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HUMANITARIAN LOGISTICS AND INVENTORY MODEL BASED ON PROBABILISTIC CELLULAR AUTOMATA

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Abstract. *Logistics and inventory operations, which involve transportation, communication, and storage management, are a crucial part of disaster relief. Chaotic conditions after a disaster might cause imbalances in the inventory level at each storage location or shelter. To ensure an even level of inventory among shelters, a new approach for modeling logistics and inventory operations after a natural disaster using probabilistic cellular automata is proposed. In our model, two states – normal and abnormal – represent the inventory level of each shelter. Each shelter receives items from a central warehouse and can transfer their items to other shelters. Our model uses eight parameters to characterize the dynamic interactions among shelters.*
Keywords: Logistics and inventory model, Probabilistic cellular automata, Mutual supply, Disaster relief supply, Dynamic interaction

1. **Introduction.** The need to help people after a disaster is not diminishing and may even be growing due to the increasing number of natural disasters recently [1]. Humanitarian relief operations may involve various local and international organizations, host governments, the military, and private companies. With their capacity and logistics expertise, such organizations are able to supply daily essentials such as food, clothing and medicine.

There have been a few cases of successful coordination in disaster relief, in which all parties involved effectively coordinated their logistics planning and management. The inventory or supply system plays a critical role in emergency situations, including storing and managing essential items and providing them to disaster victims. Logistics operations and rate of consumption affect the inventory level. The role of logistics and inventory in famine relief and disaster operations amid complex environments has been explicitly described [2].

After a disaster, the demand for essential items usually fluctuates drastically and irregularly. In most disaster-relief operations, information on the demand for emergency resources is collected mainly at the operational level and then flows upward to the higher level [3]. However, after a disaster it is usually difficult to collect reliable information, including information about the demand at each shelter. Even if such information is available, it may be unreliable due to chaotic conditions. This situation leads to imbalances in the level of inventory among shelters. If each shelter shares some of their stock to help others, then imbalance situation in the inventory level among shelters is solved.

In enterprise environment, this sharing activity is known as lateral transshipment. Flow of goods in lateral transshipment is within the same or adjacent level, i.e., between wholesalers and retailers [4]. This flow complements existing inventory system flows which is hierarchical from one level to the next, i.e., from suppliers to manufacturers, from manufacturers to wholesalers, from wholesalers to retailers, and from retailers to customers.

Lateral transshipments between inventory locations (shelters) would help even out the level of stock among shelters [5]. A simple system for lateral transshipment of inventory, as illustrated in Figure 1, consists of a single central warehouse supplying four inventory locations. Lateral transshipment, as well as regular delivery of inventory, needs strong support from logistics operations. In order to implement lateral transshipment into famine relief logistics and inventory operations, we need a reference model as a basis of deciding lateral transshipment parameters.

If the information about demands and supplies is correctly acquired during disaster, then operation research approach is the best option for modeling lateral transshipment operations. Since that information is difficult to be gathered during disaster, it is necessary to find another robust approach. The self-repair approach inspired by the cooperative work of immune cells in immunity-based system theory [6] is suitable for a basis of modeling lateral transshipment operations. Even if information on demand is not available or is greatly biased, the approach may be able to distribute the inventory level among shelters. However, this approach could actually cause the inventory performance to worsen, like a double-edge sword effect. In terms of cost, there is a trade-off in lateral transshipment between reducing the "out of stock" cost and increasing the transportation cost. It is therefore necessary to find appropriate parameters for lateral transshipment that improve inventory performance while reducing overall cost.

The theory of self-repair approach is once mentioned in self-repair network (SRN) model in the field of computer science. The self-repair network model involves collaboration in the computer network whereby each computer tries to repair other computers by mutual copying [7]. The difference between self-repair network model and inventory lateral transshipment is the resources used for the repair process. The repair process for the self-repair network does not consume resources, whereas in the repair process for lateral transshipment, its own resources are consumed by transferring them to others. The SRN model uses the cellular automata as a basis of representing an entity and its interactions.

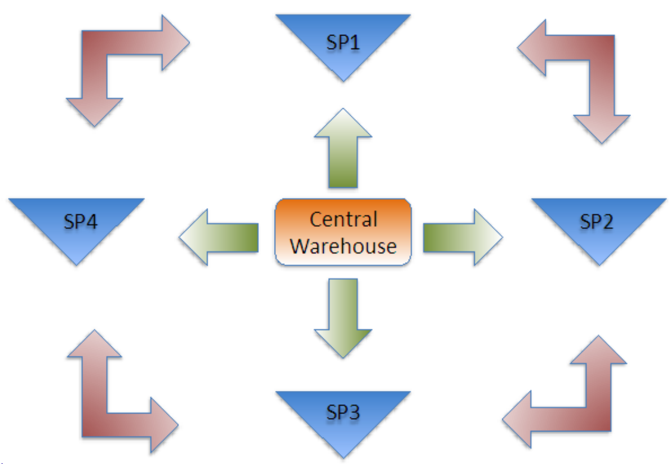

FIGURE 1. Lateral transshipments between stock points. Central warehouse supplies four stock points (SP1 to SP4) regularly. Each of them tries to help their neighbors.

The cellular automata model is a tool for modeling complex phenomena [8]. Each entity (cell) in cellular automata has specific characteristics, has the ability to interact with neighboring cells, and also has the ability to change dynamically according to some rules. In order to increase the performance of the humanitarian logistics and inventory system, we propose a humanitarian logistics and inventory model based on probabilistic cellular automata, which has the characteristics of a self-repair system. The cellular automata model is appropriate as a base model, since we can model dynamic interaction among shelters as interaction among cells. Our model assumes that lead-time is instantaneous and there are sufficient vehicles for the required logistics operations. We include three types of cost in our humanitarian logistics and inventory model with lateral transshipment: procurement cost, delivery cost, and "stock-out" cost.

2. **Related Work.** Recently, there has been much interest in improving the response to rapid-onset disasters [9]. The effectiveness of the humanitarian relief response depends on the speed with which supplies can be procured, transported and managed at the site [10]. It is indeed humanitarian logistics that contributes most to disaster relief, estimated to account for at least 80% of the cost of a disaster [11]. Humanitarian logistics is closely related with inventory management at humanitarian relief sites.

The enterprise inventory model has been developed and is widely used, while the disaster-relief inventory model is still under development. There are slight differences between the two models, such as the environment and characteristics of disaster-relief inventories in all areas from acquisition through to storage and distribution [12]. Nevertheless, the fundamental principle of the enterprise inventory model can be used to build an inventory model in disaster situations.

