Agent-based Modeling and Simulation for Emergency Scenarios: A Holistic Approach

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***Abstract*—Agent-based Modeling and Simulation is a powerful technique which allows to study the interactions in complex systems, and allows to explore or even foresee the emergence of more complicated properties or behaviors related to the interaction among the simpler agents in the environment. In the context of emergency or crisis scenarios, Agent-based Modeling and Simulation can allow to effectively study emergency plans, with the goal of assessing their viability, also with respect to the number of possible fatalities. In this paper, we analyze Agent-based Modeling and Simulation for crisis scenarios from a methodological and empirical point of view, with the goal of identifying what are the behavioral parameters that a model should encompass, in order for the results of the simulation to be useful for emergency plan assessment and/or compilation. We also experimentally provide a characterization of the effects of such behavioral parameters.**

***Keywords*—Agent-Based Modeling and Simulation, Emergency Simulation, Planning.**

I. Introduction

Agent-Based Modeling and Simulation (ABMS) is a powerful paradigm in which the system is represented by a collection of autonomous decision-making entities (the agents) which are set out in an environment [1], [2]. Each agent individually assesses the surrounding environment, also taking into account the presence of other agents, and makes decisions on the basis of a certain set of rules which implement their behavior. During its lifetime, an agent can decide to change its behavior, also depending on the environment state and interactions with other agents. The actions that agents take might also have effects on other agents and/or on the surrounding environment—for example, an agent can *produce*, *consume*, or *exchange* items.

ABMS is considered incredibly powerful for multiple applications and real-world business problems for a number of reasons. First of all, the model developer can concentrate on the design of agents behavior independently of *where* the agents will act. This significantly simplifies the development of complex models, allowing to reach results which could be difficult when relying on more traditional mathematical methods [3], [4]. Second, the interaction of multiple agents in a system can exhibit complex behavioral patterns [5], able also to show (or even anticipate) what is commonly referred to as *emergent behavior*. Emergence occurs when an entity is observed to have properties its parts do not have on their own. These properties or behaviors emerge only when the parts interact in a wider whole. Several approaches have also coupled sophisticated models with neural networks [6], evolutionary algorithms [7], or other learning techniques in order to provide the agents with behavioral adaptation, making ABMS even more powerful and realistic.

ABMS can be regarded as an effective methodology to address the problem of studying the behavior of crowds when emergency situations arise. This is particularly important for large-scale events, which are prone to natural disasters and chaos generated by people, which could cause severe threat to crowds. Among the possible events which should be subject to careful analysis we can enumerate religious service, sport events, cultural shows, public demonstrations and marches of any sort and kind. In many countries, the organization of these events must be accompanied by the compilation of ad-hoc security and evacuation plans, to reduce the risk of accidents and fatalities. When these plans are compiled, it is fundamental to identify solutions which allows the crowd to escape from catastrophic events in the shortest possible amount of time and/or minimize the number of people injured or subject to death—in many real-world scenarios, simply following the shortest path to an exit might not deliver optimal results. Plans should also consider the possibility that some security exits are blocked, or that the direction to be followed should change during the escape—this could be the case, for example, of cascading catastrophic events, such as the collapse of part of a building due to a fire.

In many scenarios, compiling these plans is difficult. Indeed, only real-world experience based on real accidents (which involve real people) could provide the required information to compile the plans. Of course, this is not viable: real-world experience or experiments with real people can be too costly, dangerous, or might be simply impossible, as in the case of the compilation of evacuation plans for buildings or architectonic ensembles which are not yet built.

In the case of a catastrophic event, a fundamental aspect to be taken into account is to consider (especially in large environments) that people do not immediately become aware of the risk or the occurrence of the event itself. In these circumstances, the panic generated by the event could be worsened by detrimental behavior due to people observing escaping crowds, without knowing the reason for it. For this reason, the law in several countries demands the escape plans to explicitly consider the presence of police (or other law/security enforcement agencies) which should monitor the emergency situation, inform the people by technological means such as loudspeakers, and/or guide the crowd towards the best-suited security exit. Disregarding the possibility that the crowd ignores the information provided by security agents—we will deal with this possibility in Section III—could be a source of ineffectiveness of the plan itself. Additionally, when compiling (or actuating) a security plan, a fundamental question is: "*how many security agents should be used to minimize the number of fatalities, and what is their best-suited position in the environment?*"

In this paper, we explore ABMS as a technique to support the compilation of these security plans, explicitly accounting for different behavioral aspects which should be considered when designing the logic behind single agents, so as to capture in a highly-realistic way emergent behavior of crowds. ABMS has features (autonomy, reactivity, pro-activity, and social interaction of the agents) which make this method a natural choice for scenarios requiring autonomous and adaptive participating agents [8]. Nevertheless, particular care must be put in the design of such models. Indeed, one way of modeling for such scenarios is to focus on global flow consideration [9], or on local interactions only [10]. Structurally, an egress scenario can be studied taking into account all the reachable exists, while distributing evenly (in terms of egress time) the population, as it is typically done in flow control [11], [12]. Nevertheless, at an individual level, agents are not particles, but social entities [13].

