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Joint decisions on inventory classification, supplier selection and production policy for a multi-item EPQ inventory system under uncertainty

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Abstract *– There is a great need to improve the classical inventory models so that they can address real-world problems more properly. The presence of multiple products and a variety of inventory items have complicated the inventory control process, so companies need to classify inventory items to reduce costs. On the other hand, the supplier selection problem is important, as there may be several suppliers with different options in the market. Also, several factors impact the demand for products and cause uncertainty for this parameter. This research develops a multi-product EPQ model that simultaneously classifies products, selects the best possible supplier for each group, and determines the replenishment policy under uncertainty in demand. To solve the proposed model, we present a simulation-optimization approach. This approach uses genetic and simulated annealing metaheuristic algorithms to solve the problem. Also, there is a simulation module that helps the algorithm to evaluate the fitness function. The parameters of algorithms are tuned by employing the Taguchi method. The results are analyzed for three categories of examples. Finally, the sensitivity of the objective function to the input parameters is also analyzed. We found that the system's total cost is highly sensitive to products unit holding cost.*

Keywords *– Inventory Classification, Demand Uncertainty, Supplier Selection, Genetic Algorithm, Simulation Annealing Algorithm*

I. INTRODUCTION

Over the past decades, many companies have taken inventory management seriously because of the need for more profit. Economic order quantity (EOQ) and economic production quantity (EPQ) models were developed several decades ago as two of the first basic models for inventory management by Harris (1990) and Taft (1918), respectively. Afterward, researchers tried to provide new concepts and tools to help managers properly control inventory. For example, the initial inventory models, such as EOQ and EPQ, assumed only one product inventory system. However, this assumption is invalid in many real-world situations, and several products may simultaneously be in an inventory system (Pasandideh et al., 2015a). In this situation, the determination of the replenishment policy of each product with ignoring the presence of other products does not guarantee a globally optimal solution. In other words, the optimal replenishment policy of

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products impacts the whole system, and a joint replenishment policy should be determined to reduce the cost of the system as much as possible. The development of multi-product models was one of the important tools for addressing multi-product inventory systems. In the mentioned multi-product inventory systems, the systems analysis reveals that the products are not equally important (Keshavarz-Ghorbani & Pasandideh, 2022). In fact, the performance of an inventory system is more impacted by some products. Considering the difference in the importance of products, the classification seems as critical as the determination of ordering policy. Therefore, classification techniques should be utilized to determine the degree of importance of each product in the system (Rezaei & Salimi, 2015). For this goal, researchers tried to develop different classification techniques for multi-product inventory systems in recent years. The ABC classification method is one of these techniques that has been the focus of many works in recent years (Razavi Hajiagha et al., 2021).

On the other hand, one of the main factors of stability and survival in today's highly competitive environment is the reduction in product production costs (Cheraghalikhani et al., 2019; Mokhtari & Hasani, 2017). Since the cost of raw materials and components of the product accounts for a large part of the product cost in most industries, proper supplier selection can significantly reduce production costs and increase an organization's competitiveness. One of the other drawbacks of basic EOQ and EPQ models is that they consider only one supplier for the system. However, several suppliers in the market may compete with each other by proposing different options for a particular product. In fact, the suppliers differ in several features, such as product price, supplying cost quality, etc. Consequently, the suppliers can significantly impact the inventory performance, and there should be proper attention to supplier selection policies for inventory systems.

Finally, several factors may cause product demand uncertainty (Sadeghi et al., 2023b). Service level requirements, customer response time, the range of required products, price violation, etc., are some of these factors. More precisely, the demand for inventory systems is stochastic in a real-world setting (Sana, 2015), and considering demand uncertainty is another paradigm in the inventory systems literature that tries to consider and handle the uncertainty to improve the quality of the decision-making process.

To the best of our knowledge, none of the previous papers studied these critical features of inventory systems in an integrated framework. This paper aims to address the gap in the literature by presenting an EPQ model for a manufacturing environment that deals with multiple suppliers and the classification of multiple products. To bring the problem into real-world assumptions, the uncertainty in demand for products is also considered. In other words, the presented model can simultaneously classify inventory products, selects the proper supplier for each class, and determines the production policy for an EPQ inventory control system under uncertain conditions. We present a simulation-optimization solution methodology. A simulation approach is presented to deal with the demand uncertainty. Considering the dimension and nonlinearity of the problem, genetic algorithm (GA) and simulated annealing (SA) metaheuristic algorithms are employed to find proper solutions.

The main components of the current study can be briefly expressed as follows:

- Developing a multi-product EPQ model to determine inventory classification, supplier selection, and production replenishment policies.
- Considering uncertainty in demand for products.
- Using simulation to deal with uncertainty.
- Designing and implementing GA and SA metaheuristics as a solution approach.
- Using the Taguchi method for parameter tuning of algorithms.

The rest of this article is organized as follows. In Section II, a review of the literature is provided. In Section III, the problem definition and mathematical modeling are presented. In Section IV, the solution approach is discussed. In Section

V, computational results and related analysis are presented. In Section VI, the paper is concluded, and some directions for future research are suggested.

II. LITERATURE REVIEW

In this section, we will review the relevant papers in the literature. As pointed out, Harris (1990) developed EOQ 100 years ago. The authors tried to extend this model by considering several assumptions in the next year. The presence of defective items, withdrawal policies, trade credits, environmental concerns, pricing concerns, transportation decisions, reliability, etc., are some of the newly considered aspects in the literature (Asadkhani et al., 2022; Chen et al., 2013; Fallahi et al., 2021a; Sadeghi, 2019; Sadeghi et al., 2022; Salameh & Jaber, 2000; Taheri-Tolgari & Mirzazadeh, 2019; Taleizadeh, 2014).

We focus on the relevant papers to our work in the literature review. For this goal, we classify the literature review to provide a better understanding of the literature for the readers. First, the papers on product classification in inventory systems are reviewed. Then, we investigate the works on the supplier selection problem. Finally, the previous works on multi-product inventory management are discussed.

A. Product classification in production-inventory systems

Several methods are presented in the literature for classifying products in inventory systems. Cook et al. (1996) used data envelopment analysis to classify products in inventory systems. Ramanathan (2006) presented a linear weight optimization method for the classification of products. They considered multiple criteria for classification. Zhou & Fan (2007) developed the previous work by considering two weight factors for each product. Ng (2007) proposed a linear weight model for the ABC classification problem. This approach was improved by Hadi-Vencheh (2010), who developed a nonlinear model for ABC classification. Chen (2011) presented a new based on the peer-estimation approach for multi-criteria ABC classification. Torabi et al. (2012) introduced a new method that considered both quantitative and qualitative criteria in classifying products in an inventory system. Mohammaditabar et al. (2012) focused on joint inventory classification and replenishment decisions in an inventory planning problem. Park et al. (2014) designed a cross-evaluation-based weighted linear optimization for a multi-criteria ABC classification problem. They used simulation to show that this approach is more effective than some well-known methods in the literature. Kaabi et al. (2015) designed an artificial intelligence-based method for ABC classification. In this approach, the weight of the criteria was calculated using the VNS metaheuristic, and TOPSIS was used to calculate the score of each product. Cherif & Ladhari (2016) used an integration of the artificial bee colony" (ABC) metaheuristic and Vikor multi-criteria decision-making method for multi-criteria ABC of products. In this approach, the weight parameters of the Vikor method were modified using the ABC metaheuristic. In their other paper, Cherif & Ladhari (2017) suggested another combination of multi-criteria decision-making and metaheuristic, including Electre III and differential evolution algorithm. Keshavarz-Ghorbani & Pasandideh (2022) used the ABC method to classify products and determined the optimal ordering decisions for group B products.

Also, uncertainty programming methods such as fuzzy programming are used for product classification in inventory systems. For example, Hadi-Vencheh & Mohamadghasemi (2011) presented an integration of the fuzzy analytic hierarchy process (FAHP) and DE for multi-criteria ABC classification of products. The presented approach used FAHP to determine the weight of criteria, which DEA determined the values of the linguistic terms. Chu et al. (2008) presented a new method to handle nominal and non-nominal properties. The method was called ABC–Fuzzy Classification (ABC – FC), and the authors used the Keelung Port data to evaluate their approach's performance. Rezaei & Salimi (2015) developed a new optimization model based on interval programming to address two main problems in inventory classification. The first problem was the necessity of expert opinion, and the second was the requirement for precise parameters. This stochastic approach could solve both problems in a proper way.

