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A multi-echelon inventory management framework for stochastic and fuzzy supply chains

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ABSTRACT

In this paper, for effective multi-echelon supply chains under stochastic and fuzzy environments, an inventory management framework and deterministic/stochastic-neuro-fuzzy cost models within the context of this framework are structured. Then, a numerical application in a three-echelon tree-structure chain is presented to show the applicability and performance of proposed framework. It can be said that, by our framework, efficient forecast data is ensured, realistic cost titles are considered in proposed models, and also the minimum total supply chain cost values under demand, lead time and expediting cost pattern changes are presented and examined in detail.

1. Introduction

Supply chain inventory management (SCIM) is an integrated approach to the planning and control of inventory, throughout the entire network of cooperating organizations from the source of supply to the end user. SCIM is focused on the end-customer demand and aims at improving customer service, increasing product variety, and lowering costs (Giannoccaro, Pontrandolfo, & Scozzi, 2003).

Most manufacturing enterprises are organized into networks of manufacturing and distribution sites that procure raw material, process them into finished goods, and distribute the finish goods to customers. The terms "multi-echelon" or "multi-level" production/distribution networks are also synonymous with such networks (or supply chains (SCs)), when an item moves through more than one step before reaching the final customer (Ganeshan, 1999; Rau, Wu, & Wee, 2003). Fig. 1 shows a multi-echelon system consisting of a number of suppliers, plants, warehouses, distribution centers and customers (Andersson & Melchiors, 2001; Axsater, 1990; Axsater, 2003).

The analysis of multi-echelon inventory systems that pervades the business world has a long history (Chiang & Monahan, 2005). Given the importance of these systems, many researchers have studied their operating characteristics under a variety of conditions and assumptions (Moinzadeh & Aggarwal, 1997). Since the development of the economic order quantity (EOQ) formula by Harris in 1913, researchers and practitioners have been actively concerned with the analysis and modeling of inventory systems under different operating parameters and modeling assumptions (Routroy & Kodali, 2005). Research on multi-echelon inventory models has gained importance over the last decade mainly because integrated control of supply chains consisting of several processing and distribution stages has become feasible, through modern information technology (Diks & de Kok, 1998; Kalchschmidt, Zotteri, & Verganti, 2003; Rau et al., 2003). Clark and Scarf (1960) were the first to study the two-echelon inventory model (Bollapragada, Akella, & Srinivasan, 1998; Chiang & Monahan, 2005; Diks & de Kok, 1998; Dong & Lee, 2003; Rau et al., 2003; Tee & Rossetti, 2002; van der Vorst, Beulens, & van Beek, 2000). They proved the optimality of a base stock policy for the pure serial inventory system and developed an efficient decomposing method to compute the optimal base stock ordering policy. Bessler and Veinott (1965) extended the Clark and Scarf (1960) model to include general arborescent structures. The depot-warehouse problem was addressed by Eppen and Schrage (1981) who analysed a model with stockless central depot (van der Heijden, 1999). Several authors have also considered this problem in various forms (Bollapragada et al., 1998; Dong & Lee, 2003; Moinzadeh & Aggarwal, 1997; Parker & Kapuscinski, 2004; Tee & Rossetti, 2002; van der Heijden, 1999; van der Vorst et al., 2000).

Sherbrooke (1968) constructed the METRIC (Multi-Echelon Technique for Recoverable Item Control) model, which identifies the stock levels that minimize the expected number of backorders at the lower echelon subject to a budget constraint. Thereafter, a large set of models that generally seek to identify optimal lot sizes and safety stocks in a multi-echelon framework were produced by many researchers. In addition to analytical models, simulation models have also been developed to capture the complex interactions of the multi-echelon inventory problems. For detailed

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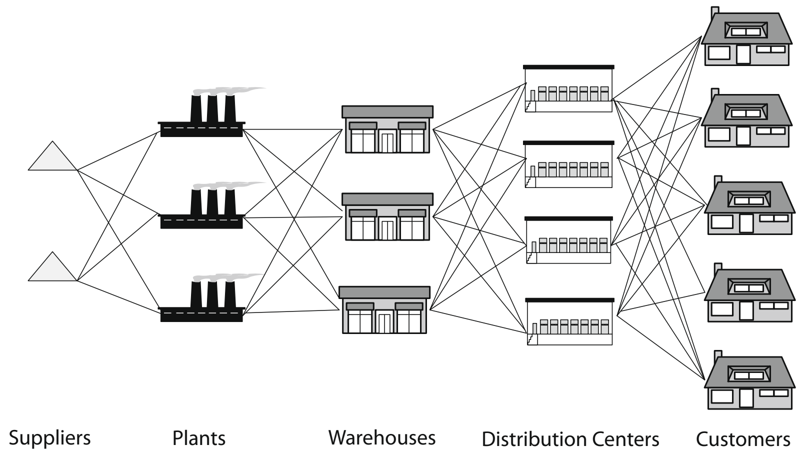