We define several building blocks of the agents which we consider fundamental to execute significant ABMS simulations of evacuation scenarios. We believe that such an analysis could be helpful for people studying the behavior of crowds, and for practitioners which are involved in the development of assistive tools for the compilation of security plans. In particular, we consider the modeling methodology presented here as effective for evacuation simulations in the context of earthquakes, landslides, floods, fires, terrorism attacks, crazy drivers, shooting, collapses, bombing, panic by misbehaving people, or abandoned objects which could be thought to be bombs, just to mention a few. Anyhow, depending on the specific scenario, fewer aspects of the holistic modeling approach which we propose can be considered, as the behavior of the agents is fully probabilistic.

We complete our exploration with an experimental characterization of the effects of the different behavioral aspects and parameters on the final results of the simulations. With this study, we stress the need for a holistic approach in ABMS for evacuation scenarios.

The remainder of this paper is structured as follows. In Section II we discuss related work. Our modeling methodology is presented in Section III. The experimental characterization is reported in Section IV.

II. Related Work

A lot of work has been done on ABMS, especially in the context of frameworks and runtime environments to support their execution on large-scale clusters. We refer the reader to the comprehensive work in [14] for a thorough discussion on the technical aspects related to the deploy of agent-based models.

From the point of view of ABMS as a methodology to study crowds in the context of evacuations, it has been proven to be an effective way to model and analyze the movements and the behavior of very dense crowds. This approach has been applied to many diverse scenarios, such as malls, airports, or parks. Abdelghany et al. [15] have presented a simulation-optimization modeling framework to study the evacuation of large-scale pedestrian facilities with multiple exit gates. In their work, they couple genetic algorithms and ABMS to generate optimal evacuation plans for hypothetical crowded exhibitions halls. The authors assume that the involved people receive evacuation instructions, which is an important aspect, but they nevertheless do not take into account the possibility that security exits become unavailable while the crowd is evacuating the building. Moreover, they assume that the people will follow the provided instructions accurately and unequivocally, which is a strong assumption for real-world emergency scenarios.

Wang and Wainer [16] have presented a distributed framework for modeling evacuation of crowds which models the environment in a realistic way starting from CAD/BIM authoring tools. This work illustrates the importance of relying on realistic environments for real-world models. We consider the environment to be a fundamental aspect in the modeling methodology, and we discuss how general environments should be modeled, although we do not retain the capability of using authoring tools out of the box.

Zheng et al. [17] have evaluated different methodologies to carry out crowd evacuation simulations. The evaluated methodologies include cellular automata models, lattice gas models, social force models, fluid-dynamic models, agent-based models, game theoretic models, and approaches based on experiments with animals. The authors conclude that psychological and physiological elements affecting individual and collective behaviors should be also incorporated into the evacuation models, the assessment of which is exactly part of the characterization which we carry out in this paper.

The importance of aspects such as physiological, emotional, and social group attributes has been studied in [18]. This work shows that when social group and crowd-related behaviors are modeled according to findings and theories observed from social psychology, and when the interactions among individuals is realized by means of agent-based execution processes, it becomes easier to simulate persons awareness of the situation and consequent changes on the internal attributes, and the results are realistic at both individual and group level.

Du et al. [19] have shown that evacuation plans could be significantly suboptimal if the involved people are significantly older that average situations. In their work, they have shown that older people are often not taken into account with great care also when compiling evacuation plans for senior apartment buildings. Older people typically have a different behavior in emergency situation as they move slower and might demand for help [20], and have a higher fall probability [21]. Puts et al. [22] have shown that by 2050 the world population with an age greater than 60 years will be composed of 22 billion people, and Prot and Clements [23] have shown that older people are more subject to accidents than other people. All in all, by this body of work, it is quite clear that it is not possible to avoid considering age in ABMS of evacuation plans, as the presence of elderly might also lead to unexpected emergent behavior of the crowd.

Chu et al. [24] have shown that egress simulations produce significantly different results when taking into account different agent behavioral models, namely following familiar exits, following cues from building features, navigating with social groups, and following crowds. Similarly, Zia and Ferscha [25] have shown that it is fundamental to combine individual, social and technological models of people during evacuation, in order to obtain results which are close to real-world scenarios. These are aspects which we explicitly retain, while we combine them with additional behavioral characteristics.

Overall, we consider all the aforementioned aspects in this paper (and additional ones), we try to orchestrate the concepts in a holistic way with respect to the modeling strategy, and we provide an experimental characterization of the effects of these behavioral parameters on the overall simulation results.

III. The Modeling Approach

The modeling approach which we propose and study in this paper can be regarded as a tool for analysis, study, and forecast of the behavior of crowds in closed or open space environments, with a special focus on evacuation in case of crisis scenarios. The approach is based on ABMS, and we define and combine the characteristics of each behavioral aspect which we consider fundamental for a significant simulation able to also produce realistic emergent behavior. The ultimate goal of this modeling approach is to allow for a what-if analysis of the evacuation plans of buildings and/or public events.

