



# CellEVAC: An adaptive guidance system for crowd evacuation through behavioral optimization

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## ABSTRACT

A critical aspect of crowds' evacuation processes is the dynamism of individual decision making. Identifying optimal strategies at an individual level may improve both evacuation time and safety, which is essential for developing efficient evacuation systems. Here, we investigate how to favor a coordinated group dynamic through optimal exit-choice instructions using behavioral strategy optimization. We propose and evaluate an adaptive guidance system (Cell-based Crowd Evacuation, CellEVAC) that dynamically allocates colors to cells in a cell-based pedestrian positioning infrastructure, to provide efficient exit-choice indications. The operational module of CellEVAC implements an optimized discrete-choice model that integrates the influential factors that would make evacuees adapt their exit choice. To optimize the model, we used a simulation–optimization modeling framework that integrates microscopic pedestrian simulation based on the classical Social Force Model. In the majority of studies, the objective has been to optimize evacuation time. In contrast, we paid particular attention to safety by using Pedestrian Fundamental Diagrams that model the dynamics of the exit gates. CellEVAC has been tested in a simulated real scenario (Madrid Arena) under different external pedestrian flow patterns that simulate complex pedestrian interactions. Results showed that CellEVAC outperforms evacuation processes in which the system is not used, with an exponential improvement as interactions become complex. We compared our system with an existing approach based on Cartesian Genetic Programming. Our system exhibited a better overall performance in terms of safety, evacuation time, and the number of revisions of exit-choice decisions. Further analyses also revealed that Cartesian Genetic Programming generates less natural pedestrian reactions and movements than CellEVAC. The fact that the decision logic module is built upon a behavioral model seems to favor a more natural and effective response. We also found that our proposal has a positive influence on evacuations even for a low compliance rate (40%).

## 1. Introduction

Destructive and uncoordinated crowd behaviors such as herding or stampede are recognized as being responsible for pedestrians' death and injury in large-scale crowd evacuations during emergencies. Evacuees tend to seek their safety and exhibit selfish attitudes that may go against the collective benefit. An efficient evacuation plan is of paramount importance to coordinate and direct evacuees out of dangerous areas in a safe and timely manner. This coordination can be achieved by deploying guidance systems capable of providing information for each user on the exit gate, the path to follow, and possibly the time when evacuation should start (Abdelghany et al., 2014). These systems may embed real-time routing algorithms that provide adaptive plans or use pre-deployed static plans based on prediction and analysis (Bi and

Gelenbe, 2019).

It is well known that the performance of evacuation processes can be strongly affected by exit-choice decision making at the individual level (Haghani and Sarvi, 2019). Research on human responses to multiple sources of directional information has shown that directional information has a significant effect on human exit route choice (Bode et al., 2014). For instance, (Feliciani et al., 2020) studied how egress time can be reduced if wheelchair users are informed on exit type and location. Thus, there are research efforts in the area of real-time routing for crowd evacuations that have focused on studying mechanisms for providing optimal exit-choice information. These mechanisms have been mainly implemented using optimal static plans obtained through simulation–optimization methods (Abdelghany et al., 2014; Guo, 2018). However, since the dynamics of the environment change over time in

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unpredictable ways during emergency evacuations, adaptive strategies appear more appealing (Zhong et al., 2016).

Developing evacuation systems based on adaptive exit-choice information is challenging. For example, human response to information given by the system during emergencies should be easy to understand and follow, but most existing research addresses the algorithmic perspective and overlook the systemic view and usability. We consider this aspect as essential if we want to take these systems to real environments. When optimizing evacuation plans in general, the overall objective has been minimizing the total evacuation time, average evacuation time, or maximizing the cumulative exit throughput within a given period. Surprisingly, the safety dimension has not been explicitly considered, being considered a consequence of applying different optimization objectives on the facility configuration and demand profiles. We believe that safety should be an explicit objective when optimizing evacuation plans because evacuation time and safety dimensions are closely related to each other in emergency evacuations and under extreme conditions. Finally, though it is widely accepted that the modeling of evacuation behavior is essential for developing efficient evacuation systems, the primary attention has been being paid to investigate the problem from architectural or path-planning optimization perspectives (Duives et al., 2013; Vermuyten et al., 2016; Zhao et al., 2017). The potential of behavioral strategy optimization for improving both evacuation time and safety has been overlooked in the design of adaptive evacuation systems.

We are interested in quantifying the benefits of using evacuation behavior models to implement adaptive evacuation systems' decision logic. Another central question of this study concerns the topic of safety. We would like to quantify how important it is to explicitly model safety, and which could be a reasonable safety metric.

With the purposes mentioned above, this paper proposes an adaptive guidance system (Cell-based Crowd Evacuation, CelleVAC) that dynamically maps exit-choice indications in a cell-based positioning infrastructure. During the evacuation process, colors (indications, instructions) corresponding to an exit gate are dynamically displayed in pedestrians' wearable or personal handheld devices depending on the current pedestrian cell-position. The kernel of the system is a Multinomial Logit Model (MLM) taken from discrete choice theory, which has been widely used to model human behavior in evacuations and many other areas such as economics or transportation (Press, 1985; Duives and Mahmassani, 2012). In our study, we use it to implement the decision logic module that dynamically allocates colors to cells. This module embodies the influential primary factors that would operate on individual exit-choice decision making within the context of descriptive behavior modeling. These factors include the (i) group size of pedestrians along a path, (ii) congestion at exits, (iii) width of exit gates, (iv) distance, and (v) personal attitude to maintaining previous decisions.

Haghani and Sarvi (2019), authorities in evacuation behavior modeling, report that most research has been focused on modeling directional decision making, while the decision adaptation phenomenon has been largely overlooked. For example, exit-choice decisions at the beginning and end of evacuations may be completely different. An explicit factor is needed to model the variation in personal attitude towards exit-choice changing. Thus, we include the 'personal attitude' factor to model uncertainty and adaptation in exit-choice decision making and study its influence on evacuation performance. Another factor that plays a leading role in our MLM model is 'congestion at exits', which is known to have a strong influence on pedestrians' evacuation behaviors (Liu et al., 2009). Typically, this factor models the number of pedestrians at exits. However, this approach neglects the exit gates' evacuation dynamics, which is crucial to optimize the available capacity and to improve safety. For this purpose, a method is proposed to characterize exit gates' evacuation dynamics. This method is based on obtaining the Pedestrian Fundamental Diagrams (i.e., the relationship between pedestrian flow and density) (Hoogendoorn et al., 2017), and then applying a curve fitting function to parameterize each exit gate in

terms of congestion levels. Using these congestion levels, we can define a safety metric and use it in the MLM simulation-optimization process.

A simulation-optimization modeling framework has been developed to determine the optimal configuration of the MLM and obtain a near-optimal adaptive evacuation plan. This framework integrates a microscopic pedestrian simulation based on the classical Social Force Model (SFM) (Helbing and Molnár, 1995). The simulation-optimization process adopts a Tabu-Search algorithm (TS) (Glover, 1997), which iteratively searches for the near-optimal evacuation plan (optimal configuration of the MLM). At the same time, the microscopic crowd simulation guides the search by evaluating the evacuation time and safety of the solutions generated by the TS algorithm. The proposed system is tested in a simulated real scenario (Madrid Arena) under different external pedestrian flow patterns that simulate complex pedestrian interactions. The research also presents a comparison between traditional nearest-gate evacuation strategies and an existing approach based on Cartesian Genetic Programming (CGP) (Zhong et al., 2016) that we adapted to include the input factors used in our MLM.

The rest of the paper is organized as follows. Section 2 surveys the works related to crowd evacuation modeling. Section 3 outlines our modeling framework, which includes the evacuation scenario, a proposal of system architecture for CelleVAC, the MLM used to build the decision logic module of CelleVAC, and the microscopic simulation framework to perform the simulation-optimization processes. The modeling of exit gates' evacuation dynamics and safety are described in Section 4. Section 5 presents the experimental evaluation, results, and discussion. The last section provides concluding comments and possible research extensions.

## 2. Related work

In this section we offer a summary of the previous work in the context of crowd behavior modeling in evacuation scenarios, simulation modeling and evacuation wayfinding algorithms.

### 2.1. Exit-choice behavior modeling

It is widely accepted that understanding the influence factors on pedestrian behavior is fundamental in the design of large-scale public facilities and evacuation planning. To capture the influence of these factors and understand pedestrian behavior avoiding the potentially dangerous real simulations, researchers have to rely on, for instance, simulated environments (Bode et al., 2014; Bode et al., 2015) or decision-making models built upon revealed and stated preferences (Haghani et al., 2014).

The exit-choice strategies play a main role in the behavioral dimension of evacuations (Hoogendoorn and Bovy, 2004; Kinateder et al., 2018; Chen et al., 2018; Duives and Mahmassani, 2012). The existing research has identified numerous factors that explain exit-choice decision making including the pedestrian emotion, distance to exits, visibility, size of the queue, cooperation, route length and capacity, illumination, or route familiarity (Duives and Mahmassani, 2012; Cuesta et al., 2015; Lovreglio et al., 2016b; Haghani and Sarvi, 2016b; Kinateder et al., 2018). Assumptions about how an individual decides on an exit route, have a significant influence on the overall evacuation effectiveness (Duives and Mahmassani, 2012; Haghani et al., 2014; Zhou et al., 2019). Some models assume that the exit-choice is only based on shortest distance optimization (Hoogendoorn and Bovy, 2004; Klüpfel et al., 2005). (Kinateder et al., 2018) also found that exit-choice was influenced by exit familiarity and neighbor behavior. Using a virtual crowd evacuation environment, (Bode and Codling, 2013) showed that individuals preferred routes with which they were familiar only when they were presented with motivational messages. Also, they found an evident influence of age and gender on reaction times. (Guo et al., 2012) revealed several behavior patterns related to preference for a destination, effect of capacity, interaction between pedestrians, following

behavior, and evacuation efficiency. The trade-offs associated with these interactions (Duives and Mahmassani, 2012; Augustijn-Beckers et al., 2010; Shi et al., 2009) are present especially connected to the exit-choice decision. In (Liao et al., 2017), the authors studied how time-independent and time-dependent information affects subsequent changes in route choices and builds a simulation model to illustrate simple behavioral mechanisms are sufficient to describe the evacuation dynamics. They found evidence that dynamic route choice behavior was comparatively rare.

A growing body of literature has investigated how to model different exit-choice behaviors in crowd evacuation simulations. Various approaches have been proposed to solve this issue using discrete choice models (Press, 1985; Ben-Akiva and Bierlaire, 1999). These models have been frequently used to define safety measures based on guidelines discussing variables such as the exit door locations, or the maximum density of people (Ronchi et al., 2016; Gao et al., 2020). Research in this field has focused primarily on the Multinomial Logit Model (MLM) (Ben-Akiva and Bierlaire, 1999), mainly used to model the likelihood of individual choices from a discrete set of alternatives.

In (Duives and Mahmassani, 2012) the authors investigated an MLM to evaluate different exit-choice strategies. Their results suggest that group following behavior has a significant impact on evacuation. (Haghani et al., 2014; Haghani et al., 2015; Haghani and Sarvi, 2016a; Haghani and Sarvi, 2016b; Haghani and Sarvi, 2017a; Haghani and Sarvi, 2017b; Haghani and Sarvi, 2017c; Haghani and Sarvi, 2018) reported on different methods to estimate random-utility models of pedestrian exit-choice, and investigate crowd choice behavior during evacuations of built environments. They propose a mixed (random-coefficient) nested logit framework in (Haghani et al., 2015) and investigate underlying behavioral differences between normal egress and emergency evacuations in (Haghani and Sarvi, 2016a) using error-component mixed logit model of discrete choice analysis. (Lovreglio et al., 2016a) investigate the effect of environmental and social factors on local exit-choice. They use an online stated preference survey using non-immersive virtual reality, and a mixed logit model is calibrated.. More recently (Haghani and Sarvi, 2017a; Haghani and Sarvi, 2017b) report on wayfinding decision experiments that simulated the escape from multi-exit spaces, and conclude that the assumption of herd-like behavior does not necessarily apply to all contexts of evacuations.

Above mentioned studies have mainly dealt with the development of descriptive models of evacuation behavior that simulate the real movement of crowds (Duives et al., 2013; Ronchi et al., 2016). These models allow studying the influence of different behavior strategies on evacuation performance (Zhou et al., 2019). However, behavioral strategy optimization is neglected to great degrees (Berseth et al., 2015; Noh et al., 2016; Ding et al., 2017). Among the body of studies on optimization, the majority have investigated the problem from a path-planning (Vermuyten et al., 2016; Noh et al., 2016) or architectural perspective (Zhao et al., 2017). Exit-choice behavioral optimization for designing evacuation guidance systems remains a major knowledge gap that we address in this paper.

Recently, (Haghani and Sarvi, 2019) quantitatively investigate the importance of including a decision changing module for modeling adaptive decision-making in exit choices. They propose a two-layered model with an exit-choice changing module and an exit-choice module. The exit-choice changing module is a simple binary logit formula that decides if pedestrians change their chosen exits. This formula depends on directional attributes and a prefixed parameter that calibrates the inertia to exit-choice changing. In case of change, the exit-choice module, which implements a classical MLM, chooses a new exit. Results showed a substantial difference in enhancing the accuracy of the simulation outputs. They conclude that an intermediate degree of decision changing is the most beneficial strategy.

We have also explicitly paid particular attention to the exit-choice changing phenomenon by modeling the pedestrians' attitude towards changing their previous decisions. Instead of using a two-layered model

(Haghani and Sarvi, 2019), our approach uses a single-layered MLM that embeds both the directional and exit-choice changing decision making components. This approach shortens the number of parameters of the model, simplifying the optimization process. Moreover, exit-choice decision changing is modeled as a time-dependent personal attribute. It allows us to adapt the inertia to exit-choice changing during the evacuation process, whereas in (Haghani and Sarvi, 2019) the inertia is an immutable parameter. For instance, this approach may be useful to reflect that confusion level changes during the evacuation process, and therefore the level of inertia to decision changing.

## 2.2. Simulation modeling

Much of the related work on crowd behavior and evacuations must rely on detailed simulations. In their recent survey of algorithms and systems for evacuation, (Bi and Gelenbe, 2019) offer state-of-the-art knowledge on emergency evacuation and wayfinding. According to their work, crowd behavior simulation models for evacuation wayfinding can be classified into cellular automata models (Pelechano and Malkawi, 2008; Feliciani and Nishinari, 2016), social force models (Helbing and Molnár, 1995), fluid-dynamics models (Henderson, 1971), lattice gas models (Takimoto and Nagatani, 2003), game theoretic models (Hoogendoorn and Bovy, 2003) and computer agent-based models (Pan et al., 2007).

