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Toward sustainability in designing an agricultural supply chain network: A case study on palm date

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Abstract. Nowadays, the agricultural and food supply chains have attracted both academia and industrial practitioners. This paper first considers the characteristics of the date product as one of the most well-known and rich fruits to design and address its supply chain design. Special characteristics in date products have made the supply chain design to be unique. Therefore, considering different customers along with the specific product flow is another contribution of this paper. Reportedly, there is no work on this topic. Several old and recent meta-heuristic algorithms are utilized in multi-objective meta-heuristics to reach better intensification and diversification trade-offs. By the Taguchi design experiment method, appropriate parameter values of the proposed algorithms are chosen. Besides, the solution quality is investigated by approaches including the Relative Percentage Deviation (RPD), CPU time, and weighted LP-metric method. The results showed that a Multi-Objective Keshtel Algorithm (MOKA) is more efficient and consistently outperforms other utilized algorithms.

1. Introduction

Recent developments in the Supply Chain Network Design (SCND) have led many companies and their users in public and private sectors to implement its settings in their industries to achieve the most added values out of a specific type of product. While many of them utilized the SCND to address their company's mission and vision, others tried to consider designing networks according to reducing costs, considering sustainability aspects, covering the ignored parts of different products, servicing customers, and enhancing the overall efficiency chains [1]. In this regard, companies avert their attention toward sustainable design. Agricultural products are among the most important products in production for society and addressing the potential market demand. However, far less attention

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has been devoted to designing an effective network for such products.

Previous studies only suggest minor contributions for these types of products, and hence the utilized supply chain networks often failed to introduce an efficient network for them. In addition, considering sustainability is mainly ignored, and therefore the proposed supply chain network could not find its optimized efficiency. van Berlo [2] presented a supply chain operations of vegetable processing. Their model incorporates farmer decisions to reduce supply chain costs and lacks location decisions. Jolayemi [3] considered a specific planting period and location of agricultural products to maximize profit. The model selects the most profitable product among a large number of products. In addition, the author tried to determine the amount of increase or decrease in profit from co-cultivation of any number of crops compared to their cultivation.

Allen and Schuster [4] reduced the amount of waste in agricultural production and focused on harvesting and storage capacities. Rantala [5] developed a model for seedlings and transportation and considered capacity constraints and product perishability, in addition to minimizing the costs and meeting customer demands. Designing a pea-based protein food SC network was considered by Apaiah and Hendrix [6]. The authors presented a supply chain model to reduce the costs considering chain equilibrium constraints, the capacity of each plant, and the different modes of transport.

Ferrer et al. [7] proposed a model for harvesting, transporting, and packaging crops. Manzini and Gebennini [8] designed a real-world model by adding time delay constraints at different distribution stages. In addition, by adding these constraints. Ahumada and Villalobos [9] and Ahumada et al. [10] planned to grow tomatoes and red peppers in the state of Sinaloa (northeastern Mexico) on farms with different locations, with employment constraints, holding and harvesting criteria, as well as water consumption. The proposed model evaluates these factors in two definite and uncertain conditions. Navazi et al. [11] designed a Closed-Loop Supply Chain (CLSC) for perishable products concerning recycling level in the reverse flow. The results of the problem showed enhancement in the environmental effect of waste reduction. Hajikhani et al. [12] designed a new plan to select the best supplier within a real agricultural case study. Using multi-objective functions, the results of using multiple metaheuristic algorithms revealed that the proposed algorithm applies to real-world problems. Kazemi et al. [13] designed an agricultural supply chain for rice products. Two objectives are presented to reduce total costs and also reduce soil erosion. Considering various scenarios, the results of the study showed improvements to the considered objectives.

Ahumada and Villalobos [14] worked quality and price of products based on the value of products, labor costs, and transportation modes. They developed an Mixed-Integer Programming (MIP) model in a limited time (several weeks). The most important feature of their problem is to consider several farms in specific places. In this model, the quality of the product decreases during the shipping and delay stages. This model aims to maximize the farmer's income according to the quality of the products. In their model, the type and time range of cultivation is specified. Rong et al. [15] provided an optimization model about perishable products and focused mainly on maintaining the quality of products. In this model, the quality of agricultural products is reduced according to the temperature and storage time at each stage and product transfer conditions. This paper is to minimize overall SC costs while maintaining acceptable product quality. Teimoury et al. [16] considered the same chain in this area and probed the effect of supply, demand, and price.

Few studies have been conducted to address the reverse logistics issues of fresh fruits. Ahumada and Villalobos [17] worked on the perishability of agricultural products and vegetables as one of the first studies. Later, a mathematical model was presented for the same chain by Soto-Silva et al. [18] to optimize fruit freshness. A transportation planning model was provided to set some storage in the non-harvest season by Nadal-Roig and Plà-Aragonés [19]. Etemadnia et al. [20] also found the optimal locations of the wholesale facilities for the same chain.

Several works in this area have focused on multi-objective optimization approaches, aiming to make a trade-off between several conflicting goals [21]. For instance, Sarker and Ray [22] utilized the Epsilon-constraint and multi-objective optimization algorithms to address their multi-objective optimization model. Besides, most of the papers in this area mainly focused on price and demand. Paksoy et al. [23] minimized carbon dioxide emissions in forward logistics and supply chain costs in reverse logistics.

Recently, such concepts have been replaced by sustainability in this supply chain. Dehghanian and Mansour [24] measured responsibilities to examine social effects and the profit objective function to examine economic effects.

Recently, waste recovery and management were among the main suppositions in this area [25]. By considering reverse logistics, we consider all activities from the end to the beginning of a chain to re-use and reproduce that product or its variations [26]. Using reverse logistics can have more and better competitive advantages [27]. Also, a few works consider waste to design closed-loop chains in the literature [28].

Banasik et al. [29] firstly considered industrial mushrooms and developed a CLSC by the MILP, considering the economic and environmental aspects. Cheraghalipour et al. [30] considered citrus in their CLSC to minimize costs and maximize customer demand in both flows.

Supply chain responsiveness is also one of the key factors in such chains [31]. By growing population, day to day, researchers and the corresponding organizations know the importance of designing such chains in an optimized fashion better. According to Food and Agriculture Organization (FAO) in 2020, about 30% of global food production would be wasted. Consequently, the production resources waste, such as fuels, water, fertilizers matter, and cause negative effects [32]. In a nutshell, environmental aspects, strict regulations on waste, reverse logistics, and CLSC design are the major concerns in designing supply chain networks in this area. However, the only limited study addressed such issues for fruit and agricultural products. Jabarzadeh et al. [33] utilized concepts of reverse logistics for fruit supply chains. In their model, they minimized both costs and carbon dioxide emissions. Recently, Salehi-Amiri et al. [34] designed a CLSC network to minimize the total flow cost in both directions. They firstly considered walnut characteristics to model their network. Chouhan et al. [35] designed a multi-echelon sugarcane CLSC network. They addressed the model by recent metaheuristic algorithms.

