Evaluating and Optimizing Evacuation Plans for Crowd Egress

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Evacuation planning is an important and difficult task in building design. The proposed framework can identify optimal evacuation plans for specific spatial locations. A new quantitative metric can evaluate evacuation performance based on many of the important aspects.

Crowd behavior has been the subject of study in many research areas, including psychology, safety engineering, and entertainment. Researchers have developed various scientific models to computationally simulate a crowd's behavior in a specific environment. When simulating crowds, a set of parameters should be considered that reproduces coherent behaviors. Such parameters aim to represent four key components: *environmental physical structure*, the information about building features such as the dimensions, number of floors, number of rooms, and number and location of exits and stairs; *environmental functionality*, the functionality of the place, such as an office, hospital, school, airport, stadium, or arena, which affect how people might use it; *population data*, the number of people in the environment, their spatial distribution, and their demographics, such as age, gender, and relationships among them; and *environmental condition*, the factors in a specific environment that can affect its navigability, such as time of day or the presence of smoke, fire, or heat.

Such factors are just a small set of points that can impact an evacuation process, however. The variations in human behaviors based on these and other factors make the reproduction and virtual simulation of an evacuation process a complex and challenging problem. In this article, we present a framework to identify optimal evacuation plans using decision points, which control the ratio of agents that select a particular route at a specific spatial location. We optimize these ratios to achieve the best evacuation based on a new, qualitatively validated metric for evacuation performance. This metric captures many of the important aspects of an evacuation: total evacuation time, average evacuation time, agent speed, and local agent density. To our knowledge, this is the first metric proposed that can quantitatively evaluate evacuation performance. The proposed approach was validated using a nightclub model that incorporates real data from an actual evacuation.

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State of the Art

The study and modeling of pedestrian traffic and the inherent relationships among behavior, environment, and context is vital to the use of critical spaces.[1–4] Modern hardware and computational methods afford large-scale simulations of such pedestrian crowds in arbitrary environments.[5,6]

Evacuation Simulation

There are several ways to simulate pedestrian crowds in evacuation scenarios. One method uses cellular automata. For instance, several works reproduce pedestrian behavior and exit selection using a least-effort cellular automaton algorithm in which the motions and goals are probabilistic.[7–9]

Agent simulations provide a rich way of simulating evacuation scenarios and may give rise to emergent behaviors found in difficult scenarios, such as high density and panic. Force-based models have gained considerable attraction in evacuation simulations.[10] SAFEgress (Social Agent For Egress) is a force-based approach that models evacuating pedestrians.[11] SAFEgress agents can base their actions on their knowledge of the environment and their interactions with the social groups and the neighboring crowd. Mimosa (Mine Interior Model Of Smoke and Action) is a context-specific application of agent modeling, that integrates a virtual underground coal mine, a fire and smoke propagation model, and a human physiology and behavioral model.[12] Other example frameworks for crowd simulation are Menge (gamma.cs.unc.edu/Menge/), SteerSuite,[13] and Explicit Corridor Map (ECM).[14]

Other works have studied the effect of obstacles on crowd flow for a range of situations, including the optimal placement of pillars in evacuation scenarios that featured a single exit.[15–18] In contrast, our approach focuses on optimal evacuation strategies that involve *decision points*, which are situations where agents at specific locations have multiple distinct routes (decisions) available to them. We also propose a qualitative metric for evaluating evacuation plans that accounts for evacuation time and the local density of agents and their speeds.

Model Validation

The ability to validate evacuation models is crucial to their acceptance in real-world design decisions. Erica Kuligowski and Steve Gwynne provided evaluation guidelines that incorporate project requirements and a detailed review of the simulation model.[19] Other approaches describe validation as an ongoing activity that must take into account

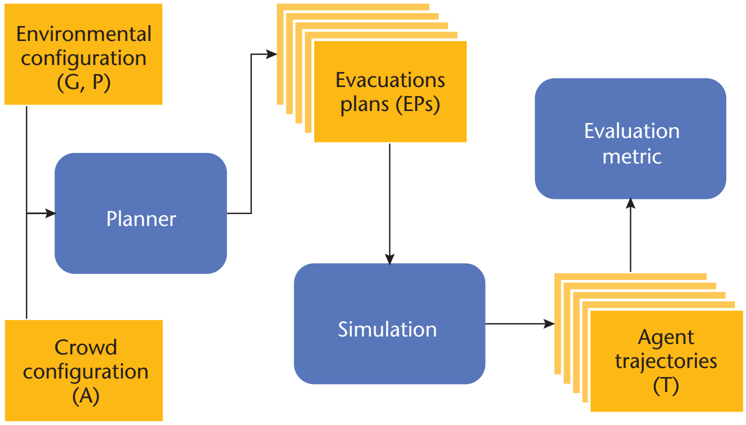


Figure 1. Method overview. The proposed approach includes the data flow and process to simulate and evaluate all generated evacuation plans.

four key aspects: component testing, functional validation, qualitative validation, and quantitative validation.[20]

In the context of crowd simulation, comparison with real-world data is another possibility for validating crowd evacuations. Important limiting factors in these validations are the ethical and safety considerations when capturing or re-creating real-world evacuation scenarios. The validation approach for EvacSim, a multiagent evacuation simulator, consists of comparing results with real-world pedestrian data from a controlled environment including flow rates, density, and velocity for corridor entry and for merging groups.[21] Another data-driven approach proposes a fair evaluation between steering algorithms by first optimizing them with respect to real-world crowd data.[22,23] Finally, the flow characteristics of two different crowds can be compared statistically, regardless of the data source.[24]

Framework Overview

In any emergency scenario, the main goal is to identify the best evacuation routes (given different aspects such as comfort, average time, total time, and so on) for a specific population when leaving a particular building. Crowd simulation can be a powerful tool to compute egress alternatives for specific groups of people. Data from different evacuation plans can provide important information to be analyzed in order to identify the most applicable plan to be performed by a given population in a specific building during an egress situation.

