Modeling and Optimization of Building Emergency Evacuation Considering Blocking Effects on Crowd Movement

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***Abstract*—In building emergency evacuation, the perception of hazards can stress crowds, evoke their competitive behaviors, and trigger disorder and blocking as they pass through narrow passages (e.g., a small exit). This is a serious concern threatening evacuees' survivability and egress efficiency. How to optimize crowd guidance while considering such effects is an important problem. Based on advanced microscopic pedestrian models and simulations, this paper establishes a new macroscopic network-flow model where fire, smoke, and psychological factors can evoke a crowd's desire to escape—the desired flow rate. Disorder and blocking occur when the desired flow rate exceeds the passage capacity, resulting in a drastic decrease of crowd movement in a nonlinear and random fashion. To effectively guide crowds, a divide-and-conquer approach is developed based on groups to reduce computational complexity and to reflect psychological findings. Egress routes for individual groups are optimized by using a novel combination of stochastic dynamic programming and the rollout scheme. These routes are then coordinated so that limited passage capacities are shared to meet the total need for joint movement. Numerical testing and simulation demonstrate that, compared with a strategy of merely using nearest exits, our solution can evacuate more people more rapidly by preventing or mitigating potential disorder and blocking at bottleneck passages.**

***Note to Practitioners*—Effective building evacuation in case of emergencies, such as fire and smoke, has long been recognized as an important issue. Effective crowd guidance can improve evacuees' survivability and egress efficiency. In practice, most guidance (e.g., an exit sign) directs evacuees to the nearest exits. As crowds move and fire spreads over time, however, such guidance is questionable because some exits may be overcrowded or obstructed by fire and smoke. This paper establishes a new network-flow model, where crowd evacuation behaviors are supported by psychological findings and simulation studies. Novel optimization techniques are then used to find egress routes for effective evacuation. Numerical results show that our solution will update guidance when the emergency situation significantly changes. Compared with using nearest exits, our solution can help evacuate people more efficiently.**

***Index Terms*—Blocking effects, building emergency evacuation, crowd movement, guidance optimization, macroscopic model, psychological features.**

I. Introduction

EVACUEES were pushing against each other trying to get to the front door as fast as possible, but they were trampled underfoot and the door was simply blocked. Such a tragedy happened in a Bangkok nightclub fire on January 1, 2009, and as the fire spread through the entire building within 10 min, 61 people were killed and more than 200 injured in the horrible moments of intense heat, smoke, and trampling (Mydans [31]). Similar scenes of disorder and blocking were observed in the Rhode Island nightclub fire in 2003 (Grosshandler *et al.*, [13]) and several other building emergencies. How to optimize building egress to prevent or mitigate such disasters is an important topic in egress study.

As identified by recent egress research, a fundamental cause of such disorder and blocking is the psychological stress of emergencies on crowd motion (Proulx [38]; Fahy and Proulx [9]). Under intense stress, people may move faster than normal. If they cannot move as desired (e.g., when passing through a small exit), disorder and blocking at a bottleneck passage may arise. However, disorder and blocking have long been ignored in traditional egress models, where crowds were simply captured as an unthinking mass flowing in a passage-and-area network. Such network-flow models enable optimization of egress (Chalmet *et al.* [7], Hamacher and Tjandra [14]), but the vital feature of blocking is ignored.

To better characterize crowd behaviors for egress analysis, microscopic pedestrian models have been developed during recent decades where an evacuee's behavioral/psychological status can be modeled and simulated. A representative model is the social-force model by Helbing *et al.* [16]. In this model, a key concept—desired velocity, was introduced to describe the inner drive of an individual to escape, especially in a stressful condition. By simulating many such individuals collectively, blocking was observed at a narrow passage,

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This paper has supplementary downloadable multimedia material available at http://ieeexplore.ieee.org provided by the authors. This includes simulation videos, which show a comparison between the strategy of using nearest exits and our optimized guidance strategy. This material is 19.4 MB in size.

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and further intensified as the individuals' desired velocity increased. This simulation reflects what happens in reality, and it yields emergent group-level behavior akin to a psychological phenomena found in individuals: excess stress can degrade human performance. However, such microscopic simulations are computationally complex making it difficult to be used directly for crowd guidance optimization.

Drawing from advances in psychological studies, behavioral findings and pedestrian modeling and simulation, this paper establishes a new model for egress analysis. In this model, an important concept—the desired flow rate, is introduced as a macroscopic counterpart of the desired velocity in Helbing *et al.* [16], and it aggregates individual-level motivation to escape in terms of group-level flow dynamics. Disorder and blocking are then characterized to occur when the desired flow rate exceeds the maximum achievable rate as specified by the passage capacity, resulting in a drastic decrease of crowd movement in a nonlinear and probabilistic fashion. The desired flow rate and direction are captured through a probabilistic graph in Section III, where potential disorder and blocking can be predicted for egress performance analysis. The key question here is how to select a set of passages with proper capacities to maximize the egress speed. Such an optimization problem is formulated in Section IV where the optimized route will be conveyed to evacuees via informational devices (e.g., dynamic exit signs). Such guidance will be assumed to be properly updated, and represents the decision variables of the formulated problem.

In view of the nonlinearity and randomness of the egress model, the optimization problem turns out to be a Markov decision problem. This problem is required to be solved in a timely fashion because of the time-criticality of emergency response. A divide-and-conquer approach is then developed in Section V, where evacuees are divided into groups based on their relative proximity. Escape routes for each group are then individually optimized and coordinated with each other for an integrated egress solution. Such a grouping method is also consistent with existing social psychological studies—crowd evacuation behaviors usually emerge at the level of groups (Santos and Aguirre [40]).

Due to the nonlinearity of the crowd flow, a major difficulty lies in how to decompose an overall crowd flow into group subflows. To overcome this difficulty, a method is used where each group is iteratively optimized. Limited passage capacities are thus properly shared among multiple groups to meet their total need for joint movement. The Lagrangian relaxation framework serves as a mathematical basis for operationalizing this divide-and-conquer approach.

Numerical testing is presented in Section VI using two examples, where our optimized solution shows that, compared with merely using the nearest exits, properly updating guidance can improve the egress speed and safety by preventing or mitigating disorder and blocking at bottleneck passages. For the validation of our entire approach, more efforts will be made in the future, for example, in the form of fire drills or virtual reality experiments.

A preliminary version of the work was presented at the 2008 IEEE Conference on Automation Science and Engineering. Major improvements have been made in terms of stronger psychological justification, complete mathematical formulation, detailed method derivation, more numerical testing with video simulation, as well as overall presentation.

II. Literature Review

This section reviews relevant literature on building egress systems (Section II-A), emergency events (Section II-B) and modeling and simulation of crowd evacuation (Section II-C).

A. Building Egress Systems

A building egress system is mainly considered as a structural layout equipped with devices for information collection and dissemination for safe and efficient evacuation in emergencies. Various areas in the building and passages connecting them are the structural aspects of an egress system. Such layouts including the 3D-geometry, construction materials, etc., can be described by advanced microscopic simulators such as building EXODUS (Galea *et al.* [12]), Simulex (Thompson and Marchant [45]), Fire Dynamics Simulator with Evacuation (Korhonen and Hostikka [27]), etc., (Kuligowski and Peacock [28]). By abstracting key ingredients from these simulators, macroscopic models have been established where each area is represented by a node with a specified capacity, and passages between areas by an arc with a specified capacity (Chalmet *et al.* [7]; Hamacher and Tjandra [14]). These network models form a basis for both egress performance analysis based on linear system properties and for optimization by using network optimization methods. Building egress systems also include devices for information collection and dissemination such as smoke detectors and exit signs. Recently, several new devices have been developed, such as smart signs (Lijding *et al.* [29]), as well as new methods of fire detection (Toreyin *et al.* [46]). With technological advancements in these areas, we hope that providing real-time guidance will be possible in the future.

