

Supply chain focus dependent safety stock placement

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Abstract Increasing globalization, growing product range diversity, and rising consumer awareness are making markets highly competitive, forcing supply chains to adapt constantly to different stimuli. Growing competition between supply chains (as well as players within them) is also warranting a priority for overall supply chain performance over the goals of individual players. It is now well established in the literature that, among the many order winners, both overall supply chain cost and responsiveness (i.e., supply chain lead time) are the most significant determinants of supply chain competitiveness. The literature, however, mostly focuses on supply chain cost minimization with rather simplistic treatment of responsiveness. By introducing the concept of a coefficient of inverse responsiveness (CIR), we facilitate efficient introduction of responsiveness related costs into the scheme of supply chain (SC) performance evaluation and/or optimization. Thus, our model aids supply chain managers in achieving better strategic fit between individual business unit strategies and overall supply chain requirements in terms of cost efficiency and responsiveness. In particular, it aids in strategic placement of safety stocks at different stages in the supply chain. Our model also offers managerial insights that help improve our intuitions into supply chain dynamics. The model is more suited for

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strategic SC alignment, for example, when dealing with product changeovers or introduction of new product, rather than for operational control.

Keywords Supply chain strategy · Business strategy · Safety stock costs · Cost of responsiveness · Supply chain cycle time · Coefficient of inverse responsiveness

1 Introduction

In today's dynamic global market environment, it has become necessary for organizations to focus upon all the relevant performance metrics. Hill (1993) advocates close attention to functional perspectives, customers' views, and actual orders while determining order winners and qualifiers. Among the possible order winners, supply chain (SC) cost and responsiveness turn out to be more crucial than others. Responsiveness here is the ability of the supply chain to respond quickly to changing customer needs, preferences, and options through improved supply chain cycle time (i.e., velocity), and not the higher service levels achievable through increased distribution of channel inventory. The optimal supply chain strikes the right balance between supply chain cost efficiency and responsiveness, depending on the nature of product(s) supplied by it.

Figure 1 divides the cost-responsiveness spectrum of the SC into four basic quadrants, and provides some indications of their appropriateness. In reality, the treatment will not be that distinct, and depending on the type of products and markets targeted by the SC, the focus could be anywhere on the spectrum. In this context, Fisher (1997) emphasizes the importance of considering the nature of product demand before devising the respective supply chains. More precisely, one needs to account for both the nature of the product as well as uncertainty from both demand and supply in designing the SC (Chopra and Meindl 2004). Similar comments have been echoed in industry literature. Nazzal et al. (2006) present a case study for Agere Systems, focusing upon the increase of market share and profits by reducing lead times in the highly competitive semiconductor manufacturing industry. So is the example of Revlon whose supply chain includes more than 5,000 active finished good stock keeping units (SKUs) with product lifecycles spanning less than 3 years. To meet aggressive inventory reduction targets and achieving high customer service levels, Revlon is emphasizing reduction of manufacturing and supplier lead times and the associated variability (Davis et al. 2005). Yang and Geunes (2007) emphasize that longer lead times, in addition to reducing customer responsiveness, increase demand forecast error, since forecast error generally increases as the forecast horizon increases. In addition, longer lead times expose the supply chain to more in-process inventories, design changes, degradation, accidents, changes in demand patterns, etc. (Felgate et al. 2007), which in turn increase the supply chain costs. In summary, striking the right balance between supply chain cost efficiency and responsiveness is critical, which can be neglected at one's own peril. On the contrary, existing literature overly focuses on just one order winner: cost efficiency.

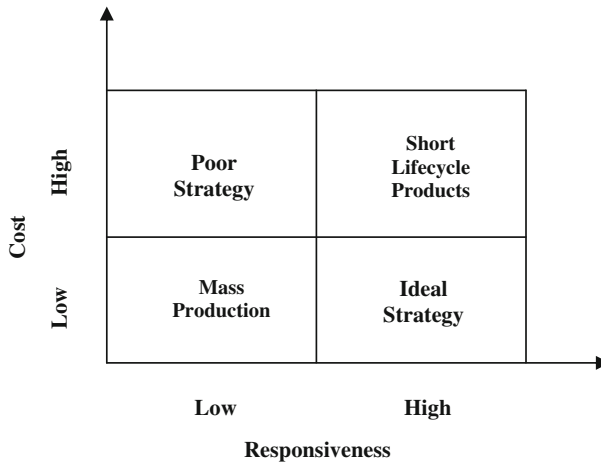


Fig. 1 Supply chain responsiveness versus cost (source: Vanteddu et al. 2006)

There are primarily four drivers influencing the performance of the SC, namely, infrastructure, inventories, transportation, and information (Chopra and Meindl 2004). Given our assumption that the necessary network topology is already in place, we do not need to include infrastructure related cost elements and transportation related aspects explicitly in our model. These issues, however, are addressed in an indirect fashion in our model. For example, cost added at a stage can be considered to be a function of fixed costs associated with infrastructure such as location, buildings, machinery, etc. and transportation to the immediate downstream (D/S) stage. Even though we are developing the model assuming that all the stages are involved in manufacturing, a stage purely dealing with transportation could be easily accommodated. We are also assuming information symmetry at all the stages and leave information asymmetry related issues for future research. Thus, we are primarily considering the inventory cost driver in our model.

Among inventory cost elements, safety stock, maintained to account for the internal and external variability in the supply chain, is vital in the sense that it directly affects customer satisfaction and constitutes a significant portion of the cost of goods sold (COGS).

In summary, in terms of supply chain strategy, one can choose to compete purely on price (for a commodity product) or product velocity (fashion industry, for example) or choose a third path, a niche strategy, a hybrid of the other two (Cherukuri et al. 1995). Our research primarily focuses upon the third strategy, where there are opportunities to be exploited with respect to both order winners.

The rest of this manuscript is organized as follows: Sect. 2 discusses relevant literature; Sect. 3 deals with development of the overall cost expression for the supply chain, which accounts for supply chain (SC) responsiveness; Sect. 4 offers managerial insights into strategic safety stock placement in a serial supply chain; Sect. 5 describes how one can use the model for achieving the strategic fit; finally,

Sect. 6 offers conclusions and limitations that should be addressed in future research.

