Self-organizing Network of Relief Logistic and Inventory

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Abstract

The operation of logistic and inventory has been recognized as an important aspect of disaster relief. The role of logistics is delivering the needed items to the disaster victims quickly and efficiently even in very remote parts of the disaster area and under difficult circumstances. Furthermore, inventory play critical role in managing all the life support items and delivering those items to the victims whenever they need it. Pre-positioning relief inventory during disaster preparedness enable each inventory location to fulfill the demand for the short period after the disaster. However, due to sudden demand after disaster and chaotic condition at that moment, relief inventory level at each inventory location may vary significantly and some of them may shortage of necessary items.

Accurate information about demands and supplies acquired during disaster is extremely important in generating action plan of relief logistic and inventory including lateral transshipments. The operational research approach is the best option for modeling lateral transshipments operation assuming an existence of that accurate information. However, accurate information about demands and supplies during disaster is difficult to acquire due to loss of communication abilities and infrastructure damages. To overcome this constraint, we propose a lateral transshipment model of relief inventory to leverage the inventory level between locations using self repair and self recognition network designed for relief logistic and inventory management. This model uses cellular automata and spatial game theory. We address the following research question in detail: (i) How does the self-repair and self-recognition network of relief logistic and inventory improve their system performance? (ii) What is the best model to choose and under which circumstance that model work well? (iii) What the necessary preparation for getting the best performance of lateral transshipment and avoiding the reverse effect?

In self-repair network model, we use eight parameters to characterize the dynamic interactions among inventory location (disaster's shelters). This model is able to increase performance of lateral transshipment under inaccurate information situation, however there is no mechanism to control the dynamic of the lateral transshipment. To overcome that, we further developed self-recognition network model using spatial game theory. Finally, we enclosed our research with cluster formation of inventory location before disaster, to further increase performance of the lateral transshipment. The case of two volcanic eruptions in Indonesia (Merapi Mountain and Sinabung Mountain in 2010 and 2013) validates the robustness of our approach. On the basis of our finding, we provide a guideline for relief organization on how to use and get benefit from our approach in post disaster situation.

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Table of Contents

List of Figures

List of Tables

Nomenclature

EOQ = economic order review
FOR= fixed order review
CA = cellular automata
GT = game theory
SRN = self repair network
SRP = stable roommate problem

1 Introduction

1.1 Background and Context

Natural disasters strike unpredictably all over the world causing infrastructure damage, losing human lives, and making many thousand of people leave their home. The need to help people after a disaster is continuously growing due to the increasing number of natural disasters recently [1]. The emergency events database (EMDAT) contains essential core data on the occurrence and effects of mass disasters in the world from 1900 to the present[2]. A wide variety of disasters are recorded: from natural events like floods, pandemics and earthquakes to human activity based disasters like terrorism, train accidents, and nuclear power plant failures.

Large disasters such as the 2004 Indian Ocean Tsunami, 2005 Hurricane Katrina, 2010 Haitian Earthquake, and the 2011 earthquake and tsunami in Japan bring the unpredicted impact to the social and economic system. The consequences of a natural disaster are calculated in terms of the loss of thousands of human lives and a terrible economic impact to the concerned area.

Recently, information systems for disaster relief have improved greatly, leading to better coordination among each organization involved. Management of information needs to be addressed when defining an inventory management concept because decision-making structure is closely related to information [3]. 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[4]. Many literatures provide a useful generalization for managing the coordination required between organizational levels and different organizations during the response effort [5].

Humanitarian disaster relief operations are extremely needed after the disaster since the victims lose their ability to sustain their own life for some periods of time after that onset event. The practice of humanitarian disaster operations has huge consequences that calculated in terms of the loss of thousands of human lives and a terrible economic impact to the concerned area. In 2010, there are more than 297,000 people were killed and over 217 million were suffered by natural disaster that bring an economic damage at over USD 129.9 billion [2].

The humanitarian disaster relief operations must be provided within the first hours after the disaster to increase the survival rate of the disaster victims [6]. These operations usually involve various local and international organizations, host governments, military, and private companies. Their activities including: relocating victims, delivering health care, and providing shelters and life support items. With their capability and expertise, such organizations are able to supply daily essentials such as foods, clothing, medicines, etc [7]. Those critical supplies available in the affected areas are either destroyed by the disaster event, or quickly depleted during immediate response, necessitating the rapid deployment of humanitarian logistical activities to reduce further damage[8].

The core of humanitarian logistic is delivering aid to helpless people quickly and efficiently even in very remote parts of the disaster area and under difficult circumstances. The logistics system can be represented as a social network of Individuals conducting a set of technical activities (e.g., routing, inventory management) over a set of supporting systems (e.g., transportation, communications) [9].

Humanitarian inventory play critical role in managing all the life support items and delivering those items to the victims whenever they need it. Logistic and inventory system cannot be separated each other and have to work collaboratively to achieve best performance. The role of logistic and inventory system for disaster relief is mentioned by [10] that describe an environment for those systems operation.

Humanitarian logistic and inventory involves all activities conducted at the different phases of emergency management: mitigation, preparedness, response, and recovery[11]. The mitigation and preparedness are conducted before a disaster, to reduce the potential economic, social and physical impacts of an event, and include such activities as the pre-positioning of critical supplies, improvement of building codes, and the development of response plans. At this phase, each shelter location keeps some amount of inventory called pre-positioning inventory as a part of disaster preparedness implementation [12]. The aim is decreasing disaster potential devastating effects [7]. Immediately after a disaster, emergency responders initiate the response phase, which includes search and rescue, and transporting the equipment, personnel and materials required for impact assessment and repairs. This phase is followed by recovery activities in which humanitarian logistic and inventory takes the major roles in it.

Opposite with the humanitarian logistics and inventory, the features and dynamics of commercial logistics are well known with highly sophisticated analytical models to optimize the various components and enhanced its performance [9]. Their original design of logistic and inventory system is hierarchical where transportation flows from higher echelon to the next. This inventory system tends to have less flexibility since each inventory point cannot interact or help each other to get a better performance. 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. The more flexible logistics and inventory system allows lateral transshipment within same or adjacent echelon [13]. Formally, lateral transshipment in an inventory system means the movement of stock between locations at the same level[14].

Due to chaotic condition after disaster, relief logistic and inventory faces a several problems:

1. Excessive demand at very short period after disaster.
2. Unbalance inventory level between inventory locations (shelters).
3. Low credibility of information that comes from many sources: firefighter, police, transporter, eyewitnesses, etc.
4. Damage of the infrastructures.

The lateral transshipment option in logistics and inventory is beneficial for relief disaster operations. Figure 1 illustrates a simple system for lateral transshipment of inventory that consist of a single central warehouse supplying four shelters. With this option, the shelter (inventory location) having excessive number of stock may share some of their stock to the neighborhood shelter having low stock. In this way, the stock level among all shelters is hopefully matched with their demand. The benefits of lateral transshipment in avoiding zero stock level at each shelter and balancing the stock level among them is mentioned by[15]. After disaster, the accurate and reliable information about shelter condition (demand pattern and stock level) is difficult to acquire due to loss of communication abilities and infrastructure damages. The lateral transshipment in this situation may lead to even worst condition (high stock out and unbalance level) and high cost (transportation and handling). Based on those facts, we aims to

1. Find appropriate parameters including their range of value that directly or indirectly has an effect to the success of lateral transshipment operation.
2. Control the lateral transshipment process.
3. Make supportive preparation before the disaster that contributes positively to the success of lateral transshipment operation.

Accurate information about demands and supplies acquired during disaster is extremely important in generating action plan of relief logistic and inventory including lateral transshipments. The operational research approach is the best option for modeling lateral transshipments operation assuming an existence of that accurate information. If the sufficient information is not available, operation research approach is no longer appropriate for modeling and solving lateral transshipment problem. We have to develop method that maximizes the usage of local information.

In computer science there is a collaborative network system called self-repair network (SRN) having characteristic like lateral transshipment of inventory. The self-repair network model involves collaboration in the computer network whereby each computer tries to repair other computers by mutual copying[16]. The main 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. This model mentioned that sharing action has side effects such as spreading contamination and consuming resources. In relief inventory, lateral transshipment has a side effect of reducing the service level of the sender and consuming resources in term of transportation[15].

The cellular automata model is a tool for modeling complex phenomena [17]. 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[18]. 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.

Firstly we will model the behavior and measure the performance of lateral transshipment in humanitarian logistic and inventory using probabilistic cellular automata. The cellular automata model is appropriate as a base model, since it can model dynamic interaction among shelters (inventory locations) as interaction among cells[18]. With this method, we can model the interaction of the shelters even without accurate information of demand trends and supplies in each shelter. In addition, we get the better performance of lateral transshipment comparing with the regular logistic and inventory practices (without lateral transshipment). The model is inspired by the cooperative work of immune cells in immunity based system theory[20]. In this model, we assume that there is a predetermined level of altruism in each agent (shelter) and we neglected the cost as a performance measure. 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 Merapi Mountain, Indonesia [21].

Secondly, we intend to control lateral transshipment process of relief inventory using spatial game theory in order to get best strategy of lateral transshipment in relief logistic inventory and reduce it related costs. Each shelter has a freedom to help or not help based on its current situations. We model the distribution and inventory operation of ready to use food items during the disaster recovery with the case of volcanic eruption at Sinabung Mountain Indonesia in 2013 [22].

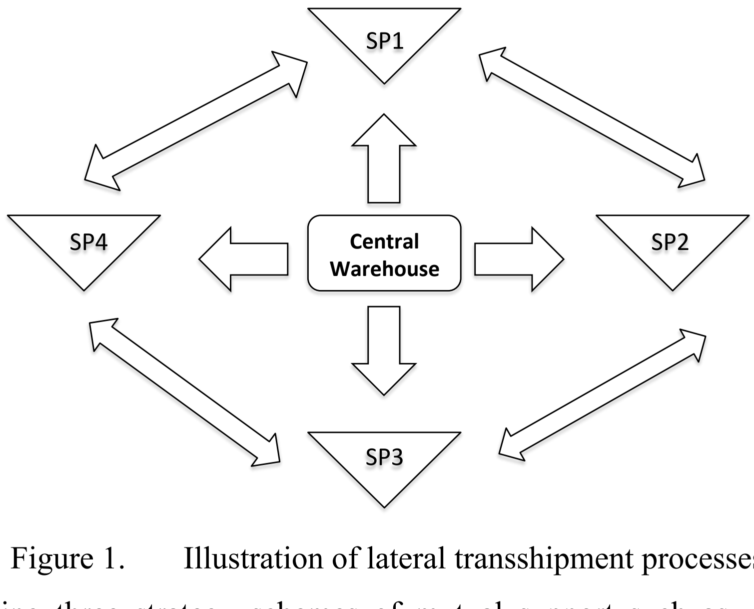

Figure 1. Illustration of lateral transshipment processes

By comparing three strategy schemes of mutual support such as without lateral transshipment, with fully lateral transshipment, and partial lateral transshipment. The first two schemes don't have strategy update mechanism or in other words their strategy is static. The last scheme has strategy update that consists of three types: maximum payoff, static support level, and dynamic support level. The second strategy is similar with the first and second strategy scheme (without and with lateral transshipment), but the level of support is previously defined such as 50% support. We demonstrate the strengths and weaknesses of each strategy scheme. We use inventory related cost as performance measure such as procurement cost, transportation cost, holding cost, and "stock out" cost.

Lastly, we complete our previous model with shelter's cluster formation at the preparation phase (before disaster) to further improve the performance of the lateral transshipment system for relief logistic and inventory. We propose two stages mechanism in building the cluster using nearest neighbor algorithm and stable roommate algorithm. Figure 2 illustrates relationships between chapter 3, 4, and 5.

Overall, in this research we address the following research question in detail: (i) how's the mechanism of lateral transshipment can improve the performance of humanitarian logistic and inventory? (ii) What is the best strategy to control lateral transshipment system in relief disaster logistic and inventory, and under which circumstance that scheme work well? (iii) What the necessary preparation for getting the best performance of lateral transshipment and avoiding the reverse effect.

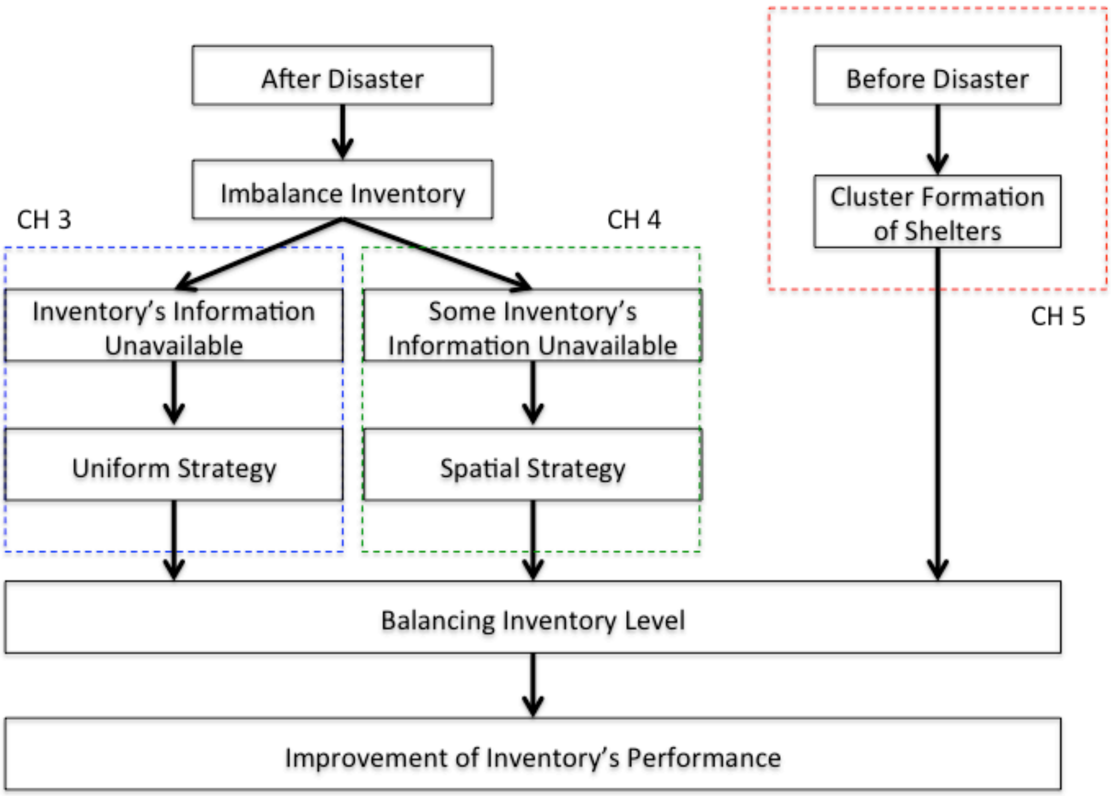

Figure 2. Relationship between chapters

1.2 Scope and Objectives

The objective of our research is building a model of humanitarian logistic and inventory transshipment operation using the logic of self-repair and self-recognition network. We use cellular automata, spatial game theory, and stable roommate algorithm as a development basis. We limit our research into a scope of relief logistic and inventory with some assumption:

1. Inventory in each shelter is safe from disaster impact.
2. The cost of logistic and inventory includes: purchasing, handling, transportation, and stock out.
3. Enough number of transportation vehicles.
4. Number of shelters (or inventory location) is static.
5. Total number of stocks in all shelters is above their average capacity.