Many studies have been published using cellular automata models, which discretize a given space into uniform "cells" where each cell holds a person or vehicle (Cruz-Piris et al., 2019). However, as mentioned by (Bi and Gelenbe, 2019), these models are ineffective at depicting movement speed and direction, making it relatively challenging to customize physical attributes or heterogeneous individuals with different characteristics. Social force models (SFM) overcome these issues. These argue that pedestrians' motion is mainly affected by the destination, the repulsive forces from pedestrians and obstacles, and the attractive forces from other objects (e.g., signals). Fluid-dynamics and lattice gas model-based algorithms are better at simulating the movement of large crowds under normal situations. Because of these approaches' macroscopic nature, the modeling of complex interactions and individual behaviors such as panic or uncertainty is difficult. Game-theoretic approaches (Fudenberg and Tirole, 1991) model the cooperative and competitive behaviors during the evacuation process, which is useful for mimicking the interactive decision-making and strategy-adapting among evacuees. However, these approaches have difficulty in capturing the dynamics of an evacuation process. Hence, the agent-based models representing an environment with autonomous decision-making agents, have drawn considerable attention in recent years (Lopez-Carmona et al., 2017). Agents have the ability to evolve, learn, and interact, which can lead to unanticipated behaviors during simulations.

In our research, we opted for a multi-agent microscopic simulation framework based on SFM due to its flexibility and ease of integration of complex behavior and interaction models. This approach integrates the potential of SFM to mimic physical interactions among evacuees, and of multi-agent systems to simulate complex behaviors and interactions, learn and evolve.

## 2.3. Evacuation wayfinding algorithms

Many algorithms have been proposed (Bi and Gelenbe, 2019) for the development of evacuation wayfinding systems. Network flow-based algorithms consider evacuation planning as a minimum cost network flow problem (Ford and Fulkerson, 1962). The main downside of network flow-based algorithms is that evacuees must follow the paths accurately and reach every node on schedule. Various approaches have been put forward to solve this issue using geometric graphs (Li et al., 2003b). For instance, in (Chen et al., 2008) a wireless sensor network is partitioned into triangular areas based on the average detected



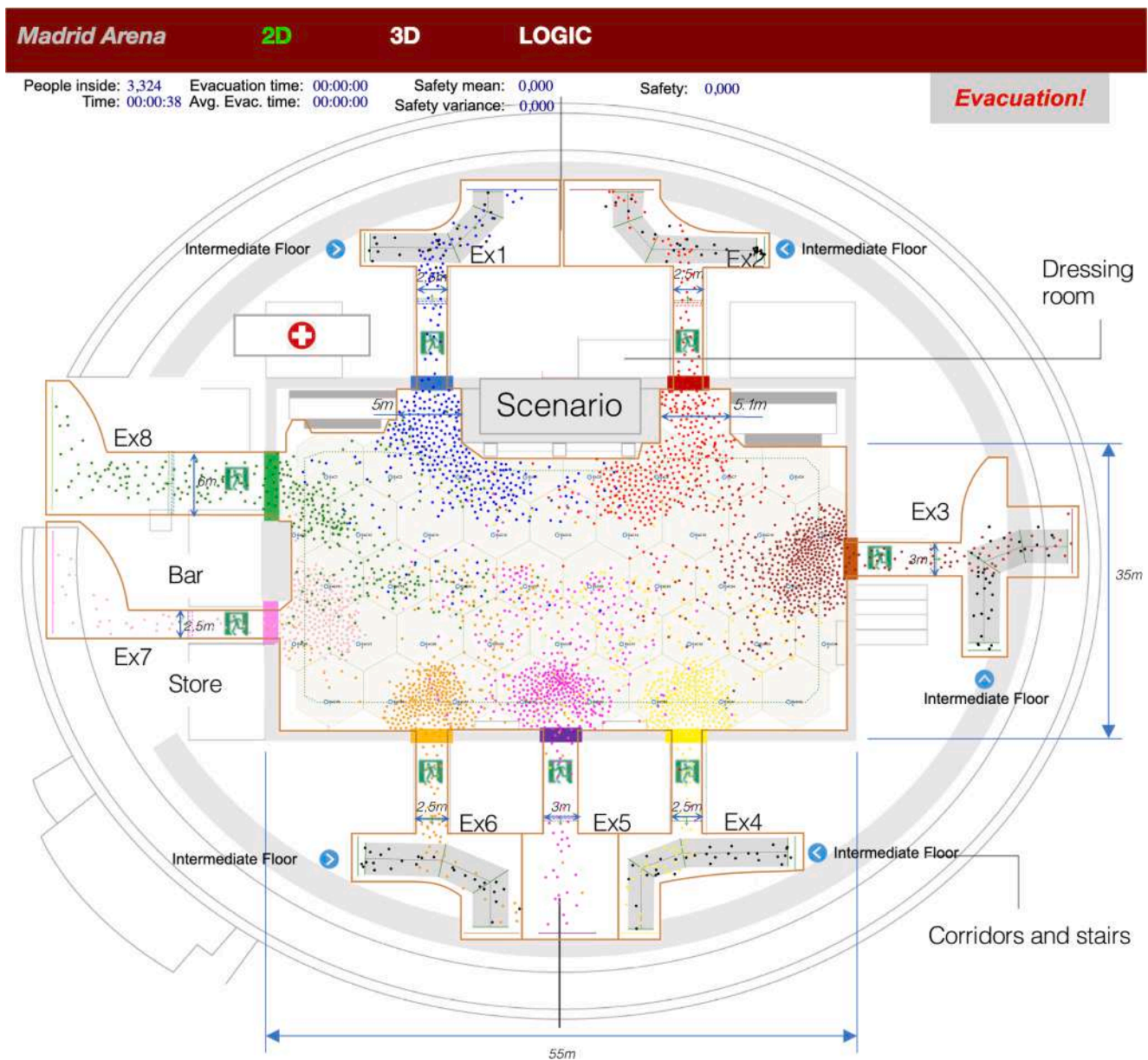


Fig. 1. Madrid Arena layout (ground floor).

temperature of the associated sensors and safe egress paths are calculated. A change of the topology induces redeployment and recalibration. More recently, (Guo, 2018) proposed a potential-based dynamic pedestrian flow assignment model to optimize evacuation time. Optimization is performed by employing a space potential formulation and solving a proportional swapping process between cells. Though the model is potentially applicable during evacuation time, this work focuses only on obtaining an assignment of pedestrians' exit choices at the beginning of the evacuation. Besides, they propose two classes of guide sign systems that can guide pedestrians to the corresponding exit.

Following this trend, queuing models (Newell, 2013) transfer building graphs to a queuing network to estimate congestion and evacuation delays. In (Chalmet et al., 1982, Yuhaski and Smith, 1989, MacGregor Smith, 1991, Wang et al., 2008, Lino et al., 2011) we may find studies in this area which are mainly focused on predicting and optimizing the probabilistic choices in evacuations. Various approaches dynamically develop navigation paths by assigning artificial potential fields to the exits and hazards (Koditschek, 1989; Hill et al., 2000; Li et al., 2003a). Unfortunately, this mechanism suffers from several

pitfalls, among which is the convergence time for network stabilization, and the fact that multiple exits may affect its search efficiency.

There is a vast amount of literature on biologically-inspired algorithms that employ heuristics to search for optimal routes or recommend exits. In (Li et al., 2010) a multiobjective evacuation route assignment model based on genetic algorithm (Holland, 1992; Gelenbe et al., 2006) is proposed. This approach resembles the well known dynamic traffic assignment (DTA) problem from the field of transport modeling (Bazzan and Klügl, 2013). In a similar approach, (Abdelghany et al., 2014) employed a simulation-optimization framework that integrates a genetic algorithm and a microscopic pedestrian simulation-assignment model. Evacuees are assumed to receive exit-choice indications that may include the optimal start time of evacuation. Its major drawback is that the calculated plan does not allow an adaptive response. In (Samadzadegan and Yadegari, 2010) bee colony optimization is used to displace evacuees to safe areas. Its main drawback is the relatively high communication overhead. (Ferscha and Zia, 2010) developed a wearable device named LifeBelt that recommends exits to individuals based on the sensed environment.

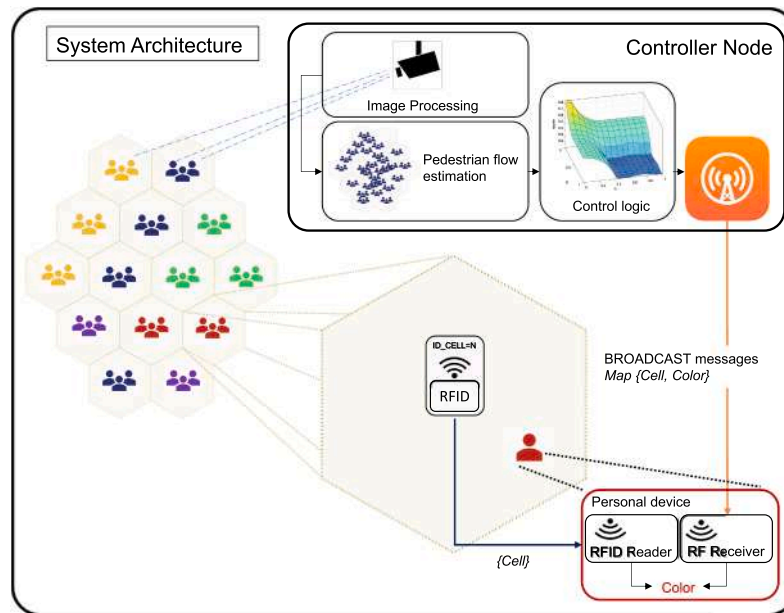


Fig. 2. CellEVAC System Architecture.

Similarly, in (Zhong et al., 2014) the idea is to use a gene expression programming to find a heuristic rule. This rule is used to indicate people in the same sub-region to move towards the same exit. The main drawback of this solution is that it does not consider the dynamic environment features in the evacuation planning process. Later in (Zhong et al., 2016), they propose a heuristic rule that considers the distance and width of exit doors as fixed input parameters and density around a given subregion as a dynamic parameter. The crowd evacuation planning problem is converted to finding the optimal heuristic rule that minimizes the total evacuation time. To solve this problem, the authors adopt the Cartesian Genetic Programming (CGP) (Miller, 2011). As we will show, the learning process using CGP is complicated, and the control actions derived generate abnormal behaviors. Moreover, they ignore the safety performance indicators in the optimization process. Finally, in (Wong et al., 2017) a shortest path algorithm is used to compute routes by iteratively partitioning graph edges at critical division points. Routes are iteratively refined offline until an optimal state is achieved. This approach assumes that a crowd distribution is known in advance, not considering safety or dynamic changes during evacuation.

As in (Abdelghany et al., 2014), our work develops a simulation–optimization modeling framework that searches for the optimal evacuation plan through meta-heuristic optimization methodology. However, we obtain adaptive evacuation plans capable of responding to changing environmental conditions. The CGP based crowd evacuation planning developed by (Zhong et al., 2016) adapts to changing conditions, but its formulation is complex and challenging to interpret. As mentioned above, the optimization process is complex and difficult to configure and does not consider safety. Moreover, the obtained evacuation heuristics functions for exit-choice selection generate unnatural pedestrian movements. In contrast, the CellEVAC system is easier to configure and optimize, and experiments suggest a much more natural behavior. Also, we include a safety metric in the optimization process. As far as we know, there are no studies on how to include a safety metric in the simulation–optimization processes to obtain evacuation plans.

### 3. Simulation–optimization modeling framework

#### 3.1. Evacuation scenario

Our investigation focused on Madrid Arena, an indoor arena located in Madrid (Spain). The pavilion was designed to host sports events,

commercial, cultural and leisure activities. It has three floors (access, intermediate, and ground) and 30,000 m<sup>2</sup>, with a maximum capacity of 10,248 spectators for basketball. Its central court has three retractable bleachers, allowing the surface to change depending on the type of event. On November 1, 2012, a stampede at a Halloween party resulted in the death of five girls by crushing (BBC news, 2012). According to the police investigation, the cause was the excess of capacity and the following errors in the indications of private guards and police. There were not any guidance system to help evacuees choose a safe exit gate.

We studied the evacuation of the ground floor, which has a maximum capacity of 3,400 spectators with the retractable bleachers removed. Fig. 1 shows the ground floor layout, with 1,925 m<sup>2</sup> and eight exit gates (Ex1 to Ex8) with different widths between 2.5 m and 6 m. Each exit gate merges with exit corridors from the intermediate floors, generating complex interactions between different pedestrian flows. Pedestrian flows from intermediate floors were simulated by injecting pedestrians at exits 1, 2, 3, 4, and 6 at the entry points highlighted with a blue dot.

#### 3.2. CellEVAC system architecture

A system architecture was defined to illustrate a realistic deployment of our CellEVAC guidance system in Madrid Arena. The architecture assumes the utilization of existing off-the-shelf technologies, including wearable devices or smartphones. The use of specific technologies and its in-depth analysis and evaluation is beyond the scope of this paper and is already underway. We aimed to conceive a generic architecture focusing on the functional aspects of the system rather than on the intrinsic elements of a specific technology. Although we include examples of concrete technologies for some of the components of the architecture, these are not claimed to be necessarily the only or best alternatives. However, we believe that this proposal is generic enough to leave room for exploring different technological alternatives.

For the specific case of Madrid Arena, the ground floor was divided into 42 regular hexagonal cells of 9 m<sup>2</sup> and 6 m width (Fig. 1). These dimensions were chosen to provide a reasonable balance between control capability, wireless coverage, and computational efficiency. Fig. 2 presents the system architecture, where a controller node embeds three functional blocks: pedestrian flow estimation, control logic, and Radio Frequency (RF) transmitter. The pedestrian flow estimation block takes as input periodically sampled images that are preprocessed to estimate

pedestrian density at each cell. Obtained densities feed the decision logic block to compute the optimal allocation of colors to cells. With eight exits and 42 cells, we have a space of  $2^{126}$  control actions at each control step. The RF transmitter broadcasts messages periodically containing 42 tuples  $\{Cell, Color\}$  that assign a color to each cell.

Each cell node is equipped with an active Radio Frequency Identification (RFID) tag that periodically transmits a cell identification signal to personal devices embedding an RFID Reader, whose purpose is to provide location-aware capability. One real possibility to improve cell detection accuracy is to implement a received signal strength RFID-based indoor location mechanism (Alvarez Lopez et al., 2017). The other module in the personal device is the RF Receiver. It periodically receives the broadcast messages from the controller node. By matching the pedestrian's cell-position and cell-color tuples, the personal device lights up with the corresponding exit gate color.

From an implementation point of view, the most critical part of this architecture is the positioning functionality. The RFID subsystem that connects cells and personal devices have to cope with a complex signal propagation environment and highly populated communication channels. The RF channel is defined as a broadcast communication channel, and consequently, it presents fewer problems. Finally, pedestrian counting technology to estimate pedestrian density is widely available in the market, though it should be tested and analyzed to assess its adequacy depending on the specific application scenario.

### 3.3. Pedestrian behavior modeling

The first step in the development of the CelleVAC guidance system was to model pedestrians' exit-choice decisions using a discrete choice model. This choice was aimed at using the most widely applied theoretical framework to model behavior in crowd evacuations. However, in contrast to most existing research, our aim was not to calibrate the model with real or survey data but to study the critical factors in exit-choice decision making and then explore optimal pedestrian behavior strategies. Furthermore, as mentioned in Section 2, in an attempt to simplify the model optimization, it was decided to use a single-layered discrete choice model avoiding a separate structure for exit-choice changing and exit-choice behaviors. For those readers interested in an example of calibrated exit-choice decision model, (Duives and Mahmassani, 2012) reported a comprehensive model calibrated using responses to an Internet questionnaire conducted in the Netherlands and United States.

