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Post-seismic supply chain risk management: A system dynamics disruption analysis approach for inventory and logistics planning

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ABSTRACT

Post-seismic inventory and logistics planning under incomplete and fuzzy information is an important yet understudied area in supply chain risk management. The goal of this paper is to propose a system dynamics model to analyze the behaviors of disrupted disaster relief supply chain by simulating the uncertainties associated with predicting post-seismic road network and delayed information. The simulation results indicate: (1) information delay has different influences over the relief headquarter (the upstream) and the disaster-affected areas (the downstream); and (2) the change of road conditions and shipment schedules have impact on the on-time transportation rate in supply chain management. Furthermore, this paper defined and tested supplies' replenishment solutions combined with three inventory planning strategies and four forecasting methods under different lead time uncertainties. The results show that: (1) a strategy that considers information from both the post-seismic management center and the affected areas can provide a better logistic plan than an one takes information from one side; (2) the smooth-the-trend forecasting method is suitable for inventory and logistic planning when the post-seismic situations are volatile, while the quick-response forecasting method has good performance in stable environments. In addition, this paper proposes decision tree to help decision makers choose the appropriate stocking strategies.

1. Introduction

With the frequent occurrence of disasters and incidents in recent years, there has been an increase in the interest of the international academic community in the challenges of the humanitarian supply chain [1]. Whybark et al. [2] reviewed scholarly journal articles after the January 2010 Haiti earthquake, and suggested that the disaster relief supply chain is a subset of the humanitarian supply chain because its operating environment is extremely uncertain and dynamic. Beamon [3] made a detailed comparison list between disaster relief operations and normal commercial activities, including demand pattern, lead times, distribution network, inventory control, information system, and strategic goals. Consequently, practices that may work well in commercial settings may not be appropriate in disasters responses [2].

Road conditions varied under different geological conditions. After the 2008 Wenchuan earthquake, some roads were damaged or even disrupted for a long period. Some roads were quickly repaired and were destroyed again by aftershocks and secondary disasters, while some others maintained a fluctuating transportation capacity. The transport time of supplies varied in this circumstances. In addition, information regarding demand and material inventories was often delayed and disrupted by dynamic information delay (ID), and was even completely unavailable in some circumstances. Such wide-ranging uncertainties present significant challenges to make the replenishment decisions. However, comparing with the studies on demand forecasting, there has been less studies in the dynamic lead times prediction.

System dynamics (SD) is a popular approach to study such problems for its ability to deal with high levels of uncertainty, causal ambiguity, and complexity. In this paper, we implement an SD model to describe the disaster relief supply chain with dynamic road conditions and ID by combining existing researches on transportation, supply chains, and seismic risk assessment. To evaluate the impact of the environmental factors and the effect of the response decisions, the replenishment solutions are combined with three inventory planning strategies and four forecasting methods, and different scenarios which match solutions with the dynamic circumstances were also suggested. After the analysis of the simulation results, a decision tree is proposed to assist the decision-makers to choose the stocking strategies based on quantified risks after a disaster strikes.

The rest of this paper is organized as follows: Section 2 reviews the related works in supply chain risk management and system

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dynamics disruption analysis. Section 3 defines the research problem and describes the proposed system dynamics model. Section 4 represents the simulation results and discusses how the inventory and logistics planning decision should be made. Section 5 summarizes the paper with conclusions and future research directions.

2. Literature review

Since Lee et al. [4] indentified the bullwhip effect and its causes, lots of studies have been conducted on demand forecasting, information sharing, and coordination among supply chain members. Factors such as variable lead times and/or delayed information transfers are also included in such studies. However, in commercial supply chain research, researchers usually focus on just one of these factors to assure a stable environment in term of lead times. For example, He et al. [5] assumed lead time to be stochastic and measurable; Handfield et al. [6] described lead times as a fuzzy set; and Song and Zipkin [7] compared the performances of a multiple source supply system with different types of lead times that were constant, stochastic, and exogenous. Only a few studies have considered the delay of lead times. For example, Bensoussan et al. [8] studied the ID of an inventory system caused by the instability or failure of a data management system, and they used several stochastic ID and one constant transport delay.

Researchers also made similar assumptions in humanitarian logistic and disaster relief supply chains research. In resource scheduling models in emergency situations, the transport delay is usually set as a fixed value [9,10]. However, in the real-life dynamic situations in disaster areas, according to Özdamar et al. [11], actual vehicle numbers is more accurate in representing the limitations of transport capacity.

SD models were introduced to describe and analyze the behavior of the supply chain, with different types of delay. Barlas and Gunduz [12] defined three typical ordering policies in an SD model to investigate the structural sources of the bullwhip effect, and explored the effectiveness of information sharing to eliminate undesirable fluctuations. Ge et al. [13] presented an SD model to analyze the bullwhip effect in the supply chain of a supermarket. They compared the system performances of eight scenarios based on different assumptions of ID, demand forecasting, and information sharing. Rubiano and Crespo [14] evaluated the impact of using Internet-based e-collaboration tools in supply chain management. They built an SD model that consisted of four trade partners, and the four types of collaborative approaches among them were compared. In the researches above, unique lead times in material transportation and delay times in order transfer are assumed to be constant for each supply chain member.

SD models have been used to simulate a wide range of disasters, such as road rush-repairs after an earthquake [15,29], coal mine accidents [16,17], and floods [18,19]. For an example, Besiou et al. [20] discussed the advantages of studying disaster relief issues using SD methodology, and took an example of field vehicle fleet management to show how SD captures complexity. However, less studies have been done on selection of inventory planning strategies and forecasting methods in emergency supply chain management. In this research, we will discuss how the replenishment process of emergency supplies could be impacted by the dynamic environmental factors comparing with the traditional supply chain model.

3. Analysis of the problem and the system dynamics model

Suppose there exists a post-seismic area shown in Fig. 1. The shaded part at the left represents mountain area, and the remaining white area represents plain area. The epicenter is located in the mountain area with several disaster-affected towns surrounding it. During a disaster relief operation, supplies must be delivered from the relief headquarters (HQ) to those towns. Thus, a two-stage relief supply chain is established. Unlike the usual commercial supply chain, material and information flows are affected by the earthquake and continual aftershocks, which cause dynamic transport delays and ID. Each town will suffer different degrees of delays because of their geological conditions and distance from the epicenter. The environmental assessment and the decision-making structure are described in this section.

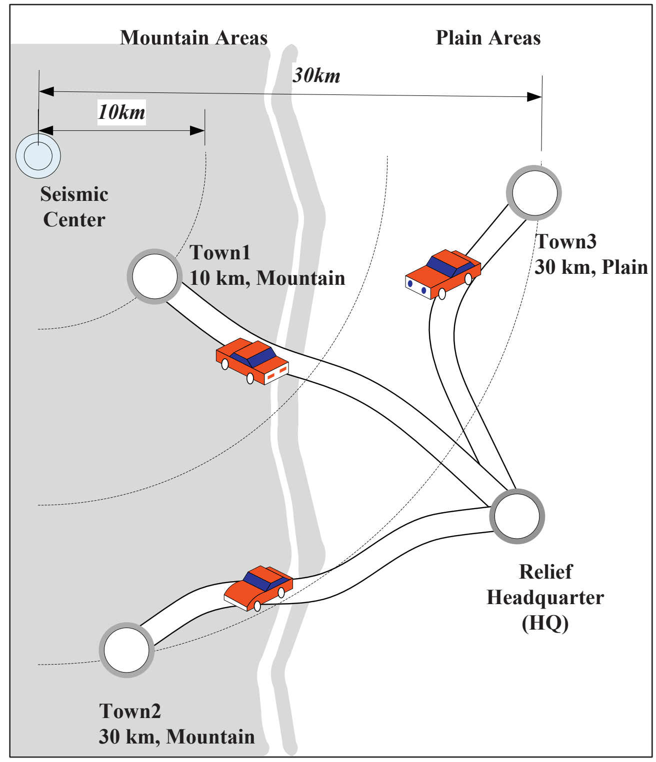

Fig. 1. Environment of post-seismic relief.