B. Supplier selection in production-inventory systems

Ghodsypour & O'Brien (1998) claimed that there are several problems in using optimization tools for supplier selection, as they cannot address the qualitative factors properly. Therefore, they suggested an integration of AHP and linear programming for this problem. Basnet & Leung (2005) investigated the supplier selection problem of an inventory system with discrete demand. Liao & Rittscher (2007) developed a multiobjective problem for supplier selection problem. In addition to the total cost, their model considers other important factors such as quality, delivery time, and flexibility. Rezaei & Davoodi (2008) studied a supplier selection problem for an inventory system with imperfect products. The operational constraints, such as the supplier capacity and warehouse space, were formulated in this model. Awasthi et al. (2009) presented a model to select suppliers for a manufacturer which faces random demand. In this study, the goal was to select a set of suppliers with the lowest possible cost. Several operational constraints, such as the threshold on the number of orders, were also considered. Burke et al. (2009) developed a new model for the supplier selection problem. The uncertainty in the reliability of suppliers and the demand for products were considered. In this paper, the buyer could select single-supplier or multi-supplier purchasing strategies. Li & Zabinsky (2011) presented two-stage stochastic programming and chance constraint programming as two stochastic approaches to address the supplier selection problem's uncertainty. This work aimed to determine the minimum number of suppliers and the optimal received orders from each supplier. Bilsel & Ravindran (2011) investigated a multiobjective supplier selection problem, in which the risk management assumptions were also considered. This paper considered uncertainty in several parameters, such as demand, suppliers' capacities, and cost parameters. Zhang & Zhang (2011) developed a supplier selection and order allocation model for an inventory system under a shortage. The demand was formulated as a random variable, and order threshold limitations were also considered. Scott et al. (2015) developed a supplier selection and order allocation problem under uncertainty. The authors used a combination of AHP and (Quality Function Development) QFD to evaluate and rank the customers. Memon et al. (2015) questioned the applicability of probability and fuzzy theories for stochastic supplier selection problems. They suggested integrating grey system theory and uncertainty theory as a more efficient approach. Dobos & Vörösmarty (2019) tried to redesign DEA in such as way that it can address both managerial and green criteria in supplier selection process. The performance of this new framework was evaluated using an EOQ model. Lamba et al. (2019) developed a mixed-integer nonlinear programming model for a sustainable supplier selection and order allocation problem. The problem was formulated under carbon tax, cap-and-trade, and direct cap as three well-known governmental emission regulations. Ayatollahi & Jafari (2022) developed a new EOQ model for supplier selection of a single-product system in the presence of defective products. They converted the model to a mixed-integer linear programming model, and solved the model via CPLEX solver.

C. Multi-product production inventory systems

Pasandideh et al. (2011) worked on an EOQ model for a two-echelon supply chain with multiple products and suggested GA solve the problem. Pasandideh et al. (2013) suggested a multiobjective multi-product EPQ to simultaneously minimize total cost and warehouse space. The multiobjective versions of GA and PSO metaheuristics, NSGA-II and MOPSO, were implemented to find a set of non-dominated solutions. Pasandideh et al. (2015a) developed a multi-product EPQ under uncertainty in the system's resources. The sequential programming approach was utilized to calculate the optimal values of the decision variable. Pasandideh et al. (2015b) proposed a multi-product EPQ for production systems with imperfect items. One of the new components in the total cost function was the warehouse construction cost. Mousavi et al. (2016) suggested a multi-product EOQ for an inventory system under shortage, discount, and inflation. Total cost and total warehouse space were the objective functions, and the multiobjective model was solved using NRGA, NSGA-II, and MOPSO. Sadeghi et al. (2016) addressed the uncertainty in demand of multi-product inventory systems and formulated this uncertainty using fuzzy theory. The near-optimal solutions were obtained using GA and PSO. The multi-product extension of EOQ for growing items was introduced by Khalilpourazari & Pasandideh (2019). Their solution approach was two hybrid metaheuristic algorithms, called Sine Cosine-Crow Search and Water Cycle Moth–Flame Optimization. Mokhtari et al. (2021) presented a multi-product EPQ for an inventory system with reworkable imperfect products. The model was decomposed, and solved using Lagrangian relaxation. Mokhtari et al. (2022) also presented a multi-product EPQ in which the substitution of products was possible. They codded the model in

GAMS programming environment and used BARON solver to determine the EPQ. Fallahi et al. (2022a) recently developed a multi-product EOQ model for reusable inventory systems. The author designed machine-learning-based metaheuristics as the solution approach. Table I gives a general view of the features of the past papers in the literature and the contributions of the current study.

Table I. The contribution of this work against the previous papers in the literature

Article	*Model type*		*Objective function*			*Demand*		*Product number*		*Inventory decisions*			*Solution Approach***
	EOQ	*EPQ*	*Single*	*Multiple*	*Type**	*Deterministic*	*Stochastic*	*Single*	*Multiple*	*Products classification*	*Replenishment*	*Supplier selection*	
Ghodsypour & O'Brien (1998)	✓		✓		(1)	✓		✓			✓	✓	(1,6)
Basnet & Leung (2005)	✓		✓		(1)	✓		✓			✓	✓	(1)
Ramanathan (2006)	✓		✓		(7)	✓			✓	✓			(1)
Ng (2007)	✓		✓		(7)	✓			✓	✓			(1)
Liao & Rittscher (2007)	✓			✓	(1,8,12, 13)		✓	✓				✓	(2)
Zhou & Fan (2007)	✓		✓		(7)	✓			✓	✓			(1)
Rezaei & Davoodi (2008)		✓	✓		(2)	✓		✓			✓	✓	(2)
Chu et al. (2008)	✓		✓		(7)	✓			✓	✓			(1)
Awasthi et al. (2009)	✓		✓		(1)		✓	✓			✓	✓	(1)
Burke et al. (2009)	✓		✓		(2)		✓	✓			✓	✓	(1)
Hadi-Vencheh (2010)	✓		✓		(11)	✓			✓	✓			(1)
Zhang & Zhang (2011)	✓		✓		(2)		✓	✓			✓	✓	(1)
Chen (2011)	✓		✓		(7)	✓			✓	✓			(2)
Pasandideh et al. (2011)	✓		✓		(1)	✓			✓		✓		(2)
Hadi-Vencheh & Mohamadghasemi (2011)	✓		✓		(7)	✓			✓	✓			(4)
Li & Zabinsky (2011)	✓			✓	(1,10)		✓	✓			✓	✓	(1)
Bilsel & Ravindran (2011)	✓			✓	(1,8,9)		✓	✓			✓	✓	(1)
Mohammaditabar et al. (2012)	✓		✓		(1)	✓			✓	✓	✓		(2)
Pasandideh et al. (2013)		✓		✓	(1,4)	✓			✓		✓		(2)
Park et al. (2014)	✓		✓		(7)	✓			✓	✓			(3)

Pasandideh et al. (2015a)		✓	✓		(1)	✓			✓		✓		(1)
Kaabi et al. (2015)	✓		✓		(1)	✓			✓	✓			(1,5)
Memon et al. (2015)	✓		✓		(6)		✓	✓			✓	✓	(1)
Pasandideh et al. (2015b)		✓	✓		(1)	✓			✓		✓		(1)
Rezaei & Salimi (2015)	✓		✓		(1)		✓		✓	✓			(1)
Scott et al. (2015)	✓		✓		(5)		✓	✓			✓	✓	(1)
Mousavi et al. (2016)	✓			✓	(1,4)	✓			✓		✓		(2)
Cherif & Ladhari (2016)	✓		✓		(1)	✓			✓	✓			(2)
Sadeghi et al. (2016)		✓	✓		(1)		✓		✓		✓		(2)
Cherif & Ladhari (2017)	✓		✓		(1)	✓			✓	✓			(2)
Dobos & Vörösmarty (2019)	✓		✓		(1)	✓		✓				✓	(3)
Khalilpourazari & Pasandideh (2019)	✓		✓		(2)	✓			✓		✓		(2)
Lamba et al. (2019)	✓		✓		(1)	✓			✓		✓	✓	(1)
Mokhtari et al. (2021)		✓	✓		(1)	✓			✓		✓		(1)
Mokhtari et al. (2022)		✓	✓		(1)	✓			✓		✓		(1)
Keshavarz-Ghorbani & Pasandideh (2022)	✓			✓	(1,3)		✓		✓	✓	✓		(1)
Fallahi et al. (2022a)	✓		✓		(1)	✓			✓		✓		(2)
Ayatollahi & Jafari (2022)	✓		✓		(1)	✓		✓			✓	✓	(1)
This paper		✓		✓	(1)		✓	✓	✓	✓	✓	✓	(2)

