Abstraction of an Affective-Cognitive Decision Making Model based on Simulated Behaviour and Perception Chains

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Abstract. Employing rich internal agent models of actors in large-scale socio-technical systems often results in scalability issues. The problem addressed in this paper is how to improve computational properties of a complex internal agent model, while preserving its behavioral properties. The problem is addressed for the case of an existing affective-cognitive decision making model instantiated for an emergency scenario. For this internal decision model an abstracted behavioral agent model is obtained, which ensures a substantial increase of the computational efficiency at the cost of approximately 1% behavioural error. The abstraction technique used can be applied to a wide range of internal agent models with loops, for example, involving mutual affective-cognitive interactions.

1 Introduction

Large-scale socio-technical systems are characterized by high structural and behavioral complexities (e.g., emergency response organizations, air traffic management systems). Modeling and analysis of such systems is a challenging task. On the one hand, models of such systems should account for complexity of human behavior, heterogeneity and autonomous behavior of technical systems, and interaction among all system actors. On the other hand, the models should ensure acceptable computational efficiency. Models for large-scale socio-technical systems have been developed in several areas. In the area of Social Physics socio-technical systems are often modeled from a lattice gas perspective by representing the system's actors by particles interacting through forces and fields [5]. Although such models are highly scalable, they ignore (complex) internal dynamics underlying the decision making of actors, and, thus, cannot be used in cases for which rich cognitive and affective representations are required (e.g., reasoning, human decision making). System Dynamics models of socio-technical systems abstract from single events, entities and actors and take an aggregate view on the system dynamics (e.g., [9]). On the one hand, such models are highly computationally efficient. On the other hand, it may be difficult to map the actual system structures and processes to the abstract aggregated model variables. By doing so, the link to the behavior of actors and their interactions is lost, so that the level of analysis is reduced. Moreover, social dynamics of interacting actors may result in unexpected emergent effects in the system, which cannot be analysed using the aggregate view. Agent-based modeling approaches take into account the local perspective of separate actors and their specific behavior and interactions, and models them as interacting agents in a multi-agent system. To ensure computational efficiency on a large scale, models of agents are often kept overly simple. The plausibility of such models has been often criticized [4, 8]. The generic agent-based affective-cognitive decision making model from [13] is among few exceptions with rich cognitive representations based on findings from Cognitive Science, Neurology, and Social Science. However, because of its high complexity, this agent model has limited scalability. The problem addressed in this paper is how to improve the computational properties of the agent model from [13], while preserving its behavioral properties. This is illustrated in this paper for a variant of the model instantiated for an emergency case. To address this problem, a loop abstraction technique from [14] has been used. This technique is based on identifying how equilibrium states for loops in an internal agent model depend on inputs for these loops. The abstracted agent model obtained ensures a more than twice increase of the computational efficiency of large-scale multi-agent systems based on the original model. This is achieved at the cost of 1% behavioural error, which is, however, not critical for most applications. Moreover, the abstraction of individual agent models presented in the paper enables analytical identification of stable states of the whole multi-agent system.

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 a given ontology Ont, state properties are specified as propositions that can be made in the form of conjunctions from (negations of) ground atoms. LEADSTO enables modeling 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 indicating timing parameters. 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 the timing parameters are chosen in a uniform manner, it is written $\alpha \twoheadrightarrow \beta$. To indicate the type of a state property sometimes prefixes input(A), internal(A) and output(A), will be used, where A is the name of an agent. For example, consider an example dynamic property with e = f = 0 and g = h = Δt:

input(A)|observation_result(fire) $\twoheadrightarrow$ output(A)| performed(runs_away_from_fire)

Informally, this example expresses that if agent A observes fire at t, lasting until t+Δt, then at t+Δt A will run away from the fire. LEADSTO is a hybrid modelling language: it allows expressing mathematical operations, e.g. has_value(x, V) $\twoheadrightarrow_{e, f, g, h}$ has_value(x, 0.25*V).

