Toward a sustainable economic production quantity model employing triple bottom line strategy: Uncertain multi-objective optimization with lost sales and full back-order

Elnaz Ebrahimi [1],
[1] Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran,
(+98)911-100-2406, Elnazebrahimi211@yahoo.com

Babak Shirazi[1] *,
[1] Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran,
(+98)-912-109-9654, shirazi_b@icloud.com

Iraj Mahdavi [1],
[1] Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran,
(+98)911-113-1380, Arashiraj@rediffmail.com

Alireza Arshadi Khamseh[2]
[2] Industrial Engineering Department, Faculty of Engineering, Kharazmi University, Tehran, Iran,
(+98)910-212-5323, Ar_arshadi@khu.ac.ir

Abstract

The triple bottom line (TBL) strategy has provided the manufacturers with optimized production systems to simultaneously achieve their economic, environmental, and social goals. This paper presents a multi-objective mixed-integer programming model for the sustainable economic production quantity (S-EPQ) based on the TBL strategy. The model is to optimize the total profits, environmental emissions of manufacturing activities, and the turnover cost of the workers, which leads to keeping a sustainable number of workers as the social factor based on the working hours. According to numerous uncertain factors in the production process, demand uncertainty and the possibility of shortage have been considered, including lost sales and full back-order. Due to the NP-hardness of the problem, Particle Swarm Optimization (PSO) algorithm is employed to find the optimal solutions and make the operational decisions for the production system. To prove the applicability of the proposed sustainable production system, a case study was conducted in the dairy industry of Iran. Moreover, an extensive analysis was done to evaluate the performance of the proposed multi-objective optimization model and heuristic solutions, and finally, some managerial insights were carried out for manufacturers of the dairy industry respecting the challenge of TBL.

Keywords: Sustainable EPQ (S-EPQ); uncertainty; full back-order; lost sale; triple bottom line.

1. Introduction

Sustainable manufacturing has absorbed a great deal of interest in recent years, optimizing production systems based on economic, environmental, and social goals. A sustainable manufacturing trend is generally motivated by the triple bottom line (TBL) approach [1],[2]. The TBL approach employs the concept of sustainable development goals to simultaneously contribute to the economic, environmental, and social factors. The convergent objectives of TBL need to reinforce, and a trade-off is necessary among divergent ones. For instance, producing smaller batches of various product types decreases holding costs and emissions. However, this conflicts with production emission and setup time reduction, leading to higher person-hour requirements [3]. Meanwhile, a higher inventory level is recommended to face the volatile market, but it contradicts environmental policy and increases expiration risk. Hence, this study aims to find a solution to attain an interaction between sustainability goals for a dairy manufacturing system.

This study follows an economic production quantity (EPQ) concept to model a sustainable manufacturing system. This inventory model is shown its applicability in the industrial dairy companies to find an optimal production quantity, physical inventory, imperfect and expired goods, demand forecasting, emission cost and inventory cost [4], [5]. The EPQ is a classical inventory algorithm that focuses on economic performance while improving the impact of globalization and growing industrialization worldwide [6]. This study aims to shift the EPQ model conceptually to an S-EPQ to consider the environmental emissions of manufacturing, storage, and social justice for workers simultaneously. In this regard, the EPQ model is merged with the TBL strategy in a dairy manufacturing case study.

The dairy industry generates massive emissions, discharges wastewater, and energy consumption [7],[8]. In this regard, environmental sustainability is a big challenge for dairy manufacturing. The first environmental emission is the first environmental emission of water consumption at cleaning the process line in each product type changeover for the production system. The wastewater is another emission resource collected from different salons and conveyed to the wastewater treatment centres. This process is directly affected by the variety of product types and the inventory levels for holding. The current EPQ model measures the emission of production, wastewater discharging, disposing of the imperfect items, holding products, and depleting expired products to achieve environmental sustainability.

The last criterion of the TBL approach is social sustainability. Due to the lack of literature and the complex nature of the social dimension, it remained underexplored [9], [10]. The proposed EPQ model endeavors to achieve social justice as one of the TBL goals to enhance the workers' performance. The high competitiveness of the companies to meet the demand of customers in the volatile market caused the high variation in the required person-hour for production. This variation in working hours affects the hiring and firing rate of the worker. A high turnover rate discredits the company's reputation, directs the worker disloyal, and consequently harms performance. Based on this definition, the proposed EPQ model focuses on balancing the person-hour requirement, which significantly influences the company's social vision to achieve social sustainability. The proposed EPQ system not only links with the criteria of the TBL but also manages the uncertainty for dairy manufacturing. The products with deterministic shelf life become outdated and deplete at the end of a lifetime [11]. In addition, demand is one of the most efficient factors to decide on dairy manufacturing decisions. The value of most of the parameters in an inventory model is usually non-crisped, impacting the entire system's behavior [12]. Manufacturers ought to be capable of producing products with a lower cost and higher quality in the shortest feasible time to supply the products on time to consumers [13]. As studied in most of the works, the demand has been considered a crisp number, which cannot present the fluctuation of market demand correctly. The proposed EPQ is also a multi-product and multi-period planning horizon by considering the shortage in each period. This study reflects the demand uncertainty and shortage conditions concerning perishability in dairy manufacturing.

The literature on EPQ is very rich in using different exact and heuristic algorithms. The level of decisions is operational, and the production managers may need to find a solution in a reasonable time. This study employs particle swarm optimization [14] as a traditional swarm-based method. In conclusion, the core contributions of the paper are addressed as follows:

- Developing a novel multi-objective mixed-integer programming model to find an interaction between economic, environmental, and social goals.
- Shifting the traditional EPQ model to an S-EPQ that is multi-product and multi-period.
- Considering the uncertainty of manufacturing activities with demand and shortage conditions, including lost sales and full back-order.
- Applying the dairy manufacturing case study to the proposed model.

The rest of this article is summarized: Section 2 reviews the relevant studies in production systems with different inventory models. Section 3 addresses the statement of the S-EPQ problem and establishes the proposed multi-objective optimization model. Section 4 innovates a heuristic solution like the combination of two metaheuristics. In Section 5, the model's validation, comparison, and sensitivity analysis are carried out. Finally, the discussion of results, findings, and the conclusion of this paper is presented in Section 6.

2. Literature review

Numerous researchers have urged the study of Sustainable Production and Consumption issues to decrease environmental damages and enhance the overall condition since the rates of pollution and environmental calamities are caused by industrial production [15], [16]. Recent years have seen a great deal of interest in merging the concept of TBL with manufacturing systems modelled by advanced inventory theories. For example, Battini, Persona and Sgarbossa, [17] developed a sustainable economic order quantity (EOQ) model linking the material lot sizes from the purchase order to the end of the life cycle inside the buyer plant based on the life cycle assessment (LCA) approach. They provided a comparison study between a sustainable EOQ model and the traditional inventory system based on purchasing decisions. Next, Hovelaque and Bironneau, [18] proposed an inventory policy for the EOQ model to maximize the retailer's profit and minimize carbon emissions. Their model contributed to pricing decisions and the price-depended demand under two approaches of exogenous and endogenous prices. Kumar and Goswami, [19] investigated a single-period EPQ model for imperfect quality items under uncertain demand. They developed an EPQ model restricting the budget and allowable shortages as fuzzy numbers.

Next year, Majumder *et al.*, [20] formulated an EPQ model with a partial trade credit policy from suppliers to the retailers and the retailers to their customers. Their primary assumption was that the demands depended on a time. The generalized Hukuhara derivative approach was applied to minimize the inventory cost of the model. In another research, Ghiami and Beullens, [21] presented an EPQ inventory system with deteriorating products and a partial back-ordering approach.

Another essential factor that affects the inventory systems is perishability. The food supply has become a severe challenge due to the notable increase in the global population Sazvar, Rahmani and Govindan, [22]. The design of the inventory system for perishable products is highly significant since meeting the uncertain demand increases the risk of expired product quantity and unsatisfied demand [23]. As far as we know, the study of [24] was the first optimization model for the perishable inventory with a lifetime. They studied the order quantity of perishable products and evaluated the system performance in a very shortsighted bound. Also, different classifications and considerations in perishable inventory models were examined during the time. Recently, perishability has been very active in inventory management studies. For instance, Chang *et al.*, [25] focused on the pricing strategy of the perishable goods that the prices set according to freshness, inventory and cost.

Further Chen, Li and Jin, [26] proposed EOQ/EPQ model considering stochastic demand and deteriorating characteristics of perishable foods. Lot-sizing was firstly contributed to sustainable manufacturing by Battini et al [27], that developed an ergonomic lot-sizing by integrating economic aspects to maintain a low level of fatigue and ergonomic risk. They estimated the economic impact of different workload levels using a simulation-optimization-based method.

Taleizadeh, Soleymanfar and Govindan, [28] proposed an EPQ model considering the economic and environmental aspects simultaneously under uncertain demand. The shortage is analyzed under three different approaches, including lost sales, back-ordering, and partial back-ordering. The emission of inventory holding, obsolesces, and production are considered. Zadjafar and Gholamian, [29] revised an EOQ model by integrating the income of selling the waste, organic pollution of several gases, and the effect of emissions on human health. Furthermore, Debnath, Majumder and Bera, [11] formulated the fuzzy S-EPQ to maximize the profit simultaneously minimize the carbon emission cost. The demand factor depended on the product price and stock quantity under a fuzzy environment.

Recent studies provided some real-life constraints to the EPQ and EOQ models. For example, the production system may go through an imperfect production situation due to the failure or deterioration of machines. Heeding this, Kazemi *et al.*, [4] and Tayyab and Sarkar, [30] considered non-conforming products in their study. Kazemi *et al.*, [4] developed an EOQ model for the imperfect items and emission costs due to warehousing and waste disposal activities. The results illustrated that the buyer policy converted by adding emission costs to the imperfect supply process. Hence, smaller batches tend to decrease the total profit. In another similar contribution, Tayyab and Sarkar, [30] provided an EPQ model with uncertain demand and process information in a multi-stage production process. The defective products are generated in the manufacturing process at an uncertain rate and then reworked into perfect quality products to reduce wastage.

More recently, Nobil, Kazemi and Taleizadeh, [31] provided a case study of a dairy company to analyze and plan for the demand meeting and supply limitations, while almost the peak of demand is on the less supply of milk. This case urges an exact trade-off between lost sales and wasted products. Another study Lin, [32] studied the EPQ inventory model dealing with an imperfect production process under the backlogged scenario and uncertain demand. A stochastic programming model is designed for a green closed-loop supply chain by Kalantari and Pasandideh [33]. They examined the various factors that influence the total cost to improve the overall performance of the supply chain. A stochastic programming model is designed for a green closed-loop supply chain by Kalantari and Pasandideh [33]. The upper bound's demand and gas emission are considered uncertain factors.