Recently, information systems for disaster relief have improved greatly, leading to better coordination among each organization involved [5]. Better communication, coordination, early warning systems, evacuation procedures, inventory and logistics systems, and firefighting and rescue equipment have all helped reduce the impact of disasters. Achieving an integrated global relief chain is a remaining challenge even though current and emerging efforts to improve disaster relief coordination are promising [13].

Sharing items between shelters is one way to reduce the lack of necessary items and improve the effectiveness of humanitarian relief activities. In enterprise inventory model theory, this practice is called lateral transshipment. Formally, lateral transshipment in an inventory system means the movement of stock between locations at the same level [3]. These stock movements can be conducted periodically at predetermined times, and can proactively redistribute stock to meet the demand that cannot be met from the stock on hand.

In the field of computer science, the self-repair network (SRN) consists of units capable of repairing other connected units in a synchronous fashion based on a probabilistic cellular automata model [7]. Each unit tries to repair its adjacent units and clean up contamination in the network with mutual copying. The SRN consists of three elements: a set of units, the topology of connections among units, and a set of rules. Development of the SRN model was inspired by the immunity-based system, which is self-maintaining and adaptive [6].

Cellular automata, as a reference model for the SRN, is a collection of cells, each of which is in one of a finite number of states [14]. Cellular automata have been used to model a wide range of physical phenomena including traffic flows, disease epidemics, stochastic growth, predator-prey dynamics, invasion of populations, earthquakes, and dynamics of stock markets. Cellular automata models can be either deterministic or probabilistic, depending on the component for updating rules. It may be possible to combine the power of enterprise inventory theory, probabilistic cellular automata, and the self-repair network model to build a logistics and inventory model applicable to humanitarian relief situations.

3. **Logistics and Inventory Model.** Formally, the model consists of a set of cells C in two-dimensional space, time step t as discretization in time space, and a set of interaction rules R between cells. In a humanitarian relief situation, cells represent inventory locations for relief activities, which are usually located at nearby relief shelters. We assume that each cell has four neighbors, as shown in Figure 2. The state of cell (i, j) at time t, $S^t_{i,j}$, can be either 1 or 0 representing a normal or abnormal condition of inventory. In this case, the value of state, 1 or 0, is not essential. We can assign -1 and 1 to the states like the Ising model, or black (1) and white (0) [15]. The cell state represents the inventory level of shelters. In our model, the cell state of 0 (abnormal) represents an inventory location having a low inventory level and vice versa. Generally, in enterprise inventory theory, inventory level less than multiplication of average usage rate and average lead-time can be considered as low.

There are three types of activities that affect inventory level: consumption of items, delivery of new items from the central warehouse, and lateral transshipment. Every time, disaster victims consume items that delivered regularly from central warehouse. At some periods of time, the shelters having enough inventory level, send some of their items to the other shelters (lateral transshipment). Consumption of items and delivery of new items from central warehouse are not affected by the inventory level. We assume that disaster victims consume items with the same rate, and delivery of new items is placed on the same time period. On the other hand, lateral transshipment is directly affected by inventory level. The shelter, which has low inventory level, will share small amount of items with the others and vice versa.

Regarding consumption, we define two parameters (p_1, p_2) representing the probability of cell (i, j) at time t maintaining or increasing the cell state to 1 (normal) at time $t + 1$ from state 1 and 0, respectively. These two parameters can be expressed mathematically as:

$$p_1 = prob(S^{t+1}_{i,j} = 1 | S^t_{i,j} = 1) \tag{1}$$

$$p_2 = prob(S^{t+1}_{i,j} = 1 | S^t_{i,j} = 0) \tag{2}$$

New items can be delivered from the central warehouse regularly at predetermined times or reactively in order to meet the demand. The latter requires a smooth flow of information between shelters, but this is impossible in a disaster situation, so our model assumes the periodic delivery of new items. As new items are received from periodic delivery, we define two parameters (p_3, p_4) representing the additional probability of cell (i, j) at time t becoming state 1 at time $t + n$ from state 1 and 0, respectively. Variable n represents time periods when new items are delivered to shelters. For example, if $n = 2$ then this probability occurs at time period of 2, 4, 6, and so forth, as shown in Equations (3) and (4). The probability calculated by these equations could actually be larger than

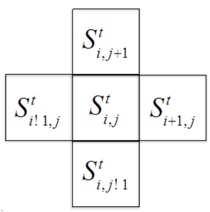

Figure 2. A cell and its neighbors

1 for the parameter set of (p_1, p_2, p_3, p_4), in which case the probability is set to 1.

$$p_1 + p_3 = prob(S_{i,j}^{t+2} = 1 | S_{i,j}^{t+1} = 1) \tag{3}$$

$$p_2 + p_4 = prob(S_{i,j}^{t+2} = 1 | S_{i,j}^{t+1} = 0) \tag{4}$$

Lateral transshipment is the most complex activity in the model. We introduce five parameters (p_h, p_5, p_6, p_7, p_8) representing the detailed activities. Each cell wants to help its neighboring cells with probability p_h. At time t, some cells (helper cells) will help other cells by sending some of their resources, though this might harm their own state (decrease to abnormal). p_5 represents the probability of a cell's state reducing to 0 at time $t+1$ due to helping other cells when its previous state is 1. On the other hand, p_6 is used when the cell state at t is 0. Because of helping activity, neighboring cells get a chance to increase their states. At time t, the probability of a cell's state increasing to 1 at time $t+1$ due to receiving help is represented by p_7 if its previous state is 1, otherwise the probability is p_8. Figure 3 illustrates the helping process and its related probabilities without periodic delivery from the central warehouse. In the figure, each cell has four neighbors with different states, for example: 0 normal and 4 abnormal neighboring cells, 1 normal and 3 abnormal neighboring cells, etc. Each combination is associated with different transition probabilities; corresponding equations are shown below each of the figures that follow. For example, consider the configuration of cells where 1 normal cell has 1 normal neighboring cell and 3 abnormal neighboring cells. We assume that at that particular time the central warehouse does not send new items to any shelter, so the transition probability consists of the following components:

- Consumption probability (p_1)
- Additional probability of receiving help from neighboring cells $(p_h p_7 + 3 p_h p_8)$
- Reduction in probability of sending help to neighboring cells $(p_h p_5)$

If at that time the central warehouse sends new items, then the transition probability will be increased by adding the probability of receiving new items from the central warehouse (p_3).