The paper is organized as follows. In Section 2 the model from [13] instantiated for an emergency scenario is presented. The model abstraction is considered in Section 3. In Section 4 behavioral and computational properties of the abstracted model obtained are considered. Section 5 concludes the paper.

2 An Affective-Cognitive Decision Making Model

In this section the affective-cognitive decision making model from [13] is introduced and illustrated as instantiated for an emergency scenario. In the scenario a group of agents considers two options (paths) to move out of a burning building. An option is a (partially) ordered sequence of actions (i.e., a plan) to satisfy the agent's goals. The goal of each agent in the scenario is to be outside of the building. Options are represented internally in agents using the neurological theory of simulated behaviour and perception chains proposed by Hesslow [6]. A simulated chain is formed as follows: some situation elicits activation of s1 in the agent's sensory cortex that via associations leads to preparation for action r1. Then, further associations are used such that the preparation state for r1 will generate s2, which is the most connected sensory representation of a consequence of the action for which r1 was generated. This sensory representation state serves as a trigger for a new response preparation, and so on. In such a way the agent simulates mentally the complete sequence of preparations of actions constituting an option, including perception of their effects. In the scenario an option is specified by a sequence of (intermediate) locations to be reached with an exit as the last location This sequence is represented using the predicate follows_after(move_from_to(p1, p2), move_from_to(p2, p3)). The strength of a link between a preparation for an action and a sensory representation of the effect of the action (see Fig.1) is considered to represent the confidence value of the agent's belief that the action leads to this effect. In the scenario, if the agent's confidence of the belief that location p1 is accessible from location p2 is ω, then the strength of the link between the states preparation_for(move_from_to(p2, p1)) and srs(is_at_location(p1)) is given the value ω.

The simulated sensory representation states relate to emotions, which provide either positive or negative reinforcement of the simulated actions, and thus guide the agent's decision making process. By evaluating sensory consequences of actions in simulated behavioural chains using cognitive structures from the OCC model [10], different types of emotions can be distinguished. In the example two types of emotions - fear and hope – are distinguished, which are often considered in the emergency domain. According to [10], the intensity of fear induced by an event depends on the degree to which the event is undesirable and on the likelihood of the event. The intensity of hope induced by an event depends on the degree to which the event is desirable and on the likelihood of the event. Thus, both emotions are generated based on the evaluation of a distance between the effect states for the actions from an option and the agent's goal state. In the evacuation case the goal is to be outside of the building, thus the evaluation functions for both emotions can be defined over the distance between the agent's location and the nearest reachable exit. In particular, the evaluation functions were specified as follows.

for hope: $eval_1(g, effect(a)) = e^{-\omega|effect(a) - g|}$;

for fear: $eval_2(g, effect(a)) = 1 - e^{-\omega| effect(a) - g |}$,

where effect(a) is the agent's location after the execution of action *a*; *g* is the aimed location (i.e., the nearest exit); ω is a parameter.

In literature [2,3] it is recognized that emotions emerge and develop in dynamics of reciprocal relations between cognitive and body states of a human. These relations, omitted in the OCC model, are modelled from a neurological perspective using Damasio's principles of 'as-if body loops' and somatic marking [2,3]. An 'as-if body loop' is described by the following causal chain:

sensory state → preparation for the induced bodily response →
sensory representation of the bodily response → induced emotion → sensory state

