공학석사 학위논문

Mathematical Model and Heuristic Algorithm for Simultaneous Evacuation and Entrance Planning

진입계획과 대피계획을 동시에 고려한

수리모형 및 휴리스틱 알고리즘 개발

2017 년 2 월

서울대학교 대학원

산업공학과

신 영 철

Abstract

Mathematical Model and Heuristic Algorithm for Simultaneous Evacuation and Entrance Planning

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Numerous emergency situations, such as the terrorist attacks in France in 2015 and Belgium in 2016, have transpired throughout the world. Accordingly, research on evacuation plans for people experiencing terrorism, fire, and natural disaster has gained significant attention. However, previous researchers have primarily focused on evacuation planning. For responders, such as special weapons and tactics teams or firefighters, entrance planning is considered as important as evacuation planning for effective amelioration of dangerous situations. Therefore, this paper presents mathematical models that address the simultaneous evacuation of victims and entrance of responders. By developing the model based on the dynamic network flow model, the solution provides the optimal routes for evacuees and responders within a critical timeframe. However, the mathematical model has two weaknesses: difficulty solution interpretation and lengthy computation time. To overcome these problems, a heuristic algorithm based on the capacity constrained route planner is also developed. This study pioneers mathematical models and a heuristic algorithm that account for both evacuation and response plans.

Keywords: dynamic network flow; entrance plan; evacuation plan; heuristic algorithm; integer programming
Student Number: 2015-21137

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Chapter 1. Introduction

1.1. Background

Numerous large cities have confronted various problems related to overpopulation, and these municipalities encounter tremendous damage, including casualties, when faced with terrorism, fire, or natural disaster. Recently, worldwide threats and emergency situations, such as the terrorist attacks in France in 2015 and Belgium in 2016, have garnered significant attention and highlighted the importance of research on evacuation plans.

In emergency situations, such as fire or terrorism, in a congested area or inside a building, victims search for the nearest exit [1]. In so looking, they tend to follow the majority of other evacuees such that they move in the same direction [2]. Because of such behavior, numerous evacuees reach exits simultaneously, creating a queue. Consequently, the evacuation time for all victims is extended; that is, the local optimization of each evacuee precludes the global optimization for all the evacuees. Therefore, crowded exits should be efficiently prevented by assigning all evacuees to appropriate exits.

Real-time analysis of building structure, location of the emergency situation, and location of evacuees has become possible due to the advances of modern technology, such as the internet of things, communications networks, and process methods for big data. Furthermore, now people onsite can be apprised of dangerous situations and escape information in real time. The synergy between technology and information makes possible research on optimal evacuation routes in preparing emergency situations.

1.2. Literature review

In the past, much research related to evacuation planning was conducted in a variety of fields. (e.g. civil engineering, operation research, mass psychology, safety engineering, computer science, etc.) In this thesis, research relevant to mathematical modeling and simulation are surveyed in the literature review.

Hamacher and Tjandra [3] proposed a classification for the research on evacuation planning based on macroscopic and microscopic models. Macroscopic models emphasize optimization problems in which evacuees are considered as a homogeneous group. In general, macroscopic models are represented as dynamic network flow models. (e.g. maximum dynamic flow model, universal maximum flow model, quickest flow model) In these models, solutions provide the optimal egress routes and schedules for evacuees. Microscopic models are developed as simulation models based on individual behaviors of evacuees and emphasize interactions between each evacuee during the egress. In recent research, a cellular automata is widely used for modeling the microscopic models.

Using macroscopic models, Francis [4] proposed the uniformity principle for building evacuation problems explaining that if evacuation is conducted within minimum time in building, all route evacuation times are the same. Chalmet et al. [5] developed an evacuation problem as a network model that minimizes the time to evacuate by routing the people in the building. Kisko and Francis [6] developed EVACNET+, a computer program that models building evacuations. By describing the building and related information as a network, they provided an optimal evacuation plan. Choi et al. [7] described network flows with side constraints that come from variable arc capacities in evacuation problems. They developed three types of objective functions and proposed greedy algorithms in cases of building evacuation problems. Lin et al. [8] developed a multi-stage time-varying quickest-flow approach that expands the dynamic model into a time-varying dynamic model. Abdelghany et al. [9] developed a simulation-based optimization modeling framework through which researchers apply a genetic algorithm to a microscopic simulation model. The framework minimizes the average evacuation time in situations with many occupants in facilities with multiple exits. Chen and Miller-Hooks [10] proposed a mixed integer program to determine the set of routes that all evacuees can use to escape to a safety area in minimal time. They also developed a Benders decomposition algorithm to solve the problem more efficiently. Chiu et al. [11] developed a single-destination cell-transmission-model based on linear programming for solving a no-notice mass evacuation problem, which is characterized by a large and unexpected incident. Lim et al. [12] developed a time-expanded network model for finding the optimal path for evacuees by maximizing the number of evacuees out to the safety area within a certain time. They also developed a heuristic algorithm to efficiently solve the problem in terms of computation time. Kang et al. [13] developed an algorithm based on linear and integer programming models to solve building evacuation planning and conducted a case study. Kim et al. [14] developed a bottleneck relief heuristic to reduce congestion that also minimizes the evacuation time. Bretschneider and Kimms [15] developed a dynamic network flow problem with additional variables for the number and direction of used lanes. They also developed an adjustment heuristic to solve the problem more efficiently. Miller-Hooks and Sorrel [16] developed a mathematical model formulated as dynamic expected flows and a noisy genetic algorithm to determine route instructions while maximizing the expected number of evacuees within a given time.

Using microscopic models, Jha et al. [17] developed a microscopic simulation model for emergency situations found in traffic. Doheny and Fraser [18] developed a software tool that supports decision makers in emergency situations. Løvs [19] developed a simulation model that accounts for the selection of evacuation routes from one point to another. Okazaki and Matsushita [20] developed a simulation model for pedestrian movement in architectural and urban space, which helps find design problems by identifying the queue spaces in cases of fire. Shi et al. [21] developed an agent-based simulation model with a physical model and a mathematical model. They also conducted a case study based on the 2008 Beijing Olympic Games and found that occupant behavior under emergency conditions is influenced not only by environmental elements, but also by some inherent human qualities.

1.3. Contributions

As seen in the literature review, most studies only emphasize the egress for evacuees and not the entrance of responders. For responders, such as special weapons and tactics teams and firefighters, entrance planning for effectively resolving dangerous situations holds an importance equal to evacuation planning. In the case of Brussels in 2016, the terror was caused by multiple and consecutive bombings. In this case, responders needed to access several target locations to handle the risk agilely within a period that maximizes the possibility of rescue: a golden time. The action, such as schedule and moving routes of responders, is determined by the arbiter of the special response team, who most often uses intuition and advanced information to determine responder routes to the emergency situation. This strategy may lead to route congestion for both evacuees and responders and prolong the total evacuation and entrance times. Hence, demand for systematic evacuation planning that accounts for simultaneous entrances and exits has emerged.

Accordingly, this paper presents mathematical optimization models and a heuristic algorithm by focusing on both the exit of evacuees and the entrance of responders. Both the models and the algorithm are based on macroscopic models in which evacuees and responders are considered a homogenous group. The mathematical optimization models were developed through integer programming based on the discrete dynamic network flow model. The heuristic algorithm model was developed by extending the Capacity Constrained Route Planner (CCRP) [22], which accounts for simultaneous evacuations and entrances. The methodology of this research and related works are summarized in Table 1.

The remainder of the paper is structured as follows. Section 2 presents explanations on the relevant integer programming models. Section 3 explains the heuristic algorithm. Section 4 presents a case study with the mathematical models and a heuristic algorithm. Section 5 summarizes the findings of this research.

