulsiveness but when they have a seizure they become highly impulsive.

**Sensitivity to alcohol:** Persons with brain deviations are more likely to turn to drinking and taking drugs. Moreover, their brains react in a different way to the effects of drugs and alcohol. For psychopaths and persons with APD, only a small amount of alcohol or drugs can become a compulsion and, through a genetic and neurological mechanism, result in violent behaviour. Persons with IED can have seizures triggered by the smallest amount of alcohol; a tiny stimulus may be all that is necessary to unleash the electrical storm in the emotional centre of the limbic system (e.g., [30], p.201, p.258).
Table 1. Overview of commonalities and differences in characteristics for the three types of violent criminals

<table>
<thead>
<tr>
<th></th>
<th>Anxiety threshold</th>
<th>Excitement threshold</th>
<th>Theory of mind (care)</th>
<th>Theory of mind (self interest)</th>
<th>Positive emotional attitude to others</th>
<th>Negative emotional attitude to others</th>
<th>Aggresiveness</th>
<th>Impulsiveness</th>
<th>Sensitive to alcohol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Violent Psychopath</td>
<td>high</td>
<td>high</td>
<td>high</td>
<td>low</td>
<td>low</td>
<td>low</td>
<td>high</td>
<td>high</td>
<td>yes</td>
</tr>
<tr>
<td>Antisocial Personality Disorder</td>
<td>medium</td>
<td>high</td>
<td>low</td>
<td>low</td>
<td>medium</td>
<td>high</td>
<td>high</td>
<td>high</td>
<td>yes</td>
</tr>
<tr>
<td>Intermittent Explosive Disorder</td>
<td>normally medium in episode: high</td>
<td>normally medium in episode: low</td>
<td>normally medium in episode: low</td>
<td>normally medium in episode: low</td>
<td>normally medium in episode: high</td>
<td>normally medium in episode: high</td>
<td>normally medium in episode: high</td>
<td>normally medium in episode: high</td>
<td>yes</td>
</tr>
</tbody>
</table>

3. Modelling Approach

The challenge is to model the biological, psychological and social aspects in an integrated manner. On the one hand, qualitative aspects have to be addressed, such as beliefs, desires, and intentions, certain brain deviations, and some aspects of the environment such as the presence of certain agents. On the other hand, quantitative aspects have to be addressed, such as testosterone and serotonin levels, and in the environment distances and time durations. Furthermore, it should be possible to model on a higher level of aggregation or abstraction, as it would not be feasible, for example, to model the brain anatomy at the level of neurons.

The modelling approach based on the modelling language LEADSTO [9] fulfils these desiderata. It is possible to use it to model at higher levels of aggregation, and it integrates qualitative, logical aspects and quantitative, numerical aspects; cf. [10]. This integration allows the modeller to exploit techniques from both areas. As the latter type of aspects are fully integrated in the former, methods for logical analysis can be exploited. Conversely, as the former type of aspects are fully integrated in the latter, a simulation environment is offered that extends the usual possibilities to simulate dynamical systems by numerical methods by incorporating qualitative elements.

The language LEADSTO enables to model direct temporal dependencies between two state properties in successive states by means of so-called dynamic properties, which are comparable to rules as occurring in specifications of a simulation model; for example:

\[
\text{If \quad in \ the \ current \ state, \ state \ property \ p \ holds,} \\
\text{then \quad in \ the \ next \ state, \ state \ property \ q \ holds}
\]

Here basic (atomic) state properties can have a qualitative, logical format, such as an expression \( \text{desire}(dt) \), expressing that desire \( dt \) occurs, or a quantitative, numerical format such as an expression \( \text{has value}(x, v) \) which expresses that variable \( x \) has value \( v \). Such atomic state properties can be combined to more complex state properties by taking conjunctions by means of the logical operator ‘and’.

To be more precise, the LEADSTO format is defined as follows. Let \( \alpha \) and \( \beta \) be state properties of the form ‘conjunction of ground atoms or negations of ground atoms’. In the leads to language the notation \( \alpha \rightarrow_{\text{e, i, g, h}} \beta \), means:

24
If state property $\alpha$ holds for a certain time interval with duration $g$,
then after some delay (between $e$ and $f$) state property $\beta$ will hold
for a certain time interval of length $h$.

For more details of the language LEADSTO, see [9].

4. The Integrated Simulation Model
In this section the simulation model that has been developed is described in more detail. In Appendix A, a complete overview of the model is given.

4.1 Global Structure of the Simulation Model
The integrated simulation model has been built by composing a number of submodels for different aspects, including (but not limited to) a model based on beliefs, desires and intentions (BDI) and a model for the environment. The BDI-model bases the preparation and performing of actions on cognitive state properties of type belief, desire and intention, and is described in Section 4.2. The BDI-model describes how desires can lead to intentions and how intentions can lead to actions, when the appropriate opportunities are there. It needs as input desires and beliefs in opportunities. For these elements additional models have been developed. More specifically, the integrated simulation model is composed of submodels for the biological, psychological and social/environmental aspects in the following manner:

1. a submodel for reasoning about beliefs, desires and intentions, based on the BDI-model (Section 4.2)
2. a submodel to determine desires needed as input for the BDI-model; this model incorporates various biological and psychological aspects and their interactions (Section 4.3)
3. a submodel to determine how observations lead to beliefs in an opportunity as needed as input for the BDI-model; this model is based on the Routine Activity Theory (Section 4.4)
4. a geographical model of the world; this is represented by a labeled graph of locations and connections (Section 4.5)
5. a submodel for the multi-agent society; this concerns generation of the actions for the different types of agents to let them move in the world and to determine the effects of all actions performed (Section 4.6).

Note that the biological and psychological aspects of the criminal are addressed in the submodels 1. and 2., the social and environmental aspects are addressed in submodels 4. and 5., and submodel 3. relates society aspects to psychological aspects.

4.2 Reasoning about Beliefs, Desires and Intention
Part of the model for criminal behaviour presented in Section 4 is inspired by the so-called BDI-model, a model that bases the preparation and performing of actions on beliefs, desires and intentions (e.g., [13, 21, 28, 34]). The BDI-model incorporates a pattern of reasoning to explain behaviour in a refined form. Instead of a process from desire to action in one step, as an intermediate stage first an intention is generated, and from the intention the action is generated. Thus the process is refined into a two-step
process. See Figure 1 for the generic structure of the BDI-model. In this figure, the box indicates the borders of the agent, the circles denote state properties, and the arrows indicate dynamic relationships. Note that the picture does not show issues like recovery from failure (re-planning), or multiple possible actions to fulfil a given desire, which are taken into account in the standard BDI-model.

![Figure 1 Structure of the Generic BDI-model](image)

In the BDI-model an action is performed when the subject has the intention to do this action and it has the belief that the opportunity to do the action is there. Beliefs are created on the basis of stimuli that are sensed or observed. The intention to do a specific type of action is created if there is a certain desire, and there is the belief that in the given world state, performing this action will fulfil this desire (this is the kind of rationality criterion discussed above; e.g., what is called means-end analysis is covered by this). As whether or not a given action is adequate to fulfill a given desire depends on the current world state, this belief may depend on other beliefs about the world state.

For the submodel to reason about beliefs, desires, and intentions presented in this paper, parts of the generic BDI-model have been reused. In particular, the following dependencies are used (shown in formal LEADSTO format), which correspond to some of the arrows in Figure 1:

\[
\text{desire}(d1) \land \text{belief}(\text{satisfies}(a1, d1)) \quad \rightarrow \quad \text{intention}(a1) \\
\text{intention}(a1) \land \text{belief}(\text{opportunity_exists_for}(a1)) \quad \rightarrow \quad \text{to_be_performed}(a1)
\]

Note that the beliefs used here both depend on observed stimuli, as shown in Figure 1. Furthermore, \(\land\) stands for the conjunction operator (and) between the atomic state properties (in the graphical format denoted by an arc connecting two (or more) arrows).

Often dynamic properties in LEADSTO are presented in semi-formal format, as follows:

26
At any point in time
if desire d1 is present
   and the belief that action a1 satisfies d1 is present
then the intention for action a1 will occur

At any point in time
if the intention for action a1 is present
   and the belief that there is an opportunity to perform a1 is present
then the action a1 will be performed

Within this BDI-based submodel, for reasons of simplicity, per desire only one action that can satisfy the desire is included (and one intention for that action). When a number of intentions are possible for one desire, then the model can be extended by a more specific decision making approach, such as utility-based multi-objective decision making, to rank the possible actions with respect to the degree in which they can fulfill the desire.

Assuming that beliefs in reason for intentions are internally available, what remains to be generated in this model are the desires and the beliefs in opportunities. For desires, there is no generic way (known) in which they are to be generated in the standard model. Actually, in many applications of the model it is assumed that certain desires are just there. In other cases, generation of desires depends on domain-specific knowledge, which also seems to be the case for criminal behaviour. In particular a number of biological aspects play a role here as well, such as certain brain deviations and levels of serotonin. This will be discussed in some further detail in Section 4.3. For beliefs in opportunities, they are strongly dependent on the (social) environment, which is the next theme discussed. The general pattern used is that an observation of a suitable target and the observation that no social control is present lead to the belief in an opportunity; in other words, the notion of opportunity is based on two of the three criteria as indicated in the Routine Activity Theory by [15] which is one of the most influential theories within Criminology to explain the occurrence of crime. The third criterion of the Routine Activity Theory, the presence of a motivated offender, is indicated by the intention in the BDI-model. This way, the presence of the three criteria together leads to the action to perform a criminal act, as indicated by [15].

4.3 The Submodel to Determine Desires

To determine desires a rather complex submodel is used incorporating, for example, biological dynamical system models for testosterone, serotonin, adrenalin, insulin and blood sugar levels over time. Also brain configuration aspects are incorporated in this submodel. These biological aspects are related to a number of psychological elements that are relevant for the generation of desires, such as levels of arousal, aggressiveness, impulsiveness, risk-taking, thrill-seeking, understanding others, and feeling for others. The biological and psychological aspects involved are of different types. On the one hand there are qualitative aspects, such as anatomical aspects concerning brain deviations (e.g., the absence of certain connections). On the other hand there are quantitative aspects, such as biochemical aspects concerning testosterone levels and serotonin levels. To model these, both causal and logical relations (as in qualitative modelling) and numerical relations (as in differential equations) have to be integrated in one modelling framework. This integration was accomplished, using the LEADSTO language as a modelling language.

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The variety of biological and psychological aspects that were found relevant in the literature (such as [5, 17, 30]) and are taken into account in this model, covers:

(a) the extent to which a theory of mind was developed (to understand others)
(b) dynamics of testosterone levels and aggressiveness
(c) dynamics of dealing with anxiety
(d) social-emotional attitudes with respect to others (e.g., feel pity for someone)
(e) stimuli assessment; excitement arousal and thrill seeking
(f) dynamics related to serotonin levels
(g) interactions of blood sugar, insulin and impulsiveness

For more details of how the model incorporates these aspects, see Figure 2 and Appendix A’. Different combinations of such elements lead to different types of (composed) desires, for example:

- the desire to perform an exciting planned nonaggressive nonrisky action that harms somebody else (e.g., a pick pocket action in a large crowd),
- the desire to perform a exciting impulsive aggressive risky action that harms somebody else (e.g., killing somebody in a violent manner in front of the police department)

The following LEASTDSTO rule generates a composed desire out of the different ingredients covered by (a) to (g) above:

**LP31**

A combination of values for theory of mind, aggressiveness, the desire to cope with anxiety, the desire to ignore anxiety, the desire for actions with strong stimuli, impulsiveness, emotional attitude towards others(pos) and emotional attitude towards others(neg) will lead to a specific composed desire, represented as “d(x₁, x₂, x₃, x₄, x₅, x₆, x₇, x₈)”.

∀x₁,x₂,x₃,x₄,x₅,x₆,x₇,x₈:SCALE

theory_of_mind(x₁) ∧ aggressiveness(x₂) ∧ desire_to_cope_with_anxiety(x₃) ∧ desire_to_ignore_anxiety (x₄) ∧ desire_for_actions_with_strong_stimuli(x₅) ∧ impulsiveness(x₆) ∧ emotional_attitude_towards_others(pos,x₇) ∧ emotional_attitude_towards_others(neg,x₈) → desire(d(x₁, x₂, x₃, x₄, x₅, x₆, x₇, x₈))

Note that, in the above and the following LEASTDSTO rules, the values for the timing parameters e, f, g, h (see Section 3) have been left out. In the presented simulations, for each of these rules the default parameter combination (0, 0, 1, 1) has been chosen. For future work, it is planned to investigate whether it is beneficial to use more realistic temporal parameter settings that correspond to the literature.

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* The relationship between psychological and biological states can be modelled more precisely, for example taking feedback loops into account. For a further elaboration of this, see [8].
Figure 2. Graphical Overview of the Simulation Model.
4.4 The Submodel to Determine Opportunities

In the use of the BDI-model to model criminal behaviour, the notion of opportunity is based on two of the three criteria as indicated in the Routine Activity Theory by [15]:

- a suitable target
- absence of a guardian

This was specified by the following local property in LEADSTO format:

LP41
When agent a1, who is a criminal, is at location l and he observes a passer by at location l and he does not observe a guardian at location l, then agent a1 believes that there is an opportunity to assault someone.

\[
\forall a_1, a_2: \text{AGENT} \quad \forall l: \text{LOCATION} \\
\text{observes}(a_1, \text{agent_of_type_at_location}(a_1, \text{criminal}, l)) \land \text{observes}(a_1, \text{agent_of_type_at_location}(a_2, \text{passer_by}, l)) \land \\
[ \forall a_3: \text{AGENT} \quad \text{not}\text{observes}(a_1, \text{agent_of_type_at_location}(a_3, \text{guardian}, l)) ] \implies \text{belief}\text{(opportunity\text{(assault))}}
\]

The third criterion of the Routine Activity Theory is the presence of a motivated offender. This part is covered in the model by the submodel to determine desires (see Section 4.3).

The generic rule to generate the action performance from the intention and the belief in the opportunity is specified within the BDI-submodel as:

LP33
The belief that there is an opportunity to perform a certain action combined with the intention to perform that action will lead to the performance of that action.

\[
\forall a: \text{ACTION} \quad \text{belief}(\text{opportunity}(a)) \land \text{intention}(a) \implies \text{to}_\text{be_performed}(a)
\]

In this dynamic property, the third criterion of the Routine Activity Theory, the motivated offender, is represented by the intention to perform some action. One step earlier, within the BDI-submodel, this intention is generated by a desire and a belief in a reason to go for the action to fulfill the desire, according to the following rule:

LP32
Desire \( d(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8) \) combined with the belief that a certain action will lead to the fulfillment of that desire will lead to the intention to perform that action.

\[
\forall x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8: \text{SCALE} \quad \forall a: \text{ACTION} \\
\text{desire}(d(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8)) \land \text{belief}(\text{satisfies}(a, d(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8))) \implies \text{intention}(a)
\]

4.5 The Geographical Environment Model

For the simulation presented in this paper, the social, multi-agent aspect is modelled by an environment, in which a number of agents move around and sometimes meet at the same location. Four types of agents are considered. One of the agents is the criminal agent that is analysed, the others are potential victims (passers-by) and guardian agents. The passers-by are assumed to be suitable targets, for example, because they look rich and/or weak. However, as also the guardians are moving around, such targets may be protected, whenever at the same location a guardian is observed by the criminal. This
models the aspect of social control. Finally, in some simulations also agents with provoking behaviour are present. This was done in order to ensure that they could trigger an aggressive episode in a criminal with Intermittent Explosive Disorder when (s)he encounters them. From now these types of agents are referred to as negative agents. In case a criminal agent with IED encounters such a negative agent, then part of the biological model is activated in order to ensure that the criminal enters an episode (see the left hand side of the model in Figure 2).

The interaction between a specific agent and the environment is modelled by (1) observation, which takes information about the environment as input for the agent (e.g., about at which location it is, where suitable targets are, and whether social control is present), and (2) initiating actions, which is an output of the agent affecting the state of the world (e.g., going to a different location).

The geographical information of the world in which the criminal and the guardians are active is described by a labeled graph as depicted in Figure 3. Here relevant locations are indicated by nodes A, B,..., and routes connecting locations by edges E1, E2,... Each time step, the agents move from location to location via these edges, by randomly selecting one of the edges that is connected to the current location. Edges have lengths related to them, so that travelling over them takes time, depending on these lengths. However, during travelling, agents cannot meet each other; encounters between agents only take place at the locations.

![Figure 3. Example World Geography](image)

4.6 The Submodel for the Dynamics of the Society

To model the dynamics of the agents moving around in the environment, a number of dynamic properties are used that relate successive states to each other. Roughly spoken the following cycle is used for each of the agents: observe, determine next action, determine effects of this action. In some more detail, the model is based on the following LEADSTO properties:
1. Properties expressing what is observed; for example, observing stimuli or other agents:

   At any point in time
   if another agent is present at the agent’s location,
   then the agent will observe this

2. Properties expressing which next action is to be undertaken; for example,

   At any point in time
   if the agent currently is at location l
   and it has stayed at this location for duration s,
   and location l is connected to edge e1, e2, and e3
   then it will move (randomly) to e1, e2, or e3

   Within the model, probabilities are used to make random choices between different options.

3. Properties expressing the effects of actions undertaken; for example,

   At any point in time
   if the agent starts to move to a next location over edge e
   and edge e has length d,
   then it will arrive at the next location after duration d

Also to model such properties the LEADSTO modelling language introduced in Section 3 was used.

A visualisation of the part of the model (in particular, the part dealing with biological/psychological aspects of the criminal) is provided in Figure 2. The circles denote state properties, and the arrows indicate local dynamic (LEADSTO) properties. Note that the characteristics to be set at beforehand and the inputs for the model over time together constitute all the circles in Figure 2 that have no incoming arrow (except the beliefs that lead to the belief that there is an opportunity; these are created on the basis of the social/environmental model, which is not shown in Figure 2). These inputs for the model are to be included in scenarios for simulation.

5. Settings for the Model

The model can be set with initial characteristics to tune it to a specific type of violent criminal: the violent psychopath, the person with APD or the person with IED. The idea is that, if the characteristics of a specific type of violent criminal are set as input, the model has to show the behaviour as known for this specific type of criminal as output. More specifically, the characteristics to be set at beforehand are as follows: testosterone level during pregnancy, basic adrenaline level, basic serotonin level, basic oxytocin level, brain configuration (for sensitivity to alcohol, anxiety threshold, excitement threshold and emotional attitude toward others) and beliefs about which action satisfies which desire. Inputs for the model over time are: stimuli (i.e., external events that have a certain impact on arousal, anxiety, ...), taking alcohol, taking Prozac, and taking Ritalin.

Finally, some characteristics of the environment have to be set at beforehand: presence of certain types of agents (criminals, guardians, passers-by) at certain locations.
Violent psychopath

For the trace discussed in the next section, the following initial state properties have been chosen for the violent psychopath: the testosterone level during pregnancy is high, the basic adrenalin level is medium (value 5), the basic level of serotonin is low (value 3) and the basic level of oxytocine is low. The brain is configured for the following characteristics: high theory of mind with respect to self interest, low theory of mind with respect to care, sensitivity for alcohol, a high anxiety threshold (value 8), a high excitement threshold (value 8), a low positive emotional attitude towards others and a low negative emotional attitude towards others. The psychopath has a belief that assaulting someone can be done in such a manner that this will lead to the fulfillment of a desire that is characterised by the following elements: high theory of mind with respect to self interest, low theory of mind with respect to care, high aggressiveness, a low desire to cope with anxiety, a low desire to ignore anxiety, a high desire for actions with strong stimuli, high impulsiveness, a low positive emotional attitude towards others and a low negative emotional attitude towards others.

In addition, some inputs for the model over time are provided. These inputs are as follows: initially there is a rather neutral stimulus present, which is not very dangerous nor exciting (both aspects have value 2), alcohol is used during the whole scenario, no Prozac is taken and no Ritalin is taken.

Finally, the initial characteristics of the environment are set as shown in Figure 3: the violent psychopath is at location A, there are guardians at location C and E, and there are passers-by at location F and G. There are no “negative agents” in this scenario.

Antisocial Personality Disorder

The following initial settings have been chosen for the person with an Antisocial Personality Disorder: the testosterone level during pregnancy is high, the basic adrenalin level is medium (value 5), the basic level of serotonin is low (value 3) and the basic level of oxytocine is low. The brain is configured for the following characteristics: low theory of mind with respect to self interest, low theory of mind with respect to care, sensitivity for alcohol, a medium anxiety threshold (value 5), a high excitement threshold (value 8), a low positive and a medium negative attitude towards others. The person with APD has a belief that assaulting someone will lead to the fulfillment of a desire that is characterised by the following elements: a low theory of mind (both for self interest as for care), high aggressiveness, a high desire to cope with anxiety, a low desire to ignore anxiety, a high desire for actions with strong stimuli, high impulsiveness, a low positive emotional attitude towards others and a medium negative emotional attitude towards others. The initial settings of the environment are identical to the environment used for the violent psychopath.

Intermittent Explosive Disorder

For the trace of the person diagnosed with IED, as discussed in the next section, the following initial state properties have been chosen: the level of testosterone during pregnancy was high, the basic adrenalin level is medium (value 5), the basic level of serotonin is low (value 3) and the basic level of oxytocine is low. The brain is configured for the following characteristics: medium theory of mind for self interest, medium theory of mind for care, sensitivity for alcohol, a medium anxiety threshold (value 5), a medium excitement threshold (value 5), both a medium positive and
negative emotional attitude towards others and this person is extra sensitive to negative events. The person with IED has a belief that assaulting someone can be done in such a manner that this will lead to the fulfillment of a desire that is characterized by the following elements: a low theory of mind (both for self interest as for care), high aggressiveness, a high desire to cope with anxiety, a low desire to ignore anxiety, a high desire for actions with strong stimuli, high impulsiveness, a low positive emotional attitude towards others and a high negative emotional attitude towards others.

The initial characteristics of the environment are identical to the characteristics used in the previous 2 scenarios (i.e., criminal at location A, guardians at location C and E, and passers-by at location F and G), with one difference: now, there are “negative agents” at location B and H.

6. Example Simulation Traces

A number of simulation traces have been generated for the behaviour of the three types of violent offenders under different circumstances. In this section, per offender one specific simulation trace is described in detail. In Section 6.1, the trace of the behaviour of the violent psychopath is described. Next, Section 6.2 addresses the simulation of the behaviour of someone with APD, and Section 6.3 discusses the simulation trace of someone diagnosed as having IED. In Section 6.4 the issue of validation of such simulation traces is addressed.

6.1 The Violent Psychopath

Figure 4 depicts the biological/psychological aspects of the behaviour of the violent psychopath agent within the example simulation trace, such as change of serotonin levels and the generation of beliefs, desires and intentions. In such pictures, time is on the horizontal axis, and the different state properties are on the vertical axis. A dark box on top of a line indicates that a state property is true at that time point. In Figure 4, the upper five lines contain the state properties that are relevant for the BDI-based model, i.e., beliefs, desires, intentions, and actions. The rest of the lines contain the state properties that address the biological and psychological aspects (in alphabetical order). The graph at the bottom of the picture displays the amount of environmental stimuli the violent psychopath experiences. Finally, the environmental aspects (such as the locations of the different agents in the world) are shown in Figure 5.

As can be seen in Figure 4, the initial settings mentioned earlier lead to the following characteristics in the psychopath criminal type agent: the insulin level is high, the anxiety threshold is high (value 10), the person is sensitive for alcohol, and his emotional attitude towards others, both positive and negative, is low. In addition, he has a low neural self. This leads to a low me-other differentiation, low empathy, and eventually, to a low theory of mind with respect to care. His high level of initial testosterone leads to a high current level of testosterone, which in turn leads to high aggressiveness. Moreover, the medium level of initial adrenaline leads to a medium current level of adrenaline (value 5). This current level of adrenaline, combined with a low level of oxytocine, leads to a low desire to cope with anxiety and a low desire to ignore anxiety. Furthermore, the low initial serotonin level (value 3) leads to a low current level of serotonin (also value 3). This current level of serotonin combined with sensitivity for alcohol and taking alcohol leads (at time point 2) to a decreased level of serotonin (value 0). The current serotonin level also leads to an increased excitement.
threshold (from value 10 to value 13). The high insulin level leads to a low blood sugar level and a high impulsiveness.

Figure 4. Example simulation trace: the biological/psychological aspects of the violent psychopath’s behaviour

When the excitement/psychological threshold is higher than the strength of the observed stimuli, then the violent psychopath will become bored. This leads to the desire for actions with strong stimuli at time point 4. As a result of this desire and several other characteristics mentioned above, the violent psychopath eventually (time point 5) develops a desire for an action that is characterised by the following aspects: a low theory of mind, high aggressiveness, a low desire to cope with anxiety, a low desire to ignore anxiety, a high desire for actions with strong stimuli, high impulsiveness, a low positive attitude towards others and a low negative attitude towards others. This desire, combined with
the belief that assaulting someone will lead to the satisfaction of such a desire, leads to
the intention to assault someone at time point 6.

In the meantime, the agent has started to move around in the world (see Figure 5). In
total, in this example trace, which was kept simple for reasons of presentation, there are
5 agents in the world: agent 1 is a criminal (i.e., the violent psychopath described in
Figure 4), agents 2 and 3 are guardians, and agents 4 and 5 are passers-by (i.e., potential
victims). These agents are moving through the world. For example, agent 1 starts at
location A (time point 0), then moves to location B (time point 4), and so on. Note that
the time that an agent takes to travel to a location depends on the length of the edge to
that location, and the duration that an agent stays at a location depends on the agent’s
personal preference (see local property LP41 in Appendix A). When a criminal meets a
passer-by without a guardian present then the criminal will believe that there is an
opportunity to assault the passer-by. As can be seen in Figure 5, there is an
opportunity to assault a passer-by at time point 15. This opportunity has arisen because
agent 1 is at location G and agent 5 is also at this location, and there are no guardians
present (agents 2 and 3 are respectively at location E and H). At time point 43 there is
another opportunity for agent 1 to assault someone. This is because agent 1 is at
location H together with agent 5, and agents 2 and 3 are not present.

When going back to Figure 4, one can see that the psychopath’s beliefs about
opportunities are also depicted there. When such a belief is present, together with the
intention to assault someone, the actual action to assault the passer-by is performed.
This happens twice in the trace: at time point 16 and 44.
Finally, note that, when a violent psychopath assaults someone, this significantly raises the amount of stimuli he experiences. The values of these stimuli are shown in the bottom part of Figure 4. When this value passes his excitement threshold, he will stop being bored. As a consequence, also his desire for actions with strong stimuli will be fulfilled, and his desire and intention for an action that is characterised by this desire (among others) will disappear. However, after a while, the increased value of the experienced stimuli will gradually decrease and the psychopath will be bored again. This will lead to new desires, new intentions, and eventually (at time point 44), to a new assault.

6.2 Antisocial Personality Disorder

The simulation trace of a person with APD is quite similar to the simulation trace of the violent psychopath. The reason for this is that the characteristics of both types of agents are very similar. The only differences are that the violent psychopath has a high theory of mind with respect to self interest while the person with APD has a low theory of mind for self interest; furthermore the psychopath has a low negative emotional attitude towards others while the person with APD has a medium negative emotional attitude towards others. Because the differences in the simulation traces are so small, the trace of the person with APD is not shown.

6.3 Intermittent Explosive Disorder

Figure 6 depicts the biological/psychological aspects of the behaviour of the IED agent within the example simulation trace. As shown by Figure 6, the IED criminal initially has a desire (represented as desire(medium, medium, high, low, low, high, high, medium, medium)) for actions that are characterised by the following elements: a medium theory of mind (for self interest as well as for care), high aggressiveness, a low desire to cope with anxiety, a low desire to ignore anxiety, a high desire for actions with strong stimuli, high impulsiveness and both a medium positive and negative emotional attitude towards others. However, at time point 10 the criminal is at location G, where he meets a negative agent (called agent 8, not shown in Figure 6). This causes an episode of aggressiveness, which leads to an increased anxiety and excitement threshold, a highly negative emotional attitude towards others, a decreased theory of mind, and a new composed desire (low theory of mind for self interest and care, high aggressiveness, low desire to cope with anxiety, low desire to ignore anxiety, high desire for actions with strong stimuli, high impulsiveness, low positive emotional attitude towards others and a high negative emotional attitude towards others). Notice that aggressiveness and impulsiveness already occurred in the previous desire, but now the brakes are no longer there: no concern for other persons or anxiety plays a role anymore. This desire, combined with the belief that performing an assault leads to the satisfaction of this desire, leads to the intention to assault someone. At time point 15, the IED criminal is again at location G, but now together with a passer by (agent 5) without a guardian present (agents 2 and 3 are respectively on location H and E). This leads to the belief that there is an opportunity to assault someone. This belief combined with the intention leads to the performance of the assault. Because of the assault, the stimuli of the world increase, which satisfies the desires of the criminal.

Although the simulation examples as presented here involve only 8 agents, it has been found that they easily scale to a society of several hundreds of agents (processing
time staying within one hour). However, the overall pattern for such larger numbers is not essentially different from the traces shown here.

**Figure 6.** Example simulation trace: the biological/psychological aspects of the behaviour of someone with IED
7. Validation of the Simulation Model

The simulation model has been made with the aim to formalise, in a computationally useful manner, the analysis of the criminal behaviour of the type as described based on the literature in Section 2. A main criterion for validation is whether the behaviour shown by the model indeed corresponds to behaviour of the types of offenders as described in Section 2. Here some aspects may need some more discussion. Two views on such behaviour are possible: an external view or an internal view. The external view abstracts from the internal functioning of the underlying biological and psychological systems, and describes how the circumstances an agent meets in the environment relate to certain actions of the agent. In contrast, the internal view addresses all details of the dynamics of the underlying biological and psychological systems. Validation can be done according to these two views.

Validation for the internal view needs empirical data for the different types of violent offenders in the process of committing a crime on all of the biological and psychological states as described: levels of adrenaline, blood sugar, arousal, et cetera. To obtain such empirical data in the process of committing a crime will be extremely difficult, if not impossible. On the other hand, in the literature as discussed in Section 2, a number of dynamical patterns for the internal view are described, based on research under different circumstances. If these descriptions are taken as a basis, then validation from the internal view is possible. The simulation results indeed show the dynamic patterns in the underlying mechanisms as described in Section 2. Concerning validation from the external view, the simulation results indeed show the behaviour as described in Section 2. In this sense the model has been validated positively.

However, notice that the validation as discussed is a relative validation, only with respect to the literature that forms the basis of Section 2, such as [17, 30, 33]. In cases that the available knowledge about the behaviour and biological, cognitive and social functioning of such a criminal type is improving, the validation of the model from the internal view and the model itself can be improved accordingly. The modelling approach as put forward supports such an incremental development and improvement. The simulation model has been specified in a conceptual, not implementation-dependent manner, and is easy to maintain. In this sense the approach anticipates further development of the research area of criminal behaviour.

8. Discussion

In this article, a method to analyse criminal behaviour based on integrated dynamic modelling is proposed. A generic model has been presented for the behaviour of violent criminals. As input certain parameters with respect to biological, cognitive and social aspects can be set. As output simulation traces are generated that show the behaviour of a violent offender over time under certain circumstances. As a case study, this method has been applied to analyse the behaviour of three types of violent criminals. It has been found that the model indeed shows the behaviour as known for these criminals. The model takes into account a cognitive modelling approach to the preparation of actions based on beliefs, desires and intentions (BDI) in a more or less standard manner (e.g., [28]). However, for this standard BDI-model, desires and beliefs about opportunities are required as input. Concerning the former, additional biological, cognitive, and emotional aspects have been used as a basis to generate desires. For the latter, additional social aspects have been used to generate beliefs on opportunities based on two specific
criteria (suitable target, presence of guardian) as indicated by the Routine Activity Theory in [15]. For the generation of desires various other aspects as found in the literature are taken into account, varying from specific types of brain deviations, and serotonin and testosterone levels, to the extent to which me-other differentiation and a theory of mind were developed.

Thus the model integrates biological, cognitive and socially related aspects in the process of desire generation, as extracted from literature, in particular [17, 30, 33]. These involve both qualitative aspects (such as the anatomy of brain deviations, and presence or absence of agents at a specific location in the world), and quantitative aspects (such as distances and time durations in the world and hormone ands neurotransmitter levels).

To achieve the integration of different aspects, the proposed modelling approach (based on the LEADSTO language) integrates qualitative, logical aspects and quantitative, numerical aspects. This integration allows to exploit techniques from both areas. As the latter type of aspects are fully integrated in the former, this results in a declarative specification for which automated methods for logical analysis can be exploited. Conversely, as the former type of aspects is fully integrated in the latter, a simulation environment is offered that extends the usual possibilities to simulate dynamical systems using numerical methods, by incorporating qualitative elements.

Only few papers on simulation of criminal behaviour can be found in the literature, and they usually address a more limited number of aspects than the modelling approach presented in this paper. For example, [12] discuss the possible use of agent modelling approaches to criminal behaviour in general, but do not report a specific model or case study. Moreover, in [3] a model is presented with emphasis on the social network and the perceived sanctions. However, this model leaves the psychological and biological aspects largely unaddressed. The same applies to the work reported in [29], where an emphasis is on the environment, and police organisation.

Within the literature of Agent-Based and Cognitive Modelling, a number of approaches have similarities with the approach presented in this paper. To start, the presented approach, and in particular the BDI-submodel, obviously has some similarities with the literature on which it was based, such as [13, 21, 34]. However, traditionally, within BDI-models no general model for generation of desires (or goals) is included. In many cases desires are just assumed to be there, or even communicated to the agent as goals it should adopt. This holds for the traditional BDI-based approaches mentioned above as well as for application-oriented frameworks based on BDI concepts, such as PRS [20]. Nevertheless, in recent years, extensions of BDI models are being developed in which this is the case, e.g., in Jadex [31]. One aspect that is addressed particularly there is the revision of desires as a result of undertaken actions that fulfill them. Another aspect relevant for desire generation is the biological substrate of the agent. Sometimes desires are just inherent to a certain biological makeup or state. The current paper takes a similar approach, namely to incorporate both biological and psychological factors into a submodel for generation of desires. Within the paper, a number of biological aspects as found in the literature have been taken into account in the dynamic generation of desires, varying from specific types of brain deviations, and serotonin and testosterone levels, to the extent to which a substrate for theory of mind was developed. Moreover, the generation of beliefs in opportunities has been based on environmental and social aspects involving two specific criteria (suitable target, presence of guardian) as indicated by the Routine Activity Theory in [15].

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Another novel approach in the literature that is worth comparing with our approach is the cognitive architecture CoJACK [19]. It is based on JACK, a Java-based Intelligent Agent Modelling Framework, and, like the approach presented in this paper, makes use of the BDI paradigm. Similar to our approach, CoJACK extends this paradigm with biological and psychological factors underlying behaviour. However, the intended applications of CoJACK are different: its main aim is the development of virtual agents within (military) simulation environments, whereas the current paper focuses on modelling the behaviour of violent criminals. As a result, the biological and psychological factors considered are different. For example, CoJACK addresses concepts such as fatigue and fear, whereas the current approach addresses concepts that are specific for criminal behaviour, such as aggressiveness and impulsiveness.

The current model forms a good basis for further development. It will not be difficult to take into account other or new useful literature on relevant (biological, cognitive, social) factors and their relationships as soon as it is made available. The model was kept simple in the generation of intentions for a given integrated desire: only one intention is possible per desire. When a number of intentions are possible for a given desire, then more specific decision making aspects come in the play, for example, involving utility-based (multi-objective) decision making; e.g., as described in [16], or sophisticated planning mechanisms as described in [29]. Also such approaches can easily be added to the model. In the current model, only few quantitative aspects have been incorporated, but this can be extended easily, as is shown, for example, in [6], where numerical adaptation techniques are part of the model. Also approaches as proposed in [22] can be incorporated.

In addition, the model may be extended with probabilistic notions. Although the presented version of the model incorporates only deterministic relationships, the latest version of LEADSTO (see [9]) enables the modeller to specify non-deterministic dependencies of the format \( \alpha \rightarrow \beta_1 \lor \beta_2 \), where different probabilities can be attached to the consequents \( \beta_1 \) and \( \beta_2 \). This may be a promising direction, for example, to model biological processes for which only knowledge exists about rough correlations, instead of well-established causal relations. A drawback is however that this approach forces the analyst to perform large numbers of simulations (as in Monte Carlo simulation) instead of just one. This direction will be further explored in future research.

The team of outstanding domain experts from psychology and criminology who have evaluated the work reported here, consider it as quite valuable and promising. In their view this work is a substantial step to obtain a solid basis to develop future applications to support policy makers and practitioners who have to handle the problem of crime in society. However, still there is quite some way to go. The problem of crime in society has substantial complexity and is a major challenge to be addressed. Therefore steps in this direction are to be considered with an appropriate extent of modesty. At this point in time ready-to-use applications are asked far too much, as much more work on research and development has to be invested, both in modelling and in the empirical area. For the empirical area systematic validation experiments to be set up are a challenge by themselves. For the modelling area, given the modest perspective as sketched, dynamical models for criminal behaviour of the types as discussed above can be useful in a number of ways. In the first place, as shown in the current paper, they can be used to simulate behaviour for given scenarios of circumstances occurring over time. This can be used to find out for such a given scenario of circumstances, whether a criminal of a certain type may show certain behaviour under these given circumstances. Moreover, as to be explored further in future work, such a model can be used in the
opposite direction, i.e., given a certain behaviour, to determine what kind of scenario of circumstances could lead to this behaviour. Some initial steps in this direction have been made in [7]. More generally, the model can be used in the situation that the circumstances and/or the behaviour are only partially given. In that case, the model can be used to complete this partial information, i.e., to find out which (completed) behaviour could be consistent (or inconsistent) with which (completed) circumstances, and to find out which additional information should be investigated to determine one or more completions of the partial information that are realistic [11]. Finally, such a model can be used for therapeutical reasoning. For example, it may be used to predict which behaviour a certain type of criminal will show if circumstances are avoided or slightly changed (what-if reasoning). Using this approach, the behaviour of the subject can be modified by selecting or avoiding the appropriate circumstances. Another possible use of such a model in therapeutical reasoning is to determine a (cognitive) training program for the criminal to adapt the relationship between circumstances and behaviour.

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**References**


Appendix A - Overview of the Simulation Model

All local properties (LP’s) that have been used for the simulation model are provided below in textual form, both in an informal notation and in a formal (LEADSTO) notation. Many of these properties are based on theories and experiments presented in the literature on criminal behaviour. Note that some of the formulae and their specific values (e.g., the value of 10 in LP15) have been estimated in order to get an effect as qualitatively described in the literature, rather than that they are known from this literature. However, if more biological knowledge becomes available, such values can be validated and, if needed, easily be incorporated in an improved form in the approach. In a similar manner, the model may be extended with probabilistic aspects, and more realistic timing parameters may be chosen.

The model is composed of the following submodels (see also Section 4.1):

1. a submodel to determine desires needed as input for the BDI-model; this model incorporates various physical and mental aspects and their interactions
2. a submodel for reasoning about beliefs, desires and intentions, based on the BDI-model
3. a submodel for the multi-agent society; this lets agents move in the world and determines the effects of actions performed.
4. a submodel to determine how observations lead to beliefs in an opportunity as needed as input for the BDI-model; this model is based on the Routine Activity Theory
5. a geographical model of the world; this is represented by a labeled graph of locations and connections

Each of these submodels is described by LEADSTO properties.

A.1 The Submodel to Determine Desires

This submodel covers many mental and physical elements, modelled by about 40 LEADSTO properties, which can be grouped according to the following aspects:

- Development of a Theory of Mind
- Interactions for Testosterone and Aggressiveness
- Dealing with Anxiety
- Social-Emotional Attitudes
- Stimuli Assessment
- Interactions involving Serotonin
- Interactions involving Blood Sugar, Insulin and Impulsiveness
- Development of Episodes

Development of a Theory of Mind

LP1

A certain level of testosterone during pregnancy will lead to the same level of inhibition in development of the thymus gland during pregnancy. In this property (and in many others), SCALE indicates the set {low, medium, high}.

∀x:SCALE
chemical_state(testosterone,during_pregnancy,x) → 0, 0, 1, 1
inhibition_in_development_of_thymus_gland_during_pregnancy(x)

LP2a
A high level of inhibition in development of the thymus gland during pregnancy leads
to a low developed thymus gland. In this property (and the two properties below), p stands for the duration of the pregnancy, and l stands for the life time of the person.
inhibition_in_development_of_thymus_gland_during_pregnancy(high) → 0, 0, p, l
developed_thymus_gland(low)

LP2b
A medium level of inhibition in development of the thymus gland during pregnancy
leads to a medium developed thymus gland.
inhibition_in_development_of_thymus_gland_during_pregnancy(medium) → 0, 0, p, l
developed_thymus_gland(medium)

LP2c
A low level of inhibition in development of the thymus gland during pregnancy leads
to a high developed thymus gland.
inhibition_in_development_of_thymus_gland_during_pregnancy(low) → 0, 0, p, l
developed_thymus_gland(high)

LP3
A certain level of development of the thymus gland leads to the same level of
development of a neural self.
∀ x : SCALE
developed_thymus_gland(x) → 0, 0, 1, 1 neural_self(x)

LP4
A certain level of development of the neural self leads to the same level of development
of the “me-other differentiation” (i.e., the ability to distinguish between the self and
others).
∀ x : SCALE
neural_self(x) → 0, 0, 1, 1 me_other_differentiation(x)

LP5
A certain level of me-other differentiation leads to the same level of empathy.
∀ x : SCALE
me_other_differentiation(x) → 0, 0, 1, 1 empathy(x)

LP6
A certain level of empathy combined with a brain that is configured for a theory of mind
with regard to care lead to the same level of theory of mind concerning other persons.
∀ x, y, z, s1 : SCALE ∀ x, y : INTEGER ∀ s1 : SIGN
empathy(z) ∧ brain_configuration(tom_self_interest(x), tom_care(y)),
emotional_attitude_towards_others(positive,x7), emotional_attitudes_towards_others(negative,x8),
anxiety_threshold(x), excitement_threshold(y), sensitivity_for_alcohol(s1)) → 0, 0, 1, 1 tom_care(x)

LP7
When the brain is configured for a theory of mind with regard to self interest of x, then
the theory of mind with regard to self interest is x.
∀ x, y, z, s1 : SCALE ∀ x, y : INTEGER ∀ s1 : SIGN

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\textbf{Interactions for Testosterone and Aggressiveness}

\textbf{LP8}
A certain testosterone level during pregnancy will lead to the same level of initial testosterone.
\[\forall x : \text{SCALE}\]
\[\text{chemical\_state(testosterone,during\_pregnancy,x)} \rightarrow_{0,0,1,1} \text{chemical\_state(testosterone,initial,x)}\]

\textbf{LP9a}
A certain initial testosterone level will lead to the same level of current testosterone. In this property, \(p\) stands for the duration of the initialisation phase (i.e., the period of pregnancy in this case), and \(l\) stands for the life time of the person.
\[\forall x : \text{SCALE}\]
\[\text{chemical\_state(testosterone,initial,x)} \rightarrow_{0,0,1,1} \text{chemical\_state(testosterone,current,x)}\]

\textbf{LP9b}
An episode increases the level of testosterone.
\[\text{chemical\_state(testosterone,\text{current,low}) \land episode} \rightarrow_{0,0,1,1} \text{chemical\_state(testosterone,\text{current,medium})}\]
\[\text{chemical\_state(testosterone,\text{current,medium}) \land episode} \rightarrow_{0,0,1,1} \text{chemical\_state(testosterone,\text{current,high})}\]

\textbf{LP10}
A certain level of current testosterone will lead to the same level of aggressiveness.
\[\forall x : \text{SCALE}\]
\[\text{chemical\_state(testosterone,\text{current},x)} \rightarrow_{0,0,1,1} \text{aggressiveness(x)}\]

\textbf{Dealing with Anxiety}

\textbf{LP11a}
When the brain is configured for an anxiety threshold of \(x\), and the person does not have an episode, then the anxiety threshold is \(x\).
\[\forall x,y : \text{INTEGER}\ \forall s_1 : \text{SIGN}\ \forall x_0, x_1, x_7, x_8 : \text{SCALE}\]
\[\text{brain\_configuration(tom\_selfinterest(x0), tom\_care(x1), emotional\_attitude\_towards\_others(pos,x7), emotional\_attitudes\_towards\_others(neg,x8), anxiety\_threshold(x), excitement\_threshold(y), sensitivity\_for\_alcohol(s1))} \land \text{not\_episode} \rightarrow_{0,0,1,1} \text{anxiety\_threshold(x)}\]

\textbf{LP11b}
When the brain is configured for an anxiety threshold of \(x\), and the person has an episode, then the anxiety threshold is \(x-4\).
\[\forall x,y : \text{INTEGER}\ \forall s_1 : \text{SIGN}\ \forall x_0, x_1, x_7, x_8 : \text{SCALE}\]
\[\text{brain\_configuration(tom\_selfinterest(x0), tom\_care(x1), emotional\_attitude\_towards\_others(pos,x7), emotional\_attitudes\_towards\_others(neg,x8), anxiety\_threshold(x), excitement\_threshold(y), sensitivity\_for\_alcohol(s1))} \land \text{episode} \rightarrow_{0,0,1,1} \text{anxiety\_threshold(x-4)}\]
When a stimulus with a higher level of danger than the anxiety threshold is observed, internal alarm bells will go off.

\[ \forall s_1, s_2, y: \text{INTEGER} \]
\[ \text{observes_stimulus}(s_1, s_2) \land \text{anxiety_threshold}(y) \land s_1 > y \rightarrow \text{0, 0, 1, 1, internal_alarm_bells} \]

LP13a
A current adrenalin level lower than 10 combined with internal alarm bells will increase the current adrenalin level by 1.

\[ \forall x: \text{INTEGER} \]
\[ \text{chemical_state(adrenalin, current, x)} \land x < 10 \land \text{internal_alarm_bells} \rightarrow \text{0, 0, 1, 1} \]
\[ \text{chemical_state(adrenalin, current, x + 1)} \]

LP13b
A current adrenalin level that is not influenced by internal alarm bells will remain the same.

\[ \forall x: \text{INTEGER} \]
\[ \text{chemical_state(adrenalin, current, x)} \land \text{not internal_alarm_bells} \rightarrow \text{0, 0, 1, 1} \]
\[ \text{chemical_state(adrenalin, current, x)} \]

LP14
A certain initial adrenalin level will lead to the same current adrenalin level. In this property, p stands for the duration of the pregnancy.

\[ \forall x: \text{INTEGER} \]
\[ \text{chemical_state(adrenalin, initial, x)} \rightarrow \text{0, 0, p, 1} \]
\[ \text{chemical_state(adrenalin, current, x)} \]

LP15
When you have an adrenalin level of 10, it will not increase further because 10 is the maximum.

\[ \text{chemical_state(adrenalin, 10)} \rightarrow \text{0, 0, 1, 1} \]
\[ \text{chemical_state(adrenalin, 10)} \]

LP16a
A current adrenalin level above 5, combined with a high oxytocine level will lead to the desire to ignore anxiety.

\[ \forall x: \text{INTEGER} \]
\[ \text{chemical_state(adrenalin, current, x)} \land x > 5 \land \text{chemical_state(oxytocine, high)} \rightarrow \text{0, 0, 1, 1} \]
\[ \text{desire_to_ignore_anxiety(high)} \]

LP16b
A current adrenalin level above 5, combined with a high oxytocine level will not lead to the desire to cope with anxiety.

\[ \forall x: \text{INTEGER} \]
\[ \text{chemical_state(adrenalin, current, x)} \land x > 5 \land \text{chemical_state(oxytocine, high)} \rightarrow \text{0, 0, 1, 1} \]
\[ \text{desire_to_cope_with_anxiety(low)} \]

LP16c
A current adrenalin level higher than 5 combined with a low oxytocine level will lead to the desire to cope with anxiety.

\[ \forall x: \text{INTEGER} \]
\[ \text{chemical_state(adrenalin, current, x)} \land x > 5 \land \text{chemical_state(oxytocine, low)} \rightarrow \text{0, 0, 1, 1} \]
\[ \text{desire_to_cope_with_anxiety(high)} \]
LP16d
A current adrenalin level higher than 5 combined with a low oxytocine level will not lead to the desire to ignore anxiety.
\[ \forall x \in \text{INTEGER}\]
\[ \text{chemical\_state(adrenalin, current, } x \text{) } \land \ x > 5 \land \text{chemical\_state(oxytocine,low)} \rightarrow \text{desire\_to\_ignore\_anxiety(low)} \]

LP16e
A current adrenalin level of 5 or lower will not lead to the desire to ignore anxiety.
\[ \forall x \in \text{INTEGER}\]
\[ \text{chemical\_state(adrenalin, current, } x \text{) } \land \ x \leq 5 \rightarrow \text{desire\_to\_ignore\_anxiety(low)} \]

LP16f
A current adrenalin level of 5 or lower will not lead to the desire to cope with anxiety.
\[ \forall x \in \text{INTEGER}\]
\[ \text{chemical\_state(adrenalin, current, } x \text{) } \land \ x \leq 5 \rightarrow \text{desire\_to\_cope\_with\_anxiety(low)} \]

Social-Emotional Attitudes

LP17a
When the brain is configured for a positive emotional attitude towards others of \( x_7 \), and the person does not have an episode, then the positive emotional attitude towards others is \( x_7 \).
\[ \forall x, y \in \text{INTEGER} \ \forall s_1 \in \text{SIGN} \ \forall x_0, x_1, x_7, x_8 \in \text{SCALE} \]
\[ \text{brain\_configuration(tom\_selfinterest}(x_0), \text{tom\_care}(x_1), \text{emotional\_attitude\_towards\_others}(\text{pos, } x_7), \text{emotional\_attitude\_towards\_others}(\text{neg, } x_8), \text{anxiety\_threshold}(x), \text{excitement\_threshold}(y), \text{sensitivity\_for\_alcohol}(s_1)) \land \text{not episode} \rightarrow \text{emotional\_attitude\_towards\_others}(\text{pos, } x_7) \]

LP17b
An episode decreases the positive emotional attitude towards others.
\[ \forall x, y \in \text{INTEGER} \ \forall s_1 \in \text{SIGN} \ \forall x_0, x_1, x_7, x_8 \in \text{SCALE} \]
\[ \text{brain\_configuration(tom\_selfinterest}(x_0), \text{tom\_care}(x_1), \text{emotional\_attitude\_towards\_others}(\text{pos, } x_7), \text{emotional\_attitude\_towards\_others}(\text{neg, } x_8), \text{anxiety\_threshold}(x), \text{excitement\_threshold}(y), \text{sensitivity\_for\_alcohol}(s_1)) \land \text{episode} \rightarrow \text{emotional\_attitude\_towards\_others}(\text{pos, low}) \]

LP18a
When the brain is configured for a negative emotional attitude towards others of \( x_8 \), and the person does not have an episode, then the negative emotional attitude towards others is \( x_8 \).
\[ \forall x, y \in \text{INTEGER} \ \forall s_1 \in \text{SIGN} \ \forall x_0, x_1, x_7, x_8 \in \text{SCALE} \]
\[ \text{brain\_configuration(tom\_selfinterest}(x_0), \text{tom\_care}(x_1), \text{emotional\_attitude\_towards\_others}(\text{pos, } x_7), \text{emotional\_attitude\_towards\_others}(\text{neg, } x_8), \text{anxiety\_threshold}(x), \text{excitement\_threshold}(y), \text{sensitivity\_for\_alcohol}(s_1)) \land \text{not episode} \rightarrow \text{emotional\_attitude\_towards\_others}(\text{neg, } x_8) \]

LP18b
An episode leads to a negative emotional attitude towards others.
\[ \forall x, y \in \text{INTEGER} \ \forall s_1 \in \text{SIGN} \ \forall x_0, x_1, x_7, x_8 \in \text{SCALE} \]
\textbf{Stimuli Assessment}

\textbf{LP19a}
When the brain is configured for an excitement threshold of \( y \), and there is a serotonin level of \( z \), and the person does not have an episode, then the excitement threshold becomes \( y + 5 - z \).
\[
\forall x, y, z: \text{INTEGER} \quad \forall s1: \text{SIGN} \quad \forall x0, x1, x7, x8: \text{SCALE}
\text{brain\_configuration}(\text{tom\_selfinterest}(x0), \text{tom\_care}(x1), \text{emotional\_attitude\_towards\_others}(\text{pos}, x7), \text{emotional\_attitude\_towards\_others}(\text{neg}, x8), \text{anxiety\_threshold}(x), \text{excitement\_threshold}(y), \text{sensitivity\_for\_alcohol}(s1)) \land \text{not\_episode} \longrightarrow_{b, 0, 1, 1} \text{emotional\_attitude\_towards\_others}(\text{neg}, \text{high})
\]

\textbf{LP19b}
When the brain is configured for an excitement threshold of \( y \), and there is a serotonin level of \( z \), and the person has an episode, then the excitement threshold becomes \( y + 5 - z \).
\[
\forall x, y, z: \text{INTEGER} \quad \forall s1: \text{SIGN} \quad \forall x0, x1, x7, x8: \text{SCALE}
\text{brain\_configuration}(\text{tom\_selfinterest}(x0), \text{tom\_care}(x1), \text{emotional\_attitude\_towards\_others}(\text{pos}, x7), \text{emotional\_attitude\_towards\_others}(\text{neg}, x8), \text{anxiety\_threshold}(x), \text{excitement\_threshold}(y), \text{sensitivity\_for\_alcohol}(s1)) \land \text{chemical\_state}(\text{serotonin}, z) \land \text{episode} \longrightarrow_{b, 0, 1, 1} \text{excitement\_threshold}(y + 3 - z)
\]

\textbf{LP20}
Ritalin will decrease the excitement threshold by 1.
\[
\forall y: \text{INTEGER}
\text{takes\_ritalin} \land \text{excitement\_threshold}(y) \longrightarrow_{b, 0, 1, 1} \text{excitement\_threshold}(y - 1)
\]

\textbf{LP21}
Observation of a stimulus with an excitement level that is lower than the excitement threshold will lead to boredom.
\[
\forall s1, s2, y: \text{INTEGER}
\text{observes\_stimulus}(s1, s2) \land \text{excitement\_threshold}(y) \land s2 < y \longrightarrow_{b, 0, 1, 1} \text{boredom}
\]

\textbf{LP22}
Boredom leads to a high desire for actions with strong stimuli.
\[
\text{boredom} \longrightarrow_{b, 0, 1, 1} \text{desire\_for\_actions\_with\_strong\_stimuli}(\text{high})
\]

\textit{Interactions Involving Serotonin}

\textbf{LP23a}
When the brain is configured for sensitivity for alcohol \( s1 \), and the person does not have an episode, then the sensitivity for alcohol is \( s1 \).
\[
\forall x, y: \text{INTEGER} \quad \forall s1: \text{SIGN} \quad \forall x0, x1, x7, x8: \text{SCALE}
\text{brain\_configuration}(\text{tom\_selfinterest}(x0), \text{tom\_care}(x1), \text{emotional\_attitude\_towards\_others}(\text{pos}, x7), \text{emotional\_attitude\_towards\_others}(\text{neg}, x8), \text{anxiety\_threshold}(x), \text{excitement\_threshold}(y), \text{sensitivity\_for\_alcohol}(s1)) \land \text{not\_episode} \longrightarrow_{b, 0, 1, 1} \text{sensitivity\_for\_alcohol}(s1)
\]
LP23b
An episode leads to a high sensitivity for alcohol.
∀x,y:INTEGER ∀s1:SIGN ∀x0,x1,x7,x8:SCALE
brain_configuration(tom_selfinterest(x0), tom_care(x1), emotional_attitude_towards_others(pos, x7), emotional_attitude_towards_others(neg, x8), anxiety_threshold(x), excitement_threshold(y), sensitivity_for_alcohol(s1)) ∧ episode  → 0, 0, 1, 1 sensitivity_for_alcohol(pos)

LP24
A certain initial serotonin level will lead to the same current serotonin level. In this property, p stands for the duration of the pregnancy.
∀x:INTEGER
chemical_state(serotonin, initial, x)  → 0, 0, p, 2 chemical_state(serotonin, current, x)

LP25a
A negative sensitivity for alcohol combined with no alcohol and no prozac will lead to the same serotonin level.
∀x:INTEGER
sensitivity_for_alcohol(neg) ∧ not drinks_alcohol ∧ chemical_state(serotonin, current, x) ∧ not takes_prozac  → 0, 0, 1, 1 chemical_state(serotonin, current, x)

LP25b
A negative sensitivity for alcohol combined with no alcohol and prozac will increase the serotonin level by 1.
∀x:INTEGER
sensitivity_for_alcohol(neg) ∧ not drinks_alcohol ∧ chemical_state(serotonin, current, x) ∧ takes_prozac ∧ x≥9  → 0, 0, 1, 1 chemical_state(serotonin, current, x+1)

LP25c
A negative sensitivity for alcohol combined with alcohol and no prozac will decrease the serotonin level by 1.
∀x:INTEGER
sensitivity_for_alcohol(neg) ∧ drinks_alcohol ∧ chemical_state(serotonin, current, x) ∧ not takes_prozac ∧ x≥9  → 0, 0, 1, 1 chemical_state(serotonin, current, x+1)

LP25d
A negative sensitivity for alcohol combined with alcohol and prozac will lead to the same serotonin level.
∀x:INTEGER
sensitivity_for_alcohol(neg) ∧ drinks_alcohol ∧ chemical_state(serotonin, current, x) ∧ takes_prozac  → 0, 0, 1, 1 chemical_state(serotonin, current, x)

LP25e
A positive sensitivity for alcohol combined with no alcohol and no prozac will lead to the same serotonin level.
∀x:INTEGER
sensitivity_for_alcohol(pos) ∧ not drinks_alcohol ∧ chemical_state(serotonin, current, x) ∧ not takes_prozac  → 0, 0, 1, 1 chemical_state(serotonin, current, x)

LP25f
A positive sensitivity for alcohol combined with alcohol and no prozac will decrease the serotonin level by 3.
∀x:INTEGER
sensitivity_for_alcohol(pos) \land \text{drinks\_alcohol} \land \text{chemical\_state(serotonin, current, x)} \land \text{not takes\_prozac} \land x \geq 3 \rightarrow_{0, 0, 1, 1} \text{chemical\_state(serotonin, current, x-3)}

