Engineering Optimization

ISSN: 0305-215X (Print) 1029-0273 (Online) Journal homepage: http://www.tandfonline.com/loi/geno20

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ENGINEERING OPTIMIZATION, 2018
VOL. 50, NO. 7, 1198–1211
https://doi.org/10.1080/0305215X.2017.1419345

Early stage response problem for post-disaster incidents

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ABSTRACT

Research on evacuation plans for reducing damages and casualties has been conducted to advise defenders against threats. However, despite the attention given to the research in the past, emergency response management, designed to neutralize hazards, has been undermined since planners frequently fail to apprehend the complexities and contexts of the emergency situation. Therefore, this study considers a response problem with unique characteristics for the duration of the emergency. An early stage response problem is identified to find the optimal routing and scheduling plan for responders to prevent further hazards. Due to the complexity of the proposed mathematical model, two algorithms are developed. Data from a high-rise building, called Central City in Seoul, Korea, are used to evaluate the algorithms. Results show that the proposed algorithms can procure near-optimal solutions within a reasonable time.

ARTICLE HISTORY
Received 30 May 2017
Accepted 15 December 2017

KEYWORDS
Disaster response logistics; response time minimization; evacuation modelling and management; emergency response team

1. Introduction

Forests of buildings are commonly observed in a modern society, and the structures have become more complex in architectural design and increasingly more capable of holding dense populations. For example, in multiplexes or department stores, numerous shops and facilities are located in a single building, and each may be crowded with customers. Such buildings experience critical damage from disasters. Since the building damage or collapse can harm the lives and assets significantly, the structure of the building has become a main target for terrorism. Recent terror attacks, such as those in Paris in 2015, the bombings in Brussels 2016, and the Iskandariya suicide bombing in 2016, share similarities in that the events occurred in populated public areas. Therefore, the importance placed on establishing emergency procedures in large public buildings has increased.

Various efforts have been conducted to minimize building damage caused by disasters, and they can be classified as pre-disaster and post-disaster management. In pre-disaster management, some up-to-date technologies have been improved recently for efficient building evacuations (Chen and Miller-Hooks 2008). Specifically, smart sensor devices help collect, share information and alert dangerous situations (Johnston *et al.* 2007; Wang, Zhao, and Winter 2015). Others have tried to find efficient ways to provide information for evacuations (Wang, Zhao, and Winter 2015; Tan, Hu, and Lin 2015). Likewise, the pre-planned response procedures help responders take action in disasters within a short space of time. The training of decision makers for response activities is another related issue (Hosseini and Izadkhah 2010; Berariu *et al.* 2016).

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It is assumed that the building in this study is well equipped with the up-to-date Internet-of-Things (IoT) device technologies. Therefore, responders can share information throughout the building during response activities. Responders and the decision-makers are well trained such that they have sufficient knowledge about the building to undertake emergency actions. However, if their efforts do not respond to turbulent changes in the building during the evacuation process, responders may fail to lead victims successfully to egresses (Miller-Hooks and Krauthammer 2007).

To mitigate many difficulties of pre-disaster management, research on post-disaster management has also been widely conducted. The majority of previous studies about emergency management in buildings emphasized evacuation processes; however, in reality, effective responses are as important as efficient evacuations. The Brussels bombing attack in 2016 serves as important evidence to indicate the importance of efficient responses. According to Neofotistos (2016), the terror attack was caused by multiple consecutive bombings that resulted in 32 casualties and hundreds of injuries. The damage would have been worse if the first-response agencies had failed to locate the unexploded bombs. Hence, to secure safety, the importance of immediate responses to eliminate future hazards cannot be overlooked. For this reason, this study covers the problem of responding in the early stage of an emergency situation.

A *responder* is a trained individual employed to undertake response actions and a *target* is an area with hazards. The characteristics of responders and targets in an early stage of post-disaster management were analysed. With the help of new technologies and pre-planned efforts, it is assumed that various information about the building structures, responders, and targets are known during response activities. The early stage response problem (ESRP) is studied to produce a schedule for responders to maximize risk prevention in a building. Because of the complexity in the problem under consideration, a greedy algorithm (GA) and a revised greedy algorithm (RGA) were proposed to generate solutions in a short amount of time. The data from a real-world building were used to evaluate the performances of the proposed algorithms. Computational results revealed that the RGA was robust and quite accurate with short computation times.

The remainder of this article is organized as follows: a literature review is presented in Section 2. Section 3 introduces the mathematical model. Section 4 explains greedy algorithms, and Section 5 describes a case study and its computation experiments. Section 6 features conclusions.

2. Literature review

The problem under consideration is viewed as an interesting model which includes routing and scheduling of responders in an early stage of emergency situations in a large public area. The problem under consideration is closely related to the evacuation problem which has been widely studied because the basic flows of responders and evacuees are quite similar.

