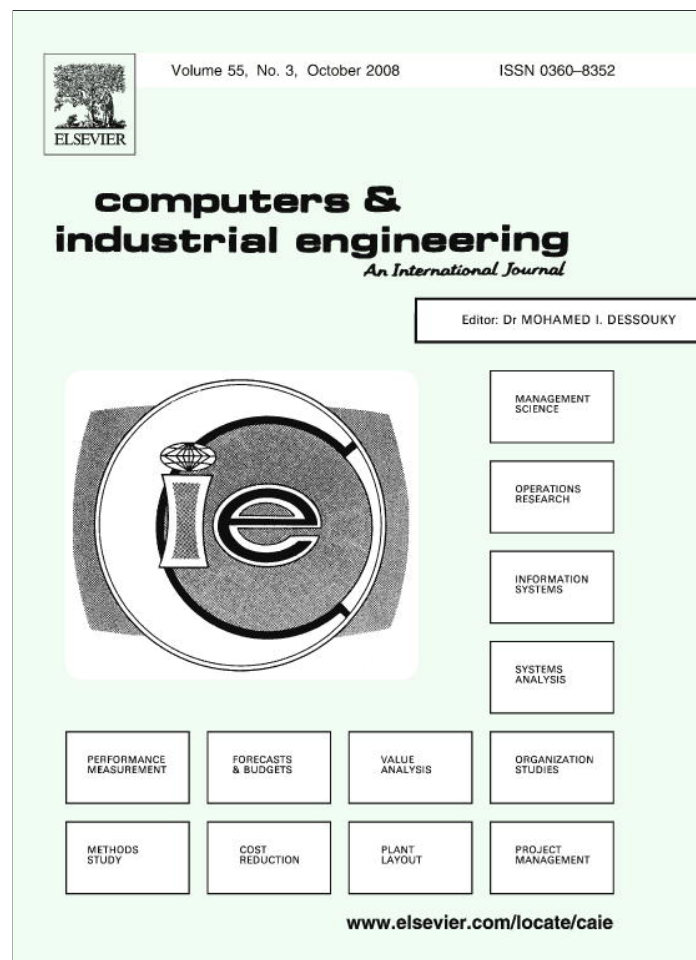




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Effects of inventory policy on supply chain performance: A simulation study of critical decision parameters

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Abstract

This paper investigates the effects of information sharing and early order commitment on the performance of four inventory policies used by retailers in a supply chain of one capacitated supplier and four retailers. Model parameters and operating conditions are emulated from a local business supplying a standard product to its retailers. Through computer simulation and subsequent analyses, we found that the inventory policy used by the retailers, information sharing, and early order commitment can significantly influence the performance of the supply chain. Out of the four inventory policies examined, the economic order quantity rule is found to be the best for the retailers and the entire supply chain, but periodic order quantity and Silver–Meal provide the best performance for the supplier. The sharing of future order plans by the retailer and the supplier is also shown to be the most effective way for reducing the supplier's cost and improving its service level; however, the magnitude of these benefits achieved is less for the retailers. In addition, early order commitment by the retailers is found to be beneficial to the supplier and retailers in reducing their total cost.

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Keywords: Supply chain management; Computer simulation; Inventory policy; Information sharing; Early order commitment

1. Introduction

The coordination of logistics and inventory decisions in a supply chain has a significant effect on the supply chain performance. Any attempts to reduce supply chain costs and improve service levels must consider the complex interactions across a wide spectrum of business organizations and their individual replenishment decisions. Until recently, most businesses have primarily focused on improving their internal operations to

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better serve their immediate customers, and have paid little attention to improving the performance of the entire supply chain by examining the impact of their decisions on other members along the supply chain.

Our research was motivated by a local manufacturer that supplied a standard product to four retailers at different locations. Each of the four retailers made their inventory decisions using simple lot-sizing rules based on their own demand forecasts. The manufacturer made its own production decisions using a capacitated lot-sizing rule, but wanted to investigate the impact of the inventory policies (IPs) used by the retailers on the performance of the supply chain and identify the best inventory ordering policy for the benefit of all members in the supply chain. Four IPs were identified for ease of implementation; these were economic order quantity (EOQ), periodic order quantity (POQ), Silver–Meal (SM), and part-period balancing (PPB). In addition, neither information sharing nor early order commitment was currently used, but these policies would be initiated if such efforts could have been justified by a significant reduction in total supply chain cost or improvement in service level.

To gain a better understanding of the performance of the four IPs under different operational scenarios, we developed a computer simulation model that incorporated a variety of basic environmental and decision variables. The simulation model incorporated many scenarios that would affect the ordering decisions of the retailers and the production lot-sizing decisions of the manufacturer. While addressing the unique issues raised by the local manufacturer and its retailers, we also wanted to subject our simulation to a larger set of operating characteristics so that the results could be generalized and helpful to other supply chains. As a result, we used a combination of demand patterns, capacity, and cost structure variables throughout our simulation. By analyzing the findings from our simulation model, we have sought to provide managerial insights into the following questions:

- (1) How does the inventory policy used by the retailers influence the costs of the supplier, retailers, and the entire supply chain?
- (2) How does the inventory policy used by the retailers influence the service levels of the supplier and the retailers?
- (3) How does the inventory policy used by the retailers influence the value of information sharing?
- (4) How does the inventory policy used by the retailers influence the value of early order commitment?

In addition, our findings can also serve as a building block for future work in this emerging area of research. In the following sections, we first review the related literature and then describe our research designs. Subsequently, we present the simulation model parameters and the results of the statistical analyses. Finally, we describe the managerial implications and conclusions.

