



## System Dynamics Analysis for the Impact of Dynamic Transport and Information Delay to Disaster Relief Supplies

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**Abstract:** In the disaster-relief operations, the emergency supplies usually suffer heavy and dynamic transport delay and information delay. The mechanism of how those delays influence the material flow and information flow is relatively less studied. In this paper, a system dynamics model is presented to describe the disaster-relief supply chain under dynamic transport and information delays. Three levels of each delay are generated respectively and nine scenarios are cross-constructed from them. The simulation results indicate that the transport delay influences the material flow directly, while the information delay impacts the system in multiple ways. Furthermore, two enhanced inventory desiring methods trying to suppress those impacts are discussed. The improvement of performance points out that both the level and the fluctuation of transport delay are affecting the final supply level.

**Keywords:** disaster relief, dynamic delay, emergency supplies, lead time, system dynamics

### 1 Introduction

With the frequent occurrence of mass disasters and public emergencies in recent years, more and more researchers have started to concern the disaster relief operations. Beamon (2004)<sup>[1]</sup> made a detailed comparison list between the commercial supply chain and the humanitarian relief chain, included demand pattern, lead times, distribution network, inventory control, information system, strategic goals, etc. Whybark et al. (2010) reviewed the scholarly journal articles after the earthquake in Haiti at Jan. 2010, mentioned that disaster relief supply chain and commercial supply chain are different in both objectives and mechanisms, "Their operating environment is extremely uncertain and dynamic, and unique management principles are often employed."<sup>[2]</sup>

One of the most important goals in the relief activities is to deliver huge amount of medicine, food, water, equipment, medical teams and engineers to the emergency location. The "extremely uncertain" among those operations, for example, the roads are often

damaged or jammed, and the front-line information about demand and inventory are usually disturbed or unable to be obtained. Under this circumstance, the relief supplies are suffering heavy and dynamic transport delay and information delay.

In fact, the lead times and the information sharing issues are well discussed by researchers. But those dynamic delays in disaster-relief environments have not been fully investigated yet. In this paper we build a system dynamics (SD) model to describe the disaster-relief supply chain, focus on the dynamic delays. Then we crossover construct nine scenarios and run simulation to study the impact of these delays. After that we present two enhanced inventory desiring methods to suppress those impacts.

### 2 Literature review

In the traditional field of supply chain, many researchers have analyzed the impact of variable lead times and/or delayed information transfer. But they usually focused on just one of these factors due to the stable environment of common commercial activities, like Du Shao-fu et al. (2010)<sup>[3]</sup> assumed lead times as stochastic but controllable; Handfield et al. (2009)<sup>[4]</sup> described lead times as fuzzy-set; Song and Zipkin (2009)<sup>[5]</sup> compared the performances of a multiple sources supply system under different lead times as constant, stochastic and exogenous; Wang Chuan-xu and Cui Jian-xin (2007)<sup>[6]</sup> assumed a constant delay of demand information. Bensoussan et al. (2009)<sup>[7]</sup> studied the information delay of an inventory system caused by the unstable or failure of data management system. They used several stochastic information delays and one constant transit delay.

On another approach, some researchers built system dynamics models to describe and analyze the behavior of the supply chain. Since the system dynamics is usually used on complex systems over time, it is a powerful tool to analyze the impact of various delays.

Ge et al. (2003)<sup>[8]</sup> presented a SD model to analyze the demand amplification problem (also known as the bullwhip effect<sup>[9]</sup>) in a supply chain of supermarket. They compared the system performances of eight scenarios based on different assumptions of information delay,

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demand forecasting and information sharing. Six physical delays and four information delays were included in the model, but they were all assumed as constant. Rubiano and Crespo (2003)<sup>[10]</sup> evaluated the impact of using Internet-based e-collaboration tools in supply chain management. They built a SD model consisted of four trade partners, each had unique lead times in material transportation and delay times in order transfer. Also, those delays were assumed as constant.

In the field of disaster relief chain, relatively studies are few and briefly. Take for example the resource scheduling models in emergency situations, except Yang Ji-jun et al. (2009)<sup>[11]</sup> run fuzzy estimate to the traveling time of damaged roads, most other literatures set those time as fixed value<sup>[12][13][14]</sup>.

