Network repair crew scheduling for short-term disasters

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ABSTRACT

Casualties and damages caused by disasters occur every year. To reduce further damages in the post disaster period, many types of research have been conducted. The repair crew problem is one of these efforts, and it is used for deciding ways to manage repairs to destroyed roads that connect members of supply chain networks. Especially in rural areas where road networks are sparse and supply chains are limited, road-network repair is particularly important because road destruction can contribute to high rates of rural isolation. In addition, the unpredictable nature of disasters creates concerns for those effecting post-disaster management. Especially in the short-term after a disaster, damage characteristics can dramatically change. Therefore, we considered a repair crew problem in which aspects of damage vary at certain times. A mathematical formulation on the basis of mixed integer programming is introduced to minimize the weighted sum of total damages caused in isolated areas and completion time of a repair crew. To overcome the complexity issue, an ant colony system algorithm was developed. It can be used to solve a multiple repair crew problem. Our study gives new insights into ways to manage problems in the post-disaster period.

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1. Introduction

Nowadays, natural or man-made disasters are occurring frequently throughout the world. However, preparations and countermeasures for disasters are still insufficient for minimizing damage. In the case of underdeveloped countries, both direct and indirect damages are caused by lack of infrastructure and post disaster efforts. The tsunami occurred in the Indian Ocean in 2004 and the earthquake in Haiti in 2010 illustrate this situation. However, damages are also unavoidable in developed countries which thoroughly prepared for a disaster. In 2011, Japan suffered extensive human and infrastructure damages caused by the Fukushima earthquake.

Because the infrastructure of modern society is highly interdependent, when one type of infrastructure is destroyed, the entire social system can be paralyzed [1]. For example, infrastructure including electricity, communications, transportation facilities, and so forth, is vulnerable to disaster damage because necessary operations are difficult to recover [2]. In particular, when the transportation infrastructure is destroyed and the relief supply chain is thus disconnected, short-term relief efforts and long term recovery plans are hindered [3,4,5]. In a city, the vulnerable infrastructures are effectively interconnected;

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therefore, rather than the isolated recovery of a specific infrastructure, a comprehensive urban repair plan is needed. On the other hand, in rural areas, accessible routes must be secured because roads are not only the economic and social support routes but are also the supply routes for relief goods [6,7]. Because underdeveloped areas typically have relatively less accessible routes, supplying relief goods in isolated areas is difficult [8,9]. Accordingly, after a disaster in rural areas, plans and schedules for a repair crew who can fix damaged roads that connect members in the relief supply chain are needed to minimize further disaster damage in isolated areas. We focus on the scheduling issue of the repair problem in the post-disaster period.

Research on the post-disaster relief supply chain can be divided into long-term and short-term perspectives. The long-term perspective mainly focuses on the period after direct physical damages from a disaster-causing event are no longer changing or accruing. In this case, responders are partially free from time constraints and the problem is similar to that of commercial management studies on minimized costs. In contrast, the short-term perspective focuses on the situation immediately after a disaster has occurred such that the availability of a supply chain is crucial for timely delivery of relief goods, evacuation of victims, and transport of casualties [10,11]. For this reason, a study on network repair is required to address a situation in which the supply chain network might is destroyed and relief activities are thus restricted. In this study, we used the short-term perspective to consider the problem of repairing a damaged network.

In the short period in post disaster, the conditions can change dramatically. Damage conditions vary depending on the type of disaster, and recovery situation. For example, earthquakes cause not only immediate damage, but also additional damage that develop over relatively short time periods [6,12]. In contrast, radiation accidents cause extreme, long-term damages. For this reason, the long-term perspective management is particularly advantageous for addressing problems on radiation disasters. After 2012 Tohoku radioactive spill, the Japanese government ordered those on site to wait in the building rather than leave the damaged area [13]. In addition, damages can be different depending on the types and conditions of disasters. On one hand, if immediate medical assistance is not provided to seriously injured individuals, then the probability of fatalities substantially increases. On the other hand, people suffering dehydration may survive several days before the mortality rate accelerates.

Uncertainty aspects of disasters have been considered in some post-disaster problems [14,15,16]; however, they focused on high-level operations. Zokaee et al. [14] proposed a three-level relief chain model. A robust approach was applied to handle the uncertainty issues of demand, supply, and cost parameters. The data from the Alborz area were used to evaluate their proposed model. Mohammadi et al. [15] developed a multi-objective stochastic programming model for response to earthquakes. The authors combined pre- and post-disaster decisions. A particle swarm algorithm was developed to solve the problem, and a case study was conducted by assuming disaster scenarios in Tehran. Zhang et al. [16] proposed a facility location problem considering uncertainty. The authors used the data of Sichuan for the case study.

Previous research on repair problems did not consider the unpredictable characteristics of the short-term situation. Yan and Shih [6] discussed features of the earthquake and additional damages, but did not include these characteristics in their model. Instead, the authors focused on extending previous research to network repair and distribution of relief goods simultaneously. In follow-up research, an ant colony system (ACS) algorithm was developed to compensate for the limitations of previous studies and explained the additional damages caused by secondary and tertiary disasters for a future study [9]. Duque et al. [8] developed the network repair crew scheduling and routing problem (NRCSRP) and considered constant weights in isolated disaster areas.

In this study, we developed a repair crew scheduling problem based on the model proposed by Duque et al. [8]. We considered the case in which damage aspects may vary at a time point after the initial disaster has occurred. To describe the dynamic damage aspects over time, we considered the timing of additional disasters caused by the initial event and changes in the damage rate. On the basis of these considerations, we propose the network repair crew scheduling for short-term disasters (NRCSSD). We assumed that repair activities are initiated at a supply hub by a repair crew and that all damaged nodes. This model minimizes the weighted sum of total damages caused by isolation conditions and completion time of a repair crew.

Unfortunately, the proposed mathematical model is intractable in large scale instances. Duque at el. [8] already mentioned that the mixed integer programming model is intractable for solving even small problems. With simple modifications, our proposed model can be reduced to a variation of the traveling salesman problem which is an NP-hard problem. For reasons related to the complexities in calculating the optimal solution, we considered only one repair crew, for which an efficient heuristic algorithm is needed. The ACS algorithm was developed to compensate for the computational complexity of the mathematical model. We chose this meta-heuristic method in that it was initially employed to efficiently solve the traveling salesman problem [19]. In addition, the algorithm can be used to solve a multiple repair crew problem. Our study contributes to repair crew scheduling for additional disasters as well as changeable damage patterns in isolated areas. We extend Kim et al. [17] by adding the ACS algorithm and conducting more computational experiments to evaluate it.