\text{LP25g}
A positive sensitivity for alcohol combined with no alcohol and prozac will increase the serotonin level by 1.
\forall x:\text{INTEGER}
sensitivity_for_alcohol(pos) \land \text{not drinks\_alcohol} \land \text{chemical\_state(serotonin, current, x)} \land \text{takes\_prozac} \land x \leq 9 \rightarrow_{0, 0, 1, 1} \text{chemical\_state(serotonin, current, x+1)}

\text{LP25h}
A positive sensitivity for alcohol combined with alcohol and prozac will decrease the serotonin level by 2.
\forall x:\text{INTEGER}
sensitivity_for_alcohol(pos) \land \text{drinks\_alcohol} \land \text{chemical\_state(serotonin, current, x)} \land \text{takes\_prozac} \land x \geq 2 \rightarrow_{0, 0, 1, 1} \text{chemical\_state(serotonin, current, x-2)}

\text{LP26}
When you have a current serotonin level of 0, it will not decrease further because 0 is the minimum.
\text{chemical\_state(serotonin, current,0)} \rightarrow_{0, 0, 1, 1} \text{chemical\_state(serotonin, current, 0)}

\text{LP27}
When you have a current serotonin level of 10, it will not increase further because 10 is the maximum.
\text{chemical\_state(serotonin, current,10)} \rightarrow_{0, 0, 1, 1} \text{chemical\_state(serotonin, current, 10)}

\text{LP28}
A serotonin level lower than 5 leads to a high insulin level.
\forall x:\text{INTEGER}
\text{chemical\_state(serotonin, x)} \land x < 5 \rightarrow_{0, 0, 1, 1} \text{chemical\_state(insulin, high)}

\text{Interactions Between Blood Sugar, Insulin and Impulsiveness}

\text{LP29a}
A high insulin level leads to a decreased blood sugar level.
\text{chemical\_state(insulin, high)} \rightarrow_{0, 0, 1, 1} \text{chemical\_state(blood\_sugar, low)}

\text{LP29b}
A medium insulin level leads to a medium blood sugar level.
\text{chemical\_state(insulin, medium)} \rightarrow_{0, 0, 1, 1} \text{chemical\_state(blood\_sugar, medium)}

\text{LP29c}
A low insulin level leads to an increased blood sugar level.
\text{chemical\_state(insulin, low)} \rightarrow_{0, 0, 1, 1} \text{chemical\_state(blood\_sugar, high)}

\text{LP30a}
A low blood sugar level leads to high impulsiveness.
\text{chemical\_state(blood\_sugar, low)} \rightarrow_{0, 0, 1, 1} \text{impulsiveness(high)}
LP30b
A medium blood sugar level leads to medium impulsiveness.
chemical_state(blood_sugar, medium) \rightarrow_{0,0,1,1} impulsiveness(medium)

LP30c
A high blood sugar level leads to low impulsiveness.
chemical_state(blood_sugar, high) \rightarrow_{0,0,1,1} impulsiveness(low)

Development of episodes

LP31
When agent a1, who is a criminal, is at location l and observes a ‘negative’ agent at location l, then agent a1 will have an episode.
\forall a1,a2:\text{AGENT} \forall l:\text{LOCATION} 
\text{observes}(a1,\text{agent_of_type_at_location}(a1,\text{criminal},l)) \land \text{observes}(a1,\text{agent_of_type_at_location}(a2,\text{neg_agent},l)) 
\rightarrow_{0,0,1,1} \text{has\_episode}

Consequences of episodes

LP31a
An episode will lead to a decreased anxiety threshold for someone with IED.
\forall x,y:\text{INTEGER} \forall s1:\text{SIGN} \forall x0,x1,x6,x7:\text{SCALE} 
\text{brain\_configuration}(\text{tom\_selfinterest}(x0), \text{tom\_care}(x1), \text{emotional\_attitude\_towards\_others}(\text{pos},x6), \text{emotional\_attitude\_towards\_others}(\text{neg},x7), \text{anxiety\_threshold}(x), \text{excitement\_threshold}(y), \text{sensitivity\_for\_alcohol}(s1), \text{ied}(\text{pos})) \land \text{episode} 
\rightarrow_{0,0,1,1} \text{anxiety\_threshold}(x-4)

LP31b
A certain excitement threshold y combined with a current serotonin level of z and an episode will lead to an excitement threshold of y+3-z for someone diagnosed with IED.
\forall x,y,z:\text{INTEGER} \forall s1:\text{SIGN} \forall x0,x1,x6,x7:\text{SCALE} 
\text{brain\_configuration}(\text{tom\_selfinterest}(x0), \text{tom\_care}(x1), \text{emotional\_attitude\_towards\_others}(\text{pos},x6), \text{emotional\_attitude\_towards\_others}(\text{neg},x7), \text{anxiety\_threshold}(x), \text{excitement\_threshold}(y), \text{sensitivity\_for\_alcohol}(s1), \text{ied}(\text{pos})) \land \text{chemical\_state}(\text{serotonin, current, z}) \land \text{episode} 
\rightarrow_{0,0,1,1} \text{excitement\_threshold}(y+3-z)

LP31c
Someone diagnosed with IED is sensitive for alcohol during an episode.
\forall x,y:\text{INTEGER} \forall s1:\text{SIGN} \forall x0,x1,x6,x7:\text{SCALE} 
\text{brain\_configuration}(\text{tom\_selfinterest}(x0), \text{tom\_care}(x1), \text{emotional\_attitude\_towards\_others}(\text{pos},x6), \text{emotional\_attitude\_towards\_others}(\text{neg},x7), \text{anxiety\_threshold}(x), \text{excitement\_threshold}(y), \text{sensitivity\_for\_alcohol}(s1), \text{ied}(\text{pos})) \land \text{episode} 
\rightarrow_{0,0,1,1} \text{sensitivity\_for\_alcohol}(\text{pos})

LP31d
During an episode, someone with IED has a low positive emotional attitude towards others.
\forall x,y:\text{INTEGER} \forall s1:\text{SIGN} \forall x0,x1,x6,x7:\text{SCALE}
brain_configuration(tom_selfinterest(x0), tom_care(x1), emotional_attitude_towards_others(pos,x6), emotional_attitude_towards_others(neg,x7), anxiety_threshold(x), excitement_threshold(y), sensitivity_for_alcohol(s1), ied(pos)) \land episode 
\rightarrow 0,0,1,1 \emotional_attitude_towards_others(pos,low)

LP31e
During an episode, someone diagnosed with IED will have a high negative emotional attitude towards others.
\forall x,y:INTEGER \forall s1:SIGN \forall x0,x1,x6,x7:SCALE 
brain_configuration(tom_selfinterest(x0), tom_care(x1), emotional_attitude_towards_others(pos,x6), emotional_attitude_towards_others(neg,x7), anxiety_threshold(x), excitement_threshold(y), sensitivity_for_alcohol(s1), ied(pos)) \land episode 
\rightarrow 0,0,1,1 \emotional_attitude_towards_others(neg,high)

A.2 The BDI-Submodel

LP32
A combination of values for theory of mind for care and self interest, aggressiveness, the desire to cope with anxiety, the desire to ignore anxiety, the desire for actions with strong stimuli, impulsiveness, emotional attitude towards others(pos) and emotional attitude towards others(neg) will lead to a specific composed desire, represented as “d(x1, x2, x3, x4, x5, x6, x7, x8)”. 
\forall x0,x1,x2,x3,x4,\ldots,x8:SCALE 
tom_selfinterest(x0) \land tom_care(x1) \land aggressiveness(x2) \land desire_to_cope_with_anxiety(x3) \land desire_to忽略_anxiety(x4) \land desire_for_actions_with_strong_stimuli(x5) \land impulsiveness(x6) \land emotional_attitude_towards_others(pos,x7) \land emotional_attitude_towards_others(neg,x8) \rightarrow 0,0,1,1 
desire(d(x1, x2, x3, x4, x5, x6, x7, x8))

LP33
Desire d(x0, x1, x2, x3, x4, x5, x6, x7, x8) combined with the belief that a certain action will lead to the fulfillment of that desire will lead to the intention to perform that action. 
\forall x0,x1,x2,x3,x4,\ldots,x8:SCALE \forall a:ACTION 
desire(d(x0, x1, x2, x3, x4, x5, x6, x7, x8)) \land belief(satisfies(a, d(x0, x1, x2, x3, x4, x5, x6, x7, x8))) 
\rightarrow 0,0,1,1 intention(a)

LP34
The belief that there is an opportunity to perform a certain action combined with the intention to perform that action will lead to the performance of that action. 
\forall a:ACTION 
belief(opportunity(a)) \land intention(a) \rightarrow 0,0,1,1 performed(a)

A.3 The Submodel for the Society

LP35
When there is a certain stimulus for the excitement threshold and there is an assault, then the stimulus for the excitement threshold will increase by 25. 
\forall s1,s2:INTEGER 
stimulus(s1,s2) \land performed(assault) \rightarrow 0,0,1,1 stimulus(s1,s2+25)

54
LP36
When the stimulus for the excitement threshold is 1 or higher and there is no assault,
then the stimulus for the excitement threshold will decrease by 1.
\( \forall s_1,s_2:\text{INTEGER} \)
stimulus\((s_1,s_2) \land s_2=1 \land \text{not performed(assault)} \) \( \rightarrow \) \(0,0,1,1\) stimulus\((s_1,s_2-1)\)

LP37
When the stimulus for the excitement threshold is 0 and there is no assault, then the
stimulus for the excitement threshold stays 0.
\( \forall s_1:\text{INTEGER} \)
stimulus\((s_1,0) \land \text{not performed(assault)} \) \( \rightarrow \) \(0,0,1,1\) stimulus\((s_1,0)\)

LP38
Each stimulus is observed.
\( \forall s_1,s_2:\text{INTEGER} \)
stimulus\((s_1,s_2) \) \( \rightarrow \) \(0,0,1,1\) observes\_stimulus\((s_1,s_2)\)

LP39
When agent \( a_1 \) is at location \( l \) and agent \( a_2 \) is also at location \( l \) and agent \( a_2 \) is of type \( t \)
then agent \( a_1 \) observes agent \( a_2 \) (of type \( t \)) at location \( l \).
\( \forall a_1,a_2:\text{AGENT} \land l:\text{LOCATION} \land t:\text{TYPE} \)
is\_at\_location\((a_1,l) \land is\_at\_location\((a_2,l) \land is\_of\_type\((a_2,t)\) \( \rightarrow \) \(0,0,1,1\)
observes\((a_1,agent\_of\_type\_at\_location\((a_2,t,l)\))\)

LP40a
If agent \( a \) is at a location \( l \), which is connected to two edges, \( e_1 \) and \( e_2 \), then agent \( a \) goes
to one of these edges (with a probability of 50% for each edge).
\( \forall a:\text{AGENT} \land t:\text{TYPE} \land l_1,l_2,l_3:\text{LOCATION} \land e_1,e_2:\text{INTEGER} \)
observes\((a,agent\_of\_type\_at\_location\((a,t,l_1) \land \text{neighbours\((l_1,l_2) \land \text{connected\_to\_via\((l_1,l_2,edge\((e_1)\))\) \land \text{performed\((a,go\_to\_location\_via\_edge\((l_2,edge\((e_1)\)))\) \lor \text{performed\((a,go\_to\_location\_via\_edge\((l_3,edge\((e_2)\)))\))}\)}\)

LP40b
If agent \( a \) is at a location \( l \), which is connected to three edges, \( e_1, e_2 \) and \( e_3 \), then agent \( a \) goes
to one of these edges (with a probability of 33% for each edge).
\( \forall a:\text{AGENT} \land t:\text{TYPE} \land l_1,l_2,l_3,l_4:\text{LOCATION} \land e_1,e_2,e_3:\text{INTEGER} \)
observes\((a,agent\_of\_type\_at\_location\((a,t,l_1) \land \text{neighbours\((l_1,l_3) \land \text{connected\_to\_via\((l_1,l_3,edge\((e_1)\))\) \land \text{performed\((a,go\_to\_location\_via\_edge\((l_2,edge\((e_1)\)))\) \lor \text{performed\((a,go\_to\_location\_via\_edge\((l_3,edge\((e_2)\)))\) \lor \text{performed\((a,go\_to\_location\_via\_edge\((l_4,edge\((e_3)\)))\))}\)}\)

LP41
When agent \( a \) goes to location \( l \) via edge \( e \), and edge \( e \) has length \( d \), and agent \( a \) has the
tendency to stay at a location for \( s \) time units, then after a delay of duration \( d \), agent \( a \) is
at location \( l \) for the next \( s \) time units.
\( \forall a:\text{AGENT} \land l:\text{LOCATION} \land e,d,s:\text{INTEGER} \)
performed\((a,go\_to\_location\_via\_edge\((l,edge\((e)\))) \land has\_length\((edge\((e),d) \land stays\((a,s) \) \( \rightarrow \) \(d,d,s,s\)
is\_at\_location\((a,l)\))\)
A.4 The Submodel to Determine Opportunities

LP42
When agent \(a_1\), who is a criminal, is at location \(l\) and observes a passer by at location \(l\) and does not observe a guardian at location \(l\), then agent \(a_1\) believes that there is an opportunity to assault someone.
\[\forall a_1, a_2 : \text{AGENT} \quad \forall l : \text{LOCATION} \quad \text{observes}(a_1, \text{agent_of_type_at_location}(a_1, \text{criminal}, l)) \land \text{observes}(a_1, \text{agent_of_type_at_location}(a_2, \text{passer_by}, l)) \land (\forall a_3 : \text{AGENT} \quad \text{not observes}(a_1, \text{agent_of_type_at_location}(a_3, \text{guardian}, l)) \Rightarrow 0, a, 1, 1) \quad \text{belief}(\text{opportunity}(\text{assault}))\]

A.5 The Geographical Environment Model

To model the geographical environment, the following kinds of facts about agent characteristics and the configuration of the world were used:

\begin{align*}
\text{is_at_location}(\text{agent1}, 'A') \\
\text{is_at_location}(\text{agent2}, 'C') \\
\text{is_at_location}(\text{agent3}, 'E') \\
\text{is_at_location}(\text{agent4}, 'F') \\
\text{is_at_location}(\text{agent5}, 'G') \\
\text{is_at_location}(\text{agent6}, 'B') \\
\text{is_at_location}(\text{agent7}, 'H') \\
\text{is_at_location}(\text{agent8}, 'D') \\
\text{is_of_type}(\text{agent1}, \text{criminal}) \\
\text{is_of_type}(\text{agent2}, \text{guardian}) \\
\text{is_of_type}(\text{agent3}, \text{guardian}) \\
\text{is_of_type}(\text{agent4}, \text{passer_by}) \\
\text{is_of_type}(\text{agent5}, \text{passer_by}) \\
\text{is_of_type}(\text{agent6}, \text{passer_by}) \\
\text{is_of_type}(\text{agent7}, \text{neg_agent}) \\
\text{is_of_type}(\text{agent8}, \text{neg_agent}) \\
\text{stays}(\text{agent1}, 1) \\
\text{stays}(\text{agent2}, 3) \\
\text{stays}(\text{agent3}, 3) \\
\text{stays}(\text{agent4}, 2) \\
\text{stays}(\text{agent5}, 2) \\
\text{stays}(\text{agent6}, 2) \\
\text{stays}(\text{agent7}, 2) \\
\text{stays}(\text{agent8}, 2) \\
\text{neighbours}(A', 2) \\
\text{neighbours}(B', 2) \\
\text{neighbours}(C', 3) \\
\text{neighbours}(D', 3) \\
\text{neighbours}(E', 2) \\
\text{neighbours}(F', 2) \\
\text{neighbours}(G', 3) \\
\text{neighbours}(H', 3) \\
\text{connected_to_via}(A', B', \text{edge}(1)) \\
\text{connected_to_via}(B', A', \text{edge}(1)) \\
\text{connected_to_via}(B', C', \text{edge}(2)) \\
\text{connected_to_via}(C', B', \text{edge}(2)) \\
\text{connected_to_via}(C', D', \text{edge}(3)) \\
\text{connected_to_via}(D', C', \text{edge}(3)) \\
\text{connected_to_via}(D', E', \text{edge}(4)) \\
\text{connected_to_via}(E', D', \text{edge}(4)) \\
\text{connected_to_via}(E', F', \text{edge}(5))
\end{align*}
connected_to_via(F, 'E', edge(5))
connected_to_via(A, 'G', edge(6))
connected_to_via(G, 'A', edge(6))
connected_to_via(G, 'H', edge(7))
connected_to_via(F, 'G', edge(7))
connected_to_via(F, 'H', edge(8))
connected_to_via(G, 'C', edge(9))
connected_to_via(C, 'G', edge(9))
connected_to_via(H, 'D', edge(10))
connected_to_via(D, 'H', edge(10))

has_length(edge(1), 1)
has_length(edge(2), 1)
has_length(edge(3), 1)
has_length(edge(4), 1)
has_length(edge(5), 1)
has_length(edge(6), 2)
has_length(edge(7), 2)
has_length(edge(8), 2)
has_length(edge(9), 1)
has_length(edge(10), 1)
Agent-Based Simulation of Episodic Criminal Behaviour

Tibor Bosse, Charlotte Gerritsen, and Jan Treur

Abstract. Criminal behaviour often involves a combination of physical, mental, social and environmental (multi-)agent aspects, such as neurological deviations, hormones, arousal, (non)empathy, targets and social control. To study the dynamics of these aspects, this paper contributes a dynamical agent-based approach for analysis and simulation of criminal behaviour. It involves dynamically generated desires and beliefs in opportunities within the social environment, both based on literature on criminal behaviour. The approach is illustrated for the case of an Intermittent Explosive Disorder.

1. Introduction

Within Criminology the analysis of criminal behaviour addresses physical, mental, environmental and social aspects; e.g., [5, 15, 24, 27, 32]. Only few contributions to the literature address formalisation and computational modelling of criminal behaviour, usually focussing only on some of the factors involved; e.g., [3, 22, 23]. This paper is part of a large interdisciplinary research project (involving parties from computer science, criminology, psychology and social science) that has as main goal to develop a modelling approach for criminal behaviour, which integrates physical, mental, environmental and social aspects. To this end, in this research project the standard BDI-model for action preparation based on motivations [14, 28] is taken as a basis and is extended by specific models for generation of desires and for generations of beliefs in opportunities. These extensions are based on available literature on criminal behaviour and the underlying aspects. For the generation of desires, dynamical models were incorporated involving internal states, for example, for neurological, hormonal, and emotional aspects and their interaction; e.g., [24, 27]. For the generation of beliefs in opportunities, a model was incorporated formalising the well-known Routine Activity Theory within Criminology; e.g., [15]. This (informal) theory assumes motivation of the criminal and covers environmental and social aspects such as the presence of targets and social control.

The overall modelling approach for criminal behaviour involves models at two different levels. At the level of single agents, the decisions of individuals and the underlying biological and psychological aspects are addressed. At the level of the multi-agent system, the impact of such decisions on the society as a whole are addressed. The current article focuses on the latter aspect, i.e., it presents an approach to study the dynamics of a group of agents given certain assumptions about the behaviour of individuals and characteristics of the environment. For example, it aims to answer questions such as “how are crime rates influenced by the size of a city?”, or “how are crime rates influenced by the amount of police?”. Since they involve the interaction of different types of agents over time and space, such questions are usually not easy to answer analytically. Therefore, the current paper presents an approach to explore the dynamics of crime via simulation and formal techniques. As such, the main users of the approach are considered to be social scientists and researchers in applications of
modelling in criminology. However, in case it leads to interesting results, these results may also be presented to policy makers.

Since this article focuses on the social aspects of crime, the description at the level of the individual agents is kept abstract; these behaviours are modelled in terms of simple input-output relationships. However, more information about the underlying biological/psychological models in the context of the research project as a whole can be found in [6], and the way that these models are connected to the BDI-model is explained in [7].

To address the type of questions given above, an artificial society has been modelled, where on a map (represented by a labeled graph) agents move around and meet each other. Agents may be of four types: potential criminal, agent with negative appearance, potential victim, and guardian*. The models for the agents and their environment have been formally specified in dynamical systems style [2, 26] by executable temporal/ causal logical relationships, extended by probabilities. To obtain these, knowledge from the literature in Criminology, and the different disciplines underlying it, was exploited; e.g., [17, 24, 27, 32].

Although the model is generic, the current paper focuses on a specific type of crimes, namely those that are performed by persons with Intermittent Explosive Disorder (IED), a disorder of impulse control, characterised by short episodes of aggression. This is an interesting case study, because these types of crimes on the one hand have a biological background (the presence of the disorder highly increases the probability of these persons to perform certain assaults), but on the other hand involve a social aspect (the episodes of aggression are usually triggered by encounters with other people).

The challenge is to model the variety of physical, mental and social aspects as mentioned above in an integrated manner. On the one hand, qualitative aspects have to be addressed, such as epistemic and motivational states, certain brain deviations, and some aspects of the environment such as the presence of certain agents. On the other hand, quantitative aspects have to be addressed, such as testosterone and serotonin levels, and (in the environment) distances and time durations. Furthermore, it should be possible to model on a higher level of aggregation or abstraction, as it would not be feasible, for example, to model the brain anatomy at the level of neurons. The modelling language LEADSTO [9] fulfils these desiderata. It allows to model at higher levels of aggregation, and it integrates qualitative, logical aspects and quantitative, numerical aspects; cf. [11]. In LEADSTO direct temporal dependencies between two state properties in successive states are modelled by executable dynamic properties. The format is briefly defined as follows. Let α and β be state properties of the form ‘conjunction of ground atoms or negations of ground atoms’. In the LEADSTO language the notation α →→ e. t. g. h. β, means:

If state property α holds for a certain time interval with duration g, then after some delay (between e and f) state property β will hold for a certain time interval of length h.

Here atomic state properties can have a qualitative, logical format, such as an expression desire(d), expressing that desire d occurs, or a quantitative, numerical format

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* For simplicity, it is assumed that every agent belongs to one of the four types. Although clearly an over-simplification of reality (e.g., a potential criminal may also be a victim, and a potential victim may also act as a guardian), this assumption considerably reduces the complexity of the model and its analysis.
such as an expression has_value(x, v) which expresses that variable x has value v. For more details of the language LEADSTO, see [9].

Section 2 discusses a summary from the literature on criminals with Intermittent Explosive Disorder. In Section 3 the simulation model is presented, and Section 4 discusses the results of the simulations by referring to an example simulation trace. Section 5 presents a number of global dynamic properties of the society and their logical formalisation and discusses automated verification of the simulation results against them. Section 6 discusses a probability-based analysis of similar properties, also automatically verified on a set of generated traces. Finally, Section 7 discusses related work, and Section 8 is a concluding discussion about the approach.

2. Case Study: a Criminal with IED

An Intermittent Explosive Disorder (IED) is a disorder of impulse control, characterised by several episodes (usually of 10 to 20 minutes each) in which aggressive impulses are released and expressed in serious assault or destruction of property, although no such impulsiveness or aggressiveness is shown in the periods (usually weeks or months) between episodes. To evoke such episodes, often only a minor stimulus is sufficient, such as an encounter with someone that has a negative, provoking, appearance or behaviour. It is estimated that about 7% of the adult population in the US can be diagnosed as having IED. Offences by persons with IED concern a disproportionate reaction, usually to an acquaintance or family member. After the episode the offender has no recollection of his actions and, when informed, has feelings of remorse [24]. The following sketch illustrates the interplay of the physical, mental and social aspects involved. Suppose the criminal meets somebody with negative, provoking behaviour (social aspect). This is interpreted by the criminal (mental aspect), provokes stress, and leads to an episode with an epileptic state of the brain (neurological, physical aspect). This state leads to changes in hormonal (physical) and emotional (mental) states, which lead to a certain type of desire, providing the motivation for some criminal action (mental aspect). As soon as an opportunity of a suitable potential victim with not much social control (social aspect) is perceived (mental aspect), the desire leads to the criminal action.

The scenario described above on the one hand involves epistemic and motivational concepts (e.g., the desire to act aggressively, and the belief that certain actions can fulfil this desire), but on the other hand biological concepts (e.g., disorders in the limbic system and high levels of testosterone [24]). In order to integrate these notions within one agent-based model, the standard BDI-model for rational reasoning (e.g., [14, 28]) has been extended by a model that generates desires based on underlying biological and psychological factors. Some of these factors, which are particularly important to model the behaviour of a person with IED, are impulsiveness, aggressiveness, emotional attitudes towards others, tendencies to become anxious or excited, and capabilities to understand the mental states of others.

In order to convert these elements into complex desires, the physiological makeup of each agent has been modelled via a number of numerical parameters (e.g., level of testosterone, serotonin, and so on). These parameters, and the relations between them, were identified in collaboration with domain experts. The model has been designed in such a way that combinations of these parameters result in an assignment of values to the characteristics mentioned above (e.g., aggressiveness, impulsiveness), on a qualitative scale. Eventually, these characteristics are combined into composed desires,
which play the role of regular desires in a BDI-model. This model (as well as a
discussion about its validation) is described in detail in [6], and its integration within the
BDI-model is described in [7]. The remainder of this paper assumes these models as
given, and focuses on the social/environmental aspect of criminal behaviour by IED
patients. To this end, in this paper the model to generate complex desires is simply
represented in terms of a (probabilistic) input-output relationship, i.e., a relationship
between incoming stimuli and the desires of the person.

3. The Simulation Model

In this section the overall simulation model as developed is described in more detail.
The combination of physical, mental and social aspects involved requires integration of
models for internal physical and mental functioning of an agent with a model at the
social level. To this end, as mentioned earlier, the simulation model has been composed
from submodels, integrating different aspects, including (but not limited to) a decision
making model based on beliefs, desires and intentions (BDI) and a model for the social
environment. The BDI-submodel describes how actions relate to desires and intentions,
when appropriate opportunities are there. It needs as input desires and beliefs in
opportunities. For these elements additional models have been developed. Thus the
simulation model is composed of four submodels:

1. a submodel for reasoning about beliefs, desires and intentions (BDI-model)
2. a submodel to determine desires needed as input for the BDI-model
3. a (small) submodel to determine how observations lead to beliefs in an opportunity as
   needed as input for the BDI-model; this model is based on the Routine Activity Theory
4. a submodel for the society; this model has two aspects namely, a geographical aspect;
   this is represented by a labeled graph of locations and connections and a multi-agent
   societal aspect; this lets agents move in the world and determines the effects of actions
   performed.

Note that submodels 1. and 2. address physical and mental aspects, submodel 4.
addresses social and environmental aspects, and submodel 3. relates society aspects to
mental aspects.

Overview of the Simulation Model: Graphical Form

A visualisation of the simulation model is provided in Figure 1. In this picture, the
circles denote state properties, and the arrows indicate causal relationships, which can
be represented by local dynamic (LEADSTO) properties (LP’s). An arc connecting
multiple lines indicates that the conjunction of multiple state properties influences
another state property. The dotted box indicates the borders of the agent: all circles that
are depicted inside the box are internal state properties, all circles depicted outside the
box are external world state properties, and all circles depicted at the left (right) border
of the box are input (output) state properties. The solid boxes indicate submodels
(which are not further worked out in the current paper).

The BDI-submodel

The BDI-submodel bases preparation and performance of actions on beliefs, desires and
intentions, e.g. [14, 28]: an action is performed when the subject has the intention to do
this action and it has the belief that the opportunity to do the action is there. Beliefs are
created on the basis of stimuli that are observed. The intention to do a specific type of
action is created if there is a certain desire, and there is the belief that in the given world state, performing this action will fulfil this desire. The generic rule to generate the action performance from the intention and the belief in the opportunity is specified within the BDI-submodel as:

**LP33**  The belief that there is an opportunity to perform a certain action combined with the intention to perform that action will lead to the performance of that action.

\[ \forall a : \text{ACTION} \quad \text{belief}(\text{opportunity}(a)) \land \text{intention}(a) \rightarrow \text{performed}(a) \]

The effects of actions (e.g., the decrease of stimuli) are modelled in the submodel for the society. For simplicity, we assume that actions always succeed. The intention is generated by a desire and a belief in a good reason, according to the following rule:

**LP32**  Desire \( d \) combined with the belief that a certain action will lead to the fulfilment of that desire will lead to the intention to perform that action. Here, \( d \) is a specific combined desire that consists of multiple characteristics as described in Section 2 (see also the next submodel).

\[ \forall d : \text{DESIRE} \quad \forall a : \text{ACTION} \quad \text{desire}(d) \land \text{belief}(\text{satisfies}(a, d)) \rightarrow \text{intention}(a) \]

![Figure 1. Graphical Overview of the Simulation Model.](image)

Within the BDI-submodel, for reasons of simplicity, per desire only one action that can satisfy the desire is included. What remains to be generated are the desires and the beliefs in opportunities. For desires, the standard BDI-model [28] does not prescribe a generic way in which they are to be generated. Recent extensions of BDI models do comprise models for generation of desires (e.g., [25]) ; this often depends on domain-specific knowledge, which also seems to be the case for criminal behaviour. Therefore, a similar approach is adopted here. In particular, for EED patients, a number of physical aspects play a role, such as certain brain deviations and serotonin levels, as discussed below in some further detail. For beliefs in opportunities, they are strongly dependent on the (social) environment, which is another theme discussed below.

The Submodel to Determine Desires

To determine desires a rather complex submodel was built based on literature such as [5, 17, 24, 27], incorporating, for example, testosterone, serotonin, adrenalin, blood sugar levels and brain configuration aspects. These physical aspects relate to mental
aspects such as arousal, aggressiveness, impulsiveness, risk-taking, thrill-seeking, understanding others, and feeling for others. The aspects involved contain both qualitative aspects (e.g., the existence of certain brain deviations) and quantitative aspects (e.g., levels of testosterone or serotonin). To model these, both causal and logical relations (as in qualitative modelling) and numerical relations (as in differential equations) have to be integrated in one modelling framework, using the LEADSTO language.

As mentioned earlier, this submodel is explained in detail in [6]. However, since the current paper focuses on social/environmental aspects of crime, in the presented simulations an abstraction of the submodel to determine desires has been made. To be specific, it has been replaced by the following two rules:

LP30 When agent $a_1$, who is an IED agent at location $l$, and observes a ‘negative’ agent at location $l$, then agent $a_1$ will have an aggressive episode.

$$\forall a_1, a_2 : \text{AGENT} \rightarrow \text{EVENT}$$

\[
\text{has\_episode} \rightarrow \text{desire\_aggressive\_action}
\]

LP42 An agent that has an aggressive episode has the desire to performs an aggressive action.

$$\exists a_1 : \text{AGENT} \rightarrow \text{EVENT}$$

The Submodel to Determine Opportunities

As another input for the BDI-model, the notion of opportunity is used. For the current domain, this is modelled via a single rule, based on criteria indicated in the Routine Activity Theory [15]: a suitable target and absence of a guardian. This was specified by:

LP41 When agent $a_1$, who is an IED agent, is at location $l$ and observes a passer-by at location $l$ and does not observe a guardian at location $l$, then agent $a_1$ believes that there is an opportunity to assault someone.

$$\forall a_1, a_2 : \text{AGENT} \rightarrow \text{EVENT}$$

\[
\text{has\_episode} \rightarrow \text{desire\_aggressive\_action}
\]

In dynamic property LP32 shown earlier, the third criterion of the Routine Activity Theory, the motivated offender, is represented by the intention to perform some action. Note that LP41 is a domain-dependent rule. For other domains, the submodel can be filled with rules that generate beliefs in opportunities for other actions than assaults. Also, the perception process that generates beliefs based on observation can be modelled in more detail. However, since the main goal of the current paper is to study the patterns that result from the Routine Activity Theory, there is no need to further refine this submodel.

The Submodel for the Society

The social, multi-agent aspect is modelled by a simple environment, in which a number of agents move around and sometimes meet at a location. One of the agents is the criminal agent with IED, the others are guardian agents, potential victims (passers-by) and agents with provoking behaviour (so that they may trigger an episode in the criminal when (s)he encounters them), from now on referred to as negative agents. The

† According to Moir and Jessel ([24], pp. 184-194) an episode may be provoked by various types of unpleasant encounters with other people. Examples are a certain negative look or an unfriendly remark or question by someone. For simplicity, all these events are summarised here as encounters with a negative agent.
passers-by are assumed to be suitable targets, for example, because they appear rich and/or weak. However, as also the guardians are moving around, such targets may be protected, whenever at the same location a guardian is observed by the criminal: formal control.

**Figure 2.** Example World Geography (with an initial distribution of agents over locations; agent 1 is the agent with IED, agent 2 and 3 are guardians, agent 4, 5 and 6 are passers-by (potential victims), and agent 7 and 8 are ‘negative’ agents.

The interaction between a specific agent and the environment is modelled by (1) observation, which takes information on the environment as input for the agent (e.g., at which location it is, where suitable targets are, and whether social control is present), and (2) performing actions, which is an output of the agent affecting the state of the world (e.g., going to a different location, or committing a crime). The geographical information of the world is described by a labeled graph as depicted in Figure 2. Relevant locations are indicated by nodes A, B,…, and routes connecting locations by edges E1, E2,… The agents move from location to location via these edges. Edges have lengths; travelling takes time, depending on these lengths.

To model the dynamics of an agent moving in the environment, the following cycle is used: observe, determine next action, determine effects of this action. In some more detail, the model is based on (1) properties expressing what is observed, for example, stimuli or other agents: if another agent is present at the agent’s location, then the agent will observe this, (2) properties expressing which next action is to be undertaken; for example, if the agent has stayed at its location for duration s, and the next location to reach is l, then it will move to this next location (probabilities are used to make random choices between options), and (3) properties expressing the results of actions undertaken; for example, if the agent starts to move to a next location over edge e and edge e has length d, then it will arrive at the next location after duration d.

**Settings for the Model**

The model is initialised by setting the initial locations in the world of all agents: IED agents, guardians, passers-by, and negative agents. These inputs are included in scenarios for simulation. For the simulation trace explained in the following section, the

---

‡ For future work, it is planned to incorporate informal social control as well, e.g., by allowing a group of passers-by to act as one guardian - and prevent crimes - as well.
settings shown in Figure 2 were chosen, i.e., consisting of 8 locations that are populated by 1 IED agent, 2 guardians, 3 passers-by, and 2 'negative’ agents.

4. Simulation Traces

A large number of simulation traces (200 in total) have been generated for the behaviour of the IED criminal under different circumstances using the simulation model. Below, an example simulation trace is shown in Figure 3, which was generated using the simulation model. In this picture, time is on the horizontal axis; state properties are on the vertical axis. A dark box on top of the line indicates that the property is true during that time period, and a lighter box below the line indicates that the property is false. The first eight lines display the characteristics of the agents involved. The next 5 lines show the BDI-based decision making process of agent 1, which is the agent with IED, and the rest of the trace shows the movement of the two agents (agent 1 and 8) over the environment. For simplicity, all other events, such as the generation of actions to move to another location, the locations of agents 2-7, and the physiological processes underlying agent 1’s behaviour, are not shown.

As shown by Figure 3, the example environment contains 8 agents and 8 locations. Agent 1, the agent with IED, initially does not have a desire to perform aggressive actions. However, at time point 46 this agent is at location C, where he meets a negative agent (agent 8). This causes an episode, which leads to the desire to perform an aggressive action. This desire, combined with the belief that performing an assault leads to the satisfaction of this desire\(^5\), leads to the intention to assault someone. At time point 51, the IED agent is at location B, together with a passer by (agent 4, not shown) without a guardian present (agents 2 and 3 are both on location F, not shown). This leads to the belief that there is an opportunity to assault agent 4. This belief combined with the intention leads to the performance of the assault. Because of the assault, the stimuli of the world increase, which satisfies the desires of agent 1. Later, at time point 91, agent 1 again generates an aggressive episode, but because it does not encounter any opportunities, it does not perform any assaults.

As mentioned above, various similar simulation experiments have been performed. Among the different experiments, several parameter settings were varied, in particular the number of agents, the ratio between different types of agents, and the number of locations. In general, the generated traces indeed show the behaviour of crimes performed by IED patients, as described in literature such as [17, 24, 27]. Moreover, these simulation experiments may give insight into the impact of different types of populations or geographical environments on crime rates. For example, is it better to invest in more police at a particular location or to prevent passer-by from going to that location?

Obviously, when the number of simulations becomes large, it becomes impossible to study all simulation traces by hand. Therefore, in the next sections it is explained how this investigation process automated analysis techniques.

Furthermore, although the simulation examples as presented here involve only 8 agents, it has been found that the model easily scales to a society of several hundreds of agents (processing time staying within one hour). Nevertheless, complexity problems

\(^5\) Although the model allows multiple actions to fulfill a particular desire, the current paper only addresses those desires for aggression that are so strong that assault is considered the best (and most immediate) solution.
may arise when populations of (more than) thousands of (heterogeneous) agents are
considered. These problems could be solved by translating the current simulation model
to a stochastic model, as is done, for example, in the analysis of epidemics [1]. To make
such a translation, the description of the dynamics of a population will shift from a
“micro” perspective (at the level of individual agents) to a “macro” perspective (at the
level of groups of agents). For example, the number of criminals, guardians, negative
agents, and passers-by at certain locations may be described by global variables, which
are influenced by probabilistic rules. The main advantage of these types of macro-level
approaches is that they can deal with larger populations. An inevitable drawback is
however that they imply a loss of detail at the individual agent level. In future work, the
benefits of such approaches will be explored.

5. Logical Analysis
When the number of simulation traces becomes large, automated support for analysis of
the traces becomes very useful. To this end, the TTL Checker tool [8] may be used. This
piece of software takes as input a number of simulation traces and a logical formula
(represented in the predicate logic-based language TTL), and verifies whether the

![Example Simulation Trace](image-url)
property holds for the traces. Moreover, in case a property does not hold, the software automatically provides a counter example, i.e., a combination of traces, time points, and variable instantiations for which the property fails. This allows the analyst to formulate properties that (s)he expects to hold for a certain process, but also to study those situations for which the property does not hold in more detail (e.g., by investigating those simulation traces by hand), and explain what causes the unexpected behaviour.

Following this approach, a number of properties of criminal behaviour have been identified and formalised. Some of these properties have a logical character and some have a probabilistic character. Both types of properties have been automatically verified for the simulation traces. In this section the logical properties are discussed, in the next section the probabilistic ones. For a multi-agent system, dynamic properties can be identified at different aggregation levels, roughly spoken (1) the level of the behaviour of a single agent (external perspective), (2) the level of the internal functioning of an agent (internal perspective), and (3) the level of the multi-agent system as a whole (society behaviour). For each of these levels, relevant properties are identified and formalised.

**Behavioural Properties of Agents**

The properties that have been identified and formalised in the logical language TTL [8] to characterise the behaviour of the criminal agent (from an external perspective) are as follows (where $t$ is the duration of the reaction time from observations to internal states or from internal states to actions):

**BP1 From Circumstances to Criminal Action** If an IED agent meets a negative agent, and within duration $a$ an opportunity occurs, then an assault will be performed.

$$\forall t \exists a_1, a_2 : \text{agent} \forall l : \text{location} \left\{ \begin{array}{l} \text{state}(\gamma, t) \models \text{observes}(a_1, \text{agent} \_ \text{of} \_ \text{type} \_ \text{at} \_ \text{location}(a_1, \text{IED}, l_1)) \land \text{observes}(a_1, \text{agent} \_ \text{of} \_ \text{type} \_ \text{at} \_ \text{location}(a_2, \text{passer-by}, l_1)) \land \forall a_3 : \text{agent} \text{state}(\gamma, t) \not\models \text{observes}(a_1, \text{agent} \_ \text{of} \_ \text{type} \_ \text{at} \_ \text{location}(a_3, \text{guardian}, l_1)) \land \exists t \leq t \leq t_1 \land \text{state}(\gamma, t_1) \models \text{observes}(a_1, \text{agent} \_ \text{of} \_ \text{type} \_ \text{at} \_ \text{location}(a_4, \text{neg-agent}, l_2)) \end{array} \right\} \Rightarrow \exists \exists \leq 1 \leq 2 + 2 t & \text{state}(\gamma, l_2) \models \text{performed} (\text{assault}) \right\}$$

Here state($\gamma$, $t$) $\models X$ denotes that within the state state($\gamma$, $t$) at time point $t$ in trace $\gamma$ state property $X$ holds (and with $\not\models$ that it does not hold), with the infix predicate $\models$ within the language denoting the formalised satisfaction relation. See [8] for more details of TTL.

**BP2 From Criminal Action to Circumstances** If an assault is performed, then the opportunity was there and earlier (at most a $b$ back in time) the IED agent encountered a negative agent.

$$\forall t \left\{ \begin{array}{l} \text{state}(\gamma, t) \models \text{performed} (\text{assault}) \Rightarrow \exists \exists t \leq 1 \leq 2 t & \exists \exists a_1, a_2 : \text{agent} \exists l : \text{location} \left\{ \begin{array}{l} t \leq t_1 \land \text{state}(\gamma, t_1) \models \text{observes}(a_1, \text{agent} \_ \text{of} \_ \text{type} \_ \text{at} \_ \text{location}(a_1, \text{IED}, l_1)) \land \text{observes}(a_1, \text{agent} \_ \text{of} \_ \text{type} \_ \text{at} \_ \text{location}(a_2, \text{passer-by}, l_1)) \land \forall a_3 : \text{agent} \text{state}(\gamma, t) \not\models \text{observes}(a_1, \text{agent} \_ \text{of} \_ \text{type} \_ \text{at} \_ \text{location}(a_3, \text{guardian}, l_1)) \land \exists t \leq t \leq t_1 \land \text{state}(\gamma, t_1) \models \text{observes}(a_1, \text{agent} \_ \text{of} \_ \text{type} \_ \text{at} \_ \text{location}(a_4, \text{neg-agent}, l_2)) \end{array} \right\} \end{array} \right\}$$

Notice that these properties summarise how the agent functions in the context of society, abstracting from the internal mechanisms underlying this behaviour. Logical consequences of these external agent behaviour properties include the following external behavioural property:

**BP3 No Opportunity No Crime** If no opportunities are offered, then no criminal action occurs.

$$\forall t \exists a_1, a_2 : \text{agent} \forall l : \text{location} \left\{ \begin{array}{l} \text{state}(\gamma, t) \not\models \text{observes}(a_1, \text{agent} \_ \text{of} \_ \text{type} \_ \text{at} \_ \text{location}(a_1, \text{IED}, l_1)) \land \text{state}(\gamma, t) \not\models \text{performed} (\text{assault}) \end{array} \right\}$$
observes(a1, agent_of_type_at_location(a2, passer_by, l)) &
\forall a3\text{agent}
\forall a4\text{agent}

state(y, t) |\#\text{observes(a1, agent_of_type_at_location(a3, guardian, l))}

\Rightarrow [ \forall \text{state(y, t) |\#\text{performed\text{assault}} } ]

**Internal Properties of Agents**

Although for an analysis at the level of the society as a whole, details of internal mechanisms and processes are not needed, from the perspective of justifying, understanding and explaining whether, how and when such behaviour can occur, still the internal agent dynamics are interesting to formalise. Knowledge of these mechanisms may also be useful as a basis for therapy and/or medication. The following internal behavioural properties of the criminal agent were identified and formally specified:

**IP1a (Episode Provoking)** If the IED agent observes an agent which has a negative appearance, then from \( t \) to \( t+e \) the IED agent will have an episode.

\[ \forall t \ [ \text{state(y, t) |\#\text{observes\text{negative\_event, pos)}}] \]

\[ \Rightarrow \exists t1 [ t1 \leq t+e \Rightarrow \text{state(y, t1) |\#\text{has\_episode} } ] \]

**IP1b (Episode Grounding)** If the IED agent has an episode, then at some time point between \( t+e \) and \( t \) the IED agent observed an agent which has a negative appearance.

\[ \forall t \ [ \text{state(y, t) |\#\text{has\_episode} } ] \]

\[ \Rightarrow \exists t1 [ t+e \leq t1 \& \text{state(y, t1) |\#\text{observes\text{negative\_event, pos}} } ] \]

**IP2a (Crime Committing)** If the IED agent has an episode, and it believes there is an opportunity to commit a crime, then it will perform criminal action \( a \).

\[ \forall t \ [ \text{state(y, t) |\#\text{belief\text{opportunity, pos}}} \wedge \text{has\_episode} ] \]

\[ \Rightarrow \exists t1 [ t \leq t1 \& \text{state(y, t1) |\#\text{performs\_action(a) } } ] \]

**IP2b (Crime Grounding)** If the IED agent performs criminal action \( a \), then it believes there is an opportunity to commit a crime, and it has an episode.

\[ \forall t \ [ \text{state(y, t) |\#\text{performs\_action(a) } } ] \]

\[ \Rightarrow \exists t1 [ t \leq t1 \& \text{state(y, t1) |\#\text{belief\text{opportunity, pos}}} \wedge \text{has\_episode} ] \]

**IP3a (Belief Generation)** If the IED agent observes \( X \), then it will believe \( X \).

\[ \forall t \ [ \text{state(y, t) |\#\text{observes\text(X, S) } } ] \]

\[ \Rightarrow \exists t1 [ t \leq t1 \& \text{state(y, t1) |\#\text{belief\text(X, S) } } ] \]

**IP3b (Belief Grounding)** If the IED agent believes \( X \), then before it has observed \( X \).

\[ \forall t \ [ \text{state(y, t) |\#\text{belief\text(X, S) } } ] \]

\[ \Rightarrow \exists t1 [ t \leq t1 \& \text{state(y, t1) |\#\text{observes\text(X, S) } } ] \]

In fact, the properties IP1a and IP1b express that having an episode has a backward representation relation (within duration \( e \)) to meeting a negative agent, and IP2a and IP2b that it has a forward representation relation to conditionally performing a criminal action as soon as (within duration \( e \)) an opportunity occurs; cf. [10]. The properties IP1a, IP1b, IP2a and IP2b can be refined further into more local properties describing the criminal agent’s internal mechanisms.

**Note**: Note that, in case the whole underlying biological and cognitive model of the IED agent is incorporated, these properties would rather be used to analyse given traces of behaviour, instead of generating them. Moreover, also probabilistic variants of these properties may be defined (see Section 6).

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Here, the following abbreviations are used:

negative_encounter(γ, k) ≡ \( \forall γ,γ': \text{negative_encounter}(γ, k) \Rightarrow γ' \neq γ \)

state(γ, k) ≡ \( \exists a_1, a_2: \text{observes}(a_1, \text{agent_of_type_at_location}(a_2, \text{neg_agent}, l)) \)

opportunity(γ, k) ≡ \( \exists a_1, a_2: \text{observes}(a_1, \text{agent_of_type_at_location}(a_2, \text{IED}, l)) \land \text{observes}(a_1, \text{agent_of_type_at_location}(a_2, \text{passer_by}, l)) \land \forall a_3: \text{observes}(a_1, \text{agent_of_type_at_location}(a_3, \text{guardian}, l)) \)

Notice that the above properties compare two traces with each other. In the language TTL, it is possible to express such properties, in contrast to, for example, modal temporal logics.

Verification of the Logical Properties

Verification of properties at the three aggregation levels can be done in different ways. One way is to check whether the properties hold in the different simulation traces that have been generated, using the TTL Checker tool [8]. When compared to other verification approaches such as model checking, this approach has as advantage that it is relatively cheap (since basically one checks a formula against a limited set of traces instead of ‘exhaustively’ against all possible traces of a model). As a result, the verification process is quicker, and more expressive properties can be checked. In practice, the duration of such checks usually varies from one second to a couple of

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minutes, depending on the complexity of the formula and the traces under consideration. With the increase of the number of traces, the checking time grows linearly. However, it is polynomial in the number of isolated time range variables occurring in the formula under analysis. Nevertheless, for the purpose presented in this paper, all properties could be checked in a couple of seconds. For an extensive comparison between the different verification approaches, see [8] and [12].

All of the properties as discussed have been checked automatically for all 200 simulation traces using the TTL Checker. Using these checks, the behavioural and internal agent properties were all found satisfied. However, the society properties turned out not to hold for all combinations of traces. The reason for this is that, by chance, there are some traces in which there is not much crime although many negative agents are encountered (for example, because there are no opportunities). Likewise, there are some traces where there is not much crime although many opportunities arise (e.g., because the criminals have no episodes). These individual traces cannot be distinguished by checking properties such as SP1 and SP2. For this reason, a probabilistic approach is sometimes more useful. Such a probabilistic approach is worked out in the next section.

Another way of verification is by establishing interlevel relations between dynamic properties. For example, the properties IP1a, IP2a and IP3a together (logically) imply behaviour property BP1, and IP1b, IP2b and IP3b together imply BP2, by the following interlevel relations:

\[
\begin{align*}
\text{IP1a} \land \text{IP2a} \land \text{IP3a} & \Rightarrow \text{BP1} \\
\text{IP1b} \land \text{IP2b} \land \text{IP3b} & \Rightarrow \text{BP2}
\end{align*}
\]

These interlevel relations have been verified as well.

6. Probabilistic Analysis

In this section properties are analysed from a probability perspective. At the society level, a main property is the parameterised global property below, addressing the expected number of crimes occurring within a certain time interval.

**GP1(t, d, EC) Crime Occurrence Expectation**

The expected number of crimes that take place from \( t \) within duration \( d \) is \( EC \).

Later on an expression will be shown for the expected number of crimes \( EC \) in this property with the following parameters:

- \( M \) total number of locations that can be visited
- \( N \) total number of agents with negative appearance
- \( V \) total number of agents offering an opportunity (potential victims)
- \( G \) total number of guardian agents

To analyse property GP1 in more detail, it is related to two more refined properties:

- the probability that within a certain duration \( dl \) (for the first time) a negative agent is met
- the probability that (after meeting a negative agent) within a duration \( e1 \) (for the first time) an opportunity for crime is met

Here \( e \) is the assumed duration of the episode.
GP2(t1, d1, p1)Provocation Occurrence Probability
The probability that from t₁ after duration d₁ a negative agent is met is p₁.

GP3(t2, e1, p2)Opportunity Occurrence Probability
The probability that from t₂ after duration e₁ a first opportunity is met and in the meantime no negative agent is met is p₂.

A first step is to assume invariance over time, so that these probabilities do not depend on the time parameters. Then these parameters will be left out. As a next step it is assumed that meeting a negative agent before t₁ and an opportunity after t₁ are independent events. Moreover, the behavioural properties IP₁ and IP₂ of the criminal agent are used.

Relating the probabilities and expected crimes
As a first step the probability p in GP₁ will be related to the probabilities p₁ and p₂ in GP₂ and GP₃. This is done by the following logical relation.

\[ IP₁ \& IP₂ \& EC = \sum_{d₁} p₁(d₁, p₁) \sum_{e₁} p₂(e₁, p₂) \Rightarrow GP₁(d₁+e₁, EC) \]

This relation collects all paths that can lead to a crime, indicated by the time that a negative agent was met and the (first) time that an opportunity was met. A next step is to find out what reasonable estimations are for the probabilities in GP₂ and GP₃. After this step the relation above will be used to find an estimation for EC. First GP₂ is addressed. For convenience the following short notations are used: \( a = (1 - 1/M) \), \( b = 1 - (1 - a^n)a^0 \).

Estimating the probability to meet a negative agent
A next assumption is that, by their moving, the agents will be present at locations according to a uniform probability distribution, so for any agent A and location L, at any point in time, the probability that agent A is at location L is \( 1/M \). The probability that it is not at L is \( 1 - 1/M \equiv a \). A further assumption is that agents move independently, and hence their locations are independent. Therefore for a given location L at point time t, the probability that there is no agent with negative appearance at L is given by \( p(\text{no negative agent at L}) = a^n \), and, the probability that there is at least one agent with negative appearance at L is: \( p(\text{at least one negative agent at L}) = 1 - a^n \). This gives an estimation of how the probability \( p₁ \) in property GP₂(d₁, p₁) depends on d₁, or, expressed differently, it has been found that by estimation it holds: GP₂(d₁, (1 - \( a^n \))).

Estimating the probability to meet an opportunity
The next step addresses the probability to meet an opportunity within duration e, as indicated by property GP₃. Here, the additional condition is that at t₁ it is the first time that in the interval e an opportunity is met, and that no further negative agents were met in the meantime. Then the probabilities that at that location no victims and no guardians are met are as follows (with \( a = 1 - 1/M \)):

\[
\begin{align*}
  p(\text{no victim at L}) & = a^e \\
  p(\text{no guardian at L}) & = a^e
\end{align*}
\]

Therefore the probability that an opportunity is met (i.e., a victim and no guardian present) is (with \( b = 1 - (1 - a^n)a^0 \)):
\[ p(\text{opportunity at } L) = (1 - a^V) a^G = (1 - b) \]

The probability that no opportunities and no negative agents are met is:

\[ p(\text{no opportunity no neg at } L) = a^N (1 - (1 - b)) = a^N b \]

The probability that at \( e1 \) locations \( \{0, \ldots, e1-1\} \) of a sequence no opportunities and no negative agents are met is:

\[ p(\text{no opportunity met up to}(e1-1)) = (a^N b)^{e1} \]

Based on this, the probability that in a sequence of \( e1 \) locations at the \( e1 \)-th element a first opportunity is met, whereas at all locations before \( e1 \) no opportunity and no negative agent was met is given by:

\[ p(\text{first opportunity met after}(e1)) = (a^N b)^{e1}(1 - b) \]

This gives an estimation of how the probability \( p2 \) in property \( GP3(e1, p2) \) depends on \( e1 \), or, expressed differently, it has been found that by estimation the following holds:

\[ GP3(e1, (a^N b)^{e1}(1 - b)) \]

**Estimating the Expected Number of Crimes**

Now that estimations for the probabilities in \( GP2 \) and \( GP3 \) have been found, it is possible to estimate the expected number of crimes in \( GP1 \), on the basis of the following calculation for \( EC \):

\[
\sum_{0 \leq d1 \leq d} \sum_{0 \leq e1 \leq e} \sum_{p1 \text{ with } GP2(d1, p1)} \sum_{0 \leq e1se} \sum_{p2 \text{ with } GP3(e1, p2)} \sum_{p1 \text{ and } p2} p1 \cdot p2
\]

Substituting here the probabilities as specified by \( GP2 \) and \( GP3 \) in the form \( GP2(d1, (1 - a^V)) \) and \( GP3(e1, (a^N b)^{e1}(1 - b)) \) obtains the following for the probability in \( GP1 \) that a crime is committed within duration \( d + e \):

\[
EC = \sum_{0 \leq d1 \leq d} \sum_{0 \leq e1 \leq e} \sum_{p1 \text{ with } GP2(d1, p1)} \sum_{0 \leq e1se} \sum_{p2 \text{ with } GP3(e1, p2)} \sum_{p1 \text{ and } p2} p1 \cdot p2
\]

Substituting here the probabilities as specified by \( GP2 \) and \( GP3 \) in the form \( GP2(d1, (1 - a^V)) \) and \( GP3(e1, (a^N b)^{e1}(1 - b)) \) obtains the following for the probability in \( GP1 \) that a crime is committed within duration \( d + e \):

\[
EC = \sum_{0 \leq d1 \leq d} \sum_{0 \leq e1 \leq e} \sum_{p1 \text{ with } GP2(d1, p1)} \sum_{0 \leq e1se} \sum_{p2 \text{ with } GP3(e1, p2)} \sum_{p1 \text{ and } p2} p1 \cdot p2
\]

This implies that

\[
GP1(d+e, d \cdot (1 - a^N) \cdot ((1 - (a^N b)^{e1}(1 - (a^N b)))/(1 - (a^N b)))) \cdot (1 - b))
\]

holds. Substituting \( b = 1 - (1 - a^V) a^G \) and \( a = (1 - 1/M) \) provides for \( EC \) an expression in the basic parameters. To evaluate the behaviour of this expression for the expected number of crimes, depending on different parameter settings for the 6 basic parameters \( M, V, G, N, d, e \), the expression has been implemented in a spreadsheet†† (in Microsoft Excel).

†† See URL: http://www.cs.vu.nl/~tbosses/crim/AAMAS07.xls
Using this spreadsheet, the impact of different parameters on the total amount of crime has been tested in a systematic manner. In the following graphs (Figure 4a - 4c) the relation between different variables and crime is shown. In each of these tests, two of the variables $M, N, V, G, d, e$ have been manipulated whilst the other four variables have been kept constant.

![Expected Crime Rate vs Potential Victims and Guardians](image)

**Figure 4a.** Relation between potential victims ($V$), guardians ($G$) and crime ($EC$). Here, the following parameter values were kept constant: $M=8$, $N=2$, $d=30$ and $e=10$.

![Expected Crime Rate vs Negative Agents and Episode Duration](image)

**Figure 4b.** Relation between negative agents ($N$), duration of an episode ($E$), and crime ($EC$). Here, the following parameter values were kept constant: $M=8$, $V=3$, $G=2$ and $d=30$. 

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Some observations that are plausible from the context are indeed shown by these tests, as well as by the implementation. For example:

- $EC$ is monotonically increasing in its dependence on each of $N$, $V$, $d$, $e$
- $EC$ is monotonically decreasing in $G$
- For $N=0$ or $V=0$ or $M$ very large, $EC$ becomes 0

Furthermore, the expected number of crimes has been automatically verified against a set of simulation traces. To this end, another set of $n=200$ simulation traces has been generated. These traces were similar to the ones mentioned in Section 4, but used a fully connected graph for the geographical model (because of the assumption that the location of agents is independent of their previous location). For these traces, the following TTL formula:

$$\exists w \left[ \sum_{k=1}^{n} \sum_{t=0}^{d} \text{case(state}(\gamma(k), t) |\text{ performed(assault)}, 1, 0) / n \& \text{ EC} - \delta \leq w \& w \leq \text{ EC} + \delta \right]$$

was checked with suitable values for parameters $EC$ (given above) and $\delta$. For the expected number of crimes $EC$, the value of 4.14 was chosen, as predicted by the above probabilistic analysis (with $M=8$, $N=2$, $V=3$, $G=2$, $d=40$, $e=10$). For $\delta$, the value of 0.1 was chosen (i.e., about 2.5% of $EC$). Based on these parameter values, the TTL formula mentioned above indeed succeeded (in a few minutes), since in the 200 traces under investigation 809 crimes were performed. This is an average of 4.04 crimes per trace, which lies just within $\delta$ from the number of 4.14 expected crimes. This is an indication that the probabilistic analysis is an adequate alternative for the simulation-based approach, as long as the analyst is interested in overall numbers, rather than in the local mechanisms that cause certain types of criminal behaviour.
7. Related Work

Although it is recognised that computer support in the area of crime investigation is an interesting challenge, only few papers on simulation and formal analysis of criminal behaviour can be found in the literature (see [21] for an extensive overview); they usually address a more limited number of aspects than the approach presented in this paper. For example, Brantingham and Brantingham [13] discuss the possible use of agent modelling approaches to criminal behaviour in general, but do not report a specific model or case study. Moreover, in [3] a model is presented with emphasis on the social network and the perceived sanctions. However, this model leaves the mental and physical aspects largely unaddressed. The same applies to the work reported in [23], where an emphasis is on the environment, and police organisation. Finally, [19] explores the usefulness of collaborative network theory to study organised crime, but does not provide a computational model. The contribution put forward in the current paper and its counterparts [6, 7] shows that an agent-based modelling approach is possible where both a complex internal agent model is involved (addressing physical and mental aspects) and a model for the multi-agent society.