2 Literature review

Gallego and Zipkin (1999) develop and analyze several heuristic methods to study the problem of stock positioning in serial production-transportation systems and offer a number of interesting insights into the nature of the optimal solution. A stochastic service model as advocated by Graves and Willems (2003) addresses the issue of strategic placement of safety stocks across a multi-echelon SC in the presence of demand uncertainty. As with Graves and Willems (2003), the primary emphasis of our research is to provide decision support for SC design, rather than SC operation, and the intent is not to find inventory control policies as is the case with much of the multi-echelon inventory literature. Another common feature is that the local decisions (decentralized control as opposed to central control) are made at each stage based on local information. It is worth noting at this point, as supported by Graves and Willems (2003), that a SC subjected to decentralized control is not equivalent to a SC being locally optimized. In an optimization context, the model attempts to find the optimal parameter values, under the assumption of decentralized control, that minimize the total SC cost. The primary purpose of their model is to develop a multi-echelon model, and the relevant optimization algorithm is specifically designed for optimizing the placement of safety stocks in a real-world SC. Unlike Graves and Willems (2003), where inventory is the only lever to counter demand and supply variability, our model has two levers, namely, echelon inventory and responsiveness (cycle time).

The supply chain configuration problem, a special case of the supply chain design problem, consists of the set of decisions that are made after the network design that act to configure each stage in the network by taking into account certain relevant parameters; see Graves and Willems (2003), who argue that the central question is to determine what suppliers, parts, processes, transportation modes (called options) to select at each stage in the supply chain. Our model is similar in spirit to their optimization model (Graves and Willems 2003). The primary similarity is that both models balance the increase in cost of goods sold (COGS) against the decrease in inventory related cost, though the two models differ significantly with regard to the methodology adopted and serve different end purposes.

For a stochastic service model (Graves and Willems 2003; Simchi-Levi and Zhao 2005; Lee and Billington 1993; Ettl et al. 2000), which we have adopted in our model, we assume that the increase in cost at a stage depends on the opportunities that exist for resource flexibility and model it as a continuous function of a novel dimensionless parameter called the coefficient of inverse responsiveness (CIR), with a focus on: (a) developing managerial insights with regard to strategic safety stock placement in a serial supply chain and (b) achieving strategic fit between the supply chain strategy and the individual business strategies for a given set of parameter values.

Assuming an installation, continuous time base stock policy for supply chains with tree network structures, another interesting paper that is based on the stochastic

service model concept is that by Simchi-Levi and Zhao (2005) in which they derive recursive equations for the back order delay (because of stock out) at all stages in the supply chain, and, based on those recursive equations, dependencies of the back order delays across different stages of the network are characterized and useful insights with respect to the safety stock positioning are developed in various supply chain topologies. The two other papers that use a stochastic service approach that are relevant to our research are those by Lee and Billington (1993) and Ettl et al. (2000). We share the ample production capacity assumption with Simchi-Levi and Zhao (2005) and Graves and Willems (2003). For capacitated models using a modified base stock policy, the reader can refer to Glasserman and Tayur (1995, 1996) and Kapuscinski and Tayur (1999). Simchi-Levi and Zhao (2005) enhance the work of Gallego and Zipkin (1999) and provide stronger results. They also point out through their computational study of the Bulldozer supply chain problem (Graves and Willems 2003) the perils of ignoring lead time uncertainties, which is accounted for in our model. In addition, Simchi-Levi and Zhao (2005) present a nice summary of the literature for installation policies that are used in various network topologies: multistage serial systems (Simpson 1958; Hanssmann 1959; Lee and Zipkin 1992) and distribution systems (Axsäter 1993; Graves 1985; Lee and Moinzadeh 1987a, b).

Given the size and complexity of supply chains such as those found in the computer, electronics, and auto industries, a common problem for asset managers is not knowing how to quantify the trade-off between service levels and the investment in inventory required to support those service levels (Ettl et al. 2000). This problem is compounded by the response related performance measures. Similar to Ettl et al. (2000) model, our model is also intended to be a strategic model not caring much about the operational details.

Eppen and Martin (1988) present a very nice critique of the standard procedure using a (Q,r) model for setting safety stocks in the presence of stochastic lead time and demand. Chopra et al. (2004) build on the work of Eppen and Martin (1988) but their focus is on the flaws in the managerial prescriptions implied by the normal approximation. In particular they infer the following by using the exact demand during the lead time instead of the normal approximation: For cycle service levels above 50% but below a threshold, reducing lead time variability increases the reorder point and safety stock, whereas reducing the lead time decreases the reorder point and safety stock. Our research addresses the issue of reducing lead time variability indirectly as a result of reducing the lead time because of the flexibility options available at a stage.

For a thorough comparison of installation and echelon stock policies for multilevel inventory control, the reader is referred to Axsäter and Rosling (1993), who primarily consider serial and assembly systems and prove that for (Q,r) rules echelon stock policies are, in general, superior to installation stock policies.

Advocating the necessity of models that include both cost and responsiveness, Moon and Choi (1998) suggest extending the lead time reduction concept to different inventory models to justify the investment to reduce the lead times. Choi (1994) used an expediting cost function to reduce the variance of suppliers' lead times.

As opposed to network design models that focus on the trade-off between the fixed costs of locating facilities and variable transportation costs between facilities and customers, Sourirajan et al. (2007) present a model for single-product distribution network design problem with lead times and service level requirements, which enables them to capture the trade-off between lead times and inventory risk pooling benefits. The objective is to locate distribution centers (DCs) in the network such that the sum of the location and inventory (pipeline and safety stocks) is minimized. Our CIR concept is similar in spirit to the replenishment lead time calculation at a DC (Sourirajan et al. 2007), which depends upon the volume of flow through the DC.

One very interesting (Q,r) model with stochastic lead times that could serve as a building block in supply chain management was proposed by Bookbinder and Cakanyildirim (1999) as opposed to the constant lead time assumption in many other studies. This paper introduces a term called an expediting factor for the lead time, which is similar in spirit to the dimensionless quantity proposed in our model, CIR. Ryu and Lee (2003) consider dual sourcing models with stochastic lead times in which lead times are reduced at a cost that can be viewed as an investment. They make use of the concept of expediting factors proposed by Bookbinder and Cakanyildirim (1999) in their model. They analyze (Q,r) models with and without lead time reduction and compare the expected total cost per unit time for the two models.

Even though we did not consider product mix flexibility related issues in our model, the reader can refer to Upton (1997) to explore the relationship between process range flexibility and structure, infrastructure and managerial policy at the plant level. We assume information symmetry at all the stages in our model. The effect of information sharing for the time series structure of the demand on safety stocks is addressed in Gaur et al. (2005).

