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ORIGINAL PAPER

Dynamic assessment of control system designs of information shared supply chain network experiencing supplier disruption

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Abstract

The importance of acquiring and sharing real-time disruption information in the supply chain for proper deployment of disruption mitigation strategies is well-known in the literature. However, studies in this direction are limited in the domain of supply chain dynamics. In this paper, we investigate the effect of sharing real-time disruption and inventory information to mitigate supplier disruption through proper order allocation between the suppliers. We consider a three-echelon manufacturing supply chain network where a manufacturer and first-tier suppliers adopt dual sourcing. At the first-tier supplier level, the supply chain network is subjected to random disruption. Using control engineering modeling and simulation, we first evaluate the value of information sharing in disruption mitigation efforts, and further, we examine the effect of various control system design configurations of the manufacturer to maximize its dynamic performance in the information shared supply chain settings. The results show that, in the case of upstream supplier disruption, information transparency on the vulnerabilities among supply chain members improves the performance. Further, it is observed that for a given control structure, the selection of decision parameters affect the dynamic performance of the supply chain with proper order allocation strategy during the disruption. The findings of this research can provide the basis for managers to make informed decisions about using mitigation strategies with their supply chain partners.

Keywords Information sharing · Supplier disruption · Supply chain dynamics · Simulation · Supply chain

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1 Introduction

The prompt detection of an impending disruption provides sufficient time for the firms to prepare and adopt appropriate mitigation strategies for disruption management. In the case of a global supply chain, real-time information on suppliers disruption provides weeks for the execution of mitigation strategies (Sheffi 2015). Having advanced information helps firms to take actions such as securing material from other suppliers and moving away inventory and assets from affected areas. Additionally, the companies that are vigilant to identify disruptions early have a significant competitive advantage over others (Zsidisin and Smith 2005). For instance, Nokia's prompt detection of the disruption of its sole supplier's plant (Philips), enabled them to identify alternate suppliers whereas Ericsson, in a similar situation, could not. The strategy enabled Nokia to dominate the market later (Chopra and Sodhi 2012). In this paper, an attempt is made to evaluate the effect of real-time sharing of disruption information in a supply chain experiencing supplier disruption. Additionally, with the help of control engineering modeling and simulation, a detailed system dynamic analysis is carried out to obtain an improved supply chain design from a system level control perspective.

There is a growing body of literature emphasizing the need to obtain real-time disruption information (Sheffi 2015; Ye et al. 2015; Sarkar and Kumar 2015; Blackhurst et al. 2005; Hendricks and Singhal 2005). There are several ways of obtaining information on disruption. The most typical way is to obtain information directly from supply chain members, and the willingness to share the private information on disruption is usually driven by proper collaboration and coordination through contracts between channel partners (Wakolbinger and Cruz 2011; Tang 2006; Kouvelis et al. 2006). Some firms make public announcements of their disruptions (Hendricks and Singhal 2003, 2005). For example, in 2005, Airbus announced the issues it faced regarding the supply and installation of electrical parts in their new A 380 jumbo jet (Schmidt and Raman 2012). The legislation of some countries, make the public announcement of disruption mandatory (Sarkar and Kumar 2015). The availability of information on drivers of supply chain disruption is generally limited and expensive (Ye et al. 2015). Nevertheless, the information on economic performance could be readily available. Therefore, studies (Ye et al. 2015; Schmidt and Raman 2012; Hendricks and Singhal 2005) have proposed the use of statistical techniques on the economic data of firms to identify disruptions. Advanced information technology also helps in the real-time identification of disruption. Nine data sources have been proposed by Sheffi (2015), for the early detection of disruption, which include weather, news, sensor, supply base monitoring information, and so on. Emerging technologies such as the electronic supply chain (e-SCM) (Lin 2014; Gonul Kochan et al. 2018), internet of things (IoT) (Townsend et al. 2018), cloud computing (Cao et al. 2017; Yu et al. 2017), cloud manufacturing (Xu 2012; Liu et al. 2018), and cyber-physical systems (Bogataj et al. 2017; Kusiak 2018), help in improved collaboration and acquisition of information whereas technologies such as big-data analytics (Barbosa et al. 2018) and predictive analytics (Gunasekaran et al. 2017; van der Spoel et al. 2017), with the help of advanced computing and storage facilities, enable proper interpretation of information for the identification/prediction of issues. For example, organizations can routinely check and obtain real-time information on supply chain wide business operations, using RFID/IoT technology and a sensor network (Townsend et al. 2018).

In this paper, we attempt to evaluate the value of information sharing in a three-echelon manufacturing supply chain network model in generic settings that are experiencing disruption at the level of first-tier suppliers. The shared information includes real-time disruption information as well as on-hand inventory information with the suppliers. In addition to that, the following research questions are addressed:

1. What are the different control system designs for the manufacturer to improve the dynamic performance, during the disruption in information shared supply chain networks?
2. What is the effect of various control designs on the performance of information shared supply chain networks?

For the purpose of this research, control engineering modeling and simulation is adopted. We have employed benchmark models with additional considerations to represent various nodes of the supply chain. The extent of the backlog is used as a performance measure in the first part of the analysis, for evaluating the value of information sharing. In the second part of the analysis, a transient control engineering performance measure is considered, as proposed by Spiegler et al. (2012).

Our study differs from previous studies in the following ways. Studies on supply chain dynamics, using control engineering methods, usually employ two-echelon models (Spiegler et al. 2012, 2015; Yang and Fan 2016) whereas we have considered three-echelon converging supply chain network models. Previous studies have considered downstream disturbance using a step function; however, to study the dynamics of the supply chain to derive supply chain risk mitigation strategies, we have considered upstream supplier disruptions and modeled them, thereby explicitly characterizing phases of maximum impact and recovery. Previous studies have considered information sharing in the domain of supply chain dynamics to study topics such as supply chain uncertainty (Yang et al. 2011), order variability (Dejonckheere et al. 2004; Cannella et al. 2011), coordination (Cannella et al. 2015b) and collaboration (Disney and Towill 2003; Disney et al. 2003; Xie and Ma 2014), our work examines real-time information sharing to devise disruption mitigation strategies. Additionally, the present study considers the sharing of real-time disruption information.

The contribution of this research towards the extant body of knowledge is two-fold. This paper investigates the influence of real-time information sharing on supplier risk mitigation in a dynamic setting, an area that has not received much attention in the literature. Secondly, our study provides insights on how dual sourcing strategy, a well-established strategy for risk mitigation, can be implemented more effectively with the help of real-time information sharing and a dynamic procurement policy to reduce the impact of upstream supplier disruption.

The remaining parts of the paper are organized as follows. Section 2 presents a review of the relevant literature on information sharing in the supply chain, and on information sharing strategies within the context of supply chain disruption management. Section 3 explains the manufacturing supply chain network model considered in this study. Section 4 describes the order allocation strategies of downstream members of the supply chain between their suppliers with and without information sharing scenarios. Section 5 presents a numerical study of supplier disruption and the results obtained on performance variations. Section 6 presents the effects of various control structures of the manufacturer on its dynamic performance. Section 7 concludes by reflecting on the managerial implications of the study.

