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BI-OBJECTIVE OPTIMIZATION MODELING OF A THREE-LEVEL SUPPLY CHAIN IN PRODUCTION PLANNING AND SCHEDULING CONSIDERING PRICE-DEPENDENT DEMAND: A CASE STUDY OF A SOAP FACTORY

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Abstract. Effective competition in the manufacturing industry requires careful planning and scheduling of production activities, commonly referred to as production planning and scheduling (PPAS). Furthermore, today, all organizations are striving to preserve the environment and improve the climate by reducing greenhouse gas emissions. This study presents a bi-objective mathematical model for a three-level supply chain. The primary objective of the model is to maximize profit, while the secondary objective is to minimize greenhouse gas emissions. By adopting this model, companies can strive towards achieving their business goals while simultaneously contributing to a sustainable future. Numerical experiments demonstrate the applicability of the developed model, and a case study in a soap factory is presented to calculate the optimal production quantities and determine the best price to increase demand while achieving profit. Finally, by conducting sensitivity analysis, optimal strategic decisions and useful management insights have been identified. According to the results and examination of the experiments, expanding the capacity and production rate, especially when the market potential for buying products is higher, fulfills the main goals. Also, in times of market recession, the variety of quality and price of products will lead to more profit.

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1. Introduction

Production planning and scheduling (PPAS) are critical functions in any manufacturing plant [15]. Studies have shown that implementing production schedules after planning will not give a favorable result [18]. Many studies have suggested the simultaneous use of the two [8]. Production planning (PP) involves determining what products are to be produced, the quantity of each product, and the timeline for production [28]. The importance of PPAS lies in its ability to help factories optimize their operations and increase their efficiency.

Keywords. Production planning and scheduling, three-level supply chain, environmental issues, price dependent demand, bi-objective optimization model.

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PPAS enable factories to avoid delays, minimize waste, and ensure that products are delivered to customers on time [12]. Effective PPAS can also help factories reduce their inventory costs by ensuring the correct estimation of the required raw materials [9]. In addition, PPAS can help factories improve their overall productivity by identifying bottlenecks in the production process and implementing solutions to address them [25]. Factories can increase their output and profitability by improving efficiency and reducing waste. PPAS are essential functions in factories as they help ensure that the manufacturing process runs smoothly, products are delivered on time, and costs are minimized [27]. Therefore, in this study, we developed a production planning problem in a soap manufacturing factory that simultaneously deals with production scheduling. In this model, issues such as shortage cost, parts processing cost, inventory maintenance cost, material supply cost, contract signing cost, as well as transportation cost and production overhead are considered.

Due to the damaging effects of industrial activity on the environment, an increase in restrictions, the possibility for cost savings, and the potential for enhanced efficiency, environmental concerns, and carbon dioxide emissions are becoming increasingly important issues in PPAS. To ascertain long-term sustainability, adhere to rules, and maintain their competitiveness, businesses must incorporate environmental issues into their planning [16, 24]. Adopting clean technologies, streamlining production procedures, lowering waste and pollution, and investigating alternative energy sources can all contribute to this [19]. Through the development of a bi-objective model, we attempted to reduce the quantity of pollutants and their adverse effects. In this study, we took into account the emission of carbon dioxide gas during both transportation and the manufacture of goods inside the factory.

A crucial component of PP and production scheduling is the three-level supply chain, which consists of manufacturers, suppliers, and customers [21]. Maintaining a competitive advantage and profitability for firms depends on effective three-tier supply chain management. Improved productivity, shortened delivery times, and cost reductions can result from close collaboration between the supplier, manufacturer, and the customer. Therefore, to ensure that it operates effectively and efficiently, PPAS must take the entire supply chain into account. The suppliers in this study furnish the initial raw materials required to make soap. Because they have a direct impact on the quality and availability of the materials used in production, suppliers play a crucial role in the supply chain. As a result, it's important to manage supplier relationships effectively and guarantee a steady supply of resources [31]. On the second level, producers create several varieties of soap using parallel production lines from raw ingredients. Production capacity, sequencing, process planning, and inventory level management are all included in PPAS. The objective is to streamline the production process to quickly satisfy demand points while lowering costs and reducing environmental impact [14]. At the end of the supply chain, demand points receive the manufactured soaps at the third level. The entire supply chain is influenced by customer demand, and manufacturers must meet those needs. In this study, the demand of distribution points depends on the price of the product. The demand for each product has its own potential in the market, and the demand changes depending on price values [1, 33]. In order to achieve the best possible usage of production capacity, prediction consumer demand is crucial to PPAS [13]. Among other issues that should be considered in PP is the shortage. Shortages in PP can significantly impact a company's ability to deliver products on time and meet customer demands [32]. Therefore, it is very important to consider shortages when developing production plans. In this regard, in this study, we tried to reduce the shortage to its minimum value in each period by considering a penalty for each shortage unit.

Therefore, in this study, to solve the problem of PP by considering price-dependent demand, an attempt has been made to answer the following questions:

- What is the optimal sequence of parts, and when will the production of each part start and when will it end?
- Each raw material is provided by which supplier and in what quantity?
- How much of each product should be produced to maximize the factory's profit?
- What is the optimal inventory level and shortage amount in each period?
- How much of each product will be sent to each demand point in each period?

- Considering the dependence on price demand, how much should the price of each product be determined to maximize the factory's profit?
- How many trucks should be used along the supply chain to minimize carbon emissions?

This study considers a three-level supply chain model to answer these questions. In the environment of engineering, procurement and manufacturing projects, suppliers are often qualified based on their annual turnover and some other indicators. As a result, a number of them are selected [30]. In the first level, raw materials are sent to the factory by trucks after selecting the suppliers. In the second level, the factory turns the raw materials sent by the suppliers into the final product. At this level, the operational sequence of the products, as well as each product's start and end time, is determined. Finally, in the third level, the final products produced by the factory will be sent to the demand points.

The structure of the rest of this research is as follows. The next section provides a literature review of the study. The problem description and the developed mathematical model are discussed in the third section. The problem-solving approach is described in the fourth section. The fifth section examines the numerical example. In order to test the effectiveness of the model in the real world, a case study has been conducted and presented in the sixth section. The results and sensitivity analysis of the model are done in the seventh section. In the eighth section, managerial insights to improve the organization's goals are expressed, and conclusions and suggestions for future research are also presented in the ninth section.

2. Literature review

In a manufacturing environment with several parallel production lines for the production of different types of products, the objective is to determine the optimal production schedule, *i.e.*, the production quantity and schedule for each product, to minimize the total cost of production, inventory holding, and changeover costs, and at the same time, meet customer demand. In this direction, Bergamini *et al.* [6] presented a mixed-integer linear programming (MILP) model for a system with multiple parallel production lines and limited batch splitting in the white goods sector. The model minimizes production, inventory, and setup costs while satisfying demand and capacity constraints. Bhosale and Pawar [7] introduced a mathematical model for optimizing PPAS in parallel production lines to minimize the total production cost while considering constraints such as limited capacity and processing times. They have developed a mixed integer programming model for production schedule optimization and scheduling for concurrent optimization. In addition, Kim and Glock [22] proposed a PP model for a two-stage system with parallel machines and variable production rates. They developed a mixed-integer programming model to minimize the total production and inventory cost. In this model, they considered a fixed production sequence, constant setup times, and machine-independent processing times. Yue *et al.* [38] proposed a model to minimize production costs and make span while considering the availability of materials. The approach involves developing a Pareto-based guided artificial bee colony algorithm to integrate lot sizing and scheduling decisions. Also, Özcan [26] introduced the task balancing and scheduling problem on parallel lines with sequence-dependent startup times (PALBPS) in a work, using a binary linear programming (BLP) model and simulated annealing (SA) approach.

In order to consider the uncertainty of demand, Han *et al.* [17] developed a fuzzy bi-level decision-making approach to optimize integrated PPAS under uncertainty. In this regard, a stochastic problem of size and timing with production demand uncertainty was studied by Hu and Hu [20]. In order to reduce system costs and choose the best production sequencing and resource allocation, a multistage stochastic programming model is created. Using the moment matching technique, scenario trees were used to depict demand uncertainty. Bhosale and Pawar [8] developed a MILP model that optimizes PPAS decisions for continuous parallel lines with demand uncertainty and different production capacities. The model assumes that the demand is uncertain and follows a normal distribution. Ardjmand *et al.* [4] also proposed a model to optimize PP and pricing decisions under demand uncertainty. The study aims to minimize the expected costs of production and inventory while accounting for the variability in demand and considering a worst-case scenario approach to robustness. In another study, Chand *et al.* [10] addressed the issue of PP for a business that uses several production lines with constrained capacity to manufacture a single product. To adapt to the shifting demands of the time, the company can change the number of lines running simultaneously and, accordingly, the production rate. Wang *et al.* [35] suggested an active strategy for the integrated problem of condition-based production and maintenance planning in an uncertain situation. Using a simulation-based multi-population genetic algorithm, the complex nonlinear model's solution was produced with stability and reliability.

The majority of existing studies on production synchronization assume that machines always work flawlessly in the production process. There is no doubt that equipment failure can lead to unexpected failures that may have an immeasurable impact on production synchronization. In this regard, Liu *et al.* [23] proposed an integrated model to maximize system availability as well as minimize maintenance and production costs for synchronized parallel machines. Also, Zhu [39] discussed about how maintenance is essential for operational effectiveness and safety in a production line. To address the issue of maintenance planning and scheduling for a parallel-series production line, an integrated model is suggested coordinating maintenance planning with PP. In the meantime, Bazargan-Lari *et al.* [5] presented a model aiming to maximize total benefit, safety stock index, and physical distance, which minimizes the total cost of production and the risk of virus transmission during the COVID-19 pandemic. They also considered machine utilization and production rate constraints. Furthermore, Alimian *et al.* [3] developed a rolling horizon method that integrates lot-sizing and scheduling decisions while considering sequence-dependent setup time/cost and preventive maintenance. This model assumes deterministic demand and production facilities with parallel lines.

The growing importance of green production, in line with the achievement of social responsibilities, made Cherian Jos *et al.* [11] interested in researching the issue of reducing energy consumption in the manufacturing industry by optimizing production schedules in several parallel machines. They proposed a model for scheduling jobs in parallel manufacturing units with varying speed levels to maximize efficiency while minimizing energy consumption and carbon emissions. They have considered the fixed numbers of machines and production rates, and their solution approach involves a MILP model and a genetic algorithm. Xiao *et al.* [36] also, suggested a solution for the parallel machine scheduling problem (PMSP) in green manufacturing by proposing a branch and bound approach to minimize time and power consumption. The authors assumed energy cost is related to the machine's working speed. Torkaman *et al.* [34] investigated another aspect of this issue. They introduced a model that optimizes PP with sequence-dependent setups in a closed-loop supply chain using a hybrid SA and genetic algorithm to minimize total production costs and meet environmental regulations.