A. Representation of the Environment and Management of Correlated/Timed Events

A fundamental aspect for effective ABMS of crowd egress scenarios is to provide a high parameterization and behavioral capabilities at the level of the agents and the environment. As far as the environment is concerned, it is fundamental to specify an accurate representation of the obstacles that the agents moving around could find on their way. We consider traditional grid-based representations to be partially-suited for the purpose. In particular, the work in [26] has shown the importance in ABMS to rely on a graph-based topology to represent more complex environments. In our modeling approach, we envisage the reliance on more traditional grid based environments to represent portions of the overall space, which are then linked in a graph-like fashion from/to specific points of the grids. This solution allows to easily represent multi-level buildings, or areas which can be reached only from specific entrance points, and provides a good degree of flexibility in the configuration of the environment.

Moreover, it is fundamental to be able to specify the initial condition for the crowd distribution, and possible source points of other people entering the environment. In our approach, the steady state of the crowd distribution can be reached thanks to mobility models and/or by specifying the initial distribution of the crowd in the environment. There has been an extensive research on this aspect in the literature, and we refer the reader to the work in [27] for a discussion and a possible methodology with respect to this specific aspect.

As mentioned in Section I, we target in our modeling approach several different emergency scenarios. At the same time we advocate that, for a reliable assistive tool for the compilation of evacuation plans, it is important to take into account the *integration of multiple catastrophic events*. Therefore, an ABMS model must provide the possibility to consider that, during a single simulation, multiple events occur at different time instants. It is also fundamental to correlate such events. Therefore, the modeling approach should consider that, given the occurrence of some event in the environment, correlated events could take place after a certain amount of time, either in a fixed way, or by creating relations which are based on probability distributions. This is the case, e.g., of parts of the building collapsing some time after that an explosion took place. Another example is that of combined terrorism attacks, which take place shortly one after the other, also while the crowd is already escaping. Often, it is extremely hard to make an analysis of such events when compiling an evacuation plan, giving the high number and stochasticity of variables to account for, thus making ABMS a fundamental assistive methodology.

Another aspect to account for is the timely intervention of rescuers or police. This is an aspect that also depends on the environment. As an example, a catastrophic event happening at a concert might be more difficult to manage for rescuers, as the high-density of the crowd could prevent rescue vehicles to reach the critical points quickly. Also, the mixture of people and vehicles in the same environment could create more security risks, or increase the level of panic in the people attending the event. Additionally, the social behavior of the people is such that they could seek rescuers, also if they do not actually need assistance, thus slowing down the intervention, or creating variations in the evacuation flow as soon as rescuers reach the incident location.

As already highlighted, the way according to which evacuation starts can play a fundamental role in the evacuation process. In large environments, different people could be informed of the occurrence of an event for which they should egress. People nearby the accident will likely notice the event by themselves, while people farther away might be notified by loudspeakers, they could observe part of the crowd running away, or they could be notified "remotely" by some kind of gossip dissemination—social networks or messaging applications could also play a role here. This kind of remote interaction could also be misinterpreted, driving part of the crowd *towards* the critical place(s) in the environment, rather than in the opposite direction. This is a kind of emergent behavior which could lead to the adoption of different notification systems in the environment, or which could drive the selection of the best-suited position of law enforcement officers in the environment, e.g., during some event.

B. Behavioral Characteristics of Crowds

All the aspects which we have discussed so far have a different effect on the evacuation of the crowd depending on the characteristics of the single person which is involved in the evacuation. We advocate that there are some fundamental aspects which must be considered for an evacuation simulation to be reliable, and we stress that these aspects cannot be studied separately from each other. In the following, we describe the aspects which must be taken into account, when describing the behavior of an agent in a simulation model.

a) Emotionality and Emotional Contamination: This is a fundamental aspect to take into account to describe the behavior of the individuals, during emergency situations. Anxiety, panic attacks, fear, bewilderment, they are all aspects of the personality of an individual which could lead to "erroneous" or dangerous actions, both for the single individual and for the community during an evacuation. Emotional attitude should be described and considered, and it must also be combined with environmental aspects which can change the actions that an individual is performing during the evacuation. We model emotionality as a numerical value which is increased taking into account the presence of a number n of people in the nearby (the concept of *crowdedness*), the distance from the catastrophic event d_c, and the observability of the exit point, along with its estimated distance d_e—if the exit is not observable, we set $d_e = \infty$. Each individual is characterized by an *emotional facto*r $\eta \in [0, 1]$ which drives the speed according to which the emotionality value is updated towards the critical threshold. Overall, emotionality—which is always in the range $[0, 1]$—is updated according to Equation (1), which accounts for a very high emotionality ramp up after the occurrence of the critical event:

$$E' = \eta \frac{1}{e} \left(1 + \frac{d_c}{n \cdot d_e} \right)^{\frac{n \cdot d_e}{d_c}} + (1 - \eta)E, \tag{1}$$

where e is a control variable which is set to ∞ until the occurrence of the catastrophic event, and to 1 afterwards—it allows to prevent the emotionality value to increase in a normal environment.