B. Emergency Events

To study the propagation of fire and smoke in buildings, simulators (such as Fire Dynamics Simulator, McGrattan *et al.* [32]) are widely used. Such simulators provide detailed results regarding fire spread and smoke movement in complex building geometries, but require significant computational efforts and cannot be used during a fire to optimize evacuation guidance. Complementing the simulations, macroscopic models such as Markov chains and cellular automata are extracted from the simulation to aid analysis of the spread of fire and smoke. These high-level models mainly describe the likelihood of fire and smoke spread (Hostikka and Keski-Rahkonen [18]; Aua *et al.* [3]), and are used for hazard risk assessment. However, existing macroscopic models do not include psychological factors.

C. Modeling and Simulation of Crowd Evacuation

Over the past decade, with advances in computer technology, behavioral features of crowds have become incorporated into microscopic pedestrian model and simulation. One of the most well-known models is the social force model of Helbing *et al.* [16]. This model characterizes each individual as a Newtonian particle subject to both physical forces and psychological forces. The psychological force is induced by the derivative of a virtual velocity—the desired velocity, which specifies the speed and direction that an individual desires to realize in escape.

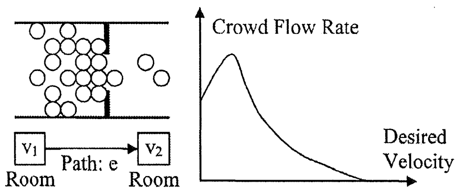


Fig. 1. The egress blocking effect.

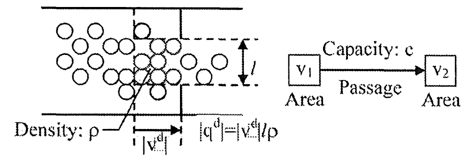


Fig. 2. Crowd flow dynamics at a passage.

From the viewpoint of psychology, the desired velocity represents the inner drive of an individual to escape, and it reflects how much the individual is stressed by perceiving the surrounding hazard (Sime [43]; Proulx [38]; Fahy and Proulx [9]). Therefore, the desired velocity (being psychological in nature) can be interpreted as a measure of stress on evacuees. By simulating a multitude of such individuals passing through a bottleneck, a phenomena emerges that is akin to psychological findings: moderate stress can improve the human performance—speeding up egress; and excess of stress can diminish such performance—slowing down egress. The negative effect has been labeled the "faster-is-slower effect" by Helbing *et al.* [16], which means a psychological increase in desired speed may inversely decrease the crowd's physical movement speed (see Fig. 1).

The social-force model has been recently adopted in many microscopic pedestrian models and simulations, and several extended versions of this model were also developed (Pan *et al.* [36]; Pelechano and Badler [37]). Recently, this model has been integrated into a well-known fire simulator, the Fire Dynamics Simulator (FDS) of NIST, with the new module "Fire Dynamics Simulator with Evacuation" (FDS + Evac) simulating pedestrians' behaviors within FDS (McGrattan *et al.* [32], and Korhonen and Hostikka [27]). Unfortunately, the version of FDS + Evac when the simulations were run (2.1.0) lacks psychological features affecting Helbing's dynamic desired velocity. Instead, its "unimpeded walking speed" for an evacuee remains constant throughout a simulation except in the presence of smoke in the immediate area around that evacuee. In this case, the unimpeded walking speed will be reduced to reflect the visual difficulties of moving within smoke. We have been working with the developers of FDS + Evac, and a psychological increase in unimpeded walking speed due to stress from impatience has already been implemented in the beta version of the program based on Helbing's model for nervousness (Helbing *et al.* [50]; see FDS + Evac Issue Tracker). Validation of the social-force model and FDS + Evac has been carried out by comparing their implications with data drawn from experiments (Helbing *et al.* [15]; Hostikka *et al.* [19] and [20]) as well as observations from natural events (Helbing *et al.* [15] and [17]; Hostikka *et al.* [19] and [20]; Johansson, *et al.* [22] and [23]). Nevertheless, this is an ongoing process as additional features are still being added to better represent the behaviors of evacuees.

In contrast to microscopic-level pedestrian models and simulations, crowds have also been viewed as a homogeneous mass that behaves like a fluid flowing along corridors with a specified rate. Such macroscopic flow models can be embedded into an egress network, resulting in a network-flow model serving as a basis for optimization of building egress (Chalmet *et al.* [7]; Hamacher and Tjandra [14]). Theoretically, such models hold the promise of being useful in real-time evacuation guidance. However, these models have not considered vital psychological features of individuals involved in the crowd, and thus ignore the blocking effect during egress.

Through the above literature review, a gap can be identified between the traditional crowd flow model without the blocking effect considered and the advanced simulation model with this feature captured. Thus, our first task is bridging the gap, i.e., establishing a model that captures the blocking effect at a macroscopic level so that it can be properly used in building egress optimization. The basis of our modeling is the social-force model and simulations.

III. AN EGRESS MODEL WITH BLOCKING EFFECTS

Based on recent advances in psychology, behavioral studies and pedestrian modeling and simulation, a new egress model is established in this section. In this model, a key concept, the desired flow of crowds, is first presented as the macroscopic counterpart of the desired velocity of Helbing *et al.* [16] (Section III-A). It reflects the intrapersonal drives underlying crowd movement in terms of flow dynamics, and it arises as crowds are stressed by fire/smoke (Section III-B). The outcomes of disorder and blocking are then modeled when the desired flow rate exceeds the achievable rate as specified by the passage capacity, resulting in a drastic decrease of crowd movement. With this model, interdependencies among crowd flows, hazards and passage capacities are captured, allowing for a shift to the important issue of how to select the passages with proper capacities (Section III-C).

A. The Blocking Effect on Crowd Movement

Existing egress research clearly indicates that disorder and blocking occur at bottlenecks in a structural layout (e.g., the doorway). Our study will focus on crowd movement at such bottlenecks rather than in open areas, and the key egress scenario to be modeled is how crowds move from one area to another via a passage. In this section, the crowd movement will be modeled in an elementary layout, as shown in Fig. 2, where two areas, v_1 and v_2, are connected by a passage. To model the blocking effect at a macroscopic level, a novel concept—the desired flow rate, will be first established based on the concept of desired velocity (Helbing *et al.* [16]).

The desired velocity in Helbing *et al.* [16] specifies two aspects of motion that an individual desires to realize—their direction and speed. As many such individuals move collectively through a passage of width l, as shown in Fig. 2, this microscopic concept can be transformed to the macroscopic level of a crowd, representing people by a density of ρ. The average speed of crowd movement can be abstracted along the direction of the passage, and is obtained by averaging each individual's speed,

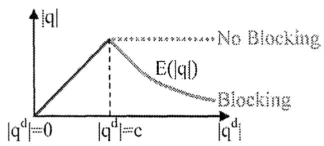


Fig. 3. The egress blocking effect.

denoted by $|v^d|$. The crowd's flow rate can thus be represented as the product of these terms

$$q^d = v^d l\rho. \tag{1}$$

The magnitude $|q^d|$ denotes the average number of people who desire to move through a passage per time unit and the sign of q^d represents the direction of their desired movement. With the direction of a passage specified (e.g., the directed arc of the network in Fig. 2), q^d is positive if the crowd desires to move along with this direction, and negative if they desire to move oppositely. From a psychological perspective, a crowd's desire to move is due to the experience of stress, and it is particularly related to perception of hazards. Thus, q^d, as an indicator for demand of escape, can also be viewed as a measure of the stress that evacuees experience.

