Aircraft Emergency Evacuation: A Multi Agent Optimization Approach

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Abstract. In this communication we consider the problem of modelling a multi agents system evolving over a bi dimensional grid. Starting from an initial state, it is considered that the overall aim of the agents population is to behave 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. The application of interest in this study is relative to emergency evacuation of aircraft and the influence of cabin crew over its performance. a non standard assignment problem is formulated so that cabin crew can be used efficiently during emergency evacuation. The solution of this problem should provide 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 substantial growth, nearly the doubling of the air traffic, into the next coming decades. These forecasts have led aircraft manufacturers to design and produce light airframes capable of carrying as much as nine hundred passengers. 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 substantial improvement in the safety standards of the aviation from design prospective to better operations and maintenance procedures have been performed along the years.
However, though the rate of accident has decreased drastically in the last three decades, the percentage of passengers surviving after an accident 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. It has been shown that more than half of them die from the direct result of the impact, and the others die from fire, smoke or problems that arise during the emergency evacuation process. 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 are of highest interest. 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 area that needs major attention is cabin safety. Cabin safety cannot be defined precisely as it covers a domain of very diverse issues such as crashworthiness, operations, human factors, psychology, and bio dynamics. However, it can be classified in three majors functional areas, interacting with each other namely: impact protection, fire survivability and emergency evacuation.

The focus of the present study is on modelling emergency evacuation, which is an event which seldom occurs at the scale of daily operations by airlines and that is extremely rare at the scale of individuals. Different modelling approaches, mainly inspired on cellular automata, are considered. Then considering that the role of cabin crew is essential for the success of emergency evacuation, a non standard assignment problem is formulated so that cabin crew can be used efficiently during emergency evacuation. Then, it is possible to consider the behavior of egressing passengers under under the optimal supervision of cain crew. The solution of this problem should provide minimum time standards as well as insights for the design of personal guidance assistance in emergency situations.

Modelling Approaches

Cellular Automata. Cellular Automata which play an important role in modeling and simulation of spatiotemporal processes appear of interest to modelize emergency evacuation processes. Indeed, 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 distributed laws.
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.
An important characteristic of a cellular automata is the geometry in the two-dimension space of the cells. Uniformly regular spaced square cells are used in the case of classical cellular automata. They are very often inadequate for an accurate representation of reality. To counter such situations irregular lattice structures are being introduced in the cellular automata framework.
Cellular automata have proven to be useful to analyze and understand the laws that govern complex phenomena. Cellular automata 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, economical 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. Then, computer simulations using Cellular Automata have been applied with considerable success in different areas.

Cellular Automata Applied to Egress Modeling. A first approach has been developped by Kirchner et al which introduced a model based on cellular automaton where space is discretized into cells (see figure 4) which can either be empty or occupied by one person (in this 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 mainly 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 that exit.
In the model proposed by Kirchner, the passengers move from one cell to another according to rules such as:

- For a passenger, 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 :

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

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. The 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:

$$Q = [\sum_i \sum_j \lambda_{ij}\,(1-n_{ij})\,e^{k_s\,S_{ij}}\,]^{-1} \qquad (2)$$

- Each passenger 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 passenger s is currently.
- Conflicts arising between two or more passengers attempting to move to the same cell are solved by a probabilistic method: a friction parameter $\mu \in [0, 1]$ is introduced so that in a conflict the motion of all involved passengers is denied with probability μ, while one passenger is allowed to move to the desired cell with probability $1-\mu$. The passenger, which actually moves, is chosen randomly with equal probability between the passengers involved in the same conflict.

Such a cellular automata model is unable to represent the external factors responsible for driving the dynamics of change affecting often the transition rules.

To overcome such limitations, different approaches have been 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 of 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.

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.

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 the field of social sciences.

Agents can be considered as a generalization of the concept of automaton, having all features of the general automaton, with a distinction that these agents can represent the external drivers responsible

for the processes. There can be as many agent-based models as the number of externalities identified driving the processes at appropriate scales. Such processes can take place at specific locations and not be 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.
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") within an unified conceptual framework is also particularly appreciated. This versatility has made multi-agents based simulation emerge as a valuable approach for the simulation of complex systems, and it is appealing to more and more scientific domains: sociology, biology, physics, chemistry, ecology, economy, etc.

