Supply Chain Inventory Control: A Comparison Among JIT, MRP, and MRP With Information Sharing Using Simulation

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Abstract: Logistics or supply chains play a central role in effective management. Inventory control systems play a significant role in managing supply chains. This article provides engineering managers with guidelines to choose a cost-effective supply chain inventory control system through analyzing push inventory systems (MRP), and pull systems (JIT). Simulation modeling was used to build and analyze the supply chains with stationary and cyclical demand patterns. The article indicates the main variables that should concern the engineering manager to choose between MRP and JIT. The paper concludes that because JIT reduces the holding cost, it becomes a more cost-effective system at a wider range as the demand level increases. The results also show that when information is shared across a supply chain that implements a MRP system, the cost reduction is significant in comparison with no information sharing especially under cyclical and highly variable demand patterns.

Keywords: Supply Chain Management, Inventory Control, Just-In-Time, MRP, Simulation

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In today’s complex marketplace, the competition is between supply chains rather than individual companies. A primary consideration of supply chain management (SCM) is the flow of goods from the source of raw materials to the ultimate end consumer. Inventory management is one of the cornerstones of SCM and inventory is a key cost-contributor in any supply chain (SC). According to the Institute of Management and Administration (IOMA), the cost of logistics in the U.S. for 1993 amounted to $936 billion. The cost of carrying inventory (including interest, taxes, obsolescence, depreciation, insurance, and warehousing) amounted to $300 billion (Institute of Management and Administration, 2004). Effective management of inventories is thus a crucial function of management and, in particular, plays a pivotal role in basic engineering management topics such as quality management and lean manufacturing.

Among the major methodological approaches to inventory management with which engineering managers are familiar are material requirements planning (MRP) and just-in-time (JIT) manufacturing. Choosing the “best” inventory management system depends on numerous parameters, among the most important of which are supply chain-related parameters, such as the demand pattern, the demand level, and the inventory costs. In this article, we present a methodology of how to carry out a comparison between these two inventory management systems in order to select the better one.

Research has also revealed that collaboration and information sharing in the SC is of vital contribution to cost-reduction and improved planning in the SC. Information technology and web-based applications have created the infrastructure for sharing information about demand levels and patterns, inventory positions, and other events that could have significant impact on members upstream and downstream in the SC. Collaborative SCM efforts started to take a real turn in 1996 when Warner-Lambert, a consumer goods manufacturer, and Wal-Mart, the department store, began a pilot study of collaborative planning, forecasting, and a replenishment software system. This software also facilitates exchange of statistical information and promotional plans, which are utilized by other SC members (Simchi-Levi, Kaminsky, and Simchi-Levi, 2000). In this article, we study the effects of information sharing on the SC cost when MRP is used. Note that in the case of JIT, information has to be shared by default.

Overview of Inventory Management Techniques

The ultimate goal of managing an SC is to satisfy the demand level at minimum cost; therefore, inventory management approaches such as MRP and JIT play a key role in achieving this goal. Some research (e.g., Nahmias, 1997) found that MRP is more appropriate for companies where there are many product options, frequent engineering changes and fluctuating product system, whereas JIT is more appropriate in environments where there are relatively few product options, engineering changes, product mix changes, and there is less variability in demand levels. Some studies attempted to integrate those two methodologies and/or compare them with different alternatives. Matsuura, Kuros, and Lehtimäki (1995) compared MRP, JIT, and optimized production technology (OPT) in Finland and Japan with respect to practices applied. They found that both countries had different interpretations of these approaches and they pointed out the differences and similarities. Benton and Shin (1998) pointed out that MRP was more beneficial in simulation-based studies such as those conducted by Krajewski, King, Ritzman, and Wong (1987) and Steele, Berry, and Chapman (1995), which were based on critical factors such as setup time, lot size, labor requirements, inventory, and past due demands. Benton and Shin (1998) also
briefly discussed the integration of MRP and JIT. They suggested that this hybridization is a result of the natural evolution of the production planning system derived from the JIT implementation in the U.S. (or, conversely, implementing MRP in Japan) to exploit the advantages of both systems and achieve better performance.

They summarized three factors that have contributed to the evolution of the hybrid manufacturing environment: (1) accumulated operating problems in implementing JIT manufacturing techniques, (2) researchers’ and companies’ understanding of compatibility between the MRP and JIT systems, and (3) MRP flexibility in the long-term capacity planning and JIT agility in daily production control. With respect to MRP/JIT integration, they concluded that this phenomenon could be considered a natural progress in academia to develop the ideal hybrid-manufacturing environment.