2. Literature review

Supply chain coordination is imperative to reducing the inventory and counteracting the demand uncertainty throughout the supply chain. Extensive research has been conducted in recent years to study the phenomenon of volatility amplification in supply chains, widely known as the bullwhip effect. Lee, Padmanabhan, and Whang (1997) identify four main causes of the bullwhip effect: demand signal processing, batch purchasing, price fluctuations, and shortage gaming. Choice of inventory policies, extent of information sharing, and use of early order commitment are often cited as effective means to achieving better supply chain coordination and alleviating the bullwhip effect.

2.1. Inventory lot-sizing policies

The lot-sizing problem has been widely studied under different aspects of demand rates (constant or time varying), demand characteristics (deterministic or stochastic), products (single or multiple), and other production–distribution characteristics. Different solution procedures, commonly known as lot-sizing policies, are available to determine the best ordering quantities and timing. Among the numerous lot-sizing policies and their performance studied in previous research, four well-known ones are investigated here: economic order quantity (EOQ), periodic order quantity (POQ), Silver–Meal (SM), and part-period balancing (PPB).

An EOQ policy attempts to balance the inventory carrying costs against the fixed ordering costs. One major problem associated with EOQ is that it assumes that the requirements are constant or stationary from period to period. The POQ lot-sizing technique overcomes this problem by determining the number of periods for which replenishment is needed to cover the demand (Berry, 1972). The POQ policy calculates the number of periods between orders that would result from the use of EOQ and then rounds the result to the nearest integer. The SM lot-sizing technique minimizes the average cost per period (Silver & Meal, 1973). In extensive testing, SM has often been found to yield a production schedule costing less than 1% above the optimal policy obtained by the Wagner–Whitin algorithm (Peterson & Silver, 1985). The PPB lot-sizing rule balances the holding cost and setup cost incurred in a lot so that the total holding cost incurred for current lot is as close to the setup cost as possible (Berry, 1972).

For retailers selling independent demand items, economic order quantity (EOQ) is often considered the best lot-sizing rule to use as it balances the ordering cost and total inventory carrying cost. The lot-sizing decision has also been one of the most important factors determining the performance of inventory systems with dependent demand like material requirements planning (MRP). Because of significant computational requirements and mathematical complexity involved in determining the optimal solution, a variety of heuristics have been proposed in the last few decades to solve the lot-sizing problems.

Along with EOQ, periodic order quantity (POQ), Silver–Meal (SM), and part-period balancing (PPB) are often discussed in the literature and operations management textbooks. Zhao, Goodale, and Lee (1995) compare these four lot-sizing rules along with nine of their modifications and compound rules in a study of their performance in MRP systems under demand uncertainty. The modifications of the lot-sizing rules are made to take into consideration of independence in the lot-sizing decisions among the items in a multilevel MRP system. The compound lot-sizing rules use the lot-for-lot rule for the dependent component while using other rules for the finished product. Because we do not consider multilevel product structure and only focus on the planning and scheduling of the end item at the MPS level in this study, we do not include the modified rules and compound rules.

2.2. Information sharing

Traditionally, retailers make their own inventory replenishment decisions based on their demand forecast and their cost structure (i.e., inventory carrying cost and ordering costs). Many supply chain related problems such as bullwhip effect can be attributed to a lack of information sharing among various members in the supply chain. In particular, sharing demand and inventory data has been shown to improve suppliers' order quantity decisions in supply chain models with known and stationary demand. See, for example, Aviv and Federgruen (1998), Bourland, Powell, and Pyke (1996), and Chen (1998). In particular, Gavirneni, Kapuscinski, and Tayur (1999) demonstrate the benefits of sharing the retailer's ordering policy with the supplier, and Aviv (2001) shows the benefits of sharing demand forecasts.

On the other hand, as noted by Huang, Lau, and Mak (2003) and Ferguson and Ketzenberg (2006), studies on the potential benefits of the reverse flow of information (from supplier to retailer) have only emerged very recently. For example, Chen and Yu (2005) show a reduction in supply uncertainty for the customers when lead time information is shared. In the context of perishable inventory, Ketzenberg and Ferguson (2005) is the first study to address the value of information sharing from the retailer to its supplier. In a subsequent study, Ferguson and Ketzenberg (2006) examine the value of reverse flow of information in which the supplier shares its inventory state with the retailer.

2.3. Early order commitment

Early order commitment (EOC) means that a buyer commits to purchase from a supplier a fixed order quantity, for a specific delivery time, before the real need occurs. By preventing a buyer from canceling an order or from changing the order quantity and delivery time, EOC helps alleviate the bullwhip effect, a phenomenon of demand variability amplification along a supply chain. While most buyers may prefer to delay commitments and sellers prefer early commitment, Ferguson (2001) finds exception to this common belief

and identifies the preferred commitment time frame depending on which member of the supply chain has the power to set the price.

Generally speaking, the effect of EOC on supply chain performance is intuitively clear. On the one hand, EOC increases a retailer's risk of mis-estimating the demand and thus increasing the inventory holding and shortage costs. On the other hand, EOC helps the manufacturer reduce inventory holding and shortage costs because of reduced exposure to demand risk. Fisher and Raman (1996) help a fashion skiwear firm use early orders to revise and improve sales forecasts. Iyer and Bergen (1997) report that explicit total quantity volume, or dollar volume commitments, from retailers helped a supplier procure materials, schedule production, and better utilize capacity.

The seller commonly offers price discounts or other incentives to the buyers in exchange for their purchase order commitment. Gilbert and Ballou (1999) conduct an analysis of a steel distribution supply chain and quantify the maximum discount that can be offered to consumers who commit to orders in advance. Cvsa and Gilbert (2002) examine the tradeoff between early order commitment and order postponement in the context of competition. Using a game theory model involving a monopolistic supplier without capacity constraint and two duopolistic buyers, they find that a supplier can influence the form of competition in the downstream market. Such a finding provides another justification for the use of EOC even in the absence of capacity or lead time considerations. Other than offering price discounts as an incentive, a buyer can also permit a supplier to offer value-added services, such as faster replenishment time, or vendor managed inventory, in lieu of price concessions (Iyer & Bergen, 1997; Lee, So, & Tang, 2000).