1.3 Achievements

We successfully build a model of humanitarian logistic and inventory that able to control the transshipment operation so that the negative side of the transshipment is avoided and the performance is boosted. In each disaster condition, we can create an action plan to implement the result of our research so that disaster stakeholders can get benefit from it.

1.4 Overview of Dissertation

This dissertation is structured as follows. First, we introduce the state of the art about relief logistic and inventory model, probabilistic cellular automata, and spatial game theory. Next, we explain our first model of probabilistic cellular automata for modeling the relief logistic and inventory trough lateral transshipment. Furthermore, we explain about our second model of spatial game theory in controlling the lateral transshipment operations. Finally, we complete the model with the cluster generation of inventory location to further increase the performance of relief logistic and inventory model. We validate both of our models using case study of volcanic eruption disaster data in Merapi Mountain and Sinabung Mountain Indonesia. Finally, we conclude this research by highlighting the findings and operational recommendation.

2 Related Work

2.1 Emergency Management

Interest continues to grow in the fields of emergency management and improving the response to rapid-onset disasters[23]. Modern emergency management developed from the civil defense and civil protection efforts that began in the 1940s to protect civilians against the effects of warfare and nuclear exchange. Emergency management has traditionally been viewed as a five-phase approach[24]:

1. Prevention: Activities taken to avoid or to stop a disaster/emergency from occurring.
2. Preparedness: Activities, programs, and systems developed and implemented prior to a disaster/emergency that are used to support and enhance mitigation of, response to, and recovery from disasters/emergencies.
3. Response: In disaster/emergency management applications, activities designed to address the immediate and short-term effects of the disaster/emergency.
4. Recovery: Activities and programs designed to return conditions to a level that is acceptable to the entity.
5. Mitigation: Activities taken to eliminate or reduce the probability of the event, or reduce its severity or consequences, either prior to or following a disaster/emergency.

Prevention, preparedness and mitigation are closely related. They all deal with the concept of eliminating or at least minimizing impacts of a disaster or incident. Prevention relates to making more informed decisions, such as determining where earthquake faults and flood plains are in order to avoid building in those areas. Prevention can also take the form of increased security measures on a property. Preparedness is used commonly in reference to educating and training residents or personnel, pre-planning, and identifying resources in advance. Mitigation can be carried out before or after an incident. Strapping down equipment, installing hurricane clips on roofs, and building storm shelters are all examples of mitigation. Implementing any of these phases involves money and time, so they may be given insufficient attention in some organizations.

Response generally refers to the immediate actions taken after an incident to save lives and protect assets. Lessening or eliminating subsequent impacts also falls in this category, such as putting out a fire in one building before it spreads to an area filled with explosives or cleaning up a hazardous material spill before it causes more contamination of the environment. Recovery starts almost immediately with response and includes the clean up and return to normal, or better than normal. Recovery can be a short or long process depending upon the incident. If an organization has to recover from a major fire, for example, the recovery process may include extensive, lengthy medical treatment for victims, interactions with insurance companies and fire inspectors, or closing a site and relocating the entire business.

According to FEMA (2003) [25], core functions necessary during emergencies are:

1. Direction and control
2. Communications
3. Warning
4. Emergency public information
5. Evacuation or in-place sheltering
6. Mass care
7. Health and medical
8. Resource management (p. 9.6)

2.2 Basic Theory of Logistic and Inventory

Logistics is the art of managing the supply chain and science of managing and controlling the flow of goods, information and other resources like energy and people between the point of origin and the point of consumption in order to meet customers' requirements. It involves the integration of information, transportation, inventory, warehousing, material handling, and packaging.

Logistics has always been an important factor in humanitarian aid operations, to the extent that logistics efforts account for 80 percent of disaster relief [26]. The speed of humanitarian aid after a disaster depends “on the ability of logisticians to procure, transport and receive supplies at the site of a humanitarian relief effort” [27].

Humanitarian logistics encompasses very different operations at different times, and as a response to various catastrophes. All these operations have the common aim to aid people in their survival. The effectiveness of the humanitarian relief response depends on the speed with which supplies can be procured, transported and managed at the site[27].

Inventories are materials stored, waiting for processing, or experiencing processing. The theory of inventory is the sub-specialty within operations research that is concerned with the design of production/inventory systems to minimize costs. It studies the decisions faced by firms and the military in connection with manufacturing, warehousing, supply chains, spare part allocation and so on; it provides the mathematical foundation for logistics. The application of operations research techniques in this area (sometimes called scientific inventory management) is providing a powerful tool for gaining a competitive edge. Inventory management concept covers four areas and acts as starting point for redesigning actions [28]: physical infrastructure, planning structure, information architecture, and organization embedding.

Figure 3. Inventory System [29]

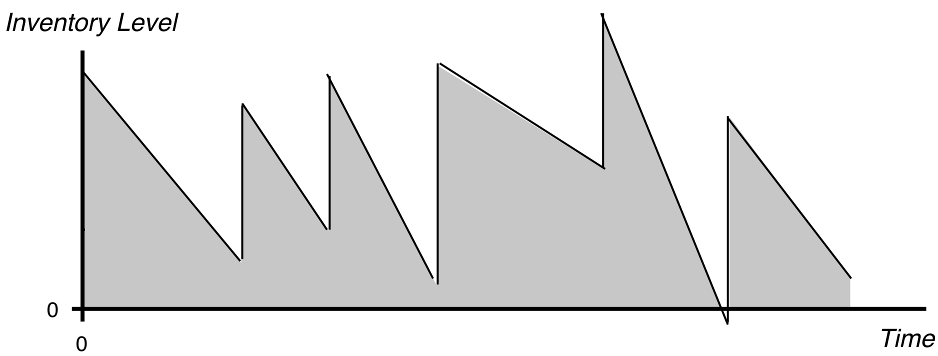

Figure 4. Inventory fluctuation throughout the time [29]

Inventory management comprising the following steps:

1. Formulate a mathematical model describing the behavior of the inventory system.
2. Seek an optimal inventory policy with respect to this model.

3. Use a computerized information processing system to maintain a record of the current inventory levels.

4. Using this record of current inventory levels, apply the optimal inventory policy to signal when and how much to replenish inventory.

The most common inventory situation faced by manufacturers, retailers, and wholesalers is that stock levels are depleted over time and then are replenished by the arrival of a batch of new units. A simple model representing this situation is the following economic order quantity model or, for short, the EOQ model (Figure 4). Furthermore, ordering raw materials or supplies in lots based on the quantity that will be used over a given time period or series of periods is called periodic order review or, famous as the POQ model (Figure 5). The last model is applicable for the relief logistic and inventory since it requires less intensive communication between supply and demand.

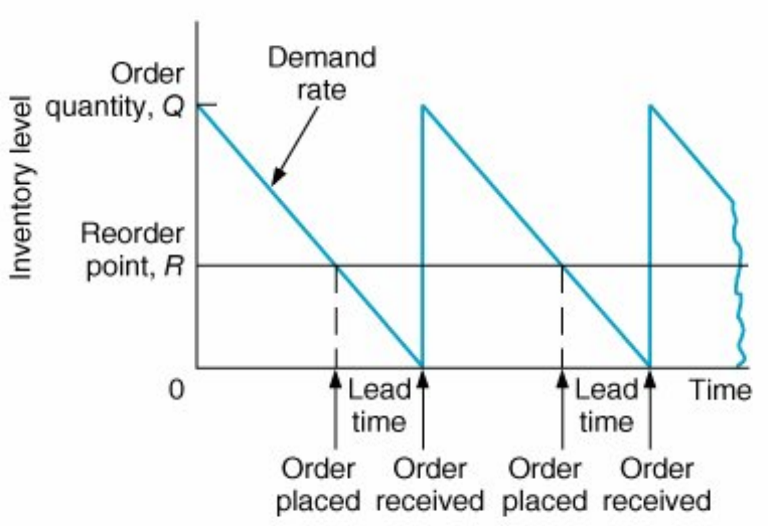

Figure 5. Economic order quantity [29]

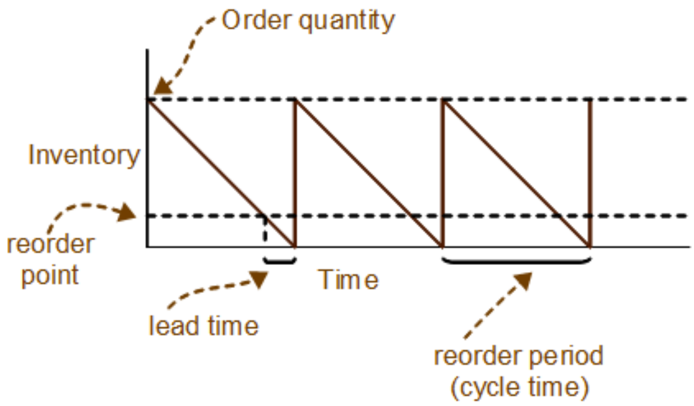

Figure 6. Periodic order quantity [29]

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[30]. Nevertheless, the fundamental principle of the enterprise inventory model can be used to build an inventory model in disaster situations.

2.3 Self-organization Network

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 [16]. 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 [18].

In self-recognition network, each unit tries to recognize the status of each other under certain credibility. Here, it assumes that there is some communication channel between each agent in the network.

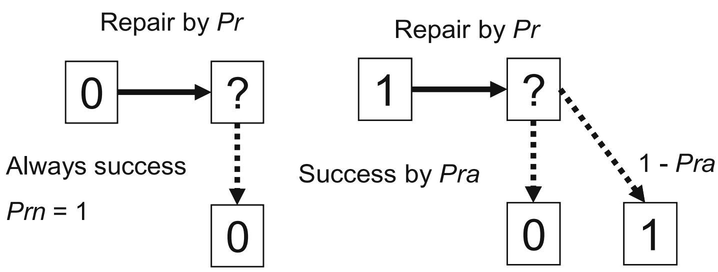

Figure 7. Repairing in Self-repair network [16]

Self-repair and self-recognition network is a specific case of self-organization network. Self-organization is a process where some form of global order or coordination arises out of the local interactions between the components of an initially disordered system. This process is spontaneous: it is not directed or controlled by any agent or subsystem inside or outside of the system; however, the laws followed by the process and its initial conditions may have been chosen or caused by an agent. Self-organization usually relies on three basic ingredients: (1) Strong dynamical non-linearity, often though not necessarily involving positive and negative feedback, (2) Balance of exploitation and exploration, (3) Multiple interactions.

3 Relief Logistic and Inventory Based on Probabilistic Cellular Automata

3.1 The Basic of Cellular Automata

3.1.1 History and Definition

Cellular automata (often termed CA) are discrete models in which the states of the variables are driven by simple rules dependent on the states of the neighbors of each variable[31]. Cellular automata are an idealization of a physical system in which space and time are discrete, and the physical quantities take only a finite set of values. Since it has been invented, cellular automata have been developed and used in many different fields.

The definition of a cellular automaton includes[31]:

1. A definition for a grid, which includes boundary conditions. Often, to avoid complications due to a boundary, periodic boundary conditions are used, so that a two-dimensional grid is the surface of a torus.
2. A finite (usually small) set of states that grid cells can have.
3. A neighborhood, which is a definition of which nearby cells may affect the state of a given grid cell
4. A local rule, by which a grid cell's state may change. This rule may be either deterministic, or in the case of a stochastic cellular automata, have a probabilistic element.

A strategy for updating the grid must also be defined whether it should be updated synchronously or asynchronously. A synchronous update, where all updates to the grid are applied at the same time, is usually employed. Oppositely, in an asynchronous update, individual cells update individually thus the new state of a cell immediately affects the calculation of the state of a neighbor.

Back to the 1940s, Von Neumann introduces cellular automata concept that constitutes the first applicable model of massively parallel computation at that time. He was thinking of imitating the behavior of a human brain in order to build a machine that is able to solve very complex problems. The machine with such a complexity as the brain should also contain self-control and self-repair mechanisms. The first replicating cellular automaton proposed by von Neumann was composed of a two dimensional square lattice and the self-reproducing structure was made up of several thousand elementary cells. Each of these cells had up to 29 possible states.

Ecological model has brought the concept of cellular automata to the attention of wide audience in 1970. A mathematician, John Conway, proposed famous example of cellular automata application known as Conway's Game of Life, or simply the Game of Life[32]. His motivation was to find a simple rule leading to complex behaviors. The Game of Life may be defined on any grid, usually a large one. Each grid cell exists in one of two possible states, alive or dead. The neighborhood of a given grid cell is made up of the eight next-nearest neighbors which are orthogonally adjacent and diagonally adjacent to that cell (this is sometimes called a Moore neighborhood). Each grid cell will be updated synchronously every time step according to the following rules:

1. If a living cell has less than 2 living neighbors it dies (as if by loneliness).
2. If a living cell has more than 3 living neighbors it dies (as if by overcrowding).
3. If a dead cell has exactly 3 living neighbors it becomes alive.

The game of life has turned out into rich behavior unexpectedly. As for the von Neumann rule, the game of life is a cellular automata capable of computational universality. The application of cellular automata in discrete dynamical system, such as traffic flow, disease epidemic, stochastic growth, predator-prey dynamic, invasion of population, earthquake, dynamic of stock market etc., has increased.

3.1.2 Deterministic Cellular Automata

In deterministic cellular automata (known as DCA) the update rules have no probabilistic component: for a given configuration of cell states the updated cell state is always the same[31]. The simplest deterministic cellular automaton is a line of cells, each of which is in one of two states: colored or uncolored. The cells are updated simultaneously; the updated state of a cell depends on its state and the states of its nearest neighbors. There are eight possible configurations for the states of a cell and its nearest neighbors; this gives eight different update rules.