Specifically, evacuees move to exits to avoid a potential hazard while responders move to the hazard to eliminate potential risk. Even though the directions of both flows are opposite, the response model under consideration in this study can be regarded as a variation of an evacuation problem. For this reason, this section focuses on evacuation models. However, it does not mean that the intrinsic characteristics of evacuees and responders are identical. Especially in a large public area, a variety of individuals occupy the place. Therefore, not only their physical characteristics but also their personal experiences of evacuation are different. On the other hand, responders are associated with the same team for emergency responses, therefore, their characteristics are relatively homogeneous.

One of the pioneer works about evacuation was published in 1982 (Chalmet, Francis, and Saunders 1982) and led to subsequent works. Zheng, Zhong, and Liu (2009) identified seven methodologies of crowd evacuation, which can be re-categorized from two dominant standpoints. According to Hamacher and Tjandra (2001), evacuation research models can be divided into macroscopic and microscopic types. In general, macroscopic planning is based on an operational view to create evacuation routes and microscopic planning is based on the behaviour of evacuees during a disaster (Yusoff, Ariffin, and Mohamed 2008).

In the macroscopic model, the population is assumed to be homogeneous and minimizing damage or maximizing the number of evacuees are the two main priorities. For macroscopic types, mathematical models provide optimal routes and scheduling for evacuation. One disadvantage of the macroscopic perspective in many studies is the limited or unrealistic models in which bottlenecks were not considered. Moreover, in many cases, evacuees do not perform ideal and logical behaviours under control and their unpredictable human behaviours are difficult to consider in macroscopic models. However, guiding the responders is easily achieved since they are homogeneous and cooperatively controllable. For this reason, a macroscopic model of evacuation has been adopted in this study.

Hamacher and Tjandra (2001) classified macroscopic and microscopic evacuation models, focusing primarily on macroscopic ones. They studied various models and algorithms related to evacuation problems. This study references the section on the discrete-time dynamic network flow model. Lin *et al.* (2008) established a multi-stage time-varying quickest flow approach, which assigns a priority value to each occupant group by considering its heterogeneous behavioural characteristics. Chen and Miller-Hooks (2008) suggested a mixed integer programming formulation and developed an exact algorithm using Benders decomposition. Kang, Jeong, and Kwun (2015) proposed both integer and linear programming models for evacuation. Wang *et al.* (2016) considered uncertain and probabilistic situations during a disaster and presented a scenario-based stochastic optimization framework. Due to the complex routing and scheduling problem in a time-dependent network, Lu, George, and Shekhar (2005) developed a capacity constraint route planner algorithm, which is widely used in macroscopic models. Chen and Feng (2009) developed the two flow control algorithms: the multiple-narrow doors flow control algorithm and the k-limited flow control algorithm. Both algorithms were tested using the data from the Takashimaya department store in Singapore, and each solved problems in less than a second.

In contrast, from the microscopic perspective, the mental characteristics of impacted individuals, including the knowledge about possible evacuation routes and their physical actions, are also important factors in the problems for minimizing damage. Microscopic models are created using probabilistic measures of individual behaviours. The microscopic perspective is more suitable for reflecting the diverse characteristics of evacuees. The expected behaviours of evacuees can be used as input data in this model.

In simulation methods, the behavior of evacuees is considered more valuable than that of attackers. Cellular automata models (Blue and Adler 2001), agent-based models (Galea and Galparsoro 1994; Thompson and Marchant 1995), and social force models (Helbing 1991; Helbing and Molnár 1995) are commonly used simulation methods (Santos and Aguirre 2004; Vermuyten *et al.* 2016). Tan, Hu, and Lin (2015) developed the agent-based model which incorporates the fire-fighting facility locations and building structures. Pelechano and Badler (2006) considered interactions between different types of people. Langston, Masling, and Asmar (2006) developed a discrete element method technique in which a single evacuee is represented as three intersecting circles. Hou *et al.* (2014) emphasized the number of leaders and their positions in the areas involved in an evacuation. Guo, Huang, and Wong (2012) developed a microscopic pedestrian model with discrete lattice space in which the visibility during an accident was limited. Shiwakoti *et al.* (2011) built a mathematical model of the collective dynamics of pedestrians that can be applicable to other animals and their simulation results were validated by experiments using ants.

3. Mathematical model

The ESRP is a special type of emergency problem, where a response plan within a given time is necessary with a limited number of responders to neutralize targets of hazards. Building structures, responders, and targets are considered as three major components of the ESRP. The proposed model is an extended work of the evacuation model proposed by Hamacher and Tjandra (2001).

3.1. Problem description

The building or a large public area can be modelled as a graph. Rooms, lobbies, and any intersections in the building are presented as nodes. Corridors, halls, and links between intersections are described as arcs. When people move to new nodes, they pass through arcs. Artificial nodes have been introduced between partially or ambiguously separated areas in a wide place. Because the capacities of rooms and corridors in a building are restricted, the amount of flow cannot exceed the physical capacity of the space. It is assumed that a building is equipped with various smart sensing devices, including high-quality cameras, iBeacons, and other sensors, which offer real-time information around the building. Information from these devices can help people estimate the states of targets, responders, and potential risks.