Our article also deals with the effect of information sharing on the SC cost. In the late 1980s, research started shifting more toward understanding the value of information sharing (e.g., Yoo, 1989). Not until the late 1990s, did we start to see significant research conducted in the area as a result of the capabilities that the Internet introduced. Information sharing researchers’ studies have tackled the benefits of information sharing (e.g., Gavirneni, Kapuscinski, and Tayur, 1999; Lee, So, and Tang, 2000), the alliances and competition in the SC (Weng, 1999), and the impact of SC integration on operating performance (Armistead and Mapes, 1993). In their research, Lee et al. indicated that Troyer (1996) showed that information sharing can save up to $14 billion in the grocery industry, whereas Chen et al. (1997) found that the SC costs are reduced by up to 9% through sharing of information, while Lee et al. indicated a 23% cost reduction for a two-level SC.

In their SC framework for critical literature review, Croom, Pietro, and Mihalis (2000) identified that information sharing is necessary between buyers and suppliers, or distributors and retailers, as it helps minimize inventories and respond to fluctuation in demand in a timely manner. Yu, Yan, and Chen (2001) studied information sharing with SC partnership. Based on a two-stage decentralized SC comprising a retailer and a manufacturer, they studied optimal inventory control policies. They showed that the average inventory level and the expected inventory cost could be reduced when information sharing is increased. Min and Zhou (2002) presented a framework that categorizes SC work into several models. One of these categories is IT-driven models, which they consider a category of high demand since IT and information sharing is a key to SC success. They emphasized, however, that this type of model is still in its infancy and not much work has been done on it.

Objective of the Study

This article argues that the selection of an appropriate inventory management methodology is an important task confronting an engineering manager. More specifically, this study aims to analyze SC costs under different inventory control systems. The total chain costs are studied when using JIT and MRP production systems, as well as the proposed MRP with information sharing system. The main SC cost drivers are the facilities, inventory, transportation, and information (Chopra and Meindl, 2004). It has been assumed in this research that the number of facilities is constant while the transportation and information costs are bundled into the ordering cost. The inventory cost driver includes the ordering and holding costs. These assumptions are reasonable given that the focus of this article is on the effect of the inventory policies on the SC costs. Numerous simulation scenarios were designed to study the impact of the inventory ordering and holding costs as well as the demand level and pattern to answer the following questions:

• Which production system provides lower total chain cost under specific SC parameters; i.e., can we come up with a “universal formula” for determining the optimal performance as a function of demand level, ordering cost, and holding cost for a given demand pattern?

• How does information sharing affect the SC costs, and what is the effect of the demand pattern on that influence?

In order to answer these questions, simulation was used for building the three models (JIT, MRP, and MRP with information sharing). Different SC parameters were then changed by increasing their values over a wide range and observing the affect on the SC ordering and holding costs. This enabled us to study the relationship between the SC parameters and the SC costs using regression analysis.

The Systems Models

Three models representing the three supply chains were built to realistically mimic a three-echelon SC. SIMAN discrete-event simulation language and ARENA modeling environment were used to build the models previously described. All the simulation and statistical conventions and requirements were followed thoroughly in order to build the 95% confidence intervals (CI) of the different statistics of interest, such as the required number of replications, warm-up period required to reach steady state, and half-width to average ratio of the CI.

The MRP-Push System

Stationary Demand Pattern Model. In this model, orders arrive on a daily basis with a stochastic number of required units given from a normal distribution with the specified average demand and standard deviation. The retailer utilizes an (r,q) model where the reorder point (ROP) and the economic order quantity (EOQ) are determined using Equations 1 and 2, ensuring a 95% service level (i.e., the probability of no stock-outs during lead time is 95%):

$$ ROP = \mu_d \times Lt + Z_{(1-\alpha)} \times \sigma \times \sqrt{Lt} \quad (1) $$

Where: $\mu_d$ is the daily demand; $Lt$ is the lead time; $Z_{(1-\alpha)}$ is the factor (from the normal distribution) required to attain (1-\alpha) service level; $\sigma$ is the standard deviation of the demand distribution.

$$ EOQ = \sqrt{\frac{2 \times S \times \mu}{h}} \quad (2) $$

Where: $S$ is the ordering cost; $\mu$ is the average annual demand; and $h$ is the annual holding cost per unit.

The orders come to the manufacturer in quantities of EOQ, with probabilistic inter-arrival times. The manufacturer updates the forecast on a monthly basis, utilizing the moving average forecasting technique, and the forecasts are used for updating the ROP and EOQ values.

