Distribution Model of Disaster Relief Supplies by Considering Route Availability

Prudensy Febreine OPIT†1 and Koichi NAKADE†1

Abstract: This paper presents a distribution model for emergency relief supplies by considering route availability in a specific period of time. This model considers a single distribution center, multiple disaster areas, a homogenous fleet of vehicles, multi-items and multi-periods. First, we develop an algorithm to generate all possible path combinations using binary code that would lead to the determination of the number of all possible scenarios. Afterward, the algorithm generates the available routes for each scenario in each planning period, and then the probability of route availability for each scenario is calculated. These two outputs, route availability and its probability for each scenario become the two important inputs for the next stage, mathematical model formulation. Second, we formulate our mathematical model as a mixed-integer programming model whose objective is to maximize the amount of relief supplies sent to disaster areas for each scenario. The optimum number of vehicles required for the distribution center in each planning period is determined simultaneously. To understand this proposed model better, we give an illustration that demonstrates a large-scale observation including all possible scenarios. Our model is intended to help the government and/or decision-maker to prepare and respond quickly as the disaster strikes.

Key words: distribution model, disaster relief, emergency relief, route availability, optimum number of vehicles

1 INTRODUCTION

The transportation of emergency relief supplies has constantly been a great challenge for years. In terms of distribution of disaster relief, various uncertainty factors such as road conditions following a disaster and the amount of emergency supplies required to be sent to the affected area is difficult to predict. In most cases, compared to using helicopter, ground vehicles such as trucks are still preferable to deliver supplies to affected areas. Normally, the decision-maker should make a quick decision whether to send a group of fully-loaded vehicles through certain routes based on incomplete information of road conditions shortly after a disaster strikes, or wait in order to gain more reliable information. Once the decision is made, it can risk human lives and health. With such complex problems, it is very interesting to study this case.

The previous work of Opit et.al. [12] who develop a stock pre-positioning model to obtain the maximum expected relief demand covered by existing distribution centers (by preventing the result of zero proportion of relief demand satisfied) under budget constraints, has also motivated us to expand our research and develop a new model that focuses on distribution planning for emergency relief supplies. In this new model, we consider transportation and vehicle purchase budgets as constraints. We realize that the governments in developing countries such as the Philippines, Indonesia or Bangladesh, who often experience disasters such as earthquakes, floods and typhoons, don’t really have large budget to be allocated for emergency response. Most of these countries highly rely on NGO, INGO or even assistance from the governments of developed countries. In the field, for example in some parts of Indonesia, the local government often reduces the number of vehicles to be deployed to disaster areas quickly after a disaster occurs. Some local governments don’t even have enough budgets to purchase or add new vehicles. Our intention is that this paper can be applied not only to developed countries, but also to developing countries.

Therefore, we propose a distribution model that considers a single distribution center, multiple disaster areas, a homogenous fleet of vehicles, multi-items and multi-periods. The objective of this paper is to simultaneously determine the maximum amount of relief supplies that can be sent to disaster areas and the optimum number of vehicles required for the distribution center by considering route availability.

In recent years, few papers have focused their studies on the transportation and distribution of disaster relief supplies. Some of these papers were reviewed in a study conducted by Manopiniwes and Irohara [9]. Lin et.al. [8] propose a multi-objective distribution model of prioritized items for disaster relief operations. They create a real-
world earthquake scenario using a GA-based approach and decomposition and assignment heuristics.

Another research conducted by Berkoune et al. [2] define and formulate a practical transportation problem often encountered by crisis managers in emergency situations, while Özdamar and Demir [13] describe a hierarchical cluster and route procedure (HOGCR) for coordinating vehicle routing in large-scale post-disaster distribution and evacuation activities. One of the chapters of a book compiled by Zeimpekis et al. [17] presents the work of Taniguchi and Thompson, who propose a multi-objective vehicle routing and scheduling problem. The model is applied to the case of Ishinomaki City following the Tohoku disaster in 2011.

