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Impacts of forecast, inventory policy, and lead time on supply chain inventory—A numerical study

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ABSTRACT

This paper first proposes the use of metaheuristic, to combine with exponential smoothing methods, in forecasting future demands and in determining the optimal inventory policy values for each node in a supply chain network based on historical demand or order streams without the need of any prior knowledge about the demand distribution or distribution fitting. The effects of five demand forecasting methods, two inventory policies, and three lead times on the total inventory cost of a 3-echelon serial supply chain system are then investigated. The effect of sharing the demand information for planning the inventories is also compared with that of no sharing. For testing, 15 quarterly and 15 monthly time series were taken from the M3 Competition and are considered as the multi-item demand streams to be fulfilled in the supply chain. The results indicate that: (1) the damped Pegel forecasting method is the best in terms of prediction errors because it outperforms others in three of five measures, followed by the simple exponential smoothing that wins one of the remaining two and ties the damped Pegel in one; (2) the supply chain inventory cost increases with increasing lead time and echelon level of the supply chain when the (s, S) policy is used, but not the (r, Q) policy; (3) the (r, Q) inventory policy generally incurs lower supply chain inventory cost than the (s, S) policy; (4) sharing demand information reduces inventory cost and the reduction is higher for (s, S) than for (r, Q); (5) the best demand forecasting method for minimizing inventory cost varies with the inventory policy used and lead time; and (6) the correlation between forecasting errors and inventory costs is either negligible or minimal.

1. Introduction

Supply chain management covers a variety of topics such as forecasting, procurement, distribution, production, logistic, inventory, and customer service. Each topic can be tackled at a different level: strategic, tactic, and operational. Of interest in this paper are forecasting and inventory, including particularly their interaction. This issue is particular acute when the economic is going through unpredictable downturn, like the one triggered by the subprime mortgages that is still with us today at the time this manuscript is prepared.

Future is always uncertain and most people do not have the crystal ball to exactly predict it. Except in some unique situations, there is always uncertainty in demand. Demand forecasting is thus never 100% accurate. To prevent loss sales, inventory is often carried to handle a variety of different uncertainties, with under-estimated demand as one of them, in business. Unfortunately, there is a holding cost associated with it. On the other hand, one would like to be able to see an economic tsunami is coming and respond to it accordingly to avoid the disaster of piling up capital on the inventory.

Traditionally, the accuracy of demand forecasting is measured by prediction error. This practice is inappropriate because it does not address the impact of forecast error on running a business. A few studies have tried to change that. Gardner (1990) studied the impact of forecasting on inventory control in a large physical distribution system and showed that for each forecasting method there existed a unique tradeoff curve between aggregate inventory investment and customer service level. Badinelli (1990) analyzed the impact of market demand misspecification and concluded that demand misspecification led to higher inventory cost. Ho and Ireland (1998) assessed the impact of forecast errors on MRP nervousness whereas Xie et al. (2004) focused on the impact on schedule instability and system service level. Kahn (2003) reviewed the potential impacts of forecast errors on an enterprise. Using a GARCH(1,1) structure to consider non-i.i.d. demand, Zhang (2007) quantified the effect of a temporal heterogeneous variance on inventory performance on a system controlled via an order-up-to-level policy and showed that ignoring temporal heteroscedasticity, by using an AR(1) model

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instead, could increase expected average inventory costs by as much as 30% when demand autocorrelation is highly positive. Manary et al. (2009) reported the procedure and algorithms that Intel developed and implemented in 2008 to counter the effect of forecast imperfection. The process resulted in safety stock reductions of approximately 15%. Lately, Kerkkänen et al. (2009) discussed the issue of assessing the impact of sales forecast errors on capacity planning, production planning, and inventory planning through a case study. These studies, however, addressed impacts only within a single echelon of the supply chain.

A search of the Web of Science database using topic=("supply chain" and forecasting and inventory) produced 94 entries on December 15, 2009. Among them, publications most relevant to our study are selected and reviewed below.

Zhao et al. (2002) presented a study of the impact of forecasting model selection on the supply chain performance and on the value of information sharing in a supply chain with one capacitated supplier and multiple retailers. Five forecasting models, which include a naïve model, a simple moving average, a two-parameter double exponential smoothing, a no-trend Winter's method, and a three-parameter Winter's model, were studied. It was assumed that the supplier made its production decisions using a capacitated lot sizing rule and retailers used EOQ to make their inventory decisions. Simulation experiments were carried out and the results suggested that: (1) higher benefits were achieved through information sharing when forecasting accuracy is higher; (2) both the demand pattern and the forecasting model significantly affected the value of information sharing; and (3) increasing forecasting accuracy without sharing information might not improve supply chain performance.

