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A NEW VENDOR-MANAGED INVENTORY FOUR-TIER MODEL BASED ON REDUCING ENVIRONMENTAL IMPACTS AND OPTIMAL SUPPLIERS SELECTION UNDER UNCERTAINTY

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Abstract. For the best implementation of (vendor-managed inventory) VMI, a vendor must choose the optimal combination of suppliers that can better meet the criteria of environmental problems. In VMI, a vendor controls some retailers' inventory decisions. This study aims to select the best suppliers in the green VMI and assign orders to them. In this study, the vendor selects suppliers by accounting for various factors, including quality factors, delivery reliability, and the reduction of the return percentage of raw materials in the developed mathematical model. For this purpose, this paper applies the Bayesian best worst approach (BWM), as one of the multi criteria decision making (MCDM) techniques, for ranking these criteria and the fuzzy technique for order of preference by similarity to ideal solution (FTOPSIS) for prioritizing the suppliers. Then, the obtained weights are plugged into the model as the inputs of the proposed model. Since the developed model is a non-differentiable, non-convex, and mixed-integer function, genetic algorithm (GA) and particle swarm optimization (PSO) are leveraged to solve the formulated model. Finally, the efficiency of the presented method is verified through a case study with actual data collected from the electronic supply chain.

1. **Introduction.** Rapid and avoidable changes in today's global market have caused companies to interact more and more with each other [18, 8, 62]. In today's competitive world, supply chain management (SCM) is significant in managing costs and integrating different parts of the organizations [16, 4]. One of the main factors in SCM is inventory management [67]. Vendor-managed inventory (VMI) is one of the most significant policies in inventory management, which is based on the cooperation of the retailer and the vendor [14, 55, 59]. VMI is an

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inventory management practice that is applied to manage the supply process by exchanging information between retailers and vendor. In this collaboration, the vendor controls the retailers' inventory decisions [32]. VMI has a significant role in supply chains to reduce costs and increase the level of service [14]. This enables suppliers to stabilize their production and optimize transportation costs. Another advantage of VMI for the supplier is the reduction of its inventory costs. Since the uncertainty is considerably reduced by VMI, the obsolescence of safety stocks at the supplier is diminished. Therefore, inventory and ordering costs can be decreased for the retailers [19, 67]. The most apparent benefits of VMI are inventory cost reduction for the retailer and total cost reduction for the supplier. The productivity and service level improvement leads to a more significant profit margin and increased sales [31, 65]. Inventory management is one of the original activities in the supply chain that generates carbon emissions. Thus, it is necessary to study environmental problems in VMI and minimize costs. In particular, inventory management is one of the significant activities of organizations concerning transportation and warehousing activities, which are the main reasons for pollution in the supply chain [39, 49]. Therefore, in addition to controlling costs, it is better to consider environmental issues in inventory management due to their simultaneous impact [19, 42]. The green supply chain can improve the competitive position of organizations by reducing costs [10, 9]. In addition to environmental issues and cost reduction, supplier selection is another significant issue in the VMI. This study aims to select the best suppliers in the green VMI and assign orders to them. Therefore, due to the importance of environmental issues in this research, the vendor not only carries out her production, maintenance, and transportation operations considering these issues but also selects his suppliers based on environmental criteria.

When in the VMI policy, the vendor is the manufacturer, and his suppliers provide the required raw materials, the success of implementing the VMI policy also depends on the proper performance of suppliers. All supply chain members can play an essential role in the relationship between the retailer and the vendor in the VMI strategy. Especially, supplier has a very influential role in this relationship because the supplier initiates any supply chain's activities. Supplier performance management dramatically impacts the quality of the vendor's product and the performance of the vendor's delivery to the retailers [8, 11]. Suppose the supplier fails to meet the vendor's appropriate criteria in the supply of raw materials. In that case, this will affect the relationship between the vendor and the retailer because the delay in delivery makes the vendor unable to deliver his products with the required quality and on time to the retailers. This strategy costs the vendor a lot to establish and use information technology [15, 43]. If the suppliers cannot deliver the orders to the retailer on time and with the required quality, this strategy will not work. Therefore, selecting suitable suppliers is a necessity to implement this policy. The vendor of final products can properly control production planning decisions and quantify orders and inventory levels when raw material suppliers have good performance. Inaccuracy in determining the optimal order from suppliers by vendor ultimately leads to retailer dissatisfaction and poor communication between the vendor and retailers in the VMI policy [1, 36, 17, 56]. Many manufacturers have realized that focusing on improving internal processes alone is not enough to improve performance [13, 35]. Consequently, understanding supply chain management practices is essential to sustaining profits in today's highly complex and competitive business world [36, 50]. Suppliers' role in affecting firms' performance has been well recognized in the literature [30]. Companies' increasing dependence on their suppliers has highlighted the need for effective supplier management costs of purchased goods and services, which typically account for about 70% of the total costs [29, 48].

To maintain a competitive position and efficiently implement the VMI, the vendor must evaluate its suppliers. Therefore, one of the essential factors that help achieve effective coordination between the vendor and the retailers is accurately determining orders from their suppliers [38, 40, 41]. For this purpose, in this study, the vendor selects suppliers using a variety of impactful factors, which includes quality, delivery reliability, reducing lead time, and reduced return percentage of raw materials in the developed mathematical model and according to these factors and green factors determines the optimal order quantity from each supplier. Also, when the suppliers are more than one level, the performance of the second-level suppliers affects the quality performance and delivery of the first level supplier. Therefore, based on the case study, this study selects its suppliers according to the desired criteria.

In this study, the vendor communicates with retailers through blockchain technology, and each retailer provides information to the vendor about the sales amounts and the inventory level. As a result, the vendor can adjust the same amount of production based on the demand for shared information [28, 61, 24]. In the VMI, the goal is to reduce the risk of unmet demand and reduce the costs of inventory shortages [21, 34]. When the vendor communicates with the retailers through the VMI, the vendor has accurate, complete information about the retailers' demand instead of forecasting retailer demand based on past data about their received orders. Therefore, the retailer attributes a probability distribution to the demand the vendor can produce based on. Due to the nature of the demand and the type of their uncertainty, chance constraint programming (CCP) is used, leading to more accurate constraints and a designed model. CCP is less conservative than the robust programming approach since they take a probabilistic approach to constraint satisfaction that allows the violation of constraints with a low probability [12, 58].

A CCP is imposed to satisfy retailers' demand from the vendor and is used to solve the resulting optimization problem. Also, in this study, lead time from suppliers to vendors and from vendor to retailers is considered random, and CCP is leveraged to develop an optimization model. Another factor that improves the relationships and implementation of VMI policy is the delivery reliability of raw materials and products. Delivery reliability in the supply chain is the critical factor determining the level of supply chain risk when retailer demand has random nature. Delivery reliability maximizes retailer satisfaction and increases market share [33, 37, 44]. Thus, in this study, the delivery reliability of raw materials from first level suppliers to vendor and delivery reliability of products from vendor to retailers are considered. In this study, considering the policy of VMI, a model with multiple second level suppliers, multiple first level suppliers, a single vendor, and multiple retailers are developed to solve the problem of order quantity determination considering the delivery reliability of the supply chain. Given that the supplier section is one of the most common activities that directly result in determining the vendor's performance in the implementation of VMI, it is essential to study it. The main contributions of this research are as follows:

1. We deployed for the first time a four-tier supply chain in the field of VMI that accounts for multi-level 2 suppliers, multi-level 1 suppliers, single vendor, and multi-retailers. This is in contrast to most of VMIs that are two-level,

including vendor and retailers, or three-level including vendor, distributors, and retailers. Besides, this study considers supplier performance management in the four-tier VMI policy. A new binary variable is added to the model to decide whether to impose or not to impose the order on suppliers. Both the optimal order quantity of the final product and the optimal order quantity of raw materials are also determined in VMI.

2. The environmental problems in VMI with one vendor have been considered more in response to environmental pollution through innovations such as replacing less polluting sources with inefficient equipment and facilities. In comparison, the significant emissions sources are business activities and operating policies. Therefore, this study examines the amount of carbon dioxide emissions from order preparation and storage activities with a different perspective from previous studies and a new objective function to control green emissions.
3. Constraints related to late delivery, lead time, return percentage, quality, and delivery reliability are studied in the VMI strategy. As a research gap in the literature of VMI, a multi-objective model is developed to account for the supplier selection, delivery reliability, and lead time between all supply chain members.

The rest of the paper is organized as follows. Section 2 describes the literature review of the subject. Section 3 discusses the research process. Section 2 describes the solving method .The findings are presented in Section 5. The conclusion is given in Section 6.

2. **Literature review.** The retailer-vendor partnership in VMI is considered in three ways: A single vendor and a single retailer; a single vendor, multi-retailers, multi-vendors, and multi-retailers. Goyal (1998) [23] first developed a VMI model for a single-vendor single-retailer inventory management system that minimizes the total costs of the supply chain. In this note, a more general joint economic-lot-size model is considered. Under VMI policy, Sadeghi et al. (2013) [56] examined the inventory management system, including multiple vendors, multiple retailers, and a central warehouse. This study aims to find the order quantities and the number of shipments retailers and vendors receive. Sadeghi et al. (2014) [57] presented a bi-objective VMI model for a multi-level supply chain by one manufacturer, one vendor, and multiple retailers. The proposed VMI model confronts several constraints, including available budget and space for machinery, the number of orders, and the vendor's budget. Karimi et al (2017) [27] examined a VMI multi-objective model with a single vendor, and multiple retailers considering the cost of carbon emissions.

The authors evaluated the tax cost of industrial carbon emissions of all products and a limitation on total carbon emissions. Also, the vendor desires to maximize the total profit and the mean time to failure of the production system. Karbasibonab et al. (2018) [26] designed a bi-objective VMI model with fuzzy demand for a supply chain with multiple vendors and multiple retailers that minimize the total cost of the supply chain and optimize the warehouse space. The vendor confronts two constraints: the number of orders and the available budget. Bieniek (2021) [11] investigated the VMI strategy considering uncertain demand. They optimized a two-stage model where first, the vendor determines the price and order quantity of the product to increase the vendor's profit, and second, the retailer specifies the retail price.

Stellingwerf et al. (2019) [62] considered a VMI multi-objective model comprising a single vendor and multiple retailers for minimizing the economic and environmental carbon emissions and economic effects. Gharaei et al. (2019) [21] examined a model in the integrated multi-product green supply chain with a single vendor and multiple retailers under the VMI policy, which has random constraints.