Other papers, such as the one written by Mete and Zabinsky [10], develop a two-stage stochastic programming approach for disaster preparedness, which consists of warehouse selection and inventory decisions, and transportation plans and demand satisfaction decisions. Abounacer et al. [1] propose a multi-objective emergency location-transportation problem for disaster response. A plan for strengthening structures of vulnerable areas, retrofitting transportation link to ease access to the affected areas, and locating and equipping emergency response centers has been presented by Edrissi et al. [4]. Nakanishi et al. [11] propose a methodology to analyze transportation demand in a post-disaster regional community. Huang et al. [6] focus on the assessment routing problem, which routes teams to different communities to assess damage and relief needs following a disaster. Rawls and Turnquist [14] discuss pre-positioning and delivery planning in the event of a natural disaster. Their model includes requirements for reliability that ensures all demands to be satisfied in scenarios comprising at least 100% of all outcomes.

Although the above papers are important for our research, as they provide several different concepts on how to develop a distribution model in order to support emergency response, the above papers do not consider route or link probability in their transportation plans. Route probability, which relates to road conditions, represents one of the uncertainty factors that occur after a disaster strikes. Therefore, it is very important to consider route probability into the model.

Hamedi et al. [5] address humanitarian response planning for a fleet of vehicles with reliability considerations. The authors focus on minimizing total time in a network with and without considering the probability of route failure. We find that the method they developed is interesting. But rather than just focus on route probability, in this paper we also focus on route availability for all possible scenarios. More precisely, first, we generate all possible scenarios based on route availability and then we calculate the probability of route available for each scenario. By analyzing route availability for all possible scenarios, we are able to adapt our model to all possible situations that will occur in the real system.

Other papers such as the one written by Ukkusuri and Yushimoto [16] develops an approach to disaster pre-positioning problems that account for the routing of vehicles and possible disruptions in the transportation network. This means the graph has a probability of failure for some preselected edges. While the authors focus on finding the best location to pre-position inventories, our research which considers a single existing distribution center, focuses on maximizing the amount of each item to be delivered to the affected areas using a certain number of vehicles in a specific period of time. In addition, not only considering a single routing problem period as appear in the pre-positioning model of Ukkusuri and Yushimoto [16], we propose a multi-period distribution model. The situation of route recovery can be considered in this multi-period distribution model. Hence, our model is more realistic to be applied to the real system.

Since we are interested in routing problems and determining the optimum number of vehicles required for the distribution center, several papers related to the topic were also studied. Choi et al. [3] present a genetic algorithm to solve the asymmetric traveling salesman problem. Kim [7] builds a dual stochastic programming model with chance constraints that concern the number for an optimal dispatch policy. Zhang and Li [18] analyze multi-periodic vehicle fleet size and routing problems. Repoussis and Tarantilis [15] design an adaptive memory programming solution approach for the fleet size and mixed vehicle routing problem with time windows. In this paper, rather than just focus on routing problem and determining the optimum number of vehicles, we also focus on determining the maximum amount of supplies to be sent to each disaster area in a specific period of time. Therefore, our proposed model integrates the transportation plans and demand satisfaction decisions by considering route availability.

2 PROBLEM DESCRIPTION

In this paper, we consider a single distribution center as the starting point for each vehicle to deliver supplies (items) to a specific disaster area. However, to deliver items to their destination, each vehicle should travel via a certain route. In terms of disaster relief transportation, after a disaster strikes, this route may or may not be available at some point in time.

To understand our proposed model better, we provide a case study as shown in Fig. 1. Figure 1 illustrates all areas affected by a disaster. Let \( N = \{1, 2, \ldots, n\} \) be the set of paths. As given in Fig. 1, we assume \( n = 6 \). Based on Fig. 1, we also assume that the probability of each path available at period 1 \( (P^1) = 0.5 \), \( n \in N \), while the probability of each path available at period 2 \( (P^2) = 0.7 \), \( n \in N \). According to Hamedi et al. [5], for real-world scenarios, one can
determine the probability of path availability using historical data and topographical GIS.

We use binary code (0,1) to represent each path availability at one point in time, where 0 means the path is unavailable and 1 means the path is available. It is important to note that, in this model, we use a homogenous fleet of ground vehicles such as trucks to deliver items to disaster areas. Hence, for example, if vehicle $v$ is assigned to deliver items to disaster area $D$, then vehicle $v$ will have two options: travel via path 3, or travel via path 2 and path 5. Let’s say that the decision-maker has assigned vehicle $v$ to travel via path 3, yet in the field, path 3 is actually unavailable, while paths 2 and 5 are both available during period 1. This means, if vehicle $v$ eventually travels via path 3 during period 1, it would not be able to reach its destination.