Every time that the emotional value E for an individual overcomes a certain threshold $\bar{E}$, the agent starts to misbehave. Misbehavior entails forgetting about its heading towards an exit, and starting moving according to a random walk, also possibly seeking rescuers if they are in the nearby. This misbehavior continues until the emotional value is reduced behind the threshold, e.g., thanks to the agent getting closer to an exit.

Emotional contamination is also taken into account in this computation: two or more individuals which are in proximity could "contaminate each other" with respect to their behavior. As an example, if multiple anxious people are gathered together, without any "leader" or "stronger" individual in proximity, they might generate collective panic crises which are detrimental to security and safety.

b) Age: As already mentioned, age is an always more important aspect to take into account when compiling security plans. The age of single individuals could alter the way according to which they move and orientate in the surrounding environment. In particular, the speed at which an individual moves in the environment is inversely proportional to its age. A *fall probability* is also defined depending on the age, which is exponential with respect to the age.

c) Grouping: Studying the emergent behavior of the crowd must be done also taking into account that multiple individuals might know each other beforehand, and that they are set in the environment as a *group*—a simple example is a family, or a group of friends. It is likely that such groups will exhibit a "pack behavior", in which the interactions with the environment and the movements happen as a group. These groups will exhibit a behavior which will try to maximize the probability for the group to stay together, and it is something that could potentially affect the emergent behavior. Different environments can be characterized by a different probability of grouping, and this should be explicitly taken into account when compiling an evacuation plan. In our approach, the grouping probability P_g tells the probability that an agent is grouped with a nearby agents.

d) Remote Grouping: The wide spread of social networks and the ubiquitous presence of communication means adds the need to account for a different kind of grouping. In particular, if a group of people entered the environment together, but later split for any reason, it is likely that if an emergency scenario arises, they will try to regroup of get in contact before leaving the environment. This could clearly create delays in the evacuation, or counter-intuitive behaviors (e.g., moving towards the accident point). Again, this is an aspect which must be taken into account to deliver reliable simulations. In our modeling approach, the remote grouping probability P_{rg} determines whether the agent will stop for a random amount of time after that it becomes aware of the emergency situation, or that it will start to move towards the other individuals forming its group. The two behaviors are chosen uniformly at random.

e) Memory and Knowledge: Different individuals might have a different knowledge of the surrounding environment, and their memory could play a fundamental role. A motivating example is a person which enters a mall for the first time in its life. They do not know where exit locations could be found, but they do remember the route they traveled to reach a certain position. During the evacuation, also related with their emotional state, they might decide to travel towards the entrance which led them into the building, possibly ignoring other factors such as the presence of more suitable exits, or information provided by security officers. Similarly, the lack of knowledge of the surrounding environment might lead the decision-making process slower, or it could possibly exacerbate the "herd effect", in which people simply follow other people during the escape. The memory probability P_m and the environmental knowledge probability P_{kn} determine how the agents will behave, once they become aware of the occurrence of a critical event.

f) Knowledge of Environmental Risks: This is another behavioral aspect which is fundamental, especially in cascading catastrophic events. A motivating example is an individual which, during a fire, moves in proximity of pillars or poles. These architectonic elements could be easily damaged by the fire, and their collapsing might produce additional fatalities. In this sense, an individual which has a higher knowledge of these risks might leave the shortest path to a security exit, just to avoid several environmental risks. If the environment is extremely crowded, this behavior could create blockages or a slowing down, which are extremely important factors from an emerging behavior point of view. The probability P_{er} determines whether an agent is aware of environmental risks. In the positive case, the agent will try to avoid all the regions in the environment which they consider to be risky to traverse.

g) Trustfulness in Other People and Institutions: This behavioral aspect describes whether an individual will likely trust other people in the escape (therefore, "joining them" and possibly forming a group), or whether they will abide by the indications of security officials and/or rescuers. It is possible that this aptitude will negatively influence the choices taken, also in case there is the availability of useful information to leave the risky environment. The probability P_t tells how probable is that an agent will trust (and implement) the evacuation plans suggested by surrounding agents, or whether it will continue to evacuate according to its own strategy.

h) Social Networks: They are always more important in daily life. Also in emergency situations, it is possible that the people will spend some time in seeking for information—this is an aspect also related to the aforementioned grouping aspect. The timeliness and quality of the retrieved information might be argued as well. In particular, inaccurate information might make the people make wrong decisions, also in proximity of secure points such as emergency exits. At the same time, this phenomenon could generate additional delays in the evacuation of some people. The P_{sn} probability determines whether an agent, upon the occurrence of the critical event, will spend a random amount of time stopped, consulting social networks.