*** Objective function type: (1) cost, (2) profit, (3) service level, (4) storage space, (5) total stakeholder satisfaction score, (6) risk, (7) dissimilarity, (8) quality, (9) waiting time, (10) number of suppliers, (11) performance, (12) flexibility rate, (13) late delivery rate**

**** Solution approach: (1) exact, (2) (meta)heuristic, (3) DEA, (4) fuzzy DEA, (5) TOPSIS, (6) AHP**

According to the summarized results in Table I, there is no paper on supplier selection and product classification in a multi-product EPQ under demand uncertainty. The work by Mohammaditabar et al. (2012) is one of the closest works to our paper. They addressed joint replenishment and product classification decisions of an inventory system. However, they studied the problem under EOQ assumptions. In addition, they completely ignored the supplier selection decisions and uncertainty in the system's demand. Our work aims to fill the gap by presenting a new constrained nonlinear programming model for a multi-product EPQ problem under demand uncertainty. The goal of the model is to determine the optimal product classification, supplier selection, and replenishment decisions of the system. Also, a simulation-optimization approach is presented as the solution methodology.

III. PROBLEM STATEMENT AND MODELING

In this section, we define the new inventory system and develop the mathematical model of the problem. For this goal, first, the assumptions are presented. Then, the problem definition is explained, considering the assumptions. Finally, the mathematical model is formulated.

A. Assumptions

The main assumptions of the presented problem can be described as follows:

1. The inventory system is based on the EPQ model.
2. There are multiple products in the system.
3. The products should be classified based on their similarity.
4. Demand is assumed to be stochastic.
5. There are multiple suppliers for each group of products.
6. The capacity of each supplier is limited.
7. Backorder or lost sale shortages are not allowed.
8. Discount is not allowed.

B. Problem definition

Consider a multi-supplier multi-product inventory system that works under the assumptions of the EPQ model. Regarding the economic benefits, the classification of products is necessary for the system. Classification techniques try to classify similar items into the same groups. Our problem defines a dissimilarity index to evaluate the similarity between each pair of products. A set of quantitative criteria can be used to classify products and calculate their similarities. It is assumed that the importance of criteria is not equal, and each has a weight parameter that determines its importance. The decision maker assigns a value to each product in terms of each criterion. The system tries to classify the products in a way that dissimilarity is minimized. In addition to the classification policy, the optimal replenishment quantity of each product should be determined. The products can be received from a set of available suppliers at a finite rate. In the real-world environment, the suppliers are different in several features such as geographical location, quality, purchasing cost, ordering cost, etc. It is more reasonable to order the products in one group from a particular supplier since such a policy reduces the cost and facilitates the purchase process. Therefore, the products of a group have a joint cycle and are received from a particular supplier in this system. Note that there is a limitation on the supply capacity of each supplier. As mentioned before, the demand for products is assumed to be stochastic. The probability density function of demand is assumed to be general. In other words, the demand can have any continuous probability distribution. The purpose of the proposed problem is to optimize the system by determination of three main decisions (1) the assignment of products to groups, (2) supplier selection for each group of products, and (3) the optimal replenishment quantity of products in each group, so that the total cost of inventory system, as the objective function, is minimized.

C. Mathematical modeling

The following sets, parameters, and decision variables are used as the notations to develop the mathematical model of the problem:

Sets

i, j	Index of products; i, j $\in \{1,2,\ldots,N\}$
g	Index of groups; g $\in \{1,2,\ldots,G\}$
s	Index of suppliers; s $\in \{1,2,\ldots,S\}$
k	Index of criteria; k $\in \{1,2,\ldots,K\}$

Parameters

D_i	The demand rate of product i
h_i	The unit holding cost of product i per unit of time
P_{is}	The sell capacity of supplier s for product i
A_{is}	The ordering cost of product i from supplier s
C_{is}	The purchasing cost of product i from supplier s
w_k	The weight of criterion k
q_{ik}	The evaluation score of product i in terms of criterion k
T_g	The inventory cycle of products in group g
d_{ij}	The dissimilarity index of product i and product j

Variables

Z	The total cost of the inventory system
PC	The total purchasing cost of products
OC	The total ordering cost of products
HC	The total holding cost of products
Q_i	The economic production quantity of product i
T_g	The inventory cycle of products in group g
x_{ig}	A binary variable; if product i is assigned to group g 1; otherwise, 0.
y_{gs}	A binary variable; if group g is assigned to supplier s 1; otherwise, 0.

As described in the problem definition, the products should be grouped based on a dissimilarity index. We define d_{ij} dissimilarity index between product i and product j, which is calculated as follows:

$$d_{ij} = \left[\sum_{k=1}^{K} w_k \left(q_{ik} - q_{jk}\right)^2\right]^{\frac{1}{2}} \tag{1}$$

$$T_g = \left[\frac{2\sum_{s=1}^{S}\sum_{i=1}^{N} A_{iS}x_{ig}y_{gs}}{\sum_{s=1}^{S}\sum_{i=1}^{N} h_i D_i x_{ig} y_{gs}(1-D_i/P_{iS})}\right]^{\frac{1}{2}} \tag{2}$$

After the calculation of T_g as the optimal cycle of products in group g, the economic replenishment quantity of product i in group g can be calculated as follows:

$$Q_i = \sum_{g=1}^{G} T_g D_i x_{ig} \tag{3}$$

In continuing, we calculate the inventory system's cost components, including purchasing, ordering, and holding costs. First, the total purchasing cost of grouped products from the suppliers can be calculated as follows:

$$PC = \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{i=1}^{N} C_{is} D_i x_{ig} y_{gs} \tag{4}$$

The placement of each order from each supplier imposes an ordering cost on the inventory system. The total ordering cost of the inventory system over the planning horizon can be calculated as follows:

$$OC = \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{i=1}^{N} \frac{A_{is}x_{ig}y_{gs}}{T_g} \tag{5}$$

The holding of received products in the warehouse imposes holding cost to the system, which is calculated as follows:

$$HC = \frac{1}{2}\sum_{s=1}^{S}\sum_{g=1}^{G}\sum_{i=1}^{N}\left[T_g h_i D_i x_{ig} y_{gs}\left(1-\frac{D_i}{P_{is}}\right)\right] \tag{6}$$

Finally, the total cost as the objective function of the inventory system can be written as follows:

$$Min\ Z = HC + OC + PC \tag{7}$$

The objective function is subjected to the following constraints:

$$\sum_{g=1}^{G} x_{ig} = 1 \qquad \forall\, i \in \{1,2,\dots,N\} \tag{8}$$

$$\sum_{s=1}^{S} y_{gs} = 1 \qquad \forall\, g \in \{1,2,\dots,G\} \tag{9}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} d_{ij} x_{ig} x_{jg} \le L \qquad \forall\, g \in \{1,2,\dots,G\}, i < j \in \{1,2,\dots,N\} \tag{10}$$

$$T_g = \left[\frac{2\sum_{s=1}^{S}\sum_{i=1}^{N} A_{iS}x_{ig}y_{gs}}{\sum_{s=1}^{S}\sum_{i=1}^{N} h_i D_i x_{ig} y_{gs}(1-D_i/P_{iS})}\right]^{\frac{1}{2}} \qquad \forall\, g \in \{1,2,\dots,G\} \tag{11}$$

$$x_{ig}, y_{gs} \in \{0,1\} \qquad \forall\, i \in \{1,2,\dots,N\}, g \in \{1,2,\dots,G\}, s \in \{1,2,\dots,S\} \tag{12}$$

Constraints (1) guarantee the grouping of all products in the inventory system. Constraints (2) ensure the assignment of a supplier to each group of items. The replenishment cycle for each group is calculated via constraints (3). Finally, constraints (4) determine the types of decision variables