In addition, Zhao, Xie, and Wei (2002) conduct extensive simulation studies on the effect of EOC on supply chain performance under various operational conditions, including demand pattern, forecast errors, cost structure, number of retailers, and capacity cushion. Their results show that EOC produces substantial cost savings for the manufacturer but increases costs for the retailer. In another paper, Zhao, Xie, and Wei (2007) develop an analytical model to quantify the cost savings of EOC in a two-level supply chain where demand is serially correlated. Their results indicate that the supply chain would experience greater savings from EOC when (a) the inventory item receives less value-added activities at the retailer site; (b) the manufacturing lead time is short; (c) demand correlation over time is positive but weak; or (d) the delivery lead time is long.

3. Research designs

Previous research has suggested that supply chain performance is dependent on the complex interaction of inventory policy, information sharing, and early order commitment decisions. In this study, we are interested in evaluating the performance of four lot-sizing rules used by the retailer and how information sharing and earlier order commitment influence the performance of the lot-sizing rules. To ensure that our simulation results could be generalized to any foreseeable, changing business environment, we also examined the interactions of these decisions under a variety of environmental variables, including demand patterns, cost structures, and capacity constraints. The impact of these decision variables was then evaluated in terms of the cost and service performance of the supplier, the retailers, and the entire supply chain.

3.1. The simulation environment

A simulation model involving a simple, two-stage supply chain was constructed, in which a single supplier had a capacitated facility producing a single product for four retailers. No explicit production lead time was considered here because a constant lead time would not change the conclusions in any way. However, the actual manufacturing lead time as a result of insufficient capacity would be implicitly determined in the supplier's production-planning decision. The average customer demand per day for each retailer was 1000 U. Furthermore, the unit shortage cost per day for the retailer was 10 times of that of the carrying cost. Retailers replenished their inventories by placing orders directly with the supplier. As a result, the supplier needed to maintain an average production rate of 4000 U per day for this product.

The shipments of products were delivered directly from the supplier to the retailers by trucks. The transportation lead time from the supplier to each retailer was one day. As each truckload was sufficiently large,

a shipment to any one of the four retailers could be completed by a single truck. When a retailer placed an order to the supplier, a fixed order processing cost of \$100 per order was incurred. Because only one truck was needed for each order delivery, the actual ordering cost for a retailer was the sum of the single truck transportation cost and the fixed order processing cost. Transportation costs were \$450, \$255, \$331, and \$553, respectively, for retailers 1, 2, 3, and 4. The production setup cost of the supplier was \$1000 per setup. Three different cost structures were considered by varying the inventory carrying costs per unit per day (h).

The length of the simulation run (410 days in this study) was selected so that the start-up and termination effect would be minimized. The first 50 days were used to estimate the initial demand forecasts, and the last 10 days were excluded from the performance calculations to eliminate any unusual inventory situation towards the end of the simulation run. Therefore, the final performance measures were calculated based on 350 simulation days (from day 51 to day 400) of operations. Furthermore, in order to avoid possible backorder for the retailers during the first few days immediately following the 50th day, sufficient initial inventory was assumed for each retailer. In this study, we set the initial inventory at day 51 for the i th retailer at $(14 + i) \times 1000$ ($i = 1, 2, 3, 4$). Different initial inventories were used to prevent all retailers from placing their first order at the same time. Our preliminary simulation runs also suggested that such a provision of initial inventories would ensure that each retailer was sufficiently stocked for the following few days after day 51. The simulation procedure is outlined in Fig. 1 and it consisted of three phases, which will be discussed below.

3.2. Phase I: generating randomized demand and production capacity

Randomized demands and available production capacities were generated for the retailer and the supplier, respectively, during the first phase of the simulation. In particular, demand for each retailer was generated by a corresponding demand generator, given by Zhao and Lee (1993):

$$\text{Demand}_t = \text{base} + \text{slope} \times t + \text{season} \times \sin\left(\frac{2\pi}{\text{SeasonCycle}} \times t\right) + \text{noise} \times \text{snormal}()$$

where

Demand_t is the demand on day t ($t = 1, 2, \dots, 410$),
 $\text{snormal}()$ is a standard normal random number generator, and
 $\text{SeasonCycle} = 7$ for demand varying weekly.

The other parameters (*base*, *slope*, *season*, *noise*) were characteristic parameters for the demand generators, among which *base* was selected to ensure that the average demand was approximately 1000 U. A normal variate in the demand generation function might mean that the demand generated takes a negative value. We eliminated this possibility by restricting the value produced by the standard normal random number generator to -3.0 and $+3.0$.

Four demand generators (LI, HI, LD, HD) were included in this study, and their characteristic parameters are listed in Table 1. These generators represented the different combinations of trend, seasonal, and noise component of variations. For example, demand generator LI represents a low positive trend with low seasonality and small variability. Five demand patterns (ILI, IHI, ILD, IHD, MIX) representing the different combinations of demand generators were used in this study. When the demand patterns of ILI, IHI, ILD, and IHD were used, all four retailers used an identical demand generator (LI, HI, LD, and HD, respectively) to generate their demand. When the demand pattern of MIX was used, the four retailers used different demand generators to generate their demands. The supplier's available capacity was determined by the corresponding demand generator and the capacity tightness factor and stayed constant for the entire simulation period. The capacity tightness factor refers to the ratio of production capacity to demand.

