Metaheuristics for a bi-objective green vendor managed inventory problem in a two-echelon supply chain network

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Abstract

Generally, finding an alternative solution for reducing fossil fuel consumption and green emissions of supply chain networks can shift the Vendor Managed Inventory (VMI) to the Green VMI (GVMI). Our literature search also confirms that the issue of environmental pollution and green emissions, is still scarce and required to be explored. This motivates our attempt to offer the issue of green backorder for the VMI in a two-echelon supply chain network among the first studies. To this end, a bi-objective non-linear optimization model with the goal of maximizing the profit of inventory and minimizing the carbon emissions of transportation, simultaneously, is developed. Another contribution of this work is to propose three capable metaheuristics to solve it optimality in large-scale samples. In this regard, the Non-dominated Sorting Genetic Algorithm (NSGA-II) as a well-known method as well as Multi-Objective of Keshtel Algorithm (MOKA) and Multi-Objective of Red Deer Algorithm (MORDA) as two recent nature-inspired algorithms are firstly applied. The outputs confirm that the allowed shortage situation along with the lack of cost reduction shows a greater amount of shipping and orders based on sensitivities. With regards to the comparison among algorithms, the performance of MORDA is highly better than MOKA and NSGA-II.

Keywords: Vendor managed inventory; Green emissions; two-echelon supply chain; Multi-Objective of Red Deer Algorithm

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1. Introduction

Academically, the supply chain is defined as a transformation system of row materials, transportation of products and purchasing between different types of levels from suppliers to customers [1-5]. Nowadays, the actual implementation of sustainability practices within the physical objects to the supply chain network throughout the world is unsustainable economically and environmentally [6-8]. The sustainable development and sustainability issues are active research topics in today's economic activities [9], needing coordinated supply chain networks, enforces the decision-makers to focus on the environmental parameters based on the lines of sustainability [10-12]. Based on this challenge, this study focuses on a two-echelon supply chain network between a supplier (vendor) and some retailers as buyers by contributing the environmental pollution to the problem in addition to the total cost [10, 13-14].

The Vendor Managed Inventory (VMI) has been studied by several researchers with the goal of decreasing the total cost which can increase the performance of the supply chain [15]. Based on the concepts of VMI, the time and amount of replenishments are determined by a vendor who has accessed to purchase input information and demand data [16]. In such systems, most of the inventory holding common costs are transferred from the vendors to the retailers [17]. With shifting the inventory management to the VMI management, vendors will be able to coordinate decisions on the inventory control and production [18]. If this VMI system is designed well, it can decrease both the inventory status and the system integrity with reducing the total cost [19].

The advantages and merits of using this VMI system have been realized and implemented by many retailers and suppliers [20]. This VMI shares the information pertaining to the points of sale and inventory with the other members of a supply chain network in order to decrease the bullwhip effect and to improve the supply chain efficiency [21]. The VMI also shows the cooperation between a supplier (vendor) and a retailer in the supply chain network to make responsiveness and efficiency [13-15]. In this regard, this VMI is an elastic replenishment system enabling a vendor to respond to real demands quickly. Therefore, it helps a vendor with the appropriate inventory levels of each product to adopt the proper approach to control these levels [22].

Another advantage of the VMI system is that by using this strategy, the retailers are exempt from all or a part of the inventory costs. On the other hand, the vendors can improve their production and transportation plans significantly by having an access to demands made by the final customers of a supply chain network. Therefore, the inventory turnover and customer service level will be improved at each stage of the supply chain [17]. Although the profits of vendors are variable, the VMI has always provided retailers with more profits. Taken together, this VMI reduces the general costs of a supply chain network. However, the purchase under certain conditions between a retailer and a vendor is so significant [14-15]. In the long term, the vendor profit is more likely to increase in comparison with in the short term [23].

Having a conclusion about the aforementioned characteristics of the proposed VMI, this study also contributes to the green backorder of this system called as green VMI (GVMI) and reduces the environmental pollution of the transportation in a two-echelon supply chain network. In this regard, the main contributions of this paper can be outlined as followed:

- ✓ A new bi-objective green vendor managed inventory model is developed.
- ✓ The model is solved the small sizes by the ε-constraint method and compared the results with the literature.
- ✓ Three multi-objective metaheuristic techniques, i.e., Non-dominated Sorting Genetic Algorithm (NSGA-II), Multi-Objective of Keshtel Algorithm (MOKA), Multi-Objective of Red Deer Algorithm (MORDA) are utilized to solve the large scale samples.
- ✓ To improve the performance of the metaheuristics, a well-known calibration method so-called, Response Surface Method (RSM), is employed.
- ✓ Considering three assessment metrics for the quality of Pareto optimal solutions and computational time for metaheuristics.
- ✓ Based on a comparative study, MORDA shows a better performance in practice.

The rest of the paper can be organized as follows. In Section 2, a relevant literature about the related papers formulating and solving the VMI concepts, is collected. The green VMI model is formulated for a two-echelon supply chain network in Section 3. Since this model is NP-*hard* [24]; [17], the ε-constraint method and also three old and recent metaheuristics for multi-objective programming, are presented in Section 4. In Section 5, the ε-constraint method is used to solve the model for one vendor and several retailers as small sizes with some analyses on the different values of shortages. Then, in Section 6, the problem in large-scale samples is optimized by three metaheuristic algorithms. In this regard, adjusting the used algorithms' parameters is selected by Response Surface Method (RSM) and three assessment metrics are utilized to compare the methods. Finally, the conclusion and suggestions are presented in Section 7.

2. Literature review

The inventory management concepts have been mathematically modeled and solved in various papers. The use of the mathematical models called as operations research in the VMI was firstly introduced by Dong and Xu [23] in 2002. They presented a mathematical model to compare the traditional system with the VMI considering constant demands, no shortages and certain delivery times in their work. They conducted investigations in both short and long terms when the inventory costs of retailers and vendors were lower after implementing the new system in comparison to the traditional system. In 2007, Yao *et al*. [20] used the same assumptions as proposed by [23]. They also assumed that the number of orders made by a vendor was the correct product of the number of orders made by a retailer. Then, they compared the traditional system of supply chain with the VMI system. In another research, Nachiappan and Jawahar [25] used a Genetic Algorithm (GA) to solve the VMI model under infinite or unauthorized backorder cost conditions by considering only one vendor with three retailers. Later, Sadeghi *et al.* [26] introduced a mathematical model for the VMI considering one vendor and several retailers for two purposes. In their model, the rate of retailer demands was certain with some constraints including total budget, vendor total replenishment frequency, required space, and inventory mean. Therefore, they aimed to determine the size of order and replenishment sequence. It is also meant to ascertain the optimal trip from retailers to vendors and the optimal number of machines used for production in order to minimize costs and maximize reliability. Since this was an NP-*hard* problem, NSGA-II was the employed algorithm to solve the model. Then, it was compared with multi-objective of simulated annealing algorithm. In 2010, Wang *et al.*, [10] commented on Yao *et al*. [20] to show the conflict of buyer's order in their conclusion.

Furthermore, in the paper proposed by Nia *et al.* [27], a multi-commodity VMI model was introduced. They used the optimal Economic Order Quantity (EOQ) model. They also added the cost of the carbon tax with a green approach. Then, they considered the warehouse capacity, delivery constraints, order boundaries, and constraints on the number of pallets by signing this VMI contract between vendors and retailers. Finally, they presented a hybrid of GA and Imperialist Competitive Algorithm (ICA) to solve the model. They validated the model by comparing the proposed algorithm with the general ideas. In addition, a low boundary was obtained for the model by freeing constraints continuously. Similarly, Park *et al.* [28] used the machine learning and GA to simulate the appropriate values of variables in a VMI system and vendors profit may model with a Design of Experiments (DOE) approach. In addition, Lee *et al.* [29] were presented a model by sharing inventory shortage cost between suppliers and customers with VMI and using the EOQ model considering the justifiability of shortage and shortage cost imposed on vendors facing limited warehouse storage. In their paper, the abovementioned model was compared with four scenarios: a traditional system; an integrated system; a VMI model by sharing inventory shortage cost and the last VMI model with constant movement cost and shared inventory shortage cost by using an EOQ model with limited capacity. As shown in their work, this model decreases system costs by designing an appropriate contract. Then it was compared with an integrated system. They also showed that a VMI could bring coordination to the supply chain network with constant movement cost and shared inventory shortage cost. In another research, Khan *et al.* [30] presented a VMI model with a single commodity during a two-stage supply chain network considering the incomplete quality of products. The commodity is owned by the vendor; however, it is kept in the retailer's warehouses which should be managed by the retailer. In this policy, the retailer's investment is not entangled with the inventory. Therefore, the retailer is ensured to be available like a constant customer, and the vendor is always available, too. Moreover, the movement time and the quantity of inventory are ensured between vendors and retailers.

