Managing Crowds in Hazards with Dynamic Grouping

Olumide J. Akinwande, Huibo Bi and Erol Gelenbe *Fellow, IEEE*
Intelligent Systems and Networks Group
Dept. of Electrical and Electronic Engineering, Imperial College, London SW7 2AZ, UK
Email: {olumide.akinwande13,huibo.bi12,e.gelenbe}@imperial.ac.uk

***Abstract*—Emergency navigation algorithms for evacuees in confined spaces typically treat all evacuees in a homogeneous manner, using a common metric to select the best exit paths. In this paper, we present a quality of service (QoS) driven routing algorithm to cater to the needs of different types of evacuees based on age, mobility, and level of resistance to fatigue and hazard. Spatial information regarding the location and the spread of hazards is also integrated into the routing metrics to avoid situations where evacuees may be directed towards hazardous zones. Furthermore, rather than persisting with a single decision algorithm during an entire evacuation process, we suggest that evacuees may adapt their course of action with regard to their ongoing physical condition and environment. A widely tested routing protocol known as the Cognitive Packet Network (CPN) with random neural networks (RNN) and reinforcement learning is employed to collect information and provide advice to evacuees, and is beneficial in emergency navigation owing to its low computational complexity and its ability to handle multiple QoS metrics in its search for safe exit paths. Simulation results indicate that the proposed algorithm, which is sensitive to the needs of evacuees, produces better results than the use of a single metric. Simulations also show that the use of dynamic grouping to adjust the evacuees' by category, and routing algorithms that have regard for their on-going health conditions and mobility, can achieve higher survival rates.**

Keywords*—Emergency navigation, QoS driven protocol, Dynamic Grouping, Cognitive Packet Network, Discrete Event Simulation.

I. Introduction

HIGH levels of occupancy and crowding in modern urbanised societies can aggravate destructive crowd behaviours during an emergency evacuation process and induce unnecessary fatalities and injuries. Hence, traditional emergency alarm systems which only alert civilians of emergencies are being superseded by emergency navigation systems which provide further guidance. Thus substantial research has been conducted to understand and model the behaviour of crowds in normal and emergency situations [1], [2], [3], [4], [5], [6], [7], [8]. Accompanying this tendency, other work has studied the design of distributed systems using sensor networks and computational resources in order to help direct people and crowds in emergency situations [9], while there has also been work on cyber attacks that can take place in such circumstances [10]. The time needed to find exits or other specific objects which are hard to see or identify in a hazardous environment, has also been studied using mathematical models [11].

In order to optimise the design of crowded sites and evaluate the clearance time for all evacuees, various cellular automata and agent based models have been employed to simulate grouping behaviours with respect to individuals' movement capabilities during emergency evacuations. In [12] a heterogeneous cellular automata model mimics the evacuation process in a retirement house; evacuees initially belong to three groups (middle-aged people, nursing staff and older people), and groups are also formed dynamically due to the follow-the-leader effect. In [13] grouping behaviours in evacuations are induced by introducing "bosons" into cells of the floor field cellular automaton [7]; bosons are placed by evacuees as markers to increase the probability for other group members to reach some particular cell. The resulting simulations indicate that the evacuation time decreases with the increasing numbers of groups. More generally, individuals may need to be treated differently during an emergency: elderly people should choose the safest paths that will remain ahead of the spreading hazard, while agile individuals may be able to take advantage of the fastest paths, and may accept some element of risk. Research on robotic and autonomous systems [14], [15] has shown the advantages of cooperative behaviour among agents. Thus in this paper we investigate the use of dynamic grouping of evacuees based on their characteristics as a way to improve the outcome of an emergency evacuation.

Therefore, in this paper, we investigate the improvements that can be offered by tailoring the evacuation strategy to diverse categories of evacuees, and by treating evacuees in a distinct manner based on their capabilities (e.g. mobility). To this effect, we will use the concepts of the Cognitive Packet Networks (CPN) which uses a neural algorithm based technique for finding paths [16], [17]. The remainder of this paper is organised as follows. We first review the literature relevant to our work, followed by Section I-B which presents CPN. The CPN variations for the evacuee routing problem and the routing metrics are presented in Section II and Section II-A, respectively. The simulation models and assumptions are then described in Section III and the details of dynamic grouping are discussed in Section IV-B. . By using these routing metrics and policies, the experimental results and discussion are presented in Section IV. Finally, we draw conclusions in Section V.

A. Literature Review

The study of emergency evacuation in confined spaces, which was initially motivated by defence applications [18],

[19], has attracted much attention owing to the potential of losses in terms of human lives and property during a disaster. Since previous research indicated that destructive crowd behaviours such as stampedes can lead to serious fatalities [8], much work has been dedicated to investigate and design crowd behaviour models [20], [21] based on cellular automata models [2], [22], social force models [23], fluid-dynamics [24], [25] and agents [26], [27]. Another tendency of this research field is emergency navigation, which concentrates on combining mathematical models [28] or algorithms [29] with underlying sensing, communications and distributed real-time computation to guide evacuees to safety in a built environment. In situations with different types of individuals, due to different speeds and delays, some individuals may overtake and pass others [30] leading to confusion in managing and accounting for the evacuees. In this literature review, we mainly focus on emergency navigation, since our work relates to navigation algorithms in emergency situations.

Due to limitations in processing power, early emergency navigation systems are commonly computer-aided information reporting systems to assist emergency managers in making decisions [31]. Associated emergency navigation algorithms at that time normally used purely mathematical models to simplify an evacuation process and seek optimal solutions. Thus in [32] evacuation planning is considered as a minimum cost network flow problem that converts the original building graph to a time-expanded network. By solving the time-expanded network via a linear programming algorithm, evacuees can obtain optimal routes and achieve shortest evacuation time.

With the fast development of information and communications technology (ICT), research then moved to the development of complex Emergency Cyber-Physical-Human systems to direct evacuees to exits with the aid of an on-site wireless sensor network (WSN). At the core of emergency navigation systems, various emergency navigation algorithms have been proposed such as network flow based algorithms [33], [34], queueing model based approaches [35], [36], potential-maintenance algorithms [14], [37], [38], biological-inspired approaches [39], [40], [41] and prediction-based algorithms [42], [43]. Network flow based algorithms commonly predict the upper bound of evacuation time and convert the original building model to a time-expanded network by duplicating the original network for each discrete time unit. Then linear programming or heuristic algorithms are used to compute the optimal evacuation plan. This approach can achieve the optimal solution but does not take the spreading of the hazard into consideration. By treating significant locations such as doorways or staircases as "servers", queueing model based approaches [44], which generalise the Markovian models of computer systems [45], transfer building graphs to a queueing network to estimate congestion and evacuation delays. Potential based algorithms normally can dynamically develop navigation paths by assigning attractive or repulsive potentials to the exits and hazards, and the evacuees move as a result of the net attraction-repulsion in various directions [46]. However, these approaches require constant information exchange to update navigation maps for evacuees, even when the maps are concentrated at a few fixed nodes and shared with the evacuees to determine their paths. Biological-inspired approaches employ heuristics to search for routes [41] such as genetic algorithms, where the "fitness" of a path is based on its length and the congestion or the hazards it may contain; initially shortest paths are selected based on distance, and then new paths may evolve incrementally through crossover and mutation. Prediction-based algorithms utilise Bayesian networks to anticipate the hazard or crowd dynamics in disasters [43] and infer the location of people and hazards. A novel e-infrastructure is presented in [42] to predict spread of hazards based on predictive models and live sensory data in a faster-than-real-time manner.