One of the main products using its fruit and sub-products with high value in the nutrition pyramid is the date [36]. Date palm tree includes various sub-products, including date honey and date pedicles. In addition, various markets can use the date for their direct and indirect use [37]. In its direct use, the date is usually sent to the packaging center and then for general markets, which most of this product usage [38]. Indirect usage includes the processing date, seedling, pedicles, leaves, etc., to use in other markets such as the medical sector, animal food, etc. [39]. However, considering these settings for date palm trees as by-products has not been conducted before. Therefore, the remainder of this valuable product that can be re-used in the reverse flow is usually ignored. Considering the sustainability of the date palm tree can significantly increase its added value. Figure 1 shows the stance date among all dried fruit production worldwide.

Therefore, in this study, the application of sustainable logistics for date products is taken into account. In this chain, the date and its sub-products are sent to various markets. Date products would send to different markets in the forward flow. Also, an environmental factor of such a program is taken into account. Two objective functions of costs and air pollution are applied for simultaneous economic and environmental consideration of the problem. A set of new multi-objective metaheuristic algorithms are utilized in this work.

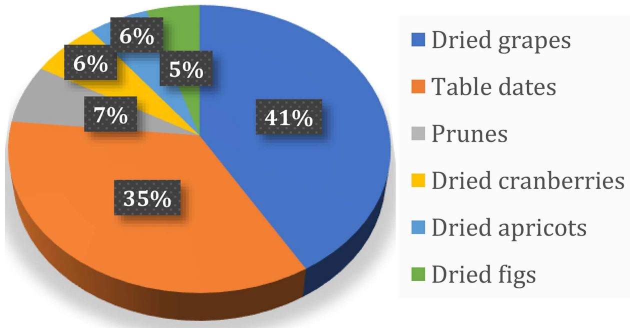

Figure 1. Production of different dried fruits in 2019 and 2020 (in 1,000 metric tons).

As a result, the following are our primary goals and contributions in the literature:

- Reportedly, no same work exists on the issue above in this area, using palm date to design a sustainable network;
- In addition, the current study created unique mathematical modeling based on its characteristics, while the majority of prior studies indicated similar logistic networks;
- Due to its unique network, this study provides a new MILP model from a mathematical standpoint;
- To address the model, a new metaheuristic and hybrid technique are used.

The following sections are sorted as explained below. Section 2 entails the problem definition and shows the structure of the proposed SCND for the date industry. Section 3 details the solution approach, including the Taguchi method, various proposed multi-objective metaheuristic algorithms, and exemplified parameter tuning. The results and their analyses are explained in Section 4, and Section 5 entails the conclusions and managerial insight.

2. Problem definition

This study is an optimization modeling for a forward date supply chain network, which embraces date palms, collection and distribution centers (DCs), date factories, customers, and by-product factories. As shown in Figure 2, the date product is collected from farmlands in the first level of the network. In the proposed network, the single-period chain is assumed. So, date product flow to collection and DC continues. After that, a percentage of products ships to date factories and market. Lastly, Waste date products are also gathered and transported to by-product factories.

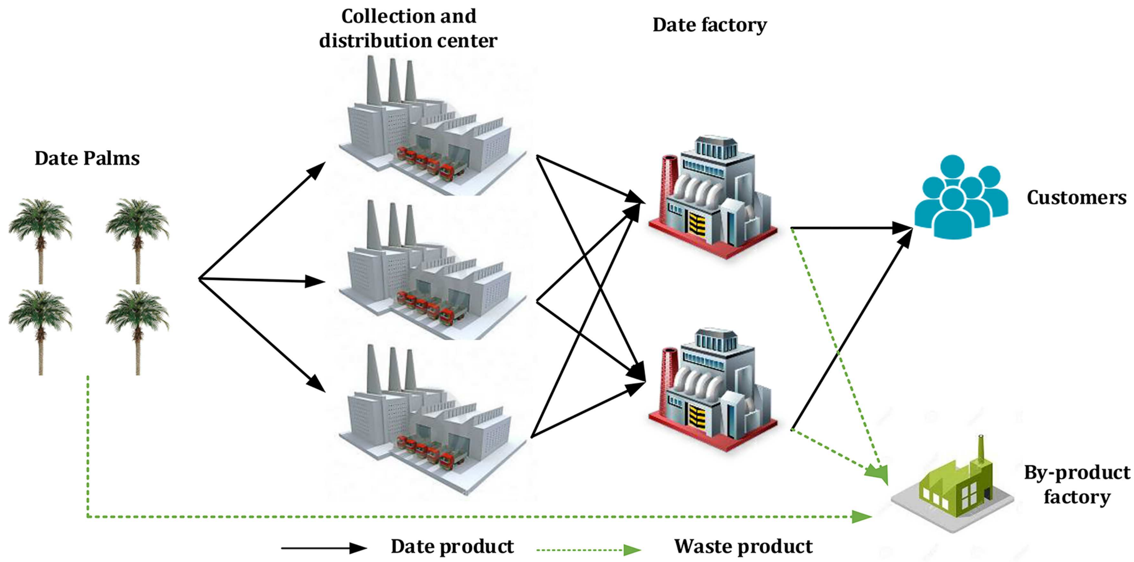

Figure 2. Proposed date supply chain network.

2.1. Proposed model

Here, we aim to develop our model based on the assumptions mentioned above. The notations of the presented model are shown in Table 1.

