Comparison of different relief allocation strategies in an environment of limited information

Rubel DAS[1] and Makoto OKUMURA[2]

[1]Member of JSCE, Assistant Professor, International Research Institute of Disaster Science, Tohoku University
(Aramaki Aoba 468-1, Aoba-ku, Miyagi 980-0845, Japan)
E-mail: rubeldas@irides.tohoku.ac.jp
[2]Member of JSCE, Professor, International Research Institute of Disaster Science, Tohoku University
(Aramaki Aoba 468-1, Aoba-ku, Miyagi 980-0845, Japan)
E-mail:mokmr@m.tohoku.ac.jp

A disaster logistics manager always struggles how relief items can be allocated among victims to bring maximum benefit from available resources. The most critical aspect, often ignored in mathematical modeling, is the shortage of information in post-disaster situation that creates confusion and difficulties in relief allocation. This study proposes an agent based model for comparing different relief allocation strategies in an environment of limited information. There are four type of agents: shelter agent; information agent; logistics manager and truck agent. We have validated our model by agent's behavior observation after the 2011 Great East Japan earthquake and the 2016 Kumamoto earthquake, Japan. Logistics manager shows dynamic decision making behavior and can utilize one of the three updated strategy. These are (1) Rigid push strategy (RPS); (2) Semi rigid push strategy (SRPS) and (3) Adjusted push strategy (APS). APS shows better performance in the criteria of average shortage per day and average perish per day when shelter capacity is lower or there are variations of shelter capacity among shelters. It also shows that data collection phase is crucial for selecting suitable relief allocation strategies.

Key Words : *Push logistics, NetLogo, TOPSIS, Agent based model; Disaster*

1. INTRODUCTION

The recent disaster notifies that we are still not prepared to face a large scale disaster. A disaster logistics manager always struggles how relief items can be allocated among victims to bring maximum benefit from available resources. A government official in Japan demonstrates the difficulties in disaster logistics after the 2016 Kumamoto earthquake by saying that "*How can onigiri (rice balls) [the prefecture] received today be delivered to evacuees on the same day? Distribution of commodities has become a difficult problem*" (The Japan News, 19 April 2016). Given limitation in transportation resources and relief supplies and damaged infrastructure, it is challenging to plan last mile operations (Balcik et al, 2008; Huang et al, 2011). However, the most critical aspect, often ignored in mathematical modeling, is the shortage of information about post-disaster situation that creates confusion and difficulties in relief allocation. Existing study assumes that a decision maker can gather sufficient information before making decisions. However, this is not the reality. Therefore application of sophisticated mathematical models in disaster response are still limited and distribution decisions are often made ad-hoc (Kovács and Spens, 2009) that lead to inefficient use of resources, slow response, and inadequate or inequitable relief deliveries. There is a probability that some areas may face large inventories and large shortage in other places. The effectiveness and efficiency of the existing disaster response systems need to be reevaluated (Cao and Huang, 2012). Still, a decision maker does not have guideline to solve post-disaster situations, For example, who should receive the limited resources? Should those with the highest risk of mortality receive intervention? Disaster logistics has come forward to play a key role in relief distribution strategies.

The disaster logistical network structure is vulnerable and the relationship among stakeholders in disaster supply chain is loosely bound. Therefore, mathematical models developed for commercial logistics cannot be utilized for disaster logistics. Table 1 presents the difference between commercial logistics and disaster logistics. Most of the disaster logistics managers do not have experience of relief distribution. Balcik and Beamon (2008) finds that disaster logistics manager aims for minimizing victims suffering. However, commercial logistics aim for maximizing revenue or minimizing logistical cost. Huang et al. (2012) show the importance of considering equity while distributing relief items.