Fig. 1. A multi-echelon inventory system.

literature review of multi-echelon models please see Taskin Gumus and Guneri (2007). After a detailed literature review about the title, it can be seen that there are several deficiencies and rough assumptions related to research technique, echelon number, inventory policy, demand and lead time assumptions, and objective function (Taskin Gumus, 2007). In this paper, some of these deficiencies are eliminated and some of the assumptions are expanded about the titles listed above.

Many researches have studied these problems as well as emphasized the need of integration among SC stages to make the chain effectively and efficiently satisfy customer requests (e.g. (Towill, 1996)). Beside the integration issue, the uncertainty has to be dealt with in order to define an effective SC inventory policy. In addition to the uncertainty on supply (e.g. lead times) and demand, information delays associated with the manufacturing and distribution processes characterize SCs (Giannoccaro et al., 2003). In the market, the participants of a supply chain not only face the uncertainties of product demands and raw material supplies but also face the uncertainties of commodity prices and costs (Liu & Sahinidis, 1997). The first concern in incorporating uncertainties into supply chain modeling and optimization is the determination of suitable representation of the uncertain parameters (Gupta & Maranas, 2003). Three distinct methods are frequently mentioned for representing uncertainty (Gupta & Maranas, 2003; Hameri & Paatela, 2005): First, the distribution-based approach, where the normal distribution with specified mean and standard deviation is widely invoked for modeling uncertain demands and/or parameters; second, the fuzzy-based approach, therein the forecast parameters are considered as fuzzy numbers with accompanied membership functions; and third, the scenario-based approach, in which several discrete scenarios with associated probability levels are used to describe expected occurrence of particular outcomes (Chen & Lee, 2004).

A number of researches have been devoted to studying supply chain management under uncertain environments (Taskin Gumus & Guneri, 2007). For example, Gupta and Maranas (2000) and Gupta et al. (2000) incorporate the uncertain demand via a normal probability function and propose a two-stage solution framework. A generalization to handle multi-period and multi-customer problems is recently proposed (Gupta & Maranas, 2003). Tsiakis, Shah, and Pantelides (2001) use scenario planning approach to describe demand uncertainties. Due to the potential of dealing with linguistic expressions and uncertain issues, fuzzy sets are used to handle uncertain demands and external raw material problems and in a later work, Petrovic, Roy, and Petrovic (1999) further consider uncertain supply deliveries. Giannoccaro et al. (2003) also apply fuzzy sets theory to model the uncertainties associated with both market demand and inventory costs. Despite their obvious negotiable and uncertain characteristics in real businesses, the product price is seldomly taken into account as a source of uncertainty in previous works (Chen & Lee, 2004). Instead, it is usually treated as known parameters.

In this paper, demand, lead time and expediting cost uncertainties are emphasized and tried to be eliminated in a realistic way for successful inventory management in supply chains, under stochastic and fuzzy environments. Hence, an inventory management framework and deterministic/stochastic-neuro-fuzzy cost models within the context of this framework are structured. Then, a numerical application in a three-echelon tree-structure chain is presented to show the applicability and performance of the proposed framework.

2. The proposed multi-echelon inventory management framework

In this section of the paper, the developed framework for effective and realistic multi-echelon inventory management and, deterministic and stochastic-neuro-fuzzy cost models are presented. Also, the methods that the framework contains as artificial neural networks and neuro-fuzzy integration, are explained and their algorithms are given to show their usage in our methodology.

2.1. The framework structure

The framework structured here considers a three-echelon tree-structure supply system, where all echelons contain one or more installations. Each echelon is modeled as a stocking point to feed lower echelon and to be fed by upper echelon. It is assumed that the last echelon (the manufacturer) is fed with limitless stock. The market demand, supply lead times between echelons and expediting costs for orders are uncertain, and they are calculated by neuro-fuzzy computations. Here, it is assumed that the delivery is expedited by an expediting cost and so the shortage is removed. A shortage in end-item demand at echelon 1 (at retailers) is backordered.

Demand from customers is met with the on-hand inventory from the retailers. If the market demand at retailers gets over the certain inventory, the difference is assumed to be backordered, as mentioned before. On the other hand, it is assumed that the central depot has limitless inventory and has to procure from an outside supplier with infinite capacity.

The first step of the framework is to develop the deterministic (TG-D) and stochastic (TG-S) models. The model TG-S is the core