3.1.3 Probabilistic Cellular Automata

In probabilistic cellular automata (known as PCA), the cells are updated synchronously and independently, according to a distribution depending on a finite neighborhood[33]. Probabilistic cellular automata can be viewed as cellular automata whose updating rule is a stochastic one, which means the new entities' states are chosen according to some probability distributions. It is a discrete-time random dynamical system. From the spatial interaction between the entities, despite the simplicity of the updating rules, complex behavior may emerge like self-organization. As mathematical object, it may be considered in the framework of stochastic processes as an interacting particle system in discrete-time.

3.2 Transition Probabilities and Rules in Relief Logistic and Inventory

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 7. The state of cell *(i,j)* at time *t*, $S_{i,j}^{t}$, 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*)[33]. 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 shelter 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:

$$p_1 = prob(S_{i,j}^{t+1} = 1 | S_{i,j}^{t} = 1) \quad (3.1)$$

$$p_2 = prob(S_{i,j}^{t+1} = 1 | S_{i,j}^{t} = 0) \quad (3.2)$$

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 3.3 and 3.4. The probability calculated by these equations could actually be larger than 1 for the parameter set of (p_1, p_2, p_3, p_4), in which case the probability is set to 1.

$$p_1 + p_3 = prob(S_{i,j}^{t+2} = 1 | S_{i,j}^{t+1} = 1) \quad (3.3)$$

$$p_2 + p_4 = prob(S_{i,j}^{t+2} = 1 | S_{i,j}^{t+1} = 0) \quad (3.4)$$

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 ph. 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 8 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).

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 3.5. y is also a binary variable having a value of *0* if period t equal with multiple value of n and vice versa, as shown in Equation 3.6. 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 3.7. Meanwhile, Equation 8 shows the relationship between variables. An analysis of the relief situation based on inventory and logistics revealed the following:

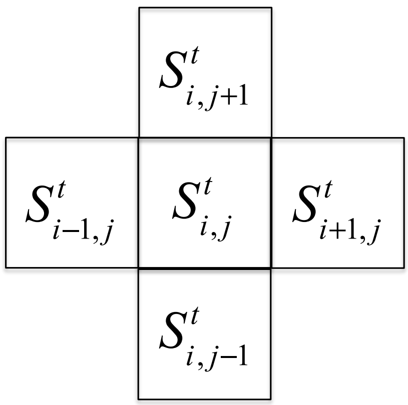

Figure 8. A cell and its neighbors

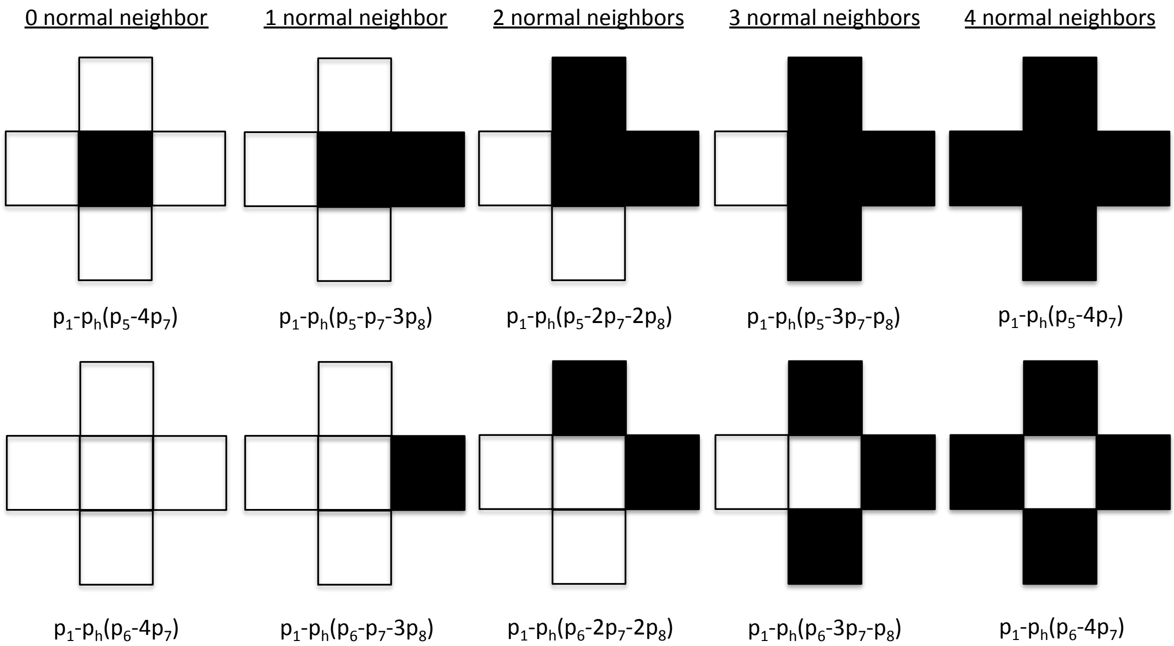

Figure 9. The transition probability of a center cell with different neighbor's states

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.

$$x = \begin{cases} 1, S_{i,j}^t = 1 \\ 0, S_{i,j}^t = 0 \end{cases} \tag{3.5}$$

$$y = \begin{cases} 1, t \ mod \ n = 0 \\ 0, t \ mod \ n \neq 0 \end{cases} \tag{3.6}$$

$$P_t = x\big(p_1 + yp_3 - p_h(p_5 - z_1p_7 - z_2p_8)\big) + (1 - x)(p_2 + yp_4 - p_h(p_6 - z_1p_7 - z_2p_8)) \tag{3.7}$$

$$\begin{gathered} p_2 \leq p_1 \\ p_4 \leq p_3 \\ p_5 \leq p_6 \\ p_8 \leq p_7 \end{gathered} \tag{3.8}$$

$$P_t = x\big(p_1 + y - p_h(p_5 - z_1p_7 - z_2p_8)\big) + (1 - x)(yp_4 - p_h(1 - z_1p_7 - z_2p_8)) \tag{3.9}$$

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 [29]:

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.

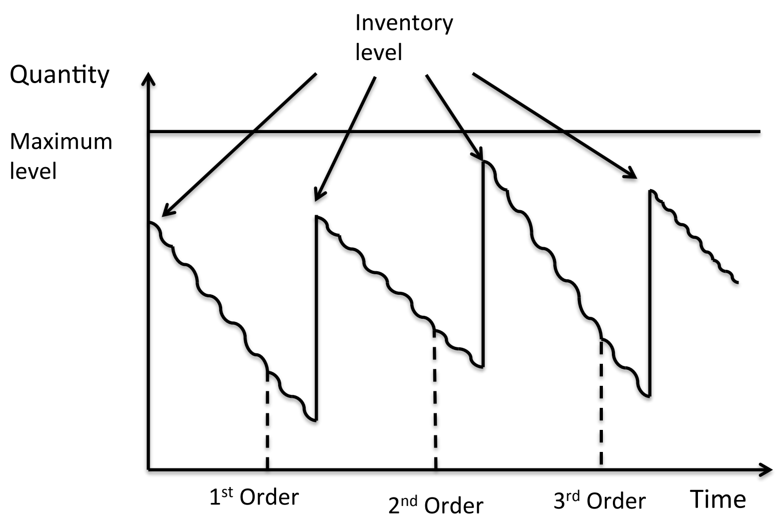

Figure 10. Basic inventory characteristic [29]

Lateral transshipment might increase the capability of the inventory system to meet the demand if there are enough vehicles to transport goods[14]. 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 3.7 and 3.8 to determine cell 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 10-13.

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. 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 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.

3.3 Performance Analysis

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 [16], 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 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 14 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 15 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 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.

Table 1. 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
p_3	0	1	0	1
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
p_h	0	0	0.5	0.5
n	3	3	3	3

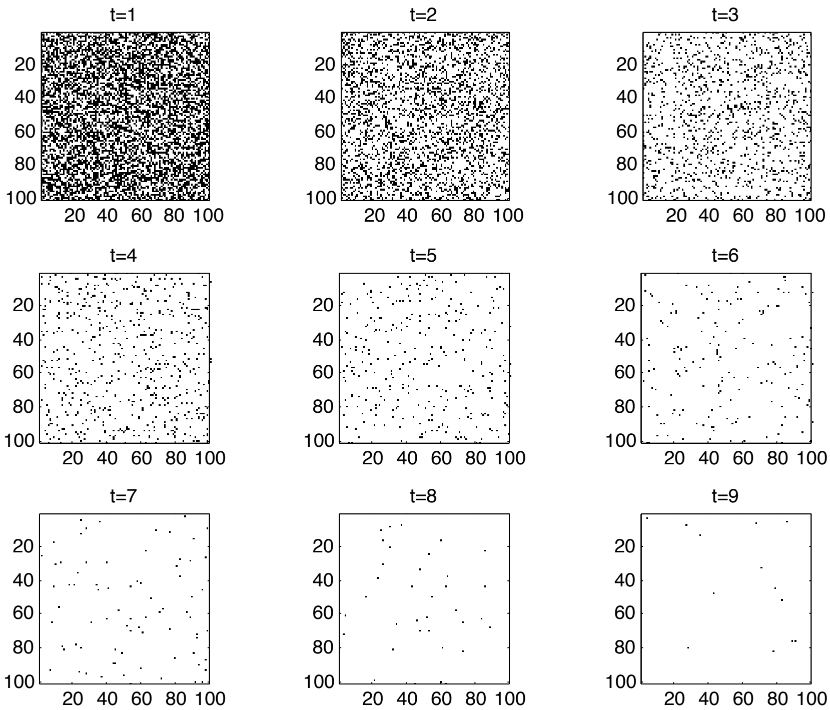

Figure 11. Scenario 1 (Simulating inventory without periodic delivery or lateral transshipment)

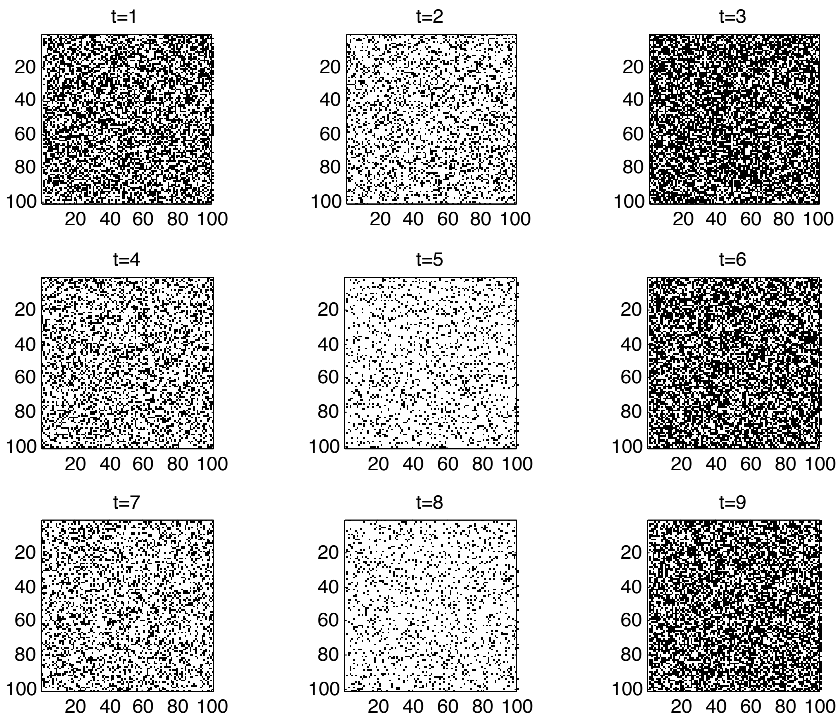

Figure 12. Scenario 2 (Simulating inventory with periodic delivery but without lateral transshipment)

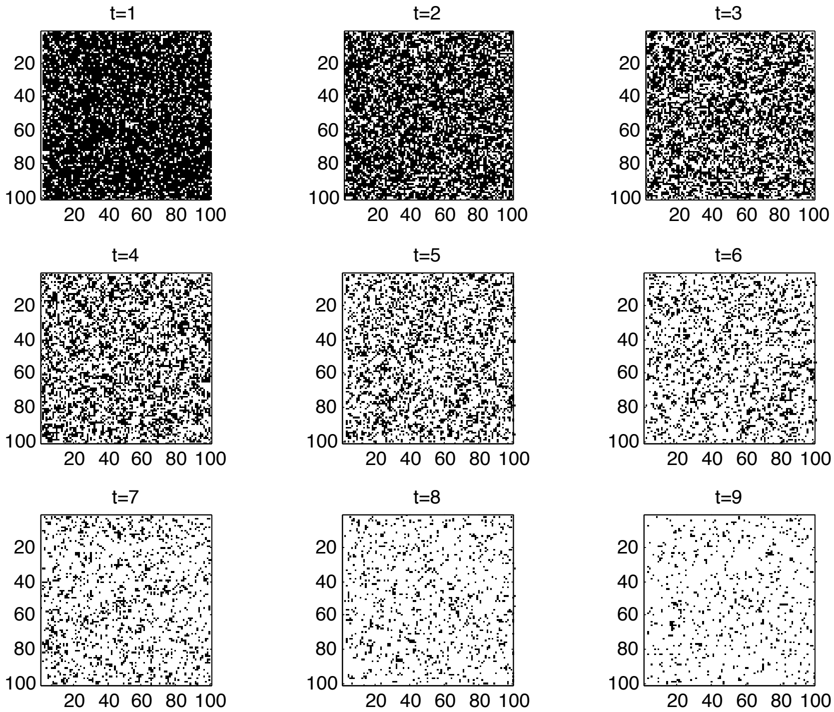

Figure 13. Scenario 3 (Simulating inventory without periodic delivery but with lateral transshipment)

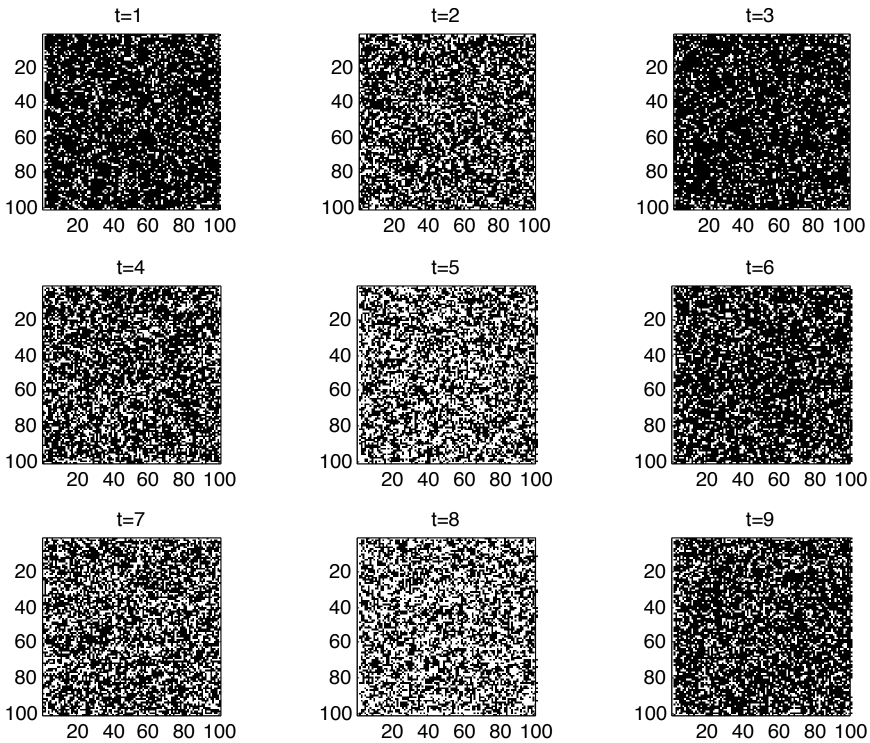

Figure 14. Scenario 4 (Simulating inventory with both periodic delivery and lateral transshipment)

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 3.10, 3.11, and 3.12 show the stock-out, procurement and transportation cost. Furthermore, Equation 3.13 shows the total cost representing the cost function of our model. By substituting the total transition probability of Equation 3.9 into Equation 3.13, we obtain a simplified form of the cost function as shown in Equation 3.14.