3 Model development

This section mostly develops the total cost expression, made up of safety stock costs and responsiveness related costs, for a serial supply chain.

3.1 Expression for safety stock costs

We follow the building block model (Graves and Willems 2003) with installation base stock policies and a common underlying review period for all stages. A typical base stock policy works as follows. When the inventory position (i.e., on-hand plus on-order minus back orders) at stage i falls below some specified base stock level B_i , the stage places a replenishment order, thereby keeping the inventory position constant. Simchi-Levi and Zhao (2005) attribute the popularity of the base stock policy to the fact that it is simple, easily implementable, and has been proven to be optimal or close to optimal in many cases. For example, in serial supply chains with zero setup costs and without capacity constraints, because the installation base stock policy is equivalent to an echelon base stock

policy under certain initial conditions (Axsäter and Rosling 1993), it is indeed optimal in these cases (Clark and Scarf 1960). In serial systems, even a modified base stock policy with capacity constraints is still close to optimal (Speck and van der Wall 1991; van Houtum et al. 1996).

In an installation policy, each facility only needs the inputs from the immediate upstream (U/S) and downstream (D/S) facilities and makes ordering decisions based on its local order and inventory status (Simchi-Levi and Zhao 2005) as opposed to an echelon base stock policy, which is a centralized control scheme that allows for a central decision maker to coordinate and control the actions at all stages in the SC (Graves and Willems 2003).

Even though our model assumes all stages to be manufacturing stages, without loss of generality, a stage could be modeled as a DC as well. A pure transportation function can also be modeled with the building block concept, wherein the transport time is the lead time with pipeline inventories.

Orders are placed at discrete time intervals and each stage is considered as a building block (Graves 1988) that generates a stochastic lead time. A building block is typically a processor plus a stock keeping facility. Depending on the scope and granularity of the analysis being performed, the stage could represent anything from a single step in manufacturing or distribution process to a collection of such steps to an entire assembly and test operation (Graves and Willems 2003). Demand is assumed to be stationary and uncorrelated across nonoverlapping intervals and there are no capacity constraints.

Our model is designed as a decentralized supply chain (Graves and Willems 2003; Lee and Billington 1993) to mimic reality more closely, with each stage following a local base stock policy. Supporting the same view, Lee and Billington (1993) state that organizational barriers and restricted information flows between stages may result in complete centralized control of material flow in a supply chain not being feasible or desirable.

The primary distinction between centralized and decentralized supply chain is put in the following succinct form by Lee and Billington (1993) “Centralized control means that decisions on how much and when to produce are made centrally, based on material and demand status of the entire system. Decentralized control, on the other hand, refers to cases where each individual unit in the supply chain makes decisions based on local information”.

Assuming that each building block operates independently using a simple installation policy, one can first characterize various building blocks such as serial, assembly, distribution, etc. and then identify the links among these building blocks (Simchi-Levi and Zhao 2005). We have chosen series system for simplicity of analysis and primarily to develop certain insights that are insensitive to the specific supply chain topology. Also, other networks such as assembly system can be reduced to an equivalent series system (Rosling 1989). Most of the features are similar to the features of a serial system presented in Gallego and Zipkin (1999) with some modifications.

There are several stages or stocking points arranged in series. The first stage receives supplies from an external source. Demand occurs only at the last stage. Demands that cannot be fulfilled are immediately backlogged. There is one product,

or more precisely, one per stage. To move units to one stage from its predecessor, the goods must pass through a supply system representing production or warehousing activities. There is an inventory holding cost at each stage and our model does not consider back-order penalty cost, which could easily be included. The horizon is finite, all data are stationary, and the objective is to evaluate the performance and optimize depending upon the supply chain focus on the cost-responsiveness spectrum. Information is centralized but control is decentralized.

As in Gallego and Zipkin (1999), the numbering of the stages follows the flow of goods; stage 1 is the first, and demand occurs at the last stage. The external source, which supplies stage 1, has ample stock and it responds immediately to orders (Fig. 2).

We have assumed that the service level targets required at each of the players are exogenous, i.e., they are dictated by the immediate D/S player or the final customer. Following Graves and Willems' (2003) treatment of stochastic service model in supply chains, let $\Phi(k_1), \dots, \Phi(k_n)$ be the service levels for corresponding safety factors k_1, \dots, k_n where $\Phi(k_i)$ represents the cumulative distribution function for a standard normal variable. k_j is the multiplying factor for the variability term for stage j , which along with the average in process inventory would give the expected base stock to achieve a given service level. Let the processing time at stage j be a random variable τ_j (measured in time periods) with mean L_j and variance σ_j^2 .

The stochastic service model (Graves and Willems 2003; Simchi-Levi and Zhao 2005; Lee and Billington 1993; Ettl et al. 2000) assumes that the delivery or service time between stages varies based on the material availability at that stage and that each stage in the supply chain maintains a base stock that is sufficient to meet its service level target (Graves and Willems 2003). If Δ_i is the random delay at the preceding stage i , then the replenishment cycle time at stage j equals

$$\gamma_j = \tau_j + \Delta_i. \quad (1)$$

We have adopted the procedure for calculating this delay due to the stock out at the preceding stage as presented in Graves and Willems (2003) and Ettl et al.(2000) with a modification that takes into account the fact that there is only one player at the preceding stage. Thus, we are assuming that the expected value of this delay is simply equivalent to the probability of stock out at the preceding stage π_i times its average processing time.