Since many emergency response systems are based on wireless sensor networks (WSN), routing protocols have been borrowed or adapted from existing solutions. However, communications which are essential in this context can easily malfunction during emergencies, and in [47] a resilient emergency support system (ESS) is proposed to disseminate emergency messages among evacuees with the aid of opportunistic communications (Oppcomms). Experimental results indicate that this system is robust to network failures during an emergency. But because Oppcomms are susceptible to malicious attacks such as flooding or denial of service [48], a defence mechanism that uses a combination of identity-based signatures (IBS) and content-based message verification to detect malicious nodes is proposed and an infrastructure-less emergency navigation system is presented in [49] to guide evacuees with the aid of smart handsets and cloud servers. Also in [50] a WSN based distributed emergency management system that uses Dijkstra's algorithm to calculate shortest paths for evacuees is considered.

Sensor nodes (SNs) collect hazard informatio, whilen decision nodes (DNs) provide advice to evacuees through visual indicators or portable devices. To avoid a full graph search and reduce communication costs, in [51] the system was modified by replacing Dijkstra's algorithm with the Cognitive Packet Network (CPN) [52] routing algorithm.

B. The Cognitive Packet Network

CPN was designed to address challenges of large packet networks where paths may not be known in advance and need to be discovered as a function of quality of service or reliability, but it's reinforcement algorithms based scheme was motivated by the adaptive routing of mobile agents and vehicles in dangerous environments [53], where the mobile agents discover the hazards in the course of their navigation. Thus one can say that CPN's specific design was actually motivated by emergency management.

Unlike traditional packet network protocols where routers have all the intelligence, CPN constructs intelligence into packets for routing and flow control through a decentralised self-adaptive decision architecture [54] and takes "soft" decisions to alter or change paths [55] using learning algorithms and adaptation.

CPN contains three types of packets: smart or cognitive packets (SP/CP), acknowledgements (ACK) and dumb packets (DP). Each CPN node maintains a Mailbox (MB) storing diverse Classes of QoS information grouped under path and associated QoS measurements, which is regularly updated by the ACKs that traverse the node. A MB will discard the expired QoS information or the worst one when it reaches its capacity. SPs are sent by CPN nodes to explore the network and gather relevant information with respect to a user-specified QoS. The measurements made by the SPs represents their "experience" of the network state and future SPs exploit this in making better decisions. The preferred learning method is the RNN [56] with reinforcement learning (RL) which penalizes or rewards SP decisions so that subsequent decisions can provide better results in meeting QoS goals. The QoS goals (routing metrics) which are detailed in Section II-A are the inputs of RNN. When an SP reaches one exit, an ACK, carrying the SP's measurements, is generated by the destination node and it travels back to the source node along the discovered loop-free path. The ACK updates the MB of every node along its path and triggers the nodes to run the learning algorithms and update the relevant decisions. The DPs, which carry the payload, are always source-routed using the highest ranked path information. The DPs can also be used to carry out measurements. In summary, the first set of SPs sent, aim to establish a connection between the source and the intended destination while the subsequent SPs update the paths to optimise a given QoS metric. To avoid burding the network, packets that are considered lost, i.e. SPs which have traversed a set maximum number of hops or travelled for a set time without reaching their destination, and ACKs or a DPs which enter a node that is not along their specified path, are simply discarded.

Each CPN node maintains a recurrent (fully connected) RNN, and each neuron in the RNN is associated with a neighbour CPN node. When a SP reaches a CPN node, in a majority of the cases it chooses, as the next hop, the neighbour node whose neuron has the highest excitation probability; however in 10% of the cases the next hop is chosen at random among all possible neighbours in order to explore new paths. The excitation probability of neurons is calculated numerically when path quality information is brought back by an ACK. The speed with which CPN reacts is due to reinforcement learning, in that the algorithm at each step seeks to make a decision that is better than the previous one, rather than an optimal decision, and also these packets are travelling at electronic speeds at least 1000 faster than the speed of the evacuees, so that path search and updates by SPs are conducted constantly and updated in advance of the motion of evacuees. The speed of adaptation of CPN, specifically in a simulation environment for emergency management, has been studied in [57], while many experiments are reported in [54].

C. Health-Aware Classification

Although we have classified evacuees into two groups that use separate routing metrics in Section II-A, it will be useful for evacuees to switch groups during an evacuation. For instance, when an individual of Class 1 is injured, it should be moved to Class 2 due to its reduced mobility. This Health-Aware Classification mechanism can be implemented so that, for instance, an individual of Class 1 whose health level has dropped below a certain percentage of its original value can be moved into Class 2. The details are shown in Pseudocode 1 and a list of symbols used is summarised in Table I.

Notation	Definition
G_{id}	Represents the group ID of an evacuee
G_{one}	Represents the group ID of "Class 1" evacuees
G_{two}	Represents the group ID of "Class 2" evacuees
G_{con}	Represents the group ID of "congestion-ease" evacuees
H_o	Represents the initial health value of an evacuee
H_t	Represents the health value threshold that triggers the "Class-switching" event.

TABLE I. LIST OF SYMBOLS USED IN THE PSEUDOCODE 1.

Pseudocode 1 The process of changing an evacuee from "Class 1" to "Class 2". DN, decision node.

```
When an evacuee reaches the vicinity of a DN, obtain G_id of the evacuee
if G_id ∈ G_one then
    gain the health value H_e, H_t of the evacuee
    if H_e < H_t then
        G_id ← G_two
    end if
end if
```

The health value of an evacuee is affected by the fatigue level and exposure to the hazard. In reality, it can be calculated by a portable device carried by evacuees. The fatigue level is determined by the walking distance of an evacuee, which can be updated when reaching a sensor node. The impact of hazard can be evaluated by the hazard intensity of all the adjacent sensors. Hence, the current health value of an evacuee can be obtained by using (1).

$$H_{c^+} = H_c - fD_w - h\frac{\sum_{i=1}^{n} H_i}{n} \tag{1}$$

where H_{c^+} represents the current health value of an evacuee and H_c represents the last health value, term f is a constant fatigue rate that coordinates the relation between health value and walking distance D_w since last updates. Term n represents the number of adjacent sensors and H_i is the associated hazard intensity. Term h is a constant that coordinates the relation between the health value and the hazard intensity.

II. CPN FOR EVACUEE ROUTING

The CPN architecture is modified to address the needs of emergency evacuation as follows. First, there are no DPs (dump packets) since the evacuees themselves are the "payload" that is being controlled by CPN. Two types of wireless nodes are used to sense (for the purpose of the SPs) and convey the information needed by CPN:

- Sensor Nodes (SNs) that sense the presence of hazards (e.g. fire, gas) and detect the presence of evacuees in their vicinity (e.g. via RFID or a smart tag that people may be carrying), are in communication with neighbouring DNs and provide them with the information that they have sense,

- Decision Nodes (DNs) that act as wireless CPN routers and transmitters for SPs (which search for evacuee paths) and ACKs (which bring back the sensed information) and provide advice to evacuees in their vicinity.

There will be a DN in each office or room in the building, and in a large room there may be many DNs. Each DN functions as a CPN node, and is placed in a fixed location (e.g. on the ceiling) known in advance to the software of the EMS. Thanks to wireless communication, each DN knows whether the DNs and SNs in its immediate environment are properly working, and this is part of the information that it uses to provide guidance to evacuees. Between any pair of DNs in a large room at least one SN is deployed, and there may be more deployed in the middle of two DNs (for instance at doors of rooms) to monitor the situation of the surrounding area.