Table 1
Summary of this study and related works

Author (year)	Methodology					Objective function	Movement of evacuees and time	
	Static network model	Dynamic network model	Heuristic	Meta-Heuristic	Characteristics		Continuous	Discrete
Francis (1981)	√					Minimize evacuation time		√
Chalmet et al (1982)	√		√		Bisection search algorithm	Min-max evacuation time		√
Choi et al (1988)	√		√		Greedy algorithm	Maximizing number of people exiting	√	
Lin et al (2008)		√	√		Bisection search algorithm	Minimizing the total evacuation time.		√
Abdelghany et al (2014)		√		√	Genetic algorithm	Minimizing the average evacuation time		√

Chen and Miller-Hooks (2008)		√	√		Benders decomposition	Minimizing the total evacuation time		√
Chiu et al (2007)		√				Minimizing the total travel time		√
Lim et al (2012)		√	√		Dijkstra's algorithm, greedy algorithm	Maximizing the total weighted outgoing flows from all centroids at time zero		√
Kang et al (2015)			√		Bisection search with lower and upper bound	Min-max average evacuation time	√	
Kim et al (2008)		√	√		Greedy heuristic, Bottleneck Relief heuristic			√
Bretschneider and Kimms (2011)		√	√		Relaxation and adjustment	Minimizing average evacuation time		
Miller-Hooks and		√		√	Noisy genetic	Maximizing the total amount of		√

Sorrel (2008)					algorithm	flow		
Qingsong et al (2005)			√		Capacity constrained routing algorithms	Minimize the evacuation egress time and computational cost		√
This study		√	√		Capacity constrained routing algorithms considering entrance plan of responders	Four types of objective functions		√

Chapter 2. Mathematical Models

2.1. General features of mathematical models

In this research, mathematical models providing the optimal routes for evacuees and responders in an emergency are developed. If evacuation and entrance plans are made separately, evacuees and responders may experience conflict at certain places, which causes congestion, and creates a queue. By simultaneously focusing on details of both routes, delays in evacuees reaching the safety area and responders entering the target area are minimized.

To realize emergency situation and evacuation planning, the network flow model based on $G = (N, A)$, with N a set of nodes and A a set of arcs, is introduced. This model represents a building and the attributes of building components in a static network. The areas where people are located in the facility, such as rooms or lobbies, are represented as nodes. Routes for evacuee or responder movement between nodes, such as corridors, are represented as arcs. The areas where the route is changed and intersection points are also represented as a node. To apply the number of moving evacuees and responders over time, the dynamic network $G^T = (N^T, A^T)$ associated with $G = (N, A)$ is defined by the time expansion of G over time horizon T. Figures 1 and 2 represent nodes and arcs in this described situation.

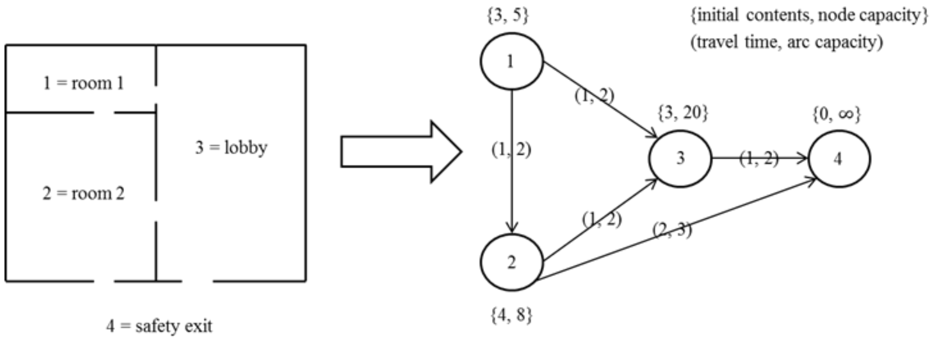

Figure 1. Static network *G* of a simple building layout [3]

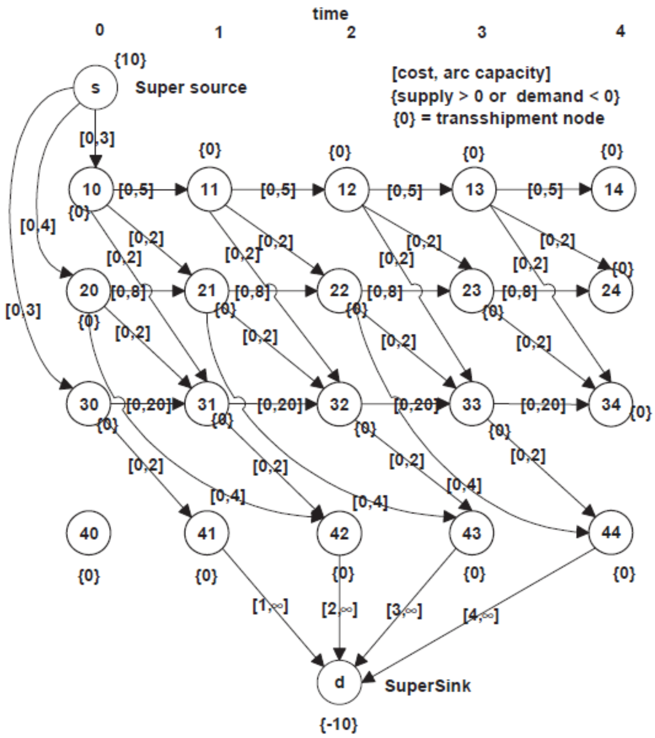

Figure 2. Dynamic network of Figure 1, with $T = 4$ [3]

In an emergency situation, evacuees are initialized separately in distinct areas. In the model, areas where initialized evacuees are found are called source nodes. To handle these multiple source nodes, a super source node s is introduced by connecting all source nodes with zero travel time and infinite arc capacity at time $t = 0$. Infinite arc capacity can be substituted with the number of initialized evacuees in each node. In addition, multiple safety areas will attract evacuees. These areas are defined as sink nodes. Similar to source nodes, these multiple sink nodes are connected with a super sink node d with zero travel time and infinite arc capacity. In this case, infinite arc capacity can be substituted with the total number of evacuees.

Node capacity is dependent on the maximum number of people located in the area while arc capacity corresponds to the maximum number of people passing through the corresponding arc in a discrete time frame. All evacuees and responders are considered members of a homogeneous group in this macroscopic model. The following assumptions are made for this research:

(1) All evacuees and responders move at the same speed.

(2) No evacuees and responders change their direction of movement from one node to another node.

(3) When the emergency situation occurs, all evacuees start evacuating at the same time, $t = 0$.

(4) Responders enter the target area, where the emergency situation occurs, from a safety area to which evacuees are fleeing.

(5) If a node or an arc reaches maximum capacity, evacuees or responders attempting to pass through the node or the arc will wait until the capacity of the arc or node increases to allow access.

(6) Arcs are bi-directional except at the source, sink, and disaster area nodes.

(7) The emergency situation occurs at $t = 0$ and the disaster areas do not move or change over time.

2.2. Four types of mathematical models

Based on the seven assumptions, four types of mathematical models are developed according to the degrees of responses that can be accomplished within the golden time. When the golden time is sufficient, it is assumed that all evacuees are able to reach the safe area and all responders enter the disaster area within the golden time. In this situation, minimizing the overall time of evacuation and entrance time is important. Therefore, two mathematical models are developed for minimizing the average evacuation and entrance times and minimizing evacuation time for the last evacuee and the entrance time of the last responder.

When the golden time is adequate for rescuing all people, ensuring the entrance plan with minimizing the average evacuation time of all evacuees within the golden time is important. Therefore, a two-step approach model is developed to minimize the average time of evacuation while accommodating the time constraints of the responders reaching the disaster area.

When the golden time is insufficient for all evacuees to exit the safety area, all responders must enter to the disaster area and rescue as many evacuees as possible within the golden time. To model this situation, the two-step approach is used to maximize the number of evacuees reaching the safety area within the golden time while satisfying the time constraints of the responders. Figure 3 explains the four types of mathematical models developed based on the achievable objectives within the golden time.