This study is organized as follows: the repair crew problem and the mathematical formulation are introduced in Section 2. Section 3 illustrates the ACS algorithm. Section 4 reveals the computation experiments designs and results. Section 5 concludes this article.
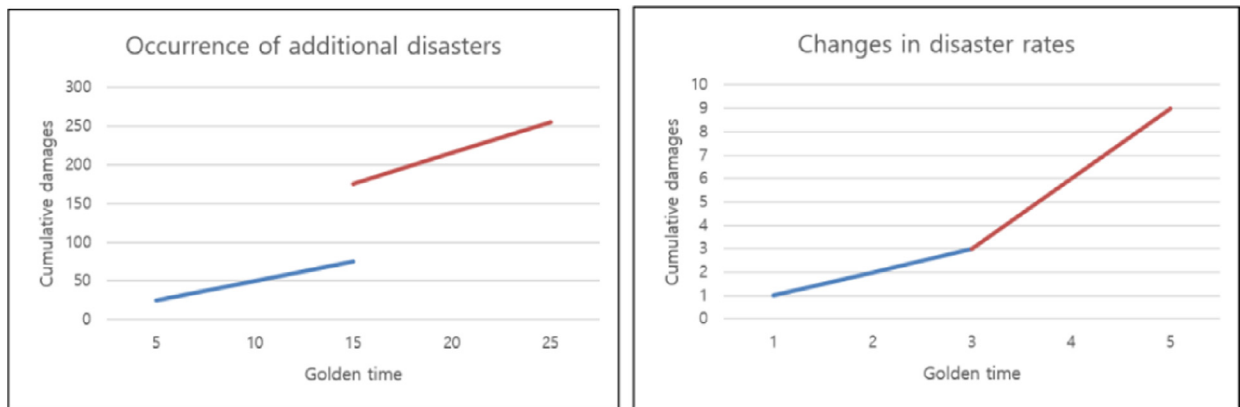
Fig. 1. Examples of cumulative damages with varying disaster aspects [17].

2. Repair crew scheduling problem

2.1. Model description

The proposed model referred to the model developed by Duque et al. [8], and we referred to the mathematical formulation introduced in Duque at al. [18]. This study is an extended work of a previous conference paper [17] and uses the same notations. We considered an undirected network, $G(V, E)$ in which V is a node set in the network which includes both damaged node set, V_r, and isolated node set, V_d. Damaged nodes are destroyed areas where repair activities are required. In addition, the repair crew cannot pass the damaged node, $i \in V_r$, before it is repaired. We assume that it takes s_i unit times for the crew to repair the damage. After a damaged node is repaired, it is treated as a normal node that does not require an additional repair process. The definition of damaged nodes covers not only damaged areas, but also damaged roads.

Isolated areas require relief supplies or evacuation activities that originate elsewhere. In the short-term post-disaster period, the aspects of a disaster in isolated areas are volatile; that is, additional disasters might occur and damage conditions can be worsened. Total damages associated with the isolation of an area, depicted in isolated Node $i \in V_d$, in the post-disaster period can be classified as a combination of (1) disaster damage caused directly by the initial additional disasters and any secondary disasters and (2) isolation damage caused primarily by a lack of connectedness to others, which hinders the supply of essential goods or treatments. Residents in an isolated state (node) suffer from lack of essential supplies until they are reconnected with other resources outside the disaster area such that the isolation problem is solved. When several isolated nodes are adjacent, they are regarded as a single isolated node because all of them are interconnected such that if one node is accessible they are all effectively connected from the supply chain.

The definition of a golden time and various aspects of a disaster are the distinctive features of our study. The golden time, g_i, is defined as the final time point in which damages can be managed in the isolated node, i; disaster aspects in isolated Node i dramatically change unless the isolation problem is solved. That is, the golden time can be regarded not only as the time to evacuate people and avoid additional disasters, but also as the time to help individuals severely threatened by isolation conditions (e.g., experiencing dehydration or hypothermia). We assume that the golden time in each isolated node is known and do not consider multiple golden times in each isolated node. Additional disasters that occur in an isolated node after the golden time, g_i, negatively influence people in the area.

Damage to people after the golden time is defined as p_i and can refer to direct disaster damages, such as an earthquake or tsunami. Damage rates caused by isolation can be categorized into the damage rate before the golden time, w_i^1, and the rate after the golden time, w_i^2. We assume that w_i^2 is larger than or equal to w_i^1 because disaster conditions usually worsen without responsive management. When people are stuck in the debris of a building without any treatment, we can expect that they will die within a few days. Likewise, many seriously injured people will die within a few hours if treatment remains unavailable to them. Duque at el. [8] could not consider these cases because they used constant weight factors in isolated areas. Cumulative damage in the cases of additional disasters and when conditions after disasters worsen are presented in Fig. 1.

Duque et al. [8] proposed a single repair crew scheduling problem from a deterministic perspective. In the previous study, the authors assumed that a weight factor (w_i) in each isolated node is constant during the disaster period. The authors suggested that the number of inhabitants in each isolated node can be a measure of the parameter. However, we contend that this measurement does not take into account the different damage conditions and other dynamic disaster aspects. Because this paper is the starting point of our research, we developed a more general model.