When analyzing a specific environment, it is possible to identify different ways to escape. Normally, public places that can hold more than a certain number of people simultaneously must present an egress plan, which is defined based on safety rules and, in general, not based on simulations. Figure 1 shows an overview of our proposed approach.

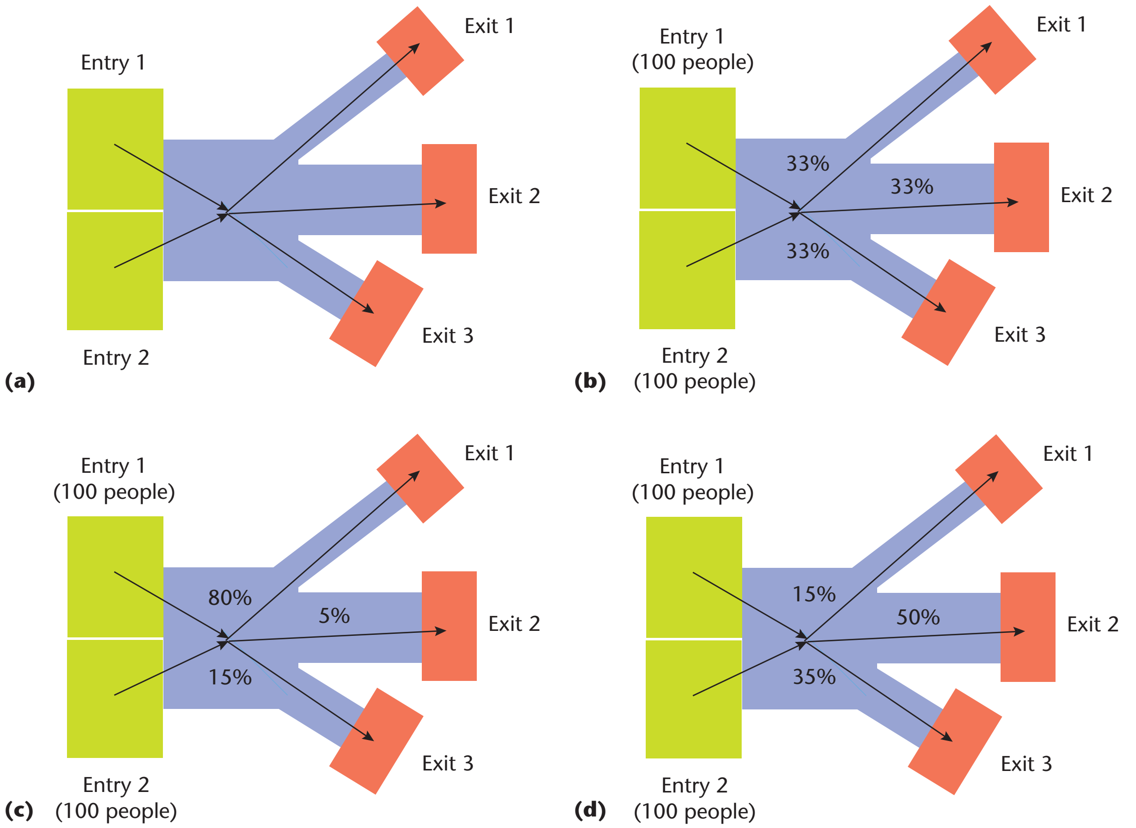


Figure 2. Evacuation plans. (a) A navigation graph in a simple environment labels entrances, exits, and the evacuation plan. Here, the entrances are in green, and the exits are in red. (b) An average evacuation plan has specific parameter values. In this case, 33 percent of the people are routed toward each exit. (c) When the parameter values are randomly generated, the plan is inefficient. Here, many people are going to exit 1, which is narrower and farther away than the others. (d) The optimized evacuation plan routes people toward exits based on all the available parameters.

Environment and Crowd Configuration

There are two primary components in any crowd simulation: the environmental configuration and the configuration of the agents inside that environment. The environmental (**E**) configuration consists of the static geometry (**G**) and its navigation graph (**P**). The navigation graph is formed by edges (routes) and rooms (nodes) in the environment, as Figure 2a illustrates.

The initial configuration of the agents in the simulation is denoted by $\mathbf{A} = (A, \beta)$, where A is the number of people to be simulated and β is the initial distribution in **E**. In the scenarios in Figure 2, **A** indicates the initial distribution of people in the entry rooms (green regions).

Evacuation Plans

The planner specified in Figure 1 reads the input information, as defined in the last section, and generates the evacuation plans. An evacuation plan EP_i instance for a specific environment and crowd configuration is defined as $EP_i = (\mathbf{A}, \mathbf{P}, \mathbf{DP}_i)$, where $\mathbf{DP}_i$ is a set of decision points between different paths in the graph P. Each decision point $v_j \in \mathbf{DP}_i$ is parameterized by a set of n_j values $p^i_{jk} \in [0,1]$ that determines the ratio of the agents that choose one path over another (among all n_j possibilities), such that $\sum k p^i_{jk} = 1$ at each decision point v_j.

The scenario in Figure 2a presents a single decision point v_1, leading to three possible paths ($n_1 = 3$). Figures 2b, 2c, and 2d illustrate three different evacuation plans obtained by changing the values of p^i_{1j}.

Simulation

In this work, we use the CrowdSim software to simulate crowds.[25] The advantages of CrowdSim are that it has been evaluated and validated[20] as well as tested in a real scenario.