Table 1 Difference between commercial logistics and disaster logistics

	Commercial logistics	**Disaster logistics**
Experience of decision maker	Usually managed by experienced person	May be managed by non-experienced about relief distribution
Aim	Maximize revenue	Minimize victims suffering
Equity	No consideration of equity	Many researchers suggest the importance of equity

The definition of disaster logistics confirms that disaster logistics manager must aim for meeting the requirement of the end beneficiary's requirement (Thomas and Fritz, 2006; Van Wassenhove, 2006). Therefore minimizing victims suffering cost is the sole objective of disaster logistics. The studies on vehicle routing problem (VRP) for relief distribution minimizes transportation cost (Balcik and Beamon, 2008). Focusing on relief response times, Campbell et al, (2008) show that the choice of objective affects how aid is distributed. Considering high time stake and dynamic situation after a disaster, the logistics manager requires user friendly and quick decision support system.

Therefore, we present an agent-based model (ABM) for relief distribution across various zones after a large-scale disaster and analyze various allocation strategies. The model has several distinctive features compared to existing research. First, it analyzes the interaction among different agents in disaster supply chain. The model provides schedules of delivering relief goods among demand points. The relationship mapping and behavior of each agent are drawn based on the survey after the 2011 great east Japan earthquake and the 2016 Kumamoto earthquake. We aim for showing outcomes of different allocation strategies.

The remainder of the paper is structured as follows. A review of the literature on resource allocation is presented in Section 2. In Section 3, we explain the task chains and interactions among agents. This section also presents the architecture of ABM. Section 4 presents a numerical analysis of the 2016 Kumamoto, Japan Earthquake using the proposed model, model validation and reports the results. Finally, Section 5 presents the conclusion of the paper and a summary of the study outcomes.

2. LITERATURE REVIEW

Relief distribution often have strong and long-lasting impacts on welfare in victims. Government and aid agencies struggle to appropriately design and implement natural disaster relief programs as to mitigate the devastating effects. Research suggests that targeting of relief is not always effective, for a variety of reasons (Franken et al, 2012). One reason is that, as with any government policy, political considerations affect relief aid allocation. Another reason is that relief aid allocation is affected by the costs of relief aid distribution. In a study of the allocation of natural disaster relief after Hurricane Mitch hit Honduras in October 1998, Morris and Wodon (2003) find that while the probability of receiving aid at household level was negatively correlated with wealth and positively correlated with assets losses, the amount of relief received was independent of these two variables. Jayne et al. (2001) finds that food aid was being used by the Ethiopian government to transfer resources to regions favored by the regime instead of those regions most in need. Some studies show that mass media can affect the process of aid allocation.

The above mentioned studies focus on long term effect of relief aid allocation. On the hand, medical professional focus on immediate response activities for example ambulance allocation for casualty movement. Childress (1970) suggests that any well-designed random selection procedure would be preferable to social worth systems, but Forsberg (1995) argues that randomness is less rational than social worth system. Kilner(1981) proposd a random selection policy from among those medically qualified but with exceptions for those facing imminent death, those requiring disproportionately few resources, and those having extreme unique moral duties, whereas other aspects, such as age, social value, and willingness. Medical professionals use triage to determine which patients receive treatments in a mass casualty disaster (Iserson and Pesik 2003). The considerations of common triage models include treating the most serious first, first come–first served, social value of the patients, and best prognosis of the patients. Recently, Persad et al. (2009) evaluated eight simple principles: lottery—allocate the resources randomly to all the patients; first come–first served; sickest first; youngest first; maximize number of lives saved; maximize life-years saved; instrumental value—allocating resources prioritized to specific individuals to enable or encourage future usefulness; and reciprocity—allocating resources prioritized to those who implement important values.

However, relief goods (food, water or shelter) distribution is neither a long term problem nor an immediate actions. Rather relief goods distribution is a repetitive actions for a middle term. However, few studies focuses on relief goods allocation strategies (Sheu, 2007; Das and Hanaoka, 2014). Sheu (2007) proposes an urgency matrix for evaluating relief allocation. However, neither studies focus on logistical function while introducing the urgency.