Although there are several research using SD models on post-disaster operations, like Zhang and Lu (2011)<sup>[15]</sup> focused on road rush-repair; Chu Wen-gong et al. (2010)<sup>[16]</sup> simulated the emergency medicine supply system throughout the country; Li Xiang-gong et al. (2009)<sup>[17]</sup> and Cooke (2003)<sup>[18]</sup> analyzed coal mine accident; Simonovic et al.(2005)<sup>[19]</sup> and Brouwers (2002)<sup>[20]</sup> studied flood. However, the impact of dynamic transport delays and information delays to the disaster relief supply chain is relatively less studied. This paper aims on this issue, using a SD approach, compares several scenarios under different delay levels.

### 3 Problem description and the SD model

#### 3.1 Causal loop diagram

To find out how the dynamics of delays impact relief supplies, our investigation starts with the basic material and information loops between one disaster-relief headquarter and one disaster-affected town(or village). Fig.1 is the diagram of the causal loop for this basic scene built in Vensim DSS 5.10.

The material flow begins at the shipment of supplies, which increase the supplies' in-transit inventory. After a period of transport delay, those supplies reach the disaster-affected town and increase the town inventory. It is obviously that the *Transport Delay* impacts this material flow by increasing the *Supplies in Transit* and decreasing the *Town Inventory*.

Other arrows in Fig.1 are information flows. The *HQ Expect Inventory* is the amounts of desired town inventory in the next turn, calculated by the headquarter bases on the feedback transport delay level and the daily demand, which increases the *HQ Order*. At the same time, the *Feedback Town Inventory* drives the positive loop that decreases the *HQ Order*. Furthermore, the *HQ Order* increases the *HQ Decision* and therefore increases the *Supplies Shipped*. However, the *Feedback in Transit Qty* reduces them.

Under this structure, all feedback information flows

(showed in figure with a delay mark) are impacted by the *Information Delay*, including the *Feedback in Transit Qty*, the *Feedback Town Inventory*, and the *Feedback Transport Delay*.

#### 3.2 Stock and flow diagram

After the analysis of the main factors with causal loop, we build SD model to simulate the processes of disaster relief supply. The diagram in Fig.2 shows the structure of stocks and flows.

In this model, it is assumed that the source of relief supplies has unlimited capacity, and the inventory adjust time equals to 1. In other words, the decision of shipment by headquarter can always be executed immediately, without any delays or any additional determines. Furthermore, the bottled water is chosen to be the specific supply. Compared to other emergency supplies like medicine or tent, the daily demand of bottled water is stabilizing and independent. Because the material flow is simplified by those assumptions, we can use just two level variables (*Supplies in Transit*, *Town Inventory*) and three rate variables to depict it.

To simulate the dynamic delays, two generators are brought in. Consider the post-disaster environment in the first 30 days, the transport delay is a result of road destruction plus the effect of heavy traffic, and the information delay is due to the damage of communication infrastructure plus the inaccuracy of information (and rumor, sometimes). Their level will be reduced with the passage of time, but their fluctuations will be kept exist. So first we use a negative exponent in generator to depict the main tendency of delay, its index points out how quick the level drops. Then we add a uniform random on it to depict the fluctuation. These two generators have the same structure, one for the *Transport Delay*, the other for the *Information Delay*. The detailed parameters for setting up those delays and the results of simulation are shown in next section.

