Integrated Modeling of Cognitive Agents in Socio-Technical Systems

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Abstract. Modern socio-technical systems are characterized by high structural and behavioral complexities, which impede understanding and modeling of such systems. In particular, reciprocal relations between diverse local system processes that determine global system dynamics are not well understood. In this paper we focus on the problem of establishing relations between cognitive processes that determine social dynamics of an actor in a socio-technical system. To address this problem, a formal, integrated, agent-based modeling approach is proposed. The approach defines relations between such cognitive processes as belief revision, trust dynamics, generation and development of feelings and emotions, and decision making. Furthermore, it is described how the behavior of an agent is related to its cognitive dynamics. Preliminary experimental results for the approach are discussed in the paper.

1 Introduction

Modern socio-technical systems are characterized by high structural and behavioral complexities. These systems include hardware and software components with a varying degree of autonomy and complexity that interact with and enable interaction between humans. Among highly autonomous technical components are ambient devices, dedicated to assist humans in the achievement of their objectives (e.g., to maintain well-being, to complete a task in time). Modeling and analysis of modern socio-technical systems is a challenging task. Models of such systems should account for complexity of human behavior, heterogeneity and autonomous behavior of technical systems, and interaction among all system actors. Both quantitative and qualitative system properties are required to be modeled. Furthermore, relations between diverse processes and states of different aggregation levels of a system should be defined explicitly. Whereas the last modeling requirement has been addressed in Systems Biology and Physics of Complex Systems with some success, it constitutes a serious issue for modeling complex socio-technical systems. In this paper we focus on the problem of establishing reciprocal relations between cognitive processes that determine decision making and social behavior of an intelligent, autonomous actor in a socio-technical system. According to the literature [3, 4] among these cognitive processes are perception, belief revision, learning, trust dynamics, generation and development of feelings and emotions. The author is not aware of any existing formal cognitive model that incorporates all these processes and defines relations between them. To address this gap, a formal approach for integrated modeling of cognitive agents in complex socio-technical systems is proposed in this paper. The proposed agent model is generic and can be used for modeling both human and artificial actors. In contrast to other existing agent models (cf [6]), cognitive states of agents (e.g., beliefs) used in decision-making are assumed to be emotionally loaded, which agrees with many research findings, e.g., [2, 3]. Furthermore, many modeling principles from Neuroscience were used in the proposed model, similar to the ones described in [2, 8].

The paper is organized as follows. A formal logic-based modeling language is introduced in Section 2. In Section 3 modeling externally observable behavior of an agent is described. Integrated modeling of cognitive dynamics of an agent is considered in Section 4. Some preliminary experimental results are provided in Section 5. Section 6 concludes the paper.

2 Modeling language

To specify dynamic properties of a system, the order-sorted predicate logic-based language called LEADSTO is used [1]. Dynamics in LEADSTO is represented as evolution of states over time. A state is characterised by a set of properties that do or do not hold at a certain point in time. To specify state properties for system components, ontologies are used which are defined by a number of sorts, sorted constants, variables, functions and predicates (i.e., a signature). For every system component A a number of ontologies can be distinguished: the ontologies IntOnt(A), InOnt(A), OutOnt(A), and ExtOnt(A) are used to express respectively internal, input, output and external state properties of the component A. Input ontologies contain elements for describing perceptions of an agent from the external world, whereas output ontologies describe actions and communications of agents. For a given ontology Ont, the propositional language signature consisting of all state ground atoms based on Ont is denoted by APROP(Ont). State properties are specified based on such ontology by propositions that can be made (using conjunction, negation, disjunction, implication) from the ground atoms. Then, a *state* S is an indication of which atomic state properties are true and which are false: S: APROP(Ont) $\to$ {true, false}.

