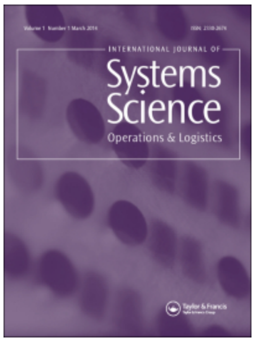

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Supply chain coordination based on mean-variance risk optimisation: pricing, warranty, and full-refund decisions

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ABSTRACT

This study focuses on optimising sales of different brands of a single-product supply chain model that consists of several manufacturers and a retailer. The price and quality of the products drive competition between manufacturers who sell a single product through a retailer to the customers. This study aims at maximising the profit values of the retailer and manufacturers, simultaneously. Accordingly, four scenarios are defined with respect to the different contracts, including the cost sharing, profit sharing, revenue sharing, and buyback. Mean-variance risk management is applied to the proposed models. A full-refund return policy and warranty are also considered. A novel hybrid metaheuristic that combines the advantages of the group search optimiser (GSO) and human behaviour-based optimisation (HBBO) algorithms, entitled 'GSO-HBBO' algorithm is provided to find the high-quality solutions in fewer numbers of the iterations. The performance of the GSO-HBBO algorithm is compared with the GSO and HBBO algorithms based on different measures such as quality of the generated solutions and CPU-Time. The results show that the presented algorithm generates much better solutions than GSO and HBBO algorithms in a reasonable time. The managerial insights confirmed that the profit-sharing and buyback contracts make the most profit for both manufacturer and retailer.

KEYWORDS

Revenue sharing contract; inventory; buyback contract; warranty policy; group search optimiser; human behaviour-based optimisation

1. Introduction

Modern supply chains (SCs) are challenged by ever-growing competition and a highly unstable business environment. Under such circumstances, the objective of making an efficient SC at the cost of effectiveness exposes the organisations to risk. The risks in SC lead to serious repercussions like inferior product quality, loss of property and machinery, loss of a firm's brand reputation, delivery delays, conflict among various shareholders, and a sharp decline in the firm's share price (Rahimi et al., 2019; Tarei et al., 2018; Tarei et al., 2022). Nowadays, the competition between brands is becoming increasingly intensive in business markets (Amrouche et al., 2022). Accordingly, in the global marketplace, distinction between brands creates competitive advantages, since the main components of a brand, including price, quality, attractiveness, risk of selling, and lead time can be distinguished to increase the market share in the competitive environment of the global markets. Since the manufacturers produce a particular product as their brand, the competition would be much intensified so that it pressures manufacturers to improve their brand performance as an asset and leverage the boosted performance against the rivals. Customers significantly notice the main components of brands, such as price points, quality, and warranties that differentiate between brands. These features completely affect a given brand's reputation and total revenue. This issue demonstrates the importance of this research and motivates us to focus on the most important components of a brand, including its pricing and warranty policies. To address this, we list the main questions of this research as follows: (i) how much is the optimum selling price per brand for a retailer? (ii) how much is the optimum wholesale price per brand for each one of the manufacturers? (iii) how many warranty periods would be economical? As a clarification on the main components of a brand, we first focus on warranty. A warranty is a type of guarantee that enables the manufacturers to ensure the specifications and durability of a product. This policy assures customers that the

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manufacturer's products work properly. The warranty is proposed because of pre-design errors that require exchange or repair. In this study, the warranty is considered as a policy that all manufacturers employ to boost demand for their products. The warranty forms the basis of a contract between the manufacturer and the customer. Some manufacturers use a warranty to send the signal to customers that they are not enjoined in a direct conventional relationship with them. Risk management as an important part of supporting brands reputations is a key main concept in supply chain management, since a supply chain with uncertain parameters leads to risky decisions that directly affect the components of a brand. This issue clarifies another part of our research importance. To address this, we investigate the risk level for inventory decisions by estimating two parameters: the expected under-stocking and over-stocking risks. The agents of the supply chain may have a specific perspective about risk. Finally, the return policy as another part of this research that directly affects the components of the brand would be investigated in this research. In marketplaces that offer multi-brand products, the customers who are not satisfied with a brand can change their choice of brand upon subsequent purchases. To consider this behaviour and keep customers committed to a particular brand, some manufacturers offer a valued-customer return policy. Although, the use of a return policy may impose negative impacts on a company, such as increasing the processing costs, devaluation of products, and delayed sales. Despite these negative impacts, a manufacturer's full-refund policy is frequently offered in the current marketplace, especially in multi-echelon supply chains.

By taking all aforesaid issues into account to address these challenges, this study designs a two-echelon supply chain with three levels that include multiple manufacturers and a retailer. In this chain, multiple brands of a product are distributed to a retailer, and then customers purchase their favourite brand from the retailer. We consider the impacts of some customer-friendly policies, such as return policies, full refund policies, and warranties, on the demand and revenue. We also investigate some contracts between the manufacturers and the retailer, with respect to risk management. These contracts are selected and compared with regard to their pricing and quality features and their applications in the existing literature. The main novelties and contributions of this research are as follows: (i) a competition-based model driven by the price and quality of products; (ii) four scenarios by taking a full-refund return policy and a warranty into account; (iii) a hybrid metaheuristic, titled 'GSO-HBBO' algorithm, that is able to find the optimum solution in less time by rapidly searching the feasible regions; and (iv) investigation of the effects of profit-sharing and buyback contracts on manufacturers and retailer profits. The remainder of the paper is organised as follows: A comprehensive review of existing literature is presented in Section 2. Section 3 presents descriptions of the problem and the proposed mathematical models for all four scenarios. The solution method, which is the GSO-HBBO algorithm, is explained in Section 4. Section 5 presents the computational results. In Section 6, the discussion revolves around managerial implications. Finally, the conclusion and future research directions are stated in Section 7.

2. Literature review

The literature is classified according to concepts considered and addressed in this study. Hence, articles about well-known contracts featuring return and refund policies, warranties, risk management frameworks, and existing solution approaches are reviewed.

Several studies correspond to cooperating contracts that incorporate practical strategies (e.g. warranties and returns, among other factors) in supply chain management. Li et al. (2017) applied a commitment unidirectional contract and commitment bidirectional contract in a decentralised supply chain. They considered one manufacturer and one retailer with uncertain demand values for seasonal products. Ghandi and Lin Lawell (2017) evaluated risk and rate of return (ROR) for an international oil company located in Iran that used a buyback contract. They noted a capital cost limit and pre-defined price in the contracts issued between 2008 and 2009. In accordance with the considered risk factors, the negative effect of a capital cost violation on company ROR was clarified. Taleizadeh and Noori-daryan (2016a) examined a return policy in manufacturing and remanufacturing models with respect to the quality level. Yoo et al. (2015) studied the application of a return policy and specific contracts, such as buy back and quantity discount, in a supply chain consisting of a supplier and a retailer. Taleizadeh and Noori-Daryan (2016b) studied the application of pricing and inventory policies on a supply chain consisting of a supplier, a producer, and multiple retailers. Chakraborty et al. (2016) considered the sensitivity of product price and quality in a competitive environment consisting of a supply chain containing a manufacturer and a retailer selling two brands of a product through an applied cost-sharing contract (Bai et al., 2017; Yang & Chen, 2018). Hu et al. (2017) applied a revenue-sharing contract in a supply chain by presuming two products which come from different manufacturers and are subject to product substitution. They concluded that a revenue-sharing contract can modify the chain. Bengal reported on a cooperation and profit-sharing contract in a supply chain made up of one manufacturer and one retailer of a perishable product; the author discovered that profit sharing can harmonise the chain and bring win- win outcomes for all members.

Additionally, some research incorporated multiple coordination contracts, and compared the corresponding results. For example, Gan et al. (2005) studied two buyback and revenue-sharing contracts in a supply chain, containing a supplier and a retailer. In some recent publications, buyback versus revenue-sharing contracts, and cost-sharing versus revenue-sharing contracts, are respectively investigated by Zhang et al. (2016) and Yu et al. (2020) in two supply chain management problems. Thereby, a proper analysis of the performance of such contracts, which are related to pricing and quality of the products, looks interesting. Wu et al. (2020) and Gharaei et al. (2023) also introduced a dual-channel reverse supply chain (DRSC) with online and offline recycling channels. They first designed a Stackelberg game model under centralised and decentralised decision making for DRSC with recycling centre and TPR, respectively, and achieved optimal and maximum profit decisions. In the following, they entered into a revenue-sharing contract between the recycling centre and TPR with the aim of optimising the interests of supply chain members under decentralised decision-making. In recent years, supply chain management has emerged as a critical area of research because of its potential to improve the efficiency and profitability of supply chain networks. Mishra et al. (2022) investigate developing environmental collaboration among supply chain partners for sustainable consumption and production. The authors focus on the auto sector supply chain and develop a framework for evaluating the environmental collaboration among supply chain partners. The results suggest that environmental collaboration can lead to improved environmental performance, reduced costs, and increased profits for all parties involved. He et al. (2022) investigate cooperation among suppliers of complementary products in repeated interactions. The authors develop a theoretical model to analyse the impact of collaboration on the pricing and inventory decisions of suppliers. The results suggest that cooperation can lead to more efficient supply chain networks and higher profits for all parties involved. Zhang et al. (2023) examine contract design and comparison under the opportunity cost of working capital. Specifically, the authors compare the buyback contract and revenue-sharing contract. The results suggest that the buyback contract is more effective in situations where the opportunity cost of working capital is high, while the revenue-sharing contract is more effective in situations where the opportunity cost of working capital is low. Finally, Koussis and Silaghi (2023) explore revenue-sharing and volume flexibility in the supply chain. The authors develop a mathematical model to analyse the impact of revenue-sharing contracts on the supply chain network. The results suggest that revenue-sharing contracts can lead to more efficient supply chain networks and higher profits for all parties involved.

In the warranty literature, Giri and Maiti (2014) applied a warranty policy in a supply chain model that featured multiple manufacturers and a retailer. Chen et al. (2016) studied the costs of a non-renewable two-dimensional combination of two warranty types used to expand the product life cycle by a remanufacturing process. They also suggested some strategies for remanufacturers to use in creating appropriate warranty periods. Alqahtani et al. (2017) investigated the effects of warranty policy for remanufactured products. They concluded that longer warranty periods create higher warranty costs. Sadeghian et al. (2016) evaluated the optimum warranty period for products that deteriorate by considering the simultaneous inspection of equipment and products. Chen et al. (2016) presumed that a retailer's order depends on the manufacturer's price and warranty period. In addition, they improved the profit function value by introducing a quality investment policy for a supply chain. Taleizadeh and Noori-daryan (2016a) investigated the effect of a warranty policy on the competitive environment between two markets with members at different levels of willingness to pay. Recently, Ji et al. (2021) examined the various effects of recycling channels and warranty channels on the manufacturer, retailer, and the entire supply chain system from the perspectives of consumers, CLSC members, and the environment. To this end, they proposed four closed-loop supply chain (CLSC) game models with recycling channels and warranty channels, and after determining the optimal strategy, presented two contracts to coordinate the supply chain members. Furthermore, Mansouri and Sahraeian (2021) optimised a closed-loop supply chain network while dealing with disruptions in distribution centres in two dimensions of economic and environmental sustainability. In this regard, adding warranty periods, reworking options and incentives to return used items were suggested as solutions to minimise customer costs. Warranty policies are an important aspect of supply chain management that can impact the profitability of manufacturers and retailers. Mutlu and Yildiz (2021) investigate the determination of the optimal warranty policy and period from the manufacturer's/seller's perspective. The authors develop a mathematical model to analyse the impact of different warranty policies on the manufacturer's/seller's profits. The results suggest that the optimal warranty policy and period depend on the product's reliability, the cost of repairs, and the selling price. Sarada and Sangeetha (2022) explore the coordination of a reverse supply chain with price and warranty dependent on random demand under collection uncertainties. The authors develop a mathematical model to analyse the impact of different warranty policies on the coordination of the reverse supply chain. The results suggest that incorporating warranty policies in the reverse supply chain can lead to more efficient supply chain networks and higher profits for all parties involved. Saha and Giri (2023) investigate consumers' purchasing decisions in a dual-channel supply chain system under return and warranty policies. The authors develop a mathematical model to analyse the impact of different return and warranty policies on consumers' purchasing decisions. The results suggest that consumers' purchasing decisions are influenced by the warranties offered by the manufacturer and retailer, and the return policy of the retailer. Ai et al. (2023) examine channel coordination with extended warranty when retailers compete. The authors develop a mathematical model to analyse the impact of extended warranty policies on the coordination of the supply chain when retailers compete. The results suggest that extended warranty policies can lead to more efficient supply chain networks and higher profits for all parties involved, but the coordination of the supply chain is challenging when retailers compete. Finally, Liu et al. (2023) investigate optimal extended warranty pricing and retailing strategies in a closed-loop supply chain. The authors develop a mathematical model to analyse the impact of different extended warranty policies on the pricing and retailing strategies in a closed-loop supply chain. The results suggest that incorporating extended warranty policies in a closed-loop supply chain can lead to more efficient supply chain networks and higher profits for all parties involved.

In the context of risk management, Choi (2013) evaluated the supply chain by mean-variance (MV) models, which were subsequently studied by Dew-becker et al. (2017), Akhtar and Jahromi (2017), and Cui et al. (2017). Shen et al. (2013) considered a risk-averse manufacturer and a risk-neutral retailer to investigate the effect of a markdown policy in a supply chain for a real case from the apparel industry. Gan et al. (2005) studied the effect of some well-known contracts on the supply chain of a risk-neutral supplier and a risk-averse retailer. They concluded that coordination in a supply chain with a risk-averse retailer with well-known contracts is infeasible. Chiu and Choi (2016) also reviewed the literature of MV analytical models in supply chain management. Recently, Bai et al. (2020) provided a single producer and single retailer supply chain with risk averse members under carbon tax policy. Taking into account the selling price and the level of sustainable technology and the advertising effort in stochastic demand, they used the mean variance approach to develop and compare two optimisation models for production-oriented decentralised supply chains with and without technology investment. Wan et al. (2022), using the mean variance approach, with the aim of minimising risk and achieving the producer profit goal, designed an inventory purchase problem. In their study, the manufacturer can reserve the components from suppliers to optional contracts or fall into the trap of an instant market to buy components quickly in order to meet definite demand. Moreover, much research corresponds to the MV risk-sensitive framework in supply chain management (Choi et al., 2019; Xue et al., 2016; Zhuo et al., 2018).

Pricing problems can be solved by using different methods. Wu et al. (2017) applied the Stackelberg game theory to obtain an optimal period for using a trade credit in a supply chain facing default risk. Mostly, game theory approaches were used to investigate the models corresponding to different contracts in such problems (Chakraborty et al., 2016; Yu et al., 2020). To the best of our knowledge, meta-heuristics are rarely conducted for supply chain management with coordinating contracts. However, some researchers developed meta-heuristic algorithms for cases with policies studied in this study. For example, Diabat et al. (2013) used a genetic algorithm (GA) and an artificial immune system to tackle a problem arising from the product return policy in a multi-echelon reverse logistic network. Moreover, Taleizadeh et al. (2019) proposed a non-dominated sorting genetic algorithm (NSGA-II), a basic bee meta-heuristic, and a teaching-learning-based optimisation algorithm for an imperfect production system taking into account the quality of the product and a return system with two warranty policies. Kaya and Uerk (2016) designed a model to determine the prices for new products, inventory amounts and optimal locations of the facilities. In addition, in order to maximise the total supply chain profit, they considered incentive values for the collection of right amount of used products. Fattahi et al. (2018) presented a novel multi-stage stochastic programme to tackle the problem of a multi-period supply chain network redesign. in their model, tactical decisions such as products' prices and strategic redesign decisions were also made. Chen and Chen (2020) presented a pricing model to determine the optimal price for the entire selling season to minimise the maximum regret. in their model, a seller sells some products during a selling horizon with limited demand information. Pando et al. (2021) developed an inventory model in which demand rate depended on the selling price and the stock level. In order to maximise the return on inventory management expense, they consider three types of variables including the reorder point, the selling price and the order-level. Zhan et al. (2020) studied the effect of including consumer behaviour application in product sales prediction research in e-commerce. Recently, Keshavarz-Ghorbani and Pasandideh (2021) also used three genetic algorithms, invasive weed optimisation algorithm, and moth flame optimisation algorithm to create a multi-stage serial closed-loop supply chain (CLSC) model considering the reworking process, batch delivery, random defective rate, quality-dependent return rate, and learning effects. Then, in order to choose the best algorithm to solve their model, they used Fibonacci algorithm. Amjadian and Gharaei (2022) developed a closed-loop supply chain including a supplier, a producer, a wholesaler, multiple retailers, and a collector in which multi-stage products are considered according to green production principles and quality control policy under various sales deficiencies and missed sales. The purpose of their study is to obtain the optimal number and volume of inventory of products so that the cost of the entire supply chain is minimised. Ultimately, Cárdenas-Barrón et al. (2021) designed a model which shortage was allowed and demand rate depended on both the selling price and time according to a power pattern. The impact of the selling price and a time power function are also combined by demand for the product. Khan et al. (2023) explore the effects of an all-units discount on the pricing and replenishment policies of an inventory model under a power demand pattern. The authors develop a mathematical model to analyse the impact of different pricing and replenishment policies on business profits. The results suggest that offering an all-units discount can lead to more efficient inventory management and higher profits for the business. Fallahi et al. (2022) investigate a constrained multi-item EOQ inventory model for reusable items. The authors develop a mathematical model to analyse the impact of reinforcement learning-based differential evolution and particle swarm optimisation on inventory management. The results suggest that the proposed model can lead to more efficient inventory management and higher profits for the business.

According to existing literature, studies on multiple manufacturers' pricing models could benefit from consideration of information gaps. Such gaps include work still needed on full refunds, returns, warranties, risk management frameworks, and comparisons of several well-known coordinating contracts in a supply chain that features multiple manufacturers and a retailer. Features from studies that attempted to fill these gaps are compared with those of our study in Table 1.

Overall, our main objective for this work is to maximise the profit functions defined in different scenarios. After we reviewed the research gaps found in the existing literature review, we believe that the unique contribution of this work could be the profit functions we propose for a two-echelon supply chain with three levels consisting of multiple manufacturers and a retailer. Other contributions of this work are as follows:

- Application of a return policy that offers a full refund, warranty, and risk management in a pricing problem;
- Evaluation of the effect of profit-sharing, revenue-sharing, and cost-sharing, and buyback contracts on the profit function;
- Use of uncertainty in a demand function in which the probability of buying each manufacturer's product follows a uniform distribution in [a, b] with mean $\mu = \frac{a+b}{2}$ and variance $\sigma^2 = \frac{(b-a)^2}{12}$; and
- A novel hybrid of the GSO-HBBO algorithm to generate high-quality solutions.

3. Mathematical models

In this section we explain the distribution and selling of a multi-brand product through multiple manufacturers and a retailer. The manufacturers produce a particular product and sell it to the retailer who sells it to customers. In this study, we combined the full-refund policy introduced by Giri et al. (2017) with cost-sharing, revenue-sharing, profit-sharing, and buyback contracts for unsold products. Uncertain demand was considered for each manufacturer's product. In addition, the proposed scenarios were investigated under mean-variance (MV) risk and a warranty policy. Some notations used in the proposed model are as follows:

Set

$i = \{1, 2, \ldots, n\}$	Manufacturers

Deterministic parameters

n	Number of brands
t	Fit cost of product
c_i	Unit production cost of ith brand's product
b_i	Unit warranty cost of ith brand's product
s	Scrap value of per unit of returned product
r	Reservation price of per unit of product
D_i	Demand of ith brand's product in retailer point
DL_i	Demand value of the loyal customers for ith brand's product
α	Sensitivity parameter for product quality ($\alpha > 0$)
η	Cost of quality improvement per unit ($\eta > 0$)
β	Rate of return for the product (when customer is dissatisfied with the product)
d	Product discrimination parameter
x_i	Probability of buying ith brand's product
f	Sensitivity parameter for product warranty ($f > 0$)

Table 1. Review of related studies.