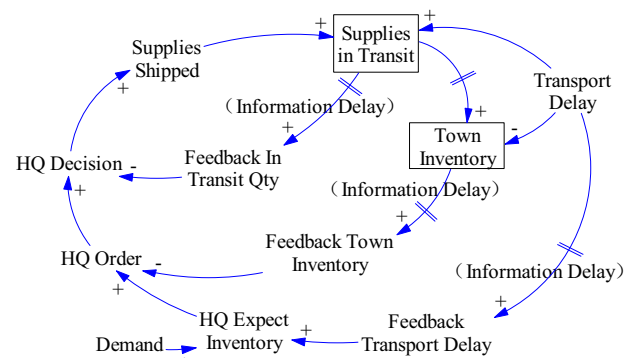
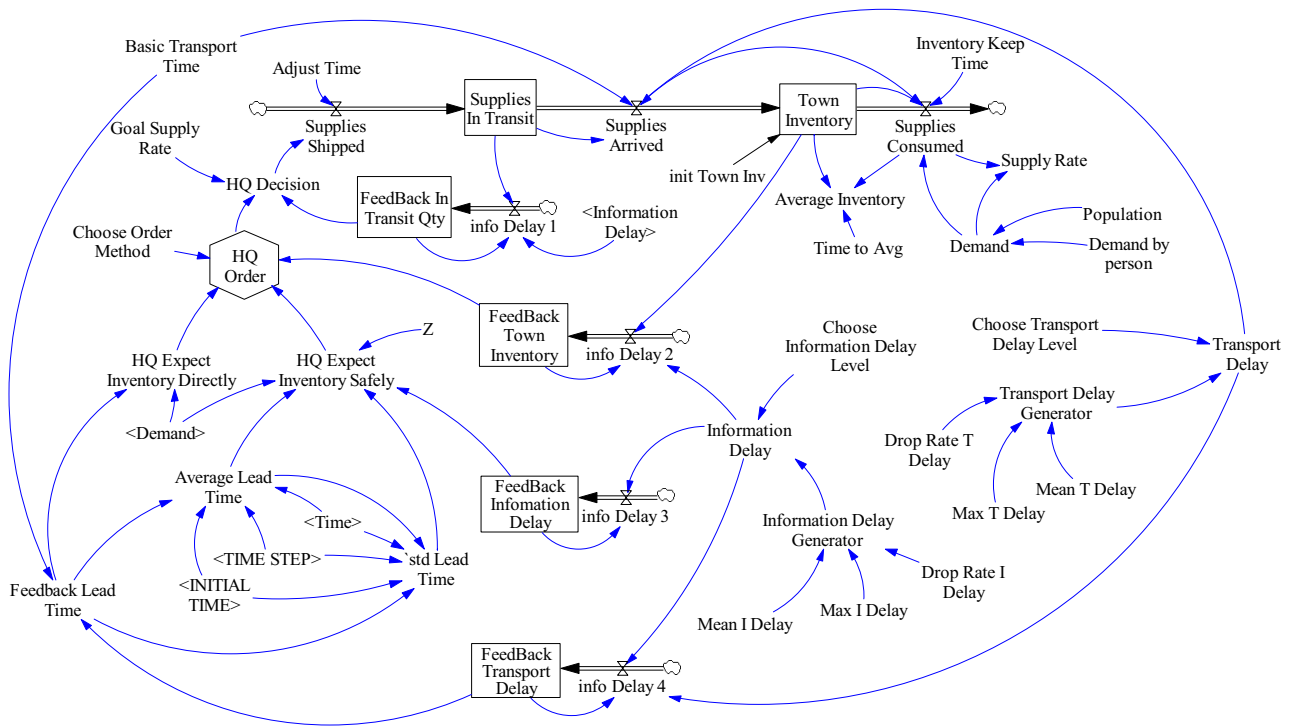


Fig.1 Causal loop diagram for relief chain with delays



**Fig.2 Stock and flow diagram for relief chain with delays**

While all required information have been collected by headquarter, the shipment decision is made from the SD equations as follows:

$$HQ \text{ Expect Inventory Directly} = \text{Feedback Lead Time} * \text{Demand} \quad (1)$$

$$HQ\ Order = HQ\ Expect\ Inventory\ Directly - Feedback\ Town\ Inventory \quad (2)$$

$$HQ\ Decision = HQ\ Order * Goal\ Supply\ Rate - Feedback\ In\ Transit\ Qty \quad (3)$$

$$\text{Supplies Shipped} = \max(\text{HQ Decision}, 0) / \text{Adjust Time} \quad (4)$$

However, this kind of decision is just too simple to resist the changing operating conditions. So an alternative path of getting the desired inventory is proposed. We calculate the safety stock which is defined by Heizer and Render(1999)<sup>[21]</sup>, then we get Eq. (5), and Eq. (2) are re-computed as Eq. (6) :

$$HQ \text{ Expect Inventory Safely} = (Average \text{ Lead Time} + Z * std \text{ Lead Time}) * Demand \quad (5)$$

$$\text{Town Inventory} = \text{HQ Order} - \text{HQ Expect Inventory Safely - Feedback} \quad (6)$$

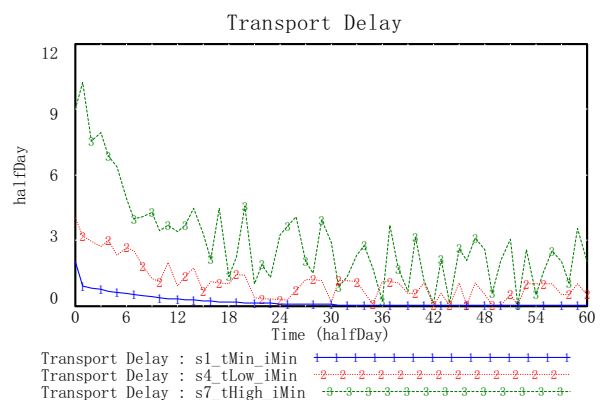
The  $Z$  value in Eq. (5) is the number of standard normal deviates. When we need a desired supply rate of 95%, the  $Z$  should be 1.65. And a switch named “Choose Order Method” is brought in the model to determine which path would be used in simulation.