Developing VMI models for the supply chain network design problem is an active topic in the last decade [2, 5, 6, 12]. In this case, Pasandideh *et al.* [31] presented a VMI model for a two-echelon supply chain network between a vendor and a retailer with a multi-product supposition. The aim of their model was to determine the quantity of orders and maximal inventory level of backlogs to minimize inventory costs. In their study, the warehouse capacity was supplied, and the number of orders which is sent by retailers, were limited. They used GA to address their model. Later in 2014, Diabat [24] introduced a VMI model for the two-echelon supply chain of a vendor and some retailers in a way that the product price was considered to be linearly and decreasingly dependent of demands. In his model, profit was regarded as the income of sales minus the costs of production and distribution (depending on the product stream and the costs of product transfer) and the costs of ordering and replenishment. Moreover, there are minimal and maximal transfers in his model in which vendors have limited capacities. Using the hybrid of GA and Simulated Annealing (SA), he solved his model to achieve the best solutions and compared it with the main algorithms. In another VMI solving by metaheuristics, Nia *et al.* [32] considered a VMI model with one retailer, one vendor, and several products in a fuzzy environment. In their model, shortage was allowed, and there were some constraints on the warehouse capacity, delivery, orders, and the number of pallets. Also, the warehouse capacity and quantity of orders were considered as fuzzy logic. They used an Ant Colony Optimization (ACO) to solve their model. They also provided a comparative study between ACO and different versions of evolutionary algorithms based on GAs. In another research, Hariga *et al.* [33] studied a VMI model with the supposition of a storage contract in a way that it was allowed to send retailers products non-consecutively and to consider the storage constraints. Their developed model also calculates extra costs of storage for the retailers. They proposed an exact solution solver by GAMS software. They also introduced an efficient method to obtain a nearly optimal solution for delivery scheduling. The results indicated that considerable savings were made in the presence of VMI when products were sent to retailers consecutively and equally. Following, Taleizadeh *et al*. [34] presented a bi-level programming model for the VMI in which one vendor and some retailers in a noncompetitive environment with the perishability rate of raw materials and final products. In the market, demands for final products are considered fixed. The aim of the retailer model is to optimize the replenishment sequence of raw materials, replenishment cycle of products, and production rate in a way that the total profit of supply chain network can be maximized. In their model, they used the game theory with the *Stackelberg* game. They regarded a vendor as a leader, whereas retailers were regarded as followers in this case.

Later in 2017, Kaasgari *et al.* [17] developed a VMI model for perishable products by considering a discount depend on the product lifetime. In order to address their model, they utilized two well-known methods, i.e., GA and Particle Swarm Optimization (PSO) were employed in their study. In 2018, Beklari et al., [35] proposed a VMI with the goal of maximizing inventory turnover in producer warehouse. Their main innovation was to employ a hybrid algorithm based on GA and PSO to solve their proposed problem.

Recently in 2019, Weraikat et al., [11] developed a VMI system to minimize the quantity of the expired products. The application of the model was tested in a pharmaceutical supply chain using a real case study. They solved the model with a Monte-Carlo simulation algorithm. They confirmed the role of safety stock to improve the pharmaceutical supply chain performance.

Safaeian et al., [36] also considered a multi-objective optimization model for a two-echelon supply chain network with several suppliers and retailers. They applied the NSGA-II to find an interaction between four goals including the total cost, quality and price of products and satisfaction levels. More recently, Dai et al., [37] proposed a VMI for perishable products by considering the stock and price which is dependent from demand. They solved it via the exact method and provided some sensitivity on the price and stock from different cases.

To have a quick review based on aforementioned works, they may be divided into three classifications. Most of them are focusing on developing novel optimization models. A group of recent works mainly tries to offer new algorithms to better solve the VMI problem. At the last, a few of them are working on improving both research classifications. This study by proposing a green VMI (GVMI) for a two-echelon supply chain network and solving it by three metaheuristics, provides new contributions in the literature.

Generally, there are several methods and elements for formulating a VMI problem. These factors not only make the VMI more practical but also increases its complexity and computational cost. These facts confirm that we need an efficient algorithm when the problem is more complex than its general version to find an optimal solution. With regards to a No Free Lunch (NFL) theory [38], no metaheuristic is able to solve all optimization problems in the best performance. Therefore, a new method may be outperform existing algorithms for a particular problem like the proposed GVMI [2, 4, 5, 9, 10]. To alleviate these limitations, this study applies two recent metaheuristics i.e., MOKA and MORDA for the first time in the literature.

In conclusion, this study not only uses the NSGA-II to solve the model but also two recent algorithms for the term of multi-objective programming is developed as MOKA and MORDA. To the best of our knowledge and aforementioned papers in the literature, the related papers paid little attention to the environment effects and green emissions in the logistics of the VMI problem. In this regard, this study offers the concept of Green Vendor Managed Inventory (GVMI) as the main contribution of this paper. In addition, this study is taken from the papers by [24] and [27] in a way that storage limits and the quantity of orders were considered along with shortage costs.

3. Problem description and model formulation

This study establishes the GVMI model for a two-echelon supply chain network. The green emissions or environment effects are studied to reduce the amount of pollution in this work by considering the customer facing to shortages of storage and the number of orders. In the developed model, the first objective aims to maximize the benefits of selling the products mines to the cost of manufacturing, distributing and inventory for the case of lack of penalties. The second objective is to determine the minimizing the green emission of transportation activities for the products. Notably, the main innovation of the proposed model is to consider a new objective function to control the green emissions as the second objective function. From Figure 1, the graphical of GVMI model is shown. In this figure, there is only one vendor with some retailers in which the shipping from vendor to retailers is identified. The costs are complied with the vendor's demand.

Figure 1. GVMI model with one vendor and some retailers

To state the developed model, the assumptions based on the related papers [24]; [27] are summarized as follows:

- ✓ There are existed expenditures by the state of facing with a shortage on penalties for the vendor.
- ✓ There is a limitation for stock by retailers.
- ✓ The number of ordering for the vendor is predefined.
- ✓ The volume of products for sending from vendor to retailers is limited by a maximum and minimum amount.
- ✓ The relationship between the price of vendor and retailer is linear and reduction.

The notations of the developed model are introduced as follows:

Indices:

j Index of retailers ($j=1,...,n$)

Parameters:

a_j The initial price of product due to the demand of retailer j

k_j Reduction slope of price due to the demand of retailer j

$y_{j\min}$ A lower bound for the amount of shipped products to retailer j

$y_{j\max}$ A upper bound for the amount of shipped products to retailer j

δ	Per unit of manufacturing cost
θ_j	The cost of flow of products from vendor to retailer *j*
v_j	Indirect cost of shipping products to retailer *j*
β_j	Amount of green emissions for each unit of shipment to retailer *j*
H_{bj}	Maintenance service for retailer *j*
π_{bj}	The cost of shortages for retailer *j*
S_{bj}	The cost of ordering for retailer *j*
S_s	The cost of ordering for vendor
H_s	Maintenance service for vendor
TIC_j	The total cost of maintenance service from vendor to retailer *j*
C	The capacity of vendor for manufacturing and shipment of products
f	Space for per unit of products
F_j	Space capacity of retailer *j*
CC	Transport capacity for products between vendor and retailers
N	The maximum number of received orders from retailers

Variables:

y_j	The volume of submitted products from vendor to retailer *j*
Q_j	Amount of ordering from retailer *j*
b	Amount of shortages from vendor
$Z_1(y_j)$	The first objective function to maximize the profit of system
$Z_2(y_j)$	The second objective function to minimize the green emissions of system

In this research, a vendor with some retailers is existed in which the vendor has a convention with each retailer (y_j) according to the volume of received products. In addition, retailers have a specified value for selling products. Following formulas are stated according to the related articles [24]; [27] in which the relationship between the price of vendor and demand of retailer is linear and reduction.

$$P(y_j) = a_j - k_j y_j \qquad \forall j \tag{1}$$

$$y_{jmin} \le y_j \le y_{jmax} \qquad \forall j \tag{2}$$

As can be seen, the products have the initial price a_j and slope of k_j according to the volume of received products. The function is $P(y_j)$ as shown in Equation (1). Accordingly, the mathematical formulation for the developed GVMI problem is stated as follows:

$$Max\,Z_1\left(y_j\right)=\sum_{j=1}^{n}\left\{a_j y_j - k_j y_j^2 - \delta y_j - v_j\theta_j y_j^2 - TIC_j\right\} \tag{3}$$

$$MinZ_2\left(y_j\right)=\sum_{j=1}^{n}\beta_j\left[\frac{y_j}{CC}\right] \tag{4}$$

St:

$$TIC_j=\frac{\left(S_s+S_{bj}\right)y_j}{Q_j^*}+\frac{\left(H_s+H_{bj}\right)b^{*2}}{2Q_j^*}+\pi_{bj}\left(Q_j^*-b^*\right)^2/2Q_j^* \tag{5}$$

$$Q_j^*=\left(\frac{2\left(S_s+S_{bj}\right)y_j}{H_s+H_{bj}}\right)^{1/2}\times\left(\frac{H_s+H_{bj}+\pi_{bj}}{\pi_{bj}}\right)^{1/2} \tag{6}$$

$$b^*=\frac{Q_j^*\pi_{bj}}{H_s+H_{bj}+\pi_{bj}} \tag{7}$$

$$\sum_{j=1}^{n}y_j\le C \tag{8}$$

$$fy_j\le F_j \tag{9}$$

$$\sum_{j=1}^{n}\frac{y_j}{Q_j^*}\le N \tag{10}$$

$$y_{jmin}\le y_j\le y_{jmax} \tag{11}$$

$$y_j\ge 0 \tag{12}$$

In this study, two objective functions are considered for the developed GVMI model. Equation (3) represents the maximum profit of the proposed network which includes selling products minus manufacturing cost, distribution cost and controlling the inventory in the case of fines shortages. The second objective function in Equation (4) aims to minimize the green emissions for transportation's system in term of shipment of products. The constraints of developed model are scrutinized from equation (5) to (12). Equation (5) states the cost of inventory in the case of fines shortages. Equation (6) explores the amount of economic ordering in the term of allowing the shortages. In addition, equation (7) explains the optimal amount of shortage. Moreover, the equation (8) shows the maximum capacity of vendor to retailers. In equation (9), the capacity of retailers to represent the maximum amount of selling products is to specify. Equation (10) shows the maximum number of received orders from retailers. In equation (11), the lower and upper bound for volume of submitted products from vendor to retailers. At the end, the continuous variables are guaranteed in equation (12).