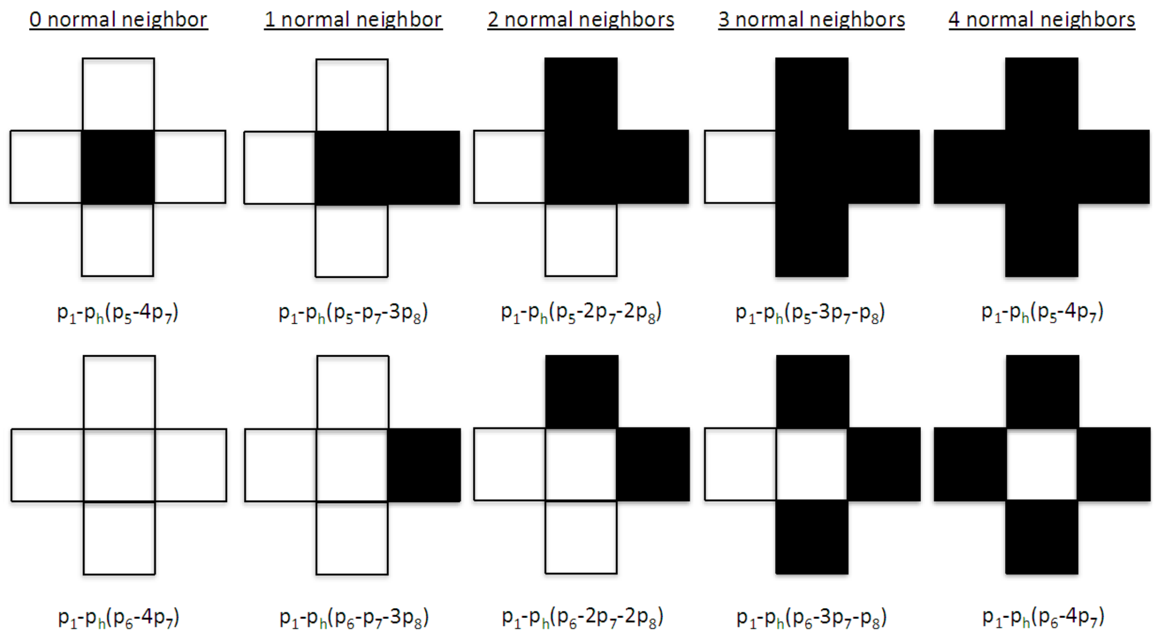

FIGURE 3. The transition probability of a center cell with different neighbor's states

In our model we introduce four more variables, x, y, z_1 and z_2. x is a binary variable having a value of 0 or 1 depending on the state of cells, as shown in Equation (5). y is also a binary variable having a value of 0 if period t equals with multiple value of n and vice versa, as shown in Equation (6). Lastly, variables z_1 and z_2 represent the number of normal and abnormal neighboring cells, respectively. The formal definition of our humanitarian logistics and inventory model is given by the transition probabilities resulting from the interaction of all variables mentioned previously, as shown in Equation (7). Meanwhile, Equation (8) shows the relationship between variables. An analysis of the relief situation based on inventory and logistics revealed the following:

1. The probability of a cell becoming state 1 at time $t+1$ from state 0 at time t (p_2) due to consumption is impossible without any help from outside parties. We set this probability to 0.
2. The additional probability for cell (i,j) at time t becoming state 1 at time $t+n$ from state 1 (p_3) due to receiving items from the central warehouse is a certainty. We set this probability to 1.
3. It is certain that the probability of a cell state decreasing to 0 at time $t+1$ due to helping activity if the cell state at t is 0 (p_6). We set this probability to 1.

Based on these findings, we simplify Equation (7) into Equation (9).

$$x = \begin{cases} 1, & S_{i,j}^t = 1 \\ 0, & S_{i,j}^t = 0 \end{cases} \tag{5}$$

$$y = \begin{cases} 1, & t \bmod n = 0 \\ 0, & t \bmod n \neq 0 \end{cases} \tag{6}$$

$$P_t = x(p_1 + yp_3 - p_h(p_5 - z_1p_7 - z_2p_8)) + (1-x)(p_2 + yp_4 - p_h(p_6 - z_1p_7 - z_2p_8)) \tag{7}$$

$$\begin{aligned} p_2 &\leq p_1 \\ p_4 &\leq p_3 \\ p_5 &\leq p_6 \\ p_8 &\leq p_7 \end{aligned} \tag{8}$$

$$P_t = x(p_1 + y - p_h(p_5 - z_1p_7 - z_2p_8)) + (1-x)(yp_4 - p_h(1 - z_1p_7 - z_2p_8)) \tag{9}$$

4. **Model Validation.** We will validate the fitness of our model by comparing it with the enterprise inventory model especially for the *fixed order review period model.* We use the enterprise inventory model as a reference model for validation, since this model provides a basic and valid building block of how the inventory system works. Our model is able to represent the basic characteristics of the inventory system, which has several characteristics according to the enterprise inventory model such as [16]:

1. Inventory has a predefined optimum level and demand rate. Over time, the inventory level will be reduced by the demand rate. The optimum combination of inventory level and demand rate determines the probability of the inventory system meeting the demand. Variables p_1 and p_2 in our model represent this situation.

2. There is a regular delivery of new items at predetermined times. This operation enables the inventory system to restore its inventory level to the original level, as illustrated in Figure 4. Without this operation, the inventory system will lose its ability to meet the demand. In our model, this characteristic is represented by variables p_3 and p_4.

Lateral transshipment might increase the capability of the inventory system to meet the demand if there are enough vehicles to transport goods [4]. In our model, this situation is represented by interaction of variables p_h, p_5, p_6, p_7 and p_8.

