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Fuzzy inference systems and inventory allocation decisions: Exploring the impact of priority rules on total costs and service levels

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ABSTRACT

Inventory allocation decisions in a distribution system concern issues such as how much and where stock should be assigned to orders in a supply chain. When the inventory level of an inventory point is lower than the total number of items ordered by lower echelons in the chain, the decision of how many items to allocate to each "competing" order must take into consideration the trade-off between cost and service level. This paper proposes a decision-support system that makes use of fuzzy logic to consider inventory carrying, shortage and ordering costs as well as transportation costs. The proposed system is compared through simulation with three other inventory allocation decision support models in terms of cost and service levels achieved. Conclusions are then drawn.

1. Introduction

An increasingly competitive world environment has forced companies to continually improve their performance. Globalization of trade, growing demand for customized products, increased competition, and unprecedented levels of innovation in process and product technologies are only some of the reasons for the pressure on companies to increase their efficiency in operations (Daniel & Rajendran, 2005). To respond to such pressure, operations and supply chain managers must rely on robust decision-making support systems that can cope with the complexities involved.

Supply chain management can be defined as the upstream and downstream management activity that delivers superior value to consumers at a low cost (Christopher, 1998). Decisions in supply chain management can be divided into three levels: strategic, tactical and operational (Daniel & Rajendran, 2005). From an operational perspective, four areas of research interest can be identified: inventory management and control; planning and production; information sharing, coordination and monitoring; and operational tools (Tayur, Ganeshan, & Magazine, 2012).

Inventory annual holding costs today can be as high as 40% of inventory value (or, in some situations, even higher), while competition continually puts pressure on companies to achieve higher service levels; therefore, efficient inventory management is essential to all companies except the few that do not deal with any type of inventory (Ganeshan, 1999). For manufacturing companies, inventories are particularly important, given that inventory can represent up to 60% of a company's total assets (Giannoccaro, Pontrandolfo, & Scozzi, 2003).

One aspect of inventory management that is relevant to supply chain efficiency is inventory allocation. Inventory allocation concerns the set of decisions about the distribution of inventories from suppliers to customers when the supplier does not have sufficient stocks to serve demand in full for all customers. Ignoring this dimension, which sometimes happens in companies, can be detrimental to their operations performance (De Vericourt, Karaesmen, & Dallery, 2002). Inventory allocation between the various echelons of the supply chain has been a recurring research topic in recent years, as noted in the works of Eren and Chan (2015), Pérez-Rodríguez and Holguín-Veras (2015), Wu and Yeh (2014), and Kristianto, Gunasekaran, Helo, and Hao (2014).

Over time, the allocation systems that are available to managers have increased in complexity and sophistication. Volatility in the economy, new business models, difficulty in estimating future demand for products with shorter life cycles and no or short his-

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torical records, and the costs of overstocking and obsolescence for products with unknown shelf lives increase uncertainty and pose additional challenges to traditional allocation policies and systems (Giannoccaro et al., 2003; Luo, Bollapragada, & Kerbache, 2017; Protopappa-Sieke, Sieke, & Thonemann, 2016).

In view of the complexities and uncertainties associated with the definitions of variables for traditional probabilistic systems, an alternative to probabilistic models for making product inventory allocation decisions is the use of soft computing, which is able to incorporate existing imprecision in human decisions into computational algorithms. Among the most commonly used types of soft computing are genetic algorithms, neural networks and fuzzy logic (Ko, Tiwari, & Mehnen, 2010). Fuzzy logic aims to solve real problems with the use of methodologies that have a flexible capacity for processing information. These fuzzy logic tools have the power to analyze incomplete and vague data and to provide satisfactory solutions at a low computational cost (Ko et al., 2010).

This study aims to adapt the fuzzy logic model developed by Xie and Petrovic (2006) to deal with the inventory allocation problem in an environment that has relevant levels of uncertainty regarding variables that usually guide allocation decision-making. Our goal is to develop a model that considers not only holding costs, but also transportation, ordering costs and shortage costs, thereby formulating a decision-making tool that takes into account more elements than that of Xie and Petrovic (2006) and that is hopefully both more representative of reality than previous models and that leads to better operational efficiency. This paper contributes to the current body of inventory management literature by filling the gap left by the scant previous research specifically analyzing inventory allocation decisions in the light of fuzzy logic. Not only were different inventory allocation approaches assessed under a comprehensive cost structure, encompassing holding, replenishment, and ordering costs, but also different retail network sizes were tested, thus allowing for a comparison of how different inventory allocation approaches behave in light of the effect of pooling varying demands. Results suggest that the proposed approach is superior in terms of total costs, especially when retail networks are large.