i) Lack of Understanding or Confusion: During an evacuation, individuals might not fully understand the information that is provided to them, also by rescuers, or they might enter a confusional state—this is also related to the aforementioned emotional aspect. These states might make the individuals forget or disregard important information related to the correct path to an exit, which they already acquired. Some people in a confusional state might take a wrong path in the evacuation, or they could simply stop, impeding the egress of other individuals. The confusion probability P_c determines whether an agent gets into the confused state. This condition can be checked multiple times during the simulation.

j) Chaos-generating Individuals: With specific respect to terrorism attacks, it is possible to suppose the presence of people which generate chaos on purpose. These people will explicitly act against the evacuation of crowds. This kind of byzantine behavior should be explicitly modeled in complex scenarios, especially because they could make an otherwise-good plan completely ineffective.

By this classification of the aspects which we consider fundamental in ABMS for evacuation purposes, it is clear that some of them partially overlap, either in the cause and/or in the effects. This is exactly the reason why we advocate that a holistic approach towards ABMS in these scenarios should consider all of them at once. In particular, we consider that, for each individual, the behavioral description should be based on probability distributions, which feed different explanatory variables describing the agents. In this sense, an evacuation plan should be considered reliable if and only if it respects some Key Performance Indicator levels under a high variability of the agents' behavioral characterization. Of course, in the context of specific public events (e.g., concerts of religious services) some configurations might be excluded. As an example, the distribution of the age of individuals can be tailored to the kind of public event. Nevertheless, an assistive ABMS-based tool could extremely simplify the compilation of a security plan, if the model is able to account for all the aspects which we have discussed at once.

C. Behavioral Characteristics of Rescuers

With respect to rescuers, we consider several different aspects and entities. One general aspect is related to the *timeliness* of the intervention. In particular, we consider the possibility that actual rescuers or law enforcement agents require some time to start acting after the catastrophic event. Indeed, this modeling approach can account also for the fact that, before intervening, individuals in charge require to coordinate. The configuration of this general aspect works at the level of the single individual, because different people might also react according to a different timeliness. The timeliness of intervention is therefore a configuration parameter which is driven from a Gaussian distribution. The mean value of this distribution can be specified at simulation configuration, accounting also for the aforementioned delay for coordination.

Another aspect is related to the possibility, the delay, and the period of repetition according to which all individuals in the environment are notified of the fact that an emergency is occurring. This aspect mimics the fact that, as we have already discussed, rescuers could inform all people of an accident by means of loudspeakers. Whether the crowd take into account this information or not, depends on the individuals' state. The modeling of this aspect is similar in spirit to that of timed events which we have discussed before.

Rescuers can be classified into *people* and *vehicles*. In the modeling approach, vehicles are set towards a specific place in the environment and they move at a speed which is inversely proportional to the crowdedness of the region. Vehicles can be of any kind, as they could represent firefighters reaching the spot of a fire, or policemen trying to reach the area of a shooting. Their target position is updated during the simulation, every time that their target changes location—think, again, of shooters. We account for a delay in the notification of the change of their target, which represents coordination and/or communication time.

With respect to people, rescuers have a twofold goal in our modeling approach. On the one hand, they instruct the people about the best-suited strategy to leave the environment. In our modeling approach, rescuers can be regarded as oracles which, at any time, give the best information. This clearly mimics the fact that during evacuations there is often a coordination system which tells the rescuers what are the proper actions to be done. Again, whether this information is used or not by individuals evacuating the environment depends on their current state. At the same time, with respect to emotional contamination, the presence of rescuers in proximity of individuals will reduce their anxiety level, therefore reducing the possibility that they misbehave.

D. Key Performance Indicators

An aspect which still requires a discussion is how to analyze the output of an evacuation simulation. In particular, ABMS could provide the end user with a bulk of data so large that it might become impossible to drive conclusions on the scenario of the simulation. If on the one hand visualization tools might become useful to interpret graphically the outcome of a simulation—we refer again the reader to the work in [16]—there are some numerical Key Performance Indicators (KPIs) which could be computed during or at the end of the simulation, for further interpreting the "goodness" of the simulated scenario. The fundamental KPIs which we envisage for catastrophic events—similar KPIs have been individuated in the work in [28]—are the following:

1) *Number of individuals evacuated per unit of time*: a "good" evacuation plan is such that it is able to maximize the number of evacuees;
2) *Time to evacuate all people* (except for fatalities): a "good" evacuation plan is such that this time is minimized;
3) *Usage of safest paths to evacuate the people*: this is especially true in the context of cascading catastrophic events;
4) *Minimization of the cost to actuate the evacuation plan*: this can be regarded as a multi-objective optimization problem, in which we want to minimize the number of fatalities, while reducing the number of security officers involved in the process.

Of course, the stochastic nature of this kind of simulations requires a large number of different runs, for each configuration, to have reliable results.