No studies compare the efficiency of different resource-rationing principles in natural disaster response. Efficiency means the proportion of lives that are saved in a natural disaster and how the available resources were utilized. After ruling out universally unacceptable allocation criteria (e.g., willingness to pay, relationship with the decision maker), the efficiency of proposed allocation systems should be considered in the development of a fair and well-articulated system when it is hard to tell which system is more fair. We have formulated an agent based model considering the logistical activities in an environment of limited information. Disaster response team all over the world faces similar situation after any large scale hazard. However, there are not enough studies that can assist a decision maker after a large scale hazard. Existing studies do not consider the post-disaster dynamic situation and the scarcity of information for making any critical decision. We have attempted to propose an ABM model for assisting decision makers in relief goods allocation.

3. METHODOLOGY

We have conducted survey among shelter managers after the 2011 great east Japan earthquake and the 2016 Kumamoto earthquake. Figure 1 is prepared based on survey results. It represents the interaction among different agents in relief allocation. There are four type of agents: shelter agent; information agent; logistics manager and truck agent. Each shelter agent prepares certain storage capacity. A shelter agent keeps the record of victims and of inventory in the shelter and distributes relief items among victims. An "information agent" conducts information management. In addition, we assume that information agent also keeps the record of relief delivery. After the 2016 Kumamoto earthquake, the prefecture established an information center for collecting information from various sources. "Logistics manager" is the key player in this simulation. Logistics manager and information agent share information frequently. Logistics manager selects strategy for relief allocation among shelter agents. Truck agent is the only moveable agent in the simulation. Truck agent travels from the logistics manager to a specified shelter agent. Small trucks are utilized in the last mile relief distribution (Huang et al. 2011) and we find that 4 ton trucks are popular in the last mile relief distribution.

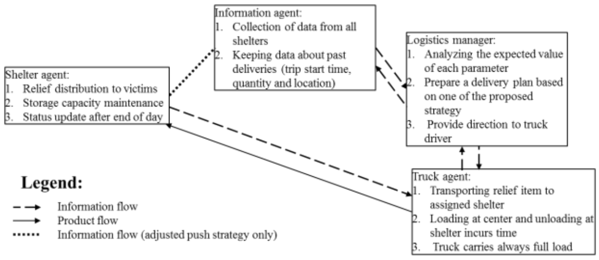

Fig. 1 Inter-connection of different agents

(1) Notation and definition

Here we have listed all symbols and explanation notes

i	:	Shelter id
k	:	Truck id
t	:	Time in a day
n	:	Number of day
v	:	Truck speed
L	:	Loading time of truck at logistics center
T_n	:	Time at the end of day n
T_{n0}	:	Time at the beginning of day n
C_i	:	Storage capacity of shelter i
d_i	:	Distance of shelter id i from logistics center
a_{it}	:	Shortage at shelter id i on time t
D_{iTn}	:	Observed demand at shelter i at the end of day n

h_{it} : On-hand inventory at shelter i on time t

I_{ni} : Effective inventory after end of day n at shelter i

R_i : Number of victims at shelter i

p_{ni} : Perished quantity after end of day n at shelter i

S_{ni} : Shortage at shelter id i on the day of n

L_{it} : Shortage at shelter id i on the day of n

N_i : Total number of deliveries at shelter i

Tot_k : Total time required for completing a tour by truck k

U_i : Unloading time from truck at shelter agent i

x_{ni} : Relief item at shelter i at the end of day n

(2) Agents behavior

a) Shelter agent

It is assumed that each shelter agent has prepared certain storage capacity. A shelter agent cannot store relief items more than its storage capacity and distribute relief items from the stock. A shelter agent will face one situation among below:

1. No delivery to the shelter on the day
2. Single delivery to the shelter on the day
3. More than one delivery to the shelter on the day

Based on the delivery situation, a shelter agent exhibits its performance.

