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SPATIAL STRATEGY OF DISASTER RELIEF INVENTORY

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Abstract. *After a disaster, a stock availability between relief inventory units is varying significantly and some of them may lack of important items. Balancing the level of relief inventory is challenging since the balancing operation may lead to further imbalanced condition. We propose a spatial strategy to even out the inventory level through transshipment, and control the transshipment operations in the environment of low credible relief's information. This information includes: number of evacuees, demand rate, logistic lead-time, etc. Here, we compared three strategy schemes: without lateral transshipment, with fully lateral transshipment, and partial transshipment. The first two strategies are representing selfish and altruistic behaviors, respectively. The later represents a moderate behavior between selfish and altruistic. In our model, each unit of inventory interacts and controls its action based on those strategies. To demonstrate applicability of our model, we used data of one volcanic eruption occurring in North Sumatra Indonesia on November 2013. The result revealed that the best performance, measured by total inventory cost and inventory's health, was achieved by the partial transshipment with an updating method called dynamic support. With this strategy, the average inventory level increased about 50% and the frequency of transshipment operations reduced to 20%. These results, however, can be achieved only on low onset type of disaster events and sufficient number of logistic transporters is available. Based on the case study, we recommend a new way of relief inventory operations, thus the government and disaster relief organizations can get benefit from it.*

Keywords: Relief inventory, Disaster response, Lateral transshipment, Volcanic eruption, Spatial game theory

1. **Introduction.** Disaster relief is a mandatory operation after disaster that involves several stake holders including: government, NGO, and donors. This operation is needed since the disaster evacuees lose their ability to sustain their life in some period of time. The goal of this operation is to save the life of disaster evacuees through some relief activities such as evacuation, health care delivery, and inventory as well as logistic. The purpose of relief logistic and inventory is to serve the evacuees with sufficient life support items, e.g., food, water, medicine, tent. Acknowledging their importance, the relief operation must be provided within the first hours after the disaster to increase the survival rate of the disaster evacuees [1]. However, this is not an easy task since the size, magnitude, and frequency of natural disaster are unpredictable. As a matter of fact, the occurrence of natural disaster shows an increasing trend recently [2].

Logistic and inventory are one of the major concerns in disaster relief operations. The role of logistics is to deliver the life support items to the disaster victims even in remote disaster areas and under difficult circumstances. Inventory plays an important role in managing all the relief items and delivering those items to the victims in timely manner. Logistic and inventory have to work collaboratively to achieve the best performance. The formal role of logistic and inventory system for disaster relief is mentioned by Long and Wood [3] with a description of the working environment.

The central problem of relief inventory is that the difference of stock level between inventory units (located at the shelters) is large. Some of them have high amount of inventory while the others do not. This is due to inaccurate information of actual demand, number of evacuees, and logistic lead-time. Even some items are prepared before disaster, the amount is not enough to even up the inventory level between units. This preparative inventory is famous as pre-positioning inventory [4]. The aim is to decrease disaster potential devastating effects [5].

To date, few researchers have addressed the problem of transshipment (redistribution) in disaster relief. Most of the transshipment research in disaster relief assumes that the information of demand is known with probabilistic nature, which is not applicable in certain cases. Reyes et al. [6] used system dynamic to model transshipment activities in relief inventory under probabilistic demand. Indeed, the best way to even up inventory level is through transshipment. This activity allows a stock delivery within same level and adjacent inventory units. The goals are to minimize number of inventory with a low level of stock and help even out the level between them. These goals can only be achieved if the number of vehicle for logistic operations is sufficient, and the shelters and central warehouse are not destroyed by the disaster [7]. Paterson et al. [8] made a classification of the transshipment research, highlighted the strength and weaknesses, and showed the gaps. To make coherent understanding of transshipment in relief inventory, Figure 1 illustrates a transshipment system that consists of a single central warehouse (WH) and four inventory units (SP).

Mulyono and Ishida [9] proposed a method based on probabilistic cellular automata to model transshipment system with the purpose of finding a parameter's threshold of successful transshipment. This model was inspired by the cooperative work of immune cells in immunity based system theory [10]. However, this model does not involve a control aspect of transshipment operations. In this model, each unit had a mandatory task of supporting its neighbors without considering own and neighbor conditions.

Controlling a system is critical toward its performance. Without firm control of delivery operations in transshipment, stock items may deliver to the units that do not actually need support. Moreover, the helper unit may fall into trouble (low inventory level) after transshipment operations. Those conditions lead to adverse effect of transshipment system.

This paper aims to extend the work of Mulyono and Ishida [9] with an intention to control the transshipment process using spatial strategy and use more comprehensive performance measures namely number of healthy inventories and inventory related cost. Mulyono and Ishida [9] model assumes information about status of inventory is unavailable and transshipment operation is controlled with uniform strategy. However, in present model neighbor's information is required and transshipment operation is controlled with spatial strategy. In spatial strategy, each inventory unit has a freedom to support or not support based on own information and neighbor information. In other words, the unit of inventory has more control of their own actions. However, concerns have arisen an issue about how to get the information of the neighbors condition. Here, we combined the information from a logistic transporter, which has certain level of cooperation, and the past history of the inventory unit's actions.

Our model used a well-known spatial version of game theory to model an interaction of inventory units in each shelter. We propose three transshipment's strategies based on spatial strategy [11]: without transshipment, with fully transshipment, and with partial transshipment. The first two strategies do not have an updating method, while the later has three types of updating strategies namely maximum payoff, static support, and dynamic support.

Our model is appropriate to be used in low onset type of disaster since evacuation shelter and central warehouse are not totally struck in that disaster's type. Moreover, sufficient number of logistic vehicle was mandatory to support transshipment operations [7]. To clarify the applicability of our model, we developed the transshipment of 'ready to use food' item for volcanic eruption evacuees. We used a volcanic eruption case of Sinabung Mountain, North Sumatra Indonesia, in 2013. We addressed the following questions in detail: (i) how do the strategies improve the performance of relief inventory? (ii) what is the best strategy and under which circumstance that strategy works well?

