A Triple Bottom Line Approach for Designing a Sustainable Closed-Loop Supply Chain Network in Fruit Industry: A Metaheuristic Solution Approach

Hossein Reyhani Yamchi
Department of Management
University of Tabriz
Tabriz, Iran
h.reyhaniyamchi@gmail.com

Younis Jabarzadeh
Liverpool Business School
Liverpool John Moores University
Liverpool, United Kingdom
y.jabarzadeh@ljmu.ac.uk
ORCID 0000-0002-0845-2170

Kannan Govindan (Corresponding author)
Department of Technology and Innovation
University of Southern Denmark
Odense-Denmark
kgov@iti.sdu.dk
ORCID 0000-0002-6204-1196

Hannan Amoozad Mahdiraji
Birmingham Business School
University of Birmingham
Birmingham, United Kingdom
h.m.amoozad@bham.ac.uk
ORCID 0000-0002-8382-6603

Abstract

In this study, the design of a sustainable closed-loop supply chain network for agricultural products with the goals of minimizing the cost and emission of greenhouse gases and maximizing the response to customer demand, and creating justice-based job opportunities, simultaneously, are aimed. The intended chain is based on the fruit supply chain study, which includes fresh fruits, concentrate, and vermicompost fertilizer. A Mixed-Integer Linear Programming (MILP) model has been developed to achieve the triple bottom line. Due to the nature of the NP-hard problem, the proposed model is solved using metaheuristic approaches consisting of two renowned algorithms, NSGA-II and NRGA, and a relatively new algorithm called NSGA-III. It is worth noting that the parameters of the algorithms are adjusted to achieve the best performance in small, medium, and large-size problems exerting the Taguchi method. After comparing the results of the three algorithms based on the well-known criteria, NRGA is introduced as the superior algorithm. Ultimately, the results of sensitivity analysis indicate that appending the possibility of using vermicompost in gardens and considering several vehicles in the proposed sustainable supply chain boosts the values of economic and environmental objective functions to about 6.4% and 8.2%, respectively.

Keywords. Agricultural food; closed-loop supply chain; network design; multi-objective; CO_2-eq emission; Meta-heuristics

1. Introduction

Global food demand is projected to increase by more than 70% of its current levels by 2050 (Krishnan et al., 2020), and agriculture plays a central role in supplying food. Nonetheless, it has a prominent role in Global Warming Potential (GWP) emissions (Tukker and Jansen, 2006) due to inefficient and unregulated methods of the conventional agricultural food supply chain (AFSC), especially in developing countries such as Iran (Frank et al., 2019). Consequently, addressing the inherent challenges of world hunger takes precedence within the United Nations' sustainable development goals program (Tanksale and Jha, 2020).

Fortunately, global cognizance of environmental and social pressures and demand for sustainable products has led managers and decision-makers (DMs) in AFSC to prioritize sustainable development practices (Jouzdani and Govindan, 2021) and invaluable and comprehensive research has been conducted to robust the management of perishable agricultural products (APs) (Chen and Chen, 2021). However, a few studies have considered APs, especially fruits, due to their unique characteristics, such as finite life and inseparability (e.g. Paksoy et al. 2019).

For instance, Cheraghalipour et al. (2018) have developed a closed-loop supply chain network design (CLSCND) for citrus, focusing on cost performance and studying social performance imperceptibly. Similarly, Roghanian and Cheraghalipour (2019) measured the environmental performance alongside prior objectives for the same SC. However, there need to be more comprehensive studies that explicitly examine sustainability-related objectives in AFSC. Furthermore, a few studies have incorporated multiple dimensions of sustainability in AFSCND optimization models (e.g. Liu et al., 2021; Darestani and Hemmati, 2019). Most published articles primarily focus on the environmental aspect of sustainability in AFSCND and economic performance. Yet, sustainability encourages researchers to consider social impacts as one of the salient aspects of SCND. Studies considering this aspect of sustainability, especially in CLAFSCND, are scarce (e.g. Seydanlou et al., 2022, Goodarzian et al., 2023). The prominence of this study is that as the cost of the CLSC is minimized, two other dimensions of sustainability are considered simultaneously.

With an annual production of about 16.5 million tons, Iran ranks among the top ten fruit-producing countries globally, following China, the United States, India, and Mexico (FAOStat, 2010). Therefore, examining the fruit SC configuration and providing a framework for DMs is crucial, considering its economic, environmental, and social importance within the global AFSC. Given these factors, the current study seeks an optimal sustainable closed-loop agricultural food supply chain network design (SCLAFSCND) for fruit, incorporating both forward and reverse flows to meet the demand for fresh fruit, fruit concentrate, and vermicompost. The multi-echelon SC includes gardens, distributors, markets, fruit concentrate factories and vermicompost plants. The objectives of the study encompass economic, environmental, and social dimensions, aiming to minimize total costs and greenhouse gas (GHG) emissions and maximize customer demand response and justice-oriented employment according to job creation priorities (based on the unemployment rate) in different social clusters. Particularly, the objectives of the study are tailored to the needs of the real world, which has a practical aspect and has yet to be seen in previous studies. Moreover, the proposed SC considers chemical and vermicompost fertilizers, which have different effects economically and environmentally, to achieve a certain productivity level for gardens. A concentrate production plant is added to a fruit SC to combine industry and agriculture sectors, leading to integrated optimization. Additionally, Since each product needs to be transported properly, different vehicles with various capacities and equipment are considered in the SC. As a result, a holistic multi-period, multi-product, and multi-vehicle SCLAFSCND is developed, and a real case study showcasing the model's first successful implementation to achieve its objectives is presented.

The resting sections of the research are as follows. Section 2 presents a literature review on AFSCND, CLSCND, and SCLAFSCND, ultimately highlighting the research gaps. Section 3 delineates the problem description and the proposed mathematical model. Three efficient metaheuristics are introduced to solve the problem in Section 4. Section 5 examines a real case study and illustrates the input parameters. Performance comparison criteria, computational results, metaheuristic comparison, and sensitivity analysis are reported in Section 6. Section 7 illustrates some insights for managers. Eventually, Section 8 concludes the research findings and suggests potential future work guidelines to expand this study.

2. Literature review

Agricultural food supply chain network design. AFs include volatile and delicate vegetables and fruits, where, as high-frequency consumer goods, freshness is crucial for value and purchasing decisions (Liu et al., 2023). Proper SCND not only reduces the spoilage of products but also improves customer responsiveness (Gürsoy and Kara, 2021). Mathematical models in AFSCND, especially the fruit supply chain, have been discussed in numerous studies. Behzadi et al. (2017) investigated a two-stage random programming model to examine the potential for fruit waste in the AFSC. They considered the SC of Kiwi, intending to maximize the profit of the chain. They concluded that when product waste is more than 30%, a risk management strategy works better than a strong strategy. A transportation planning model for AFSCND in which several storage centers provide a fruit logistics center corresponding to demand in the non-harvest season was developed by Nadal-Roig and Plà-Aragonés (2015). Another study by Etemadnia et al. (2015) considered the two-mode transportation options and suggested the optimal location of wholesale facilities exerting heuristic methods.

Closed-loop supply chain network design. Recently, reverse logistics has received much attention, particularly in AFSCs, since it meets environmental needs regarding customer rights. A CLSCND was presented to optimize economic considerations by Salehi-Amiri et al. (2021) for the walnut industry. The proposed problem was addressed using a novel approach that combined the social engineering optimizer and Keshtel algorithm, resulting in a new hybrid metaheuristic solution. Similarly, Rajabi-Kafshgar et al. (2023) examined a CLSCND within the pistachio industry. They constructed a mathematical model with a single objective and devised three hybrid algorithms to address the problem effectively. Furthermore, Salehi-Amiri et al. (2022) investigated the implications of reverse logistics on the avocado business. Their study took into account factors such as employment opportunities and cost considerations in the CLSC.

Sustainable closed-loop agricultural food supply chain network design. As the AFSCND literature review shows, AFSCs have different aspects that affect the environment and society. Few studies have acknowledged more than one dimension of sustainability in AFSCND optimization models. For example, the AFSCND multi-objective mathematical programming model was presented by Liu et al. (2021). Minimizing the cost of distribution and carbon emission and maximizing the product freshness was determined as the objectives of the model. Darestani and Hemmati (2019) considered minimizing total GHG emissions and total SC network costs in their dual-objective model for AFSCND. They evaluated the performance of three solution methods by considering numerical test problems. Their results confirmed that the Torabi-Hassani method is better than the other methods. A multi-objective linear program concerning all three aspects of a sustainable agricultural food supply chain network design (SAFSCND) was presented by Sazvar et al. (2018). Total cost, total GHG emissions, and social health, the three definitive objectives of this study, were optimized using AUGMECON. Gholian-Jouybari et al. (2023) designed a saffron SC model to cope with trade-offs between profit, satisfaction, production of developed produce, and water consumption as the pillars of sustainability. Considering uncertainty in production rate and consumer demand, they solved their problems with exact and metaheuristic mechanisms. After selecting proper food suppliers, Fathi et al. (2023) prescribed a model for SAFSCND. They attempted to minimize carbon and nitrogen emissions, cost, and delivery time while maximizing job opportunities. Jouzdani & Govindan (2021) proposed a multi-objective mathematical model for optimizing cost, energy consumption, and traffic congestion as economic, environmental, and social aspects, respectively, in a dairy SC. Their study contributed to SDGs such as Zero Hunger (SDG2), affordable and Clean Energy (SDG7), Decent Work and Economic Growth (SDG8), and Responsible Production and Consumption (SDG12).