Disaster damages can be defined differently by different decision makers. One may solely refer to human injuries while others also consider recovery costs as disaster damages. Moreover, comparing distinct types of damage (e.g., physical
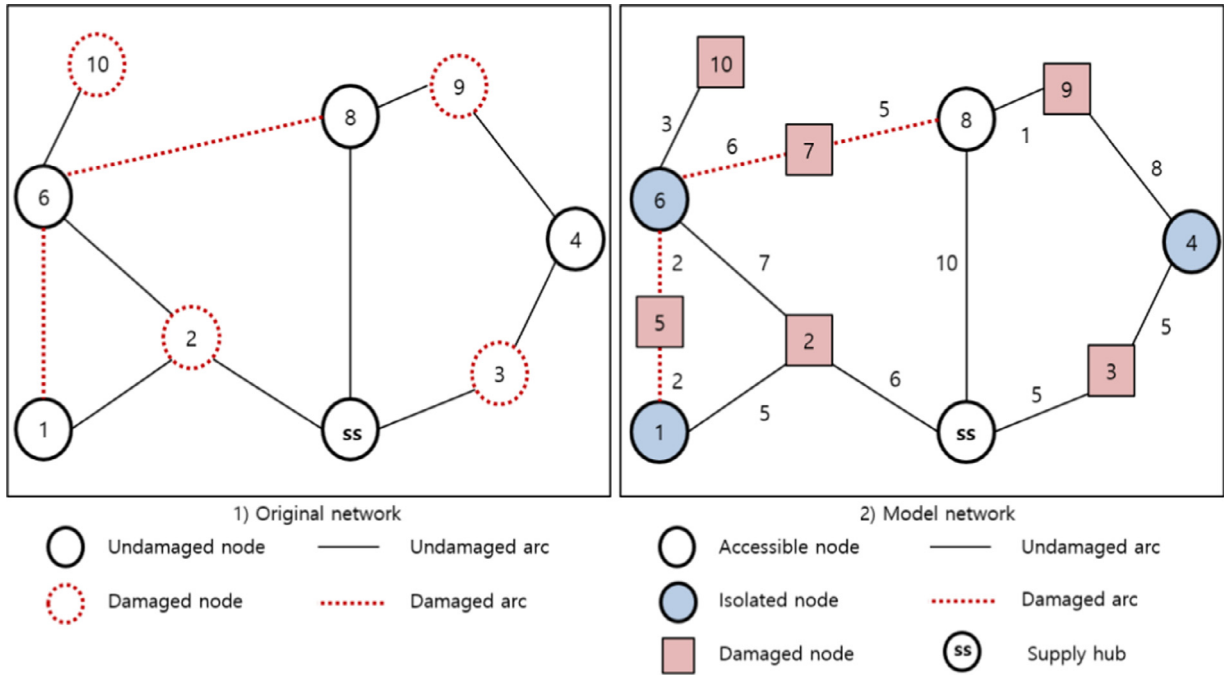
Fig. 2. Example of a damaged road network [17].

injuries, mental-health effects, and individual or social damages) cannot be objective. Unfortunately, there is not any logical or optimal way to compare these costs. For this reason, parameters should be handled with sophistication by experts and decision makers.

A supply hub is defined as an origin node where sufficient relief supplies and equipment are stored. The proposed problem is based on a single origin hub and the assumption that a repair crew initiates activities from the origin node. In this model, *ss* is denoted as the origin node. Destination node *sd* refers to a fictitious node used to denote that the repair crew has finished activities; when the repair crew arrives at the destination node, all repair processes are presumed finished. When the repair crew moves from Node i to Node j, it takes t_{ij}. Fig. 2 illustrates an example of a damaged road network. Note that the number between nodes is the travel time. In the figure, damaged nodes and arcs are transformed as damaged nodes. Nodes 5 and 7 do not exist in the original network; however, they are regarded as nodes in the model network. The definition of damaged nodes includes not only damaged, but also damaged roads. Additional Nodes 5 and 7 represent the damaged roads between Nodes 1 and 6 and between Nodes 6 and 8, respectively. The undamaged nodes can be classified as isolated nodes and accessible nodes. In the case of isolated nodes, it can be seen that the supply chain is not connected.

2.2. Mathematical formulation

Definition of sets, parameters, and decision variables for the NRCSSD are as follows:

Sets

V	Node set
V_r	Damaged node set
V_d	isolated node set
E	Set of edges (i, j), $\forall i, j \in N$
A	Set of damaged node pairs (i, j); logically possible sequences of repairing nodes; $\forall i \in V_r + ss$, $\forall j \in V_r + sd$, $(i, j) \neq (ss, sd)$

Parameters

q_1	Weight of the total damages
q_2	Weight of the completion time of the repair crew
ss	Index of an origin node
sd	Index of a destination node
s_i	Repair time for damaged Node i, $\forall i \in V_r$
g_i	Golden time; the final time point to treat damage conditions in Node i, $\forall i \in V_d$
w_i^1	Damage rate in Node i before golden time, $\forall i \in V_d$,
w_i^2	Damage rate in Node i after golden time, $\forall i \in V_d$

p_i Direct disaster damages caused by additional disasters at Node i, $\forall i \in V_d$

t_{ij} Travel time of a repair crew to move from Node i to Node j, $\forall (i, j) \in E$

F_i Parameters for calculation; cumulative damage differences before and after g_i in Node i, $\forall i \in V_d$; $F_i = p_i + g_i \cdot (w_i^1 - w_i^2)$

Decision variables

x_{ij} 1, if a repair crew moves to Node j after repairing Node i, $\forall (i, j) \in A$
         0, otherwise

r_{kl}^{ij} 1, if a repair crew moves from Node k to Node l when a repair crew moves to Node j after finishing repairs at Node i, $\forall (i, j) \in A$, $\forall k, l \in V$
         0, otherwise

a_k^{ij} 1, if a repair crew passes Node k when a repair crew moves to Node j after finishing repairs at Node i, $\forall (i, j) \in A$, $\forall k \in V_k, k \neq i \neq j$
         0, otherwise

y_{kl}^j 1, if isolated Node j is connected to a supply hub by passing through Nodes k and l sequentially, $\forall j \in V_d, \forall k, l \in V$
         0, otherwise

b_k^j 1, if isolated Node j is connected to a supply hub via Node k, $\forall j \in V_d, \forall k \in V$
         0, otherwise

c_i 1, if additional disasters occur at Node i, $\forall i \in V_d$
         0, otherwise

z_i Time when Node i is repaired, $\forall i \in V$

u_i Time when isolated Node i is connected to the supply hub, $\forall i \in V_d$

v_i Time when a repair crew arrives at damaged Node i before it is repaired, $\forall i \in V$

d_i Total damages at Node i, $\forall i \in V_d$

The mathematical formulation of the proposed model is as follows:

$$\text{Minimize} \sum_{i \in V_d} q_1 \cdot d_i + q_2 \cdot v_{sd} \tag{1}$$

Subject to

$$\sum_{i \in V} x_{ssj} = 1 \qquad\qquad (ss, j) \in A \tag{2}$$

$$\sum_{i \in V} x_{isd} = 1 \qquad\qquad (i, sd) \in A \tag{3}$$

$$\sum_{i \in V, (i,j) \in A} x_{ij} = \sum_{k \in V, (j,k) \in A} x_{jk} \quad \forall j \in V_r \tag{4}$$

$$\sum_{i \in V, (i,j) \in A} x_{ij} \leq 1 \qquad\qquad \forall j \in V \tag{5}$$

$$\sum_{k \in V, (j,k) \in A} x_{jk} \leq 1 \qquad\qquad \forall j \in V \tag{6}$$

$$\sum_{i,j \in V, (i,j) \in A} x_{ij} = |V_r| + 1 \tag{7}$$

$$\sum_{k \in V} r_{ik}^{ij} = x_{ij} \qquad\qquad \forall i, j \in V, \ (i, j) \in A \tag{8}$$