The most common theoretical framework for generating discrete choice models is random utility theory (Antonini et al., 2006; Ben-Akiva and Bierlaire, 1999; Press, 1985; Ortúzar and Willumsen, 2011) which postulates that:

1. Individuals belong to a homogeneous population  $P$ , own perfect information and act rationally.
2. There is a set  $\mathbf{E} = \{E_1, \dots, E_j, \dots, E_N\}$  of alternatives and a set  $\mathbf{X}$  of vectors of attributes of the individuals and their alternatives. A given individual  $p$  is provided with a particular set of attributes  $\mathbf{x} \in \mathbf{X}$  and will face a choice set  $\mathbf{E}(p) \in \mathbf{E}$ .
3. Each option  $E_j \in \mathbf{E}$  has associated a utility  $U_{pj}$  for individual  $p$ . It is assumed that  $U_{pj}$  can be represented by two components:
  - (a) a systematic part  $V_{pj}$  which is a function of the measured attributes  $\mathbf{x}$ ; and
  - (b) a random part  $\varepsilon_{pj}$  which reflects the idiosyncrasies of each individual and any observational error made.

Thus, we may postulate that:

$$U_{pj} = V_{pj} + \varepsilon_{pj}$$

$\mathbf{V}$  carries the subscript  $p$  because it is a function of the attributes  $\mathbf{x}$  and this may vary from individual to individual. It can be assumed

that the residuals  $\varepsilon$  are random variables with mean 0 and a certain probability distribution to be specified. A simple and popular expression for  $\mathbf{V}$  is:

$$V_{pj} = \sum_k \beta_{jk} x_{pjk}$$

where the parameters (coefficients)  $\beta$  may vary across alternatives but are assumed to be constant for all individuals.

4. The individual  $p$  selects the maximum-utility alternative  $E_j$  if and only if:

$$V_{pj} - V_{pi} \geq \varepsilon_{pi} - \varepsilon_{pj}$$

Thus, the probability of choosing  $E_j$  is:

$$P_{pj} = \text{Prob}\{\varepsilon_{pi} \leq \varepsilon_{pj} + (V_{pj} - V_{pi}), \forall E_i \in \mathbf{E}(p)\}$$

and as the joint distribution of the residuals is not known, different model forms may be generated.

In this research, we modeled exit-choice behavior using the simplest and most popular practical discrete choice model, the Multinomial Logit Model (MLM) (Duives and Mahmassani, 2012; Ortúzar and Willumsen, 2011). The model is derived under the assumption that the error terms are independent and identically distributed (IID) Gumbel (also called Weibull or, more generally, Extreme Vale Type I). With this assumption, the choice probabilities of exit  $j$  by pedestrian  $p$  are:

$$P_{pj} = \frac{\exp(V_{pj})}{\sum_{E_i \in \mathbf{E}(p)} \exp(V_{pi})} \quad (1)$$

The next step was to choose the attributes  $\mathbf{x}$  of the model (i.e., the factors that affect exit-choice decisions). The existing research on exit-choice behavior has identified a broad range of influential attributes (Haghani and Sarvi, 2019): congestion at exits, distance to exits, angular displacement, social influence, visibility, exit width, and exit familiarity as well as personal characteristics (Duives and Mahmassani, 2012; Lovreglio et al., 2014; Kinatader et al., 2018).

Several criteria were considered in choosing the attributes and structure of the exit-choice model. The first criterion was the relevance of the attributes informed by the literature and their relevance for our specific evacuation scenario. The second criterion was considerations about the number of attributes to include in the model. As stated in (Haghani and Sarvi, 2019) for the specific case of decision adaptation modeling, a long list of attributes poses significant challenges to the problem of model calibration and optimization. It imposes a limit on the number of attributes that the model can reasonably include. The third consideration was the necessity of embedding the directional and exit-choice changing decision making in a single-layered modeling structure to simplify the optimization processes. Our approach contrasts with the two-layered approach proposed in (Haghani and Sarvi, 2019), which would roughly double the number of parameters to optimize. The final consideration was the necessity of modeling the pedestrians' response to indications given by evacuation guidance systems in general and the CelleVAC system in particular.

After these considerations, we assumed that exit-choice decisions were mainly motivated by the distance, congestion at exits, width of exit gates, and the number of pedestrians along the path to each exit gate (this is named 'group size of pedestrians'). It was decided not to include visibility or angular displacement attributes because the studied scenario had no obstacles. The primary purpose of differentiating between congestion at exits and group size, was to model with more precision the pedestrian flow dynamics in critical points. We aim to model and optimize safety and capacity at exits using pedestrian fundamental diagrams, and so, it makes sense to include in the guidance systems a factor



that evaluates congestion at the exits exclusively, while group size measures congestion at inner areas. Note that both the group size and congestion factors inherently model the tendency to imitate behaviors.

The current literature informs us that individuals tend to keep their choices as much as possible (Liao et al., 2017). We reflected this in the model through a decision change attribute, which captures the tendency to maintain the current exit-choice decision. In (Haghani and Sarvi, 2019) this attribute is included in the exit-choice changing model as a constant inertia parameter. It implies that the tendency to change decisions is kept constant during evacuation. Here, we chose a more general approach by making the decision change factor time-dependent. It was reasonable to assume that uncertainty in decision making evolves as evacuation progresses, and so, the tendency to maintain the current decisions. Finally, we reflected the influence of indications of the CelLEVAC system through a specific attribute that takes into account the exit-choice indications given to each pedestrian.

Thus, the model for exit-choice is a Multinomial Logit Model based on six attributes and as many alternatives as exit gates. The systematic utility function for pedestrian  $p$  and exit gate  $j$  is given by:

$$V_{pj} = \beta_D \times \frac{DISTANCE_{pj}}{\max(DISTANCE)} + \beta_W \times \frac{WIDTH_j}{\max(WIDTH)} + \beta_G \times \frac{GROUP_{pj} - GROUP_{min}}{GROUP_{pj}} + \beta_E \times \frac{EXCON_j}{criticalDensity_j} + \beta_P(t) \times PERSONAL_{pj} + \beta_{SYS} \times SYSTEM_{pj} \quad (2)$$

The first attribute is the distance from pedestrian or cell center  $p$  to exit gate  $j$ , which is normalized in the range of 0–1 using the maximum distance in the evacuation scenario, while the second attribute represents the width of each exit gate, which is normalized in the range of 0–1 using the maximum width.

The third attribute is the *GROUP* ratio which estimates the congestion level along a path from a pedestrian to an exit gate  $j$ , relative to the congestion level at the least congested path. This estimate is converted into a unitless attribute and confined within a fixed interval 0–1, dividing it by the chosen path's congestion level. A group ratio value of 0 would indicate that the chosen path is the least congested path among the paths to the different exits. When the value of the group ratio tends towards 1 for a given exit, it means that the emptiest path's imbalance becomes large. Therefore, the parameter  $\beta_G$  is expected to be positive if pedestrians tend to follow other pedestrians and is negative otherwise. Note that with this type of normalization, the distribution of attribute values does not exhibit a priori increasing or decreasing evolution over time. Thus, we assumed that the relevance of the attribute in the systematic utility function was kept constant throughout the evacuation process.

The fourth attribute *EXCON* accommodates the congestion at exit gates. It was found reasonable to assume that pedestrians were able to perceive both the density and flow of pedestrians to estimate the congestion value. For a given density value, perceived congestion is higher if the pedestrian flow is low. We reflect this effect through critical density values obtained from the fundamental diagrams of each exit gate (see Section 4). This *criticalDensity<sub>j</sub>* value reflects the density value at which the exit gate's maximum capacity is reached. Therefore, the *EXCON<sub>j</sub>* value representing density at exit gate  $j$  is normalized by the corresponding *criticalDensity<sub>j</sub>* value. This normalization converts *EXCON* into a unitless attribute around 1. When the value of *EXCON* is above 1, it means that exit is highly congested. A value close to 0 would indicate that the exit gate is almost empty. In contrast to the normalization procedure used for the *GROUP* attribute, the distribution of *EXCON* values exhibits a decreasing evolution as the number of pedestrians in the evacuation scenario decreases. It seems reasonable to assume that the relevance of congestion at exits as a discriminant factor for exit-choice decreases when the overall number of pedestrians is low, and so *EXCON* is close to 0 at all exits. We recall that the *GROUP* attribute's

relevance is kept constant during the evacuation process, which is in charge of capturing the imitation behaviors, avoiding duplication of functions with *EXCON*.

The fifth attribute is the *PERSONAL* value associated with person  $p$  and exit  $j$ , which captures how individuals are likely to revise their previous exit-choice decision. We treat this attribute as a binary categorical 0–1 value that equals 1 if the current exit-choice of pedestrian  $p$  is  $j$ , and is 0 otherwise ( $PERSONAL = 0 \forall k \neq j$ ). Therefore, in a general context, the parameter  $\beta_P(t)$  is expected to be positive if pedestrians tend to maintain the previous exit-choice, and is negative otherwise. However, we aimed to modulate the tendency to maintain previous decisions, and so,  $\beta_P(t)$  is always positive. As was noted above, we assumed that exit-choice changing behavior evolves as evacuation progresses, and therefore the parameter that modulates *PERSONAL* is time-dependent. By observing the pattern of behavior under various simulation settings, and considering the optimization of the model, it was found reasonable that the tendency to maintain decisions increased linearly depending on the current number of pedestrians as follows:

$$\beta_P(t) = \beta_P \times \left( 1 - \frac{\text{numOfPeds}(t)}{\text{numOfPeds}(t=0)} \right) \quad (3)$$

According to Eq. (3), at the beginning of the evacuation, the parameter  $\beta_P(t=0)$  tends to 0, and so, the tendency to revise decisions is higher. As the number of pedestrians to evacuate decreases, the parameter  $\beta_P(t)$  tends to  $\beta_P$ , and the tendency is to maintain previous decisions proportionally to parameter  $\beta_P$  value.

Finally, the *SYSTEM* attribute measures pedestrians' attitude towards the exit-choice indications of the CelLEVAC system. We treat this attribute as a binary categorical 0–1 variable such that *SYSTEM<sub>pj</sub>* equals 1 if pedestrian  $p$  receives an indication to choose exit  $j$  (e.g., pedestrians see the color corresponding to exit  $j$  in their wearable devices), and is 0 otherwise.

It is important to emphasize that we do not claim that the set of attributes is comprehensive, nor is the model using these attributes claimed to be necessarily the fittest form. The model was kept as simple as possible for two reasons. Firstly, to make model optimization possible in a complex non-linear environment like this, it is important not to face too many degrees of freedom. Otherwise, the search process might be unmanageable. Secondly, to keep computational efficiency to an acceptable level when simulating large crowds. Moreover, we followed the recommendation stated in (Haghani and Sarvi, 2019) to use unit-less attributes that help keep the model's generalizability level. Note also that alternative specifications could potentially be proposed even with the same attributes used in our model. For instance, *EXCON* relevance in the systematic utility function decreases during the evacuation process, while *GROUP* relevance is maintained constant. Other alternatives could be possible depending on previous assumptions about pedestrian behavior.

Another important aspect of modeling exit-choice decisions that has been reported in (Haghani and Sarvi, 2019) is to mitigate decision changes that are not physically feasible. This aspect mainly includes pedestrians confined by a crowded jam. In their work, two measures are proposed to embody the decision-change eligibility in the simulation model, based on measures of the local crowd density and velocity experienced by pedestrians and on the definition of a set of thresholds. This strategy could have been used in our model by applying the same eligibility mechanisms and then apply or not the probabilistic stage of the exit-choice process. However, we preferred not to include this filter in our proposal for two reasons. Firstly, to not increase the degrees of freedom and computational burden. Setting the thresholds of eligibility to predefined values could bias the exploration of optimal solutions. Secondly, for the specific case of using the model to implement the decision logic of CelLEVAC, our experiments suggest that the movement is much more coordinated and homogeneous. So the probability of having 'trapped' pedestrians is lower.

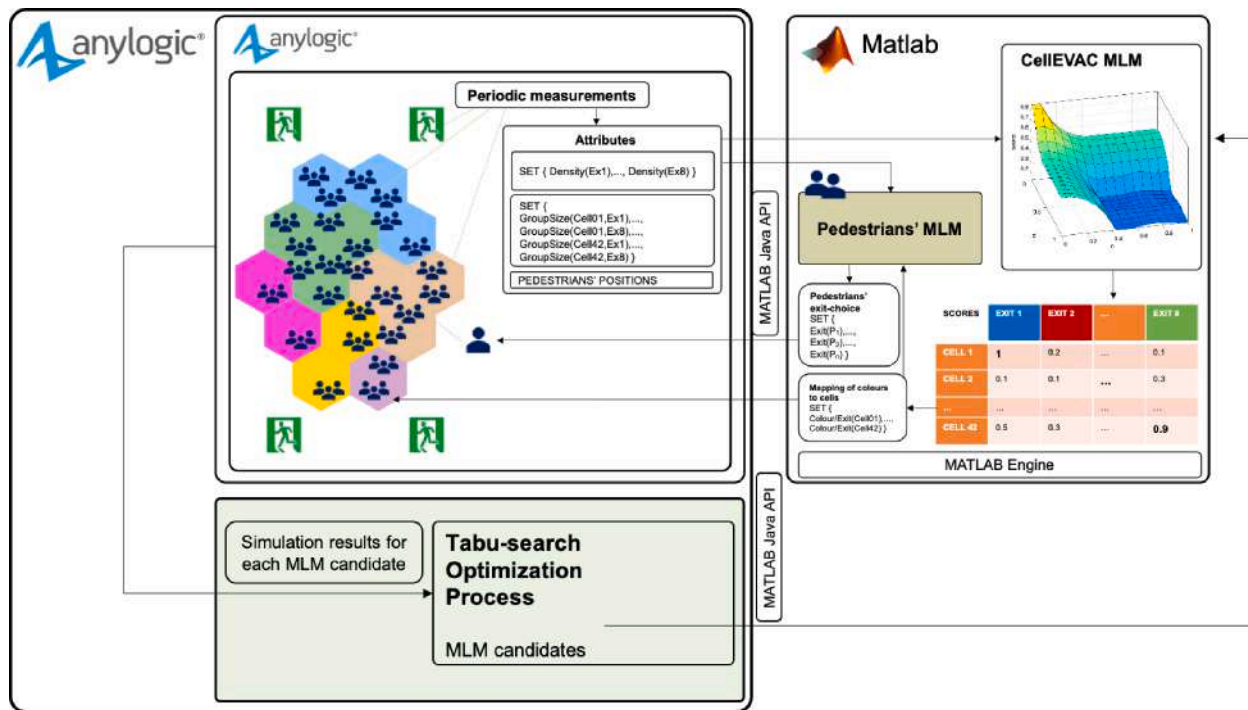


Fig. 3. Simulation-optimization software framework of CelLEVAC with control logic based on Multinomial Logit Model (MLM).