3.3. Phase II: retailers' ordering decisions

The planning horizon of the purchasing plan for a retailer was four times that of the natural ordering cycle. The re-planning periodicity was set to one day. In each re-planning cycle, the retailers used the simple moving

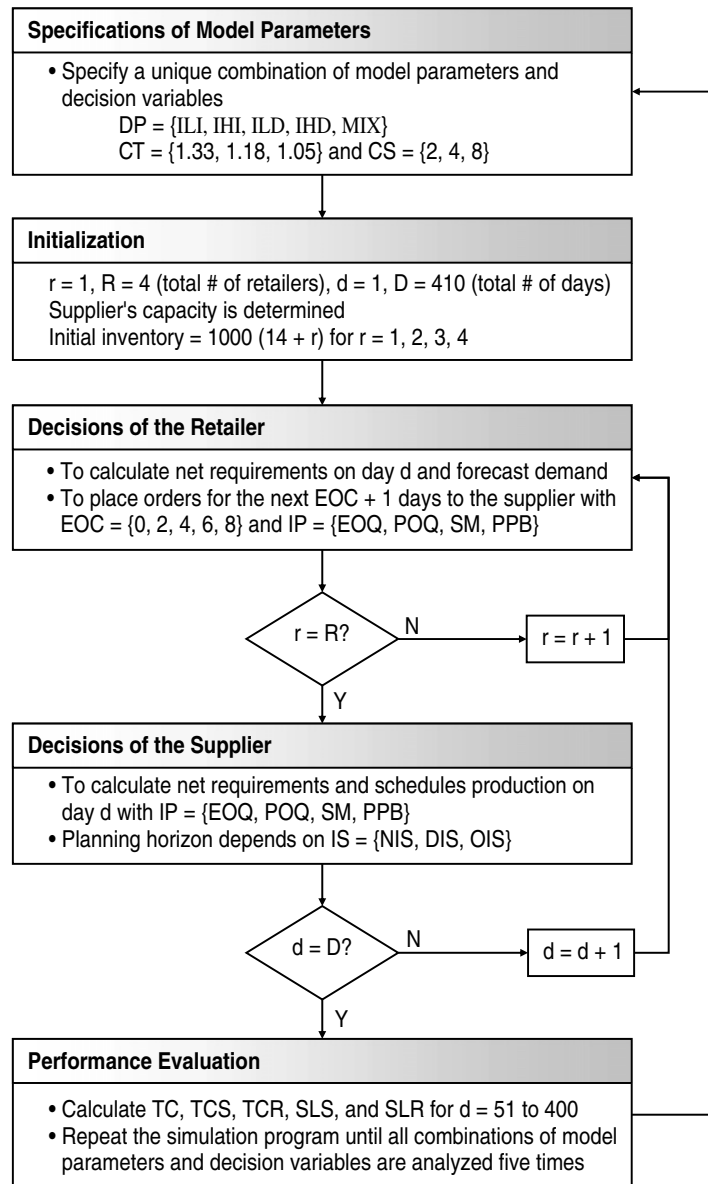


Fig. 1. Simplified simulation flow diagram.

Table 1
Demand generators and their characteristics

Demand generator	Base	Slope	Season	Noise
LI	775.5	1	100	50
HI	551.0	2	200	100
LD	1224.5	−1	100	50
HD	1449.0	−2	200	100

average forecasting method to derive their demand forecasts. Based on the demand forecasts, the retailers decided when and how many units to order using a chosen inventory policy. The only parameter required for the moving average forecasting model was the number of past periods used to average the demand, and this was determined by minimizing the mean absolute deviation (MAD) of the forecasting errors over the first 50 days of the simulation.

Since the re-planning interval was one day, a retailer only needed to calculate the net requirements for the remaining $(4 * T - EOC)$ “free” days. EOC refers to the level of early order commitment (number of days

ahead of the actual demand) and one day was added to compensate for the transportation lead time. If an order for the first free day was needed, this order was placed (and committed) to the supplier. Orders for the rest of the free days were not placed, but were updated in the next planning cycle. The retailers filled the customer's order (and backorders) by on-hand inventory, and any shortages became backorders.

3.4. Phase III: supplier's production and delivery decision

In our simulation experiment, the supplier applied a single-item, capacitated lot-sizing rule, as described by Chung and Lin (1988), for planning its production activities. At the time of this study, there was no information sharing at the local manufacturer previously mentioned and it made production decisions based only on the actual orders placed by the retailers (i.e., make-to-order). To see how much benefits can be achieved through information sharing, we simulated two cases of information sharing: (1) assuming that the retailers shared their forecasted net requirements with the supplier, both the actual orders and the forecasted net requirements were included as the gross requirements by the supplier for production decisions; and (2) assuming that the retailers shared their planned orders with the supplier, both the actual orders and the planned orders shared by the retailers were included as the gross requirements by the supplier for production decisions.

The supplier only implemented the current day's production plan. The result of the plan was subject to change, based on additional information that could become available in the future. At the end of each day, and after the current day's production was completed, the supplier made shipping decisions from its on-hand inventory. The supplier would fill each retailer's order (and any backorder) if the on-hand inventory was sufficient to do so. If the on-hand inventory was insufficient, each retailer would be allocated by a quota proportional to its order (and any backorder), and any shortages would become backorders to be filled later.

When a retailer placed an order, it was responsible for the transportation cost of that shipment, regardless of whether a portion of the shipment was to satisfy the backorder of previous orders. If the retailer did not place an order, and the shipment to the retailer was to satisfy the backorders of previous orders only, then the supplier would pay for the transportation cost of the current shipment.

This process was repeated until all ordering, production, and delivery decisions had been developed for all 410 days. After the entire simulation run had been completed, all cost items were calculated for the retailers and the supplier. The total cost (including inventory, order processing and setup, and transportation) and customer service level were then calculated (based on the data from day 51 to day 400) to measure the performance of the supply chain.

4. Simulation model parameters

A major advantage of using computer simulation models is to allow many parameters to vary in different simulation settings. In our case, we were able to determine the interaction between the inventory policy and two additional variables (information sharing and early order commitment). There were two major groups of parameters in this simulation experiment. The first group was the "environmental factors" or "operating conditions" of the systems, which included demand pattern (DP), capacity tightness (CT), and cost structure (CS). The second group comprised the decision parameters, which included the inventory policy (IP), information sharing (IS), and early order commitment (EOC). The number of levels and values of the experimental parameters are shown in Table 2 and are discussed below.