Multi-Agents Systems and Cellular Automata. The adoption of a multi-agent approach can be motivated by its ablility 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 such a simulator it is useful to differentiate between the cellular automata part and the distributed intelligence resulting of the structure of the agents which 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. In the case of modelling emergency evacuation from aircraft, the passenger can be considered to be the subject-agent while the crew constitute the actor-agents. Thus, subject-agent and actor-agents are user-agents that navigate in the cell grid, each with their own perception, intentions and behavior. The perception of the agents is in general an imperfect representation of the virtual environment including the state of other user-agents, on which the decisions of each agent are based. Their behavior is characterized by their interaction with other agents and the environment. Different styles of behavior, like anticipated behavior and unplanned behavior, can be relevent. Formally, user-agents can be defined by a 3-tuple $U =< R, A, F >$ 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 agendas of the user-agents to perform their goals and F represents the knowledge or information about their environment which user agents possess.

A Stochastic Model for Aircraft Emergency Evacuation

The considered system. Here is considered a system composed of a set I ($|I| = N_p$) of subject-agents (passengers) and a set C ($|C| = N_c$) of actor-agents (crew members) located at a grid with N positions. Among these positions, a subset N_s is composed of safe positions in connexion with the safe surroundings af the aircraft supposed to have no capacity restrictions. The current state of passenger i is represented by his position (starting from his initial position $n(i)$ in the grid) and his exposition to hazards.
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:

$$F(t), t \in \{t_0, t_0 + \delta t, \cdots, t_0 + k\ \delta t, \cdots, t_f\} \tag{3.1}$$
$$S(t), t \in \{t_0, t_0 + \delta t, \cdots, t_0 + k\ \delta t, \cdots, t_f\} \tag{3.2}$$
$$W(t), t \in \{t_0, t_0 + \delta t, \cdots, t_0 + k\ \delta t, \cdots, t_f\} \tag{3.3}$$

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 (where $P(i = n, t)$ is the probability of agent i be localized at cell n at period t):

$$\sum_{\tau=0}^{t} P(i = n, \tau)\ \varepsilon_{F,n}(\tau) \le \sigma_F \tag{4.1}$$

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

$$\sum_{\tau=0}^{t} P(i = n, \tau)\ \varepsilon_{S,n}(\tau) \le \sigma_S \tag{4.2}$$

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

$$\sum_{\tau=0}^{t} P(i = n, \tau)\ \varepsilon_{W,n}(\tau) \le \sigma_W \tag{4.3}$$

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.
If at instant t, conditions (8.1), (8.2) and (8.3) are satisfied by passenger i and at instant $t + \Delta t$, one of them is not satisfied, then:

$$L(t + \Delta t) = L(t) - \{\ i\ \} \tag{5}$$

Transition modelling. It is supposed that the behaviour of egressing passengers obeys the Markov property, i.e. the imediate future can be determined with the present state information without taking into consideration information about past states.
At start, the spatial distribution of passengers is given so that $P(i = n(i), t_0) = 1$ and $P(i = n, t_0) = 0$ if $n \ne n(i)$. Then, the probability distribution of passengers within the grid at time $t + \Delta t$, $P(i = n', t + \Delta t)$, can be expressed in terms of the conditional probabilities and the previous probability distribution at time t, $P(i = n, t)$, which is the probability that passenger i is at position n at time t:

$$P(i = n', t + \Delta t) = \sum_n p(i = n', t + \Delta t / i = n, t) P(i = n, t) \quad \forall i \in L(t) \tag{6}$$

where $L(t)$ is the set of alive passengers at time t.
Using the fact that the transition probabilities are such that:

$$\sum_m p(i = m, t + \Delta t / i = n, t) = 1 \quad \forall\ i \in L(t) \tag{7}$$

allows to rewrite the variation of the probability distribution as:

$$P(i=n',t+\Delta t)-P(i=n,t)=\sum_m p(i=n',t+\Delta t/i=m,t)P(i=m,t)-\sum_m p(i=m,t+\Delta t/i=n,t)P(i=n,t) \quad (8)$$

or:

$$P(i=n',t+\Delta t)-P(i=n,t)=\sum_m (p(i=n',t+\Delta t/i=m,t)P(i=m,t)-p(i=m,t+\Delta t/i=n,t)P(i=n,t)) \quad (9)$$