	Contracts				Policies					Solution approaches	
Paper	Revenue sharing	Profit sharing	Cost sharing	Buyback	Single manufacturer	Multiple manufacturer	Warranty	Risk management	Returns	Mathematical approach	Meta-heuristic
Diabat et al. (2013)									✓	✓	✓
Xu et al. (2014)	✓				✓			✓		✓	
Giri and Maiti (2014)						✓	✓			✓	
Zhang et al. (2016)	✓			✓	✓			✓		✓	
Li et al. (2017)				✓	✓			✓		✓	
Giri et al. (2017)	✓					✓			✓	✓	
Yoo et al. (2015)				✓	✓				✓	✓	
Ghandi and Lin Lawell (2017)				✓	✓			✓		✓	
Bai et al. (2017)	✓		✓		✓					✓	
Taleizadeh et al. (2019)					✓		✓		✓	✓	✓
Yu et al. (2020)	✓		✓		✓					✓	
Fallahi et al. (2022)			✓		✓			✓			✓
Khan et al. (2023)		✓			✓					✓	
Koussis and Silaghi (2023)	✓		✓		✓					✓	
Liu et al. (2023)	✓	✓				✓	✓			✓	
This study	✓	✓	✓	✓		✓	✓	✓	✓		✓

Decision variables

p_i	Unit selling price of ith brand's product in retailer point ($p_i > w_i$)
w_i	Unit wholesale price of manufacturer i
l	Number of warranty periods
θ_i	Quality of ith brand's product

The proposed general model was introduced by Hotelling (1990) and is known as the *Hotelling* model. In this model, an ideal priority space is considered for all brands in the market. The presumption of a uniform distribution for the customer's priority to buy the ith brand's product is typically used for a *Hotelling* model (Xu et al., 2010). The entire market is divided into n manufacturers selling a product through a retailer. Customisation leads these manufacturers to differentiate between brands. Because of the differentiation, customers set different priorities for buying each product according to its brand. The choice to buy each brand of product also depends on the customer's pocketbook. If the product fits one's budget, the customer may decide to buy it. The differentiation among the manufacturers was considered parameter d, such that a brand with a higher brand distinction d is less substitutable, and vice versa. Also, x_i was defined as the difference between a customer's likelihood of buying or not buying the ith brand's product and this likelihood parameter must be less than d. We also assume that only n manufacturers exist in the market, and no other manufacturers could enter the market; hence, more additional manufacturers do not affect the demand and the competition necessarily increases among existing manufacturers. Consequently, the sum of all likelihood values for all existing brands equals d.

$$\sum_{i=1}^{n} x_i = d \tag{1}$$

According to Giri et al. (2017), a utility function for each brand's product is defined in relation to some parameter, such as reservation price of the product (the value of a product from the customer viewpoint), product quality and price, and fit costs. In this way, the utility function has a direct relation to the reservation price and quality of the product, but it has an indirect relation to the other parameters. This definition means that when these parameters are increased, the utility of the product is also increased and the opposite is also true. However, when price or fit cost of the product is increased, the utility value is decreased (and the opposite is true). The utility function is written as follows:

$$U_i = r - p_i + \alpha\theta_i - x_i t \tag{2}$$

According to the introduced utility function for a brand's product, if $U < 0$, then the customer will not be interested in buying the product, but if $U > 0$, then the customer will find the product attractive for buying. Of course, some customers are loyal to specific brands in the market and do not buy other brands. In addition to these brand-loyal customers, however, other shoppers look for the best choice, creating competition between manufacturers for non-loyal customers. Therefore, to determine the likelihood of a customer buying a particular brand's product, we equate utility functions with respect to the proposed likelihood constraint (Equation (1)).

$$r - p_i + \alpha\theta_i - x_i t = r - p_j + \alpha\theta_j - x_j t$$
$$i, j = 1, 2, 3, \ldots, n \; (i \neq j) \tag{3}$$

According to Equations (1) and (3), for all manufacturers, the marginal likelihood of a customer buying a particular brand's product is as follows:

$$\hat{x}_i = \frac{td - (n-1)(p_i - \alpha\theta_i) + \sum_{i \neq j}^{n}(p_j - \alpha\theta_j)}{nt} \tag{4}$$

The demand value for the loyal customers (DL_i) could be calculated by considering a utility function greater than zero ($U_i > 0$), which is shown in Equation (5). Moreover, regarding Equation (4), the total demand for the ith brand's product is obtained through Equation (6) as follows:

$$DL_i = \frac{r - p_i + \alpha\theta_i}{t} \tag{5}$$

$$D_i = \hat{x}_i + \frac{r - p_i + \alpha\theta_i}{t} \quad i = 1, 2, 3, \ldots, n \tag{6}$$

To apply risk management in this study, the MV risk function was taken into account in the proposed profit functions. Furthermore, risk profit trade-off (Markowitz, 1959) is a very important objective in service science (Michalk et al., 2011; Xiao et al., 2012). Lau (1980) introduced MV function for the newsvendor problem. Lau and Lau (1999) also developed MV models for profit functions of a manufacturer and retailer. Choi (2013) used the MV model to handle a decision-making problem for a risk-averse service provider. According to the proposed utility function for each brand's product, MV models for profit functions of the manufacturer (see Equation (7)) and the retailer (see Equation (8)), respectively, are as follows:

$$U_M = E[\pi_M] - kV[\pi_M] \tag{7}$$

$$U_R = E[\pi_R] - kV[\pi_R] \tag{8}$$

In Equations (7) and (8), k is the service provider's level of risk aversion. A large value of k refers to a highly risk-averse manufacturer or retailer, and a k of 0 refers to a manufacturer or retailer that aims solely to maximise the expected profit value; that is, the manufacturer or retailer is risk neutral. In these models, $E[\pi_M]$ is the expected value for a manufacturer's profit, and $V[\pi_M]$ is the variance of the manufacturer's profit. The terms $E[\pi_R]$ and $V[\pi_R]$ denote the expected value and variance for retailer's profit, respectively.

For the proposed MV models used for considering risk, the warranty is considered in the developed profit functions in different scenarios. These scenarios were defined with respect to four contracts between the manufacturers and retailer. A full-refund policy is included in all scenarios because it helps the contracts perform better than when it is not included. Moreover, the following assumptions have been considered in the models:

- Customers dissatisfied with a product and can return it. The rate of product return is β (as per Chen & Grewal, 2013). Because of inspection and repackaging, this product cannot be resold in the same period in which it is returned.
- The salvage value of the returned product is denoted as s and is the same for each brand's products.

The ith brand's quality cost is given by $\frac{\eta\theta_i^2}{2}$, which is a convex function in θ_i (Yan & Pei, 2009).

- Modelling in each scenario is specified for the retailer's profit, each manufacturer's profit, and total profit of n manufacturers.
- Warranty cost of the ith brand's product is given by $b_i t_i$.
- The profit functions include two main parts: revenue value and total cost value for the manufacturers and retailer.
- Uniform distribution is considered for x_i to calculate the expected value and variance of the following profit functions, respectively, in the MV model: μ_x and $\sigma^2{}_x$.

3.1. Scenario 1: cost sharing under a full-refund policy

Giri et al. (2017) have shown that when demand is predictable, the retailer's order quantity aligns with the total demand at the customers' end. In this scenario, each manufacturer shares costs with the retailer, for which μ is the portion of total production cost calculated in the profit function of the manufacturer, and $(1-\mu)$ is the portion of the total cost calculated in the retailer's profit function. The profit of each manufacturer is:

$$\pi_{M,i}^{cs} = ((1-\beta)w_i + \beta s)D_i - \mu\left(c_i D_i + \frac{\eta\theta_i^2}{2} + b_i l_i\right) \tag{9}$$

Consequently, the overall profit of all manufacturers can be determined using the formula presented in Giri et al. (2017), which is as follows:

$$\pi_M^{cS} = \sum_{i=1}^{n} \pi_{M,i}^{cs} \tag{10}$$

Furthermore, the profit function for the retailer can be expressed as follows:

$$\pi_R^{cs} = \left[(1-\beta)\left(\sum_{i=1}^{n}(p_i - w_i\right)D_i)\right] - \left[(1-\mu)(c_i D_i + \frac{\eta\theta_i^2}{2} + b_i l_i)\right] \tag{11}$$

Concerning the expectation and variance of uniform distribution for x_i, the expected value and variance of profit for each manufacturer (Equations (12) and (13)) and the retailer (Equations (14) and (15)) are as follows:

$$E[\pi_{M,i}^{CS}] = ((1-\beta)w_i + \beta s)\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right) - \mu\left(c_i\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right) + \frac{\eta\theta_i^2}{2} + b_i l_i\right) \tag{12}$$

$$V[\pi_{M,i}^{CS}] = (((1-\beta)w_i + \beta s)^2\sigma_x^2) + ((1-\beta)w_i + \beta s)\left(\frac{r - p_i + \alpha\theta_i}{t}\right) - (\mu c_i)^2\sigma_x^2 - \mu\left(c_i\left(\frac{r - p_i + \alpha\theta_i}{t}\right) + \frac{\eta\theta_i^2}{2} + b_i l_i\right) \tag{13}$$

$$E[\pi_R^{CS}] = \left[(1-\beta)\left(\sum_{i=1}^{n}(p_i - w_i) + \left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right)\right)\right] - \left[(1-\mu)\left(c_i\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right) + \frac{\eta\theta_i^2}{2} + b_i l_i\right)\right] \tag{14}$$

$$V[\pi_R^{CS}] = \left[(1-\beta)\left[\sum_{i=1}^{n}(p_i - w_i)^2(\sigma_x^2) + \sum_{i=1}^{n}(p_i - w_i)\left(\frac{r - p_i + \alpha\theta_i}{t}\right)\right]\right] - \left[((1-\mu)(c_i))^2\sigma_x^2 - (1-\mu)\,(c_i + \left(\frac{r - p_i + \alpha\theta_i}{t}\right) + \frac{\eta\theta_i^2}{2} + b_i l_i)\right] \tag{15}$$

According to Equations (12)–(15), the MV objective functions for the manufacturers and the retailer are as follows:

$$U_{M,i}^{CS} = ((1-\beta)w_i + \beta s)\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right) - \mu\left(c_i\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right) + \frac{\eta\theta_i^2}{2} + b_i l_i\right) - k\left[(((1-\beta)w_i + \beta s)^2\sigma_x^2) + ((1-\beta)w_i + \beta s)\left(\frac{r - p_i + \alpha\theta_i}{t}\right)\right] - k\left[(\mu c_i)^2\sigma_x^2 - \mu\left(c_i\left(\frac{r - p_i + \alpha\theta_i}{t}\right) + \frac{\eta\theta_i^2}{2} + b_i l_i\right)\right] \tag{16}$$

$$U_R^{CS} = \left[(1-\beta)\left(\sum_{i=1}^{n}(p_i - w_i) \times \left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right)\right)\right] - \left[(1-\mu)\left(c_i\left(\frac{r - p_i + \alpha\theta_i}{t}\right) + \frac{\eta\theta_i^2}{2} + b_i l_i\right)\right] - k\left[(1-\beta)\left[\sum_{i=1}^{n}(p_i - w_i)^2(\sigma_x^2) + \sum_{i=1}^{n}(p_i - w_i)\left(\frac{r - p_i + \alpha\theta_i}{t}\right)\right]\right] - k\left[((1-\mu)(c_i))^2\sigma_x^2 - (1-\mu) \times \left(c_i\left(\frac{r - p_i + \alpha\theta_i}{t}\right) + \frac{\eta\theta_i^2}{2} + b_i l_i\right)\right] \tag{17}$$

3.2. Scenario 2: profit sharing under a full-refund policy

In the profit sharing with full-refund scenario, σ is the portion of the profit for the retailer and the remaining profit is calculated as each manufacturer's profit. The profit of each manufacturer is obtained by

$$\pi_{M,i}^{ps} = \left((1-\sigma)\left((1-\beta)\sum_{i=1}^{n}(p_i - w_i)D_i\right)\right) \times ((1-\beta)w_i + \beta s - c_i)D_i - \frac{\eta\theta_i^2}{2} - b_i t \tag{18}$$

The profit for all manufacturers is equal to the sum of each manufacturer's profit as follows:

$$\pi_M^{pS} = \sum_{i=1}^{n}\pi_{M,i}^{ps} \tag{19}$$

The profit function for the retailer is:

$$\pi_R^{pS} = \sigma\left((1-\beta)\sum_{i=1}^{n}(p_i - w_i)D_i\right) \tag{20}$$

By considering risk management, the MV objective functions for the manufacturers and the retailer are:

$$\begin{aligned} U_{M,i}^{ps} = &\left[(1-\sigma)\left((1-\beta)\left(\sum_{i=1}^{n}(p_i - w_i)\right.\right.\right.\\ &\left.\left.\left.\times\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right)\right)\right)\right]\\ &+\left[((1-\beta)w_i + \beta s - c_i)\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right)\right.\\ &\left.-\frac{\eta\theta_i^2}{2} - b_i l_i\right]\\ &-k\left[(1-\sigma)(1-\beta)\left[\sum_{i=1}^{n}(p_i - w_i)^2(\sigma_x^2)\right.\right.\\ &\left.\left.+\sum_{i=1}^{n}(p_i - w_i)\left(\frac{r - p_i + \alpha\theta_i}{t}\right)\right]\right]\\ &-k\left[\left[((1-\beta)w_i + \beta s - c_i)^2\sigma_x^2\right.\right.\\ &\left.+((1-\beta)w_i + \beta s - c_i)\left(\frac{r - p_i + \alpha\theta_i}{t}\right)\right]\\ &\left.-\frac{\eta\theta_i^2}{2} - b_i l_i\right] \end{aligned} \tag{21}$$

$$\begin{aligned} U_R^{ps} = &\left[\sigma(1-\beta)\left(\sum_{i=1}^{n}(p_i - w_i)\right.\right.\\ &\left.\left.\times\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right)\right)\right]\\ &-k\left[\sigma(1-\beta)\left[\sum_{i=1}^{n}(p_i - w_i)^2(\sigma_x^2)\right.\right.\\ &\left.\left.\times\sum_{i=1}^{n}(p_i - w_i)\left(\frac{r - p_i + \alpha\theta_i}{t}\right)\right]\right] \end{aligned} \tag{22}$$

3.3. Scenario 3: revenue sharing under a full-refund policy

In the revenue sharing with full-refund scenario, ϕ is the retailer's portion of the revenue, and the remaining revenue is calculated as each manufacturer's revenue as follows:

$$\begin{aligned} \pi_{M,i}^{rs} = &((1-\beta)(w_i + (1-\Phi)p_i) + \beta s - c_i)D_i\\ &-\frac{\eta\theta_i^2}{2} - b_i t \end{aligned} \tag{23}$$

The profit for all manufacturers is equal to the sum of each manufacturer's profit as follows:

$$\pi_M^{rS} = \sum_{i=1}^{n}\pi_{M,i}^{Cs} \tag{24}$$

The profit function for the retailer is:

$$\pi_R^{rS} = (1-\beta)\sum_{i=1}^{n}(\Phi p_i - w_i)D_i \tag{25}$$

According to the MV models, the objective functions for the manufacturers and the retailer are:

$$\begin{aligned} U_{M,i}^{rs} = &\left[((1-\beta)(w_i + (1-\Phi)p_i) + \beta s - c_i)\right.\\ &\left.\times\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right) - \frac{\eta\theta_i^2}{2} - b_i l_i\right]\\ &-k[((1-\beta)(w_i + (1-\Phi)p_i) + \beta s - c_i)^2\sigma_x^2]\\ &-k\left[\left[((1-\beta)(w_i + (1-\Phi)p_i) + \beta s - c_i)\right.\right.\\ &\left.\left.+\left(\frac{r - p_i + \alpha\theta_i}{t}\right)\right] - \frac{\eta\theta_i^2}{2} - b_i l_i\right] \end{aligned} \tag{26}$$

$$\begin{aligned} U_R^{rs} = &\left[\sigma(1-\beta)\left(\sum_{i=1}^{n}(\Phi p_i - w_i)\right.\right.\\ &\left.\left.+\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right)\right)\right]\\ &-k\left[\sigma(1-\beta)\left[\sum_{i=1}^{n}(\Phi p_i - w_i)^2(\sigma_x^2)\right.\right.\\ &\left.\left.+\sum_{i=1}^{n}(\Phi p_i - w_i)\left(\frac{r - p_i + \alpha\theta_i}{t}\right)\right]\right] \end{aligned} \tag{27}$$

3.4. Scenario 4: buyback under a full-refund policy

In the buyback with full-refund scenario, the product brand i is sold to the retailer at price $'w_i$, and y% of the products are assumed to remain unsold and are bought back by the manufacturer at price h. The profit of each manufacturer is:

$$\begin{aligned} \pi_{M,i}^{bb} = &((1-\beta)w_i' + \beta s)(1-y)D_i - (c_i + hy)D_i\\ &-\frac{\eta\theta_i^2}{2} - b_i l_i \end{aligned} \tag{28}$$

The profit for all manufacturers is equal to the sum of each manufacturer's profit as:

$$\pi_M^{bb} = \sum_{i=1}^{n}\pi_{M,i}^{bb} \tag{29}$$

The profit function of the retailer is:

$$\pi_R^{bb} = (hyD_i) + \left[(1-y)(1-\beta)\sum_{i=1}^{n}(p_i - w_i')D_i\right] \tag{30}$$

Concerning to the MV models, new profit functions for the manufacturers and the retailer are:

$$\begin{aligned} U_{M,i}^{bb} = &\left[((1-\beta)w_i' + \beta s)(1-y)\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right)\right. \\ &\left. - (c_i + hy)\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right) - \frac{\eta\theta_i^2}{2} - b_i l_i\right] \\ &- k\left[((1-\beta)w_i' + \beta s)^2(1-y)^2\sigma_x^2\right. \\ &+ ((1-\beta)w_i' + \beta s)(1-y) \\ &\left.\times\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right)\right] \\ &- k\left[(c_i + hy)^2\sigma_x^2 + (c_i + hy)\right. \\ &\left. + \left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right) - \frac{\eta\theta_i^2}{2} - b_i l_i\right] \end{aligned} \tag{31}$$

$$\begin{aligned} U_R^{bb} = &\left[\left(hy\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right)\right)\right. \\ &+ \left[(1-y)(1-\beta)\left[\sum_{i=1}^{n}(p_i - w_i')\right.\right. \\ &\left.\left.\left. + \left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right)\right]\right]\right] \\ &- k\left[\left(h^2y^2\sigma_x^2\left(\mu_x + \frac{r - p_i + \alpha\theta_i}{t}\right)\right)\right. \\ &\left. + \left(hy\left(\frac{r - p_i + \alpha\theta_i}{t}\right)\right)\right] \\ &- k\left[(1-y)(1-\beta)\left[\sum_{i=1}^{n}(p_i - w_i')^2(\sigma_x^2)\right.\right. \\ &\left.\left. + \sum_{i=1}^{n}(p_i - w_i')\left(\frac{r - p_i + \alpha\theta_i}{t}\right)\right]\right] \end{aligned} \tag{32}$$

4. Solution method: evolutionary hybrid GSO-HBBO algorithm

Meta-heuristic algorithms can be totally classified into two main parts, including population search optimisation methods (PSOMs) and local search optimisation methods (LSOMs). The LSOMs start with a solution and try to generate and improve the next solution via the neighbourhood mechanisms in the form of single-candidate agent (Bolaji et al., 2016). Actually, they benefit from these searching methods in order to catalyse the search process. However, their focus on exploring the search instead of exploitation may increase the probability of stuck in the local optimal solution. Contrary to LSOMs, the PSOMs utilise the multi agents to build one or more better agents per scope of improvements. These types of Meta heuristics can be convergent in encouraging areas, especially where the large regions are imposed. Even though, it does not perfectly utilise the hyper-wide areas of the search space (Abualigah, 2020; Taleizadeh et al., 2009a). This research hybridises two LSOMs in order to create a new approach that can reach the optimal solution in less time by rapid searching all the effective regions. Accordingly, the structure of this new approach will be explained in this section. Next section examines the performance of the proposed algorithm (Taleizadeh et al., 2008, 2009b, 2010, 2011).

