Evacuation Simulation based on Cognitive Decision making model in a Socio-Technical System

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***Abstract*—In the last decade the shift of information and communication systems from a purely system level to the social level is already observable. However, the integration of social / cognitive aspects into so-called social computing is not an easy task due to conceptual differences in domains. A Socio-Technical System (STS) is a recent term intending to differentiate between a social system mediated by natural sciences or information technology. Even if the mediation of social / cognitive aspects is "theoretically" governed by technology, the gap between "socio" and "technical" is historical and huge. Furthermore the fact that with every passing year, the technical systems become more intelligent with respect to interaction with people and their pervasiveness, a special attention should be given to modelling both social and technical components and interaction between them. For example while modelling (and simulating) an emergency situation from a public facility, the possible availability of technology at the environment (e.g. situation-aware exit signs, interactive displays, etc.) and personal (e.g. cell phones, specialized wearables etc.) level, along with its social / cognitive influence must not be overruled. To address this challenge, we have integrated cognitive decision making model abstracted from psychological, neurological and social theories of human behaviour during evacuation situations into CA based simulation. Keeping focus on a scenario in which a small population of agents is technologically assisted, some of the most interesting finding are: (i) the inclusion of a representative and authentic social behaviour model into modelling a socio-technical system essentially produces fundamental differences in methodologies, (ii) the technologically assisted agents emerge as leaders during evacuation changing the intentions of many agents within their influence (iii) even a small population of such leaders in sufficiently large population is enough to guarantee a remarkable difference; particularly improving usage of possibly under-utilized exits.**

***Keywords*-Socio-Technical Systems; Evacuation Simulation; Cognitive Agent Model; Trust Modelling;**

I. Introduction

In spite of social / cognitive science being primitive and progressive throughout human age, the recent technological era was not able to advance while remaining entangled with human-oriented knowledge (e.g. sociology, psychology, philosophy etc.). It grew primarily in isolation leaving social aspects nearly as spectators. This is particularly true for merely half a century old science of computing. However visionaries saw the inevitable to happen soon; "The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it." [1] On a system level, a "social-technical system arise when cognitive and social interaction is mediated by information technology rather than the natural world." [2]

The social aspects of a system comes from norms, culture, laws, roles etc. governed by the domain of sociology, whereas the cognitive aspects drives their foundations from the domain of psychology focusing on semantics, intentions, emotions etc. [2]. It is obvious that pervasiveness of digital contents in the environmental and personal level is on its way to fundamentally change social fabric of societies [3]. This change is bound to occur at two broad levels:

- Behavioural change caused by social / cognitive intelligence in the system
- Behavioural change due to persistence of digital contents itself

In the former case, the human behaviour is expected to change due to provisioning of the authentic contents when compared with otherwise non-availability of these. For example, a commuter while leaving a railway station may be provided with assistance to move faster to catch the bus. This is relatively an easier task when knowing the profile of the user. However modelling the affects of change in cognitive state (from relaxed to excited) due to this "un-natural" call and resulting consequence on user's social behaviour is a challenging task. The theories relating with question like "how an individual would behave (in every possible way) in a certain cognitive state?" and "how his/her behaviour would affect the social fabric and vice versa?" must be integrated in a STS. Due to rapidly advancing technologies, there is a possibility of a gap between theories and technology relating with later case which explores the change in human social / cognitive behaviour due to long-term exposure of pervasiveness of digital contents.

Representing a possible interplay between technological and social dimensions, a STS can grasp many situations and application categories never thought before including applications relating with human crowd and its dynamics. A crowd is made up of individuals. Such an individual has physical and cognitive characteristics of its own. Additionally, its behaviour would be affected by social relationships and situations in the surrounding. Modelling the required attributes of a population of individuals influencing an indi-

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vidual would act as a basis of social behaviour determination and prediction. A socio-technical crowd application thus can assist a user in evacuation, navigation, gathering, informing and service provisioning etc.

Modelling a STS starts with modelling representative individual entities constituting such a system. These entities are heterogeneous with varying character and capabilities. Additionally a STS is essentially a large scale system requiring numerous individual level interactions. Therefore it is difficult to model such a system at variable (using structural equations) or system (using differential equations) level. As an analytical method for social systems, the agent-based modelling is rapidly gaining popularity, due to its capability of directly representing individual entities and their interactions [4].

Simulating (and modelling) a large scale agent-based STS focusing on crowd events is an interesting topic for researchers because of its importance and emerging nature of the phenomena [5]. In particular, modelling and simulating a crowd evacuation situation is important due to impossibility of trial studies in an existing building or legal provisioning of a building design [6]. As behavioural rule-set, the individual level behaviour can be designed based on theoretical understanding of the phenomena or through a focused and less harmful small-scale experimental evidence.