Table 2
Factors used in the simulation model

Factor name	Label	Levels	Values
Demand pattern	DP	5	ILI, IHI, ILD, IHD, MIX
Capacity tightness	CT	3	Low, medium, high
Cost structure	CS	3	$T = 2, 4, 8$
Inventory policy	IP	4	EOQ, EPQ, SM, PPB
Information sharing	IS	3	NIS, DIS, OIS
Early order commitment	EOC	5	0, 2, 4, 6, 8

4.1. Environmental factors

As the simulation results were largely dependent on the model specifications and parameters used, we had to ensure that a reasonable range of parameters were introduced as environmental factors in the simulation model. By varying and randomizing the environmental factors, the results could be better generalized to other, similar operating conditions. One of the three environmental factors was demand pattern. Five demand patterns (ILI, IHI, ILD, IHD, MIX), representing the different combinations of demand generators, were used in this study and were described earlier.

The second environmental factor was capacity tightness (CT), which is the ratio of production capacity to demand. This is the inverse of the capacity utilization rate. In addition to the current capacity utilization of 85%, two other levels of capacity utilization (75% and 95%) were also considered in our simulation model. Consequently, three levels of capacity tightness were used: low (1.33), medium (1.18), and high (1.05), and they corresponded to a capacity utilization of 75%, 85%, and 95%, respectively.

The last environmental factor, cost structure (CS), refers to the relative magnitude of the fixed ordering cost to the unit inventory carrying cost. This is represented by the natural ordering cycle of the supplier and retailers. The natural ordering cycle represents the number of periods of demand covered by one economic ordering quantity and it is currently 4 days at the retailers. We created two more cost structure values, so that its robustness could be observed in our simulation model. Therefore, a total of three cost structure values ($T = 2, 4$, and 8) were used in this study.

4.2. Decision variables

Inventory policy (IP) was the focus of the investigation in this study. IP refers to the rule used by the retailers to make decisions on when and how much to order from the supplier. Four well-known inventory policies were investigated here: economic order quantity (EOQ), periodic order quantity (POQ), Silver–Meal (SM), and part-period balancing (PPB).

Another decision variable of interest to managers was information sharing (IS), which refers to the degree to which the retailers share demand forecasts and order information with the supplier. Three cases were examined here. In the case of no information sharing (NIS), as has been the case, retailers do not share any information with the supplier concerning their demand and inventory decisions. The supplier receives orders from the retailers and simply makes production-planning decisions according to these orders.

One possibility for improving the supply chain performance is to require the retailers to share their forecasted net demand with the supplier (i.e., demand information sharing; DIS) as soon as they have such information available. Not only do the retailers make their own demand forecasts and inventory replenishment decisions, but they also inform the supplier of their future net requirements. Therefore, the supplier will know the forecasted net requirement for each retailer, although it will not know each retailer's inventory policy. The supplier can use the actual order and demand forecast information from the retailers to make its production-planning decisions, as described earlier in Section 3.4. In the case of order information sharing (OIS), all retailers will make demand forecasts for future periods, develop future order plans in the planning horizon, and share their order plans with the supplier. As a result, the supplier can plan production activities more accurately, based on the future order plans of the retailers.

Another decision variable of interest to managers was the practice of early order commitment (EOC). EOC refers to whether the retailers are willing to place orders to the supplier in advance, and by how many days in advance. Five cases ($\text{EOC} = 0, 2, 4, 6, 8$ days) have been examined in this study. When the EOC is zero, as has been the case here, there is no EOC from the retailers, and they only need to place orders one day (i.e., to compensate for the transportation lead time) in advance. When the EOC is not zero, the retailers will make an order commitment in advance to the supplier. Conventional wisdom suggests that a larger EOC value should allow the supplier to make more efficient use of its production capacity, but it may also increase the forecasting errors, as the retailers must make a longer range forecast of demand.

4.3. Performance measures

Five criteria were used to measure the supply chain performance: three were cost related and two were service level related. The total cost for the supplier (TCS) comprises the sum of the setup cost, transportation cost (for backorder deliveries, if any), and inventory carrying cost. The total cost for the retailers (TCR) comprises the sum of the ordering cost (including transportation cost), inventory carrying cost, and shortage cost for the four retailers. The total cost for the entire supply chain (TC) is simply the sum of the TCS and TCR. The service level of the supplier (SLS) refers to the percentage of the retailers' orders satisfied through the available inventory of the supplier. It serves as an internal service performance measure within the supply chain. Finally, the service level of the retailers (SLR) is the percentage of customer demand satisfied through the available inventory of the retailers. It is averaged for all 350 simulation days and for the four retailers. The SLR can be considered as the actual service performance of the entire supply chain.

5. Analysis and results

For each combination of the independent variables (DP, CT, CS, IP, IS, EOC), five simulation runs were conducted to reduce the effects of the random variates, thus a total of $5 \times 3 \times 3 \times 4 \times 3 \times 5 = 13,500$ simulation runs were conducted. Table 2 provides a summary of the factors used in the simulation model. The simulation results were analyzed using the SAS analysis of variance (ANOVA) procedure. To meet the ANOVA assumptions of normality, independence, and equal variance of the errors, certain variable transformations were suggested and carried out by the SAS statistical software package, based on the results from residual analysis. Specifically, a reciprocal square-root transformation (i.e., $1/TC^{-1/2}$) for TC, a log transformation (i.e., $\log(TCS)$ and $\log(TCR)$) for TCS and TCR, and a square transformation (i.e., SLS^2 and SLR^2) for SLS and SLR were required and performed.