3.1. Environmental factors in post-seismic area

3.1.1. Dynamic road capacity

The factors that affect transport conditions can be described in a causal loop diagram as shown in Fig. 2. The damage energy released by the earthquake, measured as peak ground acceleration (*PGA*), will decrease over distance. Continuing aftershocks and secondary disasters like landslides and debris flows increase the level of damage to the road system. These damage types are accumulated and included as a state variable *Road Damage Stack*, which is reduced by the continual attempts at road repair, and are converted dynamically into *Road Capacity Loss*. The *Mountain Factor* aggravates the geological hazards, but decreases the effort of repair. In addition, the greater the *Road Capacity Loss*, the less the *Effective Repair Ability*.

In seismic risk assessment, researchers have developed several models to determine the performance of transportation network systems after large-scale disasters. Shinozuka et al. [21] suggested that bridges are the most vulnerable of all engineered components under seismic conditions, so the assessment of road networks can be simplified to the assessment of bridges. They developed empirical bridge damage fragility curves expressed as log normal distribution functions of *PGA*, which were evaluated using the degradation of the traffic capacities of Los Angeles networks after

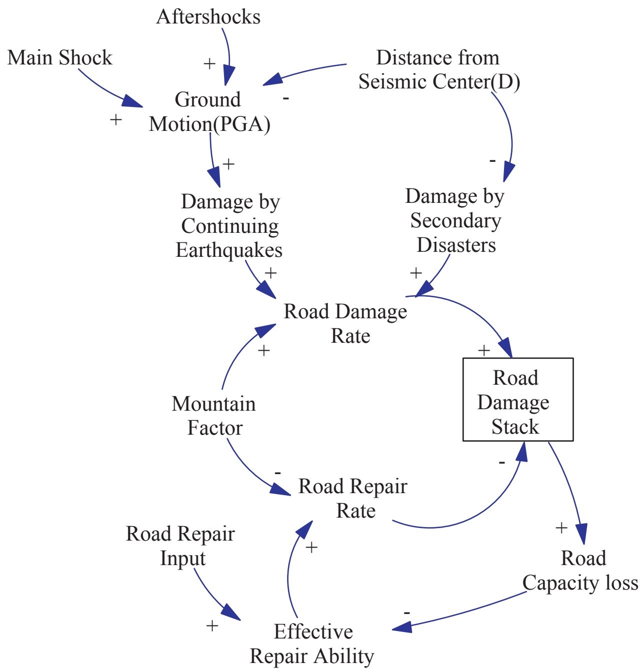

Fig. 2. Causal loop diagram of the dynamic road capacity.

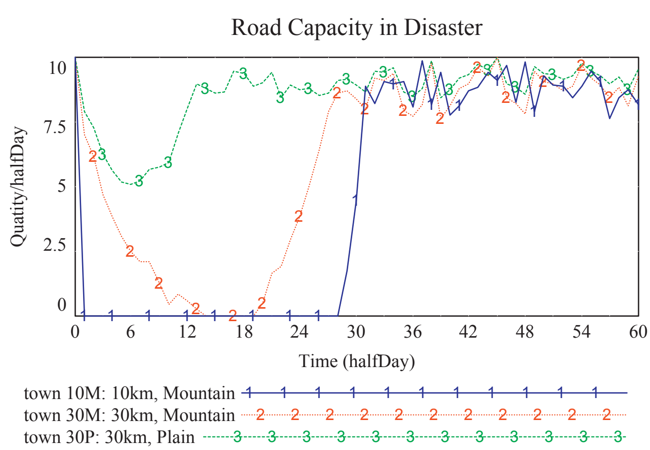

Fig. 3. Simulation results of dynamic road capacity for the three towns.

the 1994 Northridge earthquake. Shiraki et al. [22] improved these functions and optimized the method of estimating capacity losses on entire networks. A later study by Lan et al. [23] corrected some of the parameters based on data regarding previous earthquakes in China.

To calculate the seismic energy reaching the towns in our study, a formula which was verified by Chen Hou-qun et al. [24] is introduced to determine earthquake intensity transmission in southwest China using aftershock data from the 2008 Wenchuan earthquake [25] as input. The sequence of the secondary disasters was generated using a random function, while the output value also decreased over the distance from the epicenter.

The simulation results of the dynamic *Road Capacity in Disaster* of the three towns mentioned in Fig. 1 are shown in Fig. 3. The unit of time is half-day. Because of the geologic conditions, the traffic to town-10M (10 km away from epicenter, mountain area) is initially completely disrupted, and the road is partially recovered 15 days later. The road to town-30M (30 km away from epicenter, mountain area) is not destroyed by the first earthquake, but destroyed later by the continual aftershocks and secondary disasters. The road capacity of town-30P (30 km away from epicenter, plain area) is slightly damaged during the earthquake and soon the road capacity is fully recovered.

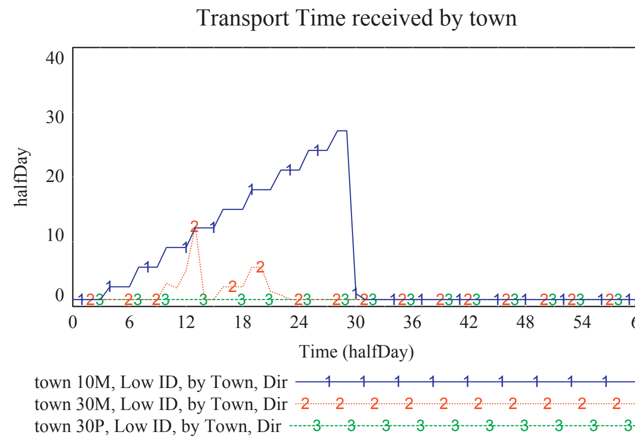

Fig. 4. Typical travel times for the three towns.

3.1.2. Travel time and the dynamic transport delay

Few studies have been done on variations in transportation times for commercial supply chains because the cargo quantity is usually significantly less than the capacity of the transport networks. However, in disaster-affected areas, road capacity is the bottleneck in supply chain due to the decrease in transportation capacity and the sudden increase of relief vehicles [20]. In transportation science, the most widely used method to estimate transport times is proposed by the Bureau of Public Roads (USA) [21,26], which can be represented as

$$T = T_0\left[1+\alpha\left(\frac{V}{C}\right)^{\beta}\right], \tag{1}$$

where T_0 is the travel time with zero vehicle flow on the road, C is the capacity of the road, and V is the current volume of cargo on the road. If the two variable parameters are set as $\alpha=0.15$ and $\beta=4.0$, it means that the travel time on a road at 100% capacity is 15% greater than at a free flow time [21]. This algorithm can simulate the severe obstruction to traffic, but once the V/C ratio is greater than 1.2, the estimated travel time will be over-exaggerated. Bertini et al. [26] revised the formula based on operating data from U.S. highways, but the estimations are still too large when $V/C>2$. Furthermore, no one have addressed the situation of roadblocks when $C=0$. Hence, the above formulas are not applicable to disaster areas.