Having a conclusion about the mentioned studies, we have classified the papers based on the economic factors, the environmental factors, including carbon emissions of holding inventory and purchasing, manufacturing, wastes, disposal, and imperfect products, as well as the environmental factor for wastewater filtering, collection, and recycling. Besides, social factors and uncertainty are other criteria to evaluate the papers. As reviewed in Table 1, the following findings can be observed:

- Except for one paper [27] that has contributed to the social factors, other papers have considered the total cost in their optimization models.
- Two studies contributed to all the environmental factors Taleizadeh, Soleymanfar and Govindan, [28], Debnath, Majumder and Bera, [11]. However, none of them considered the social factors and wastewater emissions.
- Only two papers applied the TBL strategy in their optimization models Zadjafar and Gholamian, [29]. However, they have not considered all the environmental factors, such as environmental emissions of holding.
- Uncertainty is contributed to most of the recent papers.
- Simultaneous consideration of all the economic, environmental, and social factors under uncertainty has only been presented by the current paper.

3. Proposed problem

Figure 1 exposes a schematic view of the proposed problem that seeks to capture economic, social, and environmental trade-offs through the proposed inventory system as an extension to the EPQ. The inventory system consists of a manufacturer that produces multi-product in multi periods and deals with imperfect products manufactured during the routine production process. The additional products keep in the warehouse in the presence of uncertain customer demand. If inventories are not handled appropriately, they might become unreliable, inefficient, and costly [34]. The products released from the warehouse to the market are based on the First-In-First-Out (FIFO) method. The advantage of applying the FIFO method is equalizing the physical flow of goods and minimizing expired products during storage periods. All types of products are manufactured under a single technology. The production costs and storage capacities regard as invariable within the time horizon. The demand factor has been consistently one of the most influential factors in the decisions relating to inventory and production activities [20]. Uncertain demand indicates a probability of variation between available inventory and actual demand in each period. If the production quantity is more than the demand, the extra quantities will store, and if it faces a shortage, two different policies can be applied. (i) Lost sales (ii) Full back-orders. Under the first scenario, the unmet demand is lost and cannot respond in the coming periods, while following the second scenario meeting the demand in the subsequent periods is possible.

3.1. Sustainability factors

Rapid urbanization and population increase have contributed to increased pressures on global energy, water, and food resource systems [35]. Environmental issues and regulations are growing increasingly and attracted much attention to sustainable production [36]. The presented model integrates the economic, environmental, and social pillars based on the TBL strategy. It focuses on minimizing all related costs and emissions in addition to improving performance.

3.1.1. Sustainability in the manufacturing

An assessment of the environmental emissions in the scope of manufacturing, warehousing, and disposal of expired and defective products, is provided here. The companies are urged to promote their manufacturing procedures by applying efficient and effective planning to face the competitive markets in a highly dynamic economy [37]. Determining the optimal inventory control policy for different products is one of the main issues of industrial and scientific studies, especially when the product is perishable [38]. As studied by Lee, Lu & Song [39], sustainable manufacturing can be measured as the manufacturing performance metrics for the production system concerning the economic, environmental, and social aspects. The food sector comprises multifaceted water and energy systems [40]. In the current study, we focus on the process plan at the manufacturing level. It is necessary to consider balanced production loads when production planning decisions [41]. Each production cycle needs to run the cleaning in place (CIP) operation in the food industry. The CIP is set based on changing the product type or the cycle time. It means that each change in the product type needs to run the CIP and each run of CIP requires the chemical materials, and they are time-consuming and have tremendous cost. Water, like energy, is a significant input into any economy [8]. The CIP and cleaning operations are responsible for 70% of the water requirements [42]. Therefore, this study provides a sustainable manufacturing system with CIP operations and related balance with the total emissions and cost. Regarding each machine run, there are almost fixed defective items due to imperfect processes and the machines warm-up [43], so production in larger lot sizes can lessen this quantity. It is supposed that manufacturing in each cycle (between the two CIPs) contains a fixed percentage of defective items for each product type. The companies are attempting to control the process plan to lead to a minimum number of CIP runs and, consequently, a low level of defective products, less consumed water, and shorter needed person-hour. More variety of products and demand uncertainty makes planning more complicated. In addition to the aforementioned environmental factors, this study contributes to the working hours as a social factor. If the working hours are stable and suitable for the workers, it increases their satisfaction and company reputation. From another point of view, the turnover of the workers charges the cost to the factory. It includes the cost of hiring and firing, learning the new employment, losing experienced workers, and missing workers' loyalty to the company. Hence, we aimed to keep the minimum turnover of workers during the periods and charge less cost to the company.

3.1.2. Sustainability in the warehousing

Warehousing is another challenge to achieving sustainability for the proposed EPQ system. The limitation of the repository would affect the inventory model [44]. The carbon emissions related to warehousing are a significant factor because of the considerable energy requirement for heating, cooling, material handling equipment, etc. 45]. The warehouse emissions are calculated based on the energy consumption, including electricity and fuel utilization per hour for each product. Warehousing is an essential part of inventory management when facing uncertainty. Storage can be helpful to handle the volatile market while can increase the emission and risk of expired products. Some other evolutionary algorithm recently proposed for sustainability modelling [46] . The expired products refer to the items that passed their accredited shelf life and did not sell out [1],[47]. The study scope of the sustainability for perishable food supply chains is still not thoroughly investigated

[48]. This factor makes the supply network complex, and in the case of multi-item models, it increases exponentially compared with the single-item inventory models [23]. In the current study, the fixed lifetime considers for perishable products. The decision flow chart is depicted in Figure 2.

4. Formulation

Here, the proposed S-EPQ model is introduced. Mathematical models have become an increasingly powerful means of decision-making in engineering, science, economics, and policy-making [49]. The proposed model strives to identify the optimum quantity of production, storage, and working hours to minimize the environmental emissions and the costs of manufacturing, storing, and expiring products under two different scenarios. The model also analyzes the working hours periodically to keep it sustainable. Therefore, the advantage of the TBL approach is taken to meet the standards of the economic, environmental, and social factors for an inventory model. Before introducing the developed model, the following notations were provided:

Indices:

p	Index of products, $\mathrm{p} = \{1, \dots, \mathrm{P}\}$
i	Index of time periods, $i = \{1, \dots, I\}$
w	Index of warehouse, $w = \{1, \dots, \mathrm{W}\}$

Parameters:

D_{pi} :Demand quantity of product p in period i ($unit$).

S_p : Sales price of product p ($\$/unit$t).

C_p^{pr}: Unit production cost of product p ($\$/unit$).

C_p^{Se}: Setup cost for producing product p ($\$/setup$).

C_p^{In}: Inventory holding cost of product p ($\$/unit$).

b_p : Required space for each unit of product p ($m^3/unit$).

γ_p : Fraction of imperfect production of product p.

EC_p^w: The emission of inventory holding for product p in warehouse w ($\$/unit$).

EC_p^{ex}: The emission of expired and imperfect of product p ($\$/unit$).

EC_{CIP} : The emission of cleaning in place $\$/Run$).

C_w : Total capacity of warehouse w (m^3).

CH: Cost of hiring the workers ($\$/man$).

CF: Cost of firing the workers $\$/man$).

TF_p : Standard produced tonnage of product p per full time employment.

C_{CIP}: Cost of performing the CIP

SL_p : The shelf life of product p ($days$).

M: A large positive number (the summation of capacities can be estimated)

Decision variables:

Q_{pi}: Gross production quantity of product p in period i.

SA_{pi}: Sales quantity of product p in period i.

I_{pi}: Inventory quantity of product p in period i.

Q_{pi}^{im}: Imperfect quantity of product p in period i.

Q_{pi}^{ex}: Expired quantity of product p in period i.

HI_i : Number of hired workers in period i.

FI_i : Number of fired workers in period i.

X_{pi} :1, if the product p is produced in period i, 0 otherwise.

Y_{wp}: 1, if warehouse w is appropriate for stocking product p, 0 otherwise.

Using the above notations, the proposed model aims to maximize the total profit of the EPQ system as the first objective. However, the second and the third goals are to minimize the environmental emissions for manufacturing and the cost of workers turnover. These objectives are formulated as follows:

$$Max\ Z_1 = \sum_{p=1}^{P}\sum_{i=1}^{I} \left[\left(SA_{pi}.S_p\right) - \left(Q_{pi}.C_p^{pr} + C_{CIP}.X_{pi}\right) - \left(C_p^{Se}.X_{pi}\right) - \left(C_p^{In}.I_{pi}\right)\right] \quad (1)$$

$$MinZ_2 = EC_{CIP}.X_{pi} + EC_p^{ex}.Q_{pi}^{im} + EC_p^{ex}.Q_{pi}^{ex} + \sum_{w=1}^{W} EC_p^{w}.\ I_{pi}.Y_{wp}) \quad (2)$$

$$MinZ_3 = \sum_{i=1}^{I}(CH.HI_i + CF.FI_i) \quad (3)$$

The first objective function of the model maximizes the total profit of the S-EPQ model. The first term of Eq. (1) is related to sales profit minus the cost, including the cost of production, CIP process, setup, and inventory holding.

As given in Eq. (2), the second objective function represents the environmental emission of the CIP process, imperfect and expired product disposal, and storage emission.

Eq. (3) is contributed to social sustainability. The third objective function tries to minimize the turnover cost of the workers, which leads to keeping a sustainable number of workers in each period as the social factor based on the working hours.