LEADSTO enables modelling of direct temporal dependencies between two state properties in successive states, also called *dynamic properties*. A specification of dynamic properties in LEADSTO is executable and can be depicted graphically. The format is defined as follows. Let α and β be state properties of the form 'conjunction of atoms or negations of atoms', and e, f, g, h non-negative real numbers. In the LEADSTO language the notation $\alpha \twoheadrightarrow_{e,\ f,\ g,\ h} \beta$ 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. When $e = f = 0$ and $g = h = 1$, called standard time parameters, we shall write $\alpha \twoheadrightarrow \beta$. To indicate the type of a state property in a LEADSTO property we shall use prefixes input(c), internal(c) and output(c), where c is the name of a component. Consider an example dynamic property:

input(A)|observation_result(fire) ↠ output(A)| performed(runs_away_from_fire)

Informally, this example expresses that if agent A observes fire during 1 time unit, then after that A will run away from the fire during 1 time unit.

In addition, LEADSTO allows expressing mathematical operations, e.g. has_value(x, v) $\twoheadrightarrow_{e, f, g, h}$ has_value(x, v*0.25).

3 Modeling externally observable behavior of an agent

From the external perspective the behavior of an agent is specified by dynamic relations between agent's input and output states, corresponding to interaction with other agents and with the environment. An agent perceives information by observation and communication and generates output in the form of communication or actions. Communications are formalized as speech acts (e.g., inform, request, order) using the function communicated_from_to(ag1:AGENT, ag2:AGENT, s_act:SPEECH_ACT, message:STATPROP), here agent ag1 communicates speech act s_act to agent ag2 with the content message. Agents may communicate information about the environment (e.g., accessibility of locations), about other agents (e.g., their location, physical and mental condition), about plans to act (in form of informative messages, recommendations and orders to follow). A value from the interval [0, 1] is associated with each speech act of type inform, indicating the agent's confidence in the communicated message. For this the function has_confidence(message:STATPROP, v:VALUE) is used. For example, the communication of agent a1 to agent a2 about the accessibility of a location l1 from location l2 with confidence 0.9 is formalized as communicated_from_to(a1, a2, inform, has_confidence(is_accessible_from(l1, l2), 0.9)). Note that information about the dynamics of events and processes (e.g., about the rate of change) may be also communicated by agents. For example, the communication about the rate of change of smoke concentration with confidence 0.7 is formalized as communicated_from_to(a1, a2, inform, has_confidence(has_rate_of_change(smoke_concentration, 0.0001), 0.7)).

Now observations of agents are considered. Passive and active observations are distinguished. In contrast to a passive observation, an active observation is always concerned with the agent's initiative. An active observation of a state property p by an agent in the environment is formalized using the function to_be_observed(p: STATE_PROPERTY). Observation results are provided to the agent's input using the function observation_result(p: STATE_PROPERTY), which indicates whether p holds in the environment or for another agent. Similarly to an informative communication, a degree of confidence is associated with an observation, as some observations may not be completely reliable (e.g., due to smoke).

Actions of an agent generated at its output are specified by performed(act:ACTION).

4 Modeling cognitive dynamics of an agent

From the internal perspective the behavior of an agent is characterized by causal relations between internal states of the agent, based on which externally observable behavioral patterns are generated. The externally observable behavior of an agent is determined largely by the agent's decision making. The process of decision making of an agent in a highly dynamic environment (e.g., during an evacuation) is influenced by information provided to the agent by diverse information sources. The higher the agent's trust in an information source the more the agent is apt to accept information from this source and to adapt its beliefs using this information. It is often claimed that most beliefs of a human agent are emotionally loaded [2, 3]; also trust of an agent to a source and decision making are influenced by feelings and emotions. In the following the agent's internal states and cognitive processes, and relations between them are described in detail.

