Evacuee Flow Optimisation Using G-network with Multiple Classes of Positive Customers

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***Abstract*—Previous queueing theory based emergency navigation algorithms in built environments normally treat each significant location (such as doorways and staircases) as an "independent" queue and all the evacuees in a homogeneous manner. Hence, the interactions among linked queues caused by the re-routing instructions generated by the emergency navigation system, the panic behaviours such as evacuees not following the evacuation instructions, as well as the influence of diverse mobilities of evacuees are ignored. In this paper, we employ a Cognitive Packet Network based algorithm to customise distinct paths for diverse categories of evacuees. A G-network based model is used to analyse the latency on a path via capturing the dynamics of diverse categories of evacuees under the influence of panic and re-routing decisions from the navigation system. Moreover, by modelling the probabilistic choices of evacuees towards all the linked queues, the G-network model closely approximates the movement of the evacuees under the instructions of the Cognitive Packet Network based algorithm. The simulation results indicate that the use of the G-network model can improve the survival rates and ease the congestion during an evacuation process when there is a certain likelihood that evacuees do not follow evacuation instructions due to panic.**

***Keywords*-emergency navigation; G-network; diverse evacuees; congestion management;**

I. Introduction

Since destructive crowd behaviours such as herding and trampling caused by congestion can induce serious injuries and fatalities during an evacuation process, sometimes even more severe than losses caused by fire, many congestion-free algorithms or congestion-ease algorithms have been proposed to optimise the evacuee flows. Congestion-free algorithms such as the network flow based algorithms [1], [2] allocate evacuees to building components such as rooms, stairs and corridors with respect to their capacity. However, these algorithms are suitable for normal evacuations but are impractical in emergency situations since the spreading of the hazard is not taken into account. Moreover, in order to avoid congestion, evacuees must reach each target position precisely on schedule and may have to wait idly at certain locations, which is unrealistic in an emergency evacuation process. On the other hand, congestion-ease algorithms such as queueing model based algorithms [3], [4], [5], [6], [7] and routing protocol based algorithms [8], [9], [10] re-assign evacuees to less-congested paths in accordance with the collected sensory information. Queueing model based algorithms normally estimate the potential number of evacuees at each node on a path in terms of the arrival rate and service rate, and redirect evacuees accordingly. The major drawback of these algorithms is that they consider each node (such as a doorway) as an independent "queue" rather than considering all the nodes as a "queueing network" and ignore the interaction effects among "queues". Routing protocol based algorithms commonly send network packets to collect congestion information on the paths and utilise network routing protocols to optimise the evacuee flows. However, network routing protocol based algorithms normally make decisions based on the collected congestion information rather than the estimated congestion level of a path. Therefore, when evacuees traverse that path, the congestion status could have changed owing to the highly dynamic nature of an evacuation process. Hence, in this paper, a queueing network model namely G-network [11], [12] is utilised to analyse and estimate the congestion level at each node by capturing the dynamics of diverse categories of evacuees from a global point of view and a Cognitive Packet Network (CPN) [13], [14], [15] based algorithm is used to direct diverse categories of evacuees to exits.

The remainder of this paper is organised as follows. Section II reviews the literature relevant to our work. Then we describe the framework of the cloud enabled emergency navigation system in Section III. The system approximation model and the routing metrics used to customise distinct paths for evacuees are described in Section IV and V, respectively. The simulation models and assumptions are introduced in Section VI and the experimental results are presented in Section VII. Finally, we draw conclusions in Section VIII.

II. Related Work

A. Queue theory based Emergency Navigation Algorithms

Owing to the stochastic, highly transient and nonlinear nature of an evacuation process, queueing models have been proven as a useful tool to capture and analyse the dynamics