What will occur if the crowd's desire to move keeps on increasing? Existing egress research indicates that, when the demand increases beyond a certain threshold, disorder and blocking may arise (Kachroo, *et al.* [24]). In our model, blocking may occur when the desired flow rate exceeds the achievable rate as specified by the passage capacity, resulting in an undesirable decrease in crowd movement.

To quantify the blocking effect, the crowd flow rate and passage capacity are further defined. The crowd flow rate q reflects the physical movement that the crowd actually achieves: $|q|$ denotes the number of individuals who pass through a passage per time unit, and $\mathrm{sgn}(q)$ denotes the direction of such movement. Clearly, the physical movement is directed by their psychological motivation. Thus, the crowd flow rate q is directed by the desired flow rate q^d, i.e., $\mathrm{sgn}(q) = \mathrm{sgn}(q^d)$. For the passage capacity, it is the maximal number of people who can pass through the passage per time unit, i.e., $c \equiv \max\{|q|\}$. With the above quantification in terms of flow dynamics, the blocking effect is restated as: when the desired flow rate is below the passage capacity, the crowd can move as fast as desired, i.e., $q = q^d$. If the desired flow rate exceeds the capacity, the probability of disorder and blocking increases. This will then result in a decrease of the expected crowd flow rate in a nonlinear fashion, as shown in Fig. 3.

Comparing Fig. 3 with Fig. 1 in Helbing's simulation, it can be seen that the two curves are similarly shaped. This can be partly considered as a validation of our macroscopic flow model of the egress blocking effect. The following probability distribution exemplifies the curve shown in Fig. 3.

a) If $|q^d| \geq c$, q equals q^d with probability 1, i.e.,

$$\Pr(q \mid q^d, c) = \begin{cases} 1, & \text{for } q = q^d \\ 0, & \text{otherwise} \end{cases}. \tag{2}$$

b) If $|q^d| > c$, the probability of disorder and blocking increases as the difference between q^d and c increases, i.e.,

$$\Pr(q \mid q^d, c) = \begin{cases} 1 - \exp\left(\frac{-\alpha}{|q^d| - c}\right), & \text{if } q = \mathrm{sgn}(q^d) \cdot c \\ \exp\left(\frac{-\alpha}{|q^d| - c}\right), & \text{if } q = \mathrm{sgn}(q^d) \cdot c^{\mathrm{Blc}}. \end{cases} \tag{3}$$

Here, c^{Blc} denotes a small flow rate when the passage is blocked, and $\alpha > 0$ is a parameter that affects the slope of the curve in Fig. 3 when $|q^d| > c$. In the psychological sense, α reflects the level of competitiveness in the crowd: as α goes to zero, $E(q \mid q^d)$ tends to decrease more sharply, implying an increase in the probability of disorder and blocking. As α increases, $E(q \mid q^d)$ tends to decrease less sharply, implying a decrease of the probability of blocking. The extreme case of $\alpha \to \infty$ implies an ideal situation where the evacuees are absolutely altruistic, resulting in no probability of disorder and blocking.

B. The Relation of Hazard and Stress

Psychological findings indicate that hazards can stress people and induce them to escape. In building fires, people desire to move faster as they perceive more urgent threats (Ozel [35]; Staal [41]). As a result, the demand of egress, as indicated by the desired flow rate q^d, is dependent on emergency status. In this paper, we will call this effect the "impatience effect on evacuees." To model this at the macroscopic level, a probabilistic method is developed where the binomial distribution is applied to transform individuals' impatience at the microscopic level to the collective impatience of a crowd at the macroscopic level.

Let probability p_{imp} denote the probability that an individual desires to move in the next time slot. The total number of individuals desiring to move within a time slot forms the desired flow rate $|q^d|$. As a result, $|q^d|$ is binomially distributed: $|q^d| \sim \mathrm{Bin}(|w|, p_{\mathrm{imp}})$, with

$$\Pr(|q^d| = k \mid w, s^F) = C_{|w|}^{k} (p_{\mathrm{imp}})^k (1 - p_{\mathrm{imp}})^{|w|-k}. \tag{4}$$

Here, $k = [0, |w|]$, and $|w|$ is the number of individuals who decide to take a certain path to escape, and s^F denotes the fire/smoke status in the egress layout.

The discrete parameter p_{imp} depends on the fire and smoke status, and p_{imp} increases as fire or smoke gets closer to the location of people. With the layout, as shown in Fig. 2, the probability p_{imp} can be specified as

$$p_{\mathrm{imp}} = \begin{cases} p_{\mathrm{imp}}^{H}, & \text{if fire/smoke propagates to an area} \\ & \quad \text{immediately adjacent to } v_1 \text{ or } v_2 \\ p_{\mathrm{imp}}^{L}, & \text{otherwise.} \end{cases} \tag{5}$$

C. Guidance and Way-Finding

The way people select their escape route is an important issue affecting how to effectively guide them to safety. Existing studies show that people's way-finding procedure can be considered as a process of fusing external information (e.g., exit signs) with internal information (e.g., their prior knowledge of exit locations). For external information, people often put more trust in personalized guidance (e.g., instructions from a group leader) than impersonalized ones (e.g., exit signs). For

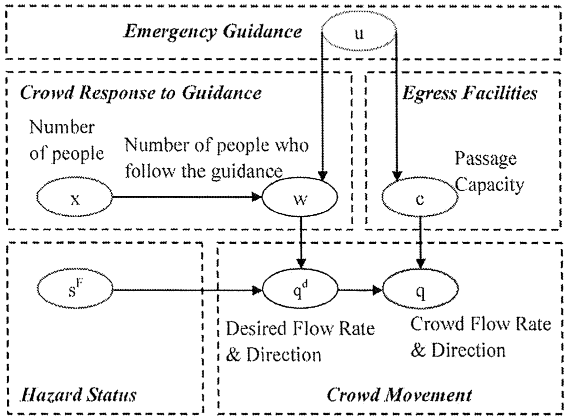


Fig. 4. The probabilistic graph.

internal information, people tend to use paths they are familiar with rather than those they are unfamiliar with (Proulx [38]; Johnson and Feinberg, 1997).

To model the above, a stochastic method is used where a binomial distribution similar to (4) is used to transform an individual probability measure to a collective probability measure. Specifically, given a guidance u, each individual is assumed to follow the guidance with a probability p_{cr}. Let x denote the total number of people in a location, then the number of people who follow the guidance is binomially distributed, i.e., $|w| \sim \mathrm{Bin}(x, p_{\mathrm{cr}})$. From a psychological viewpoint, p_{cr} reflects the level of trust that people have in the guidance, and is described by

$$p_{\mathrm{cr}} = \begin{cases} p_{\mathrm{cr}}^H, & \text{if } u \text{ is personalized instruction or } u \\ & \quad \text{guides people to a familiar path} \\ p_{\mathrm{cr}}^L, & \text{otherwise.} \end{cases} \tag{6}$$

By combining the probability distributions as given in the above three subsections, a probabilistic graph is established, as shown in Fig. 4. Each node of the graph denotes a factor being considered and their interdependencies are captured through the probability distributions of one factor conditioned on another. The guidance u, fire/smoke status s^F, capacity c and number of people x are the input to this graphical model. The crowd flow rate q is the output random variable and can be denoted by $q = q(u, c, s^F, x)$. The probability distribution of q is

$$\begin{aligned} &\Pr(q \mid u, c, s^F, x) \\ &\quad = \sum_{q^d} \sum_{w} \Pr(q \mid q^d, c) \Pr(q^d \mid w, s^F) \Pr(w \mid u, x). \end{aligned} \tag{7}$$

In the above probabilistic model [(1)–(7)], the unknown parameters include the social bond parameter α, impatience parameter p_{imp}, and trust parameter p_{cr}. Each has a psychological meaning and can be estimated with statistics, given appropriate data sets. Such data sets can be acquired from various designed experiments. For example, a psychological experiment can be conducted to find the way-finding preference of occupants in an apartment building. Video recordings can be reviewed to determine the flow rate of a passage under certain conditions (Muir et al. [34]). Additionally, virtual reality experiments have recently been conducted to determine the effect of various emergency signs on evacuees' way-finding activities (Tang et al. [44]). Nevertheless, estimating unknown parameters is not the focus of this paper. In Sections IV–VII, it will be assumed that the guidance is in good credence, and we shall examine how to guide crowds when individuals behave impatiently and competitively in emergency egress.