Another aspect that impacts on the performance of the exit-choice model, when applied to model pedestrian behavior or to implement the decision logic of a guidance system, is the frequency at which the pedestrians or the system revise their decisions. In the simulation setting used in this work, we used an update cycle of 5 s. We keep this frequency constant and control the frequency of the changes at optimal levels using the explicit coefficient  $\beta_p$  in the model.

It is also important to note that the model allows us to establish a clear distinction between environmental factors (distance, group, width, and congestion), attitudinal factor (personal) and an exogenous factor (system). Thus, the systematic utility function allows us to model many different behaviors by trading off the different parameters. For example, we may have a pedestrian who changes from making decisions based on the indications received from CelLEVAC to making decisions based on environmental factors. However, it seems reasonable to assume that a pedestrian following the indications is committed throughout the entire evacuation process. Therefore, we focused on evacuation scenarios in which a proportion of individuals (from 0% to 100%) were committed to following indications, while the rest of the individuals made their decisions based on environmental and attitudinal factors. Given the extreme nature of emergency evacuations, we assumed that individual characteristics tend to be reduced, and so all parameters  $\beta$  are defined as homogeneous values for each population group throughout the evacuation time.

### 3.4. Microscopic simulation-optimization framework

A simulation-optimization software framework was developed embedding agent-based simulation and discrete event simulation. The aim was to simulate the CelLEVAC system architecture integrating pedestrian behavior modeling, SFM for pedestrian motion, control logic of exit gate indications, and optimization features. We used as a basis the commercially available programming, modeling and simulation

software packages AnyLogic<sup>1</sup> and Matlab<sup>2</sup>. The kernel of the simulation-optimization software framework is AnyLogic, which provides multi-paradigm simulation, integrating three different modeling methods: discrete event simulation, agent-based simulation, and system dynamics, built on top of a Java-based software development framework. We used extensively the AnyLogic pedestrian library, which implements the Social Force Model (SFM) for simulating realistic pedestrian motion (Helbing and Molnár, 1995). Thus, with some particularities described below, the evacuation scenario layout, pedestrian motion, and evacuation measurements run in AnyLogic, while exit-choice decisions and control logic of exit gate indications are implemented in Matlab. AnyLogic and Matlab are interconnected in a master-slave configuration through the interface with external Java libraries provided by AnyLogic and the Matlab Java API engine (see details below). To study our CelLEVAC system based on MLM, and compare it with a Cartesian Genetic Programming (CGP) approach, two simulation-optimization software environments were developed: (a) simulation-optimization with MLM, and (b) simulation-optimization with CGP, which are described in the following subsections.

It is worth noting that we do not mean that this combination of AnyLogic and Matlab is the best possible simulation-optimization software framework. Many different pedestrian evacuation simulators could be used individually or combined with Matlab to build the models developed in this paper. Our motivation to choose AnyLogic has been: the same development platform can be used in different environments: supply chains, manufacturing, transportation, rail logistics, warehouse operations; it provides industry-specific libraries as pedestrian, rail, or road traffic libraries, which eases the development work significantly; provides multimethod simulation modeling: discrete event, agent-based, and system dynamics; we can include discrete event processes, a multi-agent system, and system dynamics in the same model; it is intuitive to build models using graphical elements, leaving room to program at a very detailed level; it provides gis maps integration, and it provides

<sup>1</sup> <https://www.anylogic.com/> Accessed 19 June 2020.

<sup>2</sup> <https://www.mathworks.com/> Accessed 19 June 2020.



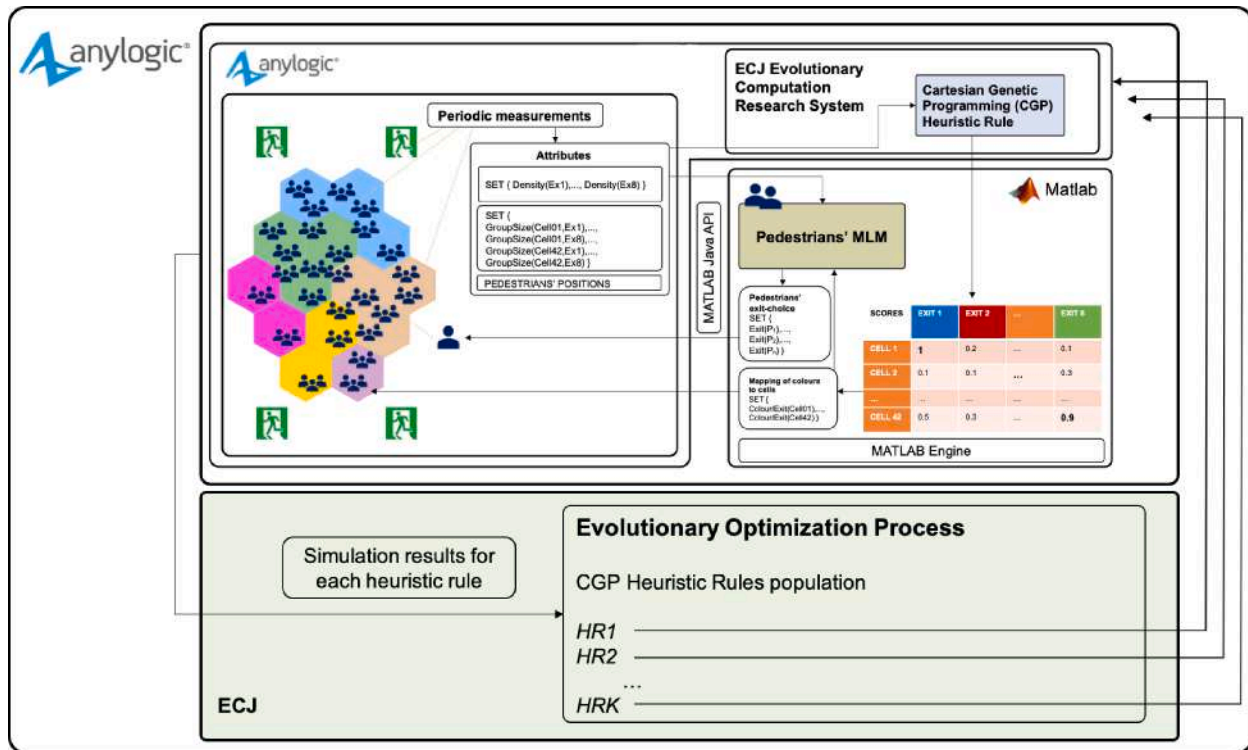


Fig. 4. Simulation-optimization software framework with control logic based on CGP.

native capabilities to develop simulations based on cellular automata or SFM. For the interested reader, in (Lovreglio et al., 2020), an online survey of pedestrian evacuation model usage is presented that studies the main trends in using pedestrian evacuation models and simulators.

#### 3.4.1. Simulation-optimization of MLM

The CelleVAC simulation model with MLM control logic is shown in Fig. 3. The evacuation scenario layout, visualization features, and all the functionality regarding the SFM based pedestrian motion were implemented within AnyLogic.

During a simulation, the first step is to send from AnyLogic to Matlab the set of parameters that configure the Pedestrians' MLM and CelleVAC MLM modules, including the set of distances from the cell centers to the exit gates. Next, the pedestrian positioning and densities at exit gates and cells are periodically measured and then transformed into the set of attributes: pedestrian positions, density at each exit gate, and group of pedestrians along the path to each exit. To obtain the number of pedestrians along a path, we used for convenience the structure of cells defined for CelleVAC in Madrid Arena. For each pedestrian within a given cell, group size is calculated by adding the pedestrians in the cells that are closer to each exit. All these attributes feed the CelleVAC MLM module in Matlab that implements the decision logic to allocate colors (exit gates) to cells. This mapping is sent back to AnyLogic for visualization purposes, and to the Pedestrians' MLM module within Matlab to generate the individual exit-choice decisions.

Note that there is one MLM model (CelleVAC MLM) to generate exit gate indications and a different MLM model (Pedestrians' MLM) used by pedestrians to make exit-choice decisions. These decisions may follow the exit gate indications through the *SYSTEM* attribute of the Pedestrians' MLM model. At one extreme, if we make  $\beta_{SYS} = 0$ , pedestrians will not follow exit gate indications from CelleVAC MLM. At the other extreme, we could make all parameters  $\beta = 0$  except for  $\beta_{SYS} = 1$ , so that all pedestrians strictly follow the exit gate indications. Also note that these two modules' systematic utility functions will generally differ in the parameter values  $\beta$  and in that the CelleVAC MLM module does not include a *SYSTEM* attribute. Moreover, the *DISTANCE* attribute in

the CelleVAC MLM module corresponds to the distance from a cell center to an exit gate, while in the Pedestrians' MLM module it corresponds to the distance from a pedestrian to an exit gate.

Finally, while individual exit-choice decisions in the Pedestrians' MLM model are probabilistic (see Eq. (1)), the exit gate indications for a given cell in the CelleVAC MLM model are based on a deterministic selection, corresponding to the exit gate with the highest utility. The deterministic selection prevents oscillations in the decision logic of CelleVAC.

As far as we know, this is the first time this simulation architecture interconnecting AnyLogic and Matlab has been implemented. Although AnyLogic is very valuable in the modeling of multiagent systems and discrete event processes at a high level of abstraction, when developing algorithms in very specialized domains (e.g., Control Systems, Fuzzy Logic, Optimization, Deep Learning, ...) or when performing highly intensive computational tasks (i.e., matrix computing), in our experience, Matlab is a more productive computing environment. Fortunately, Matlab provides flexible two-way integration with other programming languages. With AnyLogic, we used the Matlab Engine API for Java, which enables Java programs to use Matlab as a computational engine. AnyLogic imports the Java Engine API library to enable two-way interactions with Matlab synchronously or asynchronously. We found that this implementation dramatically increased productivity in model development and experimentation, facilitating the exploration of new decision making algorithms. For example, evacuation simulations execute exit-choice decisions and calculation of pedestrian distances to exit gates every few seconds and for thousands of pedestrians. While in AnyLogic these tasks would imply programming for-loops, Matlab built-in capabilities allow matrix computation at a higher speed and with only a few code lines.

To search for an optimal configuration of the CelleVAC MLM or pedestrians' MLM models, we used a simulation-optimization process that adopts a Tabu-Search algorithm (TS) (Glover, 1997), which iteratively searches for the near-optimal evacuation plan (optimal configuration of the MLM at the pedestrian level or system level). At the same time, the microscopic crowd simulation guides the search by evaluating

the evacuation time and safety of the solutions generated by the TS algorithm. The optimization process is built on top of the OptQuest<sup>3</sup> optimization engine provided by AnyLogic. Fig. 3 shows the optimization module on a green background. The parameters of the CelEvAC MLM or pedestrians' MLM models are the "MLM candidates" generated by the TS algorithm. Thus, each candidate is defined by a tentative set of parameters  $\beta$  sent to the MATLAB Engine at each iteration of the optimization process. The simulations results are sent back to the optimization module for its evaluation and thus guide the optimization process.

### 3.4.2. Simulation-optimization of CGP

Fig. 4 illustrates the simulation-optimization software framework that replaces the CelEvAC MLM module with heuristic rules (programs) based on Cartesian Genetic Programming (CGP) (Miller, 2011). A heuristic rule in CGP is a program represented in the form of a directed acyclic graph as a two-dimensional grid of computational nodes, which include input and output nodes. In our application scenario, the input nodes receive the attribute values of each pair cell-exit gate (i.e., distance from cell center to exit gate, density at the exit gate, group size, width, and tendency to maintain decisions), and a single output node returns the score of each pair. As in the CelEvAC MLM model, selecting an exit gate for a given cell is deterministic, corresponding to the exit gate with the highest score.

Each node in CGP contains a set of integers that represents what operations the node performs on the data and where a node gets its data. This set of node values make up the genotype in the CGP. When the genotype is decoded, some nodes may be excluded when they are not used to calculate the output data. Thus, while the genotype in CGP has a fixed length, the phenotype's size will be an intermediate value from 0 to the size of the genotype.

To obtain an optimal program, we used a variant on a simple evolutionary algorithm known as a  $1 + \lambda$  evolutionary algorithm (Beyer and Schwefel, 2002), widely used for CGP. Although this algorithm could be implemented using the Matlab Global Optimization Toolbox, the algorithms for decoding or evaluating a CGP genotype must be implemented from scratch. It was decided that the best procedure to implement the evaluation and learning processes was to use the ECJ<sup>4</sup> Java-based Evolutionary Computation Research System together with the contribution package provided by David Oranchak<sup>5</sup> for CGP. ECJ is an evolutionary computation (EC) framework written in Java. It provides tools that implement many popular EC algorithms and conventions of EC algorithms but with a particular emphasis on genetic programming. ECJ is free open-source with a BSD-style academic license (AFL 3.0).

We were able to integrate ECJ into AnyLogic and then use its full potential as an open-source general-purpose evolutionary computation framework. ECJ was imported as an external library within AnyLogic, and some ECJ callback functions and AnyLogic functions were customized to suit all simulation model requirements. As shown in Fig. 3, the only difference compared to the CelEvAC framework is the processing of the attributes to score the pairs cell-exit gate. In the CGP model, attributes are processed by a CGP heuristic rule in Java within AnyLogic, and the results are periodically sent to Matlab. To the best of our knowledge, no other authors have developed this integration.

To learn an optimal heuristic rule using CGP, we launch the ECJ evolutionary process within a master AnyLogic experiment by calling an ECJ 'Evolve' method (see the evolutionary optimization process module on a green background in Fig. 4). This method invokes an AnyLogic simulation experiment with CGP control logic for each candidate heuristic rule within the population (see the CGP Heuristic Rule module on

blue background in Fig. 4). The simulation results of each experiment are then sent back to the evolutionary process in ECJ to evolve the population using a fitness function (e.g., evacuation time and safety). This process is repeated until the algorithm converges to an optimal heuristic rule.

## 4. Modeling pedestrian flows and safety

It is well known that competition between agents at exit gates slow down the evacuation processes. In the faster-is-slower effect described by (Helbing et al., 2000), waiting is seen to help coordinate activities of competing agents and speed up the process, whereas more speed and pressure slow the overall process. Increasing time-pressure causes a severe reduction in the capacity of exits and a phase transition from efficient free flow to congested flow. The main cause of capacity drop for pedestrians is arc formation due to high pressure. Moreover, when density becomes too large, the dynamics of flow are governed by physical interactions generating hazardous situations.

Evacuation systems should maintain density at exits under a critical value to reduce this effect. Hence, to evaluate evacuation processes and design effective evacuation systems, it should be deemed to characterize flow dynamics at exits and consider both evacuation time and safety metrics. To this end, the pedestrian Macroscopic Fundamental Diagram (MFD) has proven to be a powerful concept in understanding and controlling pedestrian flow dynamics. Similar to MFD for vehicular networks, a relation exists between pedestrians' density and the average flow (number of pedestrians per meter and per second) in an area. (Hoogendoorn et al., 2017) provides results showing theoretically and empirically the existence of pedestrian MFDs and the impact of density spatial variation on MFDs. They conclude that the spatial density variation on flow is likely to be dependent on the flow configuration. In general, decreasing the spatial density variation will increase capacity. This fact has implications in the construction of MFDs using microscopic simulation. The shape of the MFDs will depend on the simulated flows' directions, levels and time profiles.