$$\sum_{k \in V} r_{kj}^{ij} = x_{ij} \qquad\qquad \forall i, j \in V, \ (i, j) \in A \tag{9}$$

$$\sum_{k \in V} r_{kl}^{ij} + \sum_{m \in V} r_{lm}^{ij} = 2 \cdot a_l^{ij} \qquad \begin{matrix} \forall i, j, l \in V, \ (i, j) \in A, \\ l \neq i \neq j \neq sd \end{matrix} \tag{10}$$

$$\sum_{i,k,l \in V, (i,sd) \in A} r_{kl}^{isd} \leq 1 \tag{11}$$

$$\sum_{i,j,k \in V, (i,j) \in A} r_{ksd}^{ij} = 1 \tag{12}$$

$$x_{ij} \leq \sum_{k,l \in V} r_{kl}^{ij} \leq M \cdot x_{ij} \qquad \forall i, j \in V, \ (i, j) \in A \tag{13}$$

$$\sum_{k \in V} y_{ssk}^{i} = 1 \qquad \forall i \in V_d \tag{14}$$

$$\sum_{k \in V} y_{ki}^{i} = 1 \qquad \forall i \in V_d \tag{15}$$

$$\sum_{k \in V} y_{kl}^{i} \leq 1 \qquad \forall i \in V_d, \ \forall l \in V \tag{16}$$

$$\sum_{m \in V} y_{lm}^{i} \leq 1 \qquad \forall i \in V_d, \ \forall l \in V \tag{17}$$

$$\sum_{k \in V, k \neq j} y_{kl}^{j} + \sum_{m \in V, m \neq ss \neq sd} y_{lm}^{j} = 2 \cdot b_{l}^{j} \qquad \forall j \in V_d, \ \forall l \in V, l \neq j \neq ss \tag{18}$$

$$z_i + \sum_{k,l \in V} t_{kl} \cdot r_{kl}^{ij} + M \cdot (x_{ij} - 1) \leq v_j \qquad \forall (i, j) \in V, (i, j) \in A \tag{19}$$

$$v_i + s_i = z_i \qquad \forall i \in V_r \tag{20}$$

$$z_k + M \cdot (b_k^i - 1) \leq u_i \qquad \forall i \in V_d, \forall k \in V_r \tag{21}$$

$$z_k + M \cdot (a_k^{ij} - 1) \leq z_j \qquad \forall i, j \in V, \ \forall k \in V_r, \ (i, j) \in A \tag{22}$$

$$u_i - g_i \leq M \cdot c_i \leq M + u_i - g_i \qquad \forall i \in V_d \tag{23}$$

$$w_i^1 \cdot u_i \leq d_i \qquad \forall i \in V_d \tag{24}$$

$$w_i^2 \cdot u_i + F_i + M \cdot (c_i - 1) \leq d_i \qquad \forall i \in V_d \tag{25}$$

$$r_{lk}^{ij} + r_{kl}^{ij} \leq 1 \qquad \forall i, j, k, l \in V, (i, j) \in A \tag{26}$$

$$y_{lk}^{j} + y_{kl}^{j} \leq 1 \qquad \forall j \in V_d, \ \forall k, l \in V \tag{27}$$

$$x_{ij} \in \{0, 1\} \qquad \forall i, j \in V, \ \forall (i, j) \in A \tag{28}$$

$$r_{kl}^{ij} \in \{0, 1\} \qquad \forall i, j, k, l \in V, \ \forall (i, j) \in A \tag{29}$$

$$a_k^{ij} \in \{0, 1\} \qquad \begin{array}{l} \forall i, j, k \in V, \ \forall (i, j) \in A, \\ k \neq i \neq j \end{array} \tag{30}$$

$$y_{kl}^{j} \in \{0, 1\} \qquad \forall j \in V_d, \forall k, l \in V \tag{31}$$

$$b_k^{j} \in \{0, 1\} \qquad \forall j \in V_d, \ \forall k \in V \tag{32}$$

$$c_i \in \{0, 1\} \qquad \forall i \in V_d \tag{33}$$

$$z_i, v_i \in R_+ \qquad \forall i \in V \tag{34}$$

$$u_i, d_i \in R_+ \qquad \forall i \in V_d \tag{35}$$

Table 1
Results of a numerical example.

	Isolation nodes	1	4	6
NRCSRP	Isolation damages	60	90	24
	Direct disaster damages	0	100	0
	Damages in each node	60	190	24
	Total damages		274	
	Completion time		76	
	Objective value		350	
NRCSSD	Isolation damages	142	30	66
	Direct disaster damages	0	0	0
	Damages in each node	142	30	66
	Total damages		238	
	Completion time		70	
	Objective value		308	

The objective function (1) minimizes the weighted sum of total damages in isolation and the completion time of a repair crew. The term v_{sd} refers to the time when a repair crew arrives at destination Node sd. It is the same term as the time when a repair crew finishes repair activities. Constraints (2) to (7) restrict the sequence of damaged nodes repaired by the repair crew. Constraints (2) to (3) denote that the repair crew starts repair activities from origin Node ss and finishes all activities in destination Node sd. Constraints (4) to (6) enforce flow constraints for the repair crew. Constraint (7) refers to the number of damaged nodes to be repaired. The repair crew finishes repair activities after arriving to destination Node sd; therefore, a total of $|V_r| + 1$ nodes should be repaired. Constraints (8) to (13) determine the route of a repair crew. Constraints (8) to (9) restrict the conditions of a departure node and an arrival node when a repair crew moves. Constraint (10) enforces the flow condition when a repair crew visits an undamaged node. Constraints (11) and (12) ensure that the repair crew visits destination node sd once in the entire activities. Constraint (13) means that the route of a repair crew is related to the sequence of damaged nodes. Constraints (14) to (18) restrict the route to connect isolated node. Constraints (14) to (15) enforce that the route to connect isolated Node i starts at Node ss and finishes at i, $\forall i \in V_d$. Constraints (16) to (18) denote an isolated node connected with Node ss. Constraints (19) to (21) denote arrival, repair, and isolation times, respectively, of a node. Constraint (19) restricts the duration between the time of departure from Node i and the time of arrival to Node j. Constraint (20) describes the repair time for a damaged node. Constraint (21) defines the time when an isolated node is connected to the supply hub. Constraint (22) enforces that the completion time to repair a damaged node follows the sequence for repairing damaged nodes. Constraint (23) refers to the case of an isolation time for isolated Node i that is greater than the golden time. Constraint (24) defines total damages of the case in which the isolation time of isolated Node i is less than the golden time. Constraint (25) defines total damages for an isolation time of isolated Node i greater than the golden time. Constraints (26) and (27) eliminate unnecessary tours. The other constraints denote general conditions associated with the decision variables.