Other agent models for human-like behaviour incorporating more cognitive and social aspects (such as trust and theory of mind) are described in [29, 30, 31]. These references focus on the internal architecture of an agent, and the applications aimed at are mainly in the area of games and virtual reality. An interesting extension of the work reported in the current paper would be to design more complex internal models for criminals (incorporating, for example, aspects such as trust and theory of mind in a more detailed manner) and perform social simulations with them. In such extensions the challenge how criminal agents come to their decisions in the context of a large variety of internal aspects can be addressed in more detail.

8. Conclusion

This paper presents results from an interdisciplinary research project that is aimed at the development of an agent-based modelling approach to analyse criminal behaviour in its social context. Agent-based modelling approaches often either address the internal functioning of an agent in an extensive manner but leave the social context limited, or address the social interactions at the level of the multi-agent system as a whole, thereby taking the internal models of the agents of limited complexity. As in many cases the interaction of physical, mental and social aspects is crucial, a model covering both levels is required. The proposed model adopts a general BDI-agent-model [14, 28] extended by specific models to generate desires and beliefs in opportunities, exploiting literature on criminal behaviour, in particular [17, 24, 27]. It involves both qualitative aspects (such as the anatomy of brain deviations, and presence or absence of agents at a specific location in the world), and quantitative aspects (such as distances and time durations in the world and hormone and neurotransmitter levels).

One of the challenges met when designing an agent model for criminal behaviour, is the large variety of different types of criminals and the amount of literature of different scopes about them. Often knowledge is formulated in a manner that does not make it clear how much certainty can be attached to it and/or in which context it would be valid. By focussing on the Intermittent Explosive Disorder (IED) type of criminal and using knowledge about this type of criminal that is confirmed in different sources in the literature, this challenge was addressed. It has been found that the model indeed shows
the behaviour as known from the literature of this type of offender within the given social context, as described in criminological literature.

The presented approach in general involves models at two different levels: submodels at the level of the biological/physiological aspects of single agents and submodels about the multi-agent society as a whole. The current paper specifically focuses on analysis of the dynamics of the latter. At this level, typical questions asked by criminologists are “how are crime rates influenced by the size of a city?”, or “how are crime rates influenced by the amount of police?”. Due to the high number of parameters and interactions involved, these questions are difficult to be answered analytically. Therefore, this paper presents an approach (based on simulation and formal analysis) that can be used as an experimental tool to address such questions, by offering the analyst the possibility to predict crime rates given various characteristics of the population and the environment (often called “what if”-scenarios). As such, the tool can be used by researchers in modelling applied to criminology, and social scientists, but (in the long term) also by policy makers. In future work, the possibilities will be explored to apply these methods to real data, to be able to make predictions about crime in existing cities.

In addition, to analyse the model in more detail, a number of dynamic properties have been formalised in the TTL language, and (using an automated checker tool) have been (successfully) verified against a large set of simulated traces. These dynamic properties, both of logical and probabilistic type, comprise not only behavioural and internal properties of the agents involved, but also properties that address the society as a whole. Especially the latter type of properties may have a complex structure, e.g., because they compare multiple traces with each other, or because of the probabilistic aspects involved. The language TTL and its software environment turned out useful for these purposes.

In literature such as [14, 28], within standard BDI-models no general model for generation of desires is included. In many cases desires are just assumed to be there, or even communicated to the agent as goals it should adopt. Recently, extensions of BDI models are being developed in which this is the case, e.g., in Jadex [25]. One aspect that is addressed particularly here is the revision of desires as a result of undertaken actions that fulfill them. Another aspect relevant for desire generation is the biological substrate of the agent. Sometimes desires are just inherent to a certain biological makeup or state.

The project of which the current paper reports results, takes a similar approach, namely to incorporate both biological and psychological factors into a submodel for generation of desires, see [6, 7]. Within the project, a number of biological aspects as found in the literature have been taken into account in the dynamic generation of desires, varying from specific types of brain deviations, and serotonin and testosterone levels, to the extent to which a substrate for theory of mind was developed. For the current paper, however, this model has been abstracted to a more high-level behavioural model. Moreover, the generation of beliefs in opportunities has been based on environmental and social aspects involving two specific criteria (suitable target, presence of guardian) as indicated by the Routine Activity Theory in [15]. Within the BDI-submodel, for reasons of simplicity, per desire only one action that can satisfy the desire is included (and one intention for that action). When a number of intentions are possible for one desire, then the model can be extended by a more specific decision making approach, such as utility-based multi-objective decision making; cf. [7, 16].

Further future work will address a number of extensions to the model. Among the factors that will be added are attractiveness and reputations of locations, informal social
control by passers-by, adaptivity of individual agents, and different surveillance strategies (e.g., random, planning-based, or area-based) of the guardians.

**Acknowledgements**

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**References**


Grounding a Cognitive Modelling Approach for Criminal Behaviour

Tibor Bosse, Charlotte Gerritsen and Jan Treur

Abstract. This article presents a cognitive modelling approach for criminal behaviour, which is illustrated by a case study for the behaviour of three types of violent criminals as known from literature within the area of Criminology. The model can show each of their behaviours, depending on the characteristics set and inputs in terms of stimuli from the environment. Based on literature in Criminology about motivations and opportunities and their underlying factors, it is shown by a formal mapping how the model can be related to a biological grounding. This formal mapping covers ontology elements for states and dynamic properties for processes, and thus shows how the cognitive model can be biologically grounded.

1. Introduction

The field of Criminology, which addresses the analysis of criminal behaviour, is a multi-disciplinary area with a high societal relevance; e.g., [11, 12, 16, 24, 26, 27]. Criminal behaviour, which is shown by a minority of the overall population, typically comes in many types and variations, often related to specific individual characteristics. Not many contributions in the literature can be found that address formalisation and computational modelling of criminal behaviour; e.g., [1, 10, 20, 21].

This paper first discusses a modelling approach at the cognitive level for different types of violent criminal behaviour. The cognitive model involves motivations (in particular desires and intentions) and beliefs in opportunities; e.g., [15, 25]. Dynamical models were incorporated, addressing psychological factors relating to desires, such as levels of anxiety and excitement arousal, empathy or theory of mind (TOM), impulsiveness, and aggressiveness; e.g. [13, 22, 24]. For example, certain types of criminal actions are more likely to be performed by persons that have a high impulsiveness, or a lack of empathy. Another part of the cognitive model addresses the generation of beliefs in opportunities, formalising the well-known Routine Activity Theory within Criminology; e.g., [11]. This (informal) theory assumes a certain motivation of the criminal and covers opportunities based on the perceived presence of targets (e.g., potential victims) and social control (e.g., guardians). The resulting cognitive model covers eight categories of aspects that play a role in criminal behaviour, and dynamical system models for these aspects.

To show how this cognitive model can be grounded in biological states and processes, a formal mapping was defined. This mapping relates ontology elements describing cognitive states to ontology elements describing biological states. Moreover, it relates temporal relationships between cognitive states, specified in the form of dynamic properties, to corresponding relationships between biological states. This mapping, covering both states and processes shows how the cognitive model can be grounded in the biological area.

To formalise the overall model, the language LEADSTO [8] has been used. In LEADSTO direct temporal dependencies between two state properties in successive states are modelled by executable dynamic properties. The format of such dynamic
properties is defined as follows. Let $\alpha$ and $\beta$ be state properties of the form ‘conjunction of
ground atoms or negations of ground atoms’. In this language the notation $\alpha \rightarrow_{e, f, g, h} \beta$
means:

If state property $\alpha$ holds for a certain time interval with duration $g$,
then after some delay (between $e$ and $f$) state property $\beta$ will hold
for a certain time interval of length $h$.

Here atomic state properties can have either a qualitative, logical format, such as an
expression $\text{desire}(d)$ (expressing that desire $d$ occurs), or a quantitative, numerical
format, such as an expression $\text{has_value}(x, v)$ (which expresses that variable $x$ has value
$v$). For more details of the language LEADSTO, see [8].

The cognitive model as presented involves a variety of cognitive characteristics and
states that affect the motivational states and hence the behaviour. A relevant, but
nontrivial question is how these characteristics and states can be grounded. In [9] three
ways of grounding of a cognitive state are considered: (1) by its functional role, (2) by
its representation relations, (3) by its physical realisation. For the various cognitive
states in the model, these types of grounding are addressed in the current paper. In the
first place, the functional roles of the cognitive states are specified in a formal manner
that is also used as a basis for the simulation model. Second, representation relations
[19] can be obtained by a transitive closure of such functional role descriptions. Finally,
for each of the cognitive states it is shown how it can be mapped onto a biological state
that plays the role of realiser of this cognitive state; cf. [19, 23]. This mapping between
states has been formally defined, and extended to dynamic properties, as a variant of the
concept of interpretation mapping in Logic.

2. Three Types of Criminals

The case study made in this paper focuses on three types of violent offenders: the
violent psychopath, the offender with an antisocial personality disorder (APD), and the
offender who suffers from an intermittent explosive disorder (IED). Below, these types
of criminals are briefly introduced and differences between them are discussed, based
on [13, 22, 24]:

- Violent psychopaths do not have feelings like the rest of us. They lack the normal
mechanisms of anxiety arousal, which ring alarm bells of fear in most people. Their
kind of violence is similar to predatory aggression, which is accompanied by minimal
sympathetic arousal, and is purposeful and without emotion. Moreover, they like to
exert power and have unrestricted dominance over others, ignoring their needs and
justifying the use of whatever they feel compelling to achieve their goals. They do not
have the slightest sense of regret.

- Persons with APD have characteristics that are similar to the psychopath. However,
they may experience some emotions towards other persons, but these emotions are
mainly negative: they are very hostile and intolerant.

- Persons with IED, in contrast, appear to function normally in their daily life. However,
during some short periods (which will be referred to as episodes from now on), their
brain generates some form of miniature epileptic fit. As a result, some very aggressive
impulses are released and expressed in serious assault or destruction of property. After
these episodes, IED persons have no recollection of their actions and show feelings of
remorse.
These three types of criminals can be distinguished by taking a number of aspects into account (which are all incorporated in the model):

**Anxiety Threshold**: this is a threshold that needs to be passed by certain stimuli, in order to make a person anxious. Thus, when a person’s anxiety threshold is high, it is very difficult for this person to become anxious (and as a result, (s)he hardly knows any fear). This is the case for the violent psychopath and the person with APD: in these persons, a notion of fear is almost completely lacking. In contrast, persons with IED have a medium anxiety threshold. Nevertheless, in some special circumstances (i.e., during episodes) the anxiety threshold of a person with IED suddenly becomes much higher.

**Excitement Threshold**: this is a threshold that needs to be passed by certain stimuli, in order to make a person excited. Thus, when a person’s excitement threshold is high, it is very difficult for this person to become excited (and as a result, (s)he is often bored). This is the case for the violent psychopath and for persons with APD. Persons with IED have a medium excitement threshold, but under certain circumstances (during episodes) their excitement threshold becomes high, and they get bored very easily. Consequently, they will generate the desire to perform certain actions that provide strong stimuli (which are often criminal actions).

**Theory of mind**: the notion of theory of mind (e.g., [2, 14, 17]) covers two concepts: 1) having the understanding that others (also) have minds, which can be described by separate mental concepts, such as the person’s own beliefs, desires, and intentions, and 2) being able to form theories as to how those mental concepts play a role in the person’s behaviour. The violent psychopath has a theory of mind that is specialised in aspects that can contribute to his own goals. He is able to form theories about another person’s beliefs, desires and intentions and may use these theories (e.g., to manipulate this person), but just does not care about these states. A person with APD has a less developed theory of mind. Persons with IED mostly have a normal theory of mind and can make the distinction between themselves and others, but during episode, their theory of mind decreases.

**Emotional attitudes towards others**: these concepts express the extent to which a person may have positive or negative feelings with respect to other persons’ wellbeing. For the violent psychopath, both attitudes are low: these persons hardly show any emotion concerning other persons, so for them, both the positive and the negative emotional attitude towards others are low. For the criminal with APD, the situation is slightly different. Like the violent psychopaths, these persons do not have many positive feelings towards others, but they may have some negative feeling towards others. Finally, criminals with IED usually have a normal (medium) positive and negative emotional attitude towards others, but during episodes, all their positive feelings disappear, and substantial additional negative feelings arise.

**Aggressiveness**: since this paper focuses on violent criminals, by definition all considered types of criminals are aggressive. However, the criminals with IED only become highly aggressive during episodes, whereas the other two types are always aggressive.

**Impulsiveness**: when someone acts impulsive, this means that the action was not planned. All types of violent criminals mentioned in this paper are impulsive, but they differ in the type of impulsive action they perform. While the APD offender may lash out in disproportionate overreaction, the psychopath, with his emotional detachment, will impulsively take whatever course of action will supply him with the necessary
gratification. Persons with IED normally have a medium impulsiveness but during episodes they become highly impulsive.

**Sensitivity to alcohol:** For psychopaths and persons with APD, a small amount of alcohol or drugs can result in violent behaviour. For persons with IED, episodes can be triggered by small amounts of alcohol.

### 3. The Simulation Model

In this section the simulation model that has been developed is described in more detail. It has been built by composing three submodels:

1. a model to determine actions based on beliefs, desires and intentions (*BDI-model*)
2. a model to determine desires used as input by the BDI-model
3. a model to determine beliefs in an opportunity as input for the BDI-model

The BDI-model bases actions on motivational states. It describes how desires lead to intentions and how intentions lead to actions, when the appropriate opportunities are there. It needs as input desires and beliefs in opportunities, generated by the other two submodels.

**The BDI-submodel**

Part of the model for criminal behaviour is based on the BDI-model, a model that bases the preparation and performing of actions on beliefs, desires and intentions (e.g., [15, 18, 25]). This model shows a long tradition in the literature, going back to Aristotle’s analysis of how humans (and animals) can come to actions. In this model an action is performed when the subject has the intention to do this action and it has the belief that the opportunity to do the action is there. Beliefs are created on the basis of stimuli that are sensed or observed. The intention to do a specific type of action is created if there is a certain desire, and there is the belief that in the given world state, performing this action will fulfil this desire:

\[
desire(d) \land belief(satisfies(a, d)) \rightarrow intention(a) \\
intention(a) \land belief(opportunity_for(a)) \rightarrow is\_performed(a)
\]

Assuming that beliefs about how to satisfy desires are internally available, what remains to be generated in this model are the desires and the beliefs in opportunities. Generation of desires often depends on domain-specific knowledge, which also seems to be the case for criminal behaviour. Beliefs in opportunities are based on the Routine Activity Theory by [11].

**The Submodel to Determine Desires**

To determine desires, a rather complex submodel is used incorporating various aspects. To model these, both causal and logical relations (as in qualitative modelling) and numerical relations (as in differential equations) have been integrated in one modelling framework. This integration was accomplished, using the LEADSTO language as a modelling language. A variety of aspects, which were found relevant in the literature (such as [3, 13, 22, 24]) are taken into account in this submodel. These aspects can be

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* Appendix A in [www.cs.vu.nl/~thoos/crim/sim-model.pdf](http://www.cs.vu.nl/~thoos/crim/sim-model.pdf) shows a complete overview of the model (both in textual and in visual representation) and some simulation traces.
grouped as: (a) use of a theory of mind (e.g., understanding others), (b) desires for aggressiveness (e.g., using violence), (c) desires to act (no matter which type of action) and (d) to act safely (e.g., avoiding risk), (e) desires for actions with strong stimuli (e.g., thrill seeking), (f) desires for impulsiveness (e.g., unplanned action), and (g) social-emotional attitudes with respect to others (e.g., feel pity for someone). Note that these aspects are derived on the basis of (but not exactly equal to) the eight characteristics as described in the previous section. Different combinations of such elements lead to different types of (composed) desires, for example:

- the desire to perform an exciting planned nonaggressive nonrisky action that harms somebody else (e.g., a pick pocket action in a large crowd),
- the desire to perform an exciting impulsive aggressive risky action that harms somebody else (e.g., killing somebody in a violent manner in front of the police department)

The following LEADSTO property (LP) is used to generate a composed desire out of the different ingredients covered by (a) to (g) above; here the \( x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8 \) are qualitative labels (e.g., high, medium, low) or numerical values (integer or real numbers):

\[
\text{LP24} \quad \text{A combination of values for theory of mind, desire for aggressiveness, desire to act, desire to act safely, desire for actions with strong stimuli, desire for impulsiveness, emotional attitude towards others(pos) and emotional attitude towards others(neg) will lead to a specific composed desire, represented as } d(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8).
\]

\[
\forall x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8: \text{SCALE} \quad \text{theory of mind}(x_1) \land \text{desire for aggressiveness}(x_2) \land \text{desire to act}(x_3) \land \text{desire to act safely}(x_4) \land \text{desire for actions with strong stimuli}(x_5) \land \text{desire for impulsiveness}(x_6) \land \text{emotional attitude towards others}(\text{pos}, x_7) \land \text{emotional attitude towards others}(\text{neg}, x_8) \\
\rightarrow \text{desire}(d(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8))
\]

Due to space limitations, the parts of the submodel to determine each of the ingredients (a) to (g) cannot be described in detail. To give an impression, a rough sketch of part of this submodel is given. Stimuli are labeled with two aspects, indicating the strength with respect to anxiety (risk), and with respect to excitement (thrill), respectively. For both aspects, thresholds represent characteristics of the person considered. The excitement threshold depends on other aspects in the model, such as sensitivity for (and use of) drugs and alcohol, and basic sensitivity to stimuli. A stimulus with excitement strength below the excitement threshold leads to being bored, and being bored leads to a desire for actions with strong(er) stimuli (which are often criminal actions). In contrast, a stimulus with anxiety strength above the anxiety threshold leads to internal alarm bells, which (depending on another characteristic, the tendency to look for safety) leads to the desire to perform only ‘safe’ actions (which are usually not criminal actions).

The Submodel to Determine Opportunities

Beliefs in opportunities are based on two of the three criteria as indicated in the Routine Activity Theory by [11], namely the presence of a suitable target, and the absence of social control (guardians). The third criterion of the Routine Activity Theory, the presence of a motivated offender, is indicated by the intention in the BDI-model. This way, the presence of the three criteria together leads to the action to perform a criminal act, in accordance with [11]. This was specified by the following property in LEADSTO format:
When a suitable target for a certain action is observed, and no suitable guardian is observed, then a belief is created that there is an opportunity to perform this action.

\[ \forall a : \text{ACTION} \]
\[ \text{observes}(\text{suitable_target_for}(a)) \land \neg \text{observes}(\text{suitable_guardian_for}(a)) \rightarrow \text{belief}(\text{opportunity}(a)) \]

4. An Example Simulation Trace

The model described in the previous section has been used to generate a number of simulation traces for the different types of violent criminals addressed. In Figure 1, an example simulation trace is depicted, addressing the case of the criminal with APD. Here, time is on the horizontal axis; state properties are on the vertical axis. A dark box on top of the line indicates that the property is true during that time period, a lighter box below the line indicates that it is false.

Figure 1. Example simulation trace.

The initial state properties that have been set to model the person with APD are (see time point 0): low psychological self, low preparedness to look for safety, high potential aggressiveness, rather high potential anxiety and excitement threshold (resp. value 6 and 8), potentially a low positive and a medium negative emotional attitude towards others, a low potential sensitivity for stimuli (value 3), and (s)he drinks alcohol and is sensitive for it. These initial characteristics, combined certain world stimuli, eventually lead to a specific composed desire d(l, h, l, h, l, m) (see time point 5), characterised by the following ingredients: low theory of mind, high aggressiveness, high desire to act, low
design to act safely, high desire for actions with strong stimuli, high impulsiveness, low positive and medium negative emotional attitude towards others. As a result, the criminal generates an intention to perform a specific type of assault (denoted by assault), and, as soon as the opportunity is there, actually performs the assault. As a result, the stimuli increase, which satisfies the desires of the criminal.

5. Mapping Cognitive to Biological States

The psychological concepts used within Criminology to describe criminal behaviour are often complex concepts for which it is not always easy to give a precise definition. It may even be argued that for some of these concepts, there is a risk of circularity. For example, the internal state of aggressiveness may be related to aggressive or violent behaviour. To clarify such issues, it may be worthwhile to have some reflection on how these concepts are embedded in reality. In [9] three perspectives are put forward: (1) specification of functional roles, (2) specification of representation relations, cf. [19], and (3) specification of realisation relations. Here (1) is already covered by the LEADSTO properties of the simulation model. Moreover, (2) can be obtained from these functional role specifications by determining their transitive closure. For the third way of grounding of the cognitive model, a mapping from this model to biological concepts has been established; this maps cognitive states to anatomical, neurophysiological and biochemical states, and cognitive dynamics onto biological dynamics. In this section it is discussed how a conceptualisation based on cognitive state properties can formally be mapped onto a conceptualisation based on biological states properties. In the following section this basic mapping is extended to a mapping of dynamics based on traces, executable (LEADSTO) properties and more complex dynamic properties.

In literature within Criminology, often relationships between cognitive states and biological (anatomical, neurological, biochemical) states are discussed; e.g., [22, 24]. A mapping from the cognitive to a biological conceptualisation of the case study is shown in Table 1. Here a state property \( a \) in the left hand side column corresponds to the state property \( \phi(a) \) as indicated in the right hand side column; for example,

\[
\phi(\text{desire for aggressiveness}(v)) = \text{chemical state} (\text{testosterone}, v).
\]

The assumption behind the mapping is that if \( b = \phi(a) \), then \( b \) is true if and only if \( a \) is true.

In the literature on reduction in Philosophy of Mind or Philosophy of Science, this mapping is called a biconditional bridge principle, sometimes denoted by \( a \leftrightarrow b \); e.g., [19], [23]. Based on this mapping of state properties, cognitive states as a whole can be mapped onto biological states. A state \( S \) over state ontology Ont is characterised by an assignment of truth values \( S: \text{Ont} \rightarrow \{\text{true, false}\} \). Each cognitive state \( S \) can be mapped onto a biological state \( \phi(S) \) by \( \phi(S)(\phi(a)) = S(a) \) for any cognitive ground atom \( a \) (with \( \phi(a) \) the corresponding biological atom). In other words, the truth value of any mapped ground atom \( \phi(a) \) in the mapped state \( \phi(S) \) is the truth value of the original atom in the original state. The next question to be addressed is whether this mapping of state properties preserves temporal relations. This will be done in a number of ways in the next section.

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² A similar example is: “Opium puts people to sleep, because it contains a dormative principle” [4].
Table 1. Mapping cognitive to biological state properties.

<table>
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<th>Biological Conceptualisation</th>
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<td>chemical_state(oxytocine, v)</td>
</tr>
<tr>
<td>desire_for_impulsiveness(v)</td>
<td>chemical_state(bloodsugar, v)</td>
</tr>
</tbody>
</table>

6. The Extended Mapping for Dynamic Properties

Above it was shown how the basic interpretation mapping can be defined as a mapping between state properties. The next question is how this mapping preserves temporal relationships, for example, in the following sense:

- if α holds at time point i in a trace γ, then also φ(α) holds at i in a corresponding trace
- if a temporal relationship α → β holds, then also the temporal relationship φ(α) → φ(β) holds
- if a more complex temporal relationship holds, expressed in the logical language of temporal logic, then also this relationship holds between the mapped states

First it is addressed how a cognitive trace can be mapped onto a biological trace. This can be done as follows, based on the mapping of states defined above: a trace over state ontology Ont is a time-indexed sequence of states over Ont and is characterised by an assignment of states over Ont to time points: γ: TIME → STATES(Ont). Each cognitive trace γ can be mapped onto a biological trace φ(γ) by φ(γ(t)) = φ(γ(t)) for any time point t. In other words, the state at i in the mapped trace φ(γ) is the mapped state of γ at i.

The above mapping shows one answer to the question how temporal relationships are preserved. Another answer addresses temporal LEADSTO relationships. The mapping between state properties can be extended to a mapping between local dynamic properties in LEADSTO format as follows, where α and β are conjunctions of literals:

\[ \varphi(\alpha \rightarrow \beta) = \varphi(\alpha) \rightarrow \varphi(\beta) \]
\[ \varphi(\alpha_1 \land \alpha_2) = \varphi(\alpha_1) \land \varphi(\alpha_2) \]
\[ \varphi(\neg \alpha) = \neg \varphi(\alpha) \]
and when \( \alpha \) is an atom that is not an internal state property (e.g., an inequality relation or observation state)

\[ \varphi(\alpha) = \alpha \]

Using this mapping, combined with the basic mapping of the state ontology elements described above, mappings between the dynamic LEADSTO properties of the case study can be found. For example:

\[
\begin{align*}
\varphi(\text{anxiety_threshold}(y)) \land \text{observes_stimulus}(x_1, x_2) \land x_1 > y & \rightarrow \text{preparedness_to_act}(w) \\
\varphi(\text{anxiety_threshold}(y)) \land \text{observes_stimulus}(x_1, x_2) \land x_1 > y & \rightarrow \varphi(\text{preparedness_to_act}(w)) \\
\varphi(\text{anxiety_threshold}(y)) \land \varphi(\text{observes_stimulus}(x_1, x_2)) \land \varphi(x_1 > y) & \rightarrow \varphi(\text{preparedness_to_act}(w)) \\
\text{brain_state_for_anxiety_threshold}(y) \land \text{observes_stimulus}(x_1, x_2) \land x_1 > y & \rightarrow \text{chemical_state(adrenalin, w)}
\end{align*}
\]

The mapping of traces shows that the syntactic mapping between local properties preserves semantics: if the cognitive relationship \( \alpha \rightarrow \beta \) holds in cognitive trace \( \gamma \), then the corresponding biological relationship \( \varphi(\alpha) \rightarrow \varphi(\beta) \) holds in the corresponding trace \( \varphi(\gamma) \).

In addition, it is possible to extend the mapping to the wider class of temporal relationships expressed in the dynamic modelling language TTL [7]. TTL expressions are predicate logical formulae, built on atoms of the form \( \text{state}(\gamma, t) \models p \), which indicates that state property \( p \) is true in trace \( \gamma \) at time point \( t \). By the basic mapping the cognitive state property \( p \) can be mapped onto \( \varphi(\rho) \) in the biological conceptualisation, and cognitive trace \( \gamma \) can be mapped onto the corresponding biological trace \( \varphi(\gamma) \). Then the extended interpretation mapping for \( \text{state}(\gamma, t) \models p \) is defined by \( \text{state}(\gamma, t) \models p \) = \( \text{state}(\varphi(\gamma), t) \models \varphi(p) \). After these TTL-atoms have been mapped, TTL expressions as a whole can be mapped in a straightforward compositional manner:

\[
\begin{align*}
\varphi(A \land B) & = \varphi(A) \land \varphi(B) & \varphi(A \lor B) & = \varphi(A) \lor \varphi(B) \\
\varphi(\neg A) & = \neg \varphi(A) & \varphi(A \rightarrow B) & = \varphi(A) \rightarrow \varphi(B) \\
\varphi(\forall v A(v)) & = \forall v \varphi(A(v)) & \varphi(\exists v A(v)) & = \exists v \varphi(A(v))
\end{align*}
\]

7. Discussion

In this paper, a method to analyse criminal behaviour based on cognitive modelling has been proposed and applied, in a case study, to three types of violent criminals: violent psychopaths, criminals with an antisocial personality disorder (APD), and criminals who suffer from an intermittent explosive disorder (IED). A cognitive model has been developed that indeed can show the behaviour as known for the three types of criminals. Within the model, various psychological aspects as found in the literature are taken into account; e.g., [13, 22, 24]. By means of this model, it was shown how the internal process within the criminal subjects can be conceptualised and formalised from a cognitive perspective. However, as a main contribution, it was also shown how this model can be biologically grounded. To this end it was shown how an ontological mapping from the cognitive model to a biological formalisation can be formally defined. For example, the fact that under certain circumstances states of impulsiveness and aggressiveness that play a role in the cognitive model, may lead to an impulsive, violent crime can be described in terms of biological states concerning high testosterone and low blood sugar. It has been shown in detail how ontology elements for such
psychological states can be formally mapped onto ontology elements for biological states. Moreover, this formal ontology mapping has been extended to a formal mapping of temporal dynamic properties. Thus it is shown how the process description at the cognitive level relates to a process description at the biological level. Having a mapping as described above allows one on the one hand to explain behaviour in terms of psychological concepts, but on the other hand to relate it to a biological grounding.

In principle, validation can address both the dynamics of the cognitive model and the dynamics of the underlying biological model. Moreover, the mapping between the cognitive and the underlying biological model can be validated. All of these have been validated positively against literature on the specific types of criminals addressed. Here one remark can be made on validation of the mapping. For some of the cognitive states used in the cognitive model, it is not clear how they would be defined without reference to underlying biological states. Within literature on reduction, such as [19, 23], such reduction relations are called definitional, in contrast to those that are empirical.

Concerning related work, only a handful of other papers address computational modelling of criminal behaviour. However, most of the existing papers concentrate more on social and environmental aspects (e.g., [1, 6]), whereas the current article focuses on cognitive aspects and their relation to biology. Cognitive models for criminal behaviour as presented in this paper are very useful for case analysis, i.e., given a certain crime case, to find out which type of person has performed this crime. For more information about this topic, see [5].

References

Case Analysis of Criminal Behaviour

Tibor Bosse, Charlotte Gerritsen, and Jan Treur

Abstract. In this paper, it is shown how behavioural properties can be specified for three types of violent criminals. Moreover, it is shown how empirical material in the form of informal descriptions of traces of crime-related events can be formalised. Furthermore, it is shown how these formalised traces and behavioural properties can be used in automated analysis, for example in order to determine which type of criminal can have committed such a crime. Moreover, an underlying dynamical model is presented that shows causal mechanisms behind each of the behaviours, and their dependencies on the characteristics of the type of criminal and inputs in terms of stimuli from the environment.

1. Introduction
Criminology is a multi-disciplinary area focusing on the analysis of criminal behaviour; e.g., [1, 9, 10, 14, 20, 22, 23]. Some contributions to the literature addressing formalisation and computational modelling of criminal behaviour are found in [2, 8, 17, 18]. This paper first presents a modelling and analysis approach for certain types of violent criminal behaviour against data available from crime cases. The paper addresses the question: given information about a committed crime, and a number of suspects, what can be said about the person who committed the crime? It is shown how also automated tools can be used to address this type of question. In particular, it is shown how dynamic properties can be specified that characterise the behaviour of certain types of criminals and how they can be automatically checked on formalisations of partially given traces of crime-related events.

Dynamic properties that characterise the behaviour of a criminal can be specified from an external or from an internal perspective. From an external perspective more complex temporal relationships between inputs and outputs over time have been expressed using the Temporal Trace Language TTL [6]. Dynamic properties from an internal perspective involve direct temporal or causal relationships between internal state properties and have been specified using the language LEADSTO [7]. This is an executable language that also can be used for simulation: given some input in terms of characteristics of a particular type of criminal and stimuli from the environment, the behaviour of this type of criminal in that particular environment can be simulated.

In Section 2 a brief overview of the types of criminals addressed is given. Section 3 addresses formalisation of partially given traces of crime-related events. Section 4 discusses the behavioural properties from an external perspective, and formal analysis of these properties against formalised cases. Section 5 discusses dynamic properties formalising the mechanisms underlying the criminal behaviours as considered from an internal perspective. In Section 6 one of the generated simulation traces is shown. Section 7 is a discussion.

2. Three Types of Criminals
The case study made in this paper focuses on three types of violent offenders: the violent psychopath, the offender with an antisocial personality disorder (APD), and the
offender who suffers from an intermittent explosive disorder (IED). Below, these types of criminals are briefly introduced and commonalities and differences between them are discussed, based on [11, 19, 20]:

- Violent psychopaths do not have feelings like the rest of us. They lack the normal mechanisms of anxiety arousal, which ring alarm bells of fear in most people. Their kind of violence is similar to predatory aggression, which is accompanied by minimal sympathetic arousal, and is purposeful and without emotion. Moreover, they like to exert power and have unrestricted dominance over others, ignoring their needs and justifying the use of whatever they feel compelling to achieve their goals. They do not have the slightest sense of regret.
- Persons with APD have characteristics that are similar to the psychopath. However, they may experience some emotions towards other persons, but these emotions are mainly negative: they are very hostile and intolerant.
- Persons with IED, in contrast, appear to function normally in their daily life. However, during some short periods (referred to as episodes from now on), their brain generates some form of miniature epileptic fit. Such episodes can be triggered by minor negative experiences. As a result, some very aggressive impulses are released and expressed in serious assault or destruction of property. After these episodes, IED persons have no recollection of their actions and show feelings of remorse.

Table 1. Overview of characteristics for the three types of violent criminals

<table>
<thead>
<tr>
<th></th>
<th>Anxiety threshold</th>
<th>Excitement threshold</th>
<th>Theory of mind</th>
<th>Positive emotional attitude to others</th>
<th>Negative emotional attitude to others</th>
<th>Aggressiveness</th>
<th>Impulsiveness</th>
<th>Sensitive to alcohol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Violent Psychopath</td>
<td>high</td>
<td>high</td>
<td>high</td>
<td>low</td>
<td>low</td>
<td>high</td>
<td>high</td>
<td>yes</td>
</tr>
<tr>
<td>Antisocial Personality Disorder</td>
<td>medium</td>
<td>high</td>
<td>low</td>
<td>low</td>
<td>medium</td>
<td>high</td>
<td>high</td>
<td>yes</td>
</tr>
<tr>
<td>Intermittent Explosive Disorder</td>
<td>normally medium in episode: high</td>
<td>normally medium in episode: high</td>
<td>normally medium in episode: low</td>
<td>normally medium in episode: low</td>
<td>normally medium in episode: high</td>
<td>normally medium in episode: high</td>
<td>normally medium in episode: high</td>
<td>yes</td>
</tr>
</tbody>
</table>

These three types of criminals can be distinguished by taking a number of aspects into account (see also Table 1 for an overview); these are also the aspects incorporated in the model from an internal perspective.

Firstly, the Anxiety Threshold is a threshold that needs to be passed by certain stimuli, in order to make a person anxious. Thus, when a person’s anxiety threshold is high, it is very difficult for this person to become anxious (and as a result, (s)he hardly knows any fear). This is the case for the violent psychopath and the person with APD: in these persons, a notion of fear is almost completely lacking. In contrast, persons with IED have a medium anxiety threshold. Nevertheless, under some special circumstances (i.e., during episodes) the anxiety threshold of a person with IED suddenly becomes much higher. Moreover, the Excitement Threshold needs to be passed by certain stimuli, in order to make a person excited. Thus, when a person’s excitement threshold is high, it is very difficult for this person to become excited (and as a result, (s)he is often bored). This is the case for the violent psychopath and for persons with APD. Persons with IED have a medium excitement threshold, but under certain circumstances (during
After a couple of minutes, person 1 meets person 3 and assaults this person 3. He hits him over 10 times in his face and stomach. For the assault he uses a large stick that he found on the street. During the assault, person 1 constantly calls person 3 names.

3. Formalising Crime Cases

In this section, it is shown how partial information related to a crime case can be formalised, in order to characterise the type of person who committed this crime case. Below, two of such cases are shown, in the form of partially given traces (comparable to descriptions of real scenarios as reported by the police).

Case 1 Person 1 is walking down the street. Person 2 approaches him and asks for a light for his cigarette. Person 1 answers that he does not have a lighter and continues his walk. After a couple of minutes, person 1 meets person 3 and assaults this person 3. He hits him over 10 times in his face and stomach. For the assault he uses a large stick that he found on the street. During the assault, person 1 constantly calls person 3 names.
Using a formal ontology, the dynamics as described by Case 1 can be formalised and visualised as shown in Figure 1. Here, assault1 stands for the assault as described in the story. Moreover, the encounter with person 2 is assumed to be a ‘negative experience’, which might be sufficient for persons with IED to cause an episode; this is formalised by state property observes(negative_agent). Moreover, observes(suitable_target_for(assault1)) formalises that the agent observes an opportunity for a crime of type assault1. In addition, some atoms of the form has_property(...) are shown. These atoms do not represent events in the scenario, but rather describe some useful common background knowledge (e.g. the fact that hitting someone in the face is a highly aggressive act). Similarly, the dynamics as described by Case 2 below are visualised in Figure 2.

**Case 2** Person 1 is walking down the street. He is on his way to the ATM because he needs some money for the groceries. However, an old lady is standing in front of the ATM. She is not very fast and it takes her some time to get the money. Person 1 sees a stick lying on the ground, picks it up and hits the old lady. She steps away for the machine because it really hurts. Person 1 walks past her and uses the ATM.

---

**4. Formalising Criminal Behaviour: External Perspective**

In this section it is shown how dynamic properties can be specified to characterise the types of criminals discussed earlier from an external perspective. Moreover, it is discussed how these dynamic properties can be automatically checked against the example traces to find out which type of criminal performed the crime. To analyse traces as discussed in the previous section, the following dynamic properties have been specified in the Temporal Trace Language TTL [6] to characterise, from an external perspective, the different types of violent criminal behaviour considered. To characterise an assault by an IED criminal, two properties are used. The first property checks whether a negative person has been encountered just before the assault (which might have caused an episode); the second property checks whether the assault itself corresponds to some typical characteristics for crimes by persons with IED.
Intermittent Explosive Disorder

a) The assault was performed by a person that first met a negative agent, and later met a pass-by.

\[ \text{IED1}(\gamma, \text{TRACE}, t, \text{TIME}, a, \text{ACTION}) \equiv \]
\[
\exists t', t'' \; [ t' < t'' < t \&
state(\gamma, t') \models \text{observes(negative\_agent)} \&
state(\gamma, t'') \models \text{observes(suitable\_target\_for(a))} \&
state(\gamma, t) \models \text{is\_performed(a)}]
\]

b) The performed assault is characterised by a high aggressiveness, a high impulsiveness, a low positive emotional attitude towards others, and a high negative emotional attitude towards others.

\[ \text{IED2}(\gamma, \text{TRACE}, t, \text{TIME}, a, \text{ACTION}) \equiv \]
\[
state(\gamma, t) \models \text{is\_performed(a)} \wedge
\text{has\_property(a, aggressiveness, high)} \wedge
\text{has\_property(a, impulsiveness, high)} \wedge
\text{has\_property(a, positive\_emotional\_attitude\_towards\_others, low)} \wedge
\text{has\_property(a, positive\_emotional\_attitude\_towards\_others, high)}
\]

Here \( state(\gamma, t) \models X \) denotes that within the state \( state(\gamma, t) \) at time point \( t \) in trace \( \gamma \) state property \( X \) holds, with the infix predicate \( \models \) within the language denoting the formalised satisfaction relation. Similarly, \( state(\gamma, t) \not\models X \) denotes that \( X \) does not hold. See [6] for more details of TTL. Next, the following property characterises an assault by a violent psychopath:

**Violent Psychopath**
The performed assault is characterised by a high aggressiveness, a high impulsiveness, a low positive emotional attitude towards others, and a low negative emotional attitude towards others.

\[ \text{psychopath}(\gamma, \text{TRACE}, t, \text{TIME}, a, \text{ACTION}) \equiv \]
\[
state(\gamma, t) \models \text{is\_performed(a)} \wedge
\text{has\_property(a, aggressiveness, high)} \wedge
\text{has\_property(a, impulsiveness, high)} \wedge
\text{has\_property(a, positive\_emotional\_attitude\_towards\_others, low)} \wedge
\text{has\_property(a, positive\_emotional\_attitude\_towards\_others, low)}
\]

These dynamic properties have been checked automatically for the cases 1 and 2 described above (see also Figure 1 and 2) using the TTL checker tool [6]. For case 1 it turns out that IED1 and IED2 hold and psychopath does not hold. For case 2 psychopath holds and IED1 and IED2 do not hold. This indicates that the first case the criminal may be of IED type and in the second case a violent psychopath. Thus, using these checks, it indeed turned out possible to assign certain types of criminals to certain (partial) traces.

5. Formalising Criminal Behaviour: Internal Perspective

In this section, it is shown how criminal behaviour is formalised from an internal perspective. A dynamical system model for the underlying mechanisms that has been developed is briefly described. This model was developed within the LEADSTO environment, see [7]. In LEADSTO, direct temporal dependencies between two state properties in successive states are modelled by *executable dynamic properties*, defined as follows. Let \( \alpha \) and \( \beta \) be state properties of the form ‘conjunction of ground atoms or negations of ground atoms’. In the LEADSTO language the notation \( \alpha \rightarrow e, \ t, \ g, \ h \ \beta \), means:

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if state property $\alpha$ holds for a certain time interval with duration $g$,
then after some delay (between $e$ and $f$) state property $\beta$ will hold
for a certain time interval of length $h$.

Here atomic state properties can have a qualitative, logical format, such as an
expression $\text{desire}(d)$, expressing that desire $d$ occurs, or a quantitative, numerical format
such as an expression $\text{has\_value}(x, v)$ which expresses that variable $x$ has value $v$. For
more details, see [7]. The dynamical system model has been built by composing three
submodels:

1. a BDI-model to determine actions based on beliefs, desires and intentions
2. a submodel to determine desires, used as input by the BDI-model.
3. a submodel to determine beliefs in an opportunity, as input for the BDI-model.

The BDI-model bases the preparation and performing of actions on motivational
states such as beliefs, desires and intentions e.g., [13, 16, 21]. It uses as input desires
and beliefs in opportunities, generated by the other two submodels. In this model an
action $a$ is performed when the subject has the intention to do this action and it has the
belief that the opportunity to do the action is there. Beliefs are created on the basis of
stimuli that are sensed or observed. The intention to do a specific type of action $a$ is
created if there is a certain desire $d$, and there is the belief that in the given world state,
performing this action will fulfil this desire.

\[ \text{desire}(d) \land \text{belief}(\text{satisfies}(a, d)) \rightarrow \text{intention}(a) \]
\[ \text{intention}(a) \land \text{belief}(\text{opportunity\_for}(a)) \rightarrow \text{to\_be\_performed}(a) \]

Assuming that beliefs in reason for intentions are internally available, what remains to
be generated in this model are the desires and the beliefs in opportunities. Generation of
desires often depends on domain-specific knowledge, which also seems to be the case
for criminal behaviour. Beliefs in opportunities are based on the Routine Activity
Theory by [9].

The submodel to determine desires is a rather complex submodel, incorporating
various aspects. To model these, both causal and logical relations (as in qualitative
modelling) and numerical relations (as in differential equations) have been integrated in
one modelling framework. This integration was accomplished, using the LEADSTO
language as a modelling language. The variety of aspects that were found relevant in the
literature, such as [4, 11, 19, 20] and are taken into account in this submodel, are: (a)
use of a theory of mind (e.g., understanding others), (b) desires for aggressiveness (e.g.,
using violence), (c) desires to act (no matter which type of action) and (d) to act safely
(e.g., avoiding risk), (e) desires for actions with strong stimuli (e.g., thrill seeking), (f)
desires for impulsiveness (e.g., unplanned action), and (g) social-emotional attitudes
with respect to others (e.g., feel pity for someone). Note that these aspects are derived
on the basis of (but not exactly equal to) the characteristics as described in Table 1.
Different combinations of such elements lead to different types of (composed) desires,
for example:

- the desire to perform an exciting planned nonaggressive nonrisky action that harms somebody
  else (e.g., a pick pocket action in a large crowd)
- the desire to perform a exciting impulsive aggressive risky action that harms somebody else
  (e.g., killing somebody in a violent manner in front of the police department)
The following LEADSTO property (LP) is used to generate a composed desire out of some of the ingredients mentioned above; here the x1, x2, x3, x4, x5, x6, x7, x8 are qualitative labels (e.g., high, medium, low) or numerical values (integer or real numbers):

**LP24** A combination of values for theory of mind, desire for aggressiveness, desire to act, desire to act safely, desire for actions with strong stimuli, desire for impulsiveness, emotional attitude towards others (pos) and emotional attitude towards others (neg) will lead to a specific composed desire, represented as d(x1, x2, x3, x4, x5, x6, x7, x8).

\[
\forall x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8 : \text{SCALE} \\
\text{theory_of_mind(x1)} \land \text{desire_for_aggressiveness(x2)} \land \text{desire_to_act(x3)} \land \text{desire_to_act_safely(x4)} \land \text{desire_for_actions_with_strong_stimuli(x5)} \land \text{desire_for_impulsiveness(x6)} \land \text{emotional_attitude_towards_others(pos,x7)} \land \text{emotional_attitude_towards_others(neg,x8)} \\
\rightarrow \text{desire(d(x1, x2, x3, x4, x5, x6, x7, x8))}
\]

Due to space limitations, the parts of the submodel to determine each of the ingredients (a) to (g) cannot be described in detail. To give an impression, a rough sketch of part of this submodel is given. Stimuli are labeled with two aspects, indicating the strength with respect to anxiety (risk), and with respect to excitement (thrust), respectively. For both aspects, thresholds represent characteristics of the person considered. The excitement threshold depends on other aspects in the model, such as sensitivity for and use of drugs and alcohol, and basic sensitivity to stimuli. A stimulus with excitement strength below the excitement threshold leads to being bored, and being bored leads to a desire for an action with strong(er) stimuli. Similarly, a stimulus with anxiety strength above the anxiety threshold leads to internal alarm bells, which (depending on another characteristic, the tendency to look for safety) leads to the desire to take into account anxiety.

The submodel to determine opportunities is based on two of the three criteria as indicated in the Routine Activity Theory by [9]. The third criterion of the Routine Activity Theory, the presence of a motivated offender, is indicated by the intention in the BDI-model. This way, the presence of the three criteria together leads to the action to perform a criminal act, in accordance with [9]. More specifically, the notion of opportunity is based on the presence of a suitable target, and the absence of social control (guardian). This was specified by the following property in LEADSTO format:

**LP34** When a suitable target for a certain action is observed, and no suitable guardian is observed, then a belief is created that there is an opportunity to perform this action.

\[
\forall a:\text{ACTION} \\
\text{observes(suitable_target_for(a))} \land \neg \text{observes(suitable_guardian_for(a))} \\
\rightarrow \text{belief(opportunity(a))}
\]

### 6. Simulated Criminal Behaviour from an Internal Perspective

The model described in the previous section has been used to generate a number of simulation traces for the different types of violent criminals addressed. In Figure 3, an example trace is depicted, which addresses the case of the criminal with IED. In this picture, time is on the horizontal axis; state properties are on the vertical axis. A dark box on top of the line indicates that the property is true during that time period, and a lighter box below the line indicates that the property is false. The lower part of the picture depicts some quantitative information: the thresholds for anxiety and excitement, and the strength of the world stimuli.
Figure 3. Example simulation trace for a criminal with IED
The initial state properties that have been set to model the person with IED are as follows (see time point 0): low preparedness to look for safety, low psychological self, high potential aggressiveness, medium potential positive and negative emotional attitude towards others, medium potential anxiety and excitement threshold (both value 5), a low potential sensitivity for stimuli (value 3) and (s)he drinks alcohol and is sensitive for it. Later, at time point 25, (s)he encounters a negative agent and generates an episode, which has some important consequences. Because of the episode, the person with IED generates a desire (at time point 29) that is characterised by the following elements: low theory of mind, high aggressiveness, high desire to act, low desire to act safely, high desire for actions with strong stimuli, high impulsiveness, low positive emotional attitude towards others, high negative emotional attitude towards others. As a result, the criminal generates an intention to perform a specific type of assault (denoted by assault), and, as soon as the opportunity is there, actually performs the assault. As a result, the stimuli of the world increase, which satisfies the desires of the criminal. Note that, in order to classify these kinds of simulation traces, they can also be verified against the properties shown in Section 4. This has been performed successfully, using the TTL checker.

7. Discussion

For the analysis of criminal behaviour computer support is more than welcome, but almost inexistent. As one of the ways to address this, a formal method to analyse crime cases against known types of criminal behaviour was presented. As a case study, this method has been applied to three types of violent criminals. It was shown how the temporal language TTL [6] can be used to specify dynamic properties that characterise the behaviour of different types of criminals from an external perspective. Moreover, it was shown how crime cases, for example as reported by the police, can be formalised. Furthermore, it was shown how the automated TTL checker can be used to verify the behavioural properties for the formal (partial) traces describing specific crime cases. Note that the properties addressed in this paper and the two cases considered are only meant as an illustration of the approach, and are therefore not too complex. However, the expressivity of TTL allows it to handle more complex properties and cases (involving, e.g., real values, or more time points). Thus, in the future the approach will be applied to such more complex realistic cases and properties as well.

In addition, from an internal perspective a model has been developed that describes the dynamics of the basic mechanisms underlying the criminal behaviour types considered. This executable model can be set with characteristics of any of these three types of criminals and used to simulate behaviour. It has been shown that, if the right characteristics are set, the model indeed shows the behaviour as known for the corresponding type of criminal.

The presented modelling approach integrates qualitative, logical aspects and quantitative, numerical aspects. This integration allows the modeller to exploit techniques from both areas, such as automated methods for logical analysis and possibilities to simulate dynamical systems using numerical methods, also incorporating qualitative elements. The model was validated by comparing it to patterns described in criminological literature.

In comparison to existing work in the formalised analysis of criminal behaviour, an important distinction is that the research presented here focuses on the dynamical aspect of criminal behaviour. Most approaches to the analysis of criminal behaviour that have
been proposed are basically static and usually based on profiling. In contrast, the work reported here (1) takes the dynamical systems perspective on behaviour as a point of departure, which considers behaviour as emerging from a dynamic interplay of various components and aspects, and (2) exploits and integrates qualitative and quantitative techniques developed to model such complex dynamical systems. This is shown, for example, in the simulation of a criminal with IED, where personal characteristics may change dramatically due to events that are encountered.

Similar to the current paper, [5] also incorporates formal methods applied to criminal behaviour. However, that paper focuses only on the IED criminal, whilst the current paper addresses three types of violent criminals. Moreover, [5] does not concentrate on crime case analysis but on simulation and evaluation of simulated traces with respect to environmental properties, including some probabilistic properties.

References

Combining Rational and Biological Factors in Virtual Agent Decision Making

Tibor Bosse, Charlotte Gerritsen and Jan Treur

Abstract. To enhance believability of virtual agents, this paper presents an agent-based modelling approach for decision making, which integrates rational reasoning based on means-end analysis with personal psychological and biological aspects. The agent model developed is a combination of a BDI-model and a utility-based decision model in the context of specific desires and beliefs. The approach is illustrated by addressing the behaviour of violent criminals, thereby creating a model for virtual criminals. Within a number of simulation experiments, the model has been tested in the context of a street robbery scenario. In addition, a user study has been performed, which confirms the fact that the model enhances believability of virtual agents.

1. Introduction

In recent years, human-like virtual agents are increasingly being applied in various domains ([33, 36]). Typical examples are agents in (serious) games (e.g., an instructor in a naval training simulator [17]), character agents in computer-generated virtual stories [12], or conversational agents (e.g., seller representatives on the internet [29]). Recently, much research has been dedicated to developing virtual agents with more realistic graphical representations. However, the behaviour of such agents is usually not very human-like. For example, although many virtual agents currently have the ability to somehow show emotions by means of different facial expressions, it is quite difficult for them to show the right emotion at the right moment. This is in conflict with the requirement of virtual agents to closely mimic human affective behavior. Several studies in Social Sciences have shown that this is an important prerequisite for an agent to increase human involvement in the virtual environment [22]. Therefore, existing systems based on IVAs are not as effective as they could be.

A known problem encountered by developers of human-like virtual agents is to create realistic decision making behaviour for such agents. For humans it is known that the process of decision making is determined partly by rational means-end reasoning, and partly by subjective personal biological and psychological aspects (including, for example, their motivational and emotional state, see, e.g., [15, 18, 28, 42]). On the one hand, humans have various kinds of – partly biologically determined – desires, but on the other hand, they may have to reason rationally about which desires to fulfil. For example, a person may have the desire to eat but may decide rationally not to do this because it will make him/her fat. However, if the biological desire is too strong, the person may decide to eat nevertheless. Thus, some mechanism is used that enables humans to make decisions in situations where both rational and biological/psychological factors play a role.

This paper introduces an approach to incorporate such mechanisms within virtual agents in order to make their behaviour more human-like. In principle, the approach is generic, i.e., it can be used to model virtual agents in various types of applications (varying from serious games to virtual stories) and in various domains (varying from flight simulators to adventure games). As an illustration of the approach, in the current
paper a specific domain is chosen, namely the domain of crime. This is an interesting case study, since this is a typical domain in which both rational decision making and biological and psychological aspects play a role. Within the area of Criminology, a longstanding debate is whether criminal behaviour is driven by a criminal’s subjective, personal biological and psychological background, or is the result of a rational, calculated choice; e.g., [14, 31]. The current paper will show how the two viewpoints can be integrated, thereby creating a behavioural model for a “virtual criminal agent”.

As a starting point, the criminal agent model described in [6] has been taken, which focuses specifically on violent criminals (such as psychopaths and persons with the Intermittent Explosive Disorder), and its embedding in a social context described in [5]. This model addresses action generation based on beliefs, desires and intentions (BDI), and generation of desires and beliefs in opportunities. However, for the sake of simplicity, only one action per desire was assumed in that model, so no decision making was covered involving a choice between different options for actions to fulfil a desire. The current paper extends that model with a mechanism for utility-based multi-criteria decision making (e.g., [25, 37]) within a BDI-setting. This decision model provides a formalisation of the Rational Choice Theory within Criminology; e.g. [14]. This theory as informally discussed within Criminology describes crime as an event that occurs, for example, when an offender decides to take risk breaking the law, after considering his or her own need for money, personal values or learning experiences and how well a target is protected. The criminal assesses the chances of getting caught, the expected penalty, the value to be gained by committing the act, and his or her immediate need for that value.

In the decision model introduced in this paper, this process is modelled by introducing utilities for different possible intended actions. The utility of a certain (option for an) action is then assessed according to the extent to which it fulfils the agent’s desire. In this way utilities are assessed with respect to a subjective measure focusing on a specific desire, which may be affected by the subject’s specific biological and psychological background. In other words, for the individual agent, rational choice means the choice to fulfil its own desires in the best possible way. Thus, the model for desire generation based on the biological and psychological factors is integrated with a rational decision model for the choice of (intended) actions.

In this paper, Section 2 discusses the dynamic modelling approach that was used at a global level. In Section 3, a brief summary from the literature is presented on the role played by biological and psychological factors in criminal behaviour. Next, the two main components of the simulation model are presented: Section 4 briefly presents the model to determine desires (inspired by [6]) and Section 5 presents the utility-based decision making model. In Section 6, some simulation results are shown, addressing an example street robbery scenario. Section 7 describes the results of an experiment to evaluate how the generated simulation traces are appreciated by humans. Finally, the approach and its possible applications are discussed in Section 8.

2. Modelling Approach

Modelling the various aspects related to criminal decision making of virtual agents in an integrated manner poses some challenges. On the one hand, qualitative aspects have to be addressed, such as beliefs, desires, and intentions, certain brain deviations, and some aspects of the environment such as the presence of certain agents. On the other hand, quantitative aspects have to be addressed, such as testosterone and serotonin levels, and
utilities. Moreover, the aspects have to be integrated in such a way that the resulting model can easily be implemented within a virtual agent. For example, it should be possible to connect them to concrete events and states that occur in a virtual world, such as encounters between agents, and goals of individual agents.

It was not easy to find a modelling approach that fulfilled all of the above desiderata. Within the cognitive modelling area, a number of generic architectures exist for computational modelling of cognitive processes such as attention, memory, and decision making, for example ACT-R [1], Soar [27], and Clarion [45]. These approaches have as advantages that they distinguish in some way or another - between implicit (or subconscious) and explicit (conscious, rational) processes. For this reason, the approach put forward in this article was inspired by these approaches. However, they could not be used directly, for two reasons. First, these approaches were originally designed for the purpose of representing cognitive processes in much detail (including, for instance, specific timing parameters in terms of milliseconds), and were therefore not directly applicable to virtual agents, which need modelling constructs at a much higher level of abstraction. Second, they do not provide any mechanism to model biological factors, such as testosterone and serotonin levels.

To solve the first problem, it was decided to also take some inspiration from the area of Artificial Intelligence (and, more specifically, agent-based modelling). In this area, it is quite common to model an agent's behaviour in terms of beliefs, desires, and intentions [21, 35, 39, 40]). Thus, it was decided to take the standard BDI-model [21, 40] as a basis, and extend this with a mechanism to represent implicit, sub-conscious processes as done in cognitive modelling architectures. However, since the second problem (the lack of constructs for biological factors) could not be solved directly by the BDI-model, the authors decided to develop a new model, thereby integrating the BDI-model with constructs for both psychological (cognitive) as well as biological factors.