Focusing on evacuation simulation methodologies, social aspect of agents can be described by category of crowd behaviour models named as microscopic models. Microscopic crowd models describe the behaviour, actions and decisions of individuals with their interaction with others (particularly in physical vicinity). For example, **rule-based models** [7], [8] achieve more realistic human movement for low- and medium-density crowds in a flocking or swarming style. Although different behavioural rules are applied to the crowd, group, or individuals to achieve more believable overall crowd behaviour [9], [10]. But the primary focus has been to achieve a realistic "human-like" locomotion and navigation while preserving the otherwise a "cognition-less" boids [7] like arrangements. The **social force models** [11], [12] are used in panic situation and describe collective panic behaviour using a self driven many particle system framework based on Newton's laws of motion (repulsive interaction, friction forces, dissipation and fluctuations) where each self driven particle has a target and is prepared to move at a given velocity. Although these models are extended to include individual preferences [13], but these are far from representing a social behaviour. The **Cellular Automaton** (CA) [14], [15], [16], [17] is an artificial intelligence approach to model space and time in discrete intervals and physical quantities take a finite set of discrete values. The modelling is simple and the execution speed is fast. CA based models are criticised for its discreteness which is not realistic for a human, however, the capability of CA to represent geometry of space with relative ease has persuaded many in its favour. It also allows a natural and simplistic marriage of (mostly) passive space and more active agents on top [18]. Being intelligent, autonomous, adaptive and goal-oriented, an agent is capable of representing a true social / cognitive entity. An agent-based model constituted by such social agents is fully capable of modelling (and simulating) an evacuating crowd emphasizing social dimension of it, a tip we are pointing at of a literally untouched iceberg.

One of the most important question while modelling a STS relating with crowd evacuation is the choice of cognitive / social aspect to model between literally infinite possibilities. Based on mandate of the EU project SOCIONICAL [19], we have focused on a situation in which the environment is augmented with Ambient Intelligence (AmI). In the case study relating with emergency situation in which a small population of agents is AmI-assisted (e.g. provided with intelligent directional guidance towards the most suitable exit based on crowd and environmental dynamics), we model the cognitive influence of individual's trust on nearby AmI assisted agents (e.g. fire-fighters).

With this paper, we have reported the results of an agent-based evacuation simulation in which each agent follows microscopic CA based locomotive rules in addition to possibility of acting as an AmI assisted variant if designated likewise. Additionally all the agents are incorporated with social dimension affectively acting as decision making model based on intentions and emotions of agents and their perceptions. According to the model, an AmI assisted agent due to high trust embodied into it may act as a "leader", possibly diverting agents away from their initial beliefs. Hence the focus of the simulation is to study the effects of change in beliefs of agents from potentially a less efficient (nearest) exit towards a more efficient (recommended) exit.

The rest of the paper is organized as following. Section II describes the cognitive affective decision making model used in the simulation. Section III outlines the case study whereas section IV details the setup of the simulation. Section V is devoted to the discussion of the results followed by section VI concluding the paper.

II. Cognitive Agent Model

Trust plays an important role in evacuation situations. Whether an evacuee makes a decision under the influence of human activity in the surrounding and / or some assisting infrastructure in the form of direct human steering (e.g. a fire-fighter) or directional clue provided by infrastructure (e.g. exit signs) or a personal device (e.g. a wearable LifeBelt [20], cell phone), the role of trust on the available information stays central. In fact the decision would be a by-product of personal intentions / preferences, influence of surrounding activity / emotions, and trust on assistance being provided. In our scenario we consider that the assistance is being provided through a single unit supporting directional guidance (i.e. LifeBelt) to a subset of population (i.e. fire-fighters). That is the reason, it is also important to know that whether an AmI equipped agent (fire-fighter) would trust the technology himself.

A. Trust in Technology in emergency

To support the evacuation process of commuters from emergency situations, we have developed a wearable device,

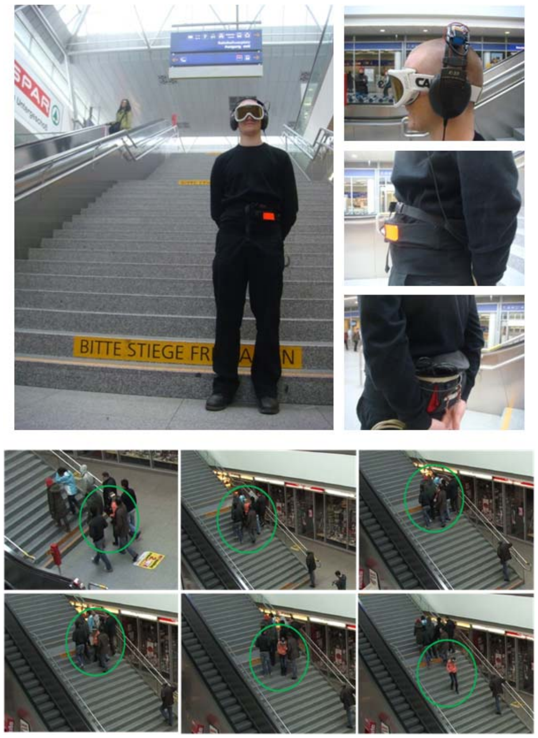

Figure 1. LifeBelt Trust Experiment: a test person (Above); test person trusts the LifeBelt, supernumeraries moves on towards the exit (Below).

LifeBelt [21], for vibro tactile guidance of individuals in panic towards exits. LifeBelt as a coordinated navigation device builds on a subtle directional vibration stimulation to navigate and guide individuals to escape. The system addresses the challenge of overseeing and overhearing in situations when there is abundance of visual and auditory stimulations. At this level of human concentration, it is important to notify the user with information about a potential threat in an un-obstructive yet demanding manner, so that his/her attention is not diverted. In some situations, human senses may generate a false or limited perception, particularly when visual and auditory perceptions are restricted by environmental constraints (e.g. full or partial darkness). The LifeBelt generates notifications about distance, where region of belt vibrating represents the orientation whereas intensity of vibration represents the distance.