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 [13]. Based on Equation 3.14, 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.

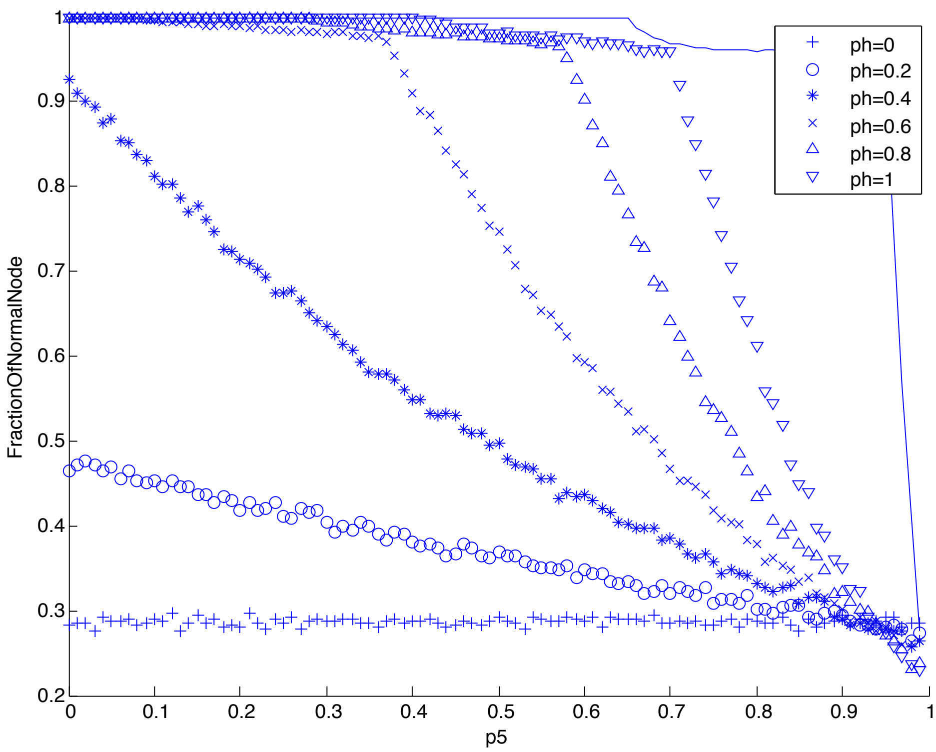

Figure 15. The Effect of helping on system performance

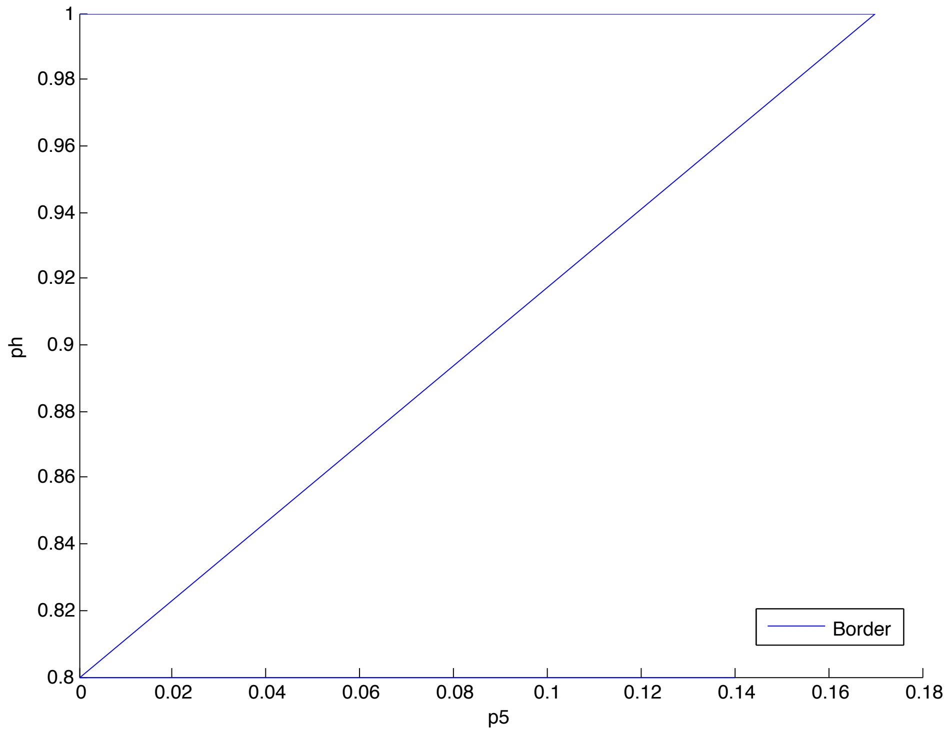

Figure 16. Frozen (upper left) and active (lower right) regions

$$TC_s = (1 - P_t)C_s \tag{3.10}$$

$$TC_p = (xy + (1 - x)yp_4)C_p \tag{3.11}$$

$$TC_t = \Big(x\big(y - p_h(p_5 - z_1p_7 - z_2p_8)\big) + (1 - x)\big(yp_4 - p_h(1 - z_1p_7 - z_2p_8)\big)\Big)C_t + (xy + (1 - x)yp_4)C_t \tag{3.12}$$

$$TC = (1 - P_t)C_s + \Big(x\big(y - p_h(p_5 - z_1p_7 - z_2p_8)\big) + (1 - x)\big(yp_4 - p_h(1 - z_1p_7 - z_2p_8)\big)\Big)C_t + (xy + (1 - x)yp_4)(C_p + C_t) \tag{3.13}$$

$$TC = (1 - P_t)C_s + (P_t - xp_1)C_t + (xy + (1 - x)yp_4)(C_p + C_t) \tag{3.14}$$

3.4 Model Implementation in Real Disaster Case (Merapi, Indonesia)

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 16 [21]. 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.

For validation purposes, we use inventory settings similar to those numerically simulated by Mulyono, 2011 [14]:

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%

Table 2. Number of evacuees on 14 November 2010 [21]

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*

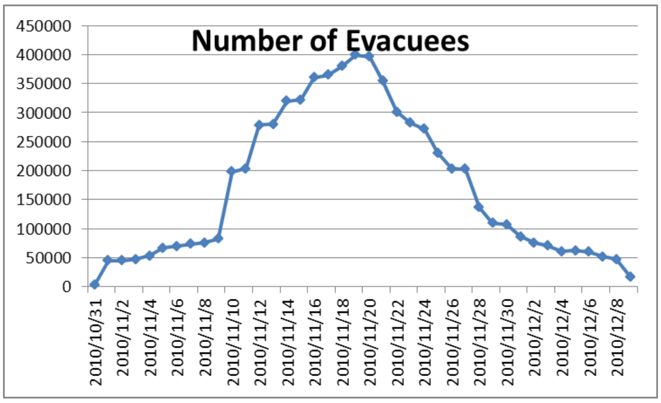

Figure 17. Number of evacuees during the eruption [21]

Furthermore, we convert those parameters into probability parameters as follows:

1. $p_1 = 1 - \dfrac{\text{demand rate}}{\text{target inventory}} = 0.93$
2. $p_2 = 0$
3. $p_3 = 1$
4. $p_4 = \dfrac{\text{quantity delivered}}{\text{target inventory}} + \text{abnormal threshold} \simeq 1$
5. $p_5 = p_n = 0.2$
6. $p_6 = 1$
7. $p_7 = \dfrac{p_n}{4} = 0.05$
8. $p_8 = \dfrac{p_a}{4} = 0.025$
9. $p_h = 0.9$

Figure 17 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 for various values of p_5 as seen in Figure 3.13. 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.

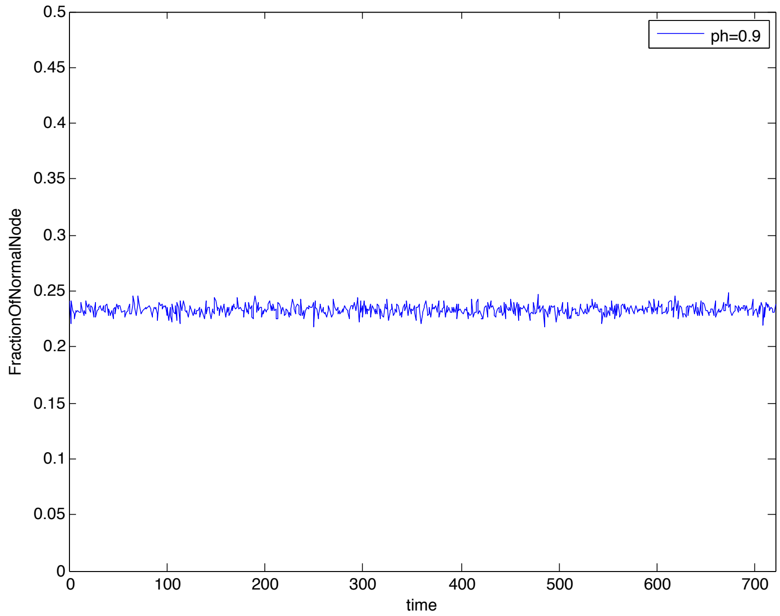

Figure 18. Fraction of normal nodes over time

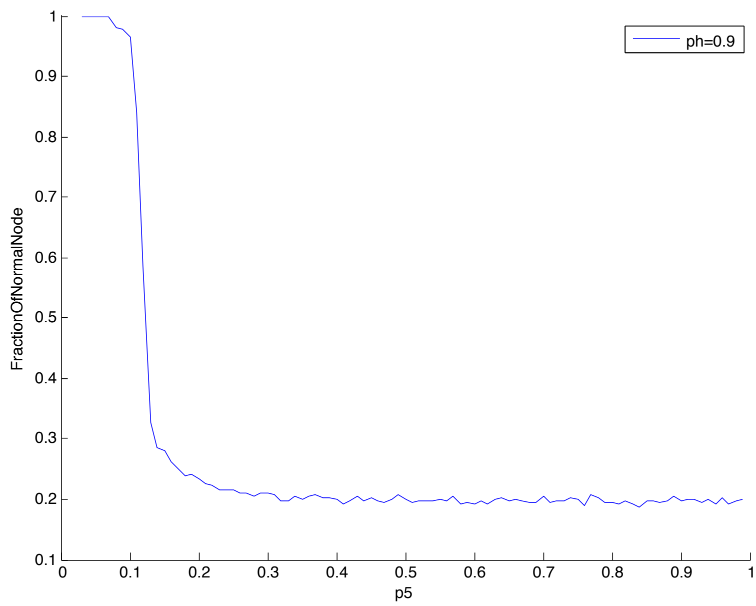

Figure 19. Fraction of normal nodes with varying p_5

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 [14] that mentioned the minimum number of resources necessary for successful lateral transshipment operations.

3.5 Concluding Remarks

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.

4 Strategy Selection of Relief Logistic and Inventory using Spatial Game Theory

4.1 The Basic of Game Theory

Game theory (known as GT) is a study with the main purpose of finding an answer to the question: how to react in both conflict and cooperation situations, as well as combined ones[34]. This idea pre-defines a condition that there must me at least two sides in a relation towards each other to talk about conflict/cooperation. In the game theory nomenclature, these are players; in reality these can vary depending on the situation. Starting with the basic association of two players leaning over a board or holding a deck of cards, through people going about their daily activities (regardless of how common/uncommon these are), until entire nature's living, selfish organisms and social groups that, nonetheless, influence other "players". Selfish is the keyword here – player's priority is his or her own interest.

The game theory assumes a rational behavior, i.e. one that will make the players situation better. They will design their tactics to earn as much as possible, therefore their motivation will be purely egotistical. The paradox is that even the altruistic players fit a certain model and can be classified as getting satisfaction from their own activities [35]. Two terms that will need further explanation are: modeling and winning.

A game, by definition, should guarantee a result (a payoff). The result is strictly connected with the level of player's satisfaction from participating in a game. The payoffs have a numerical value and are an example of reality modeling. Unfortunately, the complexity of payoff theory does not allow an in-depth analysis of all its aspects. If, for example, we were to portray a conflict situation between two entities, the number of variables (non-linear, in most cases), would obstruct the legibility of the model [36].

This introduces a new, highly important for the game theory term that needs defining – a strategy. A strategy is a set of rules, that if the point of reference for every possible situation during a game. In theory, each player's strategy is known prior to the game and the crossing of these yields a pre-defined result. In reality, the number of possible strategies, even for a simple game of chess, can be so big that finding the "optimal" one will not be possible anytime soon (even taking into consideration the advanced mathematical calculations and today's technology). We can risk a statement that even if we were presented with such a strategy (for example, by some intelligent life force not know to us), our memory capacity would make it impossible to store is, let alone use it without any aids. The example is to point out to the weight of the problem a gamer has to deal with.