The details of the MILP model are as follows:

$$\text{Min } Z_1 = \sum_{i=1}^{I} f_i U_i + \sum_{k=1}^{K} f_k W_k + \sum_{m=1}^{M} f_m B_m + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij} X_{ij} + \sum_{j=1}^{J}\sum_{k=1}^{K} C_{jk} G_{jk} + \sum_{k=1}^{K}\sum_{l=1}^{L} C_{kl} S_{kl} + \sum_{k=1}^{K}\sum_{m=1}^{M} C_{km} E_{km} + \sum_{i=1}^{I}\sum_{n=1}^{N} C_{im} R_{im}, \tag{1}$$

$$\text{Min Z}_2 = \left(\sum_{i=1}^{I} U_i + \sum_{k=1}^{K} f_k + \sum_{m=1}^{M} f_m\right) \times EM, \tag{2}$$

s.t.:

$$(1 - v_i) \times \xi_i \times U_i = \sum_{j=1}^{J} X_{ij} \qquad \forall i \in I, \tag{3}$$

$$\sum_{j=1}^{J} Y_j \geq 1, \tag{4}$$

$$\sum_{i=1}^{I} X_{ij} \leq \xi_j \qquad \forall j \in J, \tag{5}$$

$$\sum_{k=1}^{K} G_{jk} \leq \sum_{i=1}^{I} X_{ij} \qquad \forall j \in J, \tag{6}$$

$$\sum_{k=1}^{K} W_k \geq 1, \tag{7}$$

$$\sum_{j=1}^{J} G_{jk} \leq \xi_k \times w_k \qquad \forall k \in K, \tag{8}$$

$$\sum_{k=1}^{K} S_{kl}^{t} = D_l \qquad \forall l \in L, \tag{9}$$

$$\sum_{m=1}^{M} B_m \geq 1, \tag{10}$$

$$\sum_{i=1}^{I} R_{im} + \sum_{k=1}^{K} E_{km} \leq \xi_m \times B_m \qquad \forall m \in M, \tag{11}$$

$$\sum_{i=1}^{I} R_{im} \leq \xi_i \times v_i \qquad \forall m \in M, \tag{12}$$

$$\sum_{k=1}^{K} E_{km} = \xi_m \times \rho_k \qquad \forall m \in M, \tag{13}$$

$$\mathrm{U_i}, \mathrm{W_k}, \mathrm{B_m} \in \{0,1\} \quad \forall i \in I,\ \forall k \in K,\ \forall m \in M, \tag{14}$$

$$\mathrm{X}_{ij}, \mathrm{G}_{jk}, \mathrm{S}_{kl}, E_{km}, R_{im} \geq 0$$

$$\forall i \in I,\ \forall j \in J,\ \forall k \in K,\ \forall l \in L,\ \forall m \in M. \tag{15}$$

According to the objective function (1), the objective function for the date supply chain network is provided.

Table 1. Notations of the presented model.

Indices	
i	Index of date farmland ($i = 1, 2, ..., I$)
j	Index of collection and distribution center ($j = 1, 2, ..., J$)
k	Index of date factory ($k = 1, 2, ..., K$)
l	Index of customer ($l = 1, 2, ..., L$)
m	Index of by-product factory ($m = 1, 2, ..., M$)
Parameters	
f_i	Fixed costs of opening date farmland i
f_k	Fixed costs of opening date factory k
f_m	Fixed costs of opening to by-product factory m
C_{ij}	Processing and transportation cost from farmland i to collection and distribution center j
C_{jk}	Processing and transportation cost from collection and distribution center j to date factory k
C_{kl}	Processing and transportation cost from date factory k to customers l
C_{im}	Processing and transportation cost from farmland i to by-factory m
C_{km}	Processing and transportation cost from date factory k to by-factory m
D_l	Demand of date by costumer l
ξ_i	Production capacity of farmland i
ξ_j	Capacity of collection and distribution center j
ξ_k	Production capacity of date factory k
ξ_m	Production capacity of by-product factory m
v_i	Waste rate by date farmland i
ρ_k	Waste rate by date factory k
EM	Total amount of CO_2 emission
Decision variables	
X_{ij}	Transported quantity of product from farmland i to collection and distribution center j
G_{jk}	Transported quantity of product from collection and distribution center j to date factory k
S_{kl}	Transported quantity of product from date factory k to customer l
E_{km}	Transported quantity of product from date factory k to by-product factory m
R_{im}	Transported quantity of waste date from date farmland i to by-product factory m
U_i	1 if date farmland i is opened during location; 0, otherwise
W_k	1 if date factory k is opened at location; 0, otherwise
B_m	1 if cosmetic factory m is opened at location; 0, otherwise

Objective function (2) minimizes total CO_2 emission using opened facilities. In Constraint (3), the production capacity of each farmland must be equal to or greater than the number of products shipped from date farmlands to collection and DCs. Here, waste products are excluding from the shipped products to collection and DCs. In Constraint (4), we ensure that at least one DC and collection should be opened. Constraint (5) assures the capacity of DCs if it is opened should be equal to or greater than the quantity of date products transported from farmlands to collection and DCs. We imply that the quantity of products transported from date farmlands to collection and DCs should be equal or greater than the quantity of products transported from collection and DCs to date factories in Constraint (6). Constraint (7) ensures that at least one date factory should be opened. If it is opened, the capacity of factories should be equal to or greater than the quantity of products transported from collection and DCs to date factories in Constraint (8). Constraint (9) indicates that the quantity of products transported from date factories to customers should be equal to customers' demand. Constraint (10) determines that at least one by-product factory should be opened. We indicate that the capacity of dye factories if it is open, should be equal to or greater than the quantity of waste products transported from farmland and date factories to dye in Constraint (11). The quantity of waste shipped from date farmlands to dye factories should be equal to or greater than the waste products of farmlands in Constraint (12). Constraint (13) shows that waste production of farmlands should be equal to or greater than the quantity of waste products shipped from date factories to dye factories. Constraint (14) represents the binary variables. Constraints (15) enforces the positivity of the decision variables.

2.2. Applied stochastic programming

Stochastic programming is a prevalent method to address uncertainty in parameters and situations where the objective value function is deemed to carry out well on its average values. This method is utilized in multi-tire programming [40,41]. Therefore, basic linear methods cannot be applied when dealing with uncertain objective functions in this condition and to find the best answers. The uncertain situation when dealing with customers and uncertainty in their daily demand for date products made problem to employ a stochastic approach. Utilizing this approach enables to conduct the problem in a real-world condition where daily demand is not certain. To apply this uncertainty chance constraint method is taken into account. Some previous works have considered the same approach to deal with their problems [42–44]. According to the chance constraint approach, $\bar{x}$ is regarded as a decision variable to include a possibilistic limit into the model [45]. The following equation shows how this method is applied for the considered modeling:

$$Pr\left(\sum_{k=1}^{K} S_{kl}^{t} - D_l - \bar{x}\right) \geq \psi. \tag{16}$$

Using the confidence level ψ, we have:

$$\bar{x} = \min\left\{x \middle| Pr\left(\sum_{k=1}^{K} S_{kl}^{t} - D_l \leq \bar{x}\right) \geq \psi\right\}. \tag{17}$$

The Eq. (17) can be converted into the following equation:

$$G = \sum_{k=1}^{K} S_{kl}^{t} - D_l - \bar{x}. \tag{18}$$

Here we define γ_s as an uncertain parameter with the normal distribution. Hence, G also follows a normal distribution.