2 Literature survey

For several decades, the topic of information sharing has been widely addressed in the literature (Forrester 1958; Sterman 1989; Lee et al. 1997a). Broadly classified, the relevant literature falls into two categories: studies on improvement of supply chain dynamics by reducing the bullwhip effect, as well as supply chain coordination and collaboration studies to prevent the occurrence of the double marginalization effect. The bullwhip effect or amplification of demand variability across the upstream side of the supply chain was first observed by Forrester (1958), and later, the term was proposed by Lee et al. (1997b). Giard and Sali (2013) and Huang et al. (2003) have given a detailed review of the impact of information sharing between supply chain partners with a focus on the dynamic performance of the supply chain. A comprehensive review of supply chain coordination and information sharing on supply chain can be found in the studies of Cachon and Lariviere (2001), Chen (2003), and Montoya-Torres and Ortiz-Vargas (2014).

Table 1 presents a representative list of various information sharing studies and the shared information mentioned in the studies.

Using mathematical programming, studies have investigated in greater details the value of having advanced disruption information in mitigating disruption. Most of

Table 1 Studies on shared information mentioned in literature

Literature	Shared information
Huang and Wang (2017), Gu et al. (2017), Ha et al. (2017), Muzaffar et al. (2017), Costantino et al. (2014), Wang and Zhang (2010)	Demand
Cachon and Lariviere (2001)	Demand, forecast
Cachon and Fisher (2000), Gavirneni et al. (1999), Chen (1998)	Demand, order
Lv (2017), Srivathsan and Kamath (2017)	Inventory
Choudhary et al. (2016), Choudhary and Shankar (2015), Datta and Christopher (2011)	Inventory, demand
Chen (1999)	Inventory, order
Lau et al. (2002)	Production information
Li et al. (2016)	Inventory, capacity
Tao et al. (2016)	Inventory, capacity
Banerjee and Golhar (2017)	Product design information
Esmaeili et al. (2017)	Lead-time, service level
Zhang et al. (2006)	Shipment quantity
Li et al. (2006)	Demand, inventory, shipment

these studies assumed that firms are aware of the exact disruption process and considered a distribution for the disruption process. Snyder and Tomlin (2008) studied inventory strategies to mitigate disruption, when advanced warning of disruption is available about a defaulting supplier. Song and Zipkin (1996) and Lewis et al. (2013) employed the Markov process for model building when disruption information is unavailable, as a result of the lack of historical data or unwillingness of the firms to share private information. To obtain accurate disruption information, mathematical modeling approaches either resort to a forecasting-based method (Tomlin 2009) or deploy an incentive mechanism that would reveal private disruption information (Yang et al. 2008). Although these studies provide insights into the impact of disruption and mitigation strategies, they cannot provide complete information on the dynamic impact of the disruption risks (Yang and Fan 2016).

Considering the practical difficulties involved in full information sharing (Fawcett et al. 2011; Spekman and Davis 2016), there is a growing stream of literature on the partial information sharing scenario. Using a mathematical modelling approach, Lau et al. (2004) investigated the impact of various degrees of partial information sharing on the inventory replenishment process of the members of a three-stage divergent supply chain. Huang and Iravani (2005) studied a partial information sharing scenario where a manufacturer receives demand and inventory information from any of their two retailers and investigated the optimal production policy of the manufacturer based on the shared information. Ganesh et al. (2014a) considered partial information sharing at both the upstream and downstream levels and investigated the value of information sharing for the members of a multi-echelon supply chain. Ganesh et al. (2014b) investigated how product and demand characteristics influence the value of information sharing in a multi-echelon supply chain with upstream and downstream levels of information sharing. Shnaiderman and Ouardighi (2014) explored the case of partial information sharing between a retailer and a manufacturer, where the retailer reveals the demand information within an interval. Shang et al. (2015) derived the conditions under which a common retailer shares information to upstream manufacturers of two competing supply chains through which the manufacturers sell their products. Cannella et al. (2015a) conducted a discrete event simulation study to examine how the interaction between various levels of information sharing between supply chain partners and choice of inventory control policies affect the supply chain performance. Using the multi-agent modeling approach, Dominguez et al. (2018a, b) examined the partial demand information sharing structures between four heterogeneous retailers and a single wholesaler in a four-echelon supply chain model. In contrast, our work considers real-time sharing of full information between the upstream and the downstream members with the aim of improving operational performance under supplier disruption risks.

Today's global supply chains are usually multi-echelon networks with each echelon spread across different geographical regions. Various members or echelons need not be simultaneously affected by a single disruption. Using a case study approach, Scheibe and Blackhurst (2018) was able to study the drivers of supply chain disruption propagation and emphasized the need to consider the structure of supply chain and managerial policies in addressing this issue. Using discrete event simulation methodology, Ivanov (2017) examined the ripple effect of disruption in a four echelon supply chain in the case of less frequent/high impact disruption and observed that simulation studies can provide insights into ripple effect with respect to the disruption characteristics. Macdonald et al. (2018) developed a methodology for exploring the factors affecting supply chain performance through disruption propagation with the help of discrete event simulation approach. Considering the information sharing aspect as well, Schmitt et al. (2017) investigated the ripple effect of disruption in a multi-echelon supply chain. Their study was focused on revealing the adverse effects of information availability and flexibility that can trigger adverse consequences such as the bullwhip effect. Ivanov and Rozhkov (2017) studied coordination issues in the ordering and production of control activities of a fast moving consumer product industry. They adopted a combined multi-agent based modeling and discrete event simulation methodology that modifies the order allocation algorithm, to avoid redundant order allocation during a disruption.

One supply chain simulation study, which explicitly considered real-time disruption information sharing, is the work of Sarkar and Kumar (2015). The study explored a behavioral aspect of policy making in a multi-echelon supply chain of beer distribution facing disruption. Their study showed that, in the context of a well-known supply chain simulation game on beer distribution, it is always advantageous to communicate upstream disruption information with downstream members.

Most of the works on supply chain dynamics focused on reducing uncertainty and order variability in a bullwhip-like situation. However, researchers have now begun to focus on disruption management in the supply chains. Highlighting on system dynamics in the face of a disruption, Spiegler et al. (2012) focused on the improvement of supply chain resilience, using control engineering modeling and simulation. Their study proposed a control engineering metric to quantify the resilience of the supply chain system. Spiegler et al. (2015) extended the same methodology and used nonlinear control theory to study the performance improvement of the distribution system of the UK grocery industry. Yang and Fan (2016) used control engineering methodology to examine the effect of information management strategies on supply chain disruption mitigation. Their study considered the bullwhip metric to measure the operational risk and found a balance between operational and disruption risks. Although these studies provide in-depth analysis on the dynamic performance of the system experiencing disruption, they restrict the size of the supply chains to a maximum of two echelons and only consider demand side disruption. On the contrary, our study considers three echelons and models the supply side disruption process.