2.3. Numerical example

A numerical example is explained to promote better understanding for our model. We used the same network shown in Fig. 2. We added Node sd to calculate the time when a repair crew finishes repair activities. In this network, ss is 0 and sd is 11. Therefore, the network node set, V, is {0, ..., 11}, and he damaged node set, V_r, is {2, 3, 5, 7, 9, 10}, and the isolated node set, V_d, is {1, 4, 6}. The repair times for damaged nodes are 6, 5, 3, 2, 7, and 4, respectively. We set parameters for isolated nodes as follows: $w_i^1 = \{5, 3, 2\}$, $w_i^2 = \{6, 5, 3\}$, $p_i = \{0, 100, 0\}$, and $g_i = \{20, 25, 15\}$. To explain the difference between the NRCSRP and NRCSSD, experiments were conducted under the same conditions. However, the NRCSRP did not consider w_i^2, p_i, and g_i. Therefore, we must schedule the repair crew in the NRCSRP, and then, using this schedule, calculate total damages while considering dynamic disaster aspects. We also added the completion time of the repair crew in the objective function of the NRCSRP because NRCSRP did not reflect the completion time of the repair crew in the objective function.

Damaged Nodes 2 and 3 are related to isolated nodes. From the perspective of minimizing total isolation damage, the problem can be reduced to set the priority between the two nodes. After isolated nodes are connected, the schedule to repair remaining damaged nodes is determined. On the other hand, when we also consider the completion time of the repair crew, the problem would be more complex. Both total isolation damages and completion time of the repair crew should be considered at the same time. In this example, q_1 and q_2 was set as 1.

The detailed results of the experiment are presented in Table 1. In the case of the NRCSRP, the route of the repair crew to connect isolated Nodes were 0-2-0-3. For better understanding of the mathematical model, we explained the solutions of selected decision variables. A repair crew moves from the supply hub through arc (0, 2) to damaged Node 2. Therefore, $x_{02} = 1$ and $r_{02}^{02} = 1$. After repairing Node 2, the repair crew passes through arcs (2, 0) and (0, 3) to damaged Node 3, $x_{23} = 1$ and $r_{20}^{23} = r_{03}^{23} = 1$. In this case, the crew passes through undamaged Node 0 and $a_0^{23} = 1$.

The route was valid under static conditions; that is, the sum of the damage rates related to damaged Node 2 was 7, and that related to damaged Node 4 was 4. On the other hand, the solutions differed in cases of dynamic disaster conditions. First, isolated Node 4 must be freed from an isolation state because of the possible damages caused by additional disasters. Therefore, the route of the repair crew moving to connect isolated nodes in the NRCSSD was 0-3-0-2. The total damage under the NRCSRP was 274, and that of the NRCSSD was 238. The result shows that the NRCSSD can decrease total damages better than the NRCSRP.

The remaining schedule of the repair crew can be used to figure out the route to repair all damaged nodes. The remaining route of the NRCSRP was 3-4-9-8-7-6-5-6-10 and the whole schedule was completed at 76. The remaining route of the NRCSSD was 2-1-5-6-10-6-7-8-9 and at the repair crew finished to repair all damaged nodes at 70. Therefore, the objective value of the NRCSRP was 350 and that of the NRCSSD was 308. The result shows that the NRCSSD can reduce the objective value significantly.

3. Ant colony system algorithm

The NRCSSD can find the optimal solution; however, it only solves limited-size problems. Therefore, the ACS algorithm was developed to overcome the limitation of the NRCSSD. The ACS algorithm was introduced by the work of [19], and it has been widely used to solve complex problems. Although it cannot guarantee the optimal solution, the ACS algorithm can be used to find near-optimal solutions within a reasonable time. In addition, the ACS features a relatively simple structure to describe the schedule of a repair crew. This characteristic helps describe solutions for a relatively complex problem such that the proposed algorithm can be used to solve a multiple repair crew problem. First, the ACS for the NRCSSD is introduced, and then, the ACS that takes into account multiple repair crews is explained. We refer readers to the work of [9,12,19] for further explanation.

In the proposed ACS algorithm, ants did not consider the whole sequence of visiting nodes but considered the repairing sequence of damaged nodes. This method can reduce the solution space of each ant, and the whole solutions can be calculated using the sequence of repairing damaged nodes. Therefore, we used a reduced graph which consists of *ss*, *sd*, and damaged nodes, similar to the reduced graph defined in the work of Duque [8]. The ACS algorithm repeats route searches and updates pheromones at each generation. Ants start to move from the origin node, and each ant repeatedly moves to the next damaged node with a determined probability. However, an ant can generate the infeasible sequence of repairing damaged nodes. To avoid this case, the existence of the route between damaged nodes was checked, and node candidates were generated thereafter. The feasibility check was conducted with the Dijkstra algorithm. The probability is affected by the amount of pheromone. Note that general ACS algorithms also exploit preferences of the ants, but for simplification, we did not consider preferences. The probability p_{ij}^k that ant k moves from Node i to Node j is as follows:

$$p_{ij}^k = \tau_{ij}^\alpha / \sum_{l \in allowed_i} \tau_{il}^\alpha$$

τ_{ij}^α is defined as the amount of pheromone between Nodes i and j, $(i, j) \in A$. α is the parameter that controls the effect of pheromones on each ant and has a positive value. $allowed_i$ refers to nodes which can be accessible from Node i.

When it chooses to move to the next node, such as Node j, an ant remembers the shortest route and quickest travel time from the current node: Node i to Node j. At the time Node j is repaired, z_j is calculated using the time when the current node, Node i is repaired, z_i; the travel time between nodes, t_{ij}; and the repair time, $s_j(z_j = z_i + t_{ij} + s_j)$. Note that t_{ij} is calculated using the network containing all nodes. During this calculation, the algorithm searches the isolated Node $m \in V_d$, which is accessible from repaired Node j. If isolated Node m is found, the isolation time of the node, u_m, becomes z_j, and damages in isolated Node m, d_m, are calculated as follows:

$$md = \begin{cases} w_i^1 \cdot u_i, & if\ u_i\ is\ less\ than\ or\ equlas\ to\ g_i \\ w_i^2 \cdot u_i + F_i, & otherwise \end{cases}$$

This calculation is repeated until an ant finishes its tour, and then, the route and total damages can be calculated. When all ants finish their tours, pheromones in the network have also evaporated. The evaporation rate is controlled by parameter ρ, and the amount of evaporated pheromones is as follows;

$$\tau_{ij} \leftarrow (1 - \rho) \cdot \tau_{ij}$$

Pheromones are also influenced by ants. Therefore, the updating pheromone process caused by ants needs to be considered. To search better routes, the algorithm chooses q_0 number of ants that searched good routes in a rank-based order. The update process is as follows:

$$\tau_{ij} \leftarrow \tau_{ij} \sum_k \Delta \tau_{ij}^k$$

$\Delta \tau_{ij}^k$ is defined as the additional amount of pheromone that ant k sprays between Nodes i and j, and it is derived as follows:

Table 2
Differences between the NRCSRP and NRCSSD for small networks.