We simulate the crowd **A** in the environment configuration **E** given an instance of the parameterized plan EP_i. CrowdSim uses a navigation graph **P** to describe the environment. The navigation graph is formed by edges (routes) and rooms (nodes) in the environment, as Figure 2a illustrates. Although we use a navigation graph, the agents do not only walk along the edges. In fact, in

CrowdSim, agent goals are distributed in randomly determined positions in the walkable spaces, avoiding rigid line-following behaviors (similar to navigation meshes).

The simulation results in a vector of trajectories for each agent k: $\mathbf{T}_k^i = \text{Simulate}(EP_i)$. Metrics can be computed for the agent trajectories $\mathbf{T}_k^i$ to qualitatively compare different evacuation plans—for example, the longest time taken by any agent to exit a building. Given a metric or set of metrics, we can find the optimal set of parameters EP_{opt} that determine the best evacuation plan EP given a particular environment configuration $\mathbf{E}$.

Evaluation Metric for Evacuation Plans

Our main goal is to define a quantitative value that characterizes the quality of a given egress plan so that it is possible to objectively compare different plans for a given scenario. Also, we can use the objective measure to select the best plan among all possibilities. In this section, we present the proposed evaluation metric, analyze its value for several different plans generated for the same scenario, and then validate the best plans selected according to the proposed metric using a human expert.

Human experts take into account several factors when designing an evacuation plan.[20] A good plan will enable higher speeds and both lower density and evacuation time. For this purpose, we propose using a 4D vector $\boldsymbol{M}$ to characterize the evaluation metric for a given evacuation plan:

$$\begin{aligned}\boldsymbol{M} &= \left(t_g, \bar{t}, \bar{d}, \bar{s}\right) \\ &= \left(t_g, \frac{\sum_{k=1}^{A} t_k}{A}, \frac{\sum_{k=1}^{A} d_k}{A}, \frac{\sum_{k=1}^{A} d_k}{A}\right),\end{aligned} \tag{1}$$

where t_g is the total evacuation time, or the time for the last agent to evacuate. The parameter $\bar{t}$ is the average time needed for all agents to escape to valid exits, and t_k is the individual evacuation time achieved by each agent k. The parameter $\bar{d}$ is the average density occupied by all agents, and d_k is the local density computed for each agent k, which is computed by considering agent k in the center of a 1 m^2 region where the number of agents is known. In addition, the average speed $\bar{s}$ is also computed based on the mean speed s_k for each agent k. Finally, A represents the total number of agents in the simulation. Other parameters could also be used; for this work, we empirically defined the most important to be used in the automatic evaluation of evacuation plans, and we have informally verified them with the expert.

To correctly quantify a given evacuation plan's quality, we propose including the complexity of the environment. More precisely, we use simulated data generated for a single agent in the environment (which we call a reference agent). We use this data to normalize the evaluation parameters (except for $\bar{d}$, because the density for a single agent is always constant and does not depend on the environment). The proposed normalization scheme is given by

$$t'_g = \frac{t_g}{t_{\text{ar}}}, \tag{2}$$

$$\bar{t}'_g = \frac{\bar{t}_g}{t_{\text{ar}}}, \tag{3}$$

$$\bar{s}' = \exp\left(\frac{s_{\text{ar}}}{s}\right), \tag{4}$$

where t_{ar} and s_{ar} are the evacuation time and mean speed for the reference agent, respectively.

As a rule of thumb, lower values for each normalized parameter are better. Also, using them individually to select the best plan may lead to a different plan for each metric. This behavior can help evaluate one particular safety aspect, but it is also important to present a global metric that encodes all information in a single value. This metric should monotonically increase with respect to any individual parameter so that smaller values yield better plans. Although we acknowledge that finding the best combination is a complex task and there are many possibilities, in this work we propose using the harmonic mean to obtain the global metric:

$$\xi = \frac{4}{\left(\frac{1}{t'_g} + \frac{1}{t'} + \frac{1}{d} + \frac{1}{\bar{s}'}\right)}. \tag{5}$$

To determine if the global metric ξ provided by Equation 5 indeed provides a good combination of the individual factors, we ran crowd simulations on a virtual version of a real environment. This environment is a nightclub that was evaluated by a safety engineering expert and for which an actual evacuation exercise was performed.[25] This nightclub presents three *bifurcations* (decision points with only two possible outcomes) and has a total area of 1,010 m^2 distributed across four floors. We generated the navigation graph related to each evacuation plan automatically based on the environment geometry (see Figure 3). In Figure 3, red circles represent the rooms occupied by agents at the beginning of the simulation, and the blue