$$E(G) = \sum_{k=1}^{K} S_{kl}^{t} - D_l - \bar{x}, \tag{19}$$

$$Var(G) = Var\left(\gamma_s\right)\left[\sum_{k=1}^{K} S_{kl}^{t} - D_l\right]^2, \tag{20}$$

where $E(G)$ is the expected value of G. Since G follows a normal distribution, the following equation follows a standard normal distribution:

$$Pr\left(\frac{G - E\left(G\right)}{Var\left(G\right)} < -\frac{E\left(G\right)}{Var\left(G\right)}\right) > \psi, \tag{21}$$

If we define $\omega = \frac{G-E(G)}{\sqrt{Var(G)}}$, then we have:

$$Pr\left(\omega \leq \frac{E\left(G\right)}{\sqrt{Var\left(G\right)}}\right) > \psi, \tag{22}$$

$$\varphi^{-1}\left(\psi\right) \leq -\frac{E\left(G\right)}{\sqrt{Var\left(G\right)}}. \tag{23}$$

Here, we can write:

$$\varphi^{-1}\left(\psi\right)\sqrt{Var\left(G\right)} \leq -E\left(G\right), \tag{24}$$

$$\varphi^{-1}\left(\psi\right)\sqrt{Var\left(\gamma_s\right)}\left[\sum_{k=1}^{K} S_{kl}^{t} - D_l\right] \leq \sum_{k=1}^{K} S_{kl}^{t} - D_l \times \mu_i + \bar{x}. \tag{25}$$

2.3. Weighted LP-metric method

The LP-metric method, also known as the comprehensive benchmark method, is to solve multi-objective models. For a problem with n objective functions, the optimal value of each objective function (from the first to the nth) must be calculated independently of the rest of the other n-1 objective functions, taking into account all the constraints of the problem. Since the closer the objective functions are to their optimal values, the more desirable the answers to the problem, the problem looks for an objective function that uses all those functions to get closer to their optimal values. Therefore, we define the objective function as follows:

$$\text{Min } Z = \sum_{i=1}^{k}\left(\frac{f_i^* - f_i}{f_i^*}\right)^p. \tag{26}$$

In Eq. (26), the values of f_i^* are equal to the optimal objective function values of the problem, and the values of f_i are the values related to each of the objective functions of the problem.

2.3.1. Defining norm

In functional algebra and analysis, a norm means a vector or a continuous function that assigns a positive number called length or size to any vectors in a vector space. Different values are given for p, some of which are considered $p = 1$ and some $p = 2$; it is clear that the first case means that the relative sum of deviations is minimized, and the second case means minimizing the sum of the second power of relative deviations.

2.3.2. LP-metric characteristic

This method minimizes the sum of the relative deviations of the objectives from their optimum value and combines multiple objective functions into a single objective [46]. The LP-metric method receives more attention for two reasons:

- It requires less information from the decision-makers;
- It is easy to use in practice.

The measure of the proximity of a solution is as follows, so for minimizing Z, we have:

$$\text{Min } Z = \sum_{i=1}^{k} W_i \left(\frac{Z_i^* - Z_i}{Z_i^*}\right)^p. \tag{27}$$

Eq. (27) is the same as Eq. (26). The difference is that the weight values of W_i have been added to it. These weight values will help the objective function to achieve the optimal state more quickly. On the other hand, with the finding of the optimal level in the LP-metric method, this weight vector function will advance the answer to the optimization more quickly. Also, the following equation for the sum of W_i is considered:

$$\sum_{i=1}^{k} W_i = 1. \tag{28}$$

To eliminate the problem of differences in the scales of the objectives, the deviation of the ideal answer of the ith objective will be divided by Z_i^*. It also determines the degree of emphasis on deviations so that the larger the value, the greater the emphasis on the largest deviation [47]. The overall objective function of the LP-metric method must also be minimized to minimize deviations from the ideal.

In this method, we optimize the objective functions separately through optimization software, considering all the limitations of the problem, and consider the optimal solutions obtained from each objective function as Z_i^*. Now, we will try to minimize the deviation function resulting from the above two functions. Therefore, the LP-metric method is defined as follows:

$$\text{Min } Z = \sum_{i=1}^{k} W_i \left(\frac{Z_i^* - Z_i}{Z_i^*}\right)^p, \tag{29}$$

s.t.:

$$g_i\left(X_i, X_1, X_2, \cdots, X_n\right) \le b_i, \tag{30}$$

$$Z_i = f_i\left(X_1, X_2, ..., X_n\right), \tag{31}$$

$$X_i \ge 0 \qquad i = 1, 2, ..., k, \tag{32}$$

$$\forall Z_i. \tag{33}$$

Using the first norm, the proposed modeling can be changed and obtained by Eq. (34) as shown in Box I.

Using Eq. (34) as an objective function and Eq. (27) in the constraints, the problem can be solved with different Pareto solutions to find the optimum answer.

3. Solution approach

This study formulates a bi-objective programming model, which considers the total costs of the proposed SCND for date product and CO_2 emission. This model uses several binary variables for opening different centers, which ultimately leads to the complexity of the proposed model. Generally, the problem size is directly associated with the problem complexity as a larger-sized problem yields more complexity [48,49]. In addition, exact approaches to find optimal solutions can

$$\text{Min } Z = w_1 \frac{\left(\begin{array}{c}\sum\limits_{i=1}^{I} f_i U_i + \sum\limits_{k=1}^{K} f_k W_k + \sum\limits_{m=1}^{M} f_m B_m + \sum\limits_{i=1}^{I}\sum\limits_{j=1}^{J} C_{ij} X_{ij} + \sum\limits_{j=1}^{J}\sum\limits_{k=1}^{K} C_{jk} G_{jk} + \sum\limits_{k=1}^{K}\sum\limits_{l=1}^{L} C_{kl} S_{kl} \\ + \sum\limits_{k=1}^{K}\sum\limits_{m=1}^{M} C_{km} E_{km} + \sum\limits_{i=1}^{I}\sum\limits_{n=1}^{N} C_{im} R_{im}\end{array}\right)}{Z_1^*} + w_2 \frac{Z_2^* - \left(\left(\sum\limits_{i=1}^{I} U_i + \sum\limits_{k=1}^{K} f_k + \sum\limits_{m=1}^{M} f_m\right) \times EM\right)}{Z_2^*}. \tag{34}$$

Box I

Section 1					Section 2				
i		*j+m*			*j*		*k*		
0.46	0.84	0.32	0.61	0.49	0.24	0.09	0.14	0.91	0.12
2	1	3	1	2	1	2	2	1	3

Section 3				
k			*l+m*	
0.29	0.41	0.33	0.19	0.34
2	1	3	2	1

Figure 3. Encode/decode strategy for Sections $1-5$.