Some more details of this model are: by assuming that the headquarter makes the decision of shipment once per half day, the units for simulating time is set as “half day”. So every simulation runs 60 turns, equals the first 30 days of post-disaster operation. The town’s population is assumed 10 thousand persons, and the demand of

bottled water is 2 bottles/person/half day, thus the total demand is 20 thousand bottles per turn. The initial of town inventory is 10 thousand bottles. The *Basic Transport Time* is assumed 1 turn, which is the usual delivery time without any traffic or road damaging.

### 3.3 Settings of delays

As mentioned in prior section, each of the two delays is assembled by a negative exponent and a uniform random. To study the impact of delays in different types and different levels, we generate three levels respectively for each of them by changing the parameters {Max(of turns), Mean(of turns), Drop Rate}. The values used for *Transport Delay* in this paper are: Minimum{1, 1, 10}, Low{3, 1.5, 10}, High{8, 3, 10}. The values used for *Information Delay* are: Minimum{1, 1, 5}, Low{3, 1, 5}, High{6, 2, 5}. The results are shown in Fig.3 and Fig.4.



**Fig.3 Three levels of transport delay**

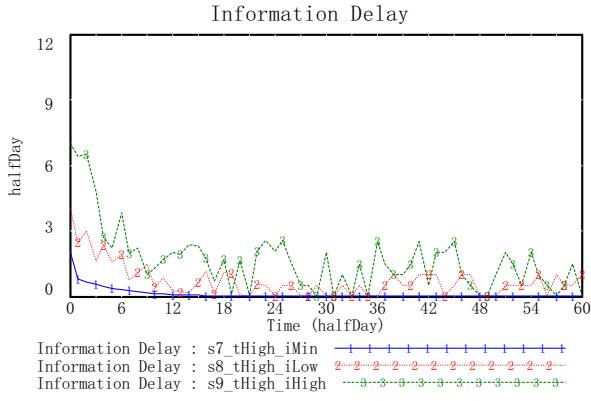


Fig.4 Three levels of information delay

Tab.1 Scenario definitions and simulation results

s	Trans- port Delay	Infor- mation Delay	Expect Inv Directly		Expect Inv Safely	
			Supply Rate	Average Inventory	Supply Rate	Average Inventory
1	min	min	52.8%	0.72	68.6%	1.27
2	min	low	55.3%	0.74	69.8%	1.26
3	min	high	58.0%	0.88	69.6%	1.17
4	low	min	60.8%	1.54	88.5%	3.43
5	low	low	62.3%	1.98	87.7%	3.81
6	low	high	62.7%	1.64	77.7%	3.29
7	high	min	67.9%	6.06	84.4%	12.03
8	high	low	71.4%	13.13	84.4%	20.92
9	high	high	63.5%	4.24	83.0%	4.85

\* The unit of Average Inventory is 10 thousand bottles.

\*\* The values of Supply Rate and Average Inventory are the mean of simulation results within 60 turns.

## 4 Simulation result and discussion

By cross comparing those different levels of transport and information delays, we build nine scenarios to analyze the impact of dynamic delays. The definitions and the simulation results of each scenario are listed in Tab.1, every scenario runs 60 turns in both the path “HQ Expect Inventory Directly” and the path “HQ Expect Inventory Safely”. And the discussions followed.

### 4.1 Impact of the transport and information delays

To focus on the impact of delays, discussions in this section are based on the ordering path of “HQ Expect Inventory Directly” only.

Fig.5 shows the system performances indicated by *Average Inventory* under different levels of transport delays while the level of information delay keeps at minimum. It is obviously that the higher the transport delay, the higher the average inventory. This may be confirmed by the simulation results listed in Tab.1. No matter which level the information delay contains, the higher transport delay always increases the amount of supplies in transit, then higher the town inventory, and

finally leads to better supply rate.

