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Safety stock placement in supply chains with demand forecast updates

Youssef Boulaksil*

Assistant Professor of Operations Management and Logistics, UAE University, College of Business and Economics, P.O. Box 15551, Al Ain, United Arab Emirates

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ABSTRACT

Supply chains are exposed to many types of risks and it may not be obvious where to keep safety stocks in the supply chain to hedge against those risks, while maintaining a high customer service level. In this paper, we develop an approach to determine the safety stock levels in supply chain systems that face demand uncertainty. We model customer demand following the Martingale Model of Forecast Evolution (MMFE). An extensive body of literature discusses the safety stock placement problem in supply chains, but most studies assume independent and identically distributed demand. Our approach is based on a simulation study in which mathematical models are solved in a rolling horizon setting. It allows determining the safety stock levels at each stage of the supply chain. Based on a numerical study, we find that a big portion of the safety stocks should be placed downstream in the supply chain to achieve a high customer service level.

1. Introduction

Many firms and supply chains are under the pressure to offer a high customer service level while operating efficiently with low inventory levels. At the same time, supply chains are exposed to different types of risks, such as uncertain customer demand, uncertain supply, uncertain yields, uncertain lead times, and natural and man-made disasters [17]. Several strategies have been developed to hedge against these risks, such as safety time, safety stocks or a combination of both [4].

The objective of this paper is to present an approach that allows determining safety stocks to hedge against demand uncertainty. Demand uncertainty is the risk factor that is supposed to have the biggest impact on the performance of supply chains [17]. Setting safety stocks along a supply chain has been described by Graves and Willems [7] as a strategic effort in supply chain planning that allows absorbing demand uncertainties and avoiding lost sales and backorders.

The main contributions of this paper are twofold. First, we develop an approach that determines the safety stocks in supply chains by assuming that the demand follows the Martingale Model of Forecast Evolution process. Based on a case study and an extensive simulation study, Heath and Jackson [9] shows that MMFE is a better approach to model the demand evolution. It better reflects the demand pattern for many products in a real-life situation, compared to modeling it as independent and identically distributed demand. Our second contribution is that we provide managerial insights about where the safety stocks should be positioned in the supply chain: at downstream stages close to the customer or upstream in the supply chain where the inventory holding cost is lower, but the response time longer.

In our approach, we assume that the supply chain is controlled by a central authority, which has full visibility on the status of the supply chain. Nowadays, many companies have implemented Advanced Planning Systems that allow full visibility of the supply chain and that assist in the coordination and decision making in the supply chain [16]. These systems use mathematical programming models to decide on the optimal quantities to be produced, given several parameters, materials and resources constraints, and the target service level [3].

The remainder of this paper is organized as follow. In the next section, we review the most relevant studies from the literature. The model formulation and the solution approach are presented in Section 3. In Section 4, we present the results of a numerical study, and in Section 5, we draw a few conclusions and present the main managerial insight from this study.

2. Literature review

An extensive amount of literature studies supply chains and inventory systems under uncertain demand. We refer the reader for good reviews to Axsater [1], Federgruen [6], Van Houtum et al.

* Corresponding author.
E-mail address: y.boulaksil@uaeu.ac.ae, youssef.boulaksil@gmail.com

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[19], and Inderfurth [10]. A large number of studies addresses the safety stock placement problem, but we will only discuss the most relevant ones.

Graves and Willems [7] discuss the so-called guaranteed-service model for setting safety stocks in a supply chain under demand uncertainty. They develop a model for determining safety stock levels in a supply chain where each stage is controlled by a basestock policy and under the assumptions that an upper bound exists for the customer demand and infinite capacity constraints. Although the objective of this paper is similar to ours, the modeling approach and assumptions are fundamentally different. Other studies that also assumed uncapacitated supply chains are Simchi–Levi and Zhao [14] and Ettl et al. [5]. Sitompul et al. [15] extend this stream of papers by considering capacity constraints. They find that safety stocks should be increased by a constant correction factor which is dependent on the capacity limitation.

Other relevant studies that used a simulation approach to determine safety stock levels are Jung et al. [11], Jung et al. [12], and Boulaksil et al. [3]. Jung et al. [12] propose a simulation-based approach to determine the safety stocks in a chemical process supply chain. Jung et al., (2008) extend this work by including capacity constraints. Boulaksil et al. [3] develop simulation based optimization approach to determine the safety stocks for a multi-stage supply chain. The safety stock levels were determined based on a simulation approach in which the planning model was solved in a rolling horizon setting.

All these studies have in common that they assume that the customer demand is independent and identically distributed, which may not be a realistic assumption in many business contexts [9]. Evolving forecasts and demand patterns may be more realistic in a real-life setting. A few papers have considered such demand patterns, but with a strong focus on improving the forecasting method or on inventory planning.