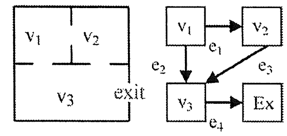


Fig. 5. An egress network.

In sum, excessive stress can lead to disorder and blocking in emergency egress. The model established in this section characterizes this effect at the macroscopic level. It describes how situational information (i.e., perceived hazards or received guidance) affects psychological factors (e.g., the desired flow rate q^d) and how these factors further affect the physical movement of crowds in egress.

IV. An Overall Optimization Formulation

In this section, the model established above will be extended in both spatial and temporal dimensions, and a Markovian network-flow model will be presented to capture crowd movement through a building in a dynamic manner (Section IV-A). Fire and smoke information will also be described by a Markovian process and be integrated into this network-flow model (Section IV-B). To properly guide crowds to safety, a snapshot problem is formulated as a Markov decision problem with the objective to maximize both the egress speed and number of people evacuated (Section IV-C).

A. Network-Flow Dynamics

The structural layout of an egress system is represented as a network $G = (V, E)$ (Hamacher and Tjandra, 2001), where each area is denoted by a vertex $v \in V$ and each passage connecting areas is denoted by an arc $e \in E$. Because an egress network abstracts a layout for evacuation, its arcs are usually directed to the exits or the safety areas. Fig. 5 illustrates a planar layout and the corresponding network model.

By embedding the crowd flow in a network, a network-flow model is obtained. Let $q_e(t)$ be the extension of q in both the temporal and spatial dimensions. The magnitude $|q_e(t)|$ denotes the number of people passing through arc e during the interval $[t, t + \Delta t$, and the sign $\mathrm{sgn}[q_e(t)]$ denotes the direction of their motion in the same interval. Let $x_v(t)$ denote the number of evacuees in area v at time t. As the crowd moves through each area, the number of people $x_v(t)$ is updated according to the following mass balance equation:

$$x_v(t+1) = x_v(t) + \sum_{e \in E} b(v, e) q_e(t) \tag{8}$$

where the arc direction is indicated by

$$b(v, e) = \begin{cases} 1, & \text{if arc } e \text{ is directed into vertex } v \\ -1, & \text{if arc } e \text{ is directed from vertex } v \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

$$
B = \begin{array}{c}
\begin{array}{cccc} e_1 & e_2 & e_3 & e_4 \end{array} \\
\begin{bmatrix} -1 & -1 & 0 & 0 \\ 1 & 0 & -1 & 0 \\ 0 & 1 & 1 & -1 \\ 0 & 0 & 0 & 1 \end{bmatrix}
\end{array}
\begin{array}{l} \\ v_1 \\ v_2 \\ v_3 \\ \mathrm{Ex} \end{array}
$$

Fig. 6. The matrix representation of an egress network in Fig. 5.

The set of such equations can be put in the matrix form

$$x(t+1) = x(t) + Bq(t), \tag{10}$$

which is a standard linear network-flow model. For the example in Fig. 5, B is represented by the matrix below.

In the literature, a network-flow model takes the flow rate $q(t)$ as decision variables (Chalmet *et al.* [7]), implying that we can control how many evacuees will move through each passage during each time step. This assumption is questionable since humans cannot be viewed as machines or robots under our complete control. Rather, humans initiate actions in response to their subjective impressions of emergency events. Ignoring such subjective initiative may lead to disorders or blocking as we discussed in Section III.

The traditional model can be improved by capturing critical human factors. Our new crowd flow dynamics, as presented in Section III, is incorporated into this mass balance equation where the flow rate $q_e(t)$ is replaced by $q_e\left(x(t), u_e(t), s^F(t), c\right)$, which includes several psychological factors

$$x_v(t+1) = x_v(t) + \sum_{e \in E} b(v,e) q_e\left(x_v(t), u_e(t), s^F(t), c_e\right). \tag{11}$$

In (11), q, q^d, w, and u are extended in both temporal and spatial dimensions, resulting in $q_e(t)$, $q_e^d(t)$, $w_e(t)$, and $u_e(t)$. The passage capacity c is labeled with only the arc index, i.e., c_e, as it is derived from the dimensional size of a doorway or stairs. The fire/smoke status s^F denotes the overall hazard status within the egress layout, and is thus labeled only with the time index $s^F(t)$. Here, the guidance $u_e(t)$ is considered a decision variable instead of the flow rate $q_e(t)$ as in the traditional model. The guidance $u_e(t)$ is specified as

$$u_e(t) = \begin{cases} +1, & \text{if along with the direction of arc } e \\ -1, & \text{if opposite to the direction of arc } e \\ 0, & \text{if arc } e \text{ should not be used.} \end{cases} \tag{12}$$

By vectorizing $q_e(t)$, $q_e^d(t)$, $w_e(t)$, and $u_e(t)$ with arc subscripts, an overall crowd flow equation can be obtained, and a restatement of (10) is given below

$$x(t+1) = x(t) + Bq(x(t), u(t), s^F(t), c). \tag{13}$$

In the event of a complicated building layout, the model can be simplified by only keeping prominent choices based on experimental data or heuristics. The vector $u(t) = [u_1(t) \cdots u_{|E|}(t)]$ specifies an egress decision at each passageway at time t. These decisions, when put together, can provide egress routes for individual groups. Fig. 7 illustrates three candidate routes for either Group 1 or Group 2 in the building.

Egress decisions will be conveyed to evacuees through the building guidance system, e.g., exit signs, audio broadcasting, or through personalized guidance such as instructions from safety staff (Aguirre, 1994; Pelechano and Badler [37]).

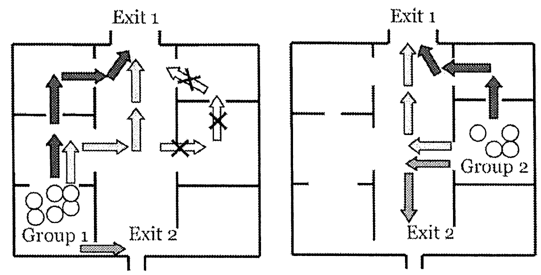


Fig. 7. Evacuation routes and strategies.

