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A multi-period humanitarian logistics model considering limited resources and network availability

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Abstract

Increased frequency of natural disasters keeps reminding us of the importance of effective pre-planning for the post-disaster situation. Efficient and timely humanitarian logistics can make a difference between life and death of the affected people and reduce trauma. Often marked with limited resources and partially available network capacity, post-disaster response mostly fails to address the needs of all affected people. This paper presents a humanitarian logistics model that considers the limited availability of resources, equity of distribution and the available residual capacity of road network in a multi-period optimization environment. A case study based on the Minato ward of Osaka city is presented, where a mega scale Nankai trough earthquake has been predicted in near future. Using scenario analysis, the case study illustrates determination of efficient depot location, critical infrastructure and supply strategy.

Keywords: humanitarian logistics; Nankai trough earthquake; Residual road capacity; Equity; Genetic Algorithm.

1. Introduction

Among large-scale natural disasters, earthquakes are considered the most fearful and deadly due to practically no moving to safety time as well as no advance warning systems. Especially in Japan, there is a long history of suffering due to earthquakes; Kobe-Awaji earthquake (1995), Great East Japan earthquake (2011), Kumamoto earthquake (2016) and Hokkaido earthquake (2018) are some of the recent disastrous events faced by this developed and (supposedly) well equipped country. However, humanitarian logistics experience after a large catastrophic event always leaves with the urge and sentiment of doing more and doing it in a better way. After the East-Japan earthquake

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and Tsunami (2011), there has been renewed concern over the possibility of occurrence of a Tonankai Trough (fault line near Tokyo) and Nankai Trough (fault line near Kinki area: Osaka, Kochi, etc.) earthquake. Large earthquakes in the southern coast of Honshu have an occurrence rate of once every 100 to 200 years (Hyodo and Hori, 2013). Recently, the expected worst-case magnitude of such an earthquake has been increased from M8.8 to M9.1. It is expected that Osaka city may receive shocks of seismic intensity of lower 6 (Japanese seismic scale) due to the Nankai Trough earthquake. Osaka city government has designated many facilities, which would be used as shelters in any unfortunate case of the disaster.

As discussed earlier, usually, there is no warning or move to safety time margin available in earthquakes and also due to the fear of Tsunami in the coastal areas, most of the people fleeing to shelters may not bring sufficient supplies with them. This will leave them to rely on the preparedness of the local authorities and disaster management forces. An interview survey (Holguin-Veras, et al., 2014) identified that most of the local authorities found it very hard to cope with the last-mile delivery of the life line supplies due to shortage of available resources (such as fuel, truck drivers and the relief goods). This situation may lead to a shortage of relief supplies at shelters, which may cause a decrease in the resilience of the affected population and may raise equity issues in the relief distribution. It was also confirmed in an interview meeting of the authors with staff of disaster management division of Osaka prefecture. It was found that although macroscopic plans are well thought out, there are no detailed plans at the micro level or for the last mile. Therefore, it is very important for academia and professionals to work with the local authorities and come up with tools and studies related with the last-mile distribution of relief goods. Qureshi et al. (2018) presented a weighted sum approach that considered minimization of shortage penalties as well as routing cost in a multi-period humanitarian logistics model addressing equity issues as well. However, important questions such as ideal depot location and network availability in post-disaster logistics were not considered. Even though cities have been focusing on strengthening their road networks, some of the road links may not be available or not working at their full capacity due to damage and debris. Therefore, this paper addresses this issue in a scenario analysis by considering the available capacity of the road network and ideal location of the depot in a case study based on Minato ward of Osaka city, which may get seriously affected due to a Nankai trough earthquake and resulting Tsunami.

