Journal of Transport Geography 19 (2011) 443–451

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Hierarchical multi-objective evacuation routing in stadium using ant colony optimization approach

Zhixiang Fang [a,b,*], Xinlu Zong [c,*], Qingquan Li [a,b], Qiuping Li [a], Shengwu Xiong [c]

[a] State Key Laboratory for Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, 129 Luoyu Road, Wuhan 430079, China
[b] Engineering Research Center for Spatio-Temporal Data Smart Acquisition and Application, Ministry of Education of China, 129 Luoyu Road, Wuhan 430079, China
[c] School of Computer Science and Technology, Wuhan University of Technology, Wuhan 430070, China

ARTICLE INFO

Keywords:
Space–time path
Evacuation routing
Multi-objective optimization
Ant colony optimization

ABSTRACT

Evacuation planning is a fundamental requirement to ensure that most people can be evacuated to a safe area when a natural accident or an intentional act happens in a stadium environment. The central challenge in evacuation planning is to determine the optimum evacuation routing to safe areas. We describe the evacuation network within a stadium as a hierarchical directed network. We propose a multi-objective optimization approach to solve the evacuation routing problem on the basis of this hierarchical directed network. This problem involves three objectives that need to be achieved simultaneously, such as minimization of total evacuation time, minimization of total evacuation distance and minimal cumulative congestion degrees in an evacuation process. To solve this problem, we designed a modified ant colony optimization (ACO) algorithm, implemented it in the MATLAB software environment, and tested it using a stadium at the Wuhan Sports Center in China. We demonstrate that the algorithm can solve the problem, and has a better evacuation performance in terms of organizing evacuees' space–time paths than the ACO algorithm, the *k*th shortest path algorithm and the second generation of non-dominated sorting genetic algorithm were used to improve the results from the *k*th shortest path algorithm.

1. Introduction

Human populations in large public buildings (e.g. stadium, library, exhibition hall, underground railway station or airport) are at risk from many natural accidents , man-made accidents and intentional acts, including earthquake, fire, terrorist attack and so on (Pu and Zlatanova, 2005; Stepanov and Smith, 2009). Evacuation is a common strategy following the occurrence of these accidents or acts. Owing to the frequent occurrence of them, the study of evacuation planning has become one of the hottest research topics in scientific and industrial communities. Simulation-based approaches and optimization-based methods are the predominant paradigms in evacuation studies. Simulation-based approaches provide practical tools for building designers and transportation network planners for evaluating the evacuation performance of buildings or networks, and optimization-based methods offer useful tools for government or legislators to generate evacuation plans. Our objective in this work was to organize space and time efficiently for the evacuation from a stadium. The organization of space–time paths of evacuees provides an alternative way to analyze the evacuation routing problem, which involves the congestion evacuees concerned as well as the evacuation time and distance planner focused on.

Currently, simulation is widely used to evaluate the dynamic evacuation process and to test the evacuation performance of buildings and transportation networks. Lin et al. (2008) and Xie et al. (2010) listed many simulation software packages that are able to evaluate a set of predefined candidate plans, including EXODUS, SIMULEX, EGRESS, EXITT, SGEM, EVACNET, NETVAC, IDYNEV, MASSVAC, OREMS and CEMPS. The methodological approaches in most of these packages has been reviewed by Zheng et al. (2009). Evacuation simulations provide practical ways to evaluate evacuation plans due to their scenario-driven methodology (Xie et al., 2010).

The optimization-based methods (including routing optimization models, scheduling optimization models and network optimization models) categorized by Xie et al. (2010) are important approaches to the generation of evacuation plans from a systematic perspective. One of the major challenges in evacuation planning is to determine the evacuation routings from locations of evacuees to safe areas. Some research has addressed this challenge using multi-objective optimization approaches. For example, Saadatseresht et al. (2009) solved a spatial multi-objective optimization problem (MOP) of evacuation routing in MATLAB software. Stepanov and Smith (2009) used M/G/c/c software to optimize

* Corresponding authors. Address: Transportation Research Center, Wuhan University, P.O. Box C307, 129 Luoyu Road, Wuhan University, Wuhan 430079, China. Tel.: +86 27 68778222x8110; fax: +86 27 68778043 (Z. Fang).
E-mail addresses: zxfang@whu.edu.cn (Z. Fang), zongxinlu@126.com (X. Zong).

0966-6923/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.jtrangeo.2010.10.001

egress route assignment with muliti-objectives, including clearance time, total distance travelled and blocking probabilities. Multi-objective optimization approaches have proven to be feasible ways to address the realistic requirements of evacuation planners (Andreas and Smith, 2009; Stepanov and Smith, 2009; Lin et al., 2008). However, the majority of optimization methods use pseudo-random proportional processes (Deb et al., 2002; Bell and McMullen, 2004) to select the next trials often result in blind searching.

This study solves the evacuation routing problem using the analysis of space–time paths in a hierarchical directed network, which is implemented by a multi-objective approach based on an ant colony optimization (ACO) algorithm. The evacuation routes in a stadium are represented as a hierarchical directed network, which contains destination-oriented links, and has the advantage of arriving quickly at a safe area. This organization avoids blind searching in calculating an evacuation plan by virtue of destination-oriented heuristic information. The evacuation problem in a stadium based on this hierarchical directed network is defined here as a hierarchical multi-objective evacuation routing problem (HMERP). An HMERP algorithm based on an ant colony optimization (ACO) algorithm is proposed to solve this problem by generating some feasible evacuation plans of evacuation routings of evacuees in a stadium. These results allow governments and/or legislators to understand the spatial and temporal aspects of evacuee movements in order to formulate feasible evacuation plans.

This paper is organized as follows. Section 2 discusses previous work related to evacuation routing optimization. Section 3 presents an HMERP to model the issues of evacuation routing optimization in a stadium. Section 4 introduces an HMERP algorithm based on ACO to finding optimal evacuation routing solutions. Section 5 analyses the results of computational experiments. Finally, Section 6 draws conclusions and discusses directions for future research.

