A multi agent systems approach for aircraft emergency evacuation

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Minesh Poudel[1], Rakia Kaffa-Jackou[1,2], Felipe França[3], and Félix Mora-Camino[1,4]

[1] LARA, Air Transportation Department, ENAC, 7 avenue Edouard Belin, 31055 Toulouse, France.
[2] EAMAC, Niamey, Niger, BP 746,
[3]PESC/COPPE, Universidade Federal do Rio de Janeiro, Brazil
P.O. Box 68511, 21941-972, Rio de Janeiro, RJ,Brazil
[4]LAAS du CNRS, DISCO Group, 7 avenue du Colonel Roche, 31077 Toulouse, France.
Minesh.poudel@airbus.fr,rkaffa@eamac.ne, felipe@cos.ufrj.br, felix.mora@enac.fr

Abstract
In this communication we consider the problem of optimal control of a multi agents system evolving over a bi dimensional grid. Starting from an initial state, the aim of the problem is to find a global strategy so that the system reaches a desired final state in a minimum time. Each agent is characterized by motion parameters while to each cell is associated a current capacity. Objectives and constraints of this optimal control problem are discussed and a solution strategy based on dynamic programming solution approach is proposed for this discrete optimization problem. The application of interest in this study is relative to emergency evacuation of aircraft. The solution of this problem provides minimum time standards as well as insights for the design of personal guidance assistance in emergency situations.

Introduction
Demand for air travel has increased steadily over the last decades and the aviation Industry has forecast that-further substantial growth, nearly doubling of the air traffic, into the next coming decades. These forecasts have led aircraft manufacturers to design and produce airframes capable of carrying as much as nine hundred passengers as well as newer generation airframes made of composites. One of the important aspects from the beginning of the aviation history is that the passenger safety has always been taken with high priority within the industry. Henceforth we have seen substantial improvement in the safety standard of the aviation from design prospective to better operations and maintenance procedures. However, though the rate of accident has decreased drastically in the last three decades, the percentage of passengers surviving after the accident/incident has not decreased in comparison to the improvements achieved in other areas. A survey by the European Transport Safety Council assesses that 40 percent out of the 1500 persons who die every year in aircraft accidents, around 600 passengers die in technically "survivable" accidents. This study shows that more than half of them die from the direct result of the impact, and the others die because of fire, smoke, or problems that arise during the emergency evacuation process.

Figure 1 . A310: March 07- Dubai International Airport

Due to these reasons, not only the issues concerned with the prevention of the occurrence of accidents are tackled with great care but also issues contributing to improving the survival rate in the event of an accident/incident. Accidents can be classified either as fatal (non-survivable), non-fatal (survivable) or technically survivable. There are two ways to prevent fatalities in air travel: by preventing accidents and by protecting aircraft occupants when accidents occur.
In order to increase the survivability of passengers in case of an accident, one major area that needs immediate attention is cabin safety. Cabin safety cannot be defined precisely as it covers a very diverse responsibility and interests, which mainly includes crashworthiness, operations, human factors, psychology, and bio dynamics. However, it can be classified in three majors areas, interacting with each other namely: impact protection, fire survivability and emergency evacuation.
The focus of the present study is on emergency evacuation, which is an event which seldom occurs at the scale of airlines and that is extremely rare at that of individuals. However, it is under these scenarios that the role of the effective cabin improvements at the design stage have to be taken into account in order to prevent the accident and to develop best methods to deal with the reality of emergency evacuation. Improving survivability will therefore necessitate comprehensive review of all promising options available to regulators and Industry. More research is necessary to be conducted, in order to better understand the reality and prepare effective solutions. After reviewing different modeling approaches a non standard assignment problem is formulated so that cabin crew can be used efficiently during emergency evacuation.