2. Literature review

Relief distribution experience after a large catastrophic event always leaves the urge of doing more and doing it in a better way sentiment. Yet, very little academic research is available on this topic (Kovacs and Spens, 2007). Uncertainties involved in the distribution of relief goods (such as changing number of affected people, their locations, connectivity and rehabilitation of the left-over infrastructure) have been the main barriers in efficient response to this complex problem (Sheu, 2007). Balcik et al. (2008) optimized the last-mile using a two-phase model framework, where all possible combinations of demand locations are considered for a route in the first phase and for each such combination, the route with the minimum travel time is found by solving the Traveling Salesman Problem (TSP) in the second phase. Lin et al. (2011) added the time windows and split delivery concepts in the multi-period relief distribution of prioritized items. Tzeng et al. (2007) developed a multi-objective model for relief distribution for displaced people minimizing the sum of total cost, total travel time and customer satisfaction. Wang et al (2014) allowed the split delivery in the routing model and considered the reliability of different routes in the multi-objective framework of location routing problem for disaster relief. Vadhani et al. (2016) further added a road repair objective to the set of multi-objectives. Another stream of relief distribution-related research combines the optimal location of the relief facilities as well. For example, Ceselli et al. (2014) presented a column generation based algorithm to solve the vaccine delivery problem in the aftermath of a disaster or emergency; they formulated the problem as the location routing problem. Rath and Gutjahr (2014) considered three objective functions *viz*. minimization of depot cost, budget requirement and maximization of the supply at each shelter location. Vitoriano et al. (2011) also presented a multi-objective formulation that included equity and priority in the model formulation. Abounacer et al. (2014) added the minimization of the difference between the demand and the supply (i.e. the shortage) along with minimization of the number of the emergency workers required. Lack of available resources, infrastructure, and incomplete information in the immediate post-disaster situation, results in a relief distribution that is either less than the required amount or arrives after a long wait effecting the resilience of the affected population.

Also, Holguin-Veras et al. (2012) described that the periodicity of the regular humanitarian logistics is relatively repetitive in nature. Such a nature of relief distribution operation requires a multi-period evaluation. However, most of these models represented a traditional single period relief distribution model and they also did not consider any penalty on the unmet demand or carryover effect of unmet demand in the next period. Yi and Kumar (2007) handled a very similar problem as ours, where the unmet demand in a period is prioritized (penalized). However, their model also did not take into consideration of any carryover impact of shortage of relief supply on the resilience of the affected population in the next time period, which is exclusively handled in our model. Caunhye et al. (2012) provided an excellent review of relief distribution models.

It is a well-known fact that the resilience of human beings goes on decreasing with sustained lack of food, water and medicine. However, the demand for food, water and medicines is not additive in itself, i.e. a shortage of one day cannot be carried over to the next day but the resulting shortage does decrease the resilience of the affected person in the next day. However, the relief distribution models reviewed above, do not explicitly incorporate the complex characteristics of the relief demand that include its non-additive nature and the related depletion in resilience of the affected population due to either shortage or delay in fulfilment of this relief demand. Distribution time and its reliability can be crucial in such cases, which depend on available network capacity after a disaster and the location of the depot. Therefore, this research tries to extend our earlier work (Qureshi et al., 2018) to develop a relief distribution model, which is capable of providing an equitable multi-period plan considering the decrease in resilience for unmet demand as well as the network.

3. Modelling and solution algorithm

Availability of limited resources and limited network availability are basic assumptions of the model. The limited resources can be a direct result of limited relief supplies at the depot, or due to limited capacity of the transportation resources (such as the number of trucks, drivers or even fuel) (Holguin-Veras, 2014). Qureshi et al. (2018) addressed the balance between supply and demand of relief goods in multi-period optimization by minimizing the shortage penalties using dynamic penalty factors ($p^t{}_i$) defined in equation (1) (where, demand is represented by d_i at the shelter i, $s^t{}_i$ is the delivered supplies in time period t, and α is a user defined parameter representing the penalty update factor). In a post-disaster scenario, a bridge/road segment can be damaged or become unavailable due to debris or inundation caused by tsunami waters. However, the routing cost component in the objective function in Qureshi et al. (2018) (equation (2)) did not consider any time or residual capacity effect. In this paper, we introduce the effect of limited network availability in the form of various scenarios, discussed in next section.