1. Parameter setting, Land the $\{N\}$ Keshtels as solutions and evaluate the fitnesses
2. Do nin-dominate sorting and calculate the corwding distance (*CD*)
3. Sort Keshtels, respect to the *CD*
4. Find the Lucky Keshtels (*LK*)
5. Find the Best *LK*
6. **For** each LK (N_1) **do**
   6.1. Swirl the Nearest Keshtel (*NK*) around the *LK*
   6.2. In case better food is obtained, *NK* is replaced by *LK*. For new *NK* go to Step 6.1
   6.3. Excess food available attracts *NK*, do swirling, else go to step 8
7. Let the *LKs* remain in the lake
8. The (N_3) Keshtels with worst fitnesses be replaced with the new randomly generated Keshtels
9. Move the remaining Keshtels (N_2)
10. Merge the population [N_1; N_2; N_3]
11. Do non-dominate shorting and crowding distance
12. Again, sort the non-dominated Keshtels based on crowding distance
13. Select (N) better Keshtels from this merged population for the next generation
14. Do Steps 11 and 12 for the new population
15. Stop if stopping criteria meet; otherwise, go to Step 5

Figure 4. Implemented steps of the MOKA.

always be time-consuming in these problems [50]. So, in this section, we explained the implemented strategy for the encoding/decoding plan for the suggested meta-heuristics.

3.1. Encode/decode plan

Strategies such as using the matrix of Michalewicz by Michalewicz et al. [51], Prufer numbers by Prüfer [52], and priority-based solution method by Gen et al. [53] represent multiple approaches to encode the problem solutions. The proposed method by Gen et al. [53] (priority-based solution method) is utilized in this work. The schematic plan to encode and decode the purpose for chromosomes is shown in Figure 3. Each section has three rows in which the first one shows the flow among the defined centers in the problem. The other two rows are the developed random number between [0] and 1, and the last one represents the priority decode plan.

3.2. Multi-Objective Keshtel Algorithm (MOKA)

The KA, developed by Hajiaghaei-Keshteli and Aminnayeri [54], is based on observation and applying the unusual behavior of Keshtel ducks when feeding.

Considering these amazing characterizes, the MOKA [30] considers simultaneous objectives and optimizes them. The prosperity of this solution method is that it also guarantees the problem's feasibility [55]. The overview of this solution method is depicted in Figure 4.

3.3. Multi-Objective Simulated Annealing (MOSA)

The SA algorithm, proposed by Kirkpatrick et al. [56], is one of the famous single-solution algorithms in this regard [57]. Eq. (35) examines this procedure for this algorithm as follows [58]:

$$\begin{aligned} &x: \text{ Initial solutions} \\ &x': \text{ Newly developed solutions} \\ &\Delta f_j = f_j(x') - f_j(x) \qquad j = 1, 2, ..., n. \end{aligned} \tag{35}$$

Figure 5 shows the pseudocode of the proposed MOSA.

3.4. Implemented NSGA-II and NRGA

This section considers the NRGA and NSGA-II proposed by Al Jadaan et al. [59] and Deb et al. [60], respectively.

The selection mechanism is one of the different points when using NRGA or NSGA-II, as the NRGA

1. Parameter setting
2. Initialize and evaluation *fitness functions* $(x, f_j(x))$
3. Best solution = $(x, f_j(x))$
4. **For** 1 to max-iteration
  4.1. **Do** *mutation* operator (x')
  4.2. Calculate the fitness function and (Δf_j)
    4.3.1. If $\Delta f_1 \leq 0 \;\&\&\; \Delta f_2 \geq 0$
      Update the Best solution = $(x', f_j(x'))$
      Update the solution $x=x'$
    4.3.2. Else if $\Delta f_1 \geq 0 \;\&\&\; \Delta f_2 \geq 0 \;\|\; \Delta f_1 \leq 0 \;\&\&\; \Delta f_2 \leq 0$
      Put this solution in *Pareto* set
    4.3.3. Else $\Delta f_1 \geq 0 \;\&\&\; \Delta f_2 \leq 0$
      $P_1 = \exp\left(\frac{-\Delta f_1}{T}\right), \quad P_2 = \exp\left(\frac{-\Delta f_2}{T}\right)$, h=rand
      If $h<P_1$ && $h<P_2$
      Update the solution $x=x'$
5. Update *temperature* $(T=\alpha * T)$
6. **Do** non-dominate sorting in this *Pareto* set.
7. If stopping criteria are satisfied, stop, if not, go to Step 4.1.

Figure 5. Implemented steps of multi-objective simulated annealing algorithm.

and NSGA-II use the roulette wheel and binary tournament, respectively [61]. Figure 6 shows the pseudocode of these two algorithms.

4. Computational results

An intelligent experiment would be catered to investigate the efficiency of the utilized approaches, which are investigated at three levels. Random data are first created. The Taguchi approach and Response Surface Methodology (RSM) are carried out [62,63]. Finally, the results would be compared, and the best method is picked base on the defined norms [64].

4.1. Generating data

To investigate the productivity of the presented algorithms, three diverse problem sizes are proposed. Table 2 illustrates the problem sizes and their associated settings. The proposed meta-heuristic algorithms are investigated by the instances. These settings include the dimensions from small sizes to large-sized problems.

Table 2. Problem classification.

Classification	Instance	Problem size $(i, j, k, l, m,)$
Small	SP_1	(6, 6, 6, 6, 6, 6)
	SP_2	(7, 8, 8, 8, 6, 7)
	SP_3	(15, 12, 12, 12, 8)
Medium	MP_4	(25, 25, 25, 25, 12)
	MP_5	(35, 35, 35, 35, 35, 35)
	MP_6	(60, 60, 45, 45, 45, 45)
	MP_7	(70, 65, 50, 50, 50, 50)
Large	LP_8	(120, 100, 100, 100, 80)
	LP_9	(150, 150, 150, 150, 80)
	LP_{10}	(200, 200, 200, 200, 100)

In this regard, a set of farmlands (i), collection and DCs (j), date factories (k), customers (l), and by-product factories (m) are considered. Also, Table 3 represents the considered parameters and their values to initialize the given problem.

4.2. Parameter setting

To get the most benefits out of the utilized metaheuristic algorithms, each associated parameter should be tuned. Tuning enables the metaheuristic algorithms to perform much better, and ultimately, they will get better output results. This enhancement in the algorithm's performance shows itself in both the quality of the solutions and the time to reach the optimum answer. The Taguchi method is employed to ascertain an appropriate value for the proposed algorithm's parameters. Table 4 shows the parameters and their levels.