Thanks to the neighbouring SNs, each DN knows the state of the link or hop to its neighbouring DNs, and it sends out SPs that move from DN to DN, to obtain the state of the paths to exits: thus each SP sent out by a DN will collect path information as it moves through DNs, while DNs themselves will know the state of each neighbouring hop segment from the SNs in their immediate vicinity. ACKs which are paired with specific SPs will head back from the exit destination to the nodes

Thus using the CPN algorithm, the DN will select the best (i.e. the shortest among the safest, or overall safest) path from its own location to a safe exit. The CPN algorithm will also return an ACK packet from an exit to the DN that has sent out an SP, when that SP reaches the exit with the path information (including path quality). Thus by sending out multiple SPs, each DN maintains a list of paths to exits together with the "age" of the path, and the path's quality metric. However, contrary to CPN, evacuees, will obtain advice successively from different DNs (by wireless or via direction signs) and will not use a fixed "source routed" path, and the evacuees' path will be updated as they move and receive new advice. Although all evacuees receive full path information, a movement depth value is set so that as long as there is no path blockage due to increased hazards or congestion, evacuees are encouraged to traverse a given number of nodes before using the newly obtained path update. Each SP is assigned a "maximum lifetime" which is simply the maximum number of hops that it is allowed to traverse before it is discarded, the purpose being to reduce congestion. The maximum number of hops is set to the total number of DNs in the network plus one.

A. Routing Metrics

The routing metrics that we define are the QoS goals used in the RNN based reinforcement learning algorithm of CPN. When an ACK brings back sensory data to the source node, the collected information will be used to compute the current values of the routing metrics, and the result will be used to update the weights of the RNN. We specifically use a time-oriented and a hazard oriented metric, as defined below.

In Figure 1, we show how the graph of the building is constructed with the nodes being the locations of the DNs, while the SNs, collectively called the set S, are placed on the edges between nodes. SNs provide real-time information regarding hazards. A DN i receives data from a set of nearby SNs, defined as the set N_i. A SN s belongs to N_i if the Euclidean distance between the s and i is not greater than R: $N_i = \{s \in S : ||l(i) - l(s)|| \leq R\}$ where $l(.)$ denotes the "location" or cartesian coordinates of a DN or SN. Each SN s estimates the hazard intensity $H(s,\tau)$ at time τ of the edge where it is located:

$$H(s,\tau) = \begin{cases} 1 & \text{if no hazard is present} \\ k \cdot 10^3 & \text{otherwise} \end{cases}$$

where τ is the time at which the measurement is made and k is an integer in the interval $[1, 8]$ that indicates the level or intensity of the hazard. For instance, this could be the temperature (when there is a fire), or the amount of gas that is detected.

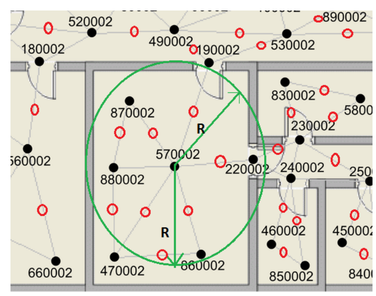

Fig. 1. DNs are located on the black dots while SNs are positioned on the red rings. SNs in the green circle belong to N_{570002}.

Let $L(s)$ be the phsyical length (say in meters) of the edge where a sensor s is located. Its effective length $L_e(s,\tau)$ at time τ will combine its real physical length with the hazards detected by s plus the average value the hazards in the vicinity defined by the radius R:

$$L_e(s,\tau) = L_{(s)}.[H(s,\tau) + \frac{\sum_{j:\ ||l(j)-l(s)||\leq R} H(j,\tau)}{|\{j \neq s:\ ||l(j) - l(s)|| \leq R\}|}] \quad (2)$$

If $R = 0$, the effective length becomes $L_e(s,\tau) = L(s).H(s,\tau)$.

A path exposed to fire (or another major hazard) can be labelled as such, in addition to the distance metric. However in our case, the multiplicative factor used to signal the hazard is chosen so that hazardous paths will always have a distance greater than the safe paths in the built environment.

We now introduce two quality of service goals or metrics that the EMS will pursue to find the best paths for the evacuees. The Time Metric (TM) is quite simple and it seeks a fast evacuation path; it will be used by the EMS for the Class 1 evacuees, who try to get out quickly but can afford to try a different path if they discover a hazard along their path. On the other hand, the Safety Metric (SM) will be used for the Class 2 or "weaker" evacuees who move more slowly and who are less able to try alternate routes if their initial routes turn out to be unsafe or clogged due to a hazard or congestion.

1) The Time Metric (TM): The Time Metric (TM) denoted by $G(i, \pi, \tau)$ is used to choose egress paths that minimise the time it takes to evacuate the evacuees. A path π is a sequence of nodes and edges starting at some node i, so that we may write $\pi = (i_1, s_1, i_2, \ \dots \ , s_n, i_{n+1})$ where $i_1 = i$ is the first node on the path, s_1 is the sensor on the edge from node i to the next node on the path, and so on until s_n, which is the sensor on the edge linking to the last node i_{n+1} on the path.

Each node can be viewed a queue with a "server", where the service time is the time the evacuee needs to determine the next direction (by gaining suggestions from portable devices) plus the time it needs to physically move through the node. A recent study shows that Little's formula can be a useful approximation to estimate delays in emergency evacuations [58] even when transients are being considered. Assuming that this queue is stable (i.e. the arrival rate is smaller than the service rate), the average total time through a path can be estimated with Little's formula applied to each successive node in the path, including possible queueing times, and evaluated at time τ:

$$G_T(i, \pi, \tau) = \sum_{j=1}^{n} [\frac{L_{(s_j)}}{V} + \frac{q_{i_j}(\tau)}{a_{i_j}(\tau)}], \quad (3)$$

where V is the estimated speed of the evacuee, where the observed number of evacuees is q_{i_j} at node i_j (when this can be measured), and $a_{i_j}(\tau)$ is the observed arrival rate of evacuees at node i_j. Note that in many cases sensors will not be able to provide estimates of queue length and arrival rates, in which case these terms will just be dropped.

The TM does not consider the spreading of the fire, it only seeks to guide evacuees to exits as soon as possible. However, the "virtual health" value introduced in Section I-C helps evacuees that use the TM to adapt their strategy before they may enter a hazardous area.

2) The Safety Metric (SM): The Safety Metric (SM) for path $\pi = (i_1, s_1, i_2, \ \dots \ , s_n, i_{n+1})$ on the other hand, denoted by $G_S(i, \pi, \tau)$, is used to seek paths that help the evacuees avoid hazards:

$$G_S(i, \pi, \tau) = \sum_{j=1}^{n} L_e(s_j, \tau) \quad (4)$$

Since the effective length of a path exposed to fire is always be greater than any other safe path in the building, the SM will help evacuees find the *shortest* among all the safe paths.

III. The Simulation Model and its Assumptions

To evaluate the proposed routing scheme for evacuees, we employ an existing Java based distributed simulation tool, the Distributed Building Evacuation Simulator (DBES) [59], and we use fire-related scenarios in the simulations. DBES can simulate large scale environments (such as city neighbourhoods) [60] and is used to evaluate different courses of action in emergencies of varying danger and severity. As a multi-agent simulator, each entity in DBES is represented by a software agent that interacts with its environment. Figure 2 shows an example of the graphical user interface (GUI) of DBES with one "floor agent" in charge of managing the state of a given building's floor, and ten agents representing evacuees.