Therefore, expected replenishment cycle time at stage j is given by

$$E[\gamma_j] = L_j + \pi_i L_i, \quad (2)$$

where

$$\pi_i = 1 - \Phi(k_i) \quad (3)$$

Assuming that the demand is $N(\mu, \sigma^2)$, where μ is the mean demand during one time period and σ^2 is the demand variance during one time period, to satisfy average demand μ , given the average replenishment cycle time from (2), the average cycle stock is given by

$$\mu \times (L_j + (1 - \Phi(k_i))L_i). \quad (4)$$

Assuming the independence of processing times at a stage and between the stages, we realize that

$$\sigma_{\Delta_i}^2 = \sigma_i^2(1 - \Phi(k_i)) \quad (5)$$

$$\sigma_{\gamma_j}^2 = \sigma_j^2 + \sigma_i^2(1 - \Phi(k_i)). \quad (6)$$

When the demands are uncorrelated between time periods, then the mean and variance of the demand during replenishment period for stage j denoted by the continuous random variable W_j are obtained as follows by slightly modifying the equations to account for the portion of the lead time variability transferred from the preceding stage (see, for example, Eppen and Martin 1988 and Feller 1960).

$$\begin{aligned} \mu_{W_j} &= \mu E[\gamma_j] \\ \sigma_{W_j}^2 &= \sigma^2 E[\gamma_j] + \sigma_{\gamma_j}^2 \mu^2. \end{aligned} \quad (7)$$

Now, we introduce another parameter c_j , termed the coefficient of inverse responsiveness (CIR), defined as the ratio of the average demand to the rate of production (throughput) p_j :

$$c_j = \mu/p_j. \quad (8)$$

Assuming that there is enough capacity at all the stages to satisfy a given demand, $c_j \leq 1$ at all times. When $c_j = 1$, the expected replenishment cycle time is given by (2). We also assume that there is some upper bound above which the rate of production cannot be increased further. The CIR at a stage is similar to the expediting factor proposed by Bookbinder and Cakanyildirim (1999). They define the expediting factor τ as the constant of proportionality between the random variables \tilde{T} (the expedited lead time) and T (ordinary lead time). For expedited orders ($\tau < 1$), shorter than average lead time can be obtained at a cost. Similarly, longer mean lead time results in a rebate for the customer when ($\tau > 1$). By considering a model with three decision variables (Q, r, τ) , they show that the expected cost per unit time is jointly convex in the decision variables and obtain the global best solution.

Keeping the average cycle stock constant (given in (4)), from Little's law, at expedited rates of production ($c_j < 1$), average replenishment cycle time for player j , when operating at a CIR level c_j will be equivalent to

$$E[\gamma_j] = (L_j + (1 - \Phi(k_i))L_i)c_j, \quad (9)$$

$$\sigma_{\gamma_j}^2 = (\sigma_j^2 + \sigma_i^2(1 - \Phi(k_i)))c_j. \quad (10)$$

As c_j decreases, the average replenishment cycle time for player j decreases, which means that player j is becoming more responsive. Because of this inverse relationship between c_j and the responsiveness at stage j , c_j is termed the coefficient of inverse responsiveness at stage j .

In light of Eqs. 9 and 10, we assume that demand during replenishment period W_j for stage j is normally distributed as follows:

$$\begin{aligned} \mu_{w_j} &= \mu E[\gamma_j] \\ \sigma_{w_j} &= \sqrt{\sigma^2 E[\gamma_j] + (\sigma_{\gamma_j}^2) \mu^2}. \end{aligned} \tag{11}$$

This equation considers both the demand variability and the replenishment cycle time variability. Replenishment cycle time variability is made up of two components:

1. The processing time variability at stage j .
2. The portion of the processing time variability at stage i that is transferred to stage j .

We assume that base stock at stage j is given by $B_j = \mu E[\gamma_j] + k_j \sigma_{w_j}$, where k_j is the safety factor to achieve the service level target $\Phi(k_j)$ for that stage.

After accounting for the average demand over the replenishment period, expected on-hand inventory is given by

$$E[I_j] = k_j \sigma_{w_j}. \tag{12}$$

By augmenting the above expression with the following term, which is the expected number of back orders (Graves and Willems 2003; Ettl et al. 2000),

$$E[\text{BO}] = \sigma_{w_j} \int_{z=k_j}^{\infty} (z - k_j) \phi(z) dz \tag{13}$$

we realize the following expression for the expected safety stock at stage j :

$$E[\text{SS}_j] = \sigma_{w_j} \left(k_j + \int_{z=k_j}^{\infty} (z - k_j) \phi(z) dz \right). \tag{14}$$

At stage j , let C_j be the nominal cumulative cost of the product realized when $c_j = 1$, and let h_j be the holding cost rate per period. The per-unit holding cost of safety stock at stage j per period equals $C_j h_j$. The total safety stock holding cost at stage j per period is given by:

$$C_j^{\text{SSC}} = C_j h_j E[\text{SS}_j]. \tag{15}$$

Total safety stock holding cost for the supply chain per period is given by:

$$C^{\text{SSC}} = \sum_{j=1}^n C_j^{\text{SSC}}. \tag{16}$$

3.2 Expression for responsiveness related costs

When players (1, ..., n) operate with their respective CIRs, being (c_1, \dots, c_n) , stage j incurs two types of responsiveness related costs, as described below.

3.2.1 Direct responsiveness related costs

The difference in nominal cumulative costs of the product at two consecutive stages j and i (i.e., $C_j - C_i$) will increase by a value that is assumed to be a function of $(1 - c_j)$. This is the cost that stage j will pay for operating at a higher processing speed that lowers the average replenishment cycle time at stage j .

The increase in cost is typically due to increase in investment in the so-called 5M resources (i.e., manpower, machine, methods, material, and measurement). We are addressing the issue of cycle time reduction due to the opportunities for flexibility available at a stage which can be harnessed at a cost. This should not be confused with cycle time reductions due to better operational efficiencies such as efficient removal of wastes from the processes such as downtime, setup time, etc, which we will consider in the extension of this framework. Flexibility related costs will increase/decrease depending on how flexible these 5M resources are at a stage.

Direct response related costs at stage j per period are given by

$$\text{DRC}_j = [f(1 - c_j)](C_j - C_i)\mu. \quad (17)$$

Even though we do not advocate any specific function type for modeling $f(1 - c_j)$, the cost of volume flexibility function (COF), we strongly recommend that it be derived from the historical data. For example, for a specific average demand, from the past data one could fit a regression model between $(1 - c_j)$ and the incremental cost at a stage. Moon and Choi (1998) advocate the use of a piecewise linear crashing cost function that is widely used in project management in which the duration of some activities can be reduced by assigning more resources to the activities. They used a piecewise linear crashing cost function in their model. Ben-Daya and Raouf (1994) could be a useful reference when considering using other types of crashing cost functions.

Bookbinder and Cakanyildirim (1999) assume the expediting cost per unit (because of technological investments or hiring extra workers etc.) time $\psi(\tau)$ to be a decreasing convex function of the expediting factor with $\psi(1) = 0$ (additional cost when CIR = 1 is zero in our model as well). As opposed to our model, they allow $\psi(\tau)$ to take negative values for $\tau > 1$, meaning that for longer lead times they assume that the manufacturer gives the buyer some rebate per unit time.