$$p_i^t = \begin{cases} p_i^1 \quad , & if\ s_i^{t-1} = d_i \\ p_i^{t-1} + \propto \left(\frac{d_i - s_i^{t-1}}{d_i}\right), & if\ s_i^{t-1} < d_i \end{cases} \tag{1}$$

$$\sum_{t\in T}\sum_{k\in K}\sum_{i,j\in V} c_{ij}\, x_{ijk}^t + \sum_{t\in T}\sum_{i\in C} p_i^t (d_i - s_i^t) \tag{2}$$

Using the above mentioned penalty update function and objective equation, the proposed multi-period relief distribution model is modelled on the pattern of well-known vehicle routing and scheduling model. The scheduling horizon is divided into many periods $t \in T$. Shelters (represented by set $C = \{1, 2, . . ., n\}$) and depots are located on the vertices of a given directed graph $G = (V, A)$. The arc set A consists of all feasible arcs (i, j), $i, j \in V$. A set of identical vehicles (represented by K) each with a capacity q stationed at the depot, is available to service relief demands at the shelters. Both cost c_{ij} as well as time t_{ij} are associated with each arc $(i, j) \in A$, which remain same during the whole scheduling horizon but will vary in different scenarios according to the network availability and the chosen depot. The time t_{ij} includes the travel time on arc (i, j) and the service time at vertex i, and a fixed vehicle utilization cost is added to all outgoing arcs from the depot, i.e. in $c_{0j}, j \in C$. For the detailed formulation, readers are referred to Qureshi et al. (2018).

The proposed model is NP hard, which warrents a huristics solution approach for meaningful sized problems. We will use the Genetic Algorithm (GA) developed in Qureshi et al. (2018). As there are two decision variables, viz. the order of the customers (x^t_{ijk}) and the quantity of the relief goods delivered to a shelter (s^t_i), therefore, a two tiered chromosome representation of the solution has been adopted. Each chromosome represents a complete feasible solution of the proposed multi-period relief distribution model and can have a different number of routes of different lengths in each planning period. A population size of 250 individuals were used to evolve over 1000 generations with a mutation rate of 10% and crossover rate of 98%. Elitism was adopted, thereby keeping best 2% individuals of the current population in the population of the next generation. More details about the GA, such as a description of crossover and mutation operators can be found in Qureshi et al. (2018).

4. Case study setup

This section, reports on a case study based on available data in the Minato ward of Osaka city, which may be subjected a resulting Tsunami as well, due to the Nankai earthquake. Figure 1 shows the shelters in the Minato ward along with four possible choices of the depot in the case study. Depot (D2) is considered at the ward office of the Minato ward, which represents ideal conditions (as discussed later with data) but there exists a high probability that the ward office may itself be affected due to a Tsunami and thus becomes unavailable. The other two depots are considered at the nearby ward offices (D1: Naniwa ward office and D4 Nishiyodogawa ward office), whereas, one depot (D3) has been considered at the Osaka city hall. All these depots (D1, D3 and D4) are located at higher altitude than D2 and are less liable to be affected by the Tsunami.

The initial penalty (p_i^1) (JPY/kg) is assigned randomly due to the unavailability of any reliable data on the deprivation penalty due to decrease in the resilience, which may represent the willingness to pay of the affected population/administrators for shortage of each kilogram of the relief supply. Also, as it cannot be ascertained that which of these shelters will house weak/old/wounded people at this stage, therefore, the severity level of the shortage penalty is also kept random (shown by a higher penalty cost). A uniform penalty update factor (α = 200 JPY/Kg) is used for all of the shelters. The road network is based on the GIS network of Osaka City, which includes the travel times in daytime congested situations. This travel time is multiplied by a factor of two to represent travel times in the post-disaster situation. For each depot, four scenarios have been generated. Scenario (S1) represents a full available road network. Based on the paths connecting all the shelters and depots in S1, critical bridge segments (as marked by red-links in Figure 1) are determined (on trial and error basis), which cause a big disruption on the paths (i, j) obtained in S1. In scenario (S2), all of these critical bridge segments are assumed to be unavailable.