Liu et al. (2020) [35] developed a VMI model for blood products to address the routing problem of these products. The authors considered scheduling blood products that balance supply and demand, and to solve the designed model, a decomposition-based algorithm was developed. Wettasinghe et al. (2020) [64] developed a VMI with emergency orders consisting of a single vendor and a single retailer. Formulated models are used to determine the optimal base inventory level and cycle length to minimize the total expected inventory cost. Ashraf et al. (2021) [2] considered a new interval type-2 fuzzy VMI system, in which the interval type-2 fuzzy numbers design order quantity and demand. The objective is to reduce the total cost for a single vendor and a single retailer. Najafnejhad et al. (2021) [45] considered a VMI model comprising a single vendor and multiple retailers; this study aims to find an optimal amount for order quantities, replenishment frequencies of retailers, and upper limits on the retailer's inventory level. In addition to inventory decisions, the proposed model optimizes an upper limit for inventory levels based on a penalty. Astanti et al. (2022) [3] considered the VMI with a single vendor and a single retailer. This study evaluates the effect of product failure, and the products are inspected 100 for quality assessment. Kusuma et al. (2022) [32] discussed the VMI model with three levels vendor, distributor, and retailers. In this model, retailers aim to select the best vendors. For the first time, Shang et al. (2022) combined the VMI with two approaches of routing and location.

The problem is discussed at three levels: vendor, warehouse, and retailer. Also, this approach uses robust programming to deal with demand uncertainty. Niknamfar (2015) [46], for the first time, considered the supplier level in the VMI strategy. The introduced model contains multiple suppliers, vendors, and retailers. The author combined the production distribution problem and VMI to control the bullwhip effects in the supply chain. Table 1 shows some studies on VMI problems. Most VMI studies have been conducted at two levels. The three-tier supply chain is very limited in this field, and the three-tier supply chain in this field mostly includes vendors, distributors, and retailers. Only one study [46] has studied the three-tier supply chain in the VMI field with three levels of supplier, vendor, and retailer. The aim is to determine the optimal production rate in overtime and regularly. To date, no study has examined supplier selection in the VMI. In contrast, the selection of optimal suppliers leads to improved competitive advantage and reduced costs. Also, in many organizations, the type of parts and raw materials used in the final product can significantly affect the final product's quality. For this reason, in this study, in addition to examining the suppliers who are directly related to the vendor (manufacturer), the suppliers of raw materials are also considered as the second level, and the optimal suppliers and the amount of orders optimal to be selected from each in both levels. Thus, in this study, constraints such as lead time, delivery delay, and return percentage in the selection of first and second-tier suppliers have been investigated. Table 1 shows some studies on VMI.

3. **Research process.** In this study, the criteria for selecting green suppliers are extracted using previous research results and literature studies. To obtain the most

Table 1. Some studies on VMI problems

Study	Retailer	Vendor	Distributor	Supplier	reliability	Constraints
[3]	Multiple	Multiple	No	No	Yes	No
[34]	Multiple	Multiple	No	No	Yes	Capacity and budget
[31]	Multiple	Single	Single	No	No	Capacity.
[59]	Multiple	Single	Multiple	No	Yes	Demand.
[25]	Multiple	Single	No	No	No	Maximum allowable cost
[33]	Multiple	Multiple	No	No	No	Routing and demand constraints
[63]	Single	Single	No	No	Yes	No
[20]	Multiple	Single	No	No	No	Order constraint
[49]	Single	Single	No	No	Yes	Re-manufacturing product quantity and order constraint
[29]	Single	Multiple	No	No	Yes	Quality level Number of cycles .
[45]	Multiple	Single	No	No	Yes	Acceptable retail price, Capacity, and production constraints .
[61]	Multiple	Single	No	No	No	Number of replenishment storage
[56]	Multiple	Multiple	No	No	No	Number of order storage
[40]	Multiple	Multiple	No	No	No	Number of order storage, capacity and budget
[65]	Single	Single	No	No	No	Capacity and budget
[14]	Single	Multiple	No	No	No	Capacity
[17]	Single	Multiple	No	No	Yes	Capacity
[10]	Single	Multiple	No	No	Yes	Interruption constraints
P.S	Multiple	Single	No	Yes	Yes	Late delivery, return percentage, quality, delivery reliability, capacity, budget, and lead time .

effective criteria for selecting suppliers based on success in implementing environmental factors between the studied criteria, experts' opinions are specified based on the needs of the organizations and strategy. After negotiation with the under-study company, the total number of these people is announced as about 12 people in each company (vendor and tier 1 supplier). After the necessary interviews and reviews, seven criteria of having a scientific approach to environmental protection (A), the degree of cooperation with green suppliers (B), designing products to reduce energy consumption (C), social responsibility (D), pollution control(E), the extent of attention to environmental goals(F), and using of technology sync with the environment (G) are selected from the set criteria.

3.1. **Obtaining the final score of suppliers.**

3.1.1. *Predicting the degree of importance of the criteria using Bayesian BWM.* The required data are collected using the BWM method by placing the extracted criteria in the designed questionnaire. BWM is one of the MCDM techniques based on pairwise comparisons proposed by Rezaei [53]. MCDM techniques help the decision-maker assess all these criteria [25, 42]. Since many criteria are involved in supplier selection, it is an MCDM approach. In BWM, the best and worst criteria are specified by the decision-maker and a paired comparison among each of these two criteria with other criteria is performed [6, 5, 7]. The questionnaires are related to pairwise comparisons with saaty scales (1 to 9) to compare the best criterion with other criteria and the remaining criteria with the worst criterion distributed among the company's experts. After making pairwise comparisons among the best criterion and other, and among the other and the worst criterion, the criteria weights are calculated using Bayesian BWM [40, 20]. Figure 1 presents the results of the confidence levels of the criteria pair relative to each other. The values in Figure 1 state the confidence level of each criterion relative to the other. If the confidence level of one criterion is higher than 0.5, it can be concluded that the criterion is preferable to the other criterion. As it is clear, all confidence levels of the criteria are higher than 0.5. Also, the average confidence levels of the criteria are 0.898, demonstrating the obtained results' validity.The values in Figure 2 state the confidence level of each criterion relative to the other for selecting tier 2 suppliers.

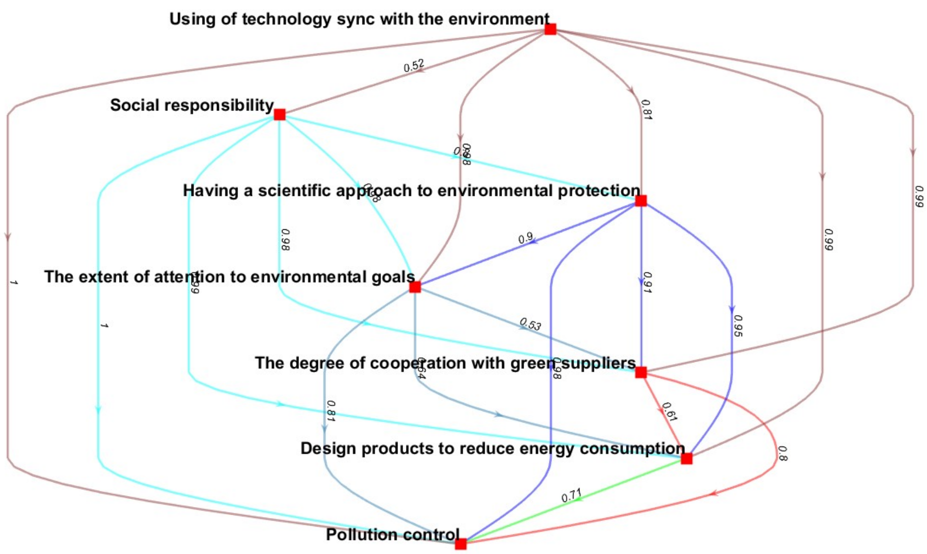

FIGURE 1. The confidence of criteria to one another using Bayesian BWM in selecting tier 1 suppliers

Table 2 presents the weight of the criteria for selecting tier 1 suppliers using the Bayesian BWM.

TABLE 2. Weight of the criteria for tier 1 supplier

Criteria	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Weight	0.1323	0.1664	0.1188	0.1591	0.1591	0.1624	0.1177

Table 3 presents the weight of the criteria for selecting tier 2 suppliers using the Bayesian BWM.

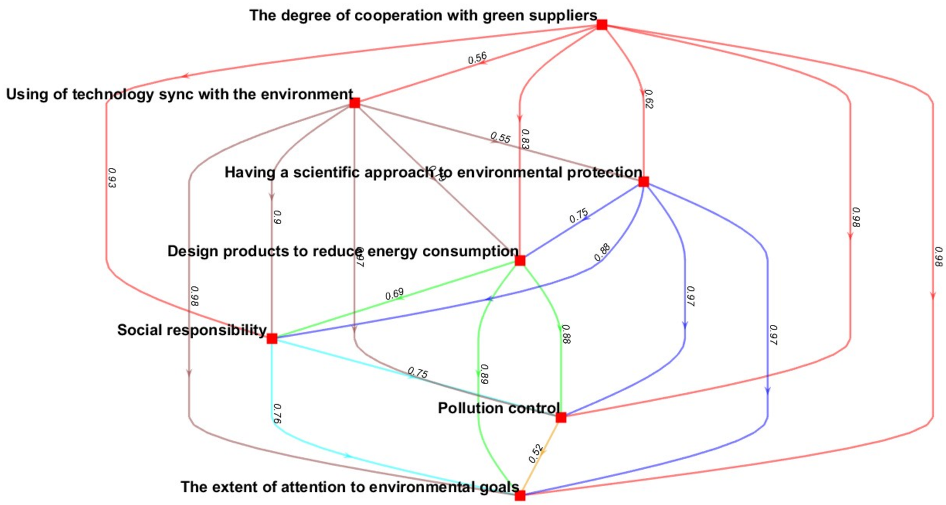

FIGURE 2. The confidence of criteria to one another using Bayesian BWM in selecting tier 2 suppliers

TABLE 3. Weight of the criteria for tier 2 supplier

Criteria	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Weight	0.1323	0.1664	0.1188	0.1591	0.1591	0.1624	0.1177

3.1.2. *Obtaining the final score of each supplier through the TOPSIS technique.* In this study, to prioritize retailers, fuzzy TOPSIS is used. In this approach, the chosen alternative must have the shortest distance from the positive ideal and, on the other hand, the maximum distance from the negative ideal. Retailers are ranked using fuzzy TOPSIS [6]. The obtained results are given in Tables 4 and 5. In these Tables, the normalized values of the weights are calculated. Based on the results of Table 4, supplier 2 gained a high weight of 0.6123. Based on the results of Table 5, supplier 1 gained a high weight of 0.5645. In the next step, the obtained weights based on Tables 4 and 5 are entered as inputs of the mathematical model.