Observed demand: The demand information can be accessed by the shelter agent, but not by the logistics manager. The shelter agent observed a random demand within a fixed range of uniform distribution. It is assumed that the observed demand per day is not constant in a shelter.

$$D_{iT_n} = \text{uniform}\ (0.8 \times R_i\ , 1.2\ \times R_i) \qquad (1)$$

Shortage computation: Shortage in each shelter agent is computed by using the conception of Figure 2. Shelter agent can distribute relief items only from its stock. If there is no stock in storage, shelter agents faces shortage during that time. Back-order is not allowed in the system. If a delivery is done just before ending a day, the relief items are distributed among victims for the remaining time of the day only.

$$a_{it} = \begin{cases} 0 & when\ h_{it} \geq D_{it} \\ D_{it} - h_{it} & when\ \ h_{it} < D_{it} \end{cases} \qquad (2)$$

$$x_{ni} := h_{iT_n} \ \text{ when day n ends} \qquad (3)$$

$$S_{ni} := \sum_{t=T_{no}}^{T_n} a_{it} \qquad (4)$$

Wastage and inventory level computation: Wastage and inventory level is computed by using Figure 2. Shelter agent can receive delivery items more than its capacity but cannot store relief items overnight more than its capacity. If available relief items at shelter at the end of day is more than its capacity, the excess relief items is considered as wastage and inventory level is adjusted. Wastage and inventory level computation are shown in eq. (5) and (6).

$$p_{ni} = \begin{cases} x_{ni} - C_i & if\ x_{ni} > C_i \\ \quad 0 & otherwise \end{cases} \qquad (5)$$

$$I_{ni} = \max\ (x_{ni} - p_{ni}, 0) \qquad (6)$$

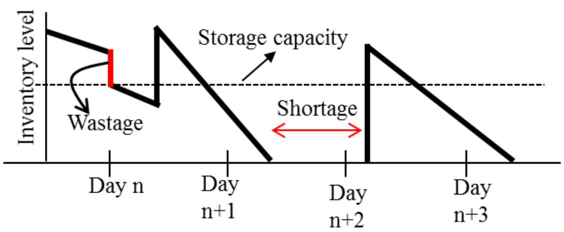

Fig 2 Status update after end of day[shelter agent]

b) Logistics manager

Logistics manager assigns id of each shelter within the jurisdiction and provides direction to truck agent. It is assumed that logistics manager have sufficient amount of relief items. Logistics manager shows dynamic decision making behavior that is shown in Figure 3. In the simulation process, there are two phase:

1. Data collection phase: Based on possible damage situation, trucks will be assigned to shelters. In our model, trucks collects demand information and storage capacity of shelter. Each shelter must be visited at least once before selecting updated strategy.
2. Update strategy phase: After collecting local information, logistics manager utilized one of the three updated strategy. These are (1) Rigid push strategy (RPS): Delivery is allocated sequential-ly among demand points; (2) Semi rigid push strategy (SRPS): Delivery is allocated based on expected inventory among shelters. It means the shelter which has lowest inventory will get relief first. and (3) Adjusted push strategy (APS) Delivery is allo-cated based on

i. Ex-pected inventory
ii. Ex-pected Demand
iii. Previ-ous day shortage
iv. Total shortage
v. Total wastage

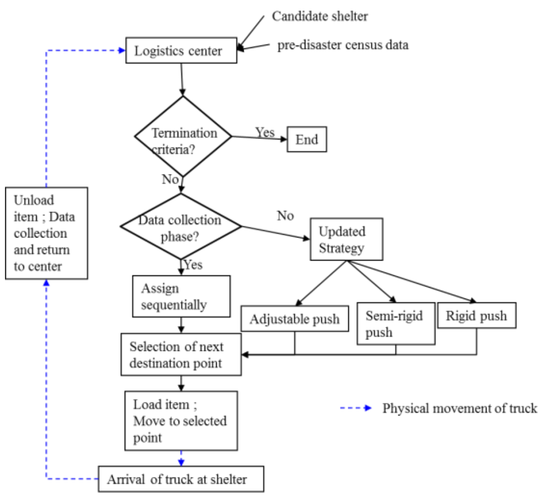

Fig. 3 Truck movement and decision strategy of logistics manager

APS considers five criteria and these criteria are selected based on discussion with disaster logistics manager after the 2011 great east Japan earthquake and the 2016 Kumamoto earthquake. TOPSIS is utilized for combining all five criterion and for making ranking among shelters and top rank shelter will get relief first. Sheu (2007) and Das and Hanaoka (2014) have demonstrated the TOPSIS method.