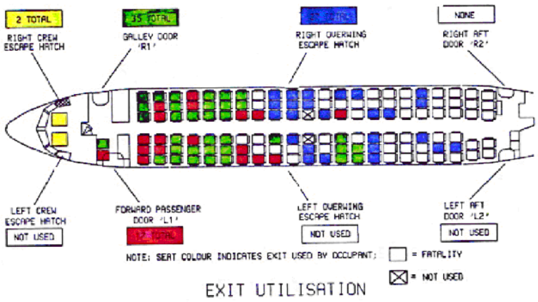

Figure 2. Exit Utilization During an Accident

II Cellular Automata

Cellular Automata play an important role in modeling and simulation of spatiotemporal processes. Cellular automata are artificial mathematical models of dynamical systems, discrete in space and in time, whose behavior is completely specified in terms of some local law. A cellular automaton can be thought of as a stylized universe:

- space is represented by a uniform grid, with each cell containing a few bits of data,
- time advances in discrete steps,
- the laws of the universe are expressed through a look-up table, through which at each step each cell computes its new state from that of its close neighbors.

Thus, the system's laws are local and uniform. The first cellular automaton used by Von Neumann was qualified as a universal computer while the Game of Life of J.H. Conway had only two states per cell, either filled or empty, 'alive' or 'dead. Essentially cellular automata allows to adopt a cell-based approach to model processes in a two–dimensional space.

A typical cellular automata system is composed of four components: cells, states, neighborhood and rules. Cells are the smallest units of the system having adjoining neighbors, they are characterized by discrete states. The state of a cell can change only based on transition rules, which are defined in terms of neighborhood functions. The transition rules are the real engines of change in cellular automata. Their rules control the transformation of a cell state to another cell state over a specific period of time depending on the neighborhood of the cells. The notion of neighborhood is central to the cellular automata paradigm.

A simple transition rule in a cellular automaton model is modeled by Li and Yeh as follows:

$$s(t+1) = f(s(t), \mathrm{N}) \qquad (1)$$

with $s \in S$ (S is the set of all possible cell states) and where N is the neighborhood of the cell, which acts as inputs for the transition rules. The function f defines the transition rules from time period t to $t + 1$. The adjacent neighbors are defined by the cells formed by the co-ordinates $\{x \pm 1, y \pm 1\}$ as in Moore's neighborhood, with, $x = 0$, $y = 0$ as the centre cell.

Typically in cellular automata, the neighbourhood and the transition rules play an important role for the automaton to initiate state transitions in a cell. In most cellular automata models, the automata are influenced only within the Moore's neighbourhood, which are the eight adjacent neighbourhood cells. Figure 3 depicts respectively the notions of neighbourhood developed by von Neumann and by Moore.

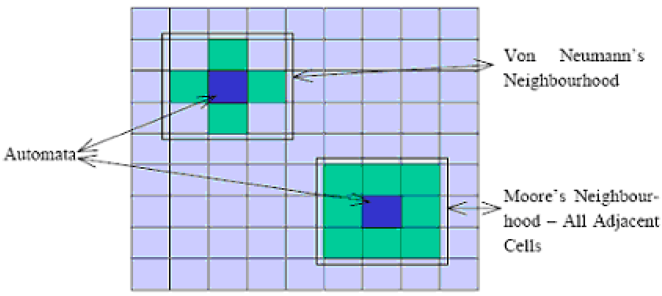

Figure 3. Cells and Neighbourhoods

An important component of the cellular automata paradigm is the geometry in the two-dimension space of the structures of the cells. The cells are of the same size and shape, and the value attributed to the cell corresponds to the whole region bound by the cell. Other different regular cell geometries are triangular and hexagonal cells. Even though uniformly regular spaced square cells are used as in the case of classical cellular automata, they are inadequate for an accurate representation of reality. Most objects in reality are not regular and hence they are not square in shape. To counter such situations irregular lattice structures are being introduced in the cellular automata framework.