The above example simply describes one possibility that could happen in the system. In a real system with various uncertainties of events, it is recommended to observe not only one possibility, but all of the possibilities that might occur in the system. Therefore, we need to generate all possible scenarios based on route availability for each period of time. Table 1 shows detailed information for each route and its destination as illustrated in Fig. 1.

As shown in Fig. 1 and Table 1, we have six paths, seven routes, four disaster areas, and one distribution center. For the sake of simplicity, we assume that the distribution of emergency relief supplies is supposed to be completed in two periods (1 period = 24 hr). This also means that each vehicle is assumed to be able to complete its round-trip travel in one period of time (including loading and unloading time). Given the number of paths ($n$ = 6), the possible scenario for period 1 is formulated as the combination of paths $= (2^6 = 64)$ scenarios.

We assume that every available path during period 1 remains available during period 2. This specific condition means the disaster occurs prior to the first delivery. There is no secondary disaster that will follow. For example, in the event of an earthquake, there are no major aftershocks occurring after the first delivery. Given $k$ combinations from set $l$ of $n$ elements, the possible scenario during period 2 is $\sum_{k=0}^{n} \sum_{k=0}^{n} (\binom{n}{k} \times \binom{k}{l}) = \sum_{k=0}^{n} (\binom{n}{k}) 2^k = 3^n = 3^6 = 729$.

| Table 1 Paths and routes used to reach each destination. |
|---|---|---|---|---|---|---|
| Path | Route | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | * | * | * | * | * | * | | |
| 2 | * | * | * | * | * | * | | |
| 3 | * | * | * | * | * | * | | |
| 4 | * | * | * | * | * | * | | |
| 5 | * | * | * | * | * | * | | |
| 6 | * | * | * | * | * | * | | |
| Destination | B | C | D | E | E | D | E |

Fig. 1 Illustration of disaster areas affected by a disaster.

To understand the concept better, let $S_1 = \{1,2,3,\ldots,S_1\}$ be the set of scenarios during period 1, and $S = \{1,2,3,\ldots,S\}$ be the set of scenarios during period 2. Additionally, let $f(s)$ be the scenario of routes available during period 1 linked to scenario $s \in S$. Table 2 explains this concept of generating the number of possible scenarios for each period with the given number of paths ($n$ = 6), as shown in Fig. 1. Based on the above assumption, paths available during period 1 would remain available during period 2. Therefore, $S_1 = \{1,2,3,\ldots,64\}$, while $S = \{1,2,3,\ldots,729\}$.

For example, scenario 2 during period 1 would be the combination of path availability $= (0,0,0,0,0,1)$, while scenario 66 during period 2 would be the combination of path availability $= \{(0,0,0,0,0,1), (0,0,0,0,1,1)\}$. Additionally, $f(s) = 1$ for each scenario $s \in \{1,2,3,\ldots,64\}$ during period 2 would be the combination of path availability of scenario 1 during period 1 $= (0,0,0,0,0,0)$ that linked to the combination of path availability of each scenario 1 to 64 during period 2.

The probability of route availability for each scenario $s$ during period 1 is denoted by $Prob_1^s, s \in S_1$, while the probability of route availability during period 2 based on the previous scenario in period 1 is denoted by $Prob_2^s, s \in S$. The calculation of probability of routes being available for each scenario $s$ (denoted by $Prob_s$) is as follows: $Prob_s = Prob_1^s \times Prob_2^s$, for $s \in S$. Table 3 describes an example to calculate the probability of route...
availability based on the probability of route availability given in Fig. 1.

Since the available paths during period 1 remain available during period 2, it is not necessary to include the probability of path 5 in the calculation of the probability of route availability during period 2 for the above scenario. Meanwhile, paths 1, 2, 3 and 4 are not available during period 1, and again during period 2, thus, it is necessary to consider the probability of paths 1, 2, 3 and 4 in the above calculation.

Now that we have the concepts to generate all possible scenarios and the probability of route availability for each scenario, the next step is to determine the maximum amount of items to be delivered to each disaster area.