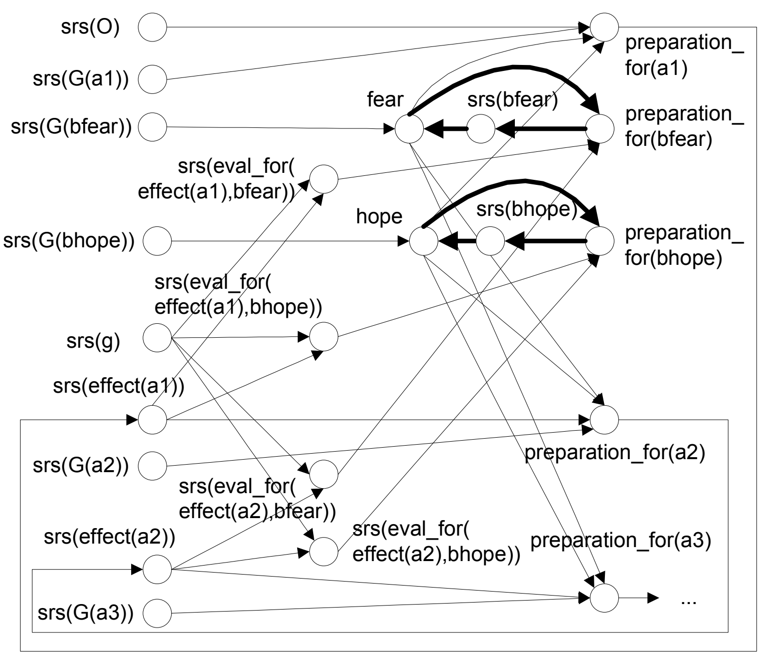

Fig. 1. A graphical representation of the affective-cognitive decision making model.

The as-if body loops for hope and fear emotions are depicted in Fig. 1 by thick solid arrows. Formally, the 'as if body loop' for hope for option o is specified for each agent A_i as follows:

srs(g, V1) & srs(effect(a), V2) & hope(o, V3) &

connection_between_strength(preparation_for(a), srs(effect(a)), V4) &
$\twoheadrightarrow$ srs(eval_for(effect(a), bhope), V4*eval$_1$(V1, V2)) (1)

$\wedge_{i=1..n}$ srs(eval_for(effect(a_i), bhope), Z_i) & hope(o, U) & preparation_for(bhope, W)
$\twoheadrightarrow$ preparation_for(bhope, (W+γ(h(f(Z_1, …, Z_n), U) - W)Δt), (2)

where f(Z_1, …, Z_n) is the arithmetic mean function, and

$$h(V1, V2) = \beta\ (1-(1- V1)(1- V2)) + (1-\beta)\ V1\ V2.$$

preparation_for(bhope, V) $\twoheadrightarrow$ srs(bhope, V) (3)

srs(bhope, V2) & srs(G(bhope), V1) & hope(o, V3)
$\twoheadrightarrow$ hope(o, V3+ γ1(g(V1, V2) – V3)Δt) (4)

where, for agents with an overestimation bias $\beta \geq 0$:

$$g(V1, V2) = \alpha V1 +(1-\alpha)V2 +\beta(1-\alpha V1-(1-\alpha)V2) \quad (5)$$

and for agents with an underestimation bias $\beta < 0$:

$$g(V1, V2) = \alpha V1 +(1-\alpha)V2 + \beta(\alpha V1+(1-\alpha)V2) \quad (6)$$

Here α indicates the importance of the group's opinion (or influence) for the agent; G(bhope) is the aggregated group preparation to the emotional response (body state) for hope. The influence of the group on the individual decision making is modelled based on *the mirroring function* of preparation neurons in humans. Such neurons, in the context of the neural circuits in which they are embedded, show both a function to prepare for certain actions or bodily changes and a function to mirror similar states of other persons; cf. [7], [11]. This mirroring function in social decision making is realised in two forms: (1) by *mirroring of emotions*, which indicates how emotional responses in different agents about a decision option mutually affect each other, and (2) by *mirroring of intentions* or *action preparations* of individuals for a decision option.

It is assumed that the preparation states of an agent for the actions constituting options and for emotional responses for the options are expressed in body states that can be observed with a certain intensity or strength by other agents from the group. The contagion strength of the interaction from agent A_2 to agent A_1 for a preparation state p is defined as follows:

$$\gamma_{pA_2A_1}=\varepsilon_{pA_2}\cdot\alpha_{pA_2A_1}\cdot\delta_{pA_1} \quad (7)$$

Here ε_{pA_2} is the personal characteristic expressiveness of the sender (agent A_2) for p, δ_{pA_1} is the personal characteristic openness of the receiver (agent A_1) for p, and $\alpha_{pA_2A_1}$ is the interaction characteristic channel strength for p from sender A_2 to receiver A_1.
By aggregating such input, an agent A_i perceives the group's joint evaluation of each option, which comprises the following dynamic properties.