We construct a Monte Carlo simulation on a square lattice, with predetermined parameters for further validation. This simulation uses Equations (7) and (8) to determine cell

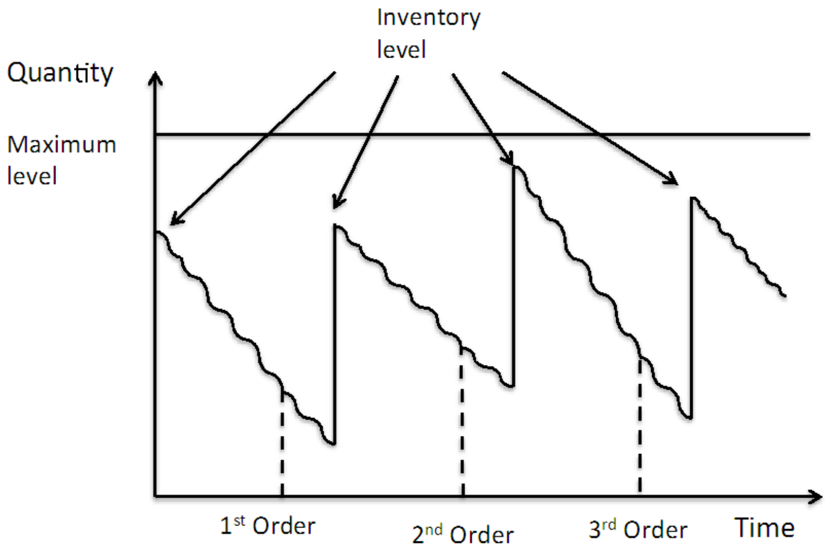

FIGURE 4. Basic inventory characteristic [16]

TABLE 1. Monte Carlo simulation parameters

Parameter	Scenario 1	Scenario 2	Scenario 3	Scenario 4
p_1	0.5	0.5	0.5	0.5
p_2	0	0	0	0
$\boldsymbol{p_3}$	**0**	**1**	**0**	**1**
$\boldsymbol{p_4}$	**0**	**0.5**	**0**	**0.5**
p_5	0.5	0.5	0.5	0.5
p_6	1	1	1	1
p_7	0.3	0.3	0.3	0.3
p_8	0.2	0.2	0.2	0.2
$\boldsymbol{p_h}$	**0**	**0**	**0.5**	**0.5**
n	3	3	3	3

states. The result is visually presented as black and white patterns on a square lattice. In this simulation, black represents a normal cell and white represents an abnormal cell. We determine that about 100 cells interact with each other in the square lattice. We propose four scenarios in this simulation illustrating the inventory characteristics as follows:

1. Simulating inventory without periodic delivery or lateral transshipment.
2. Simulating inventory with periodic delivery but without lateral transshipment.
3. Simulating inventory without periodic delivery but with lateral transshipment.
4. Simulating inventory with both periodic delivery and lateral transshipment.

Table 1 shows the simulation parameters used in each scenario. Each scenario has similar parameters, except for p_3, p_4 and p_h. Parameters p_3 and p_4 show the existence of regular delivery while p_h shows the existence of lateral transshipment. The result of each scenario is displayed in Figures 5-8.

If we take a look at each scenario, we can see that in the scenario without regular delivery or lateral transshipment, the number of normal cells decreases rapidly with time. In this case, black represents a normal cell and white represents an abnormal cell. In the scenario without lateral transshipment but with periodic delivery, the number of normal cells decreases between the period of delivery and increases during the period of delivery.

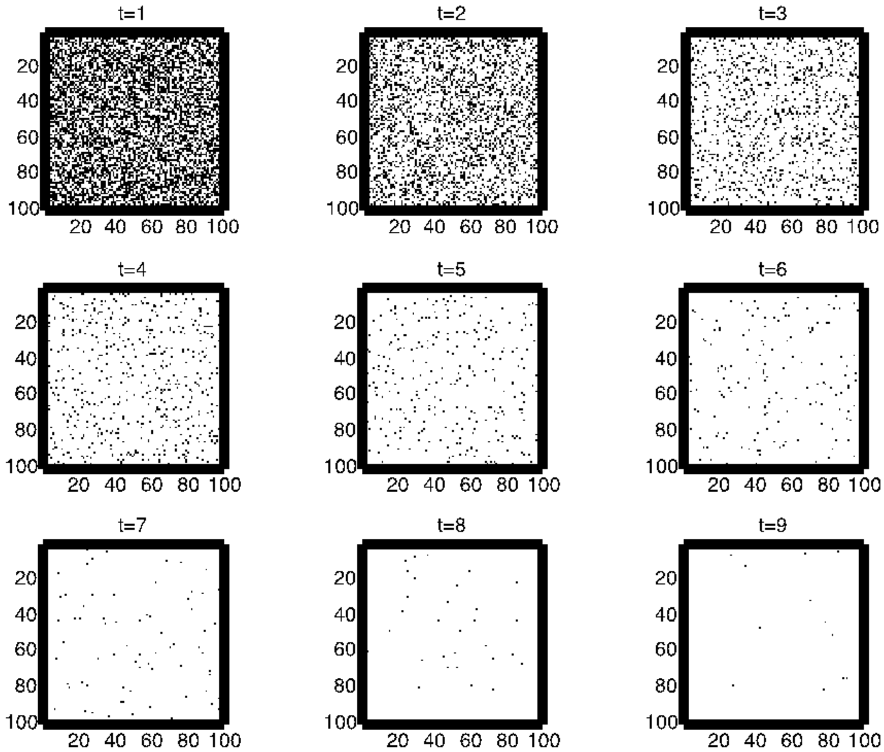

FIGURE 5. Scenario 1

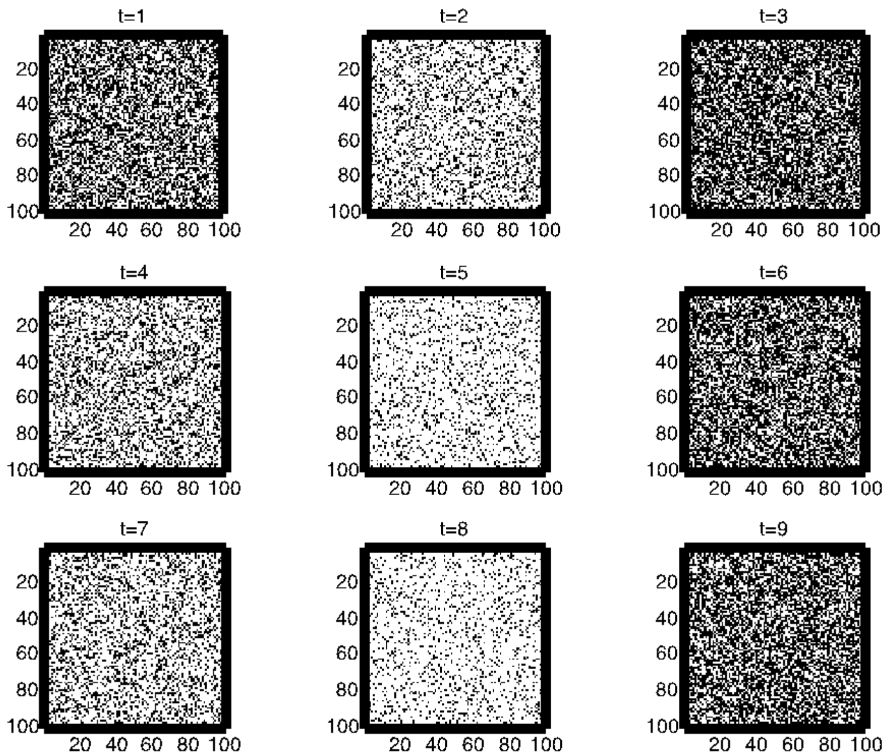

FIGURE 6. Scenario 2

In this case, the delivery of new items stabilizes the inventory level. In the scenario with lateral transshipment but without periodic delivery, normal cells are able to survive for