Table 2 Possible scenarios with a given number of paths (\( r = 6 \)).

<table>
<thead>
<tr>
<th>( S ) (scenarios during period 1)</th>
<th>Path combination availability during period 1</th>
<th>Path combination availability during period 2</th>
<th>( S ) (scenarios during period 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0,0,0,0,0,0</td>
<td>0,0,0,0,0,0</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>0,0,0,0,0,1</td>
<td>0,0,0,0,1,0</td>
<td>3</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>64</td>
</tr>
<tr>
<td>64</td>
<td>1,1,1,1,1,1</td>
<td>1,1,1,1,1,1</td>
<td>729</td>
</tr>
</tbody>
</table>

Table 3 Calculation of the probability of route availability.

<table>
<thead>
<tr>
<th>Path combination availability during period 1 ( f(s) = 2 )</th>
<th>Path combination availability during period 2 ( s = 66 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>((0,0,0,0,0,1))  ( Prob_{f(s)}^{1} = ) ((1 - P_{1}^{f}) \times (1 - P_{2}^{f}) \times (1 - P_{3}^{f}) \times (1 - P_{4}^{f}) \times (1 - P_{5}^{f}) \times (1 - P_{6}^{f}) ) ( = 0.5 \times 0.5 \times 0.5 \times 0.5 \times 0.5 \times 0.5 ) ( = 0.015625 )</td>
<td>((0,0,0,1,1))  ( Prob_{s}^{2} = ) ((1 - P_{2}^{s}) \times (1 - P_{3}^{s}) \times (1 - P_{4}^{s}) \times (1 - P_{5}^{s}) \times (1 - P_{6}^{s}) ) ( = 0.3 \times 0.3 \times 0.3 \times 0.3 \times 0.7 ) ( = 0.00567 )</td>
</tr>
</tbody>
</table>

\[ Prob_{66} = Prob_{f(s)}^{1} \times Prob_{s}^{2} = 0.00008859 \]

3 PROBLEM MODELING

3.1 Generating All Possible Scenarios Based on Path Availability during a Period of Time \( t \)

We set the single distribution center as the starting node. For each trip, vehicle \( v \) must depart from the starting node and travel straight to destination node \( j \) before heading back to the starting node. In addition, each vehicle \( v \) can serve only one disaster area \( j \) along the route \( r \). The algorithm to generate all possible scenarios and to determine the probability of route availability for each scenario are illustrated as follows:

1: Generate all possible path combinations during period 1.
2: Index each combination as a separate scenario respectively.
3: Initialize the starting node for each scenario. Assign a path between two nodes (check the predecessor requirements based on the illustration shown in Fig. 1). If the binary value of the path between two nodes is equal to 0, then set the path as unavailable (damaged by a disaster). Otherwise, the path is available (equal to 1).
4: Generate all possible routes between start and end node for each scenario. If there is at least one unavailable path along route \( r \), then set route \( r = 0 \) (unavailable), otherwise 1 (available).
5: Generate all possible path combinations during period 2 based on scenarios during period 1. Repeat steps 2 to 4.
6: Calculate the probability of route availability for each scenario \( s \) (denoted by \( Prob_s \)), where \( Prob_s = Prob_{f(s)}^{1} \times Prob_{s}^{2} \) for \( s \in S \).

As a result, we generate all possible scenarios during periods 1 and 2. We also get the results of route availability \( r \) during period \( t \) for scenario \( s \) (denoted as \( R_{rst} \), where \( R_{rst} = 1 \) if route \( r \) during period \( t \) in scenario \( S \) is available, \( 0 \) otherwise) and the probability of route availability for each scenario \( s \) (denoted as \( Prob_s \)). These two results, \( R_{rst} \) and \( Prob_s \), will be used as two important inputs in the mathematical model presented in section 3.2.