To answer the question that would a fire-fighter himself would trust the LifeBelt, we performed real experiment using our "LifeBelt" at the Linz railway station (see Fig. 1). In order to achieve a setting close to reality, evacuees were charged with both an auditory distraction signal and visual limitations, and were furthermore continuously surrounded by a group of 10 people forming an escaping crowd. The aim of the study was to investigate whether or not evacuees would trust in technology in a real hazardous situation. Our results showed, for a simulated panic situation, that almost all persons (88%) adhered to the "LifeBelt" guidance requests, even when the vibro-tactile stimuli instructed them to change direction and to move back into the dangerous area.

The above evidence most-likely infers the following hypothesis: "The evidence that the AmI assisted agent is technologically assisted would enhance trust on it." This hypothesis has no empirical evidence supporting it. But it can be inferred from trust theories. The fact that humans trust the information unless confronted with a conflicting evidence [22] suggest a high adherence level; for AmI assisted directional notification. In an emergency situation, it can be assumed that an evacuee would be in a state of panic, thus not able to perform a rational cost-benefit [23] or risk analysis [24]. Also the very fact that the decision has to be abrupt and in a "strange" environment, the factor of experience and learning [25] is negligible. Some empirical evidence also support this hypothesis. The research shows that in general, the residents has greater level of trust in evacuation information provided by local police and fire department officials (69%) and least trust on friends and neighbours (17%) [26]. It does not mean that an evacuee would not be affected by social consequences produced by activity in the surrounding or personal intentions. However its influence would be localized and limited.

Hence there is a high probability that evacuees would trust the AmI Assistance or a fire-fighter quipped with AmI assistance with a priority. In fact, for the sake of this paper, the model presented below is parametrized to represent the hypothesis that the "agents initially trust the AmI-assisted agents, but distrust slowly after negative experience." Parallel to that the model considers the effects of individual variations / intentions and effects of emotions in the surroundings in decision making.

We have also investigated other hypothesis which can be the case in other environments and / or with different individuals; for example, "humans trust technology in the same manner as to human strangers" or "humans have high initial trust to technology (initial bias), but distrust it rapidly after negative experiences." For more detailed comparison between three possible cases, refer to [27].

B. Cognitive Decision making Agent Modelling for Evacuation Situations

A general affective decision making model from [28] was instantiated for the case study. The model is formalised using a temporal state transition system format [29].

Depending on a situational context an agent determines a set of applicable options to satisfy its goal. In the case study the goal of each agent is to get outside of the building in the fastest possible way. This is achieved by an agent by moving towards the exit that provides for fastest evacuation as it perceived by the agent. Evacuation options are represented internally in agents by one-step simulated behavioural chains, based on the neurological theory by Hesslow [30] (see Fig. 2). In Fig. 2 the burning station situation (see section III) elicits activation of the state srs(evacuation_required) in the agent's sensory cortex that leads to preparation for action preparation_for(move_to(E)).

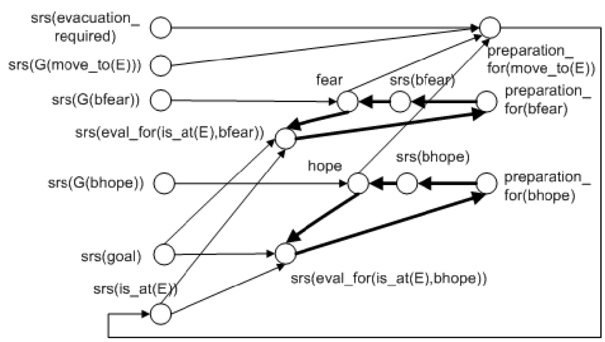

Figure 2. The emotional decision making model for the option to move to exit E.

Here E is one of the exits of the station. Note that if more than one exit is known to the agent, then in each option representation the preparation state corresponding to the option's exit is generated. Then, associations are used such that preparation_for(move_to(E)) will generate srs(is_at(E)), which is the most connected sensory consequence of the action move_to(E).

The strength of the link between a preparation for an action and a sensory representation of the effect of the action (see Fig. 2) is used to represent the confidence value of the agent's belief that the action leads to the effect.

The simulated sensory states elicit emotions, which guide agent behaviour either by reinforcing or punishing simulated actions. By evaluating sensory consequences of actions in simulated behavioural chains using cognitive structures from the OCC (Ortony, Clore and Collins) model [31], 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 [31], 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 perceived utility between the effect states for the action from an option and the agent's goal state.

In particular, the evaluation function for hope in the evacuation scenario is specified as *eval(g, is_at(E)) =* ω, where ω is the confidence value for the belief about the accessibility of exit E, which is an aggregate of the agent's estimation of the distance to the exit and the degree of clogging of the exit. Although it is assumed that the distances to the exits are known to the agents, the information about the degree of clogging of the exits is known only to AmI-equipped agents.