Proceeding from the research of Bookbinder and Cakanyildirim (1999), Ryu and Lee (2003) chose their expediting cost functions $\psi_1(\tau_1)$ and $\psi_2(\tau_2)$ to be decreasing convex functions of the expediting factors τ_1 and τ_2 . They considered $\psi_1(\tau_1) = c_1(-1 + 1/\tau_1)$ and $\psi_2(\tau_2) = c_2(-1 + 1/\tau_2)$, where c_1 and c_2 are positive coefficients. Our cost function, for example Eq. 17, looks similar in spirit to these cost functions.

Yang and Geunes (2007) expect the cost of reducing procurement time, because of supplier's investment in production processes or technologies, to increase at a nondecreasing rate with the amount of lead time reduction and therefore employ a convex function for lead time reduction. They consider a piecewise linear, convex and decreasing form (as the production lead time increases) for the unit procurement cost function but note that their analysis of this function applies to general piecewise linear functions and convexity is therefore not required, although they expect this function to be convex in practical context. For our numerical analysis, we consider a

simple increasing convex function, although the results would not be different for any nondecreasing function.

3.2.2 Indirect responsiveness related costs

In addition to the above mentioned direct responsiveness related costs, the stage will experience an increase in safety stock costs when it operates at c_j , for the reasons mentioned in Sect. 3.2.1. As a result, the difference in nominal cumulative costs of the product at stages j and i will increase by a value, which is a function of $(1 - c_j)$. Therefore, indirect responsiveness related cost at stage j is given by:

$$\text{IRC}_j = [f(1 - c_j)](C_j - C_i)h_jE[\text{SS}_j]. \quad (18)$$

Therefore, the total responsiveness related cost at stage j is given by

$$\text{TRC}_j = \text{DRC}_j + \text{IRC}_j. \quad (19)$$

Hence, total safety stock costs in the presence of increase in costs at stage j that account for increase in the responsiveness per period is given by

$$C_j^{\text{TSC}} = C_j^{\text{SSC}} + \text{TRC}_j. \quad (20)$$

Hence, the total safety stock related cost for the whole supply chain per period is given by

$$C^{\text{TSC}} = \sum_{j=1}^n C_j^{\text{TSC}}. \quad (21)$$

4 Managerial insights for strategic safety stock placement

In this section, we attempt to study the safety stock placement problem primarily with respect to the key parameters such as replenishment cycle times, replenishment cycle time variability, cost of responsiveness etc. as we travel from U/S to D/S and offer some interesting insights.

4.1 Position of the bottleneck player

We consider a hypothetical serial supply chain with five stages to study the impact of the position on the bottleneck player on supply chain performance. The different parameters for this serial supply chain are illustrated in Table 1.

For the purpose of our discussion, we consider the player with no flexibility whatsoever with respect to its processing time as the bottleneck player. The effect of changing the position of the bottleneck player on the SC safety inventory costs is depicted below. We have considered three cases, wherein the processing time variability progressively increases (IV in Fig. 3), decreases (DV in Fig. 3), and remains constant (EV in Fig. 3) as we move from the most U/S stage to the most D/S stage. For the increasing and decreasing cases, we kept the total processing

Table 1 Parameters of the five-stage serial SC adopted for numerical analysis

	Stage/player				
	1	2	3	4	5
Nominal cumulative cost C_j	80	112	175	327	863
Average demand μ	100	100	100	100	100
Demand variability σ^2	400	400	400	400	400
Mean processing time (periods) L_j	1	1	1	1	1
Processing variability ($\mu^2 \sigma_j^2$) (in number of units of product)	50	50	50	50	50
CIR c_j	1	1	1	1	1
Safety coefficient k_j	1.28	1.28	1.28	1.28	1.28
Average back order coefficient	0.1	0.1	0.1	0.1	0.1
Probability of stockout π_j	0.1	0.1	0.1	0.1	0.1
Inventory holding cost h_j	0.017	0.017	0.017	0.017	0.017
Service level $\Phi(k_j)$	0.9	0.9	0.9	0.9	0.9

variability constant and progressively increased/decreased the process variability as we move from U/S to D/S in a symmetric fashion. When a particular stage is a bottleneck, the CIR for that particular stage would be unity and for all other stages the CIR is considered to be 0.9. Response related costs are not considered in the analysis as our primary intention is to show the effect of reducing the lead time on the safety stocks as the bottleneck player moves from U/S to D/S. By considering the incremental total supply chain safety stock costs with respect to a benchmark case, wherein all the players are operating at a CIR equivalent to 0.9 and the processing variability is the same at all the stages (as with the EV case in the chart), one can clearly see that the incremental total supply chain safety stock costs progressively increase as the bottleneck player moves from U/S to D/S for all three cases.

Key managerial insight #1: Safety stock cost depends on the placement of the bottleneck player in a serial supply chain and it is desirable for the bottleneck player to be located towards the U/S rather than the D/S.

4.2 Safety stock costs versus responsiveness costs

We illustrate the impact of CIR on the different cost curves in Fig. 4, using the cost expressions developed earlier.

We know that, for any stage, safety stock related costs decrease (Eq. 15) and response related costs increase (Eqs. 17 and 18) with decrease in cycle time, or in

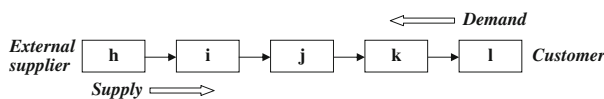


Fig. 2 Schematic description of a serial supply chain

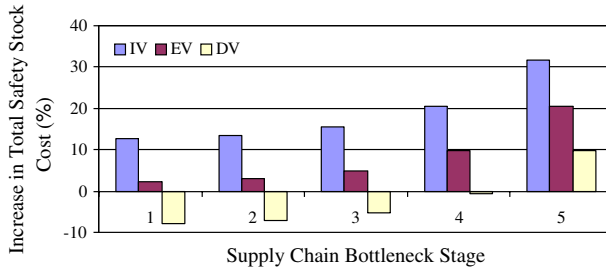


Fig. 3 Incremental SC safety stock costs versus position of the bottleneck player