3.2 Determining the Maximum Amount of Items \( i \) to be Delivered to Disaster Area \( j \)

Given \( R_{rst} \) and \( Prob_s \) from the previous stage, in this section we develop a model for determining the expected value of the maximum amount of each item to be delivered to disaster areas. This proposed model is formulated as mixed-integer programming with the assumption that the capacity of the distribution center is unlimited, which means the amount of items stocked in the distribution center can always satisfy the demand. This model simultaneously generates the optimum number of vehicles required for each period of time.
Let $I = \{1,2,3,\ldots,i\}$ be the set of item types, $T = \{1,2,3,\ldots,t\}$ be the set of planning periods, and $J = \{1,2,3,\ldots,j\}$ be the set of disaster nodes (disaster areas). Let $R = \{1,2,3,\ldots,r\}$ be the set of routes, and $R(j)$ be the destinations (disaster areas) $j$ of each route $r \in R$.

**Parameters:**

- $R_{sr1}$ route availability $r$ during period 1 in scenario $S_1$, $r \in R$, $s \in S$. $R_{sr1} = 1$ if route $r$ during period 1 in scenario $S_1$ is available, 0 otherwise,
- $R_{sr2}$ route availability $r$ during period 2 in scenario $s$, $r \in R$, $s \in S$. $R_{sr2} = 1$ if route $r$ during period 2 in scenario $S$ is available, 0 otherwise,
- $d_{ij}$ demand of item type $i$ at disaster node $j$, $i \in I$, $j \in J$,
- $C_{ir}$ transportation cost per unit of item $i$ via route $r$, $i \in I$, $r \in R$,
- $CP$ purchasing cost of a single vehicle,
- $Probs_s$ probability of route availability for each scenario $s$, $s \in S$,
- $U$ maximum load capacity of a vehicle,
- $W_i$ unit weight of item $i$,
- $\alpha_i$ criticality weight of item type $i$, $\sum_i \alpha_i = 1$ and $\alpha_i \geq 0$, $i \in I$,
- $TC$ available budget for transportation cost,
- $TP$ available budget for purchasing new vehicles,
- $M$ large positive number, where maximum value of $M = \frac{TP}{CP}$.

**Decision variables:**

- $A_{sir}$ amount of item $i$ delivered via route $r$ during period $t$ in scenario $s$,
- $N_{sr}$ integer number of vehicles required at distribution center to travel via route $r$ during period $i$ in scenario $s$.

**Objective function:**

Maximize

$$
\Sigma_{s \in S} Probs_s \Sigma_{i \in I} \alpha_i \left( \Sigma_r \left( A_{f(s)i} + A_{sir} \right) \right),
$$

(1)

**Constraints:**

- $N_{sr1} \leq M \cdot R_{sr1}$, $\forall r \in R$, $s \in S$,
- $N_{sr2} \leq M \cdot R_{sr2}$, $\forall r \in R$, $s \in S$,
- $CP \cdot \Sigma_r N_{sr} \leq TP$, $\forall s \in S$,
- $\Sigma_{s \in S} \Sigma_r \alpha_i = 1$ and $\alpha_i \geq 0$, $i \in I$,
- $\Sigma_{i \in I} A_{f(s)i} \leq TC$, $\forall s \in S$,
- $\Sigma_{s \in S} \Sigma_{i \in I} \alpha_i \leq N_{sr1}$, $\forall r \in R$, $s \in S$,
- $\Sigma_{s \in S} \Sigma_{i \in I} \alpha_i \leq N_{sr2}$, $\forall r \in R$, $s \in S$,
- $A_{sir} \geq 0$, $\forall i \in I$, $r \in R$, $s \in S$,
- $A_{sir} \geq 0$, $\forall i \in I$, $r \in R$, $s \in S$.

(2) (3) (4) (5) (6) (7) (8) (9) (10) (11)

Objective function (1) maximizes the expected value of the amount of relief supplies delivered to each disaster area. Constraint sets (2) and (3) ensure that the vehicles can only travel to certain disaster areas via available routes during a specific period of time. Constraint sets (4) and (5) guarantee that the expenditure for purchasing the required vehicles prior to the disaster is less than the available budget. Constraint set (6) assures that the transportation cost is less than the expected budget. Constraint set (7) means the amount of relief supplies distributed to each disaster area does not exceed the demand. Constraint sets (8) and (9) guarantee that the maximum load of each vehicle does not exceed its weight capacity. Constraint sets (10) and (11) describe the non-negativity constraints.