One Dimensional Cellular Automata

Cellular automata are useful to analyze and understand the laws that govern complex phenomena. In natural sciences, non-linear phenomena are often described by reaction-diffusion equations. Non-linear space-time dynamics of interacting particles, chemical or biological systems can generate numerous local and non local effects far from equilibrium such as steady state multiplicity, oscillations like limit cycles, propagating fronts, target patterns, spiral waves, pulses as well as stationary spatial patterns. Computer simulations using Cellular Automata have been applied with considerable success in different areas, such as chemistry, biochemistry, economy and physics. The cellular automata are discrete mathematical systems taking discrete values in space, time and state. In addition to have auto-replication and universal computation capabilities, they present auto organization capabilities since they can generate ordered behaviors starting from total disorder. This capability is very useful to try to explain certain kind of behaviors observed in physical and biological phenomena. So, the cellular automata have been used to build numerical models of processes as diverse as chemical reactions, diffusion processes, hydrodynamic flows, mechanic, filtration and percolation.
With respect to the structure of a cellular automaton it can be considered as a dynamic system that represents a grid of locally connected finite automata. Each automaton produces and output from several inputs, modifying its state in this process by means of a transition function. The state of a cell of a cellular automaton in a particular generation only depends of the states of its neighboring cells and the state the cell had in the previous generation. Cellular automata are formally defined as quadruples:

$$CA = (d, S, N, f) \tag{2}$$

- the integer d is the dimension of the space in which the cellular automaton works.
- $S = \{0; 1;: : : ; s\text{-}1\}$ is called the set of *states*.
- the *neighborhood* $N = (n_1; : : : ; n_v)$ is a v-tuple of distinct vectors of Z^d.
- the n_i's are the relative positions of the neighbor cells with respect to the current center cell, the new state of which is being computed. The states of these neighbors are used to compute the new state of the center cell.
- the *local function* of the cellular automaton ($f : S^v \rightarrow S$) gives the local transition rule.
- a *configuration* is a function from Z^d to S. The set of all configurations is $C = S^{Z^d}$.
- the *global function* A of the cellular automaton is defined via f as follows:

$$\forall\, c \in C, \forall\, i \in Z^d,\ A(c) = f(c(i + n_1), \cdots, c(i + n_v)) \tag{3}$$

which correspond for instance to rules such as:

1. If a cell at the time t is inactive (0), is activated at the time t+1 if some of the previous adjacent cells (left) is active (1).
2. An active cell at the time t, is turned inactive at the time t+1 if its adjacent cell (left) is inactive.
3. In other case a cell preserve its previous state.

In Figure 4 a graphical representation of these transition rules is presented and in figure 5 the evolution of this cellular automata is shown.

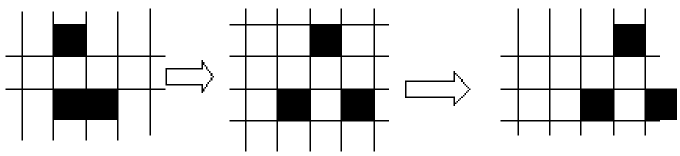

Figure 4 . Example of Transition Rules

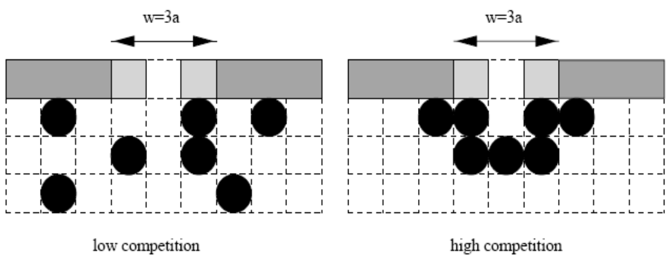

Figure 5 . Example of Evolution of Cellular Automata

3. Cellular Automaton Egress Modeling

This approach has been adopted by Kirchner et al which introduced a model based on cellular automaton where space is discretized into cells (see figure 6) which can either be empty or occupied by one person (in their case a passenger). Each person can move to one of its unoccupied next-neighbor cells (i, j) at each discrete time step $t \rightarrow t$ +1 according to certain transition probabilities p_{ij} . These probabilities are environment dependent. A move is only possible towards one of the direct neighbor cells. For the case of the evacuation processes, the environment of a person is characterized by the shortest distance to an exit door, which can be measured by the minimum number of cells that have to be crossed to reach the exit.