4.1. Group search optimiser (GSO)

The use of nature-inspired optimisation algorithms such as evolutionary algorithms has become popular due to their flexibility and simplicity. GSO is one of the types of evolutionary algorithms (EAs) developed by He et al. (2009) based on the animal's behaviour in search of resources to solve continuous optimisation problems. Animal search behaviour can be considered as a search for food, mates, nesting sites and the like (Bell, 1990). The three main factors influencing the success of animal search operations are:

(1) The strategies used with respect to access to resources and their spatial and temporal distribution.
(2) Their efficiency in locating resources.
(3) The theory of natural selection, meaning that animals have a tendency to survive, and therefore their search strategies are such that they can optimise the possibility of access to resources.

In addition, many studies have been performed on the group life of animals, which have shown that the result of this tribal life is an increase in the rate of finding resource groups and a decrease in the variance of search success (McNamara et al., 2001).

There are two types of group search strategies:

- Producing, which means searching for food.
- Scrounging, which means joining the resources discovered by other members (Brockmann & Barnard, 1979).

There are two types of models for evaluating the optimal affiliate policy:

- The IS model, which assumes that each member can simultaneously search for its resources as well as search for a position to obtain another member's achievement.
- The PS model, which assumes that each member can only take on one of the producing and scrounging modes. This model is more commonly observed, especially for birds that feed on the ground (Giraldeau & Beauchamp, 1999).

The population considered in the GSO algorithm is called a group, and each individual in the population is called a member of that group. In a n-dimensional search space, the ith member of the iteration k of the algorithm is denoted by X_k^i; this member has a head angle. The head angle which is a unit vector, is obtained by a polar equation conversion at the head angle of each member to find the *i*th member (Mustard, 1964).

$$d_{i_1}^k = \prod_{q=1}^{n-1} cos(\varphi_{i_q}^k)$$

$$d_{i_j}^k = sin(\varphi_{i_{j-1}}^k). \prod_{q=1}^{n-1} cos(\varphi_{i_{j-1}}^k)(j = 2, 3, \ldots, n-1)$$

$$d_{i_n}^k = sin(\varphi_{i_{n-1}}^k) \tag{33}$$

In the GSO algorithm, each group consists of three types of members: producer, scrounger and dispersed members from the group by random movements. For the simplicity of the algorithm it is assumed that there is one producing member in each iteration and the others are from the two other groups. Also, in each iteration the members of each type of groups are the same and can be placed in different groups. In each iteration, the member in the best position relative to the resource is considered as the producer. In the GSO algorithm, scanning is very important for the producer. It is used in the proposed model of the scanning strategy provided by white crappie (Barnard & Sibly, 1981). In iteration k, the producer behaviour algorithm is:

1. The producer scans with zero degree and creates three more points by random sampling in the field of view: one point in zero-degree, one point on the right and one point on the left side of the space.

$$X_z = X_p^k + r_1 l_{max} D_p^k(\varphi^k) \tag{34}$$

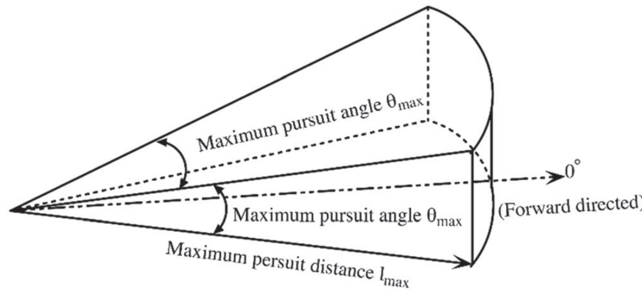

Figure 1. Scanning field in 3D space (Bell, 1990).

There is a point on the right-hand side of hypercube:

$$X_r = X_p^k + r_1 l_{max} D_p^k(\varphi^k + r_2 \Theta_{max}/2) \tag{35}$$

There is a point on the left-hand side of hypercube:

$$X_l = X_p^k + r_1 l_{max} D_p^k(\varphi^k + r_2 \Theta_{max}/2) \tag{36}$$

In these Equations (37) and (38) r_1 is a random number with a normal distribution, the mean of zero and the variance of one, and r_2 is a uniform random number in the range of zero and one.

2. The producer selects the best point with the best resources and moves towards that point if it is better than its current position, otherwise it stays there and changes its angle randomly.
3. If the manufacturer cannot find a better position after a iteration, it returns to zero degree.

$$\varphi^{k+a} = \varphi^k \tag{37}$$

Barnard and Sibly observed that a group of members who are selected as scrounger members perform the following activities:

(I) Copying the producer area
(II) Tracking another member
(III) Snatching the producer resources.

In the stated algorithm, it is assumed that there is only the first case, i.e. copying, and in the k iteration, the behaviour of copying the region by the *i*th member is expressed as follows:

$$X_i^{k+1} = X_i^k + r_3 \circ (X_p^k - X_i^k) \tag{38}$$

In one iteration, if a scrounging member finds a better position than the producer agent, it will become a producer in the next iteration. Other members are different and less efficient (Caraco, 1979). If the *i*th member is dispersed, it moves and makes random movements to find randomly distributed sources. In the k iteration it obtains a head angle and then selects a random distance.

$$l_i = \alpha . r_1 l_{max} \tag{39}$$

Subsequently, move to the new point:

$$X_i^{k+1} = X_i^k + l_i D_i^k(\varphi^{k+1}) \tag{40}$$

Finally, the members use restrictive strategies for profitable resources to maximise their chances of finding resources. According to this strategy, if a member is outside the search space, it returns by defining the variables that break the boundaries to their previous values.

4.2. Human behaviour-based optimisation (HBBO)

Optimisation is about getting the best results under certain conditions (Rao, 2019). Maximising profits or minimising costs is the ultimate goal of these methods. This benefit or cost can be expressed as an objective function. Optimisation can be defined as the method of finding suitable variables that provide the minimum or maximum of these objective functions. Over the past few decades, due to the importance of optimisation techniques, many new metaheuristic optimisation algorithms have been developed. Metaheuristic algorithms have different sources of inspiration that have no limits. Many of them use nature as their main source of inspiration. Regardless of the source of inspiration, a powerful optimisation algorithm can solve many important problems and is a vital need. Optimisation algorithms are widely used in many fields of science such as business, computer science, economics and engineering. The HBBO algorithm was first introduced by Ahmadi (2017). Unlike many optimisation algorithms that use nature as their primary source of inspiration, HBBO uses human behaviour as its primary source of inspiration. In the following, some human behaviours that are needed to understand the algorithm are discussed and then it is shown how it can be used to solve practical optimisation problems. HBBO is able to solve many types of optimisation problems such as multidimensional functions that have multiple local minima and unimodal functions (Ahmadi, 2017). Everyone in human society is constantly moving towards their personal goals, but it is possible that they have not yet reached it. A person who achieves all his goals will be a successful person and he must strive to be his best. The differences in people's views will cause each individual to move in a certain direction towards success and choose to achieve specific goals. That's why people work and study in different fields and seek to master them. For example, one may see success in sports and another may choose arts. In any field that different people work, one person is more specialised than others, so others try to learn from him and improve their skills. In addition, people have many different interests that may differ from their professional background. For example, a civil engineer may be interested in music in addition to his field of study. People's views are not fixed despite many differences in life. Everyone connects with different people and uses their ideas and advices of to improve his life. Each of these people can be considered as a counsellor who can be effective or ineffective in the direction of that individual (See Figure 1) .

In addition, meeting people with different beliefs and specialisations may change a person's opinion, and in some cases it is even possible to change their professional background due to consultation in order to gain a better position to improve his situation. The result of modelling these simple behaviours discussed is a powerful optimisation algorithm described below. The main structure of this algorithm consists of five steps as follows:

(1) Initialisation
(2) Education
(3) Consultation
(4) Field changing probability
(5) Finalisation

4.2.1. Initialisation

In the first stage, an initial population of initial individuals is considered and each of them is assigned to a category, which is shown in Figure 2.

In an optimisation problem with N_{var} variables, an individual is defined as follows:

$$\text{Individual} = [x_1, x_2, \ldots, x_{N_{var}}] \tag{41}$$

This algorithm creates N_{pop} of initial people and randomly distributes them among N_{field} initial fields. These people make up the community. The number of initial people in each field is as follows:

$$N.Ind_i = round\left\{\frac{N_{pop}}{N_{field}}\right\} \tag{42}$$

where $N.Ind_i$ is the number of initial individuals in the ith field. After creating the initials, the function values are calculated. The function values are defined for an individual as follows:

$$\text{function value} = f(x_1, x_2, \ldots, x_{N_{var}}) \tag{43}$$

4.2.2. Education

Every individual in the community tries to improve himself in the education process by moving towards the

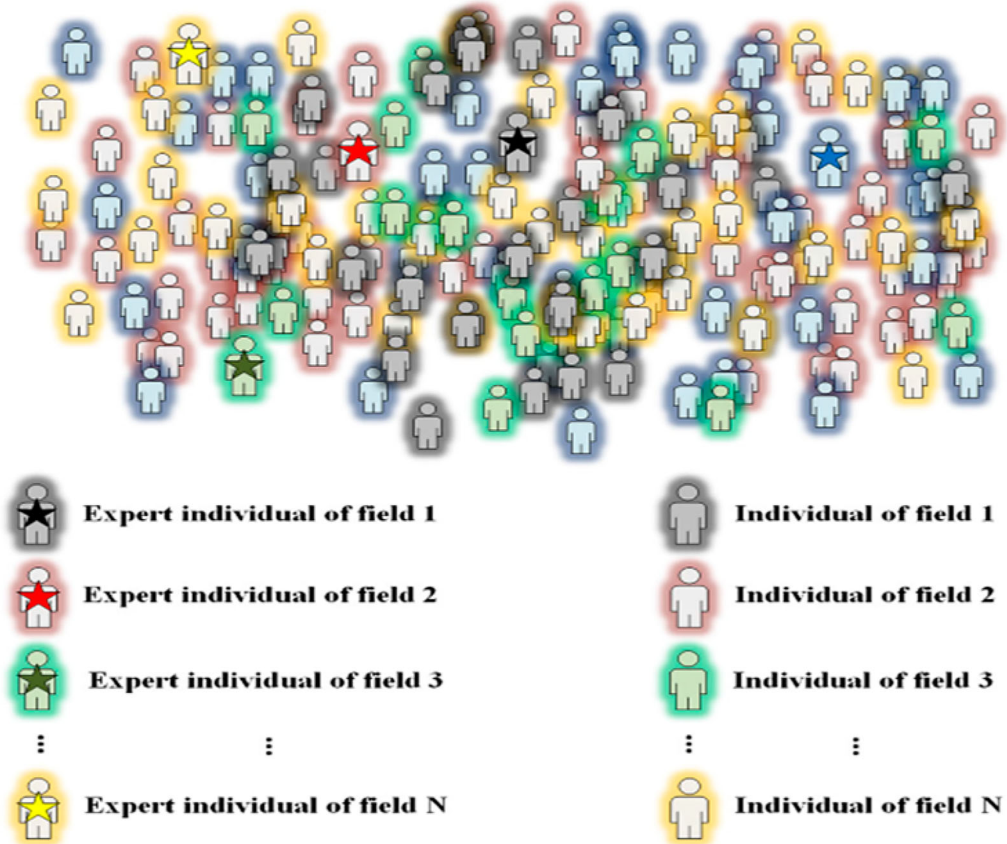

Figure 2. Initialisation (Ahmadi, 2017).

best people in their field who are called experts. The expert is the one who has the best function value in each field (the best value in the maximisation problem is its maximum and in the minimisation problem is its minimum). In order to model this method, the coordinate system is implemented and the expert is the origin. This movement around the expert is shown in Figure 3 for a three-dimensional problem and is done by changing the coordinates of the individuals in the spherical coordinate system. Movement space is limited by a sphere around the expert. Using a spherical coordinate system for the n-dimensional Euclidean space in an optimisation problem, this algorithm finds a random radial coordinate (r) between $r_{min} = k_1 d$ and $r_{max} = k_2 d$, d is the Euclidean distance between the origin and the individual. In a N dimensional optimisation problem using the definition of a spherical coordinate system for the N dimensional Euclidean space, the algorithm finds a random radial coordinate (r) between $r_{min} = k_1 d$ and $r_{max} = k_2 d$, where d is the Euclidean distance between the origin and the individual, and ki is the weight factor as the parameter of the algorithm. In addition, the $N - 1$ algorithm finds random angular coordinates $(\theta_1, \theta_2 \ldots, \theta_N)$, where θ_{N-1} is found between 0 and 2π radians and other angles are selected between 0 and π radians.

4.2.3. Consultation

At this stage, each individual (except the best one in the community) finds a random counsellor from the whole community and gets advice from him. In the consultation process, the counsellor changes some individual variables in the manner shown in Figure 4. Now if the function value is obtained from new variables, it means that the consultation has been effective for them. In this case, the new set of variables replaces the previous variables. If the new set of variables does not have a better function value, nothing will change. The number of random variables that will change is as follows.

$$N_c = round\{\sigma \times N_{var}\} \tag{44}$$

where σ, as an algorithm parameter, is the consulting factor, which determines the number of random variables (N_c) that may change during the consultation process.

4.2.4. Field changing probability

In some fields, an individual may change his path in each iteration. The probability of this change for each field is calculated using rank probability method. In this method, each field is classified according to experts' function value as follows:

$$sort\ fields = [field_1, field_2, \ldots, field_n] \tag{45}$$

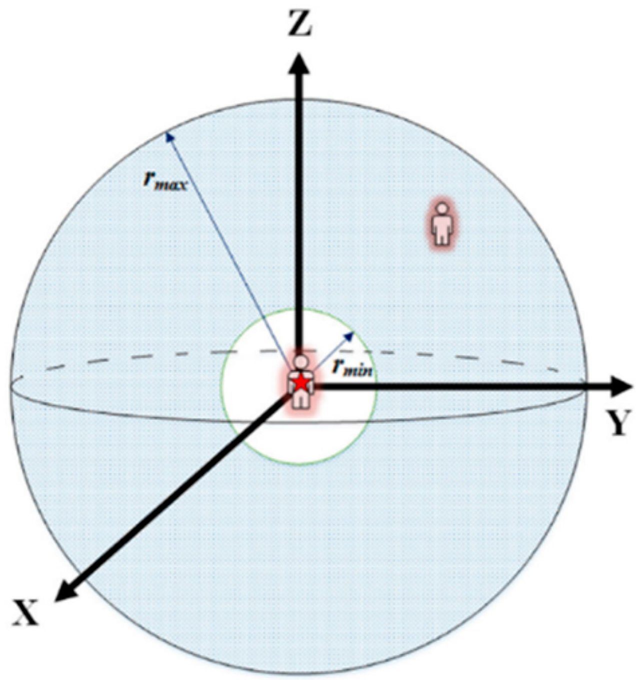

Figure 3. Education (Ahmadi, 2017).

where the expert $field_1$ and $field_n$ have the worst and best function values among others, respectively. Then, the probability of change for each field can be calculated as follows:

$$P_i = \frac{O_i}{N_{field} + 1} \tag{46}$$

where p_i and o_i are the probabilities of field change and the order of ith field, respectively. Using this method, the field in which the expert has better performance value is less likely to be changed, and the field in which the expert has worse performance value is more likely to be changed. Then, by creating a random number between 0 and 1, the following expression is checked, and if the expression is

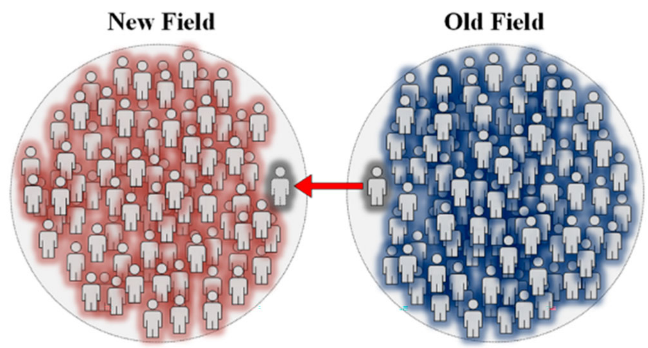

Figure 5. Field changing (Ahmadi, 2017).

met, a field change occurs for one of the people in this field:

$$if\ rand \leq P_i \rightarrow filed\ changing\ occurs$$

In the field change process, according to the function value, the probability of selection for each individual is defined as follows:

$$P.S_j = \left| \frac{f(Individual_j)}{\sum_{k=1}^{N_{ind}} (Individual_k)} \right| \tag{47}$$

where $P.S_j$ is the probability of selection for the individual jth and N_{ind} is the number of individuals in the selected field. Then, using the roulette wheel selection method (Golberg, 1989), an individual is selected and changes his field by going to a different random field, as shown in Figure 5.

4.2.5. Finalisation

By completing the consultation and education steps, individuals' position changes. Therefore, at this point, the function evaluations of the individuals are calculated, and if one of the stop criteria is met, the algorithm terminates. Otherwise, the algorithm goes to step 2.

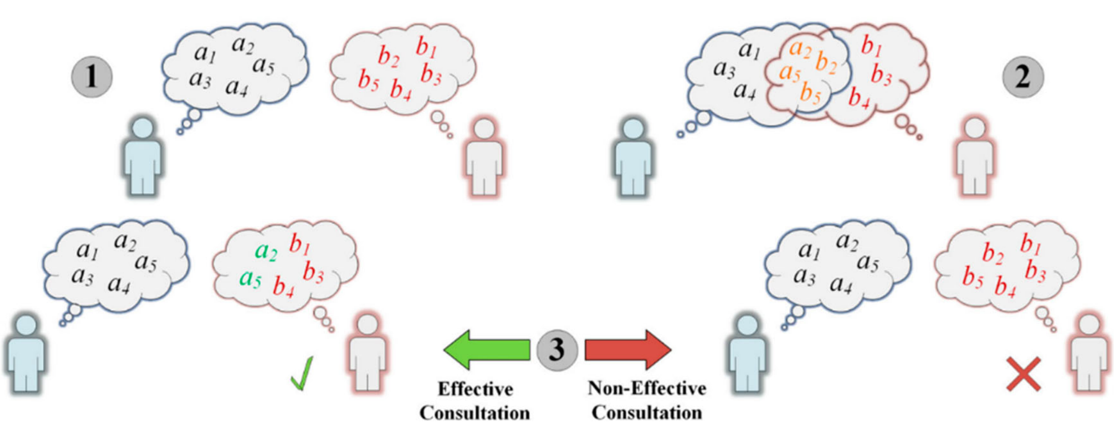

Figure 4. Consultation (Ahmadi, 2017).