Some of the most relevant research and their analyses are collected in Tables A.1 and A.2. These tables illustrate the main specifications and compare them with our research. Some of the specifications are summarized in Table A.3. According to Table A.1, few studies have considered APs, particularly fruits, in their CLSCND, due to their unique characteristics, such as finite life and inseparability. In most of the papers, sustainability in AFSCND and especially in CLAFSCND, in addition to economic performance, is more limited to the environmental aspect. At the same time, sustainability encourages researchers to consider social impacts as one of the salient aspects of SCND. Studies considering this aspect of sustainability, especially in CLAFSCND, are scarce. Accordingly, Roghanian and Cheraghalipour (2019), Seydanlou et al. (2022, 2023), and Goodarzian et al. (2023) are the only four papers in the literature that have developed the CLAFSCNDs for fruit. Apart from minimizing the cost of the CLSC, these studies scrutinize the volume of released carbon dioxide as environmental consideration. Additionally, the number of established jobs and the responsiveness rate are the social concerns of Seydanlou et al. (2022) and Roghanian and Cheraghalipour (2019). Seydanlou et al. (2023) also considered the uncertainty of key parameters for the CLAFSCND proposed by Seydanlou et al. (2022). Moreover, Goodarzian et al. (2023) introduced a new social objective, thereby seeking to establish facilities in areas with smaller population sizes as much as possible. Nevertheless, to approach real-world needs, we propose a more comprehensive model on the basis of the following novelties.

- The social objective consists of two criteria. We introduce the weighted combination of two social criteria, (i) the responsiveness to demands and (ii) the number of job opportunities created in different social clusters, as the social objective. Thus, unlike Seydanlou et al. (2022), a shortage in demand is allowed.
- Using two types of fertilizers, (i) organic (vermicompost) and (ii) chemical, can gain a certain amount of production in gardens. Still, it has to be addressed in the literature of AFSC. As chemical fertilizers have been associated with detrimental environmental effects (Adegbeye et al., 2020), and their procurement involves additional costs due to external supply; hence, this research aims to select the fertilizer based on a trade-off between environmental and economic considerations.

- Several transportation options with different equipment, such as tankers, refrigerators, etc., are studied. They have unique emission factors, capacities, and required paraphernalia, which impact the supply chain's triple bottom line, considering different products.
- Strategic, tactical, and operational decisions are made. Seydanlou et al. (2022) considered each period equal to one year, while our study takes a month into account to plan for production, holding, and transportation. This is because each entity's process in the SC lasts for finite months during a one-year horizon in real-world problems. For instance, fruit inventories with limited capacities can be replenished in specific months and meet market demand for a certain number of periods due to the limited lifespan of fruit. Thus, the product flows are a combination of continuous and discrete ones. Notwithstanding the similarity with Roghanian and Cheraghalipour (2019), our SCND is more complicated and extended.
- A real-world example is provided to support the practicality of the proposed model. The CLAFSC of apples in West Azerbaijan province, which accounts for almost 26% of the total apple production in Iran, is investigated as a case study to appraise the model.
- Since our problem is NP-hard, it is solved by focusing on genetic-based meta-heuristic algorithms. The model is implemented in the new meta-heuristic algorithm called NSGA-III, presented by Deb and Jain (2014). On the other hand, other genetic-based algorithms, namely NSGA-II and NRGA, are employed, and the performance of all three algorithms is compared.

3. Optimization Model

The importance of CLAFSC for perishable AF products, especially fruits, necessitates an efficient supply chain network to manage production, distribution, storage, and waste transfer. Recycling waste into vermicompost is one of the most well-known methods to transform AF waste while promoting environmental and social health. In this research, despite considering this method, it has been tried to prevent the creation of excessive waste; therefore, the amount of products entering the chain is considered a variable. We are developing a comprehensive CLAFSC model for fruit, considering all three pillars of sustainability: economic, environmental, and social assessment, for a compromise solution. This model plans to meet demand within specific periods (viz. one month) over a defined time horizon (viz. one year). For this purpose, the following three flows are examined (forward and reverse flows).

I. Gardens, as producers, are in the first layer, sending products to fruit markets directly or through distributors in the middle layer during the harvest season. Distributors can store products in fully-equipped warehouses to meet future demands.
II. After fruit customers' demand is met as much as possible, the remaining products from the garden during the harvest season can be transferred to concentrate production plants, converted into concentrate, and sent to concentrate markets through distribution centers. The concentrate is more durable than fruit and covers the demands for more periods.
III. Reverse logistics involves transferring waste products from production, fruit distribution and markets, and concentrate plants to vermicomposting centers. The produced vermicompost meets the demands of both gardens and the market.

The study configures a multi-echelon, multi-period, multi-vehicle, and multi-product SC by combining various strategic decisions on the number and location of network facilities with tactical and operational decisions on resource, production, purchasing, and inventory planning and distribution strategy across the network so that costs and environmental impacts are minimized, and social benefits are maximized, in a compromise solution. Mathematical modeling of the problem is employed through MILP by considering the following assumptions:

- The location of customers, producers (gardens), and concentrated production plant areas are predetermined.
- The fruit waste rate is certain in different stages.
- Products transported from gardens are deemed variable, as this network does not consider all garden products.

- Customer demand in all three markets is certain.
- The fertilizer application time is at the beginning of the second period, which affects the gardens, expectedly.
- Transportation is performed only by road vehicles such as trucks and vans.

To determine:

- the location of the required distribution centers and vermicomposting centers,
- required product flow between SC facilities,
- the required vehicles to establish flows,
- the amount of production of producers and inventory of distributors, and
- the type of fertilizer used by gardens.

The considered SC consists of eight echelons: Gardens; Fruit Distribution Centers (FDCs); Fruit Customers (FCs); Concentrate Plants (CPs); Concentrate Distribution Centers (CDCs); Concentrate Customers (CCs); Vermicomposting Centers (VCs); Vermicompost Markets (VMs), which are indexed according to Fig. 1. Forward and reverse logistics flow are shown in the stretch and dashed lines, respectively. Flows duration from each facility is altered. In this vein, the flow from gardens, CPs, FDCs, CDCs and VCs can be continued for T', T', T'', T''' and T'' periods, respectively.

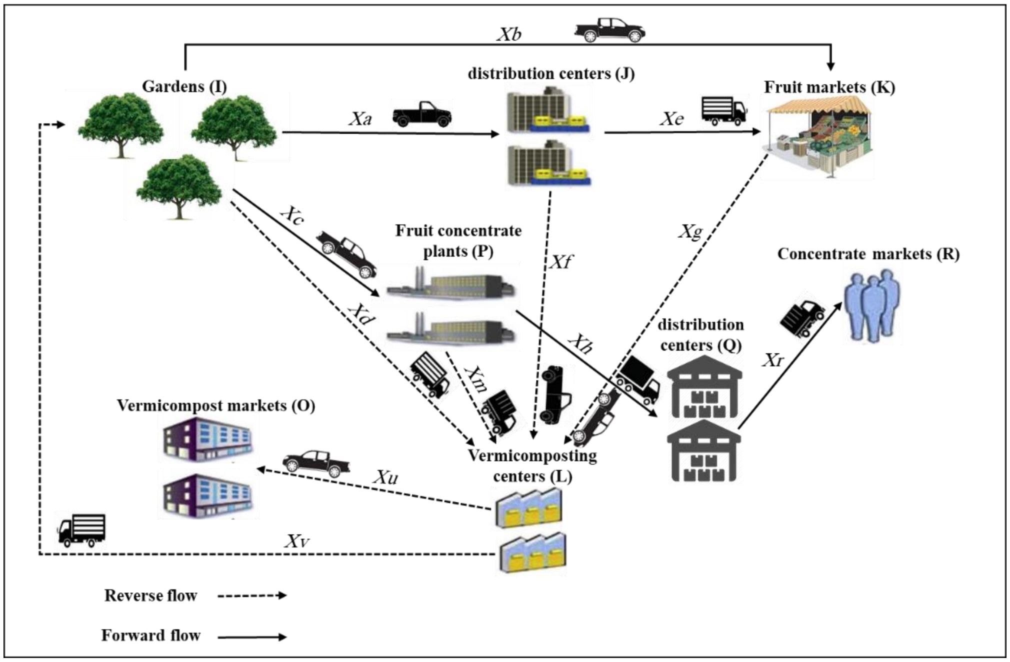


Figure 1. The proposed CLAFSC

The details of model indices, parameters, and decision variables are given in Appendix B. The description of the model constraints is made below.