The Taguchi experiment allows tuning the algorithm's parameters while reducing the number of tries to achieve them. Hence, when the objective function

1. Initialize population
2. Generate random population
3. Evaluate objective values
4. **For** eah parent and population **do**
  4.1. Assign rank based on Pareto
  4.2. Generate sets on Non-dominated solutions
  4.3. Determine Crowding distance
  4.4. Loop by adding solutions to the next generation
5. Determine population front
8. **For** each determined front **do**
  8.1. Perform binary tournament solution (NRGA)/Roulette wheel selection (NSGA-II)
9. Generate new population with crossover and mutation

Figure 6. Pseudocode of the NRGA and NSGA-II.

Table 3. Values of parameters.

Parameters	**Value**	**Parameters**	**Value**
f_i	Uniform∼[14000,24000]	D_l	Uniform∼[15000,20000]
f_k	Uniform∼[22500,37000]	ξ_i	Uniform∼[5500,7900]
f_m	Uniform∼[15000,18300]	ξ_j	Uniform∼[4150.6100]
C_{ij}	Uniform∼[7300,8500]	ξ_k	Uniform∼[6120,.7200]
C_{jk}	Uniform∼[4600,5200]	ξ_m	Uniform∼[1590,4190]
C_{kl}	Uniform∼[6940,7200]	v_i	Uniform∼[0.46,0.79]
C_{im}	Uniform∼[3000,5000]	ρ_k	Uniform∼[0.26,0.49]
C_{km}	Uniform∼[3200,4800]	EM	Uniform∼[0.11,0.91]

Table 4. Proposed meta-heuristic algorithm in terms of their levels and factors ($x = i + j + k + l + m$).

Algorithms	**Factor**	**Level 1**	**Level 2**	**Level 3**
NSGA-II	A: Pc	0.62	0.71	0.84
	B: Pm	0.16	0.18	0.21
	C: N-pop	65	125	185
	D: Max-$iteration$	2x	3x	4x
NRGA	A: Pc	0.62	0.71	0.84
	B: Pm	0.16	0.18	0.21
	C: N-pop	65	125	185
	D: Max-$iteration$	2x	3x	4x
MOKA	A: M_1	16%	14%	19%
	B: M_2	25%	15%	35%
	C: $S_{\max}$	0.22	0.26	0.31
	D: N-$Keshtel$	180	220	240
	E: Max-0$iteration$	2x	3x	4x
MOSA	A: T_0	1200	1400	1500
	B: α	0.93	0.94	0.95
	C: Max-$iteration$	2x	3x	4x

is minimization, the "smaller-is-better" concept is utilized to deal with the problem [65]. Also, Eq. (27) is represented to investigate the signal-to-noise ratio [66].

$$S/N = -10 \log \left(\frac{\sum_{i=1}^{n} Y_i^2}{n} \right), \tag{36}$$

where n determines the number of experiments while Y determines the observed data [67]. Ten test problems in three categories have been run 40 times to achieve the best levels of each algorithm. Since the problem cannot be solved and compared straight, the Relative Percentage Deviation (RPD) is used. The RPD is showed as follows [68,69]:

$$RPD = \frac{|\mathrm{Alg}_{sol} - \mathrm{Min}_{sol}|}{\mathrm{Min}_{sol}}, \tag{37}$$

where Alg_{sol} represents the value of objective in individual trials, also, Min_{sol} shows the best solution among all trials [70]. Next, this value is changed into the RPD, and mean values are achieved. Then, the Taguchi method sets the orthogonal arrays to reduce the experiments for algorithms [71]. L_9 design opts for the MOKA, L_{16} design opts for MOSA, and L_{27} for NSGA-II and NRGA [72], respectively. Figures 7–10 illustrates the signal-to-noise ratio for all the given meta-heuristic algorithms. The tuned algorithm's parameters are described in Table 5.

4.3. Comparing algorithms and the utilized metrics

To consider the applicability and practicality of the two proposed meta-heuristics, this section represents two metrics that can evaluate different characteristics of the metaheuristics, including the Mean Ideal Distance (MID) and CPU time [73,74]. These metrics are described below:

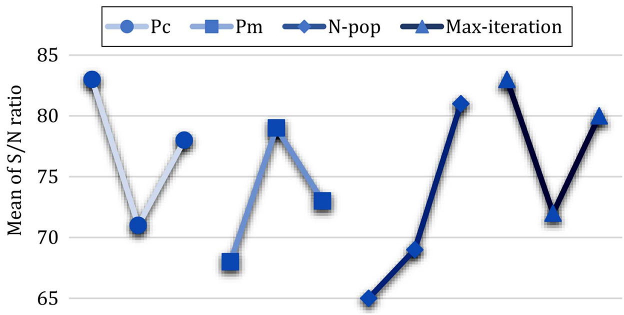

Figure 7. Signal-to-noise (S/N) plot for the NSGA-II.

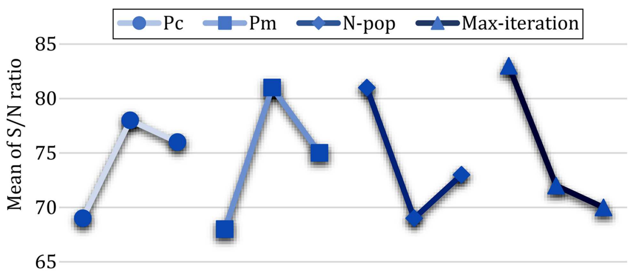

Figure 8. Signal-to-noise (S/N) plot for NRGA.

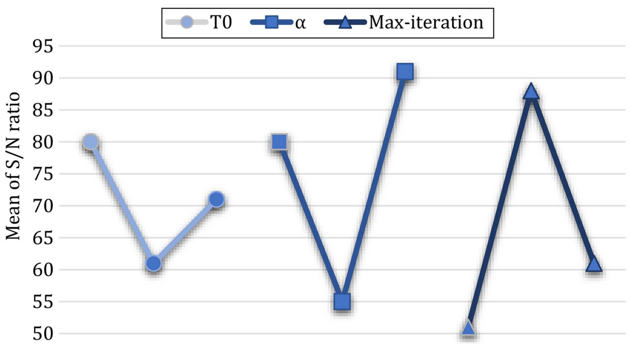

Figure 9. Signal-to-noise (S/N) plot for the MOSA algorithm.

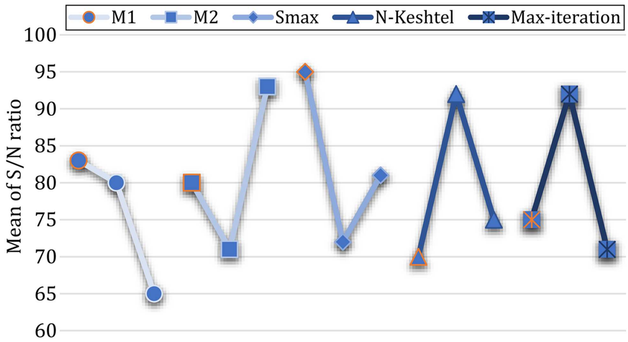

Figure 10. Signal-to-noise (S/N) plot for the MOKA.