It is supposed that the transition probability are such as:

$$P(i=n,t+\Delta t/i=n',t)=0 \quad \forall\, i\notin L(t) \quad (10)$$

$$P(i=n',t+\Delta t/i=n,t)=p_{nn'}\frac{1-\alpha(n,n')\;\rho(n',t)}{1+\lambda_F\varepsilon_{F,n}(t)+\lambda_S\varepsilon_{S,n}(t)+\lambda_W\varepsilon_{W,n}(t)} \quad \forall i\in L(t) \quad n\neq n' \quad (11)$$

where $$\rho(n',t)=\sum_{j\in L(t)}P(j=n',t) \quad (12)$$

is the probability that cell n' is occupied by a passenger at time t and $\alpha(n',n)\in[0,1]$,with:

$$\alpha(n,n^*)<\alpha(n,n') \text{ if } n^* \text{ be the best step towards an exit from } n \text{ and } \quad n'\neq n^* \quad (13)$$

Then λ_F , λ_S and λ_W are positive parameters slowing down the rate of transition from one cell to another in the presence of fire, smoke or water.
$p_{nn'}$ is related with the efficiency of the transition and is given by:

$$p_{nn'}=0 \text{ if } n'\notin A_n \text{ where } A_n \text{ is set of adjacent cells to } n \quad (14.1)$$

$$p_{nn^*}=\min_{j\in C}\min_{k\in\{1,\cdots,N\}}(1/1+\lambda_c\; x_{kj}\|n-k\|) \quad (14.2)$$

where λ_c 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. It is assumed that the presence of a crew member in a cell does not impair the capacity of the cell to host an egressing passenger. It is also supposed that the location of a crew member does not change during evacuation until all passengers under coverage have bypassed this crew member.

$$p_{nn'}=(1-p_{nn^*})/(|A_c|-1) \quad \text{for} \quad n'\in A_n,\, n'\neq n^* \quad (14.3)$$

then:

$$P(i=n,t+\Delta t/i=n,t)=1-\sum_{n'\in A_n}P(i=n',t+\Delta t/i=n,t) \quad \forall i\in L(t) \quad (15)$$

An Heuristic Approach for Egress Management

Many studies have shown the importance of the size and location of cabin crew to insure an efficient emergency evacuation of damaged aircraft. So in this section this issue is adressed through the resolution of an assignment problem.

Performance evaluation. The emergency evacuation can be considered completed at time t_f when:

$$t_f = \min t \qquad \text{with} \quad \pi_r(i,t) \geq \sigma_r \quad \forall i \in L(t) \tag{16}$$

$$\text{with} \qquad \pi_r(i,t) = \sum_{n \in N_s} P(i = n, t) \tag{17}$$

Here $\pi_r(i,t)$ is the probability that alive passenger i is safe at time t and where σ_r is a threshold parameter with $\sigma_r \in]0,1[$, but in general near to 1.

The final set of safely rescued passengers, $L(t_f)$ is such that:

$$\sum_{\tau=0}^{t_f} P(i = n, \tau)\, \varepsilon_{F,n}(\tau) \leq \sigma_F \tag{18.1}$$

$$\sum_{\tau=0}^{t_f} P(i = n, \tau)\, \varepsilon_{S,n}(\tau) \leq \sigma_S \tag{18.2}$$

$$\text{and} \quad \sum_{\tau=0}^{t_f} P(i = n, \tau)\, \varepsilon_{W,n}(\tau) \leq \sigma_W \tag{18.3}$$

There is no death caused by hazards among the cabin crew during evacuation if:

$$\max_{j \in C} \left\{ \sum_{\tau=0}^{t_f} \sum_{n=1}^{N} x_{n,j}\, \varepsilon_{F,n}(\tau) \right\} \leq \sigma_F \tag{19.1}$$

$$\max_{j \in C} \left\{ \sum_{\tau=0}^{t_f} \sum_{n=1}^{N} x_{n,j}\, \varepsilon_{S,n}(\tau) \right\} \leq \sigma_S \tag{19.2}$$

$$\text{and} \quad \max_{j \in C} \left\{ \sum_{\tau=0}^{t_f} \sum_{n=1}^{N} x_{n,j} \varepsilon_{W,n}(\tau) \right\} \leq \sigma_W \tag{19.3}$$

Crew location assignment problem during egress. The crew location problem during egress can be formulated, for a given number N_c of crew members, as the following discrete optimization problem:

$$\max_{[x_{kj}]} \left| L(t_f) \right| \tag{20}$$

with the constraints (3), (10), (11), (18), (19), (20), (21) and the classical assignment constraints:

$$\sum_{j \in C} x_{kj} \leq 1 \quad \forall\, k \in P_c \tag{21}$$

$$\sum_{k \in P_c} x_{kj} = 1 \quad j \in C \tag{22}$$

where P_c is the set of positions (aisles, emergency exit rows, common areas) elligible for cabin crew positionning.