Emotions emerge and develop in dynamics of reciprocal relations between cognitive and body states of a human [32]. 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 [32]. The as-if body loops for hope and fear emotions are depicted in Fig. 2 by thick solid arrows. The following rules describe the evolution of the emotional states:

srs(eval_for(is_at(E),bhope),V2) & srs(G(bhope),V1)

$$\begin{aligned} &hope(o, (\beta_h - \beta_h \times (1 - V1) \times (1 - a1) + \\ &\qquad (1 - \beta_h) \times V1 \times a2)/ \\ &(1 - \beta_h \times (1 - V1) \times a1 - (1 - \beta_h) \times V1 \times a1)) \end{aligned} \tag{1}$$

where
a1 = β_h - 2×β_h×V2 + V2,
a2 = β_h − β_h×(1-V2)

srs(eval_for(is_at(E),bfear),V2) & srs(G(bfear),V1)

$$\begin{aligned} &fear(o, (\beta_f - \beta_f \times (1 - V1) \times (1 - a3) + \\ &\qquad (1 - \beta_f) \times V1 \times a4)/ \\ &(1 - \beta_f \times (1 - V1) \times a3 - (1 - \beta_f) \times V1 \times a3)) \end{aligned} \tag{2}$$

where
a3 = β_f×V2+1-V2-β_f×(1-V2),
a4 = β_f − β_f×V2

here β_h is the degree of extraversion (i.e., tendency to experience positive emotions) of the agent; β_f is the degree of neuroticism (i.e., a tendency to experience negative emotions) of the agent; G(bhope) / G(bfear) is the aggregated preparation to the emotional response (body state) of the agent's social neighbourhood.

The social influence on the individual decision making is modelled based on *the mirroring function* [33] 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. 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. Furthermore, the social influence includes spread of beliefs of agents supporting or prohibiting options (e.g., the belief about the accessibility of an exit).

The mirroring is realised through information and emotion contagion processes. The contagion strength of the interaction from agent B to agent A is defined as follows:

$$\gamma_{BA} = \epsilon_B \times trust(A, B) \times \delta_A \tag{3}$$

where ϵ_B is the personal characteristic expressiveness of the sender (agent B), δ_A is the personal characteristic openness of the receiver (agent A).

Trust is an attitude of an agent towards an information source that determines the extent to which information received by the agent from the source influences agent's belief(s). 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 following property describes the update of trust of agent A to agent B based on information communicated by B to A about the degree of contagion around exit e:

trust(A_i, A_j, V1) & communicated_from_to(A_j, A_i, congestion(e, V2)) & belief(A_i, congestion(e, V3))

$$trust(i, j, V1 + \gamma_{tr} \times (V3/(1 + e^{\alpha}) - V1)) \qquad (4)$$

where α=-ω1$\times$(1-|V2-V3|) + 4

According to the Somatic Marker Hypothesis [32], 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 2. Through these connections emotions influence the agent's readiness to choose the option.

C. Related Work

The strength of our model is mapping cognition based reasoning on the decision making related to a evacuation situation from a multi-exit environment. We present explicit relationships (based on well-established neurological and psychological theories) between intentions and emotions in decision making while keeping trust on AmI-assisted agents as a priority. There *is* related work in the overall domain, however, it does not address the explicit requirements as we have stated.

For example, authors in [34] has proposed a pedestrian model based on the social comparison theory. The main focus of the model is on social contagion processes, whereas our model, in addition to the social contagion, addresses decision making based on affective reasoning. Trust relations are also not considered explicitly in the model. Similarly in [35], the dynamics of the crowd under the influence of social associations is modelled. This is rather an exploratory work in which no detailed formal computational model is provided which could address the dynamics of interaction between cognitive states of the agent. Emotional states and trust relations are also not considered explicitly.

Recently modelling of emotions has been considered in the area of virtual agents (e.g., Fear Not! [36], MRE [37], and ToK [38]). Emotions of virtual agents emerge based on cognitive structures, such as goals, memory. None of these models is based on neurological principles, as used in our model. In our model emotions emerge from dynamics of interaction between "body" and "mind" of an agent based on body loops and behavioural and perception chains, not considered in other architectures.

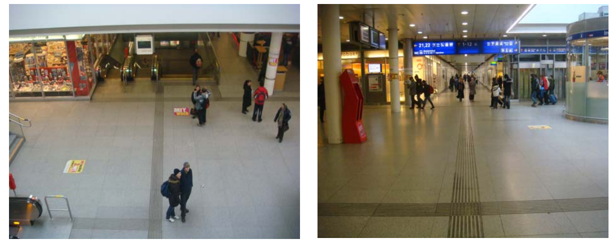

Figure 3. Linz Train Station (Incoming Commuters): Left: one of the two staircases connecting main hall with the tram station; Right: one of the two tunnels providing access to the train platforms.

The OCC model developed by Ortony, Clore and Collins [31] postulates that emotions are valenced reactions to events, agents, and objects, where valuations are based on similarities between achieved states and goal states; thus emotions in this model have a cognitive origin. The model proposed in this paper exploits some of the principles underlying the OCC model but embeds them in a neurological context that includes theories that cover other aspects as well, thus providing a deeper and wider level of understanding of social decision making. In VICTEC architecture for modelling crowd behaviour [39] the OCC framework was also used for modelling emotions. However, in contrast to our model, VICTEC does not embed the OCC framework in a broader context of social decision making based on neurological principles. Also, interaction of cognitive structures with body states of an agent is not considered.