Dynamic modeling studies on supply chain disruption usually adopt Forrester's (1961) system dynamics modeling and simulation approach. Bueno-Solano and Cedillo-Campos (2014) used system dynamics to study disruption and its propagation effect in a global supply chain. Similarly, Cedillo-Campos et al. (2014) investigated the issues of logistical activities of a global supply chain, resulting from disruptions and delays at international borders. Gu and Gao (2017) examined production disruption in a manufacturing supply chain with integrated remanufacturing activities. None of these system dynamics studies have considered the information sharing aspect in disruption management.

However, there are system dynamics studies that considered information sharing to mitigate supply chain disruption (Wilson 2007; Tao et al. 2016; Li et al. 2016). Wilson (2007) examined the consequences of logistic disruption on supply chain performance.

The study considered a comparison between traditional supply chain settings and a vendor managed inventory (VMI) system, to examine improvement in disruption mitigation in the VMI setting. In the VMI model, customers' demand information are shared with a first-tier supplier. Tao et al. (2016) investigated the effect of information sharing to mitigate supply disruption through proper order allocation between the suppliers. The study considered a two-echelon supply chain consisting of a retailer and two suppliers. They considered three scenarios: (1) no information sharing, (2) partial information sharing and (3) multiple information sharing. The shared information includes supplier's inventory level and production capacity. Their results showed improvement in disruption mitigation through accurate and timely response as the shared information level increases. In an extended model, Li et al. (2016) examined the same problem in a three-echelon supply chain network to improve supply chain resilience. The resilience is quantified based on back order, recovery time and inventory level. They showed that considering backlog and cumulative inventory as two objectives, a multi-objective optimization problem can be obtained with target inventory as a decision variable. Our work follows a similar framework and network structure. However, the difference is that control engineering modeling and simulation are adopted and the focus is on the effect of real-time disruption information sharing in disruption management through proper order allocation. Moreover, we conducted further analysis to obtain the best possible control structure for the information shared supply chain setting.

2.1 APVIOBPCS modeling

APVIOBPCS stands for 'Automatic Pipeline Variable Inventory and Order Based Production Control System', which is an extension of the APIOBPCS archetype developed by John et al. (1994), using classical control engineering techniques. These models are derived from the original IOBPCS archetype—a well-established framework for production planning and inventory control—introduced by Towill (1982). The archetypes are collectively called the IOBPCS family of models (Lin et al. 2016; Sarimveis et al. 2008; Lalwani et al. 2006). The derivative APVIOBPCS has been proven to be the most representative of the order-up-to (OUT) policy (Wikner et al. 2017; Dejonckheere et al. 2003). Using this ordering rule, Dejonckheere et al. (2004) studied the impact of information sharing in a supply chain to reduce the bullwhip effect. Wang et al. (2012) examined the stability of the constrained inventory systems of the APVIOBPCS archetype, and the study has been further extended to incorporate the oscillatory behavior of the system (Wang et al. 2014). White and Censlive (2013) employed the archetype to optimize the profit of the production inventory control system with various control strategies. In our work, the archetype is selected with additional considerations to model each node of the supply chain network model used in the study.

3 Supply chain model

In this study, we consider a three-echelon supply chain model consisting of a manufacturer ($i=0$), two first-tier suppliers ($i=1$, $j=1$, 2) and four second-tier suppliers ($i=2, j=1, 2\ldots 4$). In this single product supply chain, the manufacturer and first-tier suppliers adopt a dual sourcing strategy. It is assumed that both upstream suppliers are identical in terms of the products manufactured and the production cost. Each supplier/manufacturer ships a product upon receiving an order from the downstream player, after a delay of manufacturing or processing lead time. Once the product is dispatched from the supplier, it reaches the corresponding manufacturer or supplier after a transportation delay which is assumed to be a pure delay. The demand of the manufacturer is assumed to be normally distributed, and the manufacturer and the primary suppliers place an order based on the information available regarding inventory or possible disruption. Both the primary and secondary suppliers are subjected to ‘random disruption’ (Du et al. 2016; Giri and Sarker 2016), which is beyond the control of supply chain managers. The cause of such a disruption can be attributed to exogenous incidents such as a natural disaster, political turmoil, strikes, etc. During the disruption, at the initial stage, the material flow from the supplier will be nil for a certain period of time and thereafter, during the recovery stage, material flow from the supplier slowly increases until it reaches the level that was existing just before the disruption. The manufacturer and the 1st tier supplier adopt the dual sourcing strategy to mitigate disruption, under the assumption that two suppliers will not fail simultaneously.

Figure 1 presents the supply chain network under study. Table 2 presents the nomenclature used in our model.

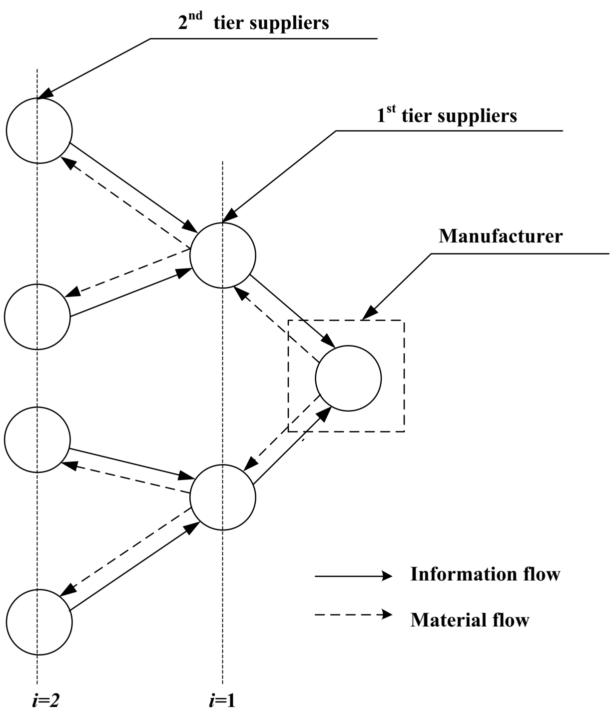

Fig. 1 Supply chain network considered for the study

Table 2 Nomenclature used in the study

α_j^i	Smoothing constant for demand forecast
$AR_{j,t}^i$	Total available raw material
$AIN_{j,t}^i$	Adjustment for finished goods inventory
$AWIP_{j,t}^i$	Adjustment for work in process inventory
$BO_{j,t}^i$	Backorder quantity
d_n	Duration of maximum impact of disruption
$D_{j,t}^i$	End customer demand
D_n	Total duration of disruption
$DIN_{j,t}^i$	Desired inventory
$DSL_{j,t}^i$	Desired sales rate
$IN_{j,t}^i$	Finished product inventory
$os_{j,k,t}^i$	Order splitting ratio
$PC_{j,t}^i$	Production completion rate
$PO_{j,t}^i$	Production order
$RM_{j,t}^i$	Raw material order rate
$SD_{j,t}^i$	Smoothed demand (demand forecast)
$SR_{j,t}^i$	Sales rate
Ta_j^i	Exponential smoothing parameter
$Td_{j,t}^i$	Transportation delay
Ti_j^i	Time to adjust inventory
$TIN_{j,t}^i$	Target inventory
Tp_j^i	Production lead-time
Tw_j^i	Time to adjust WIP
$TWIP_{j,t}^i$	Target WIP inventory
$WP_{j,t}^i$	Work in process inventory

3.1 Simulation model

Each firm in the supply chain network is modeled using the standard APVIOB-PCS (Dejonckheere et al. 2004; Lin et al. 2016; Wang et al. 2012) model structure with additional considerations of production capacity, back-order and raw material availability constraints. The APVIOPBCS system modifies the production quantity or order refill considering the discrepancy between the OUT level and the current position of the inventory. The inventory level is the sum of on-hand inventory (*IN*) and work-in-process inventory (*WP*). The model consists of two balancing or negative feedback loops: one is for accounting inventory discrepancy while the other is for correcting work-in-process inventory discrepancy. The corresponding control parameters (or gains) associated with the feedback loops are: (1/*Ti*), which is the fractional rate with which the finished inventory is to be adjusted and $(1/Tw)$, which is the fractional rate of adjustment of the *WP* inventory.