IV. Experimental Analysis

We have implemented an agent-based simulation model keeping into account all the aspects described in Section III and generating all the KPIs for each simulation run[1]. The model has been implemented on top of the open source ROOT-Sim Speculative PDES runtime environment [29], and all the simulations have been run on a hexa-core Intel i7-9750H CPU, equipped with 16 GB of RAM, running Linux 5.4.0.

[1]Our implementation is available at https://github.com/HPDCS/egress.

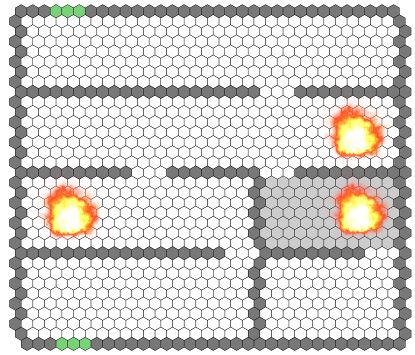


Fig. 1: Reference Emergency Scenario for the Experimental Assessment.

In our reference implementation, the different kinds of agents which we have described before belong to 5 different main classes. The first class is called *rescuers*, and implements the behavior described in Section III-C. We have then categorized agents as *group leaders* and *group members*. This classification allows to generically represent the aforementioned aspects associated with grouping, remote grouping, and social networks. We have then devised simple *individuals*, which are agents who do not belong to any group. The last class is that of *agitators*, which encompass agents which are confused, have a lack of understanding, or are generating chaos. All the other aspects discussed in Section III-B are captured in terms of explanatory variables, characterizing every single agent.

The environment in which the simulation takes place is depicted in Figure 1. The dark grey lines are obstacles (i.e. walls). An agent survives the simulated scenario if it successfully reaches one of green regions (the exits). At startup, the agents are uniformly distributed in the small gray section. A total number of 10,000 agents has been used in our simulation scenario. Three consecutive explosions take place in the simulated scenario. Before the first explosion, the agents are free to spread in the environment. At simulation time $T = 10$, the first explosion takes place in the upper right part of the map. At simulation time $T = 100$, a second explosion takes place, right in the agents' starting area—the gray area. A third explosion takes place at $T = 200$ in the left part of the map. The terrain is partitioned into hexagonal cells only for the purpose of partitioning the simulation run into multiple simulation object. One hexagonal cell has the long diagonal set to 300 meters, thus making the size of the environment non-minimal. The scenario is purposefully disastrous in order to highlight the emerging trend, especially when different simulation parameters are used.

The baseline configuration for the model is as follows. We set the average emotionality threshold to $\bar{E} = 0.9$, the average age to 40 years, the grouping probability to $P_g = 0.1$, the remote grouping probability to $P_{rg} = 0.005$, the average knowledge probability to $P_{kn} = 0.1$, the probability to rely on memory to $P_m = 0.01$, the probability of knowledge of environmental risks to $P_{er} = 0$ (no actual environmental risks are modeled in the scenario), the trustfulness probability to $P_t = 0.1$, the probability to rely on social networks to $P_{sn} = 0$, and the probability of confusion to $P_c = 0.01$. An individual is chaos-generating with probability $P_{ch} = 0.01$. Such an individual will randomly walk against the escaping crowd, while also actively trying to scare and confuse the other agents.

We modify this baseline configuration to study what happens to a subset of the KPIs which we have introduced when one single parameter is changed—for the sake of brevity we are not able to report results related to all KPIs in this paper. We have run complete simulation scenarios, meaning that the simulation is halted either when all agents have evacuated the map, or have died. Each point in the plot is averaged over 5 different simulation runs—a total of 55 runs for each plot. All different configurations of the models have been run with the same set of 5 random seeds for random-number generators, to allow for a stabler comparison. We present results associated with the variation of the percentage of fatalities over the total number of individuals in the simulations, the number of individuals evacuated per unit of time, and time to evacuate all people. These results are studied when varying different parameters, namely age (Figure 2), the confusion probability (Figure 3), the grouping probability (Figure 4), the knowledge of the environment (Figure 5), trustfulness (Figure 6), and the presence of chaos-generating individuals (Figure 7).

Experimental data show that there is a positive correlation between the fatalities rate and the individuals' average age (Figure 2). This is expected, since a higher age reduces mobility. However, the mortality doesn't increase dramatically. The standard deviation of the age distribution has been set to 15 years in order to reduce the noise over multiple simulation runs. This means that rescuers and grouped agents don't often lose sight of each other due to vast difference in mobility. This effect is also witnessed in the egress per time unit and the time to evacuate. The former decreases as the average age increases, while the latter increases linearly.

Grouping (Figure 4) has a negligible effect on the number of fatalities in our simulation scenario. As explained earlier, age variability is limited, therefore grouped agents don't often lose sight of each other. Moreover, in our simplified model, an agent that loses sight of his group simply tries to escape alone. This does not directly impact survival chance. Confusion probability (Figure 3), on the other hand, is strongly correlated with mortality rate. It is noted that all conditions impacting agents mobility have a huge influence on the outcome of this simulated scenario. This phenomenon is also reflected on the egress per time unit, which drops almost to zero for higher probabilities, and is similarly observed in the time to evacuate, which grows exponentially. This is also an expected result, because if a large fraction of the agents are confused, they start misbehaving, moving themselves farther from exits.