III. Case Study

We have focused on evacuation from a train station. The train station is comprised of three floors; the top floor (EG: Transit Hall) provide access to the road network, the middle floor (UG1: Main Hall) provide access to the train platforms and bottom floor (UG2: Tram Station) provides access to the tram service. All three floors have "exits" that can be used for evacuation. However, in the scenario, we assume that the disturbance (potentially a fire) initiates at the tram station blocking exits at that level. Consequently, all the commuters need to climb up towards main hall, from where they can either use exits on the same floor or climb up further towards transit hall; ultimately evacuating on road connection.

It is obvious that simulating only main hall would suffice in this situation given an induction of "in-coming" commuters both from tram station and train platforms. The "outgoing" commuters would be considered evacuated if they pass through two exits on the main hall or start climbing two stair cases connected with the transit hall. Fig. 3 and Fig. 4 show incoming and outgoing commuters flow on the main hall. For a detailed account of train station structure, refer to our previous work [40].

It is assumed that people are aware of "nearest exit" including people starting at the tram station with the exception

Figure 4. Linz Train Station (Outgoing Commuters): Left: left staircase connecting main hall with the transit hall; Middle: right staircase connecting main hall with the transit hall; Right: transit hall central exits; Two outward exits also available at main hall (not shown).

that the exits at the tram station are out of bound. This would act as a base case when there is no ambient assistance in the environment. Although, there would be an effect of emotional influence of surrounding, however, it is ignored due to potential chaos due to non-availability of "useful" information. Another case (optimal in current methodologies) which does not need social behaviour consideration is when everybody is (AmI) assisted at personal level. We assume (for the sake of simplicity) that there would be an unconditional and un-obstructive following of the guidance provided as seen in experiment with LifeBelt in the train station. Following the recommended exit by everyone is taken as benchmark for the study.

In normal case, a percentage of agents (in main hall only) would be AmI assisted. Given that a central evacuation control unit is aware of exit area dynamics (clogging) and agents position, a recommendation of exit choice can be provided to AmI assisted agents. The rest of the agents has an initial belief corresponding to nearest exit. According to the model presented in section II, an AmI assisted agent due to high trust embodied into it may act as a "leader", possibly diverting agents away from their initial beliefs.

IV. Simulation Setup

The simulation was performed in CA based multi-agent programmable environment [41] where space is built with a sequence of place holders (cells). In NetLogo "world" these place holders are called as patches. The size of a cell is irrelevant; however, conceptually a cell (and space) corresponds to a geometry. For example, we have converted a real geometry (Linz main railway station central floor - main hall) into NetLogo world which required 321×361 cells. In this particular case, a cell corresponds to a square of dimension equal to 0.5×0.5 m^2. We can increase or decrease the cell size which would decrease or increase the number of cells required to represent a geometry respectively. Such a cell dimension (to 0.5×0.5 m^2) is taken from EXODUS [42] which is used to get the relative coordinate space of the geometry generated automatically from AutoCAD file of the main hall.

A patch is stored with the information about all the exits in terms of direction and distance. The space generated in such a way (see Fig. 5) would act as a decision making blueprint (w.r.t. any of the exits) for all the agents it is homing.

An agent (turtle) is customized to describe current / previous exit, current direction, locomotion states (moving, waiting, panicking), distance it has travelled and whether it is an AmI assisted agent (has-device?) or not, in addition to its position (x and y-coordinate) and heading (direction for the next step). While relating an agent with a cell, the following cells occupancy rules are applied (mainly for the purpose of simplicity):

1) only one agent can occupy a single cell
2) an agent can only occupy a cell which is walkable (not a wall or obstacle)
3) an agent always resides in the centre of the cell (hence agent and cell coordinates are same)
4) as soon as an agent reaches to an exit, it is considered as been evacuated.

Initially the agents' placements are random. During the locomotion in the simulation, an agent can only acquire one of the eight directions (Moore's neighbourhood) encoded into the cell namely front (0^o), right-and-front (45^o), right (90^o), right-and-back (135^o), back (180^o), left-and-back (225^o), left (270^o), and left-and front (315^o).

The local movement decisions are based on three states of the agents which are:

1) *moving:* if last move of the agent was successful
2) *waiting:* if the last one or few moves of the agents were not successful but the *patience* level has not exceeded a pre-defined value
3) *in-panic:* if the last few moves of the agents were not successful and the patience level *has* exceeded a pre-defined value.

Patience level for each agent can be set independently, however a static value is used for this simulation. An agent moves are based on empirical evidence we collected [20]

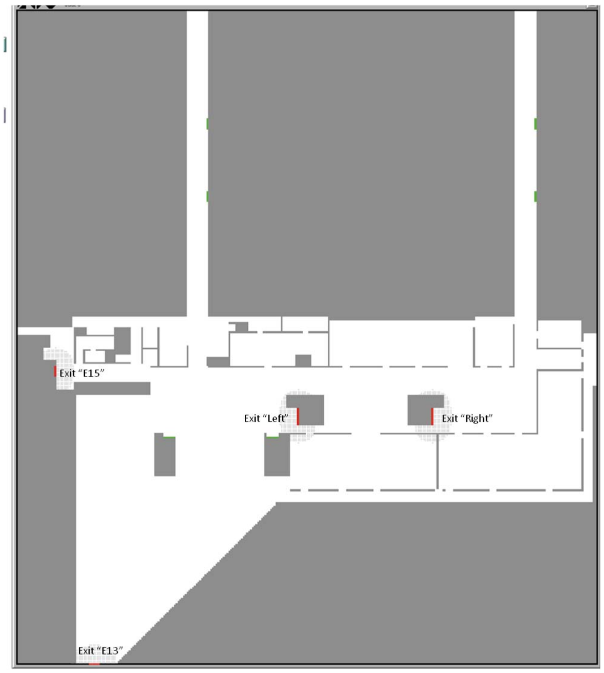

Figure 5. The floor map that is simulated.