4.1 Feelings and emotions

It is often claimed that cognitive states of a human, such as sensory or other representations induce emotions felt within the human [2, 3]. According to Damasio [2], emotion generation proceeds via a body loop in the following causal chain:

cognitive state → preparation for the induced bodily response → induced bodily response → sensing the bodily response → sensory representation of the bodily response → induced feeling

As a variation, an *as if body loop* uses a direct causal relation as a shortcut in the causal chain: preparation for the induced bodily response → sensory representation of the induced bodily response. The body loop (or as if body loop) is extended to a recursive body loop (or recursive as if body loop) by assuming that the preparation of the bodily response is also affected by the state of feeling the emotion as an additional causal relation: feeling → preparation for the bodily response. Thus, agent emotions are modeled based on reciprocal causation relations between emotion felt and body states, as shown in Fig 1. Within a model of agent's emotions both the bodily response and the feeling are assigned a level or gradation, expressed by a number, which is assumed dynamic. The causal cycle is modeled as a positive feedback loop, triggered by a cognitive state and converging to a certain level of feeling and body state. Here in each round of the cycle the next body state has a level that is affected by both the cognitive state and the level of the feeling state, and the next level of the feeling is based on the level of the body state. Formally causation relations are modeled by LEADSTO properties.

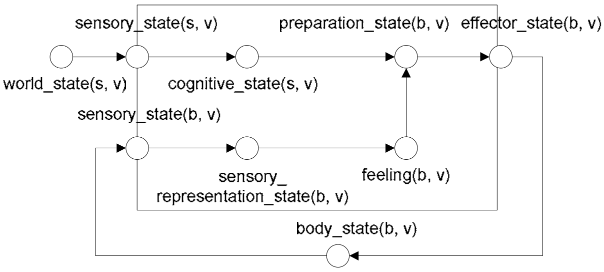


Fig. 1. Body loop induced by a cognitive state; v denotes a real variable, w is a world state and b is a body state

For example, consider a property for generation of a sensory state and for the preparation state update:

output(environment)|world_state(s, v) ↠ input(agent)|sensory_state(s, v)

internal(agent)|(feeling(b, v1) & preparation_state(b, v2)) ↠ internal(agent)|preparation_state(b, func(v1, v2))

Belief, trust, and other cognitive states considered in the agent model induce body loops similar to the one from Fig.1. In the following section, belief and trust states, and relations between them are considered in more detail.

4.2 Beliefs and trust

Beliefs of an agent are time-labeled internal representations created based on communication and observation results received by the agent. Beliefs are specified using the function belief(p:STATPROP, v:VALUE, t:TIME), here p is the content of the belief, v is the degree of confidence of the agent from the interval $[0, 1]$ that the belief is true at the time point t. After obtaining a communication from an information source, the agent creates the belief about the communication of the source. Furthermore, the agent revises its own belief(s) taking into account the communication content. Belief revision is considered further in this section. As beliefs are modeled as emotionally loaded, the confidence value for a belief state is updated continuously in an as if body loop described in section 4.1. From a neurological perspective the existence of a connection from feeling to belief may be also considered plausible, as neurons involved in the belief and in the associated feeling will often be activated simultaneously. Therefore, such a connection from feeling to belief may be developed based on a general Hebbian learning mechanism [5] that strengthens connections between neurons that are activated simultaneously. A formal model based on such a mechanism is described in [8]. Taking this model as a starting point, we extend it by relating beliefs to trust and by a belief update mechanism as described in the following.

In our model *trust* is an emotional attitude of an agent towards an information source (e.g., another human agent, an ambient device) that determines the extent to which information received by the agent from the source influences agent’s belief(s). The amount of trust to a source is represented by a feeling value - a number from the range $[0, 1]$ - which accumulates all experience with the source. The influence of information communicated by an information source s concerning a world state w on the agent ag’s belief is specified by the following property (all variables are universally quantified):

current_time(t) & internal(ag)|(feeling(b2, v2) & body_state_for(b2, accept_from(s)) & feeling(b, v4) & belief(w, v3, t) & body_state_for(b, w)) &
input(ag)|communicated_from_to(s, ag, inform, has_confidence(w, v1))
↠ internal(ag)|belief(w, $v3 + \gamma1 \cdot (g(v1, v2, v3, v4, \beta1, \beta2) - v3) \cdot \Delta t$, $t+\Delta t$),

where $g(a, b, c, d, \beta1, \beta2) = \beta1 \cdot (1-(1-h(a, b, c, \beta2)) \cdot (1-d)) + (1-\beta1) \cdot h(a, b, c, \beta2) \cdot d$ and
$h(x, y, z, \beta) = (1- \beta) \cdot z + \beta \cdot (z + y \cdot (x - z))$