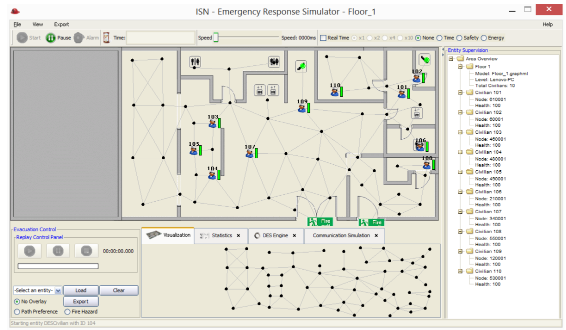

Fig. 2. The GUI of the DBES.

A. Building Model

As indicated earlier, the building model in our experiments simulates the three lower floors of the EEE building at Imperial College London. The ground floor has a dimension of $24m$ by $45m$ while the other two floors have the same dimension of $24m$ by $60m$. The height between each floor is approximately $3m$. Figure 3 shows a graph representation of the building model. The second and third floors of the building being considered have more offices and rooms than the first floor which is essentially an exit area and a coffee shop; thus the second floor has 89 DNs or CPN nodes, the third floor has 92 DNs, while the first floor has just 59 DNs.

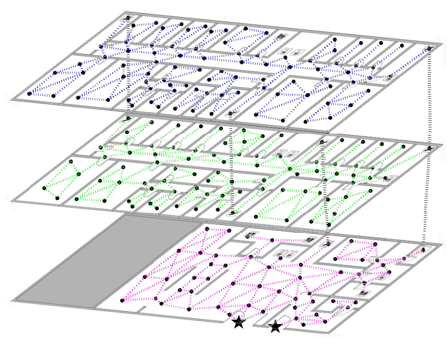

Fig. 3. Graph representation of the building.

The vertices (black round dots) in Figure 3 represent locations where people can congregate such as rooms, doorways and corridors while the two black stars on the first floor depict the exits. There is a total of 240 vertices on the graph, including the two exits, and at each vertex we assume that a DN has been placed with SNs placed between each pair of DNs. The spaced horizontal lines linking the vertices are the graph edges representing the possible paths in the building, and on each edge there will be at least one SN. The edges connecting the two floors are the stairs in the building.

B. Modeling the Evacuees

The evacuees are assumed, for simplicity, to belong to two categories based on their age:

- The Class 1 agents represent evacuees typically within the age range of 12 - 50 years.
- The Class 2 agents represent evacuees who are still individually mobile, but move more slowly such as children, older individuals, or who may have been weakened or hurt during the evacuation.

The health level of each evacuee is initialised to a value of 100, and it is decreased over the course of the evacuation simulation based on fatigue and exposure to the hazard. Each category of evacuees is characterized by their speed and their resistance to fatigue and to the hazard. Table II illustrates the speeds of the two categories of evacuees.

The mobility model of Class 1 agents uses the empirical data found in the literature. For example, the average human walking speed is $1.39m/s$ in general and is $1.19m/s$ in urban areas [61]. We reduce this value to $1.05m/s$ because evacuees need to obtain suggestions from portable devices. The walking speed for the "up stair" direction is $0.51 \pm 0.10m/s$ in [62] for a narrow staircase, and is $0.56 \pm 0.14m/s$ for a wider stair, while the down-stair motion speed is $0.72 \pm 0.29m/s$ for a narrow and $0.69 \pm 0.15m/s$ for a wider stair.

Walking Speed	Class 1 Agent	Class 2 Agent
Direct	105 cm/s	84 cm/s
Upstairs	65 cm/s	53 cm/s
Downstairs	71 cm/s	57 cm/s

TABLE II. SPEEDS OF THE TWO CATEGORIES OF EVACUEES.

The speeds for the Class 2 agents are obtained by multiplying the corresponding Class 1 agent speed by a 0.8 factor. This factor is determined by the ratio between the walking speed of young adults and aged people [63]. During the simulation, if the health level of an evacuee falls below 20%, its speeds drop to half of the values indicated in the table. We model the lower resistance of the Class 2 agents by multiplying the effect fatigue and hazard have on the health level of Class 1 agents by a factor of 1.5. The simulations are initialised by placing an evacuee in its initial location randomly at any of the nodes, and also each evacuee is initialised with probability 0.5 as belonging to either of the Classes. We also assume that all the evacuees are in possession of a wireless device that can receive path information from its neighbouring DNs.

C. Fire Source Location

The fire source location has a significant impact on the performance of the emergency navigation algorithms in the simulation. In the simulation (and perhaps also in a real situation), a fire that breaks out at a strategic location such as a staircase may result in all of the path finding algorithms to operate equally poorly because of the potential for high congestion to create a back pressure and further congestion in the higher floor(s).

To alleviate this issue by taking adequate precautions, we calculate the most "critical" nodes in the building by using the following definition: the *criticality rank* of a node, introduced in [58], is the number of shortest paths to the exit, starting from any node in the graph, that traverse the node. The highest ranked nodes by criticality for the graph used in our simulations, are shown in Table III. These top ranked nodes

	Node Id	Count
1	410001	200
2	370001	103
3	360001	102
4	120001	101
5	20001	100

TABLE III. MOST CRITICAL NODES IN THE BUILDING

form a path towards the exit that is located in the lobby on the first floor as shown in Figure 4. To evaluate the adaptiveness of the proposed algorithm, we choose Node 210001 as the fire source which is in an office on the first floor not far from the eastern staircase. By choosing this location, the fire will soon block this staircase, and this facilitates evaluating if the decision algorithms can adapt to the highly dynamic environment and discover the primary main channel marked out by the thick green lines in Figure 4.

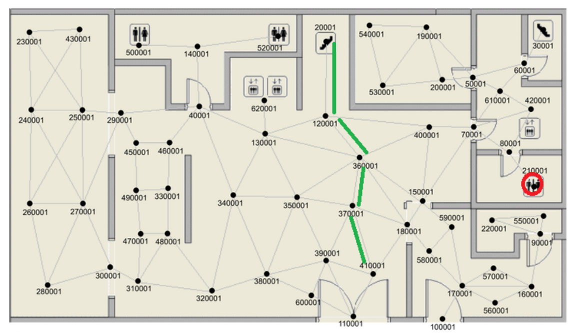

Fig. 4. This shows the most critical nodes along the primary main channel marked out by the thick green lines and the fire node is indicated by the thick red ring.

IV. EXPERIMENTS AND RESULTS

We have carried out two experiments to investigate the potential improvements offered by routing two categories of evacuees using different metrics, varying health threshold H_t (which is defined in Table I) and diverse spatial information. The level of spatial information is determined by the operating communication range of the DNs, which is set by the variable R. In the first experiment, we set H_t to 50 to study the effect of customising metrics for different categories of evacuees under different levels of spatial information.

In the first two scenarios of this experiment, we use a single metric (time metric or safety metric with $R = 300$) in routing all the evacuees, while in the remaining four scenarios, we use one specific metric for each category of evacuees. In the second experiment, we set R to 300 to investigate the impact of using different health threshold H_t. For each scenario, we run 10 simulations with random distribution of evacuees under four different levels of occupancy (30, 60, 90 and 120) in the aforementioned building model. Table IV below gives a summary of the experiments that have been performed in the first experiment.

Experiment 1	Evacuee type	Aim
CPN with safety metric (SM)	Class 1; Class 2	Safest path
CPN with time metric (TM)	Class 1; Class 2	Quickest path
CPN with safety and time metric (CM) without spatial information	Class 1; Class 2	Quickest path; safest path
CPN with safety and time metric (CM) with spatial information ($R = 300cm$)	Class 1; Class 2	Quickest path; safest path
CPN with safety and time metric (CM) with spatial information ($R = 400cm$)	Class 1; Class 2	Quickest path; safest path
CPN with safety and time metric (CM) with spatial information ($R = 500cm$)	Class 1; Class 2	Quickest path; safest path

TABLE IV. METRICS USED FOR CLASS-BASED EMERGENCY EVACUATION.

