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The impact of lead time compression on demand forecasting risk and production cost: A newsvendor model ☆

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ABSTRACT

Short lead time reduces the exposure of demand forecasting risk, but an additional production cost is incurred to pay it. To solve this trade-off problem, a model is proposed based on classical newsvendor problem with lead time as a controllable variable. In this model, the demand forecasting process and the production cost structure are assumed as general functions with the amount of compressed lead time, respectively. Our investigation shows that under some circumstances, the trade-off problem can be solved and the proposed model can increase the profitability of enterprise. Finally, some numerical examples are given to illustrate the model.

1. Introduction

Short lead time reduces the exposure of demand forecasting risk (de Treville et al., 2014a,b). According to the investigation of Wal-Mart, in the apparel industry, if the retailer orders 26 weeks before selling season, the error of market demand forecasting will be about 40%. If the retailer orders 16 weeks before selling season, then the prediction error will be about 20%, and the time of ordering is closer to selling season, the error of market demand forecasting will be only about 10% (Blackburn, 1991). Another prime example, based on the research of Iyer and Bergen (1997) in the apparel industry supply chain, is that if the order lead time is compressed from 8 months to 4 months, the prediction error will fall from 65% to 35%. Demand forecasting risk can either lower customer service level because of increasing stock-outs or higher resource wasting because of increasing stock surplus (Heydari, 2014). It generally contains two basic types (Cachon, 2003). First, there is the risk that the company overestimates demand and manufactures/orders more goods than he will be able to sell. Eventually, the company should burden the reduction of profits or even a net financial loss. The other major type of the risk is that the business underestimates demand. It leads to insufficient production levels, results in a shortage and a lost opportunity for the firm. Demand forecasting risk extensively exists in business operation of enterprises with different industries, such as apparel (Iyer and Bergen, 1997), pharmaceutical (Eberle et al., 2014), Sport-Obermeyer (de Treville et al., 2014a,b), and fresh food or parts in the semi-conductor (Huang et al., 2011) industry.

Reducing the demand forecasting risk mentioned above needs to optimize the timing of production that can be controlled by lead time compression. The shorter the lead time is, the lower the error of demand uncertainty is, according to the impact

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of the accuracy of the demand forecasting process (Chen and Chuang, 2000). Lead time is the elapsed time between placing an order and receiving it (Song et al., 2013). An effective lead time compression can decrease the demand forecasting risk, thereby lower the safety stock, reduce the out-of-stock loss, increase the customer service level and enhance the competitive ability for enterprise (Hsu and Lee, 2009; Ouyang and Wu, 1997). There is considerable anecdotal evidence of the value of reducing exposure to demand forecasting risk. Companies, however, have struggled to act on this insight and to quantify their benefits (de Treville et al., 2014a,b). Many of the companies that have succeeded are now questioning the impact of lead time compression on their bottom lines (Fisher, 1997). One of key reasons is that lead time compression needs expense crashing cost (Liao and Shyu, 1991). The extra cost for the shortened lead time, usually but not limited, consists of the following three components: administrative costs, transport costs and enterprise's speed-up costs (Liao and Shyu, 1991). Under these costs, the cost of production per unit will be increased. Usually, it is considered that lead time crash cost depends on the amount of lead time to be shortened.

While practitioners and academics surely understand the importance of lead time in business operation, there are surprisingly few research on how an enterprise should design its manufacturing process to achieve maximum total revenue through an effective balance of demand forecasting risk and production cost. Hence, solving the question of companies and making an optimum decision can provide helpful guidelines and decision-making tools for enterprises.

In this paper the issue of trade-off between demand forecasting risk and production cost is investigated. A single firm faces a classical newsvendor problem that the enterprise experiences stochastic demand and lead time is considered and then a model is proposed. In this model, lead time is modeled as endogenous decision variable and the following questions are addressed. How can the incorporation of lead time decision impact the enterprise production decision and significantly increase the enterprise's profitability? What is the optimum lead time compression for enterprise? And what is the impact of lead time compression on enterprise bottom lines? The primary differences between our model and existed inventory models are as follows.