In this research, a segment function is developed with V/C ratio to describe the effect of road conditions on travel time:

$$T_t = \begin{cases} T_{block}, & C_t = 0, \\ T_0, & \frac{V_t}{C_t} \le 1, \\ T_0\frac{V_t}{C_t}, & \frac{V_t}{C_t} > 1, \end{cases} \tag{2}$$

where T_t is the travel time estimated by decision-makers; T_0 is the road's *Normal Transport Time*. C_t is the current *Road Capacity in Disaster*, which indicates the amount of materials that could be transported per unit of time. V_t is the current volumes of supplies in transit. T_{block} is the length of time when the road is blocked (interrupted travel). In addition, $C_t=0$ means the road is blocked, $V_t/C_t \le 1$ represents a road without traffic jam, and $V_t/C_t>1$ indicates the existence of traffic jam.

Travel time is influenced by the volumes of supplies in transit and the *Road Capacity in Disaster*. The decision-makers at HQ and in the towns may assume different travel times because the V/C

ratios they received are not synchronized because of the dynamic ID. In other words, decision-makers are not aware of the real level of transport delays in relief supply chains, which is quite different from that of a commercial supply chain.

The implementation of the proposed SD mechanism is described in Fig. 7, and the simulation results are shown in Fig. 4, which assumes that all towns have the same travel time to the HQ in normal time and $T_0 = 1$. Town-10M suffers a high level of transport delay because of a roadblock. The delay in travel time to town-30M is because of roadblocks and traffic jams. Town-30P experiences no delays at all.

3.1.3. Dynamic information delay

In post-disaster areas, information delay (ID) occurs when there are failures in telecommunication facilities and ID usually decreases over time. In addition, the received information is often inaccurate or contradictory because of subjective speculation, rumors, and unexpected noise. In this research, a delay generator is proposed to simulate dynamic ID. A negative exponential function is used to characterize the general trend of gradual decline, and a random variable is introduced to simulate various noises.

Two levels of *Information Delay* are simulated by changing the parameters {Max(of time), Mean(of time), Drop Rate}. The values are Low ID{1, 1, 5} and High ID{6, 2, 5}. The results are shown in Fig. 5.

3.2. Decision structure

3.2.1. Inventory planning strategies and information sharing

Inventory planning strategies have been discussed widely in numerous studies, such as vender-managed inventory (VMI), information share, and the bullwhip effect. Several models in the SD approach have also been developed and discussed [12–14]. To test the performance of replenishment solutions in a post-disaster environment, two basic strategies (Town Order and HQ Managed Inventory) and an additional strategy (Joint Order) are proposed.

In the first strategy 'Town Order', the decision-maker in the disaster-affected town collects the necessary information and is responsible for placing replenishment orders (the *Town Order*). By the ordering policy as order-up-to-S, an order is sent out to replenish the inventory level to S when the *Town Inventory* falls below a preset stock level. The order equations are as follows:

$$O_t = \frac{(S_t - I_t)}{IAT}, \tag{3}$$

$$S_t = D_t(ID_t + \hat{T}_t + \varepsilon_t), \tag{4}$$

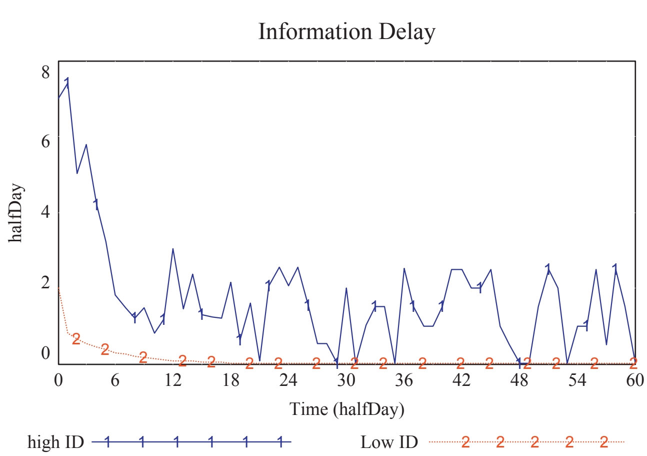

Fig. 5. Two levels of information delay.

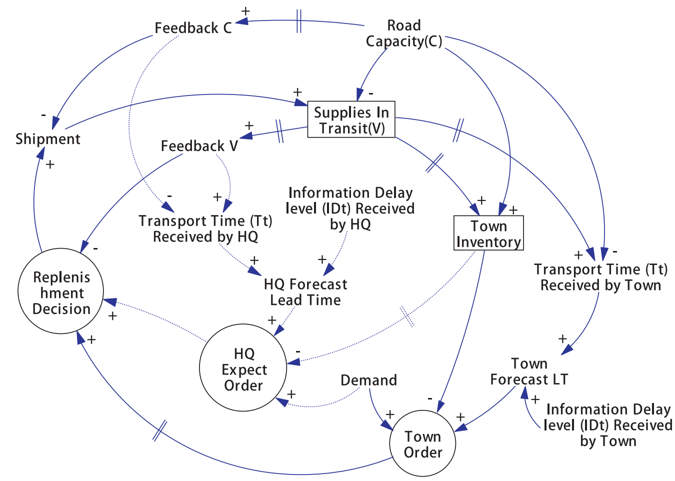

Fig. 6. Causal loop diagram for inventory planning strategies.

where O_t is the order, S_t is the order-up-to level, I_t is the current *Town Inventory*, *IAT* is the adjustment time of inventory, D_t is demand, ID_t is the current level of *Information Delay*, $\hat{T}_t$ is the estimated transport delay, and ε_t is compensation for the estimation error.

Bottled water is chosen as the supply item in our study. Compared with other emergency supplies like medicines or tents, the daily demand for bottled water is stable and independent. This makes D_t a constant. In Eq. (4), $(ID_t + \hat{T}_t + \varepsilon_t)$ represents the estimated result of the total lead time. It is obvious that the method to forecast $\hat{T}_t$ and ε_t will have significant impact on the accuracy of the order. The current value of ID_t, will be used without any further evaluation as the change in ID_t is the same in all simulation scenarios.

In the second strategy 'HQ Managed Inventory', the HQ decision-maker receives feedback on the *Town Inventory* and is responsible for placing replenishment orders (*HQ Expect Order*). A order-up-to-S policy will also be implemented for HQ Managed Inventory, however, almost every variable will be deferred by ID_t. The information flows of this strategy are shown by the dashed lines in Fig. 6. This decision process is similar to VMI, but the ID should be smaller under the VMI mode or even eliminated after the implementation of e-collaboration tools [12,14]. The high level of ID will lead to lower performance in relief operations. But this strategy still has its practical meaning because the orders from affected towns would be seriously delayed or even unavailable in a disaster area, especially in the early period of relief operations.

Both of the two strategies have obvious defects in post-disaster environments. The decision-makers in the towns know the exact quantity of the in-town inventory and the road conditions, but could not make precise prediction in lead times, and the orders will be delayed by the ID. The decision-makers at the HQ can make precise prediction in lead times but they do not have information in town inventory and road conditions when they make the prediction.

Thus, a third strategy, 'Joint Order' is proposed. Both the *Town Order* and the *HQ Expect Order* are submitted and the final quantity of the *Replenishment Decision* is the mean of the two values. This joint strategy will partially offset the impact of the ID, which can be verified in the following simulations.

The decision structure of different strategies is shown in Fig. 6.

3.2.2. Replenishment solutions and lead time forecasting

The replenishment solution includes two stages of decision-making: the inventory planning strategy and the forecasting method

Table 1
Model equations of replenishment solutions.