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.

A solution approach. The proposed solution approach is composed of different stages:

- An initialisation stage composed of the following steps:

  - step 0: First define the feasible set of positions for cabin crew. It is supposed that, since evacuation is in general a fast process, cabin crew have a clear view of the location and short term progression of the different active hazards. Then using the hazard propagation equations (3.1), (3.2) or (3.3), it is possible to define the set of positions in P_c which satisfy the crew surviviability constraints (19.1), (19.2) or (19.3). Let $\tilde{P}_c$ be this set.
  - Let $V_u, u = 1\, to\, N_s$ be a neighbourhood (the radius of this neighborhood can be taken equal to the number of seats per row near this exit, divided by two) of safe exit *s*, assign a crew member at random in a location of $\tilde{P}_c \cap V_s$. It is assumed that there are enough crew members to cover each safe exit.
  - Assign the remaining crew members to the sections of the aisles contained in $\tilde{P}_c$. For that subdivide the safe area of the cabin in as much subsections as there are remaining cabin crew and assign randomly a cabin crew to each of these subdivisions within the corresponding aisle subsection (let $W_u, u = 1\, to\, |C| - N_s$ be such sets).
  - Let $X^{(0)} = (X_1^{(0)}, X_2^{(0)}, \cdots, X_{N_c}^{(0)}) = (n(j=1), n(j=2), \cdots, n(j=N_c))$ be the initial cabin crew location solution.
  - An initial simulation stage where the set of equations (3.1), (3.2), (3.3), (4.1), (4.2), (4.3), (5), (6) (with (7) to (15)), (16), (18.1), (18.2), (18.3) is run from t_0 to t_f, provides an evaluation of $|L(t_f)|$: $\Lambda^{(0)} = |L(t_f)|$.

    While running this set of equations, figures of merit can be computed for each cabin crew location and its imediate neighbour cells either in a neighborhood V_s or a subsection W_u. An interesting figure of merit is the the mean number of passengers under coverage $\mathrm{cov}(m, j)$ during the emergency evacuation from a given location *m* in the immediate neighborhood Z_j (with $Z_j \subset V_s \cap \tilde{P}_s\ or Z_j \subset W_u \cap \tilde{P}_s$) of cabin crew location *j*. At iteration *q*, it is given by:

$$\mathrm{cov}(m, j) = \sum_{t=t_0}^{t_f} \sum_{n=1}^{N} \sum_{i \in L(t)} P(i = n, t)\ \delta_{m,n}^{j} \tag{23}$$

$$\text{where } \delta_{m,n}^{j} = \begin{cases} 1 \ \ if \quad \|m - n\| \leq \min\limits_{k=1\, to\, N_c, k \neq j} \|n - X_k^{(q)}\| \\ \qquad\qquad 0 \quad otherwise \end{cases} \tag{24}$$

-A local improvement stage where a new candidate solution is generated. It is composed of the following steps:

  - For the immediate neighborhood of each current cabin crew location *j*, find $\hat{m}(j)$ such as:

$$\hat{m}(j) = \arg\{ \max_{m \in Z_j} \mathrm{cov}(m, j) \ \} \tag{25}$$

  - A first termination test is given by:

$$if\ \mathrm{cov}(j, j) \geq \mathrm{cov}(\hat{m}(j), j) \quad \forall\ j = 1\, to\, N_c \tag{26}$$

then a local optimum appears to be achieved.

- Update the location of the j^{th} cabin crew member, j=1 to N_c, if $\mathrm{cov}(j, j) < \mathrm{cov}(\hat{m}(j), j)$:

$$X_j^{(q+1)} = \hat{m}(j) \tag{27.1}$$

otherwise:

$$X_j^{(q+1)} = X_j^{(q)} \tag{27.2}$$

- A simulation stage composed of the following steps:
  - Simulation of the set of equations (3.1), (3.2), (3.3), (4.1), (4.2), (4.3), (5), (6) (with (7) to (15)), (16), (18.1), (18.2), (18.3) is run from t_0 to t_f, with the solution $X^{(q+1)}$ provides an evaluation $\Lambda^{(q+1)}$.
  - A second termination criterium is given by:

$$\Lambda^{(q+1)} \leq \Lambda^{(q)} \tag{28}$$

  - If this termination test is not satisfied, the figure of merit for each location m in the immediate neighborhood Z_j of cabin crew location j at iteration q+1 must be computed according to (23) and (24).