The stopping criteria are as follows:

(a) The maximum number of iterations is reached
(b) The maximum number of performance evaluations is obtained.
(c) The average relative change in the value of the objective function during the stop iterations is less than the function tolerance.

4.3. Evolutionary hybrid GSO-HBBO algorithm

Hybridisation of the GSO and HBBO algorithms is designed in this section. Given the complexity of the proposed objective functions in each scenario, the main idea of this hybridisation was to provide an algorithm that could converge to the optimal solution in the shortest time. The strengths of both GSO and HBBO algorithms can be used to achieve a hybrid algorithm that can be converged to an optimal solution in less time. The most important advantage of the GSO algorithm is the search in all possible space of the problem, which allows to produce a very close answer to the optimal answer. On the other hand, categorising the answers, how to move and their movement between different fields is an important advantage of the HBBO algorithm, which makes this algorithm closer to the optimal answer in a short time. While unlike most metaheuristic algorithms, HBBO algorithm performs well on both discrete and continuous problems; So, by hybridising these two algorithms, we expect to achieve a very close to optimal solution in a short time.

The steps of the hybrid algorithm are as follows:

- At first, i agents are generated and each agent is assigned to one of the possible j fields. (X_{ij})
- For each of the agents in each field, the head angle φ_{ij} is set.
- In each field, one of the agents in that field is selected as the producer.
- Each producer agent performs the Producing operation in its respective field.
- Randomly, 80% of the remaining agents are selected in each field and perform scrounging operations in their respective fields.

Algorithm 1. The Pseudo-code of the hybrid GSO-HBBO algorithm

Set K: = 0;
Randomly initialise N agents (x_i) with φ_i head angles;
Spread the agents among n fields to have x_{ij} agents with φ_{ij} head angles;
Calculate the fitness function of each agent in each field: $f_{(x_{ij})}$;
while Max K is not met **do**
  Get the values of chaotic map C.
  for each agent i in each field j **do**
    Perform producing:
      (1) The producer of each field will check at 4 positions which consist of zero level point and 3 other points in the checking area by using equations (34) to (36).
      (2) Discover the position with the best fitness functions for each producer of each field. If the new position has a better fitness function of the producers' current position, they will move to the new position. Otherwise, they will stay in their current position and their head to a new angle randomly.
      (3) If the producers can not find a better position after α iterations, they will turn their head back to zero degree: $\varphi_{k+\alpha} = \varphi_k$.
    Perform scrounging:
      (1) Select 80% of the agents of each field randomly as scroungers.
      (2) Perform scrounging by the scrounger agents of each field by using Equation (38).
    Perform dispersion:
      (1) Select the remaining agents of each field by choosing a $\varphi_{k+1} = \varphi_k + r_2\alpha_{max}$ stochastic head angle and a $l_i = \alpha.r_1 l_{max}$ stochastic distance for each agent.
      (2) Perform ranging by the dispersion agents of each field using Equation (40).
Calculate the fitness function:
    Calculate the fitness function of each agent i in each field j: $f_{(x_{ij})}$.
  Exchange the agent:
    Exchange the agents among the fields with regard to field changing probabilities.
  End for
  Set K: = K+1;
End while

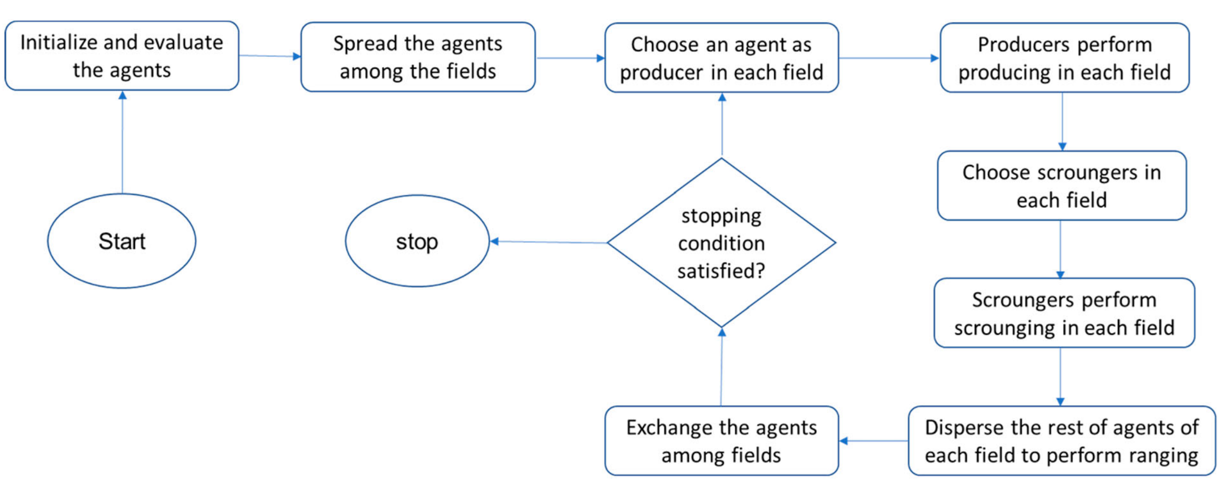

Figure 6. Flowchart of the GSO-HBBO algorithm.

Table 2. Generated parameter values for test problem ($n = 3$).

	Problem		
Parameters	1	2	3
$\hat{x}_i$	Uniform (0,1)	Uniform (0,1)	Uniform (0,1)
(c_1, c_2, c_3)	(2,1,2)	(6,5,6)	(12,10,12)
(b_1, b_2, b_3)	(1,1,1)	(2,2,2)	(3,3,3)
$({}'w_1, {}'w_2, {}'w_3)$	(7,6,7)	(12,10,13)	(22,20,24)
s	2	3	5
t	3	4	7
k	2	3	5
r	4	5	8
β	0.3	0.5	0.7
η	0.3	0.5	0.7
μ	0.3	0.5	0.7
ϕ	0.3	0.5	0.7
σ	0.3	0.5	0.7
y	0.3	0.5	0.7

- The remaining agents are selected in each field and disperse in their respective fields.
- The process of moving agents between fields is done, which is derived from the process of moving the HBBO algorithm.
- If the termination conditions are met, the algorithm stops; otherwise the algorithm steps continue in sequence.

Figure 6 shows the flowchart of the GSO-HBBO hybrid algorithm and the pseudo-code of the novel GSO-HBBO is shown by Algorithm 1.

5. Computational results and performance evaluation

In this section, in order to compare the performance of the proposed algorithm (GSO-HBBO) with the two algorithms GSO and HBBO, based on the parameters defined in Table 2, an example is solved several times and the results for the two objective functions Manufacturer and Retailer in each scenario are presented separately in order to have a detailed study on the performance of algorithms. For this purpose, two criteria of quality of produced solutions and CPU-Time are used to compare the performance of algorithms.

In particular, Percentage Relative Error (PRE) measurement is used to measure the quality of a solution, because it shows the distance between the solutions created by an algorithm and the exact optimal value. The exact value of the objective function is required to calculate the PRE determined from Equation (48). For this purpose, the objective functions in each scenario

Table 3. Computational results of OFV and measures for manufacturer (Scenario 1).

	Manufacturer objective function value								
	GSO			HBBO			GSO-HBBO		
Run#	OFV	PRE	CPU Time	OFV	PRE	CPU Time	OFV	PRE	CPU Time
1	144.65	7.72%	166.57	141.48	9.74%	145.14	152.78	2.53%	129.36
2	143.64	8.37%	170.58	143.16	8.67%	151.25	151.88	3.11%	125.62
3	146.19	6.74%	163.35	142.66	8.99%	142.19	151.01	3.66%	133.02
4	146.38	6.62%	162.88	140.61	10.30%	148.28	152.08	2.98%	129.60
5	146.42	6.59%	164.32	140.06	10.65%	141.08	150.76	3.82%	129.44
6	146.93	6.27%	176.16	139.26	11.16%	145.50	150.67	3.88%	130.14
7	145.06	7.46%	168.11	143.14	8.68%	141.86	152.31	2.84%	129.81
8	147.04	6.20%	168.10	144.21	8.00%	153.33	151.19	3.55%	126.19
9	146.80	6.35%	165.26	137.71	12.15%	142.61	152.38	2.79%	132.04
10	143.58	8.40%	176.50	142.28	9.23%	144.40	151.40	3.41%	131.44
11	146.29	6.68%	161.82	141.62	9.65%	140.30	152.79	2.53%	126.36
12	144.82	7.61%	173.89	140.15	10.59%	147.58	152.04	3.00%	130.79
13	144.97	7.52%	167.11	141.21	9.91%	144.85	150.26	4.14%	128.03
14	145.17	7.39%	167.79	142.02	9.40%	149.09	152.25	2.87%	128.67
15	146.68	6.43%	160.47	141.36	9.82%	150.72	152.28	2.85%	125.66
16	146.36	6.63%	163.94	142.82	8.89%	143.51	151.26	3.51%	131.57
17	143.26	8.61%	176.66	143.21	8.64%	152.13	152.12	2.95%	126.70
18	145.09	7.44%	171.54	137.44	12.32%	147.34	150.89	3.74%	130.11
19	144.75	7.66%	175.14	138.59	11.59%	152.60	151.86	3.12%	128.83
20	144.79	7.63%	175.08	140.84	10.15%	143.65	150.24	4.15%	126.09
21	146.49	6.55%	176.55	138.85	11.42%	144.47	150.88	3.75%	130.26
22	143.62	8.38%	172.24	138.00	11.96%	152.07	152.50	2.71%	131.99
23	147.19	6.10%	175.78	138.19	11.84%	142.63	151.27	3.50%	132.67
24	146.96	6.24%	160.88	139.16	11.22%	145.19	151.65	3.26%	130.00
25	144.87	7.58%	175.72	142.54	9.07%	147.00	151.23	3.52%	127.25
26	143.78	8.28%	177.32	139.68	10.89%	144.48	152.75	2.55%	126.12
27	145.31	7.30%	163.34	143.16	8.67%	141.33	151.62	3.28%	129.89
28	145.98	6.87%	174.25	142.20	9.28%	142.31	151.75	3.19%	126.44
29	143.62	8.38%	174.31	138.05	11.93%	146.16	151.37	3.43%	132.42
30	144.11	8.07%	171.60	138.40	11.71%	149.56	153.27	2.22%	130.14
Average	145.36	7.27%	169.91	140.74	10.22%	146.09	151.69	3.23%	129.22
Best value	147.19	6.10%	160.47	144.21	8.00%	140.30	153.27	2.22%	125.62

Table 4. Computational results of OFV and measures for retailer (Scenario 1).

	Retailer objective function value								
	GSO			HBBO			GSO-HBBO		
#Run	OFV	PRE	CPU Time	OFV	PRE	CPU Time	OFV	PRE	CPU Time
1	608.70	7.03%	194.60	600.03	8.35%	173.96	635.26	2.97%	165.69
2	603.04	7.90%	194.27	600.65	8.26%	175.92	628.13	4.06%	170.77
3	604.50	7.67%	188.11	599.38	8.45%	178.30	628.24	4.05%	165.22
4	605.88	7.46%	198.23	600.48	8.29%	174.89	633.02	3.32%	165.87
5	610.22	6.80%	195.30	595.71	9.02%	178.63	628.72	3.97%	165.16
6	613.21	6.34%	194.90	593.95	9.28%	181.00	634.71	3.06%	166.36
7	604.28	7.71%	199.09	599.27	8.47%	174.41	632.22	3.44%	165.92
8	605.19	7.57%	186.30	592.90	9.44%	174.87	632.68	3.37%	169.50
9	616.17	5.89%	198.77	599.47	8.44%	184.83	622.37	4.94%	166.19
10	610.25	6.79%	196.71	595.97	8.97%	181.31	622.56	4.91%	171.12
11	613.60	6.28%	196.67	595.09	9.11%	179.15	623.79	4.73%	168.88
12	616.61	5.82%	197.53	592.28	9.54%	173.72	634.71	3.06%	165.73
13	614.55	6.14%	194.10	593.81	9.30%	183.96	629.16	3.91%	170.09
14	601.04	8.20%	193.54	591.54	9.65%	180.53	626.76	4.27%	164.59
15	601.98	8.06%	196.55	600.10	8.34%	175.16	621.35	5.10%	164.73
16	611.15	6.66%	196.64	599.58	8.42%	177.80	637.88	2.57%	167.21
17	615.24	6.03%	195.46	591.48	9.66%	183.66	636.96	2.71%	170.34
18	606.80	7.32%	187.74	600.10	8.34%	181.51	633.03	3.31%	165.94
19	611.12	6.66%	194.98	593.90	9.29%	175.50	631.26	3.58%	165.39
20	606.60	7.35%	187.55	592.09	9.57%	184.19	629.78	3.81%	167.14
21	613.09	6.36%	187.07	600.84	8.23%	182.73	631.65	3.53%	170.43
22	604.48	7.68%	197.17	592.34	9.53%	183.33	626.89	4.25%	166.07
23	602.91	7.91%	192.12	591.77	9.62%	176.20	633.77	3.20%	169.38
24	607.23	7.26%	198.35	590.86	9.76%	181.61	630.38	3.72%	168.09
25	612.34	6.48%	185.57	590.67	9.78%	183.26	621.46	5.08%	170.82
26	612.63	6.43%	190.92	597.36	8.76%	175.77	631.26	3.58%	169.78
27	605.23	7.56%	195.99	596.76	8.85%	175.92	628.22	4.05%	169.40
28	607.55	7.21%	199.89	594.76	9.16%	175.98	634.24	3.13%	166.98
29	608.20	7.11%	185.69	599.21	8.48%	175.54	632.04	3.47%	170.29
30	613.69	6.27%	194.66	597.08	8.80%	185.17	631.35	3.57%	168.12
Average	608.92	7.00%	193.82	595.98	8.97%	178.96	630.13	3.76%	167.71
Best value	616.61	5.82%	185.57	600.84	8.23%	173.72	637.88	2.57%	164.59

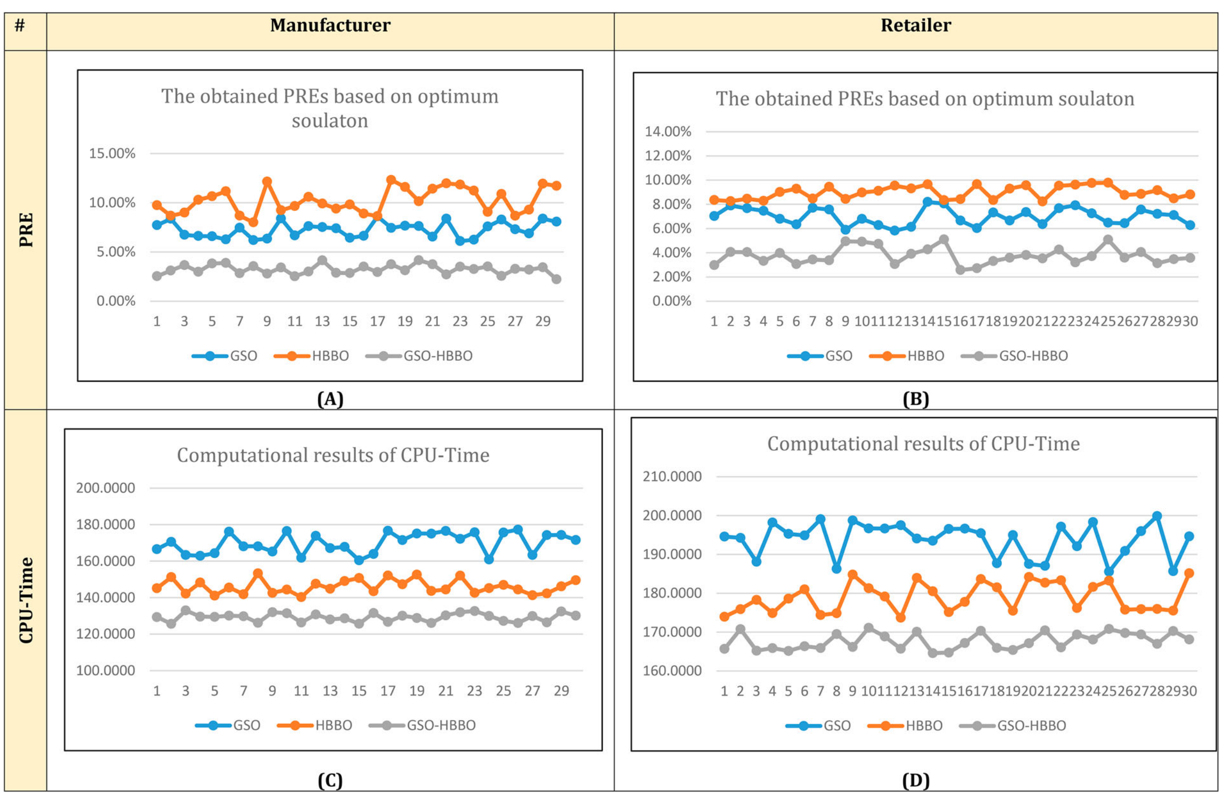

Figure 7. Comparison between proposed algorithms based on CPU-time and PREs (Scenario 1).