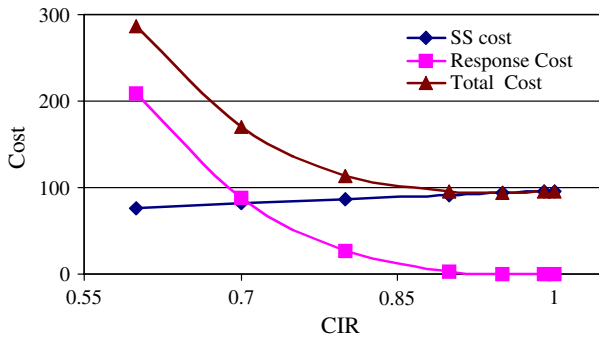


Fig. 4 CIR versus stage costs

other words, with decrease in CIR. Hence, without loss of generality, we can say that the total cost function, which is a combination of safety stock and response related costs, tends to be convex, the optimum CIR shifting either towards or away from unity depending on whether responsiveness cost component or safety stock cost component is dominating. A very interesting result relevant to the nature of the total costs is due to Bookbinder and Cakanyildirim (1999), who show that the expected cost per unit time is jointly convex in the decision variables (Q, r, τ) , τ being the expediting factor for a (Q, r) inventory system with expedited orders and random lead times.

4.3 Effect of cycle times and processing time variability on total stage cost

Figure 5 illustrates the effect of increasing processing time variability at a particular stage on the total cost while keeping the other parameters constant. For the sake of numerical analysis, we have considered the parameter values for stage 3. PV in the chart stands for processing time variability and DV stands for demand variability.

Increasing process variability tends to increase both the safety stock related costs and responsiveness related costs at different rates, primarily depending on the nominal cumulative cost C_j , the cost of volume flexibility function $f(1 - c_j)$, and the cost added at a stage $(C_j - C_i)$. In the presence of increasing processing time variability, therefore, optimum CIR either moves away from or towards unity,

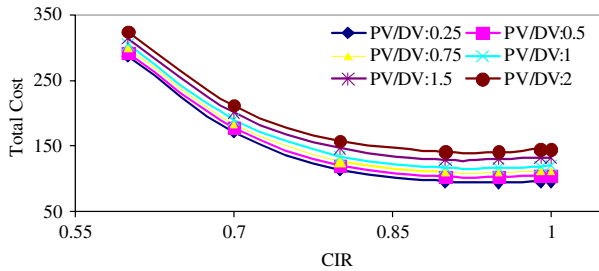


Fig. 5 CIR versus total stage costs

depending on whether safety stock cost component/or the responsiveness cost component is dominating. With increasing variability, the degree of departure of the optimum CIR value either way depends on the three factors mentioned above for a particular stage. To explain, to counter the excessive variability, a typical supply chain manager tries to reduce the cycle time (by reducing CIR), which would minimize the SS related costs. However, that action does not necessarily lead to reduction of the overall costs. For example, if the cost added at a particular stage is very high then the decrease in safety stock costs by cycle time reduction might not be able to offset the increase in cycle time reduction (responsiveness) costs. In such a scenario, moving CIR counterintuitively towards unity (i.e., increasing the cycle time), which means in the direction that increases safety stock costs, could be a better measure to reduce overall costs.

Key managerial insight #2: As the processing time variability increases for a stage, the optimum value of CIR moves away from unity if safety stock cost component dominates the responsiveness cost component and towards unity if the responsiveness cost component dominates the safety stock cost component.

In Fig. 5, optimum CIR is progressively moving away from unity as the PV/DV ratio increases, because we have considered the safety stock costs component to be larger than the responsiveness cost component for our numerical analysis. The trend will be reversed if the response related costs dominate the safety stock related costs. In Fig. 5, for the case of PV/DV = 0.25, the optimum CIR value is 0.919, for which the respective safety stock and responsiveness cost components are \$91.65 and \$1.749 per period, respectively. For the case of PV/DV = 2, wherein the process variability increases eightfold compared to PV/DV = 0.25, the corresponding safety stock and responsiveness cost components are \$138.6 and \$1.75, respectively. In this case, not only is the safety stock component larger but also the effect of increasing process variability is much greater on safety stock component compared with responsiveness cost component. Hence, the optimum CIR value for the PV/DV = 2 case will move in the direction that will mitigate the effect of increasing safety stock costs and to a point where the cost advantage in terms of safety stock cost reduction by reducing the CIR is equalized by the corresponding increase in responsiveness costs. The optimum value for the PV/DV = 2 case occurs at a CIR value of 0.909 (moving away from unity), with

corresponding safety stock and responsiveness cost components of \$137.86 and \$2.48, respectively.

We extend the above analysis by performing a simple sensitivity analysis by considering the changes in mean processing time and nominal cost added at stage 3, while keeping other parameters constant. Table 2 presents the case with the mean processing time and nominal cost added both being halved. Table 3 presents the case with mean processing time and nominal cost added both being doubled.

For the sake of simplicity, we have just considered the cases $PV/DV = 0.25$ and $PV/DV = 2$. For both of these cases, the optimum CIR for $PV/DV = 2$ occurs at a slightly lower value than that for $PV/DV = 0.25$ for the reasons mentioned in the preceding paragraph. The changes made in the parameter values are not able to make the responsiveness related costs increase at a faster rate than the decrease in safety stock related costs (with decreasing CIR), hence, the optimum CIR is still moving away from unity, primarily due to the parameter values we have assumed for our numerical analysis. We show in Sect. 4.4 that changes in the cost of flexibility function (COF), that is $f(1 - c_j)$, in our model cause the responsiveness related costs to increase at a faster rate than the decrease in safety stock related costs (with decreasing CIR), making the optimum CIR move towards unity. In a practical context, it all depends on the actual values of the parameters, which make either of the cost components dominating.

The optimum value of the CIR for a stage will primarily depend upon the cumulative cost of the product, which in turn will depend upon the position of the stage in the supply chain, the cost added, and the nature of cost of volume flexibility function. Using the cycle time reduction as a lever may or may not be cost effective depending on, for example, whether a windscreen wiper is being assembled or an engine is being assembled at a stage. For the same cost of volume flexibility function, it might be a good idea to reduce the cycle time if a windscreen wiper is being assembled as opposed to an engine. Irrespective of the component that is being assembled, this effect will be more pronounced D/S when compared to U/S because the cumulative cost of the product will progressively increase as we move D/S.

Key managerial insight #3: To reduce the safety stock costs, reducing the cycle time is a better lever at downstream stages when compared to upstream stages for a given responsiveness cost, all other parameters being held constant.