The volume of literature on GT is overwhelming and presenting all the aspects of it will not be possible due to space limitations of this thesis. For that reason this chapter will focus on the basic aspects of GT and subjects, the knowledge of which will be required in the following chapters. The purpose of this chapter is also the systemization and detailing of GT formalism, which will be used in the chapters to come. One needs to start with some assumptions on GT[34]:

1. The rules of the game are precise, comprehensible and known to all players.
2. The players adhere to these rules.
3. There are between two and an infinite number of players.
4. The game consists of moves performed at the same time (simultaneous game), or one at a time (sequential game); the number of moves is finite.
5. Each player has a set of strategies (finite or infinite). In theory, a game is restricted to choosing between strategies by each player. A choice of strategy can be a probability of selection among the subsets of strategies. What is means is that the player and their opponents do not know which strategy they will choose – this will be dictated by the chance.
6. After the game ends, each of the players gets s certain result, its value being numerical and described by means of payoff functions.

Games can be differentiated depending on[34]:

1. Random situations – if there's at least one random situation that influences the outcome, we can talk of nondeterministic games, as opposed to deterministic games; deterministic games are the only ones that it is possible to foresee the outcome of, provided that we know the strategies of all players.
2. Number of moves – in one-step (simultaneous) games, but also in multi-step (a collection of sequential and simultaneous.
3. Completeness of information – the minimal information a player should have is the knowledge of his or her own payoff function. This is called playing a game with hidden information. When a player knows the entire set of strategies (their own and other players'), as well as the position they occupy in

a game, one can talk of a game with complete information. If the players additionally know the payoff functions of other players, the history of random moves and their outcome (both their ant the other players'), one can talk of having complete information.

4. Cooperation elements – competition games are those where the win of one player has to be proportional to the loss of the other player(s). These games are zero-sum or constant-sum games. Cooperation games are those, in which players use their strategies to gain as much as possible, without worsening the condition of other players.

4.1.1 Iterated Game Theory

An iterated game is an extensive form game that consists in some number of repetitions of some base game[37]. The stage game is usually one of the well-studied 2-person games. It captures the idea that a player will have to take into account the impact of his current action on the future actions of other players. Unlike a game played once, a repeated game allows for a strategy to be contingent on past moves, thus allowing for reputation effects and retribution. In infinitely repeated games, trigger strategies such as tit for tat can encourage cooperation.

4.1.2 Spatial Game Theory

Spatial game theory is an extension model of evolutionary games that is the application of game theory to evolving populations of life forms in biology. Prisoner's Dilemma is widely employed metaphor for problems associated with the evolution of cooperative and defective behavior. In spatial game, players are classified into pure cooperators or pure defectors that interact with neighbors in some spatial array. In each generation, players add up the scores from all encounters and in the next generation a given cell is retained by its previous owner or taken over by a neighbor, depending on the rule. The spatial game can generate self-organized spatial patterns (static or dynamic) in which cooperator and defector both persist indefinitely.

4.2 Strategy Generation and Development

This research aimed to find the best strategy in delivering necessity items to the disaster victims through lateral transshipment of relief inventory. We use an approach of a spatial version of Prisoner's Dilemma in game theory. A dilemma occurs when an inventory location (shelter) want to help their neighbors. If they share their stock, they sacrifice their own stock. On the other hand, if they don't share their stock, they lost a chance to receive help in the future.

Inventory at each shelter is a player in spatial game theory. Each player tries to maximize gain or minimize loss by changing strategy dynamically. Central warehouse play important role as a main supplies of all necessity items delivered to each shelter, but not behave as player. Central warehouse does not try to increase its gain or decrease loss during the relief operation. It receives all necessity items from donor and distribute to each shelter periodically. Periodic delivery is the best option for relief inventory since information about inventory level of each shelter is unreliable. The amount to be delivered (see equation 4.1) for each shelter depends on its demand rate (d), delivery period (RP), delivery lead-time (LT), and safety stock (SS). That equation is derived from basic theory of inventory especially *periodic order review inventory system* [29]. At the beginning of the disaster response period, central warehouse sourcing capacity does not match with the overall demand. Demand of the necessity items come sharply at the few hours after disaster. Some of the demand can be satisfied with pre-positioning inventory. Since the number of donors increase after disaster, the sourcing capacity (SC) of the central warehouse increase exponentially following a logistic growth function [38] Equation 4.2 shows the implementation of logistic growth function into sourcing capacity formulation.

We propose inventory related cost [29] as a the performance measure such as procurement cost, transportation cost, holding cost, and "stock out" cost. Procurement cost or buying cost is a cost to buy the necessity items for disaster victims (See Equation 4.3). Furthermore, transportation and holding cost is a cost to deliver the necessity items to each shelter and a cost to keep those items for later consumptions (See Equation 4.4 and 4.5). Lastly, "stock out" cost is occurred when the shelter don't have any items left in stock (See Equation 4.6). In enterprise, this cost is frequently called opportunity cost. In disaster situation, "stock out" related with the amount of suffered that the disaster victim have to accept due to inexistence of the necessity items. This cost is positioned as the highest priority in disaster case and we would like to minimize it as much as possible. Unbalance level of inventory between shelter leads to high "stock out" cost. We assume that there is free cost for acquiring and transporting the information from each shelter to the central warehouse.

$$TargetDelivery = d_t(RP + L) + SS \tag{4.1}$$

$$SC_t = SC_{t-1} + IncreaseRate * SC_{t-1}\left(1 - \frac{SC_{t-1}}{Max.Cap}\right) \tag{4.2}$$

$$ProcurementCost = SetupCost + NumberOfBoughtItems * PriceEachItem \tag{4.3}$$

$$TransportationCost = NumberOfTrip * CostEachTrip \tag{4.4}$$

$$HoldingCost = NumberOfStoredItems * HoldingRate \tag{4.5}$$

$$StockOutCost = NumberOfStockOutOccurence * StockOutCostEachOccurence \tag{4.6}$$

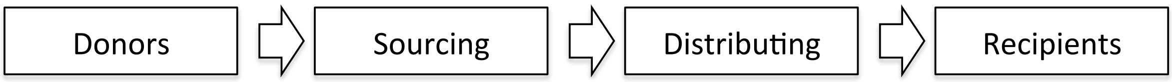

Figure 20. Relief inventory chain

Our proposed model of relief inventory with lateral transshipment works as follow

1. Every delivery period (RP), central warehouse calculate their sourcing capacity and decide the amount of inventory (TI) that should be delivered to each shelter. If the amount of inventory exceeds sourcing capacity of the central warehouse, the amount of inventory is adjusted to the sourcing capacity. At this step we calculate procurement cost and transportation cost.
2. On each delivery period, each shelter distributes their stocks to disaster victims. At this step we calculate "stock out" cost.
3. After receiving items from central warehouse, each shelter decides to help the other shelter or not help depending on their strategy scheme. This is the lateral transshipment operation of relief inventory. We calculate the effectiveness of each strategy scheme (without, with, and partial lateral transshipment) with some performance measures such as number of shelter having enough amount of inventory, total cost of inventory (procurement, transportation, holding, and stock out cost), and number of trip.
4. The central warehouse revised the amount of delivery for next period based on transporter information.

Since the information about inventory level of each shelter and its action in disaster response period is difficult to acquire, we assume the information flows trough the transporter (trucks and volunteers). The problem in this situation is credibility of that source of information. In other word, we need to evaluate whether the transporter is trusted (value=1) or not (value=-1). We assign random credibility (*$0 \leq R \leq 1$*) for each transportation vehicle and calculate its trust (Tr) as shown at Equation 7. The information is received from the transporter such as trend of demand (increase, decrease, same) and the shelter choice of action (help or not help). We make about 10% adjustment to the periodic amount of delivery based on that trust value (See Equation 4.8). This amount of adjustment comes from the maximum variability of the demand of volcanic eruption disaster in Indonesia[22]. If the transporter is trusted, the information is taken without modification. Oppositely, if the transporter is untrusted, the information is taken with modification. We took the opposite decision if the transporter is untrusted and took the same decision is the transporter is trusted for example the untrusted transporter informs that the demand is increase for the next period, then we decrease the demand. We assume that the information itself is reliable.

$$Tr = \begin{cases} -1, R < 0.5 \\ 1, R \geq 0.5 \end{cases} \tag{4.7}$$

$$TargetDelivery = \begin{cases} (d_t(RP + L) + SS) * (1 - 0.1 * Tr), d_t < d_{t-1} \\ (d_t(RP + L) + SS) * (1 + 0.1 * Tr), d_t > d_{t-1} \\ (d_t(RP + L) + SS), d_t = d_{t-1} \end{cases} \tag{4.8}$$

In general, each shelter chooses between help (C) and not help (D) based on their neighbor condition. In game theory, this is commonly called totalistic spatial strategy[39]. Each shelter knows the selected action of their neighbor based on their past action. We limit number of neighbors into four (Von Neumann neighborhood) as shown at Figure 4.3. To represent a strategy, a bit sequence of 5 elements is used whose *n* represents number of D and *(5-n)* represents number of C. This strategy focuses on generosity of the system or how many D actions in the neighbor are tolerated[39]. The *nD* strategy means the shelter should take C if the number of D in the neighbors is more than *n* and vice versa. For example strategy *3D* means maximum number of D in the neighbors is 2. If we apply this strategy to the neighbor's condition shown in Figure 3, the center shelter should take C to prevent number of D is exceeding 3.

4.2.1 Without Lateral Transshipment Scheme. The performance of this scheme becomes reference for the other scheme. In this scheme, lateral transshipment option will be eliminated so each shelter does not have any interaction with the other shelters. Each shelter receives necessity items from central warehouse for their own usage. This scheme represents selfish behavior of the shelters. The relief inventory model based on this scheme is similar with the enterprise inventory model especially the *periodic order review* model.

4.2.2 With Fully Lateral Transshipment Scheme. This scheme works oppositely with the previous scheme (without mutual support scheme). In here, lateral transshipment is fully utilized. Each shelter tries to help the other shelter with its maximum abilities. This means every times the shelters receive necessity items from central warehouse, they directly send some of the stock to help the other shelter. We set the probability of help is equal to one in this scheme. Even lateral transshipment is used in this scheme; information about condition and status of the other shelter is not necessary since the helping process is conducted without knowing other's information. This scheme may reveal the negative effect of the lateral transshipment in relief inventory operation.

4.2.3 Partial Lateral Transshipment Scheme

4.2.3.1 Maximum Payoff Strategy. In this scheme, each shelter calculates its payoff after deciding action to help (C) or not help (D). We choose inventory level as the shelter's payoff because the main goal of relief inventory located at each shelter is providing necessity items to disaster victims whenever they need. High inventory level implies high ability of providing such items when needed. Every *r-th* time, each shelter is allowed to change the strategy similar with the highest payoff neighbor's strategy. For example, if the highest payoff between four shelter neighbors is the neighbor positioned at right side with strategy 2D, then the center shelter will change strategy into 2D.

4.2.3.2 Static Support Strategy. In this scheme, we assume each shelter has a constant tendency of helping (Pr). If the tendency of helping is low, the strategy of each shelter will shift to more generous or allow more D in the neighborhood. For example if shelter strategy is 2D and Pr=0, in the next delivery period that shelter will change strategy into 3D. This mean number of D in the neighborhood increases by 1. In extreme setting, if Pr=0 then at the end of disaster response period, all shelter's strategy will become 5D and all shelter will choose not help (selfish). On the other hand, if Pr=1 then at the end of disaster response period, all shelter's strategy will become 0D and all shelter will choose help (altruism). Different with maximum payoff scheme, this scheme does not utilize information of other shelter' action in order one shelter change its strategy. Opposite with the without lateral transshipment scheme, this scheme represents some of the altruism behavior. Each shelter tries to help the other neglecting its own condition.

4.2.3.3 Dynamic Support Strategy. This scheme is similar with static support scheme in term of tendency of helping (Pr) usability. The difference is Pr in this scheme is not static trough the time. The value of Pr is changing when the level of inventory in each shelter change. We propose the basic rule that if the level of inventory increase, the value of Pr increases linearly and vice versa. This proposal based on the philosophy that the rich person should help more then the poor ones. This scheme also focuses on the self-information and do not utilize information of the other shelter's action.

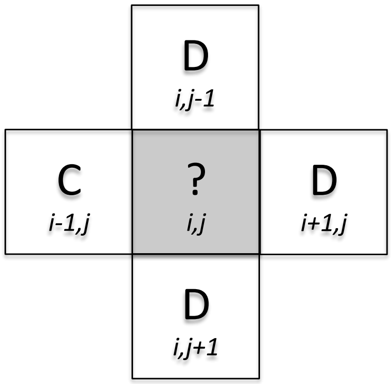

Figure 21. Shelter's action

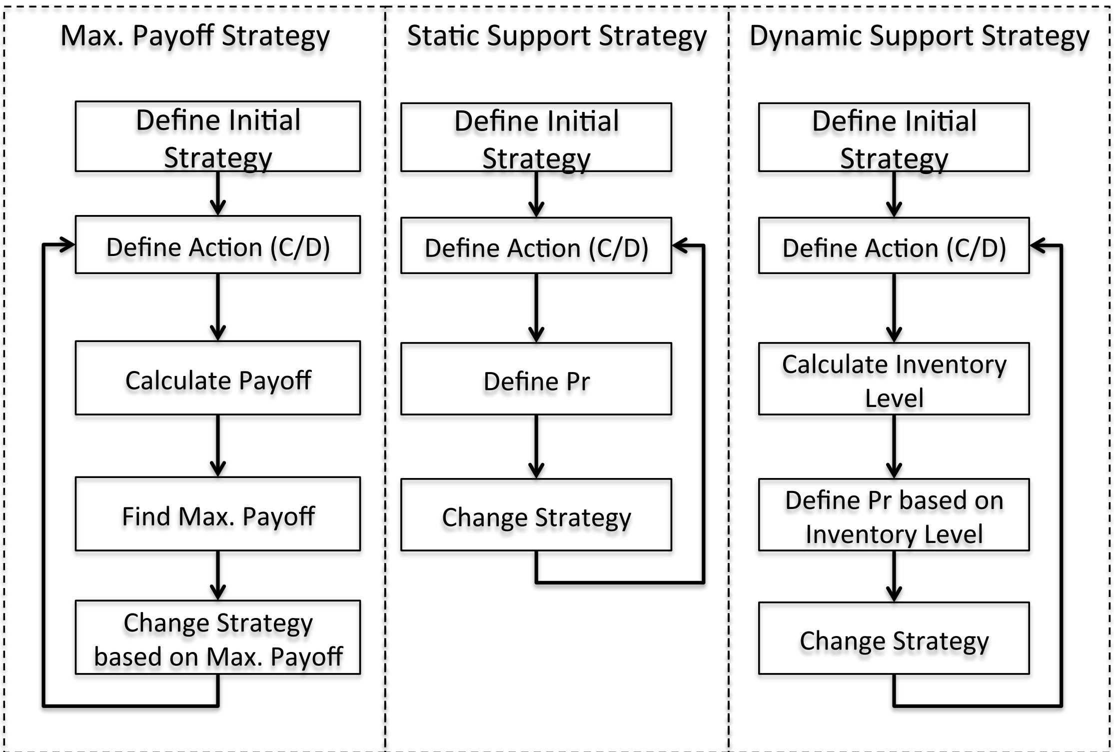

Figure 22. Partial lateral transshipment strategy

In order to change strategy, the last two strategy focuses on the self-information while the maximum payoff scheme focuses on the neighbor's information. From practical point of view, the last two schemes are more applicable in disaster situation since they do not require a lot of neighbor's information that might be difficult to acquired. But the maximum payoff scheme still practical under an assumption that the past action of each shelter is informs by the transporter or other media. The possible media in disaster response is trough items transporters, government officers, volunteers, firefighters, ambulances, police, eyewitnesses, etc. The main difference between the last three strategies is shown at Figure 21.