5.1. Performance of retailers' inventory policies

The ANOVA results suggest that different inventory policies have significant effects (all p -values < 0.0001) on all five performance variables. For easy comparison, the total cost performance measures in Table 3 are

Table 3
Effect of cost structure and inventory policy on performance

T	IP	RTC	RTCS	RTCR	SLS (%)	SLR (%)
2	EOQ	100	115	100	89.7	97.0
	POQ	106	100	108	94.4	96.2
	SM	106	100	108	94.4	96.2
	PPB	105	104	106	93.2	96.6
4	EOQ	100	100	100	87.7	97.4
	POQ	103	100	105	89.2	97.3
	SM	103	100	105	89.0	97.3
	PPB	102	100	103	88.6	97.4
8	EOQ	100	101	100	78.7	98.2
	POQ	101	100	102	80.8	98.1
	SM	101	100	102	80.9	98.1
	PPB	100	100	101	80.0	98.1
Overall	EOQ	100	105	100	85.3	97.5
	POQ	104	100	107	88.1	97.2
	SM	105	100	107	88.1	97.2
	PPB	104	101	105	87.3	97.4

Note: RTC, RTCS, and RTCR are the relative total costs of the entire supply chain, the supplier, and retailers, respectively, with a base value of 100 representing the lowest total cost of any given T . SLS and SLR represent the service levels for the supplier and retailers, respectively.

shown in relative terms, with the minimum set to 100 (i.e., the base index) for each cost structure represented by T . The service level performance values for both the supplier and retailers are given in absolute terms.

A close examination of the overall performance (at the bottom of Table 3) of the retailer's inventory policy for all three cost structures shows that EOQ results in the lowest relative total costs for the retailers (RTCR) and the entire supply chain (RTC). The total cost of using other lot-sizing rules is between 4% and 7% higher than the benchmark set by the EOQ. Overall service levels vary little for the retailers, irrespective of which inventory policy is used. However, the overall service level for the retailers (at least 97.2%) is significantly higher than that of the supplier (which is, at most, 88.1%) when these four inventory rules are used. This observation is consistent with the well-known bullwhip effect, in which the service level will deteriorate as a result of an increase in demand variability for the upstream members of the supply chain. Considering all five performance criteria, EOQ is the most robust inventory policy, for the retailers and the entire supply chain, and only results in a higher total cost (about 5%) for the supplier.

The simulation results show that the POQ and SM inventory policies yield the lowest cost for the supplier but higher for the retailer and the entire supply chain. Our findings confirm that the current practices of using EOQ among the retailers yielded the best performance for all ordering cycle length. The supplier would prefer the retailers to use other lot-sizing heuristics instead of EOQ so that it can achieve the lowest total cost for itself. Our result is slightly different from the result from previous studies on lot-sizing rules in MRP systems because we consider the cost effect of both the supplier's and retailer's decisions. For example, Zhao et al. (1995) find that SM outperforms both the EOQ and POQ rules in both total cost and schedule instability measures for MRP systems under conditions of demand uncertainty. Zhao and Lam (1997) report a similar result in multilevel MRP systems under conditions of deterministic demand.

The tradeoff for using any particular inventory policy must consider the fact that any ordering decisions by the retailers may significantly influence the supplier's production decision and capacity utilization. Therefore, any lot-sizing rule that appears to produce the best result without considering the interaction between the supplier and the retailers may not in fact result in the best overall performance for the entire supply chain. Our study indicated that the lot-sizing rule that performed the best for a supplier or manufacturer using a MRP system as in Zhao et al. (1995) may not always work well in the supply chain setting where there are interactions between the supplier and retailers.

Table 3 also shows that the performance of the four different inventory policies is also influenced by the cost structure, as represented by the natural ordering cycle T . As T increases, there seems to be less cost differences between the inventory policies examined here. A bad choice of IP may often lead to a decrease on the retailers' service level and an increase of the total cost. Our analysis suggests that the results of IP depend on the cost structure and are influenced by the interaction between the supplier and retailers.

5.2. Inventory policy (IP) versus information sharing (IS)

The ANOVA results suggest that at the 0.05 level of significance, the interaction between IP and IS will have a significant effect on each of the performance measures. Fig. 2 shows the cost and service level performance measures of the four IPs when three different IS schemes are considered. The cost performance measures are shown in relative term with a base of 100, representing the lowest cost value achieved under different IS schemes.

In terms of relative total cost for the entire supply chain (RTC), the findings reveal that sharing planned order information (OIS) is better than sharing only demand information (DIS), which, in turn, is better than no information sharing (NIS), for all inventory policies used by the retailers. However, the magnitudes of performance improvement of OIS over DIS, and DIS over NIS are quite different between the retailers and the supplier. Consider the case for the relative supplier's total cost (RTCS), there is only marginal benefit if DIS is adopted in comparison to NIS. However, the benefits become very obvious if OIS is used. For the retailers, both DIS and OIS will bring in cost savings opportunity as a result of a lower probability of stocking out when the supplier obtains more future demand information.

When the retailers use EOQ and share the planned order information with the supplier, the retailers and the entire supply chain will achieve the minimum cost. From the supplier's point of view, it will prefer the retailers to use POQ or SM, which results in the lowest total supplier's cost of all. Note that the performance of POQ