(a) **MID**: To evaluate this metric, the difference between Pareto solutions and ideal ones must be calculated [75]. This evaluation approach is described as Eq. (35) for two objectives function models [76].

$$MID=\frac{\sum_{i=1}^{n}\sqrt{\left(\frac{f_i^1-f_{\text{best}}^1}{f1_{\text{total}}^{\max}-f1_{\text{total}}^{\min}}\right)^2+\left(\frac{f_i^2-f_{\text{best}}^2}{f2_{\text{total}}^{\max}-f2_{\text{total}}^{\min}}\right)^2}}{n}, \quad (38)$$

where n is the number of non-dominated answers; f_i^1, f_i^2 are the value of the ith non-dominated answers for the two objectives.

The algorithm has better performance in fewer values of MID [77].

(b) **CPU**: The less the computational time, the better the performance of the algorithm.

Here we categorized problems into three different sizes, such as small-sized problem (1–3), medium-sized problem (4–7), and large-sized problem (8–10). The problem answers are obtained using the computer device with 12 GB RAM, 2.3 GHz CPU, windows 10 OS. The results are shown in Table 6.

The Analysis of Variance (ANOVA) is conducted to compare these two metrics. The interval plots for the mentioned metrics are shown in Figures 11 and 12.

As can be concluded from Figures 11 and 12, the MOKA has superiority in terms of the MID, and in terms of CPU time, the MOSA showed better performances. Comparing the results of CPU time indicates that MOSA is the best algorithm in all the problem samples, and it can reach its best results in a shorter time. In addition, it has the best variance. In terms of the quality of the problem outcomes, considering the MID is handy. The MOKA shows the best results since

Table 5. Algorithm's tuned parameters.

Algorithm	Parameters
NSGA-II	$Pc = 0.71$; $Pm = 0.16$; N-pop=65; Max-$iteration$= $3x$
NRGA	$Pc = 0.62$; $Pm = 0.16$; N-pop=125; Max-$iteration$= $4x$
MOSA	$T_0 = 1400$; $\alpha = 0.94$; Max-$iteration$= $2x$
MOKA	$M_1 = 19\%$; $M_2 = 15\%$; $S_{\max} = 0.26$; N-$Keshtel$=180; Max-$iteration$=$4x$

Table 6. Algorithm evaluation in each considered metric ($\times 10^6$)

Problem	*MID*				CPU time			
	NSGA-II	**NRGA**	**MOKA**	**MOSA**	**NSGA-II**	**NRGA**	**MOKA**	**MOSA**
1	1.624768	2.578007	1.536059	4.25988	68.47097	75.67316	116.7185	20.12469
2	1.219475	1.283882	1.280612	2.535287	149.7642	167.6113	281.0178	31.64245
3	2.304143	2.208677	3.183059	2.329862	258.7157	285.9377	526.7324	33.56238
4	3.936104	2.30447	2.53398	5.991338	391.9419	444.071	811.2392	36.31603
5	4.027755	2.846531	4.020017	3.503348	966.2851	1082.003	2193.278	46.1929
6	3.473815	3.056752	3.62693	5.484041	1281.524	1387.456	2446.077	50.59081
7	5.464861	5.928349	4.627248	5.252679	1494.515	1670.263	2864.669	55.64986
8	6.403497	6.169192	5.824165	5.42225	2511.428	2821.97	6080.222	87.96949
9	5.278725	4.446016	7.323934	5.601085	6013.592	5458.181	11124.6	117.0055
10	4.319274	4.040941	11.21143	6.368079	6622.533	6091.259	13198.63	127.1979

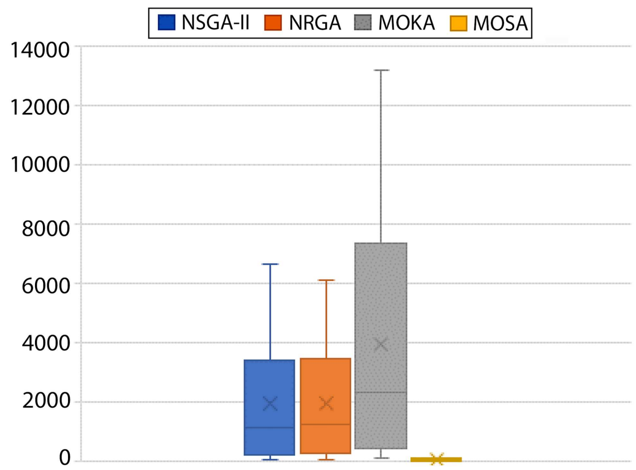

Figure 11. Interval plot of CPU time (at 95% confidence level).

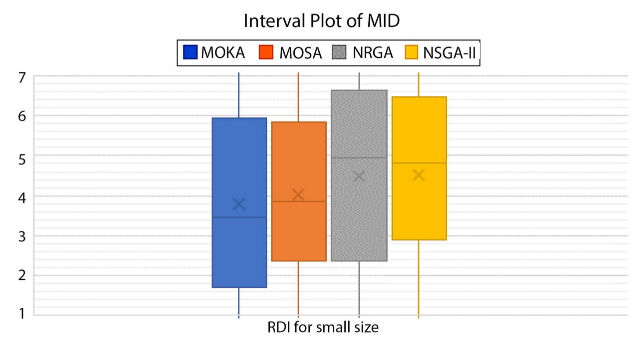

Figure 12. Interval plot of MID (at 95% confidence level).

it has a minimum MID average. Also, the second-best algorithm in this regard is MOSA, with lower variance concerning the MOKA. The Pareto solutions of the problem outcome are described in Table 7 and Figure 13 for test problem 6.

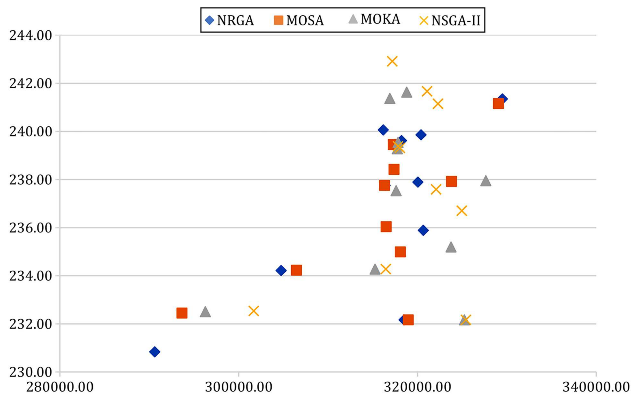

Figure 13. Pareto solution of test problem 12.