2. Related work

Evacuation routing problems are usually modelled on the basis of network flow theory (Andreas and Smith, 2009; Stepanov and Smith, 2009; Kamiyama et al., 2009). This theory for evacuation planning has been studied from three major perspectives. First, considering the evacuation route for an evacuee. Several studies were designed to provide an optimal evacuation route for an evacuee, including time-expended network flow (Chalmet et al., 1982), congestion–vulnerable traffic flow on a time-dependent network (Kaufman et al., 1998) and an evacuation network with stochastic and time-varying travel times (Opasanon, 2004). Andreas and Smith (2009) extended their work and proposed a non-simultaneous capacitated evacuation tree network which is useful in positioning direction arrows for a building's fire escape plan, or emergency evacuation route signs for a city. The second perspective is to generate an evacuation plan based on the dynamic nature of a network. Dynamic network flow models have become one of the hottest topics in the evacuation research community. Lin et al. (2008) divided dynamic network flow models into three categories: quickest, cheapest and earliest arrival. They proposed a multi-stage, time-varying quickest flow approach to address a multi-source-multi-sink problem of an evacuation situation. The third perspective is the routing from the evacuation simulation (Georgiadou et al., 2007). For example, to simulate evacuation from a building, the building zone is usually divided into a fine network, a coarse network, and an integrated approach to both. Yuan et al. (2009) implemented this integrated approach to test performance-based fire safety design. Here, we extend the second approach to propose a hierarchical directed network concept, which represents a stadium evacuation environment with phased destinations within it. We consider the dynamic nature of the network, e.g. travelling speed varies with the congestion degree.

Optimization-based approaches are usually chosen to solve evacuation routing problems which needs to satisfy several objectives, due to their advantages of intelligence and efficiency. These approaches focus on two key issues, namely, the objectives and the optimization algorithms. Most reports in the literature state their objective(s) in evacuation. For example, Stepanov and Smith (2009) generated an evacuation plan with objectives that included minimization of total clearance time (Pursals and Garzon, 2009; So and Daganzo, 2009), total distance travelled and the avoidance of blocking. In addition, several objectives, including minimization of average evacuation time, maximization of the total number of surviving evacuees and minimization of congestion on road links were identified by Lin et al. (2008). Currently, some optimization algorithms or techniques, including game theory (Lo et al., 2006), agent (Shi et al., 2009), non-dominated sorting genetic algorithm (NSGA-II; Saadatseresht et al., 2009), Benders' decomposition algorithm (Chen and Miller-Hooks, 2008), linear programming relaxation (Tayfur and Taaffe, 2009), cellular automation (Fang et al., 2010) and the Fletcher–Reeves technique (Tavares and Galea, 2009), have been used in attempts to solve routing optimization problems in evacuation. The majority of these approaches are designed to calculate a single optimal evacuation routing plan. However, evacuation routing problems need more solutions to determine several feasible evacuation plans. We use a modified ACO algorithm to address the multi-objective evacuation routing problem posed here.

3. Problem formulation

Definition 1. *A hierarchical directed network G*, derived from a directed graph, consists of some hierarchical node set V and directed edge set A $G = (V, A)$. All nodes in the same hierarchy have identical priority and the same function. Each edge in this network links two nodes in different hierarchies. For example, in Fig. 1, the black edge links two adjacent hierarchical nodes, and the red edge links two non-adjacent hierarchical nodes. The out-degree of a node defines the maximum number of nodes in the next hierarchy that it is linked to.

Generally, a stadium can be resolved into a hierarchical directed network when studying the evacuation process. Each node represents an integrated space, such as the bleachers (an American term used to describe the raised, tiered stands found in sports fields or at other spectator events), the staircase between floors, that is capable of holding a certain number of people, and the nodes act as phased destinations in egress routing. The edges represent the paths available between nodes, such as doorways, passageways and corridors.

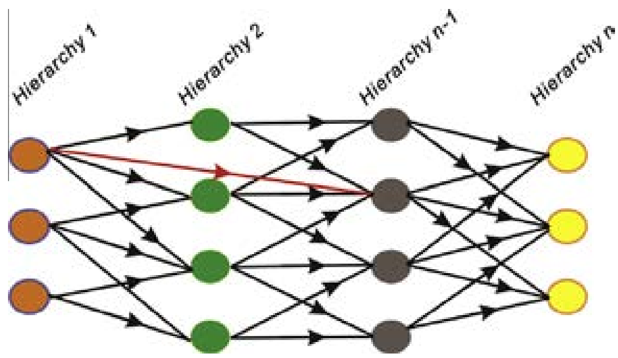

Fig. 1. Hierarchical directed network with maximum out-degree 3.

The evacuation routing problem within a stadium lies within the domain of routing optimization problems. Here, we consider this problem as a multi-objective optimization problem based on hierarchical directed network, called a hierarchical multi-objective evacuation routing problem. The proposed problem takes into account three major objectives within the evacuation process; minimal evacuation time and distance, minimal cumulative congestion degrees.

3.1. Notation

The notation used in the problem formulation is introduced below.

i	an index for network node in V
k	an index for evacuee
m	the total number of evacuees in the stadium
n	the total number of edges in the network G
C_i	the maximal evacuee capacity of node i
l_{ij}	the network distance of an edge (i,j)
$f_{ij}(t)$	the congestion degree of the edge (i,j) at time t
t_{ij}^k	the travelling time of the kth evacuee passing an edge (i,j) in an emergency situation
$Path_k$	the evacuation path of the kth evacuee
S_k^0	the nearest node of the kth evacuee in a hierarchical directed network before the evacuation time
$v_{ij}^k(t)$	the travelling speed of the kth evacuee passing an edge
(i,j)	in an emergency situation
$v_{ij}(0)$	the travelling speed when passing an edge (i,j) in normal conditions
$Num_i(t)$	the number of evacuees on the node i at time t

3.2. Mathematical formulation

The HMERP can be described as:

$$\min F_1 = \sum_{k=1}^{m} \sum_{i=S_k^0}^{(i,j)\in Path_k} t_{ij}^k \tag{1}$$

$$\min F_2 = \sum_{k=1}^{m} \sum_{i=S_k^0}^{i\in Path_k} l_{ij}^k \tag{2}$$

$$\min F_3 = \sum_{(i,j)\in G} \sum_{t=0}^{T_{\max}} f_{ij}(t)\Delta t \tag{3}$$

subject to

$$t_{ij}^k = \frac{l_{ij}}{v_{ij}^k(t)} \tag{4}$$

$$v_{ij}^k(t) = v_{ij(0)} \times e^{-(\gamma_1 \times \frac{Num_i(t)}{C_i})} \tag{5}$$

$$f_{ij}(t) = \begin{cases} 0 & \frac{Num_i(t)}{C_i} < 0.5 \\ e^{\gamma_2^*(\frac{Num_i(t)}{C_i})} & \frac{Num_i(t)}{C_i} \geqslant 0.5 \end{cases} \tag{6}$$