(a) The aggregated group preparation to (i.e., the externally observable intention to perform) each action p constituting the option. This is expressed by the following dynamic property:

$\wedge_{j\neq i}$ internal(A_j)|preparation_for(p, V_j) $\twoheadrightarrow$ internal(A_i) | srs(G(p), $\Sigma_{j\neq i}\ \gamma_{pA_jA_i} V_j / \Sigma_{j\neq i}\ \gamma_{pA_jA_i}$) (8)

(b) The aggregated group preparation to an emotional response (body state) be for each option. For each emotional response be a separate preparation state is introduced. Formally:

$\wedge_{j\neq i}$ internal(A_j)|preparation_for(be, V_j) $\twoheadrightarrow$ internal(A_i) | srs(G(be), $\Sigma_{j\neq i}\ \gamma_{beA_jA_i} V_j / \Sigma_{j\neq i}\ \gamma_{beA_jA_i}$) (9)

According to the Somatic Marker Hypothesis [3], each represented decision option induces (via an emotional response) a feeling which is used to mark the option. For example, a strongly positive somatic marker linked to a particular option occurs as a strongly positive feeling for that option. To realise the somatic marker hypothesis in behavioural chains, emotional influences on the preparation state for an action are defined as shown in Fig. 1. Through these connections emotions influence the agent's readiness to choose the option. From a neurological perspective, the impact of a sensory representation state to an action preparation state via the connection between them in a behavioural chain will depend on how the consequences of the action are felt emotionally. Thus, the preparation state for the first action from an option is affected by the sensory representations of the option, of the perceived group preparation for the action and of the emotion felt towards the option. Formally, for the emergency example:

srs(o, V1) & hope(o, V2) & fear(o, V3) & srs(G(a1), V4) & preparation_for(a1, V5)
$\twoheadrightarrow$ preparation_for(a1, V5 + γ2(h(V1, V2, 1-V3, V4) – V5)Δt), (10)

where $h(V1,V2,1\text{-}V3,V4) = \beta1(1-(1-V1)(1-V2)V3(1-V4)) + (1-\beta1)\ V1\ V2\ (1-V3)\ V4$.

Preparation states for subsequent actions a in the behavioural chain are specified by:

srs(effect(a), V1) & hope(o, V2) & fear(o, V3) & srs(G(a), V4) & preparation_for(a, V5)
$\twoheadrightarrow$ preparation_for(a, V5 + γ2(h(V1,V2,1-V3,V4) – V5) Δt) (11)

3 Abstraction of the Internal Agent Model

In this section the process of abstraction of the affective-cognitive internal agent model from Section 2 is described, making use of the procedure from [14], which allows elimination of the 'as if body loops' from the model. To apply this loop elimination procedure, the following representation of a loop is assumed:

has_value(u, V_1) $\wedge$ has_value(p, V_2) $\twoheadrightarrow$ has_value(p, $V_2 + e(V_1, V_2)\ \Delta t$) (12)

Here u is the name of an input variable, p of the loop variable, and $e(V_1, V_2)$ is a function combining the input value with the current value for p. Such a representation of an 'as if loop' can be obtained from (2)-(4):

$\wedge_{i=1..n}$ srs(eval_for(effect(a_i), bhope), Z_i) & preparation_for(bhope, W) &
srs(G(bhope), V1) & hope(o, U)
$\twoheadrightarrow_{3,3,1,1}$ hope(o, U+ γ1(g(V1,V2) – U)Δt), (13)
where $V2 = (W+\gamma(h(f(Z_1, \ldots, Z_n), U) - W)\ \Delta t$

Here srs(eval_for(effect(a_i), bhope), V_i) and srs(G(bhope), V1) are inputs to the loop.

Loop abstraction is based on identifying dependencies of equilibrium states for loops. An equilibrium state for a given input value V_1 in (12) is a value V_2 for p such that $e(V_1, V_2) = 0$. A specification of how V_2 depends on V_1 is a function g such that

$e(V_1, g(V_1)) = 0$.