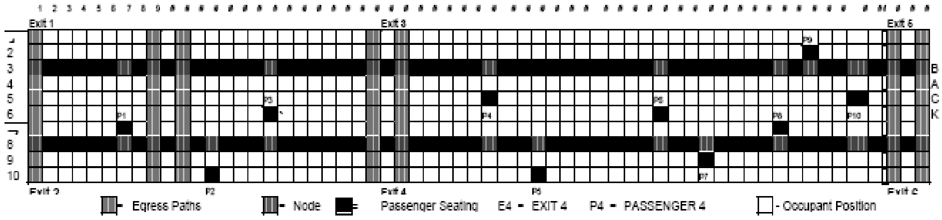

Figure 6 . Discretization of Aircraft Cabin Space

The persons move from one cell to another according to some rules. A possible set of rules is the following:

- For each person, the transition probability p_{ij} for a move to an unoccupied neighbor cell (i, j) (including the origin cell, corresponding to no motion) is given by :

$$p_{ij} = Q\, \lambda_{ij}\, (1 - n_{ij})\, e^{k_s S_{ij}} \tag{4}$$

where: $n_{ij} = 0$ if cell (i, j) is empty and 1 otherwise, and $\lambda_{ij} = 0$ if cell (i, j) is forbidden, $\lambda_{ij} = 1$, otherwise.

Coefficient S_{ij} can be taken inversely proportional to the distance from the door measured using a Manhattan metric. Here k_s is a positive scaling parameter and N is such that:

$$Q = [\sum_i \sum_j \lambda_{ij}\,(1 - n_{ij})\, e^{k_s\, S_{ij}}\,]^{-1} \tag{5}$$

- Each person s makes a probabilistic choice of a target cell according to the updated transition probability distribution $\{ p_{ij}\,,\ (i, j) \in B(s)\}$, where $B(s)$ is the set of direct neiborghs to the cell in which person s is presently.
- Conflicts arising between two or more persons attempting to move to the same target cell are solved by a probabilistic method: Here a friction parameter $\mu \in [0, 1]$ is introduced so that in a conflict the motion of all involved persons is denied with probability μ, while one person is allowed to move to the desired cell with probability 1-μ. The person, which actually moves, is chosen randomly with equal probability between the persons involved in the same conflict.

Several advances are being made to explore the possibilities of the cellular automata technique. Notable among them are calibration approaches for constrained cellular automata models, which have been applied to model slow spatial processes. These models are constrained by the causal factors driving the spatial processes. Local constraints contain detailed information for each cell, but sector constraints have only aggregated or partial-spatial information. Global constraints, however, are characterized by temporal or non-spatial information. Such an approach of defining the constraints and operating in cellular automata is a step towards achieving linkages with the causal factors.

Once the simulation is executed, the constraints would be static over time. However, there are many systems for which the constraints are dynamic dependent on the situations. And so it would require an additional framework to address issues concerning the dynamics of these causal factors and constraints. Further, in such models these constraints would not behave as an event-based system with a cause-effect relationship. Many models need to account for the external drivers that are not accounted in the transition rules of the cellular automata. Certain externalities can be system wide or specific to certain locations, for which the cellular automata models have to evolve to address such requirements. Further there are possibly also different significant processes that take place in the region in question, apart from those represented in the cellular automata model. Cellular automata models are yet incapable of representing the external factors responsible for driving the change dynamics as the transition rules account only for the states and neighborhood.

To overcome such limitations, different approaches are being suggested. Among them is the integration of agent-based models over a cellular automata framework, as agent-based models can be constructed to represent the externalities driving the processes. Thus the current research is approaching towards the integration agent-based models (multi-agent systems) with the cellular automata models, such as in the case of modelling the dynamics of emergency evacuation by incorporating different drivers as agents involved in enabling the individual spatial interactions by defining the spatial and temporal relationships to these agents.