Key managerial insight #4: All other parameters being constant, for a given cycle time reduction, the cost of flexibility function has to be milder for a stage with high cost addition when compared to a stage with low cost addition, to justify savings in safety stock costs.

Table 2 Sensitivity analysis 1

CIR	PV/DV = 0.25	PV/DV = 2
1	69.869	103.747
0.9	68.432	100.405
0.8995	68.441	100.404
0.899	68.450	100.403
0.895	68.533	100.407

Table 3 Sensitivity analysis 2

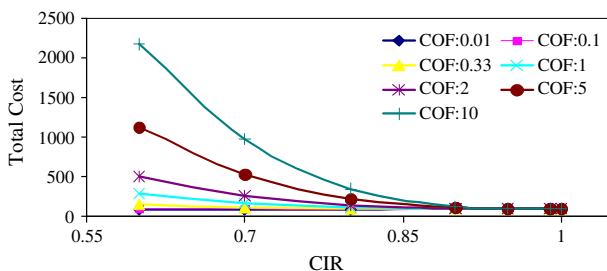
CIR	PV/DV = 0.25	PV/DV = 2
1	132.232	202.513
0.95	129.834	198.290
0.93	129.952	197.664
0.92	129.952	197.664

The insight from Ryu and Lee (2003) “that in order to attain greater savings from the symmetric cost scheme for the two suppliers, the investment cost for the supplier with the more unreliable lead time should be smaller” looks similar in essence to our key managerial insight 2, albeit in a different context. One of the key insights offered, that downstream lead times have a greater impact on system performance than upstream ones (Gallego and Zipkin 1999), is also similar in spirit to our research.

4.4 Effect of cost of volume flexibility on total stage cost

Figure 6 illustrates the effect of cost of volume flexibility at a particular stage on the total cost while keeping the other parameters constant. For the sake of numerical analysis, we have once again considered the parameter values for stage 3. COF in the chart stands for cost of volume flexibility function mildness/steepness, when compared to a randomly chosen increasing convex function (COF: 1).

In Fig. 6, as expected, optimum CIR is progressively moving towards unity as the COF increases. As opposed to processing time variability, which affects both the safety stock cost component and the responsiveness cost components, cost of flexibility affects only the responsiveness cost component. Intuitively speaking, given that the stage is not operating at optimal CIR, increasing the cost of flexibility makes a typical supply chain manager operate close to nominal cycle times (CIR close to unity), but going back to the example given earlier, if a windscreen wiper is being assembled, particularly at a D/S stage, it is quite likely that there will be significant savings in safety stock costs by reducing the cycle time (moving the CIR away from unity), overtaking the extra cost of responsiveness because of a steeper flexibility function. The opposite will be true, for example, if an engine is being assembled at a stage.

**Fig. 6** CIR versus total stage costs

Key managerial insight #5: Given that a stage is not operating at optimal CIR, as cost of volume flexibility function becomes steeper, the optimum value of CIR moves towards unity if the responsiveness costs segment dominates the safety stock cost segment, and vice versa.

Key managerial insight #6: All other parameters being constant, for the same cost addition at a stage, cost of flexibility function has to be milder at U/S than D/S for a given amount of savings in safety stock costs.

While our model assumes information symmetry, it is still applicable, including the managerial insights, in supply chains with information asymmetry. For example, in the presence of bullwhip effect attributable to information asymmetry or other related issues, demand variability will progressively increase as we move towards the upstream stages. It is still advisable that mitigating measures are put in place to reduce the causative factors of the bullwhip effect. In the absence of any mitigating measures, one could also consider the actual variability at different stages and still use the model. The effect will be to accentuate both the safety stock component and the responsiveness cost component as we proceed upstream. If the increase in the cost of responsiveness at a stage is significantly larger compared to the reduction in safety stock costs for unit processing time reduction, the optimum CIR will move towards unity. The opposite trend will be witnessed in the opposite case. The change in the optimum CIR value at downstream stages may also be significant because of larger cumulative costs and typically large amounts of cost addition, in spite of the effect of bullwhip effect being smaller compared to upstream stages.

5 Model usability for achieving strategic fit

The model can be used primarily as a building block in any kind of supply chain network both to evaluate the performance of individual stages with respect to the key order winners, cost, and responsiveness, and to optimize the supply chain depending upon the focus within the cost-responsiveness spectrum. The results can be used to evaluate the gap between the individual business strategies of different stages and the supply chain strategy, so that appropriate actions can be taken to achieve the strategic fit. Once the supply chain design is completed and the network is in place, the model will be particularly useful for making strategic decisions with regard to the safety stock placement while considering a changeover or introducing a new product.

5.1 Performance evaluation

Total safety stock related cost (safety stock cost and responsiveness cost) expression for all the stages (using Eq. 20) can be easily evaluated given the different parameter values and one can obtain the costs separately for safety stock holding and cycle time reduction (if so desired by a stage) and the expected cycle times assuming that all the stages operate without any coordination with respect to the overall supply chain strategy (that is, there is no central decision maker). This

will allow stages to evaluate their performance with regard to the key order winners of cost and responsiveness and facilitates their comparison to the internal performance benchmarks. For example, a particular stage may realize that better operations management practices that involve the reduction of waste (lean practices) that had been planned for are ineffectual. Hence, they may want to know what went wrong and implement appropriate corrective and preventive actions such that cost and cycle time reductions can be achieved without any major investments.

5.2 Optimization

Now, assuming that there is a central decision making mechanism, which acts to coordinate the whole supply chain, the overall safety stock related cost expression for the supply chain (Eq. 21) can be optimized, say for the optimal CIR values at all the stages given the constraints on target supply chain cycle time, individual stages' rates of production, service levels, inventories, cost of inventory holding, etc. The optimal costs (safety stock inventory and responsiveness) can be compared with the costs obtained assuming the absence of the central decision maker (as for performance evaluation explained in Sect. 5.1) to initiate necessary actions.

We also offer a simple optimization example based on the parameter values presented in Table 1 that lend support to the managerial insights developed in Sects. 4.3 and 4.4.

Figure 7 depicts the optimal CIR values under different scenarios considered in Sects. 4.3 and 4.4. The only constraint considered was $0 \leq c_j \leq 1$.

The total cost function was optimized under different scenarios.

SC: Standard cost of flexibility function for all stages and other parameter values as per Table 1.