The *responders* are professional people who can resolve emergency situations: security guards, firefighters, and police officers. In the post-disaster period, responders around the building try to handle the problematic situations. Responders in the building can instantly mitigate further damage, but other responders outside the building need time to arrive at critical places. The period between the initial response time and the arrival time of responders from outside is defined as the *early stage*. The length of the early stage must be relatively short but it varies under different conditions. This study focused on the management of responders inside the building during the early stage. Therefore, the number of available responders in the building is naturally limited. The initial locations of responders, defined as *source nodes*, are assumed to be known. At the end of the early stage, every responder should be located in specific areas to resolve the emergency situations, which are defined as *sink nodes*.

The conditions of the building structure vary over the time. Thus, the structure of a building can be represented as a time-expanded network, $G(N; A; T)$, such that N is a set of nodes, A is a set of arcs, and T is a discrete-time horizon. The nodes or the network will be *expanded* by duplicating all nodes over the discrete time. This model introduces super source node, s, and super sink node, d, to handle the complexity caused by the expanded source and sink nodes. Super source node s connects all source nodes at time 0 and super sink node d connects all sink nodes. This expansion of the network allows to transform the structure of the building into a single source-and-sink-node network. The complete explanation on how to transform a network can be found in Hamacher and Tjandra (2001).

In comparison to evacuees, responders have intrinsically different characteristics in their response against the hazard. Evacuees can be customers, store owners, and other people conducting business in the building. They have different ages, genders, and races; that is, their physical and mental characteristics are diverse. Moreover, their knowledge levels about evacuation likely vary because they possess different amounts of information about the building and do not have sufficient means available to share their knowledge during the evacuation. For these reasons, it is almost impossible to control evacuee behaviours in a systematic way.

However, responders are regularly trained to provide efficient responses and reactions in emergency situations. Therefore, the building structure is known to them before any emergency occurs. Because responders are mainly employed to control problems in disaster situations, they have communication devices to engage in effective response operations. The responders follow the first-in first-out rule to avoid serious bottleneck problems because they are guided by a leader using communication devices. If a room or a corridor is full, responders cannot get into the area until it is made accessible. In this case, responders can wait or detour through other areas. It makes responders ideal individuals from the macroscopic perspective of evacuation models.

In this study, targets are restricted to immobile things. Hence, moving suspects or other mobile objects, such as striking drones, are not considered. Hazards include fire spread, gas leak, explosions, and any related harm that cause potential risk. The hazards in a building do not spread to other areas because the ESRP is established in a short time frame. Instead, the degree of hazard in an area can vary over time. For instance, fire grows or gas spreads in the same area such that responders need additional time to neutralize such targets, which become increasingly dangerous. A *stationary target*

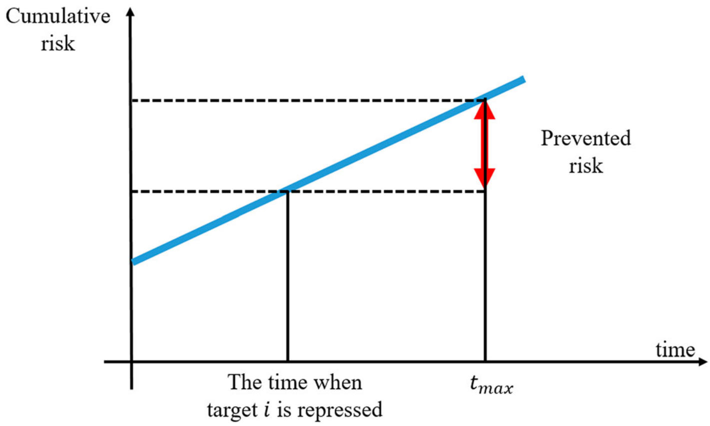


Figure 1. Graph of prevented risks.

is defined as a hazard of which the degree does not change during the early stage and a *variable target* is as a hazard of which degree varies over the time.

In the proposed model, two functions to calculate the cumulative risks and working time have been defined. The cumulative risk function indicates the accumulated risk of each target at a specific time. The working time function denotes the time necessary to neutralize a target at a specific time. The working time to neutralize a target decreases as the number of responders at the scene increases. For instance, if 60 seconds are needed to neutralize a target by one responder, then 30 seconds are needed by two responders. Quantitative values of cumulative risk and the working time are obtained from emergency management experts. The *prevented risk* in an area is defined as the maximum cumulative risk discerned during the early stage minus the risk accumulated throughout the duration of a target being neutralized. Figure 1 illustrates the concept of prevented risk.

The objective of the proposed model is to maximize the prevention of potential risks at the early stage with a limited number of responders. To achieve this goal, a team leader needs to decide targets to be removed, the timing of responders dispatched to eliminate these targets, and the ways responders move to neutralize targets.