(see Fig. 6). With the help of encoded information within a cell and these locomotive (next-step-selection) rules, there are several "exit-selection" strategies which can be incorporated to realize an evacuation [43], [44]. Previously we have performed full scale simulation of the Linz train station focusing on different exit selection strategies without cognitive modelling [45]. With this paper we augment exit selection models described in [45] with cognitive decision making.

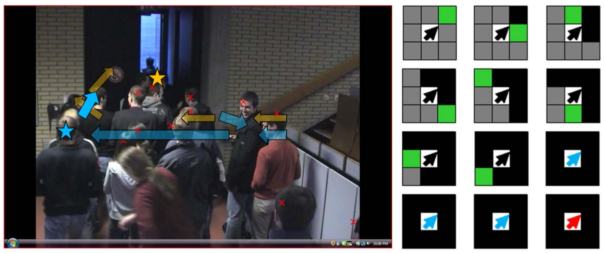

Figure 6. Left: Experimental Evidence; Right: Moore's Neighbourhood: Possible configurations of an object moving at angle 45^o. GREEN indicate adopted choice. BLUE is agent in waiting and RED is agent in panic. As soon as a move is made, the agent turns to BLACK again.

A change in emotions (fear / hope) and intentions (trust / belief) would best be realized by connecting emotional states of agents with evacuation activity, i.e. local locomotion and exit selection. That means that a change in agent belief under the influence of presence of AmI assisted agents and emotional state in the surrounding would transform into exit selection and consequently into local decision it has to make to fulfil the current goal.

A. Exit Choice Implementation

1) *Strategy1: Nearest Exit:* All the agents follow the nearest exit based on random deployment. No AmI assistance in considered in this case.
2) *Strategy 2: Optimal Exit:* Each agent is provided with a "recommended exit" in each time stamp based on its location and Exit Area (EA) dynamics. There can be many optimization techniques which can be applied, but it may require execution time reaching to n^n. Finding a computationally feasible optimization technique is another issue and is not a focus here. We have adopted the following formulation which only require a subset of area (agents) i.e. EA of an exit (e):

$$optExit = \mathbf{min}\, EADyn_e \,/\, EAUse_e \,/\, exWid_e \quad (5)$$

where *EADyn* is the parameter which we want to use as a decision parameter, e.g. agents density, aggregate agents panic etc. *exWid* is the width of the exit which means that how many commuters can pass through an exit simultaneously. Since *exWid* can vary and also due to obstacles surrounding an exit, the cells representing an EA would vary. To normalize this variation we have used *EAUse* which represents the %age of EA cells which can be used by the agents.

3) *Strategy 3: Following:* In this case, the agents are either of type "AmI-assisted" or simply "agents". The AmI-assisted agents set their *beliefs* based on *optExit* calculation based on eq. 5, i.e. 0.9 for *optExit* and 0.1 for all other exits. Then each of this AmI-assisted agent (a) updates **emotions** of each of the "neighbour" (n) within its *interaction range*. For each of the exit (e) the emotions update formulation is:

$$gxxx = gxxx + (trust_a(n) \times xxx_e) \quad (6)$$

where "xxx" represents *fear*, *hope* and *attract*. The aggregate of emotions is performed as:

$$gxxx = gxxx/count(n) \quad (7)$$

After updating the emotions, each of the AmI-assisted agent (a) would update **intentions** of the neighbours. The update of *belief* (for each exit (e)) would only be performed for simple agents whereas update of *trust* would be performed for AmI-assisted agents as well. The respective formulations are:

$$belief_n(e) = belief_n(e) + trust_n(a) \times (belief_a(e) - belief_n(e)) \quad (8)$$

$$trust_n(a) = trust_n(a) + belief_a(optExit) \times (1/(1 + (10^{-\mathbf{x}} \times (1 - Abs(belief_n(optExit) - belief_a(optExit))) + 4))) - trust_n(a) \quad (9)$$

where **x** represents 39 in case of an AmI-assisted agent and 9 otherwise.
With newly updated trust and belief and aggregation of emotions nearby, the choice of an exit by each agent would be performed. Since the belief of an AmI-assisted agent was not altered in this process, there is a high probability that it would not be affected by influence of the surrounding and would keep following the recommended exit. For other agents the belief based on trust on the source would act as the starting point towards exit selections. However, the highest believed exit could turn out to be not the adopted one due to cognitive influence of the emotions in the surrounding. The following formulations describe the emotional influence of the surrounding agents of an agent (a). The emotions of hope and fear are calculated for each exit (e).

