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Two parameter tuned multi-objective evolutionary algorithms for a bi-objective vendor managed inventory model with trapezoidal fuzzy demand

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ABSTRACT

This paper presents a bi-objective vendor managed inventory (BOVMI) model for a supply chain problem with a single vendor and multiple retailers, in which the demand is fuzzy and the vendor manages the retailers' inventory in a central warehouse. The vendor confronts two constraints: number of orders and available budget. In this model, the fuzzy demand is formulated using trapezoidal fuzzy number (TrFN) where the centroid defuzzification method is employed to defuzzify fuzzy output functions. Minimizing both the total inventory cost and the warehouse space are the two objectives of the model. Since the proposed model is formulated into a bi-objective integer nonlinear programming (INLP) problem, the multi-objective evolutionary algorithm (MOEA) of non-dominated sorting genetic algorithm-II (NSGA-II) is developed to find Pareto front solutions. Besides, since there is no benchmark available in the literature to validate the solutions obtained, another MOEA, namely the non-dominated ranking genetic algorithms (NRGA), is developed to solve the problem as well. To improve the performances of both algorithms, their parameters are calibrated using the Taguchi method. Finally, conclusions are made and future research works are recommended.

1. Introduction

Inventory management, one of the main issues in supply chain environments, plays an important role in reducing total system cost. While there are several models available in the literature to control inventories, the most well known is the classical economic order quantity (EOQ) formula proposed by Harris in 1913 [1]. Although the EOQ model was used in many practical applications due to its ease of use and simplicity, many researchers tried to extend it under real-world conditions since it involves several restrictive assumptions. Interested readers are referred to Pentico and Drake [2] for an overview of deterministic inventory models.

Several approaches such as continuous replenishment (CR), advanced continuous replenishment (ACR), quick response (QR), and vendor managed inventory (VMI) were proposed in the retailer-supplier partnerships of multi-echelon inventory systems to control demand variability [3]. Among them, the VMI approach, which was applied by successful retailers like Wal-Mart and Kmart, is the most popular one because of its benefits [3]. The VMI is an approach that controls the inventories of the retailers to reduce their total inventory cost considering the shared sale information from them. Yao et al. [4] and Sari [5] investigated supply chain improvements using the VMI policy. Elvander et al. [6] developed a framework to apply the VMI strategy better. Goyal [7] presented a single-vendor single-retailer supply chain model in production environments and Hill and Omar [8] extended it by considering different shipments made to the retailers. Moreover, Zavanella and Zanoni [9] developed the VMI model for a single-vendor multi-retailer system in which the consignment stock (CS) policy was utilized.

The EOQ formula can be used in the VMI modeling with respect to certain demand and lead-time [8]. To name a few, Yao et al. [4] modeled the VMI problem for single-vendor single-retailer supply chain; showing the advantages of using the VMI policy. Van der Vlist et al. [10] considered the costs of shipments from the supplier to the buyers for the model that was presented by Yao et al. [4]. Darwish and Odah [11] investigated a VMI model for the single-vendor multi-retailer supply chain in which the vendor pays

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a penalty if items exceed definite bounds. Besides, they applied a solution algorithm that reduces the computational efforts significantly. Pasandideh et al. [12] proposed a one-vendor one-retailer VMI model with two constraints for a two-echelon supply chain in which shortages were backordered. They applied a parameter-tuned genetic algorithm (GA) to find a near optimum solution of the complicated model developed in their research. Afterward, Cárdenas et al. [13] improved the model in [12] by taking into account a constraint in which the backorder level could not be more than the order quantity.

Sadeghi et al. [14] were the first who developed a VMI model considering the replenishment frequency at which retailers are replenished by the vendor. They developed a GA with its parameters tuned using the response surface methodology (RSM), to solve the problem. Furthermore, Yu et al. [15] provided a VMI model with respect to perishable goods, and applied a golden search algorithm for optimization. Moreover, Kristianto et al. [16] studied an adaptive fuzzy VMI model in which the Bullwhip effect is reduced. For a good review on the VMI implementations, interested readers are referred to Marqus et al. [17].

Many researchers including Nachiappan and Jawahar [18], Gupta et al. [19], Yang et al. [20], Pasandideh et al. [12], and Sadeghi et al. [14] developed meta-heuristics to solve some integer nonlinear programming (INLP) problems that could not be solved by exact methods in a reasonable time. In addition, while there are several methods such as the single aggregate objective function (AOF) and multi-objective evolutionary algorithms (MOEAs) to optimize multi-objective problems, MOEAs that apply Pareto-based ranking have become a popular approach. However, most probably the only research that uses a MOEA in the VMI literature is due to Liao et al. [21] who presented a non-dominated sorting genetic algorithm (NSGA-II) to optimize a multi-objective location-inventory model, in which the parameters of their algorithm were not calibrated.