3.2. Notation and mathematical formulation

Indices, sets, parameters, and decision variables are as follows:

Indices

s	Super source node
d	Super sink node
t_{max}	Time bound of an early stage

Sets

N	Set of nodes in a building
A	Set of arcs
S	Set of source nodes, $S \subseteq N$
D	Set of sink nodes, $D \subseteq N$
R	Set of target nodes, $R \subseteq N$
T	Discrete time horizon, $\{0, \ldots, t_{max}\}$

Parameters

$a_i(t)$	Capacity of node i at time t, $\forall i \in N, \forall t \in T$

$b_{ij}(t)$ Capacity of arc (i,j) at time t, $\forall (i,j) \in A, \forall t \in T$
q_i Initial number of responders in node i, $\forall i \in S$
λ_{ij} Travel time from node i to node j, $\forall (i,j) \in A$
$p_i(t)$ Cumulative risk function in node i at time t, $\forall i \in R, \forall t \in T$
$f_i(t)$ Working time function in node i at time t, $\forall i \in R, \forall t \in T$

Decision variables
$z_{ij}(t)$ Number of responders moving from node i to j at time t, $\forall (i,j) \in A, \forall t \in T$
$w_i(t)$ Number of responders who are working at node i from time $t-1$ to time t, $\forall i \in N, \forall t \in T$
$c_i(t)$ 1 if responders neutralize target i at time t, and 0 if otherwise, $\forall i \in R, \forall t \in T$

The integer programming (IP) formulation of the ESRP is as follows:

$$\text{Maximize} \sum_{i \in R} \sum_{t \in T \setminus \{0\}} [p_i(t_{max}) - p_i(t)] \cdot c_i(t) \tag{1}$$

subject to

$$\sum_{t \in T} c_i(t) \leq 1 \qquad \forall i \in R \tag{2}$$

$$\sum_{t_1=0}^{t} w_i(t_1) \geq f_i(t) \cdot c_i(t) \qquad \forall i \in R, \forall t \in T \tag{3}$$

$$z_{si}(0) = q_i \qquad \forall i \in S \tag{4}$$

$$\sum_{t \in T} \sum_{i \in D} z_{id}(t) = \sum_{i \in S} q_i \tag{5}$$

$$w_i(t) \leq a_i(t) \qquad \forall i \in N, \forall t \in T \tag{6}$$

$$z_{ij}(t) \leq b_{ij}(t) \qquad \forall (i,j) \in A, \forall t \in T \tag{7}$$

$$w_i(t+1) - w_i(t) = \sum_{\substack{k \in \mathrm{pre(i)} \\ t-\lambda_{ki} \in T}} z_{ki}(t - \lambda_{ki}) - \sum_{j \in \mathrm{suc(i)}} z_{ij}(t) \qquad \forall i \in N \setminus \{s, d\}, \forall t \in T \tag{8}$$

$$w_i(0) = 0 \qquad \forall i \in N \tag{9}$$

$$z_{si}(t) = 0 \qquad \forall i \in S, \forall t \in T \setminus \{0\} \tag{10}$$

$$z_{si}(t) = 0 \qquad \forall i \in N \setminus S, \forall t \in T \tag{11}$$

$$w_i(t) \in \mathbb{N} \qquad \forall i \in N, \forall t \in T \tag{12}$$

$$z_{ij}(t) \in \mathbb{N} \qquad \forall (i,j) \in A, \forall t \in T \tag{13}$$

$$c_i(t) \in \{0, 1\} \qquad \forall i \in R, \forall t \in T \tag{14}$$

The objective function (1) maximizes the prevented risks during the early stage. Constraints (2) and (3) restrict the time allotted to neutralize targets. Constraint (2) ensures that the potential risk of a target is eliminated when it is suppressed. Constraint (3) specifies the required time to neutralize target i. Elimination of target i at time t indicates that responders have worked for at least $f_i(t)$ time units until time t. Constraints (4) through (8) enforce network flows of responders. Constraint (4) addresses the initial number of responders at each source node. Constraint (5) ensures that all responders must arrive at destination nodes. Constraints (6) and (7) impose capacities for nodes and arcs. Constraint (8) enforces the flow of responders by considering their travel time with an equation that balances moving and working responders. The term *pre*(i) denotes the predecessors and the term *suc*(i) refers to successors of node i. Constraints (9) to (11) eliminate infeasible solutions. Lastly, Constraints (12), (13), and (14) define variables.