The remainder of this paper is organized as follows. Section 2 reviews the literature on the topic. Section 3 describes our methodology and the scenarios we used in our comparisons between the proposed model and alternate models, by presenting the data and structure of the simulations. Section 4 presents, analyzes and discusses the simulation results. Section 5 draws conclusions and presents suggestions for further studies.

2. Literature review

To build the theoretical framework of this study, the following topics will be covered: first, the application of fuzzy logic in inventory management; second, how the issue of inventory allocation has been explored in the literature; and finally, applications of fuzzy logic in inventory allocation. The underlying idea is to provide to the readers the perspective that, although applications of fuzzy logic in inventory control represent a growing area of research in the management science/expert systems literature, fuzzy logic applications in inventory allocation are still scarce, despite the underlying vagueness that, in reality, surrounds this kind of decision making.

2.1. Fuzzy inventory management

Fuzzy logic is an alternative to the use of traditional probabilistic methods in dealing with uncertainty in inventory management; such logic was developed from “fuzzy sets”, a concept introduced in the seminal article by Lotfi A. Zadeh (1965). While probabilistic inventory management models have been used for many decades, the use of fuzzy logic in inventory management started fairly recently, in the 90s (Kao & Hsu, 2002).

One of the first applications of fuzzy logic in inventory management was in determining Economic Order Quantity (EOQ), aiming to define the order size that minimizes total inventory-related cost. Yao and Lee (1999) used fuzzy sets and modeled order size as a trapezoidal membership function. The authors determined EOQ both through traditional calculations, using a crisp number to represent the variables involved, and via numerical simulation, using fuzzy logic to represent the variables. The total costs obtained by the authors in both cases were similar.

Samal and Pratihar (2014) modeled the variables demand, holding cost, order cost and backorder cost as fuzzy variables and conducted simulations using genetic algorithms and particle swarm optimization to define EOQ. In addition to meeting the goal of reducing total cost, they also sought to maximize the confidence that they would be able to keep the total cost within a given budget. The simulation was then validated with the use of real-life cases.

Both Yao and Lee (1999) and Samal and Pratihar (2014) simulated situations with and without backorders. However, Samal and Pratihar concluded that the total costs can be substantially reduced when using not only the order size suggested by their model but also a certain number of backorders.

Another use of fuzzy logic in inventory management can be found in research that tries to specify variables for continuous review inventory models. Such models establish an inventory level such that, when this level is reached, an order is placed to purchase a fixed order size (Tantatemee & Phruksaphanrat, 2012). When uncertainties are present in determining demand and lead time, the definition of order sizes becomes much more difficult.

Gen, Tsujimura, and Zheng (1997) used fuzzy logic to model a continuous review inventory system that provided ranges of order sizes and total cost as an output. Such a range allows managers to make decisions based on a “confidence interval” rather than based on a single value. Uncertainties related to holding and stockout costs were considered and were modeled as fuzzy variables. The demand and the order point were treated as constant variables.

Ko et al. (2010) introduce stockout costs in the total cost equation. Unlike Gen et al. (1997), they considered costs to be constant and demand to be uncertain and modeled as a fuzzy variable. They aimed to define a (Q,r) policy—that is, to define the order size and the order point with the objective of minimizing total costs. By introducing stockout costs, the authors try to resolve the trade-off between costs relating to excess inventory and costs relating to shortage.

Handfield, Warsing, and Wu (2009) also sought to define a (Q,r) policy. In addition to considering uncertainties in demand, in a way similar to that of Kao and Hsu (2002), as well as uncertainty in holding costs, as did Gen et al. (1997), the authors introduced uncertainties in variables such as lead time, supplier performance, costs related to fines and penalties, and the attitude of the decision maker towards risk.

Tantatemee and Phruksaphanrat (2012) also sought to define the order size and the order point. They modeled demand and supply availability as inputs to the fuzzy system. Using historical data to define the membership function parameters, an inventory control model was obtained that dramatically reduced overall costs, represented by the holding, ordering and stockout costs when compared to a traditional probabilistic model.

Both Handfield et al. (2009) and Tantatemee and Phruksaphanrat (2012) introduced uncertainty regarding the chain’s upstream elements; in other words, they considered certain supply inputs as fuzzy variables. Wang, Fu, and Zeng (2012) established that part of the unmet demand is represented by stockout costs, while the remainder becomes backorder. They consider two demand-