Inventory planning strategy		Forecasting method for transport delay			No.
Decision strategy	Replenishment quantity	HQ method	Town method	$(\hat{T}_t+\varepsilon_t)$	
Town Order	Town Order (O_{town})	–	Directly (Dir)	(T_t+KS_{town})	(5)
		–	Average (Avg)	$(\overline{T}_t+KS_{town})$	(6)
HQ Managed Inventory	HQ Expect Order (O_{HQ})	Directly (Dir)	–	(T_t+KS_{HQ})	(7)
		Average (Avg)	–	$(\overline{T}_t+KS_{HQ})$	(8)
		Safety stock (SS)	–	$(\overline{T}_t+Z\sigma_t)$	(9)
		Exponential smoothing (ES)	–	$[\alpha T_t+(1-\alpha)T_{t-1}+Z\hat{\sigma}_t]$	(10)
Joint Order	$(O_{town}+O_{HQ})/2$	Average (Avg)	Average (Avg)	As definitions above	(11)

for lead time in transport delays. Different forecasting methods for lead time in different decision strategy are listed in Table 1.

In Eqs. (5) and (7), the prediction of transport delay is not considered, which is not good in performance but still widely used in affected areas because of the lack of logistics talents. KS_{town} and KS_{HQ} are 'lead time inflation constant' [12] to set a desired stock level which is always greater than D_tT_t, to eliminate uncertainties. The values of KS represents the expected lead time by the decision-makers.

The 'average' method is better in predicting the fluctuation as it continuously calculates $\overline{T}_t$ as shown in Eqs. (6) and (8). The 'safety stock' method in Eq. (9) is defined by Heizer and Render [27], where $\overline{T}_t$ is also the average transport time, σ_t is the standard deviation of the forecasting error of T_t, and Z is a constant of standard normal deviations. When a desired service level is set as 95% and 99%, Z should be 1.65 and 2.33, respectively. The 'exponential smoothing' method in Eq. (10) balances the response trends and stabilizes the fluctuation. In the 'exponential smoothing' method, α is the smoothing coefficient (*Cof*), and $\hat{\sigma}_t$ and Z are the same as defined previously. However, the 'safety stock' or 'exponential smoothing' methods are not implementable in the "Town Order" strategy due to the absence of knowledgeable decision makers in town.

3.3. Stock and flow diagram

After the analysis of the main environmental factors and the decision solutions, a SD model is built to simulate the processes of disaster relief supply. In SD model, we assumed that HQ has unlimited supply of bottled water inventory and no further orders are required. Several issues related road capacity need to be addressed: (a) the amount of *HQ Shipped* must be lower than *Road Capacity in Disaster*; and (b) the volume of in-transit inventory is divided into two stocks—the *Supplies Stranded* represents the cargo that is stranded on the road because of a roadblock or traffic jam and the *Supplies in Transit* represents the cargo that can be delivered and will reach the town after a delay of the *Normal Transport Time*. These assumptions are consistent with Eq. (2) in SD.

Two variables are introduced to measure the performance of decisions. The *Total After HQ Inventory* is the sum of *Supplies Stranded*, *Supplies in Transit*, and *Town Inventory*, which represents total wasted emergency supplies. The *Supply Rate* is the value of *Town Consumed* divided by *Demand*, which is a measurement of the service level.

We also assume that the HQ makes shipment decisions once per half-day. The unit of simulation time is set as 'half-day'. Every simulation runs 60 turns, which simulates the first 30 days of a post-disaster period. The populations of the three towns are assumed to equal 10,000 persons per town, and the demand for bottled water is two bottles/person/half-day. Hence the total demand is 20,000 bottles per run. The initial *Town Inventory* is for 10,000 bottles, for all three towns. The inventory adjustment time for the HQ is set to 1, so that HQ shipment decisions can always be executed immediately.

The diagram in Fig. 7 shows the structure of the stocks and flows.

4. Simulation results and discussion

4.1. Scenario definitions and simulation results

More than 50 scenarios are created to compare the performance of various decisions by the cross-combination of the different environments and replenishment solutions. The definitions and the simulation results of each scenario are listed in Table 2. Some results such as the scenarios using methods Dir or ES with $Cof=0.6$, which has significantly poor performances, have been filtered out due to space limitation. The filtered results will be further discussed in Section 4.3.1. (In fact $Cof=0.1$–0.9 were all tested, and value 0.1 led to the best service level in all environments.)

An increase in the lead time will cause oscillations in inventory levels along the supply chain [12]. A delay in order information will significantly increase the inventory level [4,12,13]. These effects are confirmed by our experiments and the experiments also show that those effects are more complicated in disaster relief operations.

In a regular commercial supply chain, a higher inventory level would result in a better supply level when the demand is not fully met. While in a relief system with large uncertainties, according to Table 2, a better Supply Rate will not be guaranteed by increasing the Total After HQ Inventory. Taking the scenarios from 1 to 6 as an example. From scenario 5 to 6, the increasing in inventory levels causes a higher supply level. While from scenario 1 to 2, then 3, the inventory levels are raising but the supply levels remain unchanged.

Therefore, the correlation between the inventory level and the supply level can be considered as a phase function with a threshold value. The interrupted road and the traffic jam constitute new restrictions of the logistics system. The delivered supplies more than the damaged transport capacity will not reach the affected towns but just be stranded on the road. Moreover, these restrictions are dynamic and reinforced by the high level of ID. Under this circumstance, the decision-makers should choose the replenishment strategy carefully to achieve a balance between the inventory level and the supply level.