TABLE 4. The normalized values of the weights

suppliers	$D+$	$D-$	CI	Normalized weight	*Raking*
1	0.1731	0.0564	0.2234	0.1325	2
2	0.1524	0.0934	0.385	0.1854	1

TABLE 5. The normalized values of the weights

suppliers	$D+$	$D-$	CI	Normalized weight	*Raking*
1	0.0678	0.0546	0.7185	0.5645	1
2	0.073	0.1524	0.385	0.4325	2

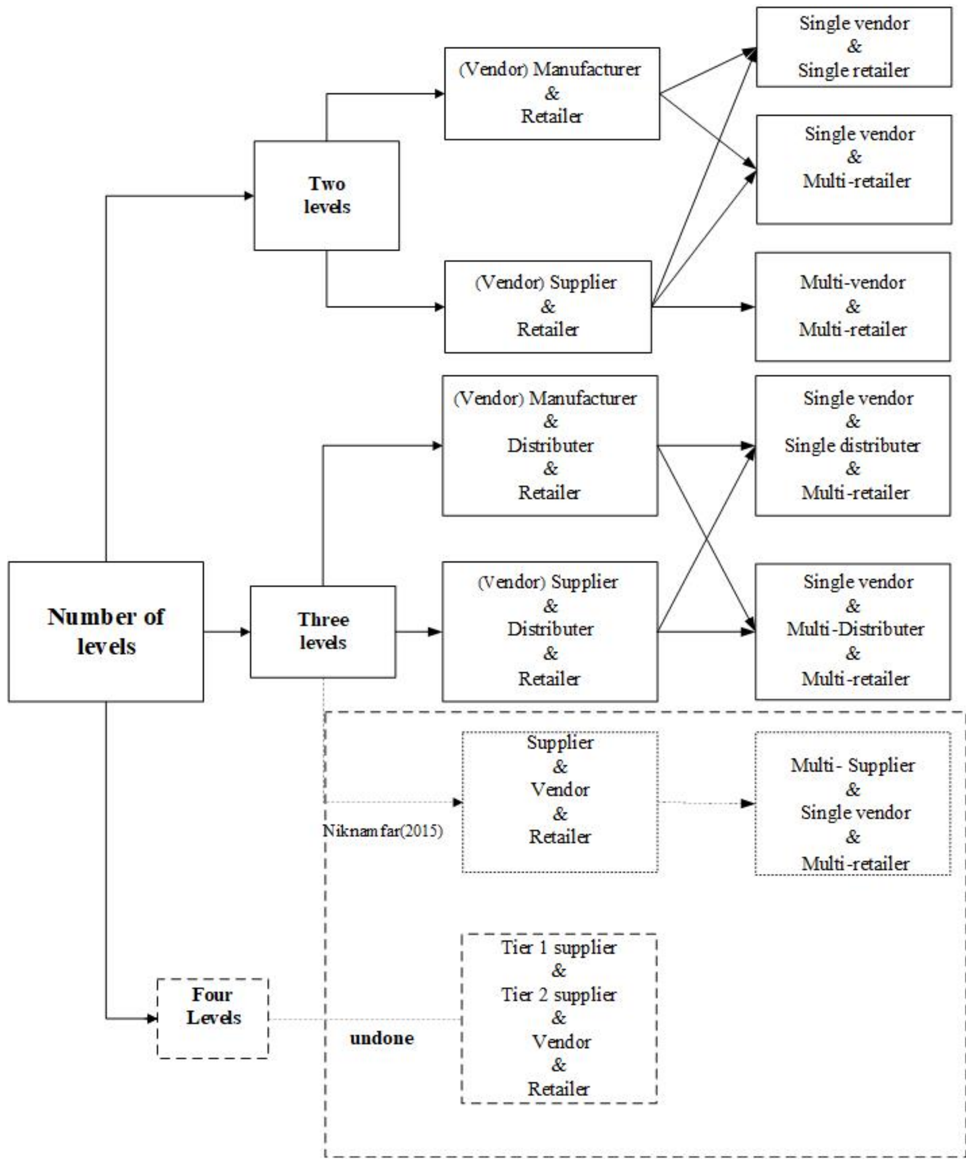

Figure 3. Structure of the designed model

Figure 3 shows the structure of the designed model. In this study, to ensure the timely production and delivery of products from vendor to the retailer, which leads to long-term communication, the optimal suppliers are selected according to lead time, return percentage, delivery reliability, and delay time. Figure 4 shows the flow diagram of the proposed model for supplier selection in VMI.

3.2. **Case study.** This model considers the case study to evaluate the designed mathematical model. The first level includes multiple retailers, the second contains one vendor, the third includes tier 1 suppliers, and the fourth includes tier 2 suppliers. Tier 2 suppliers supply some of the required parts by tier 1 suppliers. Tier 2

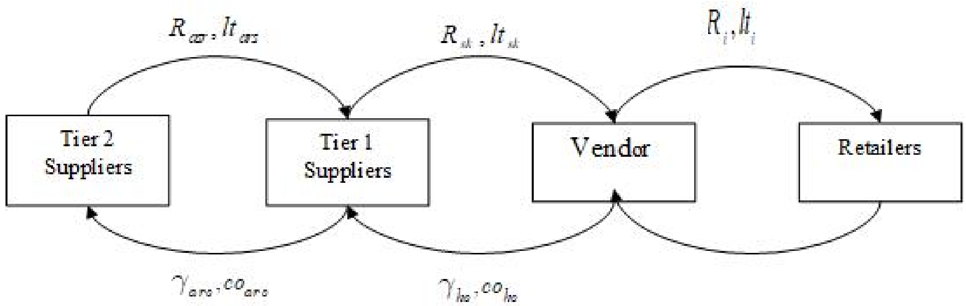

FIGURE 4. Flow diagram of the proposed model for supplier selection

suppliers are the supplier of raw materials, and tier 1 suppliers are the manufacturer of components. The vendor receives parts from the tier 2 suppliers, turns them into the final product, and sells them to retailers. In this model, raw materials are purchased from 2 suppliers and placed in the production process according to need after completion. The vendor is the manufacturer and seller of the water pump. After the production process is completed, the final product is sent to the retailers. The vendor company is located in one of the most popular cities in Iran. Figure 5 shows the supply chain network structure.

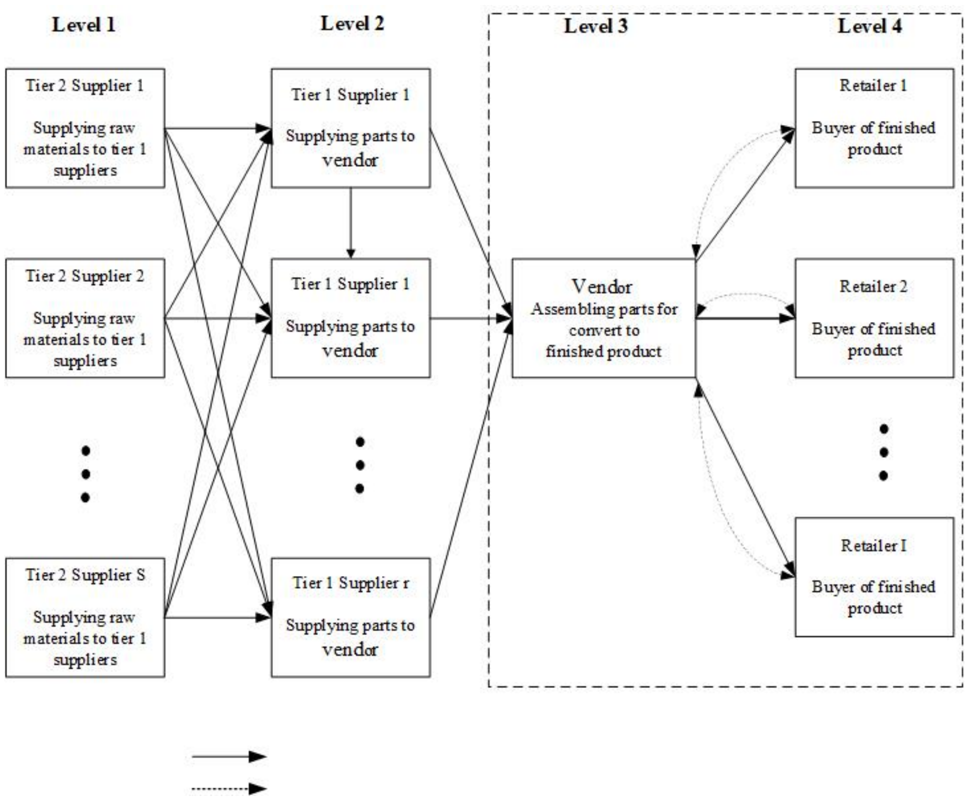

FIGURE 5. The supply chain network structure.

3.3. **Problem statement and model development.** The original purpose of designing this model is to determine the optimal allocation of vendor orders to the best tier 1 supplier, and the optimal orders to vendor from retailers. The first level of the supply chain includes four retailers, the second level comprises one vendor (manufacturer), the third level contains 2 tier 1 suppliers, and the fourth level includes 2 tier 2 suppliers. Each supplier produces one or more of the items needed to produce the seller's product. To produce the final product by the vendor (manufacturer), three parts must be assembled. The parts used by the manufacturer are supplied by tier-1 suppliers who are the manufacturer of parts. Tier 1 suppliers supply raw materials from tier 2 suppliers to produce parts. The car's water pump consists of three parts (parts), including the outer shell, blade, and shaft. The material of each component depends on its function and resistance to heat and pressure. The outer shell of the water pump is made of aluminum, and the blade and shaft are made of cast iron and steel, respectively. The tree structure of the final product is shown in Figure 6.

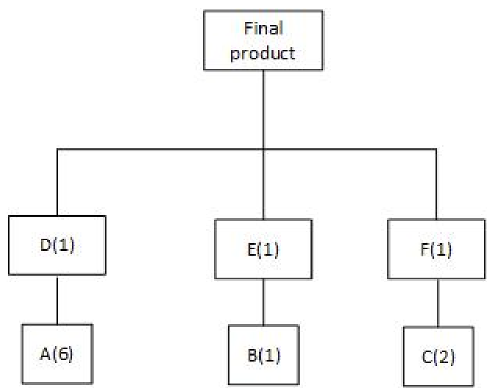

FIGURE 6. The tree structure of the final product

This study develops a multi-tier 1 supplier, multi-tier 2 supplier, single-vendor, and multi-retailer VMI model based on the problem definition and its primary assumption. The main goal is to design a reliable supply chain, and the goal is to determine the order quantity allocated to retailers. The model assumptions are as follows:

- The supply chain consists of multiple tier 2 suppliers, multiple tier 2 suppliers, a single vendor, and multiple retailers.
- The demand of retailers from the vendor is random and follows a normal distribution.
- Ordering periods for all retailers supplied by the vendor are simultaneous.
- Demand for the final product is under complete assurance conditions.
- Production capacity is constant.
- Shortages are allowed for vendor.
- The cycle time of vendor and retailers is the same.
- Discounts are not allowed.
- Inventory control is based on the model (r, Q)
- Lead time and demand during the lead time are random.