According to the APVIOPBCS ordering algorithm, the production or order processing quantity is given by:

$$PO^i_{j,t} = SD^i_{j,(t-1)} + \frac{EIN^i_{j,(t-1)}}{Ti^i_j} + \frac{EWP^i_{j,(t-1)}}{Tw^i_j} \tag{1}$$

which is the sum of smoothed demand, inventory discrepancy error plus work-in-process inventory discrepancy.

Demand smoothing is done using the exponential smoothing method with the parameter $(1/Ta)$, which is another control parameter. Unlike the original model, the target inventory is calculated by adding backorders as well as the multiple forecasted demands. The production order is further processed based on production capacity and raw-material availability. The manufacturing or order processing activity is represented using exponential delay with a control parameter *Tp* which is the manufacturing lead-time. Complete model equations are presented in "Appendix".

3.2 Modeling of disruption

Firms undergoing disruption will go through a series of stages which affect the performance of the supply chain. The most common way of modeling supply chain disruption (Snyder et al. 2016) is by assuming that the supply chain could be either completely operational (up state) or not at all operational (down state). For analytical models, the above-mentioned approximation could be sufficient. However, from a supply chain dynamics view, the response to a disruptive event will usually result in a deviation of performance from the equilibrium position, preceded by a gradual recovery (Munoz and Dunbar 2015; Melnyk et al. 2014). Sheffi (2005) proposed eight phases of a typical disruption profile depending on the nature of disruption and dynamics of response. In this work, a two-phase disruption profile is considered: the phase of maximum impact and the phase of recovery as shown in Fig. 2.

In a related study, Tao et al. (2016) considered both the up and down disruption scenarios as well as disruption with gradual recovery while modeling supplier capacity disruption. In their system dynamics simulation study, a series of step functions were employed to model gradual recovery from the disruption. Also, a similar modeling approach can be found in the studies of Li et al. (2016). Compared to these studies, the recovery phase is modeled in this paper by using a ramp function to reduce the possible disturbances in the dynamics which could arise with the use of a series of step functions. In addition, we have characterized the recovery phase by the time it takes to revert back to the initial state of operation. The duration of maximum impact is represented by d_n and the total duration of disruption is denoted by D_n.

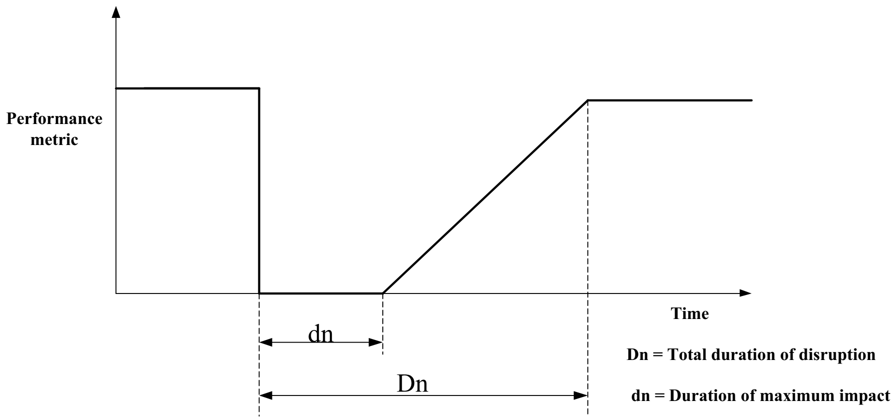

Fig. 2 Disruption profile

The disruption profile is obtained by combining the shock and ramp function, so that at the aggregate level, the profile resembles a typical disruption profile.

4 Order allocation policies with respect to information sharing

The decision on order allocation highly depends on suppliers' operational status including their risk of default. Nowadays, firms consider not only the cost of supply but also the ability of the supplier to provide materials without interruptions. Hence, companies will try to acquire information to get more insight into the suppliers' capability to provide products at the desired quantity and in a timely manner. This becomes more important when the supplier faces disruption and if the firms obtain real-time information regarding the disruption, they can manage disruption by timely diverting orders to other suppliers.

Our model employs a heuristic raw material ordering rule based on the local information available to the managers rather than an optimized one. A similar ordering rule is presented in the studies of Tao et al. (2016) and Li et al. (2016). The formulation of an ordering policy is consistent with the system dynamics modeling principle (Sterman 2000) which says that the formulation of the decision rule must be based on an understanding of the actual decision-making process, where the decision makers in practice are restricted by bounded rationality.

4.1 Ordering policy without information sharing (scenario 1)

In this scenario, it is considered that suppliers are not willing to share private retail information to their downstream retailers. Since the retailers are uninformed about the operational status of the upstream suppliers, they rely on the accumulated back order information of their respective suppliers. If there is no back order left with the two suppliers, the retailer will equally split the order between both suppliers. If both

Table 3 Order allocation based on backlog

Order splitting ratio	Backlog levels of upstream suppliers			
	$BO^{i+1}_{j,t} + BO^{i+1}_{j+1,t} = 0$	$BO^{i+1}_{j,t} \geq 0,\ BO^{i+1}_{j+1,t} \geq 0$	$BO^{i+1}_{j,t} = 0,\ BO^{i+1}_{j+1,t} \geq 0$	$BO^{i+1}_{j,t} \geq 0,\ BO^{i+1}_{j+1,t} = 0$
$os^{i}_{j,1,t}$	0.5	$= \frac{BO^{i+1}_{j+1,t}}{BO^{i+1}_{j,t}+BO^{i+1}_{j+1,t}}$	PO^{i}_{j}	0
$os^{i}_{j,2,t}$	0.5	$= \frac{BO^{i+1}_{j,t}}{BO^{i+1}_{j,t}+BO^{i+1}_{j+1,t}}$	0	PO^{i}_{j}

suppliers have unfulfilled orders, the retailer will tend to order more from the supplier having fewer backorders. Similarly, if one supplier is having backorders and the other is without backorders, the retailers will divert their entire order to the supplier having zero backorders. Table 3 presents the analytical representation of the ordering policy taking into account the above-mentioned considerations.