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of evacuees. Normally, by treating significant locations such as doorways or staircases as "servers", queueing model based approaches [16], which generalise the Markovian models of computer systems [17], transfer building graphs to a queueing network or a number of isolated "queues" to estimate congestion and evacuation delays. For instance, the process of pedestrians traversing a corridor or stairwell is analysed as a state-dependent process in Ref. [3], a $M/G/C/C$ state-dependent queue model is utilised to estimate the congestion delays at corridors or stairwells and the overall evacuation time of an evacuation process; the pedestrian flows are classified into three categories: uni-directional flow, bi-directional flow and multi-directional flow; the relationship between the crowd density and the mean walking velocity of evacuees in the three categories of pedestrian flows are derived from Ref. [18]; the capacity of a corridor or stairwell is calculated based on Ref. [19], which indicates that the evacuee flow will cease to move when the population density reaches 5 evacuees per square meter; the state-dependent service rate of the three categories of pedestrian flows can be calculated in terms of the mean walking speed and the corridor capacity; finally, the time cost for an evacuee flow to traverse a corridor or a stairwell can be computed by the mean value analysis (MVA) algorithm introduced in Ref. [20]. To ensure no corridors will be blocked during an evacuation process in a built environment, Ref. [4] considers the evacuation planning problem as a service and capacity allocation (SCA) problem and searches the smallest feasible capacity of each corridor via modelling the building as a $M/G/c/c$ queueing network; the $M/G/c/c$ queueing network model is employed to calculate the average queue length at each corridor with the following steps: (1) the average walking speed V_n of n evacuees in a corridor is calculated by the equations derived from the congestion model proposed in Ref. [21], (2) the state-dependent service rate $f(n)$ with n evacuees in a corridor can be computed by $f(n) = \frac{V_n}{V_1}$, where V_1 is the average speed of a lone evacuee, (3) term p_n, which is the probability of n evacuees in a corridor can be calculated by the equations derived from Ref. [22], (4) the average queue length of a corridor can then be computed by $L = \sum_{n=1}^{c} np_n$; to analyse the smallest capacity of each individual corridor, the generalised expansion method [23], [24] is used to expand the $M/G/c/c$ queueing network into an equivalent Jackson network via adding an artificial holding node in front of each finite queue to register the blocked evacuees due to capacity limitation; after decomposing the queueing network, a local search algorithm inspired by Ref. [25] is used to search the smallest feasible capacity of each queue. Similarly, Ref. [6], [26] utilise a $M/G/c/c$ queue model to simulate the dynamics and predict the overall evacuation time of an egress process without hazard; rooms, corridors and stairways are modelled as queues in which the service rate depends on the evacuee density; doors, exits and gateways are imitated as queues in which the service rate depends on not only the evacuee density, but also the faster-is-slower effect [27] and the crowd impatience [28]; to validate the effectiveness of the queue system, a discrete-event simulation model is implemented via the SimEvents toolbox in the MATLAB/Simulink environment and experimental results show that the egress time of evacuees in simulations highly matches with the prediction of the proposed queueing model. Rather than simulating all the building components as $M/G/c/c$ queues, Ref. [29] models doorways that can pass one person at a time as $M/M/1$ queues; on the other hand, corridors or stairs are modelled as $M/G/\infty$ queues, in which the infinite number of servers implies that no congestion occurs in corridors or stairs. Rather than using traditional closed network models which suffer from high computational costs, Ref. [7] proposes a computationally efficient open network model with product form to predict the congestion level at each point of interest and the overall evacuation time with respect to the average arrival and departure rate at each observation point; by assuming Poisson arrivals of evacuees at each originating location, uni-directional corridors that allow at most one evacuee to pass at a time and exponentially traversal delay at each corridor, a $M/M/1$ queue model is established to mimic each corridor; hence, the average delay at a corridor can be calculated by $\frac{1}{\mu-\lambda}$, where $\frac{1}{\mu}$ represents the average traversal time of a corridor and λ represents the average arrival rate of evacuees at a corridor; the average traversal time of a path can be calculated by summing the average delay of each corridor on it.

B. *Emergency Navigation Algorithms for Diverse Evacuees*

The differences among evacuees in terms of age, gender, mobility and psychology can aggravate destructive crowd behaviours such as clogging, pushing and trampling, and therefore can induce unnecessary fatalities and injuries. Hence, many crowd behaviour models such as cellular automata models [30] and agents based models [31] have been proposed to investigate the influence of diverse categories of evacuees to an evacuation process. For instance, Ref. [32] has proposed a heterogeneous cellular automata model to mimic the evacuation process in a retirement house; evacuees initially belong to three groups (middle-aged people, nursing staff and older people), and groups can also be formed dynamically due to the follow-the-leader effect. Ref. [33] presents a prototype multi-agent simulation system that can build a virtual environment with autonomous agents for safe egress analysis; the proposed system consists of a geometric engine that represents the physical environment with AutoCAD, a population generator that can produce evacuee agents with diverse age, mobility, etc., a global database which maintains all the state information of agents; a events recorder that captures the behaviours of evacuee agents, a visualiser which displays the movement of evacuees, a crowd simulation engine that is assigned to each evacuee agent to manage the individual behaviour in terms of the perception-action approach [34]; each evacuee agent is modelled to make decisions based on three basic conventions: instinct, experience and bounded rationality [35]; some emergent behaviours such as competitive, queueing and herding are observed in the simulation.

