Int. J. Production Economics 155 (2014) 259–271

Contents lists available at ScienceDirect

Int. J. Production Economics

journal homepage: www.elsevier.com/locate/ijpe

A fuzzy vendor managed inventory of multi-item economic order quantity model under shortage: An ant colony optimization algorithm

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ARTICLE INFO

Article history:
Received 3 April 2013
Accepted 17 July 2013
Available online 29 July 2013

Keywords:
Ant colony optimization
Differential evolution
Economic order quantity
Fuzzy nonlinear integer programming
Genetic algorithm
Vendor managed inventory

ABSTRACT

In this study, a multi-item economic order quantity model with shortage under vendor managed inventory policy in a single vendor single buyer supply chain is developed. This model explicitly includes warehouse capacity and delivery constraints, bounds order quantity, and limits the number of pallets. Not only the demands are considered imprecise, but also resources such as available storage and total order quantity of all items can be vaguely defined in different ways. An ant colony optimization is employed to find a near-optimum solution of the fuzzy nonlinear integer-programming problem with the objective of minimizing the total cost of the supply chain. Since no benchmark is available in the literature, a genetic algorithm and a differential evolution are developed as well to validate the result obtained. Furthermore, the applicability of the proposed methodology along with a sensitivity analysis on its parameter is demonstrated using five numerical examples containing different numbers of items.

1. Introduction

Supply chain (SC) management is the management of material and information flows both in and between facilities, such as vendors, manufacturing and assembly plants, and distribution centers (Thomas and Griffin, 1996). With the emergence of international markets and the growth of globalization, the management of supply chains has gained increased attention. The high complexity of the underlying procurement, production and distribution processes, as well as the increasing number of parties involved, create the necessity for efficient decision support systems (Schmid et al., 2013). Some inventory policies such as economic order quantity (EOQ) and economic production quantity (EPQ) are usually adopted in SCs. A century ago, Harris (1913) proposed the EOQ model and five years later, Taft (1918) recommended the EPQ inventory model; both without backorders. Later, Hadley and Whitin (1963) proposed the EOQ/EPQ inventory model with backorders. A complete review of different optimization methods used in inventory field can be seen in Cárdenas-Barrón (2011).

In traditional SC models, each player is responsible for his inventory control, production or distribution ordering activities, and each echelon only has information on their immediate customers (see Fig. 1). Since this lack of visibility of real demand causes some problems in traditional SC, many industries were required to improve their SC operations by sharing inventory or demand information for supplier and customer (Lin et al., 2010). A long evolution of SC cooperation led to emerging vendor managed inventory (VMI) type SCs in the 1980s. A VMI system suggests the vendor to manage inventories of its own and its multiple downstream retailers (Yu et al., 2012). VMI is a program that has been recognized as one of the most successful practices that enhances SC integration (Stapleton et al., 2006; Dorling, 2006; Danese, 2006; Pohlen and Goldspy, 2003). Under VMI policy, the vendor has the advantage of determining the timing and quantity of replenishment and has access to the retailer's inventory and demand data. Consequently, on the one hand, the vendor can coordinate his long-term plans and control the day-to-day flow of goods and material. On the other hand, retailers incur no ordering cost and are guarded against excessive inventory by contractual agreements. Usually, this contract includes limits on retailer's inventory level such that the vendor is penalized for items exceeding these limits (Fry et al., 2001; Danese, 2006; Shah and Goh, 2006; Chen et al., 2006). Thus, the retailer's space problem becomes the problem of the vendor to the extent that the vendor has to pay a penalty for not meeting these constraints.

There is an abundant literature that models uncertainty in demand and/or lead time using probability distributions with

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http://dx.doi.org/10.1016/j.ijpe.2013.07.017

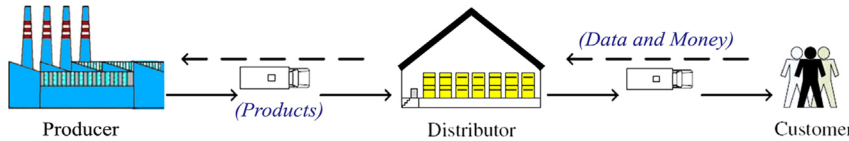

Fig. 1. An illustration of a traditional supply chain.

known parameters. However, in many cases where there is little or no historical data available to the inventory decision maker, perhaps due to recent changes in the SC environment, probability distributions may simply not be available, or may not be easily or accurately estimated (Xie et al., 2006). Additionally, in some cases, it may not be possible to collect data on the random variables of interest because of certain system or time constraints. Furthermore, other critical SC parameters, in particular the various costs that impact the system, are often ill-defined and may vary from time to time. All of these situations raise challenges for using traditional inventory models in practice. Fuzzy theory provides an alternate, flexible approach to handle such situations because it allows the model to easily incorporate various experts' advice in developing critical parameter estimates (Zimmermann, 2001). Fuzzy sets are introduced to avoid imprecise deliveries, orders and demands within SCs and they out-perform traditional VMI by Bullwhip effect and inventory declines (Lin et al., 2010). Adaptive fuzzy VMI control can always provide 100% service levels by adaptively responding to the demand changes according to production capacity, available stock and shortages (Kristianto et al., 2012).