Our paper is organized as follows. Section 2 introduces the recent literatures about relief inventory model and spatial game theory. Next, we present the transshipment strategies and their work flow. Section 4 explains the case study in detail. In Section 5, a model implementation using case study is discussed to find out the best strategy. Section 6 concludes by highlighting the findings, future directions and operational recommendations.

2. **Related Work.** Since natural disaster showed an increasing trend recently, there has been much interest in improving the relief operations [12]. The effectiveness of the relief operations relied on the speed and quantity with which life support items can be procured, transported and managed at the disaster location [13]. Indeed, the relief logistics and inventory contributed most to a disaster relief operation, estimated to account for at least 80% of the operating expenses [14].

A few decades ago, the classical inventory model had been developed and had been using widely now. On the other hand, the disaster-relief inventory model was still young and under development. There are slight differences between those two models. The differences are on the environment and characteristics of disaster-relief inventories in the areas of acquisition through storage and distribution [15]. Nevertheless, the fundamental principle of the classical inventory model can be used to build the relief inventory model.

Due to rapid development of information technologies, information systems for disaster relief have improved greatly, leading to better coordination among each organization involved [8]. Better communication, coordination, evacuation procedures, inventory and logistics systems, and rescue equipment have all helped in reducing the impact of disasters. However, accurate information about the number of evacuees, supplies, and demands was difficult to acquire after disaster. Even the accurate information was scarce; there was a method to help the disaster evacuees by sharing an inventory items [8].

Sharing items between inventory units in each evacuation shelters is one alternative way to reduce the shortage of necessary items and improve the effectiveness of disaster-relief inventory. In classical inventory theory, this practice was called transshipment. Formally, transshipment in an inventory system means the movement of stock between unit sat the same level [16]. In disaster response, periodic stock movement was better rather than volume based ones [7]. The recent research regarding transshipment had been classified according to system characteristic, ordering method, and delivery characteristic [7].

Information is the key success factor in relief inventory and logistic operations. However, previous work assumed availability of information regarding inventory and logistic parameters that was actually difficult to meet in a disaster environment. For instance, Reyes et al. [6] developed a plausible work of transshipment model using system dynamic approach. To the best of our knowledge, few researchers have addressed the issue of unavailability of information. Moreover, we need a robust modeling tool as a basis of developing relief inventory model under unavailability of accurate information.

Game theory has been used widely in many fields of application. Here, the action of sharing can be represented as cooperation in a cooperative game, where each player decides the quantity and the moment of sharing. In the field of computer science, similar action of sharing was extensively studied. The self-repair network (SRN) model proposed a methodology of cleaning up network by mutual copying [17]. The development of this model was inspired by the immunity-based system, which was characterized as self-maintaining and adaptive [10]. In this model, sharing actions has side effects of spreading contamination. In relief inventory, transshipment also had a side effect of reducing the service level of the sender and elevates the resources consumption [9]. The game theoretical approach is appropriate to use for controlling these side effects. Each agent in game selects a strategy that optimizes its performance.

3. **Model Development.** The design of our transshipment model is based on spatial version of Prisoner's Dilemma in game theory. A dilemma occurs when the inventory units have to decide whether to support or not support their neighbors. If they decide to support by sharing their stocks, they reduce own stock availability. Oppositely, if they do not support, they reduce a survival chance of others inventory units that lack of stock at that time.

Transshipment system in relief inventory consists of three entities: inventory units, central warehouse, and logistic transporters (Figure 1). The inventory units located at each shelter are players of this spatial strategy. They try to maximize benefits by changing their strategy, dynamically. The second entity, central warehouse, plays an important role as a main supplier of all items delivered to each inventory unit. However, central warehouse is not considered as a player in our model. The central warehouse receives all items from donors, pools the items and distributes them to each inventory unit periodically. The last entity, logistic transporter, has a main task in delivery activities. In

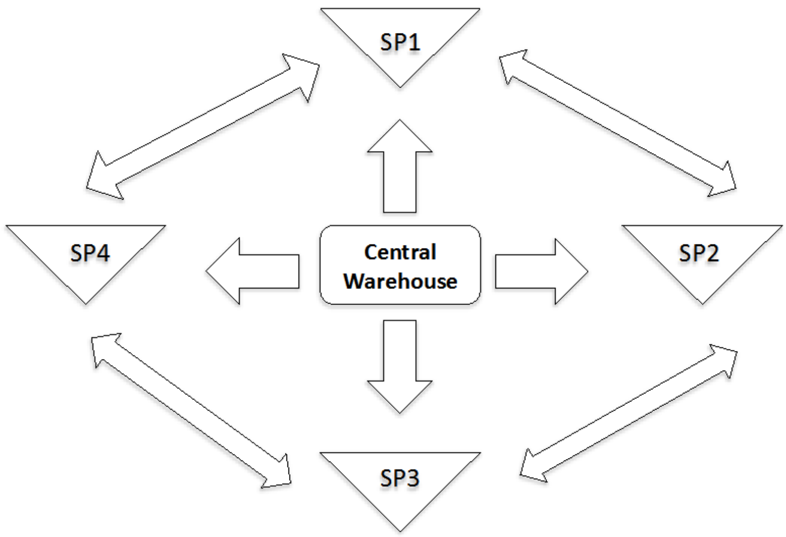

FIGURE 1. A simple illustration of transshipment system. Central warehouse supplies four inventory units (SP1 to SP4) regularly. Each of them tries to help their neighbors.

addition, they also play a critical role to convey information about the inventory level and cooperative actions of the visited inventory units. Of course, some of logistic transporters are cooperative in conveying the information and the others are not. Therefore, we attach a cooperative parameter to each transporter representing its level of cooperation.