The effect of knowledge on the environment is interesting (Figure 5), because it illustrate a predominant behavioral effect. A zero-knowledge probability generates a significantly high number of fatalities, and increases drastically the time to evacuate. This is a result which is associated with the fact that the largest part of the agents has no idea about where to go to leave the disaster scenario, and starts wandering around. Rescuers, on the other hand, try to drive people towards the exits, but are anyhow subject to the same behavior of the other agents—they tend to move farther from the explosion points. In this sense, the zero-knowledge agents are continuously subject to random movement, until they reach an exit by chance. By looking at the adversarial map, this could require a significant amount of time, and given the subsequent explosions it can be fatal for a large number of agents.

The most interesting (and possibly unexpected) result is associated with trustfulness (Figure 6). A slight increase in trustfulness generates an increase in the number of fatalities and time to evacuate. This is an emergent behavior related to contrasting information. In this scenario, there is a subset of the agents who have a non-minimal knowledge of the environment, and are already heading towards a known exit on the map. If these agents are also associated with a high trustfulness, while heading towards the exit, they might change their plan and start following indications from the rescuers—this entails heading towards a different exit. Given the adversarial map, the time to evacuate increases, and it also creates conglomerates of agents who slow down the stampede of others. When the trustfulness is increased to a higher extent, the egress becomes more organized, and the agents can reach exits in a more ordered way. It is interesting to note that it is required a factor of trustfulness set to 100% to obtain a reduction in fatalities of 50%.

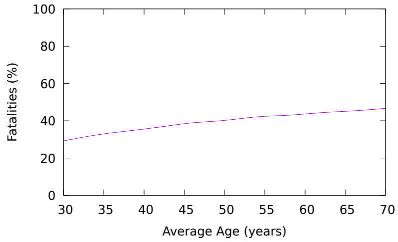
Chaos generating individuals are a vast minority of the agent population. Also, they do not directly restrict the movement of the population. In this extreme simulated scenario, the effect of chaos generating individuals is therefore insignificant—almost 40% mortality rate with default settings. Nevertheless, a minimal increase in the time to evacuate can be observed.

To conclude the experimental assessment, we report that, on average, the simulation of a complete scenario requires 55 seconds of wall-clock time.

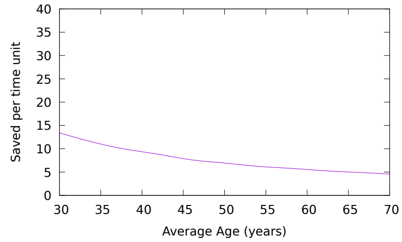
V. Conclusions and Future Work

In this paper we have discussed a holistic approach with respect to ABMS for emergency management, with a special focus on crowds escaping environments in the case of cascading catastrophic events. We have shown experimentally what is the effect of the different behavioral characteristics of individuals in the overall results of the simulation. Our results confirm that it is important to consider multiple aspects at once, because the outcome of the simulations could lead to very different results.

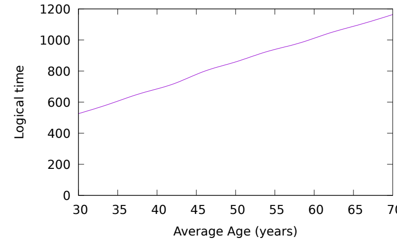
In our future work we plan to perform an in-vitro reconstruction of real-world accidents from the past. This effort will allow us to determine whether and to what extent our modeling approach is able to recreate actual evacuations in real-world accident situations. Moreover, we plan to integrate our model into a framework which will allow to automatize the exploration of different parameters given a configuration, so as to determine what could be the best-suited characteristics of a final evacuation plan.