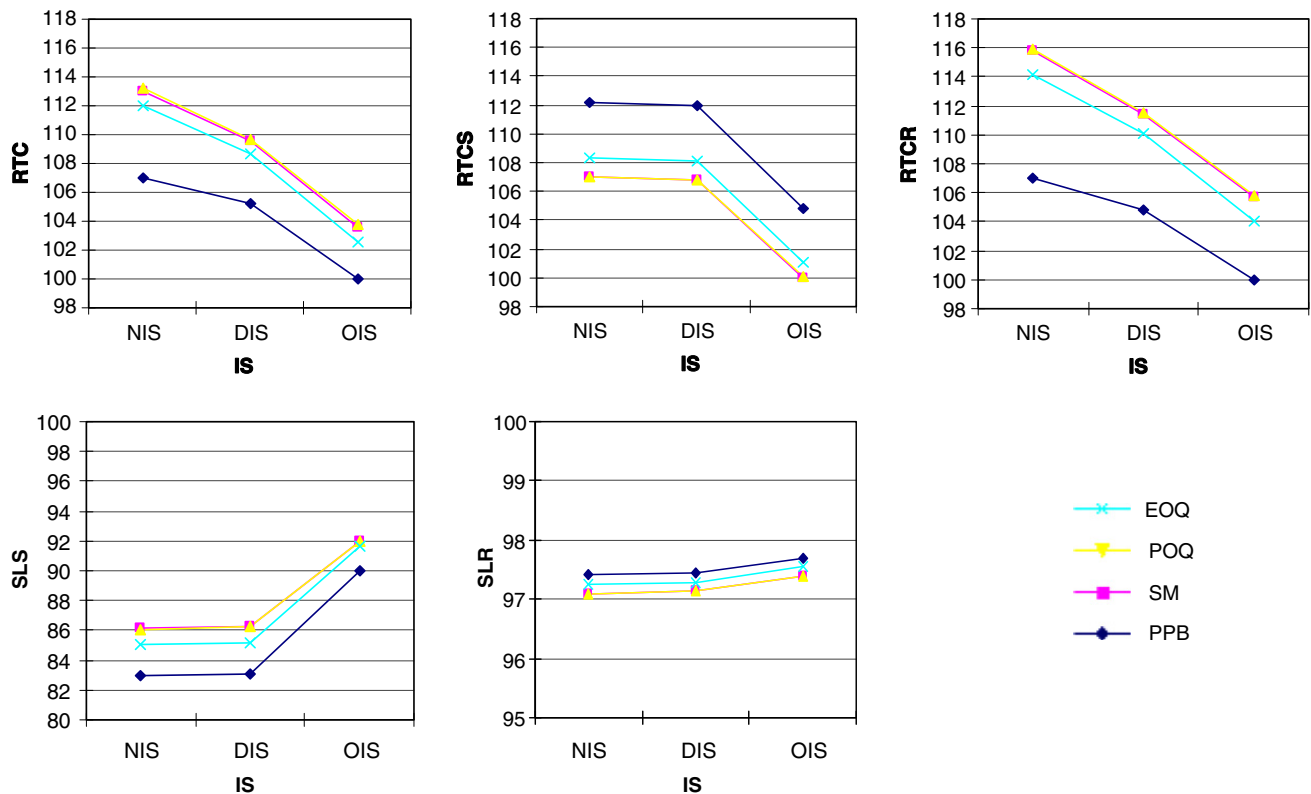


Fig. 2. The value of information sharing (IS) for different inventory policies.

and SM are very close to each other in all cost and service level performance measures. When the retailers outnumber the supplier, the total cost of the supply chain is usually dominated by the retailers' cost. We conclude that the choices of IP and IS are both important in determining the cost performance of different members in a supply chain, and that they should be considered simultaneously to achieve the optimal results.

Regarding the service level performance, the choice of the retailer's IP was found to have a more significant impact on the supplier (ranging from 83% to 92%) than on the retailers (ranging from 97% to 98%). In addition, for each IP being examined here, only a very slight improvement in service level is observed between NIS and DIS but a significant improvement between DIS and OIS. The findings indicate that the value of sharing only forecasted net requirement (DIS) is not much different from sharing no information at all. Only when the retailers are willing to share information on their future order plans (OIS), will the supplier's service level improve significantly. When OIS is implemented, the choice of the retailer's IP does not seem to significantly affect the service level, as the difference in service level performance is usually less than two percentage points between all IPs considered here.

5.3. Inventory policy (IP) versus early order commitment (EOC)

From the ANOVA results, we observed once again, at the 0.05 level of significance, that the interactions between EOC and IP have a significant effect on all five performance variables for these IPs. The performance of EOC under different IPs is presented in Fig. 3.

An examination of Fig. 3 reveals that a larger EOC value will generally reduce the total cost for both the supplier and the retailers, regardless of which IP is being used by the retailers. EOC by the retailers also produces a more significant cost improvement for the supplier than for the retailers, as indicated by the cost curves. However, as the EOC days increase, the marginal benefit becomes less for the supply chain. Note also that the choice of the retailer's IP is not as important as EOC for improving the entire supply chain performance (RTC) as each IP's performance follows similar trends as the value of EOC increases. However, to achieve best cost performance, the retailers still need to consider a combination of both factors. For the retail-