$$\frac{Num_i(t)}{C_i \times t} \leqslant 1 \tag{7}$$

where γ_1 is the parameter used to control the influence of travelling speed in an emergency situation, and γ_2 is the parameter used to control the influence of $Num_i(t)$. Formulation (1) describes the objective of minimizing the expected total evacuation time of all evacuees, and formulation (2) describes the minimal total evacuation distance of all evacuee paths. Eq. (2) represents an essential requirement of total distance travelled proposed by Stepanov and Smith (2009). Eq. (3) describes the minimal cumulative congestion degrees in the hierarchical directed network of the stadium. Eq. (3) is used to analyze the congestion effect caused by pedestrian blocking (Stepanov and Smith, 2009) in evacuation plans. Eq. (4) defines the travelling time of the kth evacuee passing an edge (i,j). Eq. (5) defines a function to calculate the travelling speed of the kth evacuee passing an edge (i,j) in an emergency situation. This travelling speed is a time-varying variable influenced by the number of arrived evacuees in the edge (i,j). Eq. (6) defines the congestion degree of the edge (i,j) at time t. When $\frac{Num_i(t)}{C_i} < 0.5$, this study considers the pedestrian flow in this edge as a free flow, and assigns 0 to the congestion degree. Otherwise, this study considers the pedestrian flow as a compulsory congestion flow. The congestion here is still underestimated in evacuation due to the evacuees' complicated psychology and emergency actions. Constraint (7) guarantees that the number of evacuees arrived at node i at time t is less than the maximal evacuee capacity of node i.

4. Methodology

To solve the proposed HMERP problem described by Eqs. (1)–(7), this study extended the ACO algorithm to finding evacuation routing solutions, and calls it an HMERP algorithm. ACO algorithms have some advantages of solving combinatorial optimization problems because of the strong exploration ability of ants (Li et al., 2009a,b). An overall introduction to ACO and a summary of recent trends has been presented by Blum (2005). Researchers usually focus on two major strategies in an ACO algorithm, such as the heuristic searching strategy of an ant and the pheromone updating method, because they can affect the quality of solutions and the convergence speed of the optimization algorithm. The HMERP algorithm differentiates itself from the ACO algorithm in the two aspects, including hierarchical heuristic searching strategy of an ant, and the binary pheromone updating strategy.

4.1. Hierarchical heuristic searching strategy of an ant

Each ant needs to escape a stadium from its nearest node in a hierarchical directed network to one of the nodes in the last hierarchy. During the evacuation process, the ant needs to reach the next destination from its current location quickly without blind searching or hesitation. Therefore, the strategy used by an ant is to move directly from its current hierarchical node to the next hierarchical node within the hierarchical directed network derived from the stadium. The representation of a link in the proposed hierarchical directed network contains a start node and a destination node. The destination node can be viewed as a candidate node when searching the next nodes from the start node in the link. Thus, the candidate node set of one node consists of all destination nodes of out links from it. Besides the nodes in the largest hierarchy, other hierarchical nodes in this network act as interim destinations to build up a travel path. Any node in the largest hierarchy can be viewed as a final destination of an evacuee's travel path.

Here, by incorporating the hierarchical nodes and the candidate node set of a node, the heuristic information used to choose the next interim destination or final destination is defined as:

$$\eta_{ij}^k = \frac{1}{t_{ij}^k \times \frac{Num_i(t)}{C_i} \times d_{ij}^{\min}} \tag{8}$$

$$d_{ij}^{\min} = \min\left(d_{ij}^{p_l}\middle| p_l \in P\right), \quad P = \{p_1, p_2, \ldots, p_n\} \tag{9}$$

where η_{ij}^{k} in Eq. (8) is the evaluated value of heuristic information, $p_1, p_2, \ldots, p_n$ are the interim or final destinations of the kth node, P is the destination node set of the kth node. $d_{ij}^{\min}$ in Eq. (9) is the minimum distance between the kth node and any element in P. The hierarchical selection of next interim or final destination is based on the heuristic information defined by Eqs. (8) and (9). Few studies using ACO algorithms have used this hierarchical heuristic searching strategy. Instead, they adopted pseudo-random proportional process (Bell and McMullen, 2004) to select the next nodes without destination-oriented heuristic information.

4.2. Binary pheromone updating strategy

In the pheromone updating strategy of ACO algorithms, the higher the level of pheromone on one edge, the more desirable it is for other ants to choose it. This strategy is unsuitable for this HMERP problem, because the strategy can easily result in heavy congestion under evacuation situations. Therefore, this study uses the following updating condition and binary strategy to update the level of pheromone on each edge in a hierarchical directed network.

The updating condition here is that if a set of evacuees' paths in one evolution generation has already constructed a Pareto optimal solution (see Appendix), the level of pheromone on each edge of paths can be updated. Using this condition, ants are able to find more optimal results in the next iterations of the proposed algorithm.

The binary strategy of pheromone updating is that the level of pheromone on each edge will be updated according to a ratio between the number of evacuees passed and the maximum evacuation capacities of individuals in the current iteration. If the ratio is less than the 0.5 in the current network, the level of pheromone on the edge will increase according to a pheromone updating function introduced by the following proposed algorithm, or the level of pheromone will not increase. This strategy attempts to balance the pedestrian flow on edges and to avoid heavy congestion in the hierarchical directed network. By using this strategy, the ants in the next generation will have a higher desire to choose edges under capacity.

4.3. Proposed algorithm

The proposed algorithm, which was developed to solve the HMERP problem, is extended from the ACO algorithm by considering the evacuation routes, and the hierarchical path searching strategy in a hierarchical directed network and specific pheromone updating strategies discussed above. This algorithm, called the HMERP algorithm, is described below.

Step 1: Initialization.

The parameters of the ACO algorithm, including the maximum number of iterations (NC_max), the current iteration number (NC) and the number of ants (*Num_ant*) are initialized. The *Num_ant* ants are assigned at random to those nodes representing the bleachers in a network for the ACO algorithm and in a hierarchical directed network for the HMERP algorithm. The network used in the ACO algorithm does not contain any destination-oriented heuristic information, and the hierarchical directed network organizes nodes with the destination-oriented heuristic information. This defines a scenario in which all evacuees escape from the bleachers. Then for each edge (i,j), its initial level of pheromone $\tau_{ij}(0)$ is assigned to 0, and the pheromone updating value $\Delta\pi_{ij}$ is also set to 0. In addition, the Pareto optimal solution set (*ND_set*) should be initialized as an empty set: *ND_set* = Φ.

Step 2: Generating an evacuation path for each ant.In the ACO algorithm, an ant k located at node i has to choose a node from all its linked nodes (*NextLINK_Set*) with a probability according to the rule of the roulette wheel, which is defined as:

$$p_{ij}^{k}(t) = \frac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{w \in NextLINK\_Set} \tau_{iw}^{\alpha}(t)\eta_{iw}^{\beta}(t)} \tag{10}$$

where $\tau_{ij}^{\alpha}(t)$ is the level of pheromone at node j at time t; $\eta_{ij}^{\beta}(t)$ is the optimization function used to provide heuristic information defined by Eq.(8), and α and β are the parameters used to control the influences of $\tau_{ij}^{\alpha}(t)$ and $\eta_{ij}^{\alpha}(t)$, respectively.