3.3.1. *Mathematical modeling.* The problem under study is to determine the optimal orders of suppliers and vendor to minimize the cost of the supply chain. Parameters, decision variables, and then the mathematical model of the problem are presented as follows:

As regards the replenishment interval is the same for all retailers who order from one vendor, i.e., $\frac{q_i}{d_i} = \frac{q_1}{q_2}$; In other words, the vendor replenishes retailers at the same interval. In this study, three objective functions are considered for the proposed VMI model, which is as follows:

Objective function 1: minimizing the total cost

$$\begin{aligned} \min z = & \sum_{i=1}^{I} \xi_i q_i(\phi_i \varepsilon_i) + \sum_{i=1}^{I} \upsilon_i q_i(1-\varepsilon_i) + \sum_{i=1}^{I} \lambda_i q_i \varepsilon_i (1-\phi_i) + \\ & + \sum_{k=1}^{K} \sum_{s=1}^{S} B_{ks} q_{ks} + \pi \tfrac{E(d)}{q} E(d>r) \\ & + \sum_{i=1}^{I} h_i (\tfrac{q_i}{2} + Z_\alpha \sqrt{\mu_{d_i} \sigma_{d_i}^2 + \mu_{d_i}^2 \sigma_{Lt_i}^2}) + \sum_{s=1}^{S} \sum_{k=1}^{K} h_{ks} \tfrac{q_{ks}}{2} \\ & + \sum_{i=1}^{I} \tfrac{E(d_i)}{q_i}(A_i + f_i) + S \tfrac{E(d)}{q} + \sum_{s=1}^{S} \sum_{k=1}^{K} (A_{ks} + f_{ks}) \tfrac{E(d_{ks})}{q_{ks}} \end{aligned} \tag{1}$$

The first objective function minimizes supply chain costs. Eq. 1 consists of eleven parts. The first part shows the total disposal cost for scrap products. This part $\phi_i \varepsilon_i$ shows the percentage of scrap products, where the multiplying amount of products ordered to vendor (q_i) by the percentage of scrap products gives the number of scrap products. The second part indicates the total procurement costs for healthy products. The part of $(1-\varepsilon_i)$ shows the portion of healthy products, where multiplying the amount of products ordered to vendor (q_i) by the percentage of healthy products gives the number of healthy products. The third part shows the rework cost for products. This part $\varepsilon_i(1-\phi_i)$ shows the percentage of reworkable goods. For calculating the reworking cost, the mentioned term is multiplied by the amount of product ordered from the vendor. The fourth part represents the total inspection cost of raw materials supplied by tier 1 suppliers. The fifth part represents the total shortage cost of the vendor. To calculate the shortage costs, we need to obtain the backorder amount. We know that demand during the lead time for vendor follows the normal distribution with:

$$N \cong (\bar{d}.L\bar{t},\ L\bar{t}.\sigma_d^2 + \bar{d}^2.\sigma_{Lt}^2) \tag{2}$$

Therefore, back order of the product for retailers during the lead time will be obtained as follow:

$$\begin{aligned} E(d>r) &= \int_r^\infty (d-r)\, f(d)\, d(d) \\ &= \int_r^\infty (d-r) \tfrac{1}{\sqrt{2\pi(L\bar{t}.\sigma_d^2 + \bar{d}^2.\sigma_{Lt}^2)}}\, e^{-\frac{1}{2}\left(\frac{(d_i - r_i)}{L\bar{t}.\sigma_d^2 + \bar{d}^2.\sigma_{Lt}^2}\right)^2} d(d) \end{aligned} \tag{3}$$

Given that the integral in Eq. 3 is very difficult to obtain, the following method is presented for obtaining this integral. To calculate the integral in Eq. 3, we first define the variables u and k according to Eqs. 4 and 5.

$$u = \frac{d-r}{L\bar{t}.\sigma_d^2 + \bar{d}^2.\sigma_{Lt}^2} \quad \Rightarrow du = \frac{1}{L\bar{t}.\sigma_d^2 + \bar{d}^2.\sigma_{Lt}^2}\, d(d) \tag{4}$$

$$k = \frac{r - \bar{d}.L\bar{t}}{L\bar{t}.\sigma_d^2 + \bar{d}^2.\sigma_{Lt}^2} \tag{5}$$

Table 6. Notations used in designed model

sets	
S	The set of tier 1 suppliers indexed by s;
R	The set of tier 2 suppliers indexed by r;
I	The set of retailers indexed by i;
K	The set of parts indexed by k;
A	The set of raw materials indexed by a;

Decision variables	
q_i	Amount of product ordered to the vendor by i^{th} retailer.
q_{ks}	Amount of k^{th} part ordered to s^{th} supplier by vendor.
q_{ars}	Amount of a^{th} raw material ordered to r^{th} supplier by s^{th} supplier.
pr	Amount of production the product by the vendor.
pr_{ks}	Amount of product ordered by k^{th} part by s^{th} supplier.
Z_s	Binary variable taking the value of 1 when s^{th} supplier is selected; otherwise, it is equal to 0.

Parameters	
A_i	The ordering cost of product for i^{th} retailer.
S	The setup cost of the vendor's product.
H_i	The holding cost of the product for i^{th} retailer.
h_{ks}	The holding cost of k^{th} part for vendor supplied by s^{th} supplier
λ_i	The rework cost of vendor's product related to i^{th} retailer.
υ_i	The procurement cost of vendor's healthy product related to i^{th} retailer.
ξ_i	The disposal cost of vendor's product related to i^{th} retailer.
f_{ks}	The transportation cost of k^{th} part from s^{th} supplier to the vendor.
A_{ks}	The ordering cost of k^{th} part for vendor supplied by s^{th} supplier.
f_{ars}	The transportation cost of a^{th} raw material from r^{th} supplier to s^{th} supplier
A_{ars}	The ordering cost of a^{th} raw material for s^{th} supplier supplied by r^{th} supplier
Cap	Maximum capacity of the vendor to maintain the product.
Cap_i	Maximum capacity of i^{th} retailer to maintain the product.
Cap_{ks}	Maximum capacity of s^{th} supplier to maintain k^{th} part.
SS_i	Safety stock of i^{th} retailer for the product.
SS	Safety stock of the vendor for the product.
B_{ks}	Inspection cost of k^{th} part by s^{th} supplier for the vendor.
Co_{ks}	Percentage of k^{th} part returned to s^{th} supplier by the vendor.
γ_{ks}	Percentage of k^{th} part delivered late by s^{th} supplier to the vendor.
γ_{ars}	Percentage of a^{th} raw material delivered late by r^{th} supplier to s^{th} supplier.
I_{ak}	The ratio of a^{th} raw material in k^{th} part.
I_k	The ratio of k^{th} part in the product .
τ_k	Maximum acceptance of return percentage of k^{th} part for the vendor.
ω_k	Maximum acceptance percentage of late delivery of k^{th} part for the vendor.
n	Procurement cost to determine the percentage of the vendor's reworked product.
e	The rework cost of the vendor's product.
k	Service level.
ϕ_i	Scrap percentage of the vendor's product related to i^{th} retailer
ε	Defective percentage of the vendor's product
ε_i	Defective percentage of the vendor's product related to i^{th} retailer
ε_{sk}	Defective percentage of k^{th} part related to s^{th} supplier
e	Maximum rework cost of the product for vendor
lt_{ks}	Lead time from s^{th} supplier to vendor to transfer k^{th} part.
lt_i	Lead time from the vendor to i^{th} retailer to transfer the product.
lt_{ars}	Lead time from from r^{th} supplier to s^{th} supplier to transfer a^{th} raw material.
l_i	Lead time from the vendor to i^{th} retailer to transfer the product.
P	Linear back order cost per unit of the vendor for the product.
$\hat{\pi}$	Fixed back order cost per unit of the vendor for the product (time-independent).
d_i	The demand of the product supplied by the vendor for i^{th} retailer
d_{ars}	The expected demand of a^{th} raw material from r^{th} supplier for s^{th} supplier.

d_{ks}	The expected demand of k^{th} part from s^{th} supplier for the vendor.
dis_i	The distance between vendor and i^{th} retailer.
UE	Greenhouse emissions due manufacturing of product for vendor.
ED	Greenhouse emissions from each truck of per kilometer
HE	Greenhouse emissions due holding of product for vendor.
G	The capacity each of the trucks.
SE	Greenhouse emissions due set up of product for vendor.
he_i	Greenhouse emissions due holding of product for i^{th} retailer.
$max\,(pr)$	The maximum amount of production the product by the vendor.

We obtain d and r from Eqs. 4 and 5. Eqs. 6 and 7 show the formula of M and r , respectively.

$$d = r + u(L\bar{t}.\sigma_d^2 + \bar{d}^2.\sigma_{Lt}^2) \tag{6}$$

$$r = \bar{d}.L\bar{t} + k(L\bar{t}.\sigma_d^2 + \bar{d}^2.\sigma_{Lt}^2) \tag{7}$$

The difference between d and r is obtained from Eq. 8.

$$d - r = u(L\bar{t}.\sigma_d^2 + \bar{d}^2.\sigma_{Lt}^2) \tag{8}$$

Therefore, the Expected of $d > r$ is obtained from Eqs. 9 and 10.

$$E(d > r) = (L\bar{t}.\sigma_d^2 + \bar{d}^2.\sigma_{Lt}^2).\int_k^\infty (u-k)\frac{1}{\sqrt{2\pi}}e^{-\frac{u^2}{2}}\,du \tag{9}$$

$$E\,(d > r) = (L\bar{t}.\sigma_d^2 + \bar{d}^2.\sigma_{Lt}^2).G(u) \tag{10}$$

Where $G(u)$ is the right-hand unit common linear loss integral. The sixth and seventh part shows the total holding of the retailers and vendor, respectively. The eighth part expresses holding costs related to parts for the vendor, respectively. The ninth part shows ordering and shipping costs for the retailers. The tenth part expresses the vendor's setup cost, and the final part shows the ordering and shipping cost of the vendor related to parts.

Objective function 2: minimizing environmental issues

$$\begin{aligned}\min Z_{\text{emission}} = &\sum_{i=1}^{I} UEd_i + \sum_{i=1}^{I} SE\tfrac{d_i}{q_i} + \sum_{i=1}^{I} HE\frac{\left[q_i(1-\frac{d_i}{p_i})-b_i\right]^2}{q_i(1-\frac{d_i}{p_i})} \\ &+ \sum_{i=1}^{I} he_i\left(\tfrac{q_i}{2} + SS_i\right) + (\left\lceil \frac{\sum_{i=1}^{I} q_i}{G}\right\rceil + 1)\frac{EDdis_i}{q_i}\end{aligned} \tag{11}$$

The second objective function aims to minimize the green emissions for business activities, operating policies, and transportation systems. Eq. 11 consists of five parts. The first part shows the greenhouse emissions due manufacture of the vendor. The second part shows greenhouse emissions due setup of the vendor. The third and fourth parts indicate greenhouse emissions due holding of products in vendor and retailers' warehouses, respectively. The last part shows the greenhouse emissions of transportation systems from the vendor to retailers.

