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Enhancement of supply chain resilience through inter-echelon information sharing

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Abstract Supply chains in the globally interconnected society have complex structures and thus are susceptible to disruptions such as natural disasters and diseases. The impact of the risks and disruptions that occur to one business entity can propagate to the entire supply chain. However, it has been proposed that cooperation amongst business entities can mitigate the impact of the risks. This paper aims to investigate the value of information sharing in a generalized three-echelon supply chain. The supply chain model is built in a system dynamics software, and three decision-making rules based on different levels of information sharing are developed. Performances of the three ordering policies with shock applied are compared. The results of the experiments prove the value of information sharing in the supply chain when shock exists.

Keywords Supply chain · Resilience · System dynamics · Simulation optimization · Inter-echelon · Information sharing

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1 Introduction

Academics and practitioners have become increasingly interested in supply chain disruptions, that can be caused by natural events, e.g., floods, earthquakes, etc., as well as intentional or unintentional human actions, e.g., industrial accidents, terrorist strikes, etc. (Snyder et al. 2012). Large scale natural disasters are an example of events requiring fast response strategies. Disruptive events may have catastrophic consequences on product manufacturing as well as service delivery. The affected companies reported, on average, 14 % increase in inventory, 11 % increase in cost and 7 % decrease in sales during the year following the disruption (Hendricks and Singhal 2005).

As highlighted in Hopp et al. (2012), globalization has played a major role in increasing the request for effective strategies for hedging against risk in supply chains. In fact, supply chains can be more vulnerable to disruptions and have to deal with more complex scenarios. In such a setting, sharing information can be a key factor for the firm success.

It is tempting to think of supply chain disruptions as rare events (Snyder et al. 2012). However, if we broaden out perspective to the several causes of supply chain disruptions, the probability that some of these disruptions will heavily affect the supply chain becomes high. Some supply chains face disruptions nearly every day; Walmart even has an emergency operations center dedicated to preparing for and mitigating the effects of man-made and natural disasters. In such a situation, it is important to adopt methodologies which are able to reproduce the detailed continuous dynamic behavior of the components of the supply chain to understand effects that small disruptions have on the system.

In this setting, this work aims to study the benefit of information sharing among the stakeholders when facing various risks in the supply chain networks and develop risk mitigation and resilience enhancement strategies. In order to evaluate and implement the policies, a system dynamics model of the supply chain is developed, which details the dynamic evolution of the system attributes. Specifically, the main contributions of this work are (1) Simulation-based framework for risk identification and evaluation; (2) Risk mitigation strategies based on multiple suppliers and different level of information sharing.

Due to the proposed framework, the firm can identify the key potential risks that supply chain networks may encounter and estimate the impacts of the risks To be more specific, supply chain network is treated as a complex system in the work. A risk identification and assessment framework is developed to categorize the potential risks a network may be exposed to. The impact of each risk on supply chain performance is then evaluated by means of system dynamics method. In particular, we propose a measurement system to quantify the resilience of a supply chain network when facing various risks.

Several relatively simple scenarios are studied first, and the result can be extended to investigate more complex networks. Since supply chains are treated as complex networks in this work, system dynamics approach is the best way to study the impact of risks on supply chain performances. After the system dynamics model has been established, it can be used as a tool for further measurements on key system performances. Since there are different kinds of private information, we identify the key potential information that should be shared according to the type of risk. The information that brings the highest benefit to the system performance is the most critical information that should be shared.

After that, indicators of supply chain resilience are defined to quantify the ability of the network to recover from the disruptions while accounting for the impact of information sharing that is used to mitigate the negative effects. The measurement of supply chain resilience helps to determine the optimal course of actions and develop risk mitigation strategies.

Based on the system dynamics model developed and indicators defined, we conduct numerical experiment compare the performance of the risk mitigation strategies at three different levels. Also, with a multi-objective simulation based optimization technique, we provide evidence to show the benefit brought by the information sharing in the supply chain.

2 Literature review

2.1 Classification of supply chain risks

There has been a fair amount of efforts devoted to describing and categorizing supply chain risks and the strategies for mitigating them (Tang and Musa 2011; Tomlin and Wang 2011). Johnson (2001) classified the risk in supply chain into (1) demand risks (e.g., seasonal imbalances, new product adoption), and (2) supply risks including limitations in the manufacturing or logistic capacity, political issues. Chopra and Sodhi (2012) identified the following categories linked to different mitigation strategies: system risks, receivables, inventory risk, forecasting risk, intellectual property risk, disruption, delays, procurement risks, receivables, capacity risks.

Snyder et al. (2012) individuate the several forms of supply uncertainty have been discussed in the literature. In particular, the authors highlight how, in the majority of the contributions, disruptions affect a firm's supplier; during a disruption, the supplier cannot provide any goods. Under yield uncertainty, the quantity delivered by a supplier or produced by a manufacturing process is a random variable that depends on the order quantity. The authors refer to this scenario as *capacity uncertainty*, in which the supplier's delivery capacity or the firm's manufacturing capacity is a random variable that is typically independent of the order quantity. Another identified uncertainty is the *Lead-time uncertainty*, i.e., the stochasticity in the order or processing lead time. Input cost uncertainty represents stochasticity in the procurement prices incurred by the firm. Snyder et al. (2012) recognizes how the boundaries among these forms of supply uncertainty are often blurry. For example, disruptions can often be viewed as a special case of yield uncertainty in which the yield is a Bernoulli random variable. However, yield uncertainty generally implies a continuous form of uncertainty, whereas disruptions are discrete, and therefore the two are often quite different in terms of both the approach toward modeling them and the managerial insights gained from them. The same is true for capacity uncertainty and lead-time uncertainty.

2.2 Uncertainty on supplier's capacity

With respect to these definitions, in this work, we deal with a capacity uncertainty problem. In order to mitigate risks, SC managers apply appropriate strategies (Schmitt and Tomlin 2012). They must detect the possible risks in their system, predict the possible outcomes and try to use appropriate proactive and reactive strategies. Mohammaddust et al. (2015) investigates how organizations should design their supply chains and use risk mitigation strategies to meet different performance objectives. The authors use a four-tier supply chain as a reference and look specifically into four strategies: (1) holding backup emergency stocks at the Distribution Centers (DCs); (2) holding backup emergency stock for transshipment to all DCs at a strategic DC (for risk pooling in the SC); (3) reserving excess capacity in the facilities; (4) using other facilities in the SCs network to backup the primary facilities. Barlas and Gunduz (2011) showed the different ordering and decision strategies that different echelons make, the order-up-to policy, the anchor and adjust policy and the (s, S) policy, and how each strategy performs under different demand distributions and the bullwhip effect on these different strategies. Certain literature pertaining to the use of information sharing has also been explored.

Among the several hedging strategies, *Substitute supplier or facility* represents one of the most common approaches (Mohammaddust et al. 2015; Chopra and Sodhi 2012). Sawik (2013) is concerned with the optimization of this strategy. Similarly to our approach, the authors consider a different ratio for the allocation of the order to the different suppliers. However, they do not consider information sharing. In fact, Sawik (2013) extends the approach in Sawik (2011) for the combined selection and protection of part suppliers and order quantity allocation in a supply chain with disruption risks. In particular, the protection decisions include the selection of suppliers to be fortified against disruptions and the allocation of inventory of parts to be prepositioned at protected suppliers, where the protected suppliers are capable of supplying parts in the face of disruption events. Given the demand for products, the decision maker needs to decide from which supplier to purchase parts required for products, which of the selected suppliers to protect against disruptions and how to allocate the inventory of required parts among the protected suppliers to minimize total cost and mitigate the impact of disruption risks. This results in a multi–objective problem as the one proposed in this work, where backlog is put in the trade-off with the inventory at each supplier.

2.3 Information sharing for risk mitigation

When multiple suppliers are present, it is apparent how the performance of a supply chain in terms of risk mitigation largely depends on how its players corporate with each other (Wakolbinger and Cruz 2011; Zhang 2012). To do so, information sharing plays a significant role in achieving supply chain corporation. Banerjee et al. (2003) explored the effect of lateral information sharing policies within the tier of the supply chain and their effect on supply chain performance. Sahin and Robinson (2005) studied the impact of information sharing on make-to-order systems using a simulation study.

Prior to these papers, much literature has also focused on the demand disruption in the supply chain. Li (2002) studied how to incent firms to sharing information vertically in a two-level supply chain where the retailers are engaged in a Cournot competition. Wu et al. (2010) evaluated the benefits of sharing information on suppliers product quality with the buyer and investigated how the buyer uses this information to reduce quality uncertainty in the products he received. The research also developed equilibrium strategies for the suppliers with quality information sharing by means of game theory. Ren et al. (2010) studied demand forecast sharing and supply chain coordination with a game-theoretical model and found equilibrium from a long-term relationship. Yang and Fan (2016) used control theory modeling and simulation showing that information sharing reduces the bull-whip effect under demand disruptions. Priya Datta et al. (2007) analyzed the effect of information sharing on supply chain resilience with agent-based modeling.