Following constraints (Eqs. (4) and (5)) provide that the total demand for products must be met per period.

$$SA_{pi} \le D_{pi} \qquad \forall p, i \qquad (4)$$

$$SA_{pi} \ge 0 \qquad \forall p, i \qquad (5)$$

Eqs. (6) to (8) determine the production quantity per period.

$$Q_{pi} - Q_{pi}^{im} \ge D_{pi} - I_{pi-1} \qquad \forall p, i > 1 \qquad (6)$$

$$Q_{pi} \le X_{pi}.M \qquad \forall p, i \qquad (7)$$

$$Q_{pi} \ge 0 \qquad \forall p, i \qquad (8)$$

Eqs. (9) to (11) cover the assumptions of the shelf-life products. Based on this assumption, the product cannot be delivered to the market after the termination of the shelf life, and the expired products are collected at the disposal center.

$$Q_{pi}^{ex} = 0 \qquad \forall p, i \le SL_p \qquad (9)$$

$$Q^{ex}_{pi} \geq I_{pi-(SL_p+1)} - \left[\sum_{i=i-SL_p}^{i} SA_{pi} + \sum_{i=i-SL_p}^{i-1} Q^{ex}_{pi}\right] \qquad \forall p, i > SL_p \tag{10}$$

$$Q^{ex}_{pi} \geq 0 \qquad \forall i, p \tag{11}$$

Eq. (12) guarantees that imperfect quantity during production is determined based on a fraction of production.

$$Q^{im}_{pi} = \gamma_p . Q_{pi} \qquad \forall p, i \tag{12}$$

There is a capacity limitation for storage in each warehouse, as given in Eq. (13).

$$\sum_{p=1}^{P} b_p . Y_{wp}\left(Q_{pi} - Q^{im}_{pi} + I_{pi-1} - SA_{pi} - Q^{ex}_{pi}\right) \leq C_w \qquad \forall i, w \tag{13}$$

Eqs. (14) to (16) state the equilibrium of product flow and the initial inventory of products,respectively.

$$I_{pi+1} = Q_{pi+1} - Q^{im}_{pi+1} + I_{pi} - SA_{pi+1} - Q^{ex}_{pi} \qquad \forall p, i \neq 1 \tag{14}$$

$$I_{p1} = 0 \qquad \forall p \tag{15}$$

$$I_{pi} \geq 0 \qquad \forall p, i \tag{16}$$

As given in Eqs. (17) to (20), the requirement of hiring or firing the workers depends on theproduction quantity that presents in the following equations.

$$HI_i - FI_i = \left(Q_{pi} - Q_{pi-1}\right)/TF_p \qquad \forall i, p \tag{17}$$

$$HI_i . FI_i = 0 \qquad \forall i \tag{18}$$

$$HI_i \geq 0 \qquad \forall\, i \tag{19}$$

$$FI_i \geq 0 \qquad \forall\, i \tag{20}$$

Finally, the binary decision variables are indicated in Eq. (21).

$$X_{pi}, Y_{wp} \in \{0,1\} \qquad \forall p, i \tag{21}$$

4.1. S-EPQ model considering lost sales

Here, an extension of the primary model introduced earlier is provided. In this case, the unmet demand in each period is lost sales and cannot be back-ordered. The penalty cost for lost customers is charged in each period. The optimal production quantity is direct by the trade-off among inventory holdings cost, holding emission, expired quantity, and lost sales expenses. Following parameters were added to the main notations:

C^p_i: The cost of lost sales of product p in period i

LS_{pi}: The lost sale quantity of product p in period i

After updating the basic model with lost sales, the objectives are rewritten as follows:

$$Max\, Z_1 = \sum_{p=1}^{P} \sum_{i=1}^{I} (\left[\left(SA_{pi}.S_p\right) - \left(\, Q_{pi}.C^{pr}_p + C_{CIP}.X_{pi}\right) - \left(C^{Se}_p.X_{pi}\right) - \left(C^{In}_p.I_{pi}\right) - C^{L}_p.LS_{pi}\right] \tag{22}$$

$$MinZ_2 = \; EC_{CIP}.X_{pi} + EC^{ex}_p.Q^{im}_{pi} + EC^{ex}_p.Q^{ex}_{pi} + \sum_{w=1}^{W} EC^{w}_p.\; I_{pi}.Y_{wp}) \tag{23}$$

$$MinZ_3 = \sum_{i=1}^{I} (CH.HI_i + CF.FI_i) \tag{24}$$

The constraints of the model are the same as the basic model as follows:

$$SA_{pi} \leq D_{pi} - LS_{pi} \qquad \forall\, p,i \qquad (25)$$

$$SA_{pi} \geq 0 \qquad \forall p,i \qquad (26)$$

$$Q_{pi} \leq X_{pi}.M \qquad \forall p,i \qquad (27)$$

$$Q_{pi} \geq 0 \qquad \forall p,i \qquad (28)$$

$$C_p^L = \left(S_p - C_p^{pr}\right) + \left(C_g\right) \qquad \forall p \qquad (29)$$

$$D_{pi} - \left(Q_{pi} - Q_{pi}^{im} + I_{pi-1} - Q_{pi}^{ex}\right) \leq LS_{pi} \qquad \forall p,i \qquad (30)$$

$$LS_{pi} \geq 0 \qquad \forall p,i \qquad (31)$$

$$Q_{pi}^{ex} = 0 \qquad \forall p, i \leq SL_p \qquad (32)$$

$$Q_{pi}^{ex} \geq I_{pi-SL_p} - \left[\textstyle\sum_{i=i-(SL_p-1)}^{i}\left(SA_{pi} + Q_{pi}^{ex}\right)\right] \qquad \forall p, i > SL_p \qquad (33)$$

$$Q_{pi}^{ex} \geq 0 \qquad \forall i,p \qquad (34)$$

$$Q_{pi}^{im} = \gamma_p.Q_{pi} \qquad \forall p,i \qquad (35)$$

$$\textstyle\sum_{p=1}^{P} b_p.Y_{wp}\left(Q_{pi} - Q_{pi}^{im} + I_{pi-1} - SA_{pi} - LS_{pi} - Q_{pi}^{ex}\right) \leq C_w \qquad \forall i, w \qquad (36)$$

$$I_{p1} = 0 \qquad \forall p \qquad (37)$$

$$I_{pi+1} = Q_{pi+1} - Q_{pi+1}^{im} + I_{pi} - SA_{pi+1} - Q_{pi}^{ex} \qquad \forall p, i \neq 1 \qquad (38)$$

$$HI_i - FI_i = \left(Q_{pi} - Q_{pi-1}\right)/TF_p \qquad \forall i,p \qquad (39)$$

$$HI_i.FI_i = 0 \qquad \forall i \qquad (40)$$

$$HI_i \geq 0 \qquad \forall\, i \qquad (41)$$

$$FI_i \geq 0 \qquad \forall\, i \qquad (42)$$

$$X_{pi}, Y_{wp} \in \{0,1\} \qquad \forall p,i \qquad (43)$$

4.2. S-EPQ model considering full back-ordering

The model proposed in Section 3.2.1 reformulates by the full back-ordering supposition. Based on this model, the unsatisfied demand is considered fully back-ordered. Likewise, the defined amount of cost charged for deliveries by the delay. The following parameters have been added to the basic model:

Parameters:

C_b : Back-ordering cost of products

B_{pi}: The back-ordered quantity of product p in period i

Binary variables:

X_{pi}^{B} : 1, if back-ordered product p is responded in period i, 0 otherwise.

Based on these definitions, the final model is adjusted as follows:

$$Max\ Z_1 = \textstyle\sum_{p=1}^{P}\sum_{i=1}^{I}\left(\left[\left(SA_{pi}.S_p\right) - \left(\ Q_{pi}.C_p^{pr} + C_{CIP}.X_{pi}\right) - \left(C_p^{Se}.X_{pi}\right) - \left(C_p^{In}.I_{pi}\right) - C_b.B_{pi}\right]\right)$$

(44)

$$MinZ_2 = EC_{CIP}.X_{pi} + EC_p^{ex}.Q_{pi}^{im} + EC_p^{ex}.Q_{pi}^{ex} + \sum_{w=1}^{W} EC_p^{w}.\ I_{pi}.Y_{wp}) \qquad (45)$$

$$Min\ Z_3 = \sum_{i=1}^{I}(CH.HI_i + CF.FI_i) \qquad (46)$$

The constraints of the model are developed as follows:

$$SA_{pi} \leq D_{pi} - B_{pi} + \sum_{t=1}^{i-1} B_{pt}.\left(1 - X_{pt}^{B}\right) \qquad \forall\ p, i \qquad (47)$$

$$SA_{pi} \geq 0 \qquad \forall p, i \qquad (48)$$

$$Q_{pi} \leq X_{pi}.M \qquad \forall p, i \qquad (49)$$

$$Q_{pi} \geq 0 \qquad \forall p, i \qquad (50)$$

$$D_{pi} - \left(Q_{pi} - Q_{pi}^{im} + I_{pi-1} - Q_{pi}^{ex} - B_{pi-1}\right) \leq B_{pi} \qquad \forall p, i \qquad (51)$$

$$B_{pi} \geq 0 \qquad \forall p, i \qquad (52)$$

$$B_{p1} = 0 \qquad \forall p \qquad (53)$$

$$\sum_{p=1}^{P} b_p.Y_{wp}.\left(Q_{pi} - Q_{pi}^{im} + I_{pi-1} - SA_{pi} - B_{pi} - Q_{pi}^{ex}\right) \leq C_w \qquad \forall i, w \qquad (54)$$

$$Q_{pi}^{ex} = 0 \qquad \forall p, i \leq SL_p \qquad (55)$$

$$Q_{pi}^{ex} \geq I_{pi-SL_p} - \left[\sum_{\acute{i}=i-(SL_p-1)}^{i}\left(SA_{p\acute{i}} + Q_{p\acute{i}}^{ex}\right)\right] \qquad \forall p, i > SL_p \qquad (56)$$

$$Q_{pi}^{ex} \geq 0 \qquad \forall i, p \qquad (57)$$

$$Q_{pi}^{im} = \gamma_p.Q_{pi} \qquad \forall p, i \qquad (58)$$

$$I_{p1} = 0 \qquad \forall p \qquad (59)$$

$$I_{pi+1} = Q_{pi+1} - Q_{pi+1}^{im} + I_{pi} - SA_{pi+1} - Q_{pi}^{ex} \qquad \forall p, i \qquad (60)$$

$$I_{pi} \geq 0 \qquad \forall p, i \qquad (61)$$

$$HI_i - FI_i = \left(Q_{pi} - Q_{pi-1}\right)/TF_p \qquad \forall i, p \qquad (62)$$

$$HI_i.FI_i = 0 \qquad \forall i \qquad (63)$$

$$HI_i \geq 0 \qquad \forall\ i \qquad (64)$$

$$FI_i \geq 0 \qquad \forall\ i \qquad (65)$$

$$X_{pi}, X_{pi}^{B} \in \{0,1\} \qquad \forall p, i \qquad (66)$$

5. Solution method

As highlighted in the literature, the multi-product EPQ model with shortage was NP-hard [50]. Also, the EPQ model with warehouse capacity limitation is another example of NP-hard problems [51]. Since the similar models are concluded as NP-hard, the proposed S-EPQ that is multi-product and multi-period is also NP-hard. The model is also more complex than most of the literature due to the perishability limitations of the dairy manufacturing case study [52].

5.1. Solution representation

Both red deer algorithm (RDA) and particle swarm optimization (PSO) use a continuous search space. As a combinatorial optimization like the proposed model, we need to transform the continuous variables into integer ones. In this regard, the random key method is used [53]. In this regard, a heuristic strategy is applied to transform an infeasible solution into a feasible one. Only for binary variables, in our optimization model, we need to add this procedure.

In this example, assume that we have five possible orders and want to select the optimal one. For each response, a uniform number is chosen from the logic of the meta-heuristics. Then, the highest values are opted to be one. The criterion to stop the selection is the shelf life of the product. After each order is selected, the cost calculates to check the objective functions.