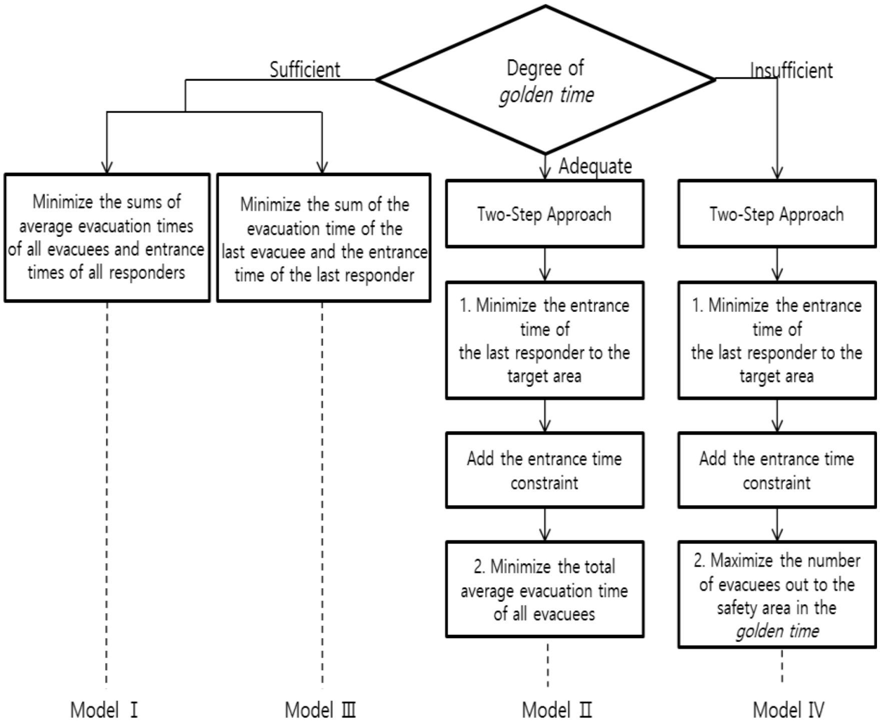

Figure 3. Four types of mathematical models developed based on three situations in the golden time

The following notations are used to present the four types of mathematical models based on the discrete time dynamic network flow problem:

Indices

i, j	: Node (i, j =1, 2, ... , I)
t	: Period (t =0, 1, ... , T)
s	: Super source node
d	: Super sink node

Parameters

λ_{ij}	: Travel time of evacuees and responders from node i to node j
a_i	: Capacity of node i

b_{ij} : Capacity of arc from node *i* to node *j*
c_i : Minimum number of required responders at node *i*
q_i : Number of evacuees in node *i* at *t* = 0
q'_i : Number of responders in node *i* at *t* = 0
k_1 : Weight (importance) of evacuation
k_2 : Weight (importance) of response
T : Golden time
e : Initial time of responders entering the safety area
M_1 : Large number
M_2 : Large number
ε : Tolerance

Sets
N : Set of nodes
S : Set of source nodes
D : Set of sink nodes
R : Set of disaster area nodes
A : Set of arcs

Decision variables
$x_{ij}(t)$: Number of evacuees moving from node *i* to node *j* at time *t*
$z_{ij}(t)$: Number of responders moving from node *i* to node *j* at time *t*
$y_i(t)$: Number of evacuees staying in node *i* at time *t*
$w_i(t)$: Number of responders staying in node *i* at time *t*

2.3. Model Ⅰ - Minimize the average evacuation and entrance times

Model I is generated to minimize the sums of average evacuation times of victims and entrance times of responders. The average evacuation time and entrance time can be formulated as $\frac{\sum_{t=0}^{T}\sum_{i\in S} t*x_{id}(t)}{\sum_{i\in S} q_i}$ and

$\frac{\sum_{t=0}^{T}\sum_{i\in R} t*z_{is}(t)}{\sum_{i\in S} q'_i}$, respectively. Because $\sum_{i\in S} q_i$ and $\sum_{i\in S} q'_i$ are constants, they do not need to be represented in the objective function. By adding these two components and multiplying them by weights k_1 and k_2, respectively, an objective function which represents the sums of the average evacuation and entrances times is developed. As k_1 and k_2 vary in the objective function, the priority between entrance and evacuation can be changed. If the decision maker prioritizes responder entrance over victim evacuation, k_1 is set to be smaller than k_2. Otherwise, k_1 is larger than k_2. The objective function and constraints are as follows:

Objective function

Minimize $$k_1 * \sum_{t=0}^{T}\sum_{i\in S} t * x_{id}(t) \; + \; k_2 * \sum_{t=0}^{T}\sum_{i\in R} t * z_{is}(t) \tag{1}$$

Subject to

$$x_{si}(0) = q_i, \quad \forall i \in S \tag{2}$$

$$z_{di}(e) = q'_i, \quad \forall i \in D \tag{3}$$

$$\sum_{t=0}^{T}\sum_{i\in D} x_{id}(t) = \sum_{j\in S} q_j \tag{4}$$

$$\sum_{t=e}^{T}\sum_{i\in R} z_{is}(t) = \sum_{j\in D} q'_j \tag{5}$$

$$y_i(t+1) - y_i(t) = \sum_{k\in pred(i)} x_{ki}(t-\lambda_{ki}) - \sum_{k\in succ(i)} x_{ij}(t)$$
$$t = 0, \cdots, T, \; \forall i \in N \tag{6}$$

$$w_i(t+1) - w_i(t) = \sum_{k\in pred(i)} z_{ki}(t-\lambda'_{ki}) - \sum_{k\in succ(i)} z_{ij}(t)$$
$$t = e, \cdots, T, \; \forall i \in N \tag{7}$$

$$y_i(0) = 0, \forall i \in N \tag{8}$$

$$w_i(t) = 0, \forall i \in N,\ t = 0, \cdots, e-1 \tag{9}$$

$$y_i(t) = 0, \forall i \in D; t = 0, \cdots, T \tag{10}$$

$$w_i(t) = 0,\ \forall i \in R; t = 0, \cdots, T \tag{11}$$

$$\begin{cases} y_i(t) \le a_i, & t = 0, \cdots, e-1;\ \forall i \in N - D \\ y_i(t) + w_i(t) \le a_i, & t = \mathrm{e}, \cdots, T;\ \ \forall i \in N - D \end{cases} \tag{12}$$

$$\begin{cases} x_{ij}(t) + x_{ji}(\tau)\ \le b_{ij}, \quad t = 0, \cdots, e-1; i\ \ne j; \\ \ \ \tau = t - (\lambda_{ij} - 1),\ \ldots, t, \ldots,\ t + (\lambda_{ij} - 1) \\ x_{ij}(t) + x_{ji}(\tau) + z_{ij}(t) + z_{ji}(\tau)\ \le b_{ij}, \quad t = e, \cdots, T; i\ \ne j; \\ \ \ \tau = t - (\lambda_{ij} - 1),\ \ldots, t, \ldots,\ t + (\lambda_{ij} - 1) \end{cases} \tag{13}$$

$$\sum_{t=e}^{T} \sum_{i \in R} z_{id}(t) \ge c_i,\ \ \forall i \in R \tag{14}$$

$$x_{ij}(t),\ z_{ij}(t),\ y_i(t),\ w_i(t) \in\ Z_+^n\ \ \{0, 1, 2,\ \cdots\} \tag{15}$$

The objective function (1) minimizes the sums of the average evacuation times of evacuees and entrance times of responders. The weights k_1 and k_2 can be set in accordance to the circumstance. Constraint (2) indicates the number of evacuees moving from the super source node to each source node at the start of the evacuation. Constraint (3) indicates the number of responders moving from the super sink node to each sink node as responders' entrance commences. Constraint (4) indicates the number of evacuees moving from a sink node to the super sink node. Constraint (5) indicates the number of responders moving from a disaster area to the super source node. Constraint (6) indicates the balance equation for the number of remaining and moving evacuees in each node at time t. Constraint (7) indicates the balance equation for the number of remaining and moving responders in each node at time t. Constraint (8) indicates no remaining evacuees in each node at time $t = 0$. Constraint (9) indicates no responders remaining in each node at time $t = 0, \cdots, e-1$. Constraint (10) prevents evacuees from being in a sink node. Constraint (11) prevents responders from being in a source node. Constraint (12) indicates the capacity of node i at time t. Constraint (13) indicates the flow capacity of arc (i, j) at time t. With regard to arc capacity, if the travel time between the nodes is 1, the general arc capacity '$x_{ij}(t) + x_{ji}(t) + z_{ij}(t) + z_{ji}(t) \leq b_{ij},\ t = 0, \cdots, T; i \neq j$' can be used. However, when the travel time is greater than 1, these constraints have limited application because they indicate the capacity at the starting period for each evacuee and responder. Therefore, the arc constraint is formulated as Constraint (13). Figure 4 explains the problem of applying a general arc capacity when the travel time is 4 and the arc capacity is 3. Constraint (14) indicates the minimum number of responders who must reach the disaster area. Constraint (15) means that the decision variables $x_{ij}(t)$, $z_{ij}(t)$, $y_i(t)$, and $w_i(t)$ are integers.