4 COMPUTATIONAL EXPERIMENTS

Based on the illustration shown in Fig. 1, we conduct computational experiments that focus on large-scale observation, and analyze the best option to obtain the optimum result. We code each step explained in section 3.1 on Python 2.7.6. The solving time was less than 5 min. The mathematical model presented in section 3.2 is coded on GAMS 24.1.3 and run by CPLEX 12.5.1.0 solver on an Intel® Core™ i7-3770 Dual Processor with 24 GB RAM and 3.40 GHz CPU. The computation time of each test problem was less than 3 min.

Here is the rest of the data used in the mathematical model presented in section 3.2. We assumed that there are two types of relief items to be delivered immediately: type 1 is medicine (unit) and type 2 is water (bottle). Demand for type 1 in disaster areas B, C, D and E is 50,000, 50,000, 70,000 and 85,000, respectively, while demand for type 2 in disaster areas B, C, D and E is 10,000, 10,000, 20,000 and 25,000, respectively.

The transportation costs per unit of type 1 delivered via routes 1 to 7 are $5.00, $5.20, $5.20, $6.00, $7.00, $6.80 and $7.20, respectively, while transportation costs per unit of type 2 delivered via routes 1 to 7 are $5.20, $5.50, $5.50, $6.20, $7.20, $7.00 and $7.50, respectively. Unit weights of Type 1 and Type 2 are 1 kg and 18 kg, respectively, while the maximum load capacity of each vehicle is 14,000 kg. Criticality weights for Type 1 and Type 2 are set at 0.55 and 0.45, respectively. The price of a single vehicle is estimated to be $15,000.

Here is the rest of the data used in the mathematical model presented in section 3.2. We assumed that there are two types of relief items to be delivered immediately: type 1 is medicine (unit) and type 2 is water (bottle). Demand for type 1 in disaster areas B, C, D and E is 50,000, 50,000, 70,000 and 85,000, respectively, while demand for type 2 in disaster areas B, C, D and E is 10,000, 10,000, 20,000 and 25,000, respectively.

The transportation costs per unit of type 1 delivered via routes 1 to 7 are $5.00, $5.20, $5.20, $6.00, $7.00, $6.80 and $7.20, respectively, while transportation costs per unit of type 2 delivered via routes 1 to 7 are $5.20, $5.50, $5.50, $6.20, $7.20, $7.00 and $7.50, respectively. Unit weights of Type 1 and Type 2 are 1 kg and 18 kg, respectively, while the maximum load capacity of each vehicle is 14,000 kg. Criticality weights for Type 1 and Type 2 are set at 0.55 and 0.45, respectively. The price of a single vehicle is estimated to be $15,000.

Table 4 presents a sensitivity analysis of the computational experiments, while Table 5 shows the maximum value of the objective function for each computational experiment. We calculate the results shown in Table 4 by multiplying the proportion of relief demand satisfied (during periods 1 and 2) with the probability of route availability for each scenario. To demonstrate the importance of the probability of path availability denoted by $P^1$ and $P^2$, we changed the probability of path availability from 0.5 (period 1) and 0.5 (period 2) to 0.5 (period 1) and 0.7 (period 2).
average proportions of relief demand satisfied. Since we experiment No. 1 and 2; and No. 3 and 4). Then we set the restricted budget, first, we set the transportation budget to supplies delivered to disaster areas. To discover the most TP 0.5 and 0.5. This result generally follows by higher 5) compared to experiment No. 3 with the probabilities of resulted in a higher objective function value (refer to Table experiment No. 4, with the probability of 0.5 and 0.7, — for the difference of the probability of path availability (denoted by TC) and vehicle purchase budget (denoted by TP). These two budgets restrict the amount of relief supplies delivered to disaster areas. To discover the most restricted budget, first, we set the transportation budget to be smaller than the purchase budget (refer to Table 4, see experiment No. 1 and 2; and No. 3 and 4). Then we set the purchase budget to be smaller than the transportation budget (see experiment No. 5 and 6; and No. 7 and 8).

If we compare the computational experiments based on the difference of the probability of path availability— for example, experiment No. 3 and 4 (refer to Table 4)—the experiment No. 4, with the probability of 0.5 and 0.7, resulted in a higher objective function value (refer to Table 5) compared to experiment No. 3 with the probabilities of 0.5 and 0.5. This result generally follows by higher average proportions of relief demand satisfied. Since we set the critical weight for Type 1 items (denoted by \( \alpha_i \)) to be higher than Type 2 items, the results of the average proportion of relief demand satisfied for Type 1 items in each disaster area is greater than or equal to Type 2 items.