In our proposal to derive an MFD for each exit gate, we used microscopic simulation. Being our aim to obtain a safety metric using the fundamental diagrams, we took a conservative approach. Each simulation entailed pedestrians from four different directions heading to an exit to induce a significative variation in spatial density and model complex interactions. Thus, for each exit, four pedestrian flows were injected at four cells around. Pedestrians had a preferred evacuation speed obtained from a uniform distribution between 1.24 and 1.48 m/s. Each flow was linearly increased for 10 min leading to exceeding capacity and then linearly decreased to 0 for 10 min. This sequence was repeated three more times to simulate queue build-up and recuperation phases until a simulation interval of one hour was completed. At minute 50, the exit was locked to characterize pedestrian dynamics in the event of a fall. This repeating pattern and locking phase was based on experimentation, aiming to generate shockwaves and a representative number of points in the fundamental diagram.

Depending on the exit, peak flows ranged from 4 to 8 peds/s to exceed each particular critical density. With a two-second sampling period, density was measured in an area defined by the four closest cells to each exit while we took pedestrian flow measurements at each exit gate.

By following the procedure described above, we were able to obtain the MFDs shown in Fig. 5. In blue are represented the Flow vs. Density measurements during the first 50 min of simulation, while the red dots show the exit blocking phase. We fitted curves to data using regression to characterize all the points of interest in the MFDs homogeneously. We found the polynomial model as the ideal candidate after exploring different alternatives of curve fitting, such as smoothing splines, rational polynomials, or gaussian models. Firstly, polynomials are often used when a simple empirical model is required to obtain critical parameters. Furthermore, we were able to easily parameterize the different phases of

<sup>3</sup> <https://www.opttek.com/> Accessed 22 June 2020.

<sup>4</sup> <https://cs.gmu.edu/~eclab/projects/ecj/> Accessed 3 March 2020.

<sup>5</sup> <http://www.oranchak.com/cgp/doc/> Accessed 3 March 2020.

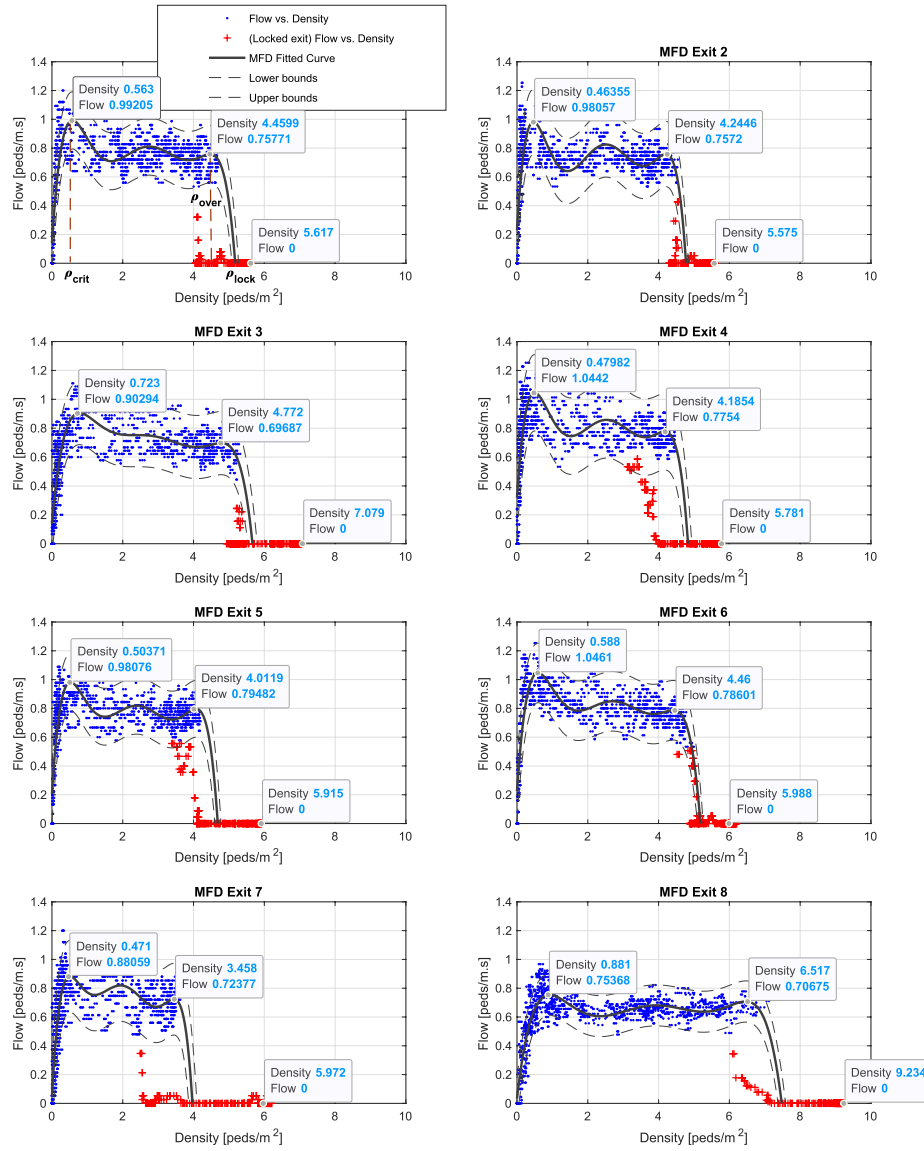


Fig. 5. Fundamental Diagrams of exit gates. The lower and upper bounds represent the 90% confidence intervals.

pedestrian flow, looking at the fitted curve, and judging the reasonable values for the critical densities. In all the cases, we used the bisquare weights method for robust linear least-squares fitting and a sixth-order polynomial.

In the MFD of Exit 1, it can be observed the different phases of pedestrian flow during evacuation. Each phase is delimited by the density value at which there is a flow peak. The critical density  $\rho_{crit}$  delimits the free-flow region. During the simulations, we observed that once the capacity value was reached, a fast backpropagation shockwave was formed that rapidly carried the density value to  $\rho_{over}$ . This state around  $\rho_{over}$  is stable until flow decreases, and a hysteresis path moves density to lower values. We observed that this stable state maintained as long as the arc formation due to high pressure was present. During the locking phase, the density value increased beyond  $\rho_{over}$  up to  $\rho_{lock}$  due to queue accumulation. When comparing the different MFDs, we found only slight differences between the first seven exits, which is an expected result considering that the evacuation scenario's geometry is quite regular, without obstacles, and widths are similar. However, during simulations, we observed a faster transition from  $\rho_{crit}$  to  $\rho_{over}$  at Exits 1 and 2 due to their funnel shape, which may contribute to more dangerous situations at these exits. Exit 8 shows higher density values but lower flow values. The only explanation for this is that it is located in

a corner. Note that lower flow values do not mean, in this case, lower evacuation capacity. For instance, while at its maximum capacity Exit 8 is able to evacuate  $0.75 \times 6 = 4.5$  peds/s, Exit 1 evacuates 2.5 peds/s.

These density thresholds were used to build our safety value for evacuation. Firstly, the safety value at each exit gate  $j$  is given by the following equation:

$$Sf_j = \left( -\bar{\rho}_j - \gamma \cdot \sigma_j^2 \right) \times 100, \quad (4)$$

such that

$$\bar{\rho}_j = \frac{1}{N} \sum_{n=1}^N \frac{\rho'_j(n) - \rho_{sf_j}}{\rho_{lock_j} - \rho_{sf_j}}, \quad (5)$$

$$\sigma_j^2 = \frac{1}{N} \sum_{n=1}^N \left( \frac{\rho'_j(n) - \rho_{sf_j}}{\rho_{lock_j} - \rho_{sf_j}} - \bar{\rho}_j \right)^2, \quad (6)$$

with



$$\rho'_{sf_j}(n) = \begin{cases} \rho_j(n) & \rho_j(n) \geq \rho_{sf_j} \\ \rho_{sf_j} & \rho_j(n) < \rho_{sf_j} \end{cases}, \quad (7)$$

$$\rho_{sf_j} = f(\rho_{crit_j}, \rho_{over_j}, \rho_{lock_j}) \quad (8)$$

Given a set of  $N$  density values measured periodically at exit gate  $j$ , Eqs. (5) and (6) represent the time-mean density and density time-variation values in the safety Eq. (4) respectively, which are weighted by a configuration parameter  $\gamma$ . Density time-variation measures the negative impact of variations of pedestrian flow, as explained above. Both terms are normalized to 1 using the range defined by  $\rho_{lock_j}$  and a predefined threshold  $\rho_{sf_j}$ . In Eq. (7), those values below  $\rho_{sf_j}$  are equal to  $\rho_{sf_j}$  to make safety metric independent of the evacuation periods that are considered safe. Thus, in a worst-case scenario in which exit gate  $j$  is locked,  $Sf_j = -100$ , while in a safe scenario where densities are always below  $\rho_{sf_j}$ ,  $Sf_j$  equals 0.

The value given to  $\rho_{sf_j}$  (see Eq. (8)) is defined as a function of  $\rho_{crit_j}$ ,  $\rho_{over_j}$  and  $\rho_{lock_j}$ . This function will depend on the specific scenario and the availability of calibration data. Since in our study  $Sf_j$  is used primarily for comparison purposes and not for its calibration with real data,  $f(\cdot)$  was defined merely as the following weighted-average function:

$$\rho_{sf_j} = 0.9 \cdot \rho_{crit_j} + 0.1 \cdot \rho_{over_j}$$

Moreover, we decided to make  $\gamma$  equal to 5 to strengthen the influence of density time-variations.

Finally, to characterize the overall safety value of the evacuation process, we used the average safety (Eq. (9)) and variance of the safety (Eq. (10)) values at the exit gates:

$$Sf = \frac{1}{|E|} \sum_{j=1}^{|E|} Sf_j, \quad (9)$$

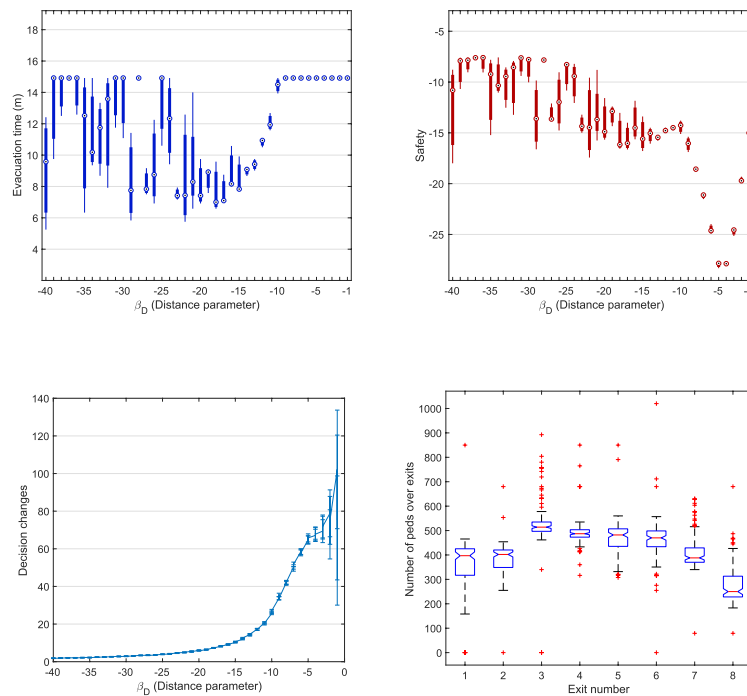
$$Sf_{var} = \frac{1}{|E|} \sum_{j=1}^{|E|} (Sf_j - Sf)^2 \quad (10)$$

The variance of safety  $Sf_{var}$  was used to estimate the imbalance of safety between the exit gates. Note that in contrast to the time-based measurements used to calculate safety values at exit gates, safety values to characterize the overall evacuation process are spatial-based measurements.

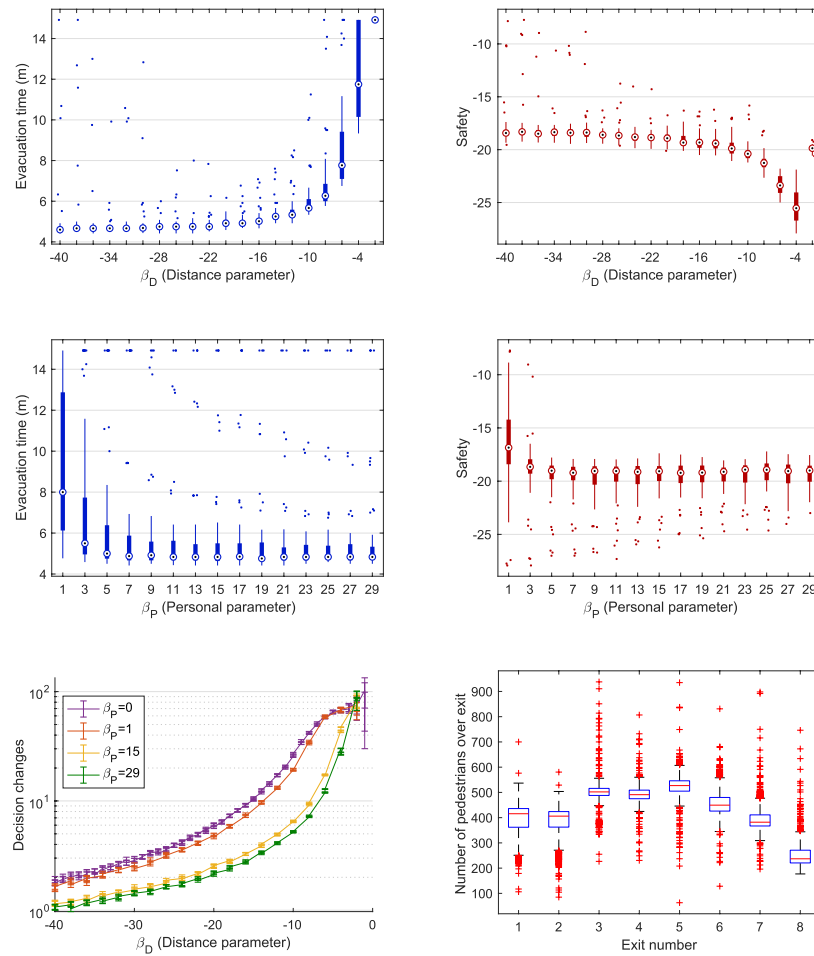
## 5. Simulation-optimization experiments and results

In this section, the experimental results are shown and discussed. The performance measurements in all the experiments were the total evacuation time, average and variance of safety values (Eqs. (9) and (10)), and the average number of decision changes. The users' average evacuation time would be an alternative to total evacuation time, which could be more suitable for evacuation scenarios where time to evacuate is homogeneous, and there are no areas that need excessive time to evacuate. However, our evacuation scenarios include external pedestrian flows that increase the variance of evacuation times between exit gates.