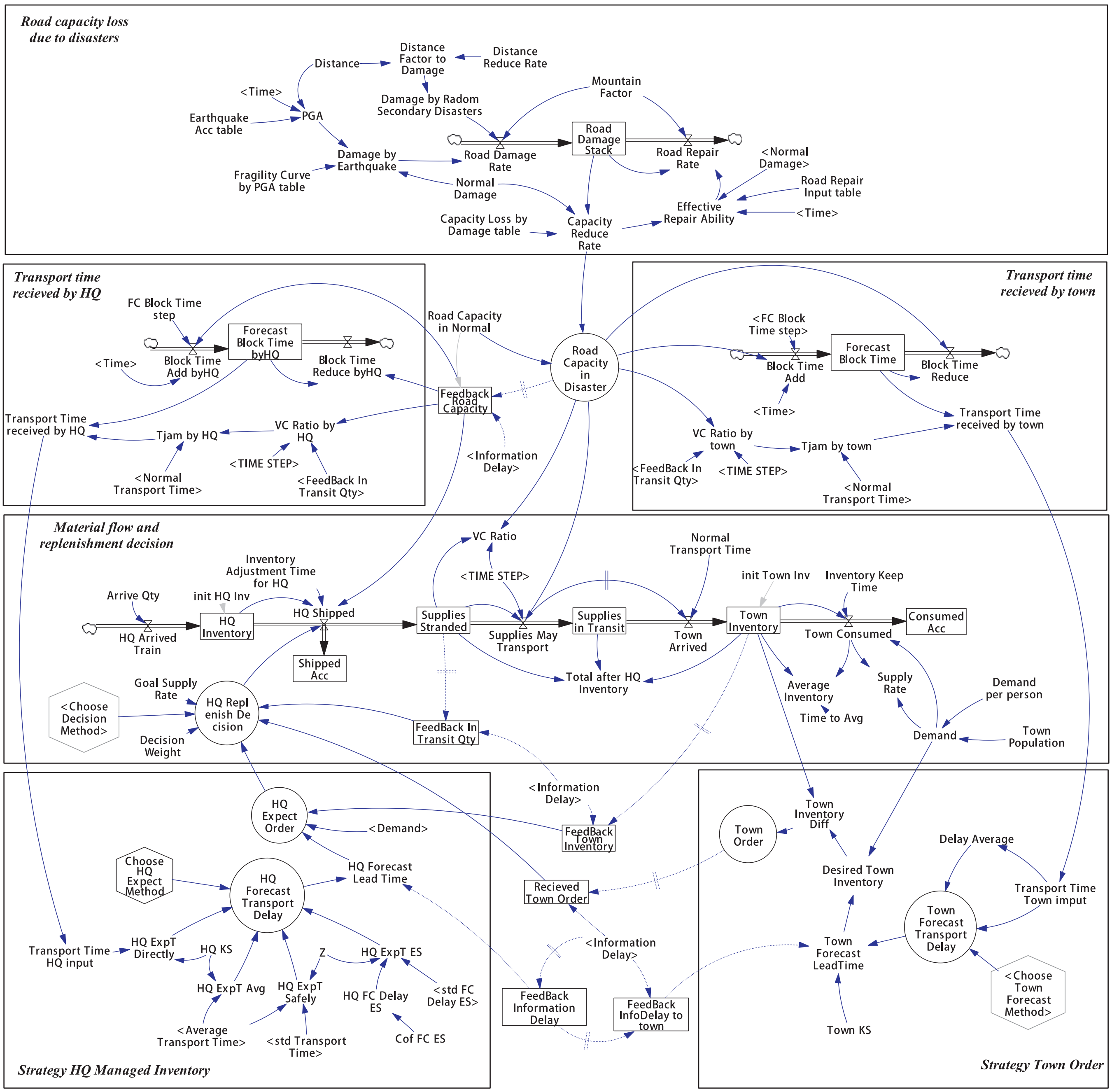

Fig. 7. Stock and flow diagram for relief supply chain in post-seismic environment.

4.2. Analysis of the effect of post-disaster environment

4.2.1. Effect of information delay

ID affect the relief supply chain in three aspects: (1) delays the submission process of town orders, (2) prevents HQ from making a timely response to the changing environment because of delays in feedback, and (3) as an integral part of the lead time, a high level of ID leads to greater order quantities and higher inventory levels.

A delay in the *Town Order* causes significant differences in the simulation results listed in Table 2. All the solutions based on the strategy Town Order produce a lower *Supply Rate* than those solutions based on HQ Managed Inventory using the same prediction method. It is noted that this strategy is commonly used in affected areas and it usually results in less waste of supplies when ID is low.

Fig. 8 compares the shipment sequences under different levels of ID. The two scenarios use the same solution combined with the Town Order strategy and forecasting method Dir. The figure shows that the higher ID actually defers the shipment. Fig. 9 compares the shipment sequences under different strategies in same environment with forecasting method Dir. It shows that the order submitted by HQ is not affected by the high ID while the town's order is affected.

To the decision-makers in the HQ, ID defers all kinds of feedback. On the one hand, HQ needs the *Feedback Town Inventory* to calculate the correct order quantity. On the other hand, the *Feedback Road Capacity* and the *Feedback in-Transit Qty* are designed as the threshold to prevent HQ from sending too many supplies via traffic-logged roads. With high levels of ID, more cargos will be transported on the road, which leads to heavier

Table 2
Scenario definitions and simulation results.

ID	Environment		Inventory planning strategy	Lead time forecasting method				Supply rate		Total after HQ Inventory[a]		
	Geologic condition	Information delay		HQ	Param.	Town	Param.	Mean (%)	Std. dev.	Max	Mean	Std. dev.
1	10 km Mountain (town-10M)	High	HQ Managed Inventory	Avg	$KS=1$			49.8	0.49	29.09	21.72	7.20
2				SS	$Z=1.65$			49.8	0.49	63.16	26.16	17.01
3				SS	$Z=2.33$			49.8	0.49	63.16	28.09	18.43
4				ES	$Cof=0.1$ $Z=2.33$			49.6	0.49	50.34	26.34	12.21
5			Town Order			Avg	$KS=1$	46.3	0.49	53.41	14.70	17.86
6			Joint Order	Avg	$KS=1$	Avg	$KS=1$	49.8	0.49	35.74	16.60	7.00
7		Low	HQ Managed Inventory	Avg	$KS=1$			49.8	0.49	38.91	14.66	9.00
8				SS	$Z=1.65$			49.8	0.49	62.68	23.27	22.17
9				SS	$Z=2.33$			49.8	0.49	75.71	27.54	27.38
10				ES	$Cof=0.1$ $Z=2.33$			44.5	0.48	42.51	10.37	13.32
11			Town Order			Avg	$KS=1$	46.5	0.49	37.27	10.22	11.91
12			Joint Order	Avg	$KS=1$	Avg	$KS=1$	49.8	0.49	37.43	12.34	10.30
13	30 km Mountain (town-30M)	High	HQ Managed Inventory	Avg	$KS=1$			80.5	0.34	22.55	10.87	6.00
14				SS	$Z=1.65$			79.0	0.37	42.63	18.19	11.27
15				SS	$Z=2.33$			79.0	0.37	42.63	21.35	13.13
16				ES	$Cof=0.1$ $Z=2.33$			77.9	0.38	25.42	12.87	6.39
17			Town Order			Avg	$KS=1$	62.0	0.45	20.72	8.67	5.70
18			Joint Order	Avg	$KS=1$	Avg	$KS=1$	76.7	0.38	24.29	11.11	5.31
19		Low	HQ Managed Inventory	Avg	$KS=1$			66.7	0.39	9.64	5.51	2.12
20				SS	$Z=1.65$			66.4	0.39	12.98	5.63	3.52
21				SS	$Z=2.33$			69.9	0.39	16.71	6.83	4.42
22				ES	$Cof=0.1$ $Z=2.33$			57.4	0.43	13.50	4.83	3.35
23			Town Order			Avg	$KS=1$	58.7	0.40	9.64	4.25	2.34
24			Joint Order	Avg	$KS=1$	Avg	$KS=1$	67.5	0.37	8.79	5.17	1.81
25	30 km Plain (town-30P)	High	HQ Managed Inventory	Avg	$KS=1$			77.8	0.39	22.00	9.72	6.00
26				SS	$Z=1.65$			66.4	0.42	15.16	5.28	3.79
27				SS	$Z=2.33$			66.8	0.42	15.15	5.29	3.77
28				ES	$Cof=0.1$ $Z=2.33$			80.3	0.37	29.32	11.92	8.08
29			Town Order			Avg	$KS=1$	66.3	0.43	15.72	6.36	4.25
30			Joint Order	Avg	$KS=1$	Avg	$KS=1$	76.0	0.39	14.77	6.80	3.71
31		Low	HQ Managed Inventory	Avg	$KS=1$			57.1	0.42	9.64	4.24	2.52
32				SS	$Z=1.65$			37.1	0.29	5.64	2.19	1.13
33				SS	$Z=2.33$			37.1	0.29	5.64	2.19	1.13
34				ES	$Cof=0.1$ $Z=2.33$			61.6	0.42	15.07	5.00	3.40
35			Town Order			Avg	$KS=1$	56.4	0.43	9.64	4.06	2.60
36			Joint Order	Avg	$KS=1$	Avg	$KS=1$	65.0	0.35	7.49	4.11	1.48

[a] The unit of *Total After HQ Inventory* is 10,000 bottles.