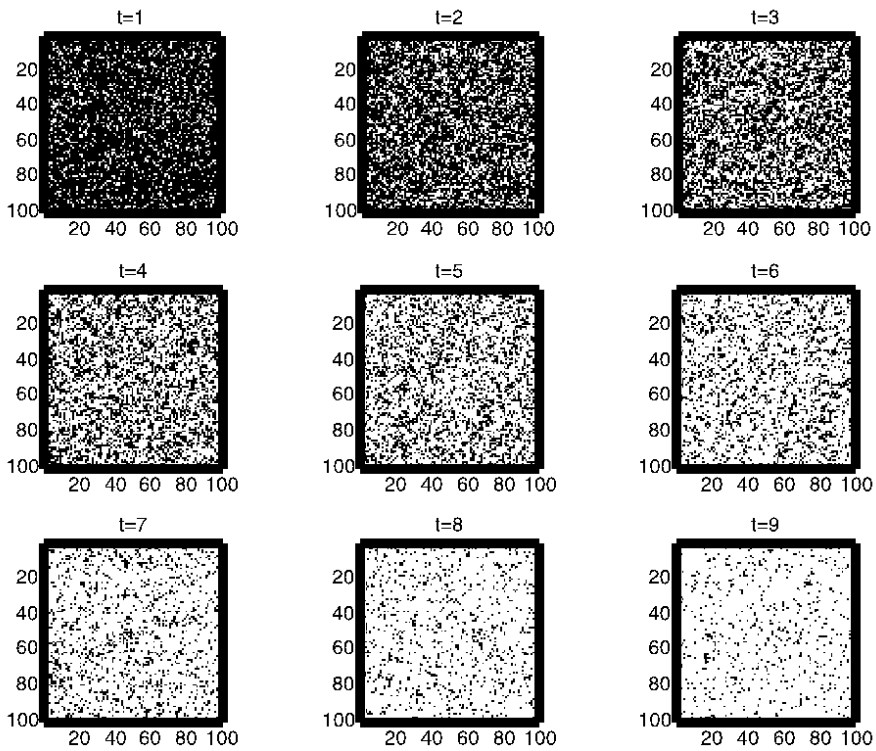

FIGURE 7. Scenario 3

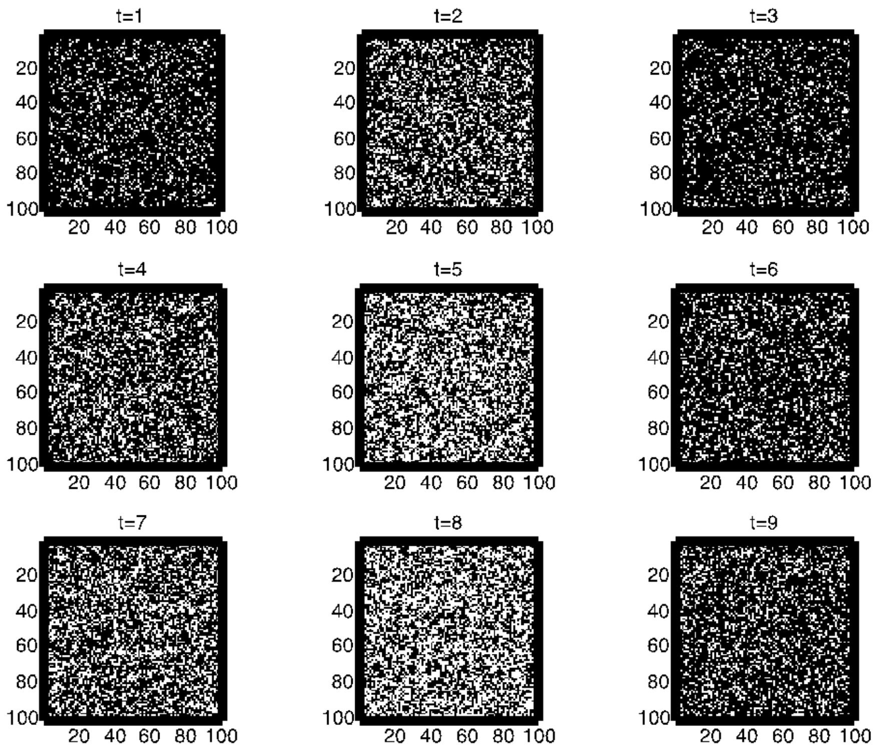

FIGURE 8. Scenario 4

longer than the usual scenario (without both lateral transshipment or periodic delivery).

Lastly, the number of normal cells increases when lateral transshipment and periodic delivery are activated.

5. **Analysis and Discussion.** Based on the transition probability equation mentioned previously, we further analyze the model to understand the effects of important variables on the performance measured by fraction of normal nodes (cells). Similar to the SRN model [7], we are interested in finding ways to improve inventory performance: we want to maximize the number of normal cells without sacrificing cells that share their resources. One important variable in this situation is p_5, which represents the ability of normal cells to remain normal after helping.