B. Fire/Smoke Propagation

As fire and smoke propagate in an egress network, the network-flow model given in (13) requires incorporation of fire/smoke information. Such information is described in a probabilistic sense in this paper. A cellular automaton model is used to characterize the likelihood of the spread of fire and smoke in buildings. In this automaton, a cell represents an area of the egress network and the cell's state represents its hazard status

$$s_v^F(t) = \begin{cases} 1, & \text{if area } v \text{ is on fire at time } t \\ 0, & \text{otherwise.} \end{cases} \tag{14}$$

The overall fire/smoke state at time t is then

$$s^F(t) = \left(s_1^F(t), s_2^F(t) \cdots s_{|V|}^F(t)\right)^T. \tag{15}$$

The transitions of cell states are governed by the conditional probabilities that fire or smoke propagates to an area given the status of its direct adjacencies, i.e.,

$$\Pr\left(s_v^F(t+1) = 1\right) = 1 - \prod_{\{v'\}} \left(1 - p_{v'v}^F \Pr\left(s_{v'}^F(t) = 1\right)\right) \tag{16}$$

where $\{v'\}$ denotes the set of direct adjacencies of area v, and ${p_{v'v}}^F$ is the conditional probability that fire or smoke will propagate from v' to v

$$p_{v'v}^F = \Pr\left(s_v^F(t+1) = 1 \mid s_{v'}^F(t) = 1\right). \tag{17}$$

The conditional probabilities can be estimated via statistical methods based on experimental data. The resulting model is a Markov process. Since the fire and smoke dynamics as specified in (16) are uncontrollable, our decision will be to properly select and update a set of passages for safe egress.

C. Formulation for the Optimization Problem

To select or update a set of passages in emergency egress, an optimization problem is formulated, consisting of system dynamics, constraints and an objective function.

To capture the overall egress situation, the system dynamics consists of the network-flow model (13) with the fire/smoke dynamics (16), where $(x(t), s^F(t))$ is the system state and the guidance strategy $u(t)$ is the system input. Here, the evolution of $x(t)$ can be described by

$$x(t+1) = f(x(t), s^F(t), u(t)). \tag{18}$$

Similarly, the evolution of $s^F(t)$ is specified by

$$s^F(t+1) = h(s^F(t)) \tag{19}$$

resulting in a Markov process.

The constraints for the problem can be categorized in two sets. The first set refers to the size of a passage that constrains the speed of crowd movement as described by (2) and (3). The second set refers to the rationality of the disseminated crowd guidance—the guidance should not lead evacuees to an area that is currently on fire, contains smoke or will soon be hazardous. These constraints are given as

$$u_e(t) \neq 1, \text{ if } \Pr\left(s_{v'}^F(t+k) = 1\right) > \beta, \\ \text{for } k = 0, 1, 2 \cdots K. \tag{20}$$

Here, β is a threshold for fire risk measure, and K is the length of the future to take into account. Symbol v' denotes an area directly adjacent v as in (16). Since our problem does not consider fire-fighting efforts, the probability of an area catching fire will increase over time, and this implies that (20) can be simplified to

$$u_e(t) \neq 1, \text{ if } \Pr\left(s_{v'}^F(t+K) = 1\right) > \beta. \tag{21}$$

To goal of crowd guidance is to evacuate as many people as possible and as rapidly as possible. The objective function to be maximized is thus a weighted sum of the expected number of total people evacuated and the expected cumulative number of people evacuated. Given a time horizon $[0, T]$, the total expected number of people evacuated is evaluated by

$$R_1 = \sum_{v \in \{\text{exit}\}} E[x_v(T)]. \tag{22}$$

To evacuate people as fast as possible, the cumulative number of people evacuated is evaluated by

$$R_2 = \sum_{t=0}^{T-1} \sum_{v \in \{\text{exit}\}} E[x_v(t)]. \tag{23}$$

The corresponding objective function is then

$$\text{Maximize } J, \text{ with } J = c_{\text{avg}} \cdot R_1 + R_2, \tag{24}$$

where c_{avg} is a weight.

With the above objective function in a time additive form, the optimization problem is formulated as a Markov decision problem. The people's locations and fire/smoke status form its state space $\{(x(t), s^F(t))\}$, and crowd guidance makes up its decision space $\{u(t)\}$.

The above problem will be used as a snapshot problem and solved in the moving window manner. In view of the nonlinearity and randomness of the above formulation, it has a high computational complexity. Solving the problem in a timely fashion is challenging because of the time-criticality of emergency operations.

V. Solution Methodology

To efficiently solve the optimization problem formulated in (18)–(24), a divide-and-conquer approach is developed. Evacuees are divided into groups based on their initial locations, and the evacuation route for each group is optimized. These routes are then coordinated with each other for an overall egress solution. To prevent potential disorder and blocking in group evacuation, the desired flow rates of evacuees are used to coordinate multiple groups so that the limited path capacities can be properly allocated. The Lagrangian relaxation framework is used to operationalize such coordination (Section V-A), and each group subproblem is solved by using the dynamic programming method and the rollout scheme (Section V-B).

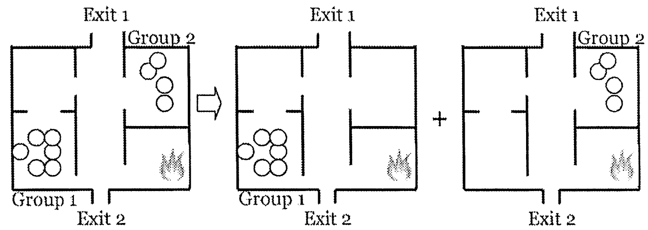


Fig. 8. Grouping of evacuees.

A. The Divide-and-Conquer Approach

To develop a divide-and-conquer approach, crowds will be first divided into groups, as shown in Fig. 8. Grouping is an important vehicle for accelerating computation in optimization since we can then deal with individual groups in areas as opposed to dealing with all the crowds simultaneously in the building. Also, grouping reflects a well-accepted social psychology finding in egress research—people are drawn to evacuate with others rather than alone (Cornwell [8]) and their movement toward exits is influenced by others' behavior (Santos and Aguirre [40]). For example, individuals move in directions that they see others move (Low [30]) and they will delay evacuation if others are not moving. Moreover, individuals seek confirmation from others as to whether an emergency is even occurring (Aguirre *et al.* [2]), and they often strive to exit with others they know (Sime [42]). Thus, dividing crowds into groups enables us to capture these psychological findings by using different parameters and motion features in the group subdynamics. The overall crowd dynamics (18) can be decomposed into group subdynamics as

$$x^i(t+1) = f(x^i(t), s^F(t), u^i(t), c^i), \\ \text{for } i = 1, 2 \cdots I, \tag{25}$$

where I is the total number of groups under consideration. For simplicity, it is assumed that the groups will not merge or separate within the time horizon, and that they are able to receive separate sets of guidance.

The above group subdynamics is not as simple as one might think. Groups are coupled when they come into contact with each other by using the same passages at the same time. As seen in Fig. 3, the nonlinear crowd dynamics is described by a piecewise function, where a linear segment is for $\left|q_e^d(t)\right| \geq c_e$ and a nonlinear segment is for $\left|q_e^d(t)\right| > c_e$. The linear segment represents that the passage capacity is sufficient for the crowd's desire to move. The nonlinear segment implies that the passage capacity is not sufficient, and groups compete for the limited passage capacity in a nonlinear and complicated fashion. As a result, the overall crowd dynamics cannot be decomposed into independent group dynamics. A surrogate method is therefore developed to approximate such nonlinear coupling of groups, where each group subproblem is solved with the aggregation of the latest results from all other groups (Zhao *et al.* [49]).

Whether the system evolves in the linear segment or not is decision-dependent, making it important to coordinate the groups so that the egress evolves in the linear segment as much as possible. This coordination is also used to approximate the overall system dynamics when the egress has to evolve in the nonlinear segment. A soft constraint is therefore imposed to limit the crowd flow dynamics within the linear segment, thus preventing the nonlinearity of disorder and blocking

$$\left|q_e{}^d(t)\right| c_e \text{ for } \forall\, e \in E, t = 0, 1, \ldots T. \qquad (26)$$

This inequality can be viewed as a criterion for preventing disorder and blocking, and implies that the egress demand should not exceed the total passage capacity. The psychological interpretation of (26) is that the stress on people should not exceed a limit for safe egress. From the perspective of optimization, (26) expresses our hope that the optimized solution will be in the linear segment (without the risk of disorder or blocking).