This research introduces a novel framework for optimizing production planning and scheduling in parallel manufacturing lines, differentiating Itself significantly from prior studies in this field. Unlike many existing models, which often address production planning and scheduling as distinct entities, this study integrates these processes into a unified optimization approach. Previous studies typically treat production scheduling and planning as separate processes. The integrated approach in this research captures the interdependencies between scheduling and planning, offering a more cohesive solution that minimizes overall costs while effectively meeting demand. A notable advancement in this research is the dynamic relationship it establishes between product demand, pricing, and market potential. Unlike the static demand or fixed pricing assumptions, this study integrates these variables into the production planning process. This dynamic approach enables a more adaptable and responsive production strategy, enhancing profitability by aligning production schedules with fluctuating market conditions. This study highlights environmental considerations by seeking to reduce pollution while maximizing factory profits. This approach differs from earlier models that treated Environmental impacts and energy consumption separately. By integrating Environmental factors into the optimization model, the study reflects a modern manufacturing strategy that balances economic and ecological objectives. In summary, this research offers a comprehensive, integrated, and environmentally-conscious approach to production planning and scheduling, setting it apart from existing literature and contributing valuable insights to the field.

Briefly, the main contributions of this study are summarized as follows:

- Considering production planning and scheduling simultaneously in a manufacturing plant.
- Considering all types of supply chain costs including shortage and inventory holding costs etc.
- Relating product demand to product price and market potential.

– Paying attention to minimizing environmental pollution while maximizing the profit of the factory.

Figure 1 provides a brief overview of the research framework for this study.

3. Mathematical model

The purpose of the mathematical formulation presented in this paper is to maximize profit while also considering environmental impact within a three-level supply chain. As shown in Figure 2, at the first level of the supply chain, the problem involves selecting optimal suppliers based on their location and cost. After selecting the suppliers, raw materials are transported to the factory using trucks. In the second stage, the production process includes determining the optimal amount of each product for production based on factors such as product demand, production and maintenance costs, and the amount of carbon produced. This process takes into account the price of each product and other costs associated with production. Finally, in the third level, final products are sent to demand points.

At first, the assumptions of the proposed model will be examined, and then the notations of the mathematical model will be introduced.

3.1. Assumption

– The production of a product can begin after the processing of the previous product is completed.
– Interruption of operation is not allowed.
– The shortage is allowed and if we cannot satisfy all the existing demands in one period, we have to pay the penalty and the unanswered demand cannot be compensated in the next period.
– The time to start manufacturing a product must be greater than or equal to zero.
– The setup time depends on the sequence, and if the color of two consecutive products is the same, the color change time is zero. If the size of two consecutive products is the same, the resizing time is zero. And if the raw material of two consecutive products is the same, the time of material change will be zero.
– The amount of CO_2 emitted is the same for each product.

The assumptions of the proposed model offer a valuable analytical framework, but they might not capture the complexities of real-world production systems. Further refinements are essential to address operational disruptions, flexible scheduling, and varying environmental impacts for improved applicability.

3.2. Notation

Sets

$i \in \{1, 2, 3, \ldots, N\}$	Set of manufactured products
$l \in \{1, 2, 3, \ldots, L\}$	Set of production lines
$t \in \{1, 2, 3, \ldots, T\}$	Set of time slots
$j \in \{1, 2, 3, \ldots, J\}$	Set of raw material suppliers
$m \in \{1, 2, 3, \ldots, M\}$	Set of raw material type
$k \in \{1, 2, 3, \ldots, K\}$	Set of demand points

Parameters

D_{lt}	Duration of time slot t for production line l
R_{il}	Production rate of product i on production line l
Cap_l	Capacity of production line l
$D_{\text{change}_{il}}$	Duration of the change of product i on the production line l
$D_{\text{process}_{il}}$	Duration of the product i on production line l
C_{shortage_i}	Unit cost of product shortage i
$C_{\text{process}_{il}}$	Unit cost of processing product i on production line l
$C_{\text{mat}_{mj}}$	Unit cost of purchasing raw material type m which is procured from supplier j

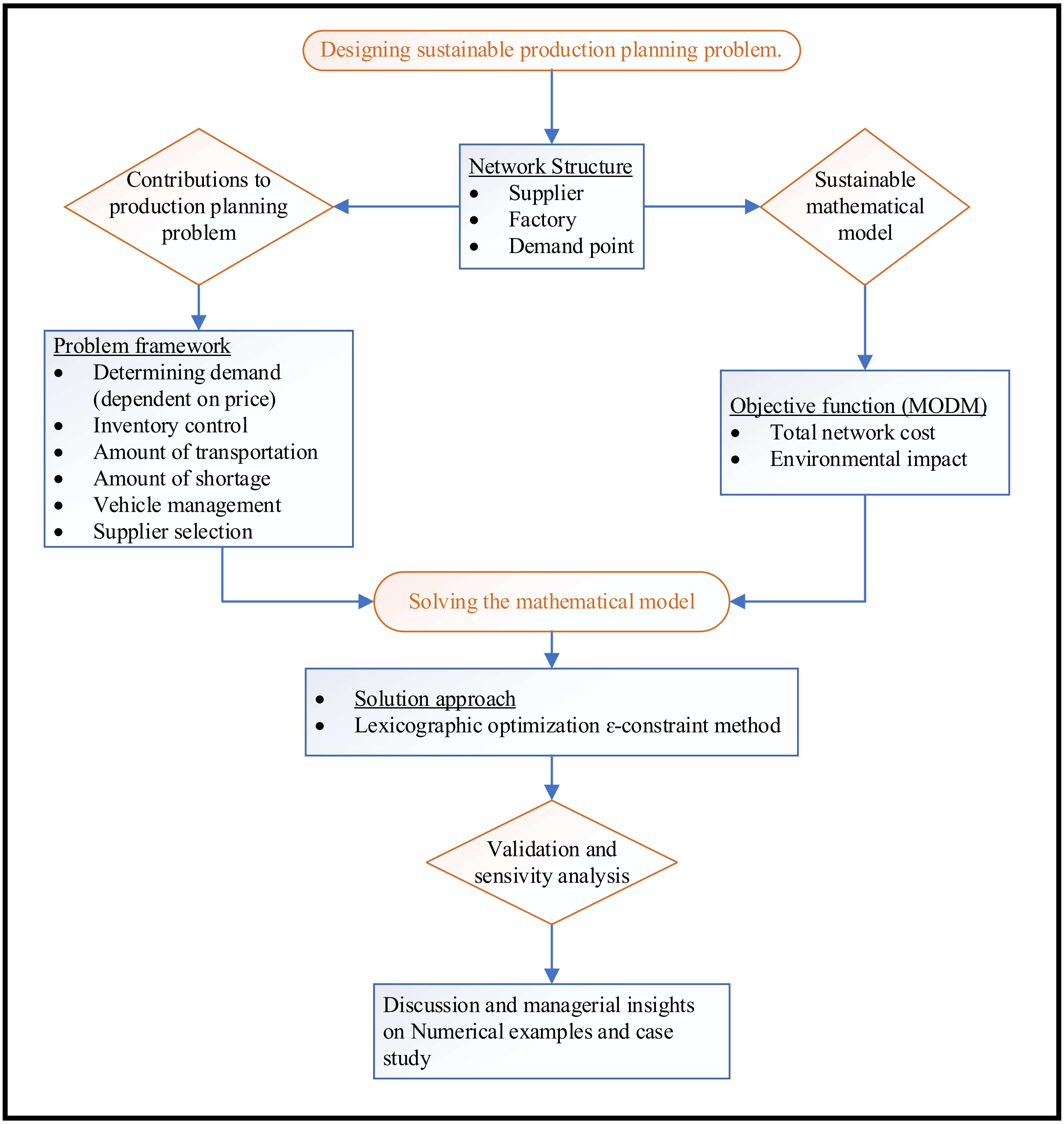

FIGURE 1. Research framework.

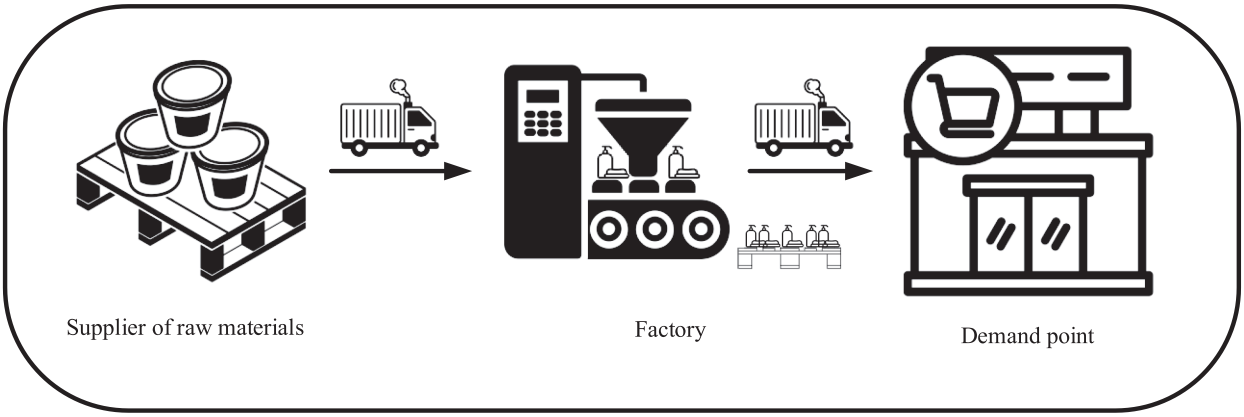

FIGURE 2. Three-level supply chain of cosmetic products.