2.4 Resilience quantification and simulation

A relative amount of research has been dedicated to the quantification of the supply chain risk and the effect of the mitigation strategies (Son and Orchard 2013; Talluri et al. 2013; Spiegler et al. 2012; Carvalho 2011). In general, simulation plays a fundamental role in the case where complex multi-echelon supply chains are of concern. Wilson (2007) used system dynamics simulation to assess the impact of transportation disruptions on the performance of two kinds of supply chains. Fiala (2005) and Barlas and Gunduz (2011) proposed a similar approach. And Priya Datta et al. (2007) applied the approach of agent-based simulation modeling. However, these contributions mainly focus on *demand uncertainty*.

Fiala (2005) illustrates the STELLA software and how systems dynamics can be used to simulate information sharing. Schmitt and Singh (2012) analyzes inventory placement and backup methodologies in a multi-echelon network and view their effect on reducing supply chain risk. The authors focus on both risk from both supply disruptions and demand uncertainty. The impact of these different scenarios and the different mitigation strategies are investigated. A simulation model developed to capture a real network for a consumer packaged goods. Snyder and Shen (2006) use discrete-event simulation models to contrast supply uncertainty and demand uncertainty in optimal system design. They show that design decisions may be reversed when disruptions happen. Deleris and Erhun (2005) also use simulation in examining supply chain disruptions. Their Monte Carlo model requires entire branches of a supply chain to be non-functional if a disruption occurs at any stage in the branch. Schmitt and Singh (2009) use a combination of Monte Carlo and discrete-event simulation to model downtime due to disruptions, they allow the rest of the supply chain to function if a single stage is down.

3 Methodology

In contrast to the research works which studied information sharing strategies with focus on demand disruption, this paper first develops information sharing strategies to mitigate supply chain risk caused by supplier's capacity uncertainty, and analyzes the strategies by system dynamics modeling and multi-objective simulation-based optimization.

Particularly, in this paper, we focus on a three-echelon supply chain consisting of four suppliers which satisfy end customers' demand for a single type of product through two distributors and one retailer (Fig. 1). Without loss of generality, we assume that Supplier 1 and 2 take order from Distributor 1, Supplier 3 and 4 take order from Distribution 2, and the two distributors take order from the retailer. Each of them makes their own decisions on the ordering quantities and whether to share relevant information with other parties in the supply chain.

3.1 System dynamics model

A system dynamics model is developed to describe the three-echelon supply chain and investigate how it responds to disruptions with different levels of information sharing. This section explains the detailed formulation of the supply chain model from supplier level to distributor level and then to retailer level. In Fig. 2, we demonstrate how the system dynamic model can be implemented in iThink.

Notation-wise, in a general term, we use following notations to indicate variables related to product-flows: C for capacity, M for manufacturing rate, O for ordering rate, S for shipment rate, and D for customer demand rate; for variables related to product-stocks, we have I for inventory, P for stock in pipeline, and B for backorders; besides, we use time variables L to indicate the lead-time, and R for the refilling period (i.e., the expected time to replenish to the target stock).

In addition, we use superscript $\cdot^{s}$ for variables related to suppliers, $\cdot^{d}$ for distributors, and $\cdot^{r}$ for retailers; index i is to indicate four different suppliers, and index j for two distributors; last but not least, $\hat{\cdot}$ is to describe full or target values, and $\tilde{\cdot}$ is for aggregated values.

3.1.1 Supplier level

Each Supplier i has a full capacity $\hat{C}_i$ and a realized capacity C_i, and $C_i = \hat{C}_i$ when there is no shock occurring at this sub-supplier. $C_i = 0$ when the supplier is attacked

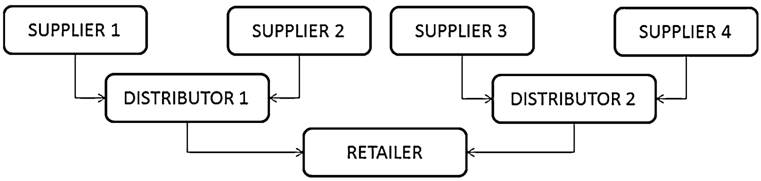


Fig. 1 Three-echelon supply chain with single type of product

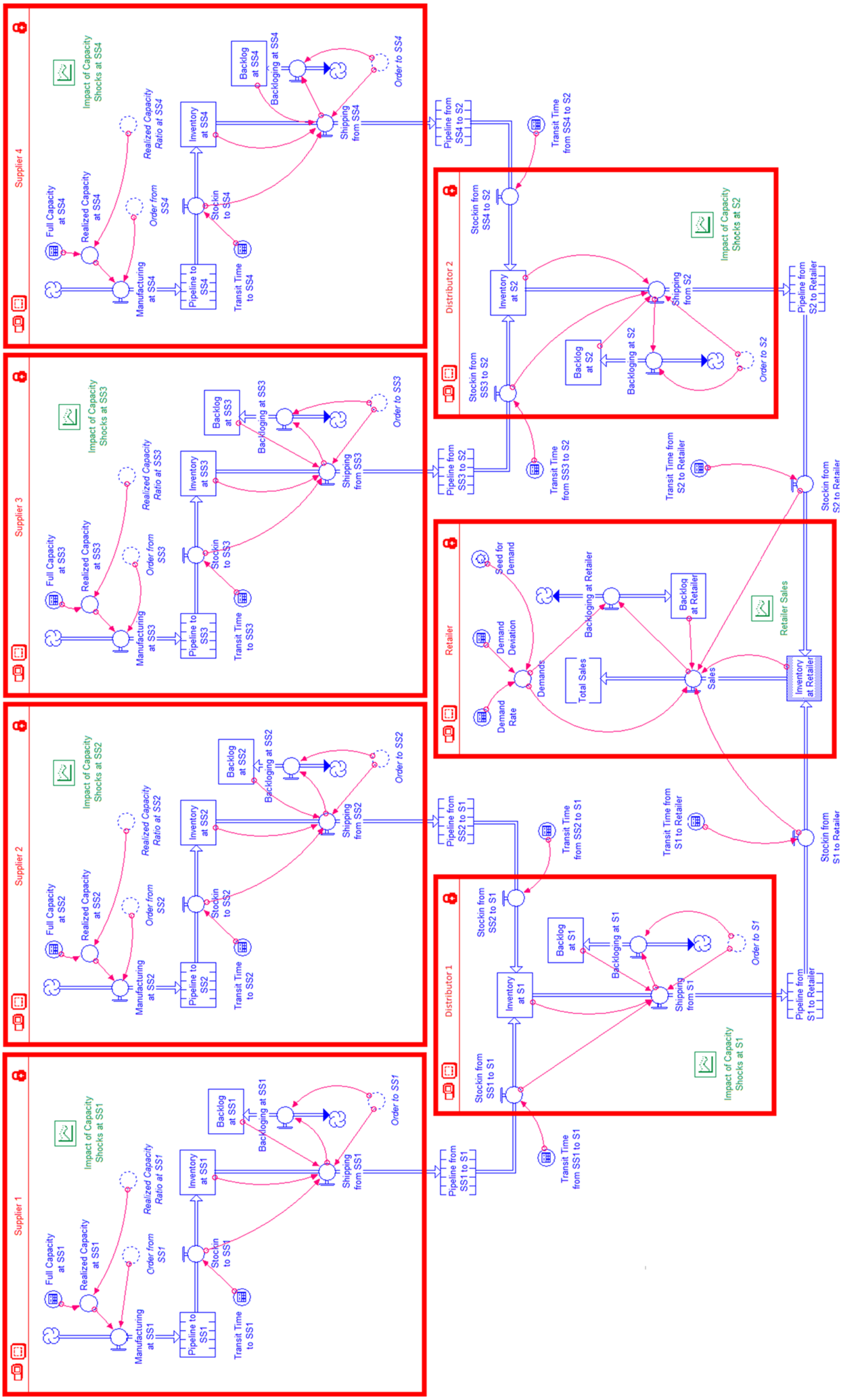


Fig. 2 The supply chain entity sector of the three-echelon supply chain

by shock, and C_i increases linearly from 0 to $\hat{C}_i$ during the capacity recovery period after the shock. The supplier decides how much to manufacture as M_i based on C_i and O_i^{s}, the order made by the supplier itself. If it can fulfill the amount it orders to itself, it will produce at the rate of O_i^{s}; if it cannot, it will produce at the largest capacity, it is able to achieve to get rid of the backlogs as well as to reach its target inventory level as quickly as possible. I.e.,

$$M_i = \min\left\{C_i, O_i^{\mathrm{s}}\right\}. \tag{1}$$

Supplier i makes order to itself to fulfill simultaneously the order from distributor j $O_{i,j}^{\mathrm{d}}$, its target inventory $\hat{I}_i^{\mathrm{s}}$, the target pipeline inventory $\hat{P}_i^{\mathrm{s}}$, and its own backorders B_i^{s}, i.e.,

$$O_i^{\mathrm{s}} = O_{i,j}^{\mathrm{d}} + \frac{\hat{I}_i^{\mathrm{s}} + \hat{P}_i^{\mathrm{s}} - I_i^{\mathrm{s}} - P_i^{\mathrm{s}} + B_i^{\mathrm{s}}}{R}. \tag{2}$$

Note that, I_i^{s} is the actual inventory held by the supplier, and P_i^{s} is the actual pipeline inventory which is in transition from manufacturing to stock within the supplier. The required refilling period to fulfill backorders is R. It is assumed that inventory is to be adjusted within one time period, i.e., $R = 1$.