IV. SOLUTION APPROACH

This section explains our proposed solution methodology to solve the problem. This solution methodology is a simulation-optimization approach, incorporating two metaheuristic algorithms and a simulation module. The presented model is a constrained nonlinear programming inventory management model. In this situation, the exact methods or commercial solvers do not necessarily reach optimal solutions in a reasonable time (Pasandideh et al., 2011). Consequently, we utilize metaheuristic algorithms to search the solution space and find high-quality solutions. The metaheuristic algorithms are applied to a wide range of complex real-world optimization problems such as medical decision-making, healthcare operations management, production scheduling, etc. (Fallahi et al., 2021b; Fallahi et al., 2022d; Rezvan et al., 2021; Sadeghi et al., 2023a; Varmazyar et al., 2020; Varmazyar & Salmasi, 2012). These algorithms are also widely used for inventory optimization problems (Mousavi et al., 2016; Pasandideh et al., 2013; Sadeghi et al., 2016). The metaheuristic algorithms are divided into two general categories of population-based and single solution-based algorithms. GA, (particle swarm optimization) PSO, (differential evolution) DE, and (ant colony optimization) ACO are examples of population-based algorithms, while algorithms such as SA, variable neighborhood search (VNS), and Tabu search (TS) are single solution-based algorithms. We use GA and SA as two population-based and single solution-based algorithms to solve the presented model in this work.

A. Genetic algorithm

GA was developed as one of the earliest metaheuristic algorithms by Holland (1992). This algorithm utilizes a set of operators to evolve randomly generated initial solutions in the space. The type of operators may highly impact the GA results. More specifically, different operators may have different impacts on various problems. Based on the computational results, we use the most suitable operator for each step and try to use the best combination of operators.

The algorithm randomly generates a set of chromosomes as the initial population in the first iteration. GA needs to evaluate the chromosomes using a fitness function. We define the inverse of the objective function as the fitness function of the GA algorithm, which is calculated as follows:

$$\hat{Z}(x_{ig}, y_{gs}) = \frac{1}{Z(x_{ig}, y_{gs})} \tag{10}$$

where $\hat{Z}(x_{ig}, y_{gs})$ is the inverse of the objective function. The higher value of this fitness function is more desirable. In the next iterations, similar steps are executed until a termination condition is reached. First, the algorithm needs to select a set of parents to generate the chromosomes for the next iteration. In this process, the parents with higher fitness values have more chances of being selected. Roulette wheel selection and rank selection are two of the methods that are used for the selection of chromosomes. The crossover operator uses the selected parents to generate the new chromosomes. The number of crossovers is determined using a crossover probability parameter p_c, which is one of the input parameters of the GA algorithm. Single-point, double-point, and uniform methods are three well-known crossover operators of the GA algorithm that are widely used in literature. After the crossover operator, GA tries to ensure the diversity of solutions using a mutation operator. The number of mutations for the generated chromosomes is determined using a mutation probability p_m. We also consider three types of single-point, double-point, and uniform mutation operators for mutation. After these operators, the previous chromosomes should be replaced with the newly generated chromosomes. Complete replacement and steady-state replacement are the operators used for the replacement process in GA variants. The explained operators and components are summarized in Table II.

Table II. The components of the presented GA metaheuristic

Algorithm component	*Details*
Input parameters	Number of iterations
	Number of chromosomes
	Crossover probability
	Mutation probability
Selection operator	Roulette wheel selection
	Rank selection
Crossover operator	Single-point
	Double-point
	Uniform

Mutation operator	Single-point
	Double-point
	Uniform
Replacement operator	Full replacement
	Steady-state replacement

One of the important requirements in the design of metaheuristic algorithms is the solution encoding scheme. The solution encoding affects the performance of the algorithm in terms of quality and CPU time. For solution encoding, we consider x_{ig} and y_{gs} as the two variables inside each chromosome, both variables are binary and are represented using binary matrices.

B. Simulated annealing algorithm

Kirkpatrick et al. (1983) developed the simulated annealing algorithm for the first time. The algorithm is one of the famous single solution-based metaheuristics that tries to imitate the annealing process of physical materials to search for solutions of an optimization problem. A metal is cooled down from a high temperature to room temperature and the least energetic point during the annealing process. In SA, first, a solution is randomly generated for the problem. Then, the algorithm finds a solution in the neighborhood of the previous solution using a search mechanism. This procedure is continued until a termination criterion is met. We use the following six methods to search and find new solutions in the neighborhood.

- Method 1: In this method, one column breakpoint for both x_{ig} and y_{gs} matrices is determined. Then, the position of the breakpoints' left and adjacent right columns are changed.

- Method 2: In this method, two-column breakpoints for both x_{ig} and y_{gs} matrices are determined. Then, the position of the left adjacent column of the first breakpoint and the adjacent right column of the second breakpoint are changed.

- Method 3: In this method, two random matrices with the size of variable matrices are generated with. The values are in $(0,1)$ interval. Then, the value of the random matrices and the main matrices are compared. If an element is less than 0.5 in random matrices, the corresponding element in the main matrix should be changed. If the value is 0, it will be set to one, and vice versa.

- Method 4: In this method, one row of both x_{ig} and y_{gs} are randomly selected. Then, all values of the selected rows are set to zero. Afterward, the algorithm randomly selects an element in the rows, and sets the value of the element to one.

- Method 5: In this method, two rows of both x_{ig} and y_{gs} matrices are randomly selected. Then, all values of the selected rows are set to zero. Afterward, the algorithm randomly selects an element in the rows and sets the element value to zero. In other words, this method is a generalization of method 4.

- Method 6: In this method, a random value from (0,1) interval is assigned to each row of both x_{ig} and y_{gs} matrices. Then, the algorithm applies method 4 to the rows with a random value less than 0.05

The newly found solution is accepted if it has a better quality than the previous solution. The algorithm also accepts the solutions with lower quality using the following rate:

$$P = e^{\frac{-\Delta E}{T}} \tag{10}$$

where ΔE is the difference of objective function between the previous and current solution, and T is the current temperature. The temperature is decreased using a cooling rate in each iteration of SA. A predetermined number of search iterations are performed for each temperature value, and the temperature is gradually reduced. Different methods are used to reduce the temperature. We use linear, geometric, and logarithmic methods, and select the best one based on the computational results. This process is continued unit a termination criterion is met. We set the number of consecutive temperature reductions without improvement as the stopping criterion. The explained operators and components are summarized in Table III. Note that the solution representation is similar to the presented solution representation for GA.

Table III. The components of the presented SA metaheuristic

Algorithm component	*Details*
Input parameters	Initial Temperature
	Number of iterations per temperature
	Maximum number of temperature reductions without improvement
Annealing rule	Linear method
	Geometric method
	Logarithmic method

C. Simulation module

As mentioned before, the demand for an inventory system may not be deterministic, and several factors impact the demand during the planning horizon. We consider the demand uncertainty and use a simulation-optimization approach to deal with this uncertainty. In the previous section, we introduced GA and SA as two metaheuristic algorithms that play the optimization module role in our solution approach. The simulation module receives the generated solutions by each algorithm, returning an objective function estimation to them. To be more specific, the simulation module calculates the objective function estimation through the simulation of demand in a limited number of scenarios. The presented simulation-optimization approach can successfully handle any form of probability density function for demand. Fig. (1) shows a general outline of the proposed simulation-optimization framework.