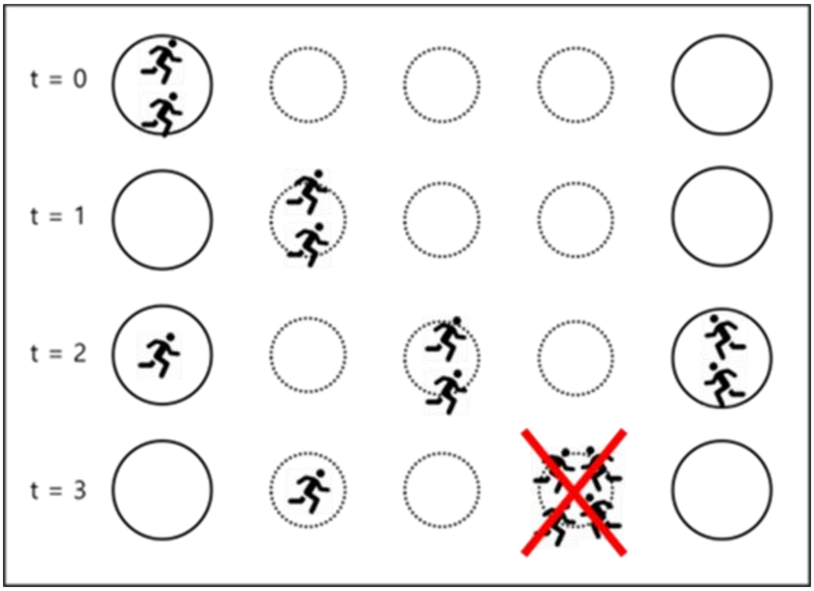

Figure 4. Drawback of using general arc capacity constraints when the travel time is 4 and the arc capacity is 3

2.4. Model Ⅱ – Minimize the average evacuation time while satisfying the entrance time constraints

Model II minimizes the average evacuation times while satisfying the time constraints of responders reaching the disaster area. It is based on a two-step approach. Table 2 explains the procedure.

Table 2
Procedure of Model II

Model II – Two-Step Approach
1. First step Minimize the time for the last responder to move from the safety area to the disaster area → Return the least entrance time $e + \sum_{t=e}^{T} \alpha(t)$ 2. Second step Multiply tolerance (ε) and the least entrance time as determined in Step 1 → $\varepsilon{*}(e + \sum_{t=e}^{T} \alpha(t))$ Add the $\varepsilon{*}(e + \sum_{t=e}^{T} \alpha(t))$ as the time constraint for all responders who must reach the disaster area Minimize the average evacuation time of evacuees

In the first step, the least entrance time of the last responder moving from the safety area to the target area is determined. To conduct this procedure, the integer variable $\xi(t)$ and binary variable $\alpha(t)$ are introduced.

$\xi(t)$: Cumulative sum of responders reaching the disaster area within time t

$\alpha(t)$: Binary variable

$$\begin{cases} = 1, & \text{If there exisits remaining responders} \\ & \text{who fail to reach the target area within time } t \\ = 0, & \text{Otherwise} \end{cases}$$

The values from multiplying the tolerance with the returned least entrance time are added in Constraint (23). Because $e + \sum_{t=e}^{T} \alpha(t)$ is the value of the least entrance time, the tolerance value is set by the decision maker in accordance with the situation. If the decision maker gives a sufficient tolerance value, time constraints allow enough time for responders to reach the target areas. Otherwise, the time constraints for the responders are set tightly. The objective function and constraints of the two-step approach are as follows:

Two-step approach

1. Minimize $\sum_{t=e}^{T} \alpha(t)$ (16)

Subject to

(2), (3), (5), (7) - (15)

$\xi(t) = 0, t = 0, \cdots, e$ (17)

$\xi(t) = \xi(t-1) + \sum_{i \in R} x_{id}(t)\,,\ t = e, \cdots, T$ (18)

$M_1 - \xi(t) \le M_1 * \alpha(t),\ t = 0, \cdots, e$ (19)

$\alpha(t) \in B_{+}^{n}\ \{0, 1\}$ (20)

$\xi(t) \in Z_{+}^{n}\ \{0, 1, 2, \cdots\}$ (21)

M_1 is a large number

2. Minimize $\sum_{t=0}^{T} \sum_{i \in S} t * x_{id}(t)$ (22)

Subject to

(2) - (4), (6) - (15)

$$\sum_{t=e}^{\varepsilon*(e+\sum_{t=e}^{T}\alpha(t))}\sum_{i\in R} z_{is}(t) = \sum_{i\in N} q'_i \qquad (23)$$

In the first step, the objective function (16) minimizes the entrance time of last responder. Constraint (17) indicates that no responders enter the target area at $t = 0, \ldots, e$. Constraint (18) expresses $\xi(t)$ as the sum of responders entering the target area at t. Constraint (19) indicates $\alpha(t) = 1$ if the remaining responders fail to reach the target area at t. Otherwise, $\alpha(t) = 0$. Although M_1 is a large number, it can be substituted into $\sum_{i\epsilon N} q'_i$ to make a solution bound tightly. Constraint (20) means that $\alpha(t)$ is a binary variable. Constraint (21) means that $\xi(t)$ is an integer variable. In the second step, the objective function (22) minimizes the average evacuation time of evacuees. Constraint (23) means all responders must reach to the disaster area within the time determined in the first step.

2.5. Model Ⅲ - Minimize the evacuation time of the last evacuee and the entrance time of the last responder

Model III minimizes the evacuation time of the last evacuee and the entrance time of the last responder. To solve the problem, the integer variable $\psi(t)$ and the binary variable $\beta(t)$ are introduced.

$\Psi(t)$: Cumulative sum of evacuees reaching the safety area within t

$\beta(t)$: Binary variable

$$\begin{cases} = 1, & \text{If there are evacuees} \\ & \text{who do not reach the safety area within } t \\ = 0, & \text{Otherwise} \end{cases}$$

The objective function and constraints are as follows:

Objective function

Minimize $k_1 * \sum_{t=0}^{T} \beta(t) + k_2 * \sum_{t=e}^{T} \alpha(t)$ (24)

Subject to

(2) - (21)

$\Psi(0) = 0$ (25)

$\Psi(t) = \Psi(t-1) + \sum_{i \in R} x_{id}(t),\ t = 1, \cdots, T$ (26)

$M_2 - \xi(t) \leq M_2 * \beta(t)$ (27)

$\beta(t) \in B_{+}^{n}\ \{0, 1\}$ (28)

$\Psi(t) \in Z_{+}^{n}\ \{0, 1, 2, \cdots\}$ (29)

M_2 is a large number

The objective function (24) minimizes the evacuation time of the last evacuee and the entrance time of the last responder. Constraint (25) indicates that no evacuees are at the safety area at $t = 0$. Constraint (26) illustrates that $\Psi(t)$ is the sum of the number of evacuees at the safety area at t. Constraint (27) is $\beta(t) = 1$ if some evacuees fail to reach the safety area at t. Otherwise, $\beta(t)$ = 0. Although M_2 is a large number, it can be substituted into $\sum_{j \in S} q_j$ to tighten the solution bound. Constraint (28) means that $\beta(t)$ is a binary variable. Constraint (29) means that $\Psi(t)$ is an integer variable. By minimizing the objective function, $\sum_{t=0}^{T} \beta(t)$ and $e + \sum_{t=e}^{T} \alpha(t)$ return the evacuation time of the last evacuee and the entrance time of the last responder, respectively.

2.6. Model IV - Maximize the number of evacuees within the golden time

Model IV maximizes the number of evacuees who reach the safety area within a certain time while satisfying the time constraints of responders reaching the disaster area. Table 3 explains the procedure of the two-step approach in this scenario.

Table 3
Procedure of Model IV

Model IV – Two-Step Approach
1. First step. Minimize the entrance time of the last responder moving from the safety area into the disaster area → Return the least entrance time $e + \sum_{t=e}^{T} \alpha(t)$ 2. Second step Multiply tolerance(ε) with the entrance time → ε*$(e + \sum_{t=e}^{T} \alpha(t))$ Add ε*$(e + \sum_{t=e}^{T} \alpha(t))$ as a time constraint for all responders who must reach the disaster area Maximize the number of evacuees who reach the safety area.