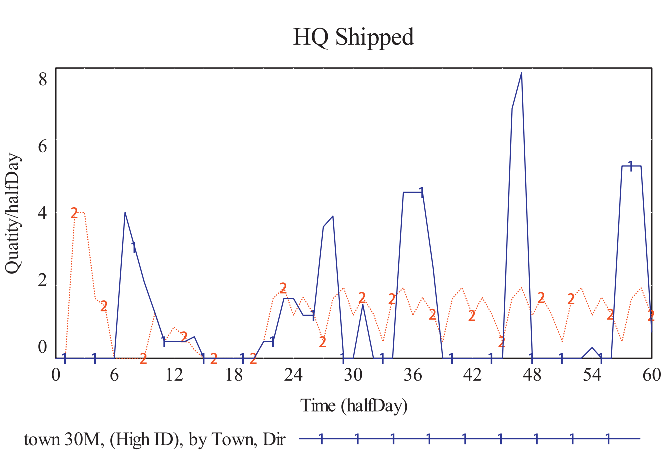

Fig. 8. Delay in submitting *Town Order*: with different levels of information delay.

traffic, and produces a further increased lead time. Figs. 10 and 11 demonstrate that the HQ receives feedback at a later time under a higher level of ID.

For the disaster relief supply chain, the ID will cause higher lead time, which means larger order quantities and higher levels of inventory. As shown in Figs. 8 and 11, the scenarios with higher ID leads to larger shipment quantities and more in-transit quantities. This is confirmed by the simulation results in Table 2. All scenarios with high ID have larger *Total After HQ Inventory* than their comparison objects using the same decision solution in the same town but with a lower ID.

In summary, the ID makes the Town Order strategy failed in *Supply Rate*, and a higher level of ID increases the inventory level.

4.2.2. *Impulse of road conditions*

As shown in Figs. 3 and 4, a heavy loss in road capacity directly leads to higher levels of transport time. However, greater transport

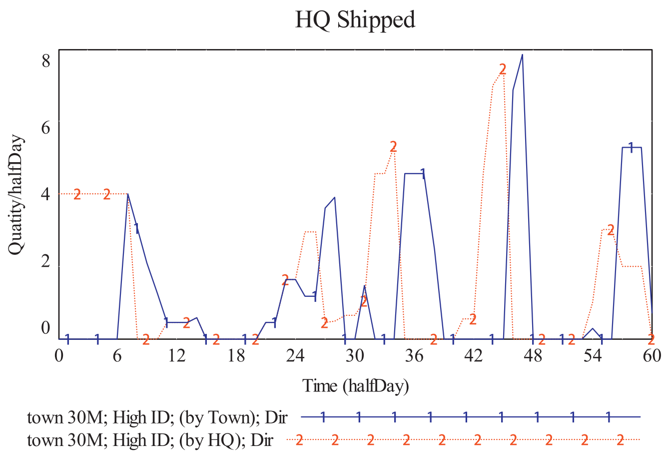

Fig. 9. Delay in submitting orders: by different inventory planning strategies.

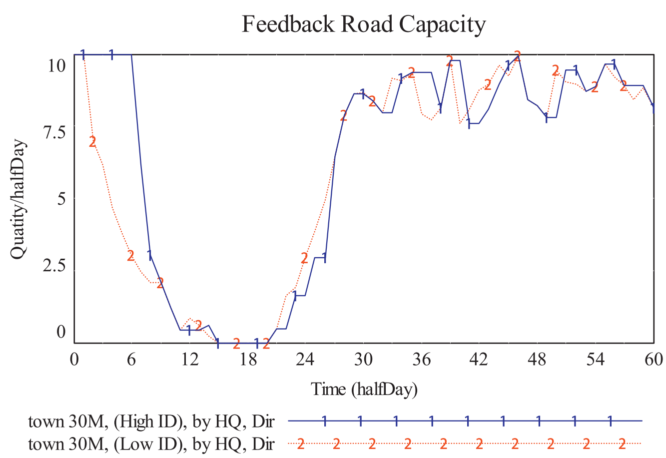

Fig. 10. Delay of *feedback of road capacity*: with different levels of information delay.

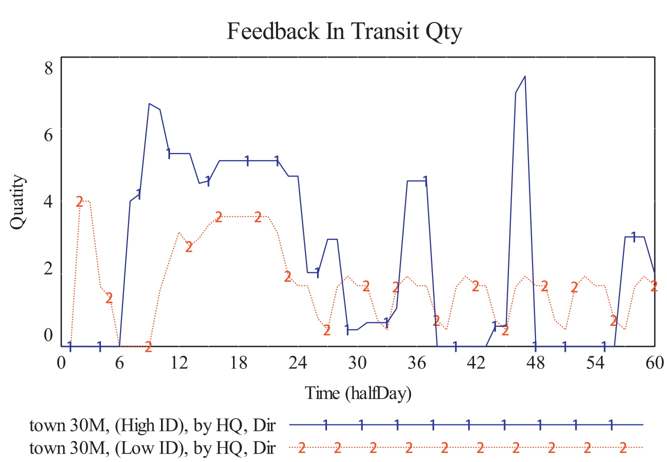

Fig. 11. Delay of *feedback in-transit inventory*, and increases: with different levels of information delay.

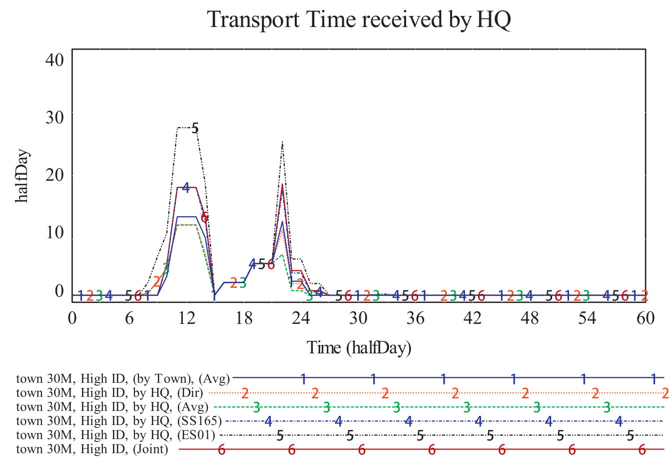

Fig. 12. Changes in transport time because of different replenishment decisions.

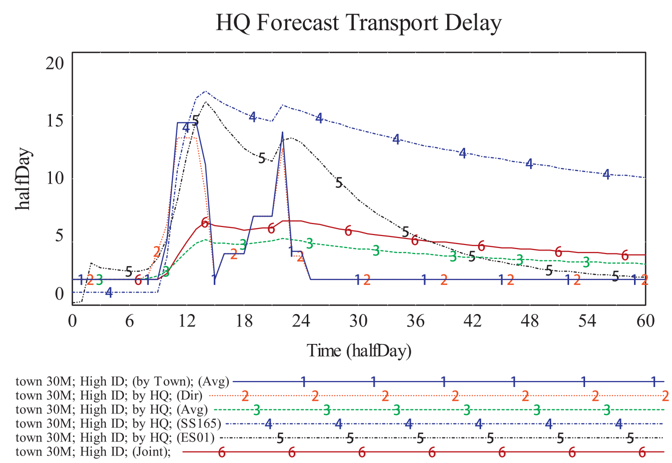

Fig. 13. Comparisons of prediction results using different forecasting methods.