In transshipment system, the way of managing inventory specifies the behavior of the transshipment's entities. From the viewpoint of classical inventory theory [18], periodic delivery is the easiest option for relief inventory, since a delivery frequency (from the central warehouse to inventory unit) is previously determined and constant throughout the disaster response period. The amount of delivery for each inventory unit (see Equation (1)) depends on its demand rate (d), delivery period (RP), delivery lead-time (LT), and safety stock (SS). Referring to Equation (1), the amount of each delivery is directly affected by dynamic change of demand rate. Since the exact value of demand rate is almost impossible to obtain in disaster response, we used the expected demand of each inventory unit that is equal to the maximum capacity of the shelter multiply with a consumption rate of each evacuee in the shelter.

The amount of delivery is influenced by capability of central warehouse that is changing over a disaster response period. This is due to the facts that the items owned by central warehouse are coming from government and NGOs donation. At the beginning of the disaster response period, those items are still limited in number and thus central warehouse could not fulfill all the demand. Here, the capability of central warehouse to fulfill the demand, called sourcing capacity (SC), increases exponentially following a logistic growth function [19]. According to that function, the sourcing capacity in time t depends on its previous value in $t-1$, rate of increase (IR) and maximum capacity (MC). The sourcing capacity of the central warehouse is denoted in Equation (2).

To measure the performance of transshipment system in relief inventory, we employed two performance measures: number of healthy inventory and inventory related costs. The inventory unit is said to be healthy if its level is above healthy threshold. Aside from the healthy parameter, the inventory unit has to consume considerably low cost for the better performance. Normally, there are four types of inventory related costs such as procurement, transportation, holding, and "stock out" cost [18]. Procurement cost, or buying cost, is triggered on the items purchasing activities (see Equation (3)). Furthermore, the transportation and the holding cost areca used by activities: items deliveries (from the central warehouse to inventory units and between units), and items storages, respectively (see Equations (4) and (5)). Lastly, "stock out" cost is raised when the items are depleted (see Equation (6)). In disaster response phase, the "stock out" condition is associated with suffer that the disaster evacuees have to be accepted due to depletion of the necessity items. The imbalance level of inventory between units of inventory also contributes to high "stock out" cost. In some inventory theories, the cost of acquiring information is taken into consideration, but in our model we assume this cost is free.

$$TargetDelivery = d_t(RP + LT) + SS \tag{1}$$

$$SC_t = SC_{t-1} + IR * SC_{t-1}\left(1 - \frac{SC_{t-1}}{MC}\right) \tag{2}$$

$$ProcurementCost = SetupCost + NumberOfBoughtItems * PriceEachItem \tag{3}$$

$$TransportationCost = NumberOfTrip * CostEachTrip \tag{4}$$

$$HoldingCost = NumberOfStoredItems * HoldingRate \tag{5}$$

$$StockOutCost = NumberOfStockOutOccurence * StockOutCostEachOccurence \tag{6}$$

In our research, the transshipment strategy taken by each inventory unit is based on spatial strategy. Each inventory unit decides whether to become supportive (C) and not supportive (D) based on its neighbors' supportive actions. The information of neighbors' supportive action is coming from the logistic transporters and the past action of each inventory unit.

Our proposed model of the transshipment system in relief inventory works as follows:

1. Everyday each unit of inventory distributes their stocks to disaster evacuees. Based on current levels of inventory in each unit, we calculate holding cost and "stock out" cost.
2. Each delivery period (RP), central warehouse calculates their sourcing capacity (SC) and decides the amount of delivery (TD). If the amount of delivery exceeds sourcing capacity, the amount of delivery is made equal with the sourcing capacity. At this step, we calculate procurement and transportation cost.
3. After receiving the items from central warehouse, each unit of inventory determines the amount to share with its neighbors based on its strategy. It may happen that sharing is not possible for some inventory unit due to their current inventory level. At this step, we calculate the performance of each strategy (without transshipment, with full transshipment, and partial transshipment).
4. The central warehouse may revise the amount of delivery for the next period based on the information through the logistic transporter (see Equations (7) and (8)). The information received is the demand condition of each inventory unit whether it is increasing, decreasing or same with the previous period. The content of information is highly affected by the cooperative action of each transporter. Here, we need to evaluate whether the transporter is cooperative ($Tr = 1$) or not ($Tr = 0$). The value of cooperation parameter below 0.5 means not cooperative, and vice versa (see Equation (7)). Knowing this situation, we make adjustments to the amount of delivery (TD) for the next period with some percentage (Adj). This adjustment is based on the reported demand condition (d_t) by the logistic transporter (see Equation (8)).

$$Tr = \begin{cases} 0|R < 0.5 \\ 1|R \geq 0.5 \end{cases} \tag{7}$$

$$TD_t = \begin{cases} (d_t(RP + L) + SS) * (1 - Adj * Tr)|d_t < d_{t-1} \\ (d_t(RP + L) + SS) * (1 + Adj * Tr)|d_t > d_{t-1} \\ (d_t(RP + L) + SS)|d_t = d_{t-1} \end{cases} \tag{8}$$

In our research, we limit the number of neighbors into four (Von Neumann neighborhood) as shown in Figure 2. To represent a strategy, a bit sequence of 5 elements is used whose l-th element is C/D if the action C/D is taken when the number of D of the neighbors is l ($l = 0, 1, \ldots, 4$). The kD strategy [20] means the inventory units should take D if the $l > k$ and C otherwise. For example strategy $3D$ means that the maximum number of D in the neighborhood is 3. If we apply the $3D$ strategy to the neighborhood condition shown in Figure 2, the inventory located in the center should take C since number of D is less than equal 3.

We use three types of transshipment strategy: without transshipment, with fully transshipment, and with partial transshipment. The strategy of *without transshipment* is similar to the traditional operation of inventory where transshipment option is eliminated. Thus, each inventory unit interacts only with the central ware house by receiving necessary items regularly for its own usage. The performance of this strategy becomes basis of comparison for the other strategies.