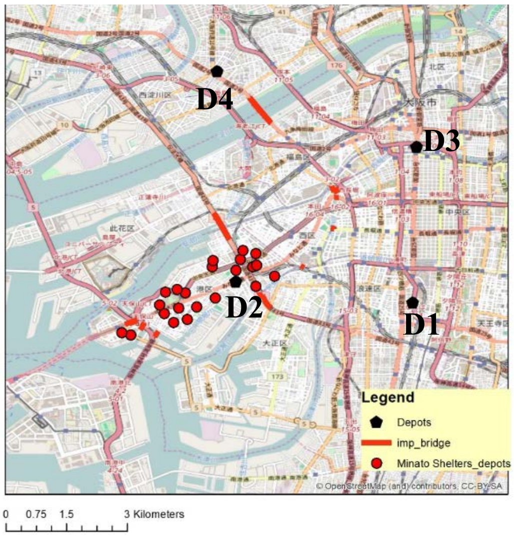

Fig. 1 Location of the shelters and depots in the Minato ward Osaka case study

Two more scenarios (S3 and S4) were created for each depot considering restoration of one of the bridges of scenario (S2). It must be mentioned that scenarios (S3 and S4) consider restoration of different bridges for each depot based on their importance for each depot. The total demand of all shelters sums to 10,315 kg, based on which, three different supply scenarios were created considering the available supply at the depot to be 100%, 75% and 50% of the demanded quantity of relief (i.e. 10,315 kg, 9,778.5 kg and 6,519 kg, respectively). It was further assumed that at least 45% and 30% of the demand relief quantity must be supplied at all shelters during each time period. The scheduling horizon has been set to five periods. A vehicle operation cost (VOC) of 14.02 JPY/minute was taken; while the fixed cost for a vehicle was set to 10,417.5 JPY. These unit cost values are based on a survey of Japanese logistics companies and most commonly used in the commercial logistics-related literature (for example, see Taniguchi et al. (2001)). Again in relief distribution, a different set of values shall be used for the VOC and fixed costs of the truck if the relevant data is available.

5. Results and discussion

Table 1 presents details of the analysis performed for the depot locations (D1 to D4) and their performance under various network availability scenarios (S1 to S4) considering a 100% demand coverage. As explained earlier, the D2 (Minato ward office), right inside the affected area, gives the best results (in fact, S2 scenario doesn't change its reliability and hence, S3 and S4 were not performed for it). However, if D2 is also assumed to be affected by the earthquake and tsunami, D1 gives better results followed by D3. Regarding the effect of the network availability D2 is more reliable with only 0.34% increase in the cost in scenario S2 as compared to D3 with a cost increase of 1.34%. Both of these depots have multiple choices to reach the affected area (i.e. Minato ward). On the other hand, D4 represents the worst choice among the considered depots, with not only a higher cost in S1 but with largest disruption cost in S2 of 6.7%. The analysis presented in Table 1 can also be used to identify priorities of critical infrastructure for the restoration operation. For example, Figure 2 shows the impact of network availability on a similar relief distribution route from D4 under S1 to S4. It can be observed that for D4, S4 gives the better restoration option (also evident from Table 1).