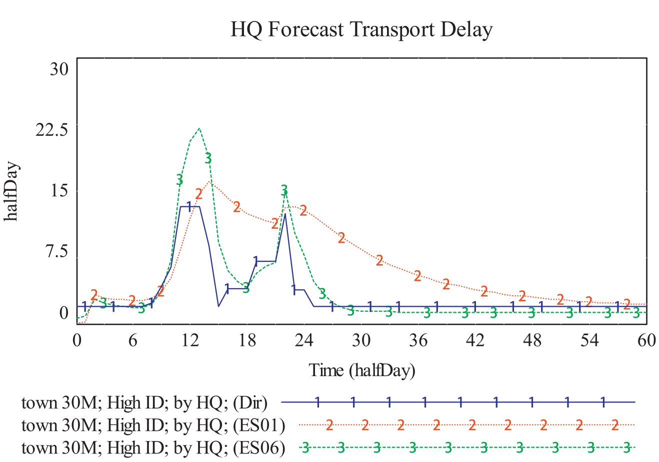

Fig. 14. Forecasting methods: quick response types.

delays will cause higher order quantities and greater shipment amounts. If the jam on the road increases because of the delays, then this will cause further delays. In other words, because of the worsening road conditions, replenishment decisions and transport delays will reinforce each other. In addition, the high level of ID will enhance this process of reciprocal reinforcement, and amplify the instability of the system. Fig. 12 presents how changes in transport delays occur because of the selection of different replenishment solutions. All scenarios are in same relief situation (town-30M with high ID). Fig. 13 shows how the different forecasting methods respond to the volatility of transport delays.

4.3. Effects of replenishment solutions

4.3.1. Forecast methods

Four forecasting methods are defined in Table 1. Six methods were tested with different environments in the simulation by

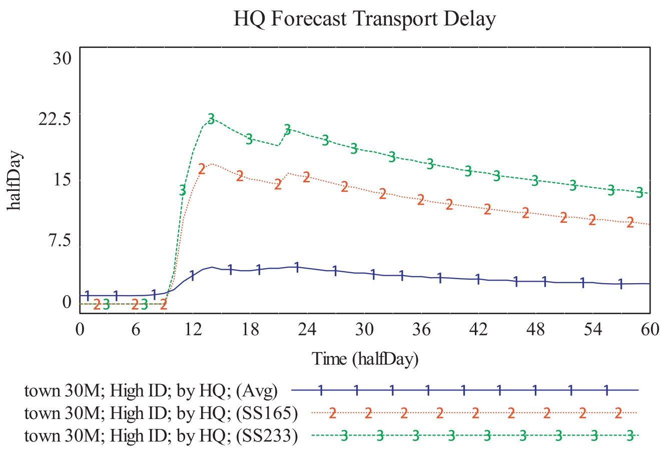

Fig. 15. Forecasting methods: trend-smoothing types.

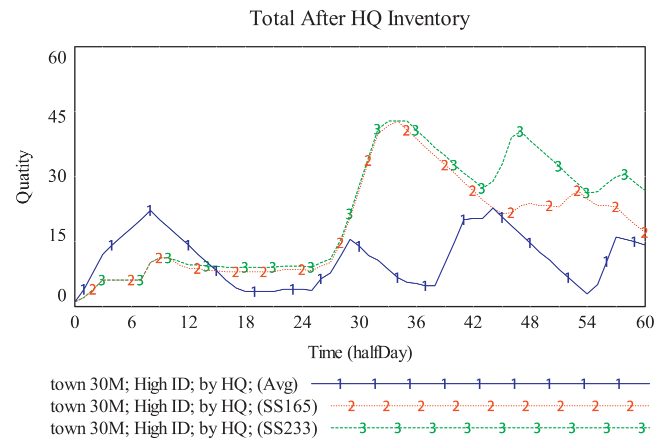

Fig. 17. Inventory level produced using trend-smoothing forecasting methods.

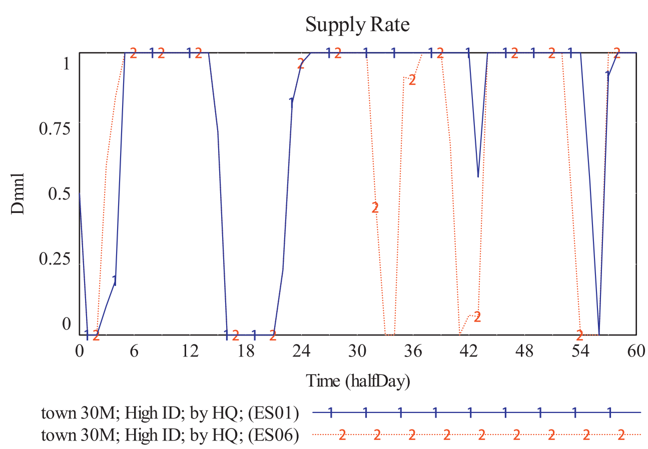

Fig. 16. Service level produced using quick response forecasting methods.

changing the parameters of 'SS' (Z=1.65, 2.33) and 'ES' (Cof=0.1, 0.6). Partial results are listed in Table 2.

There are two categories of methods in term of prediction effects. For example, Fig. 14 shows that three methods can be classified as quick response methods for town-30M with a high ID. The curve Dir is identical to *Transport Time received by HQ*. The curve ES06 is the result of the 'exponential smoothing' method with parameter Cof=0.6 and Z=2.33, which reflects the rapid changes in transport delays. The curve ES01 has a smoother result because of parameter Cof is set as 0.1. Fig. 15 shows that the other three methods can smooth the fluctuation of transport delays but cannot provide prompt response to transport delay trend. According to Table 1, these three methods are all based on $\overline{T}_t$, which smoothes the fluctuations of transport delays, and the difference is the amount of compensation (Avg: KS=1; SS165: Z=1.65; SS233: Z=2.33), which increases the level of the safety stock.

If the evaluation indicator is set that supply rate has higher priority than inventory level, the method Avg (mean *Supply Rate* of 80.5%, mean *Total After HQ Inventory* of 10.87) has the best system performance, followed by SS165 (79%, 18.19). Other methods are ranked as follows: SS233 (79%, 21.35), ES01 (77.9%, 12.87), Dir (73.6%, 8.82), and ES06 (63.6%, 8.57). The performances of Dir and ES06 are relatively poor because transport delays will become low in Dir and ES06 after a period of 30 turns, which leads to very low inventory and causes oscillations in *Supply Rate*, as shown in Fig. 16. The reason why Avg performs better than SS165 is a little more complicated. At 12 half-days, SS165 promptly responds to the sudden high latency of transport time but no cargo can be shipped because of poor road conditions. After 30 half-days, the prediction of SS165 maintains a higher value because of its algorithm of compensation, which obviously leads to excess inventory (Fig. 17). To summarize, the method Avg creates a better balance between trend responses and fluctuation smoothing in this environment.

The Dir and ES06 methods have bad system performance in all environments. So the relevant results were removed from Table 2.

The performance obtained using the forecasting method is closely related with the road conditions. With the volatility of the road capacity of town 30M, the trend-smoothing methods achieved better results. For example, as discussed above, Avg works better with a higher level of ID. In addition, SS233 is a better choice with lower ID. The low fluctuations in transport delay and the high level of inventory reduce the volatility of the service level.

For town-10M, because of its long period of road failure, all prediction methods resulted in almost identical *Supply Rate*. Thus, Avg is the appropriate choice because it lead to a lower inventory level with both high and low ID. Meanwhile, for town-30P, the loss of road capacity was insignificant, resulting in stable transport delays. This environment is very similar to a commercial supply chain. All the trend-smoothing methods failed to respond to the changes, and ES01 produced a better service level.