Similar to Model II, to find the minimum time for responders to reach the disaster area from the safety area, the binary variable $\alpha(t)$ and the integer variable $\xi(t)$ are introduced. After multiplying the tolerance with the entrance time of the last responder, these values are added in Constraint

(21). The objective function and the constraints of the two-step approach are as follows:

Two-step approach

1. Minimize $\sum_{t=e}^{T} \alpha(t)$

   Subject to

   (2), (3), (5), (7) - (15), (17) - (21)

   M_1 is a large number

2. Maximize $\sum_{t=0}^{T} \sum_{i \in S} x_{id}(t)$

   Subject to

   (2), (3), (6) - (15), (17) - (21), (23)

By maximizing the $\sum_{t=0}^{T} \sum_{i \in S} x_{id}(t)$ in the second step with Constraint (21), as many evacuees as possible escape to the safety area within $t = 0, \ldots, T$. In this model, T is smaller than that of other models but is enough for all responders to reach to the target area.

Chapter 3. Heuristic Algorithm

3.1. Procedure of heuristic algorithm

A mathematical optimization model shows two weaknesses: Interpreting the solution is difficult and computation time is long. First, the model fails to present complete routes for the evacuees and responders moving between the source and sink nodes. The decision variables $x_{ij}(t)$ and $z_{ij}(t)$ for evacuees and responders moving from node i to node j at t, respectively, account only for the paths of movement between adjacent nodes at t. In other words, when evacuees at node $i \in S$ move to node $j \in D$, the intermediate pathway of the victim remains unknown. Figure 5 shows the graphical representation of the drawback in the mathematical model. For example, three evacuees are initialized at node 1 and four evacuees are initialized at node 2. The escape path of two evacuees from node 2 to node 7 passes clearly through nodes 2-4-7. However, when three evacuees are introduced at node 1 and two evacuees are introduced at node 2, they encounter each other at node 3 and the evacuees who move to nodes 5, 6, and 7 remain unidentified. As a result, the solution does not give all the information about the number of evacuees from node 1 who move through routes 1-3-5, 1-3-6, or 1-3-7, respectively. When the number of nodes increases, interpreting the solution to determine the number of evacuees moving between nodes is increasingly difficult.

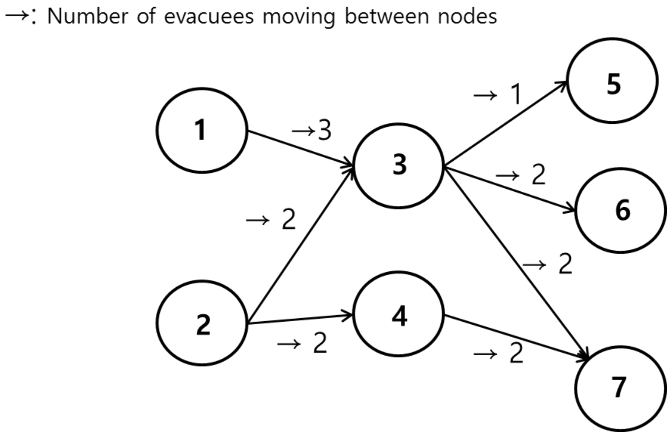

Figure 5. Drawback of the mathematical model

Second, when the data size of the problem is large, the mathematical model is difficult to solve with optimization software within a reasonable time. Because the mathematical models use time-expanded networks, computation time is affected by upper bound T, which the user defines. As Figure 2 shows, at least $(T+1)n$ nodes are needed to solve the problem. Furthermore, the outcomes of decisions based on poorly chosen values for upper bound T may be undesirable. An underestimated T leads to infeasible solutions and an overestimated T causes unnecessary computation time. Therefore, this approach restricts scaling up to large size of networks because of high computational time. However, in an emergency situation, the entrance and evacuation plans must be determined rapidly based on real-time information.

To overcome both the solution and computational time difficulties, a heuristic algorithm is developed. The algorithm can provide the complete evacuee and responder routes from source nodes to sink nodes by extending the Capacity Constrained Route Planner (CCRP) to account for the entrance of responders. Understanding the solution of the heuristic algorithm is easier than interpreting the solution from the mathematical model. The algorithm can provide sub-optimality within a reasonable time. While the mathematical model solves the problem with all input data at once, the CCRP solves it step-by-step by iterating the shortest path. The mathematical model developed in this research can be relaxed to apply the linear programming approach which has a computational cost of $O((T \cdot n)^6)$; however, the CCRP costs $O(p \cdot nlogn)$ (n: number of nodes; p: number of evacuees; T: upper-bound on evacuation time) [22]. Accordingly, large problems can be efficiently solved with the CCRP.

In the heuristic algorithm, routes for the evacuees are provided with the CCRP in the first step of the two-step approach. In the second step, optimal routes for responders are provided after all the evacuee routes have been added as parameters in the dynamic network flow model. The pseudo code for the heuristic algorithm is as follows:

Heuristic Algorithm
Input: 1) *G(N, A)*: a network *G* with *N* and *A* ✓ Each node is characterized by node capacity and number of initialized evacuees ✓ Each arc features arc capacity and travel time 2) *S*: set of source node 3) *D*: set of sink node 4) *R*: set of disaster(target) area node **Output:** Evacuation routes for all evacuees and entrance routes for all responders within time period $t = 0, \ldots, T$

Method:

1) **First step**

✓ Conduct CCRP for evacuation plan [22]

Link super source node s to each source nodes with arc capacity = ∞, travel time = 0

While any source node $i \in S$ {

While number of evacuees still at source node $i > 0$ {

obtain shortest path from source node i to super sink node d

Minimize $\sum_{t=0}^{T} \sum_{i \in D} t * x_{id}(t)$ (30)

Subject to

$$y_i(t) \le a_i, \quad t = 0, \cdots, T; \;\; \forall i \in N - D \tag{31}$$

$$x_{ij}(t) + x_{ji}(\tau) \le b_{ij}, \quad t = 0, \cdots, T; i \neq j; \quad \tau = t - (\lambda_{ij} - 1), \;\dots, t, \dots, \; t + (\lambda_{ij} - 1) \tag{32}$$

$$x_{sj}(0) = 1, \quad \forall j \in S \tag{33}$$

$$\sum_{t=0}^{T} \sum_{i \in S} x_{id}(t) = 1 \tag{34}$$

$$y_i(t+1) - y_i(t) = \sum_{k \in pred(i)} x_{ki}(t - \lambda_{ki}) - \sum_{k \in succ(i)} x_{ij}(t) \quad t = 0, \cdots, T, \; \forall i \in N \tag{35}$$

In the route of the shortest path,

min_flow = min(number of evacuees remaining at source node $i \in S$, node capacity, arc capacity)

✓ update node capacity

$$y_i(t) \le a_i - \text{min\_flow}, \quad t = 0, \cdots, T; \;\; \forall i \in N - D$$

✓ update arc capacity

$$x_{ij}(t) + x_{ji}(\tau) \le b_{ij} - \text{min\_flow}, \quad t = 0, \cdots, T; i \neq j;$$

}
}

2) Second step

Add all of the routes for evacuees as parameters in a dynamic network flow model

Minimize $$k_1 * \sum_{t=0}^{T} \sum_{i \in S} t * x_{id}(t) \; + \; k_2 * \sum_{t=0}^{T} \sum_{i \in R} t * z_{is}(t) \qquad (1)$$

Subject to

(3), (5), (7), (9), (11), (13), (14)

Output evacuation and entrance routes

In the heuristic algorithm, the objective function (30) minimizes the time for evacuees to reach the safety area. Constraint (31) represents node capacity at time t. Constraint (32) represents arc capacity at time t. Constraint (33) means there is only one evacuee moving from the super source node s to the source node $i \in S$. Constraint (34) means one evacuee initialized in a source node reaches the safety area. Constraint (35) indicates the balance equation between remaining and moving evacuees in each node at time t. By iterating the objective function (30) and Constraints (31) ~ (35), the heuristic algorithm finds the shortest path from source node to sink node and updates the node capacity and arc capacity by subtracting the min_flow, which accounts for the smallest component among the number of evacuees still at source node $i \in S$, node capacities, and arc capacities. When no evacuee remains in source node $i \in S$, all movement of evacuees as well as the node and arc capacities are set as parameters in the second step of the heuristic. At this point, by minimizing the objective function (1) with Constraints (3), (5), (7), (9), (11), (13), and (14), the heuristic algorithm provides evacuation and entrance routes.

3.2. Numerical example

In general, because evacuees typically outnumber responders, using the CCRP to determine evacuee routes and the dynamic network flow model to determine responder routes constitutes an appropriate approach to dealing with concerns about computation time. To verify performance, the heuristic algorithm is compared to the mathematical optimization model through a computational experiment. Figure 6 represents the network for conducting the numerical test.