According to the mentioned formulas, it should be noted, the manufacturing cost involves the manufacturing cost per unit product δ and submitted products y_j. In addition, the distribution cost equals the cost of products flow from vendor to retailer j ($\theta_j y_j$) multiplied by the cost of shipment products equals to $v_j y_j$. In this content, v_j is the indirect cost of shipping products such as administrative costs which is valued by 0.5 according to the related study [24]. In addition, TIC_j is the summation of maintenance and inventory costs which is related to inventory control model and shortages cost. Finally, the amount of optimized order is computed by Q_j^* and the amount of shortage is optimized to reduce the costs by b^*.

4. Solution approach

In this paper, an exact approach namely, ε-constraint method is utilized to solve the small sizes and validation of the developed GVMI model. In the term of exact solution approach, the literature shows when the size of problem increases, the time consumption for the large scale samples is so much. According to NFL, it is always possibility that a new algorithm reaches a better solution for current and new problems. So, this study presents three efficient approaches in metaheuristics. As the offered model is a multi-objective programming model, the structure of metaheuristics is changed [2]. In this case, for per iteration, the population of solutions is divided into some fronts. Each front consists of a set of solutions which are not dominated to other solution in this front. In this case, a solution is dominated to other solution, if it has a better value for all objective functions [5]. The details about the encoding plan of metaheuristics are illustrated as follows.

4.1. Encoding plan

To use of metaheuristic, a representation plan is necessary to encode the model for the search phases in metaheuristic. The encoding plan is also revealed that how the constraints of introduced mathematical model would be handled by metaheuristics. In this study, a two-stage technique, namely, Random-Key (RK) is utilized as illustrated in Figure 2. In the related articles, scholars have studied and employed this technique to encode the metaheuristics in a mathematical model [2, 5, 39-40]. The main reason of using this encoding strategy is to have less computational time with no repairing of the solutions' feasibility to encode the problem through a two-stage plan, comprehensively [40-42]. The first stage is to generate a set of random numbers due to continuous search space of the metaheuristics. After that this solution would be converted to a feasible discrete solution by a procedure [41-42]. In our encoding plan, as shown in Figure 2, at first, a matrix with |*n*| elements obtained by uniform distribution U (0, 1) is made. After, according to each element of this array, following formula is considered:

$$y_j^{'} = y_j \times \left(y_{jmax} - y_{jmin} \right) + y_{jmin} \tag{13}$$

Where $y_{j\max}$ and $y_{j\min}$ are defined as the upper and lower bound of the amount of shipped products to retailer *j*, respectively, as mentioned in Section 3. y_j is the unfeasible array, vice versa, $y_j^{'}$ is the feasible array to use in the objective functions. In this regard, metaheuristics search the feasible space by using these two steps. In Figure 2, $y_{j\max}$ and $y_{j\min}$ are estimated as 20 and 80, respectively, for this example.

Figure 2. The proposed RK utilizing in this paper

4.2. NSGA-II

The Genetic Algorithm (GA) proposed by Holland [43] is a well-known metaheuristic to solve the complex and non-linear optimization problems. The GA inspired by genetic science is a basis evolutionary algorithm which utilizes two various operators: crossover and mutation. Besides, exploration and exploitation are two main search phases for any metaheuristics. Crossover maintains the exploration properties. In this term, three procedures are proposed as illustrated in Figure 3. Generally, the crossover procedure selects two answers called parents. After that they are combined with each other to generate two new solutions called offspring. In addition to this operator, the mutation searches the neighbors around good solutions to do the exploitation phase. As such, three procedures are employed to perform the mutation operator in this study as given in Figure 4. In the term of multi-objective optimization problems, Deb *et al.* [44] for the first time introduced the Non-dominated Sorting Genetic Algorithm (NSGA-II). As a state of art metaheuristic, there are many recent papers to see more description about NSGA-II and its applications, e.g., [1, 2, 10, 12, 17]. The pseudo-code of NSGA-II is addressed as given in Figure 5.

Figure 3. The crossover operators in this paper

Figure 4. The mutation operators in this study

Figure 5. The pseudo-code of NSGA-II

4.3. MOKA

Keshtel Algorithm (KA) offered by Hajiaghaei-Keshteli and Aminnayeri [45] is inspired by Keshtel's feeding. Keshtel is a bird in *Anas* family. An amazing behavior of this animal to search the food in the lake by swirling the closest neighbor around Keshtels is the basis of this nature-inspired algorithm. This metaheuristic divides the initial population into three groups (*i.e*. *N1*, *N2* and *N3*). *N1* includes the best solutions which find the good foods to swirl the nearest neighbor. They are called lucky ones. The lucky Keshtels improve the exploitation properties and focus on the best solutions. *N2* for each iteration moves around the lucky Keshtels. These Keshtels aim to do a local search around the best solutions. Finally, some of Keshtels are flied and some new ones are arrived in the lake. These Keshtels forms the last group as *N3*. In this case, some new solutions are generated randomly to maintain the exploration phase for the algorithm. To briefly show the procedures of the algorithm, assume that Let *N* is the set of population members, then:

$$N = N_1 \cup N_2 \cup N_3 \tag{14}$$

For each lucky Keshtel, the swirling process is done. For example, Let a maximum number of swirling (S_{max}) is equaled to 3. We can create maximum (2× S_{max}–1) =5 new solution. The neighbor solutions can be generated by the following equations:

$$\begin{aligned}
Position_1 &= (a + (b - a)) \\
Position_2 &= (a + (b - a)/3) \\
Position_3 &= (Position_1 - (b - a)/3) \\
Position_4 &= (b - (b - a)/3) \\
Position_5 &= (b + (b - a)/3)
\end{aligned} \tag{15}$$

For each member of *N2* set, the changes in its position toward virgin spots based on two lucky Keshtels' positions. Let Y_i is a member of N_3 set. It changes its position as follows:

$$v_i = \lambda_1 \times Y_j + (1 - \lambda_1) \times Y_t \tag{16}$$

$$Y_i = \lambda_2 \times Y_i + (1 - \lambda_2) \times v_i \tag{17}$$

where Y_j and Y_t are two members selected randomly from *N2* set and different from Y_i. λ_1 and λ_2 are random numbers selected from the uniform distribution in [0,1].

Regarding the proposed multi-objective optimization model, a Multi-Objective of Keshtel Algorithm (MOKA) is needed to be considered. In this MOKA, we only need to change the criterion selection for N1 and the selection of the next generation which is similar to NSGA-II. In this term, the pseudo-code of algorithm is provided as seen in Figure 6.

Figure 6. The pseudo-code of MOKA

4.4. MORDA

The Red Deer Algorithm (RDA) is another nature-inspired metaheuristic introduced by Fathollahi-Fard et al., [46-47]. The main contribution of this algorithm is made a trade-off and balance between the phases by an intelligent ways. The RDA inspired by Red Deer's mating uses the behavior of this animal in a breeding season to design the search operators [48]. The initial population of RDA is divided into two groups: male Red Deers (RDs) and hinds. Note that the algorithm generates the initial population of size N_{pop}. We select a set of the best RDs to N_{male} and the rest of them to N_{hind} (N_{hind}=N_{pop}- N_{male}).

After that, each male roars to do a local search in the first step [49]. To update the position of males the following equation is proposed:

$$male_{new} = \begin{cases} male_{old} + a_1 \times \left((UB - LB) \times a_2\right) + LB), if\ a_3 \geq 0.5 \\ male_{old} - a_1 \times \left((UB - LB) \times a_2\right) + LB), if\ a_3 < 0.5 \end{cases} \tag{18}$$

where *UB* and *LB* limit the search space. They are the upper and lower bounds of search space, respectively. Note that $male_{old}$ is the current position of male RD, and $male_{new}$ is its updated position. As the roar operator is random, a_1, a_2 and a_3 are generated randomly by the uniform distribution in [0,1].

Then, males are divided into commanders and stags. The number of stags is calculated by:

$$N_{stag} = N_{male} - N_{Com} \tag{19}$$

where N_{stag} is the number of stags in regards to the population of males. Another main step of the algorithm is done by the fighting procedure. The fighting between the commanders and stags is considered to improve the exploitation properties for the algorithm. This fighting is controlled by the number of commanders and stags [50]. In this operator, two new solutions are generated as following equations:

$$New1 = \frac{(Com + Stag)}{2} + b_1 \times \left((UB - LB) \times b_2\right) + LB) \quad (20)$$

$$New2 = \frac{(Com + Stag)}{2} - b_1 \times \left((UB - LB) \times b_2\right) + LB) \quad (21)$$

where *New*1 and *New*2 are the two new solutions generated by the fighting process. *Com* and *Stag* represent the symbol of commanders and stags, respectively. As the fighting is random, b_1 and b_2 are generated by the uniform distribution function in [0,1]. The best solution among four ones, is the new commander.

In the next step, the harems are formed by commanders. The number of hinds in each harem is directly related to the power of the commander. The mating behavior inside and outside of harems are formulated to maintain the exploration phase, clearly. Moreover, stags mate with the nearest hind to perform the exploitation phase, again. This mating operator is done by the following formula

$$offs = \frac{(Com + Hind)}{2} + (UB - LB) \times c \quad (22)$$

where *Com* and *Hind* are the symbols of commanders and hinds, respectively. *Offs* is a new solution Lastly, *c* is generated randomly by the uniform distribution in [0,1].

Finally, by an evolutionary concept to select the next generation by roulette wheel, the new Red Deers are selected in this step [47-50]. Similar to two other metaheuristic employed, the Multi-Objective version of Red Deer Algorithm (MORDA) is implemented to solve the developed problem. The main difference is related to the selection of the better solution which should cover the multi-objective optimization and after each iteration, the non-dominated solution will be updated. Having more details of MORDA, a pseudo-code is given in Figure 7.