The target pipeline inventory to supplier i is the ideal amount of products that are on the way from manufacture to stock. Thus, it equals to the demand to supplier i, which is the order from its respective distributor, multiplied by production lead-time L^{s}, i.e.,

$$\hat{P}_i^{\mathrm{s}} = O_{i,j}^{\mathrm{d}} \cdot L^{\mathrm{s}}. \tag{3}$$

The backorder at supplier i is the cumulated backlogs that have not been cleared from the beginning to time t. At every instance, the backorder, if any, equals to difference between $O_{i,j}^{\mathrm{d}}$ and the shipped amount from supplier to distributor, i.e., S_i^{s}, as in

$$\int_0^t \left(O_{i,j}^{\mathrm{d}} - S_i^{\mathrm{s}}\right) dt. \tag{4}$$

The supplier will try to ship to the distributor at the rate that satisfies the current order and clears the backlog in the time unit; if it is infeasible due to limited inflow rate, it will control the shipment in the sense that the inventory will only be exhausted after the next time unit. Therefore,

$$S_i^{\mathrm{s}} = \min\left(B_i^{\mathrm{s}} + O_{i,j}^{\mathrm{d}}, I_i^{\mathrm{s}} + \frac{P_i^{\mathrm{s}}}{L^{\mathrm{s}}}\right). \tag{5}$$

Note that, since S_i^{s} is updated continuously in system dynamics, (5) only sets the convergence rate of B_i^{s} or I_i^{s} towards the value of 0 if respective scenario holds. And the rate can be adjusted by adding an coefficient to B_i^{s} or I_i^{s} in the equation.

3.1.2 Distributor level

Each distributor j makes orders to two suppliers aiming to fulfill the order from the retailer O^{r}_j, its own target inventory $\hat{I}^{\mathrm{d}}_j$, the target pipeline inventory from supplier to it $\hat{P}^{\mathrm{d}}_j$, and the cumulated backorder B^{d}_j. Although the allocation of $O^{\mathrm{d}}_{i,j}$ depends on the strategies to be proposed in Sect. 3.2, the total ordering quantity $\tilde{O}^{\mathrm{d}}_j = \sum_i O^{\mathrm{d}}_{i,j}$ holds that,

$$\tilde{O}^{\mathrm{d}}_j = O^{\mathrm{r}}_j + \frac{\hat{I}^{\mathrm{d}}_j + \hat{P}^{\mathrm{d}}_j - I^{\mathrm{d}}_j - P^{\mathrm{d}}_j - B^{\mathrm{s}}_{i_1} - B^{\mathrm{s}}_{i_2} + B^{\mathrm{d}}_j}{R}, \tag{6}$$

in which I^{d}_j is the actual inventory at the distributor, P^{d}_j is the actual pipeline inventory which is in transition from the two suppliers to the distributor, and i_1, i_2 are the two suppliers of the distributor j. The same refilling period $R = 1$ applies.

Similar to supplier, the target pipeline inventory equals to the demand to distributor j, which is the order from the retailer to distributor j, multiplied by the transportation lead-time from supplier to distributor, L^{d}. Hence,

$$\hat{P}^{\mathrm{d}}_j = O^{\mathrm{r}}_j \cdot L^{\mathrm{d}}. \tag{7}$$

Note that the backorders at the two suppliers that are supplying distributor j are deducted from $\tilde{O}^{\mathrm{d}}_j$. The reason is that backorders at the suppliers are the unfulfilled orders from the distributor, which have been placed and should not be placed again. The suppliers will take care of their own backlogs and ship them to the distributor when they have enough stocks.

Similar to (5) for suppliers, the distributors ship products to the retailer at the rate

$$S^{\mathrm{d}}_j = \min\left(B^{\mathrm{d}}_j + O^{\mathrm{r}}_j, I^{\mathrm{d}}_j + \frac{P^{\mathrm{d}}_j}{L^{\mathrm{d}}}\right). \tag{8}$$

3.1.3 Retailer level

The structure of the retailer is similar as that of the distributor. The retailer places orders to the distributor in the same way as distributors order from suppliers. It ships products to the end-users to meet their demand D. To be specific, we have following.

$$\tilde{O}^{\mathrm{r}} = \sum_j O^{\mathrm{r}}_j, \tag{9}$$

$$\tilde{O}^{\mathrm{r}} = D + \frac{\hat{I}^{\mathrm{r}} + \hat{P}^{\mathrm{r}} - I^{\mathrm{r}} - P^{\mathrm{r}} - B^{\mathrm{d}}_1 - B^{\mathrm{d}}_2 + B^{\mathrm{r}}}{R}, \tag{10}$$

$$\hat{P}^{\mathrm{r}} = D \cdot L^{\mathrm{r}}, \tag{11}$$

$$S^{\mathrm{r}} = \min\left(B^{\mathrm{r}} + D, I^{\mathrm{r}} + \frac{P^{\mathrm{r}}}{L^{\mathrm{r}}}\right). \tag{12}$$

3.1.4 Performance indicators

Because the ultimate goal of the supply chain system is to fulfill the demands from the end customers, to measure the system resilience, we mainly focus on the indicators at the retailer.

One simple measurement is to count the total amount of backlog incurred by the capacity shock, neglect how long each backlog is held before being fulfilled, i.e.,

$$\beta_1 = \int_0^t (D - S^{\mathrm{r}})^+ dt. \tag{13}$$

Another measure it to record the total time duration when retailer is having outstanding backorder, neglect of the amount of backorder held at the same time, i.e.,

$$\beta_2 = \int_0^t \boldsymbol{1}_{(B^{\mathrm{r}} > 0)}\, dt. \tag{14}$$

Meanwhile, a more comprehensive indicator could be the cumulated backorder amount on time, i.e.,

$$\mathbf{B} = \int_0^t B^{\mathrm{r}}\, dt. \tag{15}$$

which addresses both magnitude and time duration of the backorder. Obviously, all the three indicators should be minimized in a resilient supply chain system when a shock happens.

However, it can be argued that all the three indicators can be simply reduced by maintaining a larger inventory at each echelon, which might incur a higher inventory cost. Therefore, we need another indicator to track the total cumulative inventory and minimize it at the same time when backlog indicators are to be reduced, i.e.,

$$\mathbf{I} = \int_0^t \left(\sum_i I_i^{\mathrm{s}} + \sum_j I_j^{\mathrm{d}} + I^{\mathrm{r}}\right) dt. \tag{16}$$

Different from backorder indicators, inventory at all echelon players should be taken into consideration.

For the implementation of the performance indicators in iThink, please refer to Fig. 2 in Sect. 4.

3.1.5 Model assumptions

In general, several assumptions are made for this study:

- Products are manufactured only by suppliers. Suppliers produce products and their production capacities are set at a certain level. In fact, they make internal orders to themselves for production. Distributors in this model do not order components from suppliers for assembly into new products.
- There is only one product traded in the supply chain. The four suppliers manufacture the same type of product, and the two distributors resale these products. This corresponds to the real life practice of purchasing the same good from multiple suppliers in order to mitigate risks.
- Anchor and adjust policy (Mutallip 2013; Mutallip and Yasarcan 2014) is applied in this model. It is a common practice for entities in a supply chain to keep a certain level of safety stock to deal with uncertainties. The anchor and adjust policy aims to maintain the inventory of each entity in the supply chain at a constant level. Thus, in this model, a target inventory is assigned to each entity. And a refilling period is applied to indicate how long it is required to adjust back to the target inventory level for each player.
- Lead-time is a constant. The production lead-time, as well as the transportation lead-time of goods from one tier to another, are both constant. It is assumed that the production lead-time is the same for all suppliers, and the transportation lead-time is the same for all suppliers and distributors.

The proposed model is a simplified case of many realistic supply chain systems. The study is aiming to analyze the resilience of the supply chain network when the capacity of some suppliers are affected by unexpected events, of which the impact can be propagated to the distributors and retailers. Specifically, in this study we would like to evaluate the impact of the disruption at the end-customers, and how it can be mitigated through information sharing among different echelons.