4. Greedy algorithm

The concept of time-expanded network has been introduced to express the operational progress of the response activities over the network of building structure used in the mathematical model. It shows the complexity of the problem under consideration in this study is very high. Nodes in the original network are expanded to multiple nodes along with the time axis up to the length of time horizon T. Super source node s and super sink node d are added as well. The node size of a time-expanded network becomes $|T| \cdot |N| + 2$ which increases computation times significantly as T and N increase. For this reason, the proposed mathematical model has a limited ability to solve real-sized problems within a desirable computation time, especially in the initial stage of the problem where fast and accurate commands could save more lives. Thus, the issue of complexity of the problem under concern calls for an efficient and effective heuristic algorithm. The early stage response problem is restricted by the time period but the number variables for targets in this model can cause the complexity to be high. In detail, $c_i(t)$ are dependent on the length of time horizon T and linked with other variables including the number of targets. For these reasons, the complexity of the problem in this study is influenced by the number of targets and it is important to reduce the complexity problem of targets in this study.

It has been discovered that the more dangerous targets were eliminated by responders quicker than others. This finding justifies the application of the GA in this study. The proposed algorithm finds the target with the highest risk value in each iteration. Then, it solves the IP formulation of the ESRP to neutralize the most dangerous target. The IP formulation searches for the earliest path to eliminate the target and updates the prevented risks. The routes of the responders are recorded for use in the next iteration. The proposed algorithm continues until all dangerous targets are eliminated. If the algorithm cannot find a feasible solution to neutralize a target, the algorithm eliminates the target from R and repeats the iteration. As long as there exists a feasible solution, this procedure can produce feasible solutions. Although the problem in this study has high complexity, the GA reduces the computational complexity by reducing the number of targets by one in each iteration. Therefore, the computation times increase linearly to the number of targets. The pseudo-code of the proposed algorithm is shown in Algorithm 1.

Algorithm 1: Pseudocode for the greedy algorithm

```
Initialization from the input data
    Initialize sets: N, R, S, D, A, T;
    Initialize parameters: λ_ij ∀(i, j) ∈ A, q_i ∀i ∈ S, f_i(t) ∀i ∈ R,
        p_i(t) i ∈ R, a_i i ∈ N, b_ij (i, j) ∈ A, s = 0, d = |N| − 1;
Pre_route;
Prevented_risk = 0;
iter = 0;
while iter < |R| do
    Des_node = the node index of the maximum p_i(t), i ∈ R;
    (Pre_route, Greedy_time) = Find_path(pre_route, Des_node);
    R = R − {Des_node};
    Prevented_risk += (t_max − Greedy_time)·p_Des_node(t);
    iter + +;
end
Output(Pre_route, Prevented_risk);
```

The sets and parameters about the network, responders, and targets are initialized with the input data. The GA uses an iterative approach; thus, the routes that are found in previous iterations are stored and the values of the prevented risks are stacked in each iteration. The complete iteration is repeated until all targets are eliminated. Therefore, the number of repeated iterations is $|R|$.

Each iteration contains four steps. In the first step, the target posing the greatest threat Des_node g is chosen in R. The knowledge of previous routes and Des_node is used as input data to find the routes and schedules to neutralize the new target. The find_path function runs the ESRP with a single target. The algorithm considers only one target in each time. Therefore, the objective function has been re-defined as $\sum_{t\in T\setminus\{0\}} c_g(t)/t$. When the target is neutralized before all responders arrive, the responders who do not participate in neutralization can move irrationally because their movements are not related to the objective function. To remove these inefficiencies, the penalties have been assigned to decision variables by multiplying the epsilon; $t[\sum_{t\in T\setminus\{0\}} \epsilon_1 z_{gd}(t) + \sum_{t\in T\setminus\{0\}} \sum_{i\in N} \epsilon_2 w_i(t)]$. If the optimal solution is found, the Greedy_time calculated when the target is eliminated is stored. The routes and schedules of the responders are also recorded until the amount of time Greedy_time passes. As the target is suppressed, R is updated. Prevented risks are also updated using Greedy_time. When the iteration of the algorithm is repeated $|R|$ times, it returns the total prevented risks and routes.

Although the GA can find relatively good solutions in a short amount of time, it sometimes fails to obtain the target as a preferential candidate. This is due to the myopic characteristic of the greedy approach. When the number of iterations is large, this situation happens frequently. As a result, the performance of the algorithm is inevitably degraded. It was observed that the problem occurs when the second-most dangerous target is eliminated earlier than the most dangerous one. To revise this situation, the RGA has been proposed so that it searches for a solution of two candidates that are selected by the greedy approach in each iteration. Although the optimal solution of the RGA finds two targets in each iteration to eliminate, the routing and scheduling at the earliest possible time, when any of candidates is neutralized, are updated for use in the next iteration. This tactic helps to alleviate the limitation of the GA. However, the trade-off between the solution quality and computation time needs to be considered.