The forecast is transformed into a weekly master production schedule (MPS) through taking the proportion of the monthly forecast. The weekly MPS quantity is issued from the “raw materials store” to the “production floor,” in order to be processed. Whenever the raw materials inventory position (which is equal
to on-hand inventory plus on-order inventory), goes below the ROP, the EOQ is ordered from the supplier. The system does not include backlogging; hence the missed quantities are considered lost opportunities. Based on the model’s design, the lost sales are not to exceed 5% of the total orders. The ordered materials arrive to the ordering member in the SC after the respective upstream lead-time, which has a deterministic value.

**Cyclical Demand Pattern Model.** The cyclical pattern is employed in order to study the affect of the demand pattern on the general system behavior, and to mimic a seasonal demand pattern. This model is the same as the stationary demand model with the difference in the generation of orders and preparation of MPS. The cyclical demand is generated from a sinusoidal function with random noise given from the normal distribution, as depicted by Equation 3.

\[
\text{Demand} = \text{Mean} + H \times \sin(\text{Time} \times \pi / HC) + N(0, \sigma^2)
\]  

(3)

Where: \( \text{Mean} \) is the average demand rate; \( H \) is the height of the cycle; \( HC \) is the half cycle time; \( N(0, \sigma^2) \) is the stochastic “noise” generated from a normal distribution with zero mean and \( \sigma^2 \) variance.

The second difference in the stationary demand model is that the weekly MPS can not be calculated using the proportion directly as in the stationary demand pattern model, but is rather calculated through dividing the area under the average demand rate for the coming week, over the area under the curve for the current month. The areas are given through integration of the demand function, which could be given through Equation 4.

\[
\text{Period’s Area} = \text{Mean} \times \text{Time} + H \times HC / \pi \times \\
\{(\cos(T_{NOW} \times \pi / HC) - \cos((T_{NOW} + \text{Time}) \times \pi / HC))\}
\]  

(4)

Where: \( T_{NOW} \) is an internal simulation variable that represents the simulation current clock time.

**Exhibit 1.** Description of the JIT Simulation Model

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**The JIT- Pull System**

The structure of the JIT model is illustrated in Exhibit 1.

**Stationary Demand Pattern Model.** In this model, orders arrive with a stochastic number of required units the same way explained for the MRP stationary model. The retailer maintains a finished goods stock sufficient for the demand during lead-time, plus a safety stock required to ensure a 95% service level. This is the number of Kanban cards, and is calculated using Equation 1. Each of the Kanban cards is “attached” to a unit product.

The retailer uses JIT supplier-Kanban-cards, where, as demand arrives, an immediate order, of the same amount, is propagated upstream to the manufacturer. The manufacturer also maintains a finished goods inventory sufficient to satisfy 95% service level, and each Kanban card is attached to a product unit. The units pulled from the finished goods store trigger the pulling of units from the machines through use of Kanban cards. The demand is transferred upstream, again using Kanban cards, from the machines to the raw materials store, and from raw materials store to the supplier.

All of the numbers of Kanban cards are automatically calculated and updated during the simulation runs based on the demand and the upstream cycle time/lead time.

**Cyclical Demand Pattern Model.** This model is the same as the stationary model with the exceptions that the demand is generated from a stochastic sinusoidal function, and the number of cards is calculated based on the maximum forecasted demand level during the coming week.

**The MRP With Information Sharing Model**

Four types of information are typically shared in a SC: order, demand, inventory, and shipping information. In this article, a hybrid information-sharing model is applied, where the manufacturer has access to end-customer demand level and
pattern, retailer's inventory position, and shipment information. The suppliers have access to the manufacturer's demand and inventory levels, and hence they can predict when and how much the manufacturers (i.e., the downstream members in the supply chain) will order. As a result, they can plan based on "exact information" as a forecast.

Stationary Demand Pattern Model. This model is similar to the MRP Model, with the exception that the manufacturer has access to the end-customer demand level and pattern, as well as the retailer's Inventory Position. The manufacturer utilizes the end customer demand to determine the Retailer's Forecast, EOQ and ROP (alternatively, this information is directly and collaboratively provided by the retailer).