Table 1 Results for depot location and network availability

Scenario	Vehicles	Travel time (minutes	Routing Cost/day (JPY)	Routing Cost/5 days (JPY)	Shortage penalty (JPY)	Total cost (JPY)
D1_s1_100	8	665	97,430.1	487,150.5	0	487,150.5
D1_s2_100	8	758	98,733.96	493,669.8	0	493,669.8
D1_s3_100	8	738	98,453.56	492,267.8	0	492,267.8
D1_s4_100	8	667	97,458.14	487,290.7	0	487,290.7
D2_s1_100	8	300	92,312.8	461,564	0	461,564
D2_s2_100	8	301	92,326.82	461,634.1	0	461,634.1
D3_s1_100	8	742	98,509.64	492,548.2	0	492,548.2
D3_s2_100	8	766	98,846.12	494,230.6	0	494,230.6
D3_s3_100	8	752	98,649.84	493,249.2	0	493,249.2
D3_s4_100	8	761	98,776.02	493,880.1	0	493,880.1
D4_s1_100	8	868	100,276.16	501,380.8	0	501,380.8
D4_s2_100	8	1,347	106,991.74	534,958.7	0	534,958.7
D4_s3_100	8	1,009	102,252.98	511,264.9	0	511,264.9
D4_s4_100	8	875	100,374.3	501,871.5	0	501,871.5

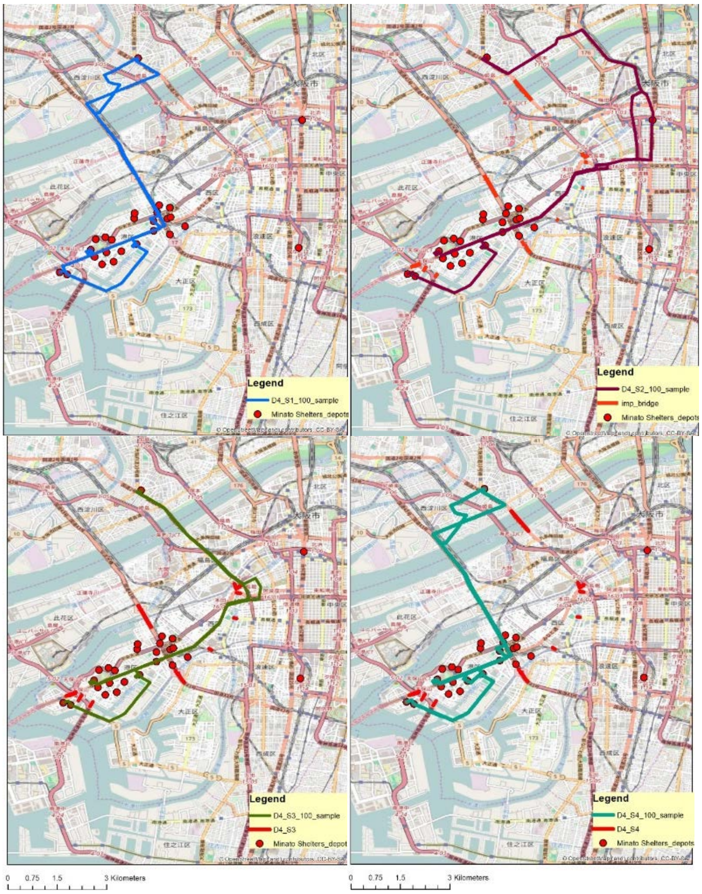

Fig. 2 Sample route from D4 under various network availability scenarios (S1 ~ S4)