DC: Decreasing cost of flexibility function (i.e., the function becomes milder compared to the SC case as we move from U/S to D/S); stage 3's cost of flexibility function remaining the same as in the SC case. Other parameters for all the other stages remain as in the SC case.

IV: Progressively increasing process variability as we move from U/S to D/S. For stage 3, process variability remains the same as in the SC case. Other parameters for all the other stages remain as in the SC case.

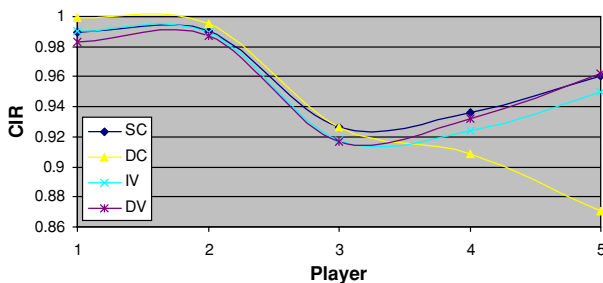


Fig. 7 Player versus optimal CIR

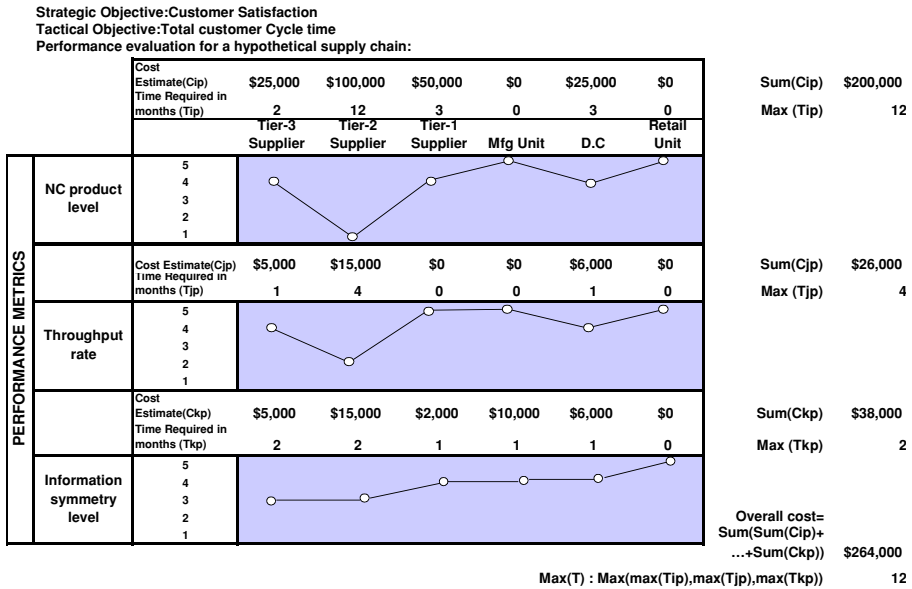


Fig. 8 Performance comparison for different players in a supply chain (adopted from Vanteddu et al. 2006)

DV: Progressively decreasing process variability as we move from U/S to D/S. For stage 3, process variability remains the same as in the SC case. Other parameters for all the other stages remain as in the SC case.

The results, as can be seen from Fig. 7, clearly reinforce the insights developed in the earlier sections. The shift in the optimum CIR value at stage 5 shows strong variability owing to the fact that cost added constitutes a significant portion of the cumulative cost at that stage, thereby increasing the cost of responsiveness significantly for the same cost of flexibility function when compared to other stages. The same is the case with stage 4, although on a reduced scale. Since stage 3 is the transition stage under different scenarios retaining the same parameter values as compared to the SC case, there is no perceptible change in the optimum CIR value.

5.3 Achieving strategic fit

If the overall costs at a stage are increasing as a result of optimization to achieve the strategic supply chain objectives, when compared to the costs in the absence of a central decision maker, i.e., by following its independent business strategy, then, by devising a scheme for the sharing of the additional profits for the whole supply chain in an equitable fashion, say, through changing the contract structure, discounts or other incentives, efforts could be made to coordinate the individual business strategies with the supply chain strategy to achieve the strategic fit.

One way of doing this is by considering the supply chain objectives at different levels, say, strategic, tactical, and operational levels, and performing a gap analysis

between the individual business strategies and the supply chain strategy in terms of costs and responsiveness. Vanteddu et al. (2006) offers a simple Excel based model to achieve strategic fit assuming that quantitative data is available to make use of the tool, as illustrated in Fig. 8.

By simply modifying the performance metrics by placing emphasis on cost efficiency and responsiveness, one can use the above model to achieve the strategic fit. Actual costs related to cost and responsiveness can be obtained by using the model proposed in this paper.

6 Conclusions

In this paper, in addition to offering several managerial insights with regard to strategic safety stock placement in a supply chain, an attempt has been made to address the problem of achieving compatibility between the supply chain strategy and the individual stage's business strategy by primarily considering safety stocks and responsiveness related costs. We introduce a new parameter called the coefficient of inverse responsiveness (CIR) to model response related costs at a stage, which also enhances the scalability of the model. The developed cost function for the building block could be easily extended for any type of supply chain network. By knowing the values of the parameters of the model, one can know the safety stock costs and responsiveness related costs at each stage and compare them to an ideal supply chain strategy in terms of cost and responsiveness to make informed decisions. The key managerial insights developed are generic in nature and applicable to any supply chain irrespective of its placement on the cost-responsiveness spectrum and topology.

To make the model more tractable we had to make certain simplifying assumptions and following are some of the limitations related to those assumptions. For example, we did not factor the bullwhip effect into our model. It would be an interesting extension to our research if the bullwhip effect and other information asymmetry related issues were factored into the model. We have not incorporated order sizes into our model because the model is supposed to be largely a strategic model. Research could be extended by incorporating this aspect into the model to see how it affects the managerial insights that we offered. Relaxing the assumptions on the stationary nature of the demand and stage base stock policy with periodic review will make the model more realistic and robust to real-world situations. Introducing contracts that affect the flexibility at a stage with financial ramifications will also be a very fertile area to pursue that will make our model mimic reality more closely. Another such area is the consideration of other types of network topologies, particularly assembly and distribution; we are planning to consider extension of the framework in this direction. It would also make more sense to consider capacity constraints at certain stages. Product mix related flexibility is also a crucial factor which is not addressed in our model. Addition of this feature would truly make the research more in tune with reality, especially in mass customization settings. Finally, we really would like to see this model used in some real-world application so that insights presented in our model could be validated.

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