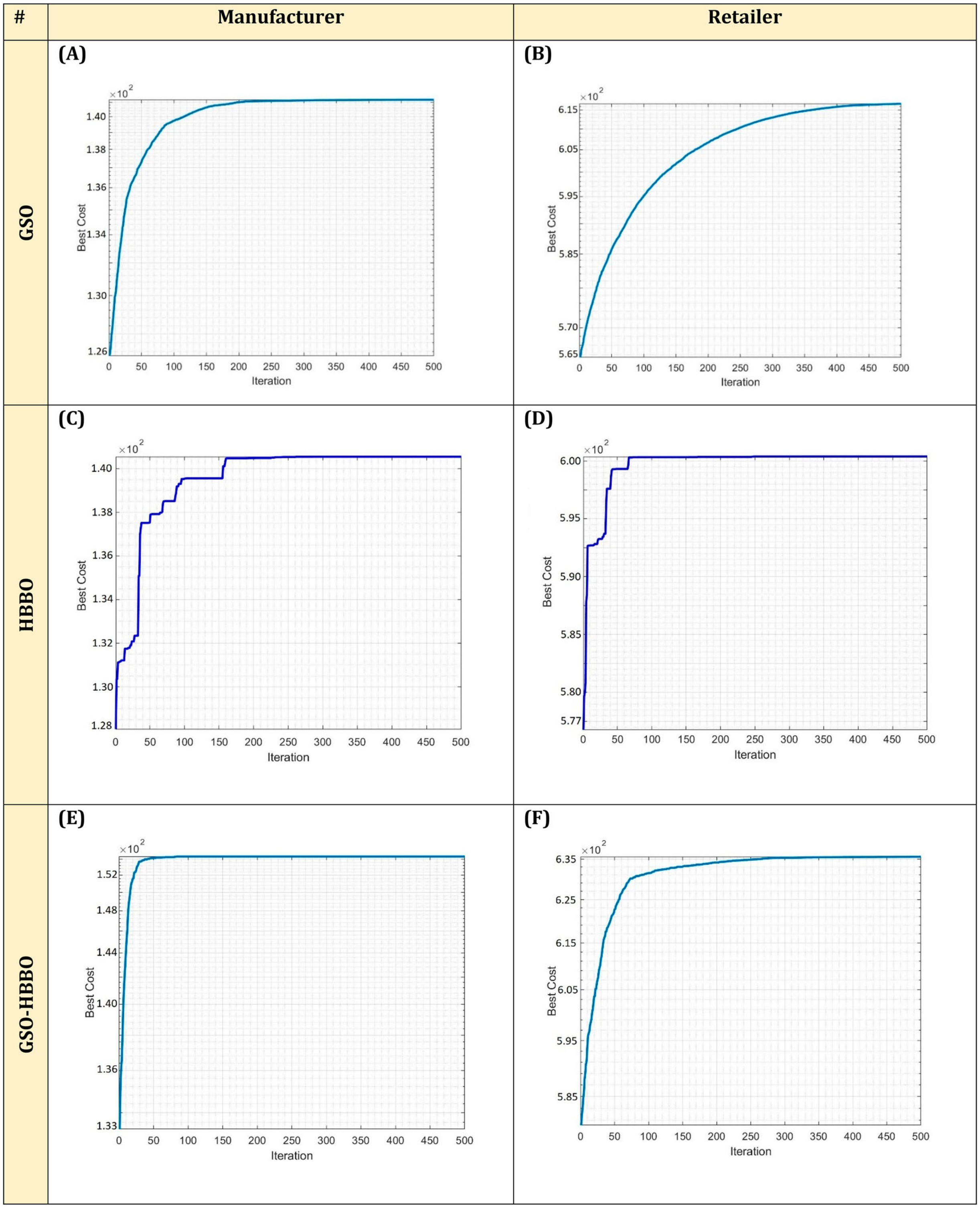

Figure 8. Convergence rate of GSO, HBBO, and hybrid algorithms for two proposed OFs (Scenario 1).

are coded in GAMS / BARON 24.8 software and the exact values of the functions are calculated by the BARON solver. In addition, the designed problem is coded MATLAB R2019-b software to be solved with metaheuristic algorithms. In this regard, an Intel(R) Core (TM) i7-6700HQ CPU @ 2.60GHz 2.59 GHz laptop with

12.00 GB RAM was employed.

$$PRE_{Algorithm} = \left(\frac{\begin{matrix} \textit{The best solution by algorithm} \\ -\textit{Exact solution} \end{matrix}}{\textit{Exact solution}} \right) * 100 \tag{48}$$

Also, another criterion for comparing algorithms is CPU-Time, which is calculated and reported in all iterations for all three algorithms.

5.1. Computational results for Scenario 1

In order to evaluate the performance of different algorithms for two proposed objective function values (OFVs) related to the cost-sharing with a full-refund scenario, the computational results are presented in Table 3 for the manufacturer and in Table 4 for the retailer. The exact values of the two proposed objective functions, namely $Z_{\text{Manufacturer}} = 156.75$ and $Z_{\text{retailer}} = 654.73$, were calculated using the formula x for each PRE iteration, and were reported accordingly. The results showed that the GSO algorithm was more responsive, but the response generated by the HBBO algorithm was not as good as that of the former. However, the proposed hybrid algorithm (GSO-HBBO) demonstrated much better performance in terms of both objective functions, with a lower error rate and in less time compared to the other two algorithms. These findings demonstrate the high efficiency of the hybrid algorithm.

Additionally, Figure 7(A,B) presents the PRE (percentage relative error) of each iteration, allowing the performance of the hybrid algorithm to be easily compared with the other two algorithms. Furthermore, Figure 7 (C,D) compares the CPU time of all three algorithms in different iterations, which shows the complete superiority of the hybrid algorithm in solving the proposed objective functions. Moreover, the study of Figure 8 (A–E) clearly shows that the convergence rate of the proposed algorithm in both objective functions has significantly improved, with a super-linear convergence rate and convergence to the optimal solution in fewer iterations.

Notably, the convergence of the algorithm in the manufacturer's objective function is particularly significant, as it converges to the optimal answer before iteration 50. These results indicate that the proposed hybrid algorithm is highly effective in solving the two proposed objective functions compared to the other algorithms evaluated in this study. Overall, these findings demonstrate the

Table 5. Computational results of OFV and measures for manufacturer (Scenario 2).

	Manufacturer objective function value								
	GSO			HBBO			GSO-HBBO		
#Run	OFV	PRE	CPU Time	OFV	PRE	CPU Time	OFV	PRE	CPU Time
1	204.09	9.21%	202.68	200.90	10.62%	183.13	212.77	5.34%	175.09
2	206.23	8.26%	203.91	202.18	10.06%	179.85	213.52	5.01%	171.62
3	203.95	9.27%	198.83	199.97	11.04%	186.39	216.18	3.83%	166.53
4	203.87	9.31%	208.14	198.23	11.82%	186.56	215.20	4.26%	174.92
5	201.47	10.37%	206.05	202.14	10.08%	188.00	213.08	5.21%	171.50
6	205.95	8.38%	201.78	201.33	10.44%	189.97	213.52	5.01%	169.79
7	201.54	10.34%	197.81	198.32	11.77%	180.95	214.39	4.63%	169.93
8	205.95	8.38%	208.85	200.29	10.90%	188.90	214.16	4.73%	166.08
9	205.46	8.60%	203.98	198.77	11.58%	185.35	214.50	4.58%	175.06
10	205.40	8.62%	208.69	200.00	11.03%	182.39	216.01	3.90%	170.99
11	205.57	8.55%	200.16	199.50	11.25%	178.26	213.32	5.10%	169.63
12	206.13	8.30%	199.41	198.88	11.52%	179.66	217.45	3.27%	174.47
13	203.61	9.42%	206.18	199.47	11.26%	181.18	212.40	5.51%	167.05
14	205.49	8.59%	204.93	201.76	10.24%	189.55	213.40	5.06%	165.59
15	204.91	8.84%	197.77	199.80	11.11%	186.09	217.80	3.11%	174.18
16	201.34	10.43%	203.30	201.63	10.30%	187.94	213.70	4.93%	170.50
17	201.54	10.34%	207.57	198.66	11.62%	181.25	215.22	4.26%	170.32
18	201.37	10.42%	200.08	201.47	10.37%	189.60	217.79	3.11%	170.97
19	205.37	8.64%	206.27	201.72	10.26%	185.71	212.43	5.50%	169.30
20	202.46	9.93%	198.94	199.99	11.03%	179.85	215.29	4.23%	169.95
21	205.46	8.60%	207.70	198.20	11.83%	189.70	216.88	3.52%	170.94
22	205.17	8.73%	203.58	198.23	11.81%	187.93	212.59	5.42%	166.85
23	202.57	9.89%	208.57	199.19	11.39%	183.66	216.32	3.77%	174.12
24	203.03	9.68%	200.23	198.73	11.59%	180.46	215.44	4.16%	168.09
25	202.49	9.92%	206.12	201.50	10.36%	183.15	215.52	4.12%	174.61
26	205.39	8.63%	208.79	202.33	9.99%	181.23	215.42	4.17%	170.80
27	205.32	8.66%	202.56	201.22	10.48%	189.37	215.23	4.25%	171.32
28	203.74	9.36%	198.97	198.52	11.68%	187.65	216.00	3.91%	165.58
29	202.84	9.76%	207.02	202.04	10.12%	183.96	217.32	3.32%	172.28
30	202.38	9.97%	198.52	199.89	11.08%	186.36	216.38	3.74%	171.91
Average	204.00	9.25%	203.58	200.16	10.95%	184.80	214.97	4.37%	170.67
Best value	206.23	8.26%	197.77	202.33	9.99%	178.26	217.80	3.11%	165.58

potential of the proposed hybrid algorithm in optimising the cost-sharing with a full refund scenario, which can have significant implications for improving supply chain management and decision-making processes.

5.2. Computational results for Scenario 2

Tables 5 and 6 present the performance of each algorithm for the two proposed OFVs related to the profit-sharing with a full refund scenario. The results reveal that, in terms of solution quality, the GSO-HBBO algorithm outperformed the other two algorithms. Additionally, the computation time of the GSO-HBBO algorithm was shorter than that of the other algorithms, indicating its superior efficiency. Furthermore, the exact values of the two proposed objective functions were calculated using the GAMS software, and the results showed that the GSO-HBBO algorithm was able to produce the optimal solutions for both objective functions, with $Z_{\text{Manufacturer}} = 224.79$ and $Z_{\text{retailer}} = 917.31$. These findings suggest that the GSO-HBBO algorithm is highly effective in optimising the profit-sharing with a full refund scenario, outperforming the other algorithms evaluated in this study. This could have significant implications for improving supply chain management and decision-making processes in a variety of industries. It is worth noting that the results presented in Tables 5 and 6 provide valuable insights into the performance of different algorithms for the profit-sharing with a full refund scenario. The GSO-HBBO algorithm, with its superior efficiency and solution quality, could be a promising solution for optimising this scenario in practice. Further research could explore the potential of this algorithm in other related scenarios and industries.

The results obtained by the GSO and HBBO algorithms in the manufacturer's objective function in this scenario showed similar performance in response production. However, the HBBO algorithm was able to solve the problem in less time. On the other hand, the proposed hybrid algorithm outperformed the other two algorithms in all iterations in terms of solution generated and CPU processing time. These findings demonstrate the effectiveness of the hybrid algorithm in optimising the manufacturer's objective function. Regarding the retailer's objective function, the hybrid algorithm demonstrated exceptional performance in generating

Table 6. Computational results of OFV and measures for retailer (Scenario 2).

	Retailer objective function value								
	GSO			HBBO			GSO-HBBO		
#Run	OFV	PRE	CPU Time	OFV	PRE	CPU Time	OFV	PRE	CPU Time
1	869.18	5.25%	213.55	856.54	6.62%	197.69	909.73	0.83%	188.09
2	856.74	6.60%	216.77	857.11	6.56%	204.85	910.13	0.78%	186.01
3	858.82	6.38%	218.66	848.82	7.47%	204.15	910.42	0.75%	197.77
4	865.72	5.62%	212.09	850.64	7.27%	210.79	908.59	0.95%	197.82
5	859.97	6.25%	219.59	859.62	6.29%	204.28	908.62	0.95%	197.29
6	869.33	5.23%	212.23	852.96	7.02%	196.39	910.85	0.71%	193.82
7	862.01	6.03%	211.31	853.84	6.92%	195.78	909.54	0.85%	188.91
8	870.48	5.11%	212.21	854.07	6.89%	202.23	910.14	0.78%	192.45
9	856.46	6.63%	219.91	847.69	7.59%	204.65	909.88	0.81%	195.44
10	869.00	5.27%	210.28	852.63	7.05%	207.10	910.55	0.74%	186.67
11	862.23	6.00%	216.16	860.05	6.24%	203.46	910.07	0.79%	196.68
12	868.89	5.28%	210.28	859.75	6.27%	204.18	909.49	0.85%	186.21
13	858.96	6.36%	211.61	842.36	8.17%	195.93	909.25	0.88%	189.21
14	858.50	6.41%	212.25	846.00	7.77%	197.84	909.84	0.82%	195.38
15	856.84	6.59%	216.90	843.44	8.05%	208.42	908.40	0.97%	188.81
16	868.61	5.31%	217.17	859.75	6.28%	206.26	910.10	0.79%	196.50
17	868.51	5.32%	214.35	858.15	6.45%	196.14	910.35	0.76%	189.91
18	866.66	5.52%	215.29	858.50	6.41%	205.20	908.52	0.96%	194.75
19	859.26	6.33%	214.36	858.92	6.37%	198.95	909.06	0.90%	188.25
20	861.45	6.09%	216.32	851.11	7.22%	212.68	910.96	0.69%	195.92
21	869.37	5.23%	216.43	858.44	6.42%	209.74	910.70	0.72%	195.25
22	866.91	5.49%	212.48	841.56	8.26%	207.26	910.70	0.72%	189.73
23	863.89	5.82%	219.86	851.78	7.14%	208.24	908.82	0.93%	194.27
24	862.00	6.03%	219.80	846.08	7.77%	200.73	910.97	0.69%	185.70
25	861.03	6.14%	219.49	843.11	8.09%	202.89	908.44	0.97%	188.46
26	862.39	5.99%	215.41	854.27	6.87%	207.50	909.88	0.81%	191.06
27	864.42	5.77%	210.92	847.67	7.59%	208.48	909.54	0.85%	188.55
28	868.93	5.28%	216.19	854.80	6.82%	212.17	908.81	0.93%	190.23
29	870.35	5.12%	218.49	846.20	7.75%	205.59	908.67	0.94%	189.60
30	869.59	5.20%	218.81	852.86	7.03%	208.50	908.93	0.91%	196.34
Average	864.22	5.79%	215.31	852.29	7.09%	204.27	909.66	0.83%	191.84
Best value	870.48	5.11%	210.28	860.05	6.24%	195.78	910.97	0.69%	185.70

responses per iteration, with an average PRE response of less than one percent. Such a low PRE response indicates that the algorithm was able to produce highly accurate solutions, which is crucial for improving supply chain management and decision-making processes. Moreover, Figure 10(A–F) shows the convergence rate of the algorithms for the two proposed OFVs in the best iteration, which highlights the superior performance of the proposed hybrid algorithm. Additionally, Figure 9(A–D) compares the PRE and CPU processing time of the algorithms for each of the objective functions. These figures illustrate the efficiency of the proposed hybrid algorithm compared to the other algorithms evaluated in this study. Overall, the results presented in this article demonstrate the potential of the proposed hybrid algorithm in optimising the profit and cost-sharing scenarios with a full refund, which could have significant implications for improving supply chain management and decision-making processes in various industries. Further research could explore the performance of the hybrid algorithm in other related scenarios and industries.

5.3. Computational results for Scenario 3

The performance of different algorithms for the two proposed OFVs related to the revenue-sharing with a full refund have been evaluated and presented in payoffs in Tables 7 and 8. The results indicate that the GSO-HBBO algorithm outperformed the other two algorithms in terms of solution quality. Additionally, the computation time of the GSO-HBBO algorithm was superior to that of the other algorithms, highlighting its efficiency in optimising the revenue- sharing with a full refund scenario. Furthermore, the exact values of the two proposed objective functions, $Z_{\text{Manufacturer}} = 158.94$ and $Z_{\text{retailer}} = 792.30$, respectively, were calculated using the GAMS software. The results indicate that the proposed hybrid algorithm is highly effective in optimising the revenue-sharing with a full refund scenario, outperforming the other algorithms evaluated in this study. Moreover, examining the results obtained in this scenario shows the complete superiority of the proposed algorithm over the other two algorithms in

Table 7. Computational results of OFV and measures for manufacturer (Scenario 3).

	Manufacturer objective function value								
	GSO			HBBO			GSO-HBBO		
#Run	OFV	PRE	CPU Time	OFV	PRE	CPU Time	OFV	PRE	CPU Time
1	148.57	6.52%	134.35	142.50	10.34%	118.54	154.11	3.04%	115.22
2	149.68	5.83%	132.58	143.62	9.64%	116.15	154.18	2.99%	114.25
3	149.33	6.04%	131.98	142.49	10.35%	118.47	154.97	2.49%	116.82
4	148.64	6.48%	130.04	143.20	9.90%	117.55	154.51	2.79%	116.64
5	148.37	6.65%	131.58	144.29	9.22%	119.13	153.31	3.54%	115.28
6	149.31	6.06%	130.44	142.47	10.36%	116.78	153.53	3.40%	113.50
7	148.06	6.85%	133.51	144.29	9.22%	117.13	153.56	3.38%	111.00
8	149.18	6.14%	132.00	144.27	9.23%	116.59	153.50	3.42%	116.98
9	149.27	6.08%	131.96	142.46	10.37%	115.98	155.01	2.47%	110.63
10	149.34	6.04%	132.36	144.92	8.82%	120.14	153.40	3.48%	111.44
11	148.49	6.57%	128.40	143.48	9.72%	116.95	153.16	3.63%	117.45
12	147.93	6.93%	129.29	143.93	9.44%	118.84	154.18	3.00%	113.25
13	148.84	6.35%	129.26	143.05	10.00%	117.70	154.18	3.00%	113.32
14	148.71	6.43%	132.25	143.07	9.98%	117.83	153.68	3.31%	115.30
15	149.03	6.23%	133.89	142.94	10.07%	118.92	154.94	2.51%	117.02
16	148.95	6.28%	133.45	143.27	9.85%	116.61	154.59	2.74%	110.86
17	148.55	6.53%	134.06	142.46	10.37%	118.20	154.57	2.75%	115.39
18	149.79	5.75%	132.56	143.76	9.55%	115.51	154.72	2.65%	110.83
19	148.11	6.81%	134.08	144.41	9.14%	119.20	153.61	3.35%	113.34
20	149.68	5.83%	134.65	142.43	10.39%	118.42	153.41	3.48%	115.06
21	150.00	5.62%	131.19	143.48	9.73%	118.45	154.68	2.68%	110.43
22	149.49	5.94%	130.07	142.89	10.10%	115.60	155.00	2.47%	115.82
23	148.47	6.59%	133.56	143.36	9.80%	117.70	154.97	2.50%	116.96
24	148.43	6.61%	131.78	143.56	9.67%	117.22	154.35	2.88%	114.03
25	150.13	5.54%	128.59	143.09	9.97%	119.89	154.56	2.75%	117.48
26	147.83	6.99%	130.70	144.69	8.96%	119.50	153.22	3.60%	117.89
27	149.38	6.01%	131.13	144.26	9.24%	117.08	153.06	3.70%	112.67
28	149.46	5.96%	134.41	143.56	9.67%	115.42	154.03	3.09%	116.83
29	148.51	6.56%	132.51	143.52	9.70%	119.48	153.38	3.49%	115.96
30	149.27	6.08%	134.35	144.93	8.81%	115.67	153.23	3.59%	112.85
Average	148.96	6.28%	132.03	143.49	9.72%	117.69	154.05	3.07%	114.48
Best value	150.13	5.54%	128.40	144.93	8.81%	115.42	155.01	2.47%	110.43

both the retailer and manufacturer objective functions. The convergence diagrams of the algorithms presented in Figure 12(A–F) demonstrate that the GSO-HBBO algorithm has a faster convergence rate in the retailer's objective function compared to the other scenarios, converging to the optimal solution before iteration 50. In addition, a noteworthy point in this scenario is the close CPU processing time of the hybrid algorithm to the HBBO algorithm in the manufacturer's objective function, as illustrated in Figure 11(E). These findings suggest that the proposed hybrid algorithm is a promising solution for optimising the revenue sharing with full refund scenario, offering superior performance in terms of solution quality and computation time. Overall, these results highlight the potential of the proposed hybrid algorithm in improving supply chain management and decision-making processes related to revenue-sharing with a full refund in various industries. Further research could explore the performance of the hybrid algorithm in other related scenarios and industries.

5.4. Computational results for Scenario 4

The performance of different algorithms for the two proposed OFVs related to the buy back with a full refund scenario have been evaluated and presented as payoffs in Tables 9 and 10. The results indicate that the GSO-HBBO algorithm outperformed the other two algorithms in terms of solution quality. Moreover, the computation time of the GSO-HBBO algorithm was superior to that of the other algorithms, demonstrating its efficiency in optimising the buy back with a full refund scenario. These findings suggest that the proposed hybrid algorithm is highly effective in solving the buy back with a full refund scenario, outperforming the other algorithms evaluated in this study. The GSO-HBBO algorithm could be a promising solution for optimising this scenario in practice, offering superior performance in terms of solution quality and computation time. Furthermore, future research could explore the potential of the GSO-HBBO algorithm in other related scenarios and industries. These

Table 8. Computational results of OFV and measures for retailer (Scenario 3).