On the other hand, limited research has been dedicated to guide diverse categories of evacuees with online emergency navigation algorithms which aim to provide evacuation paths for evacuees in a real time manner. Ref. [36], [37] have proposed a multi-path routing algorithm to direct diverse classes of evacuees out of a built environment; the proposed routing protocol is inspired by the Cognitive Packet Network, which was originally designed for large-scale multimedia packet networks to fulfil the different quality of service (QoS) requirements of diverse end-users; evacuees are classified into four types: aged people, prime-aged people, children or ill people, and disabled people in electric powered wheelchairs; for each type of evacuees, an associated class of path-finding cognitive packets called "smart packets" is utilised to search egress routes: routes with the shortest distance to exits for aged people, routes with the shortest time to exits for prime-aged people, routes with the highest safety level for children or ill people, and routes with the lowest energy utilisation for disabled people in electric powered wheelchairs. Since studies indicate that cooperative collective behaviours can benefit an evacuation process [38], Ref. [39] proposes an extended indoor emergency navigation algorithm to dynamically re-assign evacuees to different groups with respect to their on-going health conditions and mobility, and to offer appropriate egress paths for each group of evacuees; evacuees are divided into two classes (Class 1 and Class 2) in terms of age, mobility, and level of resistance to fatigue and hazard; for Class 1 evacuees, a time-oriented routing algorithm is used to search paths with the shortest time to exits; for Class 2 evacuees, a safety-oriented routing algorithm is employed to search the safest paths with the shortest distance to exits; a virtual health value is maintained by portable devices carried by evacuees, when the health value of a Class 1 evacuee drops below a certain threshold, it will be re-assigned to Class 2 and follow a safety-oriented path to the exit.

III. System Description

To guide evacuees out of a hazardous built environment, we propose a hybrid indoor emergency response system that integrates an on-site wireless sensor network (WSN) which consists of sensor nodes (SNs) and communication nodes (CNs), and an off-site cloud based decision support subsystem (CDSS). SNs and CNs are pre-installed at Points of Interest (PoIs) such as doorways or corridors where evacuees may congregate. SNs are utilised to collect hazardous information from their surrounding environment and record the arrival and departure of evacuees in proximity. CNs are responsible for relaying information among SNs, evacuees and the CDSS: sensory information gathered from a SN is transmitted to a CN in proximity and then uploaded to the CDSS. On the other hand, evacuation instructions such as suggested paths are transmitted to CNs and then sent to smart phones carried by evacuees in the vicinity of CNs. The CDSS is introduced to perform intensive computations due to limited computing power of the on-site WSN. A graph representation of the physical built environment is reconstructed on the cloud server. Each PoI is coupled with a computer agent to manage the uploaded sensory data from the SN installed at this PoI and calculate desired paths for evacuees in the vicinity of the PoI. A virtual CPN node is installed at each computer agent to generate smart packets to retrieve sensory information from other agents and search egress paths for evacuees. The discovered paths are stored in a routing list of each virtual CPN node, the top-ranked paths will be sent to evacuees as suggested evacuation instructions. A G-network model with multiple classes of positive customers is also deployed in the CDSS to analyse the congestion level of paths.

Evacuees are assumed to carry portable devices that can receive evacuation instructions within the communication range of CNs. To avoid the possible direction oscillation problem [40] caused by communication latency or the fast-changing environment, previous work [8], [36] set a movement depth for evacuees to restrict the number of nodes that an evacuee should traverse before accepting new path suggestions. Hence, portable devices only display new path suggestions for evacuees when fulfilling the movement depth restriction. In this paper, we set a similar timeout value for the received path suggestion. When the previous path suggestion is expired, the portable devices carried by evacuees are allowed to receive new paths from the next CN in contact. However, if a hazard is detected in the vicinity of a SN, the path suggestion stored in the portable devices in proximity will be considered as expired and thus disposed, so evacuees can instantly receive the latest path suggestions from the SN and can switch paths to avoid being directed into the hazard.