c) Truck agent

In our simulation, only truck agent can move from one place to another place. Truck agent carries relief item from logistics center to shelter. The speed of the truck is 45 km/hr. It takes 43 minutes for loading and 43 minutes for unloading. Note that unloading time among shelters can be different. However, we do not differentiate the shelters in terms of the unloading time. The carrying capacity of truck is 4 ton. The total required time for truck k to delivery relief items to shelter i is shown in eq. (7)

$$Tot_k = \mathrm{L} + \frac{2d_i}{v} + U_i \tag{7}$$

d) Information agent

Information agent keeps the record of delivery. This agent keeps the record of each journey start time and each truck carrying load. Moreover, information agent collects information about shelter storage capacity. Note that, the storage capacity of a shelter information will be available after a truck returning from the shelter after delivering relief items.

4. MODEL VALIDATION AND NUMERICAL ANALYSIS

(1) Validation of the model

We have validated our model by agent's behavior observation. We have interviewed personals who were involved in relief distribution after the 2011 Great East Japan earthquake and the 2016 Kumamoto earthquake, Japan.

Trucks agent plays a follower role who willingly carried the request of logistics manager. Though Kovács and Spens, (2009) found that trucks owner raises transport fare after a disaster. However, we have not found such problems in Japan and rather we have observed several commercial logistics company provides free of cost transport service. Therefore, we assume that truck agent follows logistics manager's suggestion.

Logistics manager is a key stakeholder in our model. All logistics manager asserts that relief allocation strategies should be as simple as possible. Because, the logistics manager may not have all facilities to implement complex but may be more optimized relief allocation strategies. Moreover, the logistics manager faces problems of the lack of information.

An information agent collects information from shelter agents and also keeps the delivery information.

Shelter agents struggle in managing relief goods and distribute relief items among victims. Shelter agents request for relief items. However, it cannot be confirmed whether the relief request will be fulfilled or not.

We have simulated our model for twenty (20) shelter agents, ten (10) truck agents, one logistics manager and one information agent.

(2) Model implementation and result

The ABM is implemented in the open-source tool, NetLogo. We have utilized our model for devastated area after the 2016 Kumamoto earthquake. Figure 4 shows the earthquake intensity that was published by Japan Metrological Agency (JMA) after 10 minutes of the 2016 Kumamoto Earthquake (14 April, 2016). We have utilized Figure 4 for allocating resources in data collection phase. In this analysis, the 20 shelters are the demand points and the shape of shelter in NetLogo is "house". For the network setting, the logistics manager is located in Kurume area, Kumamoto that is outside of earthquake damaged area. The shape of logistics manager (center) in NetLogo is "house two story". Figure 5 shows three different colors of truck and the shape of truck agent in NetLogo is “truck” or “truck-rear”. Truck’s color turns to red while it is loading relief items at logistics center or unloading relief items at shelter. Green color truck is heading to shelter with full of relief items, Cyan color is returning to center warehouse and it is empty. Total number of truck in our simulation is 10. All truck agents have same carrying capacity and travel speed. We assume truck carrying capacity 700 unit (that is equivalent to 4 ton). The background map in NetLogo is collected from Google map for geo-referencing

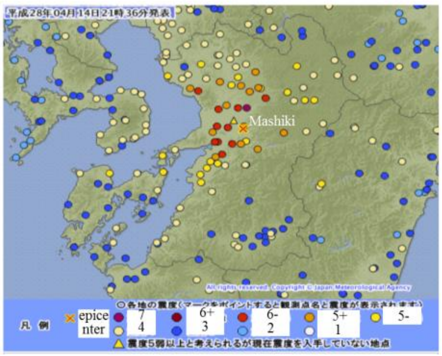

Fig. 4 Earthquake intensity after the 2016 Kumamoto earthquake (some texts are translated from Japanese language to English) (source: JMA)