While a substantial amount of research works are available in the literature, a brief review of the works on the fuzzy traditional and fuzzy VMI SC is presented in the next section.

2. Literature review

A brief review of the literature is given on the fuzzy traditional and fuzzy VMI SC inventory in the next two subsections.

2.1. Fuzzy traditional SC and inventory models

There are many important and successful contributions in the literature to treat impreciseness in SC systems using the fuzzy set theory (Petrovic et al., 1998, 1999; Petrovic, 2001). To name a few, since poor quality demand information leads to poor production and distribution performance, some contributions withstand this lack by proposing a two-level coordinated inventory control within an integrative SC to reduce the ambiguity in fuzzy demands (Xie et al., 2006). Mondal and Maiti (2002) developed a multi-item fuzzy economic order quantity (EOQ) model under fuzzy objective goal of cost minimization and imprecise constraints on warehouse space and number of production runs with crisp/imprecise inventory costs. In their work, the fuzzy inventory model has been formulated into a fuzzy non-linear decision making problems and was solved by both genetic algorithm (GA) and fuzzy non-linear programming (FNLP) method based on Zimmermann's approach. Their model was illustrated numerically and the results from different methods were compared. Wang and Shu (2005) proposed a fuzzy decision methodology that provides an alternative framework to handle SC uncertainties and to find out SC inventory strategies, while there is lack of certainty in data or even lack of available historical data.

Aliev et al. (2007) pointed out that we are usually faced with uncertain market demands and capacities in production environment, imprecise process times, and other factors introducing inherent uncertainty to the solution. In their research, they investigates a fuzzy production–distribution aggregate planning problem in SC and formulated it into a fuzzy programming model with the solution obtained by GA. Alex (2007) provided a novel approach to model uncertainties involved in the SC management using the fuzzy point estimation. Selim et al. (2008) adopted different fuzzy programming approaches for the collaborative production–distribution planning problems in different SC structure. Besides, in a non-fuzzy environment, Pasandideh et al. (2011) presented a GA for a VMI SC with several products and constraints based on EOQ with backorders considering two classical backorders costs of linear and fixed.

2.2. Fuzzy VMI supply chain

Although the VMI SC system in a fuzzy environment is closer to reality and is more applicable compared to the one used under non-fuzziness, to the best of authors' knowledge, there are just two research works that adopt fuzziness, but with the focus of reducing the Bullwhip effect. Lin et al. (2010) applied fuzzy arithmetic operations in a VMI SC with fuzzy demands. The application pays attention to the ordering process and controlling the buyer's target inventory level. Kristianto et al. (2012) proposed an adaptive fuzzy control application to produce an adaptive smoothing constant in the forecast method, production and delivery plan to remove, for example, the rationing and gaming or the Houlihan effect and the order batching effect or the Burbidge effects and finally the Bullwhip effect. The results showed that the adaptive fuzzy VMI control surpasses fuzzy VMI control and traditional VMI in terms of mitigating the Bullwhip effect and lower delivery overshoots and backorders.

In this research, some assumptions from a non-fuzzy VMI model suggested by Pasandideh et al. (2011) and Darwish and Odah (2010) are adopted and combined with the ones from a traditional SC model offered by Taleizadeh et al. (2012) to develop a fuzzy multi-item multi-constraint EOQ model with shortage under VMI policy in a single-vendor single-buyer SC. Moreover, to bring the model to be applicable to closer to reality problems, additional contractual agreement between the vendor and the buyer including constraints on the number of pallets required to deliver the items, number of deliveries, and quantity of an order under fuzzy environment are considered. In this work not only the storage capacity and the total order quantity of all items, but also demands are considered fuzzy. In addition, an ant colony optimization (ACO) is employed to find a near-optimum solution of the fuzzy nonlinear integer-programming (FNIP) problem with the objective of finding the products' orders quantities, their required number of pallets and their maximum backorder levels per cycle; in order to minimize the total fuzzy VMI inventory cost while the constraints are satisfied. Since no benchmark is available in the literature, a genetic algorithm and a differential evolution (DE) are developed as well to validate the result obtained. Furthermore, the applicability of the proposed methodology along with a sensitivity analysis on its parameter is shown using five numerical examples containing different numbers of items. In short, the highlights of the differences of this research with the previous studies are as follows:

- Considering fuzzy environment and VMI supply chain simultaneously.