4.3 Performance Review and Evaluation

In this section, we will implement our proposal into real case of disaster. In September 2013, one of the active volcanoes in Indonesia (Sinabung Mountain) erupted. Many thousand people living in radius 10 km from the mountain have to evacuate to the predetermined shelters. The local government provides 30 safety shelters to the evacuees and provides life support items for them. The detail data of each shelter and evacuees during December 2013 is shown at Table 1[22]. Even though the disaster occurs for more than 3 months, we pick up data at December 2013 as a representative data for disaster evacuees.

The government faces difficulty in providing the life support items for disaster evacuees since the number of evacuees change dynamically each day and difficult to predict. Some evacuees like to move from one shelter to the others and sometime they went back to their own home to safe their precious wealth even though the condition is dangerous. Number of evacuees will certainly affect the demand rate of relief inventory planning. Due to management problem, it is difficult to track and calculate the exact number of current inventory. Also in this type of disaster, some of the infrastructure was damaged but there is still chance to deliver life support items to each shelter trough small capacity transporter.

There are a lot of life support items needed by disaster evacuees such as food, clothes, water, medicine, blanket, etc. In this paper, we modeled the delivery process of ready to eat therapeutic food (RUTF) items, plumpy soy[40], for disaster response. We ran the simulation over 90 days with time interval 1 day. The actual length of the disaster response phase is varied depending on the type and magnitude of the disaster, but some organization consider it to last up to 90 days[41]. Using the information provided on Nutriset's website, we able to quantify the number of sachet needed to serve the needs of the disaster evacuees at Table 3. Each person needs 2 sachet of plumpy soy everyday. We will simulate the relief inventory operation for each scheme with the initial inventory level and input parameter listed in Table 4 and Table 5, respectively. The initial inventory level value is also maximum inventory level as a result of pre-positioning inventory. We got purchasing price from Nutriset's website with Euro currency. Another cost parameters use average cost practice in Indonesia such as setup cost, holding cost, transportation cost, and stock out cost. We do simulation of 3 strategic schemes such as (1) without lateral transshipment, (2) with fully lateral transshipment, (3) partial lateral transshipment: maximum payoff strategy, static support strategy, and dynamic support strategy.

Table 4 summaries the performance of relief inventory system (in term of number of shelter having normal inventory level), number of trip and total cost for each scheme. The performance is measured by accumulation of the inventory status during disaster response. Inventory status is divided into 3 types such as *normal* (value = 1), *abnormal* (value = 0), and *need help* (value = -1). The inventory is said to be "*normal*" if the amount of stock is above the normality threshold (see Table 3 for the threshold). Furthermore, the inventory is said to be "*abnormal*" if the amount of stock is below the normality threshold but above the safety stock (SS) level. In addition, the inventory is said to be "*need help*" if the amount of stock is lower than the safety stock (SS). If all the shelters have normal inventory level during disaster response period (90 days), the value of the normal shelter will be 2700 (maximum performance).

We run simulation for disaster response period (90 days) and the results is an average of 100 similar trials to avoid the effect of random number. As we can see from the summary shown at Table 6, the first scheme (without mutual support) consumes quite low cost of operation but gains the worst performance compared with the other scheme. Oppositely, the second scheme (with fully mutual support) gains almost the highest performance level but consumes the highest cost of operation compared with the other scheme. The performance of the last scheme is in between the performances of the first two. It can be seen clearly that the second scheme leads to the highest level of performance but consume the highest cost. The scheme that leads to the lowest cost is the third strategy of the third scheme (maximum payoff) even though the performance is considerably low. In addition, the performance of the static support strategy of the third scheme is in between the first two schemes since the probability of the helping is 0.5. The best performance is shown by the last strategy of the third scheme. It gains the almost similar performance with the second scheme's performance but with less cost and less number of trip. The fluctuation of performance (in term of number of shelter having normal inventory level), number of trip, and total cost for each day of all scheme are shown at Figure 22, 23, 24 respectively.

Table 3. Evacuees of sinabung mountain eruption

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

Table 4. Number of normal unit, number of trip, and accumulated cost of relief inventory (1: without mutual support, 2: with fully mutual support, 3: max payoff strategy, 4: static support strategy, 5: dynamic support strategy)

	1	2	3	4	5
Number of Normal Unit	1521	2360	1525	1977	2271
Number of Trip	540	2656	1381	1779	2285
Total Cost	36346000	41216000	37346000	39300000	41082000

Table 5. Initial Inventory Level

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

Table 6. Input parameter for simulation

Parameter	Value
Time interval	1 day
Warehouse capacity increase rate	0.8
Warehouse initial processing capacity/day	3000
Warehouse maximum processing capacity/day	10000
Delivery period (RP)	5 days
Safety stock	10% of max. level
Lead time	1 day
Setup cost	100
Price/item	6.96
Cost/trip	0.734
Holding cost/item/day	0.0048
Cost/stockout	27.84
Normality threshold	above 0.5
Proportion shared by normal unit	0.2
Proportion shared by abnormal unit	0.1
Probability of help	0.5

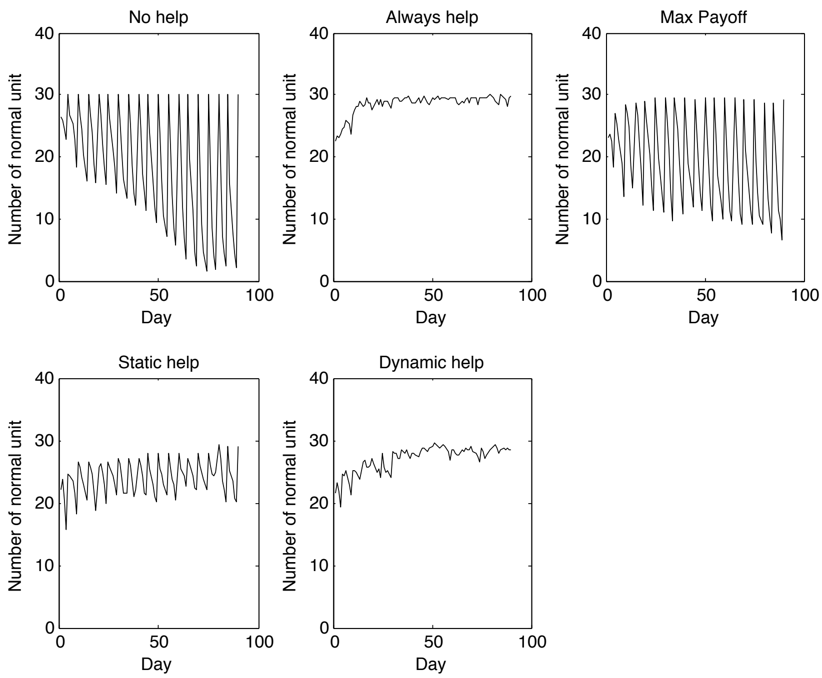

Figure 23. Performance of relief inventory measured by number of normal unit

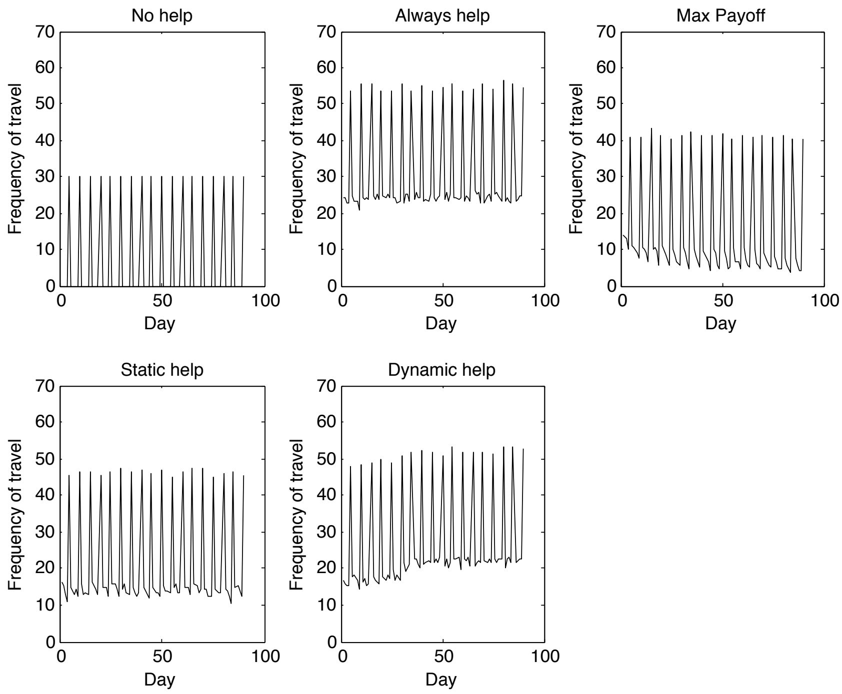

Figure 24. Number of trip of relief inventory

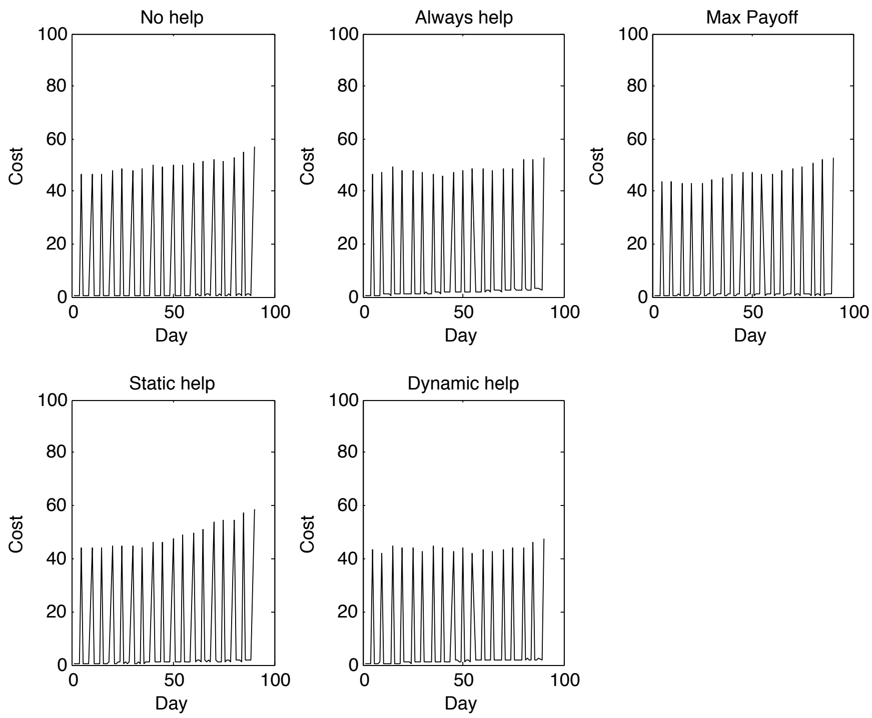

Figure 25. Total cost of relief inventory in 10^4 scales

Based on such result, we recommend using the last strategy of the third scheme for relief inventory strategy since this scheme lead to the high performance and considerably low cost compared with the second scheme. This scheme is also simple in implementation. The person in charge of the inventory is simply estimate level of inventory and decides to help or not help according to the inventory level. The higher level of inventory leads to the higher possibility of help. In some cases, if cost is limited for relief inventory, the second strategy of the third scheme can be a good solution even though that scheme cannot lead to the best performance. We simply choose the probability of helping based on the financial condition. Good financial condition leads to higher probability of helping.

4.4 Concluding Remarks

This paper successfully built a relief inventory model with lateral transshipment under condition of low credibility information. Mutual help with lateral transshipment during disaster response has certainly leaded to positive impact of relief inventory performance. Based on the criteria of performance and cost, the best scheme in mutual help is dynamic support strategy of partial lateral transshipment scheme that rely its action on the self-information. In the simulation, it is proven that decision based on low credibility information will lead to worse performance as shown in maximum payoff scheme. In addition, decision based on static mutual help lead to average performance level of the relief inventory system. The performance of the dynamic support strategy of partial lateral transshipment scheme outperforms the performance of the selfish behavior (without lateral transshipment scheme) and having similar performance with the altruism behavior (fully lateral transshipment scheme). It can be concluded that neither the selfish nor the altruism behavior that lead to the best performance, but the behavior in between of them.

This model is practically applicable to be used in relief inventory planning under low credibility information sources since it focused on self-information. Future development of this research can be directed to the optimization of model parameter, integration with the disaster mitigation planning allowing interaction of all shelters in the system.

5 Clustering Inventory Location to Improve the Performance of Disaster Relief Operation

5.1 Clustering Theories

Clustering or cluster analysis is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar to each other than to those in other groups[42]. Clustering is often confused with classification, but there is some difference between the two. In classification the objects are assigned to pre defined classes, whereas in clustering the classes are also to be defined. Clustering is used in many fields, including data mining, text mining, information retrieval, statistical computational linguistics, machine learning, pattern recognition, image analysis, information retrieval, and bioinformatics. Various algorithms that differ significantly in their notion of what constitutes a cluster can build cluster analysis.

One of the oldest methods of cluster analysis is known as k-means cluster analysis, and is available in R through the k-means function. The first step (and certainly not a trivial one) when using k-means cluster analysis is to specify the number of clusters (k) that will be formed in the final solution. The R cluster provides a modern alternative to k-means clustering (known as pam) which is an acronym for "Partitioning around Medoids". Another class of clustering methods, known as hierarchical agglomerative clustering methods (connectivity based clustering), starts out by putting each observation into its own separate cluster. It then examines all the distances between all the observations and pairs together the two closest ones to form a new cluster.