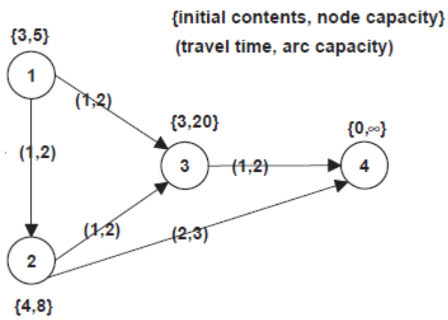

Figure 6. Network data for the numerical experiment

Three, four, and three evacuees, respectively, are initialized in node 1, 2 and 3 at $t = 0$. Five responders are initialized in node 4 at $t = 1$. Tables 4, 5, and 6 represent optimal routes for the evacuees and responders as determined by both the heuristic algorithm and Models I and III.

Table 4
Evacuation and entrance plan determined by the heuristic algorithm

Heuristic algorithm							
Time	Routes for evacuees Node→Node (Number of evacuees)				Routes for responders Node→Node (Number of responders)		
$t = 0$	1→2(1)	1→3(2)	2→4(3)	3→4(2)			
$t = 1$	2→4(2)	3→4(2)	4→5(2)		4→2(1)		
$t = 2$	4→5(5)				4→2(1)	4→3(1)	
$t = 3$	4→5(3)				4→3(2)	3→1(1)	2→1(1)
$t = 4$					1→0(2)	2→1(1)	3→1(4)
$t = 5$					1→0(3)		

Table 5
Evacuation and entrance plan determined by Model I

Model I							
Time	Routes for evacuees Node→Node (Number of evacuees)				Routes for responders Node→Node (Number of responders)		
$t = 0$	1→2(2)	2→3(1)	2→4(3)	3→4(2)			
$t = 1$	1→3(1)	2→4(2)	3→4(2)	4→5(2)	4→2(1)		
$t = 2$	3→4(1)	4→5(5)			4→2(1)	4→3(1)	
$t = 3$	4→5(3)				4→3(2)	3→1(1)	2→1(1)
$t = 4$					3→1(4)	1→0(2)	
$t = 5$					1→0(3)		

Table 6
Evacuation and entrance plan determined by Model III

Model III							
Time	Routes for evacuees Node→Node (Number of evacuees)				Routes for responders Node→Node (Number of responders)		
$t = 0$	1→2(2)	2→3(1)	2→4(3)	3→4(2)			
$t = 1$	1→3(1)	2→4(2)	3→4(2)	4→5(2)	4→2(1)		
$t = 2$	3→4(1)	4→5(5)			4→2(1)	4→3(1)	
$t = 3$	4→5(3)				4→3(2)	3→1(1)	2→1(1)
$t = 4$					3→1(4)	1→0(2)	
$t = 5$					1→0(3)		

According to the heuristic algorithm as well as Models I and III, all evacuees escape to the safety area at $t = 3$ and all responders reach the target area at $t = 5$. In this small size experiment, all solutions in Models I and III are the same. Although the solutions of the heuristic algorithm differ from those of Models I and III, the finish times of evacuation and entrance are the same. Therefore, the developed heuristic algorithm provides good quality of sub-optimality.

Chapter 4. Case Study

4.1. Backdrop of the case study

In this research, a case study was conducted with the mathematical models and the heuristic algorithm. Central City, the huge megamall in Seoul, Korea, is used as the backdrop for this case study. The original layout comes from Kang et al. [13], and it is modified and enhanced with additional data to create the network model. Each facility is set as a node and the route of movement of people between nodes is considered an arc. The travel time from a node to an adjacent node is calculated by dividing the running speed by distance. Figures 7 and 8 illustrate the layout of Central City and the schematic of the travel network as used in this case study.

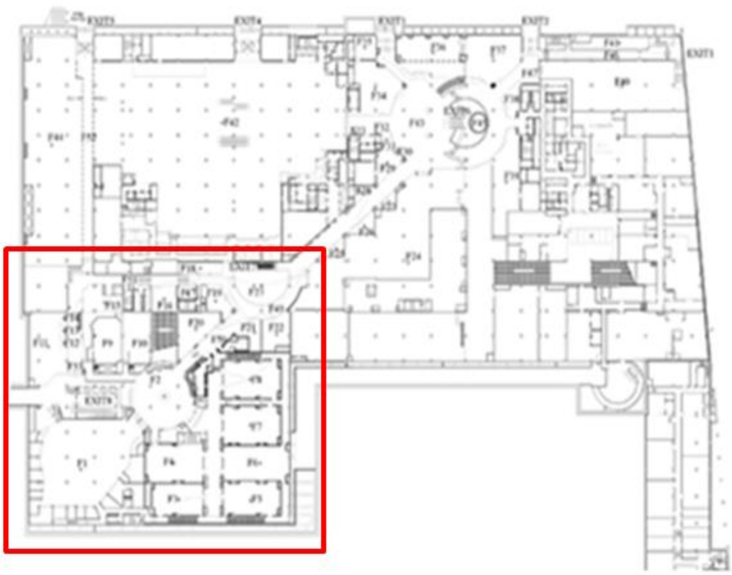

Figure 7. Floor plan of Central City; the red rectangle depicted is the arc-node network depicted in Figure 8

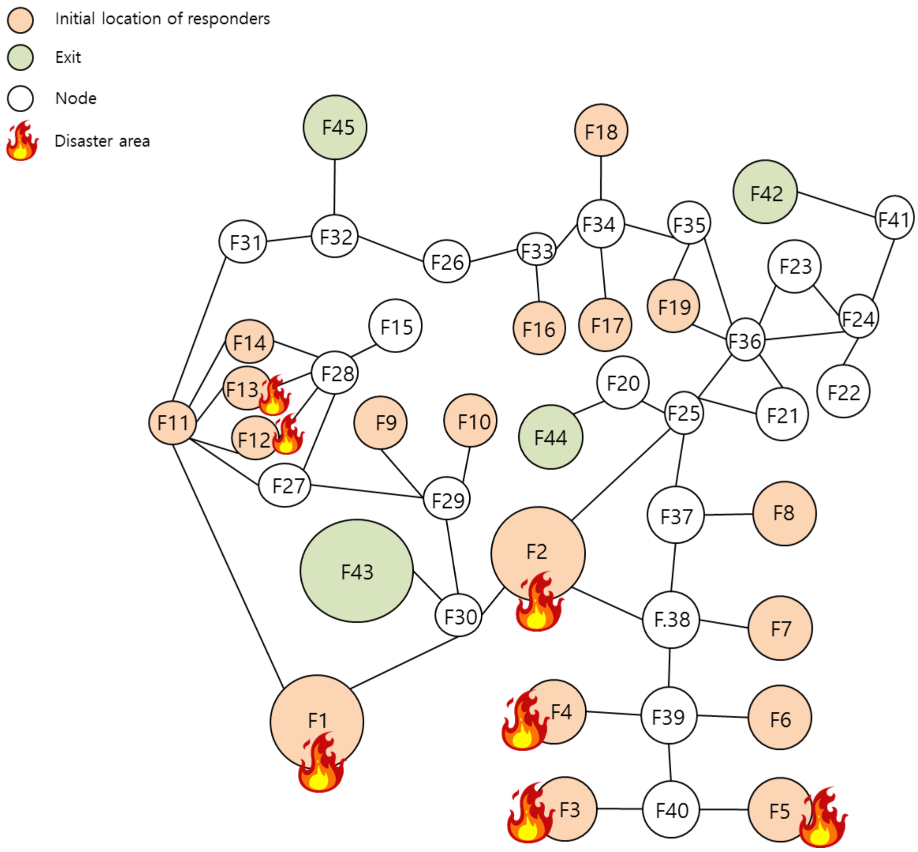

Figure 8. Modified network illustrating part of Central City, see red rectangle in Figure 7

Two types of case studies were conducted: Case study I compares and contrasts the heuristic algorithm and Models I, II, and III, and Case study II is based on the golden time T as applied in Model IV. Because Model IV features a short time frame for bound T with a value smaller than or equal to the minimum evacuation and entrance periods, this case study was carried out separately.