IV. System Approximation Model

The physical environment of the targeted building is represented by a directed graph consisting of nodes and edges. Nodes represent PoIs where evacuees of the same class are handled in a first-come-first-served manner while evacuees of different classes can be served in parallel. Sensors are installed near the PoIs to collect the necessary information. Edges are the physical links between PoIs, and are modelled as a processor sharing system [41] to represent the facts that the time taken to traverse an edge is affected by the number of evacuees on it. In contrast with previous queueing theory based algorithms which treat

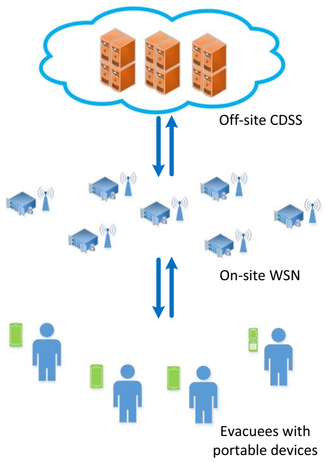

Figure 1. The architecture of the proposed system.

each node as an independent queue and all the evacuees in a homogeneous manner, we employ a G-network model with multiple classes of positive customers to analyse the interaction effects among evacuees, the effects of routing decisions towards evacuees, and the influence of diverse mobilities of evacuees towards an evacuation process.

G-networks [12], which were inspired by the random neural network [42], are a class of queueing network models with additional control capabilities such as negative customers [11] that remove normal positive customers from the system, batch removals [43], triggers [43] and resets [44]. G-networks have been used in a wide range of applications, including describing the workload in computer systems [45], [46], realising energy efficiency in packet networks [47], as well as modelling energy systems [48], [49], populations of biological agents [50], gene regulatory networks [51] and large-scale evacuations [52].

The model that is utilised to capture the dynamics of an evacuation process and analyse the effects of diverse mobilities, routing suggestions from the navigation system and the interactions among evacuees is based on the G-network model with multiple classes of signals and positive customers [53]. Positive customers and triggers in the original model are employed to represent evacuees and routing suggestions from the navigation system, respectively. Negative customers in the original model are removed since they do not have any specific entity to represent.

When an emergency occurs, since evacuees within a building will not begin to evacuate at the same time, the average external arrival rate $\Lambda_{n_i,k}$ of evacuee category k at a PoI n_i can be computed by the sensor node in proximity via recording the time when signals of the smart phone carried by evacuees of category k are detected. The average service rate of evacuee category k at PoI n_i is denoted by $r_{n_i,k}$ which depends on the area of the PoI and the average velocity of this class of evacuees. An evacuee of class k that leaves PoI n_i will either head to another connected PoI n_j with probability $P(n_i, n_j, k)$ or stop near the PoI n_i due to injury or fatality with probability $d_{n_i,k}$, hence, we have:

$$d_{n_i,k} + \sum_{j=1}^{N} P(n_i, n_j, k) = 1 \tag{1}$$

where N is the total number of PoIs in the building.

In our case, the probability $P(n_i, n_j, k)$ for an evacuee of class k to traverse from PoI n_i to a linked PoI n_j can be determined by the suggested path given by the emergency navigation system. If PoI n_j belongs to the suggested path, then $P(n_i, n_j, k) = 1$, otherwise, $P(n_i, n_j, k) = 0$.

Owing to the highly dynamic nature of a hazardous environment caused by the spreading hazard and the unstable evacuee flows, evacuees should update their egress paths frequently. Hence, in addition to the initial egress paths, re-routing decisions from the cloud-based system arrive to PoI n_i with average rate $\lambda^-_{n_i}$, instructing evacuees of class k in vicinity to move to PoI n_j with probability $Q(n_i, n_j, k)$, where $\sum_{j=1}^{N} Q(n_i, n_j, k) = 1$. The probability $Q(n_i, n_j, k)$ is affected by the suggested path (which is the top-ranked path discovered by smart packets in the Cognitive Packet Network based algorithm) and the pre-set time-out value of the path suggestion. The time-out value, which is employed to avoid path oscillation, is the time interval that an evacuee must stick to the previous path suggestion before accepting a new path suggestion. Additionally, in reality, evacuees may not follow the evacuation instructions owing to panic or other psychological reasons. Hence, $Q(n_i, n_j, k)$ is also affected by the panic behaviours. The algorithm to determine $Q(n_i, n_j, k)$ is detailed in Algorithm 1, and a list of symbols used in the algorithm is summarised in Table I