We use the "average percentage of survivors" as the performance metric to evaluate the effectiveness of different algorithms and for each level of occupancy. An evacuee is considered to be a "survivor" if it has a health level strictly greater than zero at the end of a simulation.

A. Average percentage of survivors

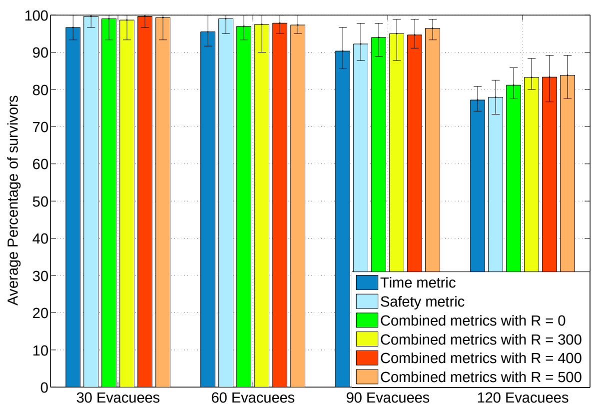

Fig. 5. The average percentage of survivors for each scenario. The results are the average of 10 randomized simulation runs, and error bars show the min/max result in any of the 10 simulation runs.

Figure 5 shows the percentage of survivors in the first experiment, which employs time metric (TM), safety metric (SM) and combined metrics with diverse R (CM). TM gives the worst performance especially at low levels of occupancy (30 and 60 evacuees). This is because unlike safety metric (SM), which tends to guide all the evacuees to the safest path, evacuees using TM may take the risk to traverse potential hazard areas in order to reduce the evacuation time. Hence, some evacuees may get injured or perish owing to the impact of hazard. However, with the increase of occupancy rate, TM can reach the performance of SM because it can effectively ease congestion which occurs frequently in high population densities (90 and 120 evacuees). On the other hand, SM performs best at low occupancy rates because it is sensitive to the hazard and can choose safest paths for evacuees. However, the performance of SM degrades considerably in densely-populated environments because some paths with acceptable safety level are excluded. Hence, evacuees tend to congregate along several safest paths and generate high level of congestion. In comparison with using one single metric, CM obtains overall best survival rates because it can tailor paths to evacuees with respect to their specific requirements. Furthermore, the concurrent use of two routing metrics can naturally distribute evacuees and alleviate congestion. The results also indicate that CM with $R = 300$, 400 and 500 achieve better performance than CM with $R = 0$. This reflects that the use of spatial hazard information (R) has a positive impact on the performance of the algorithm. The reason is because the use of spatial information can generate a safe distance between evacuees and the spreading hazard.

B. The Effect of Dynamic Grouping

In the first experiment where we consider CM, a Class 1 evacuee whose health level falls below $H_t = 50$ will be immediately considered as a member of the second Class. To evaluate the effect of H_t, in the second experiment, as shown in Table V, we concentrate on CM with $H_t = 0$, 30, 50, 70 and 90, respectively. When $H_t = 0$, two categories of evacuees will be guided with SM and TM separately and avoid changing of Classes. This means that Class 1 evacuees will use TM throughout each simulation. Figure 6 shows the comparisons of average percentage of survivors with $R = 300$.

Experiment 2	Evacuee type	Aim
CPN with safety and time metric (CM) ($R = 300cm$, $H_t = 0$)	Class 1; Class 2	Quickest path; safest path
CPN with safety and time metric (CM) ($R = 300cm$, $H_t = 30$)	Class 1; Class 2	Quickest path; safest path
CPN with safety and time metric (CM) ($R = 300cm$, $H_t = 50$)	Class 1; Class 2	Quickest path; safest path
CPN with safety and time metric (CM) ($R = 300cm$, $H_t = 70$)	Class 1; Class 2	Quickest path; safest path
CPN with safety and time metric (CM) ($R = 300cm$, $H_t = 90$)	Class 1; Class 2	Quickest path; safest path

TABLE V. THE SUMMARY OF EXPERIMENTS PERFORMED IN THE SECOND EXPERIMENT. TERM R REPRESENTS THE LEVEL OF SPATIAL INFORMATION AND H_t DENOTES THE HEALTH THRESHOLD FOR CLASS-SWITCHING.

These results indicate that the dynamic changing of Classes generally has a positive impact on the system performance. In comparison with not changing Classes ($H_t = 0$), dynamic grouping mechanism can achieve improved survival rates especially in high population densities. At low occupancy rates, CMs with different H_t achieve comparable results because when certain distant evacuees are re-directed to a safe detour path, the spreading hazard may have blocked both staircases between floor 1 and floor 2. Hence, these evacuees have to traverse hazardous areas and suffer injuries and fatalities. On the other hand, at high occupancy rates, the survival rate increases with the increase of H_t. This is because CM with a larger H_t is more sensitive to the potential hazard and can direct evacuees away from hazardous zones earlier. On the contrary, if H_t is too small, evacuees may not switch Classes

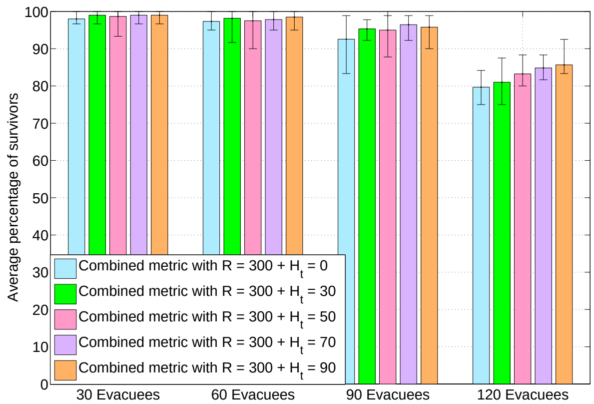

Fig. 6. The average percentage of survivors for different H_t. The results are the average of 10 randomized simulation runs, and error bars show the min/max result in any of the 10 simulation runs.

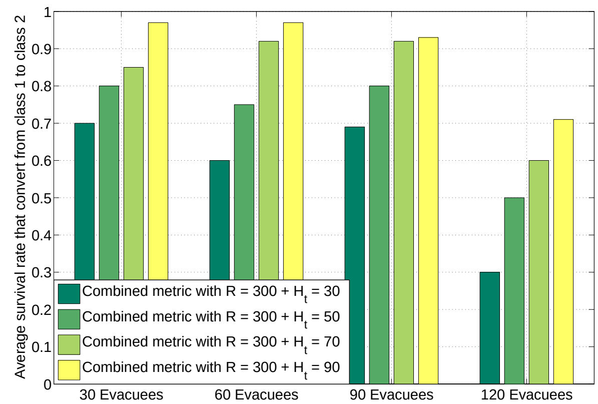

Fig. 8. The average survival rate of Class-switching evacuees during an evacuation process for each level of occupancy. The results are the average of 10 randomized simulations.

in time and may suffer serious injury and reduced mobility before being re-routed.