In the HMERP algorithm, an ant k located at node i has to choose a node from its interim destinations (*DES_Set*) as the next node with the probability defined as:

$$p_{ij}^{k}(t) = \begin{cases} \frac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{w \in DES\_Set} \tau_{iw}^{\alpha}(t)\eta_{iw}^{\beta}(t)} & \text{if } \frac{N_i(t)}{C_i \times t} < 1 \text{ and } w \notin Tabu_k \\ 0 & \text{else} \end{cases} \tag{11}$$

where $Tabu_k$, a tabu table of ant k able to store visited nodes, can be used to avoid repeating searches in generating an evacuation path. $p_{ij}^{k}(t)$ in Eq. (11) is the probability value, which is updated if and only if any note in *DES_Set* does not belong to $Tabu_k$, and the number of arrived evacuees in node i at time t is less than the maximal evacuee capacity of node i.

Repeating this choosing process can find an ant's evacuation path from its initial node to one of the final destinations in the stadium. Similarly, all ants can repeat this method to find their evacuation paths.

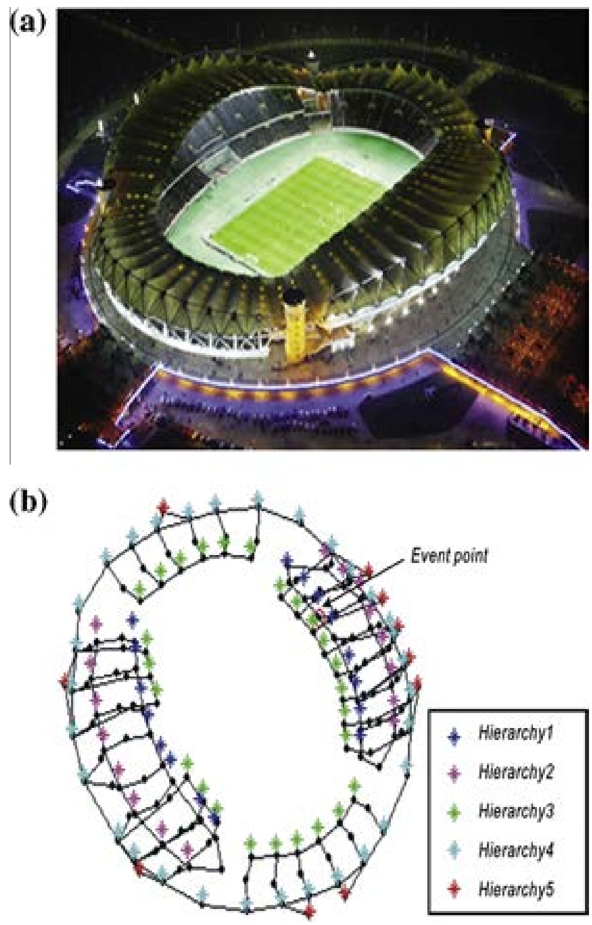

Fig. 2. The study area and experimental data: (a) the stadium at night; (b) the hierarchical directed network of the stadium.

Step 3: Updating *ND_set*.

The evacuation paths of all ants are calculated in Step 2. *Path_Set*(*NC*) represents the routing set in iteration *NC*. Then, this set can be described as: $Path\_Set(NC) = \{Path_1, Path_2, \ldots, Path_k, \ldots, Path_m\}$.where $Path_k$ is the path generated by ant k.

The routing set *Path_Set*(*NC*) is used to update *ND_set* if it is a Pareto optimal solution due to the judgment from three objectives F_1, F_2 and F_3 (see Appendix): $ND\_set = ND\_set \cup Path\_Set(NC)$. If it is not a Pareto optimal solution, *Path_Set*(*NC*) is ignored by this algorithm.

Step 4: Pheromone updating.

After updating the Pareto optimal solution set *ND_set*, the pheromone value of each edge in the ACO algorithm is updated according to:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij} \tag{12}$$

where ρ is the rate of pheromone evaporation $\rho \in [0, 1]$. pr_{ij} is the ratio of the number of evacuees passed on edge (i, j) versus the maximum evacuation time of individuals in the current iteration.

In the HMERO algorithm, the pheromone value of each edge is updated according to:

$$\tau_{ij}(t+1) = \begin{cases} (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij} & \text{if} \quad pr_{ij} < \overline{pr} \\ \tau_{ij}(t) & \text{else} \end{cases} \tag{13}$$

$$\Delta\tau_{ij} = \sum_{n=1}^{n_{size}} \Delta\tau_{ij}^n \tag{14}$$

Table 1
Parameters in the HMERP algorithm.

*NC*_max	*Num_ant*	$v_{ij(0)}$	γ_1	γ_2	α	β	ρ
200	5000	2 m/s	1	1	1	3	0.7

$$\Delta\tau_{ij}^n = \begin{cases} \dfrac{Q}{\sum_{k=1}^{m} t_{ij}^k \sum_{k=1}^{m} \frac{Num_k(t)}{C_k}} & \text{if } path_k \text{ contians edge } \{i,j\}, Path_k \in ND\_set(n) \\ 0 & \text{else} \end{cases} \tag{15}$$

where $\overline{pr}$ is the average value of this ratio on all edges in the current network and n_{size} is the number of Pareto optimal solutions in the current Pareto optimal solution set *ND_set*. Eq. (13) is the pheromone updating function in this ACO algorithm. $\overline{pr}$, the level of pheromone on edge (i, j) will be updated if pr_{ij} is less than the average value. Eq. (14) gives the residual value of pheromone derived from all elements in the current *ND_set*. Eq. (15) describes the residual value of each optimal solution in *ND_set*. The pheromone updating strategy in the HMERP algorithm is used to guide the following ants to choose edges that have less congestion degrees. This strategy aims to fully utilize the space and time of nodes in the network.

Step 5: Stopping criteria.

If *NC* < *NC*_max
  Clear the tabu table for each ant.
  Reset each ant to its original node allocated in Step 1
  $NC + 1 \rightarrow NC$
  go to Step 2
else the algorithm is terminated.