To develop this new integrated model, the modelling language LEADSTO [7] turned out to be a suitable candidate. This language integrates qualitative, logical aspects and quantitative, numerical aspects. This integration allows the modeller to exploit both logical and numerical methods for analysis and simulation. The basic building blocks of LEADSTO are so-called executable dynamic properties, by which direct temporal dependencies between two state properties in successive states are modelled. Their format is defined as follows. Let $\alpha$ and $\beta$ be state properties of the form 'conjunction of ground atoms or negations of ground atoms'. In LEADSTO, the notation $\alpha \rightarrow_{e, t, g, h} \beta$, means:

**If state property $\alpha$ holds for a certain time interval with duration $g$, then after some delay (between $e$ and $f$) state property $\beta$ will hold for a certain time interval of length $h$.**

Here, atomic state properties can have a qualitative, logical format, such as an expression $\text{desire}(d)$, expressing that $d$ occurs, or a quantitative, numerical format such as an expression $\text{has\_value}(x, v)$ which expresses that variable $x$ has value $v$. For more details of the language LEADSTO, see [7]. As stated above, the overall simulation model has been built by composing two models (see Figure 1 for an overview):
1. a model to determine desires incorporating various biological and psychological aspects and their interactions (subconscious model)
2. a model for reasoning about beliefs, desires and intentions, using a BDI-model based on utility-based decision making (conscious, rational model)

These models have both been implemented in LEADSTO. They are described in more detail in Section 4 and 5, respectively.

To create the subconscious model, we first performed an extensive research in the existing literature on criminal behaviour, in collaboration with a group of experts from different disciplines. These experts, among which psychologists, criminologists and experts in AI, together agreed upon a short list of factors that were selected to be used in the model. The biological factors that were selected are based on work by Moir and Jessel [31] and by Adrian Raine [38], a well known neurocriminologist. Some of the psychological factors are inspired by work by psychologist Martine Delfos [15]. A complete overview of the factors that were selected for the model is provided in the next section.

3. Biological and Psychological Factors

Since the BDI model [21, 40] does not prescribe a standard way to determine how desires are created, for a particular application usually domain-specific knowledge is used. For criminal behaviour, a number of specific biological and psychological aspects seem to play a role in the generation of desires. An extensive search has been performed into literature from areas such as Criminology and Psychology (e.g., [16, 31, 38]) for aspects to be incorporated in the model. The aspects that have been selected are explained below in more detail.

A theory of mind of a person (e.g., [2]) describes other persons’ minds by separate mental concepts, such as the person’s own beliefs, desires, and intentions, and how those concepts play a role in the person’s behaviour. Criminal actions are often performed by persons whose theory of mind is less developed. In recent years, more evidence is found that there often are biological reasons for this. For example, it has
been found that many psychopaths have a damaged connection between the frontal lobes (concerned with conscience and remorse) and the limbic area, which generates feelings; cf. [31].

Another important aspect in crimes is aggressiveness. Research has pointed out that there is a correlation between aggressive behaviour and the level of testosterone. In fact, 89% to 95% of all crime is performed by males [31]. In addition, the use of alcohol or drugs may increase the violence of behaviour.

A third aspect involved in criminal behaviour is the desire to act, which can be related to a high level of adrenalin. If a person’s adrenalin level becomes too high, (s)he somehow has to cope with this; acting decreases the adrenalin level. Thus, if the desire to act is high, then a criminal act more easily occurs. The specific types of actions that are chosen depend on another factor, the desire to act safely. This factor correlates with a high level of oxytocine, a hormone mainly produced by women. Persons with a high level of oxytocine have a higher tendency to cope with their desire to act by performing ‘safe’ actions (e.g., taking care of the ‘nest’) than persons with less oxytocine; they will rather perform ‘less safe’ actions (e.g., fighting) [16].

In addition, crimes are often committed by persons who are looking for a thrill. These persons in general have a high excitement threshold, which means that it is very difficult for them to become excited [31, 38]. As a result, they are often bored, so that they generate a desire for actions with strong stimuli. Such actions may become criminal actions, such as stealing, joyriding, or assaulting other people. Only by performing these actions, their desire for strong stimuli is fulfilled, and they become less bored.

Furthermore, a significant amount of committed crimes can be described as impulsive. They are not planned, but rather triggered by occasional opportunities. An important factor causing impulsive behaviour is a low level of blood sugar, which in turn is caused by a high insulin level and a low serotonin level [31].

A next factor that may affect the types of (criminal) actions that persons may perform, is the extent to which they have (positive or negative) feelings with respect to another person’s wellbeing. When someone has a low amount of positive feelings towards others, (s)he does not really care about the other. Likewise, when someone has many negative feelings towards others, (s)he may wants to cause harm towards someone else. For example, in psychopaths, both attitudes are low: these persons hardly show any emotion concerning other persons, so for them, both the positive and the negative emotional attitude towards others are low [31].

The last two factors chosen to incorporate in the model are the desire for high gain and the desire for low loss. These concepts were chosen on the basis of the Rational Choice Theory [14]. According to this theory, to determine their actions, persons will try to minimise their expected loss or penalty (e.g., being caught, getting hurt) and maximise their gain (e.g., money, status). The theory states that criminals will make a serious decision before committing a crime, weighing pros against cons.

4. Determining Desires

To determine desires, a rather complex submodel is used, incorporating dynamical system elements for the biological and psychological aspects as mentioned earlier, varying from qualitative aspects, such as anatomical aspects concerning brain deviations (e.g., the absence of certain connections) to quantitative aspects, such as biochemical
aspects concerning testosterone levels. Some example LEASTDO specifications (called Local Properties, LPs) are given below (both in informal and in formal notation)*:

**LP9** A certain level of current testosterone will lead to a corresponding level of aggressiveness.
\[
\forall x: \text{SCALE} \quad \text{chemical_state(} \text{testosterone, current,} x) \rightarrow_0 0, 1, 1 \text{ desire_for_aggressiveness}(x)
\]

**LP20** Observation of a stimulus with an excitement level that is lower than the excitement threshold will lead to boredom.
\[
\forall s_1, s_2, y: \text{INTEGER} \quad \text{observes_stimulus}(s_1, s_2) \land \text{excitement_threshold}(y) \land s_2 < y \rightarrow_0 0, 1, 1 \text{ boredom}
\]

**LP21** Boredom leads to a high desire for actions with strong stimuli.
\[
boredom \rightarrow_0 0, 1, 1 \text{ desire_for_actions_with_strong_stimuli}(\text{high})
\]

**LP29a** A low blood sugar level leads to high impulsiveness.
\[
\text{chemical_state(blood_sugar, low)} \rightarrow_0 0, 1, 1 \text{ desire_for_impulsiveness}(\text{high})
\]

The variety of biological and psychological aspects that were found relevant in the literature (such as [3, 16, 31, 38]) and are taken into account in this model, are those described in the second section above. Different combinations of these elements lead to different types of (composed) desires; e.g., the desire to perform an exciting planned nonaggressive nonrisky action that harms somebody else (e.g., a pickpocket action in a large crowd). The following LEASTDO rule generates a composed desire out of the different ingredients mentioned earlier:

**LP30** A combination of values for theory of mind, desire for aggressiveness, desire to act, desire to act safely, desire for actions with strong stimuli, desire for impulsiveness, positive and negative emotional attitude towards others, and desire for high gain and low loss leads to a specific composed desire, represented as
\[
\text{has_value(desire_for_low_loss, s10)}.
\]
\[
\forall s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8, s_9, s_{10}: \text{SCALE} \land \text{theory_of_mind}(s_1) \land \text{desire_for_aggressiveness}(s_2) \land \text{desire_to_act}(s_3) \land \text{desire_to_act_safely}(s_4) \land \text{desire_for_actions_with_strong_stimuli}(s_5) \land \text{desire_for_impulsiveness}(s_6) \land \text{emotional_attitude_towards_others}(pos, s_7) \land \text{emotional_attitude_towards_others}(neg, s_8) \land \text{desire_for_high_gain}(s_9) \land \text{desire_for_low_loss}(s_{10}) \rightarrow_0 0, 1, 1 \text{ desire}(\text{has_value(theory_of_mind, s1), ..., has_value(desire_for_low_loss, s10)})
\]

5. **Utility-Based Reasoning about Intentions**

As in [6] part of the model for criminal behaviour is based on the BDI-model, which bases the preparation and performing of actions on beliefs, desires and intentions (e.g., [21, 40]). In this model an action is performed when the subject has the intention to do this action and it has the belief that the opportunity to do the action is there. Beliefs are created on the basis of stimuli that are observed. The intention to do a specific type of action is created if there is a certain desire, and there is the belief that in the given world state, performing this action will fulfill this desire. The BDI-model was specified by:

**LP31** Desire \(d\) combined with the belief that a certain action \(a\) will lead to the fulfillment of that desire will lead to the intention to perform that action.
\[
\forall d: \text{DESIRE} \quad \forall a: \text{ACTION} \quad \text{desire}(d) \land \text{belief}(\text{satisfies}(a, d)) \rightarrow_0 0, 1, 1 \text{ intention}(a)
\]

**LP32** The belief that there is an opportunity to perform a certain action combined with the intention to perform that action will lead to the performance of that action.
\[
\forall a: \text{ACTION} \quad \text{belief}(\text{opportunity_for}(a)) \land \text{intention}(a) \rightarrow_0 0, 1, 1 \text{ performed}(a)
\]


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However, to assess and compare different options, and select a best option, as an extension to this basic BDI-model utilities are to be assigned and combined, addressing the degree to which an action satisfies a desire. The notion of utility to be used requires some reflection. Sometimes this may be considered a rational notion with an absolute, intersubjective (or objective) status. For two agents with a kind of standard internal functioning, considered rational, this intersubjectivity may be a reasonable assumption. However, if the internal processes are different it is less reasonable. One agent may have preferences different from those of the other agent, and hence be satisfied with a situation that is not satisfactory for the other agent. As an example, multi-attribute negotiation aims at exploiting such differences in preferences between agents in order to the benefit of both; e.g., [8, 24, 25, 37]. This shows that the meaning of utility can be subjective and personal. In particular, for a criminal subject, due to his or her specific biological and psychological characteristics, a desire can be quite deviant from what is commonly considered as the rational norm. For this subject the utility of a certain action a is assessed according to the extent to which it fulfils this personal desire. This shows how utilities are assessed with respect to a subjective measure focusing on a specific desire d, which is affected, or even largely determined by the subject’s specific biological and psychological background. According to this perspective, the utility-based decision model was set up as follows:

1. Aspect Utility Value Representations
   For any aspect $x_i$ with value $s_i$, introduce an aspect utility $v_i$ for any possible action $a$ by
   
   $\text{has\_aspect\_utility}(a, \text{has\_value}(x_i, s_i), v_i)$
   
   where $v_i$ is based on a closeness measure for each aspect $x_i$ of the considered option $a$ to value $s_i$, normalised between 0 (least close, minimal utility) and 1 (most close, maximal utility). For example,
   
   $\text{has\_aspect\_utility}($fight$, \text{has\_value}(\text{desire\_for\_aggressiveness, high}), 0.9)$
   
   indicates that the action of fighting contributes much to a high value for aggressiveness.

2. Aspect Weight Factor Representations
   Introduce weight factors $w_1, \ldots, w_k$ for the different aspects $x_i$, normalised so that the sum is 1, and introduce relations weight_factor($x_i, w_i$) stating that aspect $x_i$ has weight factor $w_i$.

3. Combination of Aspect Utilities to Option Utilities
   Combine the option aspect utility values $v_1, \ldots, v_k$ for a given composed desire to an overall option utility taking into account the weight factors $w_1, \ldots, w_k$ according to some combination function $f(v_1, \ldots, v_k, w_1, \ldots, w_k)$.
   
   The combination function in 3. can be formalised in a number of manners; two common possibilities are:
   
   - Euclidian Distance: $f(v_1, \ldots, v_k, w_1, \ldots, w_k) = \sqrt{(w_1 v_1^2 + \ldots + w_k v_k^2)}$
   - Manhattan Distance: $f(v_1, \ldots, v_k, w_1, \ldots, w_k) = w_1 v_1 + \ldots + w_k v_k$

   The LEADSTO property for combination is:

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LP41 \( \forall a: \text{ACTION} \quad \forall x_1, \ldots, x_n: \text{ASPECT} \quad \forall s_1, \ldots, s_n: \text{SCALE} \quad \forall v_1, \ldots, v_n, w_1, \ldots, w_n: \text{REAL} \)
belief(has_aspect_utility(a, has_value(x_1, s_1), v_1)) \land \ldots \land
belief(has_aspect_utility(a, has_value(x_n, s_n), v_n)) \land 
weight_factor(x_1, w_1) \land \ldots \land weight_factor(x_n, w_n) \rightarrow \neg \theta_{0.2, 0.2, 1, 1}
belief(has_utility(a, d(has_value(x_1, s_1), \ldots, has_value(x_n, s_n)),
\{(v_1, \ldots, v_n, w_1, \ldots, w_n)\}))

Note that the model currently assumes that a value is filled in for each aspect utility and each weight factor. However, in order to deal with missing values, it can easily be extended by defining a default value (for example, 0.5 for the aspect utilities, and 0 for the weight factors) for each of the missing factors.

Figure 2. Utility-Based BDI-model

Next, the choice process is formalised. This is done in two steps. First, LP31 is replaced by LP31a, LP31b, and LP31c:

LP31a Desire \( d \) combined with the belief that a certain action \( a \) will lead to the fulfillment of \( d \) with utility \( u \) (\( \geq c \)) will lead to the consideration of \( a \) as a possible intention option.
\( \forall d: \text{DESIRE} \quad \forall a: \text{ACTION} \quad \forall u: \text{REAL} \quad \text{desire}(d) \land \text{belief}(\text{has_utility}(a, d, u) \land u \geq c) \rightarrow \neg \theta_{0.2, 0.2, 1, 1} \land \text{is_intention_option}(a, u) \)

Here \( c \) is a threshold value, for example 0.5. This is used to generate the options to be considered. To obtain only the intentions with highest utility, as a next phase, the selection process is modelled in two steps by:

LP31b If \( a_1 \) and \( a_2 \) are both intention options, but \( a_2 \) has a higher utility, then \( a_1 \) is ruled out as an intention option.
\( \forall a_1, a_2: \text{ACTION} \quad \forall u_1, u_2: \text{REAL} \quad \text{is_intention_option}(a_1, u_1) \land \text{is_intention_option}(a_2, u_2) \land u_1 < u_2 \rightarrow \neg \theta_{0.2, 0.2, 1, 1} \land \text{ruled_out_intention_option}(a_1, u_1) \)

LP31c Eventually, an intention option that is not ruled out is selected as final intention.
\( \forall a: \text{ACTION} \quad \forall u: \text{REAL} \quad \text{is_intention_option}(a, u) \land 
\text{not ruled_out_intention_option}(a, u) \rightarrow \neg \theta_{0.2, 0.2, 1, 1} \land \text{intention}(a) \)

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The complete utility-based decision model is depicted graphically in Figure 2. The circles denote state properties, and the arrows denote dynamic (LEADSTO) properties. Notice that the state properties of the type desire(...) are generated by the model described in the previous section.

Note that, in order to describe a specific decision making scenario with this model, the agent described needs to have some expectancy about possible actions already at the start of the scenario. This expectancy may be triggered by observations (e.g., “I see a potential victim and no guardians, so I consider robbing this person”), or by other internal states (e.g., “I feel like seeking some thrill, so I consider robbing a bank this afternoon”). In the first case, the duration between the decision and the actual performance of the action is rather short, so that it is very likely that an opportunity for the considered action will indeed occur. In the second case, this duration will be longer, and it is possible that no opportunity will occur at all. The model can be used to simulate both types of processes.

6. Example Simulation Traces

Based on the model shown above, a number of simulation experiments have been performed to test (for some simple scenarios) whether it shows the expected behaviour. In this section, two example simulation traces are described in detail. Both traces address the same scenario, but the personal characteristics of the main character differ between the two traces. The first example trace involves a virtual street robber agent (indicated by criminal1) who observes some possible targets, and is deliberating about whether or not to perform an assault (and if so, which assault to perform). For simplicity, we assume that there are two possible assaults to choose from (indicated by assault1 and assault2, respectively). In case of assault1, the agent would steal an old lady’s grocery bag, without using extreme violence. In case of assault2, it would steal a young man’s brand new laptop. However, since this man seems to be rather strong, it would probably have to use violence to achieve its goal. The characteristics of both assaults, as well as criminal1’s individual preferences, are shown in Table 1.

In the second column of the table, the different weight factors assigned to criminal1 can be seen. These weight factors, which add up to 1, show the relative importance of each aspect for the agent. The weight factor for desire to act safely, for example, is 0.02. This means that criminal1 has a low interest in the desire to act safely. The weight factor for desire for actions with strong stimuli is 0.17, which means that he has a high desire for actions with strong stimuli. In the columns to the right of the weight factor, the utility of the different aspects is mentioned (in the third column for assault1 and in the column to the right for assault2). The values describe in how far the aspect is present in this particular assault. For example, has_aspect_utility(assault1, has_value(desire_for_aggressiveness, high), 0.3) shows that assault1 does not contribute much to the high desire for aggressiveness. On the other hand, has_aspect_utility(assault2, has_value(desire_for_aggressiveness, high), 0.8) shows that assault2 contributes much to the high desire for aggressiveness.
Table 1. Characteristics of criminal and possible assaults\(^7\)

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Weight Factor (Criminal 1)</th>
<th>Aspect Utility (Assault 1)</th>
<th>Aspect Utility (Assault 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theory of Mind</td>
<td>0.04</td>
<td>low, 0.7</td>
<td>low, 0.9</td>
</tr>
<tr>
<td>Desire for Aggressiveness</td>
<td>0.04</td>
<td>high, 0.3</td>
<td>high, 0.8</td>
</tr>
<tr>
<td>Desire to Act</td>
<td>0.17</td>
<td>high, 0.8</td>
<td>high, 0.8</td>
</tr>
<tr>
<td>Desire to Act Safely</td>
<td>0.02</td>
<td>high, 0.7</td>
<td>high, 0.1</td>
</tr>
<tr>
<td>Desire for Actions with Strong Stimuli</td>
<td>0.17</td>
<td>high, 0.6</td>
<td>high, 0.8</td>
</tr>
<tr>
<td>Desire for Impulsiveness</td>
<td>0.12</td>
<td>medium, 0.5</td>
<td>medium, 0.5</td>
</tr>
<tr>
<td>Positive Emotional Attitude Towards Others</td>
<td>0.02</td>
<td>low, 0.7</td>
<td>low, 0.8</td>
</tr>
<tr>
<td>Negative Emotional Attitude Towards Others</td>
<td>0.04</td>
<td>low, 0.3</td>
<td>low, 0.3</td>
</tr>
<tr>
<td>Desire for High Gain</td>
<td>0.19</td>
<td>high, 0.5</td>
<td>high, 0.8</td>
</tr>
<tr>
<td>Desire for Low Loss</td>
<td>0.19</td>
<td>high, 0.8</td>
<td>high, 0.5</td>
</tr>
</tbody>
</table>

The results of applying the simulation model to this example situation are shown in Figure 3. Here, time points are on the horizontal axis, whereas the different state properties are on the vertical axis. A box on top of a line indicates that a state property is true at that time point. As shown by this figure, the agent immediately has a certain desire, represented as \(d_1\). Note that this stands for a complex desire represented as:

\[
d(\text{has\_value}(\text{theory\_of\_mind,low}), \text{has\_value}(\text{desire\_for\_aggressiveness,high}), \text{has\_value}(\text{desire\_to\_act,high}), \text{has\_value}(\text{desire\_to\_act\_safely,high}), \text{has\_value}(\text{desire\_for\_impulsiveness,medium}), \text{has\_value}(\text{positive\_emotional\_attitude\_towards\_others,low}), \text{has\_value}(\text{negative\_emotional\_attitude\_towards\_others,low}), \text{has\_value}(\text{desire\_for\_high\_gain,high}), \text{has\_value}(\text{desire\_for\_low\_loss,high}))
\]

(which was not shown in the picture, for obvious reasons). This desire was generated by a complex process, involving a combination of biological and psychological factors. For presentation purposes, this part of the trace is not shown here either. However, more detailed simulation traces that include such processes are shown in Appendix A in [5].

Based on the desire as described above, agent \(\text{criminal 1}\) then starts assessing the utilities of the two possible assaults (see the predicates \(\text{belief(\_has\_utility(...))}\) at time point 1), based on the aspect utilities and weight factors of these assaults. The action of stealing the young man’s laptop (assault 2) is assessed with value 0.678723, whereas the action of robbing the old lady’s groceries (assault 1) has value 0.625532. Since both has\_utility-values are higher than 0.5, both actions become possible intentions (see time point 2). Next, the agent chooses the one with the highest utility, which leads to the intention to perform assault 2 at time point 3. Later, when an opportunity for assault 2 arises (time point 20), this assault is indeed performed (time point 21).

---

\(^7\) This approach assumes that an individual’s preferences (i.e., the weight factors), as well as the characteristics of certain actions (i.e., aspect utilities), can be expressed by real numbers. For the presented examples, the chosen numbers are not necessarily claimed to be realistic, and should rather be seen as estimations that were chosen to create interesting scenarios that roughly correspond to reality. All parameter settings were chosen after discussions with domain experts (that were taken from the expert group mentioned in Section 2).
In a second example trace another street robber agent (criminal 2) observes the same possible targets as criminal 1, and is also deliberating about whether or not to perform an assault (and if so, which assault to perform). Also in this case, we assume that there are two possible assaults to choose from: assault1 (stealing an old lady’s grocery bag without using extreme violence) and assault2 (stealing a young man’s brand new laptop potentially with the use of violence). The characteristics of both assaults are the same as in the previous case study. However, the preferences of the two criminals are somewhat different. The individual preferences of criminal2 are shown in Table 2.

### Table 2. Characteristics of criminal 2 and possible assaults

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Weight Factor (criminal2)</th>
<th>Aspect Utility (assault1)</th>
<th>Aspect Utility (assault2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theory of Mind</td>
<td>0.04</td>
<td>low, 0.7</td>
<td>low, 0.9</td>
</tr>
<tr>
<td>Desire for aggressiveness</td>
<td>0.04</td>
<td>high, 0.3</td>
<td>high, 0.8</td>
</tr>
<tr>
<td>Desire to act</td>
<td>0.17</td>
<td>high, 0.8</td>
<td>high, 0.8</td>
</tr>
<tr>
<td>Desire to act safely</td>
<td>0.04</td>
<td>high, 0.7</td>
<td>high, 0.1</td>
</tr>
<tr>
<td>Desire for actions with strong stimuli</td>
<td>0.15</td>
<td>high, 0.6</td>
<td>high, 0.8</td>
</tr>
<tr>
<td>Desire for impulsiveness</td>
<td>0.12</td>
<td>medium, 0.5</td>
<td>medium, 0.5</td>
</tr>
<tr>
<td>Positive emotional attitude towards others</td>
<td>0.02</td>
<td>low, 0.7</td>
<td>low, 0.8</td>
</tr>
<tr>
<td>Negative emotional attitude towards others</td>
<td>0.04</td>
<td>low, 0.3</td>
<td>low, 0.3</td>
</tr>
<tr>
<td>Desire for high gain</td>
<td>0.11</td>
<td>high, 0.8</td>
<td>high, 0.5</td>
</tr>
<tr>
<td>Desire for low loss</td>
<td>0.28</td>
<td>high, 0.8</td>
<td>high, 0.5</td>
</tr>
</tbody>
</table>

In the first column of the table, the different weight factors assigned to criminal2 can be seen. These weight factors, which add up to 1, show the relative importance of each aspect for the agent. Compared to criminal1, criminal2 has a different weight factor assigned to the desires to act safely, for actions with strong stimuli, for high gain and for low loss. The weight factor for desire for high gain, for example, is 0.11. This means that criminal2 has a high interest in the desire for high gain. However, the weight factor for desire for low loss 0.28, which means that the agent has a very high desire for low loss. For this criminal, low loss is much more important than high gain. In the columns to the right of the weight factor, the utility of the different aspects is mentioned.

The results of applying the simulation model to this example situation are shown in Figure 4. As shown by this figure, the agent immediately has a certain desire, represented as d2, which stands for a more complex desire represented as:
as can also be seen in the last two columns of Table 2. Based on the desire as described above, criminal2 then starts assessing the utilities of the two possible assaults (see the predicates belief(has_utility(...))) at time point 1, based on the aspect utilities and weight factors of these assaults. The action of stealing the old lady’s groceries (assault1) is assessed with value 0.652475, whereas the action of robbing the young man’s laptop (assault2) has value 0.637624. Since both has_utility-values are higher than 0.5, both actions become possible intentions (see time point 2). Next, the agent chooses the one with the highest utility, which leads to the intention to perform assault1 at time point 3. Later, when an opportunity for assault1 arises (time point 30), this assault is indeed performed (time point 31).

Figure 4. Example simulation trace for criminal 2.

As illustrated by the traces in Figure 3 and 4, the simulation experiments have indicated that the presented model successfully integrates personal biological and psychological aspects within the decision making process, which eventually leads to the selection of actions that correspond to the desires of the individual. Although the presented scenario was kept simple, these experiments illustrate how the model allows agents with different personal characteristics to make different decisions in the same situation (criminal1 decided to rob the old lady, whereas criminal2 decided to steal the young man’s laptop).

In addition to the simulations described above, the model has been used to generate various other simulation traces under different parameter settings. Such simulation experiments enabled the modellers to investigate (at an abstract level) whether the developed model shows satisfactory behaviour (cf. prototyping in Software Engineering). The obvious next step is to implement the model within concrete real-world applications. Due to the intuitive (causal relationship-based) format of the LEADSTO language, and the fact that it is independent of a particular implementation language, this step is relatively straightforward. For earlier work where agents models written in LEADSTO have been converted to virtual environment applications, see [9] and [11].

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7. User Study

To evaluate how humans perceive the developed agent (with our criminal decision making model) we performed an experiment. We used the scenario introduced earlier, about a street robber who has the choice between different assaults. To be able to assess the impact of the different parts of the criminal decision making model, we applied some variations of the model to the scenario.

A. The criminal decision making model with the personality traits of criminal 1.
B. The criminal decision making model with the personality traits of criminal 2.
C. Standard BDI model without any personality traits.
D. The criminal decision making model with the personality traits of criminal 1, where we deliberately implemented the decision making component incorrect. This means that the model suggests those actions that are least satisfactory to the agent’s desire as best possibilities.
E. The criminal decision making model with the personality traits of criminal 2, where we deliberately implemented the action generation component incorrect. This means that the model selects actions that do not match the agent’s intentions.

Variant D and E have been added to check whether virtual agent believability is already enhance by a criminal decision making model per se, or whether a realistic model is needed.

After generating simulation traces on the basis of these 5 models, for each of the atomic state properties that occur in the model, a mapping has been create to a text fragment. For example, the state property

is_intention_option(X,Y) (where Y is high)

corresponds to the text fragment

The agent considers X a good option.

Similarly, the state property

belief(opportunity_for(X))

corresponds to

The agent believes that there is an opportunity for X.

Using these mappings and a specific conversion program that has been written (see [10]), the LEADSTO simulation traces are automatically translated into virtual storylines in textual format. An example of such a generated storyline is shown in Figure 5.

Twenty persons participated in the experiment. The age of the participants ranged from 23 to 58 with a mean age of 32 and a standard deviation of 9. Among the participants 13 were male and 7 were female. Each participant was asked to read the five different stories (there were different versions of the experiment, each with a
different order of the stories to avoid ordering problems). After reading each scenario the participant filled out a questionnaire. This questionnaire consisted of 12 statements (see the Appendix). The participants were asked to award a measurement of agreement on these 12 statements, about how they perceived the agent. A gradual seven-point scale was used, with the following meaning: 1=’I strongly disagree’, 2=’I disagree’, 3=’I weakly disagree’, 4=’neutral’, 5=’I weakly agree’, 6=’I agree’, 7=’I strongly agree’.

![Figure 5. Example of a generated storyline.](image)

**Results**

To analyse the results of the experiment, an ANOVA has been applied on the answers to the statements of the questionnaire. In this section, the most relevant statements are addressed. These statements are: ‘The agent behaves like a real person’, ‘I liked reading this story’, ‘This is a realistic story’, and ‘The agent seems to be a nice guy’.

Recall that there were five variants of the scenario: variant A-E introduced earlier. The results are presented in Table 3 and Figure 6. The vertical axis in Figure 6 corresponds to the scale explained above. The first column of the table indicates the statement, and the other columns indicate pair wise comparisons between the different variants. The “total” column shows whether the comparison yielded a significant result or not. The cells indicate the p-value of the ANOVA (in case the difference was significant), or ‘n.s.’ (in case the difference was not significant). For example, the third cell of the first row states ‘0.023’, which means that, according to the participants, variant A behaved significantly more like a real person than variant D.

These results show that there is no significant difference between how much the different agents are liked by the participants (second row). There is a significant difference between agent A and B on the one hand and agent D and E on the other hand when it comes to their behaviour (first row). Agents A and B are the agents that behave according to the criminal decision making model. Agents D and E on the other hand, used an incorrect version of the decision making model. The participants clearly feel that agents A and B behave like real persons and agents D and E do not. There is also a significant difference between A and B on the one hand and C, D and E on the other hand when it comes to how realistic the stories are (third row). The participants agree that A and B are more realistic stories than C, D and E. Further, there is a significant difference between how nice the participants find agent B compared to agent C, D and E. This is an interesting finding. In story B the agent steals a bag of groceries without any violence, but in addition there is some background knowledge on his personal characteristics which he uses in his decision making. In story D, the agent also steals the
bag of groceries, but has different personal characteristics, which do not match his behaviour. Surprisingly, this yielded the participants to perceive this agent as less friendly.

![Figure 6. Statistical results of the experiment](image)

<table>
<thead>
<tr>
<th>Statement</th>
<th>A-B</th>
<th>A-C</th>
<th>A-D</th>
<th>A-E</th>
<th>B-C</th>
<th>B-D</th>
<th>B-E</th>
<th>C-D</th>
<th>C-E</th>
<th>D-E</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Behaves</td>
<td>n.s.</td>
<td>n.s.</td>
<td>0.023</td>
<td>0.002</td>
<td>n.s.</td>
<td>0.024</td>
<td>0.002</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>0.003</td>
</tr>
<tr>
<td>Liked</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
</tr>
<tr>
<td>Realistic</td>
<td>n.s.</td>
<td>0.013</td>
<td>0.02</td>
<td>0.000</td>
<td>0.005</td>
<td>0.008</td>
<td>0.000</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>0.000</td>
</tr>
<tr>
<td>Nice</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>0.009</td>
<td>0.009</td>
<td>0.014</td>
<td>n.s.</td>
<td>n.s.</td>
<td>n.s.</td>
<td>0.008</td>
</tr>
</tbody>
</table>

8. Discussion

In this paper, a model for decision making in virtual agents is presented, which combines a BDI-agent model with a model for multi-attribute decision making. It enables a choice between different options for actions fulfilling a complex desire, according to the Rational Choice Theory in Criminology. The resulting agent model combines qualitative, logical aspects of a BDI-model with quantitative, numerical aspects of utility theory. The model is illustrated by applying it to criminal decision making (and more specifically, focussing on certain types of violent criminals). To this end, [6]'s criminal agent model was used for desire generation. To study the behaviour of the model, it has been applied to a case of street robbery, for which various scenarios have been simulated. In addition, a user study has been performed, in which the generated simulation traces were converted into virtual storylines, which were read by
20 participants. The study confirmed our hypothesis that the model enhances believability of virtual agents. The participants appreciated those stories that were generated on the basis of the decision making better than baseline stories that were generated on the basis of a traditional BDI model, or an ‘incongruous’ variant of the decision making model.

Despite these results, a complete external validation of the model remains a nontrivial issue. At least, the present paper has indicated that it is possible to integrate biological and psychological factors with rational factors within one model. Moreover, the model indeed shows the behaviour of different types of criminals as described in literature such as [16, 31, 38], and the user study has confirmed that this leads to a higher believability. In this sense the model has been validated positively. However, notice that this is a relative validation, only with respect to the literature on criminal decision making, and the expectations by humans. In cases that the available knowledge about the behaviour and biological and psychological functioning of such criminal types is extended, the model can be validated accordingly and when needed improved. The modelling approach as put forward supports such an incremental development and improvement. The simulation model has been specified in a conceptual, not implementation-dependent manner, and is easy to maintain. In this sense the approach anticipates further development of the area of criminal behaviour.

Concerning related work, in the literature in cognitive science, more and more authors propose dual process theories, which claim that cognition can be divided into two distinct systems: a low-level, emotional and unconscious system, and a high-level, evolutionary recent, conscious system, see, e.g., [18, 44]. As a result, most contemporary cognitive modelling architectures (e.g., ACT-R [1], Soar [27], and, more recently, Clarion [45]) have evolved under the influence of these theories. For example, although ACT-R is traditionally classified as a ‘symbolic’ architecture (mainly aimed at representing logical, qualitative aspects), it has more recently been extended with ‘subsymbolic’ mechanisms to represent quantitative, numerical aspects as well. Currently, the subsymbolic part of ACT-R is represented by a large set of parallel processes that can be summarised by a number of mathematical equations, whereas its symbolic part is fulfilled by a production system. Here, the subsymbolic equations control many of the symbolic processes. For instance, if multiple production rules in ACT-R’s symbolic part are candidates to be executed, a subsymbolic utility equation may estimate the relative cost and benefit associated with each rule and select the rule with the highest utility for execution. A similar development holds for Soar, although the distinction between symbolic and subsymbolic is a bit less evident here. Clarion, instead, has always been classified as a ‘hybrid’ cognitive architecture.

Also various cognitive theories about decision making itself are inspired by the idea to distinguish two different types of processes. For example, the recognition-primed decision (RPD) theory (see [26]) for the theory, and [46] for a computational model) describes decision making as a process that consists of an ‘intuitive’ part in which the current situation is matched against patterns learned from experiences and a ‘conscious, deliberate’ part in which the consequences of actions are evaluated. Recently, the RPD theory has been applied in the area of multi-agent systems as well, see e.g. [19, 20, 32], although these applications have not addressed virtual storytelling as yet.

At first sight, our proposed model seems to show significant similarities with such theories: our model to determine desires has characteristics of an unconscious, low-level system, whereas the model for utility-based decision making resembles a conscious, high-level system. Future work will explore whether a more precise mapping can be
made between the concepts introduced in our combined model and the concepts typically used in dual process theory. One of the differences with existing ‘dual process’ approaches, seems to be the fact that our model takes biological factors into account. Another difference is that the cognitive architectures mentioned above are more generic, whether the model as presented in this paper is specialised towards modelling criminal behaviour. Finally, the original research goals underlying both methodologies are somewhat different. Cognitive architectures have (at least traditionally) as main purpose to study cognitive processes, whether the model proposed here aims at developing believable agents.

Also when comparing our model with numerical approaches to model decision making, such as neural or connectionist networks [41], a difference in perspective can be observed. The main aim of the latter class of methods is to build intelligent behaviour (e.g., to solve certain optimisation problems), whereas our approach was designed to enhance realism (and not necessarily intelligence). This difference also (partly) explains why the approach taken in this article was to use build an explicit model using existing knowledge from the literature, instead of taking a ‘black box’ approach, where it is difficult to understand the actual behaviour of the model. On the other hand, we acknowledge that the presented model does not incorporate a mechanism to improve itself in an automated manner, as is done in machine learning. Nevertheless, the model can be improved manually in an iterative manner, which is mainly done by 1) changing the settings of the parameters involved, or by 2) adding or removing factors to the subconscious model. Input for the first type of adaptation can be derived from user studies such as described in Section 7, whereas the second type of adaptation can be performed based on new insights in the expert literature on criminal decision making (as described earlier).

In addition, it is interesting to explore how our model relates to theories in which affective factors just ‘bypass’ decision making, such as in [15, 28]. In recent years, such theories have formed a source of inspiration for the development of a number of agent-based models for reasoning and (affective) decision making (which often also combine rational and non-rational aspects) within Artificial Intelligence, such as in [23, 30, 34, 43]. A difference with the presented model is that most of these models explicitly focus on the integration of emotions with rational behaviour, whereas our model tries to integrate rational behaviour with personal biological and psychological factors in general (including emotions, but also notions like aggressiveness and impulsiveness). Finally, another interesting direction for future work will be to investigate whether the presented model can easily be implemented in standard BDI-based agent modelling frameworks, such as AgentSpeak [39] or Jadex [35]. Since the basis of our model is very similar to those models, this seems like a promising direction.

Acknowledgements

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References


Appendix – Storylines and Questionnaire

Story 1: Alan

Alan has a low level of empathy; he does not really care about others. He has a strong desire to do something exciting. He is also rather impulsive and aggressive. Moreover, he has a desire for high gain; so he wants to do something with high profits. Alan believes that stealing the groceries of an old lady without violence might possibly fulfill his desire. Further he believes that stealing a young man’s notebook with violence will definitely fulfill his desire. Alan considers stealing the groceries of an old lady a reasonable option. Alan considers stealing the notebook of a young man a good option. He intends to steal the notebook as soon as he gets the opportunity. Alan believes that there is an opportunity to steal an old lady’s groceries. He also believes that there is an opportunity to steal a young man’s notebook. Alan steals the notebook.

Story 2: Bob

Bob has a low level of empathy; he does not really care about others. He has a desire to do something exciting, but if possible, he wants to do something that is safe. He is also rather impulsive. He has a desire for high gain, but he has an even higher desire for low loss. So, he wants to do something with high profit, but thinks that low risks are even more important. Bob believes that stealing the groceries of an old lady without violence will definitely fulfill his desire. Bob believes that stealing a young man’s notebook with violence might possibly fulfill his desire. Bob considers stealing the groceries of an old lady to be a good option. Bob considers stealing the notebook of a young man to be a reasonable option. He intends to steal the groceries as soon as he gets the opportunity. Bob believes that there is an opportunity to steal a young man’s notebook and that there is an opportunity to steal an old lady’s groceries. Bob steals the groceries.

Story 3: Charles

Charles has a desire to assault someone. He believes that robbing the groceries from an old lady will fulfill his desire. He also believes that stealing the notebook from a young man will fulfill his desire. Charles has the intention to rob an old lady. He also has the intention to steal a notebook. Charles believes that there is an opportunity to steal a young man’s notebook. He steals the notebook. He also believes that there is an opportunity to steal an old lady’s groceries. Charles steals the groceries.

Story 4: David

David has a low level of empathy; he does not really care about others. He has a strong desire to do something exciting. He is also rather impulsive and aggressive. Moreover, he has a desire for high gain; so he wants to do something with high profits. David believes that stealing the groceries of an old lady without violence will definitely fulfill his desire. Further he believes that stealing a young man’s notebook with violence might
possibly fulfill his desire. David considers stealing the groceries of the old lady to be a good option. David considers stealing the notebook of a young man to be a reasonable option. He intends to steal the groceries as soon as he gets the opportunity. David believes that there is an opportunity to steal an old lady’s groceries. He also believes that there is an opportunity to steal a young man’s notebook. David steals the groceries.

**Story 5: Eric**

Eric has a low level of empathy; he does not really care about others. He has a desire to do something exiting, but if possible, he wants to do something that is safe. He is also rather impulsive. He has a desire for high gain, but he has an even higher desire for low loss. So, he wants to do something with high profit, but thinks that low risks are even more important. Eric believes that stealing the groceries of an old lady without violence will definitely fulfill his desire. Eric believes that stealing a young man’s notebook with violence might possibly fulfill his desire. Eric considers stealing the groceries of an old lady to be a good option. He considers stealing the notebook of a young man to be a reasonable option. He intends to steal the groceries as soon as he gets the opportunity. Eric believes that there is an opportunity to steal a young man’s notebook and that there is an opportunity to steal an old lady’s groceries. Eric steals the notebook.
Questionnaire

Name:
Gender:
Age:
Occupation:

Please fill out the following questionnaire
(1= totally disagree, 4= neutral, 7= totally agree)

I expected Alan to steal the notebook 1 2 3 4 5 6 7
Alan behaves like a real person 1 2 3 4 5 6 7
I understand Alan’s behaviour 1 2 3 4 5 6 7
Alan is an aggressive person 1 2 3 4 5 6 7
I liked reading this story 1 2 3 4 5 6 7
This is an interesting story 1 2 3 4 5 6 7
This is a realistic story 1 2 3 4 5 6 7
I have sympathy for Alan 1 2 3 4 5 6 7
Alan seems to be a nice guy 1 2 3 4 5 6 7
Alan thinks before he acts 1 2 3 4 5 6 7
Alan behaves rationally 1 2 3 4 5 6 7
Alan reasons rationally 1 2 3 4 5 6 7
Imagine that we could predict crime. If we knew on beforehand whether someone would assault someone or would break into a house, then we would perhaps be able to stop this from happening. However, such a situation, as also described in the blockbuster movie Minority Report (2002) by Steven Spielberg, is not very realistic and unlikely to happen in real life. The main reason for this is that it is generally impossible to predict people’s actions with a 100% certainty (besides the fact that it may not be desirable), especially because in most cases behaviour is affected by multiple factors.

There are however situations in which it is possible to “predict” an action with some certainty. If enough information about the relationship between certain actions and there causes is known, then making a fairly accurate prediction may be possible. Another possibility of predicting behaviour with some certainty is when certain behaviour is mainly influenced by one factor (or a small number of factors). In such a case, there could be many more factors relevant for the emergence of that type of behaviour, but just focusing on that one factor could already help you explain and predict future actions for a large part.

In this part we focus on this last type of behaviour. We investigate to what extent it is possible to use high-level theories about social relationships as a basis for automated prediction of a certain type of deviant behaviour. The main topic that is addressed within this work is the domain of social learning of (delinquent) behaviour by adolescents. More specifically, we attempt to develop models that take a number of factors into account (e.g. peer networks, family circumstances, school characteristics and personal characteristics like impulsiveness and aggressiveness), in order to calculate the probability that someone will show delinquent behaviour within a specific timeframe. We will describe under what circumstances and criteria it is possible to develop such models, and how they can be validated with empirical data.

Within criminology a distinction has been made by Terrie Moffitt [5], who identified two groups of offenders. The first group consists of life-course-persistent offenders. These offenders show criminal behaviour throughout their entire life. Life-course-persistent anti-social behaviour is caused by neuropsychological problems during childhood that interact cumulatively with criminogenic environments across development, which leads to a pathological personality. The second group offenders are adolescent limited offenders. Their offending behaviour is limited to the period between their twelfth and eighteenth year. Adolescence-limited antisocial behaviour is caused by a gap between biological maturity and social maturity. It is learned from antisocial models that are easily mimicked, and it is sustained according to the reinforcement principles of learning theory.

Since this second group has a well defined main cause for the emergence of their delinquent behaviour (namely mimicking the behaviour of antisocial role models) and only has a certain period in which this behaviour occurs, it is an interesting research area. What if we could predict to a certain extent how the level of delinquency of a pupil changes over time? And whether certain friends or classmates would make a pupil less or more criminal? In such a case, even if such predictions would not be 100% correct, they could help us in deciding how to rearrange classes to decrease the overall level of delinquency. In the papers presented in this part we made a start with developing a (simulation)model that can help predict delinquency among adolescents, based on their

Part III –
Modelling Social Learning of Juvenile Delinquency
network of friends and a number of personality factors. This model is inspired by the theory by Moffitt in conjunction with two other theories, namely the Differential Association Theory [6] and the Social Learning Theory [1, 2, 3].

The Differential Association Theory by Sutherland [6] is a theory to explain the learning of (deviant) behaviour. His perspective explains crime as a result of learning in a social context through interaction and communication [4]. More importantly however, Sutherland argued that deviant behaviour is learned through assigning meaning to behaviour, experiences and events during interaction with others. According to Sutherland, crime is learned through association with other people. The main setting for learning is within close personal groups. Learning includes techniques to carry out certain crimes and attitudes and motives supportive of committing crime. Learning experiences will vary in frequency and importance for each individual.

Another theory concerned with learning behaviour is the Social Learning Theory by Akers [1] and Bandura [2, 3]. According to this theory, behaviour is directly learned or mimicked (by modelling and imitation) via interaction with and reinforcement from the environment. The most important models for all behaviour are to be found in the behaviour of family, friends or through cultural influences. As a result, delinquent behaviour is claimed to be reinforced by the rewards it produces. These rewards can be external (e.g. financial gain or status) but they can also be internal (e.g. excitement, pleasure, pride). Warr [7] came up with a similar theory. According to him there is more delinquent behaviour in groups because of the fear of being shut out and the need for status within the group. The common element of all of these theories is that they explain the development of criminal behaviour by referring to the interaction of the individual with other persons in the social network.

Inspired by this idea, in Chapter III.1 we present a model that can be used to study general patterns in the development of deviant behaviour during adolescence. The model is based on literature (amongst others the idea that delinquent behaviour during adolescence is learned via the social network [5, 6]) and purely theoretical (i.e., not validated w.r.t. empirical data). Our main goal here is to see how certain factors (e.g. delinquency level, delinquency of parents and peers, personal characteristics and attachment between persons) relate to each other and how they could influence the emergence of deviant behaviour during adolescence. Once we had developed the model we were able to experiment with small ‘what if’- scenarios. For example, what if we had a classroom with 10 pupils, where one of them has criminal parents and the others do not? How does this affect the level of delinquency of all pupils? The first results of these experiments are promising. They provide evidence that the proposed model is a useful experimental tool to give insight in social learning processes as described in the criminological literature. Further, the model showed some interesting patterns, namely a relative high influence of the school on delinquency and a relative low impact of attachment.

In Chapter III.2 we again present a multi-agent model that can be used to simulate the development of youth delinquency in a classroom, based on individual personality traits on the one hand, and the social network on the other hand. The main extension of this work compared to the previous paper is that this research is based on empirical data. These data were gathered by dr. Frank Weerman from the NSCR, who is a co-author of our paper. Together with his colleagues he performed a longitudinal study among high school students and obtained a lot of information on their level of delinquency (e.g. did they ever steal or vandalise something?), personal characteristics (e.g. temper, impulsivity, material needs, risk orientedness, law conformity), home situation (e.g.
support and supervision by parents) and social networks (who are their friends?, how much time do they spend together?), among others [8]. We used the data to train our model, make predictions about future levels of delinquency of the students and see whether these predictions were correct. A validation study shows that the model predicts delinquency substantially better than a baseline model that only uses the delinquency of the previous year.

In Chapter III.3 we focus on the influence of classmates on the level of delinquency. The motivation for this is that, even if they are not direct friends, classmates are found to have an influence on pupils’ behaviour. In this paper we use the model developed in Chapter III.2 to perform a number of ‘what if’ experiments based on the data mentioned above. We know (from the empirical data) how the actual level of delinquency changed over time, but explore what would have happened if there had been different classmates.

Obviously, these three papers together do not form a complete model to predict criminal behaviour among adolescents, but are a first exploration, and show that this is an area in which prediction based on simulation is an interesting possibility. Although we are not able to predict future delinquent behaviour of adolescents with 100% accuracy, these types of simulation models enable the researcher to compare various fictive scenarios, which may provide useful insights to policy makers.

The papers mentioned in this part are based on the following publications:

Chapter III.1 will appear as:


This work is also based on:


Chapter III.2 appeared as:


Chapter III.3 will appear as:

References

Modelling Social Learning of Adolescence-Limited Criminal Behaviour

Tibor Bosse, Charlotte Gerritsen and Michel C.A. Klein

Abstract. Criminal behaviour exists in many variations, each with its own cause. A large group of offenders only shows criminal behaviour during adolescence. This kind of behaviour is largely influenced by the interaction with others, through social learning. This paper contributes a dynamical agent-based approach to simulate social learning of adolescence-limited criminal behaviour, illustrated for a small school class. The model is designed in such a way that it can be compared with data resulting from a large scale empirical study.

1. Introduction

Within Criminology, the analysis of the emergence of criminal behaviour is one of the main challenges [10]. An important mechanism behind the emergence of criminal behaviour is social learning [6]. To analyse this mechanism, this paper presents an agent-based approach to simulate social learning, which specifically addresses the mutual influence of peers, parents and school, with respect to delinquent behaviour.

To formalise and analyse the emergence of criminal behaviour through social learning, an artificial society has been modelled to represent a small school class. The models for the agents have been formally specified by executable temporal/causal logical relationships, using the modelling language TTL [4] and its executable sublanguage LEADSTO [3]. This language allows the modeller to integrate both qualitative, logical aspects as quantitative, numerical aspects. Moreover, since the language has a formal logical semantics, simulation models created in TTL and LEADSTO can be formally analysed by means of logical analysis techniques.

In the field of Criminology, it is often quite difficult to perform experiments that involve changes in the real world. A model as the one presented in this paper can be used to study general patterns in the development of criminal behaviour. Simulation can help to answer what-if questions and to verify theories about the relation between different processes. Discussions with a team of criminologists taught us that the evidence provided by simulation models is already considered as useful knowledge about the relevance of criminological theories such as the differential association theory, which will be discussed below.

In a next step of the research, we plan to validate the model using data of an existing empirical study e.g. [18]. In that study, the social networks of 1730 non-delinquent, minor delinquent and serious delinquent pupils at lower-level secondary schools in the Netherlands were analysed. This paper only reports about the first step, the model and simulations.

In Section 2 a summary from the literature on social learning is presented. Section 3 discusses the chosen modelling approach. The simulation model is presented in Section 4, and Section 5 discusses simulation results. In Section 6, these results are analysed using formal techniques. Section 7 presents related work. Finally, Section 8 concludes the paper.
2. Social Learning

According to [13], two types of delinquents can be distinguished: life-course-persistent offenders, who stay criminal throughout their entire life and adolescence-limited offenders, who only show antisocial behaviour during adolescence. Life-course-persistent anti-social behaviour is caused by neuropsychological problems during childhood that interact cumulatively with their criminogenic environments across development, which leads to a pathological personality. Adolescence-limited antisocial behaviour is caused by the gap between biological maturity and social maturity. It is learned from antisocial models that are easily mimicked, and it is sustained according to the reinforcement principles of learning theory. They peak sharply at about age 17 and drop fast in young adulthood. In the current paper, we explicitly focus on the adolescence-limited offenders.

An influential theory on the emergence of adolescence-limited criminal behaviour is the differential association theory, which was first proposed by [15] and later expanded by [6]. In short, this (informal) theory states that behaviour is learned through interaction with others. We learn most from the people we are in close contact with, like parents and peers. There are two basic elements to understanding the differential association theory. First, the content of what is learned is important (e.g., motives, attitudes and evaluations by others of the meaningful significance of each of these elements). Second, the process by which learning takes place is important, including the intimate informal groups and the collective and situational context where it occurs. Criminal behaviour itself is learned through assigning meaning to behaviour, experiences, and events during interaction with others.

According to [15], the extent to which delinquent behaviour is imitated is influenced by the frequency, duration, and intensity of the contact. Frequent, long and important or prestigious contacts have a larger influence. In addition, the priority of learning influences the social learning process: the earlier behaviour is learned, the more influential it is.

3. Modelling Approach

To formalise and analyse the emergence of criminal behaviour through social learning from an agent perspective, an expressive modelling language is needed. On the one hand, qualitative aspects have to be addressed, such as certain characteristics about the agents (e.g., their age), their social relationships (e.g., who are their parents and friends). On the other hand, quantitative aspects have to be addressed. For example, an agent’s level of delinquency, which is the extent to which an agent exhibits delinquent behaviour, can best be described by a real number. The change of this delinquency can best be described by a mathematical formula. Another requirement of the chosen modelling language is its suitability to express on the one hand the basic mechanisms of social learning (for the purpose of simulation), and on the other hand more global properties of social learning (for the purpose of logical analysis and verification). For example, basic mechanisms of social learning involve decisions of individual agents to attach to their peers, whereas global properties are statements that consider the learning process over a longer period, like “eventually the delinquent pupils become less delinquent”.

The predicate-logical Temporal Trace Language (TTL) [4] fulfils all of these desiderata. It integrates qualitative, logical aspects and quantitative, numerical aspects.
This integration allows the modeller to exploit both logical and numerical methods for analysis and simulation. Moreover it can be used to express dynamic properties at different levels of aggregation, which makes it well suited both for simulation and logical analysis.

TTL is based on the assumption that dynamics can be described as an evolution of states over time. The notion of state as used here is characterised on the basis of an ontology defining a set of physical and/or mental (state) properties that do or do not hold at a certain point in time. These properties are often called state properties to distinguish them from dynamic properties that relate different states over time. A specific state is characterised by dividing the set of state properties into those that hold, and those that do not hold in the state. Examples of state properties are ‘agent 1 has a delinquency level of 0.35’, or ‘agent 2 has an attachment to agent 3 of 0.5’.

To formalise state properties, ontologies are specified in a (many-sorted) first order logical format: an ontology is specified as a finite set of sorts, constants within these sorts, and relations and functions over these sorts (sometimes also called signatures). The examples mentioned above then can be formalised by n-ary predicates (or proposition symbols), such as, for example, has_delinquency(agent1,0.35) or has_attachment_to(agent2, agent3, 0.5). Such predicates are called state ground atoms (or atomic state properties). For a given ontology Ont, the propositional language signature consisting of all ground atoms based on Ont is denoted by APROP(Ont). One step further, the state properties based on a certain ontology Ont are formalised by the propositions that can be made (using conjunction, negation, disjunction, implication) from the ground atoms. Thus, an example of a formalised state property is has_delinquency(agent1,0.35) & has_delinquency(agent2,0.45). Moreover, a state S is an indication of which atomic state properties are true and which are false, i.e., a mapping S: APROP(Ont) → {true, false}. The set of all possible states for ontology Ont is denoted by STATES(Ont).

To describe dynamic properties of complex processes such as the development of criminal behavior, explicit reference is made to time and to traces. A fixed time frame T is assumed which is linearly ordered. Depending on the application, it may be dense (e.g., the real numbers) or discrete (e.g., the set of integers or natural numbers or a finite initial segment of the natural numbers). Dynamic properties can be formulated that relate a state at one point in time to a state at another point in time. A simple example is the following (informally stated) dynamic property about the delinquency of agents:

For all traces γ,
there is a time point t such that
all agents have a delinquency that is lower than d.

A trace γ over an ontology Ont and time frame T is a mapping γ: T → STATES(Ont), i.e., a sequence of states γ (t ∈ T) in STATES(Ont). The temporal trace language TTL is built on atoms referring to, e.g., traces, time and state properties. For example, ‘in a trace γ at time t property p holds’ is formalised by state(γ, t) |= p. Here |= is a predicate symbol in the language, usually used in infix notation, which is comparable to the Holds-predicate in situation calculi. Dynamic properties are expressed by temporal statements built using the usual first-order logical connectives (such as ¬, ∧, ∨, →) and quantification (∃ and ∀; for example, over traces, time and state properties). For example, the informally stated dynamic property introduced above is formally expressed as follows:

∀γ:TRACE ∃t:TIME ∀a:AGENT ∃x:REAL
state(γ, t) |= has_delinquency(a, x) & x < d
In addition, language abstractions by introducing new predicates as abbreviations for complex expressions are supported.

To be able to perform (pseudo-)experiments, only part of the expressivity of TTL is needed. To this end, the executable LEADSTO language [3] has been defined as a sublanguage of TTL, with the specific purpose to develop simulation models in a declarative manner. In LEADSTO, direct temporal dependencies between two state properties in successive states are modelled by executable dynamic properties. The LEADSTO format is defined as follows. Let \( \alpha \) and \( \beta \) be state properties as defined above. Then, the notation \( \alpha \rightarrow_{\alpha, \beta, \gamma} \beta \) means:

\[
\begin{align*}
\text{If} & \quad \text{state property } \alpha \text{ holds for an interval with duration } g, \\
\text{then} & \quad \text{after some delay between } e \text{ and } f \text{ state property } \beta \text{ will hold for an interval with duration } h.
\end{align*}
\]

As an example, the following executable dynamic property states that “if during 1 time unit the attachment between agent \( a_1 \) and \( a_2 \) is \( x_1 \), and the difference in delinquency between both agents is \( x_2 \), then for the next 5 time units (after a delay between 0 and 0.5 time units) the attachment between both agents will be \( \beta^{x_1+(1-\beta)|x_2|} \):

\[
\forall a_1, a_2: \text{AGENT } \forall x_1, x_2: \text{REAL} \\
\text{has_attachment_to(a_1, a_2, x_1) } \land \\
\text{delinquency_difference(a_1, a_2, x_2) } \rightarrow_{0, 0.5, 1, 5} \\
\text{has_attachment_to(a_1, a_2, \beta^{x_1+(1-\beta)|x_2|})}
\]

Based on TTL and LEADSTO, two dedicated pieces of software have recently been developed. First, the LEADSTO Simulation Environment [3] takes a specification of executable dynamic properties as input, and uses this to generate simulation traces. Second, to automatically analyse the resulting simulation traces, the TTL Checker tool [4] has been developed. This tool takes as input a formula expressed in TTL and a set of traces, and verifies automatically whether the formula holds for the traces. In case the formula does not hold, the Checker provides a counter example, i.e., a combination of variable instances for which the check fails.

4. Simulation Model

To study the influence of social learning on delinquent behaviour, we modelled a school class with 10 pupils. There are three groups that influence the process of social learning, namely parents, school and peers. Therefore, each pupil is represented as an agent; the parents of the pupils and the school are modelled as groups. Each pupil is related to one parent group. The agents have a number of characteristics in our model (determined based on discussions with experts). We restricted our study to the characteristics that are collected in the empirical study [18]. The first property of an agent is its age. In our model the age is restricted to values between 12 and 17. The age is relevant for influence of peers on each other. The older an adolescent is (up to 17) the more his behaviour is influenced by peers. In addition, the age difference between peers is relevant, since older people are often more dominant in the relationship. The influence of school and parents tends to decrease as the adolescent gets older.

In addition, agents have a basic level of influenceability: this represents how easily they can be influenced. Oppositely, agents and groups have a level of dominance: this represents how easily they can influence others. For persons this is a character trait.
Schools can also have a level of dominance. A dominant school can be seen as a strict school, while a school that is less strict could be considered to be less dominant.

The social relations between pupils in a school class are modelled via *attachment* relations. All agents are attached to each other with a specific level of attachment, representing the intensity of the contact as defined by [15]. The attachment relation is also used to model the attachment of pupils to their parents and to their school. We assume that a high attachment results in a higher influence of the attached agent or group on the behaviour of the pupil.

Finally, we model a level of *delinquency* for all agents and groups, also for parents and schools. The initial value for the delinquency of an agent could be based on a measurement of the number of delinquent acts of a pupil in the past. The interpretation of the delinquency of a school is indirect: the school has a low level of delinquency if it is a good school, i.e. teachers and other staff members have a low level of delinquency. When the atmosphere in the school is less positive, then it has a higher level of delinquency.