4.2. Case study I

In Case study I, all evacuees are initialized at F1-F14 and F16-F19. F42-F45 are considered the safety area. The disaster unfolds at F1-F5, F12, and F13. Accordingly, evacuees escape from F1-F14 and F16-F19 to F42-F45 while responders reach F1-F5 and F12-F13 from F42-F45. F1-F45 corresponds to node 1-45, and node 0 and 46 are introduced as super source node s and super sink node d, respectively. The number of evacuees for each node is set as a random number between 10 and 50, and the total number of responders is set at 90. The total number of evacuees is 323 and 90 responders arrive at the safety area at $t = 5$. Ten responders must reach each disaster node. The weights k_1 and k_2 are each set at 1 and the discrete unit time t is 5 seconds. In Model II, tolerance ε is set at 1. Table 7 shows the set of nodes corresponding to the definitions used for the model.

Table 7
Input data for nodes in Case study I

N	F1-F45
S	F1-F14 and F16-F19
D	F42-F45
R	F1-F5 and F12-F13

The heuristic algorithm was solved in Java 1.8.071 language with the EXPRESS-MP library, and the Models I, II, and III were solved by FIC XPRESS-IVE version 7.9 with an Intel® Core™ i5-3470 CPU @ 3.20GHz.

4.3. Results of Case study I

Table 8 summarizes the results of the Case study I. It shows ranges of evacuation and entrance times, average times of evacuation and entrance, and computation times of the heuristic algorithm and Models I, II, and III.

Table 8
Summarization of Case study I

Method	Range of evacuation time (t)	Range of entrance time (t)	Average time of evacuation (t)	Average time of entrance (t)	Computation time (second)
Heuristic Algorithm	4 - 13	9 - 20	9.30	15.36	26.8
Model I	8 - 13	9 - 18	11.16	13.06	51.4
Model II	9 - 13	14 - 18	10.54	17.73	45.2
Model III	9 - 13	9 - 18	11.20	13.67	96.0

As Table 8 shows, the heuristic algorithm outperforms the mathematical models in computation time and provides a good quality solution. Furthermore, because it finds the shortest path through iteration, the first evacuation occurs at $t = 4$. However, by solving the evacuation problem first, the performance of the entrance problem suffers. Model I, which minimizes the sums of average times for evacuation and entrance, provides a wide range of solutions in comparison with the other mathematical models. This finding means that all evacuees and responders are distributed to safety and disaster areas more evenly in time bound $t = 0 \dots T$. Model II, which adds the time constraints of responders in a two-step approach, solves the problem by prioritizing evacuation over entrance. This model adds the times of entrance as constraints, and does not represent in the objective function. Although the average time of entrance is not good, the last responder reaches to the disaster area at $t=18$ and the model yields an average evacuation time that outperforms other mathematical models. Model III, which minimizes the evacuation time of the last evacuee and the entrance time of last responder, shows similar patterns to those of Model I, but the solutions are not as good as those of Model I and the computation time is relatively long. Figures 9 and 10 illustrate the number of evacuees reaching the safety area and number of responders entering the disaster area, respectively, over time t.

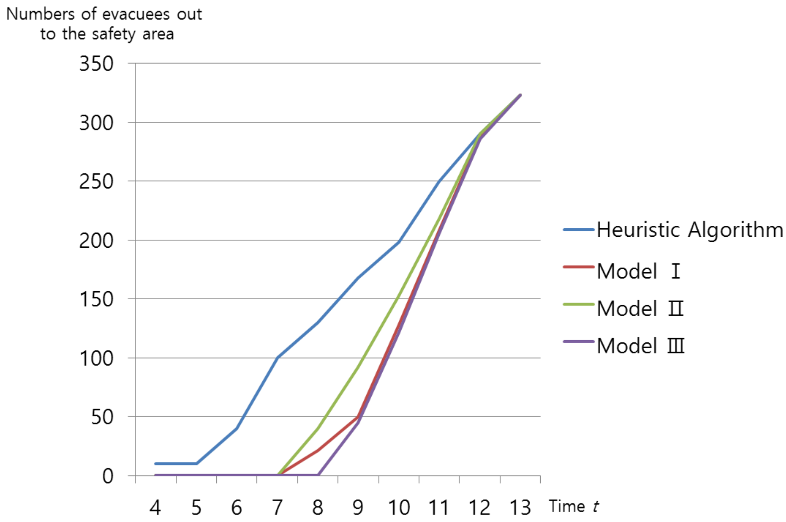

Figure 9. Number of evacuees reaching the safety area over time t

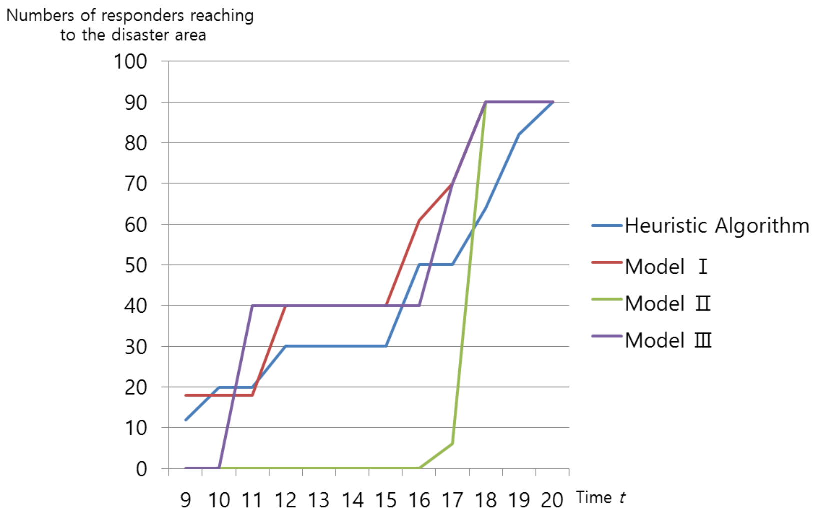

Figure 10. Number of responders entering the disaster area over time t

As Figure 9 shows, the heuristic algorithm has the best performance in determining evacuation among mathematical models. Model II shows better performance than Models I and III which offer similar solutions. However, in regard to entrance, as shown in Figure 10, the performances of Models I and III are better than the others. The heuristic algorithm finished the entrance at $t = 20$ which is the latest time among the models. Although Model II finishes at $t = 18$, which is the same as Models I and III, the first arrival time is poor compared the other models. In other words, all models developed in this study offer trade-offs between evacuation and entrance performance. According to the situation, the proper model must be chosen. Table 9 shows the number of evacuees exiting to each node in this case study.

Table 9
Number of evacuees exiting to each node in Case study I

	Number of evacuees exiting to F42	Number of evacuees exiting to F43	Number of evacuees exiting to F44	Number of evacuees exiting to F45
Heuristic Algorithm	0	160	73	90
Model I	20	144	119	40
Model II	13	125	140	45
Model III	20	127	136	40

As Table 9 shows, in the heuristic algorithm, evacuees go to nodes 43, 44, and 45, and in Models I, II, and III, they go to nodes 42, 43, 44, and 45. The results differ because the problem addressed by the heuristic algorithm is based on the shortest paths between each node and the safety area, and the mathematical models are searching the global optimality by accounting for an even distribution of all evacuees in the space. For a mean of the number expected to reach a safety area of 80.75, ($\therefore 323 \div 4 = 80.75$), the variance of each node is shown in Table 10.

Table 10
Variance of number of evacuees reaching each node in Case study I

Method	Variance of number of evacuees reaching each node
Heuristic Algorithm	3236.69
Model I	2703.69
Model II	2834.19
Model III	2635.69

As Table 10 shows, Model III has the smallest variance among models. This finding means that evacuees were distributed most evenly in Model III. Because this model emphasizes minimizing the evacuation time of the last evacuee and entrance time of the last responder, it solves the problem by spreading all evacuees and responders evenly. Due to the data properties of this case study, evacuees are not initialized in all nodes, so distributing all evacuees evenly has a negative influence on evacuation performance. Table 11 represents the number of responders entering from each node in this case study.

Table 11
Number of responders entering from each node in Case study I

	Number of responders entering from F42	Number of responders entering from F43	Number of responders entering from F44	Number of responders entering from F45
Heuristic Algorithm	0	32	40	18
Model I	0	28	42	20
Model II	20	38	18	14
Model III	0	40	30	20

As Table 11 shows, responders do not use node 42 in the heuristic algorithm or in Models I and III. Because node 42 is the farthest from the disaster area, responders have a tendency to avoid using it as an entrance route in their effort to minimize travel time. However, in the case of Model II, setting the entrance of responders as constraints, not as an objective function, affects the routes of the responders. As Tables 8 and 11 show, this model does not account for the number of respondents using the entrance; rather it only satisfies the time constraints of responders. Therefore, some responders use node 42 as an entering node even though it is the farthest from the disaster area. When node 42 is the entering node, other nodes could afford space for evacuees, which leads to a better evacuation solution than offered by the other mathematical models.