There are certain problem encountered with clustering algorithms: dealing with a large number of dimensions and a large number of objects can be prohibitive due to time complexity, the effectiveness of an algorithm depends on the definition of similarity, the outcomes of an algorithm can be interpreted in different ways.

5.2 Stable Roommate Problem

The Stable Marriage problem (SM), the Hospitals/Residents problem (HR) and the Stable Roommates problem (SR) have been studied extensively in the matching literature. Gale and Shapley (1962)[43] show that stable matching exist in every instance of marriage problem by adopting the “deferred acceptance algorithm”. A stable matching problem consists of a group of agents, and, for each agent, a preference list over those agents with whom he may be matched [44]. Stable matching problems can be defined to allow or disallow ties in the preference lists. When ties are allowed, stability is defined as the absence of an unmatched pair of agents that strict and prefers each other to their assigned mates. The roommate problem involves a single set of *n* agents where each agent having a preference lists over the other *n - 1* agent. An efficient algorithm to constructively determine for any instance of the roommate problem without ties whether a stable assignment exists (and if one exists to determine one) has recently been discovered by Irving [45].

5.3 Preference Generation and Cluster Formation

In disaster relief operation, most of the evacuees live in the shelters that are provided by government, NGO, and other organizations. These shelters are spread along the concentration of citizen population in the city, so that, distances between shelters is varied. In each shelter there are storage of life support items such as food, medicine, clothes, blanket, tent, etc. The government and any other stakeholder of disaster will regularly send those items to each shelter based on its level of inventory and demand rate. Those two parameters are difficult to predict after disaster. Evacuees come and go from the shelters freely, and the administrative action during chaotic condition after disaster made coherency between recorded parameters and the actual ones is questionable.

Each management of the shelter has an authority to deliver their excessive items to neighboring shelters (called inventory lateral transshipment). The purpose of this delivery is to support other shelters in need of life support items. The amount of delivery is based on its altruism level (willingness to help), that is, some of them deliver a large amount and the others deliver less. However, this action can lead to worst performance level since the information of inventory level and demand rate of each shelter is unknown to the others. In other cases, that information is known with low reliability due to information's infrastructure damage and chaotic condition right after disaster event.

In our model, first, we collect the data of shelter's parameter mentioned before: inventory capacity, demand rate, distances, and support level before disaster (mitigation period). Even though demand rate and support level is dynamically changes, we assume that those two parameters are constant along the disaster recovery period. Furthermore, we generate initial cluster using single linkage cluster algorithm [46] that categorized as hierarchical cluster method or connectivity based clustering. We use minimum distance between shelters as a basis for calculating clusters, so that, nearby shelters will be put into one cluster. Lastly, we refine cluster formation by evaluating its stability (based on stable roommate criteria). If it is found that initial cluster formation is not stable, we refine cluster formation using stable roommate algorithm until stability is achieved. There is a possibility that we cannot find stable cluster. In this situation, we use initial cluster for the input of lateral transshipment system. Figure 2 shows detail flowchart of our proposal.

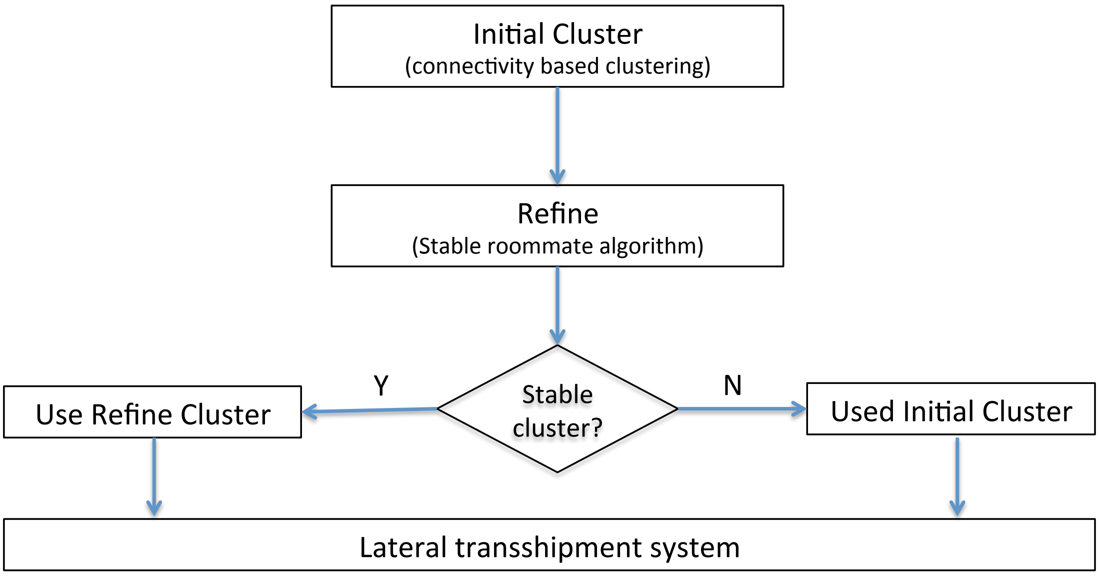

Figure 26. Proposed cluster formation logic

Following steps show the algorithm of single linkage cluster or nearest neighbor clustering [46]

1. Decide number of member n in each cluster.
2. Each shelter is in its own cluster.
3. The cluster is then sequentially combined into larger cluster by adding the shortest distance shelters into it. Formula 1 shows the Euclidean distance between shelters.
4. Stop the cluster formation if number of member inside cluster reaches n.

$$D(X, Y) = \min_{x \in X, y \in Y} d(x, y) \tag{5.1}$$

Initial cluster is necessary in case the refinement step doesn't have stable result. Following steps show the modification of Irving's algorithm [44] for determining stability and modified cluster members

Prepare preference table for each cluster shelter's member. The preference is calculated from accumulation of four score: distance score, inventory capacity score, demand rate score, and level of support score.

Create a reduced table using Gale Shapley algorithm of stable marriage problem [43] by proposing-rejecting procedures. The reduced table shows matching between members and is called stable matching when each member hold proposal from another member.

If stable matching is found, continue to rotation elimination of Irving's algorithm[44]. Otherwise, use initial cluster as input to lateral transshipment system.

After rotation elimination, if stable matching is found, use current matching as a new cluster and use it as input to lateral transshipment system. Otherwise, initial cluster should be used as input to lateral transshipment system.

The preference table for each shelter's member is calculated from each score (Formula 5.2 – 5.5) and is derived into preference (Formula 5.6 – 5.9). The score of support level is constant trough out the time. It is noted that the preference level of each shelter toward others is not linear and sometime opposite with the score. The rules for defining preference of a shelter toward others are

Preference to distance is opposite with the distance score (Formula 5.6). When shelter A and shelter B have high distance score, the more reluctant both of the shelters to be in one cluster.

If the shelter has high score of inventory capacity, it prefers shelter that has low score of inventory capacity and vice versa (Formula 5.7).

If the shelter has high score of demand rate, it prefers shelter that has high score of demand rate and vice versa (Formula 5.8). In this situation, the shelter that has high demand rate can get support from the others that has low demand rate.

Each shelter is willing to have a partner (inside cluster) that has high willingness to support others (Formula 5.9). This means that probability of help and getting help between them is high.

$$ScoreOfDistance(x,y) = \frac{distance(x,y)}{maxDistance} \quad (5.2)$$

$$ScoreOfInventoryCapacity(x) = \frac{InventoryCapacity(x)}{maxCapacity} \quad (5.3)$$

$$ScoreOfDemandRate(x) = \frac{DemandRate(x)}{maxRate} \quad (5.4)$$

$$ScoreOfSupportLevel(x) = constant \quad (5.5)$$

$$PreferenceOfDistance(x,y) = 1 - ScoreOfDistance(x,y) \quad (5.6)$$

$$PreferenceOfInventoryCapacity(x,y) = \begin{cases} ScoreOfInventoryCapacity(y) | ScoreOfInventoryCapacity(x) < 0.5 \\ 1 - ScoreOfInventoryCapacity(y) | ScoreOfInventoryCapacity(x) \geq 0.5 \end{cases} \tag{5.7}$$

$$PreferenceOfDemandRate(x,y) = |ScoreOfDemandRate(y) - ScoreOfDemandRate(x)| \tag{5.8}$$

$$PreferenceOfSupportLevel(x,y) = |ScoreOfSupportLevel(y) + ScoreOfSupportLevel(x)| \tag{5.9}$$

In this research, we limit the maximum number of shelter's member in one cluster into 2. In the lateral transshipment system, a member in one shelter's has priority to get support from other members. There is a chance for the shelter outside the cluster to get support but the priority is much lower compared with the shelter's member inside the cluster. Priority of support between inside cluster's member and outside cluster's member can be represented as percentage of time that lateral transshipment operation applies on it. This percentage is one the important parameter we are looking for in this research. Zero percentage reflects the lateral transshipment operation without preliminary cluster generation (similar with model in paper[46]).

5.4 Incorporate Cluster into Relief Logistic and Inventory Operation

Each natural disaster has unique characteristics in term of it possible occurrence and post disaster effects. The main differences between disasters are the coverage area and the level of impact. It is already known that short period after disaster, the demand increases suddenly and stabilizes after that period. The lateral transshipment system cannot be applied to that short period after disaster because there is not enough time to respond the huge increase of demand. In addition, the focus of the disaster relief operation at that time is evacuating the disaster victim from dangerous areas. The only way the humanitarian disaster's stakeholder can do to provide necessity items for the evacuees is trough pre-disaster inventory storage.

The lateral transshipment system in disaster relief logistic and inventory is applicable after that short demand peak period. Furthermore, the benefit of lateral transshipment system is come into account where the demand is dynamically changes due to continuity of disaster occurrence. The example of that disaster types are flood, fires, and volcano eruption. The evacuees of this disaster types have a tendency to return home for checking or saving their remaining asset while there is a possibility that the disaster occurs again. Hence, the number of evacuees in the evacuation shelters changes dynamically that affect the actual demand. In addition, limited information and poor management of inventory deviate the demand prediction

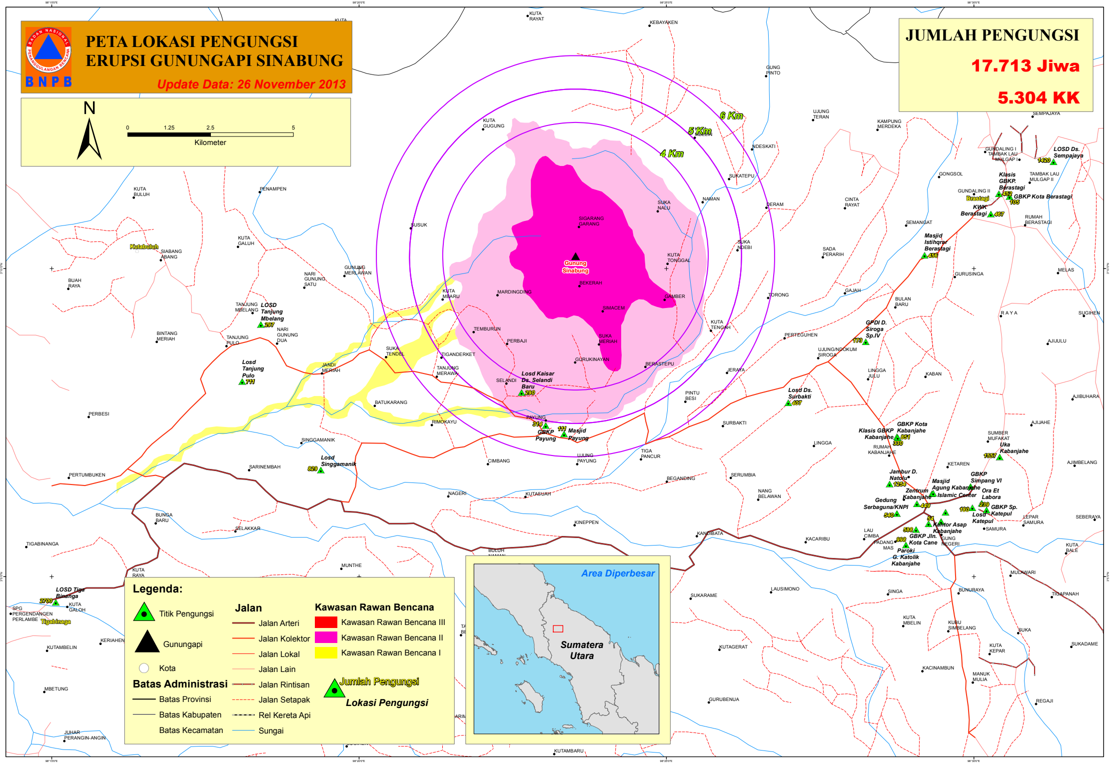

Figure 27. Shelter's location of Sinabung Volcano eruption in North Sumatra Indonesia on 2013 [47]

In this research, we used a volcanic eruption case that occurs in Indonesia, for validation purposes. In the end of 2013, one of the active volcanoes located in North Sumatra Indonesia erupted; causing thousand people leave their home and suffer. The local government and NGO prepare 30 public spaces as an evacuation shelter for the disaster victims. Figure 3 illustrates the location of each shelter. A few of them are located nearby the mountain area and the rest are located quite far. Since the eruption is occurring for several months, we select sample data of evacuees in the peak months (November 2013). Table 7 shows the average and deviation of the number of evacuees for all shelters within that month. In order to show the calculation steps clearly, we further pick up first tenth of the shelter data. The distance, in meter unit, between shelters is shown at Table 8.

As illustrated at Figure 25, the first step of lateral transshipment system is formation of initial cluster by nearest neighbor algorithm. In this algorithm, we need to calculate the distance between shelters, short those distances, and search from the top of the list, the possible cluster member. Merge the member having closest distance into one cluster.

Appendix A shows the cluster formation using the nearest neighbor algorithm. The result of clustering is presented at Table 9. This algorithm doesn't guarantee that the total distance between all cluster members is the minimum ones. From that table, if we change the cluster member such as: 4 with 8 and 1 with 7, we will got the lower total distance between members.

The next step, according to Figure 25, is to calculate score (using Formula 5.2 – 5.5) of four parameters: distance, inventory capacity, demand rate, and support level. Further, those scores are converted into preferences score using Formula (5.6 – 5.9) and further change into preference list by simply sorting the value. Based on this preference, we find out stable partner of each shelter using proposing and rejecting process of stable roommate algorithm[44]. The result of the cluster is shown at Table 4 and the detail calculation is shown at Appendix 2.