Inequality (26) can be transformed into a group form based on the additive property of $q_e^d(t)$, i.e., the total desired flow rate is equal to the sum of each group's desired flow rate. Because counterflows are not considered in our egress model, this additivity is expressed by

$$\left|q_e^d(t)\right| = \sum_{i=1}^{I} \left|q_e^{d^i}(t)\right|, \quad \text{for } \forall\, e \in E, t = 0, 1, \ldots T. \qquad (27)$$

By plugging (27) into (26) and taking expectation on both sides, a linear inequality is obtained as

$$\sum_{i=1}^{I} E\left[\left|q_e^{d^i}(t)\right|\right] \geq c_e, \text{ for } \forall\, e \in E, t = 0, 1, \ldots T. \qquad (28)$$

With the above, the objective function (24) is correspondingly transformed into a group form as

$$\text{Maximize } J, \text{ with } J = \sum_{i=1}^{I} J^i, \text{ where}$$
$$J^i = c_{\text{avg}} \cdot \sum_{v \in \{\text{exit}\}} E\left[x_v^i(T)\right] + \sum_{t=0}^{T-1} \sum_{v \in \{\text{exit}\}} E\left[x_v^i(t)\right]. \qquad (29)$$

Equations (19), (25), (28), and (29) specify our new problem formulation. To solve it, (28) is first relaxed by using Lagrangian multipliers $\{\lambda(t, e)\}$. The Lagrangian is

$$L \equiv c_{\text{avg}} \sum_{v \in \{\text{exit}\}} \sum_{i=1}^{I} E\left[x_v^i(T)\right] + \sum_{t=0}^{T-1} \sum_{v \in \{\text{exit}\}} \sum_{i=1}^{I} E\left[x_v^i(t)\right] - \sum_{t=0}^{T-1} \sum_{e \in E} \left\{\lambda(t, e)\left[\sum_{i=1}^{I} E\left[\left|q_e^{d^i}(t)\right|\right] - c_e\right]\right\}. \qquad (30)$$

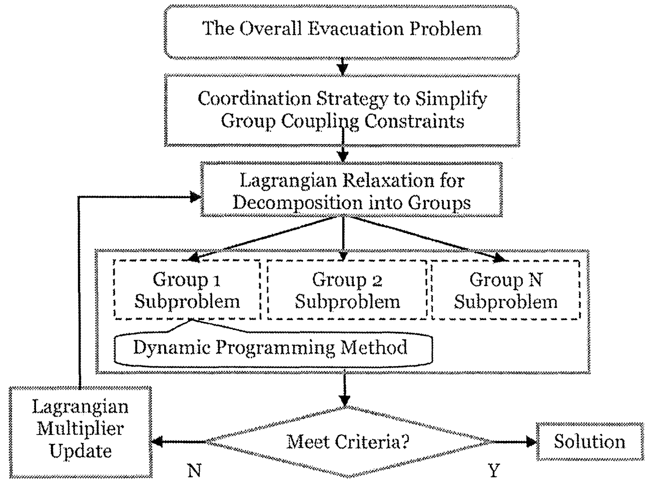


Fig. 9. The flow chart of the computation method.

By collecting all the terms related to group i, subproblem i is formulated as:

$$\max L^i \text{ with } L^i = c_{\text{avg}} \sum_{v \in \{\text{exit}\}} E\left[x_v^i(T)\right] + \sum_{t=0}^{T-1} \sum_{v \in \{\text{exit}\}} E\left[x_v^i(t)\right] - \sum_{t=0}^{T-1} \sum_{e \in E} \left\{\lambda(t, e) E\left[\left|q_e^{d^i}(t)\right|\right]\right\}. \qquad (31)$$

In view that the groups are coupled through (3) in a complicated manner, surrogate optimization is used where each group subproblem is solved with the aggregation of the latest results from all other groups (Zhao *et al.* [49]). Specifically for (3), an available passage capacity for Group i is obtained by subtracting from the total capacity of that passage the latest flow rates of other groups. The subproblem is then to maximize a time-additive objective function with group subdynamics specified by (26) as specified above. This can be solved by using stochastic dynamic programming (Bertsekas [6]). Individual groups are then coordinated by iteratively updating the Lagrangian multipliers $\{\lambda(t, e)\}$ (Bertsekas [5]; Zhao *et al.* [49]). The flowchart of the solution process is presented in Fig. 9. Here, $\lambda(t, e)$ specifies the penalty that is given based on the likelihood of disorder and blocking on passage e at time t. Such multipliers provide a marginal value of the passage capacity (called the "shadow price"), and are valuable for egress analysis.

B. The Dynamic Programming Method

The group subproblem is solved by using stochastic dynamic programming. Given the subsystem state $\left(x_t^i, s_t^F\right)$ at time t, the problem is to select u_t^i to obtain the optimal reward-to-go $L_t^i\left(x_t^i, s_t^F\right)$ based on the following Bellman Equation:

$$L_t^i\left(x_t^i, s_t^F\right) = g_t\left(x_t^i, s_t^F\right) + \max_{u_t^i}\left\{E_{x_{t+1}^i, s_{t+1}^F}\left[L_{t+1}^i\left(x_{t+1}^i, s_{t+1}^F\right) \mid x_t^i, s_t^F, u_t^i\right]\right\}. \qquad (32)$$

Here, $g_t\left(x_t^i, s_t^F\right)$ denotes the stage-wise reward at time t. Solving the subproblem by directly using (32), however, is computationally intensive (Bertsekas [6]). To reduce the computational complexity, state space reduction is used by revising the dynamic programming method as presented next.

A state for group i at time t includes two components—a crowd component x_t^i and a fire/smoke component s_t^F. The state space can be reduced because our model treats s_t^F as an uncontrollable component, therefore s_t^F can be viewed as a "disturbance" rather than as a part of the state, and L_t^i only depends on the crowd component x_t^i (Bertsekas, 2005). Here, the term "disturbance" is slightly different from the common concept of disturbance because s_t^F can be observed before u_t^i is optimized while the common disturbance occurs after u_t^i is applied. The optimal reward-to-go in (32) at time t is thus represented by

$$\hat{L}_t^i\left(x_t^i\right) = E_{s_t^F}\left\{L_t^i\left(x_t^i, s_t^F\right) \mid x_t^i\right\} \tag{33}$$

and the dynamic programming equation is then given by

$$\hat{L}_t^i\left(x_t^i\right) = g_t\left(x_t^1\right) + E_{s_t^F}\left\{\max_{u_t^i} E_{x_{t+1}^i}\left[\hat{L}_{t+1}^i\left(x_{t+1}^i\right) \mid x_t^i, s_t^F, u_t^i\right] \mid x_t^i\right\}. \tag{34}$$

Equation (33) implies that the reward-to-go can be computed with a significantly reduced state space.

Besides state space reduction, a rollout scheme is also used (Bertsekas [6]). Its main idea is to employ heuristics to approximate the optimal reward-to-go in Bellman's equation several steps into the future. For our problem the heuristic of using the nearest exit, an empirical method widely used in egress practice, is adopted.