$C_{\sup_j}$	Unit cost of contract with supplier j
$C_{\text{overhead}_{il}}$	Unit overhead cost of product i on the production line l
$C_{\text{change}_{il}}$	Unit cost of changing product i on production line l
C_{trans}	Unit cost of transportation
$C_{\text{inv}_{it}}$	Unit cost of maintaining product i inventory in period t
H_{mi}	Coefficient consumption of raw material type m in the production of product i
Dis_j	Distance of factory from the supplier j
Dis_k	Distance from factory to demand point k
Cap_{truck}	The capacity of each truck
$Cap_{\sup_{mj}}$	The capacity of supplier j to supply raw material type m
F	Amount of CO_2 emissions due to truck transport
E_i	CO_2 conversion factor produced per production of each product i
θ_i	Market potential for the product i
β_i	The coefficient of sensitivity product i to the price

Decision variables

Q_{ilt}	Number of production process of product i on line l in period t
Dem_{itk}	Demand for product i for point k in period t
W_{it}	Amount of product i produced in period t
I_{it}	Inventory level of product i in period t
TS_{ilt}	The start time of production of product i on line l in period t
TF_{ilt}	The finish time of production of product i on line l in period t
N_{jt}	The number of trucks needed to procure raw materials from supplier j to factory in period t
N_{kt}	The number of trucks needed to send products from factory to demand point k in period t
B_{itk}	Amount of shortage of product i for demand point k in period t
V_{itk}	Amount of product i sent to demand point k in period t
A_{mjt}	Amount of raw material type m procured from supplier j in period t
pr_i	The price of product i

Binary variables

X_{ilt}	1 If product i is produced on line l in period t, otherwise 0
U_{mj}	1 If raw material type m is procured from supplier j, otherwise 0

3.3. Objective functions

In many studies on the topic of production planning and scheduling, just creating a timetable and choosing the order in which to produce industrial goods has been studied in order to reduce the costs of the factory, with no focus on environmental concerns. Therefore, in this study, we looked at how to increase factory profits while reducing pollutants generated during product manufacture.

$$\begin{aligned}\max\ F_1 = {} & \sum_i \sum_k \sum_t (V_{itk} \times pr_i) - \Bigg(\sum_i \sum_l \sum_t Q_{ilt} (C_{\text{process}_{il}} + C_{\text{overhead}_{il}}) \\ & + \sum_m \sum_j \sum_t (A_{mjt} C_{\text{mat}_{mj}} + Dis_j C_{\text{trans}} N_{jt}) + \sum_k \sum_t (Dis_k C_{\text{trans}} N_{kt}) \\ & + \sum_i \sum_t (C_{\text{inv}_{it}} I_{it}) + \sum_i \sum_l \sum_t (C_{\text{change}_{il}} X_{ilt}) + \sum_i \sum_t (C_{\text{shortage}_i} B_{itk}) \\ & + \sum_m \sum_j (C_{\text{sup}_j} U_{mj}) \Bigg) \end{aligned} \tag{1}$$

$$\text{Min}\ F_2 = \sum_j \sum_t (Dis_j \times F \times N_{jt}) + \sum_i \sum_l \sum_t (Q_{ilt} \times E_i) + \sum_k \sum_t (Dis_k \times F \times N_{kt}). \tag{2}$$

As mentioned, the first objective function tries to maximize the final profit of the factory. Therefore, the total revenue obtained from different products was deducted from the total costs, consisting of production costs, overheads, supply and transportation of raw materials, inventory maintenance, cost of signing a contract with the supplier, costs related to sending the final product to the demand points, start-up costs, and also shortage costs, and tried in maximizing this value we have. The second objective function minimizes the total pollution produced during the transportation of raw materials or the delivery of final items to the demand points, as well as the pollution produced during production.

3.4. Constraints

$$\text{TS}_{ilt} = D_{\text{change}_{il}} \qquad \forall i = 1, \quad \forall l, t \tag{3}$$

$$\text{TS}_{ilt} = D_{\text{change}_{il}} + \text{TF}_{(i-1)lt} \qquad \forall i \geq 2, \quad \forall l, t \tag{4}$$

$$\text{TF}_{ilt} - \text{TS}_{ilt} = Q_{ilt} \times D_{\text{process}_{il}} \qquad \forall i, l, t \tag{5}$$

$$\text{TF}_{ilt} \leq D_{lt} \times X_{ilt} \qquad \forall i, l, t \tag{6}$$

$$\sum_i Q_{ilt} \times R_{il} \leq Cap_l \qquad \forall l, t \tag{7}$$

$$A_{mjt} \leq Cap_{\text{sup}_{mj}} \times U_{mj} \qquad \forall m, j, t \tag{8}$$

$$\sum_j A_{mjt} \times U_{mj} \geq \sum_l X_{ilt} \qquad \forall i, m, t \tag{9}$$

$$N_{jt} = \left[\frac{\sum_m A_{mjt}}{Cap_{\text{truck}}} \right] + 1 \qquad \forall j, t \tag{10}$$

$$N_{kt} = \left[\frac{\sum_i V_{itk}}{Cap_{\text{truck}}} \right] + 1 \qquad \forall k, t \tag{11}$$

$$W_{it} = \sum_l Q_{ilt} \times R_{il} \qquad \forall i, t \tag{12}$$

$$\sum_m H_{mi} \sum_j A_{mjt} \times U_{mj} \geq W_{it} \qquad \forall i,t \qquad (13)$$

$$B_{itk} = Dem_{itk} - V_{itk} \qquad \forall i,t,k \qquad (14)$$

$$I_{it} = W_{it} - \sum_k V_{itk} \qquad \forall t = 1, \quad \forall i \qquad (15)$$

$$I_{it} = I_{i(t-1)} + W_{it} - \sum_k V_{itk} \qquad \forall t \geq 2, \quad \forall i \qquad (16)$$

$$Dem_{itk} = \theta_i - (\beta_i \times pr_i) \qquad \forall i,t,k \qquad (17)$$

$$0 < pr_i \leq \frac{\theta_i}{\beta_i} \qquad \forall i \qquad (18)$$

$$\begin{cases} Q_{ilt}, W_{it}, I_{it}, \mathrm{TS}_{ilt}, \mathrm{TF}_{ilt}, N_{jt}, N_{kt}, B_{it}, V_{itk}, A_{mjt}, pr_i \geq 0 \\ X_{ilt}, U_{mj} \in \{0,1\} \end{cases} \qquad \forall i,m,j,l,t,k. \qquad (19)$$

Constraints (3) and (4) determine the start time of production of products according to the changing times of a product in each production line. Constraint (5) determines the end time of product production. Also, this equation guarantees that in case of not deciding to produce a product, its start and end times are equal. Also, since interruption is not allowed, a product can only be processed in a time slot if we have at least as much time to produce that product in that time slot. Constraint (6) will guarantee that these conditions are met. Constraint (7) guarantees that the production in a line will not exceed the capacity of that line. Constraint (8) is for choosing the supplier of each raw material according to each supplier's capacity. Constraint (9) causes raw materials to be sent to the factory in the required amount after selecting the supplier. Constraint (10) determines the number of vehicles needed to transport raw materials from suppliers to the factory, and constraint (11) determines the number of vehicles needed to transport the final product from the factory to the demand point. Constraint (12) determines the amount of product produced in a period by different production lines. Constraint (13) determines the amount of product produced in one period and on each line, considering the amount of raw material consumed in each product. The amount of shortage created in each period for each demand point is determined by constraint (14), and the remaining balance at the end of each period is determined by constraints (15) and (16). Constraints (17) and (18) establish a clear relationship between demand and product price. Specifically, if market potential remains constant, an increase in price will result in a corresponding decrease in demand, whereas a decrease in price will lead to an increase in demand for the products. This inverse relationship highlights the sensitivity of consumer purchasing behavior to price fluctuations. Furthermore, it is important to note that both demand and price are inherently positive parameters, as confirmed by equation (18). This assurance of positivity ensures that demand cannot fall below zero and that price cannot become negative, thereby reinforcing the validity of the model in representing real-world market dynamics. Overall, these constraints underscore the critical interplay between pricing strategies and consumer demand in the context of market analysis. Finally, constraint (19) defines the domains of decision variables.

Since constraints (9) and (13) are nonlinear, they must be linearized to solve the model as a mixed integer programming model. This can be obtained by replacing constraint (8) with the following set of equations.

$$\mathrm{TT} \leq A_{mjt} + M(1 - U_{mj}) \qquad \forall m,j,t \qquad (20)$$

$$\mathrm{TT} \geq A_{mjt} - M(1 - U_{mj}) \qquad \forall m,j,t \qquad (21)$$

$$\mathrm{TT} \leq M \times U_{mj} \qquad \forall m,j,t \qquad (22)$$

$$\mathrm{TT} \geq -M \times U_{mj} \qquad \forall m,j,t \qquad (23)$$

where TT is a positive variable that has replaced the multiplication of two other variables, namely A_{mjt} and U_{mj} and also M is a relatively large number. In the next section, a constraint solution method will be used to convert the proposed multi-objective model into a single-objective model.

4. Solution method

In this section, the proposed nonlinear model will be solved using an exact method. At first, the proposed model is solved by the GAMS software using the data presented in Section 5, and then the results obtained from it will be analyzed in Section 7. Also, in this research, a case study for the PPAS problem is presented in Section 6.

The proposed bi-objective model converts to a single-objective model with an upper ε boundary for the second objective function by the Lexicographic optimization ε-constraint method. The Lexicographic optimization ε-constraint method is a multi-objective optimization technique used to solve problems where multiple conflicting objectives need to be optimized simultaneously. In lexicographic optimization, objectives are prioritized in a specific order of importance. The most important objective is optimized first, followed by the next most important, and so on. After optimizing the highest priority objective, the other objectives are treated as constraints. Specifically, for each subsequent objective, a threshold (ε) is set to limit the acceptable values. This prevents the solution from being too far from the optimal value of the higher-priority objectives. With the help of this set of solutions, decision-makers can choose their approved answer from among the available answers [37]. This study used the lexicographic optimization ε-constraint method to convert the proposed multi-objective model into a single-objective model. In comparison to other multi-objective problem solving methods, this method has undeniable advantages [29].

Therefore, the objective function related to profit maximization in equation (1) is considered the primary objective function. Furthermore, the second objective function, which considers the environmental effects in equation (2), is modeled as a constraint with an upper ε boundary. In this way, the proposed multi-objective model will become the following single-objective model:

$$
\begin{aligned}
\max F_1 = {} & \sum_i \sum_k \sum_t (V_{itk} \times pr_i) - \Bigg(\sum_i \sum_l \sum_t Q_{ilt} (C_{\text{process}_{il}} + C_{\text{overhead}_{il}}) \\
& + \sum_m \sum_j \sum_t (A_{mjt} C_{\text{mat}_{mj}} + Dis_j C_{\text{trans}} N_{jt}) + \sum_k \sum_t (Dis_k C_{\text{trans}} N_{kt}) + \sum_i \sum_t (C_{\text{inv}_{it}} I_{it}) \\
& + \sum_i \sum_l \sum_t (C_{\text{change}_{il}} X_{ilt}) + \sum_i \sum_t (C_{\text{shortage}_\text{i}} B_{it}) + \sum_m \sum_j (C_{\text{sup}_j} U_{mj}) \Bigg)
\end{aligned} \tag{24}
$$

$$
\text{s.t.} \quad \sum_j \sum_t (Dis_j \times F \times N_{jt}) + \sum_i \sum_l \sum_t (Q_{ilt} \times E_i) + \sum_k \sum_t (Dis_k \times F \times N_{kt}) \le \varepsilon \tag{25}
$$

Constraints (3)–(19).