$$\Lambda_{it} \times (1-\alpha_t) = \sum_{j\in J}\sum_{sf\in SF} Xa_{ijt}^{sf} + \sum_{k\in K}\sum_{sf\in SF} Xb_{ikt}^{sf} + \sum_{p\in P}\sum_{sf\in SF} Xc_{ipt}^{sf} \qquad \forall i \in I, t \in T \tag{1}$$

$$Ihj_{j(t-1)} + \sum_{i\in I}\sum_{sf\in SF} Xa_{ijt}^{sf} = Ihj_{jt} + \sum_{k\in K}\sum_{sf\in SF} Xe_{jkt}^{sf} + \sum_{l\in L}\sum_{sv\in SV} Xf_{jlt}^{sv} \qquad \forall j \in J, t \in T \tag{2}$$

$$Ihq_{q(t-1)} + \sum_{p\in P}\sum_{sc\in SC} Xh_{pqt}^{sc} = Ihq_{qt} + \sum_{q\in Q}\sum_{sc\in SC} Xr_{qrt}^{sc} \qquad \forall q \in Q, t \in T \tag{3}$$

$$\sum_{l\in L}\sum_{sv\in SV} Xv_{lit}^{sv} = F_i A_i nc \qquad \forall i \in I, t \in T \tag{4}$$

$$\left(\sum_{i\in I}\sum_{sv\in SV} Xd_{ilt}^{sv} + \sum_{j\in J}\sum_{sv\in SV} Xf_{jlt}^{sv} + \sum_{k\in K}\sum_{sv\in SV} Xg_{klt}^{sv} + \sum_{p\in P}\sum_{sv\in SV} Xm_{plt}^{sv}\right) \times \varphi = \sum_{o\in O}\sum_{sv\in SV} Xu_{lot}^{sv} + \sum_{i\in I}\sum_{sv\in SV} Xv_{lit}^{sv} \qquad \forall l \in L, t \in T \tag{5}$$

$$\sum_{i\in I}\sum_{sf\in SF} Xc_{ipt}^{sf} \times \mu = \sum_{q\in Q}\sum_{sc\in SC} Xh_{pqt}^{sc} \qquad \forall p \in P, t \in T \tag{6}$$

Equation (1) ensures that the waste subtracted from the garden output flow equals the total flow received by FCs, FDCs, and CPs. Equations (2) and (3) guarantee FDC and CDC input flow equals output flow plus inventory difference. Constraint (4) ensures that vermicompost shipped to gardens meets requirements. Equation (5) associates with VC product balance in each period, with inflows multiplied by the percentage of fruit conversion to vermicompost (φ) equaling outflows. Constraint (6) establishes CP product balance according to fruit conversion to concentrate (μ).

$$\Lambda_{it} \le \lambda c_{it} \qquad \forall i \in I, t \in T \tag{7}$$

$$Ihj_{jt} \le \lambda h_j \qquad \forall j \in J, t \in T \tag{8}$$

$$Ihq_{qt} \le \lambda h_q \qquad \forall q \in Q, t \in T \tag{9}$$

$$\sum_{i\in I} \sum_{sf\in SF} \sum_{t\in T} Xa_{ijt}^{sf} \quad \le \lambda h_j \qquad \forall j \in J \tag{10}$$

$$\sum_{p\in P} \sum_{sc\in SC} \sum_{t\in T} Xh_{pqt}^{sc} \quad \le \lambda h_q \qquad \forall q \in Q \tag{11}$$

Equation (7) confirms that garden-produced fruit entering the SC does not exceed its capacity. Equations (8) and (9) set the maximum storage capacity for FDC and CDC, respectively. Equations (10) and (11) also constrain input flow to FDC and CDC within their processing capacity.

$$\sum_{j\in J} \sum_{sf\in SF} Xe_{jkt}^{sf} + \sum_{i\in I} \sum_{sf\in SF} Xb_{ikt}^{sf} \le d_{kt} \qquad \forall k \in K, t \in T \tag{12}$$

$$\sum_{q\in Q} \sum_{sc\in SC} Xr_{qrt}^{sc} \le d'_{rt} \qquad \forall r \in R, t \in T \tag{13}$$

$$\sum_{l\in L} \sum_{sv\in SV} Xu_{lot}^{sv} \le d''_{ot} \qquad \forall o \in O, t \in T \tag{14}$$

$$\sum_{l\in L} \sum_{sv\in SV} Xd_{ilt}^{sv} \le \alpha_t \times \Lambda_{it} \qquad \forall i \in I, t \in T \tag{15}$$

$$\sum_{l\in L} \sum_{sv\in SV} Xf_{jlt}^{sv} \le \beta_t \times \mathrm{Ihj}_{j(t-1)} \qquad \forall j \in J, t \in T \tag{16}$$

$$\sum_{l\in L} \sum_{sv\in SV} Xg_{klt}^{sv} \le \theta_t \times \left(\sum_{i\in I} \sum_{sf\in SF} Xb_{ikt}^{sf} + \sum_{j\in J} \sum_{sf\in SF} Xe_{jkt}^{sf} \right) \qquad \forall k \in K, t \in T \tag{17}$$

$$\sum_{l\in L} \sum_{sv\in SV} Xm_{plt}^{sv} \le \gamma_t \times \left(\sum_{i\in I} \sum_{sf\in SF} Xc_{ipt}^{sf} \right) \qquad \forall p \in P, t \in T \tag{18}$$

Equations (12), (13), and (14) impose demand constraints on FC, CC, and VC, respectively. These constraints limit the fulfillment of demand to the specific values within each period. Constraints (15), (16), (17), and (18) model the reversal products from the garden, FDC, FC, and CP, where the total volume of reverse products depends on the fruit entering the chain, fruit inventory, and fruit supplied to the market and CP, respectively.

$$\sum_{i\in I} \sum_{sf\in SF} \sum_{t\in T} Xa_{ijt}^{sf} \le M \times W_j \qquad \forall j \in J \tag{19}$$

$$\sum_{p\in P} \sum_{sc\in SC} \sum_{t\in T} Xh_{pqt}^{sc} \le M \times G_q \qquad \forall q \in Q \tag{20}$$

$$\sum_{i\in I} \sum_{sv\in SV} \sum_{t\in T} Xd_{ilt}^{sv} \le M \times Y_l \qquad \forall l \in L \tag{21}$$

$$\sum_{j\in J}\sum_{sv\in SV}\sum_{t\in T} Xf_{jlt}^{sv} \leq M \times Y_l \qquad \forall l \in L \tag{22}$$

$$\sum_{k\in K}\sum_{sv\in SV}\sum_{t\in T} Xg_{klt}^{sv} \leq M \times Y_l \qquad \forall l \in L \tag{23}$$

$$\sum_{l\in L}\sum_{sv\in SV} Xm_{plt}^{sv} \leq M \times Y_l \qquad \forall p \in P, t \in T \tag{24}$$

Equations (19) and (20) restrict the flows to only open FDCs and CDCs. Besides, constraints (21), (22), (23), and (24) ensure that reversal products from the garden, FDC, FC, and CP are exclusively transported to established VCs.

$$Y_l, W_j, G_g, F_i \in \{0,1\} \qquad \forall l \in L, j \in J_f, q \in Q, i \in I \tag{25}$$

$$Xa_{ijt}^{sf}, Xb_{ikt}^{sf}, Xc_{ipt}^{sf}, Xd_{ilt}^{sv}, Xe_{jkt}^{sf}, Xf_{jlt}^{sv}, Xg_{klt}^{sv}, Xh_{pqt}^{sc}, Xm_{plt}^{sv}, Xr_{qrt}^{sc}, Xu_{lot}^{sv}, Xv_{lit}^{sv}, Ihj_{jt}, Ihq_{qt}, \Lambda_{it} \\ \geq 0 \qquad \forall i, j, k, p, q, r, l, o, sf, sc, sv, t \tag{26}$$

Finally, the decision variables are defined, where constraints (25) and (26) introduce binary and non-negative variables, respectively. The first objective function, which minimizes the total cost, considers the economic performance of the SC, as shown in Equation (27). z^{FOC} calculates the fixed costs of opening potential FDCs, CDCs, and VCs, as shown in Equation (28). z^{TPC}, computed in Equation (29), is related to the transportation cost by different vehicles, which varies for different products due to the need to use ancillary equipment, and depends on parameters such as fuel price, vehicle consumption and maintenance. Equation (30) calculates z^{HIC} to determine the inventory cost in FDCs and CDCs. z^{PRC}, computed using Equation (31), covers the production costs of gardens, CPs, and VCs. Equation (32) calculates the cost of processing in distribution centers, which is considered z^{DSC}. z^{FSC}, as the supplying cost of chemical fertilizer from a third-party vendor, is computed in Equation (33). It is assumed that the third-party vendor produces and transports the chemical fertilizer.

$$Min\ Z^{economic} = z^{FOC} + z^{TPC} + z^{HIC} + z^{PRC} + z^{DSC} + z^{FSC} \tag{27}$$

$$z^{FOC} = \sum_{j\in J} f_j W_j + \sum_{q\in Q} f_q\, G_q + \sum_{l\in L} f_l\, Y_l \tag{28}$$