Notation	Definition
$S^c_{n_i,k}$	Represents the next hop on the current (latest) suggested path of evacuee class k from the source node n_i
$S^p_{n_i,k}$	Represents the next hop on the previous suggested path of evacuee class k from the source node n_i
n_j	Represents a neighbour node of the node n_i
P_{er}	Represents the probability for an evacuee to randomly choose the next node due to panic
T_t	Represents the time-out value of a suggested path
T_e	Represents the time elapsed from the node n_i received the current suggested path
N_n	Represents the number of neighbour nodes of the node n_i

Table I
LIST OF SYMBOLS USED IN THE ALGORITHM 1.

With these assumptions, the steady-state probability that a PoI n_i has one or more evacuees of class k is given by [53]:

$$q_{n_i,k} = \frac{\lambda^+_{n_i,k}}{r_{n_i,k} + \lambda^-_{n_i,k}} \tag{2}$$

Algorithm 1 The process of determining $Q(n_i, n_j, k)$

for all the neighbour node n_j of the node n_i **do**
  if $S^c_{n_i,k} = S^p_{n_i,k}$ **then**
    if $n_j = S^c_{n_i,k}$ **then**
      $Q(n_i, n_j, k) = 1 - P_{er} + \frac{P_{er}}{N_n}$
    else
      $Q(n_i, n_j, k) = \frac{P_{er}}{N_n}$
    end if
  else
    if $T_e < T_t$ **then**
      if $n_j = S^p_{n_i,k}$ **then**
        $Q(n_i, n_j, k) = (1 - P_{er}) \times \frac{T_t - T_e}{T_t} + \frac{P_{er}}{N_n}$
      else if $n_j = S^c_{n_i,k}$ **then**
        $Q(n_i, n_j, k) = (1 - P_{er}) \times \frac{T_e}{T_t} + \frac{P_{er}}{N_n}$
      else
        $Q(n_i, n_j, k) = \frac{P_{er}}{N_n}$
      end if
    else
      if $n_j = S^c_{n_i,k}$ **then**
        $Q(n_i, n_j, k) = 1 - P_{er} + \frac{P_{er}}{N_n}$
      else
        $Q(n_i, n_j, k) = \frac{P_{er}}{N_n}$
      end if
    end if
  end if
end for

where $\lambda^+_{n_i,k}$ is the total average arrival rate of evacuee class k to PoI n_i, including evacuees that were initially at n_i and are arrived from other PoIs:

$$\lambda^+_{n_i,k} = \Lambda_{n_i,k} + \sum_{j=1}^{N} q_{n_j,k}[r_{n_j,k}P(n_j, n_i, k) + \lambda^-_{n_j,k}Q(n_j, n_i, k)] \tag{3}$$

Notice that the quantities $q_{n_i,k}$ are coupled, and therefore (2) is a nonlinear equation that can be solved numerically. Term $\Lambda_{n_i,k}$ is initially determined by $\frac{N^e_t R_k}{N T_r}$ and then adapts with the arrival of evacuees. Term N^e_t represents the total number of evacuees in the system, N stands for the total number of PoIs, R_k represents the approximate proportion of evacuee class k in the population and T_r represents the average reaction time of evacuees, which is the time interval between receiving the alarm message and starting the evacuation.

For the physical paths (edges) of the building, the arrival rate of evacuees of class k to a physical link e_{ij} connecting PoIs n_i and n_j can be calculated as:

$$\lambda^+_{e_{ij},k} = q_{n_i,k}[r_{n_i,k}P(n_i, n_j, k) + \lambda^-_{n_i,k}Q(n_i, n_j, k)] \tag{4}$$