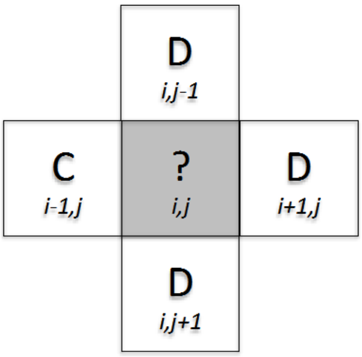

FIGURE 2. The inventory unit's choice of action (C or D)

The opposite strategy of *without transshipment* is *fully transshipment* strategy. Here, each inventory unit tries to help its neighbors all the time without considering own inventory level and neighbors' supportive action.

The strategy that lies in between the previous two strategies is called *partial transshipment* strategy. The term "partial" means that each inventory unit does not have to support its neighbors all the time nor ignore all the time. The inventory units may support whenever needed based on several factors such as their current level of inventory, their neighbors' action, and tendency of helping (Pr). This strategy consists of three updating methods: maximum payoff, static support, and dynamic support.

- In *maximum payoff* updating, each inventory unit calculates its payoff (reward) after transshipment. The payoff is determined from the inventory level. In every r period, each inventory unit is allowed to change its strategy to the one having the highest payoff among neighbors. For instance, consider the case where four neighbors have different payoff and the highest one is owned by the neighbor positioned on right side with strategy 2D. According to this updating, the center inventory unit will change its strategy into 2D.
- In *static support* updating, the inventory units are assumed to have a constant tendency of helping (Pr). Low Pr means that inventory unit is easy to shift to defection (D) in the neighborhood. For instance, if the current strategy is 2D and $Pr = 0$, in the next delivery period that the strategy will change into 3D. This means that number of D in the neighborhood increases by one. Extremely, in case of $Pr = 0$, at the end of the disaster response period all inventory units' strategy will become 5D and all units choose defection (D). Opposite case also is applied when $Pr = 1$.
- The *dynamic support* updating has similar workflow to the *static support* updating in the usability of tendency of helping (Pr). The main difference is that Pr in this updating method is changed based on the level of inventory. The higher the inventory level, the higher also the value of Pr. This means that the higher the level of inventory, the higher also frequency of helping (C).

The *static support* and *dynamic support* updating rely heavily on the self-information while the *maximum payoff* updating method uses the payoff information of the neighbors to change strategy. From the viewpoint of practical implementation, the *static support* and *dynamic support* updating are more applicable in disaster relief operation since they do not require complex information of neighbors' action that might be difficult to acquire. However, the *maximum payoff* updating method is still possible to be used under the condition that the past action of each inventory unit is well recorded and is strengthen by the information through logistic transporters. Even several differences have been notified,

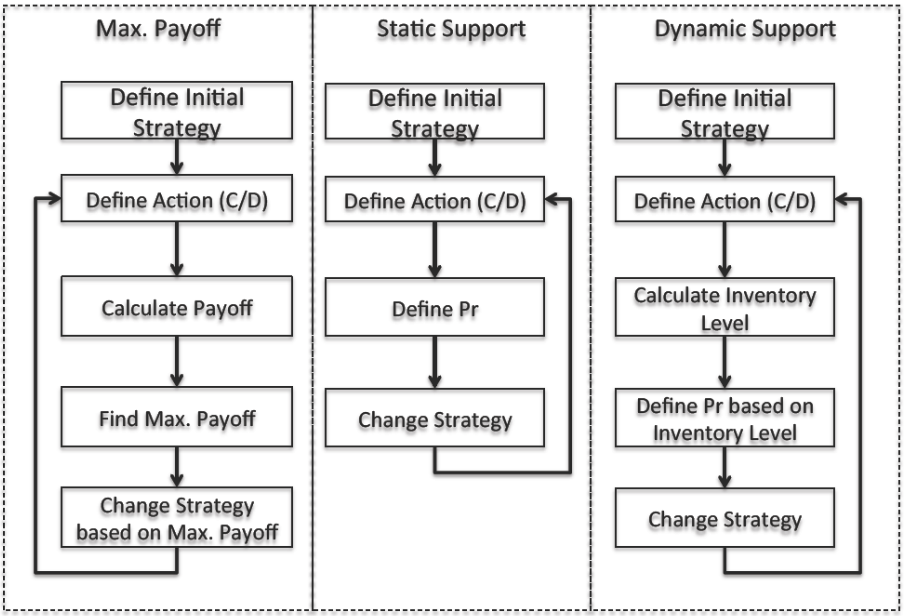

FIGURE 3. The workflow of each updating

the three updatings shared similarity in their way of deciding action based on strategy (see Figure 3).

Between all strategies, fully transshipment is the strongest candidate to reach the maximum performance with an excess of highest inventory cost. To evaluate the performance of each strategy in our model, we use a simple case of transshipment system by 9 inventory units. Evaluation is done under two conditions: low variability environment and high variability environment. In low variability environment, the maximum difference of demand rate between inventory units is 10% while in the high variability environment is up to 100%. Furthermore, the average standard deviation of demand rate in high variability environment is 10 times higher than the low variability environment. Three variables were used to evaluate the performance such as: number of normal unit, frequency of travel, and total inventory cost.

Comparing both conditions, the performance of fully transshipment strategy leads the other strategies in number of normal units but consumes the highest inventory cost (Tables 1 and 2). The partial transshipment strategy with dynamic support updating has almost similar number of normal units, and has significantly low cost and frequency of travel than the fully transshipment strategy. The number of normal unit fluctuation along 90 days for both strategies is showing a stable trend (Figures 4 and 5).

TABLE 1. Inventory performance under low variability environment. 1: Without transshipment, 2: with fully transshipment, 3: partial transshipment (maximum payoff updating), 4: partial transshipment (static support updating), 5: partial transshipment (dynamic support updating).