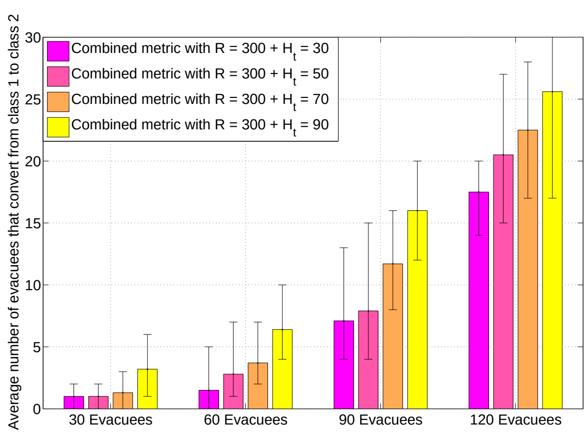

Fig. 7. The average number of evacuees that convert from Class 1 to Class 2 during an evacuation process for each level of occupancy. The results are the average of 10 randomized simulation runs, and error bars show the min/max result in any of the 10 simulation runs.

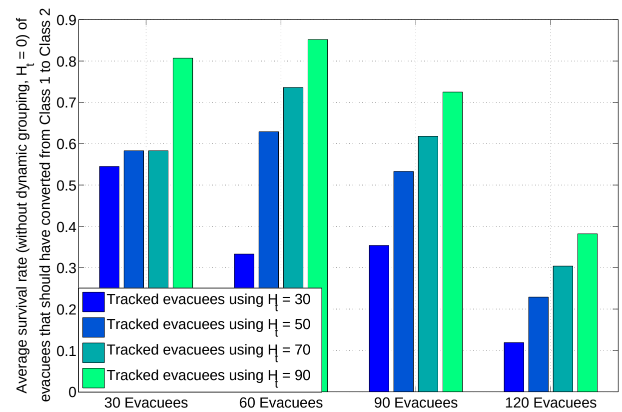

Fig. 9. The average survival rate of tracked evacuees that should have converted from Class 1 to Class 2 in scenarios without dynamic grouping for the different values of H_t. For example, “tracked evacuees using H_t = 30” shows the survival rate of evacuees that should have changed Class when H_t = 30. The results are the average of 10 randomized simulation runs.

Figure 7 shows the average number of evacuees that use the dynamic grouping mechanism. It clearly shows that, with the increase of H_t, more evacuees use dynamic grouping, and change from Class 1 to Class 2 during an evacuation. Figure 8 presents the survival rate S_c, of the number of Class-switching survivors and the evacuees that employ dynamic grouping, which is defined in 5.

$$S_c = \frac{N_s}{N_c} \tag{5}$$

where N_c is the total number of Class 1 evacuees that convert to Class 2 during an evacuation process as shown in Figure 7. Term N_s represents the number of survivors that change from Class 1 to Class 2. As expected, the results indicate that the survival rates increase with the growth of H_t. Figure 7 and Figure 8 implies that the growth of H_t can increase the number of survivors that change from Class 1 to Class 2. This is because if H_t is small, evacuees may get injured and have no remaining time, mobility or possibility to change to a safe path.

Figure 9 shows the average survival rate of evacuees that should have converted from Class 1 to Class 2 in scenarios without dynamic grouping. By comparing with Figure 8, we clearly see that the dynamic grouping mechanism can considerably improve the survival rate of these evacuees.

Figure 10 shows that the survival rates of original Class 2 evacuees remain steady regardless of the variation of H_t. This indicates that the original Class 2 evacuees are not

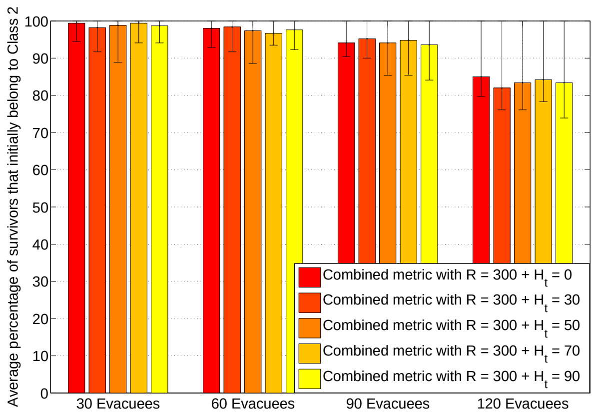

Fig. 10. The average percentage of survivors of the original Class 2 evacuees for each level of occupancy. The results are the average of 10 randomized simulation runs, and error bars show the min/max result in any of the 10 simulation runs.

remarkably affected when more Class 1 evacuees join Class 2. In other word, although dynamic grouping mechanism converts a number of Class 1 evacuees to Class 2, the newly-assigned Class 2 evacuees do not influence the evacuation process of original Class 2 civilians.

In summary, the first experiment indicates that tailoring different QoS requirements to different Classes of evacuees and dynamically assigning evacuees among Classes with respect to the on-going situation can improve the survival rates. Furthermore, the use of spatial information level R can improve the sensitivity of safety metric and also increase the survival rate. In the second experiment, we investigate the effect of varying H_t. The results show that a properly selected H_t can significantly improve the survival rate of Class 1 evacuees. Meanwhile, H_t does not have a obvious impact on the original Class 2 evacuees. Furthermore, the average percentage of survivors for diverse H_t (shown in Figure 6) is not very obvious at low occupancy rates because few evacuees will encounter the spreading hazard and switch their Classes.

V. Conclusions and Future work

In this paper, we propose a multi-path routing algorithm to direct different types of evacuees with respect to their on going requirements. The approach we propose is based on a situation where hazards, such as a fire, may move or change over time. Based on the CPN network routing algorithm, our proposed algorithm combines spatial hazard information into the routing metrics used by CPN to prevent evacuees from being guided into hazards and to offer a better prediction of the spread and location of the hazard. Specifically, the approach we use in this paper groups the evacuees dynamically based both on their physical condition and the hazards in their surroundings.

A dynamic grouping mechanism is studied and evaluated via simulations, to adjust both the type of evacuee and the associated decision algorithm with regard to evacuees' physical conditions and surroundings. The simulation results indicate that this QoS driven dynamic grouping algorithm provides improved performance to achieve higher evacuee survival rates. The simulation results also show that the appropriate setting of parameters, such as the range of the spatial hazard information, can significantly improve the performance of the evacuation algorithm. Hence, future research will focus on establishing a cloud-based faster-than-real-time simulator to select optimal parameters or choose appropriate emergency navigation algorithms, as a function of initial and ongoing conditions during an evacuation.

Additionally, to increase the reality of the simulation model, further research is needed to improve the accuracy of mobility models by using the empirical relation between the density and speed of evacuees [64], [65] . Further validation of the algorithms that we propose with the empirical collective behaviour of human beings from actual crowd measurements [66], [67] will be useful, and the 3D effects of interacting evacuees can also be studied through augmented reality technologies [19].

References

[1] G. Vizzari, L. Manenti, and L. Crociani, "Adaptive pedestrian behaviour for the preservation of group cohesion," *Complex Adaptive Systems Modeling*, vol. 1, no. 7, pp. 1–29, 2013.

[2] S. Bandini, S. Manzoni, and G. Vizzari, "Situated cellular agents: a model to simulate crowding dynamics," *IEICE Transactions on Information and Systems: Special Issue on Cellular Automata*, vol. E87-D(3), pp. 669–676, 2004.

[3] G. C. Sirakoulis and S. B. (Eds.), *Cellular Automata - 10th International Conference on Cellular Automata for Research and Industry, ACRI 2012*. LNCS 7495, Springer, 2012.

[4] Y. F. Yu and W. G. Song, "Cellular automaton simulation of pedestrian counter flow considering the surrounding environment," *Physical Review E*, vol. 75, p. 046112, 2007.