$\gamma1$ determines the speed of the belief update; parameter $\beta1$ in $g(a, b, c, d, \beta1, \beta2)$ determines the agent’s disposition to amplify positive ($\beta1 > 0.5$) or negative ($\beta1 < 0.5$)

experience (i.e., optimistic and pessimistic attitudes); parameter β in $h(x, y, z, \beta)$ determines to which extent the old confidence value is present in the new value.

From this property follows that the less the agent’s trust towards an information source (i.e., feeling for accepting information from the source), the less the effect of communication from this source on the agent’s beliefs. Agent beliefs are updated based on the agent’s own observations in a similar manner. In this case the trust value is interpreted as the agent’s estimation of the reliability of its own observation.

The trust to a source builds up over time based on the agent's experience with the source. In particular, when the agent has a positive (negative) experience with the source, the agent's trust to the source increases (decreases). Currently experiences are restricted to information experiences only. An information experience with a source is evaluated by comparing the information provided by the source with the agent's beliefs about the content of the information provided. The experience is evaluated as positive (negative), when the information provided by the source is confirmed by (disagree with) the agent's beliefs. The emotional content of trust is modeled by an as if body loop. The experience with an information source is accumulated in the feeling state for accepting information from the source. The preparation state in the as if body loop, which determines the value for the feeling state is defined formally as follows:

current_time(t) & internal(ag)|(feeling(b1, v2) & preparation_state(b1, v3) & belief(w, v4, t) &
body_state_for(b1, accept_from(s)) &
input(ag)|communicated_from_to(s, ag, inform, has_confidence(w, v1))
$\twoheadrightarrow$ internal(ag)|preparation_state(b1, $v3+ \gamma 2\cdot (g(v1, v2, v3, v4, \beta 4, \beta 5, \beta 6, \beta 7) - v3) \cdot \Delta t$)

where $g(x, y, z, u, \alpha 1, \alpha 2, \alpha 3, \alpha 4) = \alpha 1\cdot(1 - (1 - h(x, z, u, \alpha 2, \alpha 3, \alpha 4))\cdot(1-y)) + (1-\alpha 1)\cdot h(x, z, u, \alpha 2, \alpha 3, \alpha 4) \cdot y$,
$\alpha 1$ determines the agent’s disposition to amplify positive or negative experience;
$h(x, z, u, \alpha 2, \alpha 3, \alpha 4) = (1-\alpha 2)\cdot z + \alpha 2\cdot e^{r(x, u, \alpha 3, \alpha 4)}$, $\alpha 2$ determines to which extent the old preparation value is taken in the generation of the new preparation value;
$r(x, u, \alpha 3, \alpha 4) = -\alpha 3\cdot\alpha 4\cdot|x - u|$; $\beta 3$ determines the agent’s tolerance to the difference between its own beliefs and information communicated by the source.

As beliefs of an agent change over time, so changes evaluation of experiences and, consequently, the trust to sources. Every time when a trust relation with a source changes, the confidence values of the beliefs influenced by communication from this source are re-evaluated. The belief re-evaluation is done using beliefs about communications and observation received in the past. Note that a communication about a dynamic event is evaluated taking into account the agent’s belief(s) about the form of the dynamics of the event (e.g., expressed by a temporal formula). Furthermore, the more the distance between the communication time point and the evaluation time point, the less the effect of the communication on the current trust value to the source. For example, an agent may receive information about a low concentration of smoke at some location. If the agent knows that the smoke concentration at that location increases over time, then it would expect a higher smoke concentration at the location in the future (according to the communicated information) and evaluate this communication accordingly. The developed re-evaluation procedure is rather elaborated; it is provided in Appendix A with a detailed model description [9].