3.2 Information sharing policies

In this sub-section, we develop the ordering rules at three different levels of information sharing. And we assume that a single information sharing strategy can be agreed by all the entities in the supply chain to follow.

To develop the rules, we study the basic structure of one retailer with two distributors. It is established that the retailer will order according to the needs of demand and to fulfill his own policy of maintaining inventory. However, these orders have to be allocated to the two distributors. Since $\tilde{O}^{\mathrm{r}}$ is determined by (101112), here it is essential to determine r_1 and r_2 which are the ratios to allocate orders between two distributors, i.e.,

$$O_1^{\mathrm{r}} = r_1 \cdot \tilde{O}^{\mathrm{r}} \quad \text{and} \quad O_2^{\mathrm{r}} = r_2 \cdot \tilde{O}^{\mathrm{r}}. \tag{17}$$

Note that, for the rules to be generalized for the ordering from distributors to suppliers, we use B_1, B_2 and I_1, I_2 to denote the backorder and inventory of the two distributors.

3.2.1 Level 1: No information sharing

It is assumed that without information sharing between echelons, the retailer has knowledge of the backlog accumulated at each distributor, i.e., B_1 and B_2, because the unfulfilled order is placed by the retailer. Therefore, a good strategy for the retailer is to allocate the orders to each distributor based on the backlog accumulation. Here, we define the ratios,

$$r_1 = \frac{B_2}{B_1 + B_2} \quad \text{and} \quad \mathrm{r}_2 = \frac{\mathrm{B}_1}{\mathrm{B}_1 + \mathrm{B}_2}, \tag{18}$$

as the proportion of ordering quantity place to each distributor if there is any backorders. For special cases, when only one of the two suppliers has backorder, the full order quantity will be placed to the supplier without backorder; and when $B_1 = B_2 = 0$, where r_1 and r_2 are undefined, the order quantity will be split evenly between the two suppliers. The detailed rule can be concluded as following

- $B_1 > 0, B_2 > 0 \Rightarrow$ (18);
- $B_1 > 0, B_2 = 0 \Rightarrow r_1 = 0$ and $r_2 = 1$;
- $B_1 = 0, B_2 > 0 \Rightarrow r_1 = 1$ and $r_2 = 0$;
- otherwise $\Rightarrow r_1 = r_2 = 0.5$.

In the event of no information sharing, this ordering policy is chosen because it makes use of the available information, which in this case is the backlog at each distributor B_1 and B_2, in order to make a decision. Intuitively, when orders to a particular distributor are unfulfilled for some time, retailers may postulate that these distributors are not capable of fulfilling the orders and will change their ordering quantity to divert more orders to the more reliable one.

3.2.2 Level 2: Partial information sharing

If we assume that the information of inventory levels I_1 and I_2 can be shared across echelons, a smarter decision can be made when no backorder occurs in order to increase the supply chain resilience. As such, the retailer may have a simple ratio calculation based on the inventory levels, and we notice that the ratio only makes sense when both of them are positive, i.e.,

$$r_1 = \frac{I_1}{I_1 + I_2} \quad \text{and} \quad \mathrm{r}_2 = \frac{\mathrm{I}_2}{\mathrm{I}_1 + \mathrm{I}_2}. \tag{19}$$

As the result, evolving the rules in 3.2.1 by considering (19), we have the following rule:

- $B_1 > 0, B_2 > 0 \Rightarrow$ (18);
- $I_1 > 0, I_2 > 0 \Rightarrow$ (19);

- $B_1 > 0, B_2 = 0 \Rightarrow r_1 = 0$ and $r_2 = 1$;
- $B_1 = 0, B_2 > 0 \Rightarrow r_1 = 1$ and $r_2 = 0$;
- otherwise $\Rightarrow r_1 = r_2 = 0.5$.

Note that in the case when $B_1 > 0 \bigcap I_2 > 0$ or $I_1 > 0 \bigcap B_2 > 0$, both (18) and (19) provide the same ratios that allocate only to the distributor with no backorder.

With limited information sharing, this is a rather intuitive decision to make on the retailer's part. Essentially, the retailer orders less from the distributor with lower inventory levels, and more from the distributor with higher inventory levels.

3.2.3 Level 3: Full information sharing

In an ideal scenario, we assume that besides inventory information the production capacity through both distributor (total production capacity of suppliers associated with the distributor), i.e., C_1 and C_2, are also known across echelons. Then we are able to further improve the ordering strategy.

Firstly we remain the ordering strategy in trivial cases, i.e., only one of the two distributors has the backlog or both distributors have neither backlogs or inventories. Therefore, we only modify the rules when both distributors have outstanding backlogs or positive inventories.

Then consider the simpler case where both distributors have positive inventories and the order quantity can be fulfilled by the total production capacity. In such a case, in order to maintain inventory levels at both suppliers, we can allocate to them any quantity which is below their capacity. However, a fairer decision is to split the order quantity based on their capacity ratios, i.e.,

$$r_1 = \frac{C_1}{C_1 + C_2} \quad \text{and} \quad \mathrm{r}_2 = \frac{\mathrm{C}_2}{\mathrm{C}_1 + \mathrm{C}_2}. \tag{20}$$

The same strategy can be applied in the opposite case where both distributors have outstanding backorders and the ordering quantity is not smaller than the total capacity. It means that the outstanding backlogs are not expected to be cleared if the situation remains. Therefore, to distribute the impact of over-demand fairly between the two distributors, we apply the ratios as in (20).

Special consideration should be taken when both distributors have positive inventories, but the ordering quantity exceeds the total capacity. It implies that at least one distributor will expect the inventory to drop down towards 0. For a supply chain with higher resilience, we would like to prevent or postpone the situation where either supply exhaust its inventory. Therefore, the best strategy is to allocate the ordering quantity in the way that

$$\frac{I_1}{r_1 O - C_1} = \frac{I_2}{r_2 O - C_2}. \tag{21}$$

With $r_1 + r_2 = 1$, the equation above can be solved as:

$$r_1 = \frac{(O - C_2)I_1 + C_1 I_2}{I_1 + I_2} \quad \text{and} \quad \mathrm{r}_2 = \frac{(\mathrm{O} - \mathrm{C}_1)\mathrm{I}_2 + \mathrm{C}_2\mathrm{I}_1}{\mathrm{I}_1 + \mathrm{I}_2}. \tag{22}$$

Similarly, when both distributors have outstanding backlogs but the ordering quantity is less than the total capacity. It means that both distributors have the chance to clear their backlogs, and we are aiming to reach both clearances soon as possible. Thus, the following equation holds,

$$\frac{B_1}{C_1 - r_1 O} = \frac{B_2}{C_2 - r_2 O}. \tag{23}$$

Solving it, we have:

$$r_1 = \frac{(O - C_2)B_1 + C_1 B_2}{B_1 + B_2} \quad \text{and} \quad \mathrm{r}_2 = \frac{(\mathrm{O} - \mathrm{C}_1)\mathrm{B}_2 + \mathrm{C}_2\mathrm{B}_1}{\mathrm{B}_1 + \mathrm{B}_2}. \tag{24}$$

To summarize, when both inventory capacity information are shared among echelons, the rules are as following.

- $B_1 > 0, B_2 > 0 \Rightarrow$ if $O \geq C$, (20); else (24);
- $I_1 > 0, I_2 > 0 \Rightarrow$ if $O \leq C$, (20); else (22);
- $B_1 > 0, B_2 = 0 \Rightarrow r_1 = 0$ and $r_2 = 1$;
- $B_1 = 0, B_2 > 0 \Rightarrow r_1 = 1$ and $r_2 = 0$;
- otherwise $\Rightarrow r_1 = r_2 = 0.5$.

The three sets of rules discussed above can also be applied to between distributors and suppliers. We may further extend the rules to a more complex supply chain. For a supply chain with more than three echelons, the same idea applies as long as each supplier (or sub-supplier) has only one downstream customer. In an exceptional case, some coefficient can be assigned to each customer for calculating the induced capacity.

4 Numerical experiment

The structure of the supply chain as in iThink model can be perceived intuitively as in Fig. 2. The entities of the supply chain are structured according to the flow of the products, and the flows connect all the entities together as a complete supply chain. Thus, when the model is running, it can be seen clearly how products flow from the top tier to the bottom tier.

In numerical studies, we consider three scenarios. In the first two scenarios, the supply chain has the symmetric configuration, i.e., all suppliers have the same capacity of 37.5, and the target inventories at all entities are set to 25. However, in Scenario 1 we consider a constant daily demand of 100 at retailer level; and in Scenario 2, we consider its stochastic counterpart with the standard deviation of 10. For the last scenario, we experiment on an asymmetric supply chain with supplier capacity of 20, 30, 40 and 60, and the target inventory levels are also varied accordingly for all entities to provide sufficient buffer.