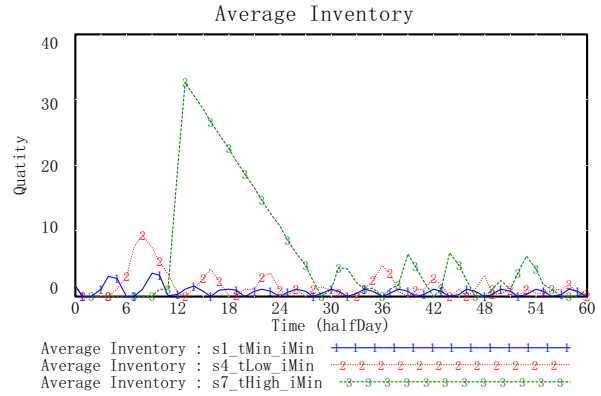


Fig.5 Impact of three levels of Transport Delays

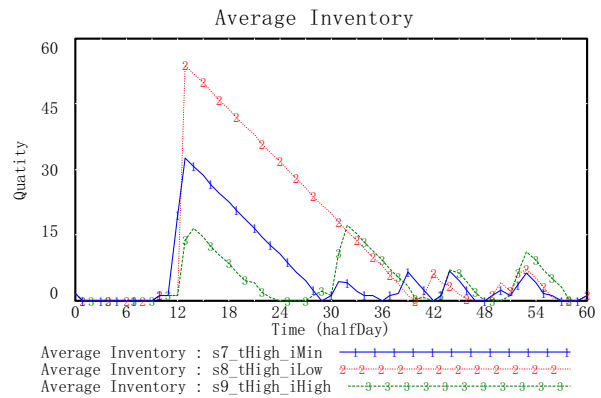


Fig.6 Impact of three levels of Information Delays

The impact of information delay is a little more complicated. According to Tab.1, the results of scenario 1 to 3 shows that the supply rate and average inventory are all increasing with the information delay levels. But the values of scenario 7 to 9 demonstrate a very different pattern. The low level information delay in s8 leads to a higher supply rate than s9, with the payment of far more larger inventory. Fig.6 confirms that.

One of the reasons is, the headquarter needs the value of transport delay to calculate the amount of shipment, but they will not know the exact value until it is feedback from the disaster-affected town. So lower information delay leads to faster reaction, causes more shipment in first few turns. As presents in Fig.7, under the lower information delay, the headquarter in scenario 7 and 8 indeed receives the feedback earlier. While in scenario 9, the headquarter gets feedback later and discards the prior data (because they have been obsolete to make decision), that means a later and lesser shipment.

But the early-shipped supplies devote not much to the supply rate because of the high level of transport delay. No matter how fast the reaction is, the supplies will reach the town at the same time, as Fig.6 shows. This is the answer of why the s8 increases the *Average Inventory* by 210% than s9, but only makes 13% improvement in *Supply Rate*.