Note that the latter expression is an implicit function definition, and under mild conditions (e.g., $\partial e(V_1, V_2)/\partial V_2 \neq 0$, or strict monotonicity of the function $V_2 \rightarrow e(V_1, V_2)$) the Implicit Function Theorem within calculus guarantees the existence (mathematically) of such a function g. When a specification of g is obtained, the loop representation (12) can be transformed into:

has_value(u, V1) $\twoheadrightarrow_{D,D,1,1}$ has_value(p, g(V1)) (14)

where D is chosen as a timing parameter for the process of approximating the equilibrium value up to some accuracy level. In an equilibrium state for the loop for hope (13) W=V2, and

$W = W+\gamma(h(f(Z_1, \ldots, Z_n), U) - W)$
$W = h(f(Z_1, \ldots, Z_n), U)$

$U = U+ \gamma1(g(V1, h(f(Z_1, \ldots, Z_n), U)) – U)$
$U = g(V1, h(f(Z_1, \ldots, Z_n), U))$

Thus, for an overestimating agent with g(V1, V2) as defined in (5):

$U = \alpha V1 +(1-\alpha)V2 +\beta(1-\alpha V1-(1-\alpha)V2)$
where $V2 = \beta1\ (1-(1- f(Z_1, \ldots, Z_n))(1- U)) + (1-\beta1)\ f(Z_1, \ldots, Z_n)\ U$.

By rearranging terms:

$U = \beta + \alpha(1-\beta)V1 +(1-\alpha)(1-\beta)V2$ where $V2=\beta1*f(Z_1, \ldots, Z_n) + (\beta1+ (1-2\beta1)f(Z_1, \ldots, Z_n))U$

Thus, in the stable state for the loop the value of the hope state depends only on the loop's input states:

$U = (\beta + \alpha(1-\beta)V1 +(1-\alpha)(1-\beta)*\beta1*f(Z_1, \ldots, Z_n))/ (1- (1-\alpha)(1-\beta)(\beta1+ (1-2\beta1)f(Z_1, \ldots, Z_n))$ (15)

For an underestimating agent with g(V1, V2) as defined in (6):

$U=\alpha V1 +(1-\alpha)V2 + \beta(\alpha V1+(1-\alpha)V2)$,
where $V2 =\beta1\ (1-(1- f(Z_1, \ldots, Z_n))(1- U)) + (1-\beta1)\ f(Z_1, \ldots, Z_n)\ U$.

By rearranging terms:

$$U=\alpha(1+\beta)V1+(1-\alpha)(1+\beta)V2,$$
$$\text{where } V2=\beta1*f(Z_1, \ldots, Z_n) + (\beta1+ (1-2\beta1)f(Z_1, \ldots, Z_n))U$$
$$U=(\alpha(1+\beta)V1+(1-\alpha)(1+\beta)\beta1*f(Z_1, \ldots, Z_n))/ (1- (1-\alpha)(1+\beta)(\beta1+ (1-2\beta1)f(Z_1, \ldots, Z_n)) \quad (16)$$

Thus, by the loop abstraction the properties (2)-(4) are replaced in the agent model specification by the property

$$\wedge_{i=1..n}\ srs(eval\_for(effect(a_i), bhope), Z_i) \ \&\ srs(G(bhope), V1) \twoheadrightarrow_{3,3,1,1} hope(o, U), \quad (17)$$

where U is calculated by (15) when $\beta \geq 0$ or by (16) when $\beta < 0$. The 'as if body loop' for fear is treated in the same manner.