Another Monte Carlo simulation is conducted using the simulation parameters of scenario 4 and the initial condition that 100 percent of cells are normal. The number of cells is 100 and each run stops at 100 steps. Figure 9 illustrates inventory performance toward p_5 and p_h (probability of helping). As shown, the greater the ability of a cell to remain normal after helping coupled with a high probability of helping will increase the number of normal cells. In addition, Figure 10 illustrates the parameter boundary region. The upper left region represents parameters that make the state of all cells normal (frozen region) while the lower right region represents parameters that make the state of some cells abnormal (active region). In this phase diagram, the frozen region is a narrow region compared with the active region. This means that lateral transshipment will be successful if willingness to help between cells is high (p_h) and after helping, a cell which shares its resources does not fall into trouble (p_5)

Even though the cost is less important than saving human life in a disaster situation, clearly it is important to plan the cost of disaster operations to avoid excessive budget spending. Similar to inventory and logistics for enterprises, humanitarian inventory and logistics involve several costs such as the stock-out cost, procurement cost, and delivery cost. The stock-out cost occurs when shelters do not have any items in stock to meet

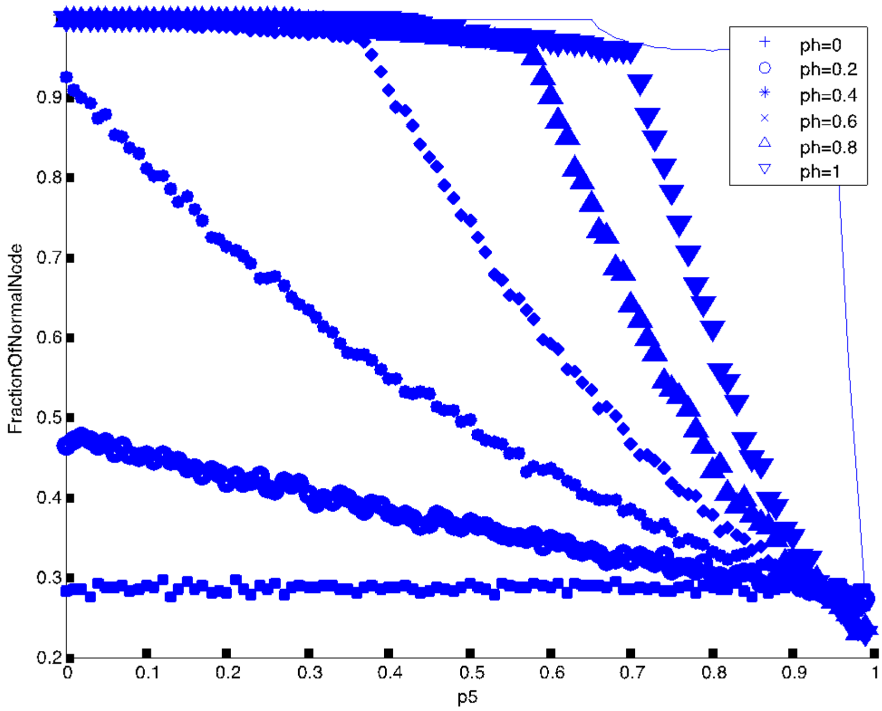

Figure 9. Effect of helping on system performance

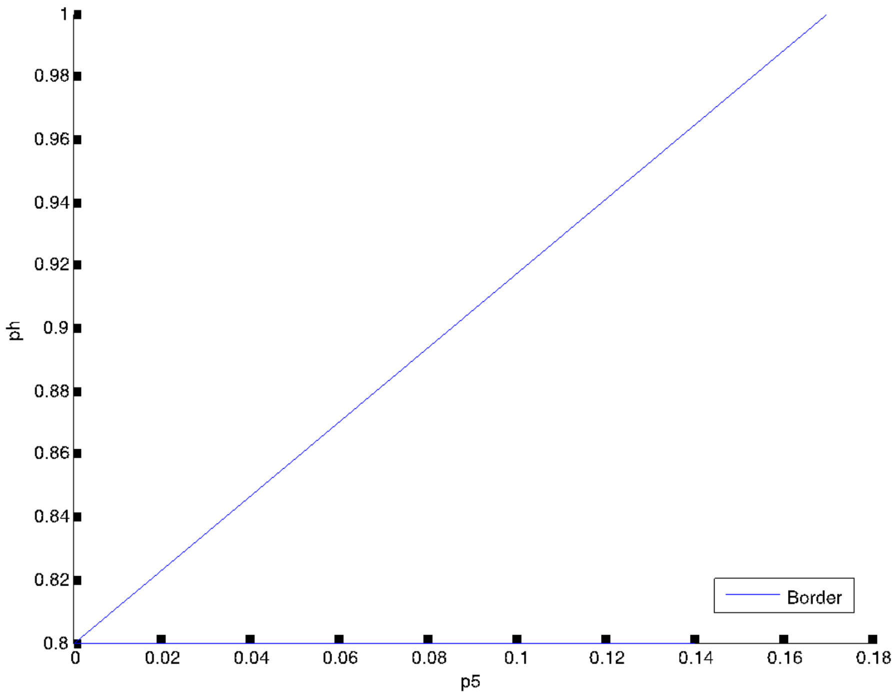

FIGURE 10. Frozen (upper left) and active (lower right) regions

the demand. For an enterprise this situation means losing customers, but for disaster relief operations it could mean loss of life or increased suffering of victims. Procurement and transportation costs are related to the activities of procuring and delivering items to disaster victims either by periodic delivery or lateral transshipment. Increasing the number of deliveries might reduce the suffering of victims, but will certainly increase the procurement and transportation costs.

Consider C_s, C_p, C_t as the unit cost of stock-out, procurement, and transportation activities, respectively. All of these costs contribute to the total cost of disaster recovery operation. Equations (10)-(12) show the stock-out, procurement and transportation cost. Furthermore, Equation (13) shows the total cost representing the cost function of our model. By substituting the total transition probability of Equation (9) into Equation (13), we obtain a simplified form of the cost function as shown in Equation (14).

Lateral transshipment demonstrates a positive impact on the performance of the inventory system during a disaster, where demand and lead-time information are greatly biased [4]. Based on Equation (14), the cost function of the inventory and logistics model is a linear function, in which there is a trade-off between the stock-out cost and the transportation cost.

$$TC_s = (1 - P_t)C_s \tag{10}$$

$$TC_p = (xy + (1 - x)yp_4)C_p \tag{11}$$

$$\begin{aligned} TC_t = &(x(y - p_h(p_5 - z_1p_7 - z_2p_8)) + (1 - x)(yp_4 \\ &- p_h(1 - z_1p_7 - z_2p_8)))C_t + (xy + (1 - x)yp_4)C_t \end{aligned} \tag{12}$$

$$\begin{aligned} TC = &(1 - P_t)C_s + (x(y - p_h(p_5 - z_1p_7 - z_2p_8)) + (1 - x)(yp_4 \\ &- p_h(1 - z_1p_7 - z_2p_8)))C_t + (xy + (1 - x)yp_4)(C_p + C_t) \end{aligned} \tag{13}$$

$$TC = (1 - P_t)C_s + (P_t - xp_1)C_t + (xy + (1 - x)yp_4)(C_p + C_t) \tag{14}$$

6. **Application.** In order to assess the applicability of the model, we implemented our model for the real case of humanitarian logistics and inventory operations of a volcanic eruption in Indonesia. Merapi Mountain, which is located on the border of the two provinces of Yogyakarta and Central Java, is the most active volcano in Indonesia. During the eruption in November 2010, most of the people living near the mountain lost their houses and belongings. For a one-month period, the government and NGOs tried to support their lives at shelters located all over the city.