	Retailer objective function value								
	GSO			HBBO			GSO-HBBO		
#Run	OFV	PRE	CPU Time	OFV	PRE	CPU Time	OFV	PRE	CPU Time
1	725.52	8.43%	209.25	705.17	11.00%	195.28	750.99	5.21%	190.15
2	723.55	8.68%	196.22	700.21	11.62%	195.00	748.17	5.57%	185.83
3	722.15	8.85%	208.53	712.00	10.13%	197.48	749.72	5.37%	190.11
4	726.48	8.31%	205.91	709.93	10.40%	191.73	749.89	5.35%	189.25
5	726.37	8.32%	206.14	704.75	11.05%	198.16	749.97	5.34%	188.13
6	726.54	8.30%	197.73	700.21	11.62%	193.56	748.07	5.58%	185.99
7	725.09	8.48%	205.44	710.20	10.36%	193.27	746.74	5.75%	186.46
8	723.54	8.68%	200.21	711.76	10.16%	197.40	746.53	5.78%	189.43
9	722.35	8.83%	206.92	708.32	10.60%	193.82	750.30	5.30%	187.34
10	724.32	8.58%	203.33	707.65	10.68%	192.79	745.44	5.91%	186.18
11	725.98	8.37%	201.00	710.28	10.35%	191.08	747.75	5.62%	189.58
12	725.98	8.37%	196.80	705.41	10.97%	194.21	745.60	5.89%	187.24
13	723.47	8.69%	209.35	705.56	10.95%	195.97	749.68	5.38%	187.72
14	725.35	8.45%	203.14	704.05	11.14%	196.41	748.97	5.47%	188.07
15	725.23	8.47%	198.58	701.21	11.50%	195.69	749.95	5.34%	189.32
16	723.25	8.71%	197.29	704.97	11.02%	192.18	747.90	5.60%	189.89
17	725.57	8.42%	197.32	705.83	10.91%	191.66	751.36	5.17%	186.04
18	724.29	8.58%	205.09	711.02	10.26%	193.05	750.41	5.29%	189.69
19	722.89	8.76%	198.35	705.01	11.02%	190.54	748.75	5.50%	185.42
20	724.37	8.57%	200.74	702.60	11.32%	192.94	749.23	5.44%	189.27
21	725.42	8.44%	210.16	703.01	11.27%	193.70	751.21	5.19%	189.14
22	722.91	8.76%	208.25	706.75	10.80%	191.20	750.43	5.28%	189.18
23	724.56	8.55%	200.98	707.12	10.75%	196.14	751.00	5.21%	187.59
24	723.38	8.70%	202.68	701.75	11.43%	192.38	751.30	5.17%	187.55
25	725.10	8.48%	195.48	705.53	10.95%	194.95	748.87	5.48%	186.23
26	722.43	8.82%	207.67	706.06	10.88%	197.15	748.56	5.52%	187.32
27	726.90	8.25%	195.52	706.72	10.80%	192.83	748.67	5.51%	186.79
28	726.25	8.34%	205.81	707.70	10.68%	193.81	749.18	5.44%	188.27
29	723.67	8.66%	203.42	700.27	11.62%	194.84	747.21	5.69%	186.42
30	726.07	8.36%	196.71	706.43	10.84%	191.09	746.67	5.76%	187.31
Average	724.63	8.54%	202.47	705.92	10.90%	194.01	748.95	5.47%	187.90
Best value	726.90	8.25%	195.48	712.00	10.13%	190.54	751.36	5.17%	185.42

Table 9. Computational results of OFV and measures for manufacturer (Scenario 4).

	Manufacturer objective function value								
	GSO			HBBO			GSO-HBBO		
#Run	OFV	PRE	CPU Time	OFV	PRE	CPU Time	OFV	PRE	CPU Time
1	201.89	10.85%	194.39	200.78	11.34%	182.16	210.42	7.08%	170.62
2	202.21	10.71%	191.99	208.54	7.91%	181.73	213.50	5.72%	171.10
3	199.52	11.90%	192.63	203.49	10.14%	181.96	212.07	6.35%	174.10
4	196.66	13.16%	190.73	202.03	10.79%	180.68	209.93	7.30%	171.28
5	198.61	12.30%	197.45	199.83	11.76%	180.78	213.70	5.64%	171.53
6	196.04	13.43%	198.60	199.20	12.04%	180.31	210.16	7.20%	174.56
7	200.17	11.61%	199.75	206.68	8.74%	180.83	213.22	5.85%	172.79
8	197.50	12.79%	193.21	205.36	9.32%	185.05	211.71	6.51%	172.01
9	202.10	10.76%	195.15	201.43	11.05%	184.22	208.89	7.76%	173.82
10	197.55	12.76%	195.53	203.61	10.09%	182.98	211.90	6.43%	173.82
11	196.42	13.26%	190.76	204.89	9.52%	182.29	211.49	6.61%	171.24
12	197.99	12.57%	191.31	199.38	11.96%	181.10	210.73	6.95%	171.77
13	201.96	10.82%	196.87	205.97	9.05%	184.13	212.43	6.20%	172.76
14	202.16	10.73%	191.46	207.08	8.56%	183.15	208.03	8.14%	173.28
15	202.14	10.74%	199.84	203.14	10.30%	181.95	211.08	6.79%	173.72
16	196.43	13.26%	195.41	199.02	12.12%	181.53	212.98	5.95%	172.88
17	196.49	13.24%	198.70	205.17	9.40%	182.03	210.92	6.86%	171.87
18	201.44	11.05%	194.42	202.81	10.44%	184.93	211.10	6.78%	173.16
19	201.71	10.93%	196.13	208.14	8.09%	182.89	207.83	8.23%	170.50
20	200.42	11.50%	191.47	200.50	11.46%	184.55	210.99	6.83%	174.01
21	197.96	12.58%	192.10	201.10	11.20%	184.98	213.74	5.62%	171.43
22	198.20	12.48%	197.58	198.75	12.23%	184.98	212.39	6.21%	172.26
23	200.26	11.57%	197.81	204.93	9.51%	182.00	208.99	7.71%	174.58
24	198.47	12.36%	191.16	202.33	10.66%	185.08	211.48	6.62%	171.95
25	195.96	13.47%	194.54	200.71	11.37%	184.35	208.33	8.01%	173.29
26	200.32	11.54%	196.67	198.64	12.28%	182.75	212.29	6.26%	174.32
27	198.08	12.53%	195.43	202.95	10.38%	180.80	210.49	7.05%	170.34
28	196.76	13.12%	194.17	200.02	11.68%	181.30	212.41	6.20%	171.30
29	200.39	11.51%	196.90	207.38	8.43%	184.97	209.16	7.64%	172.03
30	197.15	12.94%	195.29	208.32	8.01%	183.92	207.95	8.18%	171.21
Average	199.10	12.08%	194.92	203.07	10.33%	182.81	211.01	6.82%	172.45
Best value	202.21	10.71%	190.73	208.54	7.91%	180.31	213.74	5.62%	170.34

findings could have significant implications for improving supply chain management and decision-making processes, helping businesses to optimise their operations and maximise their profits.

The exact values for the two proposed objective functions in the scenario being considered were calculated using the GAMS software. The results showed that the proposed hybrid algorithm was highly effective in generating optimal solutions, with $Z_{\text{Manufacturer}} = 226.46$ and $Z_{\text{retailer}} = 910.82$. Moreover, the algorithm demonstrated excellent performance in generating optimal solutions for the retailer's objective function, with an average PRE of responses close to one percent. This indicates that the proposed hybrid algorithm was able to produce highly accurate solutions that could be used to improve supply chain management and decision-making processes. Furthermore, in all iterations, the hybrid algorithm was able to solve both objective functions in much less time than the other two algorithms, demonstrating the superiority of its performance. This means that the proposed hybrid algorithm is highly efficient, offering a promising solution for optimising the buy back with a full refund scenario (Figures 13 and 14).

Examination of convergence diagrams shows that the two algorithms GSO and HBBO have gone through many iterations (at least 250 iterations) to converge to the optimal solution in both objective functions, but the proposed GSO-HBBO algorithm in both proposed objective functions converge to the optimal answer in less than 100 iterations, which shows the excellent performance of this algorithm in dealing with different scenarios.

It is worth noting that the proposed hybrid algorithm was designed to efficiently address a range of complex problems, and the results obtained in this study demonstrate its effectiveness in solving the aforementioned problems. The algorithm was able to successfully identify and optimise the objective functions, leading to improved performance and outcomes. After a thorough examination of the proposed hybrid algorithm to compare different scenarios and analyse them based on the data presented in Table 2, the performance of the algorithm was evaluated. Three different problems were solved in each scenario, and the results were recorded in Table 11. This allowed for a comprehensive understanding of the changes in the objective functions, as outlined in Table 2. Additionally, the findings highlight the significance of considering various scenarios when analysing

Table 10. Computational results of OFV and measures for retailer (Scenario 4).

	Retailer objective function value								
	GSO			HBBO			GSO-HBBO		
#Run	OFV	PRE	CPU Time	OFV	PRE	CPU Time	OFV	PRE	CPU Time
1	846.41	7.07%	265.93	821.03	9.86%	257.38	899.50	1.24%	234.88
2	842.08	7.55%	277.88	829.40	8.94%	261.64	899.81	1.21%	239.12
3	851.19	6.55%	280.08	830.49	8.82%	264.98	901.12	1.06%	236.61
4	846.94	7.01%	269.08	829.20	8.96%	255.97	900.77	1.10%	234.37
5	846.62	7.05%	275.17	823.00	9.64%	257.06	899.97	1.19%	234.41
6	853.29	6.32%	277.54	820.51	9.92%	264.23	900.61	1.12%	239.03
7	846.87	7.02%	265.89	820.83	9.88%	258.09	900.19	1.17%	235.44
8	850.75	6.60%	267.68	823.91	9.54%	262.15	899.87	1.20%	233.20
9	852.40	6.41%	271.86	830.86	8.78%	263.71	900.90	1.09%	234.04
10	849.42	6.74%	275.43	827.45	9.15%	257.64	900.54	1.13%	240.28
11	852.55	6.40%	277.00	827.69	9.13%	255.57	900.92	1.09%	232.94
12	843.05	7.44%	274.25	825.53	9.36%	255.52	900.13	1.17%	232.14
13	841.82	7.58%	268.38	822.86	9.66%	254.43	899.93	1.20%	238.81
14	840.80	7.69%	270.01	823.66	9.57%	260.36	901.19	1.06%	232.60
15	845.58	7.16%	274.00	823.50	9.59%	263.85	899.53	1.24%	241.47
16	848.16	6.88%	278.40	829.40	8.94%	254.48	899.42	1.25%	240.86
17	848.26	6.87%	279.72	830.38	8.83%	262.24	899.76	1.21%	239.84
18	854.28	6.21%	276.53	830.74	8.79%	257.92	899.95	1.19%	234.55
19	843.90	7.35%	276.01	827.19	9.18%	260.31	900.64	1.12%	236.64
20	844.58	7.27%	271.45	823.87	9.55%	261.86	901.20	1.06%	242.00
21	844.15	7.32%	268.03	822.75	9.67%	257.59	899.91	1.20%	233.47
22	854.60	6.17%	267.32	830.55	8.81%	254.28	900.04	1.18%	238.37
23	846.38	7.08%	268.50	823.59	9.58%	260.36	900.08	1.18%	241.17
24	851.26	6.54%	277.15	820.36	9.93%	263.90	900.12	1.17%	239.41
25	850.99	6.57%	279.98	827.51	9.15%	258.11	900.81	1.10%	233.17
26	843.55	7.39%	270.05	825.37	9.38%	261.88	900.37	1.15%	237.44
27	845.67	7.15%	278.65	823.30	9.61%	264.44	901.21	1.06%	238.37
28	849.51	6.73%	267.10	828.87	9.00%	255.72	899.64	1.23%	238.22
29	844.11	7.32%	267.72	822.76	9.67%	256.85	900.84	1.10%	233.41
30	840.37	7.74%	273.37	827.01	9.20%	264.37	899.39	1.25%	234.38
Average	847.32	6.97%	273.0050	825.79	9.34%	259.5628	900.28	1.16%	236.69
Best value	854.60	6.17%	265.8938	830.86	8.78%	254.2763	901.21	1.06%	232.14

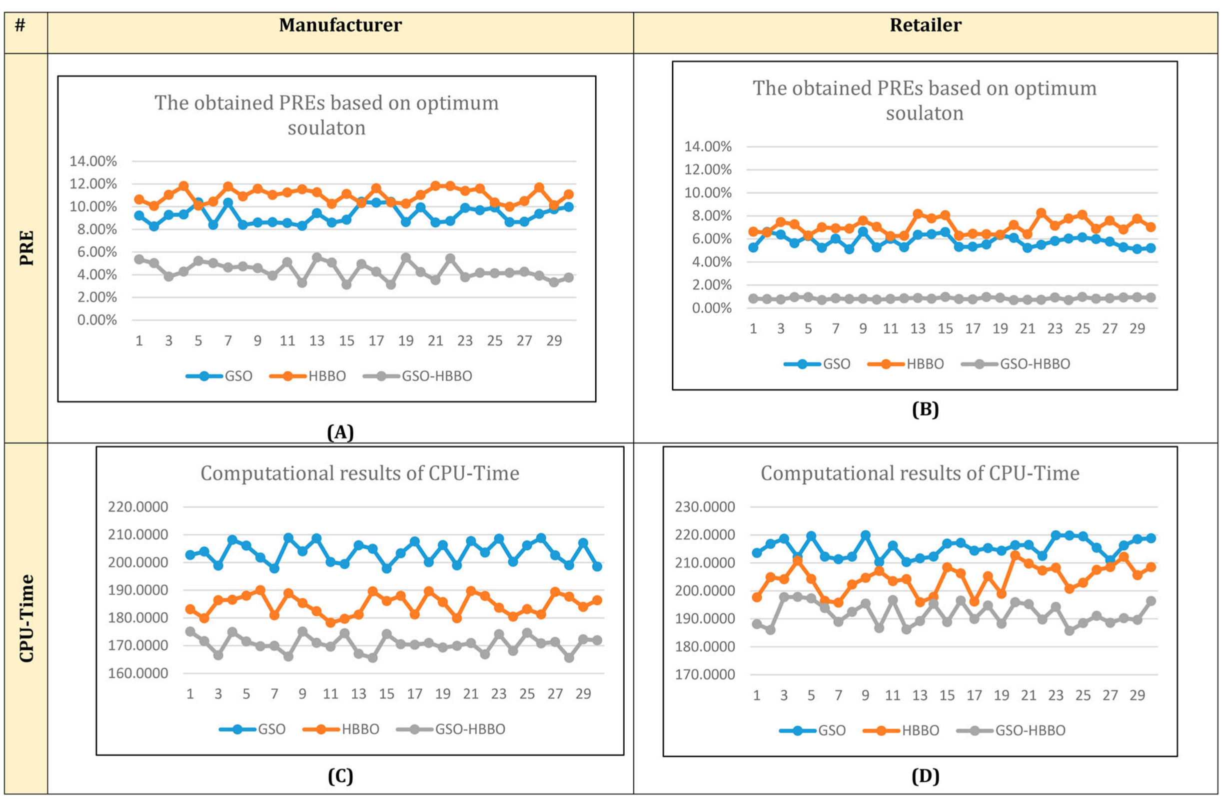

Figure 9. Comparison between proposed algorithms based on CPU-time and PREs (Scenario 2).

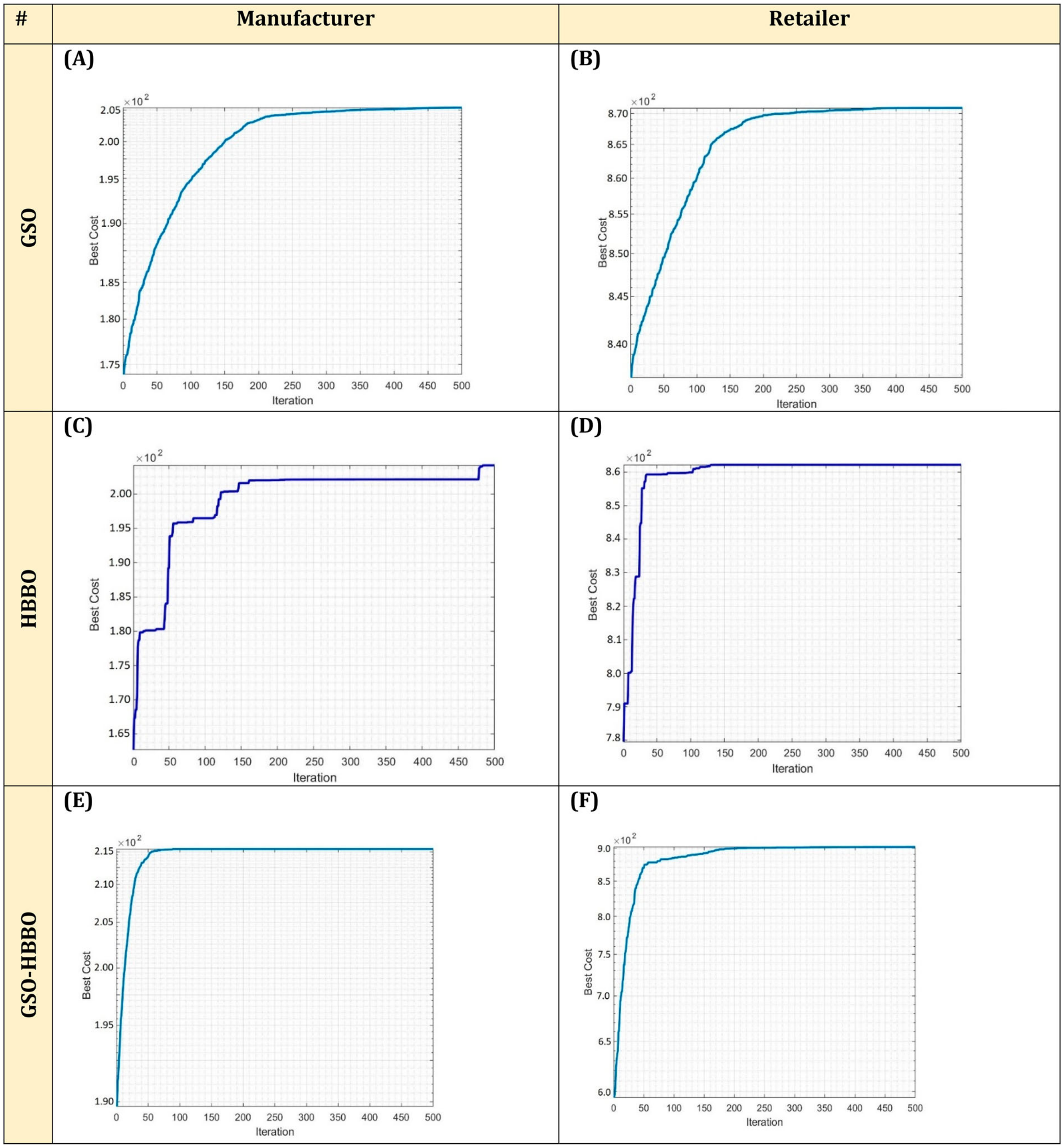

Figure 10. Convergence rate of GSO, HBBO, and hybrid algorithms for two proposed OFs (Scenario 2).

performance and outcomes. Through comparing the different scenarios, the algorithm was able to identify and address potential challenges and opportunities, leading to better overall results.