5. Numerical example

5.1. Computational experiment

This section will solve the proposed model in small dimensions with an exact method. For this purpose, it is assumed that two production lines in three-time slots will produce three final products. Each of these products requires four types of raw materials, which are sent to the final product manufacturing plant by one or more suppliers selected from the three available suppliers. Finally, the products produced in the factory are sent to three points that request the goods. In addition, two parameters $D_{\text{change}_{il}}$ and $D_{\text{process}_{il}}$, related to the duration of the change and the process, are considered non-deterministic. Some parameters of the investigated problem are shown in Tables 1–5.

This model is solved in GAMS software, version 25.1.3, using the BARON solver on a computer with a Core i7 processor and 8 GB of RAM.

TABLE 1. Parameters related to the amount of emitted CO_2.

Index	Value	Unit
F	0.08	Tkm
E_i	$[0.7 \quad 0.6 \quad 0.66]$	–

TABLE 2. Transportation parameters.

Index	Value	Unit
Cap_{truck}	15	Ton
Dis_j	$[25 \quad 45 \quad 33]$	Km

TABLE 3. Parameters related to the demand.

Index	Value	Unit
θ_i	$[1300 \quad 1350 \quad 1500]$	–
β_i	$[0.77 \quad 0.74 \quad 0.66]$	–

TABLE 4. Parameters related to the suppliers.

Index	Value	Unit
$Cap_{\text{sup}_{mj}}$	$\begin{bmatrix} 50 & 140 & 15 \\ 10 & 120 & 90 \\ 80 & 10 & 105 \\ 80 & 40 & 150 \end{bmatrix}$	Ton
C_{sup_j}	$[10 \quad 12 \quad 15]$	$
$C_{\text{mat}_{mj}}$	$\begin{bmatrix} 5 & 7 & 8 \\ 9 & 18 & 16.5 \\ 12 & 15 & 13 \\ 9 & 10 & 6 \end{bmatrix}$	$

TABLE 5. Parameters related to the production lines.

Index	Value	Unit
Cap_l	$[50 \quad 45]$	Ton
R_{il}	$\begin{bmatrix} 3 & 3 \\ 4 & 2 \\ 3 & 5 \end{bmatrix}$	–

TABLE 6. U_{mj}.

	j_1	j_2	j_3
m_1	1	0	0
m_2	1	0	0
m_3	1	0	0
m_4	1	0	1

TABLE 7. A_{mjt}.

	t_1	t_2	t_3
$m_1 \cdot j_1$	2.000	2.000	2.000
$m_1 \cdot j_2$	0.000	0.000	0.000
$m_1 \cdot j_3$	0.000	0.000	0.000
$m_2 \cdot j_1$	2.000	2.000	2.000
$m_2 \cdot j_2$	0.000	0.000	0.000
$m_2 \cdot j_3$	0.000	0.000	0.000
$m_3 \cdot j_1$	2.000	2.000	2.000
$m_3 \cdot j_2$	0.000	0.000	0.000
$m_3 \cdot j_3$	0.000	0.000	0.000
$m_4 \cdot j_1$	79.500	79.500	79.500
$m_4 \cdot j_2$	0.000	0.000	0.000
$m_4 \cdot j_3$	75.000	75.000	75.000

TABLE 8. pr_i.

i_1	1688.312
i_2	1809.459
i_3	2240.909

5.2. Examining the results and validity of the model

In this section, we will examine the results of the mathematical model presented in Section 3, considering the data provided in Section 4.

5.2.1. Results

This section is dedicated to analyzing the results obtained from the solution of the proposed model in the GAMS software in the small dimensions of the problem. After giving data to the problem's parameters according to the information in Section 4, we solved the proposed model using the software. The values of some decision variables are shown below in Tables 6–12.

The scheduling of products to go on each production line in periods 1, 2 and 3 is also shown in Figure 3. It is clear since the production tonnage of product 1 in all three time periods is equal to zero, so this product will not go on any of the two production lines of the factory in any period.

As mentioned in the modeling section, the proposed model consists of two objective functions. The first objective maximizes the factory's profit by using the difference between revenue and costs. The second objective also considers environmental issues. It is clear that these two objectives are in conflict with each other, and the increase in the factory's profit will cause an increase in pollutants. Therefore, the proposed mathematical model

TABLE 9. Number of trucks.

N_{jt}:			
	t_1	t_2	t_3
j_1	6.000	6.000	6.000
j_2	0.000	0.000	0.000
j_3	5.000	5.000	5.000
N_{kt}:			
k_1	3.000	3.000	3.000
k_2	3.000	2.000	3.000
k_3	3.000	3.000	3.000

TABLE 10. Q_{ilt}.

	t_1	t_2	t_3
$i_1 \cdot l_1$	0.000	0.000	0.000
$i_1 \cdot l_2$	0.000	0.000	0.000
$i_2 \cdot l_1$	8.000	8.000	8.000
$i_2 \cdot l_2$	0.000	0.000	0.000
$i_3 \cdot l_1$	6.000	6.000	6.000
$i_3 \cdot l_2$	9.000	9.000	9.000

TABLE 11. W_{it}.

	t_1	t_2	t_3
i_1	0.000	0.000	0.000
i_2	32.000	32.000	32.000
i_3	63.000	63.000	63.000

TABLE 12. Dem_{itk}.

	k_1	k_2	k_3
$i_1 \cdot t_1$	0.000	0.000	0.000
$i_1 \cdot t_2$	0.000	0.000	0.000
$i_1 \cdot t_3$	0.000	0.000	0.000
$i_2 \cdot t_1$	11.000	11.000	11.000
$i_2 \cdot t_2$	11.000	11.000	11.000
$i_2 \cdot t_3$	11.000	11.000	11.000
$i_3 \cdot t_1$	21.000	21.000	21.000
$i_3 \cdot t_2$	21.000	21.000	21.000
$i_3 \cdot t_3$	21.000	21.000	21.000

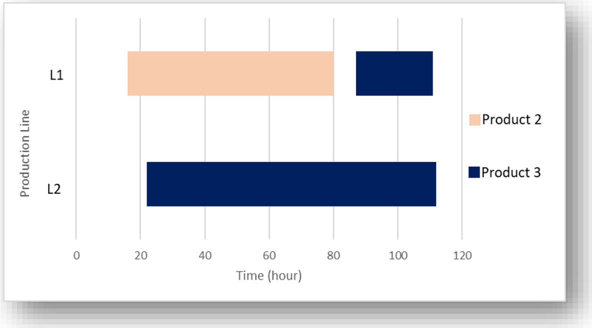

FIGURE 3. Gantt chart related to the scheduling of parts on production lines.

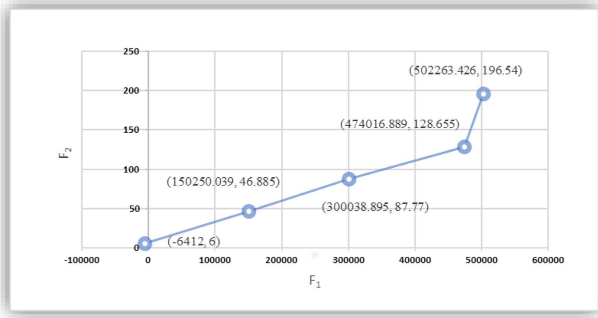

FIGURE 4. Pareto solutions diagram.

TABLE 13. Pareto solutions.

	ε_1	ε_2	ε_3	ε_4	ε_5
F_1	−6412.000	150 250.039	300 038.895	474 016.889	502 263.426
F_2	6	46.680	87.380	127.940	169.540

should show this conflict in objectives well. In the following, Table 13 shows the Pareto points of the objective functions. And also, the Pareto solutions diagram can be observed in Figure 4.

5.2.2. Model validation

In this section, we will validate the proposed model. To check the accuracy and validity of the proposed model and the reliability of the results obtained from the model, in this section, we will discuss some of the model parameters that we expect the effect of their increase and decrease on the relevant variables. For this purpose, the parameters related to supplier selection ($C_{\text{mat}_{mj}}, C_{\text{sup}_j}$, and Dis_j) at the same time, and the capacity of each supplier ($Cap_{\text{sup}_{mj}}$) will be subjected to validation. In the following, we will examine each of the mentioned items.

5.2.2.1. Change in $C_{\text{mat}_{mj}}, C_{\text{sup}_j}$, and Dis_j parameters. Table 10 shows the supplier (suppliers) that are selected to supply the raw materials. Since according to Table 4, in general, the costs related to supplier

TABLE 14. Evaluating the effect of the $C_{\mathrm{mat}_{mj}}$, C_{sup_j}, and Dis_j parameters.

Index	Value	Unit
$C_{\mathrm{mat}_{mj}}$	$\begin{bmatrix} 10 & 8 & 5 \\ 8 & 8 & 4 \\ 12 & 12 & 6 \\ 12 & 9 & 9 \end{bmatrix}$	\$
C_{sup_j}	$[20 \quad 15 \quad 10]$	\$
Dis_j	$[70 \quad 80 \quad 50]$	Km

TABLE 15. Decision variable U_{mj} in validation No. 5.2.1.

	j_1	j_2	j_3
m_1	10	0	1
m_2	0	0	1
m_3	0	0	1
m_4	0	0	1

TABLE 16. Evaluating the effect of the $Cap_{\mathrm{sup}_{mj}}$ parameter.

Index	Value	Unit
$Cap_{\mathrm{sup}_{mj}}$	$\begin{bmatrix} 0 & 140 & 15 \\ 10 & 0 & 90 \\ 80 & 10 & 0 \\ 80 & 40 & 150 \end{bmatrix}$	Ton

No. 1 are lower than the other two suppliers. Also, according to Table 2, the distance of this supplier to the factory is less than the others, so the proposed model is more inclined to choose this supplier for raw material procurement. Reveal the impact of the parameters influencing the selection of the suitable supplier, we reduced the cost of signing a contract with supplier No. 3, as well as the distance between the factory and this supplier, in addition to the cost of the relevant raw materials compared to other suppliers. The changes applied to these parameters are given below in Table 14.