$$
\begin{aligned}
z^{TPC} = {} & \sum_{i\in I}\sum_{j\in J}\sum_{sf\in SF}\sum_{t\in T}\left\lceil\frac{Xa_{ilt}^{sf}}{\lambda g^{sf}}\right\rceil dxa_{ij}tf^{sf} + \sum_{i\in I}\sum_{k\in K}\sum_{sf\in SF}\sum_{t\in T}\left\lceil\frac{Xb_{ikt}^{sf}}{\lambda g^{sf}}\right\rceil dxb_{ik}tf^{sf} \\
& + \sum_{j\in J}\sum_{k\in K}\sum_{sf\in SF}\sum_{t\in T}\left\lceil\frac{Xe_{jkt}^{sf}}{\lambda g^{sf}}\right\rceil dxe_{jk}tf^{sf} + \sum_{i\in I}\sum_{p\in P}\sum_{sf\in SF}\sum_{t\in T}\left\lceil\frac{Xc_{ipt}^{sf}}{\lambda g^{sf}}\right\rceil dxc_{ip}tf^{sf} \\
& + \sum_{p\in P}\sum_{q\in Q}\sum_{sc\in SC}\sum_{t\in T}\left\lceil\frac{Xh_{pqt}^{sc}}{\lambda g^{sc}}\right\rceil dxh_{pq}tc^{sc} + \sum_{q\in Q}\sum_{r\in R}\sum_{sc\in SC}\sum_{t\in T}\left\lceil\frac{Xr_{qrt}^{sc}}{\lambda g^{sc}}\right\rceil dxr_{qr}tc^{sc} \\
& + \sum_{i\in I}\sum_{l\in L}\sum_{sv\in SV}\sum_{t\in T}\left\lceil\frac{Xd_{ilt}^{sv}}{\lambda g^{sv}}\right\rceil dxd_{il}tv^{sv} + \sum_{j\in J}\sum_{l\in L}\sum_{sv\in SV}\sum_{t\in T}\left\lceil\frac{Xf_{ilt}^{sv}}{\lambda g^{sv}}\right\rceil dxf_{jl}tv^{sv} \\
& + \sum_{k\in K}\sum_{l\in L}\sum_{sv\in SV}\sum_{t\in T}\left\lceil\frac{Xg_{klt}^{sv}}{\lambda g^{sv}}\right\rceil dxg_{kl}tv^{sv} + \sum_{p\in P}\sum_{l\in L}\sum_{sv\in SV}\sum_{t\in T}\left\lceil\frac{Xm_{plt}^{sv}}{\lambda g^{sv}}\right\rceil dxm_{pl}tv^{sv} \\
& + \sum_{l\in L}\sum_{o\in O}\sum_{sv\in SV}\sum_{t\in T}\left\lceil\frac{Xu_{lot}^{sv}}{\lambda g^{sv}}\right\rceil dxu_{lo}tv^{sv} + \sum_{l\in L}\sum_{i\in I}\sum_{sv\in SV}\sum_{t\in T}\left\lceil\frac{Xv_{lit}^{sv}}{\lambda g^{sv}}\right\rceil dxv_{li}tv^{sv}
\end{aligned}
\tag{29}
$$

$$
z^{HIC} = \sum_{j\in J}\sum_{t\in T} Ihj_{jt}chj_{jt} + \sum_{q\in Q}\sum_{t\in T} Ihq_{qt}ch_{qt} \tag{30}
$$

$$
z^{PRC} = \sum_{i\in I}\sum_{t\in T}\Lambda_{it}cp'_i + \sum_{p\in P}\sum_{q\in Q}\sum_{sc\in SC}\sum_{t\in T}Xh_{pqt}^{sc}cm_{pt} + \sum_{l\in L}\sum_{sv\in SV}\sum_{t\in T}cr_{lt}\left(\sum_{o\in O}Xu_{lot}^{sv} + \sum_{i\in I}Xv_{lit}^{sv}\right) \tag{31}
$$

$$
z^{DSC} = \sum_{i\in I}\sum_{j\in J}\sum_{sf\in SF}\sum_{t\in T}Xa_{ijt}^{sf}\,cp_{jt} + \sum_{p\in P}\sum_{q\in Q}\sum_{sc\in SC}\sum_{t\in T}Xh_{pqt}^{sc}\,cp_{qt} \tag{32}
$$

$$
z^{FSC} = \sum_{i\in I}(1 - F_i)A_i\,ns\,cf \tag{33}
$$

The second objective function, which minimizes CO_2-eq emission, considers the environmental performance of the SC, as shown in Equation (34). z^{FOE} calculates the fixed emissions of opening potential FDCs, CDCs, and VCs, as shown in Equation (35). z^{TPE}, computed in Equation (36), is related to the emissions due to transportation by different vehicles, which varies for different products due to the use of ancillary equipment for storage and transportation, and depends on parameters such as fuel pollution and vehicle consumption and maintenance. Equation (37) calculates z^{HIE} to determine the emissions from holding inventory in the FDCs and CDCs in the designed SC network. z^{PRE}, computed using Equation (38), covers emissions from fruit, concentrate and vermicompost production in gardens, CPs, and VCs, respectively. Equation (39) calculates the emissions due to processing in distribution centers, which is considered z^{DSE}. z^{FSE}, as the emissions that the SC indirectly makes due to the use of chemical fertilizer, is computed according to Equation (40).

$$Min\, Z^{environmental} = z^{FOE} + z^{TPE} + z^{HIE} + z^{PRE} + z^{DSE} + z^{FSE} \tag{34}$$

$$z^{FOE} = \sum_{j \in J} fe_j W_j + \sum_{q \in Q} fe_q\, G_q + \sum_{l \in L} fe_l\, Y_l \tag{35}$$

$$\begin{aligned} z^{TPE} = {} & \sum_{i \in I} \sum_{j \in J} \sum_{sf \in SF} \sum_{t \in T} \left\lceil \frac{Xa_{ilt}^{sf}}{\lambda g^{sf}} \right\rceil dxa_{ij} tef^{sf} + \sum_{i \in I} \sum_{k \in K} \sum_{sf \in SF} \sum_{t \in T} \left\lceil \frac{Xb_{ikt}^{sf}}{\lambda g^{sf}} \right\rceil dxb_{ik} tef^{sf} \\ & + \sum_{j \in J} \sum_{k \in K} \sum_{sf \in SF} \sum_{t \in T} \left\lceil \frac{Xe_{jkt}^{sf}}{\lambda g^{sf}} \right\rceil dxe_{jk} tef^{sf} + \sum_{i \in I} \sum_{p \in P} \sum_{sf \in SF} \sum_{t \in T} \left\lceil \frac{Xc_{ipt}^{sf}}{\lambda g^{sf}} \right\rceil dxc_{ip} tef^{sf} \\ & + \sum_{p \in P} \sum_{q \in Q} \sum_{sc \in SC} \sum_{t \in T} \left\lceil \frac{Xh_{pqt}^{sc}}{\lambda g^{sc}} \right\rceil dxh_{pq} tec^{sc} + \sum_{q \in Q} \sum_{r \in R} \sum_{sc \in SC} \sum_{t \in T} \left\lceil \frac{Xr_{qrt}^{sc}}{\lambda g^{sc}} \right\rceil dxr_{qr} tec^{sc} \\ & + \sum_{i \in I} \sum_{l \in L} \sum_{sv \in SV} \sum_{t \in T} \left\lceil \frac{Xd_{ilt}^{sv}}{\lambda g^{sv}} \right\rceil dxd_{il} tev^{sv} + \sum_{j \in J} \sum_{l \in L} \sum_{sv \in SV} \sum_{t \in T} \left\lceil \frac{Xf_{ilt}^{sv}}{\lambda g^{sv}} \right\rceil dxf_{jl} tev^{sv} \\ & + \sum_{k \in K} \sum_{l \in L} \sum_{sv \in SV} \sum_{t \in T} \left\lceil \frac{Xg_{klt}^{sv}}{\lambda g^{sv}} \right\rceil dxg_{kl} tev^{sv} + \sum_{p \in P} \sum_{l \in L} \sum_{sv \in SV} \sum_{t \in T} \left\lceil \frac{Xm_{plt}^{sv}}{\lambda g^{sv}} \right\rceil dxm_{pl} tev^{sv} \\ & + \sum_{l \in L} \sum_{o \in O} \sum_{sv \in SV} \sum_{t \in T} \left\lceil \frac{Xu_{lot}^{sv}}{\lambda g^{sv}} \right\rceil dxu_{lo} tev^{sv} + \sum_{l \in L} \sum_{i \in I} \sum_{sv \in SV} \sum_{t \in T} \left\lceil \frac{Xv_{lit}^{sv}}{\lambda g^{sv}} \right\rceil dxv_{li} tev^{sv} \end{aligned} \tag{36}$$

$$z^{HIE} = \sum_{j \in J} \sum_{t \in T} Ihj_{jt} ehj_{jt} + \sum_{q \in Q} \sum_{t \in T} Ihq_{qt} ehq_{qt} \tag{37}$$

$$z^{PRE} = \sum_{i \in I} \sum_{t \in T} \Lambda_{it} ep'_i + \sum_{p \in P} \sum_{q \in Q} \sum_{sc \in SC} \sum_{t \in T} Xh_{pqt}^{sc} ec_p + \sum_{l \in L} \sum_{sv \in SV} \sum_{t \in T} ve_{lt} \left(\sum_{o \in O} Xu_{lot}^{sv} + \sum_{i \in I} Xv_{lit}^{sv} \right) \tag{38}$$

$$z^{DSE} = \sum_{i \in I} \sum_{j \in J} \sum_{sf \in SF} \sum_{t \in T} Xa_{ijt}^{sf}\, ep_{jt} + \sum_{p \in P} \sum_{q \in Q} \sum_{sc \in SC} \sum_{t \in T} Xh_{pqt}^{sc}\, ep_{qt} \tag{39}$$

$$z^{FSE} = \sum_{i \in I} (1 - F_i) A_i\, ns\, ef \tag{40}$$

The third objective function, which maximizes social benefits, considers the social performance of the SC. For this purpose, two SDGs are considered: (a) Decent Work and Economic Growth (SDG8), which refers to the destructive effects of job shortages in society, and (b) Responsible Consumption and Production (SDG12), which emphasizes meeting the needs of customers, especially basic needs such as water and food. The different terms of social effects multiplied by their given weights are shown in Equation (41). Equation (42) calculates the percentage of satisfying the demand in all markets according to their relative importance. This equation consists of three fractions; the numerators show the transported products to each market, while the denominators represent the total demands of that market over the planning horizon. The equation’s value is between 0 and 1, with 1 indicating the best state where all demands are met. Equation (43) computes the normalized value of job creation by opening FDCs, CDCs, and VCs in different social clusters. It serves as an indicator of social performance to maximize justice-oriented employment based on the unemployment rate in different social clusters. The equation favors opening facilities in areas with higher unemployment rates, thereby generating more job opportunities.