4. Agent Based Modeling

Agents, have their origins in software engineering and artificial intelligence where they are used in networking, communications and many more applications. The aim of agent design is to create a program, which interacts with its environment. The term 'agent' is usually applied to describe self-contained programs, which can control their own actions based on their perceptions of their operating environment. A significant definition is that, an agent is considered as a self-contained program capable of controlling its own decision-making and acting, based on its perception of its environment, in pursuit of one or more objectives. The most general way in which the term agent is used is to denote hardware or a software-based computer system that enjoys the following properties:

- Autonomy: Agents operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state;
- Social ability: Agents interact with other agents (and possibly humans) via some kind of agent-communication language;
- Reactivity: Agents perceive their environment, (which may be the physical world, a user via a graphical user interface, a collection of other agents, or perhaps all of these combined), and respond in a timely fashion to changes that occur in it;

- Pro-activeness: Agents do not simply act in response to their environment; they are able to exhibit goal-directed behavior by taking the initiative.

There are a number of points about this definition that require further explanation. Agents may be characterized by the following properties:

- clearly identifiable problem solving entities with well-defined boundaries and interfaces;
- situated (embedded) in a particular environment—they receive inputs related to the state of their environment through sensors and they act on the environment through effectors;
- designed to fulfill a specific purpose—they have particular objectives (goals) to achieve;
- autonomous, i.e. they have control both over their internal state and over their own behavior;
- capable of exhibiting flexible problem solving behavior in pursuit of their design objectives.

They need to be both reactive (able to respond in a timely fashion to changes that occur in their environment) and proactive (able to act in anticipation of future goals). Although, the origins of agent-based models have been in the artificial intelligence, they are also developed in social sciences extensively.

Agents can be considered as a special case of an automaton, having all features of the general automaton, with a distinction that these agents are mobile and they can represent the external drivers responsible for the processes (e.g. socioeconomic, population, etc.). The idea is to treat each of the individual drivers as agent-based automata enabling the spatial and temporal relationships. There can be as many agent-based models as the number of externalities identified driving the processes at appropriate scales. Such processes take place at specific locations and are generally not system wide. While a classical cellular automata transition rule is system wide, such agent-based models would only be specific to certain locations only. These agent-based models are to act in conjunction with the regular transition rules of the cellular automata.

The essential concepts of agent-based computing are agents, high-level interactions and organizational relationships**.** It can be seen that there can be numerous agents wherein specific agents can interact amongst themselves and/or have the same sphere of visibility and influence. There can also be agents who act independently without any interaction with other agents.

The classification of agents has been attempted by different investigators. The classifications are made based on the characteristics (autonomy, reactivity, social ability and pro-activeness) and applications of the agents. Agents can be classified in three broad categories according to the mobility of these agents , the agents are classified as static or mobile, according to the ways in which these agents are modeled, the agents are categorized as 'reactive' and 'deliberative' and according to several primary attributes that agents should exhibit. The three characteristics autonomous, cooperation and learning are used to derive the four types of agents: collaborative agents, interface agents, collaborative learning agents and smart agents.

Multi-agent based simulation is used in a growing number of areas, where it progressively replaces the various micro-simulation, object-oriented or individual-based simulation techniques, previously used. It is due, for the most part, to its ability to cope with very different models of "individuals", ranging from simple entities (usually called "reactive" agents to more complex ones ("cognitive" agents. The easiness with which modelers can also handle different levels of representation (e.g., "individuals" and "groups", for instance) within an unified conceptual framework is also particularly appreciated, with respect, for instance, to cellular automata.

This versatility makes multi agents based simulation emerge as the support of choice for the simulation of complex systems, and it is appealing to more and more scientific domains: sociology, biology, physics, chemistry, ecology, economy, etc.

5. Multi-Agents Systems and Cellular Automata

In a cellular automata model, space is represented as a uniform lattice of cells with local states, subject to a uniform set of rules, which drives the behavior of the system. These rules compute the state of a particular cell as a function of its previous state and the states of the adjacent cells. Several extensions have been developed:

- An extension of the basic cellular automata model allows the state of any particular cell to be influenced by more the states not only of the contingent cells, but also the by the states of more remote cells. State changes may depend on the aggregate effect of the states of all other cells, or some of their subsets.
- Another extension is to build models in which cells preserve state information and calculate their next state on the basis of their neighbors and their own history of state changes.
- Agent technology has been implemented to build a framework for multi-agent simulation. Objects (or people) moving across the network are represented in terms of autonomous agents. Each agent will be located in a simulated space, based on the cellular automata grid.