Regarding the budgets, investing more money for the transportation budget would improve the average proportion of relief demand satisfied. This also means that, in this illustration, the transportation budget could be considered one of the most restricted constraints. However, the two budgets are considered as important constraints and influence each other. Additionally, it should be noted that in some scenarios, although many routes are available, only a few routes would be traversed by the vehicles. This condition is due to the budget limitation. The bigger the budgets, the more vehicles will available at the distribution center, and the more vehicles will deliver items to disaster areas.

As for the experiment No. 7 and 8, by applying as much as $2.5 million for transportation budget and $2 million for vehicle purchase budget, we could satisfy a large proportion of demand for each scenario. In this case, by increasing the transportation budget to more than $2.5 million, the results as can be seen in Tables 4 and 5 will reach a steady-state condition. The same case applies by increasing the vehicle purchase budget to more than $2.2 million. At this state, the model has reached its optimum solution. Meanwhile, the maximum number of vehicles required at the distribution center for each experiment varied between 66 to 133 units. These numbers are massive and require a large parking area. An option available to avoid this situation is to add more time. This option can be considered in the future since this proposed model uses a single distribution center.

### 5. CONCLUSION AND FUTURE WORK

We proposed a distribution model for emergency response that simultaneously determines the maximum amount of relief supplies delivered to disaster areas and the optimum number of vehicles required for distribution center by considering route availability. This proposed model generated an extensive number of possible scenarios based on path combinations. Route availability, probability of route availability for each scenario, and budget availability were considered as important parameters in the mathematical model. One could determine the best results for overall scenarios by performing a sensitivity analysis.

This proposed model can be used for various events in response to natural disasters such as earthquakes. Moreover, this model was developed to support the government and/or decision-maker to prepare an alternative transportation/distribution plan prior to the disaster. Based on the illustration given in this paper, we solved the algorithm presented in section 3.1 with a computation time of less than 5 min. This computation time would be much longer.