Two types of shocks are tested on each scenario of the supply chain. For a single shock, we let the capacity of one supplier (i.e., supplier 1) drops to 0 at Day 200, and lasts for 60 days and recovers gradually in 30 days; and for consecutive shocks, we let the same shock applies to one supplier at Day 200 and a second supplier at Day 240. Obviously, consecutive shocks will have a larger impact on the supply chain. We would like to observe the performance of the three strategies with different magnitude of disruption.

4.1 Scenario 1: Symmetric configuration with deterministic demand

Impacted by the single and consecutive capacity shocks, the resulted inventories (or backlogs for negative values) at all entities with different information sharing levels are displayed in Figs. 3 and 4.

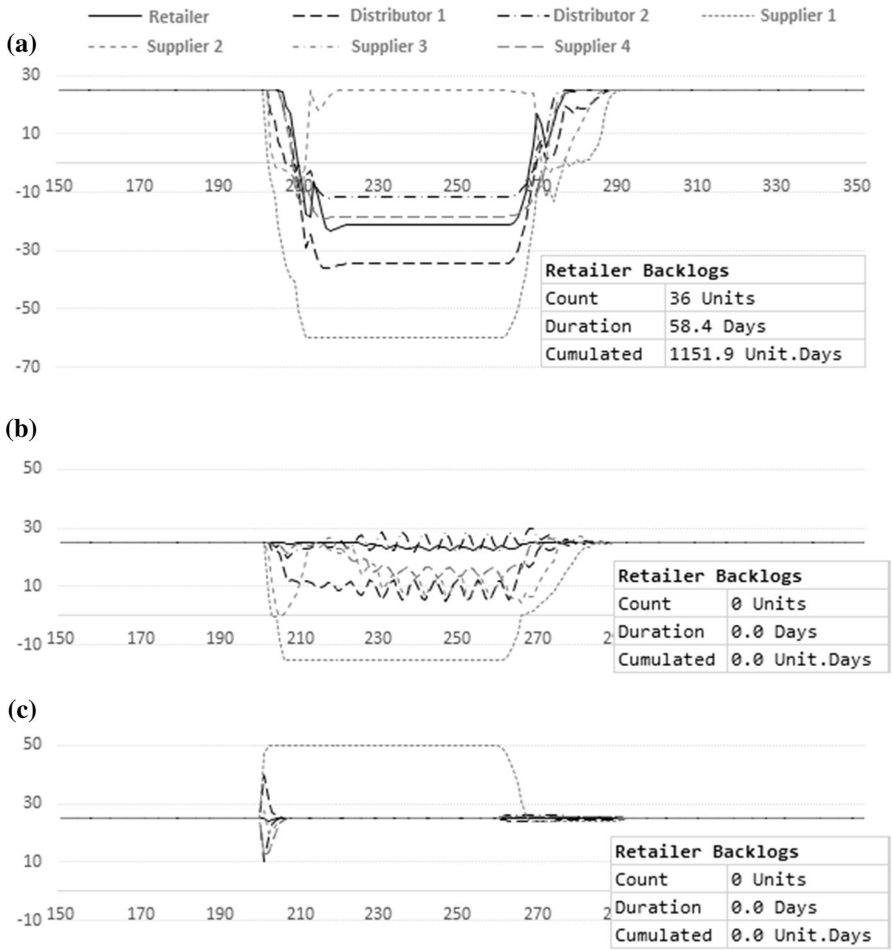


Fig. 3 Inventories impacted by the single capacity shock (deterministic demand). **a** No information sharing, **b** partial information sharing, **c** full information sharing

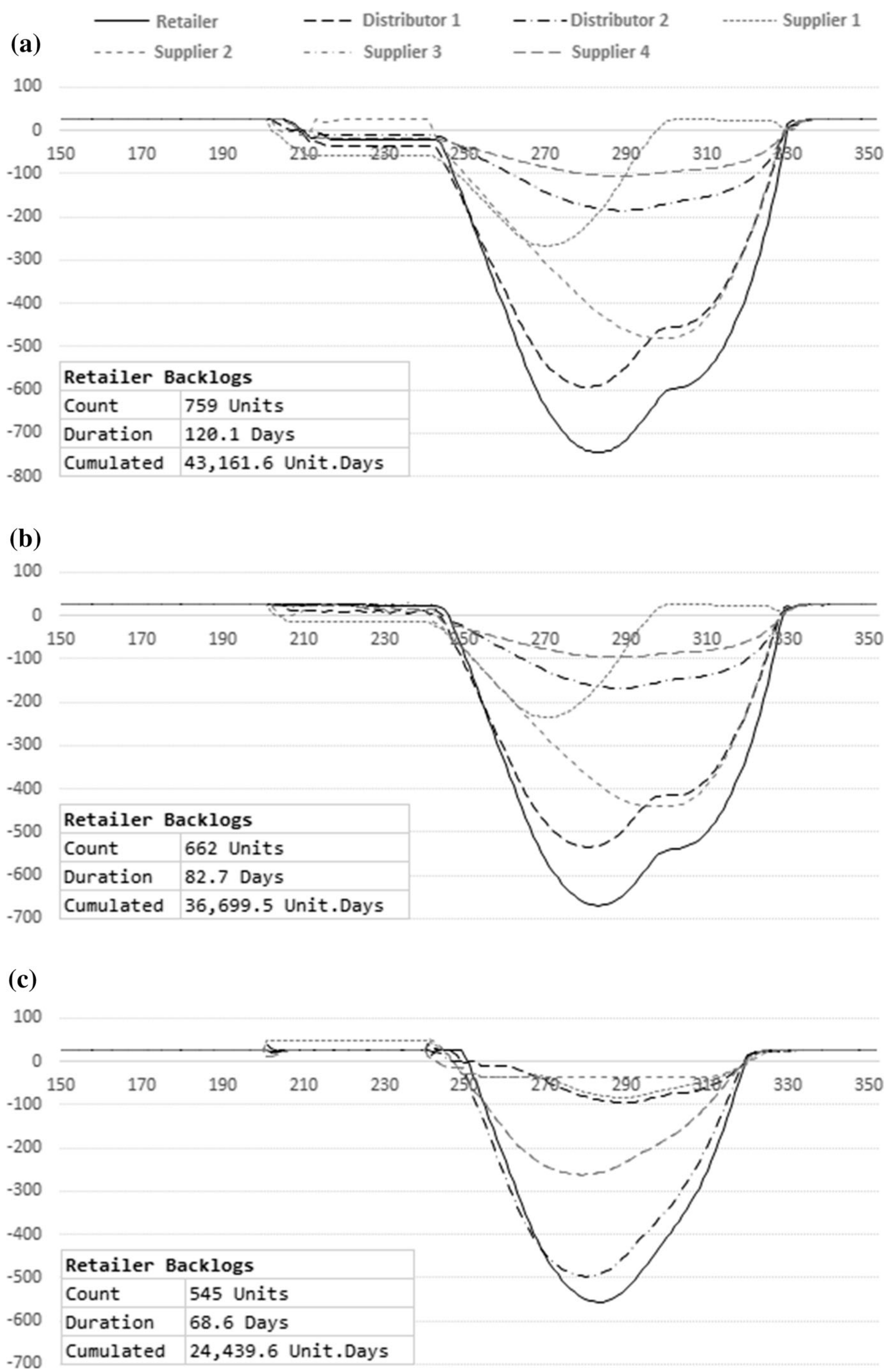


Fig. 4 Inventories impacted by the consecutive capacity shocks (deterministic demand). **a** No information sharing, **b** partial information sharing, **c** full information sharing

From the graphs, we notice that in all cases, the capacity shocks cause disturbance of inventory levels at all entities, and the impact can be recovered after the shock terminates. However, with partial and full information sharing, we could mitigate the risks incurred at the retailer level (refer to the solid lines) by eliminating or reducing its backlogs.