During the simulation, the levels of delinquency of the pupils change because of the influence of others. This process is depicted in Figure 1, where the circles denote state properties and the arrows denote dynamic properties (relationships) between them. The age of each agent increases every year. Every agent starts with a basic influenceability; together with the age of the agent and the attachment to a specific group or agent, the effective influenceability of the agent by that agent or group is determined (denoted by *has_influenceability* in Figure 1).

This effective influenceability is combined with the level of dominance of the other party, the difference in delinquency between the agent and the other party, and - in case the other party is an agent - the age difference between two agents. This leads to the so-called *delta delinquency*. The delta delinquency represents all factors that influence the level of delinquency of an agent. In order to calculate the new delinquency of an agent, the delta delinquencies of all agents and groups in its environment are combined with the old delinquency (the delinquency the agent started out with).

![Figure 1. Concepts and relations in the simulation model.](image-url)
In addition, the model is able to adapt the attachment between the agents. The idea behind this is that the strength of a relation is influenced by the overlap in values. If the difference in the level of delinquency is very high, then the attachment will decrease. However, because there are many other factors that influence the attachment as well, the difference in delinquency only causes a minor change in attachment.

The formal ontology used for the model is shown in Table 1. As can be seen, the concepts of influenceability, dominance, attachment, and delinquency are modelled as a real number between 0 and 1. Furthermore, the age is modelled as an integer between 12 and 17, and the delta delinquency as a real number between -1 and 1. For a complete overview of the simulation model, see the appendix*

<table>
<thead>
<tr>
<th>Formal predicate</th>
<th>Informal description</th>
<th>X ∈</th>
</tr>
</thead>
<tbody>
<tr>
<td>has_basic_influenceability (A:AGENT, X:REAL)</td>
<td>agent A has a basic influenceability of X (i.e., a static characteristic of an agent)</td>
<td>[0..1]</td>
</tr>
<tr>
<td>has_attachment_to (A:AGENT, G:GROUP, X:REAL)</td>
<td>agent A has an attachment to group G of strength X</td>
<td>[0..1]</td>
</tr>
<tr>
<td>has_attachment_to (A1:AGENT, A2:AGENT, X:REAL)</td>
<td>agent A1 has an attachment to agent A2 of strength X</td>
<td>[0..1]</td>
</tr>
<tr>
<td>has_age (A:AGENT, X:REAL)</td>
<td>agent A has age X</td>
<td>[12..17]</td>
</tr>
<tr>
<td>has_influenceability (A1:AGENT, A2:AGENT, X:REAL)</td>
<td>agent A2 has an influence on agent A1 with strength X</td>
<td>[0..1]</td>
</tr>
<tr>
<td>age_difference (A1:AGENT, A2:AGENT, X:REAL)</td>
<td>the age difference between agent A1 and agent A2 is X</td>
<td>[-5..5]</td>
</tr>
<tr>
<td>has_delinquency (A:AGENT, X:REAL)</td>
<td>agent A has a delinquency of X</td>
<td>[0..1]</td>
</tr>
<tr>
<td>has_delinquency (G:GROUP, X:REAL)</td>
<td>group G has a delinquency of X</td>
<td>[0..1]</td>
</tr>
<tr>
<td>delinquency_difference(A:AGENT, A2:AGENT, X:REAL)</td>
<td>the delinquency difference between agent A and agent A2 is X</td>
<td>[-1..1]</td>
</tr>
<tr>
<td>has_dominance (G:GROUP, X:REAL)</td>
<td>group G has dominance X (static value)</td>
<td>[0..1]</td>
</tr>
<tr>
<td>has_dominance (A:AGENT, X:REAL)</td>
<td>agent A has dominance X (static value)</td>
<td>[0..1]</td>
</tr>
<tr>
<td>has_delta_delinquency (A:AGENT, G:GROUP, X:REAL)</td>
<td>the amount of change of the delinquency of agent A caused by group G is X</td>
<td>[-1..1]</td>
</tr>
<tr>
<td>has_delta_delinquency (A1:AGENT, A2:AGENT, X:REAL)</td>
<td>the amount of change of the delinquency of agent A1 caused by agent A2 is X</td>
<td>[-1..1]</td>
</tr>
<tr>
<td>has_gender (A:AGENT, G:GENDER)</td>
<td>agent A has gender G</td>
<td></td>
</tr>
</tbody>
</table>

| Table 1. Formal ontology. |

The relationships between the concepts have been modelled in LEADSTO. Three example relationships (to determine the delta delinquency of groups, the new delinquency, and the new attachment to agents, respectively) are stated below. Here, the β’s are decay factors, and the w’s are weight factors. Note that these relationships correspond to (conjunctions of) arrows in Figure 1.

**Delta Delinquency Determination (for Groups)**
∀a:AGENT ∀g:GROUP ∀x1,x2,x3:REAL
delinquency_difference(a,g,x1) ∧ has_influenceability(a,g,x2) ∧
has_dominance(g,x3) →
has_delta_delinquency(a,g,β2*(β1*x1+w1*(w4*x2+w5*x3))]

**New Delinquency Determination**
∀a:AGENT ∀g:GROUP ∀d,s,p,x1,...,x10:REAL
has_old_delinquency(a1,d) ∧ has_delta_delinquency(a1, school,s) ∧
has_delta_delinquency(a1,g,p) ∧ are_parents_of(g,a1) ∧

---

* http://human-ambience.few.vu.nl/docs/ICAART09.pdf

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has_delta_delinquency(a1,agent1,x1) \land ... \\
\text{New Attachment Determination (for Agents)} \\
\forall a1,a2:AGENT \forall x1,x2:REAL \\
\text{has_attachment_to}(a1,a2,x1) \land \text{delinquency_difference}(a1,a2,x2) \rightarrow \\
\text{has_attachment_to}(a1,a2,\beta^3 x1+(1-\beta^3)\text{abs}(x2))

5. Simulation Results

A number of simulation experiments have been performed to see whether the behaviour of the model was as expected for some common scenarios. A thorough evaluation will be performed later when the results will be compared with data of an empirical study.

In the first scenario there is one bad guy with criminal parents in an otherwise reasonable school class. We are interested in the question whether the criminal boy makes the other boys bad or whether the group is able to straighten out the delinquent. In this scenario agent 1 has a delinquency of 0.8 while the other agents have a delinquency of 0.3. All agents are male\textsuperscript{\footnote{Note that the model does not incorporate a direct influence of gender. Difference between male and female pupils can be modeled indirectly by giving the males higher initial delinquencies.}} and are 12 years old at the start of the simulation. They have a basic influenceability with a value of 0.4, a level of dominance of 0.6 and a mutual attachment of 0.3. The attachments are stable in this simulation. Every agent has parents with a dominance of 0.7 and a delinquency of 0.2, except for agent 1, whose parents have a delinquency of 0.8.

![Figure 2. Delinquency in a school class with one bad guy.](image)

The resulting trace is shown in Figure 2. Here, time is on the horizontal axis and the level of delinquency is on the vertical axis. The three graphs show the combined delinquencies of all pupils, the delinquency of agent 1 and the delinquency of the other
agents (that all show the same behaviour; agent 10 is just taken as an example), respectively. The two lines in the first graph correspond to the lines in the second and third graph, respectively, where a more detailed scale is used. The results show that the interaction between the agents leads to a decreased delinquency of agent 1. The delinquency of the other agents increases slightly to 0.31 and from this point on it decreases to 0.255 at time point 100. From time point 70 on, there is a more or less stable difference in delinquency between the agent with criminal parents and the others.

In a second scenario (Figure 3), the influence of the school is examined by increasing its delinquency to 0.8. The level of delinquency of the agents and their parents were identical to the settings in the previous scenario. The results show that the increased delinquency of the school causes an increased level of delinquency of all the agents. This influence appeared to be larger than the influence of individual agents, because it propagates through to pupils, who again influence each other.

![Figure 3. Influence of a bad school.](image)

In the third scenario, half of the pupils (and their parents) have a high delinquency. The other pupils (and their parents) have the same level of delinquency as in scenario 1. In this case all agents influence each other and their delinquencies grow towards each other, while a difference remains because of the influence of the parents (see Fig. 4).

![Figure 4. Delinquency in a school class with half of the pupils being criminal.](image)

Finally, the fourth scenario represents a school class with two groups (3 delinquent pupils with a high mutual attachment, 3 extremely non-delinquent pupils with a high mutual attachment) and 4 individuals with a high basic influenceability. One of these ‘group-less pupils’ has a high attachment to a person in the criminal group, one to a person in the non-criminal group, and the others had no specific relations. The attachments can change over time. The goal of this scenario is to see whether a pupil will be incorporated in a group if he has a strong relationship with one of them. Figure 5 shows the resulting delinquencies.

Interestingly, we see that all group-less pupils reach a level of delinquencies that is close to that of the pupils in the ‘good group’, even for the pupils that have a strong relation to a pupil in one of the groups. This observation can be explained by the fact that the delinquency of the parents of the group-less pupils is close to the delinquency of the parents in the good group. However, if we look closely at the delinquencies of the group-less people (lower graph in Figure 5), we see that they develop slightly
differently (notice the different scale). Apparently, the delinquency of the pupil with a friend in the bad (good) group initially grows faster (slower), but eventually it reaches the same level as the other group-less pupils.

\[ \text{delinquencies combined} \]

\[ \text{delinquencies groupless} \]

Figure 5. Delinquencies in school class with two groups.

6. Formal Analysis

The detailed settings and results of ten simulation experiments (including the ones described in Section 5) are shown in the appendix. Among the different experiments, various parameter settings were varied, in particular the initial delinquencies of agents, parents, and school, the initial attachment between agents, and several weight factors.

To analyse the resulting simulation traces in more detail, the TTL Checker tool [4] has been used. As mentioned earlier, this tool takes as input a TTL formula and a set of traces, and verifies automatically whether the formula holds for the traces. For the current domain, a number of hypotheses have been expressed as dynamic properties in TTL, which were inspired by relevant questions in Criminology (see Sections 1 and 2). To give a simple example, consider the following dynamic property (P1), which expresses that the delinquency of an agent keeps on decreasing over time:

**P1 Strict Monotonic Decrease of Delinquency**

For all time points \( t_1 \) and \( t_2 \), if \( t_2 \) is later than \( t_1 \), then the agent’s delinquency at \( t_2 \) is lower than at \( t_1 \).

\[
P1(\gamma;\text{TRACE}, a;\text{AGENT}) = \forall t_1, t_2; \text{TIME} \forall d_1, d_2; \text{REAL} \\
[ \text{state}(\gamma, t_1) \models \text{has\_delinquency}(a, d_1) \land \text{state}(\gamma, t_2) \models \text{has\_delinquency}(a, d_2) \land t_1 < t_2 ] \Rightarrow d_1 > d_2
\]

Note that this formula comprises two free variables (the trace \( \gamma \) and the agent \( a \)), for which different values can be instantiated. For example, in order to check whether agent 1 satisfies the criterion of strict monotonic decrease of delinquency in simulation trace 5, the formula \( P1(\text{trace}1, \text{agent}1) \) should be checked. Similarly, it is possible to check whether the property holds for all agents and all traces, or for a certain percentage of them.

Besides checking whether the delinquency of agents keeps on decreasing, also other properties can be verified. A relevant question in Criminology is what the relative influences of (respectively) parents, peers, and school on the development of a person’s
delinquency are. For example, might it be the case that the biggest contribution is provided by parents and school only, and that the influence of classmates can almost be neglected? To analyse these kinds of hypotheses, properties like the following have been established:

**P2 Agent converges to Parents and School**

At the end of the trace, the delinquency of agent a lies within a margin $\delta$ of the average of the delinquencies of its parents and the school at the start of the trace.

$$P2(\gamma; \text{TRACE}, a; \text{AGENT}) = \forall d_1, d_2, d_3: \text{REAL} \quad \forall p: \text{AGENT}$$

$$\begin{array}{l}
\quad \text{state}(\gamma, \text{start\_time}) \models \text{has\_delinquency}(p, d_1) \& \\
\quad \text{state}(\gamma, \text{start\_time}) \models \text{has\_delinquency}(\text{school}, d_2) \& \\
\quad \text{state}(\gamma, \text{end\_time}) \models \text{has\_delinquency}(a, d_3) \& \\
\quad \text{are\_parents\_of}(p, a) \& \\
\Rightarrow d_3 - \delta < (d_1 + d_2)/2 < d_3 + \delta
\end{array}$$

If this property were true (for a small $\delta$), this would indicate that the development of a pupil could be predicted by taking into account the delinquency of the parents and the school only. Some initial checks have pointed out that the lowest $\delta$ for which the property satisfies all generated traces is 0.22. In other words, for all of the traces the influence of parents and school was relatively high. In addition to P2, a property was created to compare the change in delinquency between two agents $a_1$ and $a_2$.

**P3 Bigger change in Delinquency**

During the whole trace, agent $a_1$ made a bigger change in delinquency than agent $a_2$.

$$P3(\gamma; \text{TRACE}, a_1, a_2; \text{AGENT}) = \forall d_1, d_2, d_3, d_4: \text{REAL}$$

$$\begin{array}{l}
\quad \text{state}(\gamma, \text{start\_time}) \models \text{has\_delinquency}(a_1, d_1) \& \\
\quad \text{state}(\gamma, \text{start\_time}) \models \text{has\_delinquency}(a_2, d_2) \& \\
\quad \text{state}(\gamma, \text{end\_time}) \models \text{has\_delinquency}(a_1, d_3) \& \\
\quad \text{state}(\gamma, \text{end\_time}) \models \text{has\_delinquency}(a_2, d_4) \\
\Rightarrow |d_1 - d_3| > |d_2 - d_4|
\end{array}$$

This property can be used, for example, to find out whether in a school class with many “good” pupils and one “bad” guy (see scenario 1), the bad pupil tends to move towards the good ones, or vice versa. In our simulation traces, such a bad pupil indeed turned out to converge towards his classmates.

To summarise, a number of TTL properties have been checked against the generated simulation traces, as a first pilot study of the applicability of the approach. Although no real conclusions can be drawn as yet, these checks pointed out that the traces satisfy basic properties that were inspired by criminological theories, such as property P2 and P3.

Finally, it is important to note that, in addition to simulated traces, the TTL Checker can also take empirical traces as input. In future work, several properties as those introduced here will be verified against empirical traces that are constructed on the basis of experiments in real classrooms.

### 7. Related Work

With respect to related work, the research presented in this paper on the one hand has commonalities with literature from the social and behavioural sciences (in particular, the area of Criminology), and on the other hand with literature in AI and Computer Science (among others, agent-based simulation).
Concerning the criminological and psychological area, first of all the current paper is related to early articles from the 60’s and 70’s such as [1, 6, 15], which were the first to formulate (different variants of) the social learning theory. Here, the theory put forward by [1] is more generic, whereas the other two focus specifically on social learning in Criminology. For an overview of these theories, see [11]. In fact, these theories formed the basis of the research questions addressed in this paper. Based on these theories, [14] identified a number of (informal) properties that are expected to hold for social learning in Criminology, such as “the more frequently persons show deviant behaviour, the more frequently they will have contact with patterns of deviant behaviour”. Although a detailed verification (using larger-scale experiments and statistical techniques) is left for future work, an initial analysis provides evidence that our model indeed satisfies these properties. Next, a number of papers in Criminology propose more refined models for social learning, often focusing on specific aspects of the learning. For example, [16] compared three theoretical models of the interrelations among associations between delinquent peers, delinquent beliefs, and delinquent behaviour. A main difference with our work is that these models are not computational. Nevertheless, their conclusions are in agreement with the initial results found in this paper. Finally, several authors have performed empirical studies on social learning of delinquent behaviour in schools [5, 18]. Our model was designed explicitly with the purpose of reproducing such data.

Concerning the literature in AI and Computer Science, we are not aware of approaches using multi-agent technology to simulate delinquent behaviour of individuals in a group. However, various papers have similarities to the work proposed here. First, [9] present a model that is rather similar to ours, but which uses differential equations to describe the development of juvenile criminal behaviour. Another difference with our model is that they aim for an integration of multiple criminological theories (namely social learning theory, career theory, and rational choice theory), whereas we focus (in more detail) on the former only. Moreover, several authors have created models that address social learning and criminal behaviour at a more global level. For example, [7] presents an economic model for social learning, although not explicitly focussed on learning of delinquent behaviour. Similarly, [19] presents an agent-based economic model for the market for offenses. This model addresses the global development of delinquency in a population. These models differ from our model in the sense that they are situated at a macroscopic level, thereby abstracting from differences between individuals. An approach that does consider individual differences, but that addresses a different domain, is presented by [17]. They present a simulation model of the dynamics of terrorist networks, based on networks of non-deterministic finite automata. Furthermore, a large number of approaches address simulation of the environmental aspects of criminal behaviour, such as the displacement of crime and the emergence of “hot spots”, e.g., [2, 12]. Finally, relevant work is put forward by [8]. They identify a number of (cognitive) factors that are relevant in social learning in general. However, in contrast to our work, they do not provide a computational model.

8. Conclusion

This paper presented an agent-based approach to simulate and formally analyse the process of social learning of delinquency during adolescence. The general mechanism of change by influences of peers is possibly also useful in other domains in which social learning is relevant. In this paper, however, we focused on learning of delinquent behaviour. Inspired by criminological literature, the approach incorporates the
influences of three types of groups, namely peers, parents, and school. Various relevant factors were identified, such as influenceability, dominance, and attachment, and their mutual relationships were formalised by means of the hybrid modelling language LEADSTO. Moreover, it was shown how the approach can be used to generate simulation traces, and how such traces can be automatically verified against relevant properties, expressed in the language TTL. Although preliminary, the first results are promising. Firstly, they provide evidence that the proposed model is a useful experimental tool to give insight in social learning processes as described in the criminological literature. Secondly, some interesting patterns have already been found. For example, the simulation results suggest that the influence of the school on delinquency is relatively high (scenario 3), that the impact of attachment is relatively low (scenario 4), and that every individual learning process approaches a final delinquency near the average of the delinquencies of parents, school, and peers.

In the current paper, no detailed empirical validation of the model has been presented. However, as mentioned in the introduction, various empirical studies have been performed, of which large data sets are available [5, 18]. The model has been explicitly designed with the objective of using such data sets for validation in the future. Currently, some initial steps in this direction are taken. During such a validation, several questions are addressed, such as “is it realistic that the average delinquency almost always decreases?”, or “is it realistic to have a relatively stable delinquency for school and parents?”. When these questions are solved, the model can be further fine-tuned, in particular by choosing realistic values for all parameter settings and weight factors involved.

References

Development and Validation of an Agent-Based Simulation Model of Juvenile Delinquency

Tibor Bosse, Charlotte Gerritsen, Michel C.A. Klein and Frank M. Weerman

Abstract. This paper describes the development and validation of a dynamic multi-agent model to simulate social learning of adolescence-limited criminal behaviour. The parameters of the agent model have been calibrated using real-world data that has been collected in a large study. In addition, a measure for correctness has been developed. The validation shows that the developed model predicts delinquency substantially better than a baseline model that only uses the delinquency of an agent in the previous year.

1. Introduction

The area of Criminology is a multidisciplinary field, which has as main objective to analyse criminal behaviour; e.g., [10]. As such, its main research goals are to predict in which circumstances which types of criminal behaviour occur. Since a substantial amount of crimes is performed by juveniles, an important challenge within Criminology is the analysis of the emergence of criminal behaviour during adolescence.

To address this challenge, several theories have been proposed within the criminological literature, that all depend on social learning: the idea that adolescents easily copy the behaviour of their peers. According to this view, the social network of an adolescent can be seen as a multi-agent system in which various interactions take place over time. One of the influential social learning theories is the Differential Association Theory by [18] which was later expanded by [5]. This (informal) theory states that behaviour is learned in interaction with others. We learn most from the people we are in close contact with, like parents and peers. A second important theory states that there are two distinct categories of antisocial behaviour and offending, namely life-course persistent and adolescence-limited [15]. Life-course-persistent antisocial behaviour is caused by neuropsychological problems during childhood that interact cumulatively with the criminogenic environments across development, which leads to a pathological personality. Adolescence-limited antisocial behaviour is caused by the gap between biological maturity and social maturity. It is learned from antisocial models that are easily mimicked, and it is sustained according to the reinforcement principles of learning theory. In this paper we focus on the second group, the adolescence-limited offenders, since their behaviour emerges from interaction with others.

When we take a closer look at the problem of the adolescence-limited offenders, several questions may be asked, among which:

• how does the delinquency level of adolescents relate to their personality traits?
• how do the delinquency levels of adolescents and their peers relate?
• how does the level of delinquency change over time?

To answer such questions, this paper proposes to make use of Agent Based Social Simulation (ABSS) techniques [7]. Since ABSS combines the advantages of the agent paradigm (e.g., personal characteristics of the individual agents) with those of social
simulation (e.g., the possibility to perform scalable social “experiments” without much effort), it turns out to be particularly appropriate to analyse phenomena within the criminological domain [17]. Indeed, in recent years, a number of papers have successfully tackled criminological questions using ABSS, e.g., [4, 13, 14].

The current paper presents a multi-agent model that can be used to simulate the development of youth delinquency in a classroom, based on individual personality traits on the one hand, and the social network on the other hand. To calibrate the parameters of the model, data from an existing empirical study [21] have been used. In that study, the social networks of 1730 non-delinquent, minor delinquent and serious delinquent pupils at lower level secondary schools in the Netherlands were analysed. In addition, another dataset from that study (addressing a different set of schools than used for the calibration) has been used to validate the model. In future work, this model could be used to perform “what-if simulations” that can be helpful for policy makers, e.g., to investigate what is the best way to divide pupils over classes.

In Section 2 the empirical study on which our model is based is briefly summarised. Thereafter, in Section 3 we will introduce the overall approach that is used to develop and evaluate the model. Details of the simulation model are presented in Section 4, and in Section 5 validation of the model is discussed. In Section 6 related work is presented. Finally, Section 7 concludes the paper with a discussion and some ideas for future work.

2. Data Collection

The data used in this research come from the NSCR ‘School Project’ [21], a Netherlands based longitudinal study that focuses on peer network formation, personal development, and school interventions in the development of problem behaviour and delinquency. The sampling procedure was guided by two aims: one, to obtain a relatively ‘high-risk’ sample with a substantial proportion of delinquent young people, and two, to achieve enough variation in school contexts and student populations to be able to better generalise results. In order to achieve the first aim, schools and students in the lower educational strata of a major Dutch city with inner-city problems were over-represented. To achieve the second aim, students were also recruited from schools in smaller cities and towns in the vicinity. Although the sample is not a random sample, it can be considered representative of Dutch youths attending this school type (lower vocational) in the South West region of the Netherlands. In the whole country, 60% of young people attend this type of school.

For the current research, we used a cohort of students that started high school during the school year 2001/2002. The first year of secondary education in the Netherlands is comparable with 7th grade in the United States (most students are 12 or 13 years old). These students were surveyed during three consecutive years: 2002, 2003 and 2004.

Respondents’ delinquent behaviour was measured using self-reports of a variety of offences. The self report method is a standard procedure in the field of Criminology, and it results in fairly reliable estimates of delinquency levels of young people, when it is conducted in a proper way and in an anonymous setting. Respondents were asked if they had ever committed an offence and, if so, how often during the reference period. The reference period covered the interval between the last summer holiday prior to the beginning of the school year and the time when the survey was administered (spring). The measures of self-reported delinquency used in this study come from 12 questions, among which: in the last year, how many times did you: “paint graffiti”, “vandalise property”, or “steal small things from shops worth less than 5 Euros” The total
The composition of student networks was studied using questions inspired by research carried out previously in this area. Respondents were provided with a numbered list of all students in their school year (so first-year students had the names from all fellow students in their own class as well as from all in the other first-year classes in their school). Then they were asked with whom they spent a lot of time (their school contacts – up to 10 fellow students could be identified, two of which could be labelled as “best friends”). In the analyses, friends’ numbers were linked to the respondent’s own number, enabling the networks of friends to be mapped and analyzed.

Apart from the central measures of delinquency and peer network composition, the study also used a substantial number of other measures on risk factors that are central in criminological theories and have been found to correlate with delinquency in the past. These risk factors are: low supervision by parents, low support by parents, low bond with school, low law conformity, high impulsivity, high adventure and risk-orientedness, high temper, much material needs, many time spent with friends, high deviance reinforcement by peers, being a member of troublesome youth groups. The relative position of students with regard to these risk factors were also obtained through the questionnaire: each risk factor is represented by a number of question items that were combined to scales (see [20] and [21] for more information).

3. Approach

As the goal of this research is a model that can be used to realistically simulate the development of juvenile delinquency in a multi-agent setting, we followed structured methodology to develop this model. As a first step, we built an initial dynamic model for the development of delinquency through social learning in a class room, based on an analysis of the literature. A comprehensive description of this step is provided in [2]. The model describes the influences of several personal characteristics, as well as the influences of other peers.

See Figure 1 for an overview: the box to the right depicts ‘agent 1’ (which represents a particular pupil). The delinquency of this agent is influenced by its previous delinquency (hence the circular arrow), its individual personality traits shown to the right (i.e., impulsivity, risk-orientedness, and so on, see previous section), and the external factors depicted to the left (i.e., the school, the parents, and a couple of peers, which are represented by a similar model as agent 1). Although the agents in the model are not very complicated, the multi-agent approach is an essential element for the simulations. The behaviour of each agent is influenced both by individual characteristics and by the relationship with up to 12 other agents in their network (which differs per agent).

The original model (from [2]) has the form of a set of differential equations. It has been shown that this model can be used to simulate delinquency development of a small set of agents in a classroom. The simulations exhibited several patterns that would be expected based on the criminological literature [2]. However, these initial simulations were not yet evaluated with empirical data, which is the main focus of the current paper.
Second, the dataset that is described in Section 2 has been split up in a training set and test set. Each set contains the data of around 250 pupils. When making this split, we guaranteed that there was no overlap between the schools used in the training set and those used in the test set. This way, we avoided that friendship relations exist across the boundary (i.e. that some pupils in the training set have friendship relations with pupils in the test set). Moreover, this approach makes it possible to detect whether the model has over-fitted to specific schools (which is not possible if the pupils used for the test set and the training set come from the same school).

Third, an evaluation measure has been developed that can be used to quantify the correctness of models and to discriminate between the accurate and less accurate models. This measure accommodates the intuitive ideas about a correct prediction in one number. The precise description of this measure is given in Section 4.1.

In a next step, we tried to calibrate the model with the data in the training set. This has been done by taking the model from [2] (extended with some additional factors reported in [21]) as a basis, and systematically adjusting it and comparing the agreement of the simulation results with the actual measurements in the training set. The adjustment consisted of both ignoring factors in the model (i.e. leaving out variables in the formulae) and calibrating parameters (i.e. changing the value of weighting variables). The idea behind this was to take a 'principle of parsimony' approach: although the original model was composed of factors that (according to the criminological literature) play a role in juvenile delinquency, this does not necessarily mean that the best model contains all of these factors. The aim of this phase was to achieve a list of models that resulted in a high correctness score.

Finally, the second data set was used to validate the different variations of the model that seemed promising during the calibration phase. In this phase, we did not change the model or parameters, but just calculated the accuracy according the developed measure for all formulae that resulted in a high score in the first phase. This method gives an unbiased validation of the accuracy, as the validation is performed on a different data set than the tuning.
4. Models for Simulating

Before development of a simulation model itself, a measure for evaluation has been established. This is described in the next section. The subsequent sections discuss the actual models and the calibration phase.

4.1. Evaluating Measure

The development of an evaluation measure is an important step, since it has a large impact on which models are considered accurate, and which are not. Intuitively, a simulation model for juvenile delinquency can be considered accurate when for a given set of pupils (and their personal characteristics) it predicts correctly when which pupil will show delinquent behaviour. To develop an evaluation measure, each pupil is assigned a delinquency score based on their answers to the questions related to their delinquent behaviour. However, for practical reasons, the 12-point scale used in the empirical study is converted to a binary scale: all pupils that have a delinquency score of ≥1 are assigned the value 1 (i.e., delinquent), and all other pupils are assigned the value 0 (not delinquent). The main motivation for this is that the distribution of the empirical data is not uniform: by far, most of the pupils have a delinquency score of <1 on the original scale, whereas only a few of them have a score of ≥1. For the simulated pupils (the agents) the same conversion will be made.

Next, the issue of time should be solved: for which moments will the simulated data be compared with the empirical data? For this, we simply used the time points for which the empirical data was available, i.e., after 1 year and after 2 years. Thus, the problem of defining a measure of evaluation has been reduced to matching the 0’s and 1’s of the pupils in the empirical data to the 0’s and 1’s of the corresponding agents in the simulation, both for the time point after 1 year and after 2 years. A good solution to this problem would provide points for hits (i.e., cases where both the data and the simulation result in 1) and correct rejections (i.e., data=0 and simulation=0), but may provide penalty points for misses (data=1 and simulation=0) and false alarms (data=0 and simulation=1). To select such a measure, it is worthwhile to consider the following standard measures from signal detection theory [11]:

\[ \text{Hit Rate} = \frac{\text{Hits}}{\text{Hits} + \text{Misses}} \]
\[ \text{False Alarm (FA) Rate} = \frac{\text{FA}}{\text{FA} + \text{Correct Rejections}} \]
\[ \text{Accuracy Rate} = \frac{\text{Hits} + \text{Correct Rejections}}{\text{Hits} + \text{Misses} + \text{FA} + \text{Correct Rejections}} \]

For the current purpose, all four elements used in these measures are relevant: the model should maximise the amount of hits and correct rejections, and minimise the amount of misses and false alarms. Therefore, it makes sense to select the Accuracy Rate as evaluation measure. However, another problem is that in the empirical data, the amount of pupils that show delinquent behaviour is much smaller than the amount of pupils that do not show delinquent behaviour (ratio of about 1:3). Given this information, the extremely simple strategy to always predict non-delinquency would already result in a relatively high Accuracy Rate. To illustrate this, imagine a classroom of 100 pupils, of which 25 show delinquent behaviour and 75 do not. In that case, the above strategy would provide 0 hits, 75 correct rejections, 25 misses, and 0 false alarms, thus an Accuracy Rate of 75/100 = 0.75. This is not very desirable, since all crucial cases (the delinquent pupils) are missed here. To compensate for this, the following alternative Accuracy Rate has been defined:
Here, w is a weight factor, representing the importance of finding hits. For the current research, it makes sense to choose \( w=3 \), since in the data the ratio of delinquents vs. non-delinquents is more or less 1:3. Given this new formula and weight factor, the Accuracy Rate of the simple strategy defined above would become \( 75/150 = 0.5 \), which is more reasonable. For this reason, both during the calibration and the validation phase (explained below), this alternative Accuracy Rate has been used.

4.2. Development of the Simulation Model
In the simulation experiments, the delinquency of a large number of agents is calculated according to a set of formulae that determine how the delinquency of an individual agent is influenced by its own delinquency in the previous year, its personal characteristics, its peers and the delinquency of its peers. Eventually, this can be used to simulate the development of the delinquency of a large number of agents over several years.

To perform these simulations, we used standard numerical simulation software. The multi-agent system was modelled as a multi-dimensional array, where each array represented a different agent. The different dimensions represented characteristics of the agents over time. For example, these dimensions specified the individual characteristics (like impulsivity and risk-orientedness) and the relations to peers. To calculate the new delinquency of each agent, the following algorithm was used (in pseudo code):

For each agent:
1. determine current delinquency
2. determine individual characteristics
3. compose the social network (friends)
4. calculate average delinquency of social network
5. calculate new delinquency, using information from step 1, 2, and 4

For the calculation of the new delinquency of the individual agents (step 5), various variants of the model have been tried. The initial model that was used takes all risk factors mentioned in Section 2 into account for which was determined that they were statistically significant (all except “many time spent with friends” and “being a member of a troublesome youth group”). The data set contained scores for all these factors, but the maximum score for the distinct factors differed. Therefore, the scores first had to be scaled into the same dimension, i.e., between 0 and 1. As weighting factors, the delinquency odds ratio’s for the individual risk factors were used. An odds ratio is defined as the ratio between the odds of an event occurring in one group and the odds of it occurring in another group. In this particular case, they provide information about the chance on delinquent behaviour when a certain risk factor (e.g., impulsiveness) is present [21]. The main formula in the initial model (i.e., the formula to calculate delinquency in the next year, step 5) consisted of a weighted sum of all risk factors (except the “deviance reinforcement by peers”) and the average delinquency of friends in the previous year multiplied by the “deviance reinforcement by peers”. The idea behind the specific treatment of the “deviance reinforcement” factor is that this factor will leverage the influence of peers.

The main formula of the initial model is the following:
delinquency(y) = (w · delinquency(y-1) + 
oddsparent_supervision · parent_supervision(y) 
+ oddsparent_support · parent_support(y) 
+ oddsschool · bond_school(y) 
+ oddsconst · law const(y) 
+ oddsimpulsivity · impulsivity(y) 
+ oddsrisk_oriented · risk orientedness(y) 
+ oddstemper · temper(y) 
+ oddsmaterial_needs · material_needs(y) 
+ oddsdvd · deviance_reinforcement · deviance reinforcement(y) 
* average_delinquency_friends(y-1) ) / w + Σodds

This formula formed the basis for the calibrations in the next phase.

4.3. Calibration of the Model

To fine-tune the model, we followed a systematic approach in which we identified the contribution of all elements of the initial model to the overall correctness of the simulation results, by leaving out specific risk factors and/or changing the weighting or combination mechanism. In order to do so, we simulated the behaviour of delinquency for the pupils in the training set (which involved 194 pupils) and compared this to the actual data, using the evaluation measure as described in Section 4.1. This resulted in a correctness score for each variation of the model.

However, there is one additional concern. The simulation yields a real value for the delinquency, while the abstracted actual data is a binary value (0 or 1). To compare them, a specific threshold for the simulated delinquency has to be used above which an agent is considered to be delinquent. This threshold has a different optimal value for each variation of the model. Therefore, the correctness of a specific variant of the model is actually the highest accuracy for all values of the threshold. Thus, if the accuracy of a model variation is reported, the threshold at which this accuracy is reached has to be mentioned as well.

To be able to compare the quality of the predictions of the model with a baseline, we included four baseline predictions (variant 1-4). These predictions simply say, respectively, that all agents will become delinquent (i.e. regardless of all data, it will always output “1”), that no agent will become delinquent (always “0”), or predict a random distribution of delinquents and non-delinquents, either in the ratio 1:1, or in the same proportion as the empirical data (1:3). Next, different variants of the model were tried (variant 5-11), starting with the initial formula from Section 4.2. During the calibration, it turned out that many risk factors did not have a positive influence on the accuracy of the model. Leaving them out resulted in a higher accuracy rate than including them in the model. In addition, it appeared that the delinquency in the previous year is a very good predictor for the delinquency in the next year. In many variations of the model, we therefore used a disjunction of the delinquency in the last year and a combination of risk factors. Table 1 lists the most promising models, their accuracy according to the developed evaluation measure and the thresholds and weights at which this value was achieved.

Model variant 10 yielded the highest accuracy scores. This model uses, in addition to the delinquency in the previous year, the impulsivity and the product of the deviance reinforcement and the delinquency of the best friends. Conversations with criminological experts pointed out that these factors are well in line with the main theories in criminology. For the selected data of 194 pupils, model variant 10 resulted for the simulation of the first year in 46 hits, 44 false alarms, 11 misses, and 93 correct
rejections, and for the second year in 46 hits, 43 false alarms, 8 misses, and 97 correct rejections. All other variations resulted in lower accuracy scores.

Table 1. Variants of the model and accuracy values.

<table>
<thead>
<tr>
<th>Model variant</th>
<th>Main formula</th>
<th>Optimal threshold</th>
<th>Weights</th>
<th>Accuracy y1 → y2</th>
<th>Accuracy y2 → y3</th>
<th>Average accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>always 0</td>
<td></td>
<td></td>
<td>44.48</td>
<td>46.36</td>
<td>45.42</td>
</tr>
<tr>
<td>2</td>
<td>always 1</td>
<td></td>
<td></td>
<td>55.52</td>
<td>53.64</td>
<td>54.58</td>
</tr>
<tr>
<td>3</td>
<td>random 0 and 1 (with ratio 1:1)</td>
<td></td>
<td></td>
<td>51.95</td>
<td>48.68</td>
<td>50.31</td>
</tr>
<tr>
<td>4</td>
<td>random 0 and 1 (with ratio 3:1)</td>
<td></td>
<td></td>
<td>51.95</td>
<td>44.37</td>
<td>48.16</td>
</tr>
<tr>
<td>5</td>
<td>initial formula (see Section 4.2)</td>
<td>0.59</td>
<td></td>
<td>62.99</td>
<td>69.21</td>
<td>66.10</td>
</tr>
<tr>
<td>6</td>
<td>delinquency(y-1)</td>
<td></td>
<td></td>
<td>67.21</td>
<td>73.84</td>
<td>70.52</td>
</tr>
<tr>
<td>7</td>
<td>delinquency(y-1) OR delinquency_friends(y-1)</td>
<td>0.14</td>
<td></td>
<td>65.58</td>
<td>76.49</td>
<td>71.04</td>
</tr>
<tr>
<td>8</td>
<td>delinquency(y-1) OR delinquency_friends(y-1) OR risk_orientedness(y) OR temper(y) &gt; w2</td>
<td>0.34, 14, 12</td>
<td></td>
<td>70.45</td>
<td>74.83</td>
<td>72.64</td>
</tr>
<tr>
<td>9</td>
<td>delinquency(y-1) OR ( odd * risk_orientedness(y) + odd * deviance_reinforcement(y) + delinquency_friends(y-1) OR random)</td>
<td>0.55</td>
<td></td>
<td>72.08</td>
<td>75.17</td>
<td>73.62</td>
</tr>
<tr>
<td>10</td>
<td>delinquency(y-1) OR ( odd * impulsivity(y) + odd * deviance_reinforcement(y) + delinquency_best_friends(y-1) OR random)</td>
<td>0.31</td>
<td></td>
<td>75.00</td>
<td>77.81</td>
<td>76.41</td>
</tr>
<tr>
<td>11</td>
<td>delinquency(y-1) OR ( odd * impulsivity(y) + odd * deviance_reinforcement(y) + (w * delinquency_friends(y-1) + (1-w) delinquency_best_friends(y-1)) OR random)</td>
<td>0.31, 0.35</td>
<td></td>
<td>75.32</td>
<td>77.15</td>
<td>76.24</td>
</tr>
</tbody>
</table>

In addition to the above described evaluation measure, we also assessed the quality of the model using an ROC curve analysis [9]. An ROC (Relative Operating Characteristic) curve is a graphical plot of the fraction of true versus the fraction of false positives for a binary classifier system as its discrimination threshold is varied. The threshold in our model is the value of the calculated delinquency above which a pupil is classified as delinquent.

Figure 2. ROC curve for model 10 and a random prediction.
Figure 2 shows the graph of the ROC curve for the best model variant, number 10. We also calculated the area under the ROC curve (AUC), a scalar measure for the quality of the predictions. For model variant 10, the AUC is 0.79. An AUC-value larger then 0.70 is called ‘acceptable’, larger then 0.80 ‘excellent’ and larger then 0.90 ‘outstanding’ [12].

5. Validation

In order to validate the models presented in the previous section, a second dataset was used. Like the dataset used for calibration of the model, this second dataset was also taken from [21]. Thus, for each pupil the same types of information (i.e., delinquency measures, peer networks, and individual risk factors) were available; only a different pool of pupils was taken. However, as mentioned earlier, we guaranteed that there was no overlap between the schools used in both datasets. This second dataset involved 299 pupils.

As mentioned earlier, for the validation the same formulae as used for the calibration were used. This means that the same parameter values, (e.g. for thresholds, weight factors) were used. To be able to evaluate the results of the different models, also the baseline models were applied to the validation dataset. The empirical data for this dataset (of 299 pupils) were fed as input to the different models, and the Accuracy Rate was calculated.

The results of applying the different models to the validation dataset are shown in Table 2. As shown by this table, the more sophisticated models (i.e., variant 8-11) are clearly more accurate (varying from 65.35 to 66.33) than the baseline strategies (varying from 41.84 to 58.16), the initial model (57.53) and the model that predicts stability with respect to the previous year (60.53). Surprisingly, for this dataset the strategy of taking the peer network into account (variant 7) does not seem to add much with respect to the strategy of looking at the previous year only (variant 6), but does make a difference when taken in combination with the deviance reinforcement factor (later variants).

<table>
<thead>
<tr>
<th>Table 2. Validation results.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
</tr>
<tr>
<td>------</td>
</tr>
<tr>
<td>1</td>
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<td>11</td>
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</tbody>
</table>

Furthermore, it is worthwhile to note that most overall accuracy rates are slightly lower than they were for the first dataset. This is the case for all variants, except for model 1-4 (which is obvious, since these models do not make use of any predicting factor). It is however surprising that also variant 6 (the measurement that only takes the
previous year into account) scores lower here than for the first dataset. This in an indication that this second dataset was simply less ‘stable’ than the first dataset: there were more changes in delinquency, which makes it more difficult for a model to make accurate predictions. Despite this more difficult dataset, the performance of the best model (variant 8) was still more than 6 points better than the performance of the straightforward strategy of variant 6, which is about the same difference as was found for the first dataset.

For the validation, we also plotted the ROC curve and calculated the AUC value. Similar to the results using the other evaluation measure, the AUC for the validation data was less than the AUC for the training data, i.e. 0.68. This is still much larger than the 0.50 that a random prediction would yield.

6. Related Work

With respect to related work, there are both commonalities with the social and behavioural sciences, and AI and Computer Science.

Concerning the first, the current paper is related to important articles from the 1960’s and 1970’s such as [5, 18], which were the first to formulate (different variants of) the social learning theory. In fact, these theories formed the basis of the research questions addressed in this paper. Based on these theories, [16] identified a number of (informal) properties that are expected to hold for social learning in Criminology. The simulation model presented within this paper indeed satisfies these properties. Next, a number of papers in Criminology propose more refined models for social learning, often focusing on specific aspects of the learning. For example, [19] compared three theoretical (but not computational) models of the interrelations among associations between delinquent peers, delinquent beliefs, and delinquent behaviour. Finally, several authors have performed empirical studies on social learning of delinquent behaviour in schools, e.g., [20]. Our model was designed explicitly with the purpose of reproducing such data.

Concerning the literature in AI and Computer Science, we are not aware of approaches using multi-agent technology to simulate delinquent behaviour of individuals in a group. However, various papers have similarities to the work proposed here. First, [8] presents a model that uses differential equations to describe the development of juvenile criminal behaviour. They aim for an integration of multiple criminological theories, whereas we focus (in more detail) on the former only. Moreover, several authors have created models that address social learning and criminal behaviour at a more global level e.g. [22]. These models differ from our model in the sense that they are situated at a macroscopic level, thereby abstracting from differences between individuals. Furthermore, a large number of approaches address simulation of the environmental aspects of criminal behaviour, such as the displacement of crime and the emergence of “hot spots”, e.g., [1, 13]. Finally, relevant work is put forward by [6]. They identify a number of (cognitive) factors that are relevant in social learning in general. However, in contrast to our work, they do not provide a computational model.

7. Conclusion

This paper contributed the development and validation of a dynamic agent-based approach to simulate social learning of adolescence-limited criminal behaviour. This approach has been used to perform simulation experiments in which the delinquency of 250 pupils is dynamically calculated over a couple of years. This expected delinquency
is based on personal characteristics on the one hand and the delinquency of peers on the other hand. A second dataset has been used to validate the model, using a specifically developed accuracy measure. The validation shows that the model predicts delinquency substantially better than a baseline model that only uses the delinquency of the previous year.

Note that an inherent consequence of the use of empirical data is that such data is often incomplete. This incompleteness may be caused by respondents not answering all the questions or by the fact that some respondents reported friends that were not part of the study. Such incompleteness is one of the complicating factors in the development of an accurate simulation model. However, an important advantage of the approach presented in this paper is that it does not use one single formula to calculate future delinquency, but presents a whole range of different formulas. As a result, for a particular real-world case, the modeller can choose the particular formula that best fits the available information. E.g., if no information about the participant’s impulsiveness is available, then a formula can be selected that does not make use of this factor. This property of flexibility (and user transparency) of the model is an important advantage over, e.g., approaches based on machine learning. Nevertheless, for future work it is worthwhile to explore whether automated learning techniques can be exploited to improve (at least parts of) the model.

As soon as the model is sufficiently validated, an interesting direction for future work is to perform so-called “what-if simulations”, or computer-supported thought experiments. These thought experiments can be particularly useful in policy making. An interesting question could be, for example, “what would happen if we placed one bad child in a classroom full of teacher’s pets”? Will this delinquent pupil adapt himself to the environment and become good as well, or will he manage to make the entire class a bit more delinquent? How will the average class level evolve? The answers to these questions may be very important for high schools, to decide how to fill in their classes. In future work, it is planned to perform a number of such what-if simulation in a systematic manner, in collaboration with experts from Criminology.

References


1 Of course, there should be at least some factors for which information is available, but this holds for any predictive model.
Predicting the Development of Juvenile Delinquency by Simulation

Tibor Bosse, Charlotte Gerritsen, and Michel C.A. Klein

Abstract. A large number of delinquent activities are performed by adolescents and only occur during this period in their lives. One of the main factors that influence this behaviour is social interaction, mainly with peers. This paper contributes a computational model that predicts delinquent behaviour during adolescence based on interaction with friends and classmates. Based on the model, which was validated based on empirical data, the level of delinquency of pupils is simulated over time. Furthermore, simulation experiments are performed to investigate for hypothetical scenarios what is the impact of the division of students over classes on the (individual and collective) level of delinquency.

1. Introduction

One of the main challenges in Criminology is to understand, explain and predict when individuals show delinquent behaviour [4]. Obviously, there is a wide range of potential contributors to the emergence of crime, varying from environmental opportunities to social influences. In this paper we focus on the latter. Learning (delinquent) behaviour by social interaction is something that is often observed in adolescents [11]. During the period from 12 to 18 year old, people are more susceptible to the opinion of their peers. In some situations, their desire to be part of a group can be so strong that they break some rules to achieve this desire. This is consistent with the theory by Moffitt [10] who states that one can divide delinquents roughly into two groups, namely life-course persistent offenders and adolescence limited offenders. The behaviour of the first group is caused by neuropsychological problems during childhood that interact cumulatively with their criminogenic environments across development, which leads to a pathological personality. This behaviour will usually continue through life. Instead, the behaviour of adolescence-limited offenders is caused by a gap between biological maturity and social maturity. It is mainly caused by mimicking antisocial role models like peers, but also parents and school are important contributors. These offenders peak sharply at about age 17 and drop fast in young adulthood.

In this paper we exploit simulation techniques to study the development of such juvenile delinquency. As mentioned above, this type of behaviour is limited to a certain period of time, and some of its direct causes are clearly determined. This provides opportunities to develop a computational model of this process. In previous research [2], we developed such a model, which was able to predict the level of delinquency of students based on information about the personal characteristics and their peer network. The model was validated by using a large dataset with information about 1730 scholars (taken from [14]).

The main contribution of the current paper is to show how this model can be used to perform so called what-if simulation experiments. In these simulations the existing (validated) model is applied to a hypothetical situation, which is slightly different from the situation in the existing empirical data. For example, we want to see what happens to the level of delinquency (both of individuals and of the classes) when the composition of the classes is altered. Interesting questions here are, among others:
- What is the effect when we put the most delinquent students together in one class?
- Is it better to spread the delinquent and non-delinquent students equally over classes?

To answer such questions, this paper proposes to make use of social simulation techniques [3]. In recent years, a number of papers have successfully tackled criminological questions using social simulation, e.g., [7, 9]. However, the current paper differs from these approaches in that we do not attempt to reproduce existing data, but rather explore how hypothetical scenarios would evolve. We will create these hypothetical scenarios by making small modifications in existing scenarios (e.g., change the composition of classes), and run the simulation model on the modified data. The main question that we would like to answer is whether the composition of a school class has an influence on the overall level of delinquency of the pupils. This is an interesting topic, since it is often believed that the structure of schools and peer networks has an important impact on juvenile delinquency [8, 12].

The paper is organised as follows. In Section 2 we describe how the data used for the simulation experiments were collected. The simulation model itself is presented in Section 3, and the experiments in Section 4. Finally, Section 5 concludes the paper with a discussion and some ideas for future work.

2. Data Collection

The model presented in this paper is based on empirical data from a longitudinal research project. This research was performed by the Netherlands Institute for the Study of Crime and Law Enforcement (NSCR) in the so called ‘School Project’ [14], which focused on peer network formation, personal development, and school interventions in the development of problem behaviour and delinquency.

In this project, a large number of high school students were surveyed by means of questionnaires. As respondents, a cohort of students was used that started high school during the school year 2001/2002. The first year of secondary education in the Netherlands is comparable with 7th grade in the United States (most students are 12 or 13 years old). These students were surveyed during three consecutive years: 2002, 2003 and 2004.

During these three years, the respondents had to fill out a number of questionnaires. Their delinquent behaviour was measured using self-reports of a variety of offences. The self report method is a standard procedure in Criminology, and it results in fairly reliable estimates of delinquency levels of young people, when it is conducted in a proper way and in an anonymous setting. Respondents were asked if they had ever committed an offence and, if so, how often during the reference period. The measures of self-reported delinquency used in this study come from 12 questions, among which: in the last year, how many times did you: “paint graffiti”, “vandalise property”, or “steal small things from shops worth less than 5 Euros” The total delinquency measure indicates how many types of the 12 possible types of delinquent behaviours were reported by the person.

The respondents also had to answer a number of questions about their friends (e.g. with whom they spent a lot of time, who were their best friends), to obtain information about their social networks. In the analyses, friends’ numbers were linked to the respondent’s own number, enabling the networks of friends to be mapped and analysed.

Further, the study also used a substantial number of other measures on risk factors that are central in criminological theories and have been found to correlate with
delinquency in the past (e.g. low supervision and support by parents, low bond with school, low law conformity, high impulsivity, high temper). For more details of the empirical research see [13, 14].

3. Simulation Model

In this section the simulation model used for the experiments is described. First, in Section 3.1, the methodology behind the design of the model is discussed (based on [1]). Section 3.2 presents the implementation of the model, and Section 3.3 shows how the original model was extended in order to incorporate information about classes.

3.1 Design Methodology

As a first step in the process of designing the model, an initial dynamic model was developed for the development of delinquency through social learning in a class room, based on an analysis of the literature. A more detailed description of this step is provided in [1]. The model describes the influences of several personal characteristics, as well as the influences of other peers. More specifically, the delinquency of an agent is influenced by its previous delinquency, its individual personality traits (e.g. temper, impulsiveness), and external factors (i.e., the school, the parents, and peers). This original model has the form of a set of differential equations, where delinquency is measured as a real number between 0 and 1. In [1], it has been shown that this model can be used to simulate delinquency development of a small set of agents in a classroom. The simulations exhibited several patterns that would be expected based on the criminological literature.

A next step was to validate the model based on the empirical data mentioned in Section 2. In this research [2], a representative sample of the collected dataset has been selected, and has been split up in a training set and test set. Each set contained the data of around 250 pupils. When making this split, we guaranteed that there was no overlap between the schools used in the training set and those used in the test set. We developed an evaluation method that could be used to quantify the correctness of models and to discriminate between accurate and less accurate models. This measure accommodates the intuitive ideas about a correct prediction in one number. The model was calibrated with the data in the training set by taking the model from [1] extended with some additional factors reported in [14], and systematically adjusting it and comparing the simulation results with the actual measurements in the training set (scaled to a number between 0 and 1). The adjustment consisted of both ignoring factors in the model (i.e. leaving out variables in the formulae) and calibrating parameters (i.e. changing the value of weighting variables), thereby creating different variations of the model.

Finally, the second data set was used to validate the different variations of the model that seemed promising during the calibration phase. In this phase, we did not change the model or parameters, but just calculated the accuracy according the developed measure for all formulae that resulted in a high score in the first phase. This method gives an unbiased validation of the accuracy, as the validation is performed on a different data set than the tuning.

3.2 Implementation

To implement the model, we used standard numerical simulation software. A ‘school class’ was modelled as a multi-dimensional array, where each array represented a
different student. The different dimensions represented characteristics of the students over time. For example, these dimensions specified the individual characteristics (like impulsivity and risk-orientedness) and the relations to peers. To calculate the new delinquency of each agent, the following algorithm was used (in pseudo code):

For each agent:
1. determine current delinquency
2. determine individual characteristics
3. compose the social network (friends)
4. calculate average delinquency of social network
5. calculate new delinquency, using information from step 1, 2, and 4

To calculate the new delinquency of the individual agents (step 5), various variants of the model have been tried, each incorporating some of the factors identified in the previous section. These different models are depicted in Table 1. For example, model variant 1 (a baseline model), always predicts that students will not become delinquent. The last column denotes the accuracy rate for each model, which was calculated as follows:

\[
\text{Accuracy Rate} = \frac{\text{w*Hits + Correct Rejections}}{\text{w*Hits + w*Misses + False Alarms + Correct Rejections}}
\]

where Hits, Misses, Correct Rejections and False Alarms are defined according to the classical measures in signal detection theory [5]. For more details, see [2]. The factor ‘risk orientedness’ (model 8 and 9) indicates the extent to which the pupils like performing exciting activities, and the factor ‘deviance reinforcement’ (model 9-11) indicates the extent to which the pupils are sensitive to influences of their friends.

As can be seen, variants 10 and 11 have the highest accuracy. This means that the previous delinquency combined with the impulsivity, the level of deviance reinforcement by friends, and the delinquency of (best) friends, seem to be the best predictors for delinquent behaviour.

<table>
<thead>
<tr>
<th>Model variant</th>
<th>Main factors used</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>always predict non-delinquency</td>
<td>45.42</td>
</tr>
<tr>
<td>2</td>
<td>always predict delinquency</td>
<td>54.58</td>
</tr>
<tr>
<td>3</td>
<td>randomly predict non-delinquency and delinquency (with ratio 1:1)</td>
<td>50.31</td>
</tr>
<tr>
<td>4</td>
<td>randomly predict non-delinquency and delinquency (with ratio 3:1)</td>
<td>48.16</td>
</tr>
<tr>
<td>5</td>
<td>all factors identified in Section 3.1</td>
<td>66.10</td>
</tr>
<tr>
<td>6</td>
<td>delinquency last year</td>
<td>70.52</td>
</tr>
<tr>
<td>7</td>
<td>delinquency last year, delinquency friends</td>
<td>71.04</td>
</tr>
<tr>
<td>8</td>
<td>delinquency last year, delinquency friends, risk-orientedness, temper</td>
<td>72.64</td>
</tr>
<tr>
<td>9</td>
<td>delinquency last year, risk-orientedness, deviance reinforcement, delinquency friends</td>
<td>73.62</td>
</tr>
<tr>
<td>10</td>
<td>delinquency last year, impulsivity, deviance reinforcement, delinquency best friends</td>
<td>76.41</td>
</tr>
<tr>
<td>11</td>
<td>delinquency last year, impulsivity, deviance reinforcement, delinquency friends, delinquency best friends</td>
<td>76.24</td>
</tr>
</tbody>
</table>

In addition to the accuracy, the quality of the models has also been tested using a Relative Operating Characteristics (ROC) analysis. The outcome of this analysis is a
curve which represents a graphical plot of the fraction of true versus the fraction of false positives for a binary classifier system as its discrimination threshold is varied (see Figure 1). The threshold in our model is the value of the calculated delinquency above which a pupil is classified as delinquent. We calculated the area under the ROC curve (AUC), a scalar measure for the quality of the predictions, for each model. For model variant 10, the AUC is 0.79. An AUC-value larger than 0.70 is called ‘acceptable’, larger then 0.80 ‘excellent’ and larger then 0.90 ‘outstanding’ [6].

3.3 Incorporating Class Information

Although model 10 and 11 produce the highest accuracy rates, these model variants are not particularly appropriate for the aims of the current paper. That is, the goal of this paper is to predict for hypothetical scenarios (which are slightly different from the existing situation) how the delinquency of the students would have developed. And since it is not very realistic to assume that one can easily modify, say, the impulsivity or the friend network of students, variant 10 and 11 are not very useful candidates for these ‘what-if experiments’.

For this reason, two additional variants of the model have been developed. These models (variant 12 and 13) use the composition of classes. For obvious reasons, in practice it is much easier to manipulate students’ class composition than their friend networks. Therefore this factor was also manipulated within the hypothetical scenarios. To this end, variants of the model have been developed that take the delinquency of class members into account.

Model variant 12 predicts that a student will become delinquent if (s)he was delinquent in the previous year OR (s)he is part of a delinquent class AND (s)he has a high value for ‘deviance reinforcement’. Here, being part of a delinquent class is defined as the situation that the average delinquency of all students in the class is higher than a certain threshold. Note that this variant does not make use of the friend network.

The ROC curve obtained for this model variant 12 is depicted in Figure 1, when compared with a random model (variant 3). As can be seen, variant 12 performs much better than the random model. The AUC of model variant 12 was 0.734, and its accuracy is 72.33. Although this is lower than the AUC and accuracy of variant 10 (resp. 0.79 and 76.41), we decided to use variant 12 for the simulation experiments described in the next section, because (as explained above) this variant contains the students’ classes as one of the factors.

In addition, a model variant has been developed that also takes the delinquency of the friends into account. Variant 13 predicts that a student will become delinquent if (s)he was delinquent in the previous year OR delinquency of the friends times the ‘deviance reinforcement’ is higher than a certain threshold OR (s)he is part of a delinquent class AND (s)he has a high value for ‘deviance reinforcement’. For being part of a delinquent

---

1 Note that the AUC approach both has advantages and drawbacks when compared to the accuracy approach. An advantage is that this measure is rather common in the literature, which makes it easier to interpret the numbers, and to compare them with other models. A drawback is that the resulting numbers are calculated on the basis of all possible instances of the discrimination threshold, whereas in the accuracy approach only the best instance is taken. And since for the simulation experiments only this best instance will be used, the accuracy approach could be considered to be more useful.
class the same definition is used as in variant 12. The AUC of this model variant (see Figure 2) is 67.52\(^2\), and its accuracy is 72.66.

![ROC curve](image1.png)

**Figure 1.** ROC curve for model 12 and a random prediction

![ROC curve](image2.png)

**Figure 2.** ROC curve for model 13 and a random prediction

4. **Simulation Experiments**

This section describes the simulation experiments that were performed to investigate the development of the delinquency of the pupils in the dataset for hypothetical scenarios. In Section 4.1, the setup of the experiments is explained. The results of the experiments are discussed in Section 4.2.