<table>
<thead>
<tr>
<th>Exp.</th>
<th>Probability of path Availability</th>
<th>Expected budget</th>
<th>Average proportion of relief demand satisfied</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 1</th>
<th>Type 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exp.</td>
<td>t=1</td>
<td>Transport. ($)</td>
<td>Vehicle purchase ($)</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>1</td>
<td>0.5</td>
<td>1,000,000</td>
<td>2,500,000</td>
<td>0.746</td>
<td>0.276</td>
<td>0.752</td>
<td>0.303</td>
<td>0.806</td>
<td>0.262</td>
<td>0.367</td>
<td>0.036</td>
</tr>
<tr>
<td>2</td>
<td>0.5</td>
<td>1,000,000</td>
<td>2,500,000</td>
<td>0.957</td>
<td>0.276</td>
<td>0.790</td>
<td>0.274</td>
<td>0.914</td>
<td>0.914</td>
<td>0.914</td>
<td>0.914</td>
</tr>
<tr>
<td>3</td>
<td>0.5</td>
<td>2,000,000</td>
<td>2,500,000</td>
<td>0.746</td>
<td>0.149</td>
<td>0.752</td>
<td>0.150</td>
<td>0.889</td>
<td>0.889</td>
<td>0.852</td>
<td>0.849</td>
</tr>
<tr>
<td>4</td>
<td>0.5</td>
<td>2,000,000</td>
<td>2,500,000</td>
<td>0.957</td>
<td>0.191</td>
<td>0.790</td>
<td>0.158</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>5</td>
<td>0.5</td>
<td>2,500,000</td>
<td>1,000,000</td>
<td>0.746</td>
<td>0.692</td>
<td>0.752</td>
<td>0.714</td>
<td>0.891</td>
<td>0.839</td>
<td>0.854</td>
<td>0.845</td>
</tr>
<tr>
<td>6</td>
<td>0.5</td>
<td>2,500,000</td>
<td>1,000,000</td>
<td>0.957</td>
<td>0.869</td>
<td>0.790</td>
<td>0.729</td>
<td>1.000</td>
<td>0.930</td>
<td>1.000</td>
<td>0.979</td>
</tr>
<tr>
<td>7</td>
<td>0.5</td>
<td>2,500,000</td>
<td>2,000,000</td>
<td>0.746</td>
<td>0.746</td>
<td>0.752</td>
<td>0.752</td>
<td>0.889</td>
<td>0.889</td>
<td>0.852</td>
<td>0.852</td>
</tr>
<tr>
<td>8</td>
<td>0.5</td>
<td>2,500,000</td>
<td>2,000,000</td>
<td>0.957</td>
<td>0.957</td>
<td>0.790</td>
<td>0.790</td>
<td>0.995</td>
<td>0.995</td>
<td>1.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Exp.</th>
<th>Probability of path Availability</th>
<th>Expected budget</th>
<th>Average proportion of relief demand satisfied</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 1</th>
<th>Type 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exp.</td>
<td>t=2</td>
<td>Transport. ($)</td>
<td>Vehicle purchase ($)</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>1</td>
<td>0.5</td>
<td>1,000,000</td>
<td>2,500,000</td>
<td>0.746</td>
<td>0.276</td>
<td>0.752</td>
<td>0.303</td>
<td>0.806</td>
<td>0.262</td>
<td>0.367</td>
<td>0.036</td>
</tr>
<tr>
<td>2</td>
<td>0.5</td>
<td>1,000,000</td>
<td>2,500,000</td>
<td>0.957</td>
<td>0.276</td>
<td>0.790</td>
<td>0.274</td>
<td>0.914</td>
<td>0.914</td>
<td>0.914</td>
<td>0.914</td>
</tr>
<tr>
<td>3</td>
<td>0.5</td>
<td>2,000,000</td>
<td>2,500,000</td>
<td>0.746</td>
<td>0.149</td>
<td>0.752</td>
<td>0.150</td>
<td>0.889</td>
<td>0.889</td>
<td>0.852</td>
<td>0.849</td>
</tr>
<tr>
<td>4</td>
<td>0.5</td>
<td>2,000,000</td>
<td>2,500,000</td>
<td>0.957</td>
<td>0.191</td>
<td>0.790</td>
<td>0.158</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>5</td>
<td>0.5</td>
<td>2,500,000</td>
<td>1,000,000</td>
<td>0.746</td>
<td>0.692</td>
<td>0.752</td>
<td>0.714</td>
<td>0.891</td>
<td>0.839</td>
<td>0.854</td>
<td>0.845</td>
</tr>
<tr>
<td>6</td>
<td>0.5</td>
<td>2,500,000</td>
<td>1,000,000</td>
<td>0.957</td>
<td>0.869</td>
<td>0.790</td>
<td>0.729</td>
<td>1.000</td>
<td>0.930</td>
<td>1.000</td>
<td>0.979</td>
</tr>
<tr>
<td>7</td>
<td>0.5</td>
<td>2,500,000</td>
<td>2,000,000</td>
<td>0.746</td>
<td>0.746</td>
<td>0.752</td>
<td>0.752</td>
<td>0.889</td>
<td>0.889</td>
<td>0.852</td>
<td>0.852</td>
</tr>
<tr>
<td>8</td>
<td>0.5</td>
<td>2,500,000</td>
<td>2,000,000</td>
<td>0.957</td>
<td>0.957</td>
<td>0.790</td>
<td>0.790</td>
<td>0.995</td>
<td>0.995</td>
<td>1.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 5</th>
<th>Maximum value of the objective functions</th>
</tr>
</thead>
<tbody>
<tr>
<td>No.</td>
<td>1</td>
</tr>
<tr>
<td>Objective function value</td>
<td>95,048.494</td>
</tr>
</tbody>
</table>
if the algorithm is applied to a larger-scale network. In this case, we need to upgrade the algorithm or consider a new approach to obtain the near-optimal solution. Thus, in the future, we will focus on a more effective approach to solve the problem.

ACKNOWLEDGMENT
This work was supported by the Directorate General of Higher Education (DIKTI), Republic of Indonesia, under BPP-LN Scholarship Batch 1-2013. This financial support is gratefully acknowledged.

REFERENCES