(a) Fatalities

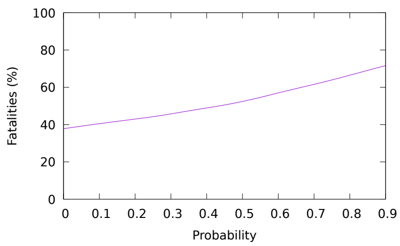


(b) Egress per time unit

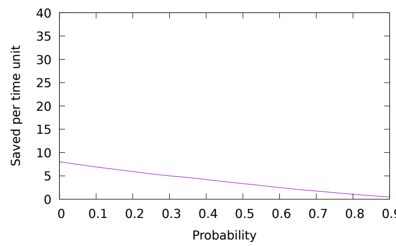


(c) Time to evacuate

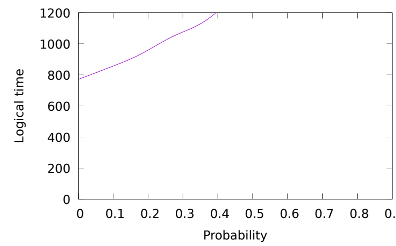
Fig. 2: Effects of Average Age



(a) Fatalities

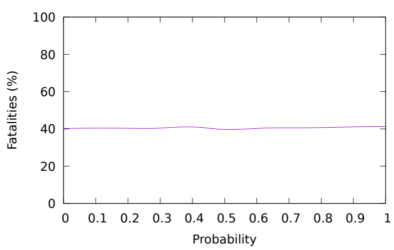


(b) Egress per time unit

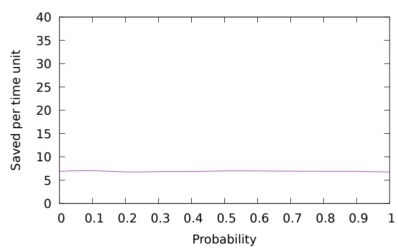


(c) Time to evacuate

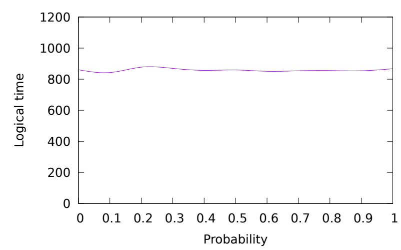
Fig. 3: Effects of Confusion Probability



(a) Fatalities

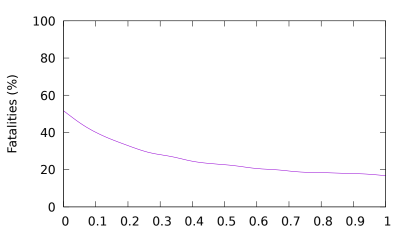


(b) Egress per time unit

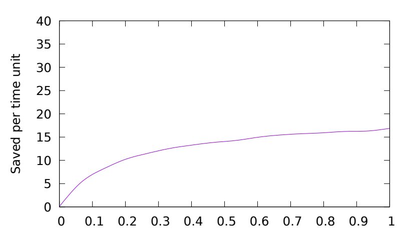


(c) Time to evacuate

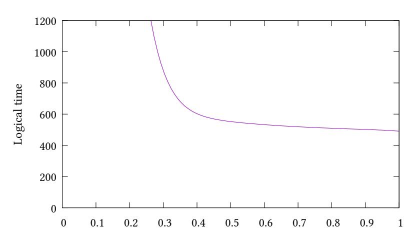
Fig. 4: Effects of Grouping Probability



(a) Fatalities

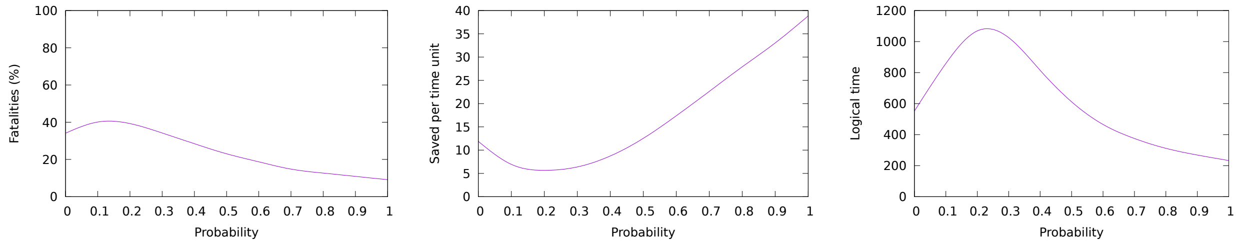


(b) Egress per time unit



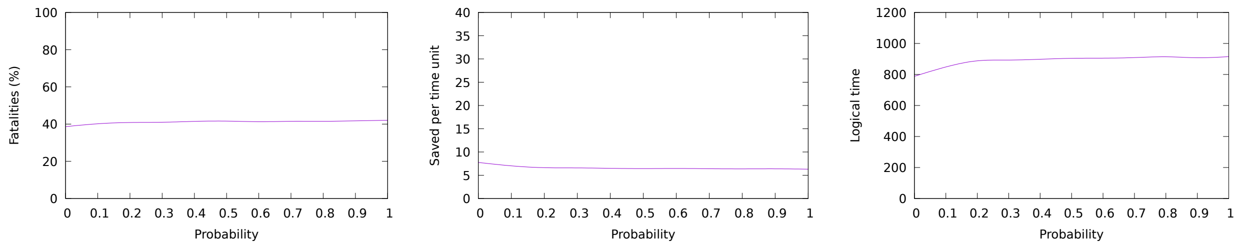
(c) Time to evacuate

Fig. 5: Effects of Knowledge of the Environment



(a) Fatalities (b) Egress per time unit (c) Time to evacuate

Fig. 6: Effects of Trustfulness



(a) Fatalities (b) Egress per time unit (c) Time to evacuate

Fig. 7: Effects of Chaos-Generating Individuals

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