	1	2	3	4	5
Number of Normal Unit	1277	1594	1304	1520	1575
Frequency of travel	162	671	360	503	617
Total Cost	3151000	4979000	3518000	4618000	4387000

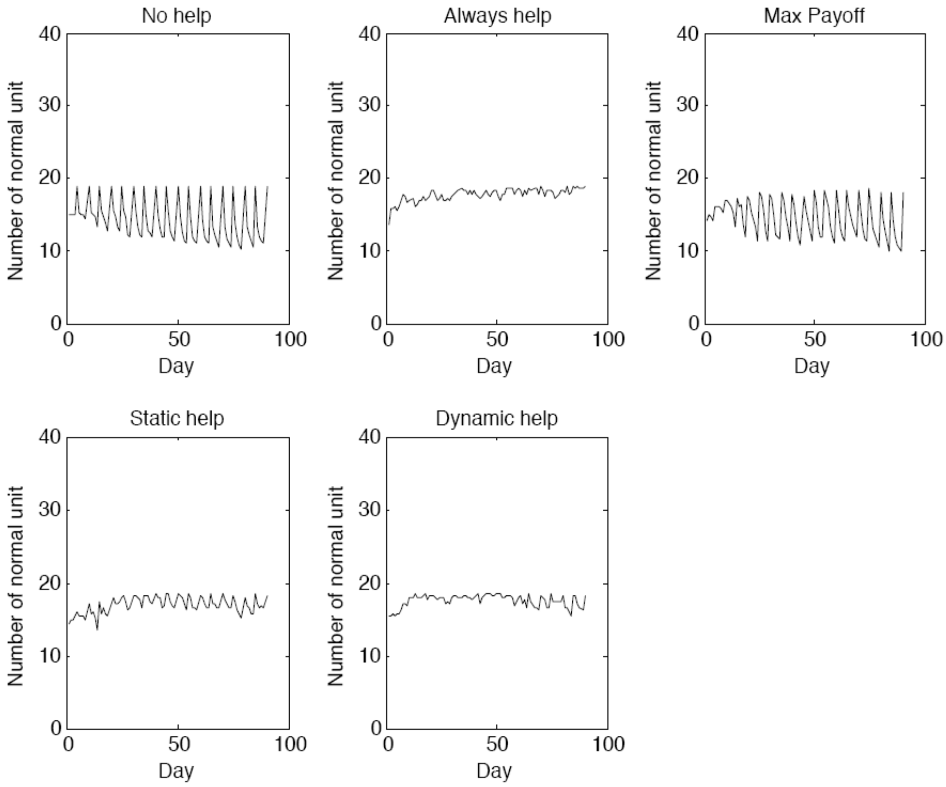

FIGURE 4. Performance of relief inventory measured by number of healthy/normal unit (low variability condition)

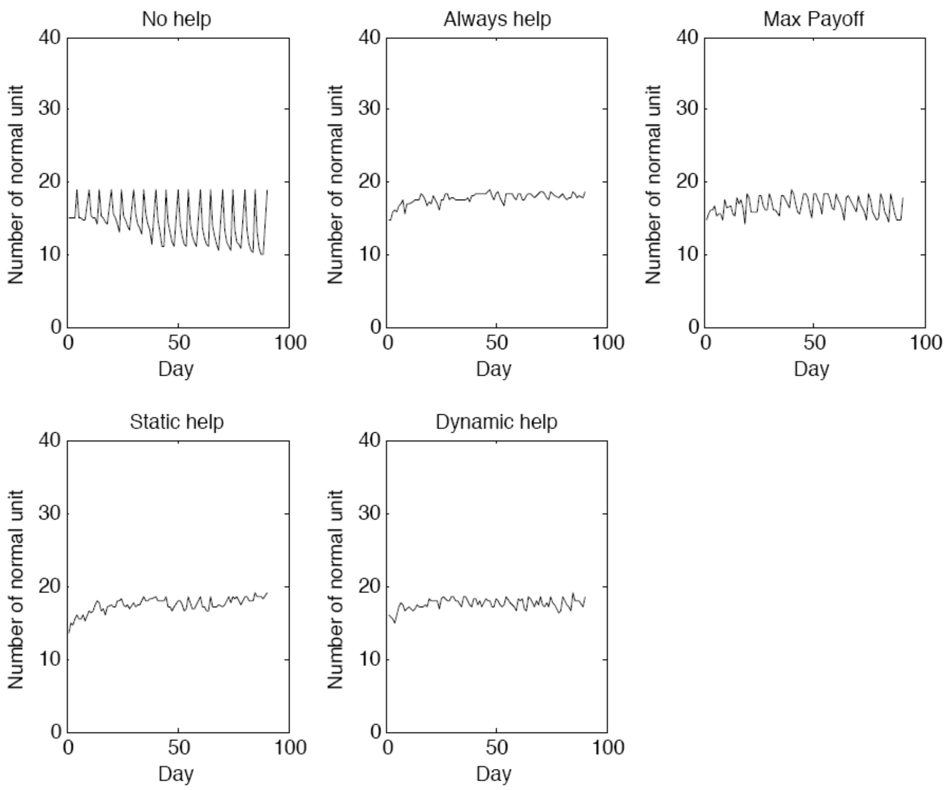

FIGURE 5. Performance of relief inventory measured by number of healthy/normal unit (high variability condition)

Table 2. Inventory performance under high variability environment. 1: Without transshipment, 2: with fully transshipment, 3: partial transshipment (maximum payoff updating), 4: partial transshipment (static support updating), 5: partial transshipment (dynamic support updating).