Data on evacuees gathered by the Indonesia National Disaster Management Agency for the two provinces during the one-month evacuation period is shown in Figure 11 [16]. The Agency announced two increases in the eruption safety zone, from a radius of 10 km to 15 km, and from a radius of 15 km to 20 km. These announcements caused the number of shelters to change dynamically. In this paper, we select the largest number of shelters and evacuees that occurred on 14 November 2010 as a basis for calculating the inventory parameters. Table 2 shows the number of evacuees and shelters for each sub-area of Yogyakarta province.

We use inventory settings similar to those numerically simulated by Mulyono, 2011 [4]:
1. Total period = 720 hours
2. Demand rate/hour = 535 units
3. Delivery period = 12 hours
4. Target inventory = 7114 units
5. Quantity delivered = Target Inventory – Current Inventory Level
6. Probability of helping = 0.9
7. Proportion of normal cells (p_n) = 0.2
8. Proportion of abnormal cells (p_a) = 0.1
9. Abnormal threshold = 30%

Furthermore, we convert those parameters into probability parameters as follows:
1. $p_1 = 1 - \frac{\text{demand rate}}{\text{target inventory}} = 0.93$
2. $p_2 = 0$
3. $p_3 = 1$
4. $p_4 = \frac{\text{quantity delivered}}{\text{target inventory}} + \text{ abnormal threshold} \simeq 1$
5. $p_5 = p_n = 0.2$
6. $p_6 = 1$
7. $p_7 = \frac{p_n}{4} = 0.05$
8. $p_8 = \frac{p_a}{4} = 0.025$
9. $p_h = 0.9$

Figure 12 shows the trend of the fraction of normal nodes (cells) over time. As shown, at $p_5 = 0.2$ about 23% of cells are in the normal state. In order to know which p_5 value maximizes the fraction of normal cells, we further simulate the inventory system

Table 2. Number of evacuees on 14 November 2010 [4]

Sub area	Area (km^2)	Evacuees	Shelter points	Evacuees/ shelter	Shelter density
Sleman	574.82	109193	74	1476	7.77
Kulon Progo	586.28	4753	16	297	36.64
Yogyakarta city	32.5	5118	14	366	2.32
Bantul	506.85	20516	17	1207	29.81
Gunung Kidul	1485.35	12162	13	936	114.26
Total	3185.8	151742	134	4282	190.8

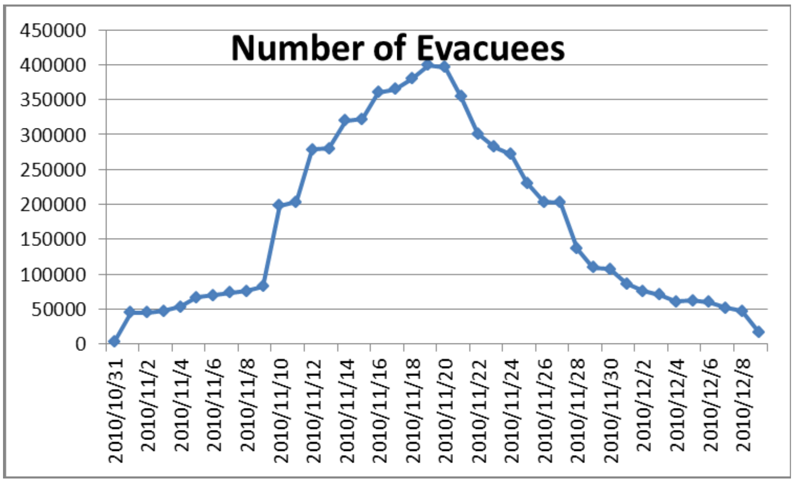

FIGURE 11. Number of evacuees during the eruption [4]

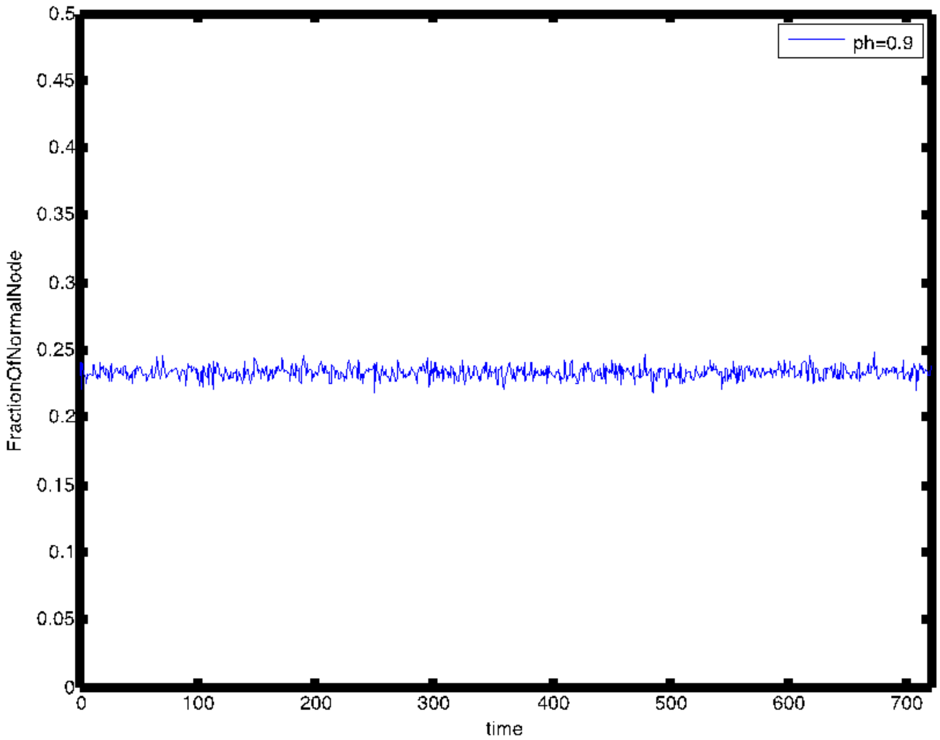

FIGURE 12. Fraction of normal nodes over time

for various values of p_5 as seen in Figure 13. This figure clearly illustrates the effect of variable p_5 on the fraction of normal cells. If p_5 has a higher value (above 0.15), then the fraction of normal cells will sharply decrease to 0.2 and stay at that value. Furthermore, when the value of p_5 is below 0.15, then the fraction of normal cells will be steady at 0.2.