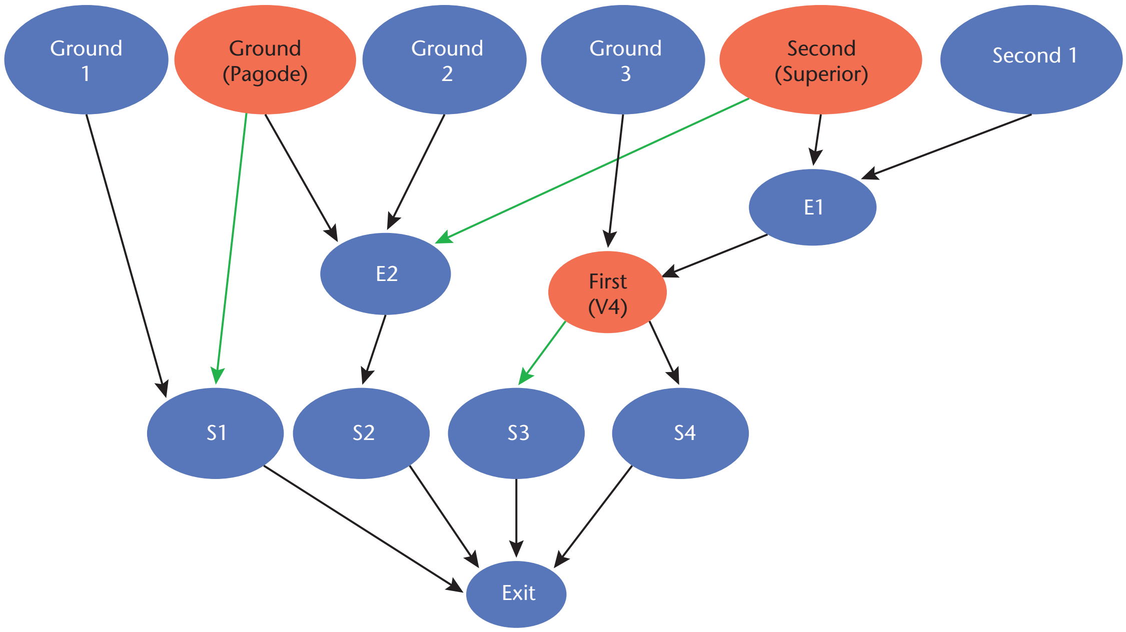


Figure 3. Example navigation graph tested by our model. The red circles represent the rooms occupied by people at the beginning of the simulation, the blue circles are rooms that serve as corridors to move from one room to another, and the green arrows represent the best configuration plan for escape.

Table 1. Simulation cases from nine different evacuation plans.

Evacuation plan	$\bar{d}$	$\bar{s}$	$\bar{t}$	t_g
EP_1	0.057	0.7934	1,008.28	1,777
EP_2	0.060	0.7934	1,002.88	1,825
EP_3	2.300	0.9000	1,045.30	1,849
EP_4	0.100	0.4000	1,001.66	1,921
EP_5	0.068	0.7934	1,018.28	1,777
EP_6	0.064	0.7934	1,002.88	1,825
EP_7	0.062	0.7934	997.80	1,873
EP_8	0.068	0.7934	1,045.30	1,849
EP_9	0.062	0.7934	1,020.66	1,921

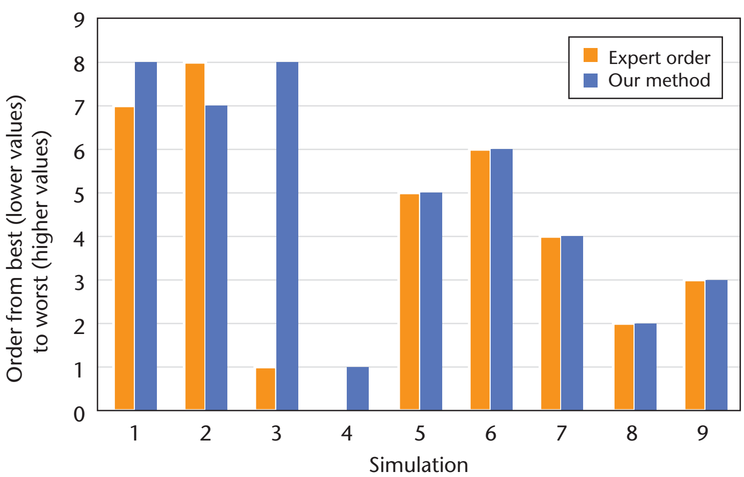


Figure 4. Ordered values for each evacuation plan made by the expert and computed by our method. The best plans are ranked with a 0. The expert ranked simulation 4 the best, and our method ranked simulation 3 the best.

circles are rooms that serve as corridors to move from one room to another.

As in earlier work,[25] we used 240 agents in the simulation, and randomly selected nine evacuation plans, computing the metrics $\bar{d}$, $\bar{s}$, $\bar{t}$, and t_g (see Table 1). We then showed these individual values to the human expert and asked him to rank the plans from worst to best.

Figure 4 compares the ordering of the nine simulations according to the expert opinion and the global metric ξ. For instance, simulation 1 was ranked the seventh best plan according to the expert and eighth according to our metric. In other examples, simulation 3 was the best according to the proposed metric (ranked as position 0) and the second best by the expert (ranked as position 1). The opposite is true for simulation 4, which was ranked the best by the expert and second according to our method. In addition, the expert and our method both ranked simulations 5, 6, 7, 8, and 9 in the same position. These small differences seem to indicate a good compromise between numerical results and the quality assessment of results, and further investigations should provide new answers from experts.

Assuming that ξ provides a good overall metric of plan quality, it can be used to select the optimal plan. More precisely, if ξ_i denotes the metric for evacuation plan EP_i, the best plan is given by $j = \text{argmin}(\xi_i)$. The next section describes a brute-force algorithm for finding the best ξ_i in the nightclub.[25] After that, we show an optimization procedure that drastically reduces the search space.

Exhaustive Sampling of Evacuation Plans

We developed a method to generate all the possible evacuation plans EP_i given a certain granularity of people as a percentage, taking each alternative path at a decision point. As we described earlier, for each decision point v_k there are n_k values p_{kj} containing the fraction of people that follow the corresponding edge in the navigation graph. Because they add up to one, there are $(n_k - 1)(n_k - 1)$ degrees of freedom for each decision point. Hence, a plan containing K decision points requires $N = n_1 + n_2 + ... + n_K - K$ degrees of freedom, which can be encoded in a vector $\boldsymbol{p}$.

For example, if a certain environment to be simulated has three bifurcations and one selected distribution variation with a granularity of 10 percent, there are 11 possibilities at each decision point, and $11^3 = 1,331$ plans are generated in the total. We executed these plans in the simulation module, in batches, and saved their results in different files for posterior analysis.