\(^2\) This relatively low number is mainly due to the dip at the right-hand side of the graph. This dip is caused by the fact that for some extreme values (which will obviously not be used in the simulation experiments) of the discrimination threshold, the model scores very bad. For this reason, in this case the accuracy may be more informative (see also footnote 1).
4.1 Approach

In the simulations, we compared the results of the simulation of the delinquency over one year using the actual class composition with the results of two simulations using a hypothetical composition, namely 1) a scenario in which all delinquent pupils are put together in the same class, and 2) a scenario in which all delinquent pupils are evenly distributed over all classes in a school. The goal of the comparison is to find out whether the change in the delinquency of pupils is positively or negatively influenced by the class composition.

The simulations are performed using three schools in our dataset, consisting of 6, 8 and 4 classes, respectively. In total 194 pupils were involved in the simulations. The simulations for the actual class composition and the two hypothetical scenarios have been performed two times, using each variant of the model that takes the class information into account (variant 12 and 13).

4.2 Simulation Results

Table 2 gives an overview of the development of the delinquency over a year according to the simulation with model variant 12 and 13. The first two columns indicate, respectively, the code of the school class in the study (e.g., ‘1 - 2’ stands for ‘class 2 of school 1’), and the amount of pupils in the class. In the next 3 columns, the ‘base before’ column shows the number of delinquent pupils in the actual class composition at the start, and the columns ‘base after v12’ / ‘v13’ the predicted number of delinquent pupils after a year using model variant 12 or 13 respectively. Similarly, the 6 subsequent columns show the number of delinquent pupils in a class at the start and the end using the hypothetical class compositions (called scenario 1 and 2). It can be seen that in scenario 1 all delinquent pupils of a school are put together in a class, while in scenario 2 the delinquent pupils are more or less evenly distributed over the classes.

Table 2. Results of the simulations of delinquency of pupils with alternative class compositions using model variant 12 and 13.

<table>
<thead>
<tr>
<th>school class</th>
<th>class size</th>
<th>base before</th>
<th>base after v12</th>
<th>base after v13</th>
<th>scen1 before</th>
<th>scen1 after v12</th>
<th>scen1 after v13</th>
<th>scen2 before</th>
<th>scen2 after v12</th>
<th>scen2 after v13</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - 1</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1 - 2</td>
<td>17</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>1 - 3</td>
<td>10</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1 - 4</td>
<td>6</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1 - 5</td>
<td>6</td>
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<tr>
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<tr>
<td>2 - 1</td>
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<td>2 - 3</td>
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<td>2 - 4</td>
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<td>5</td>
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<tr>
<td>2 - 5</td>
<td>10</td>
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<td>5</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>5</td>
<td>5</td>
<td>7</td>
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<tr>
<td>2 - 6</td>
<td>1</td>
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<td>2 - 7</td>
<td>17</td>
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<td>2 - 8</td>
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<td>2</td>
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As can be seen in Table 2, the difference between the baseline and the different scenarios is not very high. For model variant 12, the total number of delinquent pupils increases in scenario 1 from 54 to 55 instead of to 58 for the baseline, and in scenario 2 it increases as much as in the baseline. In model variant 13, the number of delinquent pupils increases to 64 in the baseline, while it increases to 67 in scenario 1 and to 66 in scenario 2.

In the simulations using variant 12 we see that the increase of the number of delinquent pupils is less for the scenario in which all bad guys are put together (scenario 1) than in the baseline scenario or the scenario in which the delinquent pupils are evenly distributed. However, this pattern is not visible when using model variant 13. Overall, the differences between the results of the baseline scenario and the two other scenarios are very small. Although care should be taken not to draw too strict conclusions from these preliminary experiments, this may be an indication that the use of alternative class compositions has little effect.

5. Conclusion

In this paper, we have presented a number of simulation experiments on juvenile delinquency. The simulations were performed using an existing model that was based on the theory of social learning. In our previous research we have used empirical data about juvenile delinquency and social networks to develop and validate this simulation model. In the current paper we have presented some novel variants of this model. Moreover, we have used the model to investigate the effect of different class compositions on the development of the delinquency in the total group of pupils.

The experiments show no significant difference between the change in the total number of delinquent pupils in the different scenarios. The two different scenarios represented two extreme situations: all delinquent pupils put together, or all delinquent pupils distributed over all classes. Therefore, our tentative conclusion is that the composition of classes has not so much effect on the overall development of the delinquency of the pupils in a school. This is an interesting finding, since it is often argued that careful composition of school classes is very important to prevent development of juvenile delinquency [8, 12].

However, there are a few remarks that can be made about our experiments, which could be of influence on this conclusion. First of all, the model is possibly not very precise (see the relatively limited accuracy) because of small size of the training set. It could be the case that with a more precise model (derived from a larger training set) stronger effects would be visible. A second remark concerns the size of the classes. The ones used in the simulated scenarios are much smaller than regular classes; as a consequence, the influence of other pupils in the class is smaller in our simulations than in reality. The class size is this small because only figures of male pupils are used. Therefore, a related remark is that the influence of female classmates is not taken into account in the model. The fact that we do not see a clear effect could also be caused by the fact that the number of offenders in our data set is relatively small. Therefore, also the number of predicted changes will always be quite small. Finally, we want to remark that the current models do not allow pupils to learn non-delinquency from their peers at school, they can become delinquent. Although this apparently follows from our dataset in the best predictive models, it might be the case that this is a bit different in reality.

Despite these remarks, the approach presented in this paper has proved to be a useful additional tool for criminology scientists, as also confirmed by our colleagues in the
Criminology department. The approach allows for experiments that can not be easily performed in the real world and could give some indication of the expected effects of class compositions on juvenile delinquency.

Acknowledgement

The authors are very grateful to Frank Weerman for his willingness to provide the empirical data from the ‘School Project’, and for a number of fruitful discussions.

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Part IV –
Modelling Spatio-Temporal Dynamics of Crime

This last part of the thesis addresses the spatio-temporal dynamics of crime. The spatio-temporal dynamics of crime are one of the main research interests within Environmental Criminology. Relevant questions within this area concern the movement and interaction of three types of agents, namely passers-by, criminals and guardians.

The main theory used as background in this part is the Routine Activity Theory (RAT) [2]. This theory states that a crime will occur when a motivated offender meets a suitable target and no capable guardian is present. Based on this theory we developed computational models that distinguish three types of agents (namely passers-by (potential victims), (formal) guardians and criminals (potential offenders)). The interaction between these types of agents in space and time is the main focus of investigation in all papers presented in this part (although their behaviour differs in the different papers). In this part we take a couple of assumptions underlying the RAT as a basis and investigate what the consequences of these assumptions are with respect to crime patterns under different circumstances. For example, how does crime shift over a city when (formal) guardians use a particular surveillance strategy?

An important concept in this area is the so called hot spot. A criminal hot spot is a location where many crimes occur [6]. These criminal hot spots tend to shift over time. This phenomenon brings up more questions. Why do hot spots emerge? And where do they emerge? How can the emergence of hot spots be prevented? In recent years, several researchers have applied different computational modelling approaches to help answer these questions (e.g. cellular automata [3, 4] or evolutionary computer techniques [5]).

These authors all share the aim of investigating crime dynamics, but differ in their underlying motivation. Some authors try to develop simulation models of crime dynamics in existing cities, which can be directly related to real world data (e.g., [4]), whereas others deliberately abstract from empirical information (e.g., [1]). Both these approaches have their pros and cons. A model that has been validated based on empirical data from existing cities could be beneficial because people can apply it to new real world situations. One can feed empirical data into the model and as a result is (hopefully) able to predict patterns of spatio-temporal dynamics of crime. However, obtaining useful empirical data is often difficult and time-consuming.

Another approach is to deliberately abstract from empirical information. In this case the model is used rather as an analytical tool. Such a model may be used by researchers to make a phenomenon more clear, and possibly discover interesting results that could be used by policy makers to improve existing policies. For example, to study the interaction of multiple agents (like for instance the inhabitants of a city), which is a process that cannot easily be studied by hand, simulation can be a very interesting option because one can adjust parameters in the model and see what happens in the simulated environment. It is an explorative process, without making many claims about the real world, to find out which factors play an important role in the spatio-temporal dynamics of crime. The downside of this approach is that the model does not take empirical information into consideration.

There are however also researchers that take an intermediate point of view. They initially build their simulation model to study the phenomenon per se, but define its basic concepts (e.g., locations, crime rates) in such a way that it can be directly
model (again focused on crimes against passers by) and on the interaction between potential victims, formal guardians and potential offenders. The difference connected to empirical information, if this becomes available. Hence, these models in principle abstract from empirical information, but do not exclude that they can be filled with empirical information in the future. The research presented in this part also takes this intermediate perspective. Its main motivation is to develop an analytical tool to gain more insight in the spatio-temporal dynamics of crime dynamics. In this sense the developed model is just an abstract model as explained before. However we developed it in such a way that if empirical data were to become available we can use this in the model. For example, the concepts that were used as basic elements of the model were chosen such that they can be directly mapped to information that can be measured in the real world like crime rate or number of formal guardians.

In Chapter IV.1 we start with a relatively simple model. Here we distinguish the three types of agents mentioned before. In this case the targets are static (e.g., houses), whilst the guardians and criminals are dynamic. We modeled four different worlds in which the attractiveness of the targets differs. In one world the attractiveness of the targets is distributed randomly, while in the second world the most attractive targets are clustered. Further there is a world with two clusters of attractive targets separated by less attractive targets, and a world where all targets are equally attractive. In these worlds potential offenders move around with a high probability to move to the most attractive neighbor. When an offender encounters a target with a value higher than his personal ‘burglary threshold’ and no guardian is present, this would count as a burglary. Moreover, the guardians move around according to one out of three strategies, i.e., 1) randomly, 2) focused on hot spots (i.e., with a probability proportional to the amount of burglaries that took place in the past, or 3) hot spot focused but within a designated area. The results pointed out that the two hot spot focused strategies perform better than the random strategy. Moreover, which of the hot spots strategies performed best depended on the total amount of guardians. These findings provided some first evidence for the usefulness of simulation to study environmental dynamics of crime.

Chapter IV.2 also contributes an agent based model of crime dynamics, but in this case the targets are dynamic instead of static as in the previous paper (from now on we do not focus on burglary anymore but instead we focus on crimes that are performed on the streets against passers by, like pick pocketing). This model specifically focuses on the interplay between hot spots and reputation. Each location in the model has a reputation with respect to the amount of assaults and arrests that take place at that location. This reputation has a different impact on each type of agent. For instance, criminals are attracted by a location with a high assault rate, since they believe this increases their chances to assault someone but they are not attracted to locations with a high arrest reputation since they do not like to run the risk of getting caught. Based on the model, a large number of simulation runs have been performed, of which the results have been formally analysed (to see whether they satisfy certain expected properties such as cyclic patterns). Also this study provided evidence that agent-based modelling is a useful approach to answer questions on the interplay between hot spots and reputation. In this chapter, it was decided to equip the guardians with a reactive strategy; this means that the guardians move towards a location after the assault reputation has increased. An extended model, including other types of strategies is presented in a later paper (i.e. see the description about chapter IV.4 below).

In Chapter IV.3 we make a shift in modelling approach. In this paper we compare an agent-based model of the spatio-temporal dynamics of crime with a population-based model (again focused on crimes on the street against passers by) and on the interaction between potential victims, formal guardians and potential offenders. The difference
between agent-based modelling and population-based modelling is that the first type is based on models of the behaviour of individual agents and the second type is based on models in which groups of agents of the same type are represented by a numerical value, indicating their density (for an example and more details, see the main introduction). The simulation results for the agent-based model using the same parameter settings show an identical trend to the population-based model, except for some minor deviations. These findings were also as confirmed by a formal evaluation. Moreover, the computation time of the population-based model was shown to be much lower than the computation time of the agent-based model. Based on these results we used a population-based model in the following papers.

In Chapter IV.4 we extended the population-based model mentioned in the third paper. Here we added a number of different strategies to govern the behaviour of the guardians. More specifically, the guardians are not only able to move after an assault has been performed but they can also anticipate on expected future assaults. We compared ten different strategies (a baseline strategy, four reactive strategies, three anticipatory strategies and two hybrid strategies) and tested these on five scenarios. The goal of the guardians involved was to distribute in such a way over the different locations that the crime rates were kept as low as possible. Simulation experiments indicate that the best results are produced by the strategy where the guardians move to new locations based on the expected amount of passers by (potential victims) in the near future. Further, we compared all strategies in terms of their effectiveness and costs. The results suggest that a hybrid strategy is most effective, but that purely anticipatory strategies are more cost-efficient. These types of findings can be very useful input for policy makers, in order to elaborate their thoughts about efficient strategies.

The chapters mentioned in this part are based on the following publications:

Chapter IV.1 is available as:


Chapter IV.2 will appear as:


This article is also based on:


Chapter IV.3 appeared as:

Bosse, T., Gerritsen, C., Hoogendoorn, M., Jaffry, S.W., and Treur, J., Comparison of Agent-Based and Population-Based Simulations of Displacement of Crime. In:
This article is also based on:


Chapter IV.4 will appear as:


This article is also based on:


References


Simulating the dynamical interaction of offenders, targets and guardians

Tibor Bosse, Henk Elffers and Charlotte Gerritsen

1. Routine activity modelling

Within the routine activity paradigm [6, 10], it is argued that crime takes place when a motivated offender finds an insufficiently guarded attractive target. The beauty of this well corroborated theory lies in its clarity and simplicity on a sufficiently abstract level [9]. However, its simplicity seems to vanish as soon as we zoom in from an abstract level towards concrete questions on underlying processes. What governs whether a motivated offender will find an attractive target? The answer is clearly dependent on the movement of offenders and the whereabouts of targets. For instance, the likelihood of such meetings will be dependent on the distribution of targets’ attraction levels, their positions in space, whether they move or not, and whether their attraction levels are constant over time or not, and if not, what is governing their change. Likewise, the occurrence of a meeting between an offender and a target will be influenced by the movement pattern of motivated offenders, may be dependent on their knowledge of target availability or on other business the offender has on his agenda, on their preferences for certain attraction levels, and on whether these characteristics are influenced by having successfully or unsuccessfully attacked a target previously. Targets may have a movement pattern, based both on their perception of criminal risk as well as of parameters governing their non-crime related behaviour (e.g., the route they take to go to work), which will also be influenced by experiencing crime. Moreover, the third routine activity factor, availability of suitable guardians, has to be taken into account as well. Are we talking about formal guardians, such as police officers and security personnel, or are we discussing informal or natural guardians, such as inhabitants and passers-by? How do guardians move around, are they aware of targets and target values, of the whereabouts of particular offenders, what about their suitability (i.e. their willingness and capability for exercising their crime hampering actions), is that constant over time, how do they react when they are or are not successful in preventing a crime from happening? It is clear that the temporal and spatial dynamics of such offender, target and guardian processes is paramount for the occurrence of crime within a routine activity context. That being so, we are faced with a considerable problem in any real life situation, as it seems rather optimistic to hope that all of the above mentioned processes can be specified, estimated and analyzed: measurement problems as well as analytical problems will be formidable.

The standard way out in such an overly complex case is simplifying the problem, by holding constant as many parameters in the processes as is feasible. E.g. we can try and compare pick pocketing rates in two neighborhoods close to each other, having a comparable population composition, but the one having houses with small windows is deemed to have low natural guardianship levels, while the other neighborhood having buildings with large windows will have a better guardianship structure. In so far as we dare to assume that offender routine patterns and target routine patterns are alike in both neighborhoods, comparing them is a fit method to investigate the effect of natural guardianship.
The second way out is experimenting, e.g. varying police surveillance intensity (as one of the guardianship parameters) over time periods in a given neighborhood. This research approach is, of course, also only feasible when many other parameters are held constant.

Dynamical aspects of the routine-activity-models are particularly devious to research in such designs, as the designs actually exploit the ‘ceteris paribus’ of all other parameters than the one under scrutiny, and hence implies an incentive on static processes, thus defying investigation of dynamics.

In the current paper, however, we intend to look into dynamical routine activity processes, by means of simulation methods, in which some routine activity processes are built into an artificial society of offenders, targets and guardians, and investigate what is happening if offenders, targets, or guardians react on what is happening, by increasing or decreasing parameters of their preferences, and by choosing the direction in which they move as a function of what is happening around them.

2. Simulation as an analytical tool

Simulation should be seen here as an analytical tool that makes it possible to investigate what is happening, given a set of rules whose mutual interactions are too complex to see through by traditional methods. Simulation is –in such an application– not an empirical, but a theoretical method, which uses computer generated instances of realizations of processes. It is meant for those cases where complexity outsmarts our capability for theoretical or mathematical analysis. Simulation departs from a given theory (in our case: routine activity theory) and looks into the dynamical interplay of various processes as specified by that theory. As such, simulation is not testing the theory from which it departs, but, on the contrary, it is explaining it, bringing forward implications of the assumptions of the theory that were not straightforward and clear before. The resulting outcomes of a set of simulation runs should then be studied and are meant to generate a deeper insight in the process that, implicitly, has been specified by the simulation model. Observing and analyzing a number of realizations of the dynamical development of resulting crime processes will enhance our understanding of the dynamics of routine activity in a given context. This usually takes the form of an input-output analysis: if we specify the parameters of the process to be simulated to be such-and-such, we observe that the outcomes end to be so-and-so. Applications of the use of simulation as an analytical tool for understanding can be found in various criminological fields. E.g. [1] has applied it for studying perceptual deterrence, while [2, 4] have used it for studying psychological processes that trigger violent behavior. Moreover, [3] apply it for studying social learning of delinquent behavior in adolescents.

Simulation may be called an ungrateful task: it usually generates tons of input-output relations, from which the researcher should make sense, either by insight or through systematic statistical analysis of the input-output connections. A very real danger is that researchers will drown in their results. It is therefore wise for researchers to restrain themselves and start with very simple simulation models. Experience shows that interpreting and understanding input – output relations is even in simple models often quite a task. A stepwise approach starts with a simple simulation model that can be made more complex only after having thoroughly understood the output of the original simple case.

It seems worthwhile to stress explicitly that simulation models in the above sense are not yet meant as theories of reality: we do know beforehand that they are too gross
simplifications of reality for that matter, indeed that is their unique selling point. By rigorous simplification we optimize the conditions for understanding the complex interplay between various parts and rules in the model. Only after having understood a relatively simple model thoroughly, we may try to go a step further and build complex models of reality, using as building blocks what we have learned from the simple simulations. Notice that this modest view on simulation research rules out the testing of model results against empirical data, which indeed would be superfluous as we already know that the models do not fit reality.

Of course, other uses of the term ‘simulation research’ and other visions on the usefulness of simulation may be found in the literature (cf. [12]) and may be useful for their own purposes as well. Indeed, many researchers propose their simulation models already as fair approximations of reality. It is our conviction that at least in the field that we are studying in this paper, the dynamics of routine activity models, that stage has not been reached [8].

3. A simple routine activity model, global description

In the present project, we will study a small society of immobile targets (‘houses that can be targeted for burglary’), located in geographical space (‘town’), with standard characteristics as ‘neighboring relations’, ‘distance to each other’, and having a certain given distribution of attraction levels over space (‘spatial autocorrelation of wealth’). Moreover, the targets have a time dependent ‘reputation’, which is high when a property has been burglarized in the recent past, and erodes again when nothing untoward is happening for some time. Through that society a number of motivated burglars move around. They take one step every period (‘day’), and have a preference to moving to more attractive targets. However, they are rather short-sighted, and can ‘see’ only targets one step away from their previous position. They chose a move with a certain probability proportional to attraction levels of targets in sight. Offenders (burglars) have a characteristic of ‘choosiness’, i.e. every offender has a certain minimal attraction threshold, different for different offenders. When arriving at a target, an offender intends to burgle it, if and only if it is worthwhile for him, which is the case if the attraction level of the prospective target is surpassing the minimal attraction threshold of that offender, cf. [5, 7]. Notice therefore that a target that is eligible for burgling to one offender may be passed over by another offender.

The last element in the model is that of the guardians, also moving around through the town. Guardians, just as offenders, walk around one step at a time, and see only targets one step away. Guardians either have no preferences, i.e. they move around randomly (‘random policing’), or have a preference for moving to targets with high reputations (‘vulnerable targets’), to which they move probabilistically with probabilities proportional to reputations being visible from the present position. This last state of affairs is called: hot spot preferences or hot spot policing. If a guardian is present at a target, he completely precludes a burglary taking place. So if an offender intending to burgle a house (because its attraction level is surpassing his threshold) meets a guardian at the spot, he refrains from executing his intentions. Of course, burglars that had judged a target as not worthwhile, will not be affected by guardians; they go on behaving themselves at that moment. Notice that our guardians are what has been called formal guardians, that is agents having an official guardian task (such as police officers or security personnel), as opposed to informal guardians, who may be
present on the spot for other reasons (inhabitants, passers-by) and then nevertheless can preclude crime from happening [11].

4. Research questions

Within the framework of the model specified, we intend to investigate the effectiveness in crime prevention of various guardianship policies (output variable, operationalized as 1 – crime rate, in which the crime rate is the observed number of crimes per spatio-temporal unit), in various circumstances as specified by the spatial attraction patterns of the targets, the number of offenders and guardians and the distribution of the attraction thresholds of the offenders (input variables).

Guardian policies to be investigated here are: random policing; hot spot policing; area (or beat) hot spot policing. The last of those policies is a hot spot policing scheme but with mutually exclusive zones allotted to the guardians, zones that they may not leave.

Circumstances we vary are: number of guardians and distribution of target attraction values. Concerning the former, we are interesting in investigating to what extent the effectiveness in crime prevention is influenced by the amount of guardians that are present in the model. To this end, the number of guardians will be varied between very few (e.g., only 2 guardians) to very many, (e.g., almost one guardian at every location). The other circumstance to be varied over the different simulations is the distribution of target attraction values. This choice was based on the hypothesis that differences in geographical makeup between areas may result in very different burglary patterns (e.g., the burglary patterns in an area where all expensive houses are clustered will be different from those in an area where all expensive houses are spread. Therefore, the distribution of attraction levels of houses over space will be varied (see Section 6).

Other parameters of the model were the number of offenders present in the simulation, and the distribution of threshold values of the offenders (i.e., the individual attractiveness levels of the offenders that a certain target should surpass in order to be judged sufficiently attractive to burglarize). However, these two parameters are kept constant over the different simulation runs.

Notice that our research question can, in principle, be investigated without simulating many instances of the process under investigation, if we would have the capability to analyze the complex interactions of the various elements in our set-up. However, as we see no way forward here, we use studying input-output relations in simulated outcomes instead. We hold that it is not clear at the outset how the various parameter settings influence the overall crime level over time.

5. Simulation model, in detail

In this section, the simulation model used within the present project is introduced in detail. The main component of the model is a virtual environment, a world which is represented mathematically by a matrix of m*n elements (and can be visualized as a grid of m*n adjacent locations). Thus, each location has maximally 4 neighbors (in case of central locations) and minimally 2 neighbors (in case of corner locations). In addition, each location (or house) has a level of attractiveness attached, which is modeled by a natural number between 1 and 10. This number is assumed to represent the attractiveness of that particular location to burglars (e.g., a high number may stand for an expensive house without surveillance cameras). Finally, each location has a
reputation attached, which is modeled by a real number $\geq 1$, and is assumed to represent the reputation of that location with respect to burglary (i.e., a high number stands for a house where many burglaries have taken place). Initially, the reputation of each location is set to the value 1. Reputation increases by 1 after a burglary takes place at that location, and decreases by 0.5 when no burglary takes place.

Within a given simulation run, the world is populated by artificial agents. Two types of agents are distinguished, namely offenders (i.e., potential burglars) and guardians. Each offender has an individual burglary threshold, modeled by a natural number between 0 and 10, which represents the threshold above which the agent considers a house sufficiently attractive to burglarize (i.e., a high number denotes a person that will only select very attractive targets). Offenders move randomly through the environment. However, to be able to compare different surveillance strategies, the guardians exist in three different types:

- **type 1 guardians** follow a random strategy: they move randomly through the environment
- **type 2 guardians** follow a hot spot strategy: they select adjacent locations with a probability that is proportional to the reputations of those locations
- **type 3 guardians** follow an area hot spot strategy: they select adjacent locations with a probability that is proportional to their reputation, but only within their individually assigned surveillance area. This means that each guardian of type 3 has a number of locations assigned (an area), which it is not allowed to leave.

In order to generate a simulation run, the following algorithm is performed (denoted in pseudo-code):

1. Initialize the simulation (either randomly or according to some setting defined by the user) according to the following steps:
   a. Determine the size of the world.
   b. For all locations, set the initial reputation to 1, and assign attractiveness levels to them.
   c. Determine the amount of agents of the different types.
   d. Assign burglary thresholds to all offenders.
   e. Assign personal areas to all type 3 guardians.
   f. Place all agents at their start locations.
2. For each time step until the end of the simulation, repeat the following cycle:
   a. For each location, if it contains at least 1 motivated offender (in the sense that its individual burglary threshold is lower than the attractiveness of the location) and no guardians of any type, then count a burglary for that location.
   b. Increase the reputation of each location that is burglarized with 1.
   c. Decrease the reputation of each location that is not burglarized with 0.5.
   d. For each offender, move to one of the adjacent locations (including the current location) with a probability that is proportional to its attractiveness. For example, suppose an offender is at a (corner) location A with two neighbors, B and C, and that the attractiveness of A, B, and C is 3, 5, and 7, respectively. Then, the probability that the agent will stay at location A is $3/(3+5+7) = 0.2$. Similarly, the probability that it will go to location B is 0.33, and the probability that it will go to C is 0.47.
   e. For each type 1 guardian, move randomly to one of the adjacent locations (including the current location). For example, in case
a guardian is at a central location, it may go north, south, west, or east, or stay at its current location, each with a probability of 0.2.

f. For each type 2 guardian, move to one of the adjacent locations (including the current location) with a probability that is proportional to its reputation. For example, suppose a guardian is at a (corner) location A with two neighbors, B and C, and that the reputations of A, B, and C are 4.5, 7.5, and 2.0, respectively. Then, the probability that the agent will stay at location A is $\frac{4.5}{(4.5+7.5+2.0)} = 0.32$. Similarly, the probability that it will go to location B is 0.54, and the probability that it will go to C is 0.14.

g. For each type 3 guardian, move to one of the adjacent locations (including the current location) within its own area with a probability that is proportional to its reputation.

As can be seen in this pseudo-code, in principle it is possible to have guardians of different types in one and the same simulation. However, in the simulations that are discussed in this paper, this is not the case, i.e., per simulation run only one type of guardians is placed in the environment.

During a simulation, various types of relevant information are stored, such as the total number of burglaries, the amount of times that offenders encounter guardians (prevention rate), and the amount of times that 2 or more guardians are present at the same location (idleness rate). Since the model contains probabilistic elements, multiple runs will provide different results. Therefore, in order to obtain reliable results, the model is run many times, to generate a large number of simulated traces (i.e. developments of all dynamic parameters over time), of which the average is then taken.

The simulation model has been implemented in Matlab (www.mathworks.com). To provide the user more insight in the exact spatial dynamics of a simulation run, the implementation offers the possibility to visualize each simulation run in terms of an animation (which can be stored as an .mpg-file). In Figure 1, a screenshot of such an animation is shown.

![Figure 1. Screenshot of the simulation environment.](image)
Here, each intersection represents a location in a city. In the example addressed here, there are 25 locations in total that are connected through edges (according to a grid or ‘block’ structure). Furthermore, there are 4 offenders (represented by the red dots) and 2 guardians (the blue dots). The black dots represent the reputation of a certain location. The bigger the dot, the higher the ‘burglary reputation’ of that location. As an illustration, a number of animations (for different guardian strategies) can be found at: http://www.cs.vu.nl/~wai/crimesim/.

6. Input parameters that are varied over different runs

The model has been used to generate a large number of simulations under different settings (input parameters). First, we used different settings for the distribution of the attraction values of the targets. In this way, four types of worlds have been created. In the first world type, all targets have the same attraction value (“equal world”). In the second world type, the attraction values are distributed without structure over the community (“distributed world”). Actually, in the present set of simulations, we once and for all simulations manually distributed values between 1 and 10 in an unsystematic way over the society. In the third world type, the values are distributed according to a concentric ring structure (“ring world”), with the highest attraction value in the southwest corner of the world and attraction values decreasing linearly with the number of concentric ‘rings’ that have to be passed from that centre. This can be compared to a city where the most expensive houses are located close to each other, and the less attractive the houses are located further away from that wealthy centre. In the fourth world type, there are two distinct areas in which the expensive houses are located (“segregated world”), which are separated from each other by houses that are less attractive. In Figure 2 these worlds are shown.

For each world, simulations have been performed with different numbers of guardians (i.e., 2, 3, 4, 5, 6, 10, 15 and 20 guardians), which were either all of type 1 (the random strategy), of type 2 (the hot spot strategy), or type 3 (the area hot spot strategy; all guardians in a given simulation get an area of approximately equal surface to survey). In each simulation, always 4 offenders were present, with burglary thresholds 4, 5, 6, and
7. Per setting, we ran 1000 simulations (of 200 time steps each). So in total we have performed 96000 simulations (= 4 worlds * 8 amounts of guardians * 3 guardian types * 1000 simulations). The most interesting results will be discussed below.

7. Simulation results

In this section, the results of the simulations will be discussed, with respect to total crime rates (Section 7.1), crime hot spot rate (Section 7.2), guardian hot spot rate (Section 7.3), guardian efficiency (Section 7.4), and the effect of larger geographical areas (Section 7.5).

7.1. Total amount of crime

In Figure 3, for the different worlds, the average crime rate is shown. In these graphs, the horizontal axis shows the different types of strategies, and the vertical axis shows the average amount of crimes per location, per time point. Note that the results for 4, 6, and 15 guardians have been left out, to improve readability.

Figure 3. Total crime rate - comparing different numbers of guardians within one world.
The different strategies seem to have the same effect in the segregated, ring and distributed society. In these societies, hot spot policing works better than random patrolling, and area hot spot surveillance works better than random patrolling. Furthermore, hot spot patrolling is better than area hot spot surveillance until you swamp society with guardians (>5). Only in the equal society, the type of guardian has hardly any influence. Overall, when there are more than 5 guardians, the guardians that patrol in an area hot spot based manner are more effective than the other types of guardians.

When we compare the crime rates in the different worlds (see Figure 4), it can be observed that they are the highest in the segregated community. In the ring and distributed society, the crime rates are about the same, and the equal society is the world with the lowest crime rate.

![Figure 4. Total crime rate - comparing different worlds for one number of guardians.](image)

7.2. Crime hot spot rate

In addition, for each location, we counted the amount of times that it was populated by 2 or more motivated offenders, per time point. Encounters between motivated offenders are independent of the amount and the type of guardians (since offenders move around in a random manner), therefore we do not show the results graphically as a function of the types of guardians. The motivated offenders encounter each other most often in the segregated world (0.017 times per location, per time point). The ring society is second (0.0095 times), the distributed society is third (0.0075), and the offenders have the least encounters in the equal society (0). There were no encounters between motivated offenders in the equal society, because in this society there was only one offender of which the burglary threshold was lower than the attractiveness of the houses.

7.3. Guardian hot spot rate

Next, we investigated the average amount of times per location that it was populated by 2 or more guardians, per time unit. The results (for the case of 2 guardians and the case of 20 guardians) are displayed in Figure 5. Our main finding is that guardians that use a hot spot strategy have more encounters than guardians that move randomly. Guardians that have an area hot spot strategy never meet each other because they are restricted to
certain areas. Although this cannot be seen in the figures (since all points overlap), the guardians encounter each other most often in the segregated world. The ring society is second, the distributed society third, and the guardians have the least encounters in the equal society. However, these differences are very small.

7.4. Guardian efficiency
The guardian efficiency is the average amount of times that a guardian meets at least one offender, per time point. The results of this are shown, for the different worlds, in Figure 6. In the segregated, ring and distributed world, hot spot patrolling is more efficient than random patrolling and hot spot patrolling is more efficient than area hot spot patrolling. Random patrolling and area hot spot patrolling are just as efficient in these worlds, at least for large amounts of guardians. However, when there are less than 10 guardians, area hot spot patrolling is more efficient than random patrolling. In the equal society, hot spot patrolling is slightly more efficient than random patrolling and area hot spot patrolling. Random surveillance and area hot spot surveillance are equally efficient. Overall, guardians are most efficient in the segregated society. Both the ring and the distributed society are second, and guardians in the equal society are least efficient.

Figure 5. Guardian hot spot rate.
Figure 6. Guardian efficiency.

7.5. Scaling up

The simulations mentioned above all were performed in a world of 5x5 (25 locations), with 4 offenders and 2 to 20 guardians. To test whether these results are independent of the size of the society, we scaled up the simulation. We created a larger world (10x10 = 100 locations), and also multiplied the number of guardians and offenders with 4. This yields a setting with 16 offenders and 8 to 80 guardians (for the time being we only considered the situation with 8 guardians). Further, we only made a comparison between the randomly patrolling guardian (type 1) and the hot spot patrolling guardian (type 2). The results are shown in Table 1 and 2. As can be seen, scaling up does not have a big impact on (normalized) findings.

Table 1. Comparing worlds with different sizes - type 1 guardians.

<table>
<thead>
<tr>
<th></th>
<th>5x5</th>
<th>10x10</th>
</tr>
</thead>
<tbody>
<tr>
<td>crime rate</td>
<td>0.0368</td>
<td>0.0369</td>
</tr>
<tr>
<td>offender hot spot rate</td>
<td>0</td>
<td>0.0006</td>
</tr>
<tr>
<td>guardian efficiency</td>
<td>0.0412</td>
<td>0.0399</td>
</tr>
<tr>
<td>guardian hot spot rate</td>
<td>0.0015</td>
<td>0.0026</td>
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8. Discussion

The simulation experiments described above clearly illustrate the usefulness of simulation as an analytical tool to investigate consequences of criminological theories under certain assumptions. In this project, the Routine Activity Theory [6, 10] was taken as a point of departure, and a number of assumptions that form the basis of the theory were formalized in sufficient detail to be able to generate a simulation model. The simulation model was focused at the domain of burglary. It allowed us to create artificial societies, and define varying circumstances for these societies, such as different attractiveness distributions of targets, different numbers of guardians, and different guardian strategies. By executing the simulation model for these varying circumstances, various ‘thought experiments’ were performed that enabled us to oversee consequences of the theory (of course, still given certain assumptions) that we would not have been able to derive by means of traditional methods like common sense reasoning or empirical methods.

For example, a first finding was that in our simulations, hot spot surveillance and area hot spot surveillance turned out to work better than random patrolling, unless all targets were equally attractive. This makes sense, because in case all targets have the same attractiveness, probably no hot spots will occur at all. Moreover, hot spot surveillance turned out to usually work better than area hot spot surveillance, unless the amount of guardians was almost as big as the amount of locations. In such a situation, clearly, it pays of to distribute guardians over locations, to prevent that multiple guardians are guarding the same location and thereby ‘wasting resources’.

With respect to the different geographical makeups of the societies, our simulations suggested that the crime rates are highest in situations where there are specific locations with a high concentration of attractive targets (such as in our segregated or ring society).

Finally, the effect of scaling up the size of the society turned out to be small. Apparently, the (relative) crime rates do not increase much when a larger area is considered, as long as the number of offenders and guardians are increased proportionally.

Obviously, these results should be interpreted with care. As mentioned earlier, a simulation model is by definition a ‘not entirely correct’ representation of reality. Various simplifying assumptions have been made when developing the model, e.g., about the distances between targets, the movement of the agents involved, and, last but not least, the individual decision making processes of the agents. In addition, the experiments described were only performed for some particular sets of parameter settings. Therefore, the results found should not directly be generalized to the real world. Nevertheless, we hope to have convinced the reader that they shed some light on

### Table 2. Comparing worlds with different sizes - type 2 guardians.

<table>
<thead>
<tr>
<th></th>
<th>3x5</th>
<th>10x10</th>
</tr>
</thead>
<tbody>
<tr>
<td>crime rate</td>
<td>0.0357</td>
<td>0.0359</td>
</tr>
<tr>
<td>offender hot spot rate</td>
<td>0</td>
<td>0.0006</td>
</tr>
<tr>
<td>guardian efficiency</td>
<td>0.0544</td>
<td>0.0525</td>
</tr>
<tr>
<td>guardian hot spot rate</td>
<td>0.0017</td>
<td>0.0027</td>
</tr>
</tbody>
</table>
interesting issues to be further investigated, such as the finding that area hot spot surveillance only works better than hot spot surveillance if the number of guardians is sufficiently large, to name a concrete example.

For future research, the current model can be extended in various directions. For instance, it would be interesting to investigate what happens if the offenders are made more intelligent, i.e., if they are able to ‘learn’ the behavior of the guardians. Similarly, the guardians can be made more intelligent, e.g., by having them anticipate on the expected movements of the offenders, instead of reacting to their actual movements. And finally, an interesting extension would be the addition of passers-by to the model (e.g., ordinary citizens that go to their work at 9 am and go back home at 5 pm, via some standard route), and study how the presence of these passers-by would influence the patterns found so far.

References

Social Simulation and Analysis
of the Dynamics of Criminal Hot Spots

Tibor Bosse and Charlotte Gerritsen

Abstract. Within the field of Criminology, the spatio-temporal dynamics of crime are an important subject of study. In this area, typical questions are how the behaviour of offenders, targets, and guardians can be explained and predicted, as well as the emergence and displacement of criminal hot spots. In this article we present a combination of software tools that can be used as an experimental environment to address such questions. In particular, these tools comprise an agent-based simulation model, a verification tool, and a visualisation tool. The agent-based simulation model specifically focuses on the interplay between hot spots and reputation. Using this environment, a large number of simulation runs have been performed, of which results have been formally analysed. Based on these results, we argue that the presented environment offers a valuable approach to analyse the dynamics of criminal hot spots.

1. Introduction

Criminology is an area of research that mainly addresses the analysis of criminal behaviour; e.g., [20, 22, 26]. It is a multidisciplinary area that contains elements of the Social and Behavioural Sciences, but also of disciplines like Neuroscience and, more recently, Computer Science [31]. Although a minority of the overall population shows criminal behaviour, it typically comes in many types and variations. Within Criminology, one of the main challenges is to predict and explain in which situations which types of criminal behaviour will occur [31]. This challenge can be addressed both from an individual (or single agent) perspective, or from a social (or multi-agent perspective). The current article focuses on the latter.

In order to explain and predict the emergence of criminal behaviour from a social perspective, several theories have been proposed within the criminological literature. Perhaps the most influential of these is the Routine Activity Theory by [20]. This (informal) theory states that three parties are relevant in the analysis of crime, i.e., offenders, targets, and guardians. More precisely, it states that a crime will occur when a motivated offender meets a suitable target and there is no guardian present.

The theory of Situational Crime Prevention is another important theory [19]. This theory states that certain crimes can be prevented by placing guardians at appropriate locations. Such guardians may vary from police officers to alarm systems or surveillance cameras.

Theories like the Routine Activity Theory and the theory of Situational Crime Prevention have triggered a widespread attention for the interplay between the behaviour of offenders, targets, and guardians, and in particular for their spatio-temporal dynamics. For example, a relevant question is which factors influence the emergence of so-called hot spots - areas in which many crimes occur [24, 45]. Based on the idea of hot spots, several related questions may be asked, among which:

- when can a location in a city be defined as being a hot spot?
- does the location of hot spots change over time?
- does the size of hot spots change over time?
• how can the emergence of hot spots be predicted?
• how can the emergence of hot spots be prevented?
• what is the relation between the emergence of hot spots and the geography of a city?
• what is the relation between the emergence of hot spots and the demographics of the population?

In the last decades, there has been a growing interest in the area of Agent Based Social Simulation (ABSS). In ABSS, which integrates approaches from agent-based computing, computer simulation, and the social sciences, researchers try to exploit agent-based simulation to gain a deeper understanding of social phenomena [2, 23]. Since this approach combines the advantages of the agent paradigm (e.g., autonomy of the individual agents) with those of social simulation (e.g., the possibility to perform scalable social “experiments” without much effort), it turns out to be particularly appropriate to analyse phenomena within the criminological domain. Indeed, in recent years, a number of papers have successfully tackled criminological questions using ABSS, e.g., [3, 15, 16, 27, 32, 33, 36].

However, agent based simulation models of crime can still be improved in several ways. The role of reputation is an example of a specific aspect that has only marginally been addressed by current approaches [15]. Therefore, the current paper introduces an ABSS approach that specifically incorporates a notion of reputation of the locations involved.

The approach we propose here makes use of the high-level declarative modelling language TTL [10] and its executable sublanguage LEADSTO [11]. This modelling language is well suited for the current purposes, since it allows the modeller to combine qualitative, logical aspects (such as high-level agent concepts like beliefs, actions, and observations) with quantitative, numerical aspects (such as real numbers and mathematical operations). Moreover, since the language has a formal logical semantics, simulation models created in TTL and LEADSTO can be formally analysed by means of logical analysis techniques (see, e.g., [9]).

Below, in Section 2, some background on the concepts of reputation and displacement is provided. Next, in Section 3, the modelling languages TTL and LEADSTO are introduced. Based on this modelling approach, Section 4 describes the simulation model for the behaviour of offenders, targets, and guardians in detail. In Section 5, the simulation results are presented and in Section 6 these results are analysed using formal techniques. Section 7 discusses related work, and Section 8 concludes the paper with a discussion.

2. Reputation and Displacement

According to the literature in criminology, the reputation\(^1\) of specific locations in a city is an important factor in the spatio-temporal dynamics of crime [28]. For example, it may be expected that the amount of assaults and the amount of arrests that take place at

\(^1\) In this paper, the concept of reputation is studied as a characteristic of a location (or geographical area). More specifically, the reputation of a location is defined as a (publicly known) measure for the amount of crime-related activities (e.g. assaults or arrests) that take place, which is built up on the basis of past events (involving multiple individuals) at that location. Note that this definition differs from the idea of reputation as a characteristic of an individual, as often used in the literature. For an overview of the different notions of reputation in different disciplines (including Evolutionary Biology, Economy, and Computer Science), see [38].
Although a location’s reputation is an important factor in the process of displacement, it is not the only factor that determines the movement of offenders, targets, and guardians. Also various other aspects of a location may play a role in attracting or repelling certain groups (e.g., escape routes, abandoned buildings, possibilities to buy drugs, and so on). These concepts are modelled in Section 4 by means of the $\text{basic_attractiveness}$ predicate.

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\[ \text{Note that this is an over-simplification of police deployment practices. Police officers are indeed more attracted to places with high crime rates, but this is usually part of larger actions against crime. An example is the Street Crime Initiative in the UK [29]. This is an initiative taken by five police forces which together accounted for 72% of all street robberies and actually targeted the ten police force areas where street crime levels were highest. Over 30 different projects were designed to tackle the street crime problem from different angles. Youth work, environmental planning, increased surveillance, reducing market of stolen goods, and targeted enforcement are just a number of possible interventions [29]. For practical purposes, in our model we decided to simplify such interventions by simply assuming that criminals attract (both formal and informal) guardians.} \]

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3. Modelling Approach

To model the different aspects of criminal displacement from an agent perspective, an expressive modelling language is needed. On the one hand, qualitative aspects have to be addressed, such as observations, beliefs, decisions to perform an assault or an arrest, and some aspects of the environment such as the presence of certain agents. On the other hand, quantitative aspects have to be addressed. For example, the reputation of locations can best be described by a real number, and the update of this reputation can best be described by a mathematical formula. Another requirement of the chosen modelling language is its suitability to express on the one hand the basic mechanisms of criminal displacement (for the purpose of simulation), and on the other hand more global properties of criminal displacement (for the purpose of logical analysis and verification). For example, basic mechanisms of displacement of crime involve decision functions for individual agents, whereas examples of global properties are the types of statements as put forward in the introduction, like “the location of hot spots changes over time”.

The predicate-logical Temporal Trace Language (TTL) [10] fulfils all of these requirements. It integrates qualitative, logical aspects and quantitative, numerical aspects. This integration allows the modeller to exploit both logical and numerical methods for analysis and simulation. Moreover it can be used to express dynamic properties at different levels of aggregation, which makes it well suited both for simulation and logical analysis.

The TTL language is based on the assumption that dynamics can be described as an evolution of states over time. The notion of state as used here is characterised on the basis of an ontology defining a set of physical and/or mental (state) properties that do or do not hold at a certain point in time. These properties are often called state properties to distinguish them from dynamic properties that relate different states over time. A specific state is characterised by dividing the set of state properties into those that hold, and those that do not hold in the state. Examples of state properties are ‘agent 1 performs an assault on agent 2’, or ‘there are 5 criminal agents at location A’. Real value assignments to variables are also considered as possible state property descriptions.

To formalise state properties, ontologies are specified in a (many-sorted) first order logical format: an ontology is specified as a finite set of sorts, constants within these sorts, and relations and functions over these sorts (sometimes also called signatures). The examples mentioned above then can be formalised by n-ary predicates (or proposition symbols), such as, for example, or number_of_criminals(locA, 5). Such predicates are called performed(assault_at(a1,a2)) state ground atoms (or atomic state properties). For a given ontology Ont, the propositional language signature consisting of all ground atoms based on Ont is denoted by APROP(Ont). One step further, the state properties based on a certain ontology Ont are formalised by the propositions that can be made (using conjunction, negation, disjunction, implication) from the ground atoms. Thus, an example of a formalised state property is number_of_criminals(locA, 5) & number_of_criminals(locB, 3). Moreover, a state S is an indication of which atomic state properties are true and which are false, i.e., a mapping S: APROP(Ont) → {true, false}. The set of all possible states for ontology Ont is denoted by STATES(Ont).

To describe dynamic properties of complex processes such as the displacement of crime, explicit reference is made to time and to traces. A fixed time frame T is assumed which is linearly ordered. Depending on the application, it may be dense (e.g., the real
numbers) or discrete (e.g., the set of integers or natural numbers or a finite initial segment of the natural numbers). Dynamic properties can be formulated that relate a state at one point in time to a state at another point in time. A simple example is the following (informally stated) dynamic property about the number of criminals at a certain location:

For all traces $\gamma$,
there is a time point $t$ such that
at location $A$, there are at least $x$ criminal agents.

A trace $\gamma$ over an ontology $O$ and time frame $T$ is a mapping $\gamma : T \rightarrow \text{STATES}(O)$, i.e., a sequence of states $\gamma(t) \in \text{STATES}(O)$. The temporal trace language TTL is built on atoms referring to, e.g., traces, time and state properties. For example, ‘in trace $\gamma$ at time $t$ property $p$ holds’ is formalised by $\text{state}(\gamma, t) \models p$. Here $\models$ is a predicate symbol in the language, usually used in infix notation, which is comparable to the Holds-predicate in situation calculus. Dynamic properties are expressed by temporal statements built using the usual first-order logical connectives (such as $\neg$, $\land$, $\lor$, $\Rightarrow$) and quantification ($\forall$ and $\exists$; for example, over traces, time and state properties). For example, the informally stated dynamic property introduced above is formally expressed as follows:

$$\forall \gamma : \exists t : \exists i : \text{TRACES} \models \text{TIME} \models \text{INTEGER}$$
$$\text{state}(\gamma, t) \models \text{number_of_criminals}(\text{loc}_A, i) \land i \geq x$$

In addition, language abstractions by introducing new predicates as abbreviations for complex expressions are supported.

To be able to perform simulations, only part of the expressivity of TTL is needed. To this end, the executable LEADSSTO language [11] has been defined as a sublanguage of TTL, with the specific purpose to develop simulation models in a declarative manner. In LEADSSTO, direct temporal dependencies between two state properties in successive states are modelled by executable dynamic properties. The LEADSSTO format is defined as follows. Let $\alpha$ and $\beta$ be state properties as defined above. Then, the notation $\alpha \Rightarrow_{e, t, g, h} \beta$ means:

If state property $\alpha$ holds for a certain time interval with duration $g$,
then after some delay between $e$ and $f$
state property $\beta$ will hold for a certain time interval with duration $h$.

As an example, the following executable dynamic property states that “if an agent $a$ goes to a location $l$ during $1$ time unit, then (after a delay between $0$ and $0.5$ time units) this agent will be at that location for $5$ time units”:

$$\forall a : \text{AGENT} \forall l : \text{LOCATION}$$
$$\text{performed}(a, \text{go_to_location}(l)) \Rightarrow_{0, 0.5, 1, 5} \text{is_at_location}(a, l)$$

Based on TTL and LEADSSTO, two dedicated pieces of software have recently been developed. First, the LEADSSTO Simulation Environment [11] takes a specification of executable dynamic properties as input, and uses this to generate simulation traces. Second, to automatically analyse the resulting simulation traces, the TTL Checker tool [10] has been developed. This tool takes as input a formula expressed in TTL and a set of traces, and verifies automatically whether the formula holds for the traces. In case the formula does not hold, the Checker provides a counter example, i.e., a combination of variable instances for which the check fails.
For more details of the LEADSTO language and simulation environment, see [11]. For more details on TTL and the TTL Checker tool, see [10].

4. The Simulation Model

This section describes the simulation model in detail, based on the LEADSTO language. One of the main advantages of using the LEADSTO environment is that it produces simulation traces which can directly be used as input for the TTL Checker Tool. As a result, the behaviour of the model can be automatically analysed, which distinguishes this approach from related approaches in the literature (see Section 7 for an extensive comparison with related work).

The geographical aspects of the environment are modelled by a graph that consists of a number of locations, some of which are connected by edges. Within this environment, several agents move around and meet at the different locations. There are three types of agents: criminals (i.e., possible offenders), passers-by (i.e., possible targets), and guardians. The passers-by are assumed to be suitable targets, for example, because they appear rich and/or weak. However, as also the guardians are moving around, such targets may be protected, whenever at the same location a guardian is observed by the criminal (i.e., social control). Thus, a criminal agent will only perform a crime when it is at a location where it observes a passer-by and no guardians. An example of a simple geographical environment is shown in Figure 1. This picture represents a small city that only consists of three important locations (called A, B, and C), and is populated by 30 agents. The black circles denote passers-by, the grey circles denote guardians, and the white circles denote criminals. As can be seen in the figure, in this situation crimes may be performed at location B, since this location contains 1 criminal, 4 passers-by, and no guardians.

The interaction between a specific agent and the environment is modelled by (1) observation, which takes information on the environment as input for the agent (e.g., at which location it is, where suitable targets are, and whether social control is present), and (2) performing actions, which is an output of the agent affecting the state of the world (e.g., going to a different location, or committing a crime).

![Figure 1. Example geographical environment.](image)

This figure shows three locations, called A, B and C. The locations are connected to each other. The green circles depict the number of passers-by present at that location, the blue circles depict the guardians and the red circles depict the number of criminals.
In order to decide to which location they will go, all agents continuously update the attractiveness (or utility) they assign to each location, which is represented by a real number in the domain \([0,1]\). This attractiveness is calculated as the weighted sum of three values (also represented by real numbers), namely:

1.  The individual basic attractiveness \(v\) the agent assigns to that location. This represents the extent to which the agent likes to go to that location, independent of its reputation. For example, some agents are more likely to go to a shopping centre, whereas others are more likely to go to a railway station.
2.  The assault reputation \(n_1\) of the location. The higher this number, the more famous the corresponding location is for assaults taking place there.
3.  The arrest reputation \(n_2\) of the location. The higher this number, the more famous the corresponding location is for arrests taking place there.

This calculation is represented by the following executable dynamic property (in LEADSTO format):

```
Decide Current Location Attractiveness
∀a:AGENT ∀l:LOCATION ∀n1,n2,v,w1,w2,w3:REAL ∀w2,w3:INTEGER
basic_attractiveness_of_agent_for_location(v, l, a) ∧
belief(a, assault_reputation_at_location(n1, l)) ∧
belief(a, arrest_reputation_at_location(n2, l)) ∧ has_weight_factor(a, w1, w2, w3) →
basic_attractiveness_of_agent_for_location(l, w1*v+w2*n1+w3*n2)
```

As can be seen from this rule, each agent possesses three individual weight factors \(w_1, w_2,\) and \(w_3\), which indicate the relative importance they attach to each of the three components introduced above. Note that these weight factors may be positive or negative. For instance, criminals will usually have a positive weight factor for assault reputation (they will tend to go to locations where many assaults have been performed in the past, since they expect that their chances to perform a next assault are higher at those locations), and a negative weight factor for arrest reputation (they will tend to avoid locations where many arrests have been performed in the past). Similarly, passers-by will usually have a very negative weight factor for assault reputation and a negative weight factor for arrest reputation. Finally, guardians will usually have a very positive weight factor for assault reputation and a positive weight factor for arrest reputation.

Based on the calculated attractiveness of the locations, each agent determines where to go, by selecting the location with the highest attractiveness.

By integrating the idea of utility-based, multi-criteria decision making with the notion of reputation, the model basically combines two distinct mechanisms for decision making\(^4\). On the one hand, the function to calculate attractiveness is inspired by the logic of rational-choice theory and forward-looking utility maximising (cf. [47, 48]). This means that agents seek to optimise their locations, in particular that criminals will look for low detection probabilities, guardians for high detection probabilities and passers-by for low assault probabilities. On the other hand, the notion of reputation reflects the logic of learning and backward-looking decision-making models (cf. [34]). This implies that agents learn from the observation of other agents’ behaviour. As a consequence, agents are assumed to copy successful behavior of agents with the same characteristic, i.e. criminals copy successful behavior of other criminals, guardians copy

\(^4\) For a comprehensive review of the differences between forward- and backward-looking decision making models with respect to crime and control (including empirical evidence), see [39].
successful behavior of other guardians and passers-by copy successful behavior of other passers-by (where the copying refers to the choice of the location).

According to Brantingham and Brantingham [14], daily life patterns of offenders might also influence the location of offending behaviour, even when the offender is engaging, to some degree, in a search pattern for a suitable target, having already decided to commit an offence. They argue that offenders are more likely to perform an assault in a neighbourhood they know well. They are more likely to avoid neighbourhoods that they are not familiar with. In the simulation model presented here, such differences in preferences for certain locations can be expressed by means of the basic attractiveness predicate.

Next, as mentioned above, the criminal agents decide to perform an assault when they are at a location where they observe a passer-by and no guardians, cf. the Routine Activity Theory [20]. This is modelled by the following dynamic property:

**Perform Assault**

\[\forall a_1, a_2 : \text{AGENT} \forall l : \text{LOCATION}\]
\[\text{observes}(a_1, \text{agent_of_type_at_location}(a_1, \text{criminal}, l)) \land
\text{observes}(a_1, \text{agent_of_type_at_location}(a_2, \text{passer_by}, l)) \land
\text{not guardian_at_location}(l) \rightarrow
\text{performed}(a_1, \text{assault_at}(a_2, l))\]

After having performed an assault, a criminal becomes a known criminal for a number of time steps. This is done to ensure that the guardians are able to recognise (and possibly arrest) a criminal that performed a crime. In the simulation runs described in the next section, criminals stay “known” for 4 iterations, which represents a period during which they are actually being wanted by the police. After such a period, these criminals become anonymous again. However, when a guardian meets a criminal that is still wanted, (s)he will arrest that criminal. This is modelled by the following dynamic property:

**Perform Arrest**

\[\forall a_1, a_2 : \text{AGENT} \forall l : \text{LOCATION}\]
\[\text{observes}(a_1, \text{agent_of_type_at_location}(a_1, \text{guardian}, l)) \land
\text{observes}(a_1, \text{agent_of_type_at_location}(a_2, \text{criminal}, l)) \land
\text{known_criminal}(a_2) \rightarrow
\text{performed}(a_1, \text{arrest_at}(a_2, l))\]

Furthermore, the assault reputation of the different locations involved is increased each time that an assault is performed, cf. the following dynamic property:

**Assault Reputation Increment**

\[\forall l : \text{LOCATION} \forall n : \text{REAL}\]
\[\text{assault_at}(l) \land
\text{belief}(\text{all_agents, assault_reputation_at_location}(n, l)) \rightarrow
\text{belief}(\text{all_agents, assault_reputation_at_location}(n + \text{inc}, l))\]

Here, inc is a constant that specifies the increment of reputation based on one assault. In the simulation runs described in the next section, \(\text{inc} = 1\). Note that this dynamic property assumes that all agents have the same knowledge about reputations. By replacing all_agents by a variable for a specific agent, variants of this rule can be created for different agents.

When no assault is performed at a location, the reputation of this location for being a hot spot slightly decreases:
Assault Reputation Decay

∀:LOCATION ∀:REAL
belief(all_agents, assault_reputation_at_location(n, l)) ∧
not assault_at(l) →⇒
belief(all_agents, assault_reputation_at_location(n*dec, l))

Here, \( \text{dec} \) is a constant that specifies the decay of reputation when there is no assault. In the simulation runs described in the next section, \( \text{dec} = 0.99 \).

To update the arrest reputation of locations, the same rules are used as shown above, where the word \( \text{assault} \) is replaced by \( \text{arrest} \).

Finally, it is assumed that the (assault and arrest) reputation of all locations is known to all agents in the population (e.g., because events like assaults and arrests are publicly discussed in the media, or because they are communicated between agents). However, the approach could be made more realistic by replacing the reputation mechanism by specific trust update mechanisms for individual agents, cf. [18, 30].

The complete set of LEADSTO rules used for the simulation model (including the time parameters) is shown in Appendix A.

5. Simulation Results

The simulation model as described in the previous section has been used to generate various simulation traces under different parameter settings. This section describes an example of a simulation trace in detail. In the next section, the global results of all simulation runs are summarised and discussed.

The parameter settings used for the simulation described in this section are identical to the ones shown in Figure 1: the population consists of 24 passers-by, 2 guardians and 4 criminals. Initially, these agents are distributed over the locations by means of their personal preferences (i.e., the \text{basic_attractiveness} predicates). Moreover, weight factors are assigned to each agent. The details of these parameter settings can be found in Appendix B.