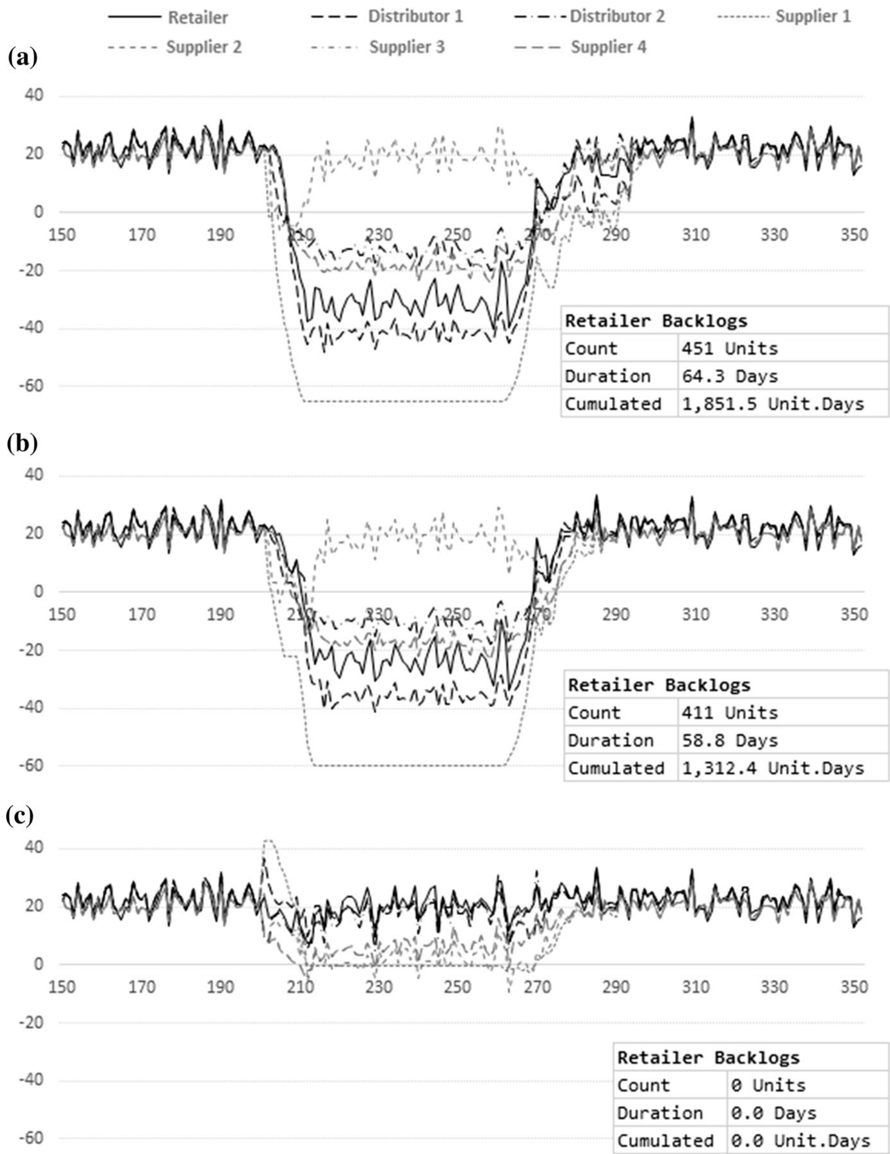
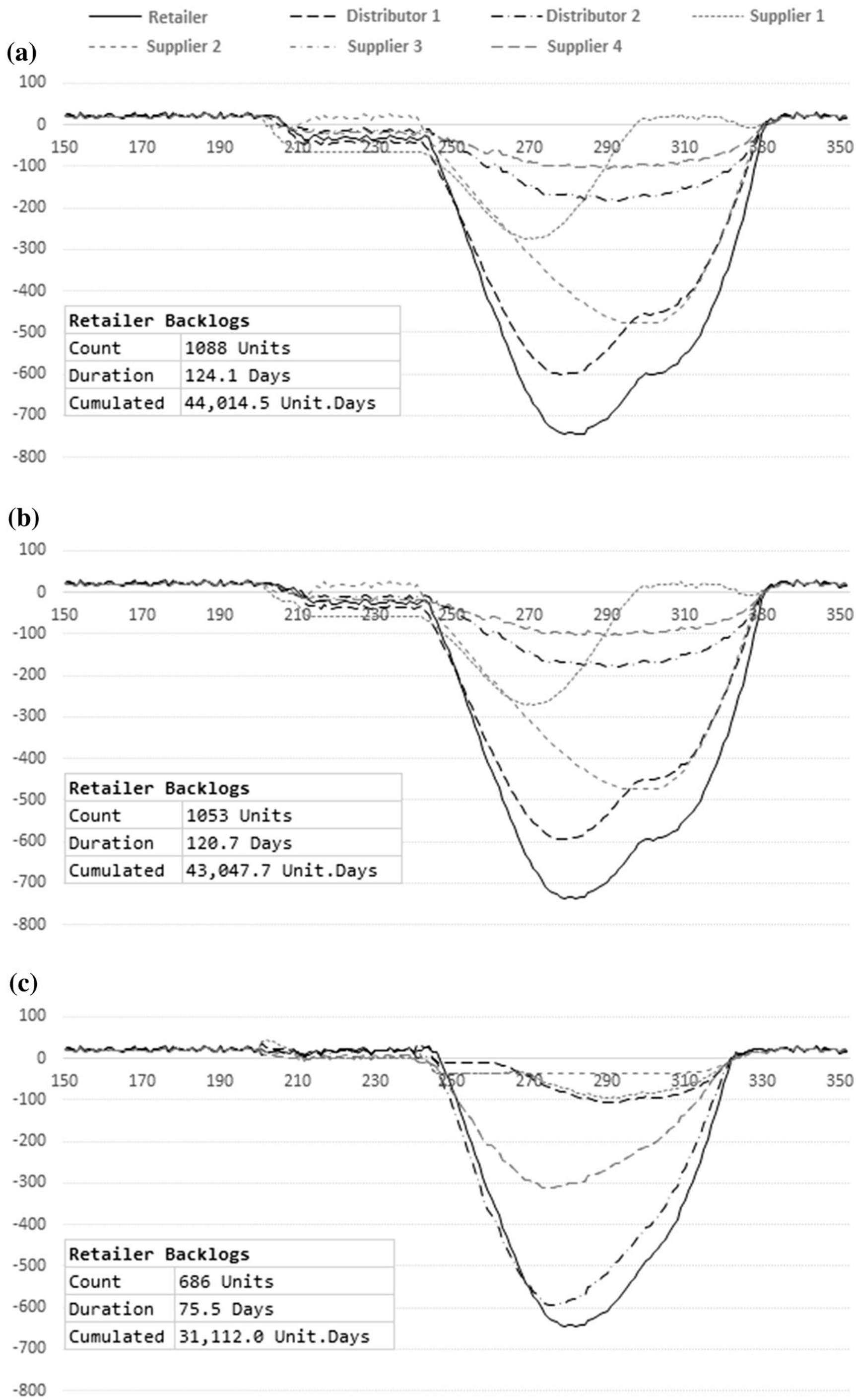


Fig. 5 Inventories impacted by the single capacity shock (stochastic demand). **a** No information sharing, **b** partial information sharing, **c** full information sharing


Retailer
Distributor 1
Distributor 2
Supplier 1
Supplier 2
Supplier 3
Supplier 4
(a)
Retailer Backlogs
Count 1088 Units
Duration 124.1 Days
Cumulated 44,014.5 Unit.Days
(b)
Retailer Backlogs
Count 1053 Units
Duration 120.7 Days
Cumulated 43,047.7 Unit.Days
(c)
Retailer Backlogs
Count 686 Units
Duration 75.5 Days
Cumulated 31,112.0 Unit.Days

◀**Fig. 6** Inventories impacted by the consecutive capacity shocks (stochastic demand). **a** No information sharing, **b** partial information sharing, **c** full information sharing

By comparing the Fig. 3a, b, we can see that when the impact of capacity shock is relatively small, the partial information sharing could stop the transmission of the backlog effect to the retailer by enabling it to wisely choose a distributor with higher inventory level. However, it may cause an oscillation between the inventory levels of two distributors when leading time is positive, which may require a larger buffer inventory to mitigate the effect. Comparatively, in Fig. 3c, full information sharing allows an immediate cut-off of the order placed to the supplier with shocked capacity, therefore, none of the entities has backlog throughout the experiment.

When, consecutive shocks happen, although none of the entities survives (i.e., free of backlogs), the discussed advantages of partial and full information sharing slows down the effect to be transmitted to the retailer; and even more, for full information sharing, when the shocked capacity starts to recover, it enables an immediate reaction at both distributor and retailer levels, so that the backlog at the retailer can be fulfilled in a shorter time.

4.2 Scenario 2: Symmetric configuration with stochastic demand

By adding the variation of the demand, the trend remains similar for comparison among different levels of the information sharing (Figs. 5, 6), unless for partial information sharing (i.e., Figs. 3b , 5b) the oscillation effect is not obvious due to the existence of demand variation. Also because of the variation, it is more likely for a retailer in Fig. 5b drops to an backlog, i.e., the advantage is weakened, although the partial information sharing is able to slow down process.

We replicate the experiment for 20 random seeds, the boxplots in Fig. 7 shows the comparison of all three backlog measurements. Partial information sharing is slightly better than no information sharing, while the advantage of full information sharing is more obvious.