Objective function 3: maximizing the weight of suppliers

$$\max \sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S} w_r q_{ars} + \sum_{k=1}^{K}\sum_{s=1}^{S} w_s q_{ks} \tag{12}$$

The thirst objective is to maximize the weight value of products by prioritizing suppliers. Eq. 12 consists of two parts. The first part shows to maximize the weight value of products by prioritizing tier-1 suppliers. The second part shows to maximize the weight value of products by prioritizing tier 2 suppliers. This objective function increases the quantity of order allocated to higher-priority suppliers.

Constraints

$$q = \sum_{i=1}^{I} q_i((1-\phi_i) + \phi_i(1-\varepsilon_i)) \tag{13}$$

$$d = \sum_{i=1}^{I} d_i \tag{14}$$

$$\sum_{r=1}^{R} R_{ars}q_{ars} \leq Cap_{as} \times Z_s \quad \forall a = 1, ..., A \; s = 1, ..., S \tag{15}$$

$$\frac{\Pr_{sk}}{(1-\varepsilon_{sk})} \leq Cap_{sk} \quad \forall s = 1, ..., S \; k = 1, ..., K \tag{16}$$

$$\frac{\Pr}{(1-\varepsilon)} \leq Cap \tag{17}$$

$$R_i q_i + SS_i \leq Cap_i \quad \forall i = 1, ..., I \tag{18}$$

$$\sum_{i=1}^{I} uq_i(1-\phi_i) + \sum_{i=1}^{I} eq_i\phi_i(1-\varepsilon_i) \leq H \tag{19}$$

$$\sum_{s=1}^{S} (q_{ks}co_{ks}) \leq \tau_k \sum_{s=1}^{S} q_{ks} \quad \forall k = 1, ..., K \tag{20}$$

$$\sum_{r=1}^{R}\sum_{s=1}^{S} q_{ars}co_{ars} \leq \tau_a \sum_{r=1}^{R}\sum_{s=1}^{S} q_{ars} \quad \forall a = 1, ..., A \tag{21}$$

$$\sum_{s=1}^{S} \gamma_{ks}q_{ks} \leq \omega_k \sum_{s=1}^{S} q_{ks} \quad \forall k = 1, ..., K \tag{22}$$

$$\sum_{r=1}^{R}\sum_{s=1}^{S} \gamma_{ars}q_{ars} \leq \omega_a \sum_{r=1}^{R}\sum_{s=1}^{S} q_{ars} \quad \forall a = 1, ..., A \tag{23}$$

$$\sum_{s=1}^{S} R_{ks}q_{ks} \geq \; d_{ks} \quad \forall k = 1, ..., K \tag{24}$$

$$\sum_{r=1}^{R} R_{ars}q_{ars} \geq \; d_{ars} \quad \forall a = 1, ..., A \; s = 1, ..., S \tag{25}$$

$$P(R_i q_i \geq d_i) \geq 1-\rho \qquad \forall i = 1, ..., I \tag{26}$$

$$P(\sum_{k=1}^{K}\sum_{s=1}^{S} Lt_{ks}q_{ks} \leq lt) \geq 1-\lambda \tag{27}$$

$$p\left(\sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S} Lt_{ars}q_{ars} \leq A\right) \geq 1-\nu \tag{28}$$

$$p\left(\sum_{i=1}^{I} Lt_i q_i \leq l\right) \geq 1-\theta \tag{29}$$

$$Max\,(pr) = Min\left\{\frac{\sum\limits_{s=1}^{S} q_{ks}}{I_k}, d\right\} \tag{30}$$

$$Max\,(pr_{sk}) = Min\left\{\frac{\sum\limits_{r=1}^{R} q_{ars}}{\sum\limits_{k=1}^{K} I_{ak}}\right\} \tag{31}$$

$$\Pr \leq \max\,(pr) \tag{32}$$

$$pr_{ks} \leq \max\,(pr_{ks}) \tag{33}$$

Eq. 13 shows the quantity of orders to the vendor is equal to the total quantity of orders received from all retailers. Eq. 14 expresses that the vendor's demand is equal to the total demand from the retailers. Eq. 15 shows the quantity of raw materials received from the tier 1 supplier is less than the vendor's capacity for raw material storage. Eq. 16 presents the quantity production of the tier 1 supplier is less than the suppliers' capacity for raw materials storage. Eq. 17 shows the quantity production of the vendor is less than the capacity of the vendor for product storage. Eq. 18 shows that the quantity of products received from the vendor is less than the retailer's capacity. Eq. 19 limits the rework cost of the product for vendors. Eq. 20 shows the maximum allowable percentage of returns for parts from tier 1 suppliers. Eq. 21 shows the maximum allowable percentage of returns for raw materials from tier 2 suppliers. Eq. 22 shows the maximum acceptance percentage of late delivery for parts from tier 1 suppliers. Eq. 23 shows the maximum acceptance percentage of late delivery for raw materials from tier 2 suppliers. Eqs. 24, 25, and 26 show allowable order limits, which must be more than demand. Eq. 27 ensures that the total lead time from tier 1 suppliers to the vendor does not exceed the maximum lead time. Eq. 28 ensures that the total lead time from tier 2 suppliers to tier 1 suppliers does not exceed the maximum lead time. Eq. 29 ensures that the whole lead time from the vendor to retailers did not exceed the maximum lead time. Eq. 30 ensures that the maximum production for the vendor can be obtained from the minimum received parts orders about the ratio of parts in which the product is used. Eq. 31 ensures that the maximum production for the tier 1 supplier can be obtained from the minimum received raw materials orders about the ratio of raw materials in which the product is used. Eqs. 32 and 33 show the limit of production capacity. Since the model contains chance constraints that are difficult to solve, they must first be turned into definite ones.

3.3.2. *Converting probabilistic constraints to deterministic constraints.* For Eqs. 26-29, given that the distribution of random variables is known, a standard stochastic chance constraint is used to convert it to a definite constraint. In explaining the uncertainty of lead times, the lead time between tier 2 supplier and tier 1 supplier, tier 1 supplier and vendor, and also between vendor and retailers are defined based on one-by-one relations with the normal distribution functions. The demand for each retailer is independent of the others. Thus the covariance among the demands of these retailers is equal to zero. Demand information is transmitted to vendors to improve and reduce the bullwhip effect. Eq. 26 is a stochastic equation with the normal distribution function when the mean of retailer's demand is μ_i and the variance of the demand is equal to σ_i^2 . Parameter $1-\rho$ means that the satisfaction probability of Eq. 26 is equal to or greater than $1-\rho$ .Therefore, Eq. 26 is equal to constraint Eq. 34 based on applying the chance constraint programming.

$$\begin{aligned} p(d_i \leq r_i q_i) \geq 1-\rho \ \Rightarrow p(\tfrac{d_i-\mu_i}{\sigma_i} \leq \tfrac{r_i q_i-\mu_i}{\sigma_i}) \geq 1-\rho \\ \Rightarrow \tfrac{r_i q_i-\mu_i}{\sigma_i} \geq Z_{1-\rho} \end{aligned} \tag{34}$$

The lead time between each tier 1 supplier and the vendor is independent of the others. Thus the covariance among the lead times is equal to zero. Eq. 27 is a stochastic equation with the normal distribution function when the mean of lead time between each tier 1 supplier and vendor is μ_{ks} and the variance of the demand is equal to σ_{ks}^2 . Therefore, Eq. 27 is equal to Eq. 35.

$$\begin{aligned} P\left(\sum_{k=1}^{K}\sum_{s=1}^{S} Lt_{ks}q_{ks} \leq lt\right) \geq 1-\lambda \ \Rightarrow P\left(\frac{\sum_{k=1}^{K}\sum_{s=1}^{S} Lt_{ks}q_{ks} - \sum_{k=1}^{K}\sum_{s=1}^{S}\mu_{ks}q_{ks}}{\sqrt{\sum_{k=1}^{K}\sum_{s=1}^{S}\sigma_{ks}^2 q_{ks}^2}}\right. \\ \left. \leq \frac{lt-\sum_{k=1}^{K}\sum_{s=1}^{S}\mu_{ks}q_{ks}}{\sqrt{\sum_{k=1}^{K}\sum_{s=1}^{S}\sigma_{ks}^2 q_{ks}^2}}\right) \Rightarrow \frac{lt-\sum_{k=1}^{K}\sum_{s=1}^{S}\mu_{ks}q_{ks}}{\sqrt{\sum_{k=1}^{K}\sum_{s=1}^{S}\sigma_{ks}^2 q_{ks}^2}} \geq Z_{1-\lambda} \end{aligned} \tag{35}$$

The lead time between each tier 2 supplier and tier 1 supplier is independent of the others. Thus the covariance among the lead times is equal to zero. Eq. 28 is a stochastic equation with the normal distribution function when the mean of lead time between each tier 2 supplier and tier 1 supplier is μ_{ars} and the variance of the demand is equal to σ_{ars}^2 .Therefore, Eq. 28 is equal to Eq. 36.

$$\begin{aligned} & p\left(\sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S} Lt_{ars}q_{ars} \leq A\right) \\ & \geq 1-\nu \Rightarrow p\left(\frac{\sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S} Lt_{ars}q_{ars} - \sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S}\mu_{ars}q_{ars}}{\sqrt{\sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S}\sigma_{ars}^2 q_{ars}^2}}\right. \\ & \left. \leq \frac{A-\sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S}\mu_{ars}q_{ars}}{\sqrt{\sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S}\sigma_{ars}^2 q_{ars}^2}}\right) \Rightarrow \frac{A-\sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S}\mu_{ars}q_{ars}}{\sqrt{\sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S}\sigma_{ars}^2 q_{ars}^2}} \geq Z_{1-\nu} \end{aligned} \tag{36}$$

The lead time between the vendor and each retailer is independent of the others. Thus the covariance among the lead times is equal to zero. Eq. 31 is a stochastic equation with the normal distribution function when the mean of lead time between vendor and each retailer. Eq. 29 is equal to Eq. 3.3.2.