Part of the simulation trace that was generated using these settings is shown in Figure 2 (A-C). Within these graphs, time is on the horizontal axis (where each geometric shape indicates a new iteration of movements), and the number of agents at a certain location is at the vertical axis. As shown in Figure 2B (and also in Figure 1), initially there are no guardians at location B. As a result, some assaults take place at that location. This leads to a change in the assault reputation of that location, which eventually results in displacement. This can be seen in the third iteration (around time point 100): most of the passers-by move away from location B (although one of them still remains at that location), whereas all criminals and all guardians move towards location B. As a result of this, some arrests take place, which leads to a change in arrest reputation of location B. As a consequence, again, the criminals move (in the fifth iteration, around time point 160), this time to location A and C. Since location A and C are now populated by criminals and passers-by, but not by guardians, some assaults take place at that location, which again leads to a change in assault reputation, and in displacement of the passers-by and the guardians. This cycle repeats itself until the end of the simulation: the passers-by move away from the criminals (and if possible, towards the guardians), the criminals follow the passers-by (as long as they do not encounter too many guardians), and the guardians follow the criminals. However, it is important to note that there is no strict sequential order in these movements (in the sense that one of the groups would always move ‘earlier’ or ‘faster’ than the others). In fact,
Figure 2 shows that in the third iteration, all groups move simultaneously (namely, the passers-by move away from location B whereas the other two groups move towards location B). However, the result of these movements is that a new situation emerges, in which apparently the criminals are least satisfied, since they are the ‘first’ to decide to move again (in the fifth iteration), whereas the other two groups decide to stay. This leads again to a new situation, in which the passers-by decide to move (in the seventh iteration), followed by the guardians (in the eighth iteration), and so on.

**Figure 2. Displacement of the three types of criminals.** Here time is on the horizontal axis and the number of agents is depicted on the vertical axis. The upper graph represents location A, the middle graph location B and the graph below represents location C. The green line shows the amount of passers-by, the red line the amount of criminals and the blue line the amount of guardians.
To understand the influence of assaults on the assault reputation, see Figure 3, which depicts the dynamics of the assault reputation of location A. Note that, as opposed to Figure 2, this picture is a screenshot of the LEADSTO simulation environment. As shown in Figure 3, whenever an assault is performed, the assault reputation of this location immediately increases. However, when no assaults are performed, the assault reputation gradually decreases. For example, at time point 160, 190, and 220, location A contains a criminal and several passers-by, but no guardians (see Figure 2A). As a result, assaults are performed, which increases the assault reputation of that location (after a small delay), as shown in Figure 3. This figure also shows the gradual decay of the assault reputation in between these three assaults.

![Figure 3. Assault reputation of location A. This figure shows an immediate increase after a crime has been committed. When no crimes are committed, the assault reputation decreases gradually due to decay.](image)

A similar trend can be observed in Figure 4, which depicts the dynamics of the arrest reputation of location A. The dynamics of the reputations of the other locations are not shown. However, these show similar behaviour as depicted in Figure 3 and 4.

![Figure 4. The arrest reputation of location A. This figure shows a similar pattern as the assault reputation. After an arrest the reputation of the location increases quite rapidly. When no arrest is performed on that location, the reputation decreases gradually.](image)

**Visualisation of Simulation Runs**

To provide the user more insight in the exact (spatial) dynamics of a simulation trace, a visualisation tool has been developed in Matlab. The tool takes an arbitrary simulation trace as input and generates an animation of the crime dynamics (which can be stored as .mpg-files). In Figure 5, a screenshot of such an animation is shown. Here, each intersection represents a location in a city. Note that this example is unrelated to the scenario addressed above. In the example addressed here, instead of 3, there are now 25 locations in total that are connected through edges (according to a grid or ‘block’ structure). However, the numbers of agents are still the same (i.e., 24 passers-by, 4 criminals, and 2 guardians). The different agents can meet each other at the
intersections. The green dots denote passers-by, the blue dots are guardians and the red dots are criminals. In addition, the black dots represent the reputation of a certain location. The bigger the dot, the higher the assault reputation of that location.

![Figure 5. Screenshot of the Visualisation Tool. In this figure, twenty-five locations are depicted (i.e., the intersections of the dotted lines). Here the blue dots represent the guardians, the red dots the criminals and the green dots the passers-by. The black dots represent the reputation of a certain location.](image)

6. Formal Analysis

All in all, a large series of simulation runs has been performed. The detailed settings and results of a simple example of these simulations (i.e., the one described in Section 5.1) are shown in Appendix B. Among the different simulations, various parameter settings were varied, in particular the number of agents, the ratio between different types of agents, the number of locations, the basic attractiveness of locations for the agents, and the weight factors of the agents.

To analyse the resulting simulation traces in more detail, the TTL Checker tool [10] has been used. As mentioned earlier, this tool takes as input a TTL formula and a set of traces, and verifies automatically whether the formula holds for the traces. For the current domain, a number of hypotheses have been expressed as dynamic properties in TTL, which were inspired by the questions mentioned in the Introduction. For example, consider the following dynamic property (P1), which expresses that the location of hot spots keeps on changing over time:
P1 Continuation of Displacement

For each time point \( t \) (except the end of the trace\(^5\)), if at \( t \) the largest hot spot is at location \( x \), then there is a later time point at which the largest hot spot is at some other location \( y \).

\[
\forall \gamma: \text{TRACES} \forall t: \text{TIME} \forall x: \text{LOCATION} \\
\quad [\text{is\_largest\_hot\_spot\_at}(x, t, \gamma) \land t < \text{last\\_time} - \delta] \\
\quad \Rightarrow [\exists t2: \text{TIME} \exists y: \text{LOCATION} \text{is\_largest\_hot\_spot\_at}(y, t2, \gamma) \\
\quad \land t < t2 \land x \neq y]
\]

In this formula, \text{is\_largest\_hot\_spot\_at} is an abbreviation, which can be determined in multiple ways. For example, by taking the location: 1) with the highest assault reputation, 2) with the highest number of criminals, or 3) with the highest number of crimes. These different possibilities are formalised as follows:

\[
\text{is\_largest\_hot\_spot\_at}(x, t, \gamma) = \exists r: \text{REAL} \forall y: \text{LOCATION} \forall r2: \text{REAL} \\
\quad [\text{state}(\gamma, t) |= \text{assault\_reputation}(x, r) \land r2 \leq r]
\]

\[
\text{is\_largest\_hot\_spot\_at}(x, t, \gamma) = \exists i: \text{INTEGER} \forall y: \text{LOCATION} \forall i2: \text{INTEGER} \\
\quad [\text{state}(\gamma, t) |= \text{number\_of\_criminals}(x, i) \land i2 \leq i]
\]

\[
\text{is\_largest\_hot\_spot\_at}(x, t, \gamma) = \exists i: \text{INTEGER} \forall y: \text{LOCATION} \forall i2: \text{INTEGER} \\
\quad [\text{state}(\gamma, t) |= \text{number\_of\_crimes}(x, i) \land i2 \leq i]
\]

In addition, a combination of the different options can be considered, for example, by calculating the weighted sum of the different numbers. Yet another variant of the dynamic property can be created, for example, by counting the number of criminals or crimes over a longer time period, instead of considering the current time point only.

Note that the term hot spot is used in many different ways by researchers and police. Although no common definition of the term hot spot of crime exists, the common understanding is that a hot spot is an area that has a greater than average number of criminal or disorder events, or an area where people have a higher than average risk of victimisation. Hot spot analysis can be performed on multiple levels, e.g., on the level of addresses, blocks, or regions [24]. This variability in definition is reflected in our approach by the possibility to choose one out of multiple formulae, as shown above.

Besides checking whether the location of hot spots is continuously changing, also other properties can be verified. A relevant property from the viewpoint of crime prevention is to check whether specific reoccurring patterns can be identified. For example, is it always the case that the criminals follow the movement of the passers-by, and that the guardians follow the criminals? And if not, are there specific circumstances in which this pattern does not occur? To analyse these kinds of patterns, properties like the following have been established:

\(^5\) the condition \( t < \text{last\\_time} - \delta \) (where \( \delta \) is the maximum duration of displacement, for example 6 iterations) was added to make sure that the property does not fail for the end of the trace.
**P2a** Criminals follow Passers-by

For each time point \( t \) (except the end of the trace), if at \( t \) most passers-by are at location \( x \), then within \( \varepsilon \) time points most criminals will be at location \( x \).

\[
\forall \gamma: \text{TRACES} \forall t: \text{TIME} \forall x: \text{LOCATION} \\
\text{[most_passers_by_at}(x, t, \gamma) & t < \text{last_time}-\delta] \\
\Rightarrow [ \exists i: \text{TIME} \text{most_criminals_at}(x, i, \gamma) & t < i < t + \varepsilon] 
\]

Here, most_passers_by_at is defined as follows:

\[
\text{most_passers_by_at}(x, t, \gamma) = \exists i: \text{INTEGER} \text{state}(\gamma, t) \models \text{number_of_passers_by}(x, i) & \\
\forall y: \text{LOCATION} \forall i_2: \text{INTEGER} [\text{state}(\gamma, t) \models \text{number_of_passers_by}(y, i_2) \Rightarrow i_2 \leq i] 
\]

Similarly, most_criminals_at is defined by taking the location with the highest number of criminals (see the second formalisation of \( \text{is_largest_hot_spot} \) at above). In addition to P2a, a similar property has been created to check whether the guardians follow the criminals:

**P2b** Guardians follow Criminals

For each time point \( t \) (except the end of the trace), if at \( t \) most criminals are at location \( x \), then within \( \varepsilon \) time points most guardians will be at location \( x \).

\[
\forall \gamma: \text{TRACES} \forall t: \text{TIME} \forall x: \text{LOCATION} \\
\text{[most_criminals_at}(x, t, \gamma) & t < \text{last_time}-\delta] \\
\Rightarrow [ \exists i: \text{TIME} \text{most_guardians_at}(x, i, \gamma) & t < i < t + \varepsilon] 
\]

Here, obviously, most_criminals_at is defined as follows:

\[
\text{most_criminals_at}(x, t, \gamma) = \exists i: \text{INTEGER} \text{state}(\gamma, t) \models \text{number_of_criminals}(x, i) & \\
\forall y: \text{LOCATION} \forall i_2: \text{INTEGER} [\text{state}(\gamma, t) \models \text{number_of_criminals}(y, i_2) \Rightarrow i_2 \leq i] 
\]

A third property has been established to check whether there are any periods during a simulation in which agents spread (more of less) equally over the different locations. This may be an indication that the presence of hot spots has (temporarily) disappeared. For example, for criminals, this can be checked via the following property:

**P3(Criminals) - Equal spread of criminals over locations**

There are time points \( t_1 \) and \( t_2 \) such that for all time points in between, and for all locations \( x \), the amount of criminals at \( x \) is within a range of \( \delta \) of the total amount of criminals \( c \) divided by the number of locations \( N_L \).

\[
\exists t_1, t_2: \text{TIME} \forall t: \text{TIME} \forall x: \text{LOCATION} \forall \text{real} \\
[\text{[}t_1 < t < t_2 & \text{state}(\gamma, t_3) \models \text{number_of_criminals}(x, i) \Rightarrow c/N_L = i \pm c^\varepsilon] 
\]

In the trace shown in Figure 2, this property clearly does not hold, since at every point in time some locations are more attractive than other locations.

Finally, a number of properties have been specified to investigate the relation between the emergence of hot spots and the number of locations, and the relation between the emergence of hot spots and the ratio between the types of agents. For example, the following formula can be used to check the property that 'more locations lead to less crime':

\[
\]
P4 - More locations lead to less crime

For all traces $\gamma_1$ and $\gamma_2$, if there are more locations in $\gamma_1$ than in $\gamma_2$, then at the end of the simulation there will be less crime in $\gamma_1$.

\[ \forall \gamma_1, \gamma_2: \text{TRACES} \quad \forall x_1, x_2, i_1, i_2: \text{INTEGER} \]
\[ \text{state}(\gamma_1, t_0) = \text{total\_number\_of\_locations}(x_1) \land \]
\[ \text{state}(\gamma_2, t_0) = \text{total\_number\_of\_locations}(x_2) \land \]
\[ \text{state}(\gamma_1, t_0) = \text{total\_number\_of\_crimes}(i_1) \land \]
\[ \text{state}(\gamma_1, t_0) = \text{total\_number\_of\_crimes}(i_2) \land \]
\[ x_1 > x_2 \implies i_1 < i_2 \]

Here, $t_0$ denotes the last time point of the simulation. Moreover, the predicate total_number_of_crimes is defined by summation of the crimes over all locations and all time points. Note that this property usually will not hold. However, in addition to simply checking whether the property holds, the TTL checking tool also allows the modeller to check how often it holds, i.e., in which percentage of the cases, and in which specific situations it does not hold. Such checks may provide the researcher important information about the relation between the geography of a city and the emergence of hot spots.

All in all, the above properties have been checked against a large number of simulation traces under different parameter settings (see also the appendix mentioned in [6]). The results pointed out that in almost all of the simulations, the same repeating pattern was found: the passers-by move away from the criminals, the criminals follow the passers-by, and the guardians follow the criminals. We therefore conclude that the pattern is quite robust to variations in parameter settings, which is an encouraging result, since the pattern is similar to the trends described in criminological literature such as [5, 21, 41], and game-theoretical literature on crime and control such as [39]. Intuitively, this finding makes sense, since the three groups involved have fundamentally conflicting interests (e.g., passers-by want to escape criminals, whilst criminals want to catch passers-by). In the game theoretical literature, this situation is referred to as ‘discoordination situation’ and is known to produce cycles due to the non-existence of Nash equilibria in pure strategies. In addition, the model has similarities with the classical Lotka-Volterra models (also known as predator-prey models) [37], which show similar cyclical behaviour (although they typically involve two groups instead of three).

Only in some exceptional cases, this cyclical pattern was not found. For example, when there are more guardians then locations, the guardians may distribute themselves over the locations, so that no crime will ever be performed, and thus no displacement will occur. This case may be compared with the ideal situation that a city has sufficient police force to prevent all crime. Another exception was a situation in which many agents have extreme preferences. For instance, if a certain location has an extremely high attractiveness to passers-by, then these passers-by will stay at that location, even though they run the risk of being assaulted.

7. Related Work

The part of criminology concerned with the displacement of crime is called environmental criminology. Within this area the key object is the study of crime, criminality, and victimization as they relate to particular places and to the way that individuals and organisations shape their activities spatially [12, 13]. Among the main research groups within this area is the Chicago School of Sociology. Shaw and McKay,
agents repeatedly face a choice between rule compliance and rule transgression. If agents transgress, they have a probability of being audited and punished. The main aim

Besides the literature in Criminology, also in Artificial Intelligence a number of modelling approaches exist that have similarities to the approach discussed in this paper. This section is not meant to provide a complete overview (see [32] for that purpose), but will discuss those approaches that, to our knowledge, are most related to the current paper.

To start, the work in [27] systematically investigates the geography of crime trajectories using a variety of spatial analysis techniques. However, a difference with the current approach is that these models do not contain an adaptive element (such as an update of reputation), which causes the results to converge quickly to an equilibrium.

Another approach to analyse the spatio-temporal dynamics of crime is presented in [16]. This approach is based on a Distributed Abstract State Machine (DASM) formalism, combined with a multi-agent based modelling paradigm. Although the agents involved are capable of learning (using a form of behaviour reinforcement learning, where based on past experiences certain preferences are developed that may influence future choices), the notion of reputation is not explicitly incorporated.

A third interesting approach is introduced in [33], which also explores the possibility of simulating individual crime events in order to generate plausible crime patterns. This approach is based on a Cellular Automaton (CA), in which the main elements are offenders, targets, and crime places. Different attributes of the model can be manipulated, among which motivation of offenders, capability of guardians, and accessibility of places. Like the approach mentioned above, the main difference with the current approach is that it does not contain an explicit notion of reputation.

Furthermore, a more specialised approach is presented in [36]. That paper describes a tool to investigate the influence that different police control routes have on the reduction of crime rates. The approach comprises an artificial society consisting of various agents, in particular criminals and policemen. As a follow-up of that work, in [40] the first results are presented that were achieved with GAPatrol, an evolutionary multi agent-based simulation tool devised to assist police managers in the design of effective police patrol route strategies.

Another more specialised approach is put forward in [3]. This approach specifically aims at simulating the process of deterrence. A simulation model is presented where each potential offender is part of a social network that consists of several agents. All agents repeatedly face a choice between rule compliance and rule transgression. If agents transgress, they have a probability of being audited and punished. The main aim
of the work is to investigate how the probability of being punished influences the amount of crime.

Although all of the papers mentioned above have some similarities with the work presented here, an important difference is that they all focus on simulation only. In contrast, the current paper proposes an approach that combines simulation with logical analysis. Since the simulation traces that result from the LEADSTO environment can directly be used as input for the TTL Checker, it is relatively easy for the modeller to verify certain global properties of the model. As such, the paper has many similarities with the work presented in [9], which also combines simulation with logical analysis. However, the domain addressed by the latter paper is completely different (namely the psychological and biological characteristics underlying the behaviour of criminals that are diagnosed with “Intermittent Explosive Disorder”). In addition, that paper does not consider the notion of reputation, nor does it address any notion of adaptivity.

8. Discussion

Within the area of Criminology, analysis of the spatio-temporal dynamics of crime is an important challenge. In particular, criminologists are interested in the question where criminal hot spot may emerge, and when they will emerge. As a first step towards answering such questions, the current paper presents an agent-based simulation model that can be used as an experimental tool to analyse spatio-temporal dynamics of crime. The simulation model particularly focuses on the interplay between hot spots and reputation, which has not been addressed in earlier work.

As usual in Agent-Based Social Simulation, the model has been set up in a generic manner, according to the principles of compositionality and knowledge abstraction [17]. This means that, when one wants to study another scenario (i.e., analyse the behaviour of another city, or population), the complete behavioural specification of the system (see Appendix A) can be re-used. All that needs to be filled in is a number of domain specific slots, e.g., concerning the geographical environment, or the initial distribution of agents.

Using the model, a series of simulation runs has been performed, under different parameter settings. The results of the simulations have been automatically verified (by means of the TTL Checker [10]) against a number of hypotheses, expressed as logical formulae. In almost all of the simulations, the same repeating pattern was found: the passers-by move away from the criminals, the criminals follow the passers-by, and the guards follow the criminals. Although there is no overall agreement in the criminological literature about an exact definition of displacement (see, e.g., [41]), this pattern is quite similar to the displacement trends described by authors such as [5, 21].

In fact, one could argue that this is a rather unsatisfactory finding, since it may lead to the conclusion that “the police always arrive too late” (or, more concretely, that decisions to establish new patrol teams, surveillance cameras, and so on, are only made after the hot spots have already emerged). Therefore, an interesting question, which we are currently focussing on, is whether simulation models of criminal displacement can be useful for anticipatory policies (i.e., to increase the number of guardians at locations where hot spots are likely to emerge, instead of at the present locations of hot spots). The first results of a extensive comparison between a number of strategies (varying from merely reactive to more anticipatory) which we are currently performing show that anticipatory strategies indeed seem to lead to less crime than reactive strategies [7].
Furthermore, note that, although the parameter settings used for the simulations described in this paper were inspired by empirical studies such as [12], no effort was put into creating settings that correspond exactly to the characteristics of real cities and populations. Therefore, the results of the presented simulations should not be considered as conclusive about real world situations. Rather, they provide preliminary insight in the process of displacement, and provide support for the usefulness of the presented approach as an analysis tool. As shown in Section 5 and 6, the presented combination of software tools (i.e., the LEADSTO simulation tool, the TTL Checker tool, and the Matlab visualisation tool) can be very useful for the researcher to study criminal displacement. In particular, the LEADSTO simulation tool can be used to generate large numbers of traces under different parameter settings. Next, the TTL Checker tool can be used to filter out those traces for which unexpected behaviour occurs. After that, these particular traces can be studied in more detail using the Matlab visualisation tool, in order to explain the unexpected behaviour.

The intended users of these tools are in the first place researchers in criminology, although on the long term they may be also useful for policy makers. When one considers the intended users of similar tools that have been proposed in the literature (such as [3, 16, 27, 33, 36, 40]), it turns out that different perspectives are taken. For example, some authors have attempted to develop simulation models of crime displacement in existing cities, which can be directly related to real world data (e.g., [33]), whereas others deliberately abstract from empirical information (e.g., [8]). The idea behind the latter perspective is that the simulation environment is used as an analytical tool, mainly used by researchers and policy makers, to shed more light on the process under investigation, and perhaps improve existing policies (e.g., for surveillance) on the long run [25]. The point of view taken in the current paper can be situated in between these two extremes. Initially, the simulation model was developed to study the phenomenon of displacement per se. However, its basic concepts have been defined in such a way that they can be directly connected to empirical information, if this becomes available. Indeed, the authors also plan to use more realistic parameter settings in the future (including temporal relationships), in order to investigate to what extent the approach is able to reproduce empirical data. As soon as the model can be sufficiently validated in such settings (i.e., the global patterns produced by the model match the empirical data), the model may be of interest for policy makers, e.g., to study “what-if” scenarios. For example, one may investigate how the crime level of a certain city will change if the policy makers invest in more surveillance in a certain area.

When such more realistic parameter settings will be considered, also scaling issues will have to be addressed. Although the current simulation model handles population sizes of hundreds of (heterogeneous) agents relatively easily, the simulation time is polynomial in the number of agents. Therefore, complexity problems will arise when populations of (more than) thousands of agents are considered. These problems could be solved by translating the current simulation model to a stochastic model, as is done, for example, in the analysis of epidemics [1]. Also for the displacement of criminal hot spots, such a translation is currently being made. An initial version of such a stochastic model of criminal displacement (where the behaviour of the different agent types was kept simple) is presented in [8]. When making such a translation, the description of the dynamics of a population shifts from a “micro” perspective (at the level of individual

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6 For example, the authors tried to pick reasonably realistic settings for agents’ preferences and ratios between types of agents.
agents) to a “macro” perspective (at the level of groups of agents). For example, the number of criminals, assaults and arrests at certain locations can be described by global variables, which are influenced by probabilistic rules. A comparable, but slightly different approach is presented in [9], where the expected number of crimes in certain populations is estimated on the basis of probabilities of opportunities. The main advantage of these types of macro-level approaches is that they can deal with larger populations. An inevitable drawback is however that they imply a loss of detail at the individual agent level. In current work in progress, the benefits of such approaches are explored in more detail.

Concerning other future work, various extensions to the model will be considered. An interesting expansion could be based on the work by [43]. They state that the social cohesion of a group is an important factor in the emergence of crime. Social cohesion among neighbours combined with their willingness to intervene on behalf of the common good, is linked to reduced violence. An interesting direction for further research would be to introduce a parameter for social cohesion, in order to investigate whether that increases the accuracy of the simulation model.

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References


Appendix A - LEADS TO Specification

Below, the complete specification of the criminal displacement model is shown, in LEADS TO notation. Note that the LEADS TO simulation software can be downloaded from the following URL: http://www.cs.vu.nl/~wai/TTL/

Decide Current Location Attractiveness
∀a:AGENT ∀l:LOCATION ∀n2, v1, w1:REAL ∀w2, w3:INTEGER
basic_attraction_of_agent_for_location(v, l, a) ∧ belief(a, assault_reputation_at_location(n1, l)) ∧ belief(a, arrest_reputation_at_location(n2, l)) ∧ has_weight_factor(a, w1, w2, w3) ∧ agents_counted
├→ 0, 0, 1
belief(a, current_attractiveness_of_location(l, w1*v1+w2*n1+w3*n2))

Go to Most Attractive Location
∀a:AGENT ∀l1, l2, l3:LOCATION ∀x1, x2, x3:REAL
belief(a, current_attractiveness_of_location(l1, x1)) ∧ belief(a, current_attractiveness_of_location(l2, x2)) ∧ belief(a, current_attractiveness_of_location(l3, x3)) ∧ l1≠l2 ∧ l2≠l3 ∧ l1≠x2 ∧ x1≠x3
├→ 0, 0, 1
performed(a, go_to_location(l1))

Arrive at Location
∀a:AGENT ∀l:LOCATION
performed(a, go_to_location(l))
├→ 0, 0, nr_agents+4
is_at_location(a, l)

Observe all Agents
∀a:AGENT ∀l:LOCATION ∀r:INTEGER ∀t:TYPE
is_at_location(a, l) ∧ has_type(a, t) ∧ round(t)
├→ 0, 0, nr_agents+1
observes(a, agent_of_type_at_location(a, t, l))

Count Types of Agents at Locations
∀a:AGENT ∀l:LOCATION
performed(a, go_to_location(a, t, l))
├→ 0, 0, 1
counting_at(1) ∧ agents_counted_of_type_at_location(0, passer_by, locA) ∧ agents_counted_of_type_at_location(0, passer_by, locB) ∧ agents_counted_of_type_at_location(0, criminal, locA) ∧ agents_counted_of_type_at_location(0, criminal, locB) ∧ agents_counted_of_type_at_location(0, guardian, locA) ∧ agents_counted_of_type_at_location(0, guardian, locB) ∧ agents_counted_of_type_at_location(0, guardian, locC)
∀k:between(0, nr_agents) ∀n:between(1, nr_agents+1) ∀t:TYPE
counting_at(n) ∧ nsnr_agents agents_counted_of_type_at_location(k, t, l) ∧ is_at_location(agent(n), l) ∧ has_type(agent(n), t)
├→ 0, 0, 1
agents_counted_of_type_at_location(k+1, t, l) ∧ counting_at(n+1)

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∀k:between(0, nr_agents) ∀l:LOCATION ∀n:between(1, nr_agents+1) ∀t:TYPE
\text{counting\_at}(n) \land n \text{sr\_agents} \land \text{agents\_counted\_of\_type\_at\_location}(k, t, l) \land
\text{is\_at\_location}(\text{agent}(n), l2) \land \lnot\text{t}(\text{has\_type}(\text{agent}(n), t))
\Rightarrow 0, 0, 1, 1
\text{agents\_counted\_of\_type\_at\_location}(k, t, l) \land \text{counting\_at}(n+1)

∀k:between(0, nr_agents) ∀l:LOCATION ∀n:between(1, nr_agents+1) ∀l2:TYPE
\text{counting\_at}(n) \land n \text{sr\_agents} \land \text{agents\_counted\_of\_type\_at\_location}(k, t, l) \land
\text{is\_at\_location}(\text{agent}(n), l2) \land \lnot\text{t}(\text{has\_type}(\text{agent}(n), l2))
\Rightarrow 0, 0, 1, 1
\text{agents\_counted\_of\_type\_at\_location}(k, t, l) \land \text{counting\_at}(n+1)

Believe Counted Types of Agents
∀k:between(0, nr_agents) ∀l:LOCATION ∀n:between(1, nr_agents+1) ∀t:TYPE
\text{counting\_at}(n) \land n > n r\_agents \land \text{agents\_counted\_of\_type\_at\_location}(k, t, l)
\Rightarrow 0, 0, 1, 1
\text{belief}(\text{all\_agents}, \text{number\_of\_type\_at\_location}(k, t, l)) \land \text{agents\_counted}

Note: all\_agents is an abbreviation for a conjunction of all the agents in the simulation.

Visualise Counted Types of Agents
∀k:between(0, nr_agents) ∀l:LOCATION ∀t:TYPE
\text{belief}(\text{all\_agents}, \text{number\_of\_type\_at\_location}(k, t, l))
\Rightarrow 0, 0, 1, 10
\text{visualise\_agents\_of\_type\_at\_location}(k, t, l)

Perform Assault
∀a:AGENT ∀l:LOCATION
\text{is\_at\_location}(a, l) \land \text{has\_type}(a, \text{guardian})
\Rightarrow 0, 0, 1, 1
\text{guardian\_at\_location}(l)

∀a1,a2:AGENT ∀l:LOCATION
\text{observes}(a1, \text{agent\_of\_type\_at\_location}(a1, \text{criminal}, l)) \land
\text{observes}(a1, \text{agent\_of\_type\_at\_location}(a2, \text{passer\_by}, l)) \land \lnot\text{guardian\_at\_location}(l)
\Rightarrow 0, 0, 1, 1
\text{performed}(a1, \text{assault\_at}(a2, l))

Count Assaults
∀a1,a2:AGENT ∀l:LOCATION
\text{performed}(a1, \text{assault\_at}(a2, l))
\Rightarrow 0, 0, 1, 1
\text{assault\_at}(l)

∀l:LOCATION ∀a:AGENT ∀n:REAL
\text{assault\_at}(l) \land \text{belief}(a, \text{assault\_reputation\_at\_location}(n, l))
\Rightarrow 0, 0, 1, 1
\text{belief}(a, \text{assault\_reputation\_at\_location}(n+\text{inc}, l))

∀l:LOCATION ∀a:AGENT ∀n:REAL
\text{belief}(a, \text{assault\_reputation\_at\_location}(n, l)) \land \lnot\text{assault\_at}(l)
\Rightarrow 0, 0, 1, 1
\text{belief}(a, \text{assault\_reputation\_at\_location}(n^\text{dec}, l))

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Perform Arrest
\(\forall a_1, a_2: AGENT \forall l:\text{LOCATION}\)
\(\text{performed}(a_1, \text{assault}_\text{at}(a_2, l))\)
\(\rightarrow 0, 0, 1, nr\_agents^4\)
\(\text{known\_criminal}(a_1)\)
\(\forall a_1, a_2: AGENT \forall l:\text{LOCATION}\)
\(\text{observes}(a_1, \text{agent\_of\_type\_at\_location}(a_1, \text{guardian}, l)) \land\)
\(\text{observes}(a_1, \text{agent\_of\_type\_at\_location}(a_2, \text{criminal}, l)) \land \text{known\_criminal}(a_2)\)
\(\rightarrow 0, 0, 1, 1\)
\(\text{performed}(a_1, \text{arrest\_at}(a_2, l))\)

Count Arrests
\(\forall a_1, a_2: AGENT \forall l:\text{LOCATION}\)
\(\text{performed}(a_1, \text{arrest\_at}(a_2, l))\)
\(\rightarrow 0, 0, 1, 1\)
\(\text{arrest\_at}(l)\)
\(\forall l:\text{LOCATION} \forall a: AGENT \forall n: \text{REAL}\)
\(\text{arrest\_at}(l) \land \text{belief}(a, \text{arrest\_reputation\_at\_location}(n, l))\)
\(\rightarrow 0, 0, 1, 1\)
\(\text{belief}(a, \text{arrest\_reputation\_at\_location}(n^{\text{inc}}, l))\)
\(\forall l:\text{LOCATION} \forall a: AGENT \forall n: \text{REAL}\)
\(\text{belief}(a, \text{arrest\_reputation\_at\_location}(n, l)) \land \text{not\_at}(l)\)
\(\rightarrow 0, 0, 1, 1\)
\(\text{belief}(a, \text{arrest\_reputation\_at\_location}(n^{\text{dec}}, l))\)

Maintain Rounds – needed for observations
\(\forall r: \text{INTEGER}\)
\(\text{round}(r)\)
\(\rightarrow 3, 3, nr\_agents+1, nr\_agents+1\)
\(\text{round}(r+1)\)
Appendix B - Example Simulation

In this section, an example simulation run is shown. For the sake of readability, a simple case of three locations is chosen. First, the simulation settings are shown, in the table below. The first column indicates the name of the agent, the second column indicates the type of agent (criminal, guardian, or passer-by), the next three columns indicate the basic attractiveness of that agent for the different locations (A, B, and C), the next three columns indicate the three weight factors of that agent ($w_1$, $w_2$, and $w_3$), and the last column indicates the initial location of the agent.

<table>
<thead>
<tr>
<th>Agent</th>
<th>Type</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>$w_1$</th>
<th>$w_2$</th>
<th>$w_3$</th>
<th>Start</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PB</td>
<td>0.87</td>
<td>0.81</td>
<td>0.74</td>
<td>0.1</td>
<td>0</td>
<td>0</td>
<td>A</td>
</tr>
<tr>
<td>2</td>
<td>PB</td>
<td>0.81</td>
<td>0.76</td>
<td>0.70</td>
<td>0.1</td>
<td>-1</td>
<td>0</td>
<td>A</td>
</tr>
<tr>
<td>3</td>
<td>PB</td>
<td>0.83</td>
<td>0.74</td>
<td>0.68</td>
<td>0.1</td>
<td>-2</td>
<td>-1</td>
<td>A</td>
</tr>
<tr>
<td>4</td>
<td>PB</td>
<td>0.77</td>
<td>0.60</td>
<td>0.51</td>
<td>0.1</td>
<td>-3</td>
<td>-2</td>
<td>A</td>
</tr>
<tr>
<td>5</td>
<td>PB</td>
<td>0.79</td>
<td>0.64</td>
<td>0.58</td>
<td>0.1</td>
<td>-4</td>
<td>-3</td>
<td>A</td>
</tr>
<tr>
<td>6</td>
<td>PB</td>
<td>0.85</td>
<td>0.60</td>
<td>0.66</td>
<td>0.1</td>
<td>-5</td>
<td>-4</td>
<td>A</td>
</tr>
<tr>
<td>7</td>
<td>PB</td>
<td>0.83</td>
<td>0.59</td>
<td>0.61</td>
<td>0.5</td>
<td>0</td>
<td>0</td>
<td>A</td>
</tr>
<tr>
<td>8</td>
<td>PB</td>
<td>0.84</td>
<td>0.63</td>
<td>0.70</td>
<td>0.5</td>
<td>-1</td>
<td>0</td>
<td>A</td>
</tr>
<tr>
<td>9</td>
<td>PB</td>
<td>0.89</td>
<td>0.66</td>
<td>0.72</td>
<td>0.5</td>
<td>-2</td>
<td>-1</td>
<td>A</td>
</tr>
<tr>
<td>10</td>
<td>PB</td>
<td>0.81</td>
<td>0.43</td>
<td>0.52</td>
<td>0.5</td>
<td>-3</td>
<td>-2</td>
<td>A</td>
</tr>
<tr>
<td>11</td>
<td>PB</td>
<td>0.86</td>
<td>0.51</td>
<td>0.62</td>
<td>0.5</td>
<td>-4</td>
<td>-3</td>
<td>A</td>
</tr>
<tr>
<td>12</td>
<td>PB</td>
<td>0.90</td>
<td>0.52</td>
<td>0.71</td>
<td>0.5</td>
<td>-5</td>
<td>-4</td>
<td>A</td>
</tr>
<tr>
<td>13</td>
<td>PB</td>
<td>0.81</td>
<td>0.90</td>
<td>0.84</td>
<td>1.1</td>
<td>0</td>
<td>0</td>
<td>B</td>
</tr>
<tr>
<td>14</td>
<td>PB</td>
<td>0.76</td>
<td>0.84</td>
<td>0.51</td>
<td>1.1</td>
<td>-1</td>
<td>0</td>
<td>B</td>
</tr>
<tr>
<td>15</td>
<td>PB</td>
<td>0.53</td>
<td>0.76</td>
<td>0.68</td>
<td>1.1</td>
<td>-2</td>
<td>-1</td>
<td>B</td>
</tr>
<tr>
<td>16</td>
<td>PB</td>
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<td>0.76</td>
<td>0.68</td>
<td>1.1</td>
<td>-3</td>
<td>-2</td>
<td>B</td>
</tr>
<tr>
<td>17</td>
<td>PB</td>
<td>0.76</td>
<td>0.64</td>
<td>0.83</td>
<td>1.1</td>
<td>-4</td>
<td>-3</td>
<td>C</td>
</tr>
<tr>
<td>18</td>
<td>PB</td>
<td>0.78</td>
<td>0.61</td>
<td>0.81</td>
<td>1.1</td>
<td>-5</td>
<td>-4</td>
<td>C</td>
</tr>
<tr>
<td>19</td>
<td>PB</td>
<td>0.79</td>
<td>0.70</td>
<td>0.84</td>
<td>2.1</td>
<td>0</td>
<td>0</td>
<td>C</td>
</tr>
<tr>
<td>20</td>
<td>PB</td>
<td>0.70</td>
<td>0.63</td>
<td>0.76</td>
<td>2.1</td>
<td>-1</td>
<td>0</td>
<td>C</td>
</tr>
<tr>
<td>21</td>
<td>PB</td>
<td>0.81</td>
<td>0.75</td>
<td>0.90</td>
<td>0.1</td>
<td>-2</td>
<td>-1</td>
<td>C</td>
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<tr>
<td>22</td>
<td>PB</td>
<td>0.74</td>
<td>0.68</td>
<td>0.79</td>
<td>0.5</td>
<td>-3</td>
<td>-2</td>
<td>C</td>
</tr>
<tr>
<td>23</td>
<td>PB</td>
<td>0.60</td>
<td>0.79</td>
<td>0.85</td>
<td>1.1</td>
<td>-4</td>
<td>-3</td>
<td>C</td>
</tr>
<tr>
<td>24</td>
<td>PB</td>
<td>0.74</td>
<td>0.80</td>
<td>0.86</td>
<td>2.1</td>
<td>-5</td>
<td>-4</td>
<td>C</td>
</tr>
<tr>
<td>25</td>
<td>G</td>
<td>0.85</td>
<td>0.74</td>
<td>0.79</td>
<td>0.1</td>
<td>4</td>
<td>3</td>
<td>A</td>
</tr>
<tr>
<td>26</td>
<td>G</td>
<td>0.81</td>
<td>0.76</td>
<td>0.83</td>
<td>0.1</td>
<td>5</td>
<td>4</td>
<td>C</td>
</tr>
<tr>
<td>27</td>
<td>C</td>
<td>0.84</td>
<td>0.81</td>
<td>0.80</td>
<td>0.1</td>
<td>2</td>
<td>-3</td>
<td>A</td>
</tr>
<tr>
<td>28</td>
<td>C</td>
<td>0.76</td>
<td>0.86</td>
<td>0.84</td>
<td>1.1</td>
<td>3</td>
<td>-4</td>
<td>B</td>
</tr>
<tr>
<td>29</td>
<td>C</td>
<td>0.78</td>
<td>0.81</td>
<td>0.83</td>
<td>1.1</td>
<td>-3</td>
<td>-5</td>
<td>C</td>
</tr>
<tr>
<td>30</td>
<td>C</td>
<td>0.83</td>
<td>0.82</td>
<td>0.85</td>
<td>2.1</td>
<td>4</td>
<td>-5</td>
<td>C</td>
</tr>
</tbody>
</table>

In this simulation, there are 24 passers by, 2 guardians and 4 criminals in the world. As shown in the resulting trace, initially, they are distributed over the location by means of their personal preferences (i.e., a predicate that states which location they find most attractive/interesting). At time point 100, there are 13 passers by at location A and there are 10 passers by at location C. At time point 160, the criminals go after the passers by. There is 1 criminal at location A and 3 criminals went to location C. This results in the movement of passers by. They want to move away from the criminals and they go to location B (time point 260). Only 100 time points later, the criminals follow the passers by and they also arrive at location B (time point 360). The passers by want to get away from the criminals and return to the locations A and C. Again 100 time points later, the criminals also move to location A and C (respectively 1 and 3 criminals). This trend repeats itself until the end of the trace. The guardians follow the criminals. They arrive at the location of the criminals 100 time points after the criminals do.
Comparison of Agent-Based and Population-Based Simulations of Displacement of Crime

Tibor Bosse, Charlotte Gerritsen, Mark Hoogendoorn, S. Waqar Jaffry, and Jan Treur

Abstract. Within Criminology, the process of crime displacement is usually explained by referring to the interaction of three types of agents: criminals, passers-by, and guardians. Most existing simulation models of this process are agent-based. However, when the number of agents considered becomes large, population-based simulation has computational advantages over agent-based simulation. This paper presents both an agent-based and a population-based simulation model of crime displacement, and reports a comparative evaluation of the two models. In addition, an approach is put forward to analyse the behaviour of both models by means of formal techniques.

1. Introduction

Within Criminology one of the main research interests is the emergence of so-called criminal hot spots. These hot spots are places where many crimes occur [13]. After a while the criminal activities shift to another location, for example, because the police has changed its policy and increased the numbers of officers at the hot spot. Another reason may be that the passers by move away when a certain location gets a bad reputation. Such a shift between locations is called the displacement of crime. The reputation of specific locations in a city is an important factor in the spatio-temporal distribution and dynamics of crime [8]. For example, it may be expected that the amount of assaults that take place at a certain location affect the reputation of this location. Similarly, the reputation of a location affects the attractiveness of that location for certain types of individuals. For instance, a location that is known for its high crime rates will attract police officers, whereas most citizens will be more likely to avoid it. As a result, the amount of criminal activity at such a location will decrease, which will affect its reputation again.

The classical approaches to simulation of processes in which groups of larger numbers of agents and their interaction are involved are population-based: a number of groups is distinguished (populations) and each of these populations is represented by a numerical variable indicating their number or density (within a given area or location) at a certain time point. The simulation model takes the form of a system of difference or differential equations expressing temporal relationships for the dynamics of these variables. Well-known classical examples of such population-based models are systems of difference or differential equations for predator-prey dynamics (e.g., [5, 10, 11, 15, 16]) and the dynamics of epidemics (e.g., [1, 5, 7, 9, 12]). Such models can be studied by simulation and by using analysis techniques from mathematics and dynamical systems theory.

From the more recently developed agent system area it is often taken as a presupposition that simulations based on individual agents are a more natural or faithful way of modelling, and thus will provide better results (e.g., [2, 6, 14]). Although for
larger numbers of agents such agent-based modelling approaches are more expensive computationally than population-based modelling approaches, such a presupposition may provide a justification of preferring their use over population-based modelling approaches, in spite of the computational disadvantages. However, for larger numbers of agents (in the limit), agent-based simulations may equally well approximate population-based simulations. In such cases agent-based simulations just can be replaced by population-based simulations. In this paper, for the application area of crime displacement these considerations are explored in more detail. Comparative simulation experiments have been conducted based on different simulation models, both agent-based (for different numbers of agents), and population-based. The results are analysed and related to the assumptions discussed above.

This paper is organised as follows. First, Section 2 introduces the population based model which has been defined for this domain. Thereafter, this model is mathematically analysed in Section 3, and simulation results are presented in Section 4. Section 5 introduces the agent-based model of which simulation results are shown in Section 6. A comparison of the two different models by means of a formal analysis method is described in Section 7. Finally, Section 8 is a discussion.

2. A Population-Based Model

In this section the population-based model is defined. Hereby, a number of variable names are used as shown in Table 1.

Table 1. Variables in population-based model

<table>
<thead>
<tr>
<th>Name</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>Total number of criminals</td>
</tr>
<tr>
<td>G</td>
<td>Total number of guardians</td>
</tr>
<tr>
<td>P</td>
<td>Total number of passers by</td>
</tr>
<tr>
<td>c(L, t)</td>
<td>Density of criminals at location L at time t.</td>
</tr>
<tr>
<td>g(L, t)</td>
<td>Density of guardians at location L at time t.</td>
</tr>
<tr>
<td>p(L, t)</td>
<td>Density of passers-by at location L at time t.</td>
</tr>
<tr>
<td>β(L, a, t)</td>
<td>Attractiveness of location L at time t for type a agents: c (criminals), p (passers-by), or g (guardians))</td>
</tr>
<tr>
<td>assault_rate(L, t)</td>
<td>Number of assaults taking place at location L per time unit.</td>
</tr>
</tbody>
</table>

The calculation of the number of agents at the various locations is determined by the movement of agents that takes place based upon the attractiveness of the location. For instance, for the criminals the formula is specified as follows:

\[
c(L, t + \Delta t) = c(L, t) + \eta_c \cdot (\beta(L, c, t) - c(L, t)/c) \cdot \Delta t
\]

This expresses that the density \(c(L, t + \Delta t)\) of criminals at location \(L\) on \(t + \Delta t\) is equal to the density of criminals at the location at time \(t\) plus a constant \(\eta_c\) (expressing the rate at which criminals move per time unit) times the movement of criminals from \(t\) to \(t + \Delta t\) from and to location \(L\) multiplied by \(\Delta t\). Here, the movement of criminals is calculated by determining the relative attractiveness \(\beta(L, c, t)\) of the location (compared to the other locations) for criminals. From this, the density of criminals at the location at time \(t\) divided by the total number \(c\) of criminals (which is constant) is subtracted, resulting in the change of the number of criminals for this location. For the guardians and the passers-by similar formulae are used:

\[
g(L, t + \Delta t) = g(L, t) + \eta_g \cdot (\beta(L, g, t) - g(L, t)/g) \cdot \Delta t
\]

\[
p(L, t + \Delta t) = p(L, t) + \eta_p \cdot (\beta(L, p, t) - p(L, t)/p) \cdot \Delta t
\]

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The attractiveness of a location can be expressed based on some form of reputation of the location for the respective type of agents. Several variants of a reputation concept can be used. The only constraint is that it is assumed to be normalized such that the total over the locations equals 1. An example of a simple reputation concept is based on the densities of agents, as expressed below.

\[
\beta(L, c, t) = \frac{p(L, t)}{c} \quad \text{for criminals}
\]
\[
\beta(L, g, t) = \frac{c(L, t)}{g} \quad \text{for guardians}
\]
\[
\beta(L, p, t) = \frac{g(L, t)}{p} \quad \text{for passers-by}
\]

This expresses that criminals are more attracted to locations with higher densities of passers-by, whereas guardians are attracted more to locations with higher densities of criminals, and passers-by to locations with higher densities of guardians. As a more general format, linear combinations of densities can be used:

\[
\beta(L, p, t) = \beta_{01} \cdot c(L, t) / c + \beta_{02} \cdot g(L, t) / g + \beta_{03} \cdot p(L, t) / p + \delta_1
\]
\[
\beta(L, c, t) = \beta_{11} \cdot c(L, t) / c + \beta_{12} \cdot g(L, t) / g + \beta_{13} \cdot p(L, t) / p + \delta_2
\]
\[
\beta(L, g, t) = \beta_{21} \cdot c(L, t) / c + \beta_{22} \cdot g(L, t) / g + \beta_{23} \cdot p(L, t) / p + \delta_3
\]

A natural setting of these values for criminals would be to have \(\beta_{03}\) positive since criminals need victims to assault, and to have \(\beta_{02}\) negative because criminals try to avoid guardians. For the guardians, \(\beta_{02}\) is likely to be positive since criminals attract guardians, whereas \(\beta_{01}\) is positive as well. Finally, for the passers-by the \(\beta_{03}\) can be taken negative as passers-by prefer not to meet criminals, and \(\beta_{23}\) (and possibly also \(\beta_{22}\) positive because guardians (and other passers-by) protect the passers-by. Besides such linear variants, more complex variants can be used in the simulation model presented here as well.

In order to measure the assaults that take place per time unit, also different variants of formulae can be used; for example:

\[
\text{assault\_rate}(L, t) = \min(\gamma_1 \cdot c(L, t) \cdot \gamma_2 \cdot g(L, t), p(L, t))
\]

Here, the assault rate at a location at time \(t\) is calculated as the minimum of the possible assaults that can take place and the number of passers-by. Here the possible number of assaults is the capacity per time step of criminals \((\gamma_1)\) multiplied by the number of criminals at the location minus the capacity of guardians to avoid an assault \((\gamma_2)\) times the number of guardians. In theory this can become less than 0 (the guardians can have a higher capacity to stop assaults than the criminals have to commit them), therefore the maximum can be taken of 0 and the outcome described above.

3. Analysis of Population-Based Model

Before performing simulations using the population-based model, a formal analysis is conducted to identify certain characteristics of the model. To obtain such a formal analysis, it is assumed that the attractivenesses of a given location are linear functions of the densities of the different populations at that location, as described in Section 2. When the densities are normalised by taking, for example \(c(L, t) = c(L, t)/c\) instead of \(c(L, t)\), then the following (homogeneous) system of linear differential equations is obtained.

\[
\frac{dc(L, t)}{dt} = \eta_{11} c(L, t) + \eta_{12} g(L, t) + \eta_{13} p(L, t)
\]
\[
\frac{dg(L, t)}{dt} = \eta_{21} c(L, t) + \eta_{22} g(L, t) + \eta_{23} p(L, t)
\]
\[
\frac{dp(L, t)}{dt} = \eta_{31} c(L, t) + \eta_{32} g(L, t) + \eta_{33} p(L, t)
\]

So \(p(L, t)\) et cetera denote the fraction of the overall population \(p\) that is at location \(L\) at time \(t\). In linear algebra notation this system can be written as \(\frac{dc}{dt} = Ax\), with \(A\) represented by a 3x3 matrix.
where \( \eta_1, \eta_2, \eta_3 \) are negative here. An equilibrium is determined by

- \( \eta_1 c(L, t) + \eta_1 p_o(L, t) = 0 \)
- \( \eta_2 g(L, t) + \eta_2 c(L, t) = 0 \)
- \( \eta_3 p_o(L, t) + \eta_3 g(L, t) = 0 \)

This is equivalent to \( p_o(L, t) = \frac{c_o(L, t)}{g_o(L, t)} \). The eigen values can be determined by the equation:

- \( -\lambda^2 + b\lambda + c \lambda d \) with

\[ b = (\eta_1 + \eta_2 + \eta_3) \]
\[ c = (\eta_1 + \eta_2 + \eta_3) \cdot (\eta_2 + \eta_3 + \eta_3 + \eta_3) \]
\[ d = \eta_1 + \eta_2 + \eta_3 + \eta_3 + \eta_3 + \eta_3 + \eta_3 + \eta_3 \]

In general it is not easy to express how the eigen values depend on the many parameters involved. However, for the special case that criminals are (only) attracted to passers-by, guardians are attracted to criminals and passers by are attracted to guardians, a number of the parameters can be taken zero, or equal:
For this equation one eigen value is \( \lambda = 0 \), and the other two are the solutions of the quadratic equation

\[
\lambda^2 - (\eta_{11} + \eta_{22} + \eta_{33})\lambda + (\eta_{11}\eta_{22} + \eta_{22}\eta_{33} + \eta_{33}\eta_{11}) = 0
\]

\[
\lambda = \frac{(\eta_{11} + \eta_{22} + \eta_{33}) \pm \sqrt{(\eta_{11} + \eta_{22} + \eta_{33})^2 - 4(\eta_{11}\eta_{22} + \eta_{22}\eta_{33} + \eta_{33}\eta_{11})}}{2}
\]

When the square root gives real numbers (positive discriminant), then both solutions will be negative, as the root is less than \(|\eta_{11} + \eta_{22} + \eta_{33}|\). When the square root gives imaginary numbers (negative discriminant), the real part of both solutions will be negative. In all cases attraction to the equilibrium will take place, in the first case monotonic, in the second case nonmonotonic. Hence, given the set of assumptions as described above, the model will eventually stabilise.

### 4. Population-Based Simulations

The model described in Section 2 and analysed in Section 3 has been used to generate simulation results. (using the Matlab programming environment). Hereby, the functions that represent the attractiveness of different locations have been varied.

#### 4.1. Simple attractiveness function

In this section the results using the simple attractiveness function presented in Section 3 are shown. The simulation results described below used the parameter settings as shown in Table 2 and 3. The settings of the parameters that correspond to the number of passers-by, criminals, and guardians have been determined in cooperation with a team of criminologists.

The resulting simulation trace is depicted in Figure 1. The first three graphs depict the movement of, respectively, criminals, guardians and passers-by over the different locations. The last graph depicts the amount of assaults performed.

<table>
<thead>
<tr>
<th>SIMULATION LENGTH</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOCATIONS</td>
<td>4</td>
</tr>
<tr>
<td>PASSERS-BY</td>
<td>4000</td>
</tr>
<tr>
<td>CRIMINALS</td>
<td>800</td>
</tr>
<tr>
<td>GUARDIANS</td>
<td>400</td>
</tr>
<tr>
<td>( \beta )</td>
<td>1</td>
</tr>
<tr>
<td>( \mathcal{A} )</td>
<td>0.5</td>
</tr>
<tr>
<td>( \mathcal{A}_t )</td>
<td>0.1</td>
</tr>
</tbody>
</table>

**Table 2. Parameter settings**

<table>
<thead>
<tr>
<th>PASSERS-BY</th>
<th>L1</th>
<th>L2</th>
<th>L3</th>
<th>L4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1500</td>
<td>500</td>
<td>750</td>
<td>1250</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>CRIMINALS</th>
<th>L1</th>
<th>L2</th>
<th>L3</th>
<th>L4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>300</td>
<td>100</td>
<td>250</td>
<td>150</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>GUARDIANS</th>
<th>L1</th>
<th>L2</th>
<th>L3</th>
<th>L4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50</td>
<td>150</td>
<td>125</td>
<td>75</td>
</tr>
</tbody>
</table>

**Table 3. Population distribution**

As shown in Figure 1, from the beginning of the simulation many passers-by move away from location 1 (where there are many criminals and few guardians), and towards location 2 (where there are many guardians and few criminals). The guardians follow the opposite pattern: they move away from location 2, and towards location 1. As soon as the number of guardians at location 1 has increased, this location becomes more
attractive for the passers-by. The criminals first move away from location 1, towards location 2, but as soon as the passers-by come back to location 1, a significant part of the criminals stays there. Eventually, all populations stabilise as expected after the mathematical analysis of the model. The total computational time needed to generate the results shown is less than one second. Besides this particular run, runs with different settings of parameters (not determined by criminologists) such as the value of β, η, and Δt have been conducted as well. Thereby similar trends are observed as shown in the graphs in Figure 1.

4.2. Complex attractiveness function

In addition, simulation runs have been generated with more complex attractiveness functions, namely the following:

\[ \beta(L, c, t) = 0.5 * p(L, t) / p + 0.5 * (1 - p(L, t) / p) \]
\[ \beta(L, g, t) = c(L, t) / c \]
\[ \beta(L, p, t) = 1 - c(L, t) / c \]

Again, the parameters shown in Table 2 and 3 have been used. The simulation results are shown in Figure 2. The figure shows the same trends (namely an equilibrium) as
have been observed before, except that the precise distribution of the various agent types is slightly different.

5. An agent-based model

In this section the agent-based model is defined and simulation results thereof are presented. Hereby, the same variable names are used as shown in Table 1. For the agent-based model, the following algorithm is used (implemented in C++):

1. initialise all agents on locations
2. for each time step repeat the following
   a. calculate the density of each type of agent $p(L, t)$, $c(L, t)$, $g(L, t)$ at all locations and communicate it to all agents.
   b. each agent calculates the attractiveness of a location depending on its type (passers-by, criminals, and guardians) for all locations using the following formulae (i.e. similar to those used in the population-based model):

   \[
   \beta(L, c, t) = \frac{p(L, t)}{p} \quad \text{for criminals}
   \]
   \[
   \beta(L, g, t) = \frac{c(L, t)}{c} \quad \text{for guardians}
   \]
   \[
   \beta(L, p, t) = \frac{g(L, t)}{g} \quad \text{for passers-by}
   \]
c. $\eta$% of the agents of each type is selected at random to decide whether the agent moves to a new location or stay at the old one.

d. the selected agents move to a location with a probability proportional to the attractiveness of the specific location (i.e. a selected agent has a higher probability of moving to a relative attractive location than to a non-attractive one).

Figure 3. Agent-based model - simulation results with simple function

Figure 4. Agent-based model - simulation results with complex function
5.1. Simple attractiveness function
The results using this agent-based model with the same parameters as the population based model with simple attractiveness function are shown in Figure 3. The figure shows the averages over 100 runs of the agent based model. Hereby, the agent-based model requires a total computation time of 16.39 seconds. It can be seen that the trends and even the number of agents at the various locations are very closely related. A maximum deviation between the number of agents of around 2% is seen. These differences are the result of the fact that agents can only move as a whole, whereas in the population based model real numbers are used to represent the densities of agents.

5.2. Complex attractiveness function
The results using the more complex attractiveness function with the same parameter settings as used in Section 4.2 are shown in Figure 4. The results are in accordance with those of the population-based model.

6. Formal evaluation
In this section, a number of dynamic properties of the displacement of crime are formalised in the Temporal Trace Language TTL [4], and checked against the simulation traces. This predicate logical temporal language supports formal specification and analysis of dynamic properties, covering both qualitative and quantitative aspects. TTL is built on atoms referring to states of the world, time points and traces, i.e. trajectories of states over time. In addition, dynamic properties are temporal statements that can be formulated with respect to traces based on the state ontology Ont in the following manner. Given a trace γ over state ontology Ont, the state in γ at time point t is denoted by state(γ, t). These states can be related to state properties via the formally defined satisfaction relation denoted by the infix predicate |=, comparable to the Holds-predicate in the Situation Calculus: state(γ, t) |= p denotes that state property p holds in trace γ at time t. Based on these statements, dynamic properties can be formulated in a formal manner in a sorted first-order predicate logic, using quantifiers over time and traces and the usual first-order logical connectives such as ¬, ∧, ∨, ⇒, ∀, ∃. A dedicated software environment has been developed for TTL, featuring both a Property Editor for building and editing TTL properties and a Checking Tool that enables formal verification of such properties against a set of (simulated or empirical) traces.

For the current domain, a number of hypotheses have been expressed as dynamic properties in TTL. For example, consider the following dynamic property (P1a), which expresses that the number of criminals at a certain location is persistent.

Pl(Criminals) - Stable number of criminals at locations
There is a time point t such that for each time point t1 and t2 after t and for all locations l, if at t1 there are x criminals at location l and at t2 there are x2 criminals at location l, then the difference between x and x2 is smaller than 2% of the total amount of criminals.

\[ \forall t: \text{TIME} \ \forall t1, t2: \text{TIME} \ \forall l: \text{LOCATION} \ \forall x, x1: \text{REAL} \\
[ t1 > t \ & \ t2 > t \ & \ \\
\text{state}(\gamma, t1) \ |= \text{agents_of_type_at_location}(x, \text{criminal}, l) \ & \ \\
\text{state}(\gamma, t2) \ |= \text{agents_of_type_of_location}(x2, \text{criminal}, l) \ & \ \\
\Rightarrow \text{abs}(x-x2) \leq c^\alpha/100] \]
This property (as well as the properties below) has been checked against the traces generated by both simulation models. In particular, they have been checked against four traces: trace1 (i.e., the population-based trace that was shown in Section 4), trace2 (which is an average trace over 100 simulation runs of the agent-based model of Section 5), trace3 (i.e., the population-based trace based on the complex attractiveness function), and trace4 (an average trace over 100 simulation runs of the agent-based model based on the complex attractiveness function). Some results of this check are shown in Table 4. It was found, among others, that for an $\alpha$ of 1.0 (i.e., 1%) stabilisation of criminals occurs at time point 35 in trace1, at time point 65 in trace2, at t.p. 51 in trace3, and at t.p. 54 in trace4 (see first column). Similar properties have been checked for passers-by and guardians. Thus, in all traces eventually a stable situation occurs, but the moment at which this occurs is a bit later in the agent-based traces. This is due to the fact that the agent-based model works with natural numbers instead of real numbers, which causes a rounding error (as explained in the Section 5.1).