Considering the EOQ approach, this paper formulates a bi-objective VMI problem of a single-vendor multi-retailer supply chain with a central warehouse. In this problem, the annual demand is assumed trapezoidal fuzzy number (TrFN) so that the centroid defuzzification is used to defuzzify the fuzzy output functions in all calculations. The first objective is to determine the replenishment rate of the vendor, the replenishment frequency of the retailers, and the order sizes to minimize the total inventory cost. Optimizing the warehouse space is the second objective. In addition, the number of orders and the available budget of the vendor are the two constraints of the problem. We show the model is of a bi-objective integer nonlinear programming (INLP) type so that the use of a multi-objective evolutionary algorithm to find Pareto front solutions is justified. Consequently, a non-dominated ranking genetic algorithm (NSGA-II) is developed to find Pareto fronts of the proposed bi-objective VMI (BOVMI) problem. Since there is no benchmark available in the literature to validate the results, another MOEA, namely non-dominated ranking genetic algorithms (NRGA) is developed as well. Since the parameters of MOEAs affect the quality of the solutions obtained, the parameters of both algorithms are calibrated using the Taguchi method.

Presenting a BOVMI model with one central warehouse under fuzzy demands and constrained number of orders and budget are the main innovation of this paper. Furthermore, applying two parameter-tuned MOEAs to optimize the BOVMI problem is another innovation in solution algorithms.

The remainder of the paper is organized as follows. In the next section, the notations and the assumptions are described. The BOVMI model and the solution algorithms are presented in Sections 3 and 4, respectively. Section 5 contains the tuning procedure of the parameters. Section 6 evaluates the meta-heuristics. Finally, conclusions and recommendations are presented in Section 7.

2. Notations and assumptions

Assumptions and notations used in this paper are as follows:

- i an index used for a retailer; $i = 1, 2, \ldots, r$
- r number of retailers
- $\tilde{D}_i$ the total annual fuzzy demand for retailer i
- $\tilde{D}$ the total annual fuzzy demand for the vendor and warehouse: $\tilde{D} = \sum_{i=1}^{r} \tilde{D}_i$
- A_i ordering cost for retailer i
- A_v ordering cost of the vendor
- A_w ordering cost of the warehouse
- h_i holding cost for retailer i
- h_v holding cost of the vendor
- H holding cost for warehouse
- R reorder point
- n replenishment frequency of retailers by vendor (a decision variable)
- m replenishment frequency of vendor by warehouse (a decision variable)
- q_i order quantity for retailer i (decision variables)
- q order quantity for all retailers: $q = \sum_{i=1}^{r} q_i$
- Q_v the annual vendor's total order quantity: $Q_v = nq$
- Q_w the annual total order quantity of the warehouse: $Q_w = mQ_v$
- T_i cycle time for retailer i
- T_R cycle time for retailers
- T_v vendor cycle time
- T_w cycle time for warehouse
- f space required storing one unit of the product
- N maximum number of orders for vendor
- c unit purchase price of the product
- C available budget for vendor
- F the warehouse space
- TC minimum total cost in the VMI system

Similar to Darwish and Odah [11] it is assumed that retailers share a unique consumption interval, that is $T_i = T_R$; $i = 1, 2, \ldots, r$. In other words, the retailers are replenished at the same time resulting in

$$\frac{q_i}{\tilde{D}_i} = \frac{q_1}{\tilde{D}_1} \Rightarrow q_i = q_1 \tilde{D}_i / \tilde{D}_1; \quad i = 2, 3, \ldots, r \tag{1}$$

where q_1 is the quantity delivered to retailer 1.

The vendor delivers a batch of size $q = \sum_{i=1}^{r} q_i$ in each cycle of length T_R. In addition, every T_v time the vendor's order quantity can be obtained by

$$Q_v = nq \Rightarrow Q_v = nq_1 \tilde{D} / \tilde{D}_1 \tag{2}$$

where n is the replenishment frequency for retailers by the vendor. In other words, all retailers are replenished in n parts, each with quantity q.

Similarly, Eq. (3) shows the total order quantity of the warehouse every T_w time:

$$Q_w = mQ_v \tag{3}$$

where m is called the replenishment frequency of vendor by warehouse.

In summary, the vendor accepts full responsibility for ordering costs and hence retailers face only holding cost. Besides, based on the EOQ policy, it is assumed that there is an instantaneous replenishment for the vendor and retailers and the reorder point is zero ($R = 0$). Further, the system will lose extra demand and does not permit any surplus shipment. It is also assumed that the retailers sell all of the products transferred by the vendor. Hence, $\tilde{D} = \sum_{i=1}^{r} \tilde{D}_i$, where $\tilde{D}$ is called the vendor's fuzzy annual demand with the trapezoidal fuzzy number (TrFN). In addition, the vendor delivers all