4.3 Decision making

Agents act according to adopted plans. A *plan* is a (partially) ordered set of actions, required to be done to satisfy agent's desires. Plans are represented as beliefs and can be communicated between agents. For example, a part of plan P1 that specifies for an agent the sequence of locations to walk through {l1, l2, l3} is formalized as belief(follows_after_in(go_to_location_from(l3, l2), go_to_location_from(l2, l1), P1), 1).

Plan descriptions vary in the degree of specificity. Abstract (or partial) plans contain high level actions that can be further refined into more specific actions. Furthermore, alternative ways of refinement of high level actions can be specified. In an evacuation scenario an agent may have several plans how to reach possible exits. These plans may be partial and contain movement actions between significant locations only (such as junction points, locations with elevators, stairs). There could be different paths between two significant positions.

In the model an agent evaluates each plan option using the following criteria:

(1) *Desirability of an option*: to which extent the option brings to the satisfaction of the current desire(s).

(2) *Possibility to realize*: indicates the agent's confidence that the plan option can be realized.

(3) *The amount of effort*: how much effort needs to be invested to realize the option (depends on the skills, knowledge, physical and other agent characteristics).

For each evaluation criterion a constraint(s) may be defined (e.g., in terms of thresholds). If in the evaluation of an action from a plan a violation of a constraint is identified, then the evaluation of the whole option can be ceased and the option is considered as inapplicable.

An agent evaluates options using its beliefs. Furthermore, a change of agent's beliefs about the environment may result into a change of agent's plan options.

The literature [4, 7] confirms that feelings influence the process of evaluation of options. To account for this in our model, an aggregated value based on the evaluated criteria (e.g., a weighed average) for an option is provided as input for an as if body loop as shown in Fig.2.

After all available plan options have been evaluated the agent chooses and commits to the one with the highest feeling value:

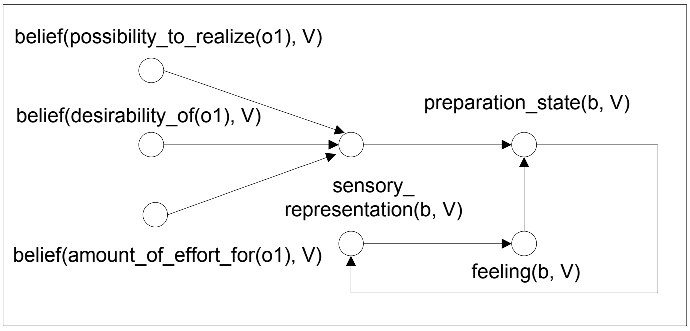


Fig. 2. As if body loop for the evaluation of an option o1; V is a real variable, b is a body state

internal(ag)|(feeling(b, v) & body_state_for(b, plan(p))) & ∀p1:PLAN, b1:BODY_STATE, v1:VALUE [internal(ag)| (feeling(b1, v1) & body_state_for(b1, plan(p1))) → v1 < v]
↠ output(ag)| performed(commit_to(p))

After the agent has committed to a plan, it evaluates all possible refinements of the first action of the plan along the same evaluation criteria as for plans and chooses the one with the highest feeling.

In the literature [4] it is recognized that when a human has a high level of stress close to panic, it uses diverse shortcuts in the evaluation of options. We elaborated a number of such shortcuts, which will be discussed elsewhere.

5 Experiments

The proposed agent model has been applied in a number of variants of a subway evacuation scenario, which is a simplified version of a real incident. In the scenario an explosion occurred in a train situated in an underground tunnel between two stations. The explosion was followed by fire and smoke, which were spreading throughout the tunnel. Because of the blast some doors were damaged, so people were able to escape outside of the train through the formed openings. Most of the people did not have a clear idea what was going on and how to escape. The train driver guided people to exits of the tunnel. Many evacuees had a high trust towards the driver. People propagated available information about paths to exits, accessibility of locations, and danger (smoke, fire) to others. All electronic communication channels with the outside world were broken. Variants of the scenario were considered in which some people possessed ambient devices, which communicated available information to other devices in their range. People were trying to find their way to an exit. In the following we consider how different aspects of this scenario were modeled.