5. Computational experiments

5.1. Experimental design

The stadium at the Wuhan Sports Center in China was selected as the study area (Fig. 2a). This stadium has 42 bleachers distributed on all three floors and 10 exits used to evacuate people; 25,000 people are allocated to 42 bleachers at random. This stadium is divided into 157 units, including bleachers, stairs, exits

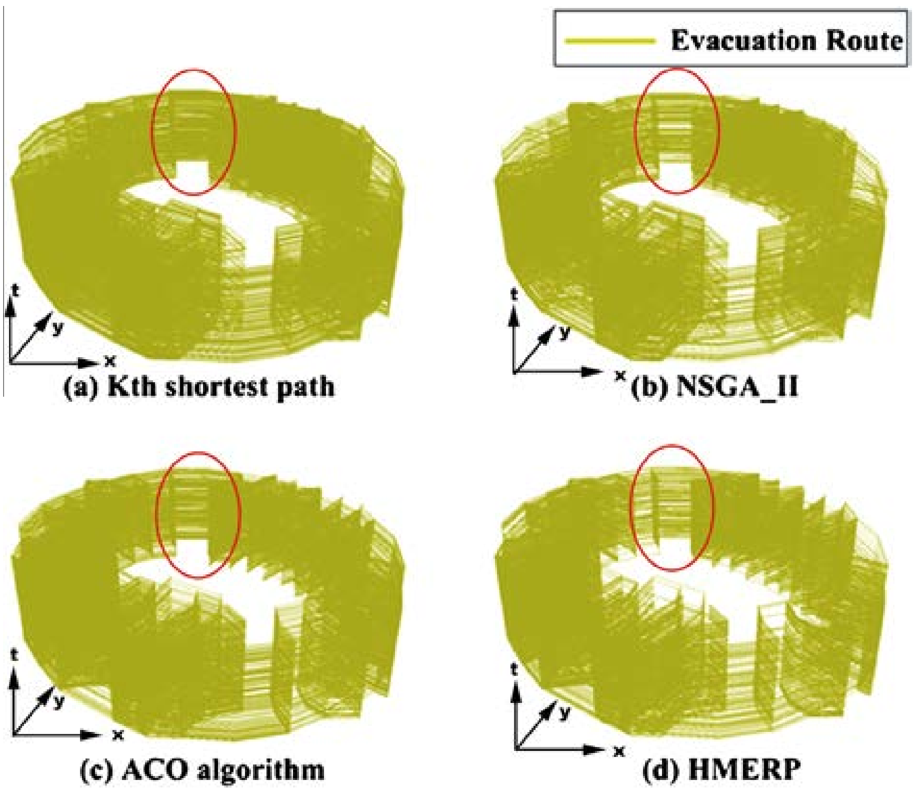

Fig. 3. The solutions of evacuation routings generated by four algorithms.

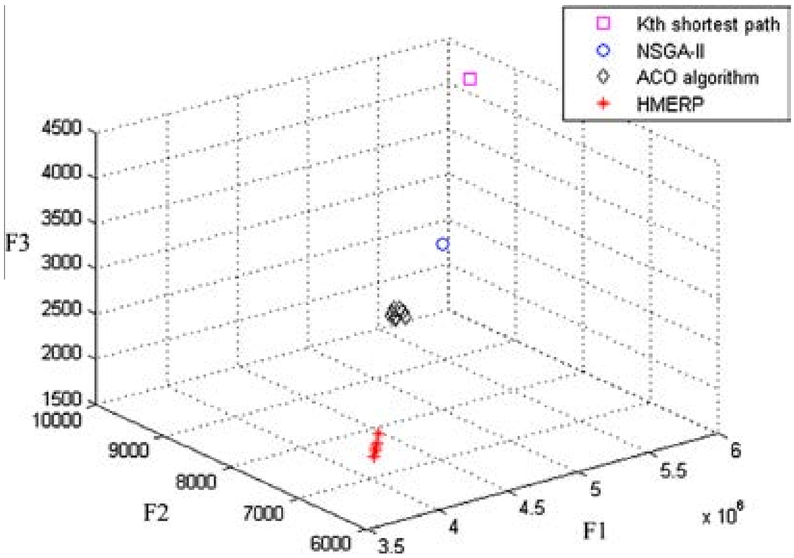

Fig. 4. The distribution of F_1, F_2 and F_3 values derived from four algorithms.

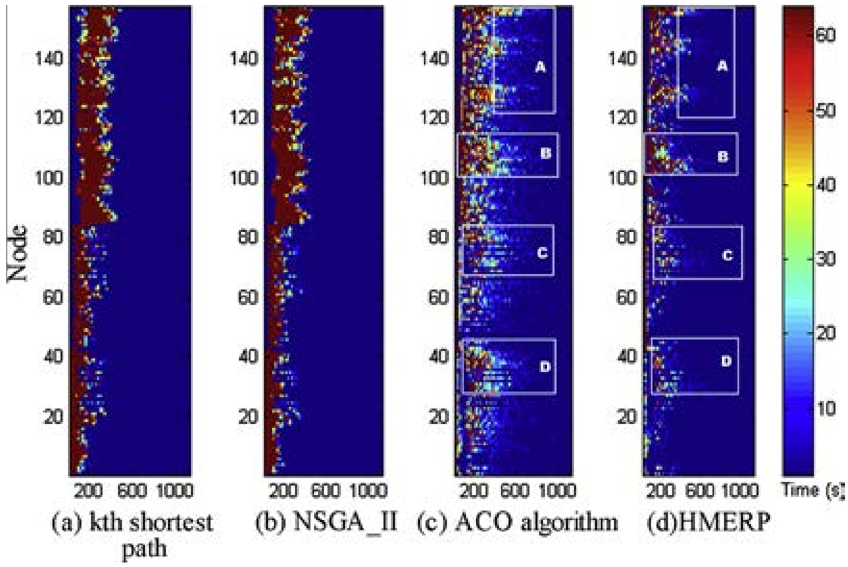

Fig. 5. Number of evacuees in nodes at different times.

and passages, and each unit has the capability of holding evacuees. In this study, each unit is viewed as a node of a hierarchical directed network. The 157 units are categorized as 5 hierarchies according to their designed function. Fig. 2b gives the hierarchical directed network in the stadium. All nodes in the same hierarchy are plotted using the same colour. The 10 nodes in hierarchy 5 are stadium exits.

The proposed HMERP algorithm and the ACO algorithm were implemented in a MATLAB software environment, and run on a personal computer with Pentium (4) CPU 3.06 GHz and 1 GB of RAM. The major steps of the ACO and HMERP algorithms are similar. The HMERP algorithm adopts the two proposed strategies described here (e.g. in Eqs. (11), (13), (14), (15)), which is different from that of the ACO algorithm (Blum, 2005). This algorithm calculates evacuation routings within a hierarchical directed network, but the ACO algorithm calculates them without destination-oriented information. The parameters used in the proposed algorithm are given in Table 1. The initial speed of each evacuee is 2 m/s according to Chen and Feng (2009).