Figure 7. The pseudo-code of MORDA

4.5. ε-constraint method

To solve the small test problems, an exact approach is implemented. The ε-constraint method proposed firstly by Haimes *et al.* [51] is utilized by this research. Basically, this technique optimizes the problem based on one objective function as the main one. As such, the rest of objectives are limited by the allowable bounds as the constraints of model. To generate more solutions, the bound would be modified, consecutively. Among initial solutions and the generated solutions by modifying the bounds, the non-dominated solutions are selected, accordingly. Having more details of this algorithm, a brief formulation of proposed problem is given as follows:

$$\begin{aligned}
&\max Z_1\left(y_j\right) \\
&s.t. \\
&\quad Eq.(5)-(12) \\
&\quad Z_2\left(y_j\right) \le \varepsilon_j \\
&\quad Z_j^{min}\left(x\right) \le \varepsilon_j \le Z_j^{max}\left(x\right)
\end{aligned} \tag{23}$$

In this way, an exact solver by using GAMS software is utilized to employ the ε-constraint method in this study. In the next part, small sizes to verify the developed GVMI model are solved by this method and comparison of results with other same studies.

5. Solving the small sizes with ε-constraint method

The numeral examples have been defined in several stages. In the first stage a single vendor is considered with respectively one, three, and five retailers with/without backorder. Values of parameters in this example are taken from the study of [24], and compared under infinite or unauthorized backorder cost conditions for this study with [23] and [25] as well. It should be noted, all tests problems are solved by GAMS software using DICOPT solution (which is used for non-linear models), in a computer with 1.7GB CPU and 6.0GB RAM.

5.1. One vendor with one retailer

In Table 1-2, details of a problem with one vendor and one retailer under infinite or unauthorized backorder conditions (*i.e*. P1-V1R1) are described.

Table 1. Amount of parameters for one retailer under infinite or unauthorized backorder conditions in P1-V1R1

Table 2. Amount of parameters for one vendor under infinite or unauthorized backorder conditions in P1-V1R1

After substituting the values form Table 1-2 in equations (3) to (12) and solving the model, the optimum value is worked out as per shown in Table 3, as follows:

Table 3. The comparison of P1-V1R1 from our study with other same researches

As shown in Table 3, the above model can be converted to the model described in the study of Diabat [24], and the model validation is completely confirmed; although the model described in this study has two objectives, and the second objective is the green emissions level. This is calculated in the last column. However, when the backorder cost is of a smaller value, after solving the model, the supply volume is logically reduced to avoid backorder as given in Table 4.

Table 4. The GVMI model with one vendor and one retailer by considering different shortages

As shown in Table 4, for the term of one vendor with one retailer, the model under authorized backorder cost condition, reducing the backorder cost increases both distribution and order quantities, reduces the optimum backorder value, and increases the profit compared to unauthorized backorder conditions. Also, given that the model has two objectives, using the ε-constraint approach, the Pareto front can be worked out for the bi-objective model (*i.e.* P4-V1R1). To do this end, lower and upper limits of the first objective (Z_1) are divided into 10 equal points. The ε-constraint diagram is drawn in Figure 8, and the respective data are shown in Table 5.

Table 5. The results of ε-constraint method for P4-V1R1

In Table 5, minimizing the green emissions function is taken into first account. In this case, the vendor's profit is reduced (undesirable), and the green emissions level is minimized (desirable). At end of the table, the vendor's profit is increased (desired), and consequently the emissions level is maximized (undesired). This is indicative of a conflict between the objective functions. Figure 8 shows the ε-constraint diagram of P4-V1R1 model, and draws process of the objective functions as can be seen.

Figure 8. The Pareto optimal front of ε-constraint method for P4-V1R1

5.2. One vendor with three retailers

Table 6-7 show the parameters of the problem with one vendor and three retailers under infinite or unauthorized backorder cost conditions (P1-V1R3): the optimum solutions were worked out as shown in Table 8.

Table 6. The parameters for retailers in P1-V1R3 under infinite or unauthorized backorder conditions

Table 7. The parameters for the vendor in P1-V1R3 under infinite or unauthorized backorder conditions

As given in Table 8, when the backorder cost is extremely high, the developed GVMI model can be converted to the other models, and the model validation is confirmed completely; although this is a bi-objective model, value of which is shown in the last column. However, under conditions where the backorder cost is of a smaller value, after solving the model, the distribution quantity which avoids backorder is of a bigger value, which is shown in Table 9.

Table 8. The comparison of P1-V1R3 from our study with other same researches

As shown in Table 9, in this case, one vendor and three retailers, the model under authorized backorder cost conditions, reducing the backorder cots increases distribution and order quantities, and therefore decreases the optimum backorder value. Accordingly, the profit margin is greater compared to unauthorized backorder conditions. Also, due to this is a bi-objective model, using the ε-constraint approach we can obtain Pareto front for the bi-objective model (*i.e.* P4-V1R3). To do this goal, the gap between higher and lower limits of the objective function (*i.e.* Z_1) is divided into 10 equal parts. The ε-constraint diagram is shown in Figure 9, and the respective data are shown in Table 10.

Table 9. The GVMI model with one vendor and three retailers by considering different shortages

According to Table 10, minimizing the green emissions function as the second objective was taken into consideration first. In this case, the vendor’s profit is reduced (undesired), and emissions level is minimized (desired), while at end of the table, the vendor’s profit is increased (desired) and consequently the emissions level is maximized (undesired); and this is indicative of a conflict between the objective functions. In addition, Figure 9 shows the Pareto optimal front for the sample of P4-V1R3 in GVMI model and the process of the objective functions.

Table 10. The results of ε-constraints method for P4-V1R3

Figure 9. The Pareto optimal front of ε-constraint method for P4-V1R3

5.3. One vendor with five retailers

Table 11-12 illustrate the parameters of problem by considering just one vendor and five retailers under infinite or unauthorized backorder cost conditions (*i.e.* P1-V1R5). The results in this term are noted in Table 13.

Table 11. The parameters for retailers in P1-V1R5 under infinite or unauthorized backorder conditions

Table 12. The parameters for the vendor in P1-V1R5 under infinite or unauthorized backorder conditions

As can be seen in Table 13, the proposed model can be converted to the other models when the backorder costs are extremely high, and the model validation is confirmed; although, as mentioned earlier, this is a bi-objective model and the second objective is the green emissions level, value of which is calculated in the last column. However, when the backorder cost is of a smaller value, after solving the model the distribution quantity which avoids backorder would be of a greater value, as depicted in Table 14.

Table 13. The comparison of P1-V1R5 from our study with Diabat [24]

With regards to Table 14, with one vendor five retailers, model under authorized backorder conditions, decreasing the backorder cost increases distribution and order quantities, and accordingly the backorder value is decreased and the vendor's profit would be greater compared to the unauthorized backorder conditions. Also, by considering both objectives, simultaneously, ε-constraints is utilized to set the Pareto optimal solutions in this case (*i.e.* P4-V1R5). Accordingly, the gap between higher and lower limits of the objective function (Z_1) is divided into 10 equal parts. The constraints diagram is shown in Figure 10, and the respective data are given in Table 15.

Table 14. The GVMI model with one vendor and five retailers by considering different shortages

As can be seen in Table 15, minimizing the emissions function is taken into consideration first. In this case, the vendor's profit is decreased (undesired) and emissions level is minimized (desired), while at end of the table the vendor's profit is increased (desired) and consequently the green emissions level is increased (undesired), and this is indicative of a conflict between the objective functions like pervious sub-sections. Figure 10 shows ε-constraints diagram of P4-V1R5 sample in the term of Pareto optimal solution sets.

Table 15. The results of ε-constraints method for P4-V1R5

In a nutshell, the three samples in the developed GVMI model with allowed backorder in a two-echelon supply chain by solving the ε-constraint method, values of the target objective functions were calculated by means of Pareto optimal front, and the values related to unauthorized backorder conditions were compared by related studies, and the modeling validation was confirmed. In this regard, in the next section, we solve the GVMI model in real dimensions by using three effective metaheuristics.

6. Solving the GVMI in large scale samples

In this paper, three metaheuristics are used to solve the model for large scale samples. By increasing the size of problem, the exact solver needs more time and so for real dimensions, it can't be useful. Accordingly, the next sub-section defines the instances of test problem. The algorithm's parameters are tuned by Response Surface Method (RSM) with a transformation to single objective approach. Then, three assessment metrics are introduced to evaluate the quality of Pareto solutions for metaheuristics. Finally, the methods are compared by different criteria to confirm the efficiency of them in real dimensions.

6.1. Instances

A set of data is adopted from literature [17] to attempt the comparison with metaheuristic and the need and benefits of them in large scale samples. Accordingly, by considering one vendor and several retailers, ten test problems are generated by considering different values of shortage. The values of parameters are similar to the last section as detailed before. Table 16 gives the instances of test problem.

Table 16. The real dimensions of instances

6.2. Parameter settings

As mentioned earlier, this study proposes three calibrated metaheuristics to solve the GVMI problem. Having a set of fine-tuned parameters, the behavior of metaheuristics would be more efficient [1-5]. This paper uses Response Surface Method (RSM) offered by John and Wilson to adjust the best value of parameters of the algorithms [52]. In this methodology, each parameter of algorithms as a factor (X_i) measured at two levels are coded between -1 to 1. These codes are used for the low level (x_l) and high level (x_h) of each variable, respectively. The independent variables of RSM are calculated by following formula:

$$x_i = \frac{2X_i - x_h - x_l}{x_h - x_l}, i = \{1, 2, ..., K\} \tag{24}$$

where K is the number of variables. As such, y is utilized to formulate the variation in response variables as follows:

$$y = \beta_0 + \sum_{j=1}^{K} \beta_j x_j + \sum_{j=1}^{K} \sum_{i<j}^{K} \beta_{ij} x_i x_j + \sum_{j=1}^{K} \beta_{jj} x_{jj}^2 + \varepsilon \tag{25}$$

where y, β_0, β_j, β_{ij}, are an estimated response, a constant, the linear coefficient, and the interaction coefficient, respectively. β_{jj}value, linear coefficient, interaction coefficient and quadratic coefficient. Furthermore, above equation may be considered in the system while there is curvature. In this regard, Table 17 provides the algorithm's parameters and their levels and also the number of experiments.