$$\begin{aligned} & p\left(\sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S} Lt_{ars}q_{ars} \leq A\right) \\ & \geq 1-\nu \Rightarrow p\left(\frac{\sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S} Lt_{ars}q_{ars} - \sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S}\mu_{ars}q_{ars}}{\sqrt{\sum_{a=1}^{A}\sum_{r=1}^{R}\sum_{s=1}^{S}\sigma_{ars}^2 q_{ars}^2}}\right) \end{aligned} \tag{37}$$

$$\leq \frac{A-\sum\limits_{a=1}^{A}\sum\limits_{r=1}^{R}\sum\limits_{s=1}^{S}\mu_{ars}q_{ars}}{\sqrt{\sum\limits_{a=1}^{A}\sum\limits_{r=1}^{R}\sum\limits_{s=1}^{S}\sigma_{ars}^{2}q_{ars}^{2}}} \Rightarrow \frac{A-\sum\limits_{a=1}^{A}\sum\limits_{r=1}^{R}\sum\limits_{s=1}^{S}\mu_{ars}q_{ars}}{\sqrt{\sum\limits_{a=1}^{A}\sum\limits_{r=1}^{R}\sum\limits_{s=1}^{S}\sigma_{ars}^{2}q_{ars}^{2}}} \geq Z_{1-\nu}$$

To linearize Eq. 30 and Eq. 31, Eqs. 3.3.2 and 38 are used:

$$\min\left\{\frac{\sum\limits_{\mathrm{s}=1}^{\mathrm{S}}\mathrm{q_{ks}}}{\mathrm{I_k}}\right\} = \psi \Rightarrow \psi \leq \frac{\sum\limits_{\mathrm{s}=1}^{\mathrm{S}}\mathrm{q_{ks}}}{\mathrm{I_k}} \Rightarrow \max\left(\mathrm{pr}\right) \leq \psi \tag{38}$$

$$min\left\{\frac{\sum\limits_{r=1}^{R}q_{ars}}{\sum\limits_{k=1}^{K}I_{ak}}\right\} = \vartheta \Rightarrow \vartheta \leq min\left\{\frac{\sum\limits_{r=1}^{R}q_{ars}}{\sum\limits_{k=1}^{K}I_{ak}}\right\} \Rightarrow max\left(pr_{sk}\right) \geq \vartheta \tag{39}$$

4. **Solving method.** Two basic techniques can be used to solve multi-objective optimization problems. A method is based on merging all objective functions and converting them to a single objective function such as weighted sum and goal programming. Another way does not examine objective functions simultaneously and first prioritizes the objective functions and solves them based on these priorities such as lexicographic [12]. In this approach, adding constraints to the model makes it more complex, and the solution time increases. Also, these techniques are mostly used when there is a big variety among prioritizing objectives. The critical differences between multi objective decision making problem (MODM) solving approaches depend on and type of information obtained from the decision maker (DM) and the time, all of which are used to estimate the utility function [11]. After converting the multi-objective to a single objective function, an approach must be used to solve it. In this paper, to unravel the proposed multi-objective model, the LP-Metrics method is used.

4.1. **LP-Metrics method.** As regards the designed model that has three objective functions, this problem is solved separately with one objective function three times. Finally, a single objective function is obtained using the solutions of each model to reduce the deviation. Since the objective function used in the developed model is a none-differentiable (because of the existence of the integer decision variables), non-convex, nonlinearity, and mix-integer function, standard optimization methods such as Lagrange, gradient, and existing convex optimization techniques are not suitable for solving the developed model. Metrics distances are used in the LP-metrics method to evaluate the proximity of the existing solution to the ideal solution. The final model is obtained according to Eq. 40 based on the Lp-metrics method.

$$[L_p(\gamma) = \left\{\sum_j \omega_j \Big(\frac{Z_j^* - Z_j}{Z_j^*}\Big))^p\right\}^{\frac{1}{p}} \tag{40}$$

ω_j is the degree of importance (i.e., weight) for j^{th} objective and p determines the degree of emphasis on the existing deviations. The greater value, the greater focus on the stronger deviations. If p be infinitive, it means that the largest deviation will consider for optimization. Z_j^* is the ideal optimal value of the objective function j by solving the single-objective model Z_j. In this paper, p is considered equal to 1.

The objective function of the final model to solve with the LP metric approach is as follows:

$$\min \ Z = \omega_1 \times \left(\frac{Z_1^* - Z_1}{Z_1^*}\right) + \omega_2 \times \left(\frac{Z_2^* - Z_2}{Z_2^*}\right) + \omega_3 \times \left(\frac{Z_3^* - Z_3}{Z_3^*}\right) \tag{41}$$

4.2. **GA and PSO algorithms: Fine-tuning and comparison.** Since there is no benchmark to evaluate the proposed model, the optimization problem is solved using two of the most famous meta-heuristic algorithms, called GA and PSO, and their performance is compared. Since the values obtained from meta-heuristic algorithms are very sensitive to their parameters, the Taguchi experimental design method [47, 48] is used to adjust them. In this paper, GA and PSO algorithms, as well-known successful meta-heuristics algorithms in solving high-dimensional non-convex optimization problems, are used in solving the proposed optimization problem. Every meta-heuristic algorithm has inherent limitations and thus several variants of the original meta-heuristic algorithms are presented to enhance their performances [52].

4.2.1. *Tuning the GA and PSO parameters.* Since the performance of the model is influenced by its parameters, the Taguchi experiment is used to run GA and PSO with the best parameters. Taguchi's experiment allows the study of the main factors and their interaction simultaneously and can examine and rank the controllable factors. The purpose of the Taguchi method is to minimize changes in the response variable and determine the optimal level of controllable factors [51, 54]. A ratio S/N is used accordingly. The value of S/N the ratio is calculated from Eq. 42 where y_i denotes the response in i^{th} experiment and n denotes the number of orthogonal arrays, on which the performance of the experiments is based. The highest S/N ratio determines the optimal level for each factor.

$$S/N = -10 \log \left(1/n \sum_{j=1}^{n} 1/y_i^2\right) \tag{42}$$

To experiment, three levels are selected for each parameter. Thus, designs with nine experiments are used.
Table 7 shows the different combinations of parameter levels in the design of experiments .

TABLE 7. Controllable factors and their levels

	Parameters	**Notations**	**Levels**			**Optimal levels**
			Level 1	**Level 2**	**Level 3**	
GA	Popsize	A	200	150	100	100
	p_c	B	0.8	0.5	0.4	0.4
	p_m	C	0.4	0.35	0.3	0.3
PSO	C_1	A	2	1.5	1	2
	C_2	B	0.9	0.8	0.7	0.8
	W	C	0.7	0.8	0.9	0.9
	W	D	0.4	0.3	0.2	0.3

Tables 8 and 9 show the Taguchi experimental results on test problem for the GA and PSO respectively.

Table 8. Taguchi experimental results on test problem for the GA

Exp NO.	Popsize	p_c	p_m	S/N
1	1	1	1	−38.04
2	1	2	2	−37.46
3	1	3	3	−38.39
4	2	1	2	−37.21
5	2	2	3	−36.61
6	2	3	1	−36.01
7	3	1	3	−36.73
8	3	2	1	−37.91
9	3	3	2	−37.57

Table 9. Taguchi experimental results on test problem for the PSO

Exp NO.	c_1	c_2	$w_{\max}$	$w_{\min}$	S/N
1	1	1	1	1	−37.38
2	1	2	2	1	−37.61
3	1	3	3	1	−37.71
4	2	1	2	2	−36.83
5	2	2	3	2	−36.49
6	2	3	1	2	−37.44
7	3	1	3	3	−37.94
8	3	2	1	3	−37.73
9	3	3	2	3	−37.71

Figures 7 and 8 show mean S/N ratios of the parameters of GA and PSO, respectively.

4.2.2. *Genetic algorithm (GA).* Because the objective function of the proposed model is NP-hard, GA is used to solve the model, which is one of the most famous algorithms in solving combinatorial optimization problems. This section details the implementation of the GA method to solve the model, which includes chromosome structure, target function, parent selection, and mutation rates.

Chromosome structure. In the presented GA solution, each candidate solution is a chromosome. The chromosome structure of GA represents these decision variables introduced in Section 3.

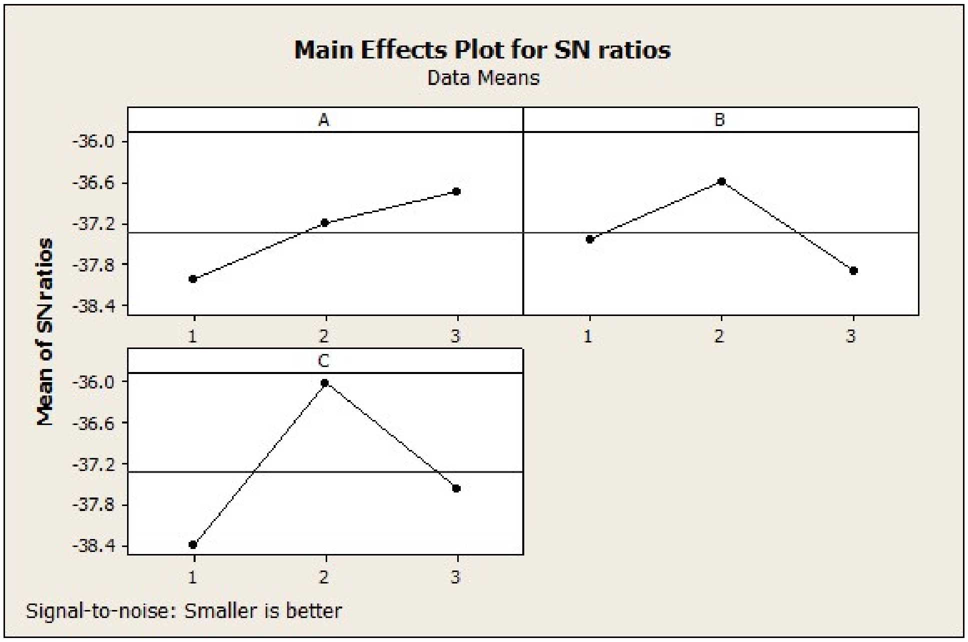

FIGURE 7. Mean S/N ratios of the parameters of GA

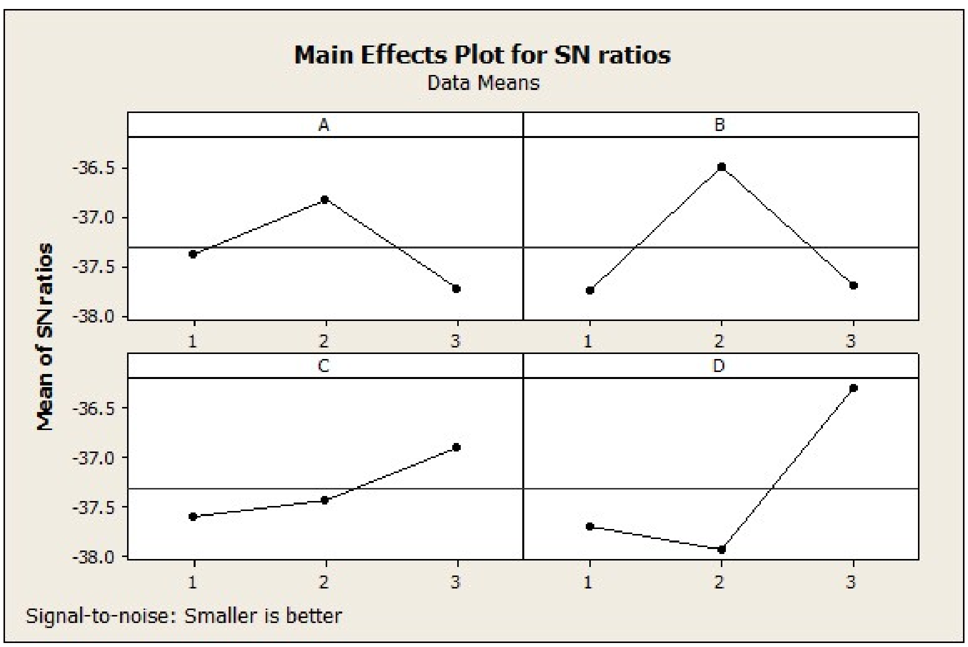

FIGURE 8. Mean S/N ratios of the parameters of PSO

Fitness function. The fitness function is examined to be a weighted sum of the penalty of constraints violation and the objective function (obtained from the LP-Metrics method). i.e., the constraints are encoded in the fitness function such that the solution violated the constraint, and the objective function is summed with an enormous penalty value. This penalty guarantees the feasibility of the solutions, including the final solution. Thus, the objective function and the constraints shown in Section 3 are defined in the Fitness Function of this problem.