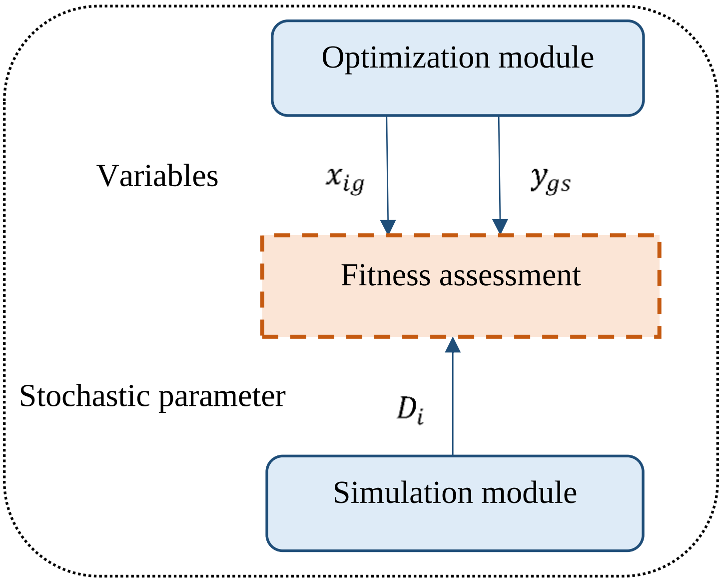

Fig 1. Outline of the proposed simulation-optimization algorithm

V. NUMERICAL EXAMPLES

In this section, we will investigate the performance of the presented algorithms in solving the developed constrained nonlinear mathematical model. We consider three example categories for this goal: small, medium, and large-sized. Four problems are randomly generated for each category. The dissimilarity between the products is calculated using three measures: annual dollar usage, lead time, and average purchasing cost. We presented different strategies for operators of metaheuristic algorithms to have the opportunity to select the best possible combination. There are 36 possible combinations of selection, crossover, mutation, and replacement operators for GA. In addition, SA can be implemented using 18 combinations of neighborhood search and temperature reduction strategies. The results showed that roulette wheel selection, two-point crossover, uniform mutation, and steady-state selection are the best operators of GA for our problem. Also, we found that method 6 and the logarithmic temperature reduction mechanism are the most suitable strategies for SA.

Before implementing metaheuristics, the value of the input parameters of algorithms should be determined. Several methods are used in the literature to determine the input parameters of metaheuristics. Trial-and-error, parameter adaption, and statistical methods are some of the widely used approaches. The statistical approaches are widely used for several goals in supply chain management problems (Sahebi-Fakhrabad et al., 2023). This paper utilizes Taguchi's design of experiments, as one of the most powerful statistical methods, for the parameter calibration of the proposed GA and SA. Taguchi divides the affecting factors into signal factors and noise factors. Then, orthogonal arrays are used to calculate the level of input parameters as signal factors to optimize the signal-to-noise ratio. More details of the method are available in the literature (Fallahi et al., 2022b; Fallahi et al., 2022c). We consider three levels for GA and SA input parameters to implement Taguchi. These three levels are presented in Table IV.

Table IV. The considered levels for parameter tuning of GA and SA

		GA parameters				*SA parameters*		
		Maximum iteration	*Population number*	*Crossover probability*	*Mutation probability*	*Initial temperature*	*Number of iterations per temperature*	*Stopping criterion*
Level	1	100	20	0.5	0.2	1000	10	100
	2	200	50	0.7	0.3	500	15	200
	3	300	80	0.8	0.5	300	20	300

L^9 orthogonal arrays of Taguchi are used for each algorithm. This means that each algorithm should be run with nine different combinations of parameters, and the signal-to-noise ratio of each combination be calculated. The optimal parameter levels are graphically presented in Figs. (2) and (3).

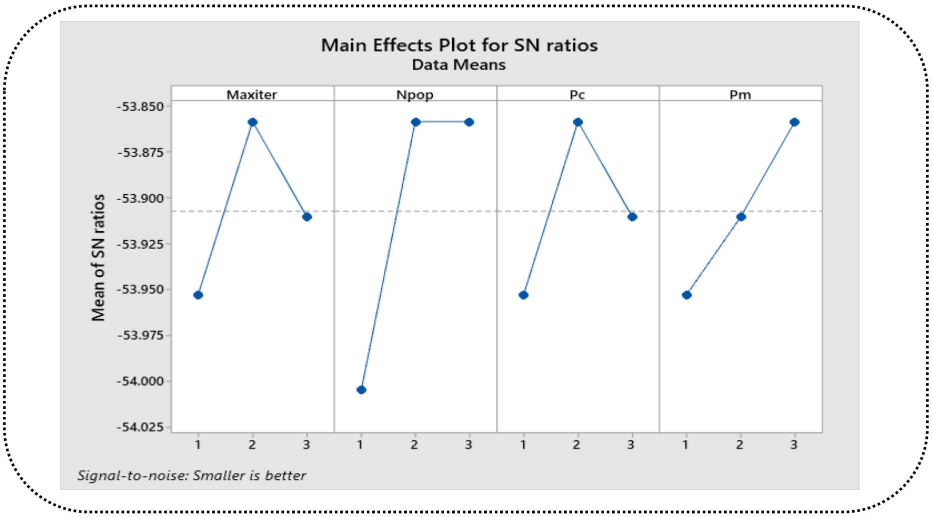

Fig 2. The optimal parameter levels of GA

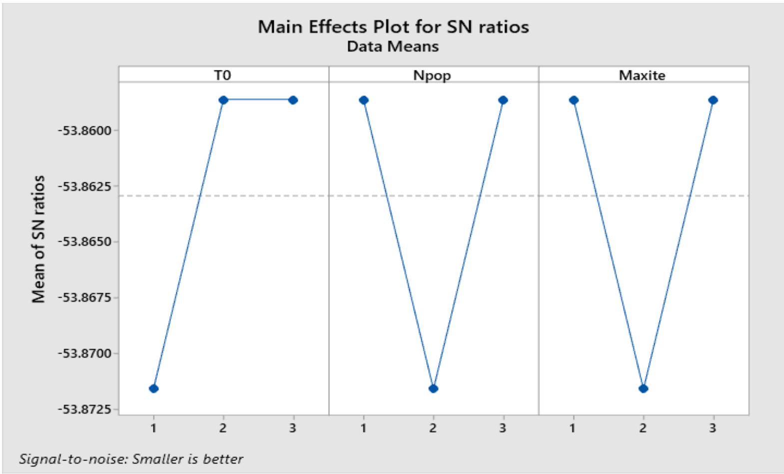

Fig 3. The optimal parameter levels of SA

In the next step, the algorithms are run by setting the input parameters to the optimal calculated levels of Taguchi. Each algorithm is run in 10 replications for each example. The algorithms are compared based on the average objective function and average CPU time in 10 replications. Table V summarizes the results of the algorithms. Furthermore, the variation percentage of SA compared to GA is also reported to provide a better comparison of algorithms.

Table V. performance comparison of metaheuristic algorithms

Example #Number	*Average objective function*		*SA variation percentage*	*Average CPU time (S)*		*SA variation percentage*
	GA	*SA*		*GA*	*SA*	
#S1	495.31	493.10	-0.44%	11.22	5.31	-110.00%
#S2	578.92	578.92	0.00%	11.36	5.69	-110.00%
#S3	39389.00	39389.00	0.00%	11.72	5.29	-110.00%
#S4	45445.00	45445.00	0.00%	8.96	5.29	-37.50%
#M1	4448.60	9914.70	122.00%	22.13	10.28	-54.50%
#M2	12522.00	11859.00	-5.29%	26.99	10.44	-61.50%
#M3	11745.00	9803.40	-16.50%	24.80	10.31	-58.30%
#M4	6582.30	10758.00	63.40%	22.06	10.40	-54.50%
#L1	182630.00	189870.00	4.00%	155.53	61.97	-60.60%
#L2	642360.00	667990.00	4.00%	176.70	61.86	-65.30%
#L3	934910.00	984010.00	5.25%	184.28	62.42	-66.30%
#L4	114040.00	138470.00	21.4%	143.92	62.03	-56.60%

As can be seen, in small-size examples, there is no significant difference between the algorithms in terms of the average objective function. The average objective function of algorithms is very competitive in medium-size examples. In this category, SA obtains better solutions for some examples, and GA calculates better solutions for others. However, the better performance of GA is evident in all large-size examples. As obvious, the average CPU time of SA is less than GA in all 12 examples.

As the last step, a sensitivity analysis is performed to see how the input parameters impact the metaheuristic algorithms' results. The first small example is selected to carry out the sensitivity analysis. The investigated parameters are the holding costs, the supplier's capacity to supply products, the unit purchasing costs, and the fixed ordering costs. We change the value of the parameters in a range from -50% to +50%, and calculate the objective function at each level. The sensitivity analysis results are summarized in Table VI. Also, the results are graphically shown in Figs. (4) to (7).