4.2 Ordering policy with information sharing (scenario 2)

In scenario 2, the retailer has more real-time information of the supplier's operational status including information regarding supply failure. In addition to disruption information, the supplier shares information regarding the current inventory status with their downstream partner. Order allocation strategy will be adopted to give priority to the disruption information. If any of the suppliers defaults and is not in a position to deliver materials, the entire order will be diverted to the next supplier, irrespective of their production capacity or inventory status. Otherwise, if both are up or one of them is partially disrupted, the order allocation decision will be performed as given in Table 4.

In the case of zero inventory level for both the suppliers, order allocation would be carried out based on back order information as explained in the previous section.

Table 4 Order allocation based on inventory

Order splitting ratio	Inventory levels of upstream suppliers	
	$IN^{i+1}_{j,t} + IN^{i+1}_{j+1,t} \geq 0$	$IN^{i+1}_{j,t} + IN^{i+1}_{j+1,t} = 0$
$os^{i}_{j,1,t}$	$= \frac{IN^{i+1}_{j,t}}{IN^{i+1}_{j,t}+IN^{i+1}_{j+1,t}}$	Based on back-order information
$os^{i}_{j,2,t}$	$= \frac{IN^{i+1}_{j+1,t}}{IN^{i+1}_{j,t}+IN^{i+1}_{j+1,t}}$	Based on back-order information

5 Numerical study

The focus of the numerical study is twofold: first is to analyze the impact of real-time information sharing in reducing the impact of first-tier supplier disruption with a stochastic customer demand. For this analysis, first-order performance metrics such as sales rate and back-order quantities are employed. The second focus is to examine how the various control parameters of the manufacturing system affect the dynamic performance of the system for the information shared setting. A range of parameter values is obtained in the numerical study which maximizes the performance of the system by reducing the inherent fluctuations. The second analysis (referred to as dynamic analysis) provides a set of control design strategies for the resilient design of the manufacturing system to mitigate disruption.

In the first part of the analysis, we investigate how the characteristics of exogenous factors such as customer demand and disruption profile influence the performance of the manufacturing system during disruption without and with information sharing settings. The characteristics of customer demand considered for the study include the mean value and the standard deviation of the demand. The disruption profile is characterized by the duration of maximum impact of disruption and the total duration of the disruption. Table 5 presents the control parameters of the model which are obtained based on a prior simulation experiment and guidelines from the literature. In the sensitivity analysis, we change the values of these control parameters of the manufacturer to study their effect on the dynamic performance of the system for the information shared scenario. For the dynamic analysis, a second order metric is employed which is adopted from the discipline of control engineering (explained in Sect. 6). The minimum value of the metric indicates the maximum performance, and hence, corresponding parameter values provide the best control design for the manufacturing system.

Table 6 provides the values of simulation settings common for both the analyses. The simulation run period is 300 weeks of time units. The nature of the disruption considered for the study is in the high-impact less-frequent category, wherefore it is assumed that each first-tier supplier is disrupted once, during the simulation period. As given in Table 6, the disruptions of the first and second suppliers are

Table 5 Control parameter settings

Control parameters	Manufacturer/suppliers
Forecasting (Ta)	4
Inventory (Ti)	2
Lead time (Tp)	2
WIP (Tw)	4
Variable inventory (a)	1

Table 6 Simulation settings (common for both the analyses)

Characteristics	Operating assumption
Simulation time	300 weeks
Warm-up period	30 weeks (omitted from analysis)
Data evaluated	Week 31–300
Customer demand	Weekly demand (integer units) generated from a normal distribution N (80, 10) (as a nominal setting)
Initial inventory values	40 units for manufacturer and 30 units for all suppliers
Production capacity	120, 100, 150 integer units for the manufacturer, 1st tier suppliers, 2nd tier suppliers respectively
Initial backlog values	0 units for the manufacturer and 10 units for all suppliers
Number of disruptions	1 for each 1st tier supplier (total 2 disruptions)
Disruption traits	Maximum impact of disruption (60 weeks), recovery time (20 weeks) for both the disruptions in nominal case
Initial point of disruption	50th week for the first supplier and 150th week for the second supplier

introduced at time periods of 50 and 150, respectively. By this, the overlapping of disruptions of the two suppliers is disregarded, so that the principle of dual sourcing is not undermined.

The model is implemented and simulation experiments are carried out using Matlab Simulink® software. Since this platform offers flexibility by integrating with other Matlab environments, such as scripting, it is possible to have a detailed analysis of a dynamic system. Figure 3 depicts the simulation model represented on the Simulink® platform. It is also known as a block diagram representation which is a control engineering technique, where all time domain equations are converted into a Laplace domain.

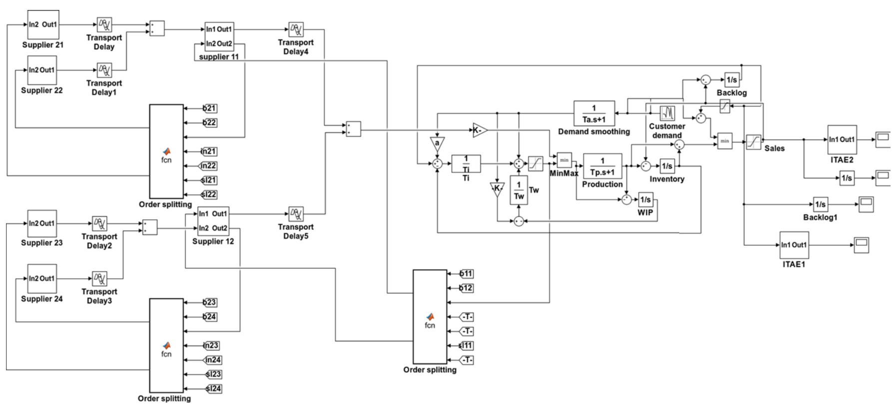

Fig. 3 Matlab Simulink® representation of the simulation model

5.1 Simulation result

Figures 4 and 5 represent the sale quantity variation during the 1st tier supplier disruption in the case of no information and information sharing scenarios, respectively.

The difference in sales quantity between the two cases is noticeable from the mean demand (80) and higher values. When the mean demand is 80, in scenario 1, both disruptions affect the sales quantity as shown in Fig. 4. However, for the same mean demand value, the sales rate is unaffected by the second primary supplier disruption. By information acquisition and subsequent ordering policy, the manufacturer manages to effectively overcome that disruption. In subsequent cases, as the mean demand increases, although the effect of the second disruption is visible in the scenario, the disruption is less when compared to the scenario without information and the recovery rate is fast.