Table 17. Algorithms and Factor levels with the total number of experiment for each method

According to RSM, the effectiveness and efficiency of the algorithms are analyzed by approximating proper parameters. By using the approach of [12], a transformation of multi-objective models based on fuzzy interactive methods is utilized in this paper as following formulas:

$$\begin{aligned} & \max \sum_{i=1}^{S} w_i \propto_i \\ & s.t. Y_i \le U_i - \propto_i \left(U_i - L_i\right) \\ & \quad -1 \le X_i \le 1 \\ & \quad 0 \le \propto_i \le 1 \end{aligned} \tag{26}$$

where S is the number of objective(s), Y_i, w_i and $\propto_i$ are the i^{th} goal function (i^{th} regression model), its weight and its satisfactory level, respectively. As such, U_i and L_i are respectively the maximum and minimum value of i^{th} column in payoff table. Moreover, the weights of objective functions are two times more than the weight of run times. Finally, Table 18 shows the tuned parameters R-squared (R^2) for algorithms as well.

Table 18. Tuned parameters of algorithms and R-squared (R^2)

6.3. Assessment metrics for the quality of Pareto front

In this paper, three measurements are applied to evaluate the quality of Pareto optimal solutions. These metrics were introduced by the related papers (mainly on: [2]; [5]; [12]). A summarized definition about these metrics is stated by follows:

- Number of Pareto Solutions (NPS): this metric shows the ability of metaheuristics to find the Pareto optimal solutions. The higher value of this metric brings the better quality of algorithms [5].

- Spread of Non-dominance Solutions (SNS): it evaluates the standard of distance from an ideal point in Pareto optimal solutions. For this metric, the higher value also shows the better capability of algorithms [2].
- Percentage of Domination (POD): the aim of this metric is to measure how an algorithm can dominate other algorithms' solutions. Having the procedure of POD, all non-dominated solutions required are composed by one Pareto frontier. After that solutions' percentage belonging to each metaheuristic is calculated. The algorithm with higher POD seems better quality of solutions [12].

6.4. Comparison among approaches

In this sub-section, the methods are compared by different terms. First of all, the presented metaheuristics are validated by ε-constraint method by mentioned exact solver procedures in a small test problem (*i.e*. T1). Figure 11 depicts the Pareto optimal fronts for three presented metaheuristics and an exact method. As can be seen, the algorithms show an acceptable overlap the exact method and among metaheuristics, MORDA is more successful than others in this case. Moreover, it should be noted, the exact solver needs 2391 seconds to solve the model. Besides, 113, 125 and 118 seconds are considered as the time consumptions for the NSGA-II, MORDA and MOKA, respectively. As a result, it shows the used metaheuristics are more reliable to solve the GVMI model.

Figure 11. The non-dominated solutions for metaheuristics and exact solver for T1

As mentioned earlier, to compare the presented metaheuristics, three assessment metrics are utilized. Table 19 shows the results of algorithm during ten test problems for each metric. In addition, Figure 12 states the behavior of algorithms in term of solution time. In this term, results inform that NSGA-II needs less time and vice versa, MOKA consumes more time to solve the test problems.

Figure 12. The behavior of algorithms in term of solution time

Table 19. The results of algorithms in term of assessment metrics

According to the results of assessment metrics, they are validated by another well-known metric as Relative Percentage Deviation (*RPD*) for analyses the performance of algorithms. *RPD* is defined by following formula:

$$RPD = \frac{|Alg_{sol} - Best_{sol}|}{Best_{sol}} \tag{27}$$

where Alg_{sol} is the output of algorithm and $Best_{sol}$ is the best value ever found in size of problem. Without considering the nature of assessment metrics, the lower value of RPD always rings better capability of metaheuristics. Finally, a set of statistical analyses based on an analysis of variance (ANOVA) is performed to analyze the results as seen in Table 18, accurately. In order to recognize the performance of metaheuristics, they are investigated separately. Figure 13 depicts the ANOVA analyses for the presented metaheuristics. Due to the results, for the term of NPS metric, MORDA and NSGA-II are more the better than MOKA. Furthermore, in SNS, NSGA-II and MOKA have a same behavior and MORDA shows a better performance. Finally, in the term of POD, MORDA and MOKA have a strong performance more than NSGA-II. In a nutshell, as can be seen, MORDA is the most successful methods during all assessment metrics in the term of solution quality.

Figure 13. Results of ANOVA analyses for the three assessment metrics for used metaheuristics (*i.e.* (a) for NPS, (b) for SNS and (c) for POD)

7. Conclusion and future works

In this paper, a bi-objective green vendor managed inventory model was proposed for a two-echelon supply chain network. The main innovation was the green emissions or the reduction of the amount of environmental pollution with respect to the transportation activities. The model was formulated by considering one vendor and several retailers. The results for small sizes were solved by ε-constraint method and compared to related studies. In addition, by considering a real case study, ten test problems in a real dimension was adopted. In this regard, three effective metaheuristics were offered to solve the problem. Algorithms were tuned by RSM to get the proper values for parameters. In addition, three assessment metrics were introduced to compare the quality of Pareto optimal solutions. Finally, MORDA shows the best performance in most of test problems.

For future works, more comprehensive analyses on our model are suggested. The results should be compared by resolving with other heuristics and metaheuristics. In addition, the presented metaheuristics can be used in other real-scale optimization problem. The main continuation of this study may be done by some real assumptions which can be added to model in practice. For instance, considering multi-period and multi-products may be a good idea. More broadly, considering vehicle routing operation to reduce the transportation cost by adding same vehicles can be ordered.

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Figures Captions:

Figure 1. GVMI model with one vendor and some retailers
Figure 2. The proposed RK utilizing in this paper
Figure 3. The crossover operators in this paper
Figure 4. The mutation operators in this study
Figure 5. The pseudo-code of NSGA-II
Figure 6. The pseudo-code of MOKA
Figure 7. The pseudo-code of MORDA
Figure 8. The Pareto optimal front of ε-constraint method for P4-V1R1
Figure 9. The Pareto optimal front of ε-constraint method for P4-V1R3
Figure 10. The Pareto optimal front of ε-constraint method for P4-V1R5
Figure 11. The non-dominated solutions for metaheuristics and exact solver for T1
Figure 12. The behavior of algorithms in term of solution time
Figure 13. Results of ANOVA analyses for the three assessment metrics for used metaheuristics (*i.e.* (a) for NPS, (b) for SNS and (c) for POD)

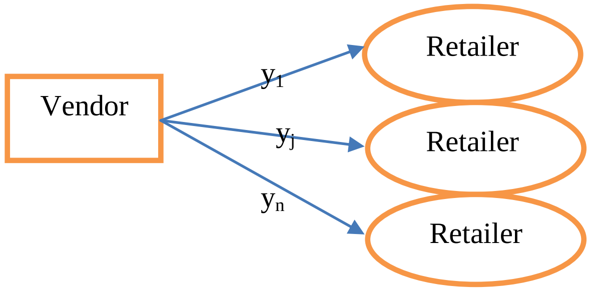


Figure 1. GVMI model with one vendor and some retailers

y_1	y_2	y_3	y_4	y_5
0.34	0.57	0.25	0.68	0.92
40.4	54.2	35	60.8	75.2

Figure 2. The proposed RK utilizing in this paper

Single-point crossover:

Parent 1	0.52	0.18	0.82	0.73	0.35	0.89	0.57
Parent 2	0.93	0.65	0.75	0.61	0.59	0.36	0.29
Offspring 1	0.52	0.18	0.82	0.73	0.59	0.36	0.29
Offspring 2	0.93	0.65	0.75	0.61	0.35	0.89	0.57

Double-point crossover:

Parent 1	0.52	0.18	0.82	0.73	0.35	0.89	0.57
Parent 2	0.93	0.65	0.75	0.61	0.59	0.36	0.29
Offspring 1	0.52	0.18	0.75	0.61	0.59	0.89	0.57
Offspring 2	0.93	0.65	0.82	0.73	0.35	0.36	0.29

Uniform crossover:

Parent 1	0.52	0.18	0.82	0.73	0.35	0.89	0.57
Parent 2	0.93	0.65	0.75	0.61	0.59	0.36	0.29
Random mask	1	0	0	1	0	1	0
Offspring 1	0.52	0.65	0.75	0.73	0.59	0.89	0.29
Offspring 2	0.93	0.18	0.82	0.61	0.35	0.36	0.57

Figure 3. The crossover operators in this paper

	Swap:						
Parent	0.52	0.18	0.82	0.73	0.35	0.89	0.57
Offspring	0.52	0.18	0.73	0.82	0.35	0.89	0.57
	Reversion:						
Parent	0.52	0.18	0.82	0.73	0.35	0.89	0.57
Offspring	0.52	0.35	0.73	0.82	0.18	0.89	0.57
	Insertion:						
Parent	0.52	0.67	0.08	0.95	0.55	0.89	0.57
Offspring	0.52	0.67	0.95	0.08	0.67	0.89	0.57

Figure 4. The mutation operators in this study

Generate random population.
Calculate the fitness of each individual chromosome by considering the approach of *RK*
Form the Pareto optimal solution fronts.
X*=the best solution.
while (i*t*< maximum number of iteration)
    Select a pair of chromosomes as parents by roulette wheel selection.
    Perform crossover and mutation to generate new chromosomes according to the type of them.
    Calculate the fitness according to the proposed *RK*.
    Merge the all chromosomes and update the Pareto front then select the new population
    Update the X* if there is better solution.
    it=it+1;
end while
return X*