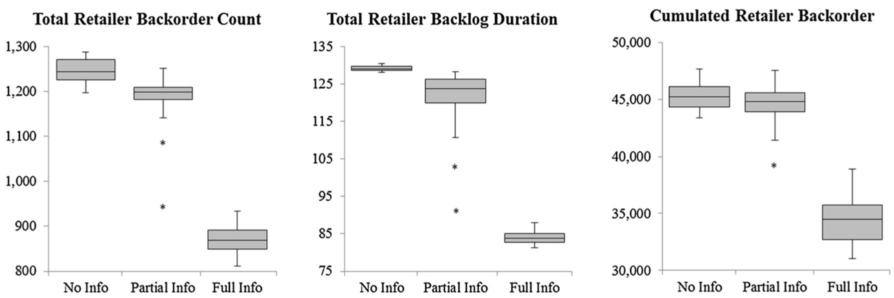
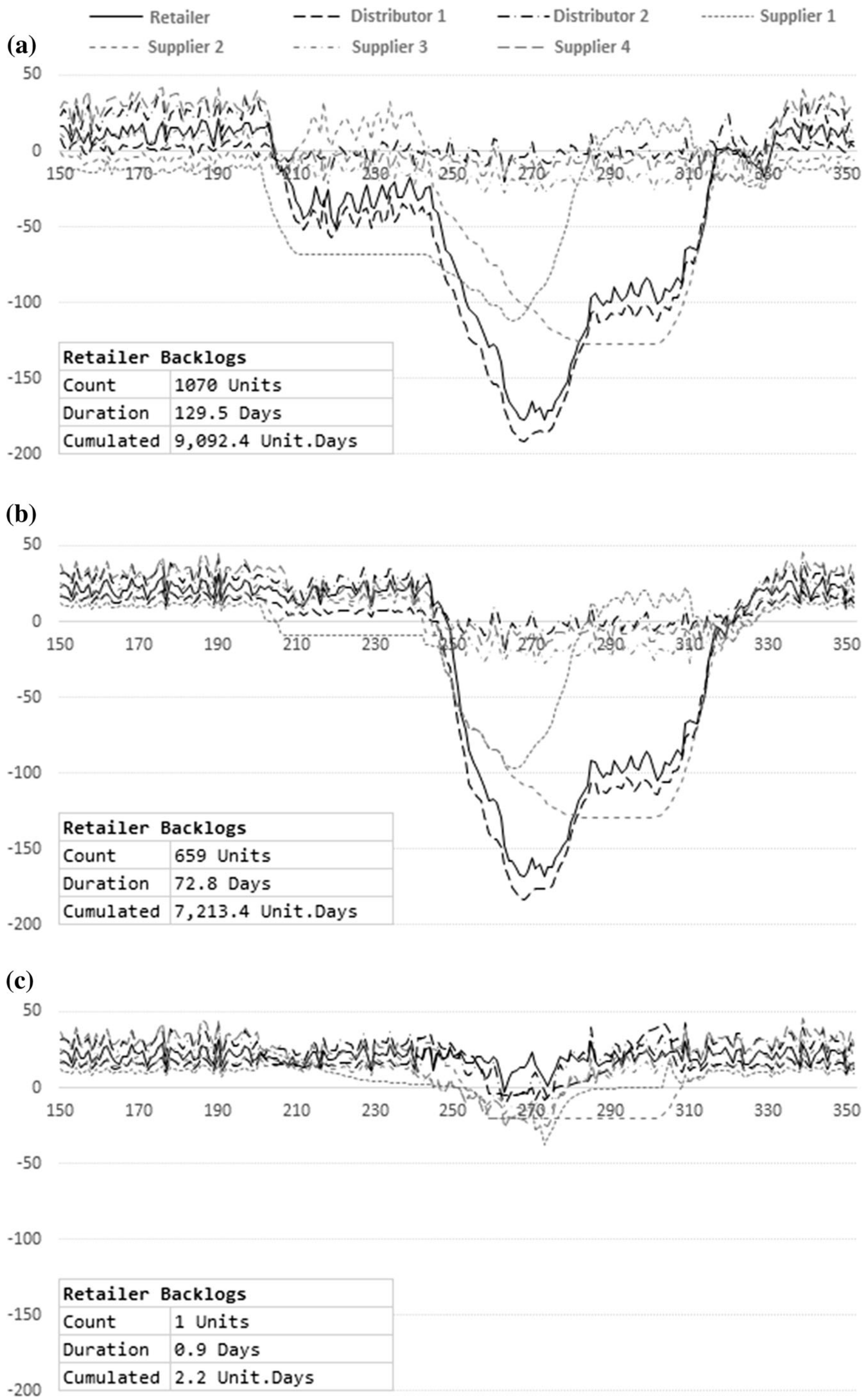


Fig. 7 Retailer backorder statuses for three information-sharing levels (symmetric capacities)


(a)
Retailer
Distributor 1
Distributor 2
Supplier 1
Supplier 2
Supplier 3
Supplier 4
Retailer Backlogs
Count 1070 Units
Duration 129.5 Days
Cumulated 9,092.4 Unit.Days
(b)
Retailer Backlogs
Count 659 Units
Duration 72.8 Days
Cumulated 7,213.4 Unit.Days
(c)
Retailer Backlogs
Count 1 Units
Duration 0.9 Days
Cumulated 2.2 Unit.Days
50
0
-50
-100
-150
-200
150
170
190
210
230
250
270
290
310
330
350

◀**Fig. 8** Inventories impacted by weak consecutive capacity shocks. **a** No information sharing, **b** partial information sharing, **c** full information sharing

4.3 Scenario 3: Asymmetric configuration

In this scenario, it is designed to test the three ordering policies in a more practical situation. In real life practices, the downstream business entities rarely order the same quantity from all the suppliers; instead, they will have a main supplier, with which it has a close cooperation, and one or many smaller suppliers in order to mitigate the consequences of risks.

When consecutive capacity shocks are applied to supplier 1 & 2, the results as in Fig. 8 is very similar to the result in Fig. 5 where a single shock is applied to supplier 1. This is because in the asymmetric case, the total capacity of supplier 1 & 2 is only 50, and even if both capacities drop to zero, the remaining capacities are still enough to fulfill customer demand. The shock barely incurs any backlog at the distributor and retailer levels of the supply chain with full information sharing. But because the inventory difference could be large on both distributor and supplier levels, sharing the inventory information becomes more importance. Therefore, the improvement from Fig. 8a, b in the early phase is obvious.

In the case where consecutive shocks are applied to supplier 3 & 4, we expect a substantial impact on the supply chain (Fig. 9) because the total capacity of the two is twice as large as that of supplier 1 & 2. After running for 20 replications, boxplots for backorder measurements are generated to compare the three levels of information sharing (Fig. 10), where the same ranking of the three information sharing strategies can be derived.

4.4 Optimal inventories

The previous section has shown that with the same target inventory levels, information sharing is able to reduce backlogs at all entities when different types of capacity shocks happen to the supply chain. However, it may be argued that the realized inventory levels will also become higher, and when the inventory cost is more significant than the penalty brought by the backlogs, the information sharing may not be the superior strategy.

To provide a more comprehensive study, in this section, we try to search out and compare the optimal solutions under each information sharing strategies, in terms of minimizing the total cumulated inventory as well as the cumulated backlog at the retailer, by manipulating the target inventory levels.

Since there are two objectives under consideration, we apply a multi-objective search algorithm MO-COMPASS (Li et al. 2015) for identifying the Pareto set. Technically, we developed an optimization platform which is adaptable to the iThink simulator, so that solutions can be sampled by the search algorithm, and evaluated and feedback by the simulator.

To reduce the complexity of the optimization, we add in a constraint that the target inventories levels for different entities at same echelon are proportional to