	1	2	3	4	5
Number of Normal Unit	1280	1589	1497	1562	1574
Frequency of travel	162	674	479	514	596
Total Cost	2779000	4933000	4262000	5018000	4173000

Table 3. Distribution of evacuees in each shelter [21]

No	Shelter Name	Mean	Deviation	No	Shelter Name	Mean	Deviation
1	Losd Tiga Binanga	2671	160	16	Paroki G. Katolik	226	10
2	Losd Tanjung Pulo	717	2	17	Serba guna KNPI	543	29
3	Losd Kaisar Ds. S. Baru	295	9	18	GBKP Sp. Katepul	231	12
4	GBKP Payung	314	1	19	Losd Katepul	213	11
5	Masjid Payung	111	1	20	Masjid Agung Kabanjahe	676	62
6	Gudang Jeruk	447	29	21	Uka K. Jahe 1	1831	100
7	GPDI D.Siroga Sp.IV	184	5	22	Uka K. Jahe 2	1054	51
8	Klasis GBKP K.jahe	350	13	23	Islamik Center	356	5
9	GBKP Kota Kabanjahe	956	73	24	Oraet Labora B. Tagi	204	3
10	Zentrum Kabanjahe	421	1	25	KWK B. Tagi	541	27
11	GBKP Asr Kodim K.jahe	207	2	26	Klasis GBKP B. Tagi	335	69
12	Kantor Asap Kabanjahe	55	3	27	GBKP Kota B. Tagi	138	20
13	Paroki G. Khatolik K.Jahe	1043	50	28	Masjid Istihrar Berastagi	474	1
14	GBKP JLN. Kota Cane	655	26	29	Losd Ds. Sempajaya	1464	33
15	GBKP Simp.VI	461	26	30	Losd Desa Telaga	339	63

4. **Case Study.** To clarify the applicability of our model in real situation, we used a real data of disaster events. This event has to be categorized as a slow onset disaster or rapid onset disaster with predictable occurrence in order to get the maximum benefits of our methods. Moreover, sufficient number of logistic transporters is necessary to make successful of transshipment operations.

Here, we used the data of volcanic eruption on Sinabung Mountain (Indonesia) [21]. In September 2013, this mountain had erupted causing many thousand inhabitants in radius 10 km left their homes. They lived in an evacuation shelter provided by local government, NGO, and other stake holders (Table 3). Since the eruption is constantly occurring, the evacuees have to stay at the shelters for about 5 months.

Relief inventory consists of several life support items, such as food, clothes, water, medicine, blanket. In case of food, the delivery of a ready to eat therapeutic food items (RUTF) was widely used, for instance plumpy soy [22]. This relief inventory was served as long as the duration of disaster response which is usually last up to 90 days [23]. In some cases, as if Sinabung Mountain eruption, the disaster response's period exceeding 90 days.

With the data on demand trend, which is extracted from the number of evacuees, and ideal number of RUTF per person per day, we were able to estimate the initial inventory level (Table 4). Moreover, the inventory related costs, e.g., procurement, holding, and stock out, could be estimated from the selling price of the food item (Table 5). Not

TABLE 4. Initial inventory level

Shelter No	Initial Inventory	Shelter No	Initial Inventory	Shelter No	Initial Inventory
1	53954	11	4192	21	36986
2	14483	12	1121	22	21291
3	5959	13	21069	23	7201
4	6343	14	13231	24	4121
5	2242	15	9322	25	10928
6	9029	16	4565	26	6777
7	3707	17	10969	27	2788
8	7070	18	4666	28	9565
9	19321	19	4313	29	29573
10	8514	20	13665	30	6848

TABLE 5. Input parameter for simulation

Relief Inventory's Parameter	Value	Relief Inventory's Parameter	Value
Time interval	1 day	Price/item	6.96
Warehouse capacity increase rate	0.8	Cost/trip	0.1468
Warehouse initial processing capacity/day	3000	Holding cost/item/day	0.0048
Warehouse maximum processing capacity/day	10000	Cost/stockout	27.84
Delivery period (RP)	5 days	Normality (healthy) threshold	above 0.5
Safety stock	10% of max. level	Proportion shared by normal unit	0.2
Lead time	1 day	Proportion shared by abnormal unit	0.1
Setup cost	100	Probability of help (static support strategy)	0.5

to mention, the transportation cost was acquired from the average cost of delivery in Indonesia.

Beside the inventory related cost, the performance of transshipment system was determined by the health of inventory. Thus, a certain threshold of inventory level has to establish as a boundary between healthy (normal) inventory level and unhealthy (abnormal) ones. The healthy inventory will certainly have larger proportion of sharing in the transshipment, rather than unhealthy ones (Table 5).

Several factors govern the health of inventory such as central warehouse processing capacity, demand rate, and logistic capability. In the beginning of disaster response period, the number of processing capacity in central warehouse was low due to limited amount of items, limited number of relief inventory's operators, and low collaborative actions between relief operation's stakeholders. Over time, the processing capacity of central warehouse increases exponentially following logistic growth function (Equation (2) and Table 5).

5. **Results and Discussion.** The most surprising result to emerge from the simulation of transshipment system was that the fully transshipment strategy and partial transshipment strategy (dynamic support updating) had a similar level of performance (Table 6 and Figure 6). This result is coherent with our simple case of transshipment system in Section 3. The total number of healthy (normal) inventories (Table 6) and their ranges of value (Figure 6) show the best performance. Moreover, the inventory cost of both systems is almost similar, even though the number of trip is different for about 20% (Table 6, Figures 7 and 8). The number of trips in the partial transshipment system, with dynamic support

updating, is certainly lower since each unit of inventory transships its items whenever the inventory level is sufficient.

We expected that the fully transshipment strategy contributed to the best performance of relief inventory with the consequence of highest inventory cost. In fully transshipment strategy, each unit has always supported their neighbor by transshipping some of the items. Contrary to the expectation, partial transshipment (dynamic support updating) was able to reach that level of performance. This is due to the fact that each unit of inventory in partial transshipment strategy transships its items whenever in healthy (normal) level.

The performance of relief inventory without transshipment placed on the bottom line of all transshipment models (Figure 6). This result is consistent with the work of Mulyono and Ishida [9] and Reyes et al. [6]. Full or partial transshipment made the performance of relief inventory better than without transshipment. Static support updating in partial

Table 6. Number of normal unit, frequency of travel, and accumulated cost of relief inventory. 1: Without transshipment, 2: with fully transshipment, 3: partial transshipment (maximum payoff), 4: partial transshipment (static support updating), 5: partial transshipment (dynamic support updating).