Figure 5. The pseudo-code of NSGA-II

```
Initialize Keshtels population.
Calculate the fitness of each individual Keshtel by considering the approach of RK.
Form the Pareto optimal solution fronts.
Sort Keshtels in three types: N1, N2 and N3 as given in Equation (14)
X*=the best solution.
it=0;
while (it< maximum number of iteration)
    for each N1
        Calculate the distance between this lucky Keshtel and all Keshtels.
        Select the closest neighbor.
        S=0;
        while (S< maximum number of swirling)
            Do the swirling as given in Equation (15).
            if the fitness of this new position is better than prior
                Update this lucky Keshtel by using RK approach as given in Equation (13).
                    break
            endif
            S=S+1
        endwhile
    endfor
    for each N2
        Move the Keshtel between the two Keshtels as given in Equations (16) and (17).
        Update this Keshtel by using RK approach as given in Equation (13).
    endfor
    for each N3
        Create a random solution for this Keshtel.
        Update this Keshtel by using RK approach as given in Equation (13).
    endfor
    Merge the N1, N2 and N3
    Sort the Keshtels and form N1, N2 and N3 for next iteration.
    Form the Pareto optimal solution fronts.
    Update the X* if there is better solution.
    it=it+1;
end while
return X*
```

Figure 6. The pseudo-code of MOKA

Initialize the Red Deers population.

Calculate the fitness by developed *RK* approach given in Equation (13) and sort them and form the hinds (N_{hind}) and male RDs (N_{male}).

Form the initial Pareto optimal fronts.

X*=the best solution.

t=0;

while (t< maximum number of iteration)

  for each male RD

    A local search according to Equation (18).

    Update the position if better than the prior ones by developed *RK* approach in Equation (13).

  end for

  Sort the males and also form the stags and the commanders as given in Equation (19).

  for each male commander

    Fight between male commander and stag as given in Equations (20) and (21).

    Update the position of male commander and stag by developed *RK* approach.

  end for

  Form harems: ($V_n = v_n - \max_i\{v_i\}$; $P_n = \left|\frac{V_n}{\sum_{i=1}^{N_{Com}} V_i}\right|$; $N.harem_n = round\{P_n.N_{hind}\}$).

  for each male commander

    Mate male commander with the selected hinds of his harem randomly as given in Equation (22) by developed *RK* approach in Equation (13).

    Select a harem randomly and name it k.

    Mate male commander with some of the selected hinds of the harem as given in Equation (22) by developed *RK* approach in Equation (13).

  end for

  for each stag

    Calculate the distance between the stag and all hinds and select the nearest hind.

    Mate stag with the selected hind as given in Equation (22) by developed *RK* approach in Equation (13).

  end for

  Select the next generation with roulette wheel selection.

  Update the Pareto optimal solutions.

  Update the X* if there is better solution.

  t=t+1;

end while

Select the best optimal front and consider the evaluation metrics.

Figure 7. The pseudo-code of MORDA

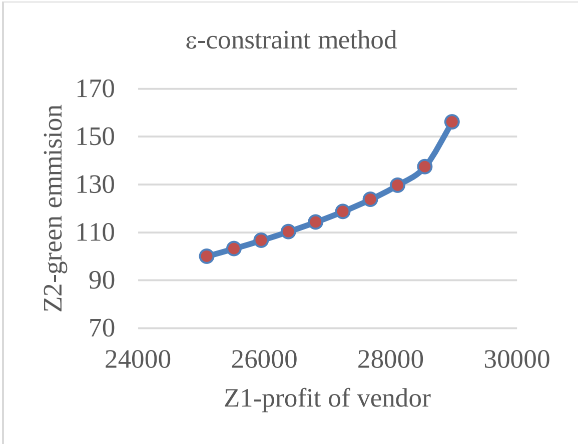


Figure 8. The Pareto optimal front of ε-constraint method for P4-V1R1

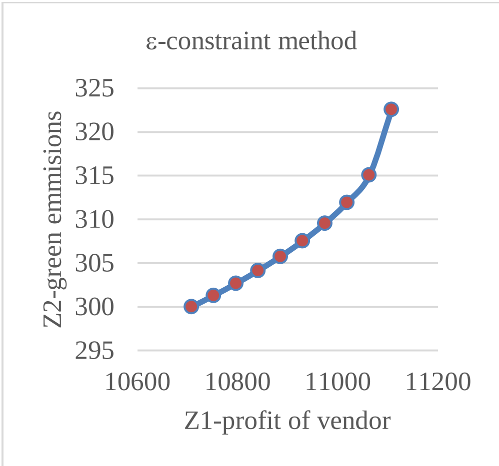


Figure 9. The Pareto optimal front of ε-constraint method for P4-V1R3

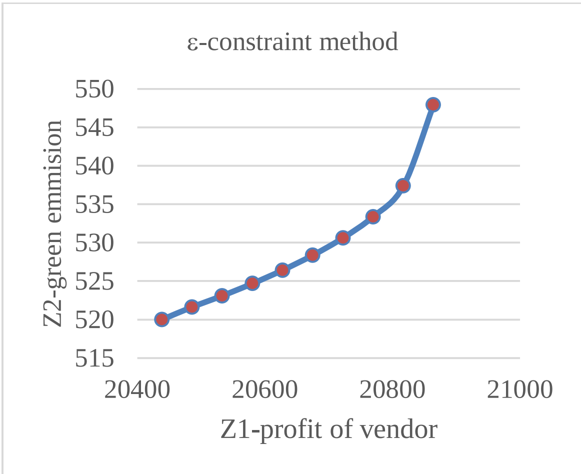


Figure 10. The Pareto optimal front of ε-constraint method for P4-V1R5

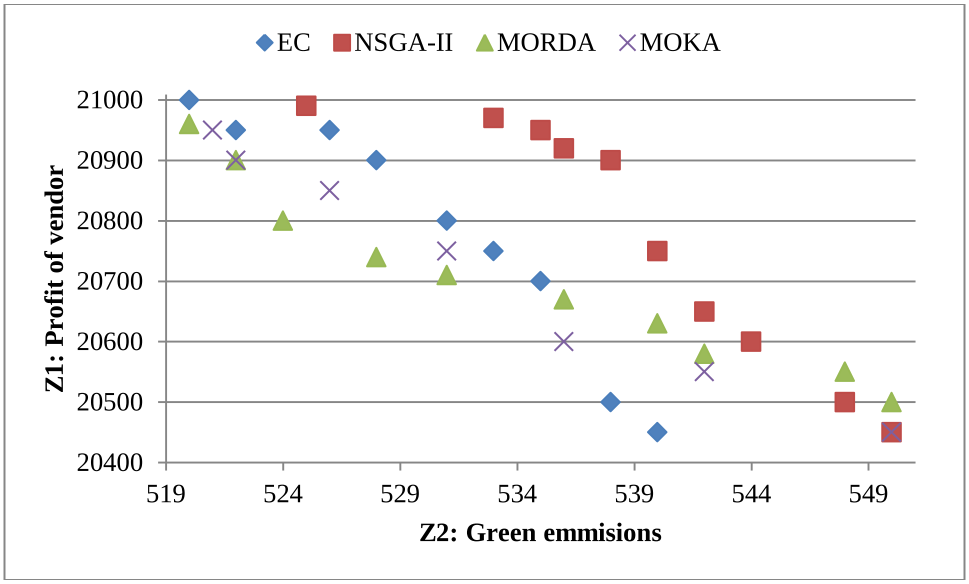


Figure 11. The non-dominated solutions for metaheuristics and exact solver for T1