Modeling the environment

The layout of the environment is modeled as a graph-like structure defined by a set of locations (nodes) that agents and passive objects may occupy and a set of edges between pairs of locations. With each edge a measure of distance is associated. Agents and other objects (e.g., smoke, fire) move around, over different locations. Objects in the environment may have certain state attributes. These attributes may change over time, for example, a person may become injured or unconscious or a location may become inaccessible. The dynamics of environmental processes is described by LEADSTO properties. For example, the propagation of smoke through a tunnel is described by the property:

internal(env) | (arrived_at_location_from(smoke, p1, p2) & connected_to_via(p1, p3, e) & p2 ≠ p3 & has_distance(e, d) & has_attribute_value(smoke, speed, v))
$\twoheadrightarrow_{d/v,\, d/v,\, 1,\, 1}$ internal(env) | (arrived_at_location_from(smoke, p3, p1))

Modeling agents

Agents communicate and maintain beliefs about: possible paths to exits; accessibility of locations on these paths; the degree of danger of each location on these paths determined by the amount of smoke and fire; the dynamics of the smoke and fire propagation; the dynamics of accessibility of locations. The creation and update of the beliefs of agents is performed as described in Section 4.2. The correctness and completeness of information about the environment possessed by agents vary depending on their previous knowledge and information acquired during the evacuation. An agent communicates its beliefs to all other agents at its location only when it has a high confidence that this information is correct (≥ 0.75). Agents do not repeat information already communicated. Information is communicated in turns. Agents are socially unrelated and have neutral trust to each other (0.5 initially). The only exception is the train driver agent, who is highly trusted (0.9 initially).

When an agent comes to a location, it updates all its plans (i.e., possible paths to exits) with respect to its current location. In the following it is discussed how plans in the evacuation scenario are evaluated along the criteria proposed in Section 4.3:

(1) Desirability of an option: depends on the agent's beliefs about how close the agent's state will be to the state of being evacuated after the execution of the plan.

(2) Possibility to realize: calculated based on the confidence values of the agent's beliefs about the accessibility of locations in the plan and the degree of danger of each of these locations. These beliefs take into account the agent's representation of the environmental dynamics (e.g., about smoke spreading) and the agent's average speed. Formally, the possibility to realize option p by agent ag is calculated as:

$r = \omega_1 \cdot \Sigma_{v_i \in PS}\, v_i / |PS| + \omega_2 \cdot \Sigma_{e_i \in DS}\, e_i / |DS|$, here ω_1 and ω_2 are weights,

PS = { (v – access_accept)/(1 – access_accept) | ∃l1, l2, l3: LOCATION, t:TIME, av, d:VALUE present_time(t) & current_location(ag, l1) & average_speed(ag, av) & distance_between (d, l1, l2) & internal(ag)| (belief(is_accessible_from(l3, l2), v, t+d/av) & belief(step_of_plan(go_to_location_from(l3, l2), p), 1, t))}

DS = { (danger_accept – v)/danger_accept | ∃l1, l2, l3: LOCATION, t:TIME, av, d:VALUE present_time(t) & current_location(ag, l1) & average_speed(ag, av) & distance_between (d, l1, l3) & internal(ag)|(belief(is_dangerous(l3), v, t+d/av) & belief(step_of_plan(go_to_location_from(l3, l2), p), 1, t))}

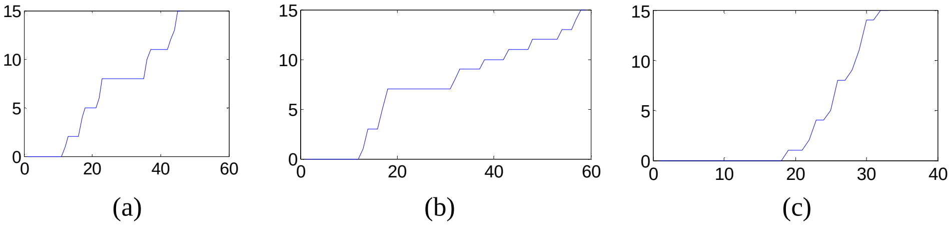
(3) The amount of effort is calculated based on the agent's beliefs about the distance to the exit: $eff_p = 2 \cdot (d-3)/(1+(d-3)^2)$, where d is the number of locations in plan p. The total value for option p is calculated as: $eval_p = \omega_3 \cdot d_p + \omega_4 \cdot r_p + \omega_5 \cdot eff_p$.