Knowing the ROP, EOQ, and the retailer's inventory position, the manufacturer forecast can be calculated using Equations 5 and 6.

\[
\text{Number of Monthly Orders} = \left\lceil \frac{\text{Retailer Forecast} - (\text{Retailer Inventory Position} - \text{ROP})}{\text{EOQ}} \right\rceil
\]  

(5)

where \(\lceil \rceil\) is the integer ceiling.

\[
\text{Manufacturer Forecast} = \text{Number Orders} \times \text{EOQ}
\]  

(6)

The manufacturer forecast is updated on a monthly basis, and is utilized for updating the manufacturer's ROP and EOQ. The system works like that of the MRP model.

Cyclical Demand Pattern Model. This model is the same as the MRP cyclical model with the exception that manufacturer's forecast is updated using Equations 3 and 4.

Results
During the initial stages of the simulation runs, an important finding was depicted, namely that the decision of which production system is more cost effective was similar for any ratio of the ordering/holding cost, regardless of the values of ordering and holding costs. Exhibits 2 and 3 highlight the fact that the breakeven point occurs at the same ratio (of 500 in this example), regardless of the ordering, holding, and total chain cost; hence, the ratio is the main driver that needs to be studied rather than the individual ordering and holding costs.

Exhibit 2. Effect of Increasing Ratio Through Increasing Ordering Cost

Simulation scenarios were run with annual demand levels ranging from 910 to 10,910 units at 500 unit increments. The corresponding breakeven points are depicted in Exhibit 5. The relationship between the ratio and the demand level could be fitted to a model using linear regression as shown in Exhibit 5. This regression line gives the breakeven ratio for a range of demand levels, after which the JIT model becomes less cost-effective. Using the regression model, one can predict the breakeven ratio for a certain demand level without the need to run the simulation.

The reason that the breakeven points' values increase with increasing the demand level is that in the JIT model the demand is continuously propagated upstream, so the ordering cost (say,
per year) is somewhat stationary at a fixed ordering cost; hence, the holding cost becomes the overriding factor, and because JIT reduces the overall holding cost, it would become more cost-effective at a wider range of ratios as the demand level increases, causing the breakeven points to increase.

**Analysis of the Value of Information Sharing at Stationary Demand Pattern.** At a stationary demand pattern, the value of information sharing was proved to be of minimal magnitude. An example of the simulation results is shown in Exhibit 6 at an annual demand level of 3,640 units. Although there seems to be a slight increase in SC cost for MRP with information sharing, there was not significant statistical evidence to conclude so. This exhibit is an example of one annual demand level. For some other demand levels, the MRP with information sharing showed slight decrease in SC cost which, again, was not statistically significant enough to make conclusions on the relationship.

**Results at Cyclical Demand Pattern**
At a cyclical demand pattern, information sharing was proved to be of significantly beneficial value. An example of the simulation results is shown in Exhibit 7 at a 1,820 average annual demand. In this specific example, the minimum cost reduction attained by information sharing was 22%.
The cost reductions attained from sharing information, over the MRP system with moving average forecasting technique, was quantified via the simulation experiments, and the results are summarized in Exhibit 8. The minimum cost reduction percentage was 17% and the relationship seemed to follow a concave pattern, but that might rather indicate that the value of information sharing might not increase indefinitely.

Conclusions
Managing supply chains is a crucial component of engineering management. Selection of the correct inventory control system has a strong impact on how a system is managed, and on the eventual outcomes. This article demonstrates that the appropriateness of an inventory management system is contingent on the situation in which it is being applied and gives an indication of some of the variables that need to be required in the selection process.

The study highlighted the fact that the decision to use either JIT-pull or MRP-push inventory control systems depends on several variables, among the most important of which are the inventory costs, demand pattern, and the average demand level. In future research, other factors such as company’s policies, risk attitude, and relationship with suppliers (e.g., whether or not they can or are willing to work in JIT mode) can be considered.

It was found that for a certain required service level, the ratio of the ordering cost to holding cost is a main driver that could be utilized as a decision variable, while the average demand level is the other main variable. Regression fitting was proposed as an approach for providing generic methodological guidelines for choosing the more cost-effective inventory control system. The generic behavior using this approach was reasonably in compliance with the research in the field, and the upward trend was explained through the fact that JIT has...
a somewhat stable ordering cost, making the holding cost the overriding factor. Because JIT reduces the holding cost, it would become more cost-effective at a wider range as the demand level increases.

The value of information sharing was analyzed, and the study showed that the value of information sharing is maximized at cyclical and highly variable demand patterns, while its effect is statistically significant at a stationary demand pattern. The cost reductions attained from sharing information, over the MRP system with moving average forecasting technique, was quantified via the simulation experiments, and the minimum reduction percentage was 17%.

References

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