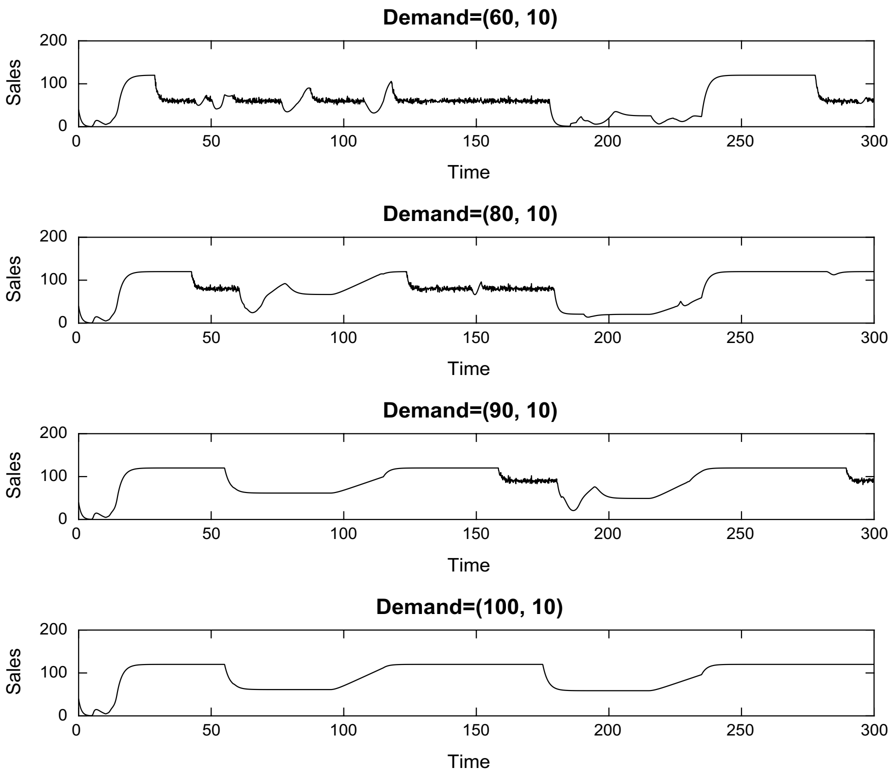

Fig. 4 Sales rate variation for scenario 1 (no information sharing)

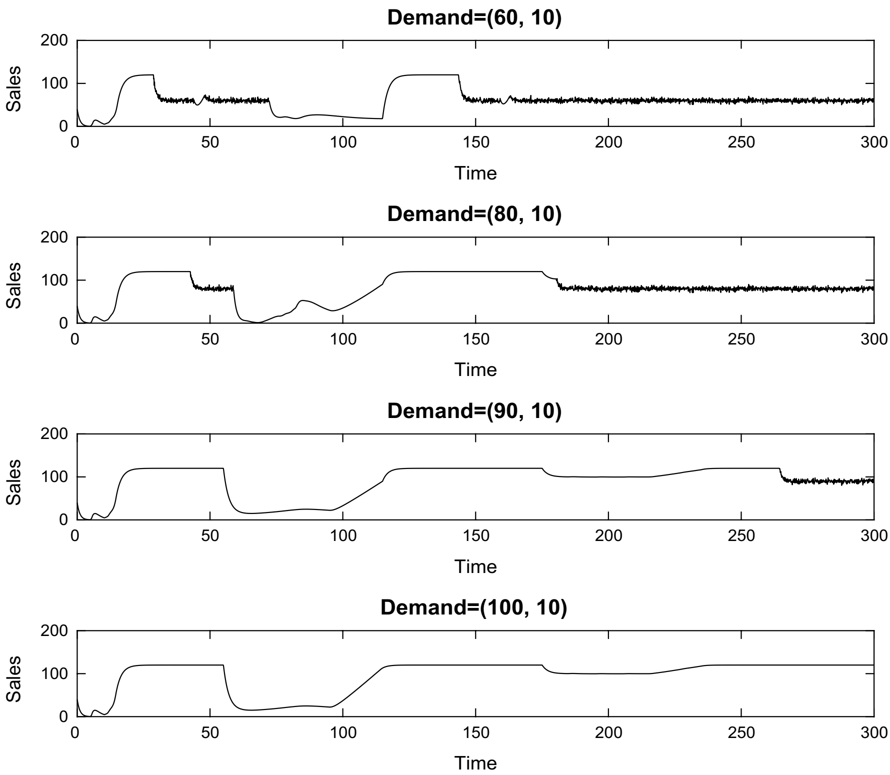

Fig. 5 Sales rate variation for scenario 2 (information sharing)

5.2 Performance variation with respect to stochastic demand parameters

The cumulated value of the unsatisfied customer demand or backlog over the simulation run period is the major performance metric adopted in this study, to quantify the overall performance of the supply chain system. This performance measure is an indication of the customer service level and is also a measure of the opportunity cost due to disruption.

In the case of a scenario without information sharing, as shown in Fig. 6, there is an increase in the backlog level as the mean value and standard deviation (s) increases. The rate of increase is more as the mean value demand reaches production capacity. For the information sharing scenario as illustrated in Fig. 7, the variation with respect to the mean value of the demand and the standard deviation(s) value is almost stagnant, until the mean value of demand reaches 90 which is close to the maximum production capacity value. In both cases, there is also a significant difference in the values of backorders. The information sharing and dynamic adjustment of procurement ordering thereafter, not only improve the supply chain performance during the disruption but also positively influence the risk associated with demand variability under the upstream disruption risk.

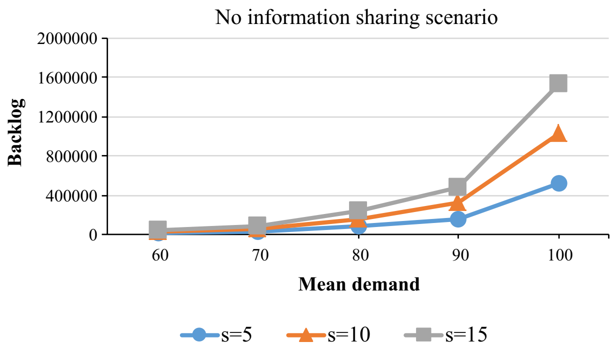

Fig. 6 Performance variation with demand in scenario 1

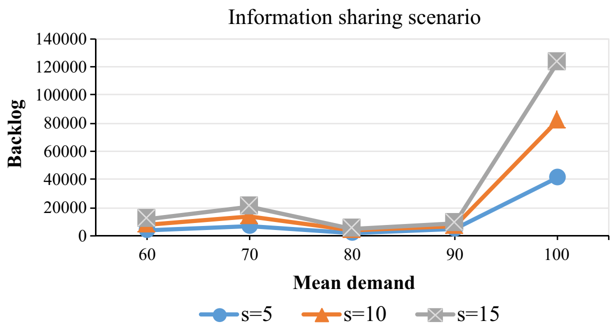

Fig. 7 Performance variation with demand in scenario 2

5.3 Performance variation with respect to disruption profile characteristics (*Dn* and *dn*)

In this section, the analysis is performed to study the effect of disruption characteristics on the performance in both scenarios. For this purpose, we set $D_n = 60$ and $d_n = 10$ as base case settings and examined how the variation happens as a percentage of the backlog quantity of this setting. The backlog values of scenarios 1 and 2 are 58,463 and 8661, respectively. As evident from these values, there is a significant difference between the scenarios. Having said that, we aim to see the variation with respect to *Dn* and *dn* values as shown in Tables 7 and 8.