$$Max\ Z^{social} = w_{rsp} z^{RSP} + w_{jc} z^{JC} \tag{41}$$

$$z^{RSP} = \rho \times \left(\frac{\sum_{i\in I} \sum_{k\in K} \sum_{sf\in SF} \sum_{t\in T} Xb_{ikt}^{sf} + \sum_{j\in J} \sum_{k\in K} \sum_{sf\in SF} \sum_{t\in T} Xe_{jkt}^{sf}}{\sum_{k\in K} \sum_{t\in T} d_{kt}} \right) + \eta \times \left(\frac{\sum_{q\in Q} \sum_{r\in R} \sum_{sc\in SC} \sum_{t\in T} Xr_{qrt}^{sc}}{\sum_{r\in R} \sum_{t\in T} d'_{rt}} \right)$$
$$+ (1 - \rho - \eta) \times \left(\frac{\sum_{l\in L} \sum_{o\in O} \sum_{sv\in SV} \sum_{t\in T} Xu_{lot}^{sv}}{\sum_{o\in O} \sum_{t\in T} d''_{ot}} \right) \tag{42}$$

$$z^{JC} = \frac{\sum_{z\in Z} \omega_z \left(\sum_{j\epsilon J} n_{jz} W_j + \sum_{q\epsilon Q} m_{qz} G_q + \sum_{l\epsilon L} b_{lz} Y_l \right)}{\sum_{z\in Z} \omega_z \left(\sum_{j\epsilon J} n_{jz} + \sum_{q\epsilon Q} m_{qz} + \sum_{l\epsilon L} b_{lz} \right)} \tag{43}$$

4. Solving Approach

Due to the NP-hardness of the problem, accurate mathematical solution strategies will undoubtedly be time-consuming. Therefore, metaheuristic methods and, specifically, those based on genetic algorithms have been developed in this research. Multi-objective genetic algorithms (MOGAs) efficiently identify multiple POSs in a single simulation implementation. The Non-dominated Sorting Genetic Algorithm (NSGA) is a popular and efficient algorithm to obtain the POS set proposed by Srinivas and Deb (1994). Seeking to modify NSGA due to its shortcomings, including lack of elitism, computational complexity, and selecting the optimal parameter value for a subscription parameter, researchers introduced the second version of NSGA (NSGA-II) (Deb et al., 2002). Then the Non-dominated Ranked genetic algorithm (NRGA), and in recent years the reference point-based Non-dominated Sorting genetic algorithm (NSGA-III) was introduced as MOGA (Al Jadaan et al., 2008, Deb and Jain, 2014). The problem in the present study is solved using NSGA-II, NRGA, and NSGA-III. Some of the solution algorithm features, such as encoding and decoding existing problem solutions and adaptive genetic operators in the structure of solution methods that contribute to achieving better and more diverse solutions, are described in Appendix D.

5. Case study

Iran ranks fifth in apple production worldwide. The data related to the model parameters were obtained from the apple supply chain of West Azerbaijan province, accounting for almost 26% of the total apple production in Iran. To evaluate the performance of the model in different sizes and the behavior of solution algorithms in the problem at hand, SCs with a different number of facilities in each echelon are considered, as presented in Table 1.

Table 1. Dimensions of different-sized problems

Test Problem		I	J	K	P	Q	R	L	O
Small	P1	3	4	3	2	4	3	4	2
	P2	5	7	5	3	5	4	7	4
	P3	7	10	7	3	7	5	10	5
	P4	9	13	9	4	10	7	13	8
Medium	P5	15	22	15	5	16	12	22	14
	P6	17	25	17	5	19	14	25	16
	P7	19	28	19	5	22	16	28	17
	P8	25	36	25	6	28	20	35	22
Large	P9	35	51	35	7	38	26	52	31
	P10	37	54	37	8	43	32	55	35
	P11	39	58	39	9	47	34	58	37
	P12	41	61	41	10	52	36	61	40

This study considers the one-year time horizon of 12 monthly periods (T'''). Subject to the apple characteristics, gardens can harvest the product for three periods (T') from the beginning of the time horizon to be transferred to FCs, FDCs, and CPs. On the other hand, FDCs can have inventory up to the eighth period (T'') to meet customer demand up to 5 months after the harvest season. Also, the conversion of fruit to concentrate in plants lasts until the end of the harvest season; then, the produced concentrate is immediately shipped to CDCs for processing and packaging. The concentrate can be stored until the end of the time horizon and meet the demands of CCs if needed. Reversal flows extend as long as the fruit would have existed in the related facilities. Therefore, waste fruits will be transported to VCs, and vermicompost will be produced by the end of the eighth period. Data relevant to the parameters used in the model are presented in this section. The average distance between the supply chain facilities are assumed to be the same distance as among the cities. These distances are in kilometers, and the average distance for different facilities in a city is 14 kilometers.

For economic objectives, fixed and variable costs for the activities of the various levels of the investigated SC are given in Table 2, along with their units. The production, processing, and storage capacity of facilities in the SC, each market's demand in each period, and each garden area are generated by a uniform distribution in the range between the real data.

Table 2. The details of Economic assessment parameters

Parameter	Value	Unite
f_j	*Uniform~[114290,185715]*	Buck($)
f_q	*Uniform~[141220,162827]*	Buck($)
f_l	*Uniform~[14285,22855]*	Buck($)
ch_{jt}	$[96,97,100,104,104,110,113,120] \quad \forall j \in J$	Buck per Ton
ch_{qt}	$[104,110,112,118,121,126,133,141,150,153,158,162] \quad \forall q \in Q$	Buck per Ton
cp_{jt}	$[143, 146, 148, 151, 156, 156, 166, 171] \quad \forall j \in J$	Buck per Ton
cp_{qt}	$[238,247,254,254,266,273,273,276,285,292,302,302] \quad \forall q \in Q$	Buck per Ton
cm_{pt}	*Uniform~[590,786]*	Buck per Ton
cr_{lt}	$[143,143,166,166,166,191,214,226] \quad \forall l \in L$	Buck per Ton
cp'_I	*Uniform~[238,309]*	Buck per Ton
cf	*Uniform~[333,428]*	Buck per Ton

For the environmental assessment of the model, the parameters related to CO_2-eq emissions due to the activity of each level of the SC are adapted from (de Figueiredo et al., 2017; UKWA, 2013). In the social objective function, job opportunities created by opening a potential facility at the levels of FDCs, CDCs, and VCs are created by a uniform distribution. The conversion rates of fruit and its wastes to concentrate and vermicompost, respectively, the quantity of each fertilizer used per area of gardens, and the fruit waste rate at each level in different periods are collected according to Table 3. Finally, the cost and emissions values and the available vehicles' capacity to transport each product are adapted according to ECTA and Cefic, 2011 and Engineering ToolBox, 2009.

Table 3. The details of other parameters

Parameter	Value	Unite
α_t	*[10,12,15]*	Percentage
β_t	*[4,4.3,5.1,6,6.5,7,7.5,8.5]*	Percentage
θ_t	*[4,4.5,5.3,5.7,6.2,6.8,7.1,8]*	Percentage
γ_t	*[18,23,28]*	Percentage
φ	*110*	Percentage
μ	*40*	Percentage
nc	*1*	Ton per Hectare
ns	*0.4*	Ton per Hectare

6. Findings and Results

In this section, some of the standard multi-objective performance measurement criteria, including Mean Ideal Distance (*MID*), Spacing Index (*SI*), Diversification Index (*DI*) and Spread of Non-dominated Solution (*SNS*), are used to compare metaheuristics (Govindan et al., 2019). First, the parameters of these metaheuristics are tuned to achieve the best possible solutions. The test problems with small, medium and large categories are tuned separately according to Table 1. Also, the social maximization objective is transformed into the minimization objective to simplify the computational process. The equivalent of the maximization objective function (Z^{social}) is $1- Z^{social}$, which has a range of [0,1] and a best value of zero. In the following section, the model is evaluated being solved with tuned metaheuristics on various problem sizes, and computational results are compared. Finally, the analysis of the solutions for one of the problems with the best metaheuristic and its sensitivity analysis in different scenarios of the problem are discussed. We have used the GAMS software 24.1.2 using the CPLEX solver to implement the ε-constraint method. All test problems and the proposed model in this research were coded in MATLAB R2016b software, which runs on a personal computer with technical specifications of Intel (R) Core (TM) i7-6700HQ CPU @ 2.60GHz and 12GB RAM under Windows 10.