5.2. Basic algorithms

5.2.1. Red deer algorithm

Evolutionary algorithms are a well-known classification of metaheuristics. These algorithms are also nature-inspired. However, from the current to the next generation, only a group of animals that are probably more potent will be kept, and other agents will be removed. As another evolutionary metaheuristic,[46] recently proposed the Red Deer Algorithm (RDA), inspired by the fantastic behaviors of males and females during a breeding season.

This algorithm studies the behavior of red deers regarding roaring, fighting, and mating behaviors. The males known as stags roar loudly and repeatedly to attract the females in the breeding season, called hinds. Based on this feature of the males, the hinds select their preferable stag, and he will create his territory and harem. A harem is a group of hinds, and a commander as the head of this group manages and controls them. The fighting action always exists among males. Stags and commanders fight, and the winner will achieve the territory and harem. This competition among males is the main activity. The last part of this season is the mating behaviors among males and hinds, and as a result, the new red deers will bear for the next breeding season. Among all roaring, fighting, and mating processes, the evolutionary concept confirms that only the strongest will always keep in nature, and this rule exists among red deers. Fard and Hajiaghaei- Keshteli, [46] modelled these facts as another evolutionary algorithm. They generated the first population of red deers as random solutions. This population is divided into males and hind. Then, males roar, and based on their power, a group of them will choose as the commanders, and the others are stags. Next, a fight between commanders and stags occurs. Later, a harem will be generated by random hinds for each commander. The number of hinds in a harem is directly related to the commander's power. The commander mate with some hinds in the harem and a few hinds in another. The stags that do not have this chance to be a commander can mate with the closest hind. After the mating, offspring create for each mating. Finally, for the next generation, the males will sort out the best solutions among all available solutions, and the hinds will pick by an evolutionary mechanism like the roulette wheel selection method. With these features, the authors developed a fascinating and successful metaheuristic and calledit RDA.

This study uses a multi-objective RDA. In this updated version of RDA, there are two main features. In the algorithm's main loop to compare two solutions, a solution is better than another if it dominates another. It means that it has a better value in at least one objective while other objectives are equal to the objectives of another solution. Another difference of the multi-objective RDA is the selection of next-generation based on the concept of non-dominated solutions and crowding distance to identify the Pareto solutions.

5.2.2. Particle swarm optimization

One of the primary swarm-based algorithms is the PSO proposed by Kennedy & Eberhart [14]. This optimization algorithm is inspired by the swarm behavior of birds and fishes. Similar to other metaheuristics, it starts with a random population. The best solution for this population is the global solution. In each iteration, each population agent moves toward the global solution and the local solution. The local solution is the current position of this search agent. The position of each search agent would be updated, with attention to the feasible space and the mirror concept of this swarm. The global solution will be updated if a better solution is found in this iteration. This process is continued until the maximum number of iterations is satisfied.

This study applies a multi-objective PSO. The main differences are evaluating the solutions to find the global one and sorting the rest of the solutions at the end of each iteration.

5.3. Proposed novel hybrid heuristic

One novelty of this paper is the development of a new optimization algorithm. This study combines RDA and PSO heuristically in a multi-objective framework. As mentioned earlier, the PSO updates the position of search agents based on a global solution and the local one. This hybrid algorithm uses this concept in the mating process to improve the diversification phase of RDA. This hybridization of RDA and PSO is called HRDPSOA.

In the proposed HRDPSOA, except for mating operators for commanders, all algorithm parts are similar to the multi-objective RDA. We consider the males and the hinds as the global and local solutions for each mating. Finally, the offspring would be considered the result of this movement from the hind to the commander. This strategy uses the benefits of PSO to improve the RDA differently.

6. Computational results

Here, we provide a comprehensive analysis to show the performance of the developed hybrid heuristic and the efficiency and applicability of the deployed optimization model. We first address our case study in dairy manufacturing in Iran and our benchmarks. Then, tuning, validation, and comparison of the algorithms are made to approve the performance of the proposed HRDPSOA. Finally, some sensitivity analyses are performed to test the efficiency of the developed optimization model in a real-world setting. It should be noted that MATLAB2013a and GAMS software took the results in a computer with 1.7GB CPU and 6.0GB RAM.

6.1. Case study and benchmarks

Nowadays, dairy products are profoundly significant in the human diet, and the food industry is one of the economic drivers in Europe and other developed markets [54], [55]. The dairy industry in Iran is considered for a case study, and the company of Kalleh is selected.

Kalleh brand was established in 1991 to improve and upgrade the food basket of the Iranian people. As a result of the activities carried out in this collection over the past years, this brand has been ranked 48th worldwide in the food industry, a popular and top brand, and was the only exporter of dairy products in Iran for seven years.

Kalleh started its activity with daily absorption of 3 liters of milk, and today it has more than 2500 tons of daily milk reception. This causes the daily production of more than 2650 tons of dairy products. In this production process, 4,000 people work daily in different sectors to get the final products to consumers. Due to security reasons, we cannot provide more details about our case study, and the interested readers can ask for further details via an email to the corresponding author.

6.2. Tuning, validation and comparison

This section aims to show the performance of the proposed HRDPSOA in comparison with PSO and RDA to solve the proposed optimization model. To have an unbiased assessment, the parameters of the algorithms must be tuned. Good tuning is highly essential to confirm the performance of the developed HRDPSOA.

To do the tuning, the Taguchi experimental design method is applied [56]. In this method, we first consider some candidate values for each, then find the best set for parameters. In this notice, Table 2 reports the results of tuning for the algorithms.

After tuning, it is essential to show that the algorithms find the optimal solution. The algorithms are employed to solve the case study in dairy manufacturing and, the exact solver checks their results via GAMS software. The epsilon constraint method [57] is utilized to find the Pareto solutions exactly. This method transforms the multi-objective model into a single objective form and limits the rest of the objectives as the allowable bounds. For the proposed case study, after updating the bounds, only three feasible solutions are found. The results of the epsilon constraint and three metaheuristics are given in Table 3. These solutions are also depicted in Figure 3. This figure shows that the solutions of the metaheuristics are optimal and validated by the epsilon constraint method. It also shows that the diversity of HRDPSOA is closer to the solutions of the epsilon constraint method and, the solutions of HRDPSOA dominate RDA and PSO.

To compare the algorithms, we have utilized four commonly used metrics in the literature comprising the number of Pareto solutions (NPS), mean ideal distance (MID), the spread of non-dominance solution (SNS), and maximum spread (MS). These metrics are defined as follows:

- NPS is the number of non-dominated solutions in the Pareto optimal set. A higher value of this metric shows a better diversity of the solutions [58].
- MS measures the distance between the best and the worst solutions in the optimal Pareto set. It can be formulated as follows:

$$MS = \sqrt{\left(\sum_{j=1}^{NO} (Z_j^{Max} - Z_j^{Min})\right)^2} \tag{67}$$

Z_j^{Max} and Z_j^{Min} are respectively the maximum and the minimum value of the objective j among all the solutions. NPS metric evaluates the diversity of the solutions. A higher value of the MS metric means a better capability of the algorithm [59] to find an optimal solution.

- MID measures the distance between solutions in the Pareto optimal set and, we can formulate it as follows:

$$MID = \frac{\sum_{i=1}^{NPS} \sqrt{\left(\sum_{j=1}^{NO} \frac{Z_j^i - Z_j^{Best}}{Z_j^{Max} - Z_j^{Min}}\right)^2}}{NPS} \tag{68}$$

Where *NO* is the number of objectives, Z_j^i is the solution *i* for objective *j*, and Z_j^{Best} is the maximum or minimum value regarding the type of the objective function. A lower value of thismetric shows a faster convergence of the solution [58].

- SNS is the spread of non-dominated solutions. This metric, similar to MS, measures the distance between the non-dominated solutions. A higher value of this metric brings a better diversity of Pareto solutions in the algorithm [58]. It is formulated as follows:

$$SNS = \sqrt{\frac{(MID - \sqrt{\sum_{j=1}^{NO}(\sum_{i=1}^{NPS} Z_j^i)})^2}{NPS - 1}} \tag{69}$$

- Ten simulated test studies are benchmarked by the data of Taleizadeh, Soleymanfar and Govindan, [28] to provide a comparison between three optimization algorithms.

- We have classified these tests into three levels, i.e., small, medium, and large, to analyze the complexity for solving our model. The first three tests are linked with the low complexity level. Tests 4, 5, and 6 are assumed as the medium size and, other tests are simulating the large scale. PSO, RDA, and the proposed HRDPSOA are implemented to solve these simulation tests. In each test problem, the non-dominated solutions found by the algorithms are analyzed by the assessment metrics defined above. Table 4 reports the results of the assessment metrics for analyzing the quality of the algorithms. Note that the best value in each test is shown in bold.

The result figuring Table 4 generally confirms that the proposed HRDPSOA is acquiring better results than PSO and RDA. To exhibit this robustness via statistical tests, we normalize the results of Table 4 and use the interval plot depicted in Figure 4.

As shown in Figure 4(a), HRDPSOA is highly more satisfying than RDA in the criterion of the NPS metric. The RDA is also more reliable than PSO in this metric. Based on the criterion of the MID metric (Figure 4(b)), HRDPSOA outperforms the PSO, and consequently, the PSO is slightly more helpful than RDA in this metric. The results are similar to the MID metric regarding the SNS metric (Figure 4(c)). HRDPSOA is significantly more beneficial than PSO and RDA. As indicated in Figure 4(d), the results are identical to the NPS metric. HRDPSOA outperforms the RDA and PSO, respectively.

The computational time of the algorithms is quite similar, and the proposed hybrid HRDPSOA is slightly inefficient; based on the quality criterion as addressed in the assessment metrics, the proposed HRDPSOA is very strong and efficient in this paper.

6.3. Sensitivity analysis

Sensitivity analysis supplies knowledge on the relative significance of model input parameters and assumptions [49] and is always a crucial element of decision making. Here, some sensitivity analyses are performed to study the efficiency and the impact of the parameters for decision-makers. The Sensitivity analysis is beneficial in situations where uncertainties exist in the definition of the various factors [60]. In this regard, we have defined two scenarios. The first scenario is the model presented in Section 3.2.1 as an S-EPQ model considering lost sales. The second scenario is presented in Section 3.2.2 as an S-EPQ model considering full back-ordering. The impact of these scenarios toward sustainability is analyzed comprehensively by the data of an actual case study in dairy manufacturing in Iran.
First sensitivity analysis is the changes in the shelf life of products on average. For both scenarios, the shelf life of products is increased from 3 days to 6 months. Ten cases are designed accordingly. The results are reported in Table 5.