Table 7 shows, in scenario 1, an increasing trend in the percentage of variation in the backlog with increasing values of duration of maximum impact (*dn*) for every total disruption duration (*Dn*) except for some cases. A similar increasing trend, as may be seen in Table 8, is absent in the information shared setting (scenario 2). Moreover, changes in percent variation in backlog values are less in scenario 2 in comparison with scenario 1. While the maximum increase is 154% in scenario 2, the increase is as high as 300% in scenario 1. This shows the significant advantage of information sharing, even if there are changes in the

Table 7 Per cent variation of backlog for scenario 1

Duration of maximum impact (*dn*)	Total disruption duration (*Dn*)						
	Dn = 60	*Dn* = 70	*Dn* = 80	*Dn* = 90	*Dn* = 100	*Dn* = 110	*Dn* = 120
dn = 10	100	85	81	68	103	164	135
dn = 20	102	93	97	166	130	106	234
dn = 30	111	114	171	147	134	272	283
dn = 40	128	171	161	157	281	305	278
dn = 50	169	169	172	279	315	301	300

Table 8 Per cent variation of backlog for scenario 2

Duration of maximum impact (*dn*)	Total disruption duration (*Dn*)						
	Dn = 60	*Dn* = 70	*Dn* = 80	*Dn* = 90	*Dn* = 100	*Dn* = 110	*Dn* = 120
dn = 10	100	65	102	99	109	75	70
dn = 20	134	132	128	85	90	85	86
dn = 30	154	147	147	139	145	107	129
dn = 40	80	134	140	124	112	97	106
dn = 50	97	86	162	149	143	123	128

characteristics of the disruption profile. Table 8 also shows that, for a particular value of *dn*, the percentage change in backlog values exhibit a decreasing trend with increasing *Dn* values in scenario 2. This indicates that, even though the recovery time is moderately long, sharing of the current level of inventory information during the recovery phase enables the manufacturer to choose an appropriate supplier, thereby increasing the performance.

6 Dynamic performance analysis

So far, analysis has been performed to evaluate the value of information sharing in mitigating supply chain disruption. In this section, we explore how to maximize the performance of the manufacturer in the information shared scenario. We study the effect of various control structures that are obtained by changing key parameter values of the manufacturing system. The performance metric used for dynamic performance evaluation is the integral time absolute error (ITAE). ITAE is a control engineering measure which indicates long-term error with fast settling time. Spiegler et al. (2012) showed that ITAE could be used to measure the resilience of the supply chain system. This measure combines two aspects of disruptions, namely: (1) recovery time and (2) variation in service level into one measure. Lower values of ITAE indicate the better dynamic performance of the system.

$$ITAE = \int_0^\infty t|e(t)|dt = \lim_{\delta t \to \infty} \sum_0^\infty t|e(t)|\delta t \tag{2}$$

where $e(t)$ is the error in service level related measure and t is time.

6.1 The effect of a forecasting parameter (*Ta*)

The forecasting parameter comes in a feed forward loop of the control mechanism, and its impact on disruption mitigation is examined. The value of α (= $1/(1 + Ta)$) varies between 0 and 1, and the production lead time *Tp* is set at a nominal value of 8, the inventory and WIP adjustment parameters *Ti* and *Tw* values are considered to be equal.

It is evident from Fig. 8 that the minimum value of ITAE is achieved when the α value approaches 0.1 from unity, and this minimum value of ITAE is the least value that can be achieved. That means a moderate level of smoothing is sufficient to achieve the maximum level of performance for the settings considered in this study. After that threshold level of smoothing, where α corresponds to 0.1, further smoothing drastically reduces the performance level. Maximum performance can be attained if the forecasting is not considered at all in the replenishment policy. Then, the supply chain follows the chase strategy to match the production capability with demand, resulting in a demand-driven supply chain. However, this strategy can lead to high variability in order, thereby resulting in increased production cost. These findings are, to a certain degree, consistent with the findings of Spiegler et al. (2012) on the resilience of a dyadic supply chain.

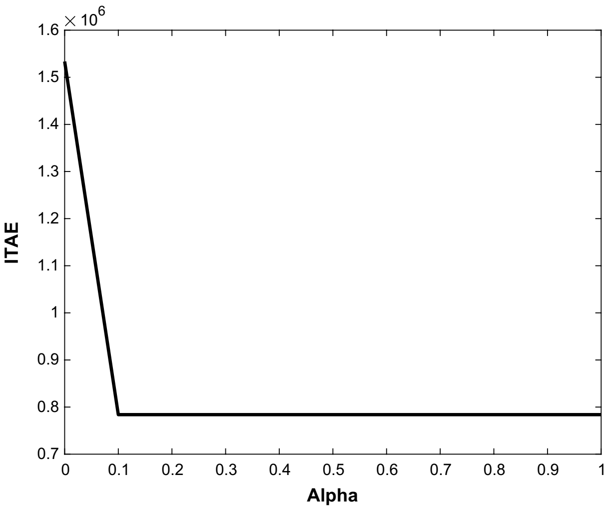

Fig. 8 The effect of forecasting parameter

6.2 Sensitivity analysis

Various combinations of control parameters represent a wide range of supply chain designs. Among these parameters, the production lead-time (*Tp*) is the particular parameter over which the supply chain designer has the least control. Therefore, normally, the supply chain design is carried out based on a known or given lead-time.

In this study, we consider a lead-time value of 8 as nominal setting and examine the impact of lead-time variation by $\pm 25\%$ and $\pm 50\%$ from the nominal setting. Figure 9 presents the assessment of dynamic performance with respect to lead-time changes.

As Fig. 9 demonstrates, when the lead-time increases, the area which represents the lowest value of ITAE, and hence, the area having a maximum dynamic performance slightly decreases. Lead-time reduction provides less flexibility for changing inventory adjustment parameters. Therefore, decision-makers should be careful with the choice of parameter and take lead-time variability into account, so that the system does not move out of the maximum performing area.

Table 9 shows the performance variation with respect to lead-time uncertainty. The least value of ITAE for each lead-time setting is found out and is compared with the nominal setting. As can be seen from the table, when the lead time decreases by 25 and 50%, there is a significant improvement in the dynamic performance level. Also, it was found that an increase in the lead-time reduces the dynamic performance. However, it is observed that the performance variation with respect to lead-time uncertainty is less for higher values of the lead-time.

Table 10 summarizes the findings and managerial insights obtained from the simulation study.