Parameters tuning. Metaheuristic algorithms have parameters that strongly affect their performance and reliability. Therefore, calibration of these parameters seems necessary. Input parameters of both NSGA-II and NSGA-III are the maximum number of iterations (Max-it), population size (NPop), crossover probability (Pc), and mutation probability (Pm). In addition to the above four parameters, NRGA has another one called selection pressure (β). The Taguchi method (Taguchi et al., 1993), as a powerful and efficient tool to calibrate the parameters of three metaheuristics, has been used to achieve the best results in this study. For this purpose, the amount of changes related to the response, the *S/N* quality index, is calculated according to the equation below. Since all three objectives of the model are minimization, the "smaller is better" is used (Maghsoudlou et al., 2016).

$$S/N = -10 \times log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \qquad (44)$$

In Equation (44), *y* and *n* represent the response values and the number of orthogonal arrays, respectively. The best level of each factor is obtained when the *S/N* index is at its highest value. Using the concept of designing experiments through the Taguchi method, orthogonal arrays are created according to the number of factors in the algorithms and the levels of these factors. Then the response for each of them is calculated. The response variable (*MOCV*) is defined based on two criteria, *MID* and *DI*, to measure the convergence and diversity of the solutions obtained by the algorithms, respectively, according to Equation (45).

$$MOCV = {}^{MID}/_{DI} \qquad (45)$$

Table 4. Metaheuristics parameters, along with their levels

Algorithm	**Parameter**	**Parameter levels**			
		Level 1	**Level 2**	**Level 3**	**Level 4**
NSGA-II	*Max-it*	300	500	1000	1500
	NPop	100	200	300	400
	Pc	0.6	0.7	0.8	0.9
	Pm	0.10	0.15	0.20	0.25
NRGA	*Max-it*	300	500	1000	1500
	NPop	100	200	300	400
	Pc	0.6	0.7	0.8	0.9
	Pm	0.10	0.15	0.20	0.25
	β	5	10	15	20
NSGA-III	*Max-it*	300	500	1000	1500
	NPop	100	200	300	400
	Pc	0.6	0.7	0.8	0.9

Algorithm	Parameter	Parameter levels			
		Level 1	Level 2	Level 3	Level 4
	Pm	0.10	0.15	0.20	0.25

Table 5. The orthogonal array L16 and Experimental results of metaheuristics for small size problems

Run order	Algorithm parameters					Response		
	Max-it	NPop	Pc	Pm	B	NSGA-II	NRGA	NSGA-III
1	1	1	1	1	1	1.443946468	1.441578996	1.632619204
2	1	2	2	2	2	1.333473623	1.241103554	1.524703616
3	1	3	3	3	3	1.294844831	1.3380473	1.307626478
4	1	4	4	4	4	1.322594986	1.063659943	1.275276342
5	2	1	2	3	4	1.29659129	1.234288601	3.148933612
6	2	2	1	4	3	1.241249345	1.186993593	1.175213578
7	2	3	4	1	2	1.292551461	1.144054594	1.795325765
8	2	4	3	2	1	1.207348688	1.076655261	1.574090574
9	3	1	3	4	2	0.952841421	1.088326754	3.082507508
10	3	2	4	3	1	0.906709537	0.935156448	1.39253379
11	3	3	1	2	4	1.147893781	1.102777007	1.272901624
12	3	4	2	1	3	1.185618047	1.312146779	1.8053398
13	4	1	4	2	3	1.081720805	1.173780252	2.947096878
14	4	2	3	1	4	1.300373079	0.971977335	1.592259018
15	4	3	2	4	1	0.984406535	0.875868452	1.437208027
16	4	4	1	3	2	0.831274365	1.132028437	1.34365326

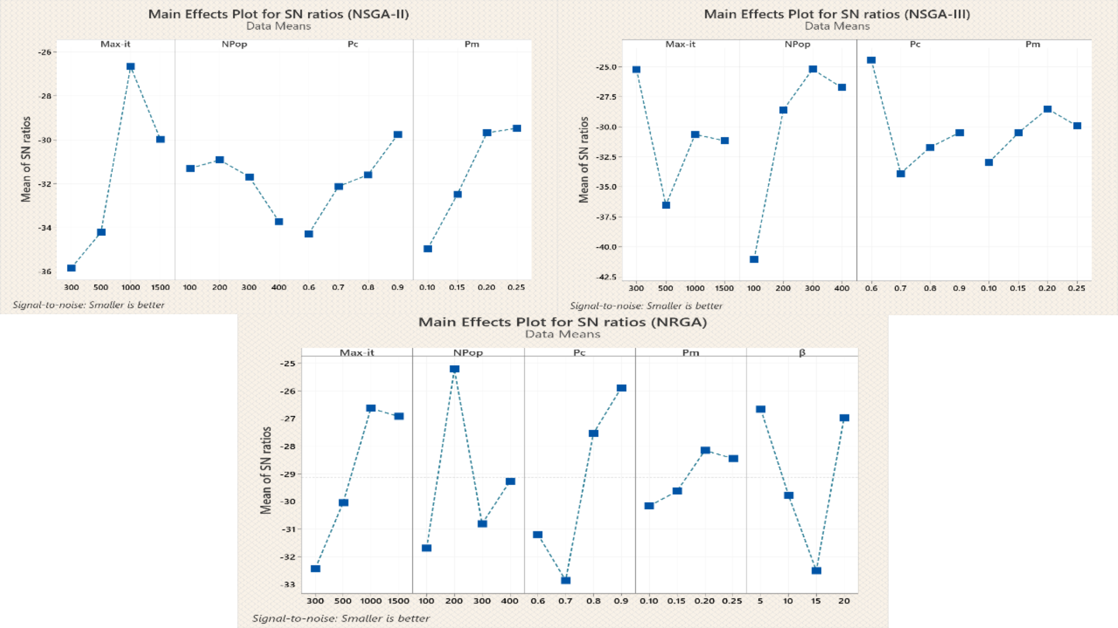


Figure 2. The S/N plots of the algorithms for small problems

The algorithms factors mentioned above for each algorithm with the considered four levels are shown in Table 4. The values of different levels related to each factor are set using the range presented in (Cheraghalipour et al., 2018; Roghanian and Cheraghalipour, 2019). The L^{16} orthogonal arrays are created using the Taguchi method on Minitab®19 software for all three algorithms. These arrays and the obtained results of each metaheuristic are presented in Table 5. Fig. 2 also shows the S/N index diagram for solution algorithms. Separate parameter tuning was made for small, medium, and large-sized problems in which P1, P5, and P9 were chosen as representatives, respectively. Also, each experiment was repeated thirty times, and the average of the obtained responses was considered. Finally, the optimal levels of each algorithm parameter in different size problems are determined, which are shaded in Table 6.

Table 6. Tuned parameters of metaheuristics for different size problems

Algorithm	**Parameter**	**Best Value**		
		Small size	**Medium size**	**Large size**
NSGA-II	*Max-it*	1000	1500	1500
	NPop	200	400	400
	Pc	0.9	0.6	0.8
	Pm	0.25	0.20	0.15
NRGA	*Max-it*	1000	500	1500
	NPop	200	400	400
	Pc	0.9	0.7	0.7
	Pm	0.20	0.20	0.25
	β	5	5	5
NSGA-III	*Max-it*	300	300	1000
	NPop	300	300	400
	Pc	0.6	0.7	0.6
	Pm	0.20	0.25	0.20

Applications and comparison. After tuning the algorithms' parameters, we proceeded to validate the mathematical model and assess the performance of the optimized algorithms by solving the twelve test problems outlined in section 5. Initially, the algorithms were validated by solving the first small problem through the ε -constraint, which gave us the performance criteria of Table (7). Since it takes approximately 219639^S to solve the problem, the exact technique can not handle other small tests, let alone medium and large problems. However, NSGA-II, NRGA, and NSGA-III could find Pareto front in 2568, 2487, and 1880 seconds, respectively.

Table 7. Evaluation of meta-heuristics for test problem 1

P	ε-constraint				NSGA-II				NRGA				NSGA-III			
	MID	*SI*	*DI*	*SNS*	*MID*	*SI*	*DI*	*SNS*	*MID*	*SI*	*DI*	*SNS*	*MID*	*SI*	*DI*	*SNS*
1	1.67	13759	0.96	0.25	1.72	11419	1.15	0.22	1.82	17791	1.13	0.26	2.34	21818	0.94	0.21

Moreover, all problems of different sizes were solved ten times independently with each meta-heuristic. Therefore, the values of multi-objective measuring criteria are calculated based on the average of values obtained from the Pareto front in different runs. One-way ANOVA has been next used to compare the algorithms and find the best algorithm decisively and statistically. For this purpose, the values of the performance comparison criteria obtained for different problems are converted to a relative deviation index (RDI) as the following equation (Govindan et al., 2019).

$$\mathrm{RDI}=\left(\frac{\left|\mathrm{Sol}_{\mathrm{alg}}-Sol_{best}\right|}{Solmin_{max}}\times 100\right) \tag{46}$$

In Equation (46), Sol_{alg} is the value of each criterion obtained by solution algorithms for a problem, and Sol_{max} and Sol_{min} are the maximum and minimum values of each criterion, respectively. Sol_{best} is also the best value obtained for the comparison criterion. Due to their nature, it is equal to Sol_{min} for the SI and MID criteria and Sol_{max} for the DI and SNS criteria. It should be added that smaller values of RDI are desirable.