Table 2 Results for supply scenarios

Scenario	Vehicles	Travel time (minutes)	Routing Cost/5 days (JPY)	Shortage penalty (JPY)	Total cost (JPY)
D1_s1_100	40	3,325	487,150.5	0	487,150.5
D1_s1_75	25	2,310	316,657.7	4,832,657.3	5,149,314.95
D1_s1_50	20	1,930	259,242.6	13,523,753	13,782,995.6
D1_s2_100	40	3,790	493,669.8	0	493,669.8
D1_s2_75	25	2,680	321,845.1	4,819,461.65	5,141,306.75
D1_s2_50	20	2,218	263,280.4	13,517,693	13,780,973.36
D1_s3_100	40	3,690	492,267.8	0	492,267.8
D1_s3_75	25	2,610	320,863.7	4,812,466.75	5,133,330.45
D1_s3_50	20	2,200	263,028	13,519,341	13,782,369
D1_s4_100	40	3,335	487290.7	0	487,290.7
D1_s4_75	25	2,380	317,639.1	4,814,622.45	5,132,261.55
D1_s4_50	20	1,975	259,873.5	13,532,814	13,792,687.5

As depot 1 performed better in the above-mentioned analysis, Table 2 gives further analysis of D1 under various supply scenarios (i.e. 100%, 75% and 50% supply of relief goods). With supply less than demand (i.e. 75% and 50%

scenarios), both parts of the objective function (Eq. 2) comes into play. It can be seen that in Figure 3 (results of D1_S1_50), the shortage penalty is much higher than the routing cost and therefore it has greater impact on the optimization process that is evident from the similar shape of the curves of total cost and shortage penalty. This condition might be the reason that caused the total cost results in S2, S3 and S4 scenarios to be less than the corresponding supply scenarios in S1. Nonetheless, the travel time of S1 scenario is the lowest in the analysis of Table 2 followed by S4 and S3. The lower travel time can be critical for disaster relief supply as it must also be quick.

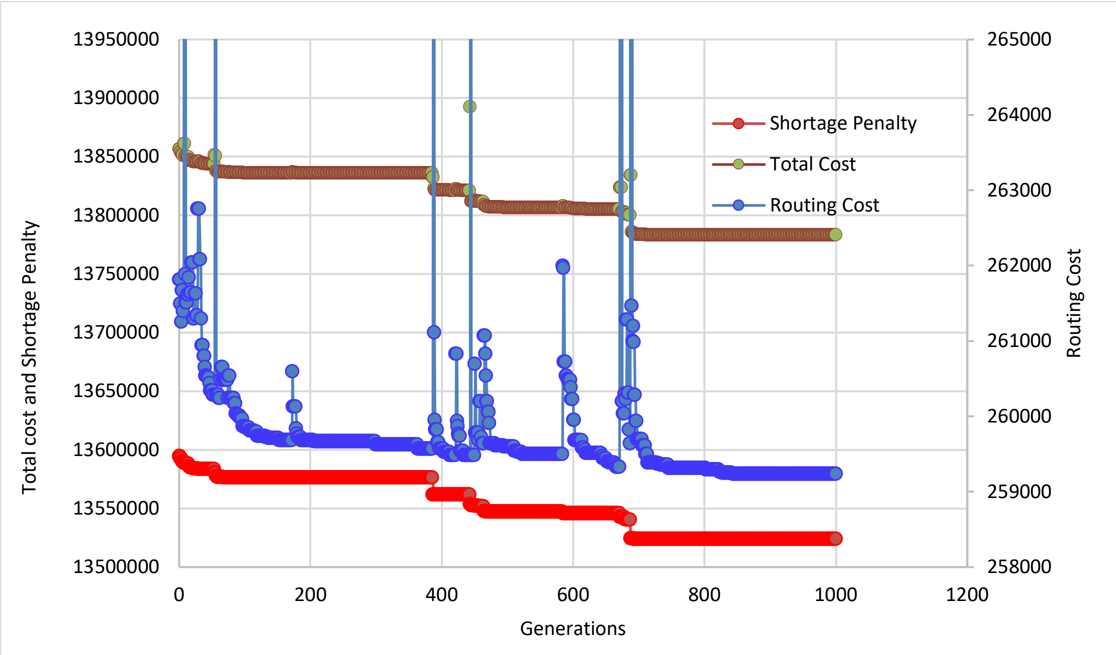

Fig. 3 Convergence of the objective function in D1_S1_50

The proposed multi-period relief distribution model considers the decaying resilience of the affected population when the supply is less than demand. Hence, it is expected that to maintain an equitable relief distribution, the relief distribution plan will compensate the shelter with lower supply today with a larger quantity of relief supplied in other periods. Figure 4 shows this effect for the solution of D1_S1_75 case for two different shelters with the same demand (514 kg) but with different initial penalty factors.