	1	2	3	4	5
Number of Normal Unit	1661	2569	1727	2160	2440
Frequency of travel	540	2715	1289	1834	2369
Total Cost	9338000	9927000	8910000	9475000	8821000

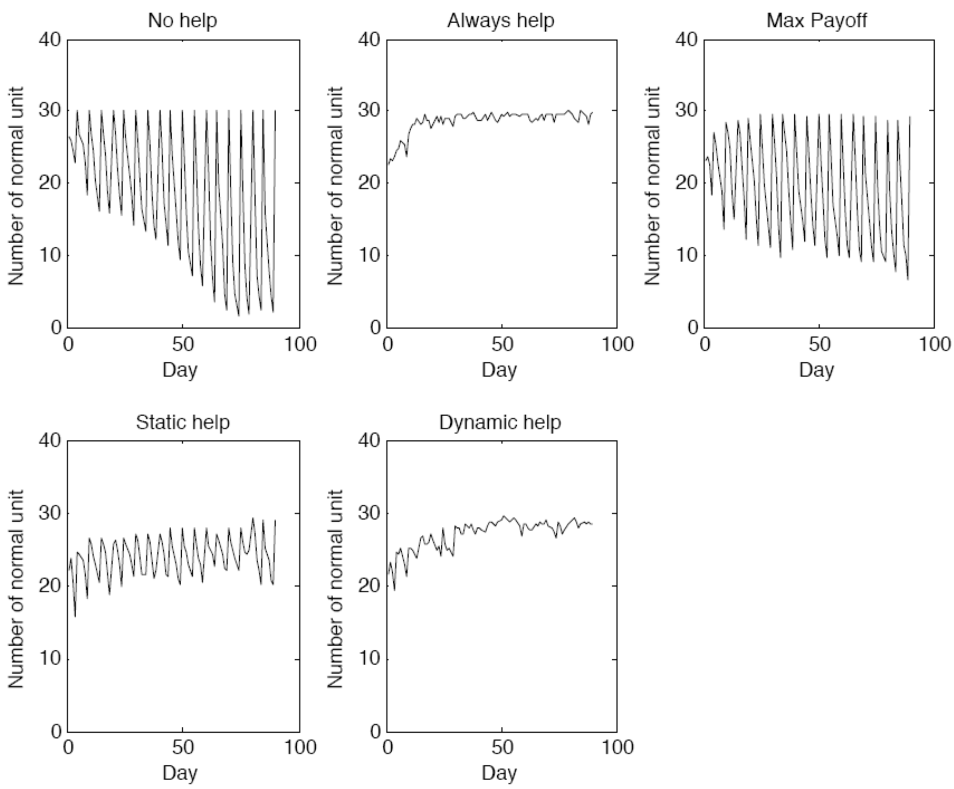

Figure 6. Performance of relief inventory measured by number of healthy/normal unit

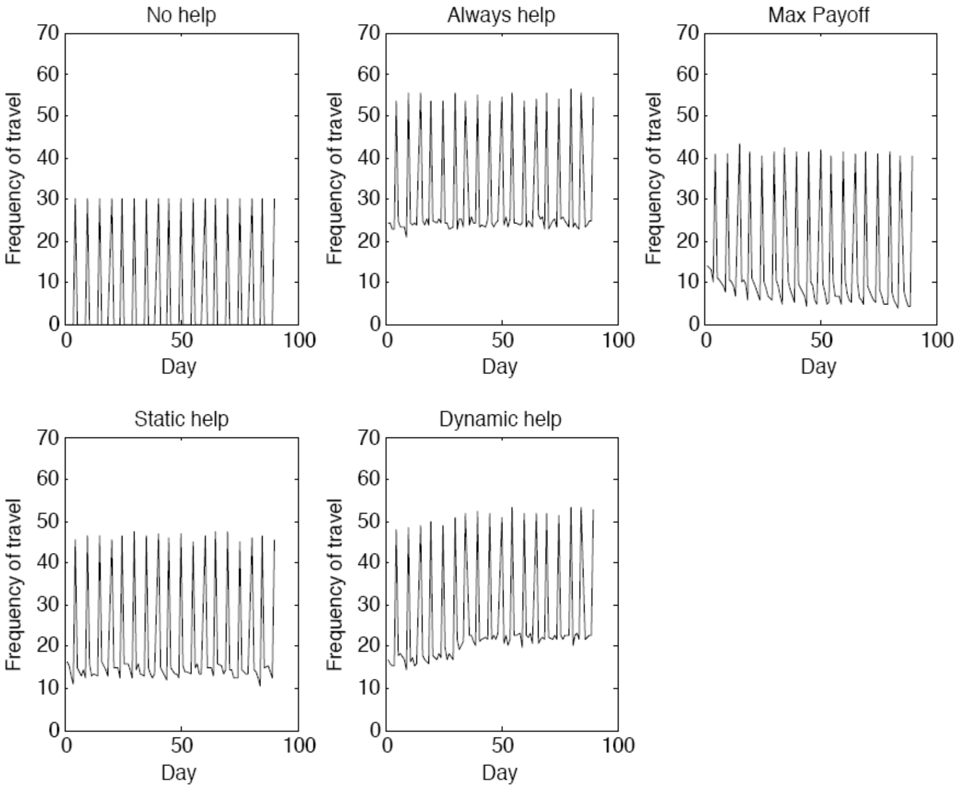

FIGURE 7. Number of trip in relief inventory

transshipment also leads to high performance level even though not as high as the dynamic support updating. The only exception is the partial transshipment with a maximum payoff updating. Its performance is considerably low and almost similar to the performance of relief inventory without transshipment.

This finding is distinguishable from the work of Ishida [17] in self-repair network of computer system. Maximum payoff is the best way of computer network to control the repairing activities and clean the contamination inside the network. The repairing process in self-repair network is by mutual copying of data between computers in the network. The activity of repairing in self-repair network is similar to the transshipment operations of relief inventory. However, a substantial difference between them is suspected to be a rationale of the differences. Transshipment system consumes resources (in term of labors, goods, logistics) while self-repair network is not. Hence, following the strategy of the wealthy neighbors (having high payoff) is not appropriate to implement into transshipment system.