Given stable emotional states, one can determine stable preparation states for actions in the behavioral chain which are influenced by these emotional states. The stable preparation state for action a is determined based on (10) and (11) as follows:

$$V5 = V5 + \gamma2(h(V1,V2,V3,V4) - V5)$$
$$V5 = h(V1,V2,V3,V4)$$

Thus, (10) and (11) are replaced by (18) and (19) correspondingly:

$$srs(o, V1)\ \&\ hope(o, V2)\ \&\ fear(o, V3)\ \&\ srs(G(a1), V4)$$
$$\twoheadrightarrow preparation\_for(a1, h(V1, V2, 1-V3, V4)) \quad (18)$$

$$srs(effect(a), V1)\ \&\ hope(o, V2)\ \&\ fear(o, V3)\ \&\ srs(G(a), V4)$$
$$\twoheadrightarrow preparation\_for(a, h(V1,V2,1-V3,V4)) \quad (19)$$

Thus, the abstracted model specification comprises the properties (1) and (17) for hope and for fear; and (7)-(9), (18), (19).

Using the obtained abstracted model specification, the stable states of the whole multi-agent system can be determined analytically as follows. A stable emotional state (i.e., hope, fear) $U_o = \{ U_{o,Ai} | A_i$ is an agent from the system $\}$ of the system towards option o is identified by solving the system of linear equations based on (15) and (16):

$$U_{o,Ai} = k_{1,o,U,Ai}+k_{2,o,U,Ai}\, g(\{U_{o,Aj,\ Aj\neq Ai}\}), \quad (20)$$

where

$k_{1,o,U,Ai} = (\beta + (1-\alpha)(1-\beta)*\beta1*f(Z_1, \ldots, Z_n))/(1- (1-\alpha)(1-\beta)(\beta1+ (1-2\beta1) f(Z_1, \ldots, Z_n))$, when $\beta \geq 0$; $k_{1,o,U,Ai} = (1-\alpha)(1+\beta)\beta1*f(Z_1, \ldots, Z_n)/(1- (1-\alpha)(1+\beta)(\beta1+ (1-2\beta1)f(Z_1, \ldots, Z_n))$, when $\beta < 0$;

$k_{2,o,U,Ai} = \alpha(1-\beta)/(1- (1-\alpha)(1-\beta)(\beta1+ (1-2\beta1)f(Z_1, \ldots, Z_n))$, when $\beta \geq 0$;

$k_{2,o,U,Ai} = \alpha(1+\beta)/(1-(1-\alpha)(1+\beta)(\beta1+(1-2\beta1)f(Z_1, \ldots, Z_n))$, when $\beta < 0$;

$g(\{U_{o,Aj,\ Aj\neq Ai}\}) = \Sigma_{j\neq I}\ \gamma_{UA_jA_i} U_{o,Aj} / \Sigma_{j\neq i}\ \gamma_{UA_jA_i}$.

Similarly, a stable preparation state for an action of the system is calculated by solving the system of linear equations based on (18) and (19):

$$p_{o,Ai} = \beta1(1-(1-s_{o,Ai})(1-hope_{o,Ai})fear_{o,Ai}(1- g(\{p_{o,Aj,\ Aj\neq Ai}\}))) + (1-\beta1)\, s_{o,Ai}\, hope_{o,Ai}\, (1-fear_{o,Ai})g(\{p_{o,Aj,\ Aj\neq Ai}\}), \quad (21)$$

$$p_{o,a,Ai} = \beta1(1-(1-e_{o,a,Ai})(1-hope_{o,Ai})fear_{o,Ai}(1- g(\{p_{o,a,Aj,\ Aj\neq Ai}\}))) + (1-\beta1)\, e_{o,a,Ai}\, hope_{o,Ai}\, (1-fear_{o,Ai})g(\{p_{o,a,Aj,\ Aj\neq Ai}\}), \quad (22)$$

where a is an action from option o, $p_{o,a,Aj,}$ is the agent's A_j level of the preparation state for action a; $s_{o,Ai}$ is the agent's A_j level of the sensory representation state of option o; $e_{o,a,Ai}$ is the agent's A_j level of the effect state of action a

$$g(\{p_{o,a,Aj,\ Aj\neq Ai}\}) = \Sigma_{j\neq I}\ \gamma_{eval\ A_jA_i}\, p_{o,a,Aj} / \Sigma_{j\neq I}\ \gamma_{eval\ A_jA_i};$$
$$g(\{p_{o,Aj,\ Aj\neq Ai}\}) = \Sigma_{j\neq I}\ \gamma_{eval\ A_jA_i}\, p_{o,Aj} / \Sigma_{j\neq i}\ \gamma_{eval\ A_jA_i}$$