Initial population. Chromosomes are randomly generated within their feasible range for the generated initial population [52]. According to Taguchi experiments, the initial population is considered to be 100.

Selection. This paper uses tournament selection for the chromosome selection to conduct mutation and crossover operators. In the tournament selection technique, the objective function must be obtained for all chromosomes in the population (called Pop). It then chooses four chromosomes randomly to pick the one with the largest fitness function among them as the parent for generating a new population. To select Pop parents, this technique will be repeated Pop times.

Crossover. The crossover operator is done with a rate of 0.4 in this study. The crossover operator will produce four offspring from each of the two chosen parents. Two premier chromosomes will be chosen for the next population out of parents and offspring with the best fitness amounts. Therefore, we will have a Pop chromosome at the end of the crossover operation. The double-point crossover is used to produce off-springs from parents.

mutation. This paper utilizes a mutation operator with a rate of 0.3. The mutation operator improves the diversity of the population of solutions and thus avoids trapping into a local optimum. To implement mutation, 30 percent of the population is randomly chosen. Then, the new mutated chromosome's fitness function is compared with the old pre-mutation chromosome's fitness. If the new fitness is better, it replaces the old chromosome.

Stopping Criteria. The GA optimization process for the presented model is stopped after a determined number of iterations (which was 100 iterations in this paper).

4.2.3. *Particle swarm optimization (PSO).* One of the most effective evolutionary optimization techniques is PSO, which was originally introduced in 1995 by Kennedy and Eberhart [28]. In this algorithm, a population of particles is considered, each of which is a possible solution to the optimization problem. These particles are initially randomly placed in space [18]. At each step, the value of each particle will move to a certain size with the help of the value function calculated by considering the best particle response in the population. Therefore, each particle of the population has a specific position and speed at each step. The performance of each individual in the population concerning the objective function is evaluated in each iteration, and then the best position of each particle across all iterations and the best position of all particles is determined as the best local position and the best general position, respectively [23, 43]. The particles or individuals are then moved towards their best local position and best general position through which better particles are found [60, 63]. That is, particle motion in this algorithm depends on two factors of collective and individual motion, and the combination of these two motions leads to the creation of an efficient model to find the best point of the objective function in optimization problems. The position of a particle at the current stage is a component of its previous position, its own best position (Pbest), and knowledge of global or their neighborhood's (Gbest). As the particle moves over time, the position of i^{th} particle changes [47, 54]. More specifically, let $X_i(t)$ denote the position of the particle at time step t in the search space. By adding a velocity, $V_i(t)$ to the position of each particle, a new position for the particle can be considered. Let $p_i(t)$ and $p_g(t)$ be the best position of i^{th} particle during its motion and the best position of the population in the iteration t, respectively. Eq. 43 shows how the position of the particle is updated.

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{43}$$

$$v_i(t+1) = wv_i(t) + c_1 r_1 \big(p_i(t) - x_i(t)\big) + c_2 r_2 \big(p_g(t) - x_i(t)\big) \tag{44}$$

w in Eq. 44 represents the weight of inertia and the coefficients c_1 and c_2 are known as the acceleration coefficients. Also, r_1 and r_2 are random numbers in the range of zero and one with uniform distribution. The inertia weight parameter regulates the ability of the particle population to explore optimal local areas. In a way, large amounts of inertia increase random search and generate new answers, while lower values of inertia increase the PSO's ability to generate local responses [50].

5. **Findings.** The GA and PSO are both coded with MATLAB R2019b. The results of GA and PSO are shown in Tables 10-13. The CPU time to get a solution for GA and PSO are 18800, and 13640 seconds, respectively.

Table 10. The quantity of orders allocated to tier 2 suppliers

Raw materials	Tier 1 supplier	Tier 2 supplier	GA	PSO
1	1	1	306.43	300.25
		2	0	0
1	2	1	253.65	220.32
		2	0	0
2	1	1	350.42	335.2
		2	0	0
2	2	1	157.76	150.35
		2	170.88	160.13
3	1	1	305.04	300.37
		2	0	0
3	2	1	300	284.54
		2	0	0

Table 11. The quantity of orders of retailers allocated to the vendor

Parameter	Retailer	GA	PSO
q_i	1	520	500
	2	500	500
	3	510	480
	4	450	420

The results demonstrate the interaction of the objective functions to obtain the optimal solution and indicate that all objective functions in some way affect the

Table 12. The quantity of products and orders allocated to tier 1 suppliers

Tier 1 supplier	Parts	GA			PSO		
		q_{sk}	pr_{sk}	Z_{sk}	q_{sk}	pr_{sk}	Z_{sk}
1	1	0	0	0	0	0	0
	2	310	560	1	302	530	1
	3	400	720	1	400	680	1
1	1	420	800	1	408	710	1
	0	0	0	0	0	0	0
	3	460	870	1	455	880	1

Table 13. The quantity of products and orders allocated to vendor

GA		PSO	
q	pr	q	pr
1980	2560	1900	2450

values of decision variables. Our designed model has advantages over previous research in such a way that the two-way relationship between retailer and vendor evaluates. Crucially, success in supply chains directly depends on managing the relationship between inventory costs, selecting the best suppliers based on the most important criteria, and reducing environmental impacts. Ultimately the proposed model can lead vendor to interact with the proper suppliers. In this research, all three objectives are considered simultaneously to determine optimal orders from suppliers. The first objective of the economic cost criterion, the second objective is for the vendor to allocate the order to the sellers who cause the least pollution for them. Orders are determined based on the balance between these three objectives. Based on the results, the seller should order parts 2 and 3 from the first supplier and parts 1 and 3 from the second supplier. Figures 9 and 10 show the convergence diagram of the best implementation of the GA and PSO implemented on the designed model, respectively. GA converges after about 55 iterations, and PSO converges after about 65.

The results clarify that answers obtained from both the GA and the PSO techniques provide similar results and almost unique optimal solutions. Because the results of the two methods are so similar to each other, thus the model has sufficient validity. As can be observed, the final results indicate selecting the most reliable suppliers, considering the cost and other criteria, vendor orders from multiple suppliers. The practical implication of these results is that considering delivery reliability, maximum allowable delay, and return percentage in selecting suppliers leads to a noticeable improvement in supplier selection problems. Proper selection of suppliers allows the vendor to complete his production on time and better meet retailers' demand. To find optimal suppliers, it is necessary to investigate appropriate important criteria in selecting suppliers. Therefore, considering that the proposed model uses a variety of factors, it can be very effective in improving the performance of the supply chain. For a vendor, if the supplier fails to deliver the

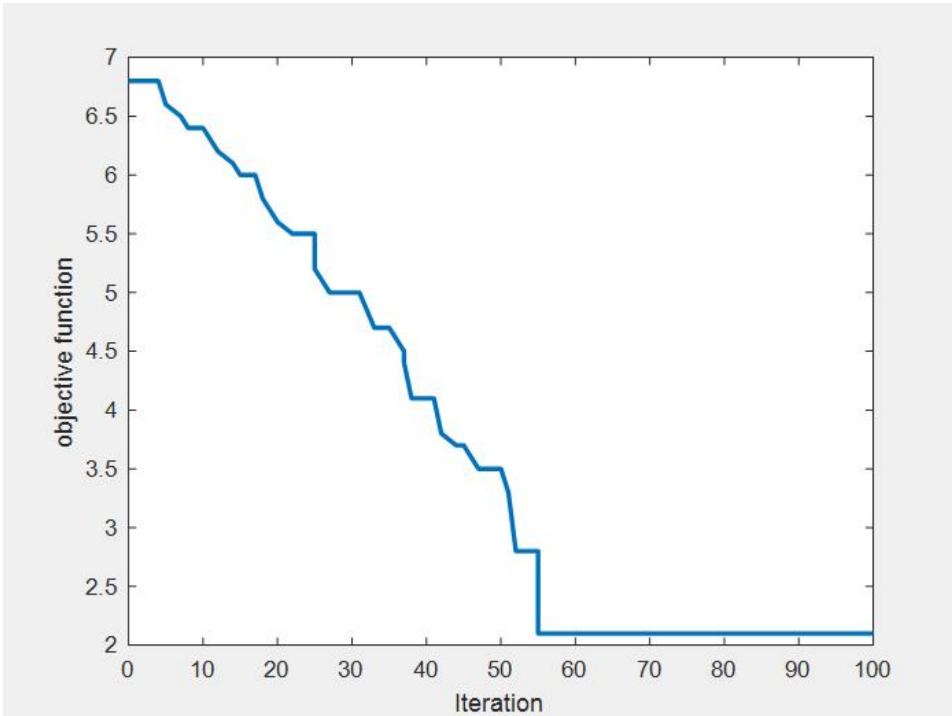

FIGURE 9. Convergence diagram of the best implementation of the GA

product on time and with the necessary quality and reliability, problems will arise in providing products and meeting retailer demand, ultimately leading to retailer dissatisfaction. Also, because the designed model uses two stochastic approaches in forecasting demand, it overlaps more with the real world. To provide valid suggestions and recommendations for managers and decision-makers, the proposed mode is solved with two tiers of vendors and retailers without considering the suppliers' level. For this purpose, variables, parameters, and constraints related to supplier levels are removed. The problem is solved without considering the constraints of return percentage, late delivery, and reliability of suppliers. The results of GA and PSO without considering suppliers' level are shown in Tables 14 and 15.