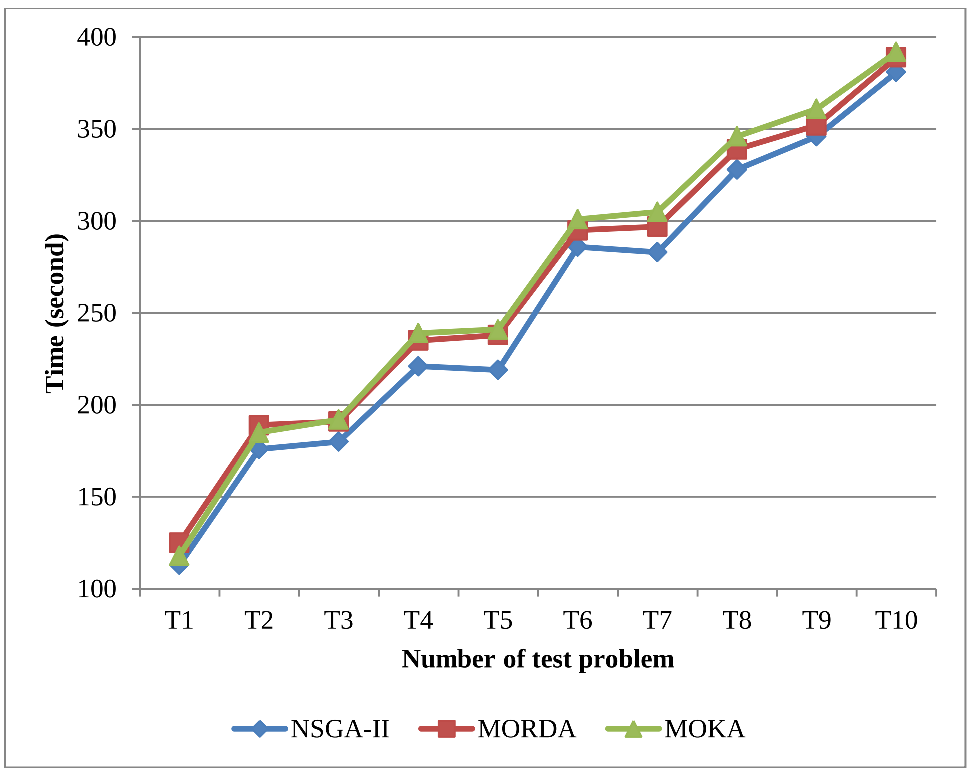
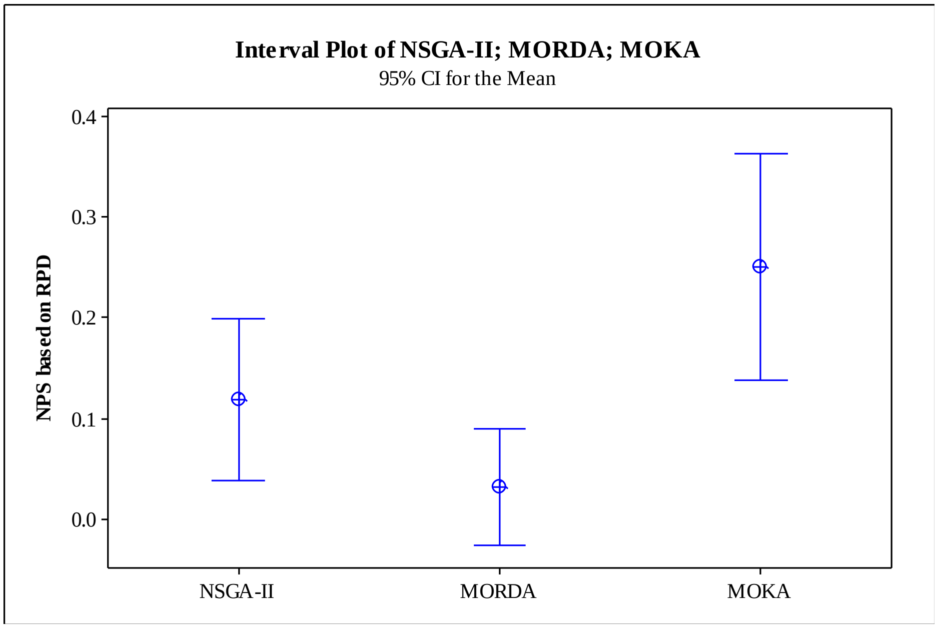
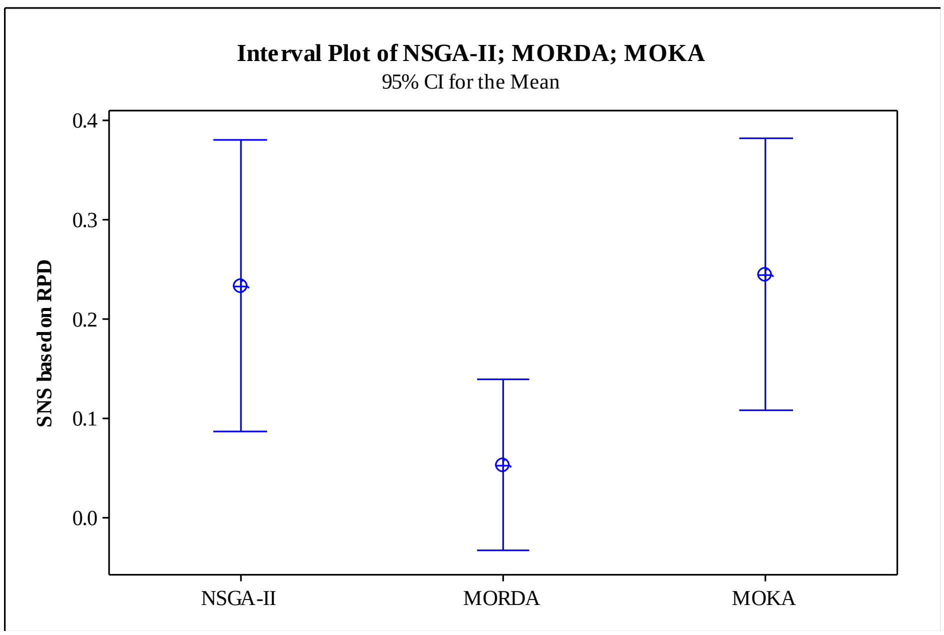
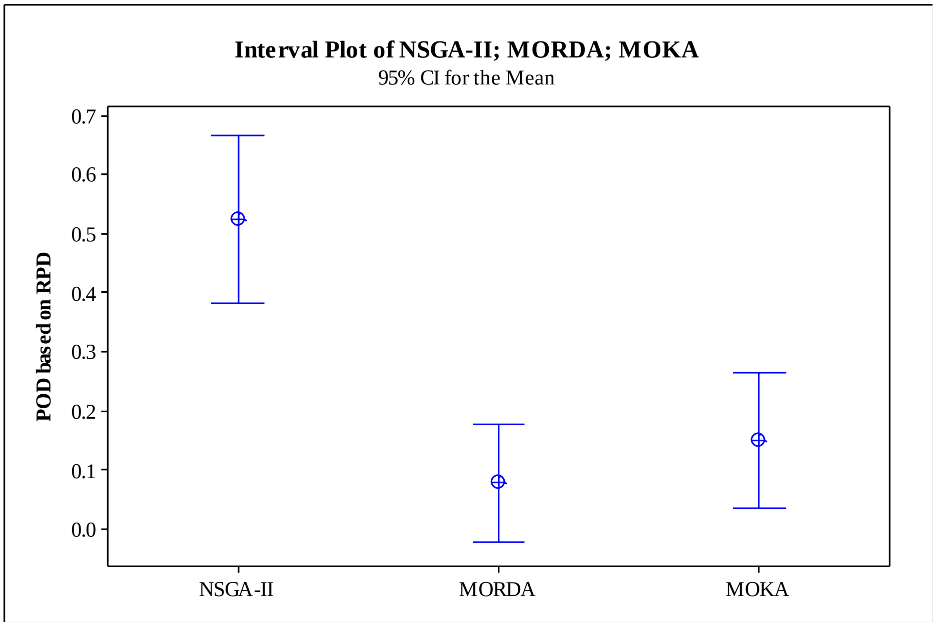


Figure 12. The behavior of algorithms in term of solution time


Interval Plot of NSGA-II; MORDA; MOKA
95% CI for the Mean
NPS based on RPD
0.4
0.3
0.2
0.1
0.0
NSGA-II
MORDA
MOKA
(a)


Interval Plot of NSGA-II; MORDA; MOKA
95% CI for the Mean
SNS based on RPD
0.4
0.3
0.2
0.1
0.0
NSGA-II
MORDA
MOKA
(b)



(c)

Figure 13. results of ANOVA analyses for the three assessment metrics for used metaheuristics (*i.e.* (a) for NPS, (b) for SNS and (c) for POD)

Tables caption:

Table 1. Amount of parameters for one retailer under infinite or unauthorized backorder conditions in P1-V1R1
Table 2. Amount of parameters for one vendor under infinite or unauthorized backorder conditions in P1-V1R1
Table 3. The comparison of P1-V1R1 from our study with other same researches
Table 4. The GVMI model with one vendor and one retailer by considering different shortages
Table 5. The results of ε-constraint method for P4-V1R1
Table 6. The parameters for retailers in P1-V1R3 under infinite or unauthorized backorder conditions
Table 7. The parameters for the vendor in P1-V1R3 under infinite or unauthorized backorder conditions
Table 8. The comparison of P1-V1R3 from our study with other same researches
Table 9. The GVMI model with one vendor and three retailers by considering different shortages
Table 10. The results of ε-constraints method for P4-V1R3
Table 11. The parameters for retailers in P1-V1R5 under infinite or unauthorized backorder conditions
Table 12. The parameters for the vendor in P1-V1R5 under infinite or unauthorized backorder conditions
Table 13. The comparison of P1-V1R5 from our study with Diabat [24]
Table 14. The GVMI model with one vendor and five retailers by considering different shortages
Table 15. The results of ε-constraints method for P4-V1R5
Table 16. The real dimensions of instances
Table 17. Algorithms and Factor levels with the total number of experiment for each method
Table 18. Tuned parameters of algorithms and R-squared (R^2)
Table 19. The results of algorithms in term of assessment metrics

Table 1. Amount of parameters for one retailer under infinite or unauthorized backorder conditions in P1-V1R1

H_{b1}	S_{b1}	a_1	k_1	y_{1min}	y_{1max}	θ_1	β_1	π_{b1}	F_1	H_s	S_s
9	300	80	0.01	1000	2000	0.005	0.1	∞	3000	9	150

Table 2. Amount of parameters for one vendor under infinite or unauthorized backorder conditions in P1-V1R1

C	δ	CC	f	N
6150	40	100	0.2	50

Table 3. The comparison of P1-V1R1 from our study with other same researches

P1-V1R1	y_{jopt}	Z_1^*	Z_2
This study	1535.03	26960.95	153.50
Dong and Xu [23]	1535	26960.49	--
Diabat [24] using LINGO and hybrid algorithm	1535	26960.49	--
Nachiappan and Jawahar [25] using GA	1535	26960.42	--

Table 4. The GVMI model with one vendor and one retailer by considering different shortages

Test problem	π_{b1}	y_{jopt}	Z_1^*	Z_2	Q_j^*	b^*
P1-V1R1	1000000	1535.028	26960.550	153.50	277.043	277.038
P2-V1R1	1000	1535.617	27004.793	153.62	279.576	274.633
P3-V1R1	100	1540.290	27356.917	154.02	301.458	255.473
P4-V1R1	10	1561.502	28975.745	156.15	467.558	166.985