- The simulation stage is repeated until either condition (28) as well as condition (26) are satisfied or a maximum number of iterations, $q_{\max}$, is reached. The achieved number of iterations is here written q_{end}.

Numerical results. Generic transportation aircraft with one or two aisles have been considered in the situation where there is fire in the tail of the cabin with slow fire and smoke propagations. Figure 1 and 2 present results obtained for different cabin crew sizes (expressed in % of total number of passengers) for a narrow body aircraft with 120 seats and 90% of occupancy and 3 available safe exits. In general the results have been obtained after about 10 to 20 iterations of the proposed heurstistic, which is an acceptable amount of computation. The two indexes of performance considered are the percentage of safely rescued passengers ($100\,\Lambda^{(q_{end})} / N_p$) and the duration of the emergency evacuation. In both cases a S-shape curve can be drown from the discrete results. Also regulations staff level ($\overline{N}$) and emergency evacuation time (90 s) have been reported. It appears that too much staff has no relevent effect on the performance, while reducing too much the available staff has decreasing second rates (the crew becomes more and more unable to manage the situation).

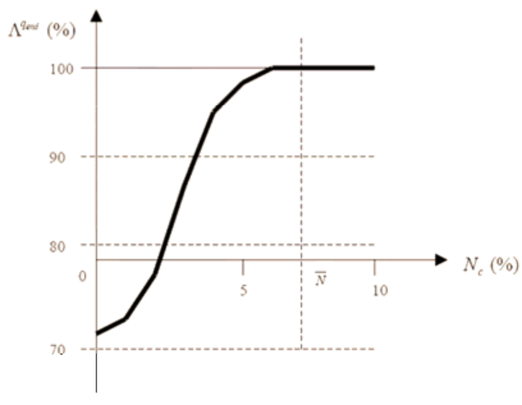

Figure 1. Optimal rescue performance with respect to crew size (one aisle)

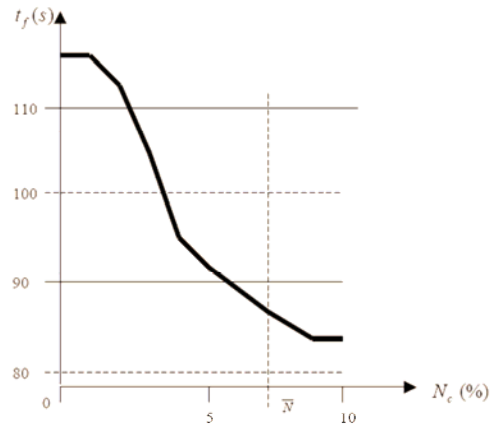

Figure 2. Optimal egress duration with respect to crew size (one aisle)

It appears that the regulations staff level ($\overline{N}$) provides a margin of security with respect to both criteria.
In the case of two aisles generic aircraft, similar results are obtained. In this case, the obtained results are much more sensitive to the seat occupancy rate, while for a given seat occupancy rate, the localization of the crew appears to be less critical than in the case of one aisle aircraft.

Comments. The proposed heuristic is of the greedy type and if some computing ressources remain available, she may be improved by widening the search space. This can be done for instance by starting from different initial conditions chosen randomly, by subdividing in different ways the safe cabin space or by going beyond condition (28) for an additional number of iterations Δq after condition (28) has been first met.
Observe that the adopted probabilistic framework allows to avoid repeated simulations (Monte Carlo approach) of the egress process using a complex simulation model to get a statistical view of the performance.
It appears also that this tool can also be used to optimize the size of cabin crew with respect to emergency evacuation.

Conclusion

This paper has first discussed different 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. A solution algorithm based on heuristic considerations and the repeated evaluation of local modifications has been proposed. This approach has been applied to different generic transportation aircraft, providing already some interesting insights with respect to aircraft emergency evacuation. Many scenarios with respect to acabin configuration, seat occupancy pattern and hazards, remain to be assessed.

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