[5] K. Nishinari, K. Sugawara, T. Kazama, A. Schadschneider, and D. Chowdhury, "Modelling of self-driven particles: foraging ants and pedestrians," *Physica A*, vol. 372, pp. 132–141, 2006.

[6] I. Georgoudas, G. Sirakoulis, and I. Andreadis, "An anticipative crowd management system preventing clogging in exits during pedestrian evacuation process," *IEEE Systems Journal*, vol. 5, no. 1, pp. 129–141, 2011.

[7] C. Burstedde, K. Klauck, A. Schadschneider, and J. Zittartz, "Simulation of pedestrian dynamics using a two-dimensional cellular automaton," *Physica A*, vol. 295, pp. 507–525, 2004.

[8] D. Helbing, I. Farkas, and T. Vicsek, "Simulating dynamical features of escape panic," *Nature*, vol. 407, pp. 487–490, 2000.

[9] E. Gelenbe and F.-J. Wu, "Large scale simulation for human evacuation and rescue," *Computers & Mathematics with Applications*, vol. 64, no. 12, pp. 3869–3880, 2012. [Online]. Available: http://dx.doi.org/10.1016/j.camwa.2012.03.056

[10] E. Gelenbe and G. Loukas, "A self-aware approach to denial of service defence," *Computer Networks*, vol. 51, no. 5, pp. 1299–1314, April 2007.

[11] E. Gelenbe, "Search in unknown random environments," *Physical Review E*, vol. 82, p. 061112, 2010.

[12] E. Spartalis, I. G. Georgoudas, and G. C. Sirakoulis, "Ca crowd modeling for a retirement house evacuation with guidance," in *Cellular Automata*. Springer, 2014, pp. 481–491.

[13] F. Müller, O. Wohak, and A. Schadschneider, "Study of influence of groups on evacuation dynamics using a cellular automaton model," *Transportation Research Procedia*, vol. 2, pp. 168–176, 2014.

[14] E. Gelenbe, N. Schmajuk, J. Staddon, and J. Reif, "Autonomous search by robots and animals: A survey," *Robotics and Autonomous Systems*, vol. 22, no. 1, pp. 23–34, 1997.

[15] C. Belta and V. Kumar, "Abstraction and control for groups of robots," *Robotics, IEEE Transactions on*, vol. 20, no. 5, pp. 865–875, 2004.

[16] E. Gelenbe and J.-M. Fourneau, "Random neural networks with multiple classes of signals," *Neural Computation*, vol. 11, no. 4, pp. 953–963, 1999.

[17] E. Gelenbe, "The first decade of g-networks," *European Journal of Operational Research*, vol. 126, no. 2, pp. 231–232, 2000.

[18] E. Gelenbe and Y. Cao, "Autonomous search for mines," *European Journal of Operational Research*, vol. 108, no. 2, pp. 319–333, 1998.

[19] E. Gelenbe, K. Hussain, and V. Kaptan, "Simulating autonomous agents in augmented reality," *Journal of Systems and Software*, vol. 74, no. 3, pp. 255–268, 2005.

[20] X. Zheng, T. Zhong, and M. Liu, "Modeling crowd evacuation of a building based on seven methodological approaches," *Building and Environment*, vol. 44, no. 3, pp. 437–445, 2009.

[21] S. Gwynne, E. Galea, M. Owen, P. J. Lawrence, L. Filippidis *et al.*, "A review of the methodologies used in evacuation modelling," *Fire and Materials*, vol. 23, no. 6, pp. 383–388, 1999.

[22] Y. Yu and W. Song, "Cellular automaton simulation of pedestrian counter flow considering the surrounding environment," *Physical Review E*, vol. 75, no. 4, p. 046112, 2007.

[23] D. Helbing and P. Molnar, "Social force model for pedestrian dynamics," *Physical review E*, vol. 51, no. 5, p. 4282, 1995.

[24] L. Henderson, "The statistics of crowd fluids," *Nature*, vol. 229, pp. 381–383, 1971.

[25] D. Helbing, I. J. Farkas, P. Molnar, and T. Vicsek, "Simulation of pedestrian crowds in normal and evacuation situations," *Pedestrian and evacuation dynamics*, vol. 21, pp. 21–58, 2002.

[26] R. L. Goldstone and M. A. Janssen, "Computational models of collective behavior," *Trends in cognitive sciences*, vol. 9, no. 9, pp. 424–430, 2005.

[27] E. Bonabeau, "Agent-based modeling: Methods and techniques for simulating human systems," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 99, no. Suppl 3, pp. 7280–7287, 2002.

[28] E. D. Kuligowski, R. D. Peacock, and B. Hoskins, *A review of building evacuation models*. US Department of Commerce, National Institute of Standards and Technology, 2005.

[29] E. Gelenbe and F.-J. Wu, "Future research on cyber-physical emergency management systems," *Future Internet*, vol. 5, no. 3, pp. 336–354, 2013.

[30] F. Baccelli, E. Gelenbe, and B. Plateau, "An end-to-end approach to the resequencing problem," *Journal of the ACM*, vol. 31, no. 3, pp. 474–485, 1984.

[31] S. Belardo, K. R. Karwan, and W. Wallace, "An investigation of system design considerations for emergency management decision support," *Systems, Man and Cybernetics, IEEE Transactions on*, no. 6, pp. 795–804, 1984.

[32] L. Chalmet, R. Francis, and P. Saunders, "Network models for building evacuation," *Fire Technology*, vol. 18, no. 1, pp. 90–113, 1982.

[33] Q. Lu, B. George, and S. Shekhar, "Capacity constrained routing algorithms for evacuation planning: A summary of results," in *Advances in spatial and temporal databases*. Springer, 2005, pp. 291–307.

[34] Q. Lu, Y. Huang, and S. Shekhar, "Evacuation planning: a capacity constrained routing approach," in *Intelligence and Security Informatics*. Springer, 2003, pp. 111–125.

[35] A. Desmet and E. Gelenbe, "Graph and analytical models for emergency evacuation," *Future Internet*, vol. 5, no. 1, pp. 46–55, 2013.

[36] L. Kerbache and J. M. Smith, "Multi-objective routing within large scale facilities using open finite queueing networks," *European Journal of Operational Research*, vol. 121, no. 1, pp. 105–123, 2000.

[37] M. Barnes, H. Leather, and D. Arvind, "Emergency evacuation using wireless sensor networks," in *Local Computer Networks, 2007. LCN 2007. 32nd IEEE Conference on*. IEEE, 2007, pp. 851–857.

[38] Y.-C. Tseng, M.-S. Pan, and Y.-Y. Tsai, "Wireless sensor networks for emergency navigation," *Computer*, vol. 39, no. 7, pp. 55–62, 2006.

[39] E. Gelenbe and S. Timotheou, "Random neural networks with synchronized interactions," *Neural Computation*, vol. 20, no. 9, pp. 2308–2324, 2008.

[40] A. Jankowska, M. C. Schut, and N. Ferreira-Schut, "A wireless actuator-sensor neural network for evacuation routing," in *Sensor Technologies and Applications, 2009. SENSORCOMM'09. Third International Conference on*. IEEE, 2009, pp. 139–144.

[41] Q. Li, Z. Fang, Q. Li, and X. Zong, "Multiobjective evacuation route assignment model based on genetic algorithm," in *Geoinformatics, 2010 18th International Conference on*. IEEE, 2010, pp. 1–5.

[42] L. Han, S. Potter, G. Beckett, G. Pringle, S. Welch, S.-H. Koo, G. Wickler, A. Usmani, J. L. Torero, and A. Tate, "Firegrid: an e-infrastructure for next-generation emergency response support," *Journal of Parallel and Distributed Computing*, vol. 70, no. 11, pp. 1128–1141, 2010.