The choice of a multi-agent system is motivated by their promise to simulate autonomous individuals and the interaction between them. Agent technology is also used to simulate the outcome of the model and the simulation. Designers can use the system to assess the likely consequences of their design decisions on user behavior.

The application of cellular automata implies the possibility to simulate how an 'agent'-user moves in a given environment, dependent of the behavior of other agents in the system.

In developing the simulator it is useful to differentiate between the cellular automata part and the distributed artificial intelligence agent's structure. The agent's structure part involves the different agents with their respective roles. Various agent types may be distinguished in the model such as user-agents that represent people in the simulation. Here the passenger can be considered to be the subject-agent. Actor-agents can simulate the crew. Thus, subject-agent and actor-agents are user-agents that navigate in the virtual environment network, each with their own behavior, beliefs and intentions. A belief is the internal, imperfect representation of the virtual environment including the state of other user-agents, on which the decisions of an agent are based. We must view behavior as the interaction between the user agents and the environment. For the subject-agent, this behavior is not an attribute of the agent, but rather lies in the mind of the subject alone. Styles of behavior like anticipated behavior and unplanned behavior can be considered. Besides a behavior-agent, we also distinguish an intra-task-agent. An intra-task-agent fulfils the intentions of a user-agent to reach a destination (goal) and/or to carry out a list of activities (a plan).

We define a user-agent as the 3-tuple:

$$U = < R, A, F > \tag{6}$$

where

- R is a finite set of role identifiers, it represents the enumeration of all possible roles that can be played by user agents;
- A represents the activity agenda of user-agent i to perform the goals and desires ($\{Ai\}$).
- F represent the knowledge or information about their environment which an user agent possesses ($\{Fi\}$), which is called *facets*.

Part of these facets is amongst others beliefs, awareness, experience, preference and choice. All these facets are dynamic and may change over time in the simulation loop, influenced by the occupation of other cells in the network. The population of crowded cells could result in emergence behavior of the crowded neighborhood. A regular lattice of width W and length L, and density (that represents the mesh of the network) can be introduced. Cells within the lattice are given the notation $\boldsymbol{c_{k,i,j}}$, where $1 \le i \le W$ and $1 \le j \le L$ and k indicates the cell type where $k \in$ {*empty*, *decision*, *wall*}. Here:

- *"empty"* means that the cell belongs to the walkway;
- *"decision"* means the cell belongs to the decision-point area where the passenger takes the decision where to go;
- *Wall* means that the cell is part of a frame (a wall, etc.).

A cell x (actually $c_{t,i,j}$) in the aisle to be *on* ($s(x)=1$) if it is occupied by a passenger, otherwise it is *off* ($s(x) = 0$). Also a density size $\delta_r(x)$ which shows the activity around cell x can be defined; it shows the number of neighbors in an *on* state in relation to the total number of neighbors in the Moore neighborhood of cell x with radius r. In a d-dimensional grid with a Moore radius r, the number of cells n in the neighborhood of cell x (x included) = $(2r+1)d$. The updated cell x depends on the *on* states of all cells in the neighborhood N of x ($N(x)$). To summarize the transition of a state of a cell,

$$s^t(x) = 0 \Rightarrow s^{t+1}(x) = 1 \quad \textit{if hit by an object or an agent} \tag{7}$$

$$s^t(x) = 1 \Rightarrow s^{t+1}(x) = \begin{cases} 1 & \textit{if cell activity remains} \\ 0 & \textit{if a user agent left the cell behind} \end{cases} \tag{8}$$

$$\delta_r(s^{t+1}(x)) = (\sum_{i=0}^{n}((s^{t+1}(x+y_i))/n) \quad where \quad y_i \in N(x),\, y_0 = 0,\, n = (2\,r+1)^d \tag{9}$$

The cellular automaton micro simulation can proceed from one time instant to the next. In each time step lane assignment and speed updates change the positions of all pedestrians according to local rules applied to each pedestrian.