Furthermore, towards evacuees of class k, the service rate of the edge e_{ij} is approximated by:

$$r_{e_{ij},k} = \frac{V_k}{L_{e_{ij}}} \tag{5}$$

where $L_{e_{ij}}$ is the physical length of the edge, and V_k is the average speed of an evacuee of class k when no other evacuees are concurrently using the path. The utilisation of the path segment then becomes:

$$\begin{aligned} q_{e_{ij},k} &= \frac{\lambda^+_{e_{ij},k}}{r_{e_{ij},k}} \\ &= q_{n_i,k}\frac{[r_{n_i,k}P(n_i, n_j, k) + \lambda^-_{n_i,k}Q(n_i, n_j, k)]L_{e_{ij}}}{V_k} \\ &\equiv q_{n_i,k}R(n_i, n_j, k) \end{aligned} \tag{6}$$

Hence, the total steady-state probability that node n_i has one or more evacuees is given by:

$$q_{n_i} = \sum_{k \in K} q_{n_i,k} \tag{7}$$

where term K is the number of categories of evacuees. Similarly, the total steady-state probability that edge e_{ij} is busy is given by:

$$q_{e_{ij}} = \sum_{k \in K} q_{e_{ij},k} \tag{8}$$

Based on (7) and (8), we can calculate the average number of evacuees at each PoI and edge:

$$N_{n_i} = \frac{q_{n_i}}{1 - q_{n_i}}, \quad N_{e_{ij}} = \frac{q_{e_{ij}}}{1 - q_{e_{ij}}} \tag{9}$$

Sometimes q_{n_i} and $q_{e_{ij}}$ may be larger than 1, then N_{n_i} and $N_{e_{ij}}$ are replaced by the empirical values.

Hence, by using Littles formula, the average traversal times on each PoI and edge are given by:

$$D_{n_i} = \frac{N_{n_i}}{\lambda^+_{n_i}}, \quad D_{e_{ij}} = \frac{N_{e_{ij}}}{\lambda^+_{e_{ij}}} \tag{10}$$

where $\lambda^+_{n_i}$ and $\lambda^+_{e_{ij}}$ are the total arrival rate of all evacuee classes entering node n_i and edge e_{ij}, respectively. They can be computed from expression (11).

$$\lambda^+_{n_i} = \sum_{k=1}^{K} \lambda^+_{n_i,k}, \quad \lambda^+_{e_{ij}} = \sum_{k=1}^{K} \lambda^+_{e_{ij},k} \tag{11}$$

where K is the categories of evacuees in the system. Since there are 3 categories of evacuees in this case, $K = 3$.

V. Routing Metrics

The proposed routing metrics are the QoS goals that are pursued by the smart packets (SPs) and optimised by the Random Neural Networks (RNN) [54], [55], [56] in the CPN. SPs are emitted by each CPN node in the CPN to search paths and collect information related to its QoS goal. When a SP reaches an exit, an acknowledgement will be generated and brought back all the gathered information to the origin node. At the origin node, the QoS value is calculated by the equations below and then used as the input of the RNN. For further information, a detailed discussion of the CPN routing algorithm can be found in [15]. The routing metrics we employ in this section are derived from [37] and contain three routing metrics: distance-oriented metric for aged evacuees, time-oriented metric for prime-aged evacuees and safety-oriented metric for children or ill evacuees. Each routing metric has an associated class of SPs.

The distance-oriented metric is used to search the shortest paths to exits and is suitable for evacuees with limited physical strength.

$$G_d = \sum_{i=1}^{n_\pi - 1} \frac{E_{e_{\pi(i),\pi(i+1)}}}{V_d} \tag{12}$$

where π represents a path discovered by a smart packet, n_π is the number of nodes on the path π, $E_{e_{\pi(i),\pi(i+1)}}$ represents the effective length of edge $e_{\pi(i),\pi(i+1)}$, $\pi(i)$ stands for the i-th node on the path π and V_d represents the average velocity of aged evacuees.

The time-oriented metric pursues the paths with the shortest time to exits. By utilising this metric, evacuees with high mobility can rapidly escape from the hazardous area via traversing less congested paths with longer distance to exits.

$$G_t = \sum_{i=1}^{n_\pi - 1} \left[D_{n_{\pi(i)}} + D_{e_{\pi(i),\pi(i+1)}} \right] \tag{13}$$

where $D_{n_{\pi(i)}}$ and $D_{e_{\pi(i),\pi(i+1)}}$ represent the delay at the node $n_{\pi(i)}$ and edge $e_{\pi(i),\pi(i+1)}$, respectively, which can be determined by (10).