The results given in Table 5 show that the second scenario is better than the first scenario in the total profit criterion. However, the first scenario is better than the second one in the second and third objectives based on environmental and social factors. Variations of the objectives in both scenarios indicate that an apparent similarity between them (Figure 5). In both scenarios, an increase in the shelf life of products leads to a reduction in the total profit, which is not suitable. However, this increases in the variations of the shelf life of products leads to an improvement in the environmental and social criteria. The last analysis on the scenarios and sustainability goals refers to the diversity of products. Following this, the diversity of products has been increased from 1 to 20 and, the results of both scenarios are noted. In this regard, 7 cases are simulated. Table 6 reports the outputs of the scenarios for the sensitivity analysis and, Figure 6 shows the variation of sustainability goals for both scenarios.

Once again, the results given in Table 6 confirm that the second scenario gives us more profit than the first scenario modeling. However, it does not improve the environmental and social criteria. The behavior of both scenarios is the same, as can be concluded from Figure 6. In both scenarios, an increase in the diversity of the products increases the total profit. However, this increases the environmental pollution and additional working hours. Therefore, the diversity of the products improves economic sustainability only. It does not improve the environmental andsocial goals.

Managerial insights

The following findings couldbe helpful for managers to make quick decisions and analyses about the implementation of TBL in dairy manufacturing systems. Among the items in our S-EPQ model, the she0lf life of productsis particularly significant on the economic, environmental, and social factors. Although anincrease in shelf life improves the environmental and social criteria, it reduces the total profit negatively.

I. The diversity of the products is another notable parameter that has a significant impact on economic sustainability. However, it damages the environmental and social criteria.
II. It has frequently been observed that some of the inventory parameters treat as uncertain variables. This phenomenon can happen in so many practical situations in real life, as the market demand, which is usually not precisely known. In this case, taking advantage of the stochastic demand would be beneficial.
III. Another significant managerial insight is to shift the traditional EPQ model to an S-EPQ facing stochastic demand. The demand uncertainty makes our model more realistic and helps the managers compute the expected total cost robustly. Therefore, the decisions made by our model are robust against the demand uncertainty.
IV. To manage the high complexity of EPQ models, an efficient solution is highly needed. Therefore, a practical and robust optimization algorithm like our hybrid of RDA and PSOcan be suggested to the managers for solving the real test optimality.

7. Conclusion and further research

In this paper, an S-EPQ model was developed to determine the optimal quantity of manufacturing for the perishable products under three pillars of sustainability simultaneously (the TBL approach). The high cost of production and storage and arising consciousness toward social factors and environmental issues led to studying the supply chain as an integratedsustainable supply chain. The model was subjected to back-order and lost sales. Hence, a multi- objective model is provided to solve the problem and assumed deterioration function during storage plus generating defective items during manufacturing.

It has been estimated stochastic to cope with the inherent uncertainty of the demand data and its variation over time. Uncertainty is inherent in managerial practice. A PSO algorithm as a powerful swarm-based method was proposed due to the NP-hard nature of the problem. Then, the proposed algorithm was tuned, validated, and compared with its individuals, and sensitivity analyses were conducted to study theperishability of the developed S-EPQ model. The results show the advantage of the developed hybrid algorithm in terms of quality Pareto solutions compared to the original version of PSO and RDA. The applicability of the proposed model and algorithm manifested in a real case studyin the Kalleh dairy industry. Finally, some sensitivity analyses were performed to study the impact of the shelf life of products and the number of products on the S-EPQ considering lost sales (the first scenario) and full back-order (the second scenario).

In conclusion, this paper presented an S-EPQ model under two scenarios, including lost sales and full back-order, that would be advantageous for companies to maximize the total profit, diminish environmental pollution, and improve social justice in the manufacturing systems. A novel hybrid algorithm was also developed. Although this study was profoundly practical and efficient for implementing the TBL strategy for dairy manufacturing, many other suppositions can be considered for further research. Vehicle routing optimization makes the proposed problem more practical and complex than the current format of this paper. Reducing the negative impacts of logistics activities is highly important in supply chain sustainability practices [61]. Combining more social factors such as job opportunities can be another interesting addition to future studies. Other novel heuristics and meta-heuristics may be suggested for our proposed model. The proposed novel hybrid algorithm in this paper can be adjusted for solving other complex optimization problems like supply chain network design and healthcare facility location.

References:

[1] Yu, H., Dai, H., Tian, G., Wu, B. Xie, Y., Zhu, Y., ... and Tang, H. “Key technology and application analysis of quick coding for recovery of retired energy vehicle battery”, *Renewable and Sustainable Energy Reviews*, *135*, pp. 110129, (2021).

[2] Rostamzadeh, R., Ghorabaee, M. K., Govindan, K., Esmaeili, A. and Nobar, H. B. K. “Evaluation of sustainable supply chain risk management using an integrated fuzzy TOPSIS-CRITIC approach”, Journal of Cleaner Production, 175, pp. 651-669, (2018).

[3] Glock, C. H., Grosse, E. H. and Ries, J. M. “The lot sizing problem: A tertiary study”, *International Journal of Production Economics*, 155, pp. 39–51, (2014).

[4] Kazemi, N., Abdul-Rashid, S. H., Ghazilla, R. A. R., Shekarian, E. and Zanoni, S. “Economic order quantity models for items with imperfect quality and emission considerations”, *International Journal of Systems Science: Operations & Logistics*, *5*(2), pp. 99-115, (2018).

[5] Ebrahimi, E., Shirazi, B., Mirzagoltabar, H. and Mahdavi, I. International Industrial Engineering Conference (IIEC 2018).

[6] Bushuev, M. A., Guiffrida, A., Jaber, M. Y. and Khan, M. “ A review of inventory lot sizing review papers”. *Management Research Review*, (2015).

[7] Kirilova, E. G. and Vaklieva-Bancheva, N. G. “Environmentally friendly management of dairy supply chain for designing a green products' portfolio”, *Journal of Cleaner Production*, *167*, pp. 493-504., (2017).

[8] Ebrahimi, E., Shirazi, B. and Mahdavi, I. “Measuring the waste water in a yoghurt production plant and redesigning the cleaning in place process (case study: Kalleh Dairy Factory)”, In *2019 15th Iran International Industrial Engineering Conference (IIIEC)*, pp. 43-46, (2019)

[9] Govindan, K., Kaliyan, M., Kannan, D. and Haq, A. N. “Barriers analysis for green supply chain management implementation in Indian industries using analytic hierarchy process”, *International journal of production economics*, *147*, pp. 555-568, (2014).

[10] Govindan, K., Shaw, M. and Majumdar, A. “Social sustainability tensions in multi-tier supply chain: A systematic literature review towards conceptual framework development”, *Journal of Cleaner Production*, *279*, pp. 123075, (2021).

[11] Debnath, B. K., Majumder, P. and Bera, U. K. “Multi-objective sustainable fuzzy economic production quantity (SFEPQ) model with demand as type-2 fuzzy number: A fuzzy differential equation approach”, *Hacettepe Journal of Mathematics and Statistics*, *48*(1), pp. 112-139, (2019).

[12] Barman, H., Pervin, M., Roy, S. K. and Weber, G. W. “Back-ordered inventory model with inflation in a cloudy-fuzzy environment”, *Journal of Industrial & Management Optimization*, *17*(4), pp. 1913, (2021).

[13] Rostami, A., Paydar, M. M. and Asadi-Gangraj, E. “A hybrid genetic algorithm for integrating virtual cellular manufacturing with supply chain management considering new product development”, *Computers & Industrial Engineering*, *145*, pp. 106565, (2020).

[14] Kennedy, J. and Eberhart, R. “Particle swarm optimization”, In *Proceedings of the ICNN*, (1942).

[15] Rajeev, A., Pati, R. K., Padhi, S. S. and Govindan, K. (2017). “Evolution of sustainability in supply chain management: A literature review”, *Journal of Cleaner Production*, *162*, pp. 299-314, (2016).

[16] Zhou, B. B. and Lv, L. “Understanding the dynamics of farmland loss in a rapidly urbanizing region: a problem-driven, diagnostic approach to landscape sustainability”, *Landscape Ecology*, *35*(11), pp. 2471-2486, (2020).

[17] Battini, D., Persona, A. and Sgarbossa, F. “A sustainable EOQ model: Theoretical formulation and applications”. *International Journal of Production Economics*, *149*, pp. 145-153, (2014).

[18] Hovelaque, V. and Bironneau, L. “The carbon-constrained EOQ model with carbon emission dependent demand”, *International Journal of Production Economics*, *164*, pp. 285-291, (2015).

[19] Kumar, R. S. and Goswami, A. “A fuzzy random EPQ model for imperfect quality items with possibility and necessity constraints”, *Applied Soft Computing*, *34*, pp. 838-850, (2015).

[20] Majumder, P., Mondal, S. P., Bera, U. K. and Maiti, M. “Application of Generalized Hukuhara derivative approach in an economic production quantity model with partial trade credit policy under fuzzy environment”, *Operations Research Perspectives*, *3*, pp. 77-91, (2016).

[21] Ghiami, Y. and Beullens, P. “Planning for shortages? Net Present Value analysis for a deteriorating item with partial backlogging”, *International Journal of Production Economics*, *178*, pp. 1-11, (2016).

[22] Sazvar, Z., Rahmani, M. and Govindan, K. “A sustainable supply chain for organic, conventional agro-food products: The role of demand substitution, climate change and public health”, *Journal of cleaner production*, *194*, pp. 564-583, (2018).

[23] Chaudhary, V., Kulshrestha, R. and Routroy, S. “State-of-the-art literature review on inventory models for perishable products”, *Journal of Advances in Management Research*, (2018).

[24] Nandakumar, P. and Morton, T. E. “Near myopic heuristics for the fixed-life perishability problem”, *Management science*, *39*(12), pp. 1490-1498, (1993).

[25] Chang, X., Li, J., Rodriguez, D. and Su, Q. “Agent-based simulation of pricing strategy for agri-products considering customer preference”, *International Journal of Production Research*, *54*(13), pp. 3777-3795, (2016).

[26]. Chen, W., Li, J. and Jin, X. “The replenishment policy of agri-products with stochastic demand in integrated agricultural supply chains”, *Expert Systems with Applications*, *48*, pp. 55-66, (2016).

[27] Battini, D., Glock, C. H., Grosse, E. H., Persona, A. and Sgarbossa, F. “Ergo-lot-sizing: An approach to integrate ergonomic and economic objectives in manual materials handling”, *International Journal of Production Economics*, *185*, 230-239, (2017).

[28] Taleizadeh, A. A., Soleymanfar, V. R. and Govindan, K. “Sustainable economic production quantity models for inventory systems with shortage”, *Journal of cleaner production*, *174*, pp. 1011-1020, (2018).