$$hope_a(e) = (bhope_a - bhope_a \times (1 - ghope) \times (1 - a4) + (1 - bhope_a) \times ghope \times a4)/ (1 - bhope_a \times (1 - ghope) \times a3 - (1 - bhope_a) \times ghope \times a3) \quad (10)$$

where a1 = dist = $belief_a(e)$
a2 = 1 - dist

a3 = $(bhope_a \times a2) + a1 - (bhope_a \times a1)$
a4 = $bhope_a - (bhope_a \times a2)$

$$fear_a(e) = (bfear_a - bfear_a \times (1 - gfear) \times (1 - a4) + (1 - bfear_a) \times gfear \times a4) / (1 - bfear_a \times (1 - gfear) \times a3 - (1 - bfear_a) \times gfear \times a3) \quad (11)$$

where a1 = a2
a2 = a1
a3 = $(bfear_a \times a2) + a1 - (bfear_a \times a1)$
a4 = $bfear_a - (bfear_a \times a2)$
Based on emotions, the attraction (*attract*) of an agent for an exit can be found as:

$$attract_a(e) = attract_a(e) + (gamma \times (battract_a \times (1 - ((1 - hope_a(e)) \times fear_a(e) \times (1 - gattarct))) + (((1 - battract_a) \times hope_a(e) \times (1 - fear_a(e)) \times gattract) - attract_a(e)))) \quad (12)$$

The exit with maximum attraction value would be selected as the exit of choice which would heavily be dependent on belief of an agent set by an AmI-assisted agent but it would also be influenced by emotions in the surrounding.

V. Simulation Results

Given that a central evacuation control unit is aware of exit area dynamics and agents' position, a recommendation of exit choice can be provided to AmI assisted agents. The rest of the agents has an initial belief corresponding to nearest exit. Since it has already been proven, e g., in [43], [44], that following the nearest exit is not the most efficient exit choice strategy due to uneven populations and exit dimensions, an AmI assisted agent may act as a "leader", diverting a normal agent away from its initial belief. This actually happens based on the cognitive agent model integrated into each and every agent's functionality.

Following populations of agents were simulated as three cases:

Case 1: 500 agents in the main hall; additionally, 250 agents each, joining in during the simulation from tram station and train platforms, respectively,

Case 2: 1,000 agents in the main hall; additionally, 500 agents each, joining in during the simulation from tram station and train platforms, respectively,

Case 3: 2,000 agents in the main hall; additionally, 750 agents each, joining in during the simulation from tram station and train platforms, respectively.

In each of above cases, all the agents are required to evacuate through one of four available exits on the main hall ("e13", "e15", "left", "right"). The emotions of agents starting from main hall is entirely different from that of agents joining in from tram station (with extreme fear and less hope) or from platforms (considerably relaxed). See Table I for complete listing. The percentage of AmI assisted agents is increasing during simulation from 0%, 1%, 5%, 10% to 100%, where 0% means no AmI assistance at all (consequently, all agents are moving towards an exit employing nearest exit strategy [43]), whereas 100% represents the optimum case where all agents are AmI assisted and where it can be assumed that there would be no affect of individual and social cognition due to absence of any leader-following behavior. All agents would unconditionally follow the exit recommendations provided, via AmI devices, by the central control unit, considering this situation as the best case (i. e., this setting is taken as benchmark for the study).

	bhope	bfear	battract	gamma
main hall	0.6	0.4	0.6	0.5
tram station	0.1	0.9	0.1	0.5
transit hall	0.8	0.2	0.2	0.5

Table I
Emotional Coefficients based on position; Trust coefficient (gamma) is assumed to have same value for all agents.

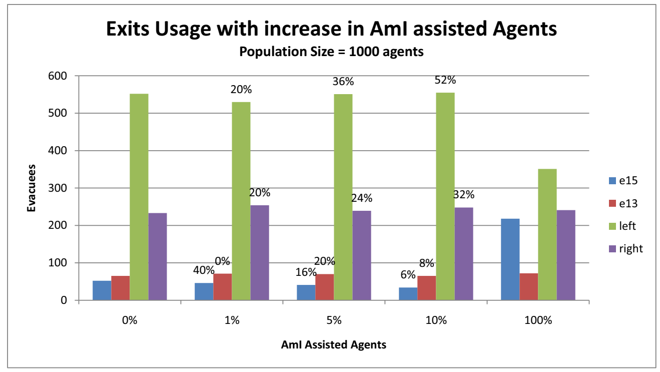

Figure 7. Case 1 (1,000 agents). Almost no effect of increase in AmI assisted %age due to too sparse population of agents.

A. Discussion

The focus of the simulation is to study the effect of change in belief of normal agents from potentially a less efficient (random) exit towards a more efficient (recommended) under the influence of cognitive agent model. However, the normal agents are not directly aware of recommended exit. They may follow one or more trust worthy AmI assisted agent within interaction range or may be affected by diffused information even if there is no such agent in the surrounding. Additionally, the presence of one or more AmI assisted agent does not always mean a change in belief (if it is required) due to other contributing attributes relating to comparison of agent's emotions with the surrounding emotions and its individualism. All these behavioural chains are modelled separately and integrated into evacuation simulation.