The first difference is the assumption of lead time. Traditional inventory models assumed that lead time is a parameter (Such as, Billington et al., 1983; Hill and Khosla, 1992; Kanet, 1986) or random/uncertain variable (Such as, Dolgui and Ould-Louly, 2002; Heydari, 2014; Ould-Louly and Dolgui, 2004) which is not a controllable factor. However, as stated by Tersine (1994), in practice, lead time usually includes more than one component such as order preparation, order transition, supplier lead time, delivery time and setup time components. Lead time could be shortened by paying an additional crashing cost. In other words, it is controllable (Priyan and Uthayakumar, 2015). Hsu and Lee (2009) stated that this crashing cost are expenditures on equipment improvement, information technology, order expedite, or special shipping and handling. In contrast to existed inventory models, it is assumed that lead time is controllable.

Although many researchers utilize controllable lead time in vendor model to reduce the customers' waiting time and increase the service level (Such as, Ben-Daya and Raouf, 1994; Huang et al., 2011; Jamshidi et al., 2015; Li et al., 2012; Liao and Shyu, 1991; Pan and Hsiao, 2005; Priyan and Uthayakumar, 2015; Yang, 2010; Yi and Sarker, 2013), these scholars assumed that there is a certain function relationship between production cost and lead time. For example, Liao and Shyu (1991) assumed that lead time could be decomposed into n mutually independent components, each with a different but fixed crash cost independent of the lead time. Ben-Daya and Raouf (1994) cited Liao and Shyu (1991) and proposed a model that treated both lead time and order quantity as decision variables. They developed two models, one of that uses the lead time crashing cost-function proposed by Liao and Shyu and that the other uses an exponential crashing cost function. Yang (2010) developed supply chain integrated inventory model with present value and the crashing cost is determined by the length of lead time, which is the polynomial form. Huang et al. (2011) studied a two-level supply chain and used a lead-time discount coordination strategy to maximize the profit of the entire supply chain by appropriately determining the optimal order quantity and lead-time. They assumed that the relative costs are the unit production cost, the unit inventory holding cost and the unit deterioration cast and assumed that the production cost is a linear function of lead time. Priyan and Uthayakumar (2015) investigated the continuous review inventory model and considered the lead time crashing cost as an exponential function of lead time. Hence, the second difference, in this paper, is the assumption of production cost structure with respect to lead time. It is assumed that the production cost structure is a general function with the amount of lead time can be shortened.

Furthermore, lead time compression allows the order decision to be made based on an updated demand forecasting. Thus, the forecasting evolution process affects the marginal value of time. When the enterprise forecasts the demand, the closer the time between the delivery and purchase is, the less the variance of the forecasted demand will be. One major setback, when studying the literature on lead time compression and stochastic demand in inventory management models, we identified that the vast majority of authors assumed that the market demand follows a specific distribution (Such as, Chen and Chuang, 2000; Hayya et al., 2011; Heydari, 2014; Jamshidi et al., 2015; Liao and Shyu, 1991; Priyan and Uthayakumar, 2015; Sarkar et al., 2015; Tyworth and O'Neill, 1997). For example, the assumption follows price-dependent, uniform, normal, exponential, lognormal and negative binomial models etc. While these models may be suitable to describe a certain industry, these resulting from a specific demand assumption cannot reveal how lead time impacts on the profits and optimal decision-making for enterprise. Hence, the last difference between our model and existed inventory models is the assumption of the structure of demand with respect to lead time. It is assumed that the demand forecasting process is a general function with the amount of compressed lead time.

Nevertheless, the proposed model does not consider supply chain management with lead time compression. This is one of the topics for our future research. In fact, many researchers have studied the supply chain management model with lead time