Although the above method enables us to compute guidance decisions in a moving window fashion, such decisions should not be updated frequently since frequent changes can cause confusion on evacuees and reduce the credibility of guidance (Proulx [38]; Fahy and Proulx [9]). Infrequent updating also works to our advantage by reducing the problem complexity, i.e., reducing the decision variables in the timeline because the guidance will be kept unchanged within a certain time period $[t, t + \delta\Delta t]$. As a result, given a current subsystem state $(x^i(t), s^F(t))$, the optimal guidance during $[t, t + \delta\Delta t]$ is optimized by

$$L_t^i\left(x_t^i, s_t^F\right) = g_t\left(x_t^i\right) + \max_{u_t^i} E_{x_{t+\Delta t}^i}\left\{\tilde{L}_{t+\Delta t}^i\left(x_{t+\Delta t}^i\right) \mid x_t^i, s_t^F, u_t^i\right\}. \tag{35}$$

Here, $\tilde{L}_{t+\Delta t}^i\left(x_{t+\Delta t}^i\right)$ is an approximation of future reward-to-go after time point $t + \Delta t$, and is approximated based on the nearest-exit heuristics and by treating the fire/smoke state components as "disturbances."

It may be necessary to consider the possibility that the information network is damaged, either due to sensor failure or guidance failure. In the event of sensor damage, evacuees should be directed away from the affected area, due to the possibility of hazards. If the guidance fails, it can be assumed that evacuees in the affected area will use a self-guided strategy, such as nearest exits. Normal guidance can resume when groups emerge from damaged areas.

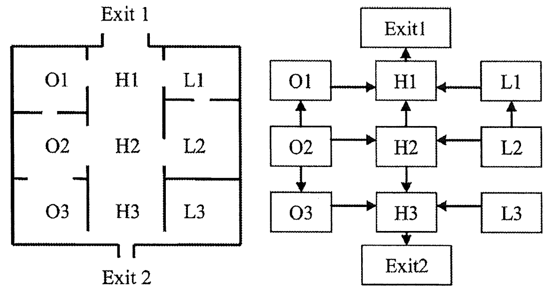


Fig. 10. An egress network.

VI. Testing and Simulation Results

Numerical testing is presented by using two examples. The first example uses a small layout to compare our network-flow model and method with traditional ones. The second example uses a larger layout (following Pan *et al.* [36]), and compares our optimization-based strategies with the strategy of using the nearest exits. For either example, an evacuation process is first simulated by FDS + Evac 2.1.0 using the default settings for adult evacuees. A macroscopic model is abstracted from the simulation results, and the egress route is then optimized based on this model in Matlab. To compare our optimized egress strategy versus other strategies, our optimized result is executed in FDS + Evac, where guidance is implemented by dynamically opening or closing certain exits. As stated in Section II-C, the current version of FDS + Evac lacks the feature of dynamic desired velocity. An evacuee has an "unimpeded walking speed," which is reduced by the presence of smoke. Nevertheless, simulation is still meaningful when comparing our results with those of using nearest exits. The reason is that if a future version of FDS + Evac with the feature of dynamic desired velocity is used, the comparison would be even drastic. This is due to more blocking by using the nearest exits caused by the increase in desired velocities, whereas changes to results using our method would be small because our guidance is designed to minimize blocking caused by high desired flow rates. Both examples run in the current version of FDS + Evac demonstrate that our optimized guidance can speed up egress by preventing potential blocking at bottleneck passages.

1) Example 1: This example studies an egress scenario in which two groups of people are guided to exits within a small planar layout. By dividing the layout into areas and passages, an egress network is abstracted, as shown in Fig. 10. Let the time unit be 8 ds. Exit 2 is of small capacity, namely, 5 persons per time unit, and Exit 1 is of relatively large capacity, 15 persons per time unit. Group 1 consists of 30 evacuees and Group 2 consists of 20 evacuees. Fig. 11 shows the initial locations of the two groups and the initial status of fire and smoke. Based upon analysis, there is little probability of smoke in the initial three time steps in the lounge areas (H1, H2 and H3), and thus Exit 2 is safe for egress within the initial three time slots.

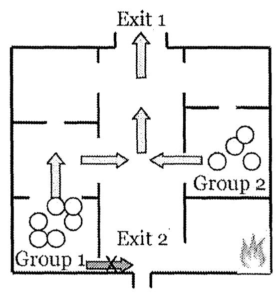


Fig. 11. Initial guidance at $t = 1$.

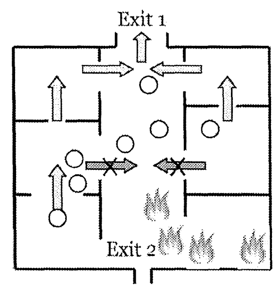


Fig. 12. Guidance updated at $t = 5$.

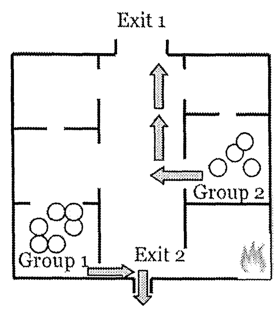


Fig. 13. Optimal guidance by the traditional model ($t = 1$).

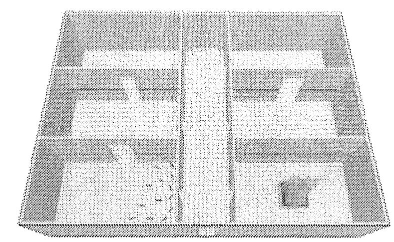


Fig. 14. Example 1 by using the nearest exits. (Video).

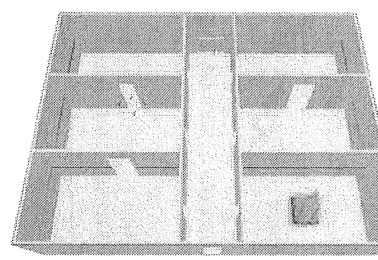


Fig. 15. Example 1 by using our optimized solution. (Video).

To find a good egress route, the guidance is optimized by using network-flow techniques. In this case the guidance is optimized in 20 sequential time steps. For each time step, we look ahead five time steps to formulate a snapshot problem as presented in Section IV.

If our network-flow model is used, the optimized route for the initial time step is as shown in Fig. 11. This route is chosen because our model and method predict that disorder and blocking will occur if people are guided to pass through the narrow passage from Office 3 to Exit 2. Thus, Exit 2 is not chosen for egress, and evacuees are guided to Exit 1. At $t = 5$, the guidance is updated, as shown in Fig. 12, because fire/smoke may propagate to the lounge area soon, affecting the availability of the previously chosen egress routes. The average optimization computation time at each t is 2.95 s (with Dell Vostro 1700; Intel Core™2 Duo CPU with 2G memory; Window Vista).

If the blocking effect is ignored, and the traditional network-flow model (10) is used to optimize the egress routes, the optimized solution for the initial three time steps is as shown in Fig. 13, where Group 1 is guided to Exit 2. The solution will be updated later, as shown in Fig. 12. This result actually suggests the strategy of using the nearest exits—each group is guided to the nearest exit with respect to their locations.

Comparing the two sets of guidance above, a major issue is whether or not to use Exit 2. To answer this question, two sets of guidance are executed in the simulation: one with and one without using Exit 2. The simulation results show that blocking occurs when the large group of evacuees in Office 3 heads to Exit 2, and after 20 time steps there are still 13 evacuees who have not been successfully evacuated. Please see the video segment attached to this paper. A snapshot of the video is shown in Fig. 14, where individuals are represented by small blue arrows.