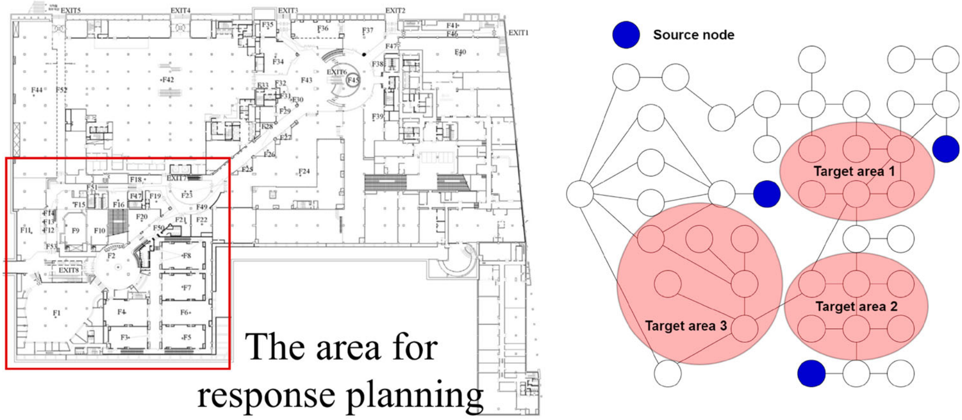
5. Case study and computation experiments

To evaluate the proposed model, a high-rise building, called Central City in Seoul, Korea, has been chosen. The experimental data of Kang, Jeong, and Kwun (2015) has been modified to accommodate the recent changes in building structure and the additional dimensions of halls and corridors were measured. The layout of the area in the experiment is shown in Figure 2a. To reduce the complexity of the problem, some small rooms were combined together. Areas from 26 rooms, main exits, and 18 intersections were transformed to nodes in a network. In the building, the emergency control tower allocates responders to handle potential risks before the incident fully unfolds. Thus, the information on the number of responders, their travel times, and initial locations are assumed to be known. Because no one can foretell an incident before it happens, the emergency data have been randomly generated to test the model.

Assume that there occur multiple bombing attacks in which the response team had information about additional undetonated bombs within the given area. In this situation, aggravating threats are variable targets and the others are stationary targets. The main distinction between them is the aggravating rate of their risks. The time required to neutralize a stationary target $i \in R$ does not change; however, when the threat associated with target $i \in R$ increases, it is classified as a variable target.

5.1. Data generation

The data on terrorist attacks and incidents in the building do not provide enough knowledge to prevent a disaster because incidents cannot be predicted. Therefore, scenario-based experiments have been conducted. Three areas were selected as source nodes of responders and a single responder was



(a) Layout of Central City, Seoul, Korea (Kang, Jeong, and Kwun 2015) (b) Example of the network

Figure 2. Experiment area and the corresponding network.

Table 1. Information of generated data sets.

Locations of target groups		3	
Number of instances		10	
Number of targets	3	4	5
Number of variable targets	1,2	1,2,3	1,2,3,4
Total number of instances	60	90	120

located in each source node. As an incident affects surroundings, the target areas are ones under the influence of the hazard assessment. The locations of source nodes and target areas are shown in Figure 2b. Three target groups are set in target areas. For example, targets in Group 1 were selected in Target Area 1. In each experiment, a target group was selected with the number of targets varying from three to five. Furthermore, the numbers of variable and stationary targets were also varied. By assuming that sink node set D was equal to R, 10 experiments on each target set have been conducted. Details are given in Table 1.

The time bound of an early stage was 225 seconds with 3 seconds as the basic time unit; thus, t_{max} was 75. The amount of risks in node $i \in R$ at time $t \in T$ were assumed to be constant and uniformly distributed between 0 and 5. It is assumed that the working time function $f_i(t)$ follows a linear trend over time based on the works proposed by Challands (2010) and can thus be expressed as $A_i + B_i \cdot t$. A_i is the initial working time for responders to neutralize target $i \in R$ at time 0. A_i was generated by the uniform distribution between 20 and 25. B_i is the incremental rate of working time required to neutralize target $i \in R$. Stationary targets and variable targets were defined according to the condition of B_i. B_i was set to 0.1 or 0 when a target was variable or stationary, respectively. Locations of targets were randomly chosen with a given target area. The detailed example is shown in Table 2. An example of generated data with five targets, two that are variable and three that are stationary targets, is shown Table 2. It can be seen that the values of B_i in the variable targets are 0.1 and those in stationary targets are 0.

5.2. Computational results

In this section, the results of experiments and some insights gleaned from the proposed algorithms are presented. To evaluate the efficiency of the GA and RGA, the sequential algorithm (SA) and the

Table 2. Example of the generated data (five targets).

$p_i(t)$	$4.7t$	$4.4t$	$3.2t$	$4.6t$	$2.0t$
A_i	24.1	21.5	22.9	24.2	20.4
B_i	0.1	0.1	0.1	0.0	0.0
type	variable	variable	variable	stationary	stationary

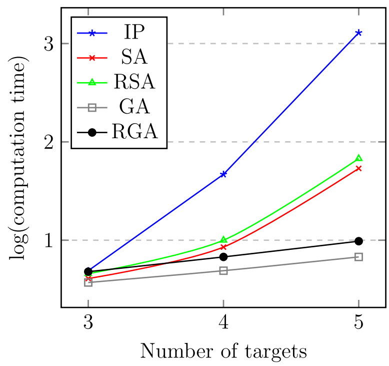


Figure 3. Comparison of computation time with respect to the number of targets.