Table VI. Sensitivity of the output of metaheuristics to the input parameters of the problem

Variation percentage	h_i		C_{is}		P_{is}		A_{is}	
	GA	*SA*	*GA*	*SA*	*GA*	*SA*	*GA*	*SA*
-50%	384.40	385.90	423.80	435.10	461.90	461.90	383.30	384.40
-20%	453.90	455.80	466.70	470.90	486.70	488.60	453.90	453.90
0	493.10	493.10	493.10	493.10	493.10	493.10	493.10	493.10
+20%	528.50	528.50	517.50	517.40	497.20	497.20	528.50	528.50
+50%	574.50	574.50	554.10	556.30	501.30	501.30	574.50	574.50

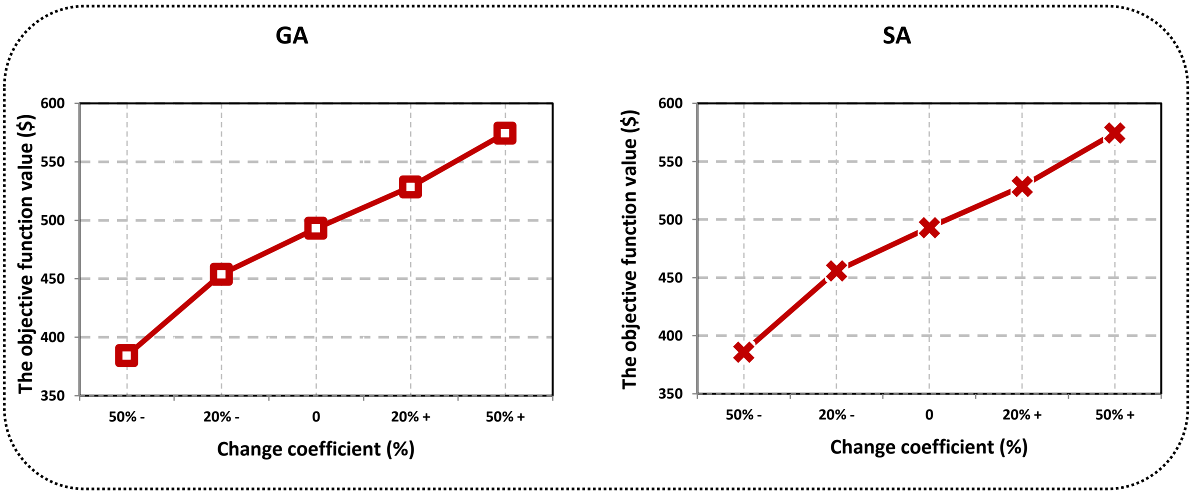

Fig 4. Sensitivity of total cost to change in h_i

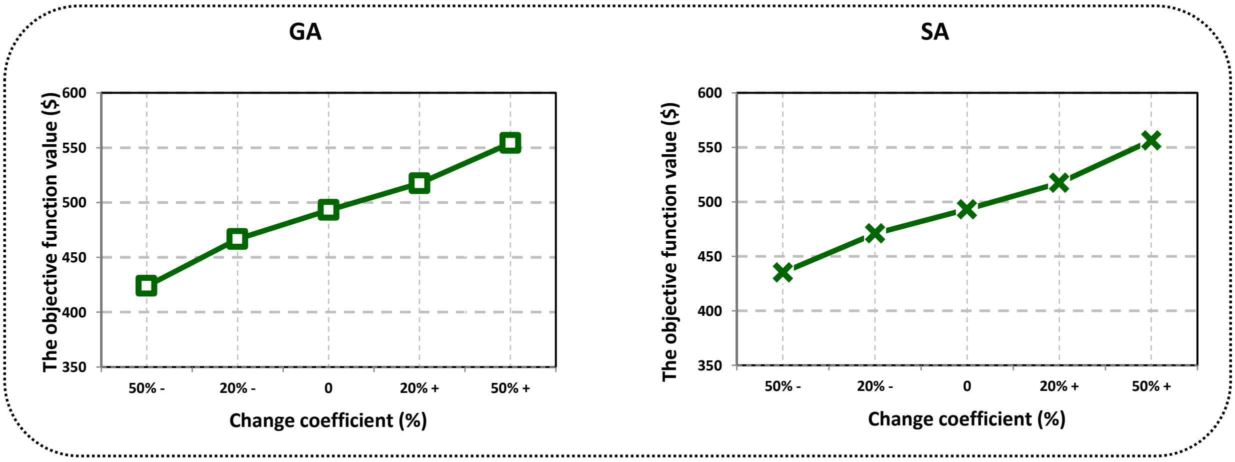

Fig 5. Sensitivity of total cost to change in C_{is}

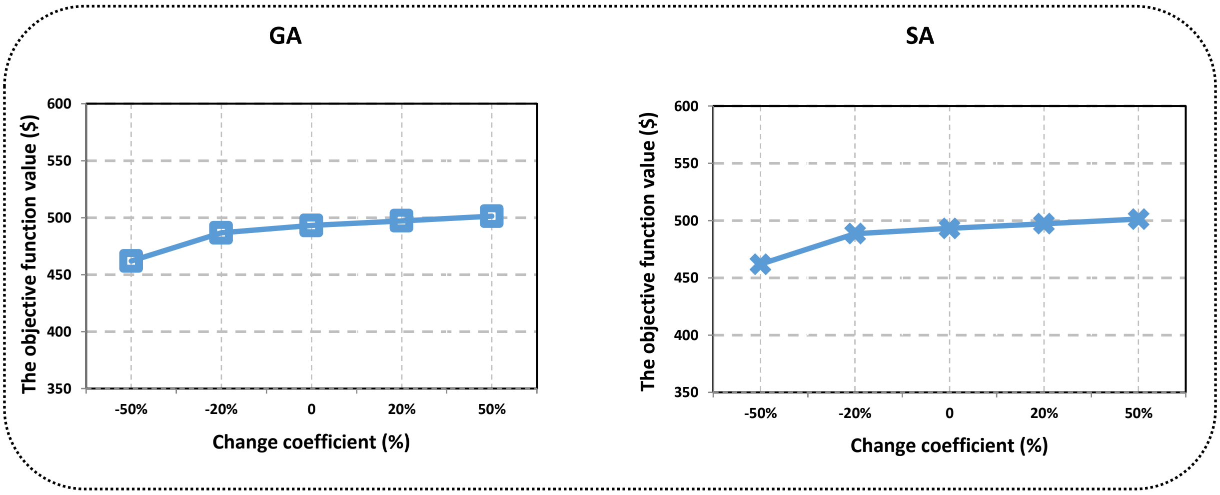

Fig 6. Sensitivity of total cost to change in P_{is}

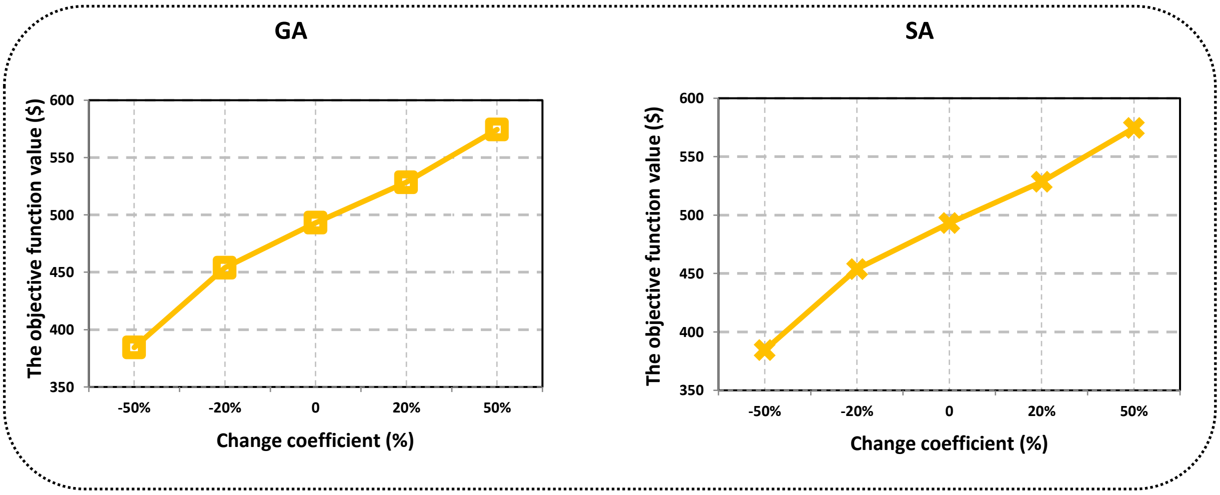

Fig 7. Sensitivity of total cost to change in A_{is}

As can be seen, there is a positive relationship between the increase in parameters and objective functions. In other words, the increasing of parameters causes the increase of objective function for both algorithms. Regarding the results, we can conclude that variation in the holding cost has the highest impact on the system's performance. Conversely, suppliers' capacity impacts the objective functions of algorithms less than the other parameters. Also, the effect of ordering costs is more significant than the purchasing costs on the total cost. To ensure the system's stability, the management should pay enough attention to controlling the holding cost of products. Finally, both algorithms have similar sensitivity to the parameters and show similar behavior to any change to the input parameters of the problem.