We conducted three main types of experiments: (i) sensitivity analysis of exit-choice changing strategies, (ii) simulation-optimization of pedestrians' behavior, CelLEVAC and CGP systems, and (iii) performance analysis of optimal configurations. In all the simulation setups, the evacuee population consisted of 3400 pedestrians on the ground floor, who had a preferred evacuation speed obtained from a uniform distribution between 1.24 and 1.48 m/s. We considered an evacuation scenario with external flows (i.e., with pedestrians coming from the upper floors) to simulate complex pedestrian flow interactions. Therefore, three exit gates were chosen at random at each simulation iteration. Two of these exit gates received an incoming pedestrian flow rate of 120 peds/min, while the third exit gate was blocked. We have chosen 120 peds/min by visual inspection, increasing the external pedestrian flows by hand until we found a flow at the corresponding exits, creating



**Fig. 6.** Sensitivity analysis of the distance  $\beta_D$  attribute without the guidance system active. The box-plots on the first row show the sensitivity of evacuation time and average safety to the  $\beta_D$  attribute. The second-row plots show the sensitivity of the number of decision changes to the  $\beta_D$  attribute, and the box-plots with the number of pedestrians evacuated by each exit gate.



**Fig. 7.** Sensitivity analysis of  $\beta_D$  and  $\beta_P$  without external pedestrian flows and the guidance system inactive. The box-plots on the first and second rows show the sensitivity of evacuation time and average safety to the  $\beta_D$  and  $\beta_P$  attributes. The plots on the third row show the sensitivity of the number of decision changes to the  $\beta_D$  attribute, and the number of pedestrians evacuated by each exit gate.

significant congestion, close to the exit's maximum capacity.

In the sensitivity analysis experiments, each experiment ran the evacuation simulation model multiple times varying one of the parameters, showing how the simulation output (i.e., the performance measurements) depended on it. Due to the stochastic nature of the evacuation processes, we used a replication algorithm to obtain representative results for a given parameter setting and a specific simulation output. This algorithm defines a minimum and a maximum number of experimental runs per parameter setting (replications of a simulation), a confidence level for the sample mean of replications (simulation output average), and an error percent. The minimum number guarantees the minimum number of replications, while the confidence level and error percent determine if more replications are needed. Simulation for a given parameter configuration stops when the maximum number of replications has been run or when the confidence level is within the given percentage of the mean of the replications to date. In our experimental setup, evacuation time was used as an output parameter to control the number of replications between 3 and 10. The confidence level was fixed to 80%, and the error percent to 0.5.

In the simulation-optimization experiments, the goal was to find the combination of parameters of the MLM or CGP models that resulted in the optimization of evacuation time and average safety through the fitness function (objective function)  $\min(\text{evacTime} - Sf)$ . We used the Tabu-search optimization algorithm or the  $1+\lambda$  genetic algorithm depending on the model MLM or CGP to optimize. As in the sensitivity analysis experiments, we used a replication algorithm with the same basic setup. For each simulation-optimization process iteration (i.e., for

the model parameter setting to simulate and evaluate at a given iteration), a minimum of 3 and a maximum of 10 simulations were run for a total of 200 iterations. However, while in the sensitivity analysis, the number of replicas was limited by the evacuation time value, in simulation-optimizations, the stop condition was controlled by the fitness function (objective function).

Finally, in the performance analysis experiments, the goal was to evaluate the performance of a given model parameter setting. For instance, for an optimal parameter setting found in a simulation-optimization experiment, a performance analysis experiment ran the optimal setting 50 times for gaining statistical significance.

To analyze and compare the results of different experiments or configurations we performed one-way analysis of variance (Montgomery and Runger, 1996) and Tukey-Kramer multiple comparison tests (Läuter et al., 1989). For most of our experimental results, regardless of the type of performance variables, the normality tests rejected the null hypothesis at 5% significance level. Thus, to provide a robust analysis of the results, the Kruskal-Wallis test was used (Montgomery and Runger, 1996).

### 5.1. Sensitivity analysis of exit-choice changing strategies

We first investigated how evacuation performance could be influenced by exit-choice changing strategies in an evacuation scenario without external flows, with the guidance system disabled (i.e., parameter  $\beta_{SYS}$  equals 0 in the pedestrians' MLM behavior model).

In these experiments, the only criterion for pedestrians' exit-choice

decision making was the distance. Parameter  $\beta_D$  was varied from  $-40$  to  $-1$  at discrete steps to perform a sensitivity analysis. Evacuation time and safety results revealed pedestrians' irregular behavior, with an unrealistic number of decision changes (see lower box-plots in Fig. 6). The visualization of simulations confirmed that the movement of pedestrians was unnatural. As expected, as  $\beta_D$  increased (i.e., the distance criterion was less critical) uncertainty in decision making was higher, the number of decision changes increased exponentially, and the safety and evacuation time worsened (Fig. 6). When  $\beta_D$  was close to  $-1$ , pedestrians were not able to escape from the evacuation scenario, and so the performance measurements were distorted. Being the distance the only criterion for evacuation, the number of pedestrians evacuated through the exit doors was unbalanced (see box-plot of the number of peds over exits in Fig. 6). For instance, exit gate 8 evacuated the least number of pedestrians, though it is the exit with the highest capacity. Overall, these results revealed the necessity of including an exit-choice changing attribute in the MLM model to modulate the number of decision changes.

The next experiments extended the previous sensitivity analysis to include the *PERSONAL* attribute, which models exit-choice changing behavior. Parameter  $\beta_P$  was varied in the range 1 to 29 at discrete steps to modulate the tendency to maintain the current exit-choice decision. Fig. 7 presents the results of the sensitivity analysis. The first row shows the results of the experiments, in which for a given  $\beta_D$  value,  $\beta_P$  is varied in the range 1 to 29 (i.e., for a given  $\beta_D$  value, we performed 29 evacuation experiments with a different  $\beta_P$  value). In the second row, the box-plots show for a given  $\beta_P$  the results of 40 evacuation experiments with a different  $\beta_D$  value. In the decision changes box-plot (third row), for each  $\beta_D$  value, we perform four experiments with  $\beta_P$  equal to 0, 1, 15 and 29.

The results obtained confirmed the hypothesis of a much more stable and realistic pedestrians' behavior. For a wide range of values of both parameters  $\beta_D$  and  $\beta_P$ , evacuation time and safety values were confined within a small range of values. Moreover, evacuation time significantly improved when compared to not using the *PERSONAL* attribute. For instance, for a value of  $\beta_D = -22$ , median evacuation time was around 4.8 minutes, while without the *PERSONAL* attribute, it varied in the range 6–12 min.

In contrast, the safety value worsened from  $-14$  to  $-19$  with the *PERSONAL* attribute. These results suggest that there is a correlation between safety and the number of decision changes. Uncoordinated movement of pedestrians far from the exit gates made the evacuation time increase, density at exit gates decrease, and so safety at exits improve. As regards the results for the number of decision changes, these revealed a significant reduction in the number of decision changes as  $\beta_P$  increased. When combined with the evacuation time and safety results, it can be seen that the optimal strategy is to make very few exit-choice changing decisions ( $\beta_P = 29$ ) based on a highly influential distance criterion ( $\beta_D = -40$ ). Finally, as in the previous experiment, there was not a fair balance between the different outflows. We replicated the experiments in an evacuation scenario with external flows. The results obtained are similar to those outlined above, except for the magnitude of the evacuation performance results.

These experiments are consistent with previous findings (Haghani and Sarvi, 2019). According to our results, it is evident that the inclusion of the decision change *PERSONAL* attribute made a very substantial difference in terms of the efficiency of evacuations. Moreover, the experiments confirmed the viability of including the modeling of exit-choice changing behavior in a single-layered MLM structure.

## 5.2. Simulation-optimization of pedestrians' behavior (OPTIMAL), the CellEVAC and CGP systems

Here we investigated the optimal individual behavior of pedestrians (OPTIMAL), and the optimal configurations of the CellEVAC and CGP guidance systems. In Appendix A are described in detail the conducted optimization processes.

**Table 1**

Optimal and standard configurations of the parameters of the pedestrians' MLM behavior model.

	$\beta_D$	$\beta_G$	$\beta_E$	$\beta_W$	$\beta_P$
STANDARD	-28	0.6	-0.5	0.6	0
OPTIMAL	-28.863	9.909	-2.801	0	8.515
CellEVAC	-17.723	-2.181	-1.671	1.064	2.594

The optimal settings found for OPTIMAL and CellEVAC have been summarized in Table 1. The STANDARD parameter setting in Table 1 models typical pedestrian behavior in which exit-choice decisions are based mainly on distance, and to a lesser extent, on imitation and visual perception of the exit gates' width. These values are based on the parameter setting obtained in (Duives and Mahmassani, 2012) for a calibrated model. However, these values are not claimed to be necessarily the fittest form of standard behavior, but a typical behavior strategy to compare. Finally, we found the following heuristic rule for the CGP system:

$$\begin{aligned} & \text{score}(\text{cell}_{i \in \{1, \dots, 42\}}, \text{exit} - \text{gate}_{j \in \{1, \dots, 8\}}) = \\ & *(-(-(-(-WW)G)(-P(+G(-PD)))) \\ & (+(+(-(-(-(/P(-PD))(/P(-PD)) \\ & (-PD)))(-WW)) \\ & (-P(/P(+G(-PD)))) \\ & (*(/P(-PD)) \\ & (/P(-PD))(-PD)))E)) \\ & (+(/(-PD)(+/P(-PD))(-(-WW)G)))E)) \end{aligned}$$

where  $D = \text{DISTANCE}$ ,  $E = \text{EXCON}$ ,  $G = \text{GROUP}$ ,  $W = \text{WIDTH}$  and  $P = \text{PERSONAL}$ .

The obtained parameter values for OPTIMAL revealed that the most influential factor was the distance. Interestingly, we found that group imitation behavior ( $\beta_G = 9.909$ ) had a positive effect. Our interpretation, corroborated by visual inspection, is that collective intelligence contributes to a better balance in exit gate sharing in the presence of complex pedestrian flow interactions.

The negative sign of  $\beta_E$  (congestion at exit gate) highlighted the benefit of avoiding congested exit gates. However, the exit gate's width was found irrelevant in scenarios with external flows. These results are in line with our hypothesis of a better evacuation performance in complex environments when using adaptive strategies. Finally, the value obtained for exit-choice changing parameter  $\beta_P$  confirmed the positive effect of gradually smoothing the number of decision changes during the evacuation process.

For CellEVAC, the parameter values also revealed that the most influential factor was the distance. Remarkably, we found that in contrast to OPTIMAL (i.e., assuming that individuals behave optimally at an individual level), the group parameter  $\beta_G$  had a negative sign. Our interpretation is that the group imitation effect is implicit in the cell-based control of pedestrian movements, so a positive value of this parameter negatively influences an excessive uniformity in the exit gate indications. Therefore, the  $\beta_G$  parameter compensates for the implicit grouping effect of CellEVAC. We also observed significant differences in magnitude in the exit gate width and decision changing parameters. The tendency to maintain previous cell indications by the CellEVAC system was significantly lower than to main previous exit-choice decisions at the individual level (2.594 vs. 8.515). The width of the exit gate, which was not considered at the individual level, appeared at system level.

The interpretation of the heuristic rule for the CGP system is not straightforward, and we would need to apply partial derivatives to extract information regarding the influence of the different attributes. Also, due to the simulation processes' stochastic nature in CGP, each optimization trial may obtain different heuristic rules, making generalization difficult.



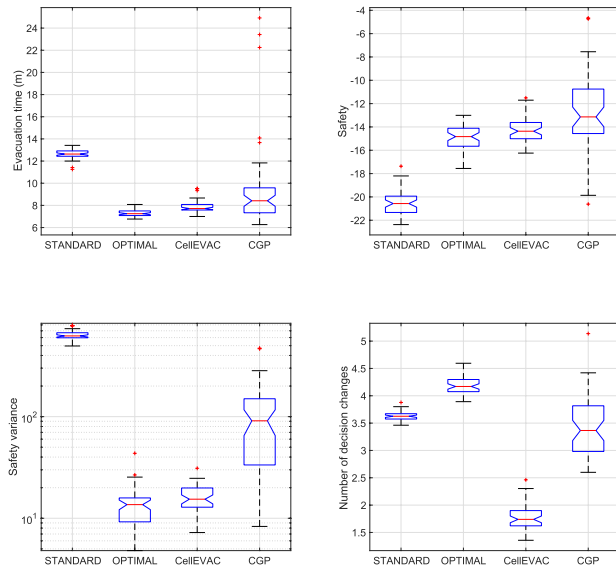


Fig. 8. Box-plots of the performance measurements for the STANDARD, OPTIMAL, CelLEVAC and CGP configurations.

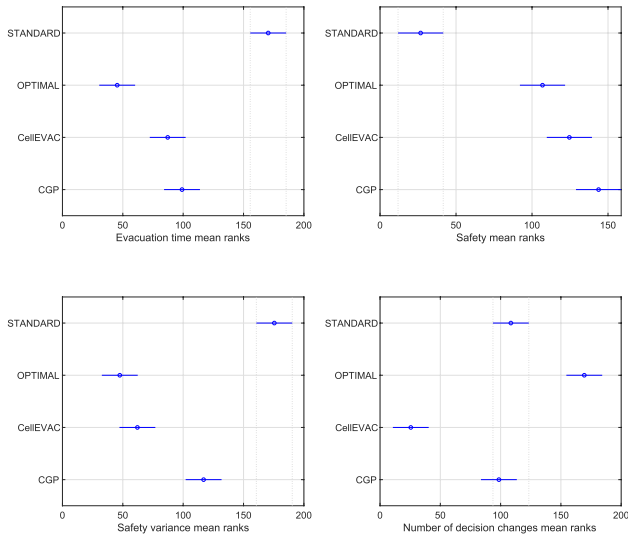


Fig. 9. Multiple comparison tests of the performance measurements for the STANDARD, OPTIMAL, CelLEVAC and CGP configurations.

### 5.3. Performance results

The performance analysis results have been summarized in Figs. 8 and 9. As expected, the experiments revealed significantly better overall performance in the optimized models than the STANDARD behavior. When using the CelLEVAC system, the results were very similar to those obtained when pedestrians followed the ideal individual strategy defined by the OPTIMAL configuration. The median evacuation time was around 8 min with CelLEVAC, only 30 s above OPTIMAL. It is interesting to note that the number of decision changes decreased dramatically with CelLEVAC due to the high degree of coordination imposed by the CelLEVAC system through the exit gate indications. When comparing CelLEVAC and CGP, the results showed a significantly better performance of CelLEVAC in terms of safety variance and the number of decision changes. It confirmed that CelLEVAC balances pedestrian flows significantly better than CGP.

The outcomes of single run simulations are shown in Fig. 10. For comparison, external flows in all simulations were injected at exits 2 and

4, while the entry at exit gate 8 was blocked. Pedestrians' speed was artificially reduced by a factor of 100 in a restricted area at the entrance of the exit gate 8 to simulate that an external event blocked the exit.

The density and safety plots for the STANDARD strategies showed highly unbalanced pedestrian flows at the exit gates. Exit 8, which was the exit with the highest capacity, was underutilized. Also, we observed low safety levels at exit gates 2 and 4 due to external flows. In contrast, CelLEVAC exhibited balanced pedestrian flows at the exit gates and significantly lower decision change values compared to the other configurations. The CGP system showed highly unbalanced pedestrian flows at the exit gates and significant oscillations in the density curves. In the same scenario, CelLEVAC presented a much more homogeneous and stable evolution of pedestrian flows. Notably, the distribution of decision change values showed an inferior performance in CGP, significantly skewed to the right.