Table 5. The results of ε-constraint method for P4-V1R1

P4-V1R1	$max\ Z_1$	$min\ Z_2$	y_{jopt}
1	25094.65	100.00	1000.000
2	25525.88	103.22	1032.170
3	25957.12	106.64	1066.413
4	26388.35	110.32	1103.191
5	26819.58	114.32	1143.173
6	27250.81	118.74	1187.385
7	27682.05	123.76	1237.551
8	28113.28	129.70	1297.038

9	28544.51	137.45	1374.533
10	28975.75	156.15	1561.376

Table 6. The parameters for retailers in P1-V1R3 under infinite or unauthorized backorder conditions

j	1	2	3
H_{bj}	7	8	9
S_{bj}	10	20	30
a_j	20	19	18
k_j	0.003	0.005	0.008
y_{jmin}	2000	500	500
y_{jmax}	4000	3000	1500
θ_j	0.003	0.005	0.008
β_j	0.1	0.1	0.1
π_{bj}	∞	∞	∞
F_j	3000	3000	3000

Table 7. The parameters for the vendor in P1-V1R3 under infinite or unauthorized backorder conditions

H_s	S_s	C	δ	CC	f	N
9	150	6150	40	100	0.2	50

Table 8. The comparison of P1-V1R3 from our study with other same researches

P1-V1R3	y_{1opt}	y_{2opt}	y_{3opt}	Z_1^*	Z_2
This study	2000	709.54	500	9903.13	320.95
Diabat [24] using LINGO	2000	710	500	9903.11	--
Nachiappan and Jawahar [25] using GA	2002	673	500	9905.51	--
Diabat [24] using a hybrid algorithm	2001	675	500	9908.49	--

Table 9. The GVMI model with one vendor and three retailers by considering different shortages

Test problem	π_{bj}	y_{jopt}	Z_1^*	Z_2	Q_j^*	b^*
P1-V1R3	1000000	2000 709.533 500	9903.13	320.95	79.063 54.056 50.004	79.063 54.056 50.004
P2-V1R3	1000	2000 709. 879 500	9928.81	320.98	79.687 54.523 50.448	78.432 53.611 49.556
P3-V1R3	100	2000 712.667 500	10134.512	321.267	85.147 58.595 54.314	73.403 50.081 46.029
P4-V1R3	10	2000 725.645 500	11107.410	322.565	127.47 89.819 83.666	49.029 33.266 29.881

Table 10. The results of ε-constraints method for P4-V1R3

P4-V1R3	$max\ Z_1$	$min\ Z_2$	y_{1opt}	y_{2opt}	y_{3opt}
1	10708.25	300.00	2000	500.00	500
2	10752.60	301.29	2000	512.93	500
3	10796.95	302.67	2000	526.69	500
4	10841.30	304.15	2000	541.47	500
5	10885.65	305.75	2000	557.54	500
6	10930.00	307.53	2000	575.31	500
7	10974.36	309.55	2000	595.47	500
8	11018.71	311.94	2000	619.38	500
9	11063.06	315.05	2000	650.52	500
10	11107.41	322.57	2000	725.65	500

Table 11. The parameters for retailers in P1-V1R5 under infinite or unauthorized backorder conditions

j	1	2	3	4	5
H_{bj}	7	8	9	7	9
S_{bj}	10	20	30	15	25
a_j	20	19	18	21	18
k_j	0.003	0.005	0.008	0.003	0.006
y_{jmin}	2000	500	500	1700	500
y_{jmax}	4000	3000	1500	3500	2500
θ_j	0.004	0.006	0.008	0.005	0.007
β_j	0.1	0.1	0.1	0.1	0.1
π_{bj}	∞	∞	∞	∞	∞
F_j	3000	3000	3000	3000	3000

Table 12. The parameters for the vendor in P1-V1R5 under infinite or unauthorized backorder conditions

H_s	S_s	C	δ	CC	f	N
9	150	9850	7	100	0.2	50

Table 13. The comparison of P1-V1R5 from our study with Diabat [24]

P1-V1R5	y_{1opt}	y_{2opt}	y_{3opt}	y_{4opt}	y_{5opt}	Z_1^*	Z_2
This study	2000	709.530	500	1700	535.806	18818.797	544.534
Diabat [24] using a hybrid algorithm	2126	653	567	1702	522	17602.15	--

Table 14. The GVMI model with one vendor and five retailers by considering different shortages

Test problem	π_{bj}	y_{jopt}	Z_1^*	Z_2	Q_j^*	b^*
P1-V1R5	1000000	2000 709.530 500 1700 535.806	18818.797	544.534	79.058 54.052 50.000 79.844 48.800	79.056 54.051 50.000 79.843 48.799
P2-V1R5	1000	2000 709.879 500 1700 536.205	18862.358	544.608	79.687 54.523 50.448 80.480 49.255	78.432 53.611 49.556 79.212 48.384
P3-V1R5	100	2000 712.667 500 1700 539.364	19211.411	545.203	85.147 58.595 54.314 85.994 53.185	73.403 50.081 46.029 74.133 45.072
P4-V1R5	10	2000 725.645 500 1700 553.583	20864.665	547.923	127.475 89.819 83.666 128.744 83.000	49.029 33.266 29.881 49.517 29.643

Table 15. The results of ε-constraints method for P4-V1R5

P4-V1R5	$max\ Z_1$	$min\ Z_2$	y_{1opt}	y_{2opt}	y_{3opt}	y_{4opt}	y_{5opt}
1	20438.883	520.000	2000	500.000	500	1700	500.000
2	20486.192	521.630	2000	512.811	500	1700	503.492

3	20533.501	523.101	2000	527.516	500	1700	503.492
4	20580.810	524.689	2000	543.396	500	1700	503.492
5	20628.119	526.428	2000	560.791	500	1700	503.492
6	20675.429	528.373	2000	580.242	500	1700	503.492
7	20722.738	530.621	2000	602.720	500	1700	503.492
8	20770.047	533.383	2000	630.342	500	1700	503.492
9	20817.356	537.383	2000	670.335	500	1700	503.492
10	20864.665	547.923	2000	725.645	500	1700	553.583

Table 16. The real dimensions of instances

The number of test problems	The number of retailers	Amount of shortage (π_{bj})
T1	5	10
T2	10	10000
T3	10	10000000
T4	15	100
T5	15	100000
T6	25	1000
T7	25	10
T8	35	1000
T9	45	10000
T10	50	10000

Table 17. Algorithms and Factor levels with the total number of experiment for each method (MaxIt=maximum number of iteration; nPop=maximum number of initial population; N_{male}=number male RDs; $P_{\propto}$=percent of mating inside the harems; P_{β}=percent of mating outside the harems; P_{γ}=percent of male commanders; P_C=percent of crossover; P_M=percent of mutation; T_C=type of crossover (1 to 3); T_M=type of mutation (1 to 3); *PN1*=The percentage of *N1* Keshtels; *PN2*=The percentage of *N2* Keshtels; Smax=The maximum number of swirling process)

Algorithm	Factors and their levels						N. of experiments; Total Number=(n_f, n_{ax}, n_{cp})
MORDA	MaxIt (150, 300)	nPop (100, 200)	N_{male} (15, 40)	$P_{\propto}$ (0.6, 0.9)	P_{β} (0.4, 0.7)	P_{γ} (0.5, 0.8)	82=(2^6, 12, 6)
NSGA-II	MaxIt (150, 300)	nPop (100, 200)	P_C (0.5, 0.8)	P_M (0.02, 0.1)	T_C (0, 3)	T_M (0, 3)	82=(2^6, 12, 6)
MOKA	MaxIt (200, 500)	nPop (100, 200)	*PN1* (0.1, 0.4)	*PN2* (0.2, 0.4)	Smax (1, 4)		48=(2^5, 10, 6)

Table 18. Tuned parameters of algorithms and R-squared (R^2)

Algorithm	Parameters	R^2 objective function (%)	R^2 CPU time (%)
MORDA	MaxIt=246; nPop=148; N_{male}=28; $P_{\propto}$=0.85; P_{β}=0.52; P_{γ}=0.77;	69	84
NSGA-II	MaxIt=250; nPop=150 ; P_M=0.05; P_C=0.7; T_M=1; T_C=3;	64	66
MOKA	MaxIt=250; nPop=186; *PN1*=0.25; *PN2*=0.3; Smax=3;	74	88

Table 19. The results of algorithms in term of assessment metrics

Number of test problem	NPS			SNS			POD		
	NSGA-II	MORDA	MOKA	NSGA-II	MORDA	MOKA	NSGA-II	MORDA	MOKA
T1	14	13	8	3540	4267	3438	0.16	0.25	0.18
T2	10	12	8	2956	3867	2865	0.24	0.24	0.26
T3	9	13	9	1475	2465	3968	0.17	0.28	0.19
T4	8	10	9	3287	2934	2968	0.12	0.22	0.33
T5	8	10	6	2465	2734	2881	0.09	0.21	0.32
T6	10	10	7	2473	2910	2473	0.08	0.29	0.28
T7	12	9	7	2855	3281	1945	0.12	0.34	0.24
T8	9	9	9	2594	3844	1673	0.14	0.28	0.29
T9	8	10	9	3193	3285	1882	0.16	0.36	0.22
T10	8	9	8	1845	3882	2519	0.12	0.32	0.26

Authors' biography:

Mohammad Mahdi Karampour was born and raised in Kermanshah, Iran. He graduated from B.Sc. in Industrial Engineering at Payamnour University, Kermanshah, Iran (2015). Then, he earned his M.Sc. in Industrial Engineering at University of Science and Technology of Mazandaran, Behshahr, Iran (2019). He currently works as a production planner and supply chain consulter at International Companies in Iran. He is interested in business management, inventory control, supply chain and logistics along with the use of mathematical models and optimization algorithms.

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