Table 3. Average and standard deviation of the computation time (seconds) with respect to the number of targets.

	IP		SA		RSA		GA		RGA	
Number of targets	Avg	Std	Avg	Std	Avg	Std	Avg	Std	Avg	Std
3	4.9	1.8	4.0	0.8	4.6	1.5	3.7	0.7	4.8	0.4
4	46.6	171.2	8.5	2.6	9.9	3.1	4.9	1.0	6.8	0.6
5	1274.7	2617.5	54.0	57.4	67.3	89.9	6.8	1.1	9.7	1.1

reverse sequential algorithm (RSA) has been developed. Both the SA and RSA are applied in the two-stage approach. In the SA, the algorithm finds a schedule to neutralize only variable targets first and then stationary targets. The RSA conducts the process in reverse order.

The mathematical model was solved by XPRESS-IVE 7.9 with the XPRESS-MP mathematical programming solver. The heuristic algorithms were developed in XPRESS-IVE 7.9 with the XPRESS-MP mathematical programming solver and Java 1.8.071 language with the XPRESS-MP library. The mathematical model and algorithms were tested with an Intel(R) Core(TM) i5-3570 CPU 3.4 GHz with 8.00 GB of RAM in Windows 10. To evaluate the algorithms, three measures are considered: 1) the computation time; 2) the solution quality, which can be checked via the optimality gap; and 3) the robustness of the solution quality. Note the objective function values of the IP, GA, and RGA are the amount of prevented risks.

The computation times of the GA and RGA outperformed those of the other models (Figure 3). The average computation times of the heuristics were similar when three targets were considered. However, they changed dramatically as the number of targets was changed. This trend was most apparent from the results of the IP, SA, and RSA, which also showed that a large number of targets leads to higher complexity. For example, when the number of targets was changed from three to five, the computation times of the IP increased more than 150 times. However, those of the GA and RGA increased linearly because additional targets did not change the complexity of the problem solved in each iteration. It only changed the number of iterations. The standard deviation also followed a similar trend (Table 3). In each case, the RGA provided the lowest standard deviation. The standard deviation values of the IP, SA, and RSA were largely influenced by the number of targets, but the GA and RGA maintained stable computation times.

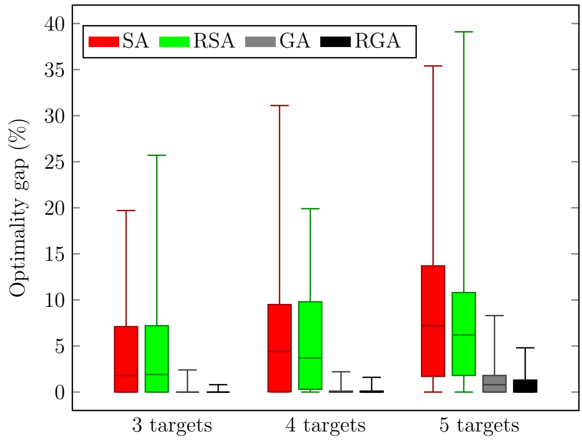


Figure 4. Average optimality gap (%) with respect to the number of targets.

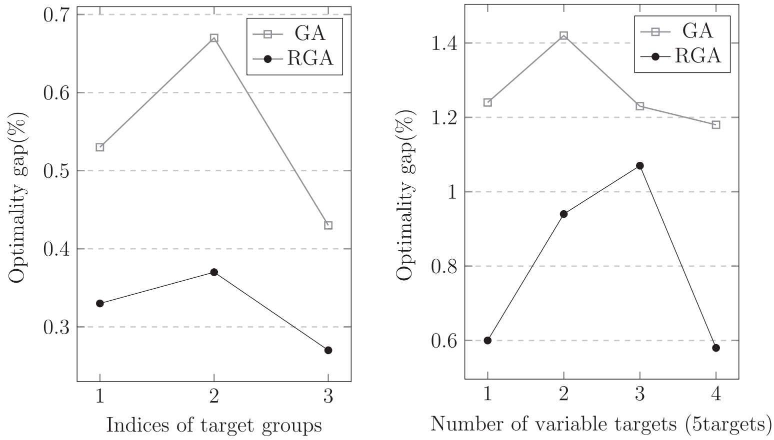
Table 4. Average and standard deviation of optimality gaps with respect to the number of targets.