To compare the result of the HMERP algorithm with that from the ACO algorithm and the kth shortest path algorithm (Stepanov and Smith, 2009) in evacuation routings, we developed two modules to calculate the evacuation routing plans in the visual C++6.0 environment. The first module was developed on the basis of the k th-shortest path algorithm, and the second module was implemented based on the NSGA-II algorithm (see Saadatseresht et al., 2009), which was used to improve the results from the first module.

5.2. Result analysis

Fig. 3 shows the solutions of evacuation routings generated by four algorithms. Fig. 3a depicts the result from the kth shortest path algorithm. Fig. 3b shows the result of Fig. 3a improved by the NSGA-II algorithm. Fig. 3c shows one Pareto optimal solution of evacuation routings generated by the ACO algorithm. Fig. 3d depicts one Pareto optimal solution derived from the HMERP algorithm. Four elliptical areas in Fig. 3 illustrate the different density

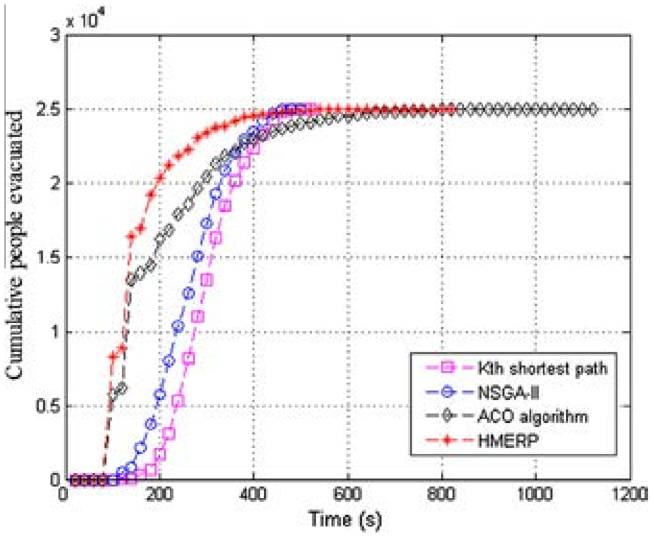

Fig. 6. Evacuation curves of the four algorithms.

of evacuation routings and distribution patterns in the stadium network but some other changes are not easy to show because of the dense routes. This phenomenon demonstrates that the Pareto optimal solutions for stadium evacuation proposed by the HMERP algorithm and the other three algorithms are different. The advantages of the HMERP algorithm are analysed below.

Fig. 4 shows the distribution of F_1, F_2 and F_3 objective values in solutions generated by the four algorithms. The red plot represents a Pareto optimal solution of evacuation routings generated by the HMERP algorithm. All Pareto optimal solutions build up a non-dominated solution set from the HMERP algorithm. This set can be presented to evacuation planners to determine feasible evacuation plans according to their situations and priorities or preferences. This figure shows that the Pareto optimal set found by the HMERP algorithm is better than that generated by other three algorithms in meeting the three objectives, suggesting that the HMERP algorithm is suitable to address this multi-objective optimization problem in evacuation situations.

Fig. 5 shows the number of evacuees in nodes at different times. Each cell in Fig. 5 represents the number of evacuees in a node for a very short time. The time-varying value of evacuee numbers at each node illustrates the evacuee process. At time zero, all evacuees are located in the 42 bleachers of the stadium and they move to other nodes with time. Fig. 5a shows the result of the *k*th shortest path algorithm, and Fig. 5b gives the improved result of Fig. 5a using the NSGA-II algorithm. The distribution patterns in Fig. 5a and b are similar; c shows the result of the ACO algorithm; and d shows the result of the HMERP algorithm. The clearance time in areas A and B of Fig. 5d is shorter than that in Fig. 5c. The clearance processes in areas C and D of Fig. 5c are improved in d. The dense plots in Fig. 5a and b show greater numbers of evacuees than the plots in Fig. 5c and d in most nodes. Fig. 5 demonstrates that the HMERP algorithm can generate a better evacuation process in a stadium than the other three algorithms.

Fig. 6 shows the evacuation curves of four algorithms. In the HMERP algorithm, 95% of evacuees have left the stadium at 400 s, whereas fewer evacuees have left the stadium at 400 s in the other three algorithms. This result is based the assumption that all evacuees left exit area outside the stadium at full speed and without resistance. This result, which is from the organization of space–time paths of evacuees in Fig. 3, seems impossible in reality, but it is possible if all evacuees are drilled (please see a website report: US Department of Homeland Security, 2008) according to the calculated plan. The evacuation curves in Fig. 6 demonstrate that the proposed HMERP algorithm can evacuate more people in the first 400 s than the other three algorithms. The maximum

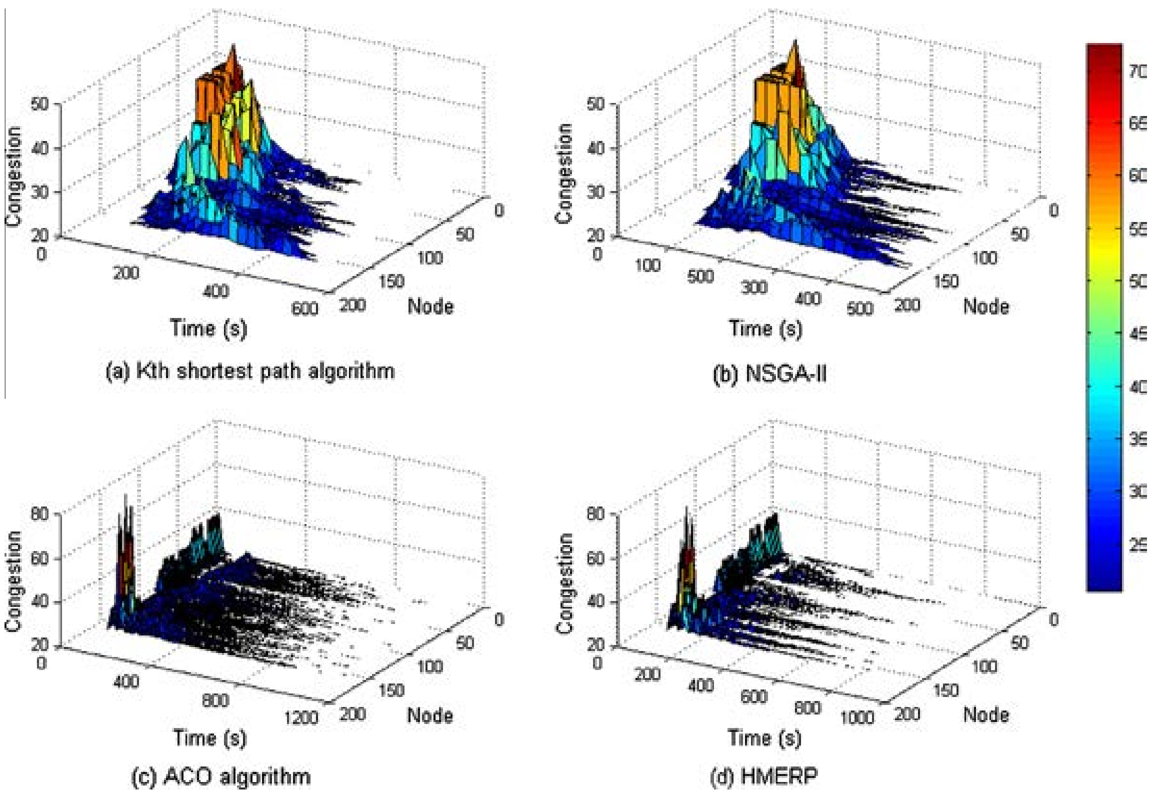

Fig. 7. Time-varying congestion degrees in four algorithms.