For interpreting the solution, the heuristic algorithm offers advantages over the mathematical models. For example, the heuristic algorithm shows evacuees in node 12 using the route 12-11-31-32-45 and in node 14 the evacuees use route 14-11-31-32-45, respectively. However, according to the mathematical model, evacuees move from node 12 to 11, node 14 to 11, and node 11 to node 1 and 31. Therefore, the number of evacuees moving from node 12 to node 1 or 31 is difficult to determine. If the size of the network were bigger, the confusion in interpreting the solution would increase. Considering the characteristics of evacuees and emergency situations, guiding the evacuees with the heuristic algorithm seems more practical. Table 12 shows the whole routes evacuees used in this case study.

Table 12
Solutions of heuristic algorithm in Case study I

	Routes evacuees use
Node 1	1→30→43→46 (30) 1→1→30→43→46 (11)
Node 2	2→30→43→46 (10)
Node 3	3→40→39→38→2→30→43→46 (19)
Node 4	4→39→38→2→30→43→46 (12)
Node 5	5→40→39→38→2→30→43→46 (1) 5→40→39→38→37→25→20→44→46 (13)
Node 6	6→39→38→2→30→43→46 (8) 6→39→38→37→25→20→44→46 (12)
Node 7	7→38→2→30→43→46 (18)
Node 8	8→37→25→20→44→46 (18)
Node 9	9→29→30→30→43→46 (6) 9→9→29→30→43→46 (4)
Node 10	10→29→29→30→43→46 (7) 10→10→29→30→43→46 (2) 10→10→29→30→30→43→46 (2)
Node 11	11→31→32→45→46 (10)
Node 12	12→11→31→32→45→46 (20)
Node 13	13→11→1→30→43→46 (20)
Node 14	14→11→1→30→43→46 (10) 14→11→11→31→32→45→46 (10)
Node 16	16→33→26→32→45→46 (20)
Node 17	17→34→33→26→32→45→46 (10) 17→2634→33→26→26→32→45→46 (10)

Node 18	18→34→33→26→32→45→46 (10) 18→34→35→36→25→20→44→46 (10)
Node 19	19→36→25→20→44→46 (12) 19→19→36→25→20→44→46 (8)

As Table 12 presents, evacuees in node 1-10, 13, and 14 moved to node 43; those in node 5, 6, 8, 18, and 19 moved to node 44; and those in 11, 12, 14, and 16-19 moved to node 45. Evacuees in node 5, 6, 14, and 18 moved in separate groups through to different destinations. Although the heuristic algorithm offers an advantage in interpreting the solutions more clearly, it has limitations when solving the problem because it conducts iterations based on the order defined by the user. In this case study, the order was set as an ascending node number. To find out whether performance is dependent on order of iteration or not, four types of experiments are conducted: ascending node number, ascending evacuees' number, descending evacuees' number, and random order number. Table 13 represents the results from these four experiments.

Table 13
Difference in selection of node order in heuristic algorithm

Method	Evacuation time of last evacuee to the safety area (*t*)	Entrance time of last responder to the target area (*t*)	Computation time (second)
Ascending Node Number	13	20	26.8
Ascending Evacuee Number	13	20	25.2
Descending Evacuee Number	13	20	27.2
Random Node Number	13	20	27.9

As Table 13 shows, in this case study, selection of node order did not affect the evacuation time. All methods provide solutions in which evacuations finish at $t = 13$ and entrances are finished at $t = 20$. The solution gap occurs between heuristic algorithm and mathematical models because the mathematical models solve the entrance problem by accounting for evacuation and entrance simultaneously, whereas the heuristic algorithm solves the entrance problem after solving the evacuation problem.

4.4. Case study II

Another case study was conducted with Model IV by changing the golden time T. Because this model maximizes the number of evacuees who reach safety within time bound T, T is set as less than or equal to the time bound, which is shortest time for completing evacuations and entrances. This model is suitable for scenarios in which the golden time is especially urgent and few responders must access certain areas. Accordingly, in this experiment, the number of responders is set to 10 and at least three responders must reach nodes 1 and 2, respectively. The first arrival time to safety the area is set at $t = 3$. Table 14 shows the results of the case study using Model IV when the golden time T varies. The Model IV was solved with FIC XPRESS-IVE version 7.9 with an Intel® Core™ i5-3470 CPU @ 3.20GHz.

4.5. Results of Case study II

As Table 14 shows, when T is 8 to 10, no one used node 42 as a destination for evacuation. Whereas, when T is 11 to 13, 20 evacuees initialized in node 19 used node 42 as a destination. They used node 44 as their destination when T is 8 to 10. Although, node 42 is farther than node 44 from node 19, when the golden time is long enough, the optimal evacuation plan is made by spreading some evacuees to the farther area to ensure other evacuees use certain routes. This allows more evacuees to escape within the golden time.

Table 14
Results of Case study II

Golden time T	Number of evacuees entering node 42	Number of evacuees entering node 43	Number of evacuees entering node 44	Number of evacuees entering node 45	Sum
8	0	72	38	20	130
9	0	90	38	40	168
10	0	100	38	60	198
11	20	102	48	80	250
12	20	112	78	80	290
13	20	132	88	83	323

Chapter 5. Conclusions

The purpose of this research is to find the optimal evacuation routes for evacuees and entrance routes for responders simultaneously. The solutions based on integer programming can support managers making decisions on evacuation planning and serving as arbiters of the response team. With four types of mathematical models, the manager can choose a proper entrance and evacuation plan depending on the specific circumstances of the emergency situation.

Integer programming with a dynamic network flow problem has two weak points: difficulty in interpreting solutions and lengthy computation times. The developed heuristic algorithm does not feature the same weak points as the mathematical model. The algorithm provides complete routes for evacuees and responders and reaches a sub-optimal solution within a reasonable time.

Because of the growth of modern technology, decision makers and planners can analyze the real-time emergency situations and related data. Also the ability to inform evacuees on escape routes and designate appropriate entrance routes for responders in real-time is now possible. To utilize these modern technologies effectively, evacuation and entrance plans must be based on these scientific approaches, and not solely on the intuitive judgement of the response team leader. Accordingly, this study suggests mathematical models and a heuristic algorithm that provide an optimal data-driven evacuation and entrance plan. Furthermore, this study pioneers a plan in which both evacuations and emergency responses take place simultaneously.

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초 록

2015 년 프랑스에서의 테러와 2016 년 벨기에에서의 테러와 같은 수많은 긴급재난상황이 전세계에 걸쳐 빈번히 발생하고 있다. 이에 따라 테러, 화재, 자연재해와 같은 긴급재난상황에서의 대피계획에 관한 연구가 주목 받고 있다. 그러나 기존의 선행 연구들은 대피계획 개발에만 국한되어 있다. 긴급재난상황을 효율적으로 종료시키기 위해서는 경찰특공대 또는 소방관들과 같은 진입대원들의 진입계획 또한 대피계획 못지 않게 중요하다. 이러한 기존 연구의 한계점을 개선하기 위해, 대피자들의 대피계획과 진입대원들의 진입계획을 동시에 고려하여 제공하는 수리모형을 개발하였다. 동적네트워크흐름 모형으로 개발함으로써, 이 모형의 해는 주어진 시간 안에서 대피자들의 최적의 대피경로와 진입대원의 최적의 진입경로를 제공해준다. 그러나 이 수리모형은 해의 분석의 어려움과 컴퓨터 연산 시간이 길다는 두 가지 단점을 지니고 있다. 이러한 문제점들을 해결하기 위해, 용량제약경로계획을 기반으로 한 휴리스틱 알고리즘을 개발하였다. 본 연구는 진입계획과 대피계획을 동시에 고려한 수리모형과 휴리스틱을 개발하였다는 점에서 관련 연구분야를 선도한다

주요어: 동적네트워크흐름 모형, 진입계획, 대피계획, 휴리스틱 알고리즘, 정수계획법

Keywords: dynamic network flow; entrance plan; evacuation plan; heuristic algorithm; integer programming

학 번: 2015-21137