[29] Zadjafar, M. A. and Gholamian, M. R. “A sustainable inventory model by considering environmental ergonomics and environmental pollution, case study: Pulp and paper mills”, *Journal of Cleaner Production*, *199*, pp. 444-458, (2018).

[30] Tayyab, M. and Sarkar, B.” Optimal batch quantity in a cleaner multi-stage lean production system with random defective rate”, *Journal of cleaner production*, *139*, pp. 922-934, (2016).

[31] Nobil, A. H., Kazemi, A. and Taleizadeh, A. A. “Economic lot-size problem for a cleaner manufacturing system with warm-up period”, *RAIRO-Operations Research*, *54*(5), pp. 1495-1514, (2020).

[32] Lin, H.-J. “An economic production quantity model with backlogging and imperfect rework process for uncertain demand”, *International Journal of Production Research*, pp. 1–16, (2019).

[33] Kalantari Khalil Abad, A. R. and Pasandideh, S. H. R. “Green closed-loop supply chain network design with stochastic demand: a new accelerated benders decomposition method”, *Scientia Iranica*, (2020).

[34] Mokhtari, H., Naimi-Sadigh, A. and Salmasnia, A. “A computational approach to economic production quantity model for perishable products with backordering shortage and stock-dependent demand”, *Scientia Iranica*, *24*(4), pp. 2138-2151, (2017).

[35] Namany, S., Al-Ansari, T. and Govindan, R. “Sustainable energy, water and food nexus systems: A focused review of decision-making tools for efficient resource management and governance”, *Journal of Cleaner Production*, *225*, pp. 610-626, (2019).

[36] Fallahi, A., Azimi-Dastgerdi, M. and Mokhtari, H. “A sustainable production-inventory model joint with preventive maintenance and multiple shipments for imperfect quality items”, *Scientia Iranica*, (2021).

[37] Nemati, Y. and Alavidoost, M. H. “A fuzzy bi-objective MILP approach to integrate sales, production, distribution and procurement planning in a FMCG supply chain”, *Soft computing*, *23*(13), pp. 4871-4890, (2019).

[38] Teimoury, E. and Kazemi, S. M. M. “An integrated pricing and inventory model for deteriorating products in a two stage supply chain under replacement and shortage”, *Scientia Iranica*, *24*(1), pp. 342-354, (2017).

[39] Lee, H. M., Lu, W. F. and Song, B. “A framework for assessing product End-Of-Life performance: reviewing the state of the art and proposing an innovative approach using an End-of-Life Index”, *Journal of Cleaner production*, *66*, pp. 355-371, (2014).

[40] Namany, S., Govindan, R., Alfagih, L., McKay, G. and Al-Ansari, T. “Sustainable food security decision-making: an agent-based modelling approach”, *Journal of Cleaner Production*, *255*, pp. 120296, (2020).

[41] Salamati-Hormozi, H., Zhang, Z. H., Zarei, O. and Ramezanian, R. “Trade-off between the costs and the fairness for a collaborative production planning problem in make-to-order manufacturing”, *Computers & Industrial Engineering*, *126*, pp. 421-434, (2018).

[42] Vasilaki, V., Katsou, E., Ponsá, S. and Colón, J. “Water and carbon footprint of selected dairy products: A case study in Catalonia”, *Journal of cleaner production*, *139*, pp. 504-516, (2016).

[43] Kangi, F., Javanmard, S. and Pasandideh, S. H. R. “Economic production quantity model with imperfect products and random order frequency under due date and limited storage capacity”, *Journal of Industrial and Production Engineering*, *34*(5), pp. 344-361, (2017).

[44] Masudin, I., Jannah, F. R., Utama, D. M. and Restuputri, D. P. “Capacitated remanufacturing inventory model considering backorder: A case study of indonesian reverse logistics”, *IEEE Access*, *7*, pp. 143046-143057, (2019).

[45] Arıkan, E., Fichtinger, J. and Ries, J. M. “Impact of transportation lead-time variability on the economic and environmental performance of inventory systems”, *International Journal of Production Economics*, *157*, pp. 279-288, (2014).

[46] Fard, A. F. and Hajiaghaei-Keshteli, M. “Red Deer Algorithm (RDA); a new optimization algorithm inspired by Red Deers’ mating”, In *International Conference on Industrial Engineering, IEEE*, 12, pp. 331-342, (2016).

[47] Fatimah, Y. A., Govindan, K., Murniningsih, R. and Setiawan, A. “Industry 4.0 based sustainable circular economy approach for smart waste management system to achieve sustainable development goals: A case study of Indonesia”, *Journal of Cleaner Production*, *269*, pp. 122263, (2020).

[48] Jouzdani, J., Fathian, M., Makui, A. and Heydari, M. “Robust design and planning for a multi-mode multi-product supply network: a dairy industry case study”, *Operational Research*, *20*(3), pp. 1811-1840, (2020).

[49] Saltelli, A., Aleksankina, K., Becker, W., Fennell, P., Ferretti, F., Holst, N. and Wu, Q. “Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices”, *Environmental modelling & software*, *114*, pp. 29-39, (2019).

[50] Pasandideh, S. H. R., Niaki, S. T. A. and Yeganeh, J. A. “A parameter-tuned genetic algorithm for multi-product economic production quantity model with space constraint, discrete delivery orders and shortages”, *Advances in Engineering Software*, *41*(2), pp. 306-314, (2010).

[51] Pasandideh, S. H. R. and Niaki, S. T. A. “A genetic algorithm approach to optimize a multi-products EPQ model with discrete delivery orders and constrained space”, *Applied Mathematics and Computation*, *195*(2), pp. 506-514, (2008).

[52] Ebrahimi, E. and Rezaeian, J. “Unrelated parallel machines scheduling with the effect of aging and learning under multi maintenance activities”, *Manufacturing Science and Technology*, *3*(1), pp. 25-31, (2015).

[53] Gonçalves, J. F. and Resende, M. G. “Biased random-key genetic algorithms for combinatorial optimization”, *Journal of Heuristics*, *17*(5), pp. 487-525, (2011).

[54] Wijnands, J. H., van der Meulen, B. M. and Poppe, K. J. “Competitiveness of the European food industry: An economic and legal assessment 2007*”*, Office for Official Publications of the European Communities, (2007).

[55] Milani, F. X., Nutter, D. and Thoma, G. “Environmental impacts of dairy processing and products: A review”, *Journal of dairy science*, *94*(9), pp. 4243-4254, (2011).

[56] Taguchi, G. and Cariapa, V. “Taguchi on robust technology development”, (1993).

[57] Laumanns, M., Thiele, L. and Zitzler, E. “An efficient, adaptive parameter variation scheme for metaheuristics based on the epsilon-constraint method”, *European Journal of Operational Research*, *169*(3), pp. 932-942, (2006).

[58] Laumanns, M., Zitzler, E. and Thiele, L. “A unified model for multi-objective evolutionary algorithms with elitism”, In *Proceedings of the 2000 Congress on Evolutionary Computation*, 1, pp. 46-53, (2000).

[59] Zitzler, E., Thiele, L., Laumanns, M., Fonseca, C. M. and Da Fonseca, V. G. “Performance assessment of multiobjective optimizers: An analysis and review”, *IEEE Transactions on evolutionary computation*, *7*(2), pp. 117-132, (2003).

[60] Govindan, K., Khodaverdi, R. and Jafarian, A. “A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach”, *Journal of Cleaner production*, *47*, pp. 345-354, (2013).

[61] Pourhejazy, P. and Kwon, O. K. “A practical review of green supply chain management: Disciplines and best practices”, *Journal of International Logistics and Trade*, *14*(2), pp. 156-164, (2016).

Table captions:

Table 1. A comparison with the contributions of this paper with the literature review

Table 2. Tuning of algorithms’ parameters

Table 3. Results of the case study

Table 4. Results of the assessment metrics

Table 5. Sensitivity analysis on the shelf life of products

Table 6. Sensitivity analysis on the diversity of products

Figure captions:

Figure 1. Schematic view of the studied S-EPQ model

Figure 2. Flow chart of the production plan

Figure 3. non-dominated solutions for the first problem

Figure 4. Interval plots for NPS(a), MID(b), SNS(c) and MS(d)

Figure 5. Sensitivity analysis on the shelf life of products

Figure 6. Sensitivity analysis on the diversity of products

Table 1. A comparison with the contributions of this paper with the literature review

Reference	Economic factors	Environmental factors				Social factors	Uncertainty
		Carbon Emission			Wastewater		
		Emission of ordering, holding, inventory and purchasing	Emission of manufacturing	Emission of wastage/disposal/ Obsolesce/Imperfect			
[17]	*	*		*			
[18]	*	*					
[19]	*			*			*
[20]	*						*

[21]	*						*
[25]	*						*
[26]	*						*
[27]	*					*	
[22]	*		*	*			
[4]	*	*		*			
[28]	*	*	*	*		*	
[29]	*		*	*	*	*	
[11]	*	*	*	*			*
[30]	*	*					*
[32]	*						*
[33]	*	*	*				*
Current Study	*	*	*	*	*	*	*

Table 2. Tuning of algorithms' parameters

Algorithm	Parameter	Value
PSO	Maximum number of iteration (MaxIt)	500
	Number of Population (nPop)	100
	Rate of weight damper (W)	0.9
	Coefficient of the global solution (C1)	2
	Coefficient of the local solution (C2)	2
RDA	Maximum number of iteration (MaxIt)	500
	Number of Population (nPop)	100
	Percentage of fighting (gamma)	0.8
	Percentage of mating in harms (alpha)	0.6
	Percentage of mating of harems (betta)	0.6
HRDPSOA	Maximum number of iteration (MaxIt)	500
	Number of Population (nPop)	100
	Coefficient of the global solution (C1)	2
	Coefficient of the local solution (C2)	2
	Percentage of fighting (gamma)	0.8
	Percentage of mating in harms (alpha)	0.7
	Percentage of mating of harems (betta)	0.5

Table 3. Results of the case study

Epsilon constraint			PSO			RDA			HRDPSOA		
Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3	Y1	Y2	Y3
31040	697.5	77.5	31180.4	706.68	78.52	31885.6	727.2	80.8	31978.5	726.3	80.7
32018	723.6	80.4	31570	711.45	79.05	32009	730.8	81.2	31993.5	732.6	81.4
32040	738	82	31862	733.14	81.46	32017	753.3	83.7	32009	735.3	81.7
-	-	-	32015	745.2	82.8	32027	756	84	32016	738.9	82.1
-	-	-	32020	749.7	83.3	32035	760.5	84.5	32029	742.5	82.5
-	-	-	-	-	-	-	-	-	32038	746.1	82.9