However, if the large group of evacuees is instead guided to Exit 1 based on our results, the simulation shows a smoother and faster evacuation process. After 20 time steps, there are only 5 people left as compared with 13 in the previous case. Thus, the simulation results verify not using Exit 2 because of the bottleneck from Office 3 to Exit 2, even though Exit 2 is nearest to Group 1. A snapshot of the video is shown in Fig. 15.

In summary, our model and method considers the blocking effect as Group 1 moves towards Exit 2, while the traditional model does not. Thus, our optimized solution suggests leading Group 1 to Exit 1, and this speeds up egress.

One possibility to be mentioned here is to guide a small portion of Group 1 to Exit 2, while the remaining evacuees go to Exit 1. In this case the egress seems to be even faster. This solution implies that a group can be split, but splitting a group is unlikely to happen in a real evacuation unless a human leader can intervene and direct individuals to use different paths. Thus, in our approach as presented in Section V, once groups are defined they will not be split or merged.

Additionally, our method with grouping is compared with the same approach but without grouping. The latter solves the problem formulated in Section IV without decomposition based on groups. The results on guidance for this particular small example turned out to be identical to the results with grouping, however, with a longer CPU time of 5.95 s (as compared to

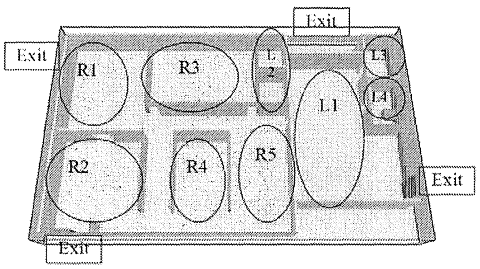
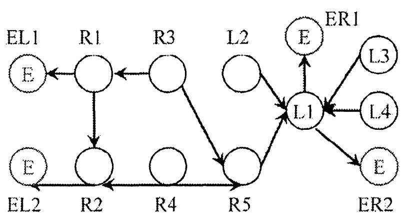


Fig. 16. An egress structural layout.



(b)

Fig. 17. An egress network abstracted.

2.95 s with grouping). It is expected that the CPU times will increase fast as the problem size increases for the method without grouping.

2) Example 2: An egress problem motivated by Pan *et al.* [36] is used as our second example. Although Pan's simulation was able to demonstrate that crowds' competitive behaviors could induce blocking and thus delay egress, no solution was given to prevent such blocking. Our model and method provide a solution to this problem by seeking better routes to speed up egress.

Following Pan's example, an egress layout is created in FDS + Evac, as shown in Fig. 15. Let the time unit be 5 s. The doorway connecting R5 and L1 has a small capacity of 10 persons per time unit. Other doorways have large capacities from 15 to 20 persons per time unit. A network model is abstracted from this layout, as shown in Figs. 16 and 17.

In this egress layout, 110 evacuees are located in areas from R1 to R5, and fire/smoke starts from L4. Five groups are formed based on their initial locations in R1 to R5. The network-flow dynamics of these groups are established and their guidance is optimized in 30 sequential time steps. To be consistent with Pan's simulation, the competitiveness of evacuees is tuned to be intensive, and this leads to a relatively small value of α in (3). Based on analysis using (16) there is little probability of fire or smoke observed in L1 within the initial 30 s. Exits ER1 and ER2 are thus considered safe for egress during this time period.

Based on the abstracted network-flow dynamics, the group guidance is optimized and the solution recommends Guidance Scheme 1 (Fig. 18) during the initial five time steps because there is little probability of hazard in L1 during this time period. Thus, exit EL1 is safe for egress. As the smoke propagates, guidance is updated according to Guidance Scheme 2 (Fig. 19) from the sixth time step and onward because the small capacity of the passage connecting R5 and L1 cannot support people's

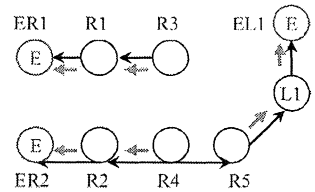


Fig. 18. Guidance scheme 1.

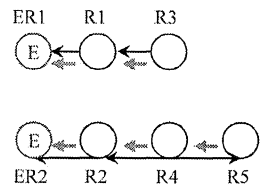


Fig. 19. Guidance scheme 2.

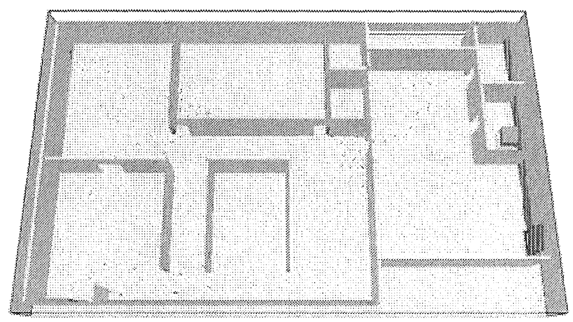


Fig. 20. Example 2: Using the nearest exit strategy. (Video).

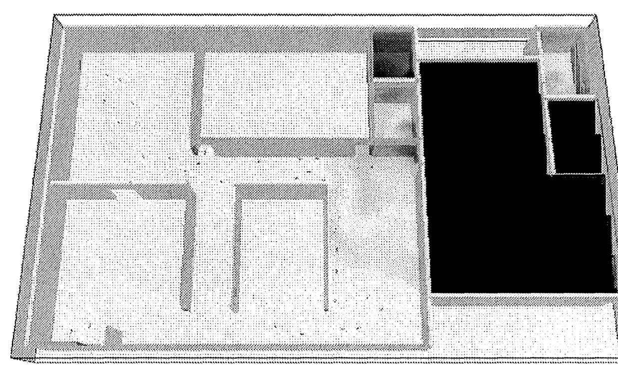


Fig. 21. Example 2: Using our optimized solution (Video).

rush to Exit ER1. The average computation time at each time point is 3.3 s.

The optimized guidance strategy is simulated to compare our method with the strategy of using the nearest exits, shown in Figs. 20 and 21. A major difference between these two strategies is whether or not the passage connecting R5 and L1 should be used. Our solution suggests that this passage should only be used by a small group of people within the initial time slots, and guidance should be updated (switched to Scheme 2) as the risk of disorder and blocking significantly increases on this passage. The remaining people are then guided to Exit EL1 or EL2. At the end of the simulation, 3 people are left in this layout after 100 s. Each run of the simulation takes roughly 12 min.

By contrast, when the nearest exit strategy is used, a large number of people may be guided to EL1. This inevitably makes a large number of people use the narrow passage between R5 and L1, and this may result in blocking. As shown in the simulation results, after 100 s there are 14 people left. Compared with 3 people in the previous case, it is clear that the nearest-exit strategy is not the optimal choice for this example.

VII. Conclusion

Based on advanced microscopic pedestrian models and simulations, this paper establishes a new macroscopic network-flow model where fire, smoke, and psychological factors can evoke a crowd's desire to escape. Our model forms a basis for the optimization of egress routes and crowd guidance in an evacuation. A divide-and-conquer approach is then developed to reduce computational complexity and to reflect psychological findings based on groups. By time-sharing passages and avoiding narrow passages to prevent potential disorder and blocking, numerical testing results demonstrate that, compared with the traditional network-flow techniques and the empirical strategy of the nearest exits, our solution can evacuate more people more rapidly.

Future efforts will be focused on validating our model and improving computation efficiency. For validation we plan to perform fire drills and virtual reality experiments to study the psychological state of evacuees. Computation efficiency can potentially be improved through model simplification and method refinement. New technologies such as cloud computing may also prove useful to provide a burst of computation power on demand in an emergency.

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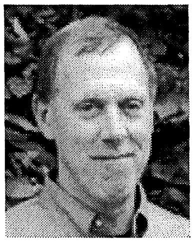

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