Zhang (2004) studied the impact of forecasting methods on the bullwhip effect for a simple replenishment system in which a first-order autoregressive process describes the customer demand and an order-up-to inventory policy characterizes the replenish decisions. A simple rule was established to help manager select a forecasting method, i.e. the minimum mean square error (MMSE) forecast should be used when inventory cost is of primary concern. The study also suggested that: (1) a positive demand autocorrelation favors the moving average method while a negative autocorrelation favors the exponential smoothing method and (2) in general, the bullwhip effect does not necessarily imply a higher inventory cost.

Considering a simple supply chain consisted of one retailer and one distributor, Chandra and Grabis (2005) investigated the impact of the forecasting method selection on the bullwhip effect and inventory performance of the most downstream supply chain unit. Compared with the traditional order-up-to-level policy, the materials requirement planning (MRP) based approach was shown to reduce the magnitude of bullwhip effect while keeping the inventory performance relatively unchanged. The inventory performance was measured by the average inventory size at the beginning of period (after previous order is received and before the demand is realized) given a fixed service level. It was also found that autoregressive models outperformed simple moving average and exponential smoothing according to the inventory size criterion.

Considering a 4-echelon supply chain as in beer game and each node operating a different inventory policy, Liang and Huang (2006) implemented a supply chain as a multi-agent system, in which agents coordinate to control inventory and minimize the total cost of a supply chain by sharing information and forecast knowledge. The 4-echelon supply chain considered consists of a supplier, a manufacturer, a distributor, and a retainer operating a (R, S), (r, Q), (R, S), and (s, S) inventory policy, respectively. In their system, demand order at each node is determined by a real-coded genetic algorithm so that the total supply chain cost over the planned periods is minimized. The proposed approach was shown to outperform MBA students, moving average, and exponential smoothing.

Agrawal et al. (2009) analyzed a 2-echelon serial supply chain to study the impact of information sharing and lead time on bullwhip effect and on-hand inventory. The assumptions include: (1) customer demand at the retailer is a first order autoregressive process and (2) both echelons use a minimum mean square error model for forecasting lead time demand and follow an adaptive base-stock inventory policy to determine their respective order quantities. Using a numeric example, they showed that lead time reduction is more effective than information sharing in reducing the bullwhip effect phenomenon.

Ferbar et al. (2009) proposed the use of the wavelet denoising method for demand forecasting and showed that it outperformed exponential smoothing in terms of minimizing total supply chain cost defined as the sum of the inventory costs and penalty costs for all nodes.

Hosoda and Disney (2009) analyzed the impact of market demand misspecification on the costs in a serially linked two-level supply chain, involving a retailer and a manufacturer. A true ARMA(1,1) demand was misspecified as an AR(1). The total cost consists of the retailer's expected inventory cost at the end of each period, and the manufacturer's production cost and expected inventory cost at the end of each period. It was assumed that the market information is shared; the order policy is order-up-to-level; and the replenishment lead time is constant and known. They concluded that higher forecasting accuracy might result in higher total supply chain costs.

Using simulation, Wadhwa et al. (2009) investigated the performance of six inventory policies under various demand variations in a 4-echelon single-product linear supply chain. Three performance measures, specifically inventory variation over time, total inventory, and standard deviation of inventory at each node, were used. The six inventory policies studied are demand flow, fixed order quantity, order-up-to level, (s, Q), (s, S), and moving average with associated parameters subjectively set. They concluded that ordering a fixed quantity was the best policy for the entire supply chain and the (s, S) policy performed better than (s, Q). The subjectively determined parameter values based on constant demand, however, put their conclusions in doubt.

This paper presents a new study that further investigates the interactions between forecasting and inventory in a supply chain system. Our study differ from the previous studies primarily in the following areas: (1) using historical demand streams directly without the need of prior knowledge about demand distribution; (2) showing the usefulness of metaheuristic, specifically the real version of ant colony optimization called ACO_R (Socha and Dorigo, 2008), for demand forecasting and for setting optimal inventory policy; and (3) comparing the impacts of five different forecasting methods, two inventory policies, and three lead times on the inventory cost in a 3-echelon serial supply chain.

The remainder of the paper is organized as follows. Section 2 describes the ACO_R algorithm and its uses for demand forecasting and for determining optimal inventory policy. Section 3 explains our study on the impacts of forecasting methods, inventory policies, and lead times. The test results are presented in Section 4, followed by the Discussion. Section 6 concludes the paper.

2. ACO_R and its uses for demand forecasting and for determining optimal inventory policy

In this section, the ACO_R algorithm is described for the sake of completeness and its tailored uses to forecast future demands and