Table 4. Results of the assessment metrics

		Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7	Test 8	Test 9	Test 10
NPS	PSO	5	10	14	15	**18**	16	18	14	**20**	18
	RDA	5	9	16	**17**	16	14	16	**20**	18	16
	HRDPSOA	**6**	**10**	**18**	**17**	17	**18**	**20**	18	16	**20**
MID	PSO	2.9316	3.7218	4.0318	**2.8172**	3.283	4.372	3.823	3.2288	3.4852	4.3881
	RDA	3.0418	2.9103	3.2864	3.2832	4.273	**3.281**	4.201	4.393	4.3882	4.2041
	HRDPSOA	**2.7581**	**2.6418**	**3.1082**	4.3821	**3.032**	3.928	**3.2837**	**2.382**	**3.2034**	**2.9231**
SNS	PSO	23086	20882	3021	3998	4294	3092	3892	3278	**5305**	3902
	RDA	21495	18045	**4046**	4263	**5021**	4397	3617	3822	5220	4201
	HRDPSOA	**26041**	**30166**	3604	**4833**	4374	**4822**	**4903**	**4318**	4683	**4520**
MS	PSO	19844	25028	22884	20743	23289	24931	22041	**27031**	21302	22033
	RDA	18655	20814	24015	26032	26042	**25041**	28403	27832	22033	24392
	HRDPSOA	**20184**	**30219**	**28918**	**28943**	**25043**	22041	**28732**	23012	**25044**	**26032**

Table 5. Sensitivity analysis on the shelf life of products

Number of cases	Shelf life of theproducts in theaverage	First scenario			Second scenario		
		Z1	Z2	Z3	Z1	Z2	Z3
C1	3 days	25739.7	2242.56	461.25	36771	2803.2	512.5
C2	5 days	25219.6	836.24	228.87	36028	1045.3	254.3
C3	10 days	25076.8	660.72	158.58	35824	825.9	176.2
C4	20 days	24383.1	651.6	101.16	34833	814.5	112.4
C5	25 days	22103.2	571.76	74.07	31576	714.7	82.3
C6	1 month	21728	558	69.75	31040	697.5	77.5
C7	2 months	20058.5	460	57.87	28655	575	64.3

C8	3 months	13058.5	261.6	43.47	18655	327	48.3
C9	5 months	8460.9	228.8	38.34	12087	286	42.6
C10	6 months	7549.5	203.2	35.55	10785	254	39.5

Table 6. Sensitivity analysis on the diversity of products

Number of cases	Number of products	First scenario			Second scenario		
		Z1	Z2	Z3	Z1	Z2	Z3
C1	1	2185	29.7	6.7	1844	32.4	7.6
C2	3	7855	105.6	18.4	9435	108.3	27.4
C3	5	13822	323.1	42.1	16073	303.5	48.3
C4	7	16954	456.9	57.3	21065	547.2	60.4
C5	10	21728	558	69.75	31040	697.5	77.5
C6	15	36293	854.9	85.4	38724	865.5	97.4
C7	20	42766	982.4	98.2	44036	1054.3	115.2