After running the model in GAMS, using changes in Table 14, the values of U_{mj} parameter is shown in Table 15. It is clear that by reducing the parameters related to supplier number 3, this supplier will be chosen instead of supplier number 1.

According to Table 15, as expected, the proposed model chose supplier No. 3, and all raw materials were procured from this supplier. Therefore, the validity of the model is confirmed.

5.2.2.2. Change in $Cap_{\mathrm{sup}_{mj}}$ parameters. According to Table 4, all suppliers can send each raw material. However, this may not be the case in the real world, and some suppliers may not be able to supply certain raw materials. In such a situation, if the modeling of the problem is executed correctly, the decision variable for choosing suppliers for a supplier that does not have a particular type of raw material available should not take a value. To check the correctness of this issue, we set the $Cap_{\mathrm{sup}_{mj}}$ parameter as shown in Table 16.

Below is the value of the decision variable related to the selection of suppliers in Table 17.

TABLE 17. Decision variable U_{mj} in validation No. 5.2.2.

	j_1	j_2	j_3
m_1	0	0	1
m_2	1	0	0
m_3	1	0	0
m_4	1	0	1

TABLE 18. The percentage of raw material consumption in all types of soap (H_{mi}).

	Bath soap	Toilet soap	Baby soap
Palm kernel oil	0.138	0.292	0.098
Castor oil	0.155	0	0.033
Colophony	0	0	0.033
Phenol	0	0	0.543
Sodium hydroxide	0.259	0.125	0.076
Sodium silicate	0.172	0	0
Zinc oxide	0	0.486	0
Soapstone powder	0.172	0	0
Dye or color	0.009	0.007	0.108
Perfumes	0.009	0.007	0.011
Water	0.086	0.083	0.098

Considering that the relevant decision variable provides each raw material only by the appropriate supplier, this section also confirms the correctness of the proposed model.

6. Model implemented a case study

6.1. Case study description

As previously stated, controlling and minimizing production costs and other related expenses is crucial in any supply chain to increase profits. Additionally, it is essential to prioritize environmental health by minimizing greenhouse gas emissions and reducing environmental pollution. Therefore, this study investigates both issues. In this section, a case study is conducted to illustrate the model's performance in the real world. The data was collected from a soap factory located in an industrial town in Varamin, south of Tehran province. The factory produces three types of soap: bath soap, toilet soap (in sizes of 100 and 150 grams), and baby soap (100 grams). (Symbolized by i_1 to i_5) Each type of soap is made from different raw materials, and their names and quantities are shown in Table 18.

As seen in Figure 5, the raw materials required for soap production are supplied from four cities: Tehran, Isfahan, Ahvaz, and Arak. (Symbolized by j_1 to j_4)

After preparation and pre-production processes, the raw materials in the factory are mixed with specific sizes in a mixer and then poured into molds on five production lines. After cooling and sealing, they are sent to the packaging area and are ready to be shipped to demand points. The soap production process is briefly shown in Figure 6. During the production process and transportation of raw materials and final products by trucks, pollution and carbon gas are produced, which have also been measured.

Some important parameters are given in Tables 19–21, with most of the real data determined by subject experts, while the rest of the parameters are extracted from historical data. Table 19 displays the parameters associated with suppliers' capacity, the cost of contract conclusion with them, and the cost of purchasing raw

FIGURE 5. Map of the cities supplying raw materials.

materials. Table 20 presents the distance between the factory location and suppliers, as well as demand points. Additionally, Table 21 illustrates the production process time and the replacement time on production lines. It is important to note that these times are subject to uncertainty and may not be highly accurate.

After packaging and loading the final products onto trucks, they are sent to four demand points in Varamin and districts 10, 14, and 20 of Tehran and then distributed to retailers across the country. (Symbolized by k_1 to k_4) Figure 7 shows the set of demand points on the map.

6.2. Result of the case study

In this section, the results of solving the case study model using the parameters provided in the previous section are presented through the GAMS software. Table 22 identifies the specific raw materials purchased from each city, and the corresponding quantities of these materials are also displayed in Table 23.

Table 24 displays the prices of each produced product in Rials, and Table 25 presents the number of trucks required for transporting both raw materials and final products.

The amount of each product that should be produced in each period and on each line is determined in Tables 26 and 27. The amount of production of each product depends on the demand of that product, while the demand of each product also depends on its price. The demand values of the products are also given in Table 28.

As can be seen, there is a demand for products 1 and 3, which are 150 gram soaps. However, currently, the production of these products at their current price is not economical for the factory. Therefore, it is preferable to focus production on 100 gram soaps. To create variety in the size of the products, two options can be considered: either the price of the two mentioned products should be increased, or the factory can plan for the production of soaps with new sizes, such as 25 gram and 50 gram soaps.

TABLE 19. Parameters related to the suppliers.

Index	Value	Unit
$Cap_{\sup_{mj}}$	$\begin{bmatrix} 0 & 10000 & 100000 & 0 \\ 0 & 10000 & 100000 & 0 \\ 3000 & 5000 & 5000 & 10000 \\ 50000 & 50000 & 50000 & 50000 \\ 30000 & 60000 & 20000 & 30000 \\ 0 & 100000 & 20000 & 0 \\ 20000 & 70000 & 0 & 50000 \\ 0 & 50000 & 0 & 5000 \\ 5000 & 5000 & 5000 & 5000 \\ 5000 & 5000 & 5000 & 5000 \\ 100000 & 0 & 0 & 0 \end{bmatrix}$	Ton
$C_{\sup_j}$	$\begin{bmatrix} 140 & 120 & 113 & 133 \end{bmatrix}$	10^3 Rial
$C_{\mathrm{mat}_{mj}}$	$\begin{bmatrix} 0 & 50 & 40 & 0 \\ 0 & 70 & 60 & 0 \\ 40 & 40 & 55 & 40 \\ 68 & 59 & 20 & 55 \\ 350 & 150 & 200 & 350 \\ 0 & 55 & 65 & 0 \\ 380 & 260 & 0 & 420 \\ 0 & 18 & 0 & 31 \\ 150 & 120 & 100 & 315 \\ 160 & 245 & 20 & 39 \\ 0.06 & 0.06 & 0.06 & 0.06 \end{bmatrix}$	10^3 Rial

TABLE 20. Parameters related to the distances.

Index	Value	Unit
Dis_j	$\begin{bmatrix} 54 & 461 & 804 & 300 \end{bmatrix}$	Km
Dis_k	$\begin{bmatrix} 36 & 72 & 109 & 105 \end{bmatrix}$	Km

TABLE 21. Parameters related to the production times.

Index	Value	Unit
$D_{\mathrm{change}_{il}}$	$\begin{bmatrix} [45,47] & [45,47] & [44,46] & [46,49] & [46,49] \\ [30,31] & [30,31] & [29,31] & [31,33] & [31,33] \\ [42,44] & [42,44] & [41,43] & [43,46] & [43,46] \\ [38,39] & [37,39] & [37,39] & [39,41] & [39,41] \\ [33,35] & [33,35] & [32,34] & [34,36] & [34,36] \end{bmatrix}$	Minutes
$D_{\mathrm{process}_{il}}$	$\begin{bmatrix} [105,110] & [104,110] & [103,108] & [108,114] & [108,115] \\ [120,126] & [119,126] & [118,123] & [123,130] & [124,131] \\ [108,113] & [107,113] & [106,111] & [111,117] & [111,118] \\ [113,118] & [112,118] & [110,116] & [116,122] & [116,123] \\ [117,123] & [116,123] & [115,120] & [120,127] & [121,128] \end{bmatrix}$	Minutes

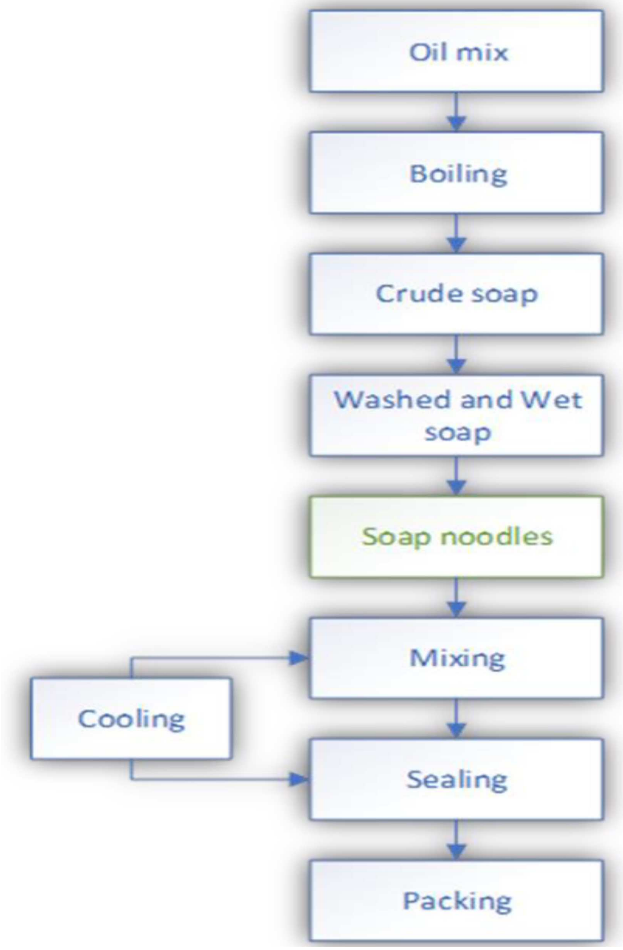

FIGURE 6. Soap production processes.