In the developed simulation model 15 unrelated heterogeneous agents were specified. The parameters of the agent models were drawn for the uniform distribution on the unit interval. Below some results for three variations of the scenario are given.

Variation 1 (Fig.3a): The driver agent provides information about paths to exits. A part of this information is incorrect. The simulation showed that some agents followed the driver's directions even after the driver's mistake was revealed. Other agents were losing trust to the driver quickly after finding the mistake, and preferred not to use the information regarding paths to exit provided by the driver after that.

Variation 2 (Fig.3b): An agent unknown to other agents possesses complete and correct information about paths to the exits. The agent communicates this information to other agents which it meets. In the simulation a small number of agents used this information and found the way to an exit quickly. Many other agents did not trust the received information and continued searching for an exit themselves.

Variation 3 (Fig.3c): 7 agents use ambient devices able to communicate to other devices (the coverage radius is 3 locations) the same types of information as human agents. A device also exchanges information with its agent-owner. 2 devices are spreading wrong information. In the simulation first many human agents were misguided because of the spread of wrong information. However, the sources of wrong information were rapidly identified by the agents and trust to them decreased rapidly. Then, as can be seen from the graph, using the correct information agents were able to find their way to an exit very quickly.



(a) (b) (c)

Fig. 3. Evacuation of the agents over time in different variants of the scenario; x-axis is time in minutes, y-axis is the number of evacuated agents.

6 Conclusion

In this paper a first step is made towards an integrated approach for modeling and analysis of complex socio-technical systems. Specifically, a formal generic agent model has been proposed with explicitly defined relations between cognitive processes that influence the agent's decision making and behavior. Such relations remain implicit in other existing agent-based models. Similarly to [8], cognitive states in the model are assumed to be emotionally loaded. The model has a high complexity. To address this issue, in the future model abstraction mechanisms will be developed. Furthermore, techniques for establishing relations between local dynamics of agents and global system properties will be developed in the future. The model will be validated in a large-scale case study in the frames of the SOCIONICAL project.

References

1. Bosse, T., Jonker, C.M., Meij, L. van der, and Treur, J., A Language and Environment for Analysis of Dynamics by Simulation. Int. J. of AI Tools, vol. 16, 435-464 (2007)
2. Damasio, A. The Feeling of What Happens. Body and Emotion in the Making of Consciousness. New York: Harcourt Brace (1999)
3. Davidson, R., Scherer, K. R and Goldsmith, H. (eds.) Handbook of Affective Sciences. New York and Oxford: Oxford University (2003)
4. Edland, A., and Svenson, O. Judgment and decision making under time pressure. In O. Svenson, O. and A.J. Maule (eds.), Time Pressure and Stress in Human Judgment and Decision Making. New York: Plenum Press, 27-40 (1993)
5. Hebb, D.O. The Organisation of Behavior. Wiley, New York (1949)
6. Jain L.C. and Nguyen N.T. (eds.) Knowledge Processing and Decision Making in Agent-based Systems. Springer Verlag (2009)
7. Janis, I., and Mann, L. Decision making: A psychological analysis of conflict, choice, and commitment. New York: The Free Press (1977)
8. Memon, Z.A., and Treur, J., Learning to Believe by Feeling: an Agent Model for an Emergent Effect of Feelings on Beliefs. In: Proceedings of the 7th International Symposium on Neural Networks, ISNN'10. Lecture Notes in Computer Science, Springer Verlag (2010)
9. Appendix A. A detailed model description. http://www.few.vu.nl/~sharp/app1.pdf