6. A Stochastic Cell Model

Here is considered a systems composed of I agents located at a grid with N positions. Among these positions, a subset N_s is composed of safe positions. The current state of agent i is represented by his position ($i(n), j(n)$) in the grid. When a system obeys the Markov property, the future is determined only by the present and not by the past. The Markov property can be stated in the following way: the configuration of the system at time $t+\Delta t$ depends only on the configuration of the system at time t. This fact allows to write the probability distribution at time $t+\Delta t$, $P(i=n, t+\Delta t)$ in terms of the conditional probabilities and the previous probability distribution at time t, $P(i=n', t)$ which is the probability that agent i is at position n' at time t :

$$P(i=n, t+\Delta t) = \sum_{n^1} p(i=n, t+\Delta t \,/\, i=n', t) P(i=n', t) \quad \forall i \in L(t) \tag{10}$$

where $L(t)$ is the set of alive agents at time t.

Using the fact that the transition probabilities are such that:

$$\sum_{\vec{n}^1} p(i=n, t+\Delta t \,/\, i=n', t) = 1 \quad \forall\, i \in L(t) \tag{11}$$

allows to rewrite the change in probability density as:

$$P(i=n, t+\Delta t) - P(i=n, t) = \sum_{\vec{n}'} p(i=n, t+\Delta t \,/\, i=n', t) P(i=n', t) - \sum_{\vec{n}^1} p(i=n, t+\Delta t \,/\, i=n', t) P(i=n, t) \tag{12}$$

or:

$$P(i=n, t+\Delta t) - P(i=n, t) = \sum_{n'} p(i=n, t+\Delta t \,/\, i=n', t)(P(i=n', t) - P(i=n, t)) \tag{13}$$

At the start of evacuation, the cabin is composed of cells which are in the following possible states: undamaged, partly damaged but transitable, destroyed or untransitable (crushed, blasted, burnt, drowned). Possible active hazards such as fire, smoke and water have a starting area covering a given set of destroyed or untransitable cells. Then propagation models of the present hazards are given by:

$$F(t), t \in \{t_0, t_0+\delta t, \cdots, t_0+k\;\delta t, \cdots, t_f\} \tag{14}$$

$$S(t), t \in \{t_0, t_0+\delta t, \cdots, t_0+k\;\delta t, \cdots, t_f\} \tag{15}$$

$$W(t), t \in \{t_0, t_0+\delta t, \cdots, t_0+k\;\delta t, \cdots, t_f\} \tag{16}$$

where $F(t)$ is the set of cells affected by fire at period t, $S(t)$ is the set of cells affected by dense smoke at period t and $W(t)$ is the set of cells affected by water at period t. Here t_0 is the initial time and t_f is the final period of the simulation.

Then it is possible to identify at each period the feasible exits as well as the passengers which are affected by the different active disasters. Agent i is alive at time t if the three following conditions are met:

$$\int_0^t \sum_n P(i=n,t)\,\varepsilon_{F,n}(t)dt \le \sigma_F \tag{17}$$

where $\varepsilon_{F,n}(t)=1\ if\ n \cap F(t) \ne \varnothing \quad \varepsilon_{F,n}(t)=0\ if\ n \cap F(t)=\varnothing$

$$\int_0^t \sum_n P(i=n,t)\,\varepsilon_{S,n}(t)dt \le \sigma_S \tag{18}$$

where $\varepsilon_{S,n}(t)=1\ if\ n \cap S(t) \ne \varnothing \quad \varepsilon_{S,n}(t)=0\ if\ n \cap S(t)=\varnothing$

$$\int_0^t \sum_n P(i=n,t)\,\varepsilon_{W,n}(t)dt \le \sigma_W \tag{19}$$

where $\varepsilon_{W,n}(t)=1\ if\ n \cap W(t) \ne \varnothing \quad \varepsilon_{W,n}(t)=0\ if\ n \cap W(t)=\varnothing$