Still images of the single run simulation experiment for the STANDARD configuration in Fig. 11 showed the accumulation of pedestrians at both exits. With STANDARD, it can be observed how exits 2 and 4 (red and yellow) are still collapsed at minute 6, while with OPTIMAL exits 1 and 5 share their capacity to discharge exits 2 and 4 respectively (Fig. 12). Contrary to expectations, safety at exit 8 was high, but the explanation is that its capacity doubles the capacity of the remaining exit gates. It is crucial to note that with the optimal strategy the balance of the pedestrians flows at the exit gates is significantly improved, and so the safety and evacuation time. These results exemplify the importance of the right balance of pedestrian flows in the improvement of evacuation processes. The simulations revealed that OPTIMAL provided a much better balance between the exit gates at the cost of significantly higher decision changes (histograms in Fig. 10).

In Fig. 13, still images of the evacuation experiment when using CelLEVAC showed how exits 1, 5, and 7 (blue, magenta, and pink) shared their capacity to discharge the congested exits 2, 4 and 8 (red, yellow and green) respectively. It is important to note that pedestrians' movement is more homogeneous when using the CelLEVAC guidance system, compared to pedestrians making decisions at the individual level without following indications (see Fig. 11). Overall, these results have further strengthened our confidence in the CelLEVAC MLM system as an effective adaptive guidance system.

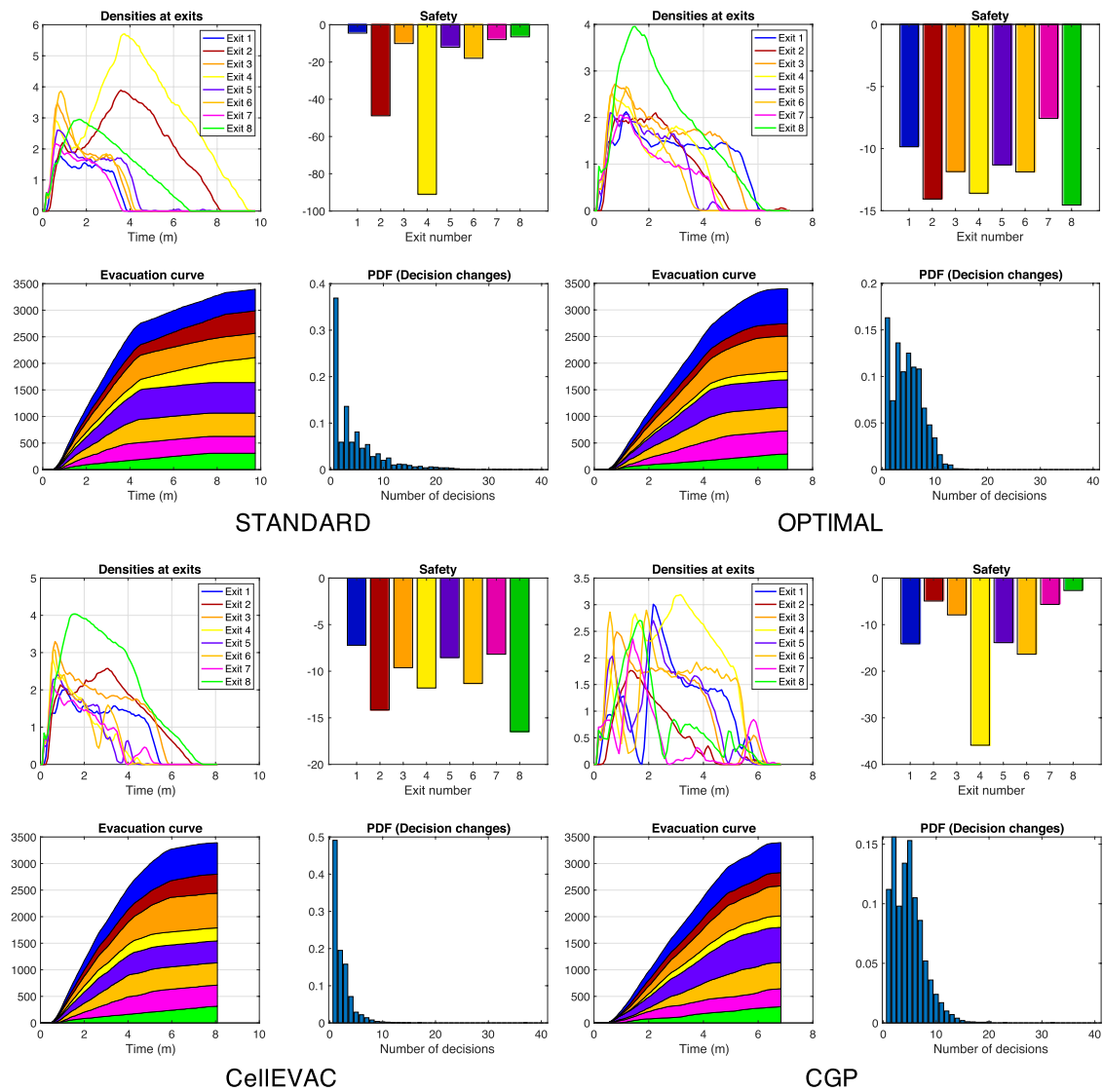
Finally, still images for the CGP single run experiment in Fig. 14 showed how different exit gates discharged the congested exit gates 2 and 8 (red and green) at different moments. However, exit gate 4 (yellow) remained congested during the evacuation process. In contrast, with CelLEVAC, the three congested exit gates were discharged by adjacent exit gates with available capacity, exhibiting a much more stable behavior. It is important to note that pedestrians' movement suffered from large oscillations, showing a highly unnatural behavior.

Using an optimized behavior model to implement the decision logic of a guidance system, as hypothesized, helps to provide adequate control actions (indications) more similar to human behavior. We believe that this kind of indication will be easier to follow by pedestrians in evacuation scenarios characterized by high uncertainty, stress, and panic.

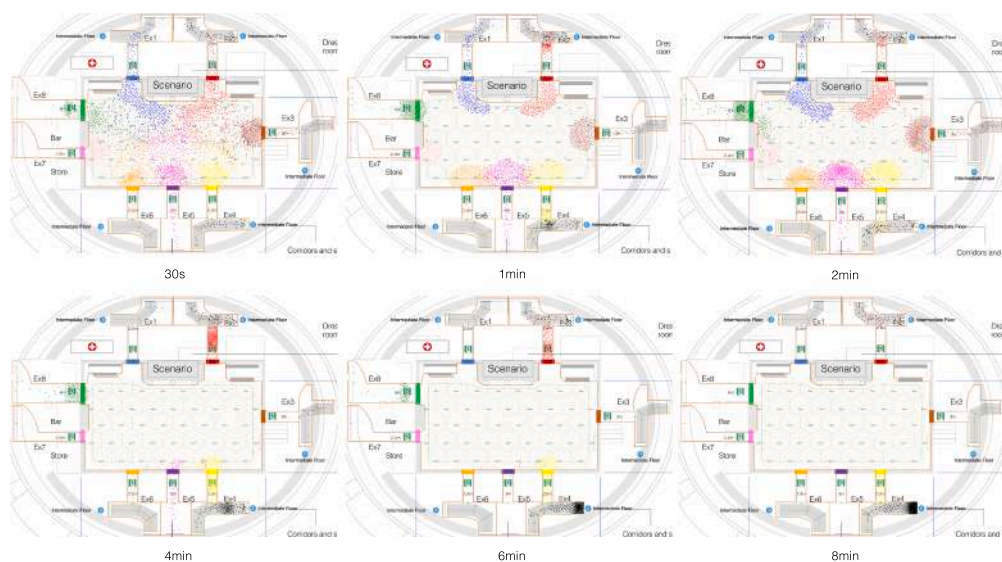
### 5.4. How the compliance rate of CelLEVAC influences evacuation efficiency

The outcomes of the CelLEVAC sensitivity analyses to compliance rate are presented in Fig. 15. Compliance rate ranged from 0% (STANDARD) to 100% (CelLEVAC) in increments of 20%. The percentage of users using CelLEVAC were committed to follow indications during all the evacuation process, while the remaining users followed the STANDARD behavior.

Based on sensitivity analyses to evacuation time, the system required 60% of people to use CelLEVAC to achieve the best value of evacuation time. As regards average safety and safety variance, results showed a linear improvement. Finally, the number of decision changes also exhibited a linear improvement with an increasing compliance rate.



**Fig. 10.** Results of single run simulations. Each sub-figure shows the evolution of the pedestrian densities, safety values and evacuation curves at each exit gate, and the histogram (probability density function) of the number of decision changes.



**Fig. 11.** Still images from the single run simulation experiments of the STANDARD behavior.

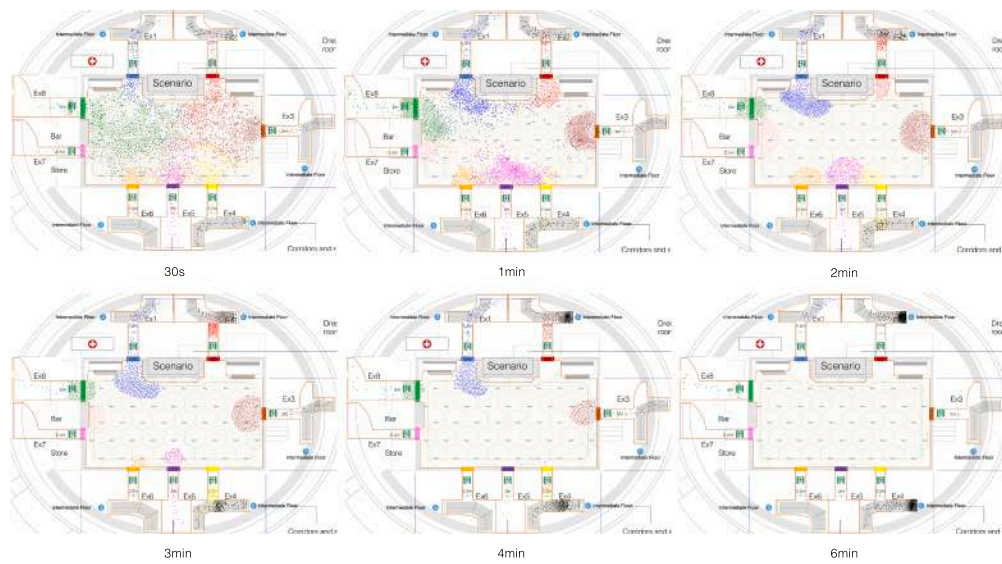


Fig. 12. Still images from the single run simulation experiments of the OPTIMAL individual behavior.

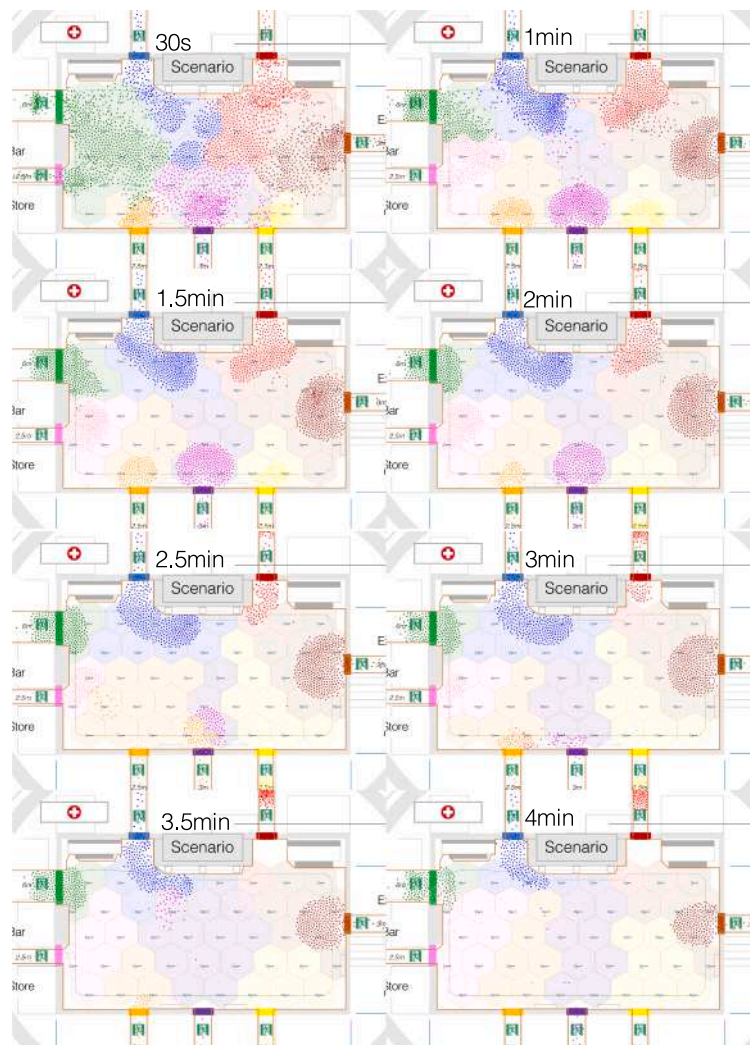
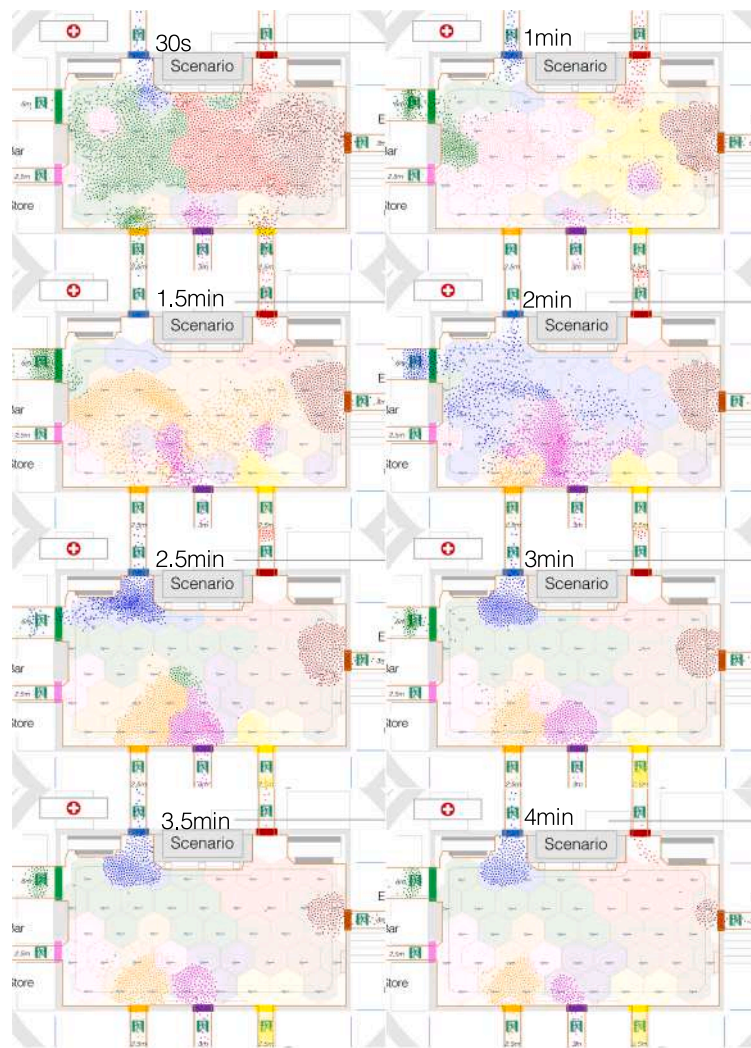


Fig. 13. Still images from the single run simulation experiments of the CelEvac system with external flows at exit gates 2 and 4, and exit gate 8 blocked. Each cell shows the color corresponding to the recommended exit gate.