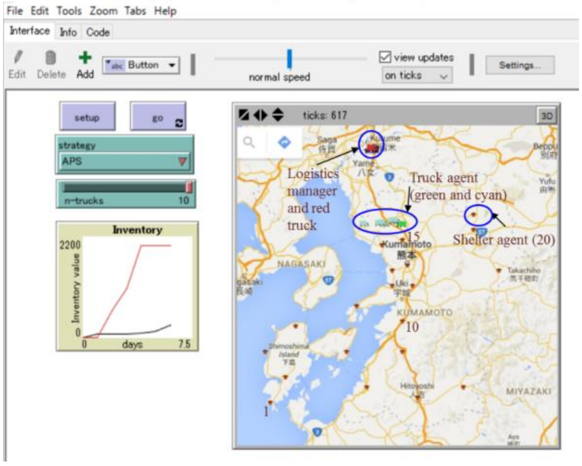

Fig. 5 Implementation of agent based model in NetLogo. Here, shelter id 1, 10,15, and 20 are also shown.

There are two buttons in Figure 5 named “strategy” and “n-trucks”. Strategy button is utilized for selecting one of three strategies: APS; SRPS and RPS. Now, n-trucks is sliding button used for selecting of number of trucks. In this simulation we utilize 10 trucks. We run the simulation for 40 days for three strategies (RPS; SRPS and APS). In the simulation we assume 100 ticks are equivalent to one day. So the simulation runs for 4000 ticks. We assume the working period in a day is 12 hours (8:00 am to 8:00 pm).

In data collection phase of simulation, information agent collects information from truck agents while truck agent returns from a shelter after delivering relief items. In the simulation we assume truck collects information about shelter capacity and number of victims at the shelter. Table 3 shows the storage capacity and number of victims in each shelter. Here number of victims in shelter is fixed. However, the demand per day, a function of number of victims as shown in eq. (1).

Table 2 Shelter id, number of victims in each shelter and shelter capacity

i	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
R_i	90	180	50	130	170	40	220	270	450	60
C_i	770	468	486	426	308	602	491	745	330	588
i	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
R_i	800	830	700	750	800	720	730	250	200	150
C_i	615	310	572	425	726	742	599	470	419	553

Figure 6 to Figure 8 present the total number of deliveries in all twenty shelters. Figure 6 shows that shelter id 1- 15 get total 24 deliveries while shelter id 16 to 20 receive total 23 deliveries in RPS strategy. Trucks were on the way to shelter id 16 to 20 while termination criteria was satisfied. In the case of SRPS and APS, total number of deliveries are different from RPS. Some shelters are served by high frequency of relief delivery and some shelters are served by less frequency of relief delivery. Shelter 1 receives less number of deliveries in SRPS and APS while shelter 15 receives more deliveries compare to RPS. As we have seen in Table 3, the number of victims in shelter id 1 is 90 person and this shelter has a capacity of 770 unit. Therefore, the stocked relief goods can satisfy the relief demand of the victims staying in the shelter. It means shelter id 1 does not require to receive relief goods every day. However, the number of shelter id 15 is 800 person and the storage capacity is 726 unit. It is obvious that shelter 15 needs frequent delivery of relief. Therefore, the number of deliveries in shelter 15 in SRPS and APS strategies are larger than in RPS system.

Figure 9 shows the delivery time in shelter id 1. It shows that first delivery in all three strategies arrives at 129 (= 100 ticks + 29 ticks) ticks. Therefore, shelter id 1 did not receive any relief goods in first day (100 ticks). The first day demand in shelter id 1 was unserved and the second day demand until (29 ticks = 3 hour 29 minutes) 11:29 am was also unserved.