Number of nodes	Differences of total damages (%)	Differences of isolation damages (%)	Differences of disaster damages (%)
8	3.3	3.6	3.2
	4.8	5.1	56.8
	2.2	2.2	91.6
9	7.7	8.4	1.1
	6.1	6.4	42.9
	4.0	4.2	36.9
10	4.9	5.5	12.3
	3.8	4.1	66.6
	5.6	5.9	30.4

$$\Delta \tau_{ij}^k = \begin{cases} Q/L_k, & \text{if ant } k \text{ moves from node } i \text{ to node } j \\ 0, & \text{otherwise} \end{cases}$$

Q is an arbitrary value, and L_k denotes the total damages following the route of ant k. After updating all pheromones, the entire process for a generation is also finished. In the next generation, ants exploit the new information from pheromones and improve solutions. The algorithm repeats the process until it meets conditions for termination.

The ACS can be extended to solve the multiple repair crew problem. In this case, a single ant from the previous ACS is defined as an ant group. The number of ants in the ant group is the same as the number of repair crews. In other words, each ant describes the schedule of a repair crew. In each iteration, an ant randomly chooses a new node among a feasible set of unrepaired nodes. It is important to consider the schedule of other ants when determining the arrival time of the node. The pseudo code of the algorithm is presented in Algorithm 1.

4. Computational experiments

Experimental designs and results of experiments are presented. The model was developed with XPRESS-IVE 7.9 and XPRESS-MP mathematical programming solver. The ACS algorithm was implemented by Java. Experiment environments were conducted with an Intel(R) Core(TM) i5-3570 CPU 3.4 GHz with 8.00 GB of RAM in Windows 10. Three sets of experiments were conducted to reveal different aspects of the problem. The first set of experiments was designed to check the differences between the NRCSRP and the NRCSSD. The second set of experiments was conducted to evaluate the performances of the ACS. The purpose of the last set of experiments was to obtain managerial insights for operating multiple repair crews. In all experiments, q_1 was the same as q_2.

For the first experiments, we modified the objective function of the NRCSRP and follow the same way in Section 2.3 to compare two models. Because of the complexity problem, only small networks were used. Travel times between nodes were randomly generated in the range from 1 to 10, and repair times of damaged nodes were assigned values between 10 and 100. Damage rates $w_i^1(w_i^2)$ and direct-disaster damages were also varied from 10 to 100. The golden time of each isolated node was set at 100. All random values followed uniform distributions. The number of nodes in a network varied from 8 to 10. In each number of nodes, 9 different network samples were made. Then, 10 examples were generated in each network sample, and thus, 270 examples were used for the experiments. Total, isolation, and direct disaster damages were calculated. The gaps between the NRCSRP [8] and NRCSSD are presented in Table 2.

The results show that the NRCSSD model can reduce additional damages to a greater extent than the NRCSRP. It is noteworthy that the NRCSSD can reduce direct-disaster damages significantly. It reduced direct-disaster damages by as much as 91.6% compared to those of the NRCSRP. In the experiments, we assumed that direct-disaster damages were not great because extremely great direct-disaster damages can overestimate the performance of the NRCSSD. However, in real situations, we can observe detrimental damages caused by additional disasters. In these cases, we expect that the NRCSSD can be more effective than the existing NRCSRP developed by Duque at el. [8].

The second set of experiments was designed to evaluate the general performances of the ACS. Three network sets were defined according to the number of nodes, and three network instances were generated for each network set. The network instances in the same network set shared a similar network structure. The appropriate size of the network sets was chosen by measuring the operation time of the Xpress-MP solver. In general, the commercial solver can find optimal solutions for small network instances within 60 s; however, the operation times of the commercial solver exceeded 1800 s for large network instances. In the case of large network instances, the Xpress-MP solver was not used because 1800 s is an inappropriately long time for determining disaster plans in the short-term period. In these network sets, fewer than one-half of the total number of network nodes were damaged. Detailed information on the network sets is explained in Table 3.

Parameters were generated with uniform and normal distributions. On the one hand, parameters generated with uniform distributions ranged between the minimum and maximum values described in Table 4. On the other hand, parameters generated by normal distributions were based on the average and variance values shown in Table 4. Only positive values were used for the experiments. The performance of the ACS depends on a parameter setting of the algo-

Table 3
Information for network instances in the second experiments.

Network size	Small			Middle			Large		
Number of nodes	10	11	12	13	15	17	19	21	23
Number of nodes in V_r	4	5	6	5	6	7	8	9	9
Number of nodes in V_d	2	3	3	7	7	8	9	10	12

Table 4
Information for parameter settings in the second experiments.

Parameters	s_i	w_i^1	w_i^2	p_i	g_i
Min	2	1	6	0	0
Average	5	3	8	200	100
Max	8	5	10	400	200
Variance	3	2	2	200	100

Table 5
Performances of the ACS for uniform distributions.

Size of networks	Number of nodes	Objective value		Optimality gap	Computation time (s)		Number of ants
		NRCSSD	ACS		NRCSSD	ACS	
Small	10	530.50	530.50	0.00%	0.59	0.07	10
	11	198.78	199.28	0.25%	3.99	0.11	
	12	230.62	232.62	0.86%	33.89	0.14	
Middle	13	923.60	923.60	0.00%	3.80	0.17	15
	15	839.98	839.98	0.00%	108.38	0.21	
	17	–	802.63	–	–	0.25	
Large	19	–	1723.24	–	–	0.41	20
	21	–	2397.74	–	–	0.51	
	23	–	2703.95	–	–	0.46	

Table 6
Performances of the ACS for normal distributions.