Table 7. Number of evacuees [22]

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

Table 8. Distance between shelters (unit in meter) [47]

		Shelter's Location									
		1	2	3	4	5	6	7	8	9	10
Shelter's Location	1	0	8860	10390	15690	15670	16520	8980	25660	25970	26100
	2	8860	0	1800	8530	8990	9700	3560	18690	19610	19720
	3	10390	1800	0	8230	8810	9570	4730	18190	19470	19570
	4	15690	8530	8230	0	1110	1630	6560	10270	11040	11190
	5	15670	8990	8810	1110	0	1000	6860	9960	10510	10650
	6	16520	9700	9570	1630	1000	0	7480	9490	9970	10050
	7	8980	3560	4730	6560	6860	7480	0	16890	17380	17440
	8	25660	18690	18190	10270	9960	9490	16890	0	3120	3110
	9	25970	19610	19470	11040	10510	9970	17380	3120	0	210
	10	26100	19720	19570	11190	10650	10050	17440	3110	210	0

Table 9. Initial cluster (nearest neighbor algorithm)

Cluster	Member	Distance (m)
A	9–10	210
B	5–6	1000
C	2–3	1800
D	4–7	6560
E	1–8	16520

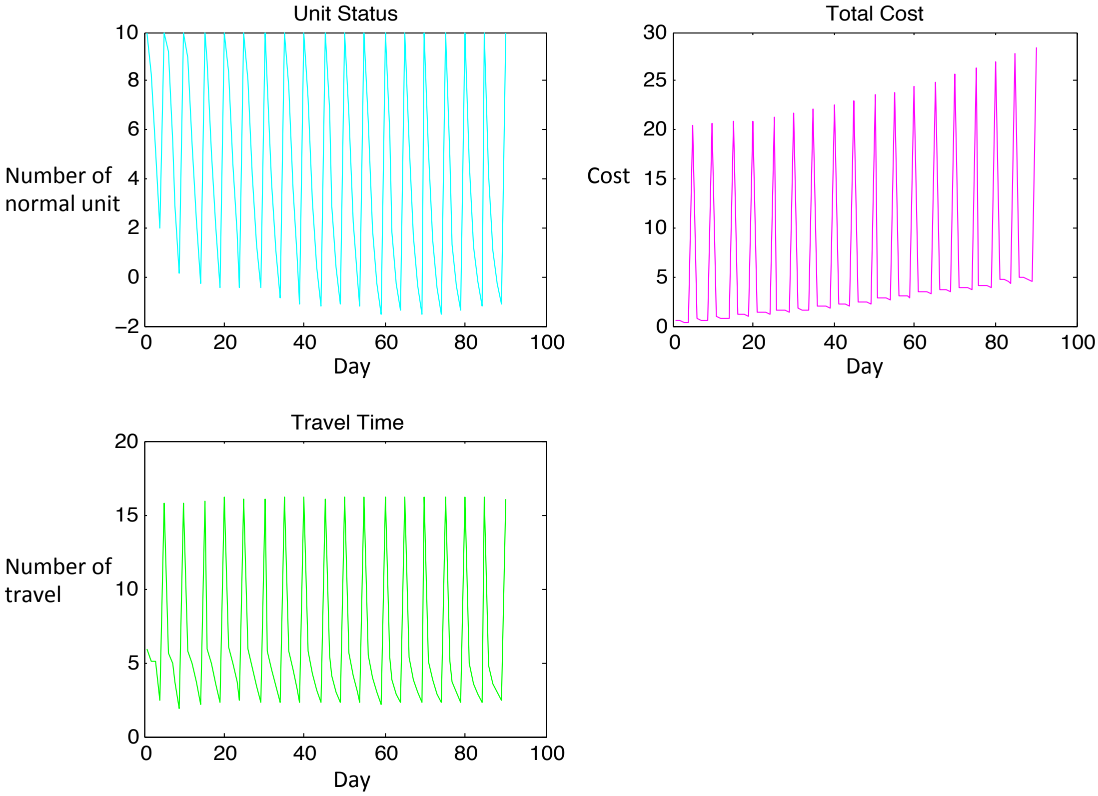

Figure 28. The lateral transshipment performance without clustering

Table 10. Refined cluster (Stable Roommate Algorithm)

Cluster	Member	Distance (m)
A	1–3	10390
B	2–4	8530
C	5–6	1000
D	7–9	17380
E	8–10	3110

Lastly, we implement the refined cluster into numerical simulation of lateral transshipment system. The setting of this simulation is shown at Appendix 2. The parameters that are used in simulation are related with the parameter of warehouse, shelter, and logistic operation between them. As illustrated in Figure 27, Figure 28 and

Table 11, there is a huge difference in total unit status between systems that is not using cluster (Figure 27) and using cluster (Figure 28). The unit status without cluster sometimes comes into stock out condition or don't have stock at all while the opposite ones always have stock. The total cost and travel time between these two systems are almost similar.

	Total Normal Unit	Total Cost	Total Travel Time
Without Cluster	381	625	572
With SRP Cluster	623	578	639

Table 11. Performance comparison (Without cluster vs. SRP cluster)

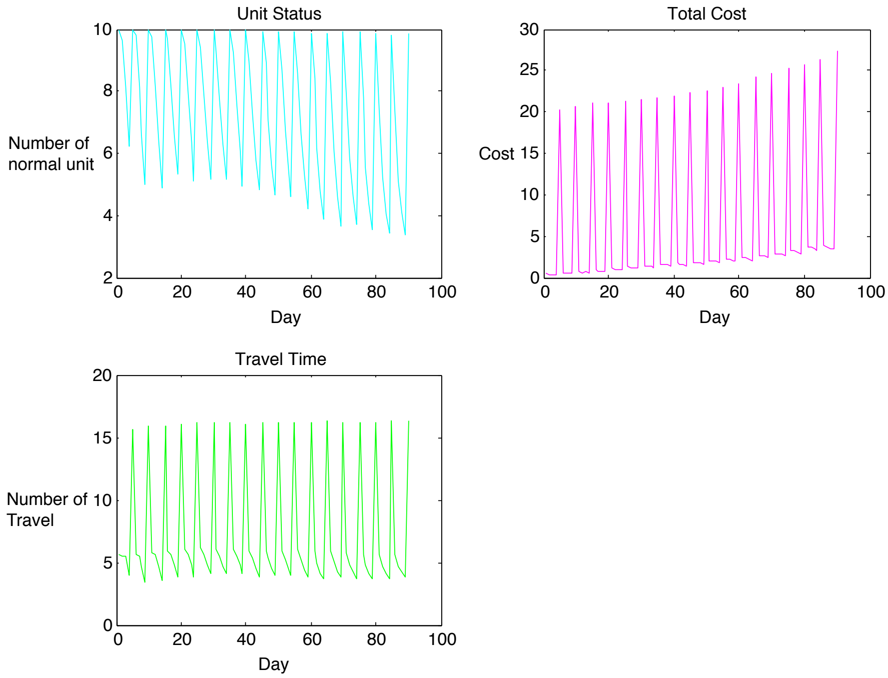

Figure 29. The lateral transshipment performance with clustering

5.5 Concluding Remarks

We successfully made a lateral transshipment model for relief logistic and inventory model using pre-cluster formation. Mutual help with lateral transshipment during disaster response has certainly contributed to positive impact of relief inventory performance. With cluster formation, the performance of lateral transshipment system for relief logistic and inventory is increase almost double compared with the regular lateral transshipment system. This is because each shelter focused on their activities to the cluster member and the credibility of information between members inside cluster can be improved.

Future development of this research can be directed to the optimization of model parameter, comparing other cluster algorithm, and allowing more members in one cluster.

6 Conclusion

6.1 Summary

We successfully built lateral transshipment model of relief logistics and inventory model based on probabilistic cellular automata, control it using spatial game theory, and boost the performance by making cluster of shelters. Even though the interaction of shelters in our model is limited to only few and closest neighbors, the model illustrates various important characteristics of lateral transshipment in relief logistics and inventory: the impact of lateral transshipment to overall system performance, condition where lateral transshipment works, the effects of lateral transshipment to the logistic and inventory costs, and the threshold of helping probability parameters in order to maximize the fraction of normal cells. The mandatory requirement for the success of lateral transshipment is enough number of inventory (on average) and enough number of transporters.

This model is suitable for disaster situations since it assumes that information on the inventory level and other logistics information is unknown or known with low credibility. Further research is required on the dynamic number of cells, delivery lead-time, and vehicle capacity constraints.

Based on the criteria of inventory level and costs of logistic and inventory, the best strategy scheme in lateral transshipment is dynamic support strategy that rely most of its action on the self-information. In the simulation, it is proven that decision based on low credibility information will lead to worse performance as shown in maximum payoff scheme. In addition, decision based on static mutual support lead to good performance level but difficult to implement since it force each shelter to support others every time. The performance of the dynamic support strategy outperforms the performance of the selfish behavior (without lateral transshipment scheme) and having similar performance with the altruism behavior (fully lateral transshipment scheme). In addition, neither the selfish nor the altruism behavior that contributes to the best performance, but the behavior in between of them.

With cluster formation at preparedness phase, the performance of lateral transshipment system for relief logistic and inventory is increase almost double compared with the regular lateral transshipment system. This is because each shelter focused on their activities to the cluster member and the credibility of information after disaster between members inside cluster can be improved.

6.2 Future Work

This model is practically applicable to be used in relief inventory planning under low credibility information and maximized local information. Future development of this research can be directed to the optimization of model parameter, comparison with other cluster's algorithm, further integration with other phase of disaster (mitigation, preparedness, and recovery), allowing interaction with all shelters in the system, and implement in other type of disaster.

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Appendix 1 – Formula Derivation

Equation 3.7

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

$$\begin{aligned} &transition\ probability\ of\ normal\ cell \\ &\quad = consumption\ probability\ (p_1) \\ &\quad + regular\ delivery\ of\ items\ from\ central\ warehouse\ (p_3) \\ &\quad - probability\ of\ helping \\ &\quad * (probability\ of\ state\ decrease\ due\ to\ giving\ help\ (p_5)) \\ &\quad - probability\ of\ state\ increase\ due\ to\ receiving\ help\ (p_7) \end{aligned}$$

$$\begin{aligned} &transition\ probability\ of\ abnormal\ cell \\ &\quad = consumption\ probability\ (p_2) \\ &\quad + regular\ delivery\ of\ items\ from\ central\ warehouse\ (p_4) \\ &\quad - probability\ of\ helping \\ &\quad * (probability\ of\ state\ decrease\ due\ to\ giving\ help\ (p_6)) \\ &\quad - probability\ of\ state\ increase\ due\ to\ receiving\ help\ (p_8) \end{aligned}$$

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

Equation 3.9

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

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

Equation 3.10

$$TC_s = probability\ of\ stock\ out * unit\ cost\ of\ stock\ out$$

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

Equation 3.11

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

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

Equation 3.12

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

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

Equation 3.13

$$TC = TC_s + TC_p + TC_t$$

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

Equation 3.14

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

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

Appendix 2 – Cluster Formation

Nearest Neighbor's Algorithm

Shelter No	Shelter No	Distance	Rank	Shelter No	Shelter No	Distance	Rank
9	10	210	1	4	8	10270	21
5	6	1000	2	1	3	10390	22
4	5	1110	3	5	9	10510	23
4	6	1630	4	5	10	10650	24
2	3	1800	5	4	9	11040	25
8	10	3110	6	4	10	11190	26
8	9	3120	7	1	5	15670	27
2	7	3560	8	1	4	15690	28
3	7	4730	9	1	6	16520	29
4	7	6560	10	7	8	16890	30
5	7	6860	11	7	9	17380	31
3	4	8230	12	7	10	17440	32
2	4	8530	13	3	8	18190	33
3	5	8810	14	2	8	18690	34
1	2	8860	15	3	9	19470	35
1	7	8980	16	3	10	19570	36
2	5	8990	17	2	9	19610	37
3	6	9570	18	2	10	19720	38
2	6	9700	19	1	8	25660	39
5	8	9960	20	1	9	25970	40
				1	10	26100	41

Stable Roommate Algorithm

(Absolute score)

Shelter	Distance	Inv. Capacity	Demand Rate	Support Level
1	0.633	1.00	1.00	0.90
2	0.069	0.40	0.27	0.77
3	0.069	0.20	0.14	0.78
4	0.251	0.15	0.11	0.53
5	0.038	0.10	0.12	0.16
6	0.038	0.10	0.04	0.47
7	0.251	0.15	0.17	0.21
8	0.633	0.10	0.07	0.54
9	0.008	0.20	0.13	0.03
10	0.008	0.50	0.36	0.05

(Score preference)

Shelter	1	2	3	4	5	6	7	8	9	10
1	0	3.66	3.94	3.57	3.24	3.6	3.45	3.29	2.6	2.09
2	3.66	0	2.81	2.28	1.84	2.2	2.09	1.89	1.39	1.65
3	3.94	2.81	0	2.17	1.72	2.08	1.99	1.79	1.27	1.8
4	3.57	2.28	2.17	0	1.76	2.11	1.7	1.82	1.36	1.9
5	3.24	1.84	1.72	1.76	0	1.77	1.31	1.47	1	1.54
6	3.60	2.20	2.08	2.11	1.77	0	1.67	1.78	1.41	1.95
7	3.45	2.09	1.99	1.7	1.31	1.67	0	1.3	0.81	1.28
8	3.29	1.89	1.79	1.82	1.47	1.78	1.3	0	1.71	2.26
9	2.60	1.39	1.27	1.36	1.00	1.41	0.81	1.71	0	1.8
10	2.09	1.65	1.80	1.9	1.54	1.95	1.28	2.26	1.8	0

(Preference list)

Shelter	1	2	3	4	5	6	7	8	9	10
1	0	3.66	3.94	3.57	3.24	3.6	3.45	3.29	2.6	2.09
2	3.66	0	2.81	2.28	1.84	2.2	2.09	1.89	1.39	1.65
3	3.94	2.81	0	2.17	1.72	2.08	1.99	1.79	1.27	1.8
4	3.57	2.28	2.17	0	1.76	2.11	1.7	1.82	1.36	1.9
5	3.24	1.84	1.72	1.76	0	1.77	1.31	1.47	1	1.54
6	3.60	2.20	2.08	2.11	1.77	0	1.67	1.78	1.41	1.95
7	3.45	2.09	1.99	1.7	1.31	1.67	0	1.3	0.81	1.28
8	3.29	1.89	1.79	1.82	1.47	1.78	1.3	0	1.71	2.26
9	2.60	1.39	1.27	1.36	1.00	1.41	0.81	1.71	0	1.8
10	2.09	1.65	1.80	1.9	1.54	1.95	1.28	2.26	1.8	0