4.3.2. *Inventory planning strategies*

Three inventory planning strategies were tested in the simulations. They were defined by Eq. (3), Eq. (4), and in Table 1. In commercial activities, a strategy like Town Order does not require any information sharing along the supply chain. In disaster relief operations, the decision-makers in the town must collect the information of in-transit inventory to estimate the transport delay. However, only HQ can provide such information. In addition, the town must share its inventory levels with HQ if the strategy HQ Managed Inventory is selected. Furthermore, Joint Order requires the integration of the order quantities from both sides, which demands a higher degree of collaboration. Thus, information sharing and collaboration are not optional actions but rather essential in the disaster relief chain. The three strategies represent different levels of sharing.

For the simulation results listed in Table 2, the strategy Town Order offers a poorer performance than HQ Managed Inventory in every measure because of ID (Section 4.2.1). However, choosing between HQ Managed Inventory and Joint Order is more difficult. If the choice is based on service level which is measured by *Supply Rate*, Joint Order performs better in half of the scenarios (town-10M, and town-30P with low ID). When the choice is dependent on a balanced indicator such as service level and inventory level, Joint Order is the better choice in almost all scenarios except for town-30M with high ID, which endures a dramatically fluctuating environment.

The joint decision outperforms the individual decisions made by either side. The level of information sharing in disaster-affected areas is always insufficient because of the dynamic ID. Thus, both sides know only part of the actual situation. The Joint Order strategy will represent a compromise of two sides. The result is a smooth curve for inventory level and the stabilization of the service level. Big shortage of materials or a large excess supplies can be avoided, which are shown in Figs. 18 and 19.

However, such compensation has its limitations. Considering the simulation results for town-30M with high ID in Table 2, the

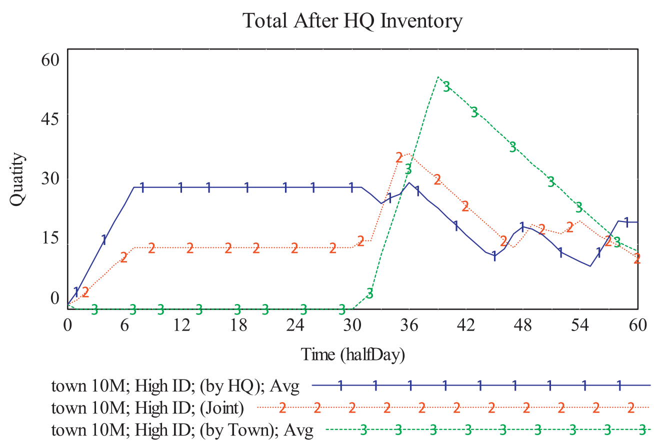

Fig. 18. Inventory levels using different inventory planning strategies in town-10M with high ID.

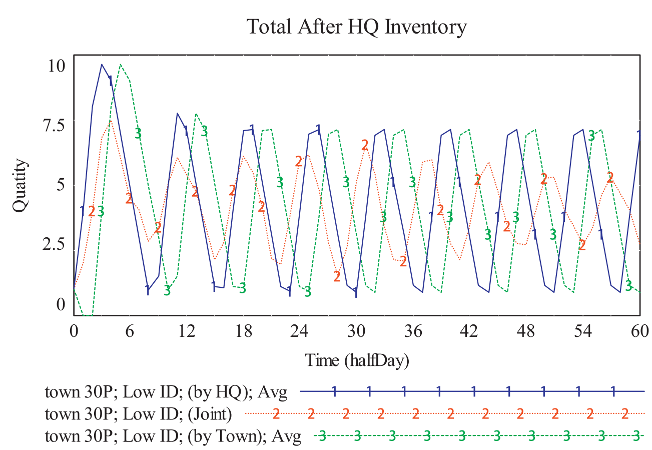

Fig. 19. Inventory levels using different inventory planning strategies in town-30P with low ID.

achievements (mean *Supply Rate*, mean *Total After HQ Inventory*) of solutions no. 13 (HQ Managed Inventory, Avg), no. 17 (Town Order, Avg), and no. 18 (Joint Order) are as follows: 80.5%, 10.87; 62%, 8.67; and 76.7%, 11.11, respectively. These data indicate that the order made by the town is valueless in the turbulent environment, so the algorithm of joint will not bring any improvement.

A collaboration in Joint Order is quite different to the practices of commercial activities. Previous literature shows that demand information and inventory level should be shared along the chain (VMI), or even the forecasting results or planning (Collaborative Planning or Continuous Replenishment Program), in order to lessen the bullwhip effect [12–14,28]. It is noted that retailers are excluded from making orders in commercial supply chains. However, in relief operations, orders made by towns should be generally included in the final replenishment decision because of the extreme lack of information, even though they are disadvantaged by high levels of ID.

4.4. *Decision tree*

A decision tree can be proposed based on the simulation results (Fig. 20). The decision regarding the replenishment solution depends on the relief objective and the features of the environment. Although the studies in this paper are based on the specific supply of bottled water, this decision tree can be extended to other types of emergency supplies. While the balanced goal which makes the selection of a replenishment solution dependent on the level of ID, is more appropriate for ordinary supplies such as instant noodles and bottled water, the goal for life-saving supplies, e.g. medical equipment, rescue tools, is only the service level and the selection of a replenishment solution is highly dependent on road conditions.

5. Conclusion

A SD model is proposed for a disaster relief chain with dynamic road conditions and ID. Replenishment solutions were then developed for three inventory planning strategies and four forecasting methods. Experiments are simulated for each of these solutions in different environmental scenarios. A decision tree was proposed based on the simulation results to help decision makers choose the appropriate stocking strategies. The research findings include:

(1) Comparing a disaster relief chain with a commercial supply chain, information sharing and collaboration have direct impact on inventory and logistics planning due to the dynamic environment.
(2) Two environmental factors were analyzed in this research:
   (a) The ID causes the orders submitted down the disaster relief chain to show poor levels of performance. High levels of ID increase the inventory levels as the decision makers have to place more orders to ensure the stocking level.

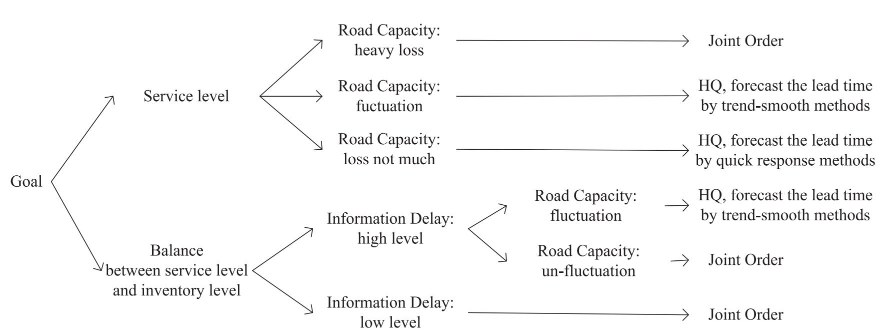

Fig. 20. Decision tree regarding the selection of an appropriate replenishment solution.

(b) The change of road conditions and shipment schedules have impact on the on-time transportation rate, while ID expedites the fluctuations in the delay of transportation which is not predictable.

(3) The replenishment solution is a two-stage decision to achieve the balance between the service level and the inventory level. First, planning inventory based on information sharing. Second, adjusting the strategy according to the predicted fluctuations of the lead time.

(4) The strategy of Joint Order obtains a more balanced performance in most circumstances. The HQ Managed Inventory produces a better service level in fluctuating situations. The smooth-the-trend forecasting method is suitable for inventory and logistic planning when the post-seismic situations are volatile, while the quick-response forecasting method has good performance in stable environments.

As future research directions, we may analyze information from clickstream in MicroBlog [30] to estimate inventory need and use questionnaire to collect expert's opinion [31] for logistic planning.

Acknowledgments

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