The safety metric provides safest paths to evacuees with lower resistance to hazard.

$$\begin{aligned} G_s = \sum_{i=1}^{n_\pi - 1} \big\{ & 1[t_s + G_t(n_{\pi(i+1)}) < t_{hr}^{n_{\pi(i+1)}}] \cdot b\big(t_s + G_t(n_{\pi(i+1)}) \\ & - t_{hr}^{n_{\pi(i+1)}}\big) + E_{e_{\pi(i),\pi(i+1)}} \big\} \end{aligned} \tag{14}$$

where $1[x]$ is function that takes a value of 0 or 1 if x is true or false. Term t_s represents the time elapsed since the evacuation process started. Term $G_t(n_{\pi(i+1)})$ is the average time cost for an evacuee to reach node $\pi(n_{i+1})$ when traversing the path π, it can be determined by (13). Term b is the fire growth rate at a node. Term $t_{hr}^{n_{\pi(i+1)}}$ represents the time cost for the hazard to reach node $n_{\pi(i+1)}$, which can be calculated as follows.

$$t_{hr}^{n_{\pi(i+1)}} = \frac{L(n_{fsl}, n_{\pi(i+1)})}{a} \tag{15}$$

where n_{fsl} represents the fire source location, term $L(n_{fsl}, \pi(n_{i+1}))$ is the shortest distance between fire source location n_{fsl} and the target node $\pi(n_{i+1})$, term a is the fire spreading rate in cm/s.

VI. Simulation Model and Assumptions

To evaluate the proposed routing algorithm for diverse categories of evacuees, we employ a multi-agent based simulation tool, the Distributed Building Evacuation Simulator (DBES) [57] to conduct a series of fire-related simulations. In the DBES, various autonomous intelligent agents are used to create a virtual hazardous environment by simulating different entities (e.g. evacuees, hazards, buildings, wireless sensors) that can interact with each other. Since Ref. [58], which utilises a reinforcement learning approach with the RNN to guide manned vehicles within a dangerous metropolitan grid, shows that augmented reality-based simulation can achieve improved levels of realism in the representation of the physical settings, the DBES contains a augmented reality interface that integrates with a real wireless sensor network to capture real network effects such as packet loss and delay [59]. The building under consideration is the three lower floors of Imperial College's EEE building as shown in Fig. 2. Vertices represent PoIs, which are places that SNs and CNs are pre-installed, such as doorways, staircases or locations that evacuees may congregate, while edges represent physical paths between PoIs.

We assume there are 3 categories of evacuees: aged people, prime-aged people and children or ill people, and the population ratio among them is 1:3:1. Hence, 20% of the population is aged people or children/ill people, while 60% of the population is the prime-aged people. Each categories of simulated evacuees has different movement speeds and initial health values. The speed of the aged people, prime-aged people and children or ill people is set to 1.2 m/s, 1.5 m/s and 1.2 m/s, respectively. The health value of the aged people, prime-aged people and children or ill people is initialised to 100, 100 and 80, respectively. Each evacuee is assumed to carry a portable device with a pre-installed software that can provide necessary personal information (e.g. gender, age) to CNs in contact, so the system can identify the category of the evacuee. We also assume that the probability for an evacuee to randomly choose the next node due to panic is 0.1. In other word, at each PoI, evacuees have a 10% chance of picking the next hop randomly rather than following the path suggestion from the cloud servers.

The suggested paths at each PoI are calculated by the cloud servers arrive at the CNs every 4 seconds ($\lambda_{n_i,k}^- = 1/4$) and the time-out of a suggested path is set to 12 seconds ($T_t = 12$). Initially, the simulated evacuees are randomly distributed in the building.

VII. Results and Discussion

The experiments are carried out on scenarios with 30,60,90 and 120 evacuees in the aforementioned building model. Both the newly proposed algorithm that combines the CPN based algorithm with the G-network model

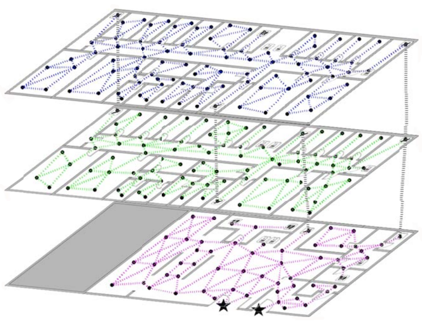

Figure 2. The graph based layout of Imperial College's EEE building. The black stars represent the exits on the ground floor.