Heath and Jackson [9] introduce MMFE as a modeling technique for evolving demand forecasts and compare it with traditional forecasting methods. The authors find that MMFE outperforms the traditional forecasting methods in terms of forecast accuracy and it results in lower total supply chain cost. Güllü [8] studies a two-echelon supply chain that consists of a central depot and multiple retailers, under forecast evolution. He obtains the system-wide order-up-to level and the expected system cost under the forecast evolution model, that he compares with the order-up-to level and the expected system cost under a standard demand model. The standard demand model results in higher order-up-to levels and higher system costs. Similar results have been obtained by Toktay and Wein [18]. Yücer [21] builds on Heath and Jackson's work to model the evolution of forecasts in a two-stage production-distribution system by using stationary, normally distributed demand with an autoregressive order-1 structure (AR-1). Using a series of simulations, the results demonstrate that his production-distribution model yields significantly better results when using MMFE demand forecasts compared to moving average or exponential smoothing.

Many more papers use the MMFE as a demand forecasting model for other purposes (see e.g. [20]). However, none of the papers determined the safety stock levels by using the MMFE demand forecast evolution, which is the objective of this paper.

3. Model formulation

We consider a supply chain with several stages, but customer demand can only be satisfied from the most downstream stage and we assume that all unsatisfied demand is backordered. The supply chain is controlled by a centralized planning system, such as an Advanced Planning System that has full visibility and supports the decision making in the supply chain. The planning problem is formulated by mathematical programming principles and assumes a planning horizon of T discrete time periods. Each time period t, the planning model is solved, given several input parameters, status information about inventory levels and backorders, and the demand forecasts for each period of the planning horizon. The solution of the planning model for time period $t=1$ are implemented, which represent production and inventory decisions for the current period. Decisions variables for future time periods represent only planned decisions. After the decisions are made, the actual demand gets revealed based on which the actual cost and customer service level are determined for the current time period. Then, the planning horizon is shifted by one period and a new planning problem arises that needs to be solved following the same approach. Each time when the horizon is shifted, the demand forecasts are updated following the MMFE method. The updates are due to updated information and circumstances. By repeating this cycle very often, we are able to derive the distribution of the inventory levels and backorders, which allows us to determine the required safety stock levels to achieve the target service level.

Our solution approach to determine the safety stock levels consists of a number of steps that are shown in Fig. 1.

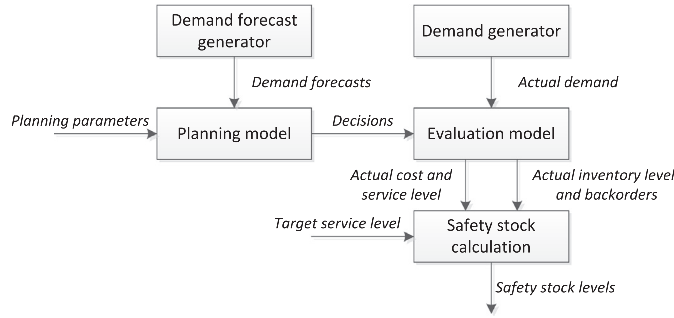

Fig. 1. A schematic overview of the safety stock placement approach.

3.1. Demand (forecast) generator

In this section, we describe the model that generates the demand forecasts that are input to the planning model. We apply the approach of Heath and Jackson [9] who propose a general technique called the Martingale Model of Forecast Evolution (MMFE). At the beginning of time period t, the demand forecasts for the coming T time periods become available, where T is the planning horizon. Kindly note that we assume that customer demand can only be satisfied from the most downstream stage. Hence, the demand (forecast) generator only generates demand (forecasts) for the most downstream stage.

Let $\vec{d_t}$ denote the forecast vector $\vec{d_t} = (d_{t,t+1}, d_{t,t+2}, \ldots, d_{t,t+T})$. In this vector, $d_{t,t+s}$ denotes the demand forecast made in time period t for the demand in time period $t+s$. We assume that for all the further periods, the demand forecast is equal to the mean demand μ. At the end of period t, D_t becomes available, which is the demand realization in time period t. The demand and demand forecasts evolve from one time period to the next according to an additive evolution model. Given $\vec{d_t}$, the forecasts get updated by:

$$d_{t+1,t+2} = d_{t,t+2} + \varepsilon_{t+1,t+2}$$
$$d_{t+1,t+3} = d_{t,t+3} + \varepsilon_{t+1,t+3}$$
$$\ldots$$
$$d_{t+1,t+T+1} = \mu + \varepsilon_{t+1,t+T+1}$$