Table 8. ANOVA for (a) the SI metric, (b) the MID metric, (c) the DI metric, and (d) the SNS metric

(a)

Source	DF	SS	MS	F	P-value
Factor	2	4626.311	2313.155	3.146	0.056
Error	33	24265.922	735.331		
Total	35	28892.233			

(b)

Source	DF	SS	MS	F	P-value
Factor	2	11367.719	5683.859	14.571	0.000
Error	33	12872.654	390.080		
Total	35	24240.372			

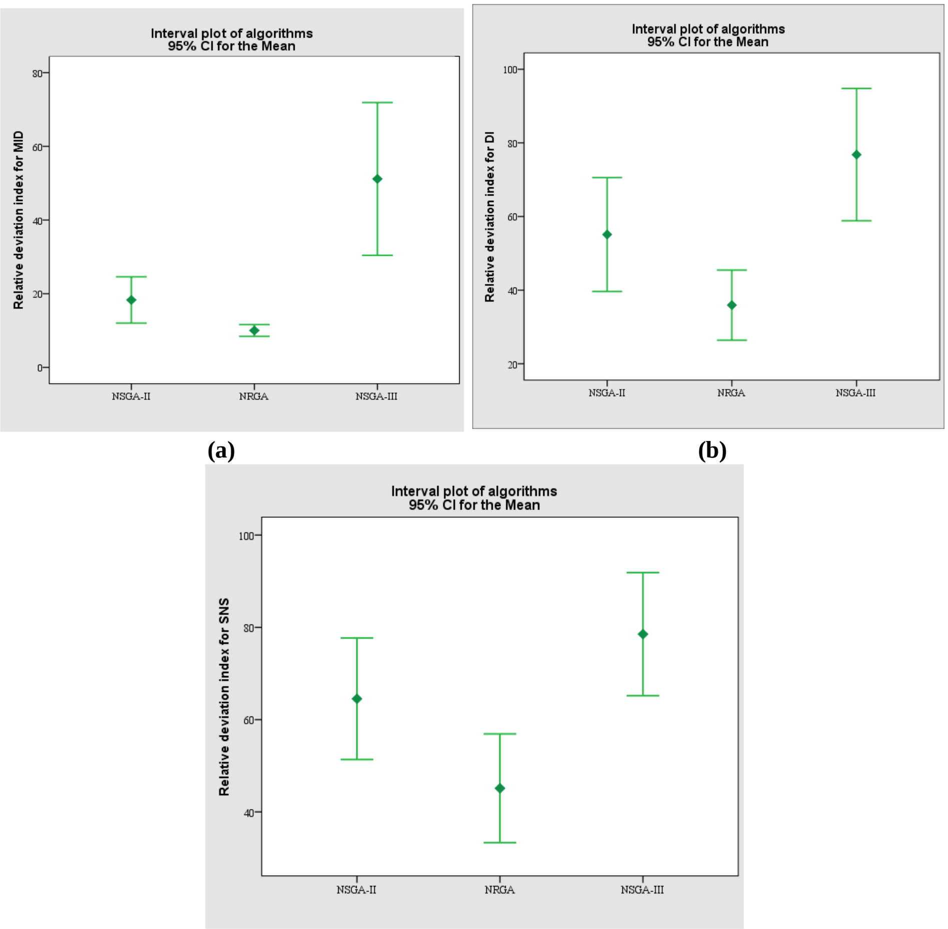
(c)

Source	DF	SS	MS	F	P-value
Factor	2	10041.596	5020.798	9.313	0.001
Error	33	17791.573	539.139		
Total	35	27833.169			

(d)

Source	DF	SS	MS	F	P-value
Factor	2	6754.241	3377.121	8.342	0.001
Error	33	13359.928	404.846		
Total	35	20114.169			

One-way ANOVA and Tukey's 95% confidence interval were performed for performance measuring criteria in three metaheuristics using SPSS 24 statistical software. Table 8 presents ANOVA results based on statistical concepts. The algorithms significantly differ in a criterion if the P-value is less than 0.05. Then, for the criteria with a statistically significant difference between the algorithms, mean plot and least significant difference (LSD) intervals are delineated to identify a more efficient algorithm for the proposed model. These diagrams are shaded in Fig. 3. As can be seen, the NRGA algorithm outperforms the other two methods regarding all three criteria, MID, DI, and SNS, and after that, NSGA-II outperforms NSGA-III. It should also be noted that there is no significant difference between metaheuristics according to SI criteria.



(a) **(b)**

(c)

Figure 3. Means and interval plot for (a) MID metric, (b) DI metric, and (c) SNS metric

In addition, Fig. 4 presents the POSs obtained by the metaheuristics for the second test problem to elucidate the proposed algorithms' performance better. To clarify the solutions in the diagram, the number of POSs is only 30. As shown in the figure, although a small number of solutions found with the NSGA-II and NSGA-III are better, it confirms the above results regarding the superiority of NRGA.

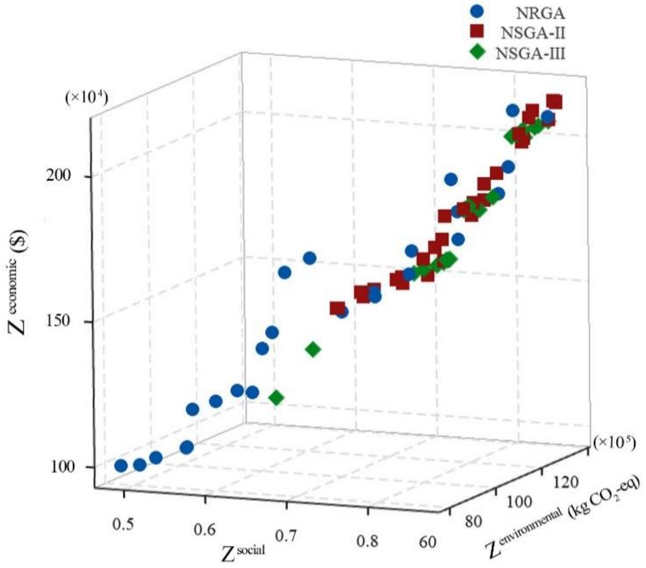


Figure 4. Obtained Pareto-front of the solution algorithms on the second test problem

Furthermore, the CPU Time (Run time to reach the Pareto front) versus the problem size diagram for NRGA was plotted to investigate the effect of the problem size on the algorithm solution time. Fig. 5 shows that CPU Time increases as expected when the problem size expands. This figure is a signal for validating the proposed model and test problems.

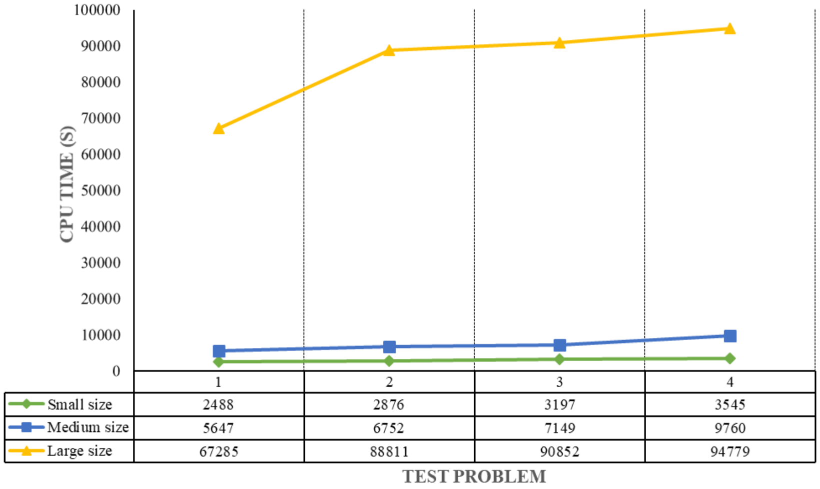


Figure 5. The interaction between problem size and CPU Time of the algorithm

In the rest of this section, we assist managers in selecting an appropriate network. The Pareto front generated by NRGA represents different SAFSCNDs and their corresponding economic, environmental, and social objectives. To evaluate the compliance of these Pareto solutions with decision-makers' preferences, we use the *WPD* measure, which calculates the weight distance between an optimal Pareto solution and the problem's ideal point. This measure for solution *e* is defined as Equation (47) (Dehghanian and Mansour, 2009).

$$WPD_e = \sum\nolimits_{m=1}^{3} \left(W_m \times \frac{f_m^{(e)} - f_m^{best}}{f_m^{nadir} - f_m^{best}} \right) \tag{47}$$

W_m denotes the weight of the objective function *m*, which depends on the decision-maker's preference. Each objective function with a high priority for the decision-maker has more weight. $f_m^{(e)}$ is the value of the *m*th objective function of solution *e*, and f_m^{best} is the *m*th objective function value of the ideal point. The values of economic, environmental, and social objective functions at the ideal point are assumed to be equal to *0*, *0* and *1*, respectively. f_m^{nadir} is also the worst value of the *m*th objective function. Because the scale of the research objective functions differs, the distances are normalized by dividing the difference between the objective function's best and worst values. The less *WPD* a solution has, the more preferable. The *WPD* for the solutions was calculated, considering the various W_m sets, as shown in Fig. 6. The various W_m sets are shown on the right of the chart, which shows the weights of the economic, environmental, and social objective functions for each graph, respectively.