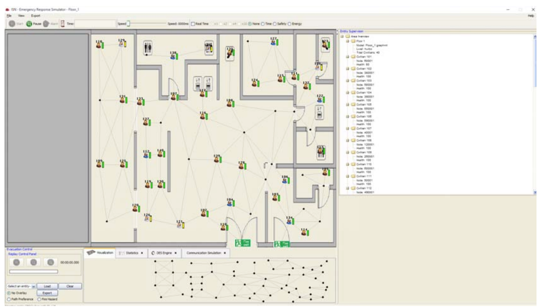

Figure 3. The GUI of the DBES.

with multiple classes of positive customers (CPNGNETWORK_MULTI) and the previous CPN based algorithm for diverse categories of evacuees [36], [37] (CPN_MULTI) are conducted for comparisons.

Figure 4 shows the average percentage of survivors for both algorithms. Compared with CPN_MULTI, CPNGNETWORK_MULTI achieves higher survival rates on the average in scenarios with different occupancy rates. This is because rather than treating each PoI as a independent queue in the CPN_MULTI algorithm, CPNGNETWORK_MULTI considers the interactions among linked queues with the aid of the G-network model. Hence, the effect of evacuees that do not follow the evacuation instructions is better represented and the predicted latencies at the nodes and on the edges are more accurate. Furthermore, by modelling the probabilities for a arrived routing suggestion to direct an evacuee to the linked nodes in Algorithm 1, the movement of evacuees under the instructions of the CPN based algorithm is closely approximated. Therefore, the delays at the nodes and on the edges is better estimated.

Figure 5 shows the average number of congestion occurred during an evacuation process. As can be seen, the use of G-network model can considerably reduce the average congestion level of paths and therefore reduce the number of congestion generated during an evacuation process. This is because the use of G-network model can better analyse the latencies of each node or edge. Hence, SPs can find more desired paths for evacuees based on these information (the congestion level of a path affects both the time-oriented metric and the safety-oriented metric).

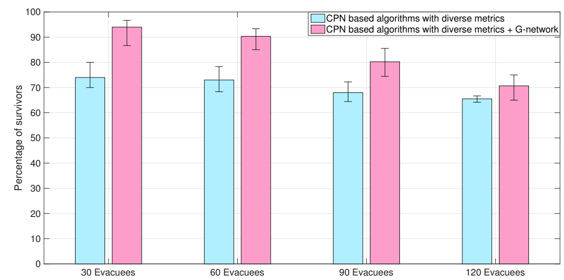

Figure 4. The average percentage of survivors for the CPN based algorithm without and with the G-network model for multiple classes of positive customers. The results are the average of 5 randomized simulation runs, and error bars show the min/max result in any of the 5 simulation runs.

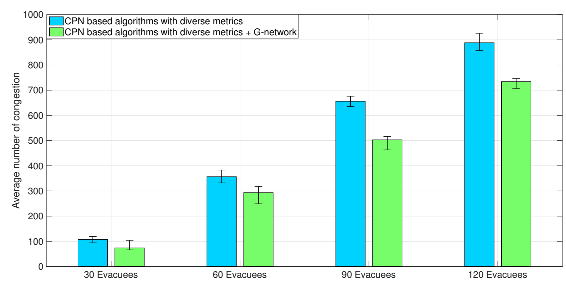

Figure 5. The average number of congestion occurred during an evacuation for the CPN based algorithm without and with the G-network model for multiple classes of positive customers. The results are the average of 5 randomized simulation runs, and error bars show the min/max result in any of the 5 simulation runs.

VIII. Conclusions

In this paper we propose a CPN based multi-path routing algorithm to customise different paths for different categories of evacuees. A G-network with multiple classes of positive customers is used to periodically calculate the utilisation rate of each node and edge in the network. Little's formula is then used to calculate the average delay of each node and edge. The average delay of a path can be calculated by summing the average delay of each node and edge on it. The average delay of a path is used in the proposed routing metrics to search desired paths for evacuees. The G-network model can mimic the movement of evacuees under the joint influence of the CPN based decision-making algorithm and panic behaviours, and therefore give a more accurate approximation of the path latency. Compared with original CPN based algorithm, the proposed algorithm achieves improved survival rates in scenarios where evacuees do not always follow the instructions of the emergency response system due to panic.

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