Figure 3 shows the example evacuation plan for the simulated nightclub. The numbers indicate how many people are present in each space and where they should go during the evacuation scenario.

Evaluating Evacuation Plans Using ξ

To evaluate if ξ can be indeed used to select the best evacuation plan, we used the nightclub scenario[25] and the navigation graph in Figure 3. This environment presents three bifurcation points, so the decisions for a given plan EP_i are characterized by $\boldsymbol{p}_i = \left(p_1^i, p_2^i, p_3^i\right)$, where p_k^i represents the fraction of agents that go to a given branch (without loss of generality, consider the left branch) at bifurcation k. Because the variables t_g', $\overline{t}'$, $\overline{d}$, and $\overline{s}'$ that are needed to compute ξ in Equation 5 depend on the chosen plan EP_i, from now on we consider $\xi(\boldsymbol{p}_i)$ the objective function to be minimized.

In this section, we evaluated a discrete subset of the evacuation plans by using $p_k = 0.1j$, for $j = 0, 1, ..., 10$, meaning that the fractions at each bifurcation were sampled with a granularity of 10 percent, yielding $11^3 = 1,331$ different evacuation plans. We computed ξ values for each one and ranked them, including the evacuation plan used in real experiment ξ_{ref}, which was chosen by the human expert and for which a real, nonemergency evacuation was performed in the actual scenario.[25] The reference plan was ranked only 663th among all the 1,331 plans, which was a surprise at first. Our hypothesis is that since the scenario uses only 240 agents, which is a low density corresponding to 25 percent of the environment's total capacity (the full capacity is achieved at a density of 1 person/m^2), even different evacuation plans achieve similar results. Our explanation is that with free space (low densities of people per m^2) different plans tend to be equally efficient.

Table 2. Absolute and relative (in parentheses) variability scores for evaluated metrics when simulating agents.

Metric	Variability (240 agents)	Variability (1,010 agents)
ξ	0.1189	0.2833
d (people/m^2)	0.0427 (53%)	0.1674 (55%)
$\overline{s}$ (m/s)	0.0054 (0.6%)	0.0565 (8%)
t (seconds)	9.616 (16%)	19.98 (22%)
t_g (seconds)	31.96 (25%)	143.76 (77%)

To further investigate this hypothesis, we resimulated the 1,331 plans with 1,010 agents to test the ξ metric in a more crowded environment (full capacity if we consider 1 agent per m^2). Table 2 presents the comparison between the two simulated populations. It presents the relative variation and the relative distance to the smallest value (as a percentage) of the non-normalized factors average density ($\overline{d}$), mean speed ($\overline{s}$), average time ($\overline{t}$), and global time (t_g) that are used to compute ξ for both simulation results. The results show that the values for all attributes (both absolute and relative variability) are higher for the simulation with 1,010 agents, as expected. In particular, the variation in the global time was considerably higher in the denser scenario because a bad balance in the bifurcation weights can lead many agents to the same room, compromising evacuation. For the sake of illustration, Table 2 also shows the variation in the ξ values. (The relative variability was not computed because ξ is already computed with normalized variables.)

To better compare the evacuation plans in both tested populations, Figure 5 presents the relative errors (variation from the best evacuation plan) for each individual metric with respect to the value corresponding to the best plan according to ξ. The first observation is that the results for the higher-density scenario present more variability, which corroborates the results in Table 2. We can also see that, in general, the graphs present coherent data, having small values for all metrics as ξ is also small. Finally, the average time *at* metric best correlates with ξ, showing a mostly increasing behavior.

It is important to note that the best evacuation plans with 240 and 1,010 agents are not exactly the same. The three fractions used to describe the bifurcations in vector $\boldsymbol{p}$ are related to the left edges in the subgraph of Figure 3, which are rooms occupied by agents at the beginning of the simulations (Pagode, Superior, and V4). The best evacuation