4 Evaluation

In this section the results of a computational complexity evaluation of the abstracted behavioural agent model from Section 3 in comparison to the more complex internal model from Section 2 are presented. For the behavioural evaluation 1000 simulation trials of both the original and abstracted models were performed. In each trial the values of the individual parameters were taken from the interval with uniformly distributed values

[0.2, 0.8] for α; [0.1, 0.9] for $\beta 1$; [-0.5, 0.5] for β;
[0, 1] for ε_{pA_i}, for $\alpha_{pA_iA_j}$, and for δ_{pA_j} for all i, j, i≠j.

Furthermore, the agent's beliefs about accessibility of locations were initialized randomly from interval [0, 1]. The behavioural error for simulation trial i for the set of all agents AG was calculated as the averaged normalized root mean squared error:

$$NRMSE^i = \sum_{a \in AG} NRMSE_a^i / |AG|, \quad NRMSE_a^i = (\sum_{t=1..end\_time} (v_{a,t}^i - w_{a,t}^i)^2 / end\_time)^{1/2} \cdot 100\%,$$

Here $v_{a,t}^i$ is the degree of agent's a preparation to choose the first option at time point t estimated using the original model from Section 2, $w_{a,t}^i$ is the degree of agent's a preparation to choose the first option at time point t estimated using the abstracted model from Section 3; end_time is the simulation time (100 time points). The maximum and average (over the simulation trials) NRMSE obtained for 10, 100, 500 and 1000 simulation trials are provided in Table 1. As can be seen from the table the NRMSE is low and almost insensitive to the amount of agents used in the simulation.

Table 1. The maximum and average normalized root mean squared errors (NRMSE) for the abstracted agent model in comparison to the original agent model.

# of agents	10	100	500	1000
Maximum NRMSE	*1.65%*	*1.5%*	*1.47%*	*1.54%*
Average NRMSE	*0.95%*	*0.89%*	*0.98%*	*0.96%*

The computational complexity evaluation is based on the estimation of the simulation time for the original and abstracted agent models. As can be seen in Table 2, the simulation time difference between the models is not very significant for a small number of agents, but becomes apparent for larger-scale multi-agent systems. Thus, the abstracted model ensures an increase of the computational efficiency at least from twice up to 3 to 4 times (and probably more) for large-scale multi-agent systems in comparison to the original model. This is achieved at the cost of approximately 1% behavioural error, which is not critical for most applications.

Table 2. Simulation time (in seconds) of the original and abstracted models

# of agents	10	100	500	1000	2000
Original model	*0.0173*	*0.59*	*12.98*	*62.12*	*281.43*
Abstracted model	*0.0157*	*0.25*	*5.28*	*20.96*	*78.18*
Gain factor	*1.1*	*2.4*	*2.5*	*3.0*	*3.6*

5 Conclusions

In the literature it is often argued that to ensure a high plausibility of models of socio-technical systems rich internal models of actors are required; cf. [4], [7]. However, such models usually involve complex interactions between cognitive and affective processes, and therefore do not scale well. In this paper it is demonstrated how an abstracted behavioral agent model can be obtained from the complex decision making model from [13]. The type of abstraction used for internal agent models has similarities to an approach known in computational biochemistry as quasi steady state approximation, to address stiff differential equation models (in which some subprocesses run very fast compared to other subprocesses that run more slowly); e.g. [12], [15].

The abstracted agent model ensures an increase of the computational efficiency from more than twice for smaller numbers upto at least 3 to 4 times for larger numbers, at the cost of approximately 1% behavioural error. The abstraction mechanism employed can be used for a wide range of agent models with internal loops limited only by the requirements identified in [14]. Further abstraction steps can be made by dynamic clustering of agents in groups considered as higher-order agents; this will be addressed in future research.

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