TABLE 22. The optimal value U_{mj} in case study.

	j_1	j_2	j_3	j_4
m_1	0	1	1	0
m_2	0	0	1	0
m_3	0	0	0	1
m_4	0	0	1	0
m_5	1	1	1	1
m_6	0	1	0	0
m_7	1	1	0	1
m_8	0	1	0	0
m_9	1	1	1	1
m_{10}	1	1	1	1
m_{11}	1	0	0	0

TABLE 23. The optimal value A_{mjt} in case study.

	t_1	t_2	t_3	t_4		t_1	t_2	t_3	t_4
$m_1 \cdot j_1$	0	0	0	0	$m_6 \cdot j_3$	0	0	0	0
$m_1 \cdot j_2$	10 000	10 000	10 000	10 000	$m_6 \cdot j_4$	0	0	0	0
$m_1 \cdot j_3$	100 000	100 000	100 000	100 000	$m_7 \cdot j_1$	20 000	20 000	20 000	20 000
$m_1 \cdot j_4$	0	0	0	0	$m_7 \cdot j_2$	70 000	70 000	70 000	70 000
$m_2 \cdot j_1$	0	0	0	0	$m_7 \cdot j_3$	0	0	0	0
$m_2 \cdot j_2$	0	0	0	0	$m_7 \cdot j_4$	50 000	50 000	50 000	50 000
$m_2 \cdot j_3$	5	5	5	5	$m_8 \cdot j_1$	0	0	0	0
$m_2 \cdot j_4$	0	0	0	0	$m_8 \cdot j_2$	5	5	5	5
$m_3 \cdot j_1$	0	0	0	0	$m_8 \cdot j_3$	0	0	0	0
$m_3 \cdot j_2$	0	0	0	0	$m_8 \cdot j_4$	0	0	0	0
$m_3 \cdot j_3$	0	0	0	0	$m_9 \cdot j_1$	5000	5000	5000	5000
$m_3 \cdot j_4$	5	5	5	5	$m_9 \cdot j_2$	5000	5000	5000	5000
$m_4 \cdot j_1$	0	0	0	0	$m_9 \cdot j_3$	4998	4998	4998	4998
$m_4 \cdot j_2$	0	0	0	0	$m_9 \cdot j_4$	5000	5000	5000	5000
$m_4 \cdot j_3$	5	5	5	5	$m_{10} \cdot j_1$	5000	5000	5000	5000
$m_4 \cdot j_4$	0	0	0	0	$m_{10} \cdot j_2$	5000	5000	5000	5000
$m_5 \cdot j_1$	30 000	30 000	30 000	30 000	$m_{10} \cdot j_3$	5000	5000	5000	5000
$m_5 \cdot j_2$	60 000	60 000	60 000	60 000	$m_{10} \cdot j_4$	5000	5000	5000	5000
$m_5 \cdot j_3$	20 000	20 000	20 000	20 000	$m_{11} \cdot j_1$	100 000	100 000	100 000	100 000
$m_5 \cdot j_4$	30 000	30 000	30 000	30 000	$m_{11} \cdot j_2$	0	0	0	0
$m_6 \cdot j_1$	0	0	0	0	$m_{11} \cdot j_3$	0	0	0	0
$m_6 \cdot j_2$	5	5	5	5	$m_{11} \cdot j_4$	0	0	0	0

TABLE 24. The optimal value pr_i in case study.

i_1	1 350 000
i_2	1 200 000
i_3	1 550 000
i_4	1 400 000
i_5	1 900 000

TABLE 25. The optimal value of number of trucks in case study.

N_{jt}:				
	t_1	t_2	t_3	t_4
j_1	9	9	9	9
j_2	8	8	8	8
j_3	7	7	7	7
j_4	5	5	5	5
N_{kt}:				
k_1	3	3	3	3
k_2	2	2	2	2
k_3	1	1	1	1
k_4	2	2	2	2

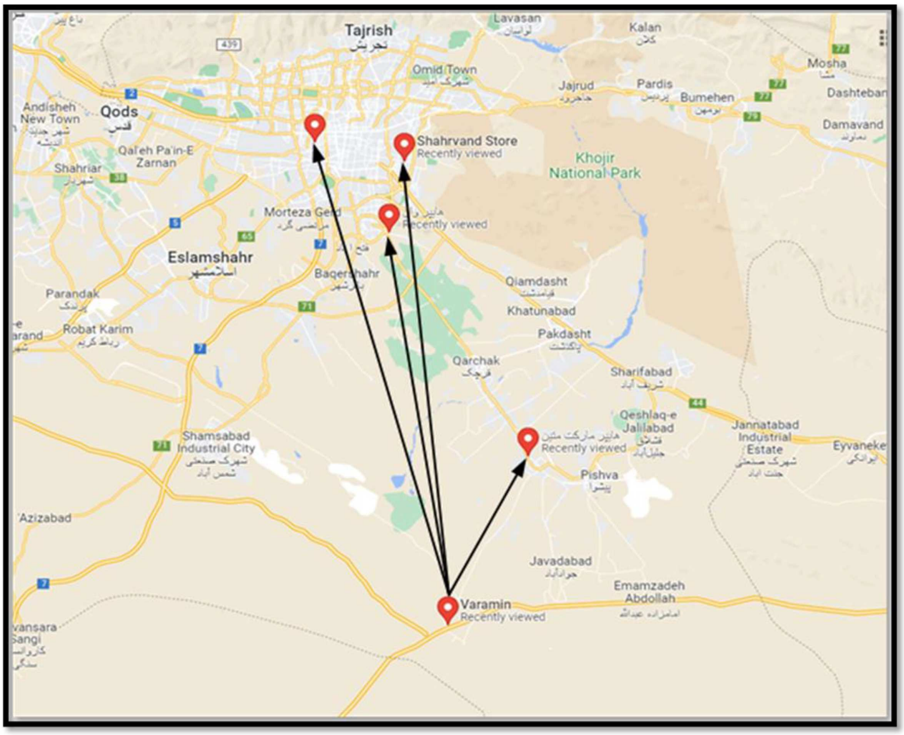

FIGURE 7. Map of demand points for final products.

TABLE 26. The optimal value Q_{ilt} in case study.

	t_1	t_2	t_3	t_4		t_1	t_2	t_3	t_4
$i_1 \cdot l_1$	0	0	0	0	$i_3 \cdot l_4$	0	0	0	0
$i_1 \cdot l_2$	0	0	0	0	$i_3 \cdot l_5$	0	0	0	0
$i_1 \cdot l_3$	0	0	0	0	$i_4 \cdot l_1$	100	100	100	100
$i_1 \cdot l_4$	0	0	0	0	$i_4 \cdot l_2$	100	100	100	100
$i_1 \cdot l_5$	0	0	0	0	$i_4 \cdot l_3$	100	100	100	100
$i_2 \cdot l_1$	0	0	0	0	$i_4 \cdot l_4$	29	29	29	29
$i_2 \cdot l_2$	0	0	0	0	$i_4 \cdot l_5$	100	100	100	100
$i_2 \cdot l_3$	3	3	3	3	$i_5 \cdot l_1$	3	3	3	3
$i_2 \cdot l_4$	0	0	0	0	$i_5 \cdot l_2$	3	3	3	3
$i_2 \cdot l_5$	0	0	0	0	$i_5 \cdot l_3$	0	0	0	0
$i_3 \cdot l_1$	0	0	0	0	$i_5 \cdot l_4$	3	3	3	3
$i_3 \cdot l_2$	0	0	0	0	$i_5 \cdot l_5$	3	3	3	3
$i_3 \cdot l_3$	0	0	0	0					

TABLE 27. The optimal value W_{il} in case study.

	t_1	t_2	t_3	t_4
i_1	0	0	0	0
i_2	924	924	924	924
i_3	0	0	0	0
i_4	126 268	126 268	126 268	126 268
i_5	3612	3612	3612	3612

TABLE 28. The optimal value Dem_{itk} in case study.

	k_1	k_2	k_3	k_4		k_1	k_2	k_3	k_4
$i_1 \cdot t_1$	33 000	33 000	33 000	33 000	$i_3 \cdot t_3$	37 000	37 000	37 000	37 000
$i_1 \cdot t_2$	33 000	33 000	33 000	33 000	$i_3 \cdot t_4$	37 000	37 000	37 000	37 000
$i_1 \cdot t_3$	33 000	33 000	33 000	33 000	$i_4 \cdot t_1$	37 000	37 000	37 000	37 000
$i_1 \cdot t_4$	33 000	33 000	33 000	33 000	$i_4 \cdot t_2$	37 000	37 000	37 000	37 000
$i_2 \cdot t_1$	33 000	33 000	33 000	33 000	$i_4 \cdot t_3$	37 000	37 000	37 000	37 000
$i_2 \cdot t_2$	33 000	33 000	33 000	33 000	$i_4 \cdot t_4$	37 000	37 000	37 000	37 000
$i_2 \cdot t_3$	33 000	33 000	33 000	33 000	$i_5 \cdot t_1$	38 500	38 500	38 500	38 500
$i_2 \cdot t_4$	33 000	33 000	33 000	33 000	$i_5 \cdot t_2$	38 500	38 500	38 500	38 500
$i_3 \cdot t_1$	37 000	37 000	37 000	37 000	$i_5 \cdot t_3$	38 500	38 500	38 500	38 500
$i_3 \cdot t_2$	37 000	37 000	37 000	37 000	$i_5 \cdot t_4$	38 500	38 500	38 500	38 500

TABLE 29. Sensitivity analysis on θ_i parameter.

Index	Value (Level 1)	Value (Level 2)	Unit
θ_i	[1820 1890 2100]	[2340 2430 2700]	–

7. SENSITIVE ANALYSIS

This section will help us to get a better understanding of the behavior of the proposed model in different conditions and ultimately help to improve the efficiency of the model.

For this purpose, we will perform sensitivity analysis in the following five sections.

7.1. Sensitivity analysis on θ_i parameter

Constraints (17) and (18) determine the effect of increasing or decreasing the market potential parameter on demand and product prices. In order to determine the effect of increasing or decreasing this parameter on the mentioned decision variables, we will perform a sensitivity analysis on this parameter in this section. Table 29 shows the new value of the θ_i parameter. This sensitivity analysis is done in two levels. In the first level, we have increased the value of this parameter by 40% and in the second level, by 80%.

By comparing Tables 16 and 12 with Table 30. We will notice that in both levels, the demand variable for product 1 is still zero; for product 2, the demand has decreased, and for product 3, we have seen an increase in demand. Also, we can see that the price has increased with the increase of θ_i.

In Table 31, we will examine the Pareto points of the objective functions at both levels of change.

According to Figure 8, the second objective function will not change as θ_i increases, but the first objective function will increase. So, in this figure, three graphs with the same increasing trend are drawn. However,

TABLE 30. Decision variable Dem_{itk} and pr_i in sensitivity analysis No. 7.1.