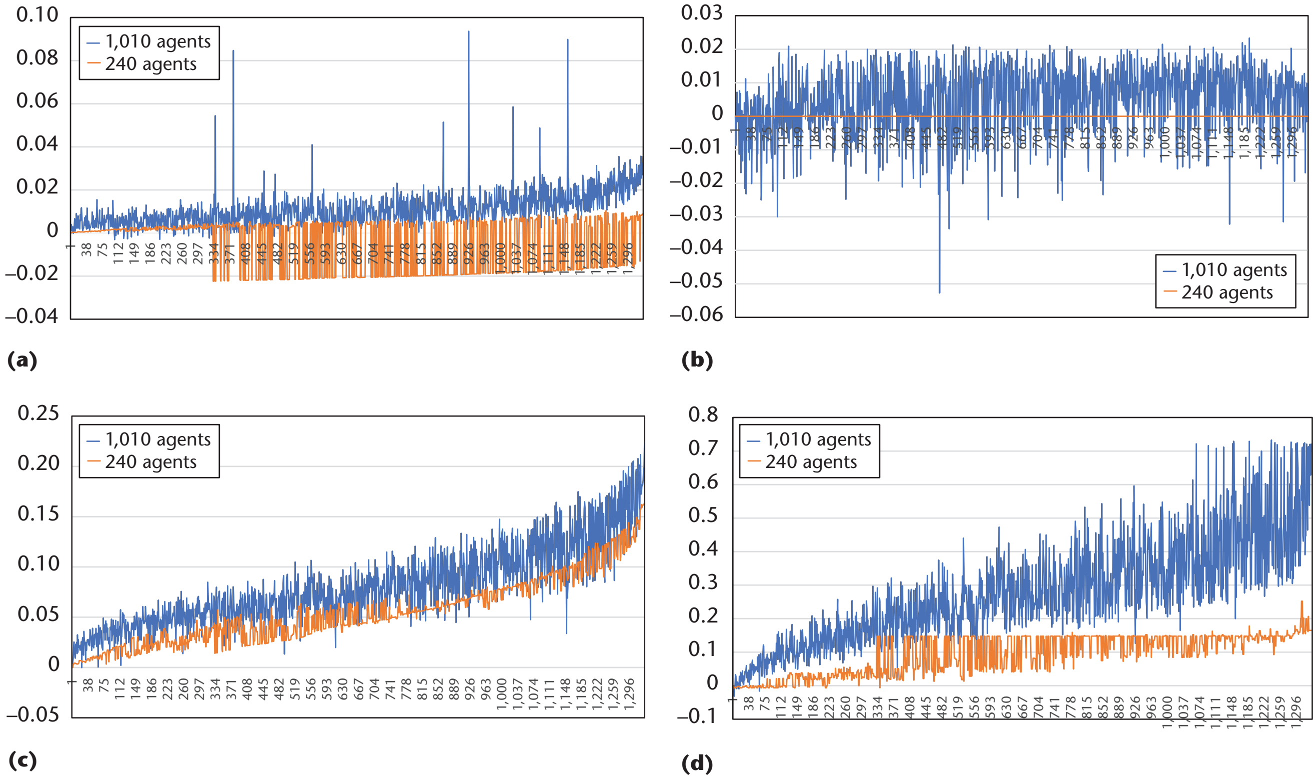


Figure 5. Relative error (difference from the best evacuation plan, lower value for ξ) for the individual metrics, ordered from best to worst according to ξ, for simulations with 240 and 1,010 agents: (a) average densities observed in the simulations, (b) mean speeds observed in the simulations, (c) average time observed in the simulations, and (d) global time observed in the simulations.

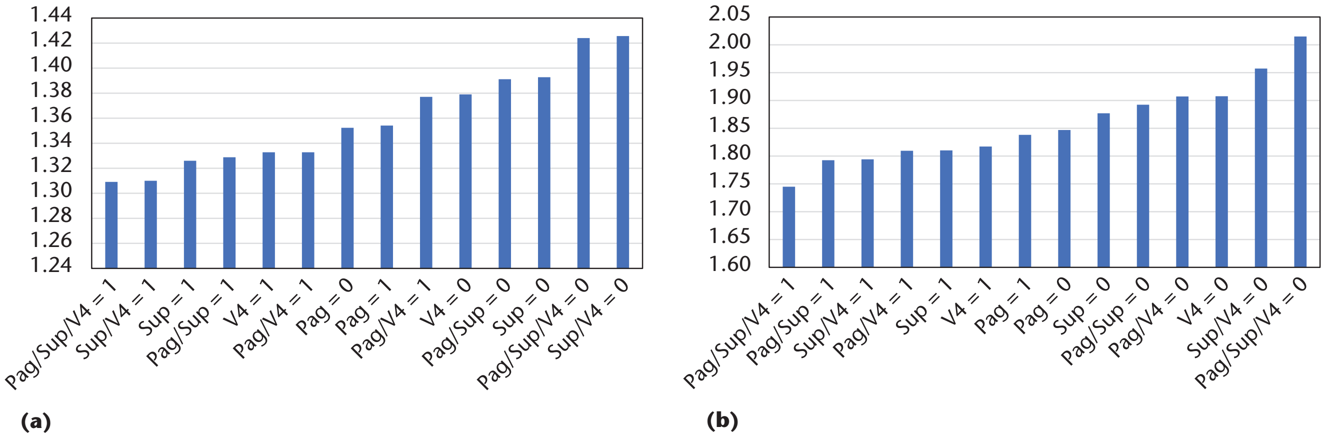


Figure 6. Average ξ values obtained for some of the main bifurcation configurations in simulations with (a) 240 and (b) 1,010 agents. On the *x* axis, the bifurcations distributions are ordered from the lowest to the highest values for the obtained average ξ.

plan for 1,010 agents, computed with a granularity of 10 percent is ID = 741, with settings $\boldsymbol{p}_{741}$ = (0.7, 1.0, 1.0) and ξ_{741} = 1.7315. The worst evacuation plan with 1,010 agents is ID = 936 and its characteristics are $\boldsymbol{p}_{936}$ =(0.0, 0.0, 0.0) and ξ_{741} = 2.0149. For the plans with 240 agents, the best plan is ID = 1,209, with settings $\boldsymbol{p}_{1,209}$ = (0.1, 1.0, 1.0) and $\xi_{1,209}$ = 1.3081; the worst one is ID = 1,256, with settings $\boldsymbol{p}_{1,256}$ = (0.4,0.0,0.0) and $\xi_{1,256}$ = 1.4260. Although the best plans are not the same, they present some similarities. For instance, in both, the second and third bifurcations lead all agents to the same edge in the graph.

To obtain an overall idea of the impact of each bifurcation, we ran another experiment using extreme values (0 or 1) for at least one of the three bifurcations, and for the remaining ones, we computed the ξ average values. Figure 6 shows the results. For instance, the distribution representing Pagode (Pag = 1.0) corresponds to the average ξ

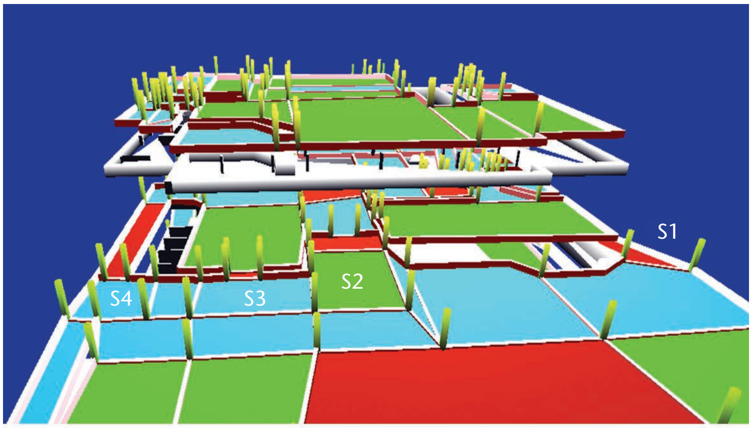
Table 3. Evaluating navigation strategies in the nightclub simulation.