TABLE 14. The quantity of orders of retailers allocated to the vendor

Parameter	Retailer	GA	PSO
q_i	1	1100	970
	2	1650	1500
	3	1000	880
	4	1800	1620

From the managerial application of this study, it can be said that when the vendor and retailers are connected through VMI, the goal is long-term and permanent

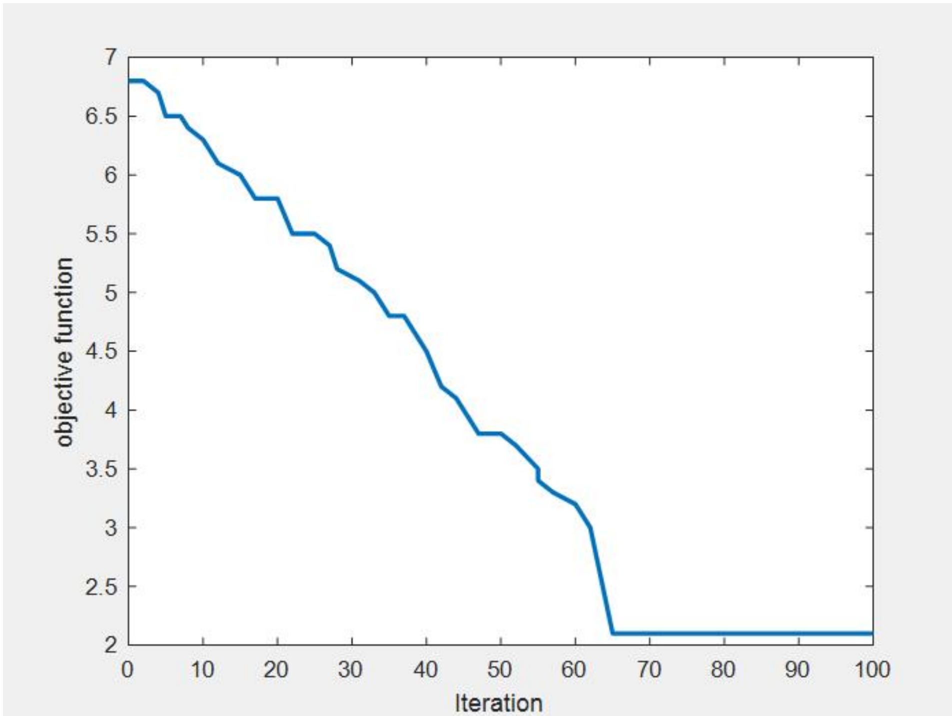

FIGURE 10. Convergence diagram of the best implementation of the PSO

TABLE 15. The quantity of products and orders allocated to tier 1 suppliers

GA		PSO	
q	pr	q	pr
5550	6860	4970	5450

relationships between them. Because suppliers in each supply chain are at the beginning of the production process, they play an important role in the vendor's time-on supply of goods to retailers. Therefore, managers should pay attention to this issue in VMI policy to pay enough attention to ordering products from their suppliers. This research has considered by considering the level of suppliers. Performance management of suppliers leads to the fact that products are delivered to customers on-time and with the required quality, and this can have a very effective role for the managers of the organization in the implementation of VMI policy. Also, this research, considering the reliability of delivery in the entire supply chain, helps managers in implementing this strategy. Considering this issue, more orders are placed from suppliers whose delivery is less likely to be late. Also, in this study, considering the uncertainty of demand and lead time can help managers reduce the shortage, surplus, shipping, setup, and ordering costs. Therefore, the developed model can help managers in the optimal implementation of VMI.

6. **Conclusion.** The VMI is one of the most popular strategies for coordinated and integrated inventory management in the supply chain. In this strategy, the vendor makes decisions related to the amount of the order based on the information received from the retailers. In VMI, the long-term relationship between the vendor and the retailer is required to meet the retailer's demand and orders accurately. In VMI, not only is the vendor's relationship with the retailer very important in ordering decisions and inventory correctly, but the vendor must be careful in selecting its suppliers. If the supplier fails to meet the vendor's appropriate criteria in the supply of raw materials, this will affect the relationship between the vendor and the retailer. Because the delay in delivery and returns beyond the permitted quantities makes the vendor unable to deliver his products with the required quality and on time. In this policy, the vendor spends a lot of costs to establish and use information technology, if the suppliers cannot deliver the orders to the retailer on time and with the required quality, this policy will not work. Therefore, selecting the right suppliers is a necessity to implement this policy. Therefore, in the VMI in addition to having an appropriate policy in relationship with retailers, the vendor must also consider a suitable strategy for selecting their suppliers. This research has developed a VMI problem in a four-echelon supply chain consisting of multi-tier 2 suppliers, multi-tier 1 suppliers, vendor, and multi-retailer. This study aims to determine the order amount of each retailer from the vendor, the order amount of vendor from tier 1 suppliers, and the order amount of tier 1 suppliers from tier 2 suppliers.

The objective of this study is the minimization of the total costs of the supply chain e.g., set-up, ordering, transportation, backorder shortage, and holding costs, and some predefined constraints such as the maximum allowable shortage, budget, warehouse, maximum allowable delay, and return percentage and other inherent constraints. Our designed model has advantages over previous research in such a way that the two-way relationship between retailer and vendor evaluates. Crucially, success in supply chains directly depends on managing the relationship between inventory costs and selecting the best suppliers based on the most significant criteria. Ultimately the proposed model can lead vendors to interact with the proper suppliers and increase supply chain reliability considering its cost. One of the factors that lead to insufficient production of products is an inaccurate forecast of demand or supply of raw materials. Therefore, sufficient attention should be paid to predicting the effective parameters in product production and modeling their uncertainties. In this study, vendor and retailers are connected through blockchain technology to reduce the risk associated with an increase or decrease in inventory.

Future research will be devoted to considering a different time cycle for vendors and retailers as well as retailers relative to each other. Also in this research, a VMI problem in a four-echelon supply chain is noted, so is proposed to develop the VMI model by considering single and multi-warehouse and by extending the supply chain the model develop to higher levels. As respect demand depends on price, it is better to address the price and discount policies of the vendor in the optimal order allocation. In addition, it is possible to create more development on the model by considering the problem in multiple periods and considering the lead times. This paper provides a solution to the optimal selection of suppliers' problems to meet essential criteria for the vendor in selecting the best suppliers for ongoing communication. In this study, it is becoming increasingly important for managers and system designers who intend to implement the VMI to develop efficient solutions to this reliability optimization problem. Designing this model will help organizations that seek to implement VMI policies and receive their raw materials from multiple suppliers. They can determine the amount of their orders by considering the essential items that are necessary for ordering suppliers. Ordering from the best suppliers reduces the likelihood of product delays, product returns, and poor quality, so the vendor can better meet retailers' orders. In the developed VMI model, a long-term relationship between the vendor and the retailer can be maintained which can help managers in communication with members of the supply chain.

Appendix: Data related to case study

TABLE 16. Data related to rework, ordering, and transportation, scrap costs for retailers

Parameters	Retailers	Values	Parameters	Retailers	Values
hc_i	1	1500	Ss_i	1	8320
	2	1200		2	7680
	3	1800		3	6500
	4	2000		4	8000
A_i	1	1250	Cap_i	1	760
	2	1450		2	667
	3	1600		3	854
	4	1400		4	788
λ_i	1	123	φ_i	1	0.35
	2	1500		2	0.43
	3	1450		3	0.23
	4	1600		4	0.36
υ_i	1	217	ε_i	1	1235
	2	321		2	1450
	3	253		3	2315
	4	214		4	2455
ξ_i	1	0.23	lt_i	1	88
	2	0.34		2	120
	3	0.25		3	100
	4	0.24		4	135
π_i	1	546	R_i	1	0.9
	2	756		2	0.84
	3	432		3	0.78
	4	732		4	0.92

TABLE 17. Data related to the vendor

Parameters	Values
S	456
h	1235
Cap	8788
SS	320
H	276
π	67
$\hat{\pi}$	87
Km	675
e	564

TABLE 18. Data related to delivery reliability, Return percentage, ordering and transportation costs, and demand for raw materials

Raw materials	Tier 1 supplier	Tier 2 supplier	R_{ars}	γ_{ars}	A_{ars}	f_{ars}
1	1	1	0.69	0.27	1500	80
		2	0.90	0.45	2000	52
1	2	1	0.83	0.33	1200	47
		2	0.74	0.12	1500	68
2	1	1	0.95	0.28	1250	61
		2	0.76	0.38	1000	73
2	2	1	0.95	0.44	1320	48
		2	0.68	0.39	1280	47
3	1	1	0.81	0.37	1300	45
		2	0.92	0.29	1400	57
3	2	1	0.87	0.19	1360	66
		2	0.93	0.17	1500	55

TABLE 19. Data related to delivery reliability, Return percentage, ordering and transportation costs, and demand for parts

Tier 1 supplier	Part	f_{ks}	A_{ks}	R_{ks}	Cap_{ks}	B_{ks}	γ_{ks}	Co_{ks}	lt_{ks}
1	1	98	1500	0.69	5678	76	0.25	0.25	110
	2	87	1450	0.76	5600	65	0.29	0.12	123
	3	86	1356	0.92	5820	48	0.17	0.18	115
2	1	75	1574	0.79	5600	76	0.13	0.15	117
	2	77	1368	0.80	5438	85	0.21	0.23	110
	3	95	1500	0.78	5670	78	0.24	0.28	100

Table 20. Data related to mean and variance of demand for raw materials from tier 2 suppliers

Raw materials	Tier 1 supplier	Tier 2 supplier	$\bar{\mu}_{ars}$	$\min(\bar{\mu}_{ars})$	$\bar{\sigma}^2_{ars}$	$\min(\bar{\sigma}^2_{ars})$
1	1	1	4500	1750	250	175
		2	4000	1800	230	185
1	2	1	4320	1650	200	180
		2	3800	1400	210	150
2	1	1	4100	1800	260	175
		2	4000	1340	230	170
2	2	1	3760	1800	180	180
		2	3500	1370	175	185
3	1	1	4300	1500	260	170
		2	4800	1750	280	180
3	2	1	3700	1600	180	165
		2	4000	1700	175	170

Table 21. Data related to value of demand for retailers

Parameters	Retailers	Values
d_i	1	$N \cong (1500, 110)$
	2	$N \cong (1800, 123)$
	3	$N \cong (1450, 88)$
	4	$N \cong (2000, 115)$

Table 22. Data related to value of uncertainty levels for stochastic constraints

Uncertainty levels	ϖ	θ	ν	λ	ξ	ρ
Values	0.03	0.04	0.05	0.03	0.02	0.04

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