4.4. Sensitivity analysis

Here, we do sensitivity analysis on the main parameters. Table 8 has demonstrated the model conduct when changing in values of demand rate. Model changeability, the effects on various parameters, and the objective functions of each metaheuristic algorithm are considered. The more the demand, the more the total costs of the proposed network. In addition, other parameters affected by this change are illustrated in Table 8.

Next, the transportation costs have been taken into account. Thus, we firstly enhanced and then declined its value by 20 and 40%. The changes in other parameters are shown in Table 9. As aforementioned, it is interesting to note that increasing the value of opening and purchasing costs increases their value. However, the increase in purchasing costs is not much. In addition, such an increase would decrease the operation cost since a new center must be opened with a lower process cost.

Last but not least, we consider the changes in the emission parameters. As stated in Table 10,

Table 7. Pareto solutions based on weights.

Weights	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Total cost	290618.59	304753.64	320647.13	316390.67	320052.75	318216.38	329500.07	320394.99	316177.14	318504.07
Total emission	230.84	234.22	235.89	237.75	237.90	239.62	241.35	239.86	240.06	232.17
Total cost	293667.80	306471.41	316503.66	316325.35	323808.47	317307.26	329059.95	318097.20	317380.28	318979.06
Total emission	232.45	234.23	236.04	237.76	237.92	239.45	241.16	234.99	238.42	232.17
Total cost	296277.81	315257.34	317618.36	317745.92	327648.99	31 7838.06	316916.04	323759.57	318803.01	325250.24
Total emission	232.51	234.27	237.54	239.28	237.95	239.55	241.37	235.20	241.64	232.17
Total cost	301692.27	316466.93	322083.67	318036.74	317826.76	322294.48	317185.26	324957.53	321074.35	325427.14
Total emission	232.54	234.28	237.59	239.32	239.38	241.15	242.92	236.71	241.67	232.17

Table 8. Behavior of the model with a change in demand rate.

		D_l		
		40% ↑	**0%**	**40% ↓**
Opening cost		0.00%	–	1.28%
Processing cost		0.01%	–	–1.10%
Transportation cost		1.52%	–	3.11%
Objective function	NRGA	3.122%	–	–2.43%
	MOSA	3.768%	–	–2.55%
	MOKA	2.131%	–	–2.25%
	NSGA-II	1.491%	–	–2.12%

the more emission will have more decision variables and objective functions. This change indicates that it must be considered when opening new facilities. Hence, the majority of the opening costs are affected by the emission ratio. Therefore, other variables are dependent on this change.

5. Conclusion and further perspective

Considering the agricultural supply chain and determining optimal flow among the different levels of a product's value chain can significantly affect the profitability of certain products. An efficient network design is required to guarantee the maximum productivity for a specific agricultural product, such as date. Designing such a network for this important product decreases the total costs of the date industry and increases the efficiency of providing the customers with their potential needs. These products can be transferred to different markets while the emission is reduced. This consideration has failed in previous studies. Therefore, an efficient network is designed for date products to increase product flow efficiency in a forward direction and reduce the total associated costs of the supply chain by optimizing the costs and emissions. The utilized MILP model is designed to calculate the number of opened centers. In addition, this model minimizes the total logistic costs.

The study's finding revealed that considering by-product factories for waste collection can significantly affect the model outcome by reducing the total costs of the proposed supply chain network and reducing CO_2

Table 9. Model behavior when changing transportation parameters.

		(Total transportation cost)				
		40%↑	**20%↑**	**0%**	**20%↓**	**40%↓**
Opening cost		36.13%	7.92%	–	0.00%	–20.20%
Processing cost		1.83%	3.04%	–	-4.45%	–1.07%
Objective function	NRGA	9.03%	9.03%	–	-7.32%	–15.16%
	MOSA	9.17%	9.17%	–	-5.47%	–13.72%
	MOKA	9.11%	9.11%	–	-7.07%	–14.54%
	NSGA-II	7.93%	7.93%	–	–6.35%	–13.39%

Table 10. Behavior of the model with change in the emission rate.

		EM (Emission rate)				
		40%↑	**20%↑**	**0%**	**20%↓**	**40%↓**
Opening cost		19.15%	0.00%	–	−5.32%	−5.66%
Operation cost		10.30%	6.17%	–	−6.52%	−13.67%
Transportation cost		14.12%	6.56%	–	−6.91%	−12.99%
Objective function	NRGA	59.24%	26.73%	–	−26.83%	−51.14%
	MOSA	59.88%	26.04%	–	−26.94%	−50.25%
	MOKA	58.56%	26.37%	–	−26.84%	−49.27%
	NSGA-II	61.76%	25.66%	–	−26.90%	−49.07%

emissions. In addition, the model is so responsive to transportation costs that increasing the logistics costs would increase opening costs. On the other hand, when the logistics costs are lower, there is less need to open new facilities since it is logical to open new facilities when logistic costs are lower. Increasing the demand rate would also increase the total costs of the date supply chain network since more demand means more transportation, opening, and procession costs. The emission rate also acts the same. To obtain expected results, managers can actively focus on various aspects of the date supply chain, such as opening and closing facilities, logistics costs, distributing their demands in various periods, and concerning environmental factors. In addition, they can adjust some of these parameters to get the desired outcome.

From the managerial aspect, considering forward direction might result in problem optimality. However, taking particular sites to by-products would guarantee the most benefit out of the date product industry. Also, the conducted sensitivity analyses on the product showed an increase in the opening costs when increasing its value. Therefore, managers could wisely decide to justify or considers a unique trade-off between these two costs. Both governmental and private sectors are the beneficiaries of the prevalent works regarding cost, quality, and social and environmental aspects of this optimization. In fact, the key factors of competitive advantages in the supply chain would be optimized by optimizing the network. So, all stakeholders relevant to the supply chain can take advantage of the benefits of these optimizations. Even the customers of this chain can utilize the better quality and the lower cost of the product. Furthermore, last but not least, by enforcing and establishing green consideration, the environmental factor is also enhanced. Thus, this action itself can provide inestimable advantages, mostly in such social and environmental aspects.

Therefore, emerging topics, including incorporating the old and new metaheuristic algorithms, are highly recommended. To accomplish a detailed managerial decision, it is quite fundamental to enforce and analyze the settings of the proposed study on other case parameters. To move forward with this study, social and environmental factors, water consumption, and job employment opportunity should help the model development for simultaneous consideration of costs.

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