Dem_{itk}:						
	Level 1			Level 2		
	k_1	k_2	k_3	k_1	k_2	k_3
$i_1 \cdot t_1$	0.000	0.000	0.000	0.000	0.000	0.000
$i_1 \cdot t_2$	0.000	0.000	0.000	0.000	0.000	0.000
$i_1 \cdot t_3$	0.000	0.000	0.000	0.000	0.000	0.000
$i_2 \cdot t_1$	3.000	3.000	3.000	3.000	3.000	3.000
$i_2 \cdot t_2$	3.000	3.000	3.000	3.000	3.000	3.000
$i_2 \cdot t_3$	3.000	3.000	3.000	3.000	3.000	3.000
$i_3 \cdot t_1$	29.000	29.000	29.000	29.000	29.000	29.000
$i_3 \cdot t_2$	29.000	29.000	29.000	29.000	29.000	29.000
$i_3 \cdot t_3$	29.000	29.000	29.000	29.000	29.000	29.000
pr_i:						
		Level 1			Level 2	
i_1		2363.638			3038.961	
i_2		2550.000			3279.730	
i_3		3137.879			4046.970	

TABLE 31. The value of objective functions in sensitivity analysis No. 7.1.

Level 1:					
	ε_1	ε_2	ε_3	ε_4	ε_5
F_1	−6412.000	291 002.380	563 508.307	733 481.669	752 287.864
F_2	6.000	56.000	106.040	154.740	206.260
Level 2:					
F_1	−6412.000	385 003.082	744 679.946	971 146.112	1 007 074.104
F_2	6.000	56.000	106.040	154.740	206.260

before the increase of θ_i, it is observed that in the initial points, the second objective function has increased significantly by increasing a small amount of the first objective function. However, this increase in the second objective function will gradually decrease. As θ_i increases, this trend will be less slope. Therefore, for increasing a certain amount of the second objective function, the more θ_i increases, the first objective function will increase to a greater extent.

The root of this can be found in the increase in prices. In fact, with the increase in market potential, the demand for the product will increase, and the market will be more inclined toward an exclusive market. For this reason, the factory can increase the price of its products and thus get more profit from the sale of products. Therefore, the factory does not need to try to increase the profit by selling more products, but only by increasing the price the profit will also increase. At this time, since the factory's production will decrease, this issue will also help reduce CO_2 emissions, and the second objective function will also be improved. Therefore, an increase in θ_i will lead to the improvement of both objective functions.

7.2. Sensitivity analysis on β_i parameter

According to the analysis presented in Section 7.1, increasing the market potential of a product may lead to an increase in the price of that product. Additionally, this increase may result in an increase, decrease, or stability of demand. In this section, the parameter β_i is subjected to sensitivity analysis to observe the effect

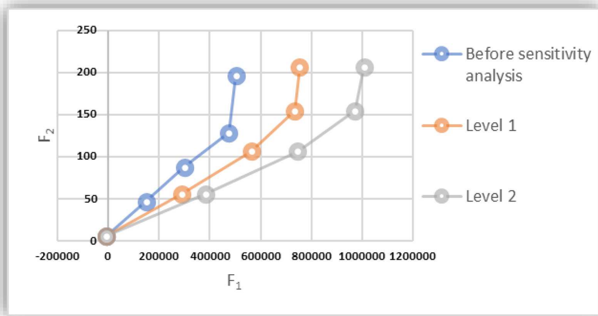

FIGURE 8. Pareto solutions diagram in sensitivity analysis No. 7.1.

TABLE 32. Sensitivity analysis on β_i parameter.

Index	Value (Level 1)	Value (Level 2)	Unit
β_i	[0.6545 0.629 0.561]	[0.385 0.370 0.330]	–

of this parameter on the decision variables and objective functions. Table 32 displays the new values of the β_i parameter. Similar to the previous sensitivity analysis, this analysis will be conducted on two levels. In the first level, this parameter will be reduced by 15%, and in the second level, it will be reduced by 50%.

As previously mentioned, the Dem_{itk} parameter can either be modified or remain constant. After running the model, it was observed that the value of this parameter remained constant for the first product, decreased for the second product, and increased for the third product. Furthermore, according to Tables 12, 16, and 22, in the first level, with a 15% decrease in the β_i parameter, the price of the products increases by approximately 18%. In the second level, when the β_i parameter is halved, the price of the products almost doubles. This increase in prices results in a higher profit for the factory, as indicated in Table 33.

In Table 34, the Pareto values of the objective functions using sensitivity analysis of parameter β_i are given in both levels.

According to Figure 9, reducing β_i causes the Pareto points of the objective functions to shift to the right. The optimal outcome resulting from this reduction occurs at level 2. In this instance, the first objective function saw a substantial increase, while the second objective function's increase was minor.

7.3. Sensitivity analysis on F parameter

Due to the importance of climate change and global warming, the amount of CO_2 emitted per transportation unit is one of the basic parameters in analyzing the results of the proposed model. In this section, we will conduct a sensitivity analysis of this parameter and its effect on the objective functions of the problem. This analysis will be done on two levels; We will add 80% in the first and 150% in the second levels to the F parameter values in Table 1. Table 35 shows the new values of this parameter in the two mentioned levels.

In Table 36, the Pareto values of the objective functions using sensitivity analysis of parameter F are given in both levels.

According to Figure 10, with the increase in CO_2 emissions, the second objective function will increase significantly, but the values of none of the decision variables will not change, and this will not increase the profitability of the factory and will only lead to more CO_2 production and create Environmental hazards will be.

TABLE 33. Decision variable Dem_{itk} and pr_i in sensitivity analysis No. 7.2.

Dem_{itk}:						
	Level 1			Level 2		
	k_1	k_2	k_3	k_1	k_2	k_3
$i_1 \cdot t_1$	0.000	0.000	0.000	0.000	0.000	0.000
$i_1 \cdot t_2$	0.000	0.000	0.000	0.000	0.000	0.000
$i_1 \cdot t_3$	0.000	0.000	0.000	0.000	0.000	0.000
$i_2 \cdot t_1$	7.000	7.000	7.000	3.000	3.000	3.000
$i_2 \cdot t_2$	7.000	7.000	7.000	3.000	3.000	3.000
$i_2 \cdot t_3$	7.000	7.000	7.000	3.000	3.000	3.000
$i_3 \cdot t_1$	25.000	25.000	25.000	29.000	29.000	29.000
$i_3 \cdot t_2$	25.000	25.000	25.000	29.000	29.000	29.000
$i_3 \cdot t_3$	25.000	25.000	25.000	29.000	29.000	29.000
pr_i:						
	Level 1			Level 2		
i_1	1986.249			3376.623		
i_2	2135.135			3640.541		
i_3	2629.234			4457.576		

TABLE 34. The value of objective functions in sensitivity analysis No. 7.2.

Level 1:					
	ε_1	ε_2	ε_3	ε_4	ε_5
F_1	−6412.000	211 023.214	412 353.132	588 948.690	608 248.148
F_2	6.000	51.440	96.780	142.020	187.900
Level 2:					
F_1	−6412.000	431 134.356	832 007.336	1 083 558.450	1 122 901.746
F_2	6.000	56.000	106.040	154.740	206.260

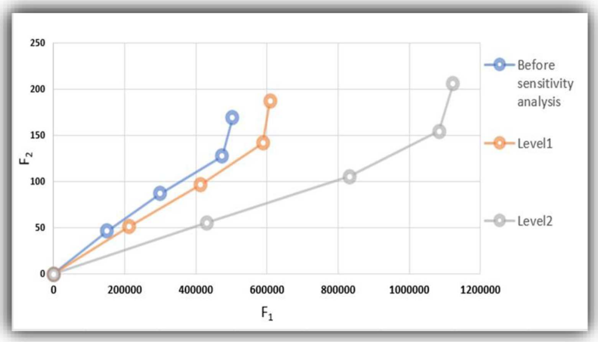

FIGURE 9. Pareto solutions diagram in sensitivity analysis No. 7.2.

TABLE 35. Decision variable F in sensitivity analysis No. 7.3.

Index	Value (Level 1)	Value (Level 2)	Units
F	0.144	0.2	Tkm

TABLE 36. The value of objective functions in sensitivity analysis No. 7.3.

Level 1:					
	ε_1	ε_2	ε_3	ε_4	ε_5
F_1	−6412.000	161 323.002	327 168.833	479 567.868	502 263.426
F_2	10.800	73.320	140.208	204.720	269.892
Level 2:					
F_1	−6412.000	173 763.032	342 808.560	483 253.995	502 263.426
F_2	15.000	100.640	186.320	271.160	357.700

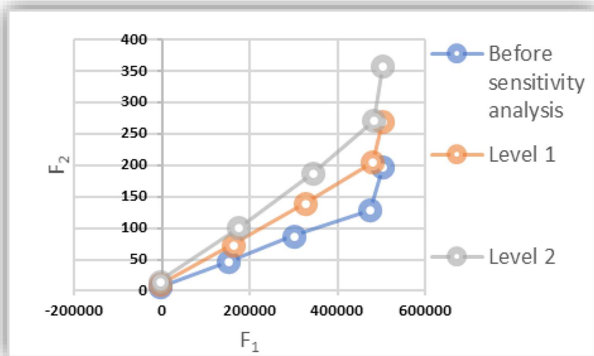

FIGURE 10. Pareto solutions diagram in sensitivity analysis No. 7.3.

7.4. Sensitivity analysis on R_{il} parameter

Figure 3 shows the scheduling of products on production lines. Besides that, this figure shows the non-production of product 1 and also the non-production of product 2 on production line number 2. It is important to mention that the depicted diagram is based on the production rate parameter (R_{il}) values listed in Table 5. In this sensitivity analysis, we intend to examine the effect of increasing the production rate on the relevant variables. In this regard, we will analyze this parameter in two levels; In the first level, we will increase the value of this parameter by 100%, and in the second level, by 150%. In bellow, Table 37 shows the changes applied to this parameter.

After running the model by applying the above changes, the new schedule will be as shown in Figures 11 and 12.

By comparing Figures 11 and 12 with Figure 2, it can be seen that increasing the production rate can lead to a reduction in the production time of products. Before doing this analysis, the production of products was completed in 112 h, but with the increase of R_{il} in the first level, this time decreased to 72 and in the second level to 59 h. Also, regarding the production of products and the workload of each station, before this analysis, product number 1 was not produced at all, and product number 2 was only produced in the first station, which

TABLE 37. Sensitivity analysis on R_{il} parameter.