Size of networks	Number of nodes	Objective value		Optimality gap	Computation time (s)		Number of ants
		NRCSSD	ACS		NRCSSD	ACS	
Small	10	149.83	149.83	0.00%	0.95	0.08	10
	11	183.64	183.64	0.00%	14.47	0.11	
	12	160.60	160.60	0.00%	31.92	0.14	
Middle	13	–	296.39	–	–	0.21	15
	15	453.85	453.85	0.00%	211.83	0.20	
	17	–	806.04	–	–	0.24	
Large	19	–	977.17	–	–	0.44	20
	21	–	1313.81	–	–	0.47	
	23	–	1361.17	–	–	0.51	

rithm. To be specific, the computation times of the ACS can be approximated by its parameter setting; *Number of iterations* × $|V_r|$ × *Number of ants* (*groups*). The total iterations were fixed to 20 to ensure that the computation times were not improved by more than a second.

To run the ant colony algorithm, one must set several parameters; however, the way to choose appropriate parameters is more of an art than a science because logical reasoning cannot be used in choosing the optimal parameters. Speculative selections are intrinsic characteristics of many meta-heuristic algorithms. To be more specific, the performance of the ACS depends on the combinations of each parameter, and there are an infinite number of combinations. The problem is that most of meta-heuristics cannot find logical relationship between parameter settings and performances. Many researchers have relied on empirical data with many experiments to find better parameter settings. In addition, the performance of the proposed algorithm contains randomness. For this reason, it is much difficult to find the best parameter setting. Even if one can find the optimal parameters, it would be the best only for the specific instance. The best parameter setting of one instance might be quite distinctive from other instances. In the experiments, parameters for the ACS were arbitrarily chosen. 10 experiments were conducted for each instance to calculate the minimum and average performances.

The results of the experiments with uniform and normal distributions are presented in Tables 5 and 6, respectively. The optimality gaps presented in the tables reflect the minimum optimality gaps between the optimal and the ACS solutions.

Table 7
Robustness of the performances of the ACS.

| Distribution	Uniform			Normal		
Number of nodes	Min	Average	Gap	Min	Average	Gap
10	530.50	530.50	0.00%	149.83	149.83	0.00%
11	199.28	198.78	0.25%	183.64	184.64	0.54%
12	232.62	232.81	0.08%	160.60	163.50	1.77%
13	923.60	923.60	0.00%	296.39	296.39	0.00%
15	839.98	843.14	0.38%	453.85	454.95	0.24%
17	802.63	827.39	2.99%	806.04	844.06	4.50%
19	1723.24	1787.94	3.62%	977.17	996.48	1.94%
21	2397.74	2491.33	3.76%	1313.81	1417.56	7.32%
23	2703.95	2798.36	3.37%	1361.17	1514.01	10.09%
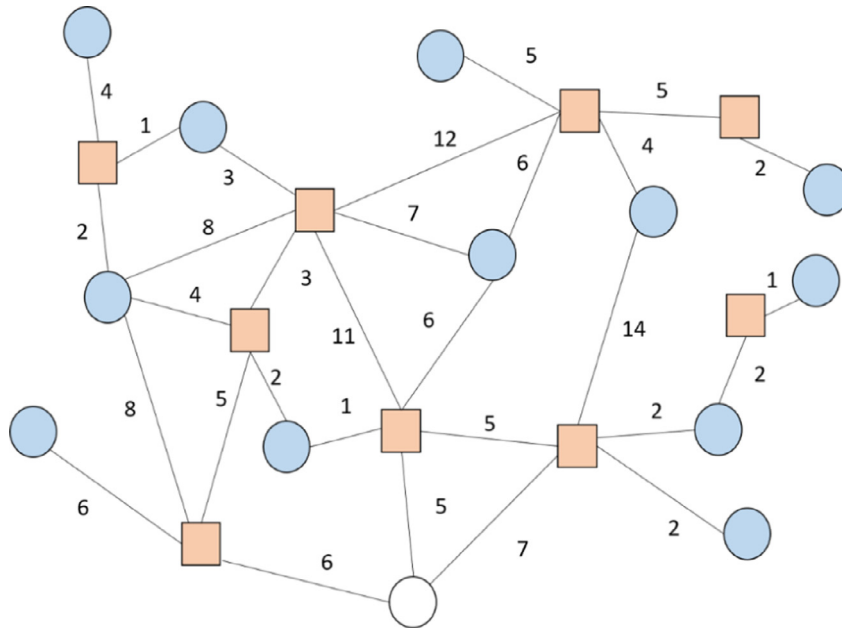
Fig. 3. Instance of a large network with 23 nodes.

The computation times of the ACS were calculated as the average values from 10 experiments. Table 5 shows that the algorithm required fairly short computation times compared to the NRCSSD. The computation times increased as the size of the network increased. The results consistently show that the algorithm performances were relatively consistent, and a similar trend is seen in Table 6.

The robustness of the ACS performances is important. For the mathematical model the computation times were difficult to predict because they were extremely random; they were not only affected by the size of the network, but also by the parameter values. Moreover, the mathematical model is intractable for solving even limited-size problems. However, the computation burdens of the ACS algorithm were relatively easy to predict because the computation times for them were mainly affected by predetermined parameters, such as the number of ants, the size of the network, and the number of iterations. Furthermore, the computation times were relatively proportional to the pre-determined parameters. Unfortunately, an intrinsic property of the ant colony algorithms is failure to guarantee the quality of solutions. However, the results of the experiments shown in Table 7 reveal that the algorithm gave relatively robust solution qualities.

To check the effect of additional repair crews on post-disaster management, we solved the ACS for the multiple repair crew problem. To derive the meaningful insights from the results, the experiments were conducted with large network instances of 23 nodes. The network structure used in the experiments is shown in Fig. 3. The number of repair crews was increased to 6 because additions to create 7 or more repair crews showed marginal differences. The parameters in each instance were different such that the value for each was randomly generated. For this reason, a ratio was defined to compare relative values (objective value of multiple vehicles / objective value of a single vehicles). The ratio can be varied depending on the parameters; therefore, average values were calculated. In the experiments, network instances with uniform and normal distributions were generated with 5 instances respectively. The ACS was run 10 times to calculate the average objective values and computation times.

Table 8
Ratios and computation times for uniform distributions with different numbers of repair crews.

Number of crews	Instance 1		Instance 2		Instance 3		Instance 4		Instance 5	
	Ratio	Time	Ratio	Time	Ratio	Time	Ratio	Time	Ratio	Time
1	1.00	0.46	1.00	0.53	1.00	0.49	1.00	0.49	1.00	0.49
2	0.65	0.43	0.42	0.51	0.59	0.51	0.57	0.51	0.50	0.49
3	0.55	0.32	0.34	0.51	0.47	0.49	0.46	0.49	0.41	0.55
4	0.53	0.49	0.33	0.57	0.41	0.46	0.43	0.51	0.39	0.55
5	0.51	0.47	0.32	0.54	0.40	0.52	0.42	0.49	0.39	0.54
6	0.52	0.48	0.32	0.54	0.40	0.50	0.41	0.48	0.39	0.53

Table 9
Optimal ratios and computation times for normal distributions with different numbers of repair crews.