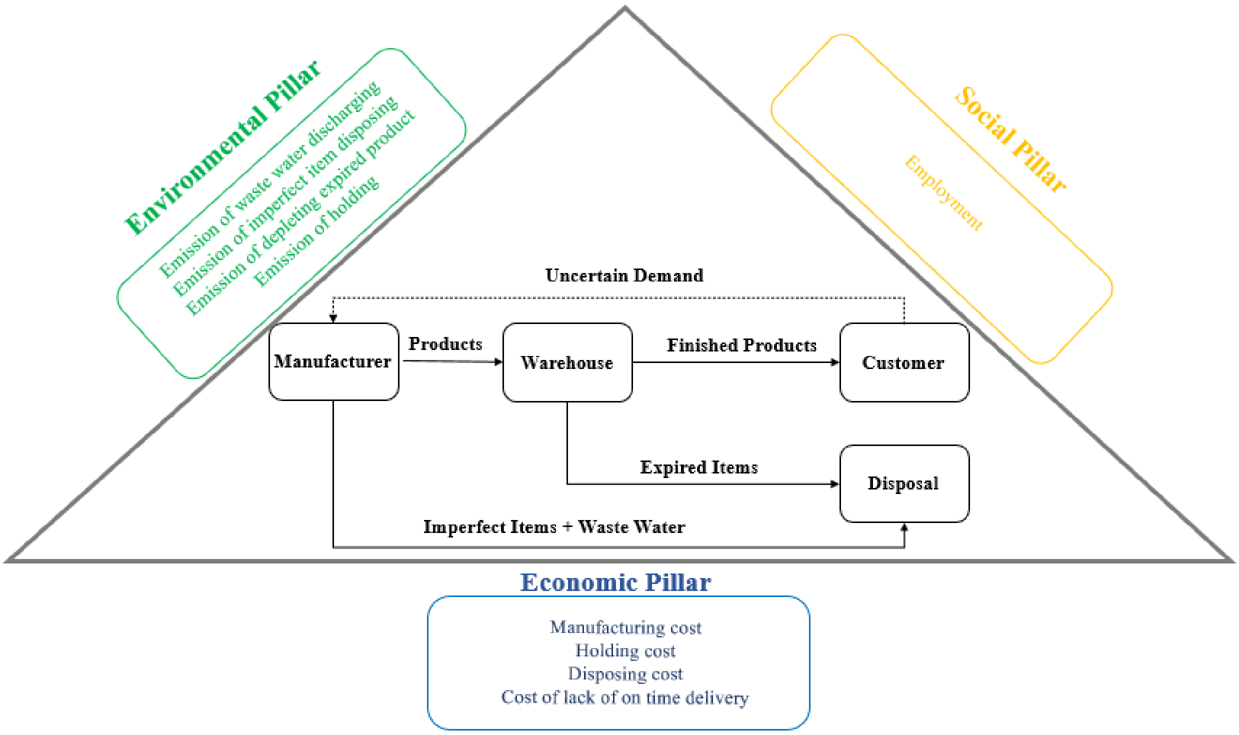


Figure 1. Schematic view of the studied S-EPQ model

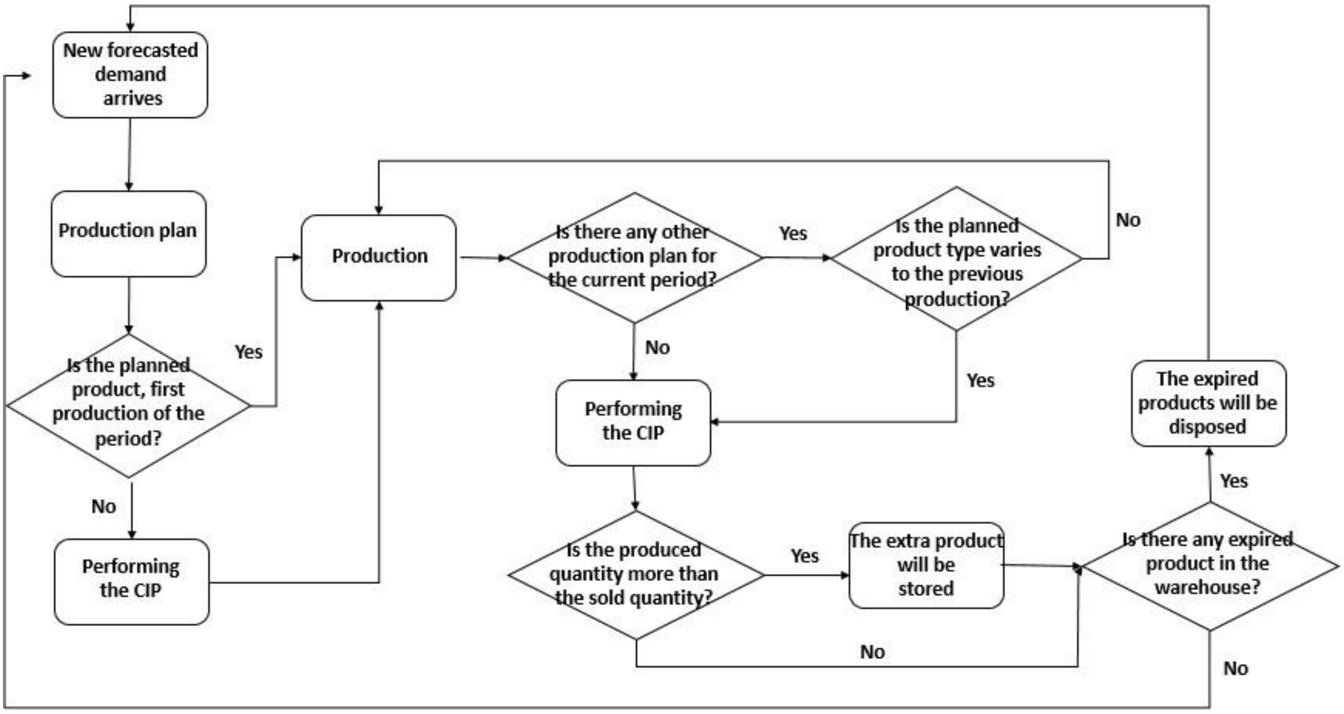


Figure 2. Flow chart of the production plan

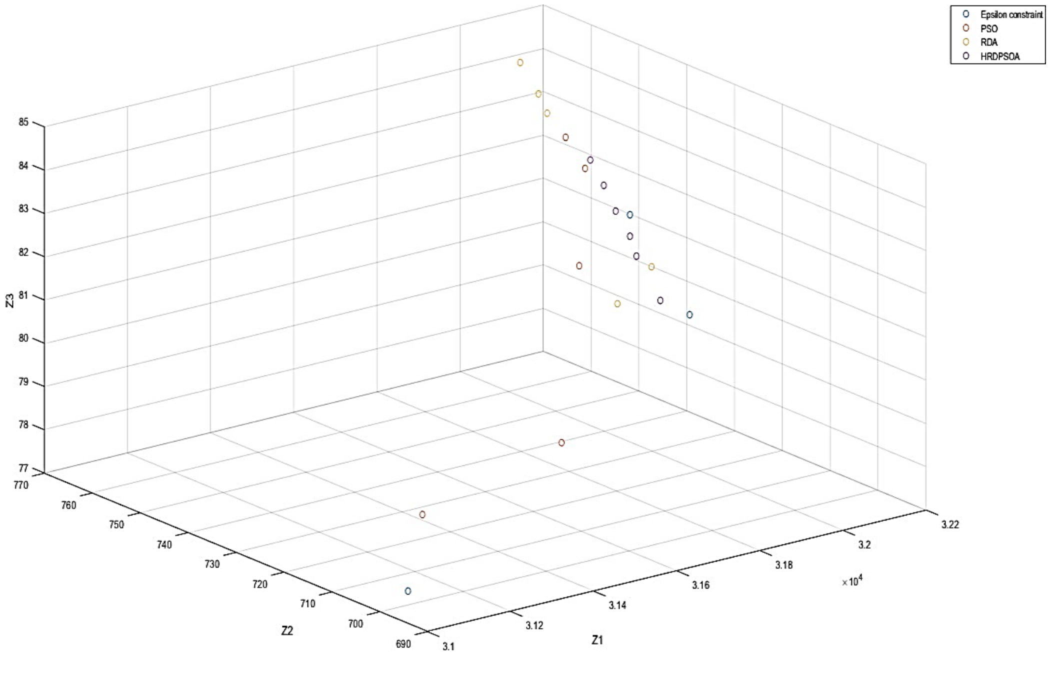
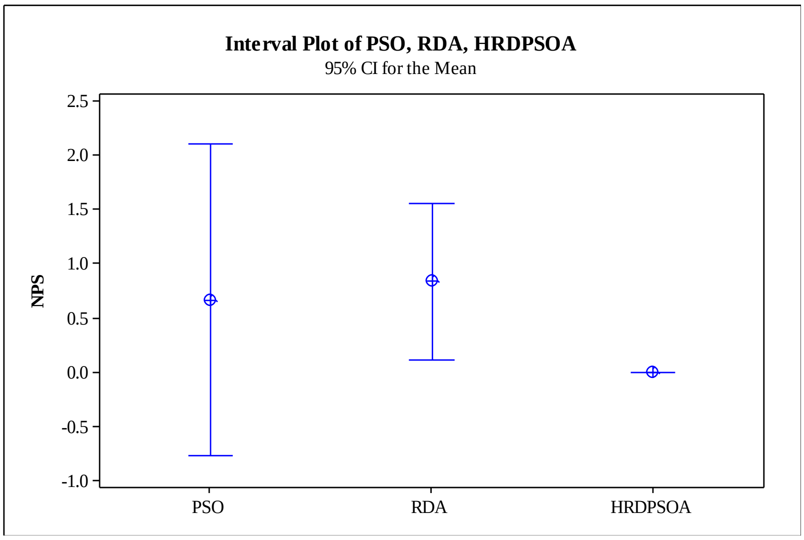
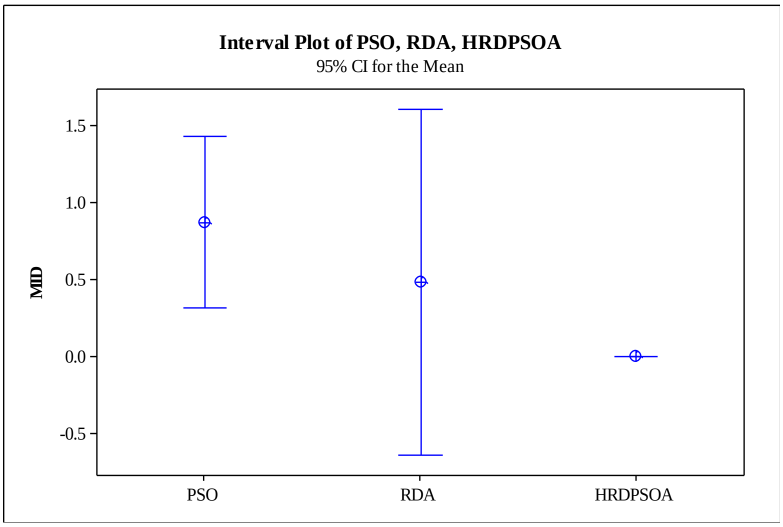


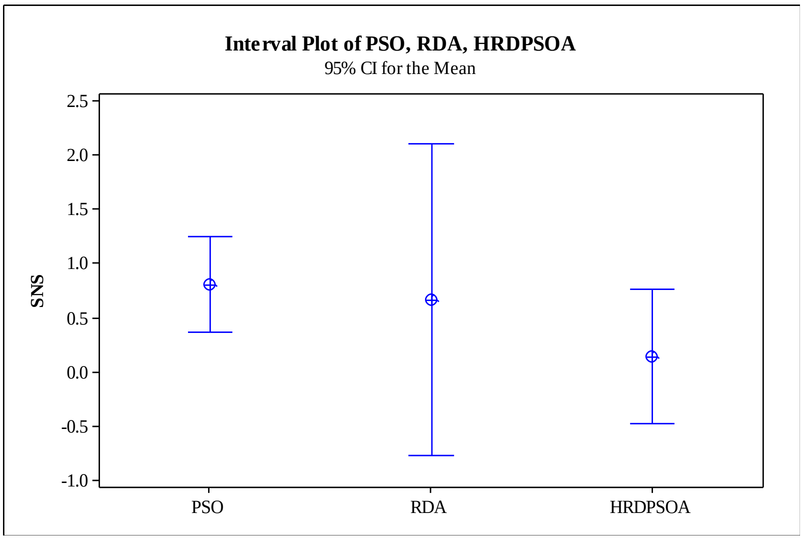
Figure 3. non-dominated solutions for the first problem


Interval Plot of PSO, RDA, HRDPSOA
95% CI for the Mean
NPS
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
PSO
RDA
HRDPSOA

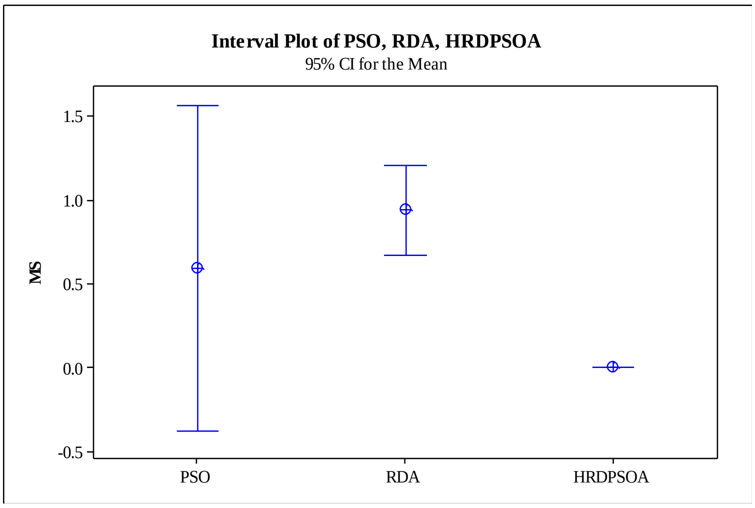
(a)


Interval Plot of PSO, RDA, HRDPSOA
95% CI for the Mean
MID
1.5
1.0
0.5
0.0
-0.5
PSO
RDA
HRDPSOA

(b)


Interval Plot of PSO, RDA, HRDPSOA
95% CI for the Mean
SNS
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
PSO
RDA
HRDPSOA

(c)



(d)

Figure 4. Interval plots for NPS(a), MID(b), SNS(c) and MS(d)

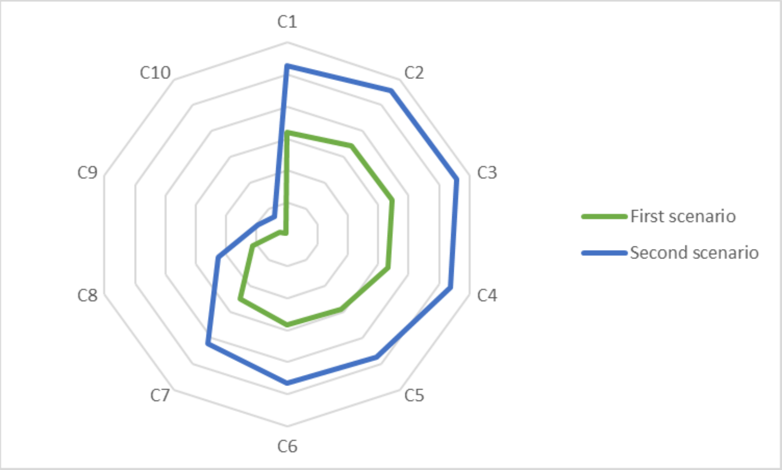


Figure 5. Sensitivity analysis on the shelf life of products

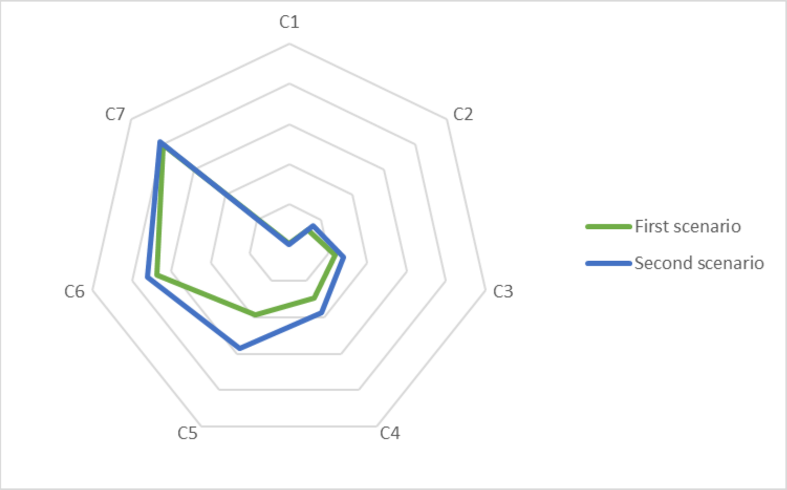


Figure 6. Sensitivity analysis on the diversity of products

Biography:

Elnaz Ebrahimi is a PhD candidate in Industrial Engineering at Mazandaran University of Science and Technology, Babol, Iran. She has graduated with MSc in Industrial Engineering. Her research interests include supply chain management, and multi-objective optimization. She has published over ten research papers.

Babak Shirazi is the associate professor of Industrial Engineering at Mazandaran University of Science and Technology, Babol, Iran. He studied Computer Engineering at Tehran University from 1996 to 2000. He graduated with an MSc and PhD in industrial engineering from Mazandaran University of Science and Technology, Babol, Iran, in 2005 and 2010. His research interests include simulation modelling in manufacturing systems and supply chain management, Enterprise Architecture, and industrial enterprise development strategy setting. He has published over 70 research papers.

Iraj Mahdavi is a full professor of Industrial Engineering at Mazandaran University of Science and Technology, Babol, Iran. He studied Industrial Engineering at the Iran University of Science and Technology. His research interests include Network design, metaheuristic methods, cloud computing, and business process. He has published over 200 research papers.

Alireza Arshadi Khamseh got his PhD in 2006 and has several years of experience working at Kharazmi University of Tehran, Iran, and Faculty of Economics Administration and Social Sciences, Istanbul Gelisim University, Turkey as an associate professor. He has obtained his Bachelor's, Master and PhD degrees in Industrial Engineering. He has been working for more than eight years in Supply Chain Management and Logistic Engineering. He has published several papers in prestigious international journals. His interest areas are Resiliency in SCM, Network Design, and Pricing.