Table 2
Number of evacuees at Exits 1–10 and differences from the HMERP algorithm.

Algorithm	Exit 1	Exit 2	Exit 3	Exit 4	Exit 5	Exit 6	Exit 7	Exit 8	Exit 9	Exit 10
*k*th shortest path	1902	2432	4479	1961	1406	1505	1375	4000	4810	1130
NSGA-II	1804	2116	4057	2008	1400	1470	1700	3890	4860	1695
ACO	1760	1545	2030	1920	1760	2090	1590	4280	4780	3245
HMERP	2140	1550	2240	1430	2145	1940	1660	4315	4140	3440
Differences from the HMERP algorithm										
*k*th shortest path	−238	882	2239	531	−739	−435	−285	−315	670	−2310
NSGA-II	−336	556	1817	578	−745	−470	40	−425	720	−1745
ACO	−434	−5	−210	490	−385	150	−70	−35	640	−195

evacuation clearance time is about 800 s in the HMERP algorithm, whereas the ACO algorithm needs about 1100 s. The *k*th shortest path algorithm and the solution from the NSGA-II algorithm need less evacuation clearance time (e.g. about 550 s for both the *k*th shortest path and the NSGA-II algorithms) than the ACO algorithm and the HMERP algorithm. The other side of the coin is that the *k*th shortest path and the NSGA-II algorithms generate higher pedestrian densities (see. Fig. 5) than the HMERP and ACO algorithms.

Fig. 7 shows the time-varying congestion degrees of the nodes in four algorithms. Fig. 7a depicts the congestion distribution and heavy congestion in nodes. This phenomenon shows that many nodes in the network are not utilized efficiently. Fig. 7b shows the improved congestion distribution with the NSGA-II algorithm. However, the space and time utilization in Fig. 7b still need much improvement. Fig. 7c and d illustrate the congestion distributions generated by the ACO and HMERP algorithms. The congestion degrees of most nodes in Fig. 7c and d are much less than those in Fig. 7a and b. The area containing the congestion in Fig. 7d is the smallest. The cumulative value of congestion degrees in the solution of Fig. 7d is also the smallest among the four algorithms, although few nodes still have high congestion degrees in a small time slice.

Figs. 5–7 show that the HMERP algorithm is able to fully utilize the nodes and to avoid congestion at most times. The patterns in these three figures reveal that the HMERP algorithm organizes the space and time in evacuation better than the other three algorithms.

Table 2 gives the number of people evacuated from the stadium's 10 exits using four algorithms. The number of evacuees using three exits (e.g. 3, 6 and 9) in the HMERP algorithm is smaller than that in the ACO algorithm. The maximum number of evacuees in the HMERP algorithm (4315 at Exit 8) is a little smaller than that in the ACO algorithm (4780 at Exit 8), the *k*th shortest path algorithm (4810 at Exit 9) and the NSGA-II algorithm (4860 at Exit 9). The largest differences of evacuee numbers in each algorithm are at Exit 10 (e.g. −2310), 3 (e.g. 1817) and 9 (e.g. 640), respectively. Most difference between the HMERP algorithm and the ACO algorithm in Table 2 are much smaller than those between the HMERP algorithm and the other two algorithms. This shows that some evacuees in the solutions from the ACO algorithm, the *k*th shortest path and NSGA-II algorithms are guided to other exits due to the requirement of the optimization process. These changed destinations reflect the influence of the three objectives on evacuation routings after using the HMERP algorithm.

6. Conclusions

We proposed a multi-objective optimization approach to solve the evacuation routing problem, which is based on the organization of the evacuees' space–time paths within a hierarchical directed network. This network describes a destination-oriented organization, which was designed to avoid the blind searching in pseudo-random proportional processes of the ACO algorithm (Deb et al., 2002). A modified ACO algorithm called the HMERP algorithm was designed to solve this evacuation routing problem in a stadium. In this algorithm, two critical strategies (the hierarchical heuristic searching strategy of an ant, and the binary pheromone updating strategy) were adopted to improve the searching efficiency of an intelligent ant's path, and three objectives (minimization of total evacuation time and distance, and minimal cumulative congestion degrees in evacuation) were invoked to constrain the organization of the evacuees' space–time paths. The computational experiment in this study demonstrated that the HMERP algorithm has the ability to solve the HMERP problem; furthermore, the HMERP algorithm has a substantial advantage of evacuation performance over the other three algorithms (the ACO algorithm, the *k*th shortest path and the NSGA-II algorithms) in terms of total congestion degrees and the number of people evacuated in the same time. The comparison of the four algorithms reveals that this proposed approach is suitable and effective for organizing the space and time of evacuees in a stadium.

It is planned to extend the proposed HMERP model to optimize evacuation routings using several approaches; for example, defining more realistic evacuation scenarios, including more evacuees from a stadium and different kinds of disasters, dividing the evacuees into individuals versus groups, the interactions among evacuees, capacity drop phenomenon (Cepolina, 2009) and even predicting the time-varying patterns of evacuation for real-time evacuation management (Hamza-Lup et al., 2008). Future research will focus on improving the space–time paths of evacuees. Another issue in solving the HMERP problem is the computation efficiency in the MATLAB environment. Promising improvements include implementing this model with C language able to address this complex problem quickly.

Acknowledgements

This research was supported in part by the National Science Foundation of China (Grants #40701153, #40971233, #40830530), partly sponsored by the Scientific Research Foundation for the Returned Overseas Chinese Scholars, State Education Ministry of China, and LIESMARS Special Research Funding. The authors would also like to thank Dr. Shih-Lung Shaw and the anonymous reviewers for their valuable comments and suggestions.