6. Managerial implications

Effective supply chain management is crucial for manufacturers and retailers seeking to optimise their profits

Table 11. The results of solving different problems in three scenarios.

		Objective function value			
		Scenario 1	Scenario 2	Scenario 3	Scenario 4
Problem 1	Manufacturer	129.15	214.78	157.89	212.46
	Retailer	692.3	826.34	745.14	842.37
Problem 2	Manufacturer	134.32	205.36	152.37	203.9
	Retailer	679.68	860.78	779.68	874.1
Problem 3	Manufacturer	156.70	192.47	147.4	194.38
	Retailer	645.14	917.31	792.3	907.82

Figure 11. Comparison between proposed algorithms based on CPU-time and PREs (Scenario 3).

in today's highly competitive business environment. The findings of this study provide valuable insights into the contractual agreements and pre-defined coefficients that can be used to achieve this objective. The study highlights the importance of implementing profit-sharing and buyback contracts as an effective means of increasing profits for both manufacturers and retailers. These contractual agreements align the goals of both parties and incentivise them to work together toward a common objective of maximising profits. Profit-sharing and buyback contracts can help to reduce the risk of misaligned incentives and conflicts between manufacturers and retailers, thus improving the overall performance of the supply chain. Furthermore, the study emphasises the impact of pre-defined coefficients such as μ, σ, ϕ, and y on the objective function values of manufacturers and retailers. These coefficients are important factors that influence the profitability of the supply chain, and supply chain managers need to take note of their impact and adjust them accordingly to achieve optimal results. By understanding how these coefficients affect their profits, manufacturers and retailers can make informed decisions and take actions to optimise their performance. Finally, the study highlights the importance of quality control measures in ensuring customer satisfaction and in reducing the extra costs associated with warranties. Manufacturers need to ensure that their products meet the expectations of their customers consistently. This can be achieved by implementing rigorous quality control measures and taking necessary steps to improve the quality of their products. By reducing the costs associated with warranties through better quality control measures, manufacturers can improve their profitability and enhance the overall performance of the supply chain. The results emphasise the importance of considering risk aversion when designing contracts for manufacturers and retailers. Managers should account for risk aversion when negotiating contract terms, particularly in profit-sharing and buyback contracts, where risk aversion plays a more significant role in determining profit outcomes.

In conclusion, the findings of this study provide valuable insights for supply chain managers seeking to optimise profits for both manufacturers and retailers. By implementing profit-sharing and buyback contracts, adjusting pre-defined coefficients, and maintaining high-quality standards, manufacturers and retailers

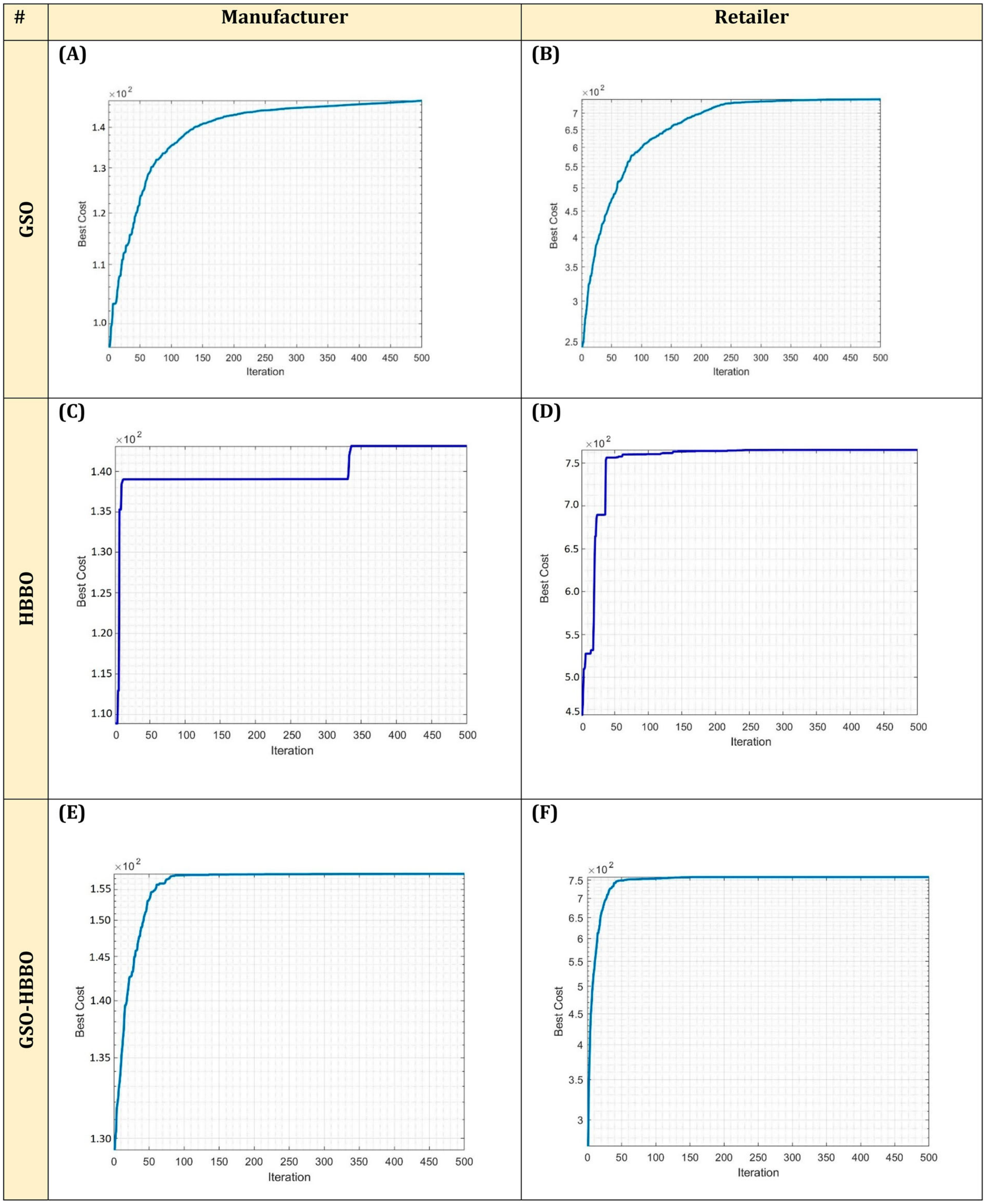

Figure 12. Convergence rate of GSO, HBBO, and hybrid algorithms for two proposed OFs (Scenario 3).

can improve their profitability and gain a competitive advantage in their respective markets. Effective supply chain management is critical for achieving long-term success in today's dynamic business environment, and this study provides valuable guidance for supply chain managers seeking to optimise their performance.

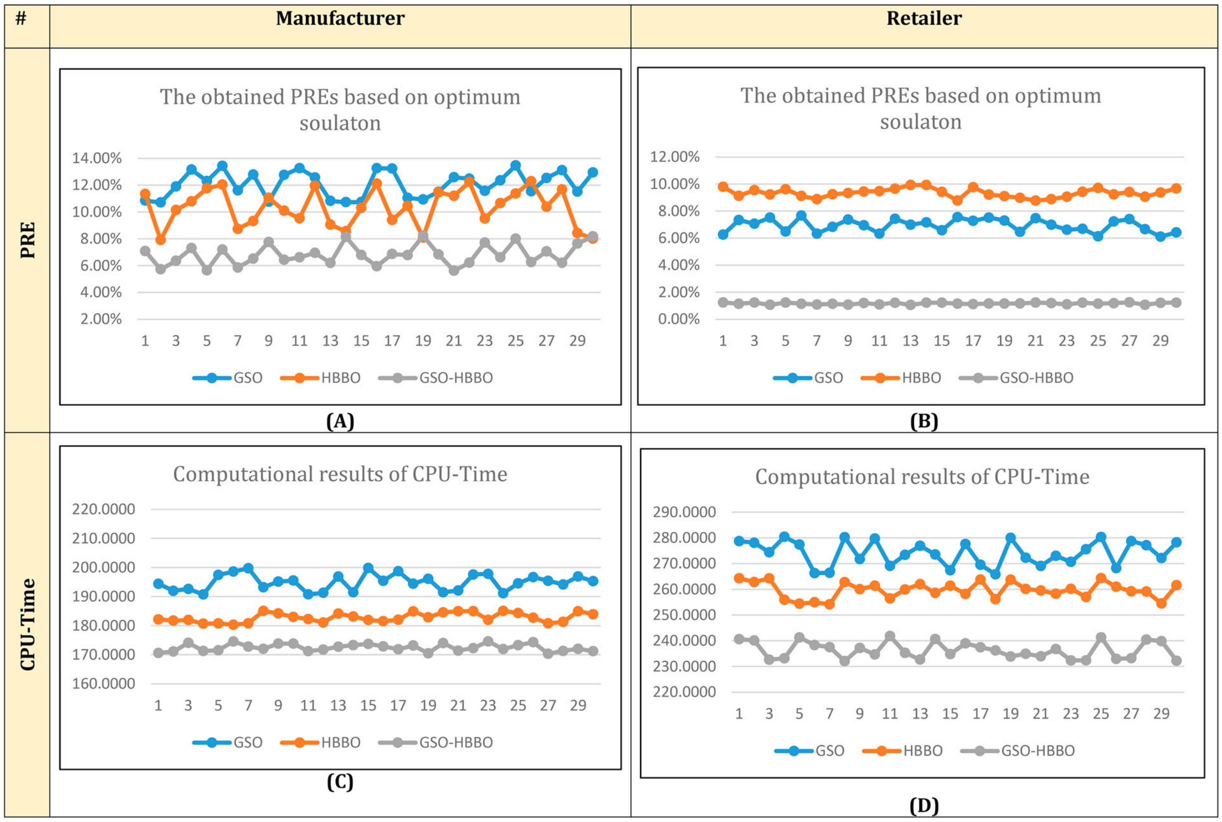

Figure 13. Comparison between proposed algorithms based on CPU-time and PREs (Scenario 4).

7. Conclusions and future research

In this study, we considered a supply chain consisting of some manufacturers and a retailer. Different brands of a single product were sold through a retailer to customers. Manufacturers compete to sell a single product with various prices and levels of quality, according to the brand. We investigated the effects of some well-known contracts – profit-sharing, cost-sharing, revenue-sharing, and buyback – on profit values of all manufacturers and the retailer. In addition, full refunds, warranties, and the proposed MV models for risk management were addressed in the proposed models. The most important contribution of this study is our investigation of these contracts through novel hybrid meta-heuristic algorithms using corresponding situations of various policies and an MV framework. The proposed models were solved using a GSO-HBBO algorithm, which is a novel metaheuristic algorithm. The results showed the acceptable performance of the mentioned algorithm in terms of generated solutions, PRE, and CPU processing time. According to the results of all four scenarios for four contracts, the profit-sharing and buyback contracts provided higher profit values for the manufacturers and retailer. Additionally, this work offers benefit by proposing several possibilities for future research opportunities. These opportunities include incorporating the risk, financing, and ordering in a special supply chain. Several contracts exist in the existing literature that are not investigated in this study. As an excellent direction for future research, it is strongly recommended to develop the model into a reverse supply chain by considering the waste management of each one of the brands. (See the conducted work by Hosseini-Motlagh et al., 2022, and Nematollahi et al., 2022.) Incorporating the flexible transfer price agreement as the coordination scheme by considering a time-based customer incentive policy can be another direction for future developments. (See the conducted works by Nami & Hosseini-Motlagh, 2022, and Hosseini-Motlagh et al., 2022.) Finally, converting the designed SC to a closed-loop SC that considers the sustainability issues would be a worthwhile avenue for future research. (See the conducted works by Hosseini-Motlagh et al., 2020, and Hosseini-Motlagh et al., 2021.)

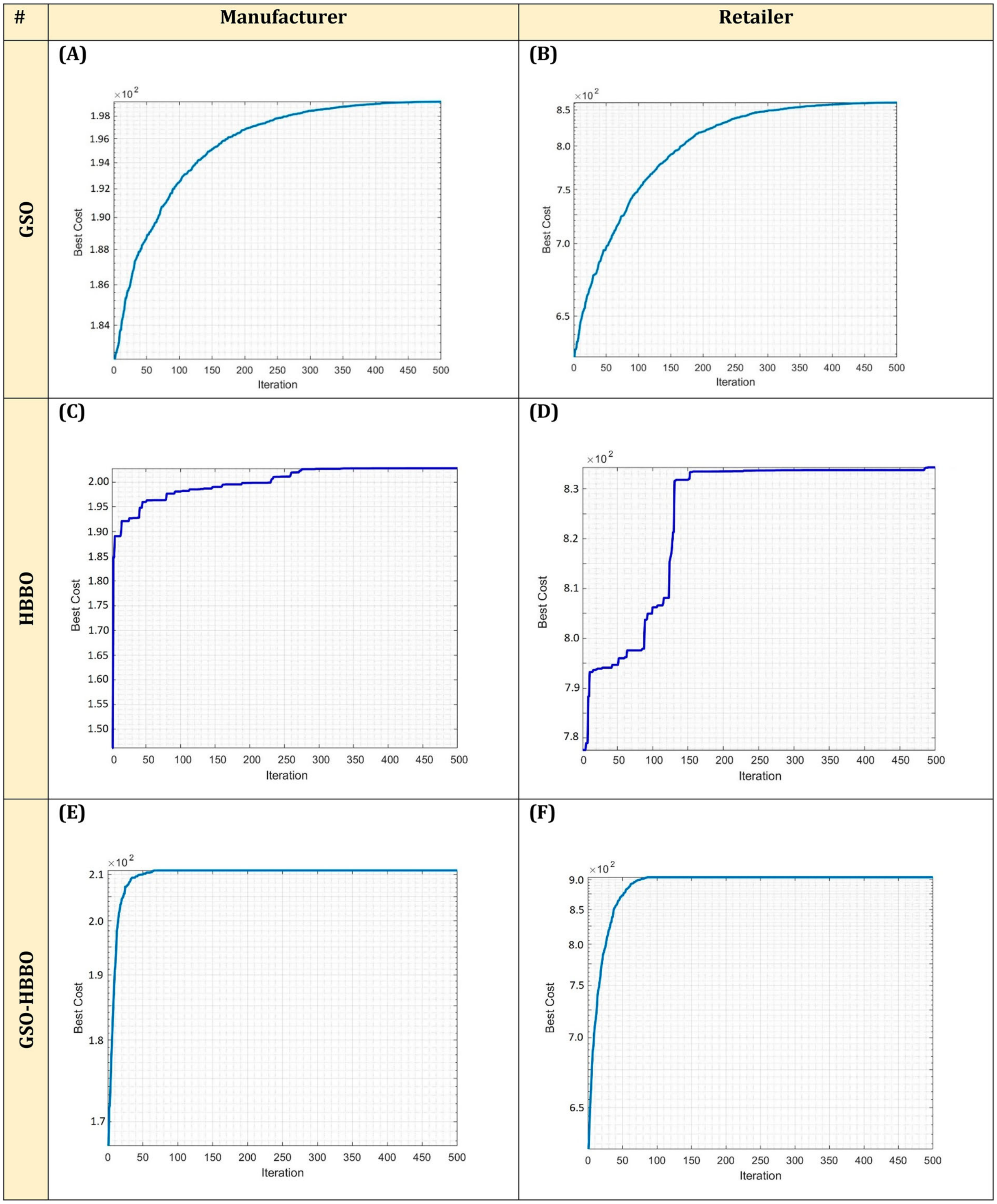

Figure 14. Convergence rate of GSO, HBBO, and hybrid algorithms for two proposed OFs (Scenario 4).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data used in this study can be released upon request.

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References

Abualigah, L. (2020). Multi-verse optimizer algorithm: A comprehensive survey of its results, variants, and applications. *Neural Computing and Applications*, *32*(16), 12381–12401. https://doi.org/10.1007/s00521-020-04839-1

Ahmadi, S. A. (2017). Human behavior-based optimization: A novel metaheuristic approach to solve complex optimization problems. *Neural Computing and Applications*, *28*(Suppl 1), 233–244. https://doi.org/10.1007/s00521-016-2334-4

Ai, X., Li, X., Zheng, C., & He, H. (2023). Channel coordination with extended warranty when retailers compete. *Journal of the Operational Research Society*, *74*(3), 826–839. https://doi.org/10.1080/01605682.2022.2122734

Akhtar, S., & Jahromi, M. (2017). Risk, return and mean-variance efficiency of Islamic and non-Islamic stocks: Evidence from a unique Malaysian data set. *Accounting & Finance*, *57*(1), 3–46. https://doi.org/10.1111/acfi.12139

Alqahtani, A. Y., Gupta, S. M., & Yamada, T. (2017). Combined two-dimensional non-renewable warranty policy analysis for remanufactured products. *Procedia CIRP*, *61*, 189–194. https://doi.org/10.1016/j.procir.2016.11.249

Amjadian, A., & Gharaei, A. (2022). An integrated reliable five-level closed-loop supply chain with multi-stage products under quality control and green policies: Generalised outer approximation with exact penalty. *International Journal of Systems Science: Operations & Logistics*, *9*(3), 429–449. https://doi.org/10.1080/23302674.2021.1919336

Amrouche, N., Pei, Z., & Yan, R. (2022). Mail-in-rebate and coordination strategies for brand competition. *International Journal of Production Economics*, *247*, Article 108453. https://doi.org/10.1016/j.ijpe.2022.108453

Bai, Q., Chen, M., & Xu, L. (2017). Revenue and promotional cost-sharing contract versus two-part tariff contract in coordinating sustainable supply chain systems with deteriorating items. *International Journal of Production Economics*, *187*, 85–101. https://doi.org/10.1016/j.ijpe.2017.02.012

Bai, Q., Xu, J., & Chauhan, S. S. (2020). Effects of sustainability investment and risk aversion on a two-stage supply chain coordination under a carbon tax policy. *Computers & Industrial Engineering*, *142*, Article 106324. https://doi.org/10.1016/j.cie.2020.106324

Barnard, C. J., & Sibly, R. M. (1981). Producers and scroungers: A general model and its application to captive flocks of house sparrows. *Animal Behaviour*, *29*(2), 543–550. https://doi.org/10.1016/S0003-3472(81)80117-0

Bell, W. J. (1990). Searching behavior patterns in insects. *Annual Review of Entomology*, *35*(1), 447–467. https://doi.org/10.1146/annurev.en.35.010190.002311

Bolaji, A. L. A., Al-Betar, M. A., Awadallah, M. A., Khader, A. T., & Abualigah, L. M. (2016). A comprehensive review: Krill Herd algorithm (KH) and its applications. *Applied Soft Computing*, *49*, 437–446. https://doi.org/10.1016/j.asoc.2016.08.041

Brockmann, H. J., & Barnard, C. J. (1979). Kleptoparasitism in birds. *Animal Behaviour*, *27*, 487–514. https://doi.org/10.1016/0003-3472(79)90185-4

Caraco, T. (1979). Time budgeting and group size: A test of theory. *Ecology*, *60*(3), 618–627. https://doi.org/10.2307/1936082

Cárdenas-Barrón, L. E., Mandal, B., Sicilia, J., San-José, L. A., & Abdul-Jalbar, B. (2021). Optimizing price, order quantity, and backordering level using a nonlinear holding cost and a power demand pattern. *Computers & Operations Research*, *133*, Article 105339. https://doi.org/10.1016/j.cor.2021.105339

Chakraborty, T., Chauhan, S. S., & Ouhimmou, M. (2016). *Product quality improvement induced by cost-sharing mechanism and competition*. CIRRELT, Centre interuniversitaire de recherche sur les réseaux d'entreprise, la logistique et le transport = Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation.