VI. CONCLUSION

In this paper, we developed a new multi-product EPQ model to determine optimal decisions on the classification of items, selection of suppliers, and replenishment quantity simultaneously. Also, demand was considered as a stochastic parameter to provide a more realistic problem. A simulation-optimization method was proposed as the solution approach. In this approach, regarding the nonlinearity of the developed mode, GA and SA metaheuristics were utilized to find near-optimal solutions. We considered different combinations of operators for these algorithms and selected the best possible combination based on the computational results. Moreover, the simulation tool was utilized to deal with the uncertainty of demand. The input parameters of metaheuristics were calibrated by Taguchi's design of experiments as a systematic statistical method. The numeral examples were solved in three categories of small, medium, and large-sized examples. The results demonstrated that GA is more powerful in searching solution space, and this algorithm finds solutions with lower objective functions than SA. Nevertheless, SA is more desirable regarding CPU time, and the algorithm requires lower computational resources. Finally, we aimed to provide more insights by analyzing the sensitivity of objective function to change in some parameters of the problem. The holding costs, ordering costs, purchasing costs, and suppliers' capacities were the parameters that were selected for the analysis. The results showed that the presented inventory system is highly sensitive to the holding cost of products. There are several suggestions for the extension of this work by future research. The uncertainty in other parameters of the model, such as the ordering cost or holding cost, can be considered. Researchers can use other methods, such as robust optimization, chance-constraint programming, etc., to address the uncertainty (Amani Bani et al., 2022; Pasandideh et al., 2015a). The model can be reformulated under carbon emission regulations to provide a more sustainable inventory system (Taleizadeh et al., 2018). Finally, some other solution approaches, such as Lagrangian relaxation or branch and price, can also be utilized to solve the problem and compare the results with GA and SA metaheuristics (Amani Bani et al., 2022; Keshavarz et al., 2015).

REFERENCES

Amani Bani, E., Fallahi, A., Varmazyar, M., & Fathi, M. (2022). Designing a sustainable reverse supply chain network for COVID-19 vaccine waste under uncertainty. Computers & Industrial Engineering, 174, 108808.

Asadkhani, J., Fallahi, A., & Mokhtari, H. (2022). A sustainable supply chain under VMI-CS agreement with withdrawal policies for imperfect items. Journal of Cleaner Production, 376, 134098.

Awasthi, A., Chauhan, S., Goyal, S., & Proth, J.-M. (2009). Supplier selection problem for a single manufacturing unit under stochastic demand. International Journal of Production Economics, 117(1), 229-233.

Ayatollahi, S. A., & Jafari, A. (2022). Economic order quantity model for items with imperfect quality and multiple suppliers. Journal of Industrial and Systems Engineering.

Basnet, C., & Leung, J. M. (2005). Inventory lot-sizing with supplier selection. Computers & Operations Research, 32(1), 1-14.

Bilsel, R. U., & Ravindran, A. (2011). A multiobjective chance constrained programming model for supplier selection under uncertainty. Transportation Research Part B: Methodological, 45(8), 1284-1300.

Burke, G. J., Carrillo, J. E., & Vakharia, A. J. (2009). Sourcing decisions with stochastic supplier reliability and stochastic demand. Production and operations management, 18(4), 475-484.

Chen, J.-X. (2011). Peer-estimation for multiple criteria ABC inventory classification. Computers & Operations Research, 38(12), 1784-1791.

Chen, X., Benjaafar, S., & Elomri, A. (2013). The carbon-constrained EOQ. Operations Research Letters, 41(2), 172-179.

Cheraghalikhani, A., Khoshalhan, F., & Mokhtari, H. (2019). Aggregate production planning: A literature review and future research directions. International Journal of Industrial Engineering Computations, 10(2), 309-330.

Cherif, H., & Ladhari, T. (2016). A novel multi-criteria inventory classification approach: artificial bee colony algorithm with VIKOR method. Paper presented at the International Symposium on Computer and Information Sciences.

Cherif, H., & Ladhari, T. (2017). Multiple criteria inventory classification approach based on differential evolution and electre iii. Paper presented at the Proceedings of the 16th International Conference on Hybrid Intelligent Systems (HIS 2016).

Chu, C.-W., Liang, G.-S., & Liao, C.-T. (2008). Controlling inventory by combining ABC analysis and fuzzy classification. Computers & Industrial Engineering, 55(4), 841-851.

Cook, W. D., Kress, M., & Seiford, L. M. (1996). Data envelopment analysis in the presence of both quantitative and qualitative factors. Journal of the operational research society, 47(7), 945-953.

Dobos, I., & Vörösmarty, G. (2019). Inventory-related costs in green supplier selection problems with Data Envelopment Analysis (DEA). International Journal of Production Economics, 209, 374-380.

Fallahi, A., Amani Bani, E., & Niaki, S. T. A. (2022a). A constrained multi-item EOQ inventory model for reusable items: Reinforcement learning-based differential evolution and particle swarm optimization. Expert Systems with Applications, 207, 118018.

Fallahi, A., Azimi-Dastgerdi, M., & Mokhtari, H. (2021a). A sustainable production-inventory model joint with preventive maintenance and multiple shipments for imperfect quality items. Scientia Iranica.

Fallahi, A., Mahnam, M., & Niaki, S. T. A. (2022b). Direct aperture optimization for intensity modulated radiation therapy: Two calibrated metaheuristics and liver cancer case study. International Journal of Industrial Engineering and Production Research, 33(2), 1-14.

Fallahi, A., Mahnam, M., & Niaki, S. T. A. (2022c). A discrete differential evolution with local search particle swarm optimization to direct angle and aperture optimization in IMRT treatment planning problem. Applied Soft Computing, 131, 109798.

Fallahi, A., Mokhtari, H., & Niaki, S. T. A. (2021b). Designing a closed-loop blood supply chain network considering transportation flow and quality aspects. Sustainable operations and computers, 2, 170-189.

Fallahi, A., Mousavian Anaraki, S. A., Mokhtari, H., & Niaki, S. T. A. (2022d). Blood plasma supply chain planning to respond COVID-19 pandemic: a case study. Environment, Development and Sustainability, 1-52.

Ghodsypour, S. H., & O'Brien, C. (1998). A decision support system for supplier selection using an integrated analytic hierarchy process and linear programming. International journal of production economics, 56, 199-212.

Hadi-Vencheh, A. (2010). An improvement to multiple criteria ABC inventory classification. European Journal of Operational Research, 201(3), 962-965.

Hadi-Vencheh, A., & Mohamadghasemi, A. (2011). A fuzzy AHP-DEA approach for multiple criteria ABC inventory classification. Expert Systems with Applications, 38(4), 3346-3352.

Harris, F. W. (1990). How many parts to make at once. Operations research, 38(6), 947-950.

Holland, J. H. (1992). Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence: MIT press.

Kaabi, H., Jabeur, K., & Enneifar, L. (2015). Learning criteria weights with TOPSIS method and continuous VNS for multi-criteria inventory classification. Electronic Notes in Discrete Mathematics, 47, 197-204.

Keshavarz-Ghorbani, F., & Pasandideh, S. H. R. (2022). A bi-objective non-linear approach for determining the ordering strategy for group B in ABC analysis inventory. Journal of Optimization in Industrial Engineering, 15(1), 79-92.

Keshavarz, T., Salmasi, N., & Varmazyar, M. (2015). Minimizing total completion time in the flexible flowshop sequence-dependent group scheduling problem. Annals of Operations Research, 226(1), 351-377.