Appendix

A.1. Pareto optimal set in a multi-objective optimization problem

A multi-objective optimization problem (Deb, 1999; Deb et al., 2002; Coello, 2003) can be stated as:

$$\min F(x) = (f_1(x), f_1(x), \ldots f_n(x))$$

where $n \geqslant 2$ is the number of objective functions; $x = (x_1, x_1, \ldots, x_m)$ is a vector of decision variables; X is the decision variable space; $F(x)$ is a vector of objectives.

A decision vector $u \in X$ dominates another decision vector $v \in X$, denoted by $u \prec v$, if and only if:

$$\forall i \in \{1, 2, \ldots, n\}, f_i(u) \leqslant f_i(v) \text{ and } \exists i \in 1, 2, \ldots, n, fi(u) < fi(v)$$

A solution $x \in X$ is Pareto optimal if and only if there is no other decision vector that dominates x in X. Such solutions are called non-dominated solutions. The set of all Pareto optimal solutions in the decision variable space is called a non-dominated set or a Pareto optimal set and the corresponding set of objective values in the Pareto optimal set is called the Pareto optimal front.

References

Andreas, A.K., Smith, J.C., 2009. Decomposition algorithms for the design of a nonsimultaneous capacitated evacuation tree network. Networks, 91–103. doi:10.1002/net.

Bell, J.E., McMullen, P.R., 2004. Ant colony optimization techniques for the vehicle routing problem. Advanced Engineering Informatics 18, 41–48.

Blum, C., 2005. Ant colony optimization: introduction and recent trends. Physics of Life Reviews 2, 353–373.

Cepolina, E.M., 2009. Phased evacuation: an optimisation model which takes into account the capacity drop phenomenon in pedestrian flows. Fire Safety Journal 44, 532–544.

Chalmet, L.G., Francis, R.L., Saunders, P.B., 1982. Network models for building evacuation. Management Sciences 28 (1), 86–105.

Chen, P., Feng, F., 2009. A fast flow control algorithm for real-time emergency evacuation in large indoor areas. Fire safety Journal 44, 732–740.

Chen, L.C., Miller-Hooks, E., 2008. The building evacuation problem with shared information. Naval Research Logistics 55, 363–376.

Coello, C., 2003. A comprehensive survey of evolutionary-based multi-objective optimization techniques. Knowledge and Information Systems 1 (3), 269–308.

Deb, K., 1999. Multi-objective genetic algorithms: problem difficulties and construction of test problem. Evolutionary Computation 7 (3), 205–230.

Deb, K., Pratap, A., Agarwal, S., et al., 2002. A fast and elitist multi-objective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation 6 (2), 182–197.

Fang, Z.M., Song, W.G., Zhang, J., et al., 2010. Experiment and modeling of exit-selecting behaviors during a building evacuation. Physica A 389, 815–824.

Georgiadou, P.S., Papazoglou, I.A., Kiranoudis, C.T., et al., 2007. Modeling emergency evacuation for major hazard industrial sites. Reliability Engineering and System Safety 92, 1388–1402.

Hamza-Lup, G.L., Hua, K.A., Le, M., et al., 2008. Dynamic plan generation and real-time management techniques for traffic evacuation. IEEE Transactions on Intelligent Transportation Systems 9 (4), 615–624.

Kamiyama, N., Katoh, N., Takizawa, A., 2009. An efficient algorithm for the evacuation problem in a certain class of networks with uniform path-lengths. Discrete Applied Mathematics 157, 3665–3677.

Kaufman, D.E., Nonis, J., Smith, R.L., 1998. A mixed integer linear programming model for dynamic route guidance. Transportation Research Part B 32 (6), 431–440.

Li, X., He, J., Liu, X., 2009a. Intelligent GIS for solving high-dimensional site selection problems using ant optimisation techniques. International Journal of Geographical Information Science 23 (4), 399–416.

Li, X., He, J., Liu, X., 2009b. Ant intelligence for solving optimal path-covering problems with multi-objectives. International Journal of Geographical Information Science 23 (7), 839–857.

Lin, P., Lo, S.M., Huang, H.C., et al., 2008. On the use of multi-stage time-varying quickest time approach for optimization of evacuation planning. Fire Safety Journal 43, 282–290.

Lo, S.M., Huang, H.C., Wang, P., et al., 2006. A game theory based exit selection model for evacuation. Fire Safety Journal 41, 364–369.

Opasanon, S., 2004. On Finding Paths and Flows in Multicriteria, Stochastic, and Time-varying Networks, Ph.D. Thesis, Department of Civil Engineering and Environmental Engineering, University of Maryland, College Park.

Pu, S., Zlatanova, S., 2005. Evacuation route calculation of inner buildings. In: van Oosterom, P., Zlatanova, S., Fendel, E.M. (Eds.), Geo-Information for Disaster Management. Springer Verlag, Berlin, Germany, pp. 1143–1161.

Pursals, S.C., Garzon, F.G., 2009. Optimal building evacuation time considering evacuation routes. European Journal of Operational Research 192, 692–699.

Saadatseresht, M., Mansourian, A., Taleai, M., 2009. Evacuation planning using multiobjective evolutionary optimization approach. European Journal of Operational Research 198, 305–314.

Shi, J.Y., Ren, A.Z., Chen, C., 2009. Agent-based evacuation model of large public buildings under fire conditions. Automation in Construction 18, 338–347.

So, S.K., Daganzo, C.F., 2009. Managing evacuation routes. Transportation Research Part B. doi:10.1016/j.trb.2009.11.002.

Stepanov, A., Smith, J.M., 2009. Multi-objective evacuation routing in transportation networks. European Journal of Operational Research 198, 435–446.

Tavares, R.M., Galea, E.R., 2009. Evacuation modelling analysis within the operational research context: a combined approach for improving enclosure designs. Building and Environment 44, 1005–1016.

Tayfur, E., Taaffe, K., 2009. A model for allocating resources during hospital evacuations. Computers & Industrial Engineering 57, 1313–1323.

Xie, C., Lin, D.Y., Waller, S.T., 2010. A dynamic evacuation network optimization problem with lane reversal and crossing elimination strategies. Transportation Research Part E 46 (3), 295–316.

Yuan, J.P., Fang, Z., Wang, Y.C., et al., 2009. Integrated network approach of evacuation simulation for large complex buildings. Fire Safety Journal 44, 266–275.

Zheng, X.P., Zhong, T.K., Liu, M.T., 2009. Modeling crowd evacuation of a building based on seven methodological approaches. Building and Environment 44, 437–445.

Website reference

US Department of Homeland Security, 2008. Mass Evacuations: Planning for Sports Venues. <http://www.cops.usdoj.gov/files/ric/CDROMs/PlanningSecurity/modules/10/module%2010%20handout%202%20-lessons.pdf> (accessed 06.06.10).