Chen, C. H., Lo, C. P., & Kan, C. C. (2016). Simultaneous settings of order quantity, wholesale price, production run length, process mean, and warranty period. *Journal of Management Analytics*, *3*(2), 174–188. https://doi.org/10.1080/23270012.2015.1063466

Chen, J., & Grewal, R. (2013). Competing in a supply chain via full-refund and no-refund customer returns policies. *International Journal of Production Economics*, *146*(1), 246–258. https://doi.org/10.1016/j.ijpe.2013.07.005

Chen, M., & Chen, Z. L. (2020). Optimal pricing to minimize maximum regret with limited demand information. *Computers & Operations Research*, *124*, Article 105070. https://doi.org/10.1016/j.cor.2020.105070

Chiu, C. H., & Choi, T. M. (2016). Supply chain risk analysis with mean-variance models: A technical review. *Annals of Operations Research*, *240*(2), 489–507. https://doi.org/10.1007/s10479-013-1386-4

Choi, T. M. (2013). Optimal return service charging policy for a fashion mass customization program. *Service Science*, *5*(1), 56–68. https://doi.org/10.1287/serv.1120.0036

Choi, T. M., Wen, X., Sun, X., & Chung, S. H. (2019). The mean-variance approach for global supply chain risk analysis with air logistics in the blockchain technology era. *Transportation Research Part E: Logistics and Transportation Review*, *127*, 178–191. https://doi.org/10.1016/j.tre.2019.05.007

Cui, X., Li, D., & Li, X. (2017). Mean-variance policy for discrete-time cone-constrained markets: Time consistency in efficiency and the minimum-variance signed super martingale measure. *Mathematical Finance*, *27*(2), 471–504. https://doi.org/10.1111/mafi.12093

Dew-Becker, I., Giglio, S., Le, A., & Rodriguez, M. (2017). The price of variance risk. *Journal of Financial Economics*, *123*(2), 225–250.

Diabat, A., Kannan, D., Kaliyan, M., & Svetinovic, D. (2013). An optimization model for product returns using genetic algorithms and artificial immune system. *Resources, Conservation and Recycling*, *74*, 156–169. https://doi.org/10.1016/j.resconrec.2012.12.010

Fallahi, A., Bani, E. A., & Niaki, S. T. A. (2022). A constrained multi-item EOQ inventory model for reusable items: Reinforcement learning-based differential evolution and particle swarm optimization. *Expert Systems with Applications*, *207*, Article 118018. https://doi.org/10.1016/j.eswa.2022.118018

Fattahi, M., Govindan, K., & Keyvanshokooh, E. (2018). A multi-stage stochastic program for supply chain network redesign problem with price-dependent uncertain demands. *Computers & Operations Research*, *100*, 314–332. https://doi.org/10.1016/j.cor.2017.12.016

Gan, X., Sethi, S. P., & Yan, H. (2005). Channel coordination with a risk-neutral supplier and a downside-risk-averse retailer. *Production and Operations Management*, *14*(1), 80–89. https://doi.org/10.1111/j.1937-5956.2005.tb00011.x

Ghandi, A., & Lin Lawell, C. Y. C. (2017). On the rate of return and risk factors to international oil companies in Iran's buy-back service contracts. *Energy Policy*, *103*, 16–29. https://doi.org/10.1016/j.enpol.2017.01.003

Gharaei, A., Amjadian, A., Shavandi, A., & Amjadian, A. (2023). An augmented lagrangian approach with general constraints to solve nonlinear models of the large-scale reliable inventory systems. *Journal of Combinatorial Optimization*, *45*(2), 78. https://doi.org/10.1007/s10878-023-01002-z

Giraldeau, L. A., & Beauchamp, G. (1999). Food exploitation: Searching for the optimal joining policy. *Trends in Ecology & Evolution*, *14*(3), 102–106. https://doi.org/10.1016/S0169-5347(98)01542-0

Giri, B. C., & Maiti, T. (2014). Multi-manufacturer single-retailer supply chain model underprice-and warranty period -dependent demand. *International Journal of Mathematics in Operational Research*, 6(5), 631–654. https://doi.org/10.1504/IJMOR.2014.064847

Giri, B. C., Roy, B., & Maiti, T. (2017). Multi-manufacturer pricing and quality management strategies in the presence of brand differentiation and return policy. *Computers & Industrial Engineering*, *105*, 146–157. https://doi.org/10.1016/j.cie.2017.01.003

Golberg, D. E. (1989). *Genetic algorithms in search, optimization, and machine learning*. Addison Wesley.

He, S., Wu, Q. H., & Saunders, J. R. (2009). Group search optimizer: an optimization algorithm inspired by animal searching behavior. *IEEE Transactions on Evolutionary Computation*, *13*(5), 973–990.

He, Y., Zhao, X., Krishnan, H., & Jin, S. (2022). Cooperation among suppliers of complementary products in repeated interactions. *International Journal of Production Economics*, *252*, Article 108559. https://doi.org/10.1016/j.ijpe.2022.108559

Hosseini-Motlagh, S. M., Ebrahimi, S., & Jokar, A. (2021). Sustainable supply chain coordination under competition and green effort scheme. *Journal of the Operational Research Society*, *72*(2), 304–319. https://doi.org/10.1080/01605682.2019.1671152

Hosseini-Motlagh, S. M., Ebrahimi, S., & Zirakpourdehkordi, R. (2020). Coordination of dual-function acquisition price and corporate social responsibility in a sustainable closed-loop supply chain. *Journal of Cleaner Production*, *251*, Article 119629. https://doi.org/10.1016/j.jclepro.2019.119629

Hosseini-Motlagh, S. M., Jazinaninejad, M., & Nami, N. (2022). Coordinating a socially concerned reverse supply chain for pharmaceutical waste management considering government role. *Environment, Development and Sustainability*, *24*, 1852–1877. https://doi.org/10.1007/s10668-021-01511-z

Hotelling, H. (1990). Edgeworth's taxation paradox and the nature of demand and supply functions. In *The collected economics articles of harold hotelling* (pp. 93–122). Springer New York.

Hu, B., Xu, D., & Meng, C. (2017). Inconsistency of a retailer's optimal policies and channel performance under revenue sharing contracts. *International Journal of Production Economics*, *183*, 53–65. https://doi.org/10.1016/j.ijpe.2016.10.011

Ji, Y., Yang, H., Qu, S., & Nabe, M. (2021). Optimal strategy for a closed-loop supply chain considering recycling and warranty channels. *Arabian Journal for Science and Engineering*, *46*(2), 1585–1601. https://doi.org/10.1007/s13369-020-04751-9

Kaya, O., & Urek, B. (2016). A mixed integer nonlinear programming model and heuristic solutions for location, inventory and pricing decisions in a closed loop supply chain. *Computers & Operations Research*, *65*, 93–103. https://doi.org/10.1016/j.cor.2015.07.005

Keshavarz-Ghorbani, F., & Pasandideh, S. H. R. (2021). Optimizing a two-level closed-loop supply chain under the vendor managed inventory contract and learning: Fibonacci, GA, IWO, MFO algorithms. *Neural Computing and Applications*, *33*(15), 9425–9450. https://doi.org/10.1007/s00521-021-05703-6

Khan, M. A. A., Cárdenas-Barrón, L. E., Smith, N. R., Bourguet-Díaz, R. E., Loera-Hernández, I. D. J., Peimbert-García, R. E., Treviño-Garza, G., & Céspedes-Mota, A. (2023). Effects of all-units discount on pricing and replenishment policies of an inventory model under power demand pattern. *International Journal of Systems Science: Operations & Logistics*, *10*(1), Article 2161712. https://doi.org/10.1080/23302674.2022.2161712

Koussis, N., & Silaghi, F. (2023). Revenue-sharing and volume flexibility in the supply chain. *International Journal of Production Economics*, *261*, Article 108845. https://doi.org/10.1016/j.ijpe.2023.108845

Lau, H. S. (1980). The newsboy problem under alternative optimization objectives. *Journal of the Operational Research Society*, *31*(6), 525–535. https://doi.org/10.1057/jors.1980.96

Lau, H. S., & Lau, A. H. L. (1999). Manufacturer's pricing strategy and return policy for a single-period commodity. *European Journal of Operational Research*, *116*(2), 291–304. https://doi.org/10.1016/S0377-2217(98)00123-4

Li, J. C., Zhou, Y. W., & Huang, W. (2017). Production and procurement strategies for seasonal product supply chain under yield uncertainty with commitment-option contracts. *International Journal of Production Economics*, *183*, 208–222. https://doi.org/10.1016/j.ijpe.2016.10.019

Liu, Z., Chen, J., Diallo, C., & Venkatadri, U. (2023). Optimal extended warranty pricing and retailing strategies in a closed-loop supply chain. *International Journal of Production Research*, *61*(10), 3435–3458. https://doi.org/10.1080/00207543.2022.2083997

Mansouri, Y., & Sahraeian, R. (2021). Facility disruptions in a closed-loop supply chain featuring warranty policy and quality-based segmentation of returns. *Scientia Iranica*. https://doi.org/10.24200/SCI.2021.57475.5257

Markowitz, H. M. (1959). *Portfolio selection* (Cowles Foundation Monograph 16). John Wiley and Sons.

McNamara, J. M., Houston, A. I., & Collins, E. J. (2001). Optimality models in behavioral biology. *Siam Review*, *43*(3), 413–466. https://doi.org/10.1137/S0036144500385263

Michalk, W., Filipova-Neumann, L., Blau, B., & Weinhardt, C. (2011). Reducing risk or increasing profit? Provider decisions in agreement networks. *Service Science*, *3*(3), 206–222. https://doi.org/10.1287/serv.3.3.206

Mishra, R., Singh, R. K., & Rana, N. P. (2022). Developing environmental collaboration among supply chain partners for sustainable consumption & production: Insights from an auto sector supply chain. *Journal of Cleaner Production*, *338*, Article 130619. https://doi.org/10.1016/j.jclepro.2022.130619

Mustard, D. (1964). Numerical integration over the *n*-dimensional spherical shell. *Mathematics of Computation*, *18*(88), 578–589.

Mutlu, H. T., & Yildiz, M. S. (2021). Determination of the optimal warranty policy and period from the manufacturer's/seller's perspective. *Communications in Statistics-Simulation and Computation*, 1–23. https://doi.org/10.1080/03610918.2021.1941110

Nami, N., & Hosseini-Motlagh, S. M. (2022). Central robust decision-making structure for reverse supply chain: A real pharmaceutical case. *Computers & Industrial Engineering*, *173*, Article 108726. https://doi.org/10.1016/j.cie.2022.108726

Nematollahi, M., Hosseini-Motlagh, S. M., Cárdenas-Barrón, L. E., & Tiwari, S. (2022). Coordinating visit interval and safety stock decisions in a two-level supply chain with shelf-life considerations. *Computers & Operations Research*, *139*, Article 105651. https://doi.org/10.1016/j.cor.2021.105651

Pando, V., San-Jose, L. A., Sicilia, J., & Alcaide-Lopez-de-Pablo, D. (2021). Maximization of the return on inventory management expense in a system with price-and stock-dependent demand rate. *Computers & Operations Research*, *127*, Article 105134. https://doi.org/10.1016/j.cor.2020.105134

Rahimi, M., Ghezavati, V., & Asadi, F. (2019). A stochastic risk-averse sustainable supply chain network design problem with quantity discount considering multiple sources of uncertainty. *Computers & Industrial Engineering*, *130*, 430–449. https://doi.org/10.1016/j.cie.2019.02.037

Rao, S. S. (2019). *Engineering optimization: Theory and practice*. John Wiley & Sons.

Sadeghian, R., Bagher Komasi, M., & Mohammadi, S. (2016). Production and warranty optimal period in deteriorating production systems by considering inspection of both manufacturing equipment and products simultaneously. *European Online Journal of Natural and Social Sciences: Proceedings*, *4*(1(s)), 1836.

Saha, M., & Giri, R. N. (2023). Consumers' purchasing decisions of a dual-channel supply chain system under return and warranty policies. *International Journal of Systems Science: Operations & Logistics*, *10*(1), Article 2173990. https://doi.org/10.1080/23302674.2023.2173990

Sarada, Y., & Sangeetha, S. (2022). Coordinating a reverse supply chain with price and warranty dependent random demand under collection uncertainties. *Operational Research*, *22*(4), 4119–4158. https://doi.org/10.1007/s12351-021-00657-y

Shen, B., Choi, T. M., Wang, Y., & Lo, C. K. (2013). The coordination of fashion supply chains with a risk-averse supplier under the markdown money policy. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *43*(2), 266–276. https://doi.org/10.1109/TSMCA.2012.2204739

Taleizadeh, A. A., Akhavan Niaki, S. T., & Hoseini, V. (2009a). Optimizing the multi-product, multi-constraint, bi-objective newsboy problem with discount by a hybrid method of goal programming and genetic algorithm. *Engineering Optimization*, *41*(5), 437–457. https://doi.org/10.1080/03052150802582175

Taleizadeh, A. A., Aryanezhad, M. B., & Niaki, S. T. A. (2008). Optimizing multi-products multi-constraints inventory control systems with stochastic replenishments. *Journal of Applied Sciences*, *6*, 1.

Taleizadeh, A. A., Khaligh, P. P., & Moon, I. (2019). Hybrid NSGA-II for an imperfect production system considering product quality and returns under two warranty policies. *Applied Soft Computing*, *75*, 333–348. https://doi.org/10.1016/j.asoc.2018.11.013

Taleizadeh, A. A., Moghadasi, H., Niaki, S. T. A., & Eftekhari, A. K. (2009b). An EOQ-joint replenishment policy to supply expensive imported raw materials with payment in advance. *Journal of Applied Science*, *8*(23), 4263–4273. https://doi.org/10.3923/jas.2008.4263.4273

Taleizadeh, A. A., Niaki, S. T. A., & Aryanezhad, M. B. (2010). Optimising multi-product multi-chance-constraint inventory control system with stochastic period lengths and total discount under fuzzy purchasing price and holding costs. *International Journal of Systems Science*, *41*(10), 1187–1200. https://doi.org/10.1080/00207720903171761

Taleizadeh, A. A., Niaki, S. T. A., & Nikousokhan, R. (2011). Constraint multiproduct joint-replenishment inventory control problem using uncertain programming. *Applied Soft Computing*, *11*(8), 5143–5154. https://doi.org/10.1016/j.asoc.2011.05.045

Taleizadeh, A. A., & Noori-daryan, M. (2016a). Pricing, inventory and production policies in a supply chain of pharmacological products with rework process: A game theoretic approach. *Operational Research*, *16*(1), 89–115. https://doi.org/10.1007/s12351-015-0188-7

Taleizadeh, A. A., & Noori-Daryan, M. (2016b). Pricing, manufacturing and inventory policies for raw material in a three-level supply chain. *International Journal of Systems Science*, *47*(4), 919–931. https://doi.org/10.1080/00207721.2014.909544

Tarei, P. K., Kumar, G., & Ramkumar, M. (2022). A mean-variance robust model to minimize operational risk and supply chain cost under aleatory uncertainty: A real-life case application in petroleum supply chain. *Computers & Industrial Engineering*, *166*, Article 107949. https://doi.org/10.1016/j.cie.2022.107949

Tarei, P. K., Thakkar, J. J., & Nag, B. (2018). A hybrid approach for quantifying supply chain risk and prioritizing the risk drivers: A case of Indian petroleum supply chain. *Journal of Manufacturing Technology Management*, *29*(3), 533–569. https://doi.org/10.1108/JMTM-10-2017-0218

Wan, N., Li, L., Wu, X., & Fan, J. (2022). Risk minimization inventory model with a profit target and option contracts under spot price uncertainty. *Journal of Industrial and Management Optimization*, *18*(4), 2827–2845. https://doi.org/10.3934/jimo.2021093

Wu, C., Zhao, Q., & Xi, M. (2017). A retailer-supplier supply chain model with trade credit default risk in a supplier-Stackelberg game. *Computers & Industrial Engineering*, *112*, 568–575. https://doi.org/10.1016/j.cie.2017.03.004

Wu, D., Chen, J., Li, P., & Zhang, R. (2020). Contract coordination of dual channel reverse supply chain considering service level. *Journal of Cleaner Production*, *260*, Article 121071. https://doi.org/10.1016/j.jclepro.2020.121071

Xiao, T., Choi, T. M., Yang, D., & Cheng, T. C. E. (2012). Service commitment strategy and pricing decisions in retail supply chains with risk-averse players. *Service Science*, *4*(3), 236–252. https://doi.org/10.1287/serv.1120.0021

Xu, G., Dan, B., Zhang, X., & Liu, C. (2014). Coordinating a dual-channel supply chain with risk-averse under a two-way revenue sharing contract. *International Journal of Production Economics*, *147*, 171–179. https://doi.org/10.1016/j.ijpe.2013.09.012

Xu, Y., Gurnani, H., & Desiraju, R. (2010). Strategic supply chain structure design for a proprietary component manufacturer. *Production and Operations Management*, *19*(4), 371–389. https://doi.org/10.1111/j.1937-5956.2009.01116.x

Xue, W., Choi, T. M., & Ma, L. (2016). Diversification strategy with random yield suppliers for a mean–variance risk-sensitive manufacturer. *Transportation Research Part E: Logistics and Transportation Review*, *90*, 90–107. https://doi.org/10.1016/j.tre.2016.01.013

Yan, R., & Pei, Z. (2009). Retail services and firm profit in a dual-channel market. *Journal of Retailing and Consumer Services*, *16*(4), 306–314. https://doi.org/10.1016/j.jretconser.2009.02.006

Yang, H., & Chen, W. (2018). Retailer-driven carbon emission abatement with consumer environmental awareness and carbon tax: Revenue-sharing versus cost-sharing. *Omega*, *78*, 179–191. https://doi.org/10.1016/j.omega.2017.06.012

Yoo, S. H., Kim, D., & Park, M. S. (2015). Pricing and return policy under various supply contracts in a closed-loop supply chain. *International Journal of Production Research*, *53*(1), 106–126. https://doi.org/10.1080/00207543.2014.932927

Yu, B., Wang, J., Lu, X., & Yang, H. (2020). Collaboration in a low-carbon supply chain with reference emission and cost learning effects: Cost sharing versus revenue sharing strategies. *Journal of Cleaner Production*, *250*, Article 119460. https://doi.org/10.1016/j.jclepro.2019.119460

Zhan, M., Gao, H., Liu, H., Peng, Y., Lu, D., & Zhu, H. (2020). Identifying market structure to monitor product competition using a consumer-behavior-based intelligence model. *Asia Pacific Journal of Marketing and Logistics*, *33*(1), 99–123. https://doi.org/10.1108/APJML-08-2019-0497

Zhang, S., Tong, X., & Jin, X. (2023). Contract design and comparison under the opportunity cost of working capital: Buyback vs. revenue sharing. *European Journal of Operational Research*, *309*(2), 845–856. https://doi.org/10.1016/j.ejor.2023.01.051

Zhang, Y., Donohue, K., & Cui, T. H. (2016). Contract preferences and performance for the loss-averse supplier: Buyback vs. revenue sharing. *Management Science*, *62*(6), 1734–1754. https://doi.org/10.1287/mnsc.2015.2182

Zhuo, W., Shao, L., & Yang, H. (2018). Mean–variance analysis of option contracts in a two-echelon supply chain. *European Journal of Operational Research*, *271*(2), 535–547. https://doi.org/10.1016/j.ejor.2018.05.033