Number	SA		RSA		GA		RGA	
of targets	Avg	Std	Avg	Std	Avg	Std	Avg	Std
3	4.2	0.6	4.6	6.1	0.2	0.5	0.1	0.2
4	6.0	6.4	5.5	5.6	0.2	0.5	0.1	0.3
5	8.4	7.8	7.7	7.8	1.2	1.6	0.8	1.1

To assess the quality of solutions, the optimal solutions have been obtained from the IP model. Then, the solution gap is calculated as (the optimal value – heuristic value)/the optimal value. It was discovered that the solution qualities of the GA and RGA were better than those of the SA and RSA (Table 4). For the number of targets in each model, the average optimality gap of the RGA was the smallest among ones of all the other heuristics. With three targets, the average optimality gap of the RGA was 0.1% while the values were 4.2%, 4.6%, and 0.2% for the SA, RSA, and GA, respectively. The performances of the GA and RGA look similar, however, the values for the standard deviation and the maximal optimality gap between these two heuristics show that the RGA generated a more robust and stable performance. The overall performances of the heuristics degraded when the number of targets increased, but each heuristic did not share the same trend. The performances of the SA and RSA did not perform well in comparison to those of the GA and RGA (Figure 4). Both of the GA and RGA retained around 1% of the average optimality gap. The difference between them is distinctive. The solution quality of the GA was approximately 40% lower than that of the RGA. Moreover, the values for the standard deviation and the maximal gap of the RGA were also smaller to those of the GA. Thus, the RGA has demonstrated a more stable and accurate solution performance.

The robustness of heuristic algorithms was examined as well. First, the difference between the average solution qualities with respect to target locations has been analysed. In each target group, the differences were not distinctive (Table 5). The total average solution gap with respect to the target groups also failed to show any specific trend (Figure 5a). Therefore, the location of target groups may exert a marginal influence on the solution qualities of the GA and RGA.

The relationship between the optimality gap and the numbers of variable and stationary targets was also investigated in relation to the robustness of heuristics (Figure 5b). Although the average optimality gaps fluctuated, their absolute values were small. The optimality gap of the GA seemed to be more stable than that of the RGA. However, the specific value of each GA experiment was more erratic than that of each RGA experiment. No distinctive trend was revealed and the range of each



(a) Optimality gaps with respect to target groups

(b) Optimality gaps with respect to the number of variable targets

Figure 5. Comparison of the optimality gaps with respect to the location of targets and the number of variable targets.

Table 5. Average optimality gap (%) with respect to target groups.

	GA			RGA		
Number of targets	3	4	5	3	4	5
Group 1	0.2	0.3	1.1	0.1	0.2	0.7
Group 2	0.2	0.1	1.7	0.0	0.1	1.0
Group 3	0.1	0.2	1.0	0.0	0.2	0.6

value seemed to fall within the error range. Thus, the results show small effects from target locations or the number of each type of target on the GA and RGA performances.

Even if the RGA outperforms the GA on average, the RGA did not always perform better than the GA. To analyse the performance between the two algorithms, 50 problems were tested, in which the objective values of the GA and RGA were different for different number of targets; three, four, and five, respectively. When the number of targets was three, the objective values of the RGA were better than those of the GA in 38 of 50 cases. Likewise, others in different numbers of targets showed that the RGA outweighed the GA in approximately 30 of 50 cases. The solution quality of the RGA was sometimes worse than that of the GA because the RGA is also limited by a myopic approach. However, as shown in the results of solution gaps, which were less than 1%, are still in a reasonable range.

6. Conclusions

The main contribution of the study is the description of emergency situations and development of efficient algorithms. The realistic conditions of the building areas, responders, and targets during the early stage of response were considered. Especially, maximizing prevented risks during the operation time with a limited number of responders, which is a critical issue during the emergency. Additionally, the model takes into account time-varying components in areas with risks. The characteristics of dangerous targets were analysed and defined into two types: stationary and variable. Thus, the model reflects dynamic changes of emergency situations, such as changes in hazard intensity and the working time to eliminate dangerous targets during the initial stages of the threat. As the mathematical programming model was too complex to solve real-size problems, two algorithms have been proposed; the GA and RGA, based on the greedy approach. The computation experiments were conducted with real data from a test building. The results of the algorithms indicated that the RGA can find near-optimal solutions within a reasonable time. In the future, different types of responses can be considered. In addition, relief operations in emergency situations can be as important as the suppression of hazards. In such cases, formulation for helping victims is required.

This research is applicable not only to cases of fire but also to other general emergency cases in which responders and dangerous targets are identified. Four solution approaches are provided and thus, leaders can easily adjust the models to meet their objectives. In particular, the GA and RGA provide near-optimal solutions in a short time, which help developers make plans for initial situations in emergencies. This study leads to more valuable results if the building is incorporated with an emergency response system that collects the information necessary in urgent situations and could share it with response team leaders. When the information from the building is updated in real time, the algorithms automatically find the routes, create schedules of responders, and share the information directly. Even if the emergency situation changes dramatically, the solution could be updated within a short time frame because of the fast performance of the algorithm. Therefore, it would consistently provide near-optimal solutions applicable to emergency situations.

Acknowledgments

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) [grant number 2017R1A2B2007812 and 2015R1A2A1A10054253].

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