Khalilpourazari, S., & Pasandideh, S. H. R. (2019). Modeling and optimization of multi-item multi-constrained EOQ model for growing items. Knowledge-Based Systems, 164, 150-162.

Kirkpatrick, S., Gelatt Jr, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. science, 220(4598), 671-680.

Lamba, K., Singh, S. P., & Mishra, N. (2019). Integrated decisions for supplier selection and lot-sizing considering different carbon emission regulations in Big Data environment. Computers & Industrial Engineering, 128, 1052-1062.

Li, L., & Zabinsky, Z. B. (2011). Incorporating uncertainty into a supplier selection problem. International Journal of Production Economics, 134(2), 344-356.

Liao, Z., & Rittscher, J. (2007). A multi-objective supplier selection model under stochastic demand conditions. International Journal of Production Economics, 105(1), 150-159.

Memon, M. S., Lee, Y. H., & Mari, S. I. (2015). Group multi-criteria supplier selection using combined grey systems theory and uncertainty theory. Expert Systems with Applications, 42(21), 7951-7959.

Mohammaditabar, D., Ghodsypour, S. H., & O'Brien, C. (2012). Inventory control system design by integrating inventory classification and policy selection. International Journal of Production Economics, 140(2), 655-659.

Mokhtari, H., & Hasani, A. (2017). A multi-objective model for cleaner production-transportation planning in manufacturing plants via fuzzy goal programming. Journal of Manufacturing Systems, 44, 230-242.

Mokhtari, H., Hasani, A., & Fallahi, A. (2021). Multi-product constrained economic production quantity models for imperfect quality items with rework. International Journal of Industrial Engineering & Production Research, 32(2), 0-0.

Mokhtari, H., Salmasnia, A., & Fallahi, A. (2022). Economic Production Quantity Under Possible Substitution: A Scenario Analysis Approach. International Journal of Industrial Engineering, 33(1), 1-17.

Mousavi, S. M., Sadeghi, J., Niaki, S. T. A., & Tavana, M. (2016). A bi-objective inventory optimization model under inflation and discount using tuned Pareto-based algorithms: NSGA-II, NRGA, and MOPSO. Applied soft computing, 43, 57-72.

Ng, W. L. (2007). A simple classifier for multiple criteria ABC analysis. European Journal of Operational Research, 177(1), 344-353.

Park, J., Bae, H., & Bae, J. (2014). Cross-evaluation-based weighted linear optimization for multi-criteria ABC inventory classification. Computers & Industrial Engineering, 76, 40-48.

Pasandideh, S. H. R., Niaki, S. T. A., & Gharaei, A. (2015a). Optimization of a multiproduct economic production quantity problem with stochastic constraints using sequential quadratic programming. Knowledge-Based Systems, 84, 98-107.

Pasandideh, S. H. R., Niaki, S. T. A., & Nia, A. R. (2011). A genetic algorithm for vendor managed inventory control system of multi-product multi-constraint economic order quantity model. Expert Systems with Applications, 38(3), 2708-2716.

Pasandideh, S. H. R., Niaki, S. T. A., Nobil, A. H., & Cárdenas-Barrón, L. E. (2015b). A multiproduct single machine economic production quantity model for an imperfect production system under warehouse construction cost. International Journal of Production Economics, 169, 203-214.

Pasandideh, S. H. R., Niaki, S. T. A., & Sharafzadeh, S. (2013). Optimizing a bi-objective multi-product EPQ model with defective items, rework and limited orders: NSGA-II and MOPSO algorithms. Journal of Manufacturing Systems, 32(4), 764-770.

Ramanathan, R. (2006). ABC inventory classification with multiple-criteria using weighted linear optimization. Computers & operations research, 33(3), 695-700.

Razavi Hajiagha, S. H., Daneshvar, M., & Antucheviciene, J. (2021). A hybrid fuzzy-stochastic multi-criteria ABC inventory classification using possibilistic chance-constrained programming. Soft Computing, 25(2), 1065-1083.

Rezaei, J., & Davoodi, M. (2008). A deterministic, multi-item inventory model with supplier selection and imperfect quality. Applied Mathematical Modelling, 32(10), 2106-2116.

Rezaei, J., & Salimi, N. (2015). Optimal ABC inventory classification using interval programming. International Journal of Systems Science, 46(11), 1944-1952.

Rezvan, M. T., Gholami, H., & Zakerian, R. (2021). A new algorithm for solving the parallel machine scheduling problem to maximize benefit and the number of jobs processed. Journal of Quality Engineering and Production Optimization, 6(2), 115-142.

Sadeghi, A. H., Bani, E. A., & Fallahi, A. (2023a). Grey Wolf Optimizer and Whale Optimization Algorithm for Stochastic Inventory Management of Reusable Products in a two-level Supply Chain. arXiv preprint arXiv:2302.05796.

Sadeghi, A. H., Sun, Z., Fakhrabad, A. S., Arzani, H., & Handfield, R. B. (2023b). A Mixed-integer Linear Formulation for Dynamic Modified Stochastic p-Median Problem in a Competitive Supply Chain Network Design. arXiv preprint arXiv:2301.11502.

Sadeghi, H. (2019). A forecasting system by considering product reliability, POQ policy, and periodic demand. Journal of Quality Engineering and Production Optimization, 4(2), 133-148.

Sadeghi, H., Mahmoodi, A., Bashiri, B., & Golbaghi, M. (2022). An EPQ model for deteriorating products with delayed payments and shortage. Journal of Quality Engineering and Production Optimization, 7(1), 160-176.

Sadeghi, J., Niaki, S. T. A., Malekian, M. R., & Sadeghi, S. (2016). Optimising multi-item economic production quantity model with trapezoidal fuzzy demand and backordering: two tuned meta-heuristics. European Journal of Industrial Engineering, 10(2), 170-195.

Sahebi-Fakhrabad, A., Sadeghi, A. H., & Handfield, R. (2023). Evaluating State-Level Prescription Drug Monitoring Program (PDMP) and Pill Mill Effects on Opioid Consumption in Pharmaceutical Supply Chain. Paper presented at the Healthcare.

Salameh, M. K., & Jaber, M. Y. (2000). Economic production quantity model for items with imperfect quality. International journal of production economics, 64(1-3), 59-64.

Sana, S. S. (2015). An EOQ model for stochastic demand for limited capacity of own warehouse. Annals of Operations Research, 233(1), 383-399.

Scott, J., Ho, W., Dey, P. K., & Talluri, S. (2015). A decision support system for supplier selection and order allocation in stochastic, multi-stakeholder and multi-criteria environments. International Journal of Production Economics, 166, 226-237.

Taft, E. (1918). The most economical production lot. Iron Age, 101(18), 1410-1412.

Taheri-Tolgari, J., & Mirzazadeh, A. (2019). Determining Economic Order Quantity (EOQ) with Increase in a Known Price under Uncertainty through Parametric Non-Linear Programming Approach. Journal of Quality Engineering and Production Optimization, 4(1), 197-219.

Taleizadeh, A. A. (2014). An EOQ model with partial backordering and advance payments for an evaporating item. International Journal of Production Economics, 155, 185-193.

Taleizadeh, A. A., Soleymanfar, V. R., & Govindan, K. (2018). Sustainable economic production quantity models for inventory systems with shortage. Journal of cleaner production, 174, 1011-1020.

Torabi, S. A., Hatefi, S. M., & Pay, B. S. (2012). ABC inventory classification in the presence of both quantitative and qualitative criteria. Computers & Industrial Engineering, 63(2), 530-537.

Varmazyar, M., Akhavan-Tabatabaei, R., Salmasi, N., & Modarres, M. (2020). Operating room scheduling problem under uncertainty: Application of continuous phase-type distributions. IISE Transactions, 52(2), 216-235.

Varmazyar, M., & Salmasi, N. (2012). Sequence-dependent flow shop scheduling problem minimising the number of tardy jobs. International Journal of Production Research, 50(20), 5843-5858.

Zhang, J.-l., & Zhang, M.-y. (2011). Supplier selection and purchase problem with fixed cost and constrained order quantities under stochastic demand. International Journal of Production Economics, 129(1), 1-7.

Zhou, P., & Fan, L. (2007). A note on multi-criteria ABC inventory classification using weighted linear optimization. European journal of operational research, 182(3), 1488-1491.