Index	Value (Level 1)	Value (Level 2)	Unit
R_{il}	$\begin{bmatrix} 6 & 6 \\ 8 & 4 \\ 6 & 10 \end{bmatrix}$	$\begin{bmatrix} 7.5 & 7.5 \\ 10 & 5 \\ 7.5 & 12.5 \end{bmatrix}$	–

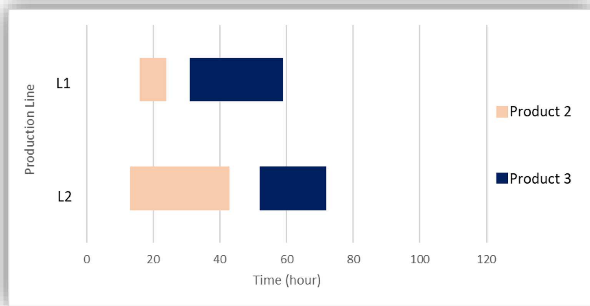

FIGURE 11. Gantt chart related to sensitivity analysis No. 4.2.2 Level 1.

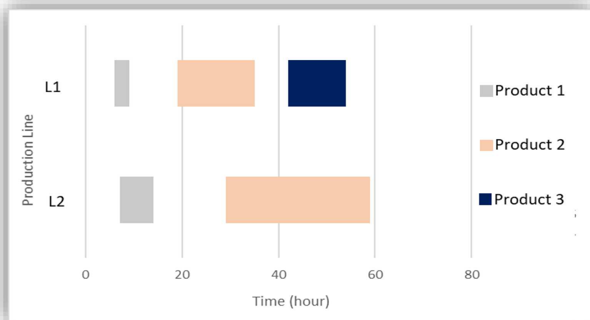

FIGURE 12. Gantt chart related to sensitivity analysis No. 4.2.2 Level 2.

caused the workload of this station to be more than the second station. In the first level of this analysis, we will see that product number 2 is produced in both stations and thus, the workload of the first station has decreased compared to the second station. In the second level of this analysis, in addition to the fact that product number 2 is produced in both lines, the production of product number 1 is also possible, and this product is produced in both lines. A relatively balanced workload also occurs in this mode.

In Table 38, the Pareto values of the objective functions using sensitivity analysis of parameter R_{il} given in both levels.

As seen in Figure 13, the second objective function will change significantly with the increase of the production rate parameter. The increase of this parameter will lead to a decrease in the decision variable Q, and a specific quantity of products will be produced in fewer production processes. In this way, it will affect the second objective function.

TABLE 38. The value of objective functions in sensitivity analysis No. 7.4.

	ε_1	ε_2	ε_3	ε_4	ε_5
Level 1:					
F_1	−6412.000	160 098.006	322 011.230	476 277.025	496 112.199
F_2	6.000	41.360	76.660	112.420	148.500
Level 2:					
F_1	−6412.000	152 263.681	325 464.274	475 888.882	497 075.074
F_2	6.000	39.280	73.380	106.500	141.2580

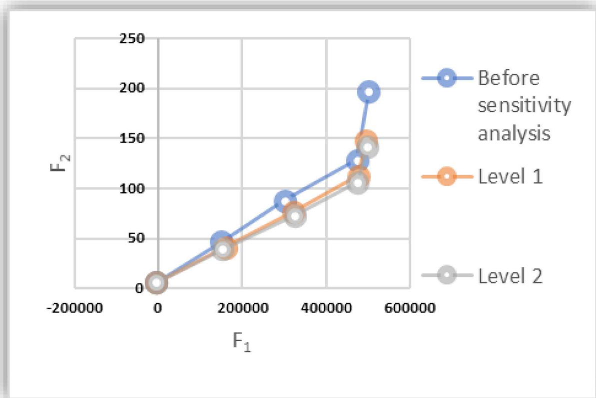

FIGURE 13. Pareto solutions diagram in sensitivity analysis No. 7.4.

TABLE 39. Sensitivity analysis on Cap_l parameter.

Index	Value (Level 1)	Value (Level 2)	Unit
Cap_l	[50 10]	[0 45]	Ton

7.5. Sensitivity analysis on Cap_l parameter

Each production line has a specific capacity, which is shown in Table 5 of these values. In this section, we will analyze the sensitivity of the capacity of production lines to see the effect of this parameter on the amount of production, demand and objective functions. In this regard, we will analyze this parameter on two levels. In the first level, the capacity of production line 1 was constant, but the capacity of production line 2 was significantly reduced, and in the second level, the capacity of production line 2 was unchanged compared to the initial state, but we disrupted production line 1 and considered its capacity to be zero. Table 39 shows the new values of this parameter.

Table 40 shows the demand values of products after changes in the capacity of production lines.

In the proposed model, demand is not one of the parameters of the problem and the model determines the optimal value. By comparing Tables 16 and 29, it can be seen that the reduction in the capacity of production lines leads to a reduction in the production of products. Also, since the shortage cost is considered in this model, it is reasonable for the model to reduce the demand values to deal with the shortage.

TABLE 40. Decision variable Dem_{itk} in sensitivity analysis No. 7.5.

Dem_{itk}:						
	Level 1			Level 2		
	k_1	k_2	k_3	k_1	k_2	k_3
$i_1 \cdot t_1$	1.000	1.000	1.000	0.000	0.000	0.000
$i_1 \cdot t_2$	1.000	1.000	1.000	0.000	0.000	0.000
$i_1 \cdot t_3$	1.000	1.000	1.000	0.000	0.000	0.000
$i_2 \cdot t_1$	6.000	6.000	6.000	0.000	0.000	0.000
$i_2 \cdot t_2$	6.000	6.000	6.000	0.000	0.000	0.000
$i_2 \cdot t_3$	6.000	6.000	6.000	0.000	0.000	0.000
$i_3 \cdot t_1$	13.000	13.000	13.000	15.000	15.000	15.000
$i_3 \cdot t_2$	13.000	13.000	13.000	15.000	15.000	15.000
$i_3 \cdot t_3$	13.000	13.000	13.000	15.000	15.000	15.000

TABLE 41. The value of objective functions in sensitivity analysis No. 7.5.

Level 1:					
	ε_1	ε_2	ε_3	ε_4	ε_5
F_1	−6412.000	91 074.096	220 259.479	292 858.119	320 541.838
F_2	6.000	33.420	61.460	90.540	119.400
Level 2:					
F_1	−6412.000	45 754.563	132 718.794	220 769.271	244 065.500
F_2	6.000	26.180	45.960	66.840	87.180

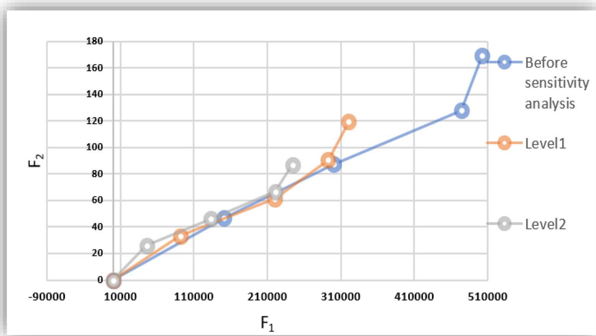

FIGURE 14. Pareto solutions diagram in sensitivity analysis No. 7.5.

In Table 41 the Pareto values of the objective functions using sensitivity analysis of parameter Cap_l given in both levels.

As can be seen in the table above and Figure 14, with the reduction of the capacity of the production lines and as a result of the reduction of production and demand, the first objective function decreases significantly, which is obvious considering that the prices of the products did not change much. As a result of production reduction, the second objective function is also affected and becomes less.

8. Discussion and managerial insights

This paper presents a novel model in the PPAS context, which differs from other related works. Previous studies, such as Bhosale and Pawar [8] and Bergamini *et al.* [6], have only focused on the constraints and internal issues of a production network. In contrast, the developed model in this paper includes more details that make it more useful for decision-makers by integrating decision analysis of production and inventory planning. The proposed model considers the limitations of a three-level supply chain in the field of production and determines the suggested price of each product to maximize the group's profit. Furthermore, the study takes into account environmental aspects to reduce pollution and covers some aspects that were omitted in previous articles.

Market potential refers to the willingness of consumers to receive a product if it is offered for free, and price sensitivity reflects how changes in the price of a product affect its supply or demand. According to Tables 3, 19, and 20, both objective functions increase with market potential. When demand increases, Figure 7 suggests that management should raise prices to maximize profit and achieve maximum profit at a lower production level without increasing pollution. The proposed model provides better Pareto solutions for management to select the most favorable solution based on them as demand increases. Thus, during the spring and summer seasons when the parameter θ_i is higher and the market has greater potential for the product, the factory's profitability is guaranteed through the first objective function. During the fall and winter seasons when this parameter is lower, and pollution is higher, the second objective function can be improved. If demand comes from an area where the parameter β_i is lower, according to Table 34, factory profits will increase. Conversely, if demand comes from an area where this parameter is higher, factory profits will decrease at the price level. To address this issue, the factory could design luxury products for the first area and offer lower-priced products for the second area to increase profits in both regions. According to Figure 9, if carbon emissions increase, pollution increases, but the profit does not change significantly. In this situation, management can increase the number of customers to boost profits by moving the Pareto chart to the right. Additionally, Figure 12 suggests that management can shift the Pareto diagram to the right by increasing the production rate or expanding production line capacity in response to increasing carbon emissions seen in Figure 9.

9. Conclusion and future study

In any manufacturing industry, PPAS rank among the most critical concerns for a factory. During the planning phase, it involves determining the quantity of raw materials to purchase from various suppliers, the optimal production volume for each product in each period to maximize profits, and the prioritization of meeting the demand for specific products. This article introduces a bi-objective optimization model that was developed for a comprehensive three-level supply chain, encompassing suppliers, factory, and demand points. The model takes into account all supply chain costs, including purchasing and transportation of raw materials, supplier contract expenses, production process costs, product maintenance expenses, overhead costs, manpower expenses, and penalties for shortages. Among the innovative aspects discussed in this article are the considerations for environmental issues and the reduction of greenhouse gas emissions resulting from the production and transportation of goods. Furthermore, the model explores the influence of product prices on consumer demand. To evaluate the model's effectiveness, a case study of a soap factory located in the southern region of Tehran province was conducted. By performing sensitivity analyses on various parameters, valuable management insights and results were obtained. It is essential to note that this study only considers one manufacturing plant at the second level of the supply chain. Future research endeavors could involve multiple manufacturing centers and incorporate location-based problem-solving to identify the most suitable locations for future factory construction, thus bringing the model closer to practical application. Additionally, at the final level of the supply chain, the article suggests examining two types of retail, namely traditional and online, along with demand queues for each retail store and production center. By studying the inventory-queue model on each floor, the proposed model can be made even more practical [2]. The article assumes uninterrupted production lines, but it acknowledges the possibility of disruptions due to equipment failures or other reasons, resulting in reduced production speeds. Consequently, exploring potential factory disturbances and uncertainties at different levels could be an intriguing avenue for future research.

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