From inspection of simulation results, it can clearly be indicated that the quantity of agents has a high influence on the quality of the applied leader-follower approach. With only low number of 1,000 agents (case 1; Fig. 7), almost no effect on an increased %age of AmI assisted agents

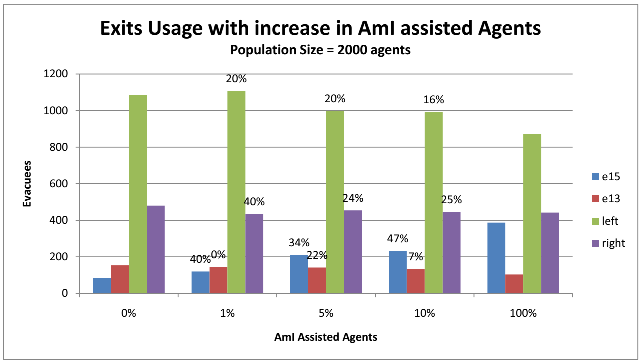

Figure 8. Case 2 (2,000 agents). Optimum exit usage (=benchmark) achieved with 100% AmI assisted agents. The higher the %age (from 1% to 10%), the better the exit usage compared to the benchmark.

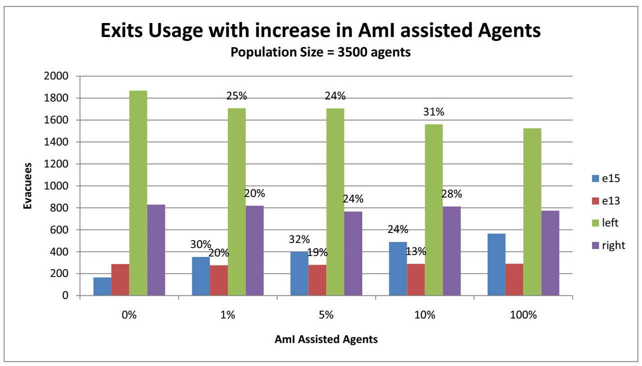

Figure 9. Case 2 (3,500 agents). Behaviour similar to case 2. The higher the quantity of agents (3,500 compared to 2,000 in case 2), the better the replication of optimum exit usage already in case of lower AmI assistant agents.

can be discovered, i. e., the exit usage is far from optimum usage (100% AmI assistance; =benchmark) for all the other settings (1 to 10%). The major reason accounting for this result is a too sparse population of agents, where all the agents keep on behaving on their own (no AmI assisted agent in vicinity).

For a more dense population of agents of 2,000 (case 2) to 3,500 (case 3), it can be seen (Figures 8, 9) that a %age of AmI assisted agents equal to only 1% provides already a major shift in the agents' exit usage towards the optimum exit usage provided by the benchmark (100% AmI assistance); a close-to-optimum approximation is achieved with 10% AmI assisted agents. From the comparison of Fig. 8 and Fig. 9 it can be indicated that the higher the quantity of agents (i. e., a more dense population where agents are "better" influencing one to the other), the less AmI assisted agents are needed to create a (close to) optimum exit usage.

In all graphs, the %age of AmI assisted agents reaching to respective exit are indicated with *text* on top of the column which is dependent on initial deployment and not a focus here. The table given in 10 summarizes the results in numerals.

VI. Conclusions

In addition to technological pursuit, it is important to model a socio-technical system at representative social (human) level. The inclusion of a representative and authentic social behaviour model into modelling a socio-technical system essentially produces fundamental differences in methodologies. For example, during evacuation we can expect a leader-following behaviour where a small specialized deployment particularly for that very purpose could generate acceptable results.

Focusing on an evacuation situation, we have integrated agent based cognitive decision making model based on psychological, neurological and social aspects into CA simulation to analyse the effect of AmI assisted (with technological assistance) agents on the intention of normal agents. The simulation results validate the following arguments; (i) the technologically assisted agents emerge as leaders during evacuation changing the intentions of many agents within their influence, (ii) even a small population of such leaders is sufficient to guarantee a remarkable difference; particularly improving usage of possible under-utilized exits. For example, in case of a fairly large population of agents (3500) with 10% being AmI-assisted, there is less than 2.5% difference in the utilization of the exits when compared with 100% AmI-assistance.

This is an ongoing research with potential of bridging the gap between social and technological systems. In addition to simulating the model for a real large scale, we would improve the model by incorporating more heterogeneity in the agents behaviour.

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Agents		1000				2000				3500			
	Exit util (%)	e15	e13	left	right	e15	e13	left	right	e15	e13	left	right
AmI-Assisted													
0%		5.764967	7.206208	61.19734	25.83149	4.603439	8.54132	60.23295	26.6223	5.268169	9.139956	59.28277	26.30911
1%		5.105438	7.880133	58.82353	28.1909	6.651885	7.982262	61.3082	24.05765	11.15689	8.748019	54.13629	25.9588
5%		4.550499	7.769145	61.15427	26.52608	11.6408	7.871397	55.32151	25.1663	12.68633	8.912147	54.1072	24.29432
10%		3.769401	7.206208	61.52993	27.49446	12.82621	7.384786	55.02499	24.76402	15.51396	9.200508	49.52411	25.76142
100%		**24.71655**	**8.163265**	**39.79592**	**27.32426**	**21.44044**	**5.761773**	**48.31025**	**24.48753**	**17.90808**	**9.223455**	**48.33597**	**24.53249**

Figure 10. Summary of Simulation Results: With increase in population size, as the %age of AmI-Assisted agents increases, the exit utilization tends to optimize.

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