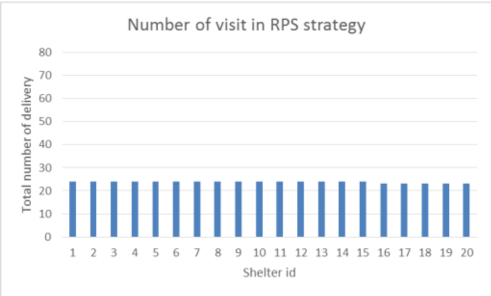

Fig. 6 Total number of deliveries in 40 days simulation in RPS strategy

Fig. 7 Total number of deliveries in 40 days simulation in SRPS strategy

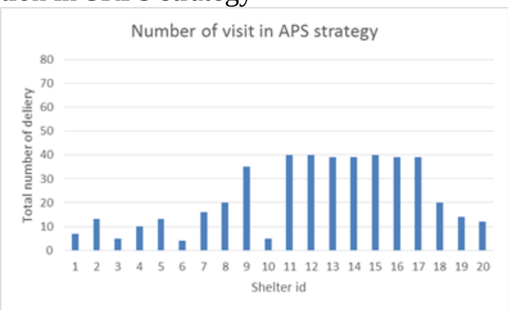

Fig. 8 Total number of deliveries in 40 days simulation in APS strategy

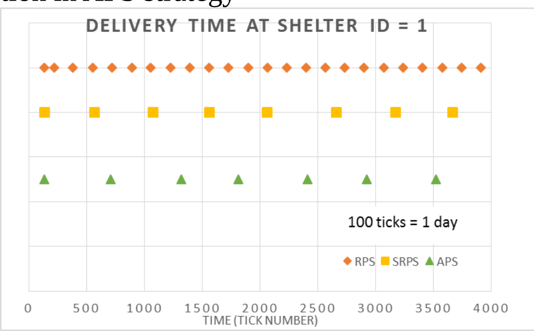

Fig. 9 Delivery time of shelter id = 1. Each dot indicates one delivery.

Our aim in this study is to see the performance of each allocation strategy. We compare the performance of each strategy based on; average inventory per day, average shortage per day and average perish per day

$$\text{avgerage inventory per day} = \frac{\sum_{n=1}^{40}\sum_{i=1}^{20} I_{ni}}{40 \times 20} \quad (8)$$

$$\text{avgerage shortage per day} = \frac{\sum_{n=1}^{40}\sum_{i=1}^{20} S_{ni}}{40 \times 20} \quad (9)$$

$$\text{avgerage perish per day} = \frac{\sum_{n=1}^{40}\sum_{i=1}^{20} p_{ni}}{40 \times 20} \quad (10)$$

Total travel distance is computed by

$$\text{total travel distance} = \sum_{i=1}^{20} 2N_i d_i \quad (11)$$

Table 4 shows the performance of each strategy. The average inventory/ per day represents the average inventory of carry over night. The average shortage per day in RPS is the highest and that in APS is the lowest. Similarly, the average perish per day in APS is the lowest. It is observed that APS out performs in all criterion. Here, total travel distance in APS is smaller than other strategies. Since the hardest hit areas (as shown in Figure 4) is closer to the logistics center. It is possible that total travel distance in APS would be higher if hardest hit areas are far away from logistics center.

Table 4 Outcomes from each strategy (Scenario 1)

	Average inventory per day	Average shortage per day	Average perish per day	Total travel distance
r	510.33	150.75	169.15	67133.52
s	510.98	106.70	152.18	65295.72
a	443.44	88.42	72.84	55509.58

r: RPS; s: SRPS; a: APS

(3) Scenario analysis

We have analyzed the model for storage capacity in each shelter as shown in Table 3 and have named it scenario 1. Now we want to analyze whether APS always generate better results or not. Therefore we have created three more scenarios (from scenario 2 to scenario 4) depending on shelter storage capacity. The outcomes of scenario 1 are explained in previous sub-section.

Table 5 scenario description

	Shelter storage capacity (unit)	Truck capacity
Scenario 1	variation (as shown in Table 3)	700

Scenario 2	2000	700
Scenario 3	900	700
Scenario 4	300	700

We have analyzed for shelter capacity of 300 unit (small sized), 900 unit (medium sized) and 2000 unit (large sized). We have kept other parameters unchanged.

Table 6 shows that the average shortage per day in SRPS is the lowest when shelter capacity is large sized. However, the average perish per day in APS is the lowest. Therefore, SRPS is the best strategy while a decision maker wants to reduce average shortage per day. On the other hand, APS strategy minimize the average perish per day and average inventory.