Number of crews	Instance 1		Instance 2		Instance 3		Instance 4		Instance 5	
	Ratio	Time	Ratio	Time	Ratio	Time	Ratio	Time	Ratio	Time
1	1.00	0.51	1.00	0.49	1.00	0.50	1.00	0.48	1.00	0.48
2	0.51	0.48	0.51	0.47	0.50	0.51	0.51	0.46	0.53	0.50
3	0.43	0.49	0.42	0.46	0.41	0.50	0.42	0.46	0.43	0.49
4	0.40	0.42	0.40	0.51	0.37	0.54	0.38	0.49	0.39	0.50
5	0.39	0.44	0.39	0.52	0.36	0.52	0.38	0.53	0.38	0.46
6	0.39	0.47	0.38	0.57	0.36	0.51	0.38	0.51	0.38	0.47

Algorithm 1 Ant colony system algorithm.

```
Initialization
    MinSol; α; ρ; Q; pheromone; TotalRoute; TotalDamage;
    iter = 0;
    While{iter < MaxIter}
    {
            Antindex = 0;
            While{VrIndex < NumVr}
            {
                    VrIndex = 0;
                    CurrentNode = 0;
                    ChooseAntGroup();
                    While{AntIndex < NumAntGroup}
                    {
                            GetFeasibleNodeSet(CurrentNode);
                            CurrentNode = GetNextNode();
                            TotalRoute + = GetRoute();
                            TotalDamage + = UpdateDamage();
                            VrIndex + = 1;
                    }
                    IIf{MinSol > TotalDamage} {MinSol = TotalRoute}
                    Antindex + = 1;
            }
            pheromone = UpdatePheromone();
            iter + = 1;
    }
```

The results are summarized in Tables 8 and 9. First, additional crews significantly reduced the relative ratios. Although the ratios were varied according to the parameters, the addition of one more repair crew reduced the ratio significantly. In cases of the uniform and normal distribution, the ratio decreased up to 0.32 and 0.36, respectively. However, the effects of additional crews dramatically decrease; marginal effects decreased extensively such that, for many cases, the use of more than 3 repair crews did not result in meaningful differences.

Fig. 4 shows the relationship between the number of vehicles and the average ratio for different distributions. The graph shows that the marginal effects of adding additional repair crews decreased for both uniform and normal distributions. In the case of normal distributions, the ratio decreased more than it did for uniform distributions; however, this finding does not mean that the effects of additional repair crews under the normal distribution always dominate those of the uniform distributions.

The result implies that the decision maker needs to contemplate the marginal effect in the post-disaster situation. For example, when the number of vehicles is restricted, the decision maker must decide on the best number of vehicles to use for repair crews. If the manager allocates too many vehicles to repair crews, other response activities, such as efficient supplying of relief goods and emergency medical services might be hindered. In addition, surplus repair crews may not
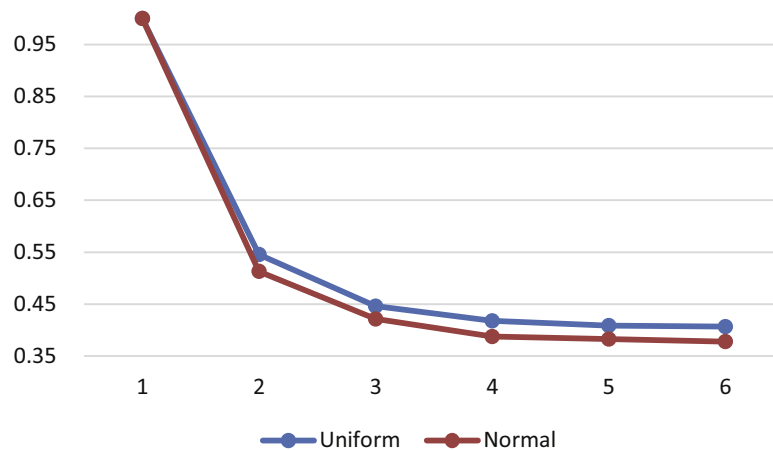
Fig. 4. Relationships between the number of vehicles and optimal ratios.

lead to better repair activities. The ACS can be applied to set the appropriate number of vehicles in the pre-disaster period. In detail, a decision maker can analyze plausible scenarios with the ACS and determine a sufficient number of vehicles to allocate to efficient repair operations.

Computation times of the ACS did not show any distinctive difference when the number of repair crews varied. This characteristic is an important advantage of the ACS because increasing the number of vehicles in the vehicle routing problem can dramatically increase computation times in general. In addition, the computational performances were not influenced by the parameters. In all cases, computation times were approximately 0.5 seconds, which means that feasible solutions were obtained within a predictable time for any parameter setting. In the post-disaster period, situations can significantly differ at each time point. Therefore, the ACS that guarantees robust performances would be practically meaningful.

5. Conclusions

In this paper, we presented a repair crew problem in which disaster aspects vary after a certain time. In developing the model, we assumed that a single repair crew departs from a single origin node. The objective of this NRCSSD was minimization of the weighted sum of total damages caused by isolation and direct (and additional) disasters and the completion time of a repair crew. To overcome the complexity problem of the NRCSSD, the ACS algorithm was developed. The proposed ACS can be used to solve not only the NRCSSD, but also the multiple repair crew problem. The results of computational experiments show that the proposed model can reduce further damages to a greater extent than the NRCSRP by Duque et al. [8] and the ACS algorithm can find good solutions in a reasonable time. In addition, the effects of additional vehicles in repair activities can be analyzed to inform managerial insights.

The main contribution of this study is a model that takes into account the various characteristics of conditions in an immediate post-disaster period. Although the model is based on a limited case in which disaster aspects vary only once during the operation time, the model expands aspects of damages in a static state to a dynamic state. Moreover, in the short term of the post-disaster period, appropriate decisions must be made quickly. The proposed heuristic algorithm helps responders make urgent decisions with accuracy. This study was based on dynamic conditions in isolated areas, but did not account for aspects that can worsen in non-isolated areas during a post-disaster period. For instance, a repaired node can be destroyed again by additional disasters. Therefore, an overall approach of disaster conditions will be examined in the future study.

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