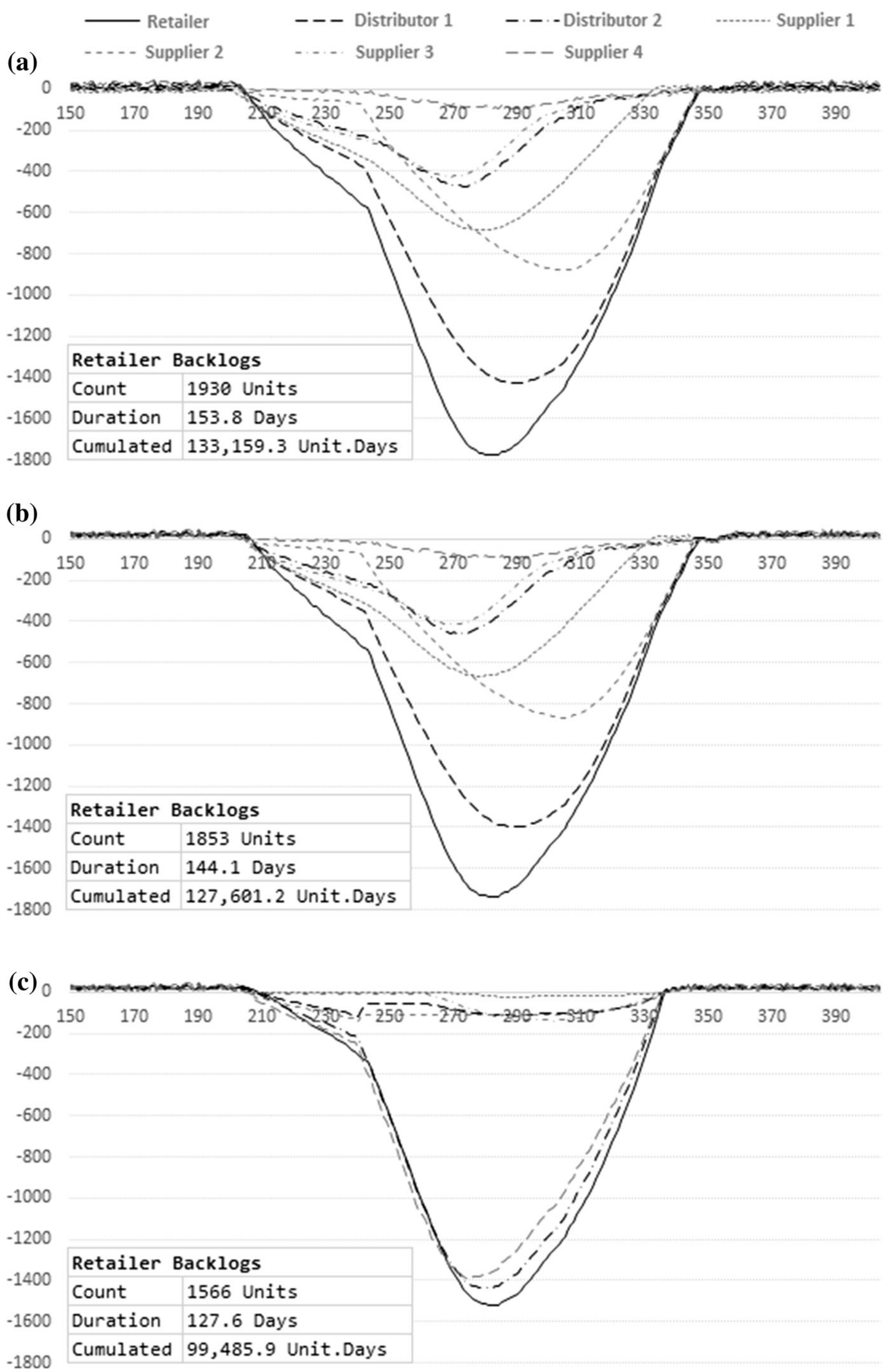


Fig. 9 Inventories impacted by strong consecutive capacity shocks. **a** No information sharing, **b** partial information sharing, **c** full information sharing

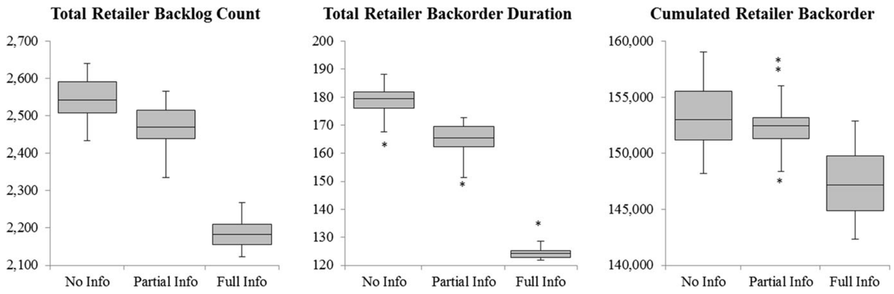


Fig. 10 Retailer backorder statuses for three information-sharing levels (asymmetric capacities)

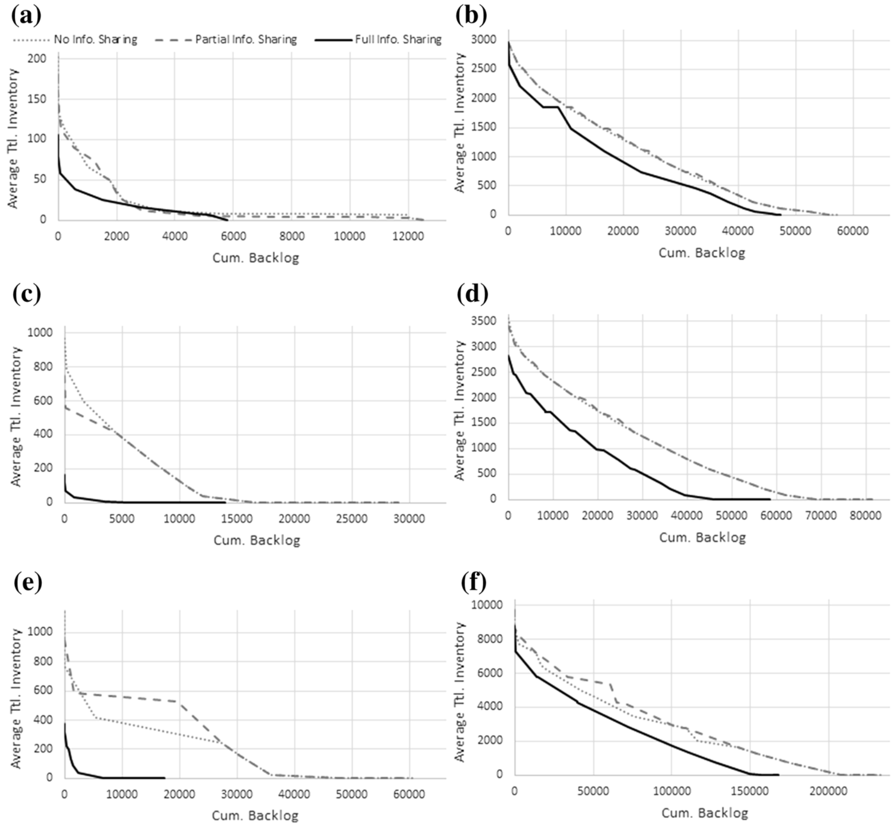


Fig. 11 Pareto solutions for different scenarios and strategies. **a** Scenario 1, single shock, **b** Scenario 1, consecutive shocks, **c** Scenario 2, single shock, **d** Scenario 2, consecutive shocks, **e** Scenario 3, weak consecutive shocks, **f** Scenario 3, strong consecutive shocks

their full capacities. Therefore, the solution space is reduced to the dimension of three. Furthermore, on each dimension only 10 discretized values are considered. Notice that, the simulation length is 1000 days for each solution, so we believe that the simulation results is sufficiently precise.

With the optimization infrastructure, by exploring $<8\ \%$ of the solution space, we are able to identify a set of Pareto solutions (further study of full enumeration verifies that the results approximate the global Pareto set) for each scenario as mentioned in Sect. 4, each with three information sharing strategies. The results are shown in Fig. 11.

From the results, we have sufficient evidence to believe that full information sharing is significantly superior to the other two strategies, when both backlog and realized inventory are considered. On the other hand, the advantage of partial information sharing is not obvious in many cases. Considering the situation where both upstream entities are with backlogs, the partial information sharing is indifferent from no information sharing. From the comparison in Sect. 4, we can see that the partial information sharing delays the occurrence of backlog, however, in this study the advantage is offset by the higher cumulated inventory. Whereas, the full information sharing gains a significant advantage because it enables faster recovery from the shock.

5 Conclusion

In this paper, we studied a three-echelon supply chain network where disruptions happen on the suppliers' capacities. Compared with existing research in literature, an innovative contribution has been made in this paper by incorporating information sharing across different echelons with supplier's capacity uncertainty, and developing a three level strategies to achieve higher resilience of the supply chain network.

We developed the system dynamic models of the three-echelon supply chain and conducted numerical experiments on several typical scenarios, i.e., deterministic vs. stochastic demand, symmetric vs. asymmetric configuration, and single vs. consecutive disruptions. Through the experiments, we are able to show that information sharing indeed helps to improve the supplier chain resilience in terms of reduced backorder amount and duration, when target inventory levels are specified.

It has been demonstrated that when both backlog and cumulated inventory is considered, and target inventory levels are treated as decision variable, a multi-objective simulation optimization technique can be applied to identify the Pareto solutions for each information sharing strategy. According to the experiment results, we have sufficient evidence to claim that full information sharing dominates the other two strategies in terms of reducing both backlogs and cumulated inventory.

In practice, although a supply chain network might have a different structure from what has studied in this paper, the same methodology for system dynamics modeling can still be applied for evaluating the supply chain resilience. Moreover, the three level strategies developed in Sect. 3.2 are intuitive and possible to be generalized for a more complex system, e.g., each entity receives products from more than two suppliers, or more than one product type are considered, which could be addressed by future studies.

Besides, a future alternative research could develop a theoretical framework for the problem addressed, and provide analytical analysis of the three-level rules proposed in this paper. For example, we could develop a mathematical formulation of the parameterized strategies and approximate their relationships with the objective to be optimized, which we have modeled in this paper through system dynamics simulation. Possibly, better strategies can be derived by identifying the optimal solutions of the analytical model.

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