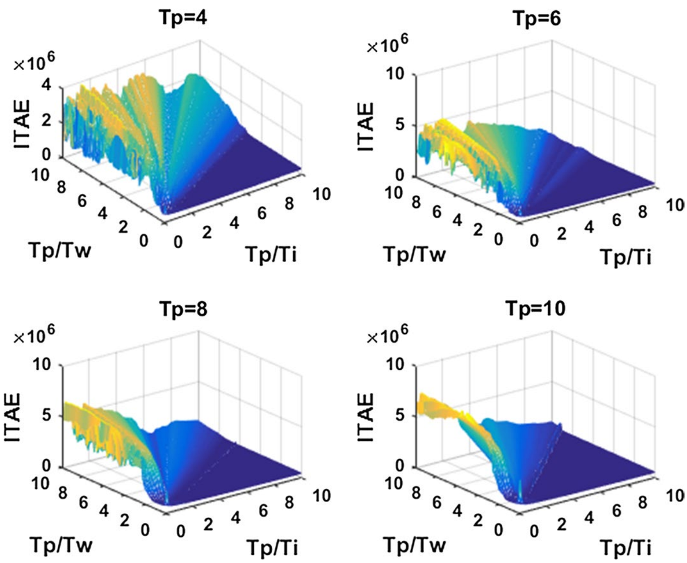

Fig. 9 Assessment of dynamic performance with respect to lead-time changes

Table 9 Performance analysis with respect to lead-time uncertainty

Tp	ITAE	Performance change (%)
4	0.62	37.65
6	0.79	20.07
8	1.00	0.00
10	1.22	– 22.80
12	1.00	– 28.30

Table 10 Findings and managerial insights obtained from the simulation study

Findings	Managerial insights
Information sharing setting improves the sales performance during disruptions	Managers need to implement strategies to timely acquire the information regarding the performance of the supplier and update ordering policies dynamically based on the information. Moreover, the awareness about the benefits of information sharing put managers in a superior position in their negotiations efforts to implement real-time information sharing channels
Increase in backlog with respect to demand volatility during disruption is comparatively less for information shared scenario	Increase in backlog can overload production capacity and transportation facility causing an increase in costs associated with it. Therefore, dynamic ordering policy based on timely available information is a plausible mitigation strategy when a supply chain with volatile customer demand experiences upstream supplier disruption
Characteristics of disruption profile influence the performance of the supply chain. For information shared setting, duration of maximum impact has significantly more impact compared to the maximum duration of the disruption	Efforts have to be made to reduce the duration of maximum impact of disruption and bring back the supplier into recovery mode. Once the supplier reaches the recovery mode, though it cannot deliver up to its nominal capacity level, the manufacturer can manage the production level with the help of dual sourcing strategy
The lower level of demand smoothing for production order determination improves dynamic performance of the manufacturer	It is desirable that the production ordering process should follow chase strategy. Therefore, flexibility in production capacity is required
The lower values of manufacturing lead-time, lead-time uncertainty affects the dynamic performance	The design strategy of the production system with lower lead-time has to focus on reducing lead-time uncertainty to be more resilient during the disruption

7 Conclusion

The value of information sharing is widely addressed in the context of supply chain collaboration and improvement in supply chain dynamics, by reducing variability in supply chain parameters. However, most of these studies have contributed to supply chain operational risk management efforts. On the contrary, the contribution of our study, lies in the management of supply chain disruption by acquiring and sharing information on supplier disruption with the help of a proper control system design. Dynamic modeling is used to evaluate the value of information sharing in executing the disruption mitigation strategy through proper order allocation between suppliers.

In the case of upstream supplier disruption, it is observed that information transparency on the vulnerabilities among supply chain members improves the performance. The findings of this research can provide the basis for managers to make informed decisions about deploying mitigation strategies with their supply chain partners.

In reference to the first research question, dynamic modeling and simulation methodology are adopted using a standard benchmark modeling approach with the help of control engineering techniques. The set of values of key parameters corresponding to major elements of the model such as on-hand and pipeline inventory control, forecasting mechanism and production process represent a supply chain control design. The dynamic performance of the system for each design is evaluated using a transient performance measure adopted from control engineering discipline. The analysis indicates that the dynamic behavior, which is driven by various managerial control policies, underlying system structure and delays happening in the feedback information, assumes a significant role in supply chain performance during the disruption. Hence, the supply chain design, which is obtained by proper selection control parameters, can also be considered as mitigation strategy which will finetune the information sharing strategy deployment.

To answer the second research question, we obtained various control designs by changing the value of key control parameters. The results show that, for a specified control structure, the selection of decision parameter affects the dynamic performance of the supply chain experiencing disruption. Concerning demand policy, it has been observed that the effect of a forecasting parameter is very little, in the dynamic performance of the supply chain. The demand-driven production ordering policy, which means ordering rule based on customer demand and inventory discrepancy, favors a better performance. However, one must be careful with this setting because it may create a lot of oscillation in the production order which will result in increased ‘production on-cost’—the cost incurred as a result of frequent ramping up and down of the production capacity. The sensitivity analysis considering production lead-time and inventory adjustment parameter showed that lead-time uncertainty affects the performance, if the firm has a lower lead-time value. The results show that manufacturers such as personal computer assembling units, having lower lead-time values, will have better dynamic performance. However, they need to be careful with the lead-time uncertainty. Industries such as the steel industry having longer lead-time, will have difficulty in achieving maximum dynamic performance, but lead-time uncertainty will not change the performance considerably.

This paper is restricted to evaluating the value of disruption information sharing and dynamic analysis of the supply chain. The study can be further extended with the inclusion of cost analysis, especially the production-on cost. The research can also be extended to examine how the disruption mitigation strategy, suggested in this study, influences the well-known bull-whip phenomenon across the supply chain members. The research work can also be extended by considering partial information sharing, instead of full information sharing, as is considered in this paper. The disruption considered in this study is exogenous in nature, that means the disruptive event is independent of the decisions of the firms. In certain situations, disruption can be endogenous, for example, labor strike against managerial policies. The consideration of such disruptions is also a promising future research area.

Appendix: Model equations

See Table 11.

Table 11 Model equations

Variables	Equations
Production order	$PO^i_{j,t} = Min\left(AR^i_{j,t}, SD^i_{j,t} + \frac{EIN^i_{j,(t-1)}}{Ti^i_j} + \frac{EWP^i_{j,(t-1)}}{Tw^i_j}\right)$
Available raw material	$AR^i_{j,t} = SR^{i+1}_{j,(t-T^{i+1}_{dj})} + SR^{i+1}_{j+1,(t-T^{i+1}_{dj+1})}$
Production completion rate	$PC^i_{j,t} = Min[PO^i_{j,(t-Tp^i_j)}, C^i_{j,(t-Tp^i_j)}]$
Desired sales rate	$DSR^i_{j,t} = BO^i_{j,t-1} + D^i_{j,t}$
Sales rate	$SR^i_{j,t} = Min[IN^i_{j,t}, DSR^i_{j,t}]$
On-hand inventory	$IN^i_{j,t} = IN^i_{j,(t-1)} + PC^i_{j,t} - SL^i_{j,t}$
Backlog	$BO^i_{j,t} = BO^i_{j,t-1} + D^i_{j,t} - SL^i_{j,t}$
Average demand	$SD^i_{j,t} = SD^i_{j,(t-1)} + \frac{1}{1+Ta^i_j}(D^i_{j,t} - SR^i_{j,t})$
Work in process inventory	$WP^i_{j,t} = WP^i_{j,(t-1)} + (PO^i_{j,t} - PC^i_{j,t})$
Error in WIP inventory	$EWP^i_{j,t} = DWP^i_{j,t} - WP^i_{j,t}$
Target WIP inventory	$DWP^i_{j,t} = Tp * SD^i_{j,t}$
Error in on-hand inventory	$EIN^i_{j,t} = DIN^i_{j,t} - IN^i_{j,t} + BO^i_{j,t-1}$
Target on-hand inventory	$DIN^i_{j,t} = a^i_j * SD^i_{j,t}$

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