Strategy	Traveled distance	Best strategy based on ξ metric	Best strategy based on distance	Worst strategy based on ξ metric	Worst strategy based on distance
Superior-E1-S3	62.30			X	X
Superior-E1-S4	67.15			X	X
Superior-E2-S2	37.28	X	X		
V4-S3	33.32	X	X		
V4-S4	37.92			X	X
Pagode-S1	59.42	X			X
Pagode-E2-S2	33.92		X	X	

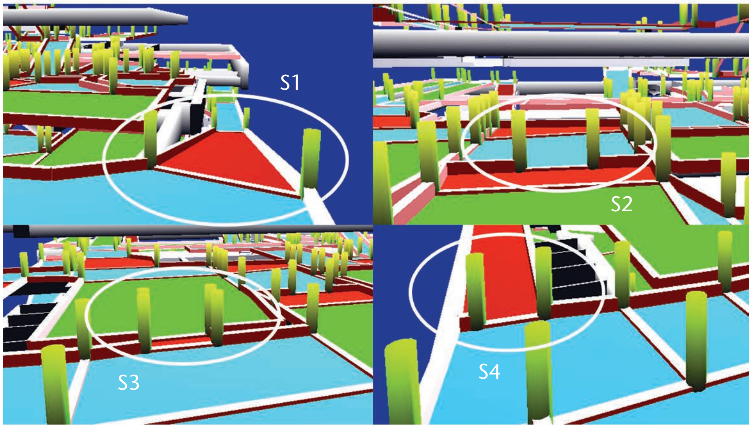
values using $\boldsymbol{p}$ = (1.0, y, z), for (y, z) = (0, 0.1, ..., 1.0). Superior/V4 (Sup/V4 = 0.0) corresponds to the average ξ values using $\boldsymbol{p}$ = (x, 0.0, 0.0) for x = 0, 0.1, ..., 1.0. In general, in this environment, when at least one of the bifurcation values is 1, the plans produce smaller ξ values. According to Figure 3, it is better if most people go from Pagode to exit S1, people from Superior go to room E2 and then to exit S2, and people from V4 go to exit S3. It might look strange that the best plans suggest that exit S4 be barely used, but this can be explained by the geometry of the environment (narrow passages, as we discuss next) and the distances that agents should move to reach each exit.

Table 3 presents traveled distances from the bifurcation nodes to the exits. In addition, we show the best strategies according to only the traveled distance and to the ξ values. For instance, the distance from V4 to S3 is shorter than the distance from V4 to S4. In the table, we can easily see that the decision that was not in accordance with the real event is between Pagode-S1 and Pagode-E2-S2. We can explain this because the best route to take from Superior is Superior-E2-S2, but this would crowd the exit. If we only consider the shortest traveled distance, the best plan could send people to Pagode-E2-S2, but in this case S2 could still be more crowded. Thus, our method suggests Pagode-S1 as the best option. Interestingly, as the better configuration emerges, we can see that it is not the shortest path for this specific crowd in this specific environment.

We also considered two other aspects. First, the door to exit S3 is wider than S4: 1.14 m versus 1.01 m. (The dimensions of doors S1 and S2 are 1.77 m and 1.1 m, respectively.) Second, the exit rooms (the last node before reaching exits S3 and S4) are very different shapes. Although the room to S3 has an area of 4 m × 5 m, the room to S4 has an area of 1 m × 5 m. Consequently, the geometry of the rooms also impacts the final result. Figure 7a shows the nightclub geometry and indicates the door locations, and Figure 7b zooms in on the doors.



(a)



(b)

Figure 7. Nightclub visualization in CrowdSim. (a) The graphic includes the locations of doors S1, S2, S3, and S4. (b) The close-up detail of the doors illustrates their sizes and the corridors or rooms leading up to them.

Optimizing Evacuation Plans

Using exhaustive sampling of evacuation plans to identify the best plan in a specific scenario is inefficient for two main reasons. First, the exhaustive process is reduced to a discrete space; that is, the method approximates the search space and cannot produce true optimal plan settings. Second, depending on the environment, number of people, and level of discretization, the processing time can present a high cost in terms of computational resources.

Table 4. Simulation cases with varying population sizes and distributions in the nightclub environment.

Agent distribution	Approach (percentage population on ground, first, and second floors)		Mean of the best p_i values (Pagode, Superior, V4)*
	Brute force	CMA-ES algorithm	
Best distribution	(51.98, 12.87, 30.19)		(0.63 ± 0.22, 0.92 ± 0.12, 0.82 ± 0.16)
		(51.98, 12.87, 30.19)	(0.61 ± 0.02, 0.9 9 ± 0.02, 0.87 ± 0.04)
Random distribution		(32.17, 47.52, 20.29)	(0.84 ± 0.11, 0.94 ± 0.06, 0.81 ± 0.09)
		(50.0, 2.37, 47.52)	(0.14 ± 0.11, 0.99 ± 0.08, 0.93±0.06)
Concentrated populations (1,010 agents)		(100.0, 0.0, 0.0)	(0.01 ± 0.01, –, 0.93 ± 0.07)
		(0.0, 100.0, 0.0)	(–, –, 0.31 ± 0.12)
		(0.0, 0.0, 100.0)	(–, 0.98 ± 0.03, 0.84 ± 0.22)
Concentrated populations (2,020 agents)		(100.0, 0.0, 0.0)	(0.53 ± 0.22, –, 0.66 ± 0.13)
		(0.0, 100.0, 0.0)	(–, –, 0.51 ± 0.16)
		(0.0, 0.0, 100.0)	(–, 0.97 ± 0.03, 0.55 ± 0.12)
Concentrated populations (4,040 agents)		(100.0, 0.0, 0.0)	(0.70 ± 0.14, –, 0.54 ± 0.10)
		(0.0, 100.0, 0.0)	(–, –, 0.61 ± 0.13)
		(0.0, 0.0, 100.0)	(–, 0.99 ± 0.01, 0.35 ± 0.21)