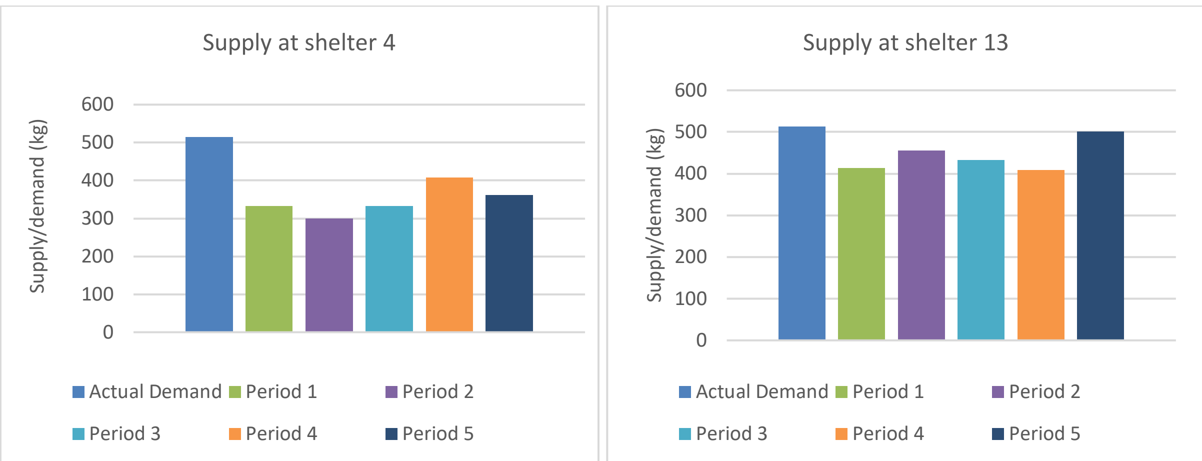

Fig. 4 Supply management in the multi-period optimization in D1_S1_75

It can be observed that shelter 13 (with initial penalty factor of 400 JPY/kg) gets more supply as compared to shelter 4 with an initial penalty factor of 100 JPY/kg. Facing a shortage in period 1, the penalty factor of shelter 13 increases and forces the model to allocate more supply at this shelter in period 2; whereas shelter 4 gets a lower supply despite some increase in the penalty factor. However, shelter 4 does not get neglected in all the following periods; the supply conditions improve as its penalty factor keeps on increasing based on continued shortage. Figure 4 shows that the model tries to manage an equitable supply at all shelters based on the resilience of the population living there, with possibilities of getting close to full demand (as shown in period 5 for shelter 13).

6. Conclusions

Relief distribution time and its reliability can be crucial, which depend on available network capacity after a disaster and the location of the depot. In a scenario analysis based on network availability, this research utilized a multi-period relief distribution model that considered an increasing penalty function in the subsequent periods if the supply doesn't meet the demand to model the decaying resilience of the affected population. In the Minato ward case study, it was found that depots located on the west side of the Yodo river (i.e. depots D1 and D3) are better choices as compared to depot D4 on the west side, as it is affected by the limited options connecting it to the affected area. The scenario analysis was helpful to decide the priority relating to infrastructure restoration in order to reduce the disruption cost. Finally, the model's application was demonstrated to provide equitable supply management (along with routing) in different supply scenarios. In order to be a truly multi-period model, network availability must be integrated into the model and the solution algorithm, instead of using scenario analysis. This is an ongoing task and the future work of this research.

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