This simulation result implies that lateral transshipment between shelters should be conducted when each shelter has a high stock level. The purpose of this condition is to prevent shelters from falling into an abnormal state after helping other shelters. This result complements the work of Mulyono, 2011 [4] that mentioned the minimum number of resources necessary for successful lateral transshipment operations.

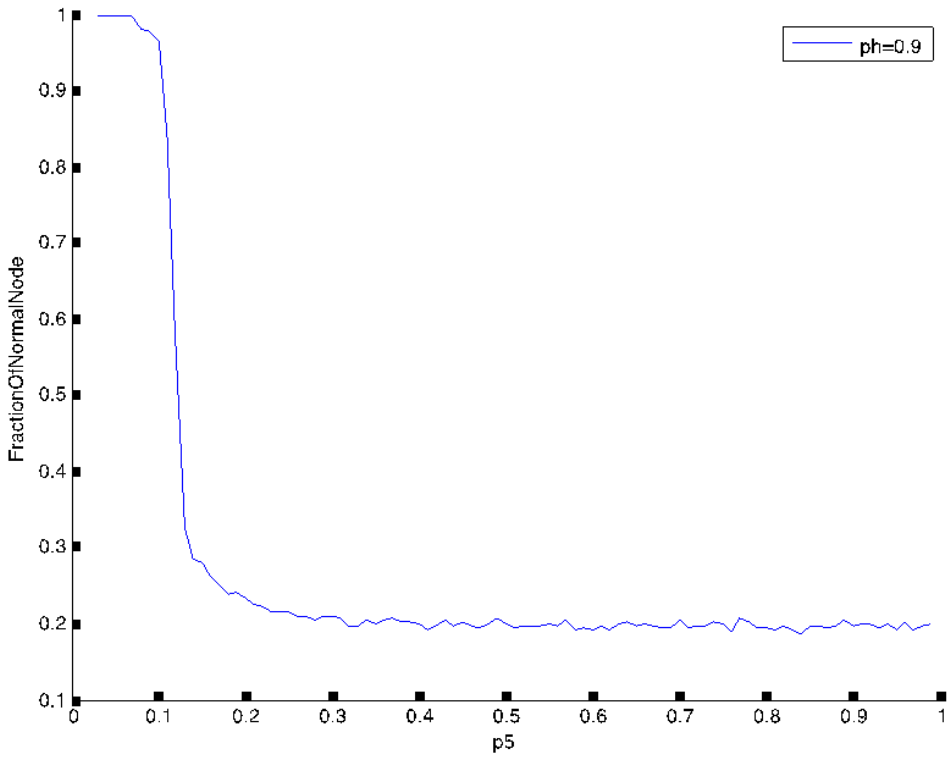

FIGURE 13. Fraction of normal nodes with varying p_5

7. **Conclusions.** We successfully built a logistics and inventory model based on probabilistic cellular automata with reference to the enterprise inventory model and self-repair network model, which is applicable to humanitarian relief situations. Even though the interaction of cells in our model is limited to their closest neighbors, the model illustrates various important characteristics of humanitarian logistics and inventory operations: the positive impact of lateral transshipment, factors affecting the overall transition probabilities, and the threshold of helping probability parameters in order to maximize the fraction of normal cells.

This model is suitable for disaster situations since information on the inventory level and other logistics information is usually unknown. Further research is required on the dynamic number of cells, delivery lead-time, and vehicle capacity constraints.

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Appendix.

Equation (7)

P_t = transition probability of normal cell + transition probability of abnormal cell

transition probability of normal cell

= consumption probability (p_1)
+ regular delivery of items from central warehouse (p_3)
− probability of helping ∗ (probability of state decrease due to giving help (p_5))
− probability of state increase due to receiving help (p_7)

transition probability of abnormal cell

= consumption probability (p_2)
+ regular delivery of items from central warehouse (p_4)
− probability of helping ∗ (probability of state decrease due to giving help (p_6))
− probability of state increase due to receiving help (p_8)

$$P_t = x(p_1 + yp_3 - p_h(p_5 - z_1p_7 - z_2p_8)) + (1-x)(p_2 + yp_4 - p_h(p_6 - z_1p_7 - z_2p_8))$$

Equation (9)

Replace the value of (p_2, p_3, p_6) of Equation (7) with (0, 1, 1):

$$P_t = x(p_1 + y - p_h(p_5 - z_1p_7 - z_2p_8)) + (1-x)(yp_4 - p_h(1 - z_1p_7 - z_2p_8))$$

Equation (10)

$$TC_s = \text{probability of stock out} * \text{unit cost of stock out}$$

$$TC_s = (1 - P_t)C_s$$

Equation (11)

$$\begin{aligned} TC_p = &(\text{probability of regular delivery to normal cell} \\ &+ \text{probability of regular delivery to abnormal cell}) \\ &* \text{number of cells} * \text{unit cost of procurement} \end{aligned}$$

$$TC_p = (xy + (1-x)yp_4)C_p$$

Equation (12)

$$\begin{aligned} TC_t = &\text{probability of transhipment} * \text{number of cells} \\ &* \text{unit cost of transportation} + \text{probability of regular delivery} \\ &* \text{number of cells} * \text{unit cost of transportation} \end{aligned}$$

$$TC_t = (x(y - p_h(p_5 - z_1 p_7 - z_2 p_8)) + (1-x)(yp_4 - p_h(1 - z_1 p_7 - z_2 p_8)))C_t + (xy + (1-x)yp_4)C_t$$

Equation (13)

$$TC = TC_s + TC_p + TC_t$$

$$\begin{aligned} TC = &(1 - P_t)C_s + (x(y - p_h(p_5 - z_1 p_7 - z_2 p_8)) + (1 - x)(yp_4 \\ &- p_h(1 - z_1 p_7 - z_2 p_8)))C_t + (xy + (1 - x)yp_4)(C_p + C_t) \end{aligned}$$

Equation (14)

Substitute Equation (9) into Equation (13) to obtain a simplified form of total cost (TC):

$$TC = (1 - P_t)C_s + (P_t - xp_1)C_t + (xy + (1 - x)yp_4)(C_p + C_t)$$