All of those results were achieved by simulating 30 units of inventories (one unit for each shelter) for 90 days of disaster response [23]. To suppress the effect of random number, 100 similar trials were employed in our simulation. At the initial condition of the simulation, all unit of inventory was in healthy condition (Table 4), and had random strategies (1D, 2D, 3D, 4D, or 4D). During the simulation, the condition of each unit might change into unhealthy/abnormal (value = 0) or remain healthy/normal (value = 1).

The major activities of transshipment system in relief inventory are delivery from the central warehouse to each unit of inventory, and transshipment delivery from each unit of inventory to its neighbors. Central warehouse delivers necessity items to the disaster evacuees on a regular basis. At the same time either, each unit of inventory transships those items to its neighbors. The decision whether the units will transship their items

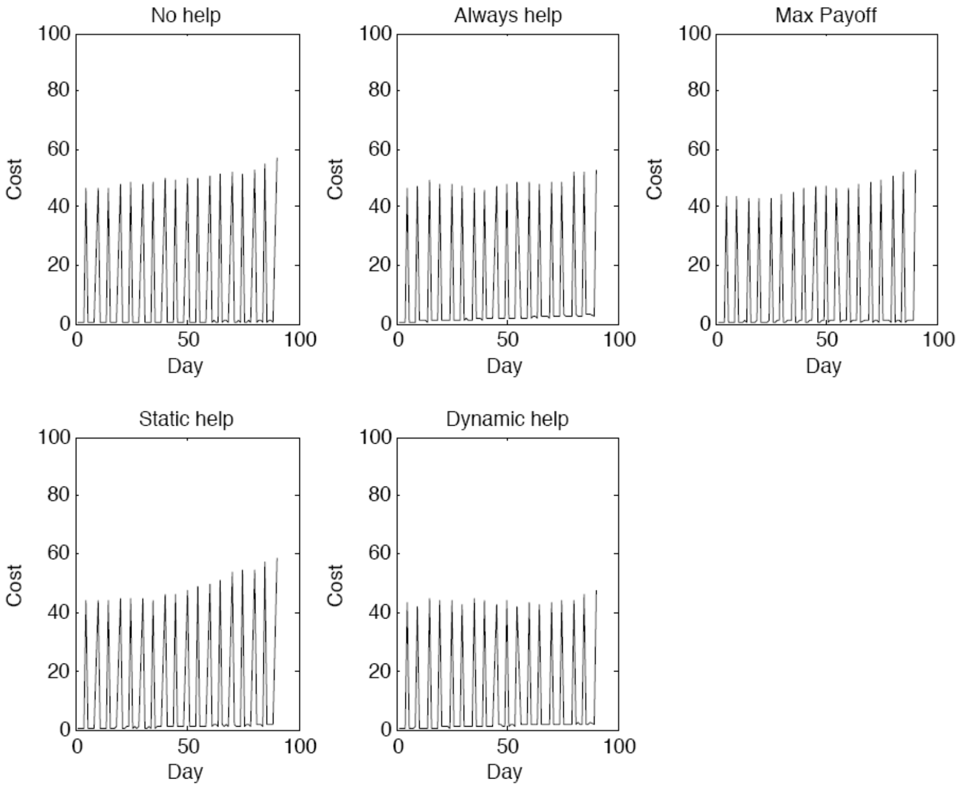

FIGURE 8. Total cost of relief inventory in 10^4 scales

or not, is different for each model. Mulyono and Ishida [9] used probability of helping in cellular automata, Reyes et al. [6] used real demand data collected from the disaster area, and we used spatial strategy. Reyes et al. assumes that information of demand was available after disaster struck and this information was possible to obtain. This, however, contradicted with our assumption about the availability of accurate information after disaster.

Due to the classification of transshipment model by Paterson et al. [8], our model is categorized as single item, single echelon, many un-identical depots (inventory units), period order timing with specific policies, proactive transshipment, complete pooling, and decentralized decision making. One downside of our model is that we are not considering the possibility of inventory units destroyed or inaccessible by the subsequent arrival of disaster. For instance, volcano is erupting again after the evacuees gather at the shelters. This subsequent arrival of disaster may come since we choose the slow onset disaster type. Reyes et al. [6] included this possibility into their transshipment model using system dynamics. He loaded tentative disaster data into simulation and drew conclusions from it.

As expected, our simulation with real disaster data is able to illustrate the behavior of transshipment system in relief inventory. The results are coherent with the previous literatures [6,7,9] with some new findings. These findings highlighted the usefulness of spatial strategy of relief inventory in the environment of inaccurate information. The best strategy was partial transshipment with the dynamic support updating. Not only high performance (in a number of healthy units) but also having a lower frequency of transportation (number of trips) compared with the full transshipment strategy. This, in the end, made logistic activities easier and cheaper. Moreover, this strategy consumes slightly lower cost, about 10%, compared with the baseline strategy (without transshipment). The fact about this best strategy proves that neither the strategy of without transshipment nor the strategy of fully transshipment contribute to the best performance, but the strategy in between of them (partial transshipment).

6. **Conclusions.** We conclude that transshipment has positive impacts on the performance of relief inventory in a low onset type of disaster. Even though, the environment of disaster response had been characterized as having inaccurate inventory's information or even unavailable, the transshipment operations contribute to the performance elevation of relief inventory. We got a solution for increasing performance of transshipment in relief inventory and controlling transshipment's operation using spatial strategy. Here, the best strategy is the partial transshipment with dynamic support updating. This strategy increased the performance of relief inventory by 50% and reduced a logistic frequency by 20% in slow onset disaster condition.

This study enhances our understanding of the transshipment operation in relief inventory and logistic under an environment of inaccurate inventory's information. We believe our work could be the basis for future development considering the more dynamic nature of disaster response. Further studies, which use transshipment in relief inventory and logistics, should involve robust planning of relief operations in disaster mitigation phase.

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