Here σ_F, σ_S and σ_W are positive threshold levels. It is supposed that the transition matrices are such as:

$$P(i=n,t+\Delta t / i=n',t)=0 \quad \forall\, i \notin L(t) \tag{20}$$

$$P(i=n,t+\Delta t / i=n',t)=p_{n'n}\ (1-\rho(n,t)) \quad \forall i \in L(t) \tag{21}$$

where
$$\rho(n,t)=\sum_{j=1}^{I} P(j=n,t) \tag{22}$$

and
$$p_{n'n}=\alpha^*_{n'n}\ w_n+(1-w_n)\,\overline{\alpha}_{n'n} \tag{23}$$

where $\alpha^*_{n'n} \in \{0,1\}$ shows the best next step towards exit and $\overline{\alpha}_{n'n} \in \{0,1\}$ is the inverse of the number of direct neighbours to cell n. The positive weight w_n can be chosen such that:

$$w_n=\min_{j\in C}\ \min_{k\in\{1,\cdots,N\}} \frac{1}{1+\lambda\ x_{kj}\,\|n-k\|}=w_n\left(\left[x_{kj}\right]\right) \tag{24}$$

where λ is a positive parameter and x_{kj} =1 if crew member number j is at position k , and x_{kj} =0 otherwise and where $\|n-k\|$ is a distance on the grid of positions n and k.
The emergency evacuation can be considered completed at time t_f when:

$$t_f=\min t \quad \text{with} \sum_{n\in N_s} P(i=n,t) \ge \sigma_i \quad \forall i \in L(t) \tag{25}$$

where σ_i is a threshold parameter with $\sigma_i \in [0,1]$ but in general near to 1. The set of safely rescued passengers, N_{srp} is such that:

$$i \in N_{srp} \quad if \quad \int_0^{t_f} \sum_n P(i=n,t)\,\varepsilon_{F,n}(t)dt \le \sigma_F\,, \quad \int_0^{t_f} \sum_n P(i=n,t)\,\varepsilon_{S,n}(t)dt \le \sigma_S \tag{26}$$

$$\text{and} \quad \int_0^{t_f} \sum_n P(i=n,t)\,\varepsilon_{W,n}(t)dt \le \sigma_W \quad \forall\, i \in I$$

Then the crew location problem during egress can be formulated as the following discrete optimization problem:

$$\max_{[x_{kj}]} \left| N_{srp} \right| \tag{27}$$

with the constraints (10), (25), (26) and the classical assignment constraints:

$$\sum_{j\in I} x_{kj} \le 1 \quad \forall\, k \in N \quad \text{and} \quad \sum_{k\in N} x_{kj}=1 \quad j \in I \tag{28}$$

Of course this is a non standard assignment problem since it includes dynamical aspects, stochastic components and dynamic opponents (hazards). An approximate solution of this problem, an heuristic based on flows in networks considerations, can be designed to tackle efficiently this problem.

7. Conclusion

This paper has discussed different modeling approaches that are currently used for modeling complex systems whose dynamics is characterized by the evolution, often competitive, of many individual agents: cellular automata, agent based simulation, multi-agents simulation and stochastic cell models. There, simulation is based on mathematical models that represent the temporal evolution of location of individual agents from cell to cell. It appears that all these modeling approaches present large limitations with respect to their application to emergency evacuation representation: the space in which agents move is in general composed of identical adjacent cells and cannot be easily adapted to represent realistically the confined cabin space; hazards dynamics are hardly considered; the motion of agents is driven by over simplified logics mainly based on the occupancy of neighboring cells; the behavior of the agents is assumed to be homogenous: many often there is no differentiation between the behavior of agents, no specific group behaviors are also considered. This has led to propose a stochastic model to represent egress dynamics and hazard progression as well as passengers health evolution during egress. Then an optimization problem considering the localization of cabin crew members during evacuation has been established. The aim of this problem is to locate optimally the cabin crew members so that they can provide efficient directives to evacuating passengers so that at the end of evacuation, the maximum number of life is saved.

8. References

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