**Table 4. Checking results of property P1.**

<table>
<thead>
<tr>
<th></th>
<th>Criminals</th>
<th>Passer-by</th>
<th>Guardian</th>
</tr>
</thead>
<tbody>
<tr>
<td>trace1</td>
<td>35</td>
<td>38</td>
<td>28</td>
</tr>
<tr>
<td>trace2</td>
<td>65</td>
<td>56</td>
<td>50</td>
</tr>
<tr>
<td>trace3</td>
<td>51</td>
<td>41</td>
<td>68</td>
</tr>
<tr>
<td>trace4</td>
<td>54</td>
<td>47</td>
<td>76</td>
</tr>
</tbody>
</table>

Besides checking whether the number of agents is persistent per location, also other properties can be verified. For example, it can be checked what the point of equilibrium is. To analyse this, properties like the following have been established:

**P2 - Equal percentage of different agents per location**

For each location $l$, for the three different agent types, the number of agents of that type at the location divided by the overall population of that agent type is the same, namely $r$.

$\forall l: \text{location} \exists r: \text{REAL} \forall x_1, x_2, x_3: \text{real}$

\[
\begin{align*}
\text{state}(\gamma, \text{last_time}) &= \text{agents}_\text{of_type_at_location}(x_1, \text{criminal}, l) \& \\
\text{state}(\gamma, \text{last_time}) &= \text{agents}_\text{of_type_at_location}(x_2, \text{passer-by}, l) \& \\
\text{state}(\gamma, \text{last_time}) &= \text{agents}_\text{of_type_at_location}(x_3, \text{guardian}, l) \\
\Rightarrow r &= x_1/c_1 + x_2/p_2 + x_3/g_3 
\end{align*}
\]

For a $\beta$ of 0.01 this property indeed turned out to be true. Table 5 indicates the values for $r$ that were found for the different locations, for all four traces. Note the small differences between trace 1 and 2, which is due to the rounding error mentioned above.

**Table 5. Checking results of property P2.**

<table>
<thead>
<tr>
<th></th>
<th>Location 1</th>
<th>Location 2</th>
<th>Location 3</th>
<th>Location 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>trace1</td>
<td>0.29</td>
<td>0.21</td>
<td>0.27</td>
<td>0.23</td>
</tr>
<tr>
<td>trace2</td>
<td>0.31</td>
<td>0.21</td>
<td>0.27</td>
<td>0.21</td>
</tr>
<tr>
<td>trace3</td>
<td>0.25</td>
<td>0.25</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>trace4</td>
<td>0.25</td>
<td>0.25</td>
<td>0.25</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Finally, a number of properties have been specified to investigate whether the spread of agents of a certain kind over the locations is equal (illustrated here for criminals):
P3(Criminals) - Equal spread of criminals over locations

There is a time point \( t \) such that for all time points \( t' \) after \( t \) for all locations \( l \), the amount of criminals at \( t \) is within a range of \( \delta \) of the total amount of criminals \( c \) divided by the number of locations \( NL \).

\[ \exists t: \text{TIME} \land \forall t': \text{TIME} \land \forall l: \text{location} \land \forall x: \text{real} \\
[t > t' \land \text{state}(t', t) \Rightarrow \text{agents\_of\_type\_at\_location}(x, \text{criminal}, l)] \\
\Rightarrow c/NL = x/c^\delta \]

As was already clear from the table above, this property generally does not hold, since the agents do not equally spread over the locations. The property only holds for a very high \( \delta \). In addition to the checks mentioned above, these properties have been checked against a number of other simulation traces under different parameter settings. Due to space limitations, the results are not shown here. All in all, these checks pointed out that in all of the cases roughly the same pattern was found. For all traces, eventually the numbers of agents of the different groups (e.g., criminals, passers-by and guardians) at the different locations more or less stabilise. Moreover, per location, eventually the same percentage of the overall population is present for the three different agent types. Finally, it turns out that the agents (per type) are not really spread equally over the locations, but this depends very much on the initial distribution.

7. Discussion

In this paper two models have been introduced to investigate the criminological phenomenon of the displacement of crime. Hereby, a population-based model has been introduced as well as an agent-based model. These models have been presented in a generic format to allow for an investigation of a variety of different functions representing aspects such as the attractiveness of locations. Using mathematical analysis, and confirmed by simulation results, the population-based model was shown to end up in an equilibrium for one variant of the model. The parameter settings for these simulations have been determined in cooperation with criminologists. The simulation results for the agent-based model using the same parameter settings show an identical trend to the population-based model except for some minor deviations that can be attributed to the fact that the agent-based model is discrete, as confirmed by the formal evaluation. The computation time of the populations-based model was shown to be much lower than the computation time of the agent-based model.

Note that the results reported in this paper are not completely in accordance with the results reported in [3]. In the results using an agent-based model reported in that paper, cyclic patterns were observed whereby there is a continuous movement of so called hot-spots (i.e. places where a lot of crime takes place). As already stated before, this paper shows that the population of agents at the various locations stabilises over time. The difference can be attributed to the fact that in [3] all agents decide where to move to based upon the attractiveness of locations, whereas in the case of the models presented in this paper only a subset of the agents move. The results can however be reproduced using the model presented in this paper as well by using an \( \eta = 1 \) and \( \Delta t = 1 \) (see the Appendix [17], Figure C and D). Determining what settings are most realistic in real life is future work.

The idea that population-based models approximate agent-based models for larger populations is indeed confirmed by the simulation results reported in this paper. Future work is to introduce a general framework to make a comparison between the models possible. Furthermore, in future work, also agent-based models will be studied where
the agents have bounded rationality (e.g., are able to sense just their local surroundings and to communicate with a limited number of other agents).

References

An Agent-Based Framework to Support Crime Prevention

Tibor Bosse and Charlotte Gerritsen

Abstract. An important research topic within Environmental Criminology is the analysis of the spatio-temporal dynamics of crime. Some of the main challenges in this area are the prediction and prevention of criminal hot spots. This paper presents an agent-based framework that is able to address such challenges. The framework exploits simulation techniques to compare different strategies for guardian movement in terms of their efficiency (low costs) and effectiveness (high prevention rate). In addition, by automated checks, more detailed properties of the different strategies can be studied. As a result, the framework can be used as a tool to assist researchers in their theory building, and potentially also policy makers in their decision making. To illustrate the approach, a number of strategies for guardian movement are compared, and the results are discussed.

1. Introduction

Within the field of Environmental Criminology, the analysis of the displacement of crime is one of the main research interests [8, 13, 18]. Certain types of crime typically cluster around specific locations in a city, such as busy shopping streets (in case of pickpocketing) or deserted railway stations (in case of assault). Such locations with a high concentration of criminal activities are usually called criminal hot spots. However, these hot spots are not always persistent over longer time periods. A number of factors are known to cause displacement of hot spots from one location to another. For instance, introducing television screens in a railway station may decrease crime rates [8, 13, 18]. This dynamic nature of criminal hot spots makes them a popular topic of scientific research. For example, typical questions that are studied in Environmental Criminology are: Where and when do criminal hot spots emerge? How long do they persist? And how can they be prevented? The classical approach to investigate these kinds of questions is to collect large numbers of empirical data (e.g. from crime report databases), and to use analysis techniques to identify trends in these data [16]. However, a drawback of this approach is that it focuses on past displacement patterns, which does not guarantee that future patterns will be similar.

As an alternative, for a number of years, criminologists have joined forces with researchers from Computer Science and Artificial Intelligence, to explore the benefits of (Agent Based) Social Simulation to investigate crime displacement. Thus, the perspective taken in these approaches is to use a simulated environment to predict dynamics of crime displacement in the future, rather than to analyse past dynamics. Since simulation permits the analyst to perform scalable social “experiments” without much effort, it turns out to be particularly appropriate to analyse phenomena within the criminological domain. Indeed, in recent years, several papers have successfully tackled criminological questions using Social Simulation [1, 3, 7, 11, 12, 15, 17].
As a follow up of that success, the current paper proposes an agent-based framework to support crime prevention. This framework consists of two main components, namely an agent-based simulation model for crime displacement, and a formal analysis method to investigate (simulation) traces in more detail. As such, it extends the existing literature in two ways. First, the simulation model allows the analyst to define different strategies for guardian movement, which makes it a test bed to compare strategies against each other. Second, the use of automated formal techniques enables the analyst to analyse large numbers of (simulation and empirical) traces in limited time.

The paper is organised as follows. Section 2 reviews existing approaches that aim at studying crime displacement by means of Artificial Intelligence techniques, and positions the current paper. In Section 3, the basic simulation model for crime displacement is presented. Next, in Section 4, a number of crime prevention strategies are introduced that can be used by the guardian agents in the simulation model. Section 5 illustrates the working of this model by means of simulations, and shows how the different strategies perform in different circumstances. Section 6 presents and illustrates the formal analysis method to investigate simulation traces in more detail. Section 7 concludes the paper with a summary and a discussion about future work.

2. Related Work

Over the last decade, various computational modelling approaches have been applied to the domain of crime displacement. A shared element within all of these approaches is that the displacement processes is studied as the result of the interaction between three types of agents: criminals, guardians and passers-by. This choice is mainly inspired by the Routine Activity Theory in Criminology [8], which basically states that crime occurs when a motivated offender encounters a suitable target, while no efficient guardian is present. However, despite this common underlying principle, there is a large variation in the modelling techniques that are used. Some authors apply agent-based modelling [1, 3, 7, 17], whereas others use population-based modelling [3], cellular automata [12, 15], different spatial analysis techniques [11], or evolutionary computing techniques [17]. Due to space limitations, we will not provide a complete comparison, but an overview is given in [14].

In addition to the differences in modelling techniques, the papers mentioned above also show differences in the specific goals they try to achieve. While some authors try to develop simulation models of crime displacement in existing cities, which can be directly related to real world data (e.g., [15]), others deliberately abstract from empirical information (e.g., [3]). The idea behind the latter perspective is that the simulation environment is used as an analytical tool, mainly used by researchers and policy makers, to shed more light on the process under investigation, and perhaps improve existing policies (e.g., for surveillance) on the long run [10]. Also, some authors take an intermediate point of view (e.g., [11]). They initially build their simulation model to study the phenomenon per se, but define its basic concepts such that it can be directly connected to empirical data, if these become available.

This intermediate perspective is also taken in the current paper. More specifically, it proposes a simulation model that can be used to compare different strategies in guardian movement in terms of their efficiency and effectiveness, combined with a formal

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1 In this paper we focus explicitly on assault, although the model is sufficiently generic to study several other types of crime as well.
analysis method to study detailed properties of the simulations. Like other approaches in
the literature, the simulation model distinguishes three types of agents (criminals,
guardians, and passers-by). To make a comparison of strategies possible, the
behavioural rules for criminals and passers-by are almost completely re-used from
existing approaches (in particular [3]), but the behaviour of the guardians is variable. A
preliminary investigation [2] pointed out that there are several possibilities to improve
existing guardian movement strategies. Whilst most currently used strategies are
reactive (i.e., guardians move to a location after many crimes have been committed
there), also anticipatory strategies (i.e., guardians move to a location as soon as they
expect that many crimes will be committed there) and hybrid strategies (i.e.,
combinations of reactive and anticipatory strategies) have a strong potential. The current
paper compares a number of these strategies in terms of their efficiency (what are the
costs?) and effectiveness (how many crimes are prevented?). This approach
distinguishes the current paper from most approaches in the literature, which mainly
simulate existing strategies instead of novel strategies. A welcome exception is [17], but
this paper addresses short term strategies (i.e., patrol routes) rather than long term
(surveillance investment) strategies.

Another element that distinguishes the current paper from existing approaches is the
use of formal techniques to analyse simulation traces (see Section 6). This idea is
similar to the approach taken in [1], which also addresses verification of dynamic
properties of simulation traces. A difference is however that that paper addresses
properties related to the spatial patterns of displacement, whereas we here focus on
efficiency and effectiveness.

3. Simulation Model

This section introduces the simulation model for crime displacement processes, inspired
by [2, 3]. Note that agent groups are modelled in terms of their density, i.e., at a global,
population-based level, not an individual level. This choice was made on the basis of
[3], which demonstrates that, to study crime displacement, population-based agent
modelling can be a computationally cheap alternative for individual-based (stochastic)
agent modelling, while still approximating the same results. Section 3.1 introduces the
main aspects of the model and their relations. Section 3.2 provides the formalisation of
the model.

3.1 Crime Displacement

As mentioned in the introduction, each large city usually contains a number of *hot spots*, i.e., locations where most of the crimes occur [9, 18]. Such locations may vary
from railway stations to shopping malls. These hot spots usually have several things in
common, among which the presence of many passers-by (which makes the location
attractive for criminals) and the lack of adequate surveillance. However, after a while
the situation often changes: the criminal activities shift to another location. This may be
caused by improved surveillance systems (such as cameras) at that location, by an
increased number of police officers, or because the police changed their policy.

Another important factor in explaining crime displacement is the *reputation* of
specific locations in a city [13]. This reputation may be a cause of crime displacement,
as well as an effect. For example, a location that is known for its high crime rates
usually attracts police officers [9], whereas most citizens will be more likely to avoid it
As a result, the amount of criminal activity at such a location will decrease, which affects its reputation again.

To summarise, in order to model the process of crime displacement, several aspects are important. First, one should have information about the total number of agents in the different groups involved, i.e., the number of criminals, number of guardians, and number of passers-by. Next, it is assumed that the world (or city) that is addressed can be represented in terms of a number of different locations. It is important to know how many agents of each type are present at each location: the density of criminals, guardians, and passers-by. Furthermore, to describe the movement of the different agents from one location to another, information about the reputation (or attractiveness) of the locations is needed. This attractiveness is different for each type of agent. For example, passers-by like locations where it is safe, e.g., locations where some guardians are present and no criminals. On the other hand, guardians are attracted by places where a lot of criminals are present, and criminals like locations where there are many passers-by and no guardians. Finally, to be able to represent the idea of hot spots, the number of assaults per location is modelled. The idea is that more assaults take place at locations where there are many criminals and passers-by, and few guardians, cf. the Routine Activity Theory by [8].

The interaction between the concepts introduced above is visualised in Figure 1. This figure depicts the influences between the different groups at one location. Here, the circles denote the concepts that were mentioned above in italics, and the arrows indicate influences between concepts (influences on attractiveness have been drawn using dotted arrows to enhance readability).

![Diagram](https://example.com/diagram.png)

**Figure 1.** Interaction between criminals, guardians, and passers-by

---

2 Note that Figure 1 does not depict the influence of some basic attractiveness of a location for certain groups (i.e., an attractiveness that is independent of the distribution of agents at the location). For the sake of readability, this notion has been left out of the picture, but it often plays a role in reality. For instance, locations like a railway station will be visited more often by passers-by than other locations, simply because people need to go there to reach their desired destination. Therefore, the notion of basic attractiveness will also be considered in this paper.
3.2 Formalisation

To formalise the concepts that were introduced above (in italics), a number of variable names are used; see Table 1.

<table>
<thead>
<tr>
<th>Name</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>Total number of criminals</td>
</tr>
<tr>
<td>$g$</td>
<td>Total number of guardians</td>
</tr>
<tr>
<td>$p$</td>
<td>Total number of passers by</td>
</tr>
<tr>
<td>$c(L, t)$</td>
<td>Density of criminals at location $L$ at time $t$</td>
</tr>
<tr>
<td>$g(L, t)$</td>
<td>Density of guardians at location $L$ at time $t$</td>
</tr>
<tr>
<td>$p(L, t)$</td>
<td>Density of passers by at location $L$ at time $t$</td>
</tr>
<tr>
<td>$\beta(L, a, t)$</td>
<td>Attractiveness of location $L$ at time $t$ for type $a$ agents: $c$ (criminals), $p$ (passers-by), or $g$ (guardians)</td>
</tr>
<tr>
<td>$\beta_{ba}(L, a, t)$</td>
<td>Basic attractiveness of location $L$ at time $t$ for type $a$ agents: $c$ (criminals), $p$ (passers-by), or $g$ (guardians)</td>
</tr>
<tr>
<td>$\text{assault}_\text{rate}(L, t)$</td>
<td>Number of assaults taking place at location $L$ per time unit</td>
</tr>
</tbody>
</table>

Next, a number of equations are introduced to represent the causal relations between these variables. Most of these ideas are taken over from [2] (and [3]). First, the calculation of the number of agents at a location is done by determining the movement of agents that takes place based on the attractiveness of the location. For example, for criminals, the following formula is used:

\[
c(L, t + \Delta t) = c(L, t) + \eta \cdot (\beta(L, c, t) \cdot c - c(L, t)) \Delta t
\]

This expresses that the density $c(L, t + \Delta t)$ of criminals at location $L$ on time $t + \Delta t$ is equal to the density of criminals at the location at time $t$ plus a constant $\eta$ (expressing the rate at which criminals move per time unit) times the movement of criminals from $t$ to $t+\Delta t$ from and to location $L$, multiplied by $\Delta t$. Here, the movement of criminals is calculated by multiplying the relative attractiveness $\beta(L, c, t)$ of the location (compared to the other locations) for criminals with the total number $c$ of criminals (which is constant). From this, the density of criminals at the location at $t$ is subtracted, resulting in the change of the number of criminals for this location. For passers-by, a similar formula is used:

\[
p(L, t + \Delta t) = p(L, t) + \eta \cdot (\beta(L, p, t) \cdot p - p(L, t)) \Delta t
\]

However, as opposed to [3], the movement of the guardians is not (necessarily) modelled using this formula. Instead, to represent guardian movement, different strategies can be filled in (see Section 4).

Next, the attractiveness of a location can be expressed based on some form of reputation of the location for the respective type of agents. Several variants of a reputation concept can be used. The only constraint is that it is assumed to be normalised such that the total over the locations equals 1. An example of a simple reputation concept is based on the densities of agents, as expressed below.

\[
\beta(L, c, t) = \frac{p(L, t)}{p} \quad \text{for criminals}
\]
\[
\beta(L, p, t) = \frac{g(L, t)}{g} \quad \text{for passers-by}
\]

This expresses that criminals are more attracted to locations with higher densities of passers-by, whereas passers-by are attracted more to locations with higher densities of guardians. This definition of reputation is used in [3]. Although this definition is simple, which makes the model well suited for mathematical analysis, it is not very realistic. To
solve this problem, in this paper, the following linear combinations of densities are used:

\[
\begin{align*}
\beta(L, c, t) &= \beta_c \cdot \left(1 - \frac{g(L, t)}{g}\right) + \beta_p \cdot \frac{p(L, t)}{p} + \beta_{bat} \cdot \text{but}(L, c, t) \\
\beta(L, p, t) &= \beta_p \cdot \left(1 - \frac{c(L, t)}{c}\right) + \beta_g \cdot \frac{g(L, t)}{g} + \beta_{bat} \cdot \text{but}(L, p, t)
\end{align*}
\]

This expresses that criminals are repelled by guardians, but attracted by passers-by. Similarly, passers-by are repelled by criminals, but may be attracted by guardians. In addition, for each type of agent some basic attractiveness can be defined. The weight factors \(\beta_c\), which may also be 0, indicate the relative importance of each aspect. Again, for the guardians no formula is specified, since this depends on the guardian movement strategy that is selected.

Finally, to measure the assaults that take place per time unit, also different variants of formulae can be used (see [3]). In this paper, the following is used:

\[
\text{assault_rate}(L, t) = \max(c(L, t), p(L, t)) \cdot \gamma \cdot g(L, t), \theta
\]

Here, the assault rate at a location at time \(t\) is calculated as the product of the densities of criminals and passers-by, minus the product of the guardian density and a constant \(\gamma\), which represents the capacity of guardians to avoid an assault. The motivation behind this is that the maximum amount of assaults that can take place at a location is \(c(L, t) \cdot p(L, t)\), but that this number can be reduced by the effectiveness of the guardians (which corresponds exactly to the Routine Activity Theory). In principle, this assault rate can become less than 0 (the guardians can have a higher capacity to stop assaults than the criminals have to commit them); therefore the maximum can be taken of 0 and the outcome described above. Based on this assault rate, the total (cumulative) amount of assaults that take place at a location is calculated as:

\[
\text{total_assaults}(L, t + \Delta t) = \text{total_assaults}(L, t) + \text{assault_rate}(L, t) \cdot \Delta t
\]

Although the model is presented here in a purely mathematical notation, its actual implementation has been done in the agent-based modelling environment LEADSTO [5]. This environment is well suited for the current purposes, since it integrates both qualitative, logical aspects and quantitative, numerical aspects, and is compatible with the TTL checker tool for verification of logical formulae [4] (see Section 6). Its basic building blocks are executable rules of the format \(\alpha \rightarrow \beta\), which indicates that state property \(\alpha\) leads to state property \(\beta\). Here, \(\alpha\) and \(\beta\) can be (conjunctions of) logical and numerical predicates.

4. Guardian Strategies

This section extends the model presented above with the possibility to specify crime prevention strategies. The idea is that, in addition to the rules that govern the behaviour of criminals and passers-by, the behaviour of the guardians can be specified by selecting one out of multiple strategies.

In current practice, the crime prevention policies that are applied by law enforcement agencies are - mostly - reactive [6, 9]. That is, these agencies often only increase the level of guardianship at locations where crimes have been committed in the past. As a

---

3 Note that these attractiveness formulae are not normalised yet. To ensure that the values stay between 0 and 1, each attractiveness value is divided by the sum of the values over all locations. Moreover, the influence by agents from the same group is not considered.

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consequence, this often means that such a decision is made too late, because the damage has already been done. Instead, we hypothesise that a more anticipatory strategy (e.g., a strategy to invest in more guardians at locations where one predicts that a hot spot will emerge) may be more efficient.

To investigate this, we present multiple strategies for movement of guardians (varying from reactive to anticipatory, and combinations of the two), and analyse for a number of scenarios which strategy yields the lowest assault rate. Most of the selected strategies are based on [2], in which they were already tested against three initial scenarios. In this paper, ten different strategies are explored in total (see also Table 2):

- The first strategy is a baseline strategy. In this case guardians do not move at all. Their density at the different locations remains stable over time.
- The second strategy (called reactive 1) states that the amount of guardians that move to a new location is proportional to the density of criminals at that location.
- The third strategy (reactive 2) states that the amount of guardians that move to a new location is proportional to the percentage of the assaults that have recently taken place at that location.
- The fourth strategy (reactive 3) states that the amount of guardians that move to a new location is proportional to the percentage of all assaults that have taken place so far at that location.
- The fifth strategy (reactive 4) states that the amount of guardians that move to a new location is proportional to the density of passers-by at that location.
- In the sixth strategy (anticipate 1), the amount of guardians that move to a new location is proportional to the density of criminals they expect that location to have in the future.
- In the seventh strategy (anticipate 2), the amount of guardians that move to a new location is proportional to the density of passers-by they expect that location to have in the future.
- In the eighth strategy (anticipate 3), the amount of guardians that move to a new location is proportional to the amount of assaults they expect that will take place at that location in the future. This predicted amount of assaults is approximated by taking the average of the expected densities of criminals and passers-by.
- The ninth strategy (hybrid 1) is a combination of reactive 2 and anticipate 2. Here, the amount of guardians that move to a new location is the average of the amounts of guardians determined by those two strategies.
- The tenth strategy (hybrid 2) is a combination of reactive 3 and anticipate 2. Here, the amount of guardians that move to a new location is the average of the amounts of guardians determined by those two strategies.

To formalise these strategies, the following formula is used:

\[ g(L, t + \Delta t) = g(L, t) + \eta \cdot \sigma(L, t) \cdot \Delta t \]

This formula is similar to the formulae used for criminals and passers-by, but the amount of guardians that move per time unit is indicated by the factor \( \sigma(L, t) \), which depends on the chosen strategy. The different definitions of \( \sigma \) are shown in Table 2. For example, for the baseline strategy, \( \sigma(L, t)=0 \), which means that the amount of guardians at time point \( t+\Delta t \) is equal to the amount at \( t \).

In the strategies reactive 2 and 3, the average assault rate \( aar(L,t) \) and the total average assault rate \( taar(L,t) \) are calculated by:

\[ aar(L,t) = \text{assault rate}(L,t) / \sum_{X} \text{assault rate}(X,t) \]
\[ taar(L,t) = \text{total assaults}(L,t) / \sum_{X} \text{total assaults}(X,t) \]
As can be seen from Table 2, the idea of the anticipation strategies it that the guardians use formulae that are similar to the formulae for movement of criminals and passers-by to predict how they will move in the near future. Obviously, these predictions will not be 100% correct, since they do not consider interaction between the different types of agents, but our assumption is that they may be useful means to develop an efficient strategy.

Furthermore, different values can be taken for the parameter $\eta_L$ in the anticipation strategies. This parameter represents the speed by which the criminals and/or passers-by move in the predicted scenario (or, in other words, the distance in the future for which the prediction is made). For example, by taking a very high value for $\eta_L$ in the anticipate 1 strategy, guardians get the tendency to move to locations that are predicted to have a high density of criminals in the very far future.

As mentioned earlier, the idea of having different strategies is that the analyst can test which one performs best. A question is however how to define the notion of a ‘good’ strategy. One possibility (see also [2]) is to look at effectiveness, e.g., by considering the strategy that results in the lowest crime rates (total_assaults) as the best. However, in reality also the costs of crime prevention play an important role. Various mechanisms to improve guardianship exist (e.g., adding and moving security guards, burglar alarms, fencing, lighting), but they all involve costs [6]. Thus, instead of only measuring the amount of assaults that result from each strategy, in the calculation of the ‘best’ strategy one should compensate for the costs involved. For this reason, the following formula (which was not included in [2]) has been added:

$$total\_costs(t+\Delta t) = total\_costs(t) + \sum_{X \in \sigma} \sigma(X,t) \cdot \varepsilon \Delta t$$

This formula counts the total costs that are spent on crime prevention (for all locations involved) during the simulation. Parameter $\varepsilon$ represents the guardian movement costs per time step.

5. Simulations

To compare the different guardian movement strategies, a large number of simulations have been performed, using different parameter settings. In this section, five of the most interesting scenarios and their results are discussed. These five scenarios are described in Section 5.1. Two example simulation traces are presented in detail in Section 5.2, and the overall results of the simulations are discussed in Section 5.3.
5.1 Scenarios

For the simulations described in this paper, five different scenarios were used. Each of the scenarios involves four locations (called L1, L2, L3, and L4). To enforce the development of hot spots, in each scenario the basic attractiveness of the locations for passers-by changes over time, resulting in different phases. Some scenarios consist of two different phases, whereas others consist of five phases. The scenarios and their consecutive phases are shown in Table 3. Here, for each phase, the cells indicate the basic attractiveness values of the different locations.

**Table 3. Simulation Scenarios**

<table>
<thead>
<tr>
<th>scenario</th>
<th>phase 1</th>
<th>phase 2</th>
<th>phase 3</th>
<th>phase 4</th>
<th>phase 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>L1=0.25</td>
<td>L1=0.7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>L2=0.25</td>
<td>L2=0.1</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>L3=0.25</td>
<td>L3=0.1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>L4=0.25</td>
<td>L4=0.1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>L1=0.25</td>
<td>L1=0.25</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>L2=0.25</td>
<td>L2=0.25</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>L3=0.25</td>
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<tr>
<td></td>
<td>L4=0.25</td>
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</tr>
<tr>
<td>3</td>
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<td>L1=0.1</td>
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<tr>
<td></td>
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<td>L2=0.7</td>
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<tr>
<td></td>
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<tr>
<td>4</td>
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<td>L1=0.3</td>
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<tr>
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<td>L4=0.1</td>
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<td>L4=0.1</td>
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</tr>
<tr>
<td>5</td>
<td>L1=0.25</td>
<td>L1=0.4</td>
<td>L1=0.1</td>
<td>L1=0.1</td>
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<tr>
<td></td>
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<td>L2=0.4</td>
<td>L2=0.4</td>
<td>L2=0.1</td>
</tr>
<tr>
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<td>L3=0.25</td>
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<td>L3=0.4</td>
<td>L3=0.4</td>
<td>L3=0.4</td>
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<tr>
<td></td>
<td>L4=0.25</td>
<td>L4=0.1</td>
<td>L4=0.1</td>
<td>L4=0.1</td>
<td>L4=0.4</td>
</tr>
</tbody>
</table>

To give an example, in scenario 2, all locations start out with the same basic attractiveness for passers-by (i.e., \( ba(L1,p,0) = ba(L2,p,0) = ba(L3,p,0) = ba(L4,p,0) = 0.25 \)). After a while (in phase 2, which starts at time point 25), the basic attractiveness of location L1 is temporarily increased (i.e., \( ba(L1,p,25) = 0.7 \), \( ba(L2,p,25) = ba(L3,p,25) = ba(L4,p,25) = 0.1 \)). This may be caused, for example, because a circus is coming to town. Some time later (phase 3), the circus moves away to another city and the basic attractiveness of all location becomes equal again (0.25).

Other parameter settings were chosen as follows (for all scenarios). The total population consists of 800 criminals, 400 guardians, and 4000 passers-by. Initially, these agents are distributed equally over the four locations (i.e., each location contains 200 criminals, 100 guardians, and 1000 passers-by). The attractiveness settings for criminals are \( \beta_c = 0.4 \), \( \beta_p = 0.6 \), \( \beta_r = 0 \) (i.e., the biggest part of their behaviour is determined by the desire to assault, and a smaller part by the desire to not get caught, whereas no basic attractiveness plays a role for them). The attractiveness settings for passers-by are \( \beta_c = 0.1 \), \( \beta_p = 0.1 \), \( \beta_r = 0.8 \) (to enforce a high influence of basic attractiveness). In all strategies, the speed factors (\( \eta \)) are set to 0.5 for all agents. Furthermore, \( \eta = 10 \) in all anticipate and hybrid strategies. Only for anticipate 3 two

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4 All scenarios and parameter settings were chosen after a number of brainstorm sessions with experts in criminology. Although the exact numbers do not correspond to actual empirical data, they were selected in such a way that the resulting patterns are realistic. In addition to the simulation experiments presented in this paper, a large number of other experiments have been performed as well (with different ratios, #locations, and so on), but the overall trends were similar to the results shown here.
variants are shown: one with \( \eta_2=10 \) (called *anticipate 3a* from now on) and one with \( \eta_2=30 \) (called *anticipate 3b*), which turned out to improve the results for that strategy. The value of \( \gamma \) (the capacity of guardians to avoid an assault) is set to 1950, and the movement cost parameter \( \varepsilon \) is set to 250 (since these values produced most realistic patterns). Finally, \( \Delta t=0.1 \), and the total simulation time is 100 steps.

### 5.2 Example Simulation Traces

To illustrate the types of patterns that result from the simulations, the dynamics of two example simulation traces are shown in detail. Both traces address scenario 2.

<table>
<thead>
<tr>
<th>Baseline Strategy</th>
<th>Anticipate 2 Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="#" alt="Baseline Strategy" /></td>
<td><img src="#" alt="Anticipate 2 Strategy" /></td>
</tr>
</tbody>
</table>

#### Total Assaults

![Total Assaults](#)

#### Amount of Criminals

![Amount of Criminals](#)

#### Amount of Guardians

![Amount of Guardians](#)

#### Amount of Passers-by

![Amount of Passers-by](#)

**Figure 2.** Simulation Traces for Scenario 2

In trace 1 (the left column of Figure 2), the results of the *baseline* strategy are depicted graphically. The results of the *anticipate 2* strategy are shown in trace 2 (the
right column of Figure 2). This figure shows, from top to bottom, the total (cumulative) number of assaults, and the amount of criminals, guardians, and passers-by at the different locations. In all graphs, the solid red line indicates location L1 and the dashed green line shows the results for locations L2, L3 and L4 (these locations have the exact same values, and are therefore shown as one single line). The dotted blue line in the upper graphs shows the total amount of assaults, i.e., the sum of the assaults at the four locations.

As can be seen in Figure 2, over the first 25 time points, there is no difference between both strategies: there is a stable situation, with an equal distribution of criminals over the four locations (and therefore also an equal distribution of passers-by and guardians). As a result, the amount of assaults increases linearly (and slowly). However, after time point 25 (the moment that the circus comes to location L1), this location becomes very attractive for passers-by (as can be seen in the lower graphs, for both strategies). The difference between the two strategies is that anticipate 2 immediately anticipates on this changed situation: many guardians are sent to L1. This causes many criminals to move away from that location. Instead, the baseline strategy does not result in any movement of guardians. As a result, many criminals can move to L1, and commit assaults without being stopped.

Although this is only one example scenario, it clearly illustrates the difference between (in this case, baseline and anticipation) strategies. Guardians that act according to a reactive strategy mainly show behaviour that is similar to the anticipation strategy, but are a bit more ‘hesitating’ in their actions. A more complete comparison between the strategies is shown in the next section.

### 5.3 Simulation Results

All 10 strategies introduced in Section 4 have been tested against the five scenarios (among others). Figure 3 shows for each strategy what was the total amounts of assaults (where the numbers of the five scenarios are accumulated).

![Figure 3. Total amounts of assaults](image)

As this figure shows, the crime rates differ significantly between the 10 strategies. The strategies reactive 1 and anticipate 1 (which react to the current or predicted amount of criminals, respectively) do not seem to add much compared to the baseline strategy. All other strategies seem to be beneficial. The lowest assault rates are found for the strategies reactive 2 (which reacts to recent assault), anticipate 2 (which anticipates on expected passers-by) and hybrid 1 (which is a combination of these two
strategies). Interestingly, the hybrid 1 strategy is even more effective than the two strategies of which it was composed separately. Apparently, this strategy exploits the useful properties of both strategies.

As explained earlier, the effectiveness of the strategies must be weighed against their efficiency. For this reason, the total costs of each strategy have also been counted, see Figure 4. This figure shows that, although very effective, the reactive 2 and hybrid 1 strategies are not very cost-efficient. For obvious reasons, the baseline strategy does not involve any costs5.

![Figure 4. Total amounts of costs](image)

When we want to weigh the costs of a particular strategy \( S \) against its benefits, also a notion of benefits is needed. This is defined as the amount of assaults that are prevented by strategy \( S \), compared to a situation in which the baseline strategy is used:

\[
\text{total prevented assaults}(t) = \sum_{X=1}^{X} (\text{total assaults}_\text{baseline}(X,t) - \text{total assaults}_S(X,t))
\]

Based on this definition, the cost-benefit ratio of a particular strategy \( S \) in a given scenario is defined as follows (where \( lt \) is the last time point of the scenario).

\[
\text{ratio}_S = \frac{\text{total costs}_S(lt)}{\text{total prevented assaults}_S(lt)}
\]

An overview of the cost-benefit ratios for the different strategies is provided in Figure 5. Here, the baseline strategy is omitted because it is used as a benchmark for the other strategies. It becomes clear that, for the given scenarios, the anticipatory strategies have the lowest cost-benefit ratio, whereas the reactive strategies have the highest ratio.

In practice, the question which strategy is ‘best’ of course depends on the preferences of the law enforcement agency (e.g., how much money can be invested?). However, the above results have illustrated that the presented simulation model can give insight in the costs and benefits of different strategies, which may provide useful information for policy makers.

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5 Note that only the costs for moving guardians are counted; for simplicity, variable costs for maintenance of existing guardianship (e.g., depending on their job description, or work times) are ignored.
6. Formal Analysis Method

As illustrated above, simulation may be a useful instrument in that it enables the researcher to perform large numbers of (pseudo-) experiments to explore certain questions. For example, based on the simulation results, it could be concluded that anticipatory strategies are usually more cost-efficient than reactive strategies. However, these results do not provide much explanation on individual cases; e.g., they do not shed any light on why some strategy performs better in one scenario than in another. To answer such questions, it is needed to study individual simulation traces in detail. However, if the number of traces is large, is not trivial to filter out those traces that are worth investigating.

For this purpose, this section introduces an automated approach to classify the simulation traces based on their behavioural patterns. The main idea is that different traces are distinguished by checking certain dynamic properties against them, cf. [4]. These dynamic properties are formalised in terms of logical statements, and are automatically verified against simulation traces. A typical example of a property that may be checked is “whether the amount of assaults is equally spread over the different locations”. By running a large number of simulations and verifying such properties against the resulting simulation traces, the modeller can separate the interesting cases from the less interesting ones within limited time. As a next step, the interesting simulation traces can be inspected by hand, to explain the unexpected behaviour.

For the presented model of crime displacement, a number of such dynamic properties have been formalised in the Temporal Trace Language (TTL) [4]. This predicate logical language supports formal specification and analysis of dynamic properties, covering both qualitative and quantitative aspects. TTL is built on atoms referring to states of the world, time points and traces, i.e. trajectories of states over time. In addition, dynamic properties are temporal statements that can be formulated with respect to traces based on the state ontology Ont in the following manner. Given a trace γ over state ontology Ont, the state in γ at time point t is denoted by state(γ, t). These states can be related to state properties via the formally defined satisfaction relation denoted by the infix predicate |=, comparable to the Holds-predicate in the Situation Calculus: state(γ, t) |= p denotes that state property p holds in trace γ at time t. Based on these statements, dynamic properties can be formulated in a formal manner in a sorted first-order
predicate logic, using quantifiers over time and traces and the usual first-order logical connectives such as ¬, ∧, ∨, ⇒, ∀, ∃. A special software environment has been developed for TTL, featuring both a Property Editor for building TTL properties and a Checking Tool that enables formal verification of such properties against (simulated or empirical) traces. This tool can also import simulation traces produced by the LEADSTO environment [5]. For more details about TTL, including complexity results, see [4].

Various dynamic properties for the model have been formalised in TTL. Below, a number of them are introduced, both in semi-formal and in informal notation (note that they are all defined for a given trace \( γ \), a time interval between \( t_b \) and \( t_e \), and an integer \( n \)):

**P1 - Maximal Adaptation Time**

For each time point \( t \) (between \( t_b \) and \( t_e \)) on which the basic attractiveness of some location \( l \) increases, it takes at most \( n \) time points until the assault rate is back to the level it had before \( t \).

\[
P1(γ; T R A C E, t_b, t_e; T I M E, n; I N T E G E R) = \\
\forall t; T I M E \ \forall x_1, x_2, y_1; R E A L \ \forall l; L O C A T I O N \\
[t_b ≤ t & t ≤ t_e & \\
state(γ, t) |= has_basic_attractiveness_for(l, passes_by, x_1) & \\
state(γ, t+1) |= has_basic_attractiveness_for(l, passes_by, x_2) & \\
x_2 > x_1 & state(γ, t) |= assault_rate_at(l, y_1)] \\
⇒ [\exists d; I N T E G E R \ \exists y_2; R E A L \\
state(γ, t+d) |= assault_rate_at(l, y_2) & 0 < d ≤ n & y_2 ≤ y_1 & \\
existence; R E A L \ \forall t_2; T I M E (t < t_2 & t_2 < t+d & \\
state(γ, t_2) |= assault_rate_at(l, y_3) ⇒ y_3 ≥ y_1)]
\]

This property can be used to find out how long it takes until a particular hot spot has disappeared. This can be useful in cases where policy makers have strict constraints in the amount of time they allow a hot spot to persist. The results of checking this property against the simulated traces are displayed in Figure 6. This figure shows, e.g., that reactive 2 is very quick in eliminating the hot spot in scenario 1, but is much slower (also compared to the other strategies) in scenario 4, involving multiple hot spots.

![Figure 6. Maximal adaptation times](image_url)
**P2 - Equal Spread of Assaults**

For each time point $t$ (between $t_b$ and $t_e$), the assault rate at the largest hot spot is at most $n\%$ of the assault rate at the smallest hot spot.

\[
P2(\gamma:TRACE, t_b, t_e:TIME, n:INTEGER) =
\forall t:TIME \forall x_1, x_2:REAL \forall l_1, l_2:LOCATION

[t_b \leq t \land t \leq t_e \land

is\_largest\_hot\_spot\_at(l_1, t, \gamma) \land

is\_smallest\_hot\_spot\_at(l_2, t, \gamma) \land

state(\gamma, t) |= assault\_rate\_at(l_1, x_1) \land

state(\gamma, t) |= assault\_rate\_at(l_2, x_2)] \Rightarrow x_1 \leq (1+n/100)*x_2
\]

In this formula, is\_largest\_hot\_spot\_at is an abbreviation, which is formalised as follows (and similarly for is\_smallest\_hot\_spot\_at):

\[
is\_largest\_hot\_spot\_at(l_1:LOCATION, t:TIME, \gamma:TRACE) =

\exists i:REAL state(\gamma, t) |= assault\_rate\_at(l_1, i) \land

\forall i_2:LOCATION \forall i_2:REAL

[\text{state}(\gamma, t) |= assault\_rate\_at(l_2, i_2) \Rightarrow i_2 \leq i]
\]

Property P2 can be used to select strategies that enforce small differences between the crime rates of different locations. Due to space limitations, the checking results are not shown here, but they were comparable with the results shown in Figure 3. I.e., the strategies reactive 2, anticipate 2, and hybrid 1 yielded the smallest differences (with anticipate 2 as absolute winner: this strategy always kept the difference in assault rates below 10).

Finally, property P3 can be used to find out the maximal rate at which guardians move for each scenario. Again, the results are not shown here, but they were comparable with Figure 4 (although with small differences, since ‘maximal’ is not the same as ‘total’).

**P3 - Maximal Movement Rate**

For each time point $t$ (between $t_b$ and $t_e$), the total movement rate is at most $n$.

\[
P3(\gamma:TRACE, t_b, t_e:TIME, n:INTEGER) =
\forall t:TIME \forall x:REAL

[t_b \leq t \land t \leq t_e \land state(\gamma, t) |= total\_movement\_rate(x) \Rightarrow x \leq n]
\]

To conclude, the formal method presented here can be used as an addition to the simulation model, in order to find more detailed properties of individual simulation traces that can not (easily) be verified by looking at the simulation runs. Moreover, besides simulation traces, the checker tool can also import traces that are constructed from empirical data, if these are available. This way, the method can be exploited to analyse existing displacement data.

**7. Discussion**

Computational modelling of crime displacement is a hot topic since a number of years. Various modelling approaches have been taken, with different perspectives and goals [1, 3, 7, 11, 12, 15, 17]. The current paper extends the state-of-the-art by proposing an agent-based framework to analyse displacement processes. The framework consists of a simulation model to compare crime prevention strategies, and a formal method to analyse detailed properties of the strategies. Using this framework, various crime prevention strategies were analysed under different circumstances. The results suggest
that a hybrid strategy is most effective, but that purely anticipatory strategies are more
cost-efficient.

Despite these encouraging results, they should not be over-generalised. They were achieved in simulations that used several specific parameters and simplifying assumptions. For example, in practice it is not always feasible to determine exact numbers for the attractiveness of a location for certain groups, or for the amount of assaults that are performed. Nevertheless, the results of such simulations may be useful input for policy makers, in order to elaborate their thoughts about efficient strategies (cf. [10]), as also confirmed by our colleagues in the Department of Criminology. In that light, an advantage of comparing multiple strategies is that one can select the most feasible one in a particular case.

As a first step to support such policy making, for future work it is planned to incorporate the presented simulation model within an intelligent support agent. Such an agent will use input from databases on citizen activities and crime records, in order to provide the police advice on how to handle in a given situation. Another further extension that will be addressed is the use of more intelligent strategies for the criminals. Although the currently used formula approximates (for large numbers) the behaviour of criminals in the real world, it would be interesting to explore how a more sophisticated formula would influence the results.

References


Part V –
Conclusions and Future Work

The main goal of the research presented in this thesis was to explore how approaches from the area of Artificial Intelligence (AI) can be used to make progress in (both theoretical and applied) research in the criminological domain. As pointed out in this thesis, various approaches from AI turned out to be beneficial for this purpose, among which population-based modelling and simulation, agent-based modelling and simulation, and mathematical modelling. To apply these approaches different modelling environments have been exploited, including LEADSTO, TTL, Matlab, Microsoft Excel and C++. To check whether the models behaved as expected both logical verification and empirical validation have been performed.

The mentioned approaches turned out to be beneficial because they could be used to gain more insights in criminological phenomena (that were not clear based on just an informal theory), without actually having to experiment with these phenomena in the real world. Further, simulation and modelling approaches turned out to be useful to test theories and to perform thought experiments. For example, what would happen if we used a different strategy for guardian surveillance? Or what would be the impact of altering school classes on the overall level of delinquency? The answers to these questions are not easy to find based on common sense reasoning; moreover, it is difficult to test this in reality because of ethical issues or costs (both time and money).

Below, the research presented in each of the parts of this thesis is discussed and possible directions for future work are mentioned for each part.

Modelling Biological and Cognitive Aspects of Violent Behaviour

Part II of the thesis is devoted to research on a rather detailed level of abstraction. We investigated biological, psychological and social aspects of three types of aggressive offenders, namely the violent psychopath, people diagnosed with an antisocial personality disorder and people diagnosed with an intermittent explosive disorder. The research presented is a first step in the development of an agent-based modelling approach for aggressive behaviour in which these aspects are integrated in one dynamical system. As shown in the different chapters, the approach provides the analyst more insight in how three specific types of violent behaviour (violent psychopath, intermittent explosive disorder, antisocial personality disorder) may result from an interaction between biological, cognitive and social factors.

We do acknowledge the fact that the model presented in this part is very specific and does not provide an approach that is directly applicable to all types of offenders. As mentioned earlier, different types of deviant behaviour are caused by different aspects. These aspects can be mainly biological, like the factors presented in this part, but there are also types of deviant behaviour that are mainly caused by, for instance, environmental influences. Thus, to be able to simulate these types of influences, the model would have to be significantly extended. Further, we also do not claim that the model is complete and includes all possible factors that lead to violent behaviour, but we included some main factors. So the model should be seen as a first explorative step to get insight in the underlying processes, but it is not expected to be fully accurate.
For future work the current model could be extended with more internal states with possibly more complex dynamics. The aspects that were used in the current model could be investigated in a more detailed manner (e.g. the notion of empathy, which is currently represented as one single state, could be represented using a complete dynamic submodel). Another possibility of future research is to extend the social/environmental aspects of the model. Among the factors that could be added are attractiveness and reputations of locations, informal social control by passers-by, and different surveillance strategies (e.g., random, planning-based, or area-based) of the guardians, as used in part IV. Such extensions of the model with both more details and more factors would make the model more generic. Also, in case appropriate empirical data would be available (e.g., from psychology or neuroscience), an interesting challenge would be to try to validate the model against these data.

**Modelling Social Learning of Juvenile Delinquency**

In Part III of this thesis, the aim is to develop and validate a model to simulate social learning of delinquent behaviour among adolescents. The model presented here simulates the development of delinquent behaviour of pupils within a class room. According to the literature, many aspects can have a contribution to this behaviour, among which some personality aspects, as well as characteristics of the school, parents and peers. We have developed different variants of the model to see which (combinations of) factors have the highest predictive value. The choice for these model variants was based on empirical data gathered in a longitudinal study by researchers from the NSCR. After the most relevant factors were determined and the model was validated, we performed ‘what-if experiments’ to see what would happen if we altered some situational parameters. For example, we investigated whether different class mates could decrease or increase a person’s level of delinquency.

The research presented in this part led to several interesting insights, such as the tentative conclusion that school has an important influence but that class composition seems to have a relative low influence. Nevertheless, a difficulty with this approach is that it is not possible to predict behaviour with 100% certainty. This is an important fact to take into account when one wants to draw conclusions from the simulation. For example, once there exists a model that predicts with an accuracy of 76, what does this mean? If in 76% of the cases the prediction is accurate, this is a lot more than in the situation when a random guess is made (then there would be a 50% accuracy rate). However, when planning to make political decisions based on the model, 76% is perhaps not much. Hence, we are planning to further develop the model so we can obtain an even higher accuracy rate. One factor to consider is the possibility that part of the respondents could be life course persistent (see introduction part III) as opposed to adolescence limited offenders, which would mean that their delinquent behaviour is merely explained by other factors than social learning. Furthermore, the conclusion of Chapter III.3 is that the influence of school class composition does not appear to be very high. In future research we would like to examine this in more detail. Do we have the correct data to draw this conclusion in general? And what is the influence of other well-known contributors like school and parents or new media like Internet, videogames and music clips? Investigating these issues is also part of future work.
Modelling Spatio-Temporal Dynamics of Crime

Part IV focuses also on social aspects of crime, but here the focus is on the spatio-temporal dynamics. As explained in detail in the introduction of part IV, the Routine Activity Theory states that crime will occur when a motivated offender encounters a suitable target and no capable guardian is present. Obviously, this theory is quite broad and can be applied from different perspectives and to different domains. For example, within this thesis some aspects of the motivated offender have been investigated in part II. Here the causes for a certain desire are examined in detail, which in turn determine the level of motivation of the offender.

In this part we study the Routine Activity Theory (and in particular its consequences) in the domain of environmental criminology, to be more specific in the context of the spatio-temporal dynamics of crime. Criminal activities tend to concentrate around certain hot spots and these hot spots tend to shift over time. The dynamics of this process are the main research topic in this part. The method to investigate these questions was, again, (agent-based) simulation. First we studied a virtual society with static targets (e.g. houses) and dynamic guardians and offenders. In later research we also considered dynamic targets (e.g. passers by). We investigated the influence of different surveillance strategies of the guardians on the total amount of assaults and eventually we have also taken costs into account.

This research was fruitful because by using simulation we found a number of insights that were not obvious before. For instance, the use of ‘pure’ hot spot patrolling turned out to work better than area-based hot spot patrolling, unless the number of guardians is very high. Furthermore, concerning the allocation of guardians over different areas of the city, hybrid strategies combining reactive and anticipatory strategies turned out to be most effective when it comes to reducing the total amount of assaults. However, when costs are taken into account in the model we see that anticipatory strategies have the best cost-benefit ratio.

Nevertheless, also in this research, we are aware of the fact that we abstract from reality, and did not use empirical data. Instead, the main goal of this research is to help researchers in their theory building. As such, the presented models can be used as an analytical tool to see how certain aspects influence the spatio-temporal dynamics of crime. We are not aiming at a directly available tool for policy makers yet, but expect that in the future such models may become elaborate enough to indeed help policy makers make their decisions. Moreover, the model was set up in such a way that it is capable to deal with empirical data when it becomes available.

Also in this part, there are several possibilities to extend the model in the future. For example, it would be interesting to add ‘informal guardians’. These are guardians that are not officially delegated with the task to guard, but also have an important influence on crime. One can think of passers by as an example. If there are lots of people of the street, these people have an effect on the number of assaults just by their presence. In addition, also their reaction to criminal events is important. For example, if people encourage deviant behaviour, this will be performed more often, but when they condemn it this also will have an effect. One step further, also the influence of passers by on each other will be part of future research. In particular, the so-called ‘bystander effect’ could be studied: if someone watches a fight and does not do anything about that, then the persons standing next to this person might think that they should not interfere either. Other interesting directions for future work are making the offenders behave
more intelligently and creating some differences in the reaction time between the different types of agents.

Comparison of Papers

When comparing all papers presented in this thesis with each other, various commonalities and differences can be found. In Table 1 an overview is presented of elements that are present in this thesis. Here the different chapters are represented in the columns and the rows represent important aspects. The first row indicates what types of theories from the literature were used as inspiration for the chapter. Here, BL = Literature from Biology, RC = Rational Choice Theory, SL = Social Learning Theory, RAT = Routine Activity Theory. The next row indicates whether the chapter focuses on biological, cognitive, or social aspects of delinquent behaviour. The third row indicates which modelling approach was used (ABM = Agent Based Modelling, PBM = Population Based Modelling, MM = Mathematical Modelling). The fourth row indicates which modelling environment was used in the chapter. The abbreviations in that row stand for the following: LT = LEADSTO, ML = MatLab, C = C++, EX = Microsoft Excel, TTL = Temporal Trace Language. The fifth row indicates whether logical verification was applied and the last row indicates whether empirical validation was performed.

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Table 1. Overview of the aspects addressed in the chapters

The table illustrates that the chapters were inspired by different theories, address different aspects of criminology (biological, cognitive and social), and exploited different modelling approaches and environments. Nevertheless, they all have in common that they took criminological literature as a basis, and formalised this literature in order to create computational models that can provide more insight in the dynamics of the process under investigation.

Moreover, when comparing the three parts of this thesis one can notice that each of them has a slightly different methodological aim, which can be summarised as combining, predicting and analysing. In Part II theories from multiple disciplines (namely biology and psychology) are combined, thereby creating an integrated perspective on different factors underlying violent behaviour. In Part III, the main goal
is to exploit existing literature to develop a model that is able to predict the development of juvenile delinquency, and Part IV mainly attempts to analyse the consequences of the Routine Activity Theory under particular circumstances. We found that each of these methodologies requires some specific preconditions that need to be met. For combining different theories, clearly, at least two theories need to be available, which are described at a sufficient level of detail. Predicting dynamics is only possible when a validated model and sufficient (empirical) data are available. Finally, to analyse the consequences of a theory one needs to have a theory, but no other theory or (empirical) data are needed. For future research, these considerations can be explored in more detail. For example, an interesting challenge is to develop a general framework that prescribes which methodology can be applied in which situation.

Based on the research presented in this thesis we can thus conclude that AI approaches, and in particular modelling and simulation approaches, can be useful in the domain of criminology. Although the research presented is just a first step in a long process, some interesting results have been revealed already. Extending the research with the plans presented above could enhance the opportunities for understanding and fighting crime even further.
Affiliations Co-authors

The research presented in this thesis has been performed by multiple authors. The names of the authors are mentioned in alphabetical order, indicating that each of the authors has contributed an equal share to the work involved. Below you can find the affiliations of the co-authors.

Tibor Bosse is an assistant professor at the department of Artificial Intelligence at VU University Amsterdam. His main research interests are agent based modelling, cognitive modelling and ambient intelligence.

Henk Elffers is a senior researcher at the Netherlands Institute for the Study of Crime and Law Enforcement. His main research interests are quality of criminological data and the rational choice theory with respect to the behaviour of potential offenders, specifically in spatial context. Moreover, he is a professor Empirical Study of Law Enforcement at the Law Faculty of VU University Amsterdam.

Mark Hoogendoorn is an assistant professor at the department of Artificial Intelligence at VU University Amsterdam. His main research interests are agent based modelling, organisational modelling and ambient intelligence.

S. Waqar Jaffry is a Ph.D. student at the department of Artificial Intelligence at VU University Amsterdam. His main research interests are multi agent systems, free and open source software technologies, and technology in education.

Michel C.A. Klein is an assistant professor at the department of Artificial Intelligence at VU University Amsterdam. His main research interest is intelligent support for humans, also called human ambience.

Jan Treur is a full professor at the department of Artificial Intelligence at VU University Amsterdam. His main research interests include ambient intelligence, agent systems, cognitive modelling, biological modelling, organisational modelling, philosophy of mind, verification and validation, and logical foundations.

Frank M. Weerman is a senior researcher at the Netherlands Institute for the Study of Crime and Law Enforcement. His main research interests are juvenile delinquency and the role of peers and social networks therein.
Samenvatting
Op Heterdaad Betrap:
Criminaliteit Onderzoeken middels Agentgebaseerde Simulatie

Crimineel gedrag is een belangrijk aspect van het dagelijks leven. Iedereen is in principe in staat crimineel gedrag te tonen en iedereen is een mogelijk slachtoffer van crimineel gedrag. Dit maakt onderzoek naar crimineel gedrag en criminaliteit maatschappelijk relevant. Vragen over wanneer we bepaald gedrag tonen en hoe we zulk gedrag kunnen voorkomen zijn hierbij van belang.

Onderzoek naar crimineel gedrag heeft van oudsher verschillende uitgangspunten. Zowel biologie, psychologie als sociologie kan hierbij een rol spelen. Het is belangrijk je te realiseren dat crimineel gedrag meestal wordt veroorzaakt door een combinatie van verschillende factoren. Iemand kan bijvoorbeeld een hoog testosteronniveau hebben, wat tot agressief gedrag kan leiden (een biologische factor), maar er moet dan ook een gelegenheid zijn om dit gedrag te uiten (een sociale factor). Om crimineel gedrag te begrijpen, verklaren en eventueel te voorspellen is het nodig meer inzicht te verkrijgen in zowel biologische, psychologische als sociale aspecten van menselijk gedrag.

In de afgelopen decennia zijn er veel successen geboekt in verschillende wetenschappelijke disciplines met betrekking tot onderzoek naar menselijk gedrag. Binnen de sociale wetenschappen ontstaan er bijvoorbeeld steeds verfijndere theorieën over menselijk gedrag. Zo heeft men steeds meer kennis over de invloed van sociale netwerken op delinquent gedrag bij adolescenten. Ook op het gebied van neurowetenschappen hebben onlangs veel ontwikkelingen plaatsgevonden. De mogelijkheid om hersenscans uit te voeren en te observeren wat er in de hersenen gebeurt onder verschillende omstandigheden is een resultaat van recente ontwikkelingen en kan behulpzaam zijn bij het begrijpen van (crimineel) gedrag.

Het groeiende inzicht in dergelijke processen die een rol spelen bij crimineel gedrag opent de mogelijkheid om deze processen te formaliseren en te bestuderen met behulp van technieken uit de informatica. Dit is de belangrijkste uitdaging van dit proefschrift. Het inzicht vergroten in waarom en wanneer bepaalde criminele acties worden uitgeoefend is belangrijk om maatregelen te ontwikkelen om dergelijke acties voortaan te helpen voorkomen of in ieder geval te verminderen. In dit proefschrift wordt dan ook aandacht besteed aan de vraag hoe processen die leiden tot crimineel gedrag bestudeerd kunnen worden met behulp van technieken vanuit het gebied van informatica, en in het bijzonder de kunstmatige intelligentie, zoals het ontwikkelen van computermodellen en het uitvoeren van simulaties.

Om deze vraag te beantwoorden worden technieken als wiskundig modelleren, agenten populatiegebaseerd modelleren, simulatie en formele verificatie gebruikt. Tevens wordt aangetoond dat de toepassing van deze technieken op criminologische theorieën nuttig kan zijn bij het begrijpen van de processen die een rol spelen bij crimineel gedrag.
Acknowledgments

When I started writing the acknowledgment section I soon filled more pages than are present in the conclusion of the thesis. Since this would be a bit awkward I started over, but it indicates that I am very grateful to many people.

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