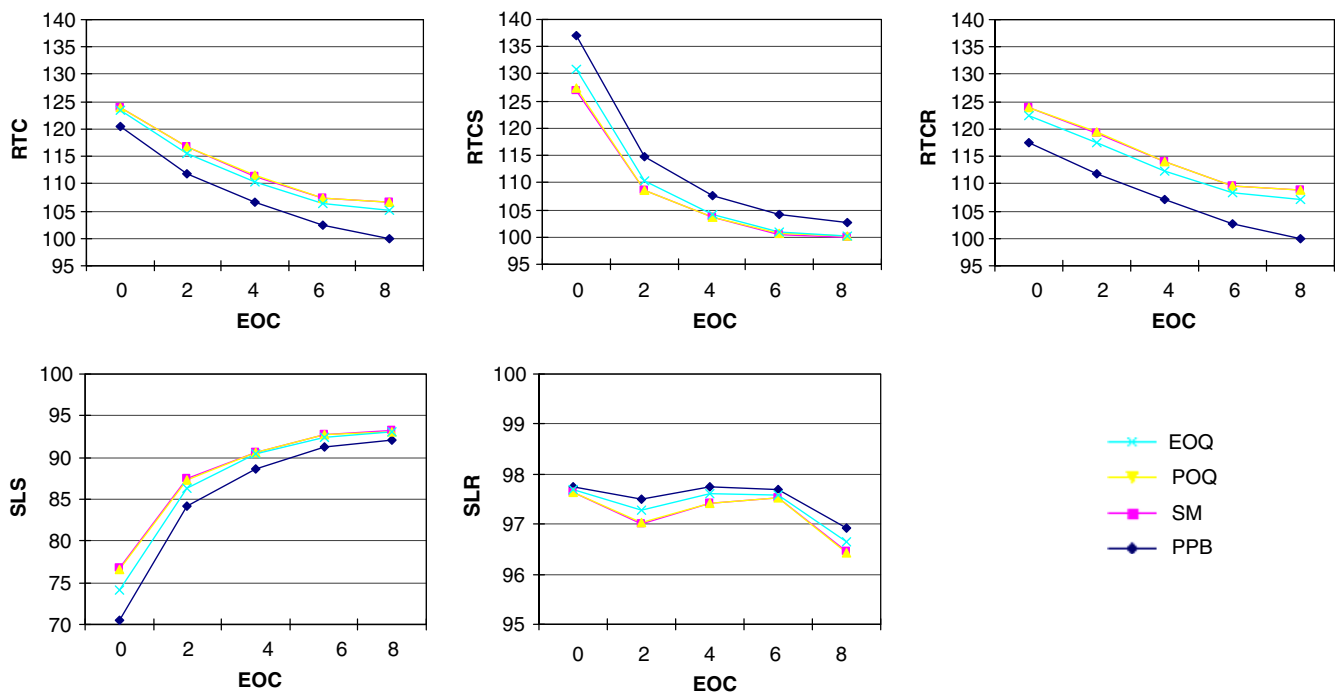


Fig. 3. The value of early order commitment (EOC) for different inventory policies.

ers and the supply chain, using EOQ will result in the lowest total cost for any given EOC value. For the supplier, POQ and SM are better IP choices as they produce a lower cost.

While the supplier's service level will significantly improve (by about 20% points) when EOC = 8 days is used instead of no early order commitment, it deteriorates slightly for the retailers (within one percentage point). This counter effect is no mystery. When the retailers commit orders in advance, the supplier will be able to better utilize the capacity to meet the retailer's demand. This explains why the supplier's service level always improves as EOC becomes larger. However, the improvement in service level will begin to level off when EOC reaches a larger value (say, 6). Regarding the retailers' service level, two factors are interacting with each other. On the one hand, placing an order earlier in advance requires the retailers to forecast further into the future, and the forecasting errors become larger as a result. This will lead to a lower service level for the retailers. On the other hand, if the retailers place early orders, the supplier will be able to improve its capacity utilization. This positive, spillover effect of the supplier's better capacity utilization and subsequent on-time delivery should be beneficial to the retailers as well. The net result for the retailer's service level depends on which one of these two factors prevails.

6. Managerial implications

Our simple two-stage supply chain simulation has demonstrated the complex interaction between the supplier and retailers as they strive to coordinate their orders. Using three well-known inventory policies (IPs) under a mix of environmental and decision variables, our findings indicate that the economic order quantity (EOQ) rule generally works the best for the retailers and the supply chain in our simulated scenarios. POQ and SM inventory policies yield almost identical results for all cost and service level performance measures in our simulation. Our analyses also put the value of sharing demand forecast in question. Sharing demand forecast has less effect on the total cost improvement than was once thought, and its effect on service level improvement is negligible. Retailers need to consider sharing their future order plans in order to significantly improve the entire supply chain performance. Our study also shows that early order commitment (EOC) by the retailers to the supplier can significantly improve supply chain performance but the benefits to the supplier are much higher than those to the retailers. Furthermore, the value of EOC will level off as it extends too far ahead of the planning horizon.

Our analyses also demonstrate a need for resolving the conflicting goals of the supplier and the retailers. For example, while the Silver–Meal inventory policy may result in the lowest total cost for the supplier, it yields the highest cost for the retailers and the entire supply chain. As the retailers are the ones to implement such inventory policy, it is inconceivable that they will go along with this decision unless the supplier can provide incentives or other benefits to them.

7. Conclusions

Most retailers make their own inventory replenishment decisions based on their demand forecasts and their cost structures (i.e., inventory carrying cost and ordering costs). To improve the performance of the supply chain under conditions of demand uncertainty, all supply chain members are now encouraged to share information and coordinate orders with each other. While many models have been developed to determine the timing and quantity of orders, most of them do not consider the complex interactions between the retailers and the supplier. This study took the initiative to examine the impact of the retailer's inventory policies (IPs) on the performance of a supply chain. As an exploratory study of its kind, we strived to gain more insight into how the IPs of the retailers influence the performance of the supply chain and how the different IPs influence the value of information sharing (IS) and early order commitment (EOC).

Our analyses showed that a combination of IP, IS, and EOC can significantly influence the performance of the supply chain. Out of the four IPs examined, the EOQ policy provided the lowest cost for the supply chain. Sharing information on the future orders plan was shown to be the most effective way for cost and service level improvement. Any EOC is better than none at all, but its benefit will level off after it has reached a certain value.

Although the findings from this simulation study shed some insights into the selection of IP, IS, and EOC between the supplier and the retailers, the limitations of the study must be noted. First, the supply chain paradigm used in this study represented a very simplified case, with one capacitated supplier and four identical retailers with one identical product. Second, we have only used a narrow range of parameters in the simulation experiment, so the results are only valid within these ranges of parameters used. Third, there are certainly plenty of alternative methods of sharing information and ordering coordination in practice, in addition to those we have proposed in this study. In order to better understand the complex relationships between IP, IS, and EOC, and their effects on supply chain performance, the above mentioned issues must be taken into consideration in future research.

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