Table 6 Outcomes from each strategy (scenario 2)

	Average inventory per day	Average shortage per day	Average perish per day	Total travel distance
r	1833.08	43.73	155.88	67133.52
s	1877.63	27.24	114.29	65295.72
a	1541.92	74.98	64.51	55509.58

r: RPS; s: SRPS; a: APS

Table 7 presents the outcomes for medium sized shelter capacity. It shows the similar result for the situation with scenario 2. Though average shortage per day in SRPS for scenario 3 is 71.4% higher than in SRPS for scenario 2. However, average perish per day in APS for scenario 3 is 3.5% higher than in APS for scenario 2.

Table 7 Outcomes from each strategy (scenario 3)

	Average inventory per day	Average shortage per day	Average perish per day	Total travel distance
r	848.27	78.84	159.5	67133.52
s	860.37	46.69	121.4	65295.72
a	719.46	75.52	66.74	55509.58

r: RPS; s: SRPS; a: APS

Table 8 presents the outcome when shelter capacity is small. It shows that APS out performs to other strategies. The results is similar to scenario 1. However, average shortage per day in APS in scenario 4 is 47.2% higher than the APS in scenario 1. Average perish per day in APS in scenario 4 is 12.7% larger than the APS in scenario 1.

Table 8 Outcomes from each strategy (Scenario 4)

	Average inventory per day	Average shortage per day	Average perish per day	Total travel distance
r	295.20	221.55	184.8	67133.52
s	290.94	171.37	180.2	65295.72
a	272.70	129.73	84.12	55509.58

r: RPS; s: SRPS; a: APS

Scenario 2 and scenario 3 shows that SRPS is a better strategy while a manager aims to reduce the average shortage per day. In scenario 2 and 3, shelter capacity is relatively larger. However, APS shows better performance for scenario 1 and scenario 4. Scenario 1 has variation of shelter capacity and scenario 4 has relatively lower shelter capacity. So, APS shows better performance in the criteria of average shortage per day while shelter capacity is lower or there are variations of shelter capacity among shelters.

Average perish per day for all scenarios is always smaller in APS. Therefore, APS strategy reduce the wastage in the system. Though minimization wastage is not always major objective in disaster logistics, wastage brings addition work pressure on shelter agents.

Here, total travel distance for all scenarios are same but it varies among strategies. Overall, the relief allocation strategy needs to consider the preparedness of affected areas and data collection phase is crucial for selecting suitable relief allocation strategies. Therefore, a logistics manager cannot ignore the data collection phase for selecting strategy.

6. CONCLUSIONS

According to disaster logistics manager, they need a simple relief allocation rule to satisfy large disaster affected areas. The proposed relief allocation model can be used to help disaster logistics manager for better understand the effect of distribution strategies. This model allows actors to investigate the effects of disaster preparedness and to understand the mechanisms of demand management in a dynamic environment. The proposed ABM includes four types of agents: shelter agent, truck agent, information agent, and logistics manager.

The ABM was validated by doing survey among logistics manager after the 2011 Great East Japan Earthquake and the 2016 Kumamoto earthquake. This study compares different relief allocation method, and analyzes the applicability of each strategy in different scenarios. The results of this study lead to the following conclusions:

- We have explored the behavior of stakeholders in a disaster logistics network.
- We have introduced three different distribution strategies and have analyzed the effect of each strategies.
- There are no strategy that can fit for sizes. APS strategy reduce the wastage in the system. Though minimization wastage is not always major objective in disaster logistics, wastage brings addition work pressure on shelter agents. SRPS also shows better performance in the performance measure of average shortage per day while storage capacity in shelter was medium or larger.

The model proposed in this study considers one-to-one delivery system, if transportation network allows it is possible to use larger truck and one-to-many system can be introduced. Again, we consider all trucks are in same capacity, it will be interesting to analyze the truck agents varies in the criteria of carrying capacity. Future research can investigate various types of contracts and their effects on social benefit. Herewith, we analyze the behavior of logistics manager based on the experience of Japan where central government and local government take leading role in relief allocation.

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