** When one or more bifurcation points do not contain people, we marked the results with a –.*

To mitigate these limitations, we explore using evolutionary approaches to efficiently search the space of permissible evacuation plans in order to automatically obtain the optimal strategy for evacuating any building.

CMA-ES Algorithm

The Covariance Matrix Adaptation Evolution Strategy (CMA-ES) is an evolutionary approach often used for solving difficult derivative-free optimization problems.[25,26] CMA-ES is robust to noise, has few optimization settings to run, and has been used successfully on many animation problems.[28] The algorithm proceeds toward an optimal strategy by approximating the mean and variance of each parameter as well as conveniences between parameters. Samples are drawn from these distributions and evaluated for quality using $\xi(\boldsymbol{p}_i)$. The mean is shifted toward samples with better values, and as high-quality samples are found to be closer together, the variance is reduced to improve convergence. In this work, we use CMA-ES to identify optimal evacuation strategies.

Results

First of all, we show that brute force (BF) and CMA-ES optimization strategies converge to similar results. We compared the average bifurcation values (along with the corresponding standard deviation) of the 20 best plans in each approach when we simulated 1,010 agents in the nightclub with the same initial distribution on the three floors in the nightclub. As Figure 3 illustrates, people on the ground floor are distributed along nodes Ground 1, Ground 2, Ground 3, and Ground (which is also a bifurcation Pagode). Similarly, people on the first floor are located along nodes E1, E2, and V4, and people on the second floor are placed along Second 1 and Second.

To compare CMA-ES and BF algorithms, we used the same population distribution in the environment: 51.98 percent on the ground floor, 12.87 percent on the first floor, and 30.19 percent on the second floor. We used these values because they correspond to the average expected distribution of people in the real nightclub, as reported in earlier work.[25]

In addition, we distributed the agents centrally with respect to the decision points—for example, see Figure 2b, where the agents are split equally among the three sides. The optimization terminated when a good but not necessarily optimal solution was found. The first two rows in Table 4 report the best average evacuation plans obtained using CMA-ES and BF, indicating that the bifurcation ratios are similar for both optimization approaches.

To show how changing the distribution of people affects the best evacuation plans, we ran another two sets of experiments. First, we randomly distributed the same number (1,010) of virtual agents across the three floors of the building (see Table 4). We also simulated concentrated distributions of people on a single floor of the nightclub. The concentrated population results in Table 4 show that the fractions at the bifurcation points vary considerably depending on the initial distribution, which indicates that the best plan should also consider the population distribution. In some of these tests, one or more bifurcation points are useless due to an absence of people, so we they are marked with a – in the results.

Finally, we repeated the experiment with concentrated distributions, increasing the total number of agents to 2,020 and 4,040 agents (see Table 4). A comparison of the best plans using the same distribution but different numbers of agents indicates that the best evacuation plan is also dependent on the total number of people.

Given an environment, the computational complexity of a single simulation primarily depends on the number of agents. This occurs in real time for 240 agents and takes approximately 20 frames/second for 1,010 agents. The method's total time depends on how many simulations are going to be performed in order to identify the best evacuation plan. For example, using a granularity of 10 percent at the bifurcations, the plans with 240 agents took about 4 hours, and 1,010 agents took approximately 30 hours. Other factors also impact performance, such as the agent density, because more collisions tests are necessary. The evolutionary algorithm does not significantly impact the total time because the simulation is much more expensive.

Effect of Crowd Configuration

The optimality of an evacuation plan can be sensitive to the initial crowd configuration. To determine an optimal evacuation plan for a particular environment, random crowd configurations could be sampled, but this could bias the result toward the distribution the random crowd samples are generated from. Ideally, if an optimal plan is desired for a real environment, the distribution of crowd configurations will need to be modeled from recorded data. With this data, a more extensive process can be done to generate the optimal evacuation plan for the real environment.

The proposed metric ξ was shown to agree with human experts in crowd egress, and our results indicated that the shortest path is not always the best way to evacuate an environment, even if it is a good initial guess. The results also indicated that the best plan for a given environment depends on the total number of simulated agents as well as their initial distribution in the virtual scenario. In fact, there is an intricate relationship between these population-related parameters and the environment's physical characteristics, such as spatial geometry and bifurcation points, which shows the usefulness of using crowd simulation to generate effective evacuation plans.

If there are known statistics about a typical occupant distribution in a given scenario (as for the nightclub explored in this work), the proposed tool can be used to guide safety engineers to select an adequate evacuation plan, which only needs to be computed one time. However, a broader and more interesting application would be to extract population-related parameters on the fly (using computer vision algorithms, for instance) and then constantly update the evacuation plan based on the current occupation. In that case, the evacuation plan could be tailored for each specific population, which we expect will be more effective than the generic plan.

Lastly, although we used CrowdSim in our experiments, the proposed metric can be easily integrated with any other crowd simulator.

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