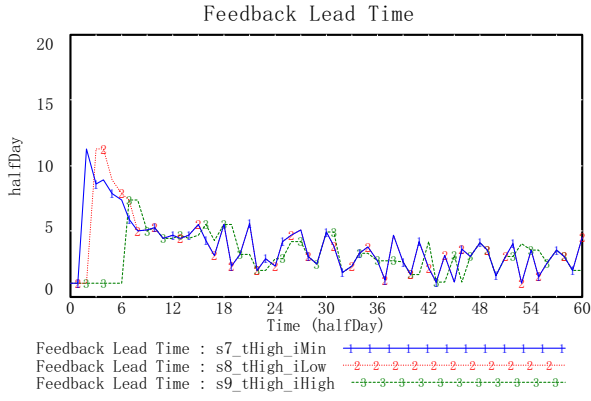


Fig.7 Headquarter received lead times

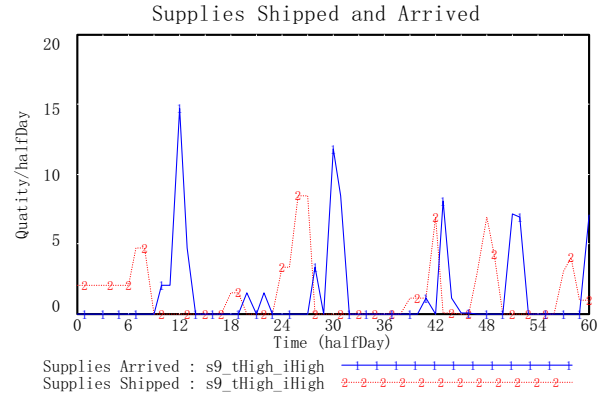


Fig.9 The delay of supplies in material flow

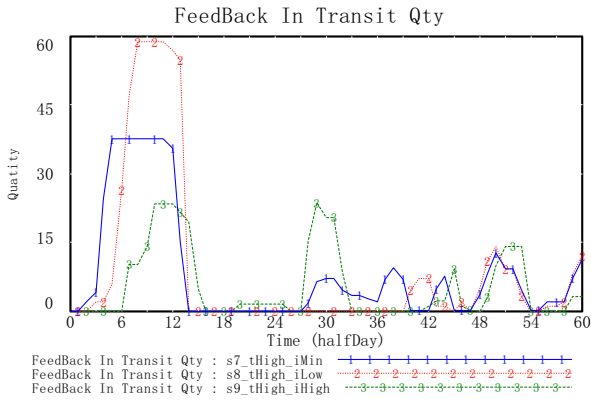


Fig.8 Headquarter received feedback in transit Qty

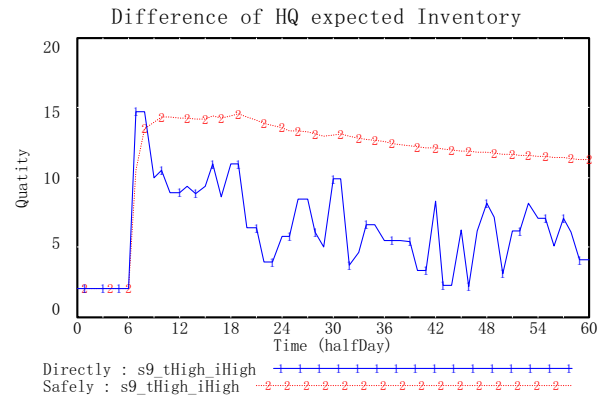


Fig.10 Compare two paths of desiring inventory

Fig.8 shows the other part of the reasons. The *Feedback In Transit Qty* is designed as a valve to prevent the headquarter from sending too much supplies in trafficked roads. When the information delay level is minimum in scenario 7, it works fine. But in scenario 8, the little bigger information delay causes a lag of feedback in the first few turns, fails the mechanism.

Up to now, we have made a full analysis about scenario 7 to 9, and discussed the complex impact of both delays. Fig.9 presents an integrated view of how the two kinds of delays work together. The horizontal line at the beginning of the curve *Supplies Shipped* is made by the information delay, because the first crest after that horizontal means that the headquarter has received the feedback information from the town. And the empty part before the first crest of the curve *Supplies Arrived* is made by the transport delay.

#### 4.2 Improvement by desiring inventory safely

Having studied the impact of delays, now we concentrate on the improvement by enhancing decision method.

The first enhancement is choosing the ordering path of “HQ Expect Inventory Safely” described earlier. According to the results of simulations listed in Tab.1, the performance improvements are significant in all scenarios, especially in s9.

Fig.10 shows the different between those two paths in s9. It is obviously that the *Average Lead Time* component in Eq. (5) smoothes the fluctuation of transport delay, and the  $Z * std\ Lead\ Time$  component raises the level of safety stock. As a consequence of these effects the oscillations of supply rate has been suppressed effectively.

The second enhancement is to expend the Eq. (5) by adding the value of *Feedback Information Delay* into the lead time, intends to gain more safety stock to compensation the lags causing by the information delay. But the simulation result shows that the supply rate will get slight improvement, while the inventory level increases disproportionate. Due to limitation of space, we skip the detailed discussions.

After all, the different results of these two enhancements indicate again that the impact of information delay is more complicated than the transport delay.

## 5 Conclusion

The impact of dynamic transport delay and information delay to the disaster-relief system are studied through the simulations of those nine scenarios described earlier in the paper, and validated by the two enhancements to improve decision methods. The

conclusions are:

1) The transport delay prevents the supplies from reaching the destination, so it increases the in-transit inventory and therefore decreases the supply level.

2) The information delay prevents the headquarter from taking reactions in time. In on hand it delays the feedback of town inventory and transport delay level, so lowers the amount of shipment. On the other hand it delays the feedback of traffic situation, so increases the in-transit inventory.

3) A better mechanism of inventory desiring may improve performance effectively. The key is to pay attention to both the level and the fluctuation of the transport delay.

The limitations of this paper are: the solutions of resisting the multi-effect of information delay are not fully discussed, and the affections of the types of disaster-relief materials are not fully considered.

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