**Fig. 14.** Still images from the single run simulation experiments of the CGP system with external flows at exit gates 2 and 4, and exit gate 8 blocked. Each cell shows the color corresponding to the recommended exit gate.

Overall, the most remarkable result of the sensitivity analyses is that the system is highly effective, even at low compliance rates.

### 5.5. Discussion

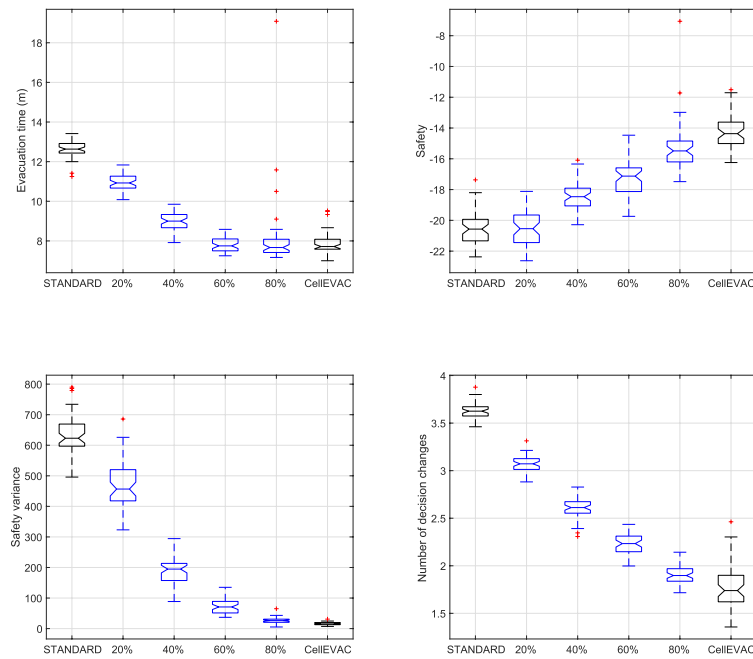
Our use of an optimized exit-choice behavior model to implement the control logic of an adaptive guidance system of exit-choice has proven to be very efficient in terms of the evacuation time, safety, and the number of decision changes. This technique improves existing non-adaptive approaches, which are very efficient in evacuation time but generate fixed plans incapable of responding to unexpected conditions (Abdelghany et al., 2014; Zhong et al., 2014; Wong et al., 2017). The experimental evaluation confirms that CelLEVAC performs better than adaptive proposals based on heuristic rules (CGP) (Zhong et al., 2016). Moreover, our experimentation with CGP was challenging concerning the optimization process.

The operation of CelLEVAC confirms the hypothesis of a much more natural response to exit-choice indications than those obtained with heuristic rules. In evacuation scenarios, characterized by high levels of stress, uncertainty, and panic, receiving instructions that are optimal and closer to human behavior patterns are particularly important for a much higher utilization rate and efficiency. Significantly, CelLEVAC proves to be effective even in scenarios with a utilization rate of 40%. Imitation behavior seems to be crucial in its effectiveness in this regard.

Up to our knowledge, this is the first evacuation guidance system architecture based on color codes for the adaptive recommendation of exit gates. We strongly believe that this architecture has a high potential for its simplicity. From the physical deployment perspective, its cost and complexity may be small, as explained in the architecture description. Besides, the human-machine interface provides clear and simple instructions that are easy to follow. This latter aspect complements the natural behavior patterns generated by the exit indications given by CelLEVAC.

Another of our main goals was to include the safety measure as a performance objective. The result is that the optimization processes search for the right balance of the pedestrian flows using the modeled dynamic response of the exit gates throughout pedestrian fundamental diagrams. This approach has allowed improving the evacuation processes significantly. Note, however, that the measurement of safety in our research depends on arbitrary density thresholds for comparison purposes. Depending on the specific scenario, and the forecast of capacity and flows, it would be necessary to apply some calibration technique to set the adequate thresholds in the pedestrian fundamental diagrams.

We are aware that the average and variance of safety at the exit gates, could be replaced by other statistics depending on the specific application, and the analysis and calibration based on real experiments. For example, instead of using the average value, we could be more



**Fig. 15.** Box-plots of the sensitivity analyses of the performance measurements to the compliance rate of CelLEVAC. Horizontal axes categorize the compliance rate from 0% (STANDARD) to 100% (CelLEVAC).

conservative using a maxi-min objective function. Finally, we have considered safety at exit gates, ignoring the analysis of safety in other areas. In an evacuation scenario with a relatively small size as the one addressed in our work, it seems reasonable to focus the study at the exit gates, which are typically the most dangerous zones. However, in larger scenarios, it would be interesting to extend the safety measurements to the entire evacuation area.

In line with (Haghani and Sarvi, 2019), modeling the exit-choice change has proven to be a critical parameter in modeling optimal individual behavior and modeling and optimizing the CelLEVAC decision control module. The integration of exit-choice changing behavior and the remaining attributes of exit-choice decision making, allowed us to significantly reduce the number of degrees of freedom of the model and simplify the optimization process. However, this does not exclude the study of alternatives based on a two-layered model.

Interestingly, the results highlight the importance of imitation patterns in individual behavior, which are nevertheless sign negative in the CelLEVAC system. The grouping effect of CelLEVAC indications seems to inherently incorporate the imitation pattern, which has to be compensated by the negative value of the parameter  $\beta_p$ .

Although the simulation–optimization modeling framework proposed in this paper is extensible to scenarios different from Madrid Arena, some aspects are specific and restrict its direct application. For instance, a different facility will require a different cell structure depending on its size and shape, maybe with cells of different sizes. Moreover, we will need to compute the fundamental diagrams of the exit gates and calibrate their density thresholds. The direct vision to all the exit gates and the absence of obstacles simplified the design of the exit-choice models and the infrastructure of light indicator panels. In scenarios without direct vision and obstacles, we would need intermediate light indicator panels, in addition to those located at the exit gates. This fact represents a significant challenge to investigate.

Regarding the simulation–optimization processes, we have followed a cross-validation method, in which two different models, for scenarios with and without external flows, are validated in scenarios with and without external flows. Another possibility would have been to generate a single optimal model by using many different pedestrian flow patterns. However, our objective was not to generalize but to investigate the

influence of different factors on evacuation processes (e.g., different fitness functions or different expected pedestrian flows). According to the experimental results, it seems reasonable that by following the same procedures, it is possible to configure CelLEVAC in very different scenarios.

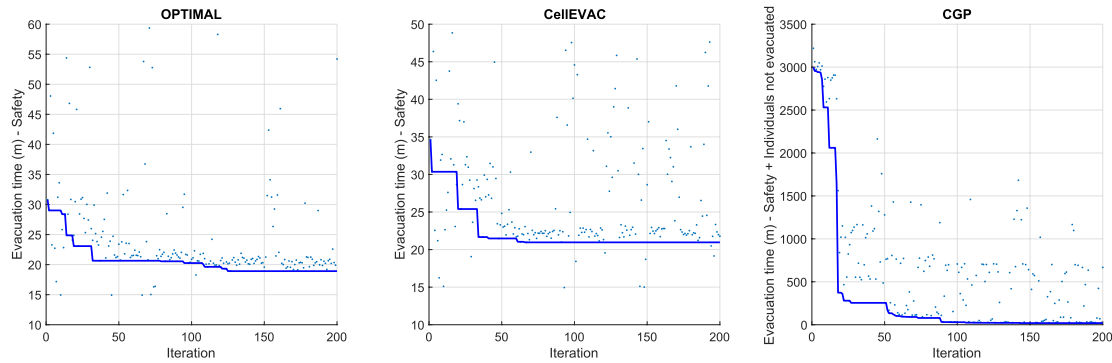
## 6. Conclusions

We have proposed an adaptive guidance system named CelLEVAC for crowd evacuations based on exit-choice indications. These indications have the form of colors displayed in personal or wearable devices that allow evacuees to find the exit gate with the corresponding colored light indicator panel. This type of indication simplifies greatly its interpretation, which is particularly important in stressful situations found typically in evacuation scenarios.

Our research focused on Madrid Arena, an indoor arena located in the city of Madrid (Spain). We have defined a system architecture that divides the facility into homogeneous cells such that evacuees in the same cell receive the same indications. The architecture assumes an indoor or outdoor positioning system that provides pedestrians location-aware capabilities. The core of the system is the controller module (decision logic module) that monitors the environment, decides on the allocation of exit gates (colors) to cells, and sends this allocation to sensor nodes located in the center of the cells. This information is transmitted periodically throughout a broadcast communication channel.

The first aim of our study was to assess the use of a pedestrians' exit-choice behavior model to implement the decision logic module. We built this module upon the simplest and most popular practical discrete choice model, the Multinomial Logit Model (MLM). Our goal was to find the optimal configuration of the model to optimize evacuation time and safety. Thus, the procedure for conducting the optimization processes was to adopt a simulation–optimization approach in which heuristic search algorithms integrate with a microscopic pedestrian simulation based on the Social Force Model.

We built two different simulation–optimization frameworks integrating pedestrian behavior modeling, social force model for pedestrian motion, control logic of exit gate indications, and optimization features.



**Fig. A.1.** Progress of the simulation-optimization processes. For OPTIMAL and CelLEVAC the blue dots below the current best-solution line represent the non-viable solutions obtained during the Tabu-search optimization process.

In the first framework, AnyLogic simulation software interconnected with a Matlab engine. We used this software framework to perform Tabu-search optimization of the MLM model and perform sensitivity and performance analyses. The second software framework interconnected AnyLogic with a Matlab engine and ECJ (Evolutionary Java Computation Framework). This configuration was used to optimize, evaluate, and compare an existing control logic based on Cartesian Genetic Programming. With the interconnection of these programming, simulation, and optimization software applications, we have found a cutting-edge solution for developing simulation-optimization in the field of pedestrian evacuation.

The second aim of our research was about defining a safety metric for evacuation processes to be used in the optimization processes as an explicit objective. Something neglected in the existing literature. We have introduced a method in which we first calculate the pedestrian fundamental diagrams of the exit gates to capture their dynamics. Based on the fundamental diagrams, the next step is to establish specific density thresholds for each exit gate that determine what is considered safe. Following this procedure, we have described overall statistics that define performance safety values systematically and objectively.

With these two main objectives in mind, we first investigated how evacuation performance could be influenced by different individual behaviors, paying attention to exit-choice changing strategies. The sensitivity analyses and optimization results have underlined the importance of imitation behaviors and exit-choice changing modeling in the performance of evacuation processes. In contrast to existing research, we incorporated the modeling of exit-choice changing behavior in the exit-choice decision model. We have confirmed the viability of this integration and the simplification of the optimization processes.

Next, we moved on to the optimization tasks at a system level. Our goal here was to optimize the MLM behavior model used in the decision logic module of CelLEVAC. We obtained the best results when the optimization objective was defined explicitly in terms of evacuation time and safety, and the evacuation scenario included complex pedestrian flows. The performance analyses of the model obtained, confirmed a balanced pedestrian flow and a natural movement to the exit gates, in addition to a similar performance when compared to the optimal

behavior at an individual level. Interestingly, imitation behavior disappeared from the optimal MLM model in CelLEVAC due to the grouping effect inherent to the CelLEVAC indications.

We compared the MLM behavior model with an existing Cartesian Genetic Programming approach based on the optimization of heuristic rules. The results confirmed the advantage of using a behavior model to control the indications of exit-gates. The use of heuristic rules exhibited a worst overall performance, with unnatural movements and an excessive number of decision changes. Moreover, we found it quite problematic to configure the optimization process.

The evidence from this study suggests the viability of CelLEVAC as an effective adaptive guidance system based on exit-choice indications. Taken together, the results confirm that optimized pedestrian behavior models can be effectively used to develop decision logic modules in adaptive guidance systems for crowd evacuations.

Several extensions are considered for this research. We are in the process of investigating specific technologies to implement and deploy the CelLEVAC. Also, we will examine the differences between a single-layered decision model and a two-layered model with separate functions for exit-choice changing and exit-choice decision. We will need to investigate how to reduce the complexity of the optimization processes with two-layered models. Effort is also underway to study the use of CelLEVAC in different evacuation scenarios with obstacles and dynamic conditions in the facility. Another research extension is related to the calibration with real data of the safety model. In a deployment of CelLEVAC in real scenarios, we will need to determine the optimal density thresholds to improve safety. Finally, in mega facilities such as grand stadiums, developing a safety metric that includes the pedestrian flow dynamics of all the facility and not the exit gates only, will need to be undertaken.

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## Appendix A. Optimization processes

Fig. A.1 illustrates the progress of the simulation-optimization processes to obtain the optimal configurations for the OPTIMAL, CelLEVAC and CGP models. We imposed an arbitrary simulation stop-limit of 15 min to evacuation time, after which the simulation iteration stopped. The aim was to avoid the consumption of simulation time in non-viable solutions during the optimization process.

In the optimization of the individual pedestrian behavior (i.e., OPTIMAL configuration) and the CelLEVAC system, a restriction to the viability of solutions was incorporated in the Tabu-search algorithm, removing solutions in which there were pedestrians pending evacuation. We discovered that the search process could find solutions in which pedestrians did not move, artificially increasing the objective value due to an average safety close to 0.

For the CelLEVAC guidance system, we assumed that the entire population of evacuees followed the indications of the CelLEVAC system, and



therefore in the pedestrians' MLM behavior model, all the parameters were equal to 0, except for  $\beta_{\text{SYS}} = 1$ .

The simulation–optimization process of the CGP model was configured following the recommendations of (Miller, 2011) as follows: population of  $1 + \lambda = 5$  (i.e., population of 5 candidate solutions per iteration of the genetic algorithm), a mutation rate  $\mu_r = 0.75\%$ , 4000 nodes, 5 input nodes, and 1 output node. We found that the algorithm did not converge to viable solutions even with short genotypes. The solution was to include in the fitness function, the number of people waiting to be evacuated at the end of the simulation deadline (15 minutes):  $\min(\text{evacTime} - Sf + \text{numberOfWaitPeds})$ . Thus, at the first iterations of the optimization process the search was directed towards minimizing pedestrians' number. Once the search process found solutions that were able to evacuate all the population, the next iterations were automatically focused on improving evacuation time and safety. In addition to this modification of the fitness function, we had to progressively increase the length of the chromosome from 50 to 4000 nodes until we finally found viable solutions.

The best solution curve shows how fitness values progressively decreased from 3000 to 20. As in the optimization of CelLEVAC, we assumed that the entire population of evacuees followed the indications of the CGP module.

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