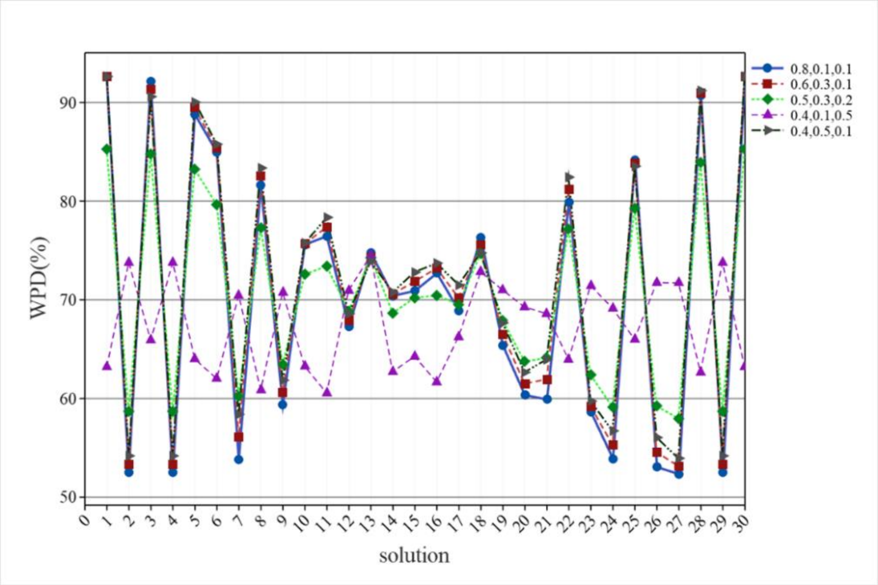
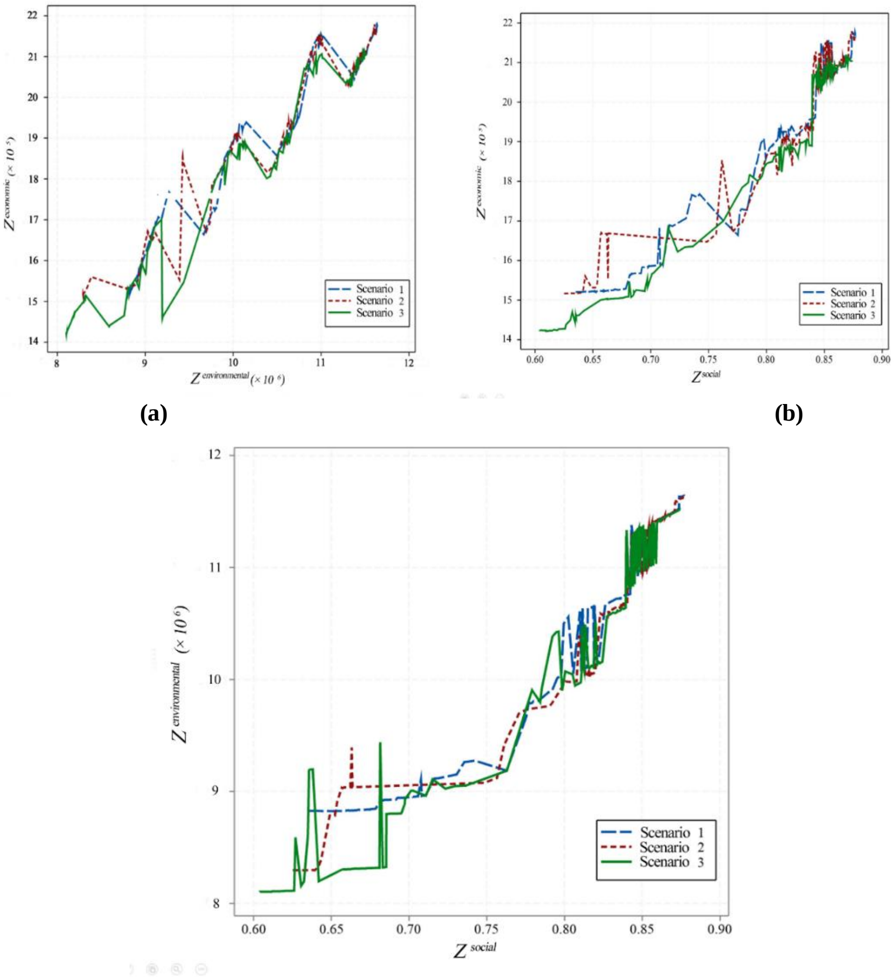


Figure 6. WPD for some of the Pareto-optimal solutions

According to the figure, the environmental objective is aligned with the economic objective. Also, with increasing social objective weight, a significant *WPD* change occurs, which is incompatible with the other two objectives. Since the growth of employment and meeting customer demand requires selecting a configuration that has a higher cost and CO_2-eq emission, it moves further away from the ideal values of the economic and environmental objectives.

- **Sensitivity Analysis.** This section conducts a sensitivity analysis of the model to test how certain model parameters impact sustainability objectives and additional assets. For this purpose, the second test problem is performed in three different scenarios; the explanations of these scenarios are given below.Scenario 1. Proposed model without fruit production in the organic procedure,
- Scenario 2. The proposed model disregards multi-type vehicles for transporting different products,
- Scenario 3. Proposed model without any changes.



(a) **(b)**

(c)

Figure 7. Obtained Pareto front of three scenarios between **(a)** economic and environmental objective functions, **(b)** economic and social objective functions, and **(c)** environmental and social objective functions

Different scenarios are solved through the superior algorithm of this research (NRGA), then the results are reported in Fig. 7 and Table 9. As shown in the figures, the Pareto solutions issued from solving the model in the third scenario are closer to optimal values than the Pareto solutions of the first and second scenarios. In addition, according to Table 9, in the third scenario, compared to the first and second scenarios, the model can improve the best value of the economic objective function by 6.4% and 6.2% and the environmental objective function by 8.2% and 2.3%, respectively. In contrast, the social objective function values remain almost constant in all three scenarios.

Table 9. The results of sensitivity analysis

Condition	Best $Z^{economic}$	Best $Z^{emission}$	Best Z^{social}
1	1519686	8821363	0.876969
2	1515878	8292397	0.876969
3	1421158	8102235	0.873807

7. Managerial and practical insights

The proposed supply chain network in this study aims to provide applicable insights to managers and practitioners that contribute to industry development. By investigating the circular economy of the AFSC and considering trade-offs between the three pillars of sustainability in the proposed SCND, the following valuable insights have been obtained that are strongly recommended for attention:

- DMs in the AF sector can choose an appropriate network based on their preferences. They can consider specific country regulations and prioritize sustainability to tailor the network accordingly.
- The inclusion of organic and chemical fertilizers in the SCND impacts the economic and environmental aspects but does not significantly affect the social aspect. Environmental pollution reduction is found to be more sensitive than the economic objective.
- The adoption of various vehicles in the SC leads to a more efficient network, primarily affecting economic performance and CO2-eq emissions but not significantly influencing the social aspect.
- All algorithms within our framework offer DMs specific optimal SC networks suitable for real-world demands. The solutions are unique due to adopting multi-objective optimization algorithms with a random search mechanism.

These insights empower DMs to make informed choices regarding the design and management of an SC network, considering the specific context and sustainability priorities of the AF sector.

8. Conclusions and future research

In the modern world, as global demand for APs and the waste generated from these products continue to rise, there is a growing awareness of global environmental and social issues. Consequently, the importance of sustainable management of the AFSC has become even more prominent. This research contributes to revealing this issue: How to integrate sustainability into the design and configuration of the AFSC? In attempting to do it, we provide a multi-objective mixed-integer mathematical programming model for designing and configuring closed-loop AFSC consisting of three sustainability pillars. This model seeks to locate some required facilities, allocate product flow between the facilities, determine the type and number of required vehicles, plan production and storage, and determine the optimal type of fertilizer used (vermicompost or chemical) in each garden. We consider GHG emissions from total SC activities at different levels as an environmental indicator, which to the best of the authors' knowledge, had never been used before in AFSCND models. However, the substantial role of agriculture in global warming is evident in the literature. As the third dimension of sustainability, the weighted combination of two social indicators is studied in this model, which allows examining the impact of responding to customer demand and locating the facilities according to social considerations on the economic performance of SC and improves its social responsibility.

The developed model was tested on twelve problems of different sizes based on a real case study to confirm its robustness. Since the problem is NP-hard, genetic-based metaheuristic algorithms, including NSGA-II, NRGA, and NSGA-III, were used to solve it with similar chromosomal structures. After calibrating the metaheuristics using the Taguchi method, we solve various-sized problems. Pareto solutions were statistically compared through four multi-objective comparison criteria, including MID, SI, DI, and SNS. Finally, in reliance on the results, NRGA was introduced as an outperforming algorithm. Because the model objectives conflicted, the WPD diagrams were drawn for 30 Pareto solutions according to different decision-makers preferences about objective functions, which can be a proper criterion to guide them in finding the desired solutions. Also, a sensitivity analysis was fulfilled to evaluate the performance of the model in different scenarios. The diagrams proved that using vermicompost possibility for gardens and considering several types of vehicles simultaneously contributes to improving the sustainability of the chain. It should be pointed out that the case study parameter values are highly correlated with the under-study geographical area, and their compatibility with other areas is not guaranteed. Despite examining the crucial aspects of the issue, much research is still required to clarify the research question. Some extensions of the study can be suggested for future research. For example, solving the model by other metaheuristics in the literature and comparing solutions with in-hand results even based on other multi-objective comparison criteria can be a significant point. Due to the need to study the impact of uncertainty on SCND (Govindan and Cheng, 2018), further research may also consider other aspects at the model level, such as the possible dynamic behavior of the network and uncertainty at the strategic level in some parameters, namely the fruit waste rate at different levels and different markets demand. Moreover, adding some elements to economic and environmental objectives, such as JIT delivery and the quality costs (Gürsoy and Kara, 2021) of fruit as well as the emission of GHG due to products' destruction in each period and level of the chain can be worth for later studies. Additionally, it is interesting to exert other indicators to evaluate the three sustainability dimensions, such as the profit index as economic performance or the average lead time to respond to customers (Yılmaz and Pardalos, 2017) and the hard work index as social performance. Finally, new meta-heuristics such as SPEA-II and PESA-II and hybrid meta-heuristics proposed in the literature (e.g. Seydanlou et al., 2022, Goodarzian et al., 2023) can be applied to our proposed model to compare the efficiency of our algorithms.

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