[43] J. Radianti, O.-C. Granmo, P. Sarshar, M. Goodwin, J. Dugdale, and J. J. Gonzalez, "A spatio-temporal probabilistic model of hazard-and crowd dynamics for evacuation planning in disasters," *Applied Intelligence*, vol. 42, no. 1, pp. 3–23, 2015.

[44] E. Gelenbe and R. R. Muntz, "Probabilistic models of computer systems, part i (exact results)," *Acta Informatica*, vol. 7, pp. 35–60, 1976.

[45] E. Gelenbe, "A unified approach to a class of page replacement algorithms," *IEEE Transactions on Computers*, vol. 22, no. 6, pp. 611–618, July 1973.

[46] Q. Li, M. De Rosa, and D. Rus, "Distributed algorithms for guiding navigation across a sensor network," in *Proceedings of the 9th annual international conference on Mobile computing and networking*. ACM, 2003, pp. 313–325.

[47] E. Gelenbe and G. Gorbil, "Wireless networks in emergency management," in *Proceedings of the first ACM international workshop on Practical issues and applications in next generation wireless networks*. ACM, 2012, pp. 1–6.

[48] E. Gelenbe, G. Gorbil, and F.-J. Wu, "Emergency cyber-physical-human systems," in *Computer Communications and Networks (ICCCN), 2012 21st International Conference on*. IEEE, 2012, pp. 1–7.

[49] E. Gelenbe and H. Bi, "Emergency navigation without an infrastructure," *Sensors*, vol. 14, no. 8, pp. 15 142–15 162, 2014. [Online]. Available: http://www.mdpi.com/1424-8220/14/8/15142

[50] A. Filippoupolitis and E. Gelenbe, "A distributed decision support system for building evacuation," in *Human System Interactions, 2009. HSI'09. 2nd Conference on*. IEEE, 2009, pp. 323–330.

[51] A. Filippoupolitis, "Emergency simulation and decision support algorithms," Ph.D. dissertation, Imperial College London (University of London), 2010.

[52] E. Gelenbe, Z. Xu, and E. Seref, "Cognitive packet networks," in *Tools with Artificial Intelligence, 1999. Proceedings. 11th IEEE International Conference on*. IEEE, 1999, pp. 47–54.

[53] E. Gelenbe, E. Şeref, and Z. Xu, "Simulation with learning agents," *Proceedings of the IEEE*, vol. 89, no. 2, pp. 148–157, February 2001.

[54] E. Gelenbe, "Steps toward self-aware networks," *Communications of the ACM*, vol. 52, no. 7, pp. 66–75, 2009.

[55] ——, "Sensible decisions based on qos," *Computational Management Science*, vol. 1, no. 1, pp. 1–14, 2003.

[56] E. Gelenbe and A. Stafylopatis, "Global behavior of homogeneous random neural systems'," *Applied Mathematical Modelling*, vol. 15, no. 10, pp. 534–541, October 1991.

[57] A. Desmet and E. Gelenbe, "A parametric study of cpn's convergence process," in *Information Sciences and Systems 2014 - Proceedings of the*

29th International Symposium on Computer and Information Sciences, ISCIS 2014, Krakow, Poland, October 27-28, 2014, 2014, pp. 13–20.

[58] ——, “Graph and analytical models for emergency evacuation,” *Future Internet*, vol. 5, no. 1, pp. 46–55, 2013. [Online]. Available: http://dx.doi.org/10.3390/fi5010046

[59] N. Dimakis, A. Filippoupolitis, and E. Gelenbe, “Distributed building evacuation simulator for smart emergency management,” *The Computer Journal*, vol. 53, no. 9, pp. 1384–1400, 2010.

[60] G. Gorbil and E. Gelenbe, “Disruption tolerant communications for large scale emergency evacuation,” in *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2013 IEEE International Conference on*. IEEE, 2013, pp. 540–546.

[61] J. J. Fruin, “Pedestrian planning and design,” Tech. Rep., 1971.

[62] H. Frantzich, “Study of movement on stairs during evacuation using video analysing techniques,” *LUTVDG/TVBB–3079–SE*, 1996.

[63] I. TranSafety, “Study compares older and younger pedestrian walking speeds,” *Road Management & Engineering Journal*, October 1997.

[64] A. Seyfried, B. Steffen, W. Klingsch, and M. Boltes, “The fundamental diagram of pedestrian movement revisited,” *Journal of Statistical Mechanics: Theory and Experiment*, vol. 2005, no. 10, p. P10002, 2005.

[65] A. Johansson, D. Helbing, H. Z. Al-Abideen, and S. Al-Bosta, “From crowd dynamics to crowd safety: a video-based analysis,” *Advances in Complex Systems*, vol. 11, no. 04, pp. 497–527, 2008.

[66] H. Klüpfel, T. Meyer-König, and M. Schreckenberg, “Comparison of an evacuation exercise in a primary school to simulation results,” in *Traffic and Granular Flow01*. Springer, 2003, pp. 549–554.

[67] A. Tsiftsis, I. Georgoudas, and G. Sirakoulis, “Real data evaluation of a crowd supervising system for stadium evacuation and its hardware implementation,” *Systems Journal, IEEE*, vol. PP, no. 99, pp. 1–12, 2015.

Olumide J. Akinwande pursues his PhD in Electrical and Electronic Engineering at Imperial College in the Intelligent Systems and Networks Group. He obtained his Master of Science degree in Control Systems from Imperial College, London, in 2014. His research interests include systems analysis, emergency management and discrete event simulation, and routing in packet networks. He received his BSc degree in Computer Engineering from the University of Lagos, Nigeria, in 2011.

Huibo Bi is a PhD candidate since 2012 in Electrical and Electronic Engineering at Imperial College in the Intelligent Systems and Networks Group. He has been active in recent years in designing and evaluating emergency management algorithms for evacuating people in built environments, and his research interests include computer networks and systems, sensor networks, emergency management and discrete event simulation. He received the B.S. degree from Qingdao University of Science & Technology and the M.E. degree from Chongqing University, P.R. China, in 2009 and 2012, respectively. His research interests include emergency navigation, disaster management and distributed computing.

Erol Gelenbe is Professor in Computer Communications at Imperial College London, and holds the Dennis Gabor Chair in the Department of Electrical and Electronic Engineering. A Life Fellow of the IEEE, and Fellow of ACM and IET (London), he graduated in Electrical and Electronic Engineering from the Middle East Technical University (Ankara), and then received Master’s and PhD degrees from the Polytechnic Institute of New York University as a Fulbright and NATO Science Fellow. He invented stochastic networks such as the G-Network class of solvable queueing models and the Random Neural Network, established their product form solutions and learning algorithms, and created the team that designed the commercial Queueing Network Analysis (QNAP) performance modelling package at INRIA. His other practical achievements include the FLEXSIM object-oriented Flexible Manufacturing System simulation method, the Distributed Building Evacuation Simulator DBES, the Cognitive Packet Network routing algorithm, the first random access fibre optics network XANTHOS and the multiprocessor voice packet based switch SYCOMORE. He is a Fellow of the Académie Nationale des Technologies (French National Academy of Engineering and Technology), the Royal Academy of Belgium, the Science Academies of Hungary, Poland and Turkey, and Academia Europaea. His honours include Chevalier de la Légion d’Honneur and Officier du Mérite (France), and Commendatore al Merito della Repubblica (Italy). His recent papers appear in the Physical Review, and in various ACM and IEEE journals.