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Hybrid meta-heuristic algorithms for optimising a sustainable agricultural supply chain network considering CO_2 emissions and water consumption

Fariba Goodarzian[a], Davood Shishebori[b], Farzad Bahrami[c], Ajith Abraham[a,d] and Andrea Appolloni[e,f]

[a]Machine Intelligence Research Labs (MIR Labs), Scientific Network for Innovation and Research Excellence, Auburn, WA, USA; [b]Department of Industrial Engineering, Yazd University, Yazd, Iran; [c]Department of Industrial Management, Faculty of Law & Economics, Arak University, Arak, Iran; [d]Center for Artificial Intelligence, Innopolis University, Innopolis, Russia; [e]Department of Management and Law, Faculty of Economics, University of Rome Tor Vergata, Rome, Italy; [f]School of Management, Cranfield University, Bedford, UK

ABSTRACT

In this research, a new mixed-integer linear programming (MILP) formulation for the production-distribution-routing problem is developed in a sustainable agricultural product supply chain network (SAPSCN) considering CO_2 emission. The objective functions of the SAPSCN model seek to minimise the economic effects containing total cost in SAPSCN and environmental impacts including production and operation emissions, water consumption in production, operational water consumption, and transportation emission, as well as to maximise social impacts including on the number of the created works. Due to the complexity and NP-hardness of the SAPSCN formulation, four multi-objective meta-heuristic algorithms were applied, and two new hybrid meta-heuristic algorithms were developed. To assess the efficiency of the suggested meta-heuristic algorithms, various test instances were used to solve the proposed model and comparisons and sensitivity analyses were carried out with various criteria. A real case study is provided to validate the mathematical model. Finally, the results of the hybrid simulated annealing and particle swarm optimisation algorithm emphasises that it is more robust than other proposed algorithms to solve the problem in a reasonable time.

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Agricultural product supply chain network; sustainability; multi-objective optimisation; hybrid meta-heuristics

1. Introduction

Agriculture is one of the most critical factors in any country's economy, performing a key role in economic and political independence (Heard et al., 2018). Also, due to their several natural resources and climate, some countries have four seasons in different regions at the same time and can therefore focus on this crucial element in their economy (Mogale, Kumar, Kumar, et al., 2018; Allaoui et al., 2018). However, it has not played a significant role in developing countries' economies despite the attempts to increase production and export agricultural products. Weak management in programming and the sustainable agricultural product supply chain network (SAPSCN) and the entry of dealers and intermediaries are possibly the main reasons for failure in this field (Mogale, Kumar, Kumar, et al., 2018).

The design of the SAPSCN is more challengeable when sustainability is accepted in common economy-centred approaches. One of the substantial challenges in this respect is the wide range of influential factors related to sustainability that should be taken into consideration; several factors of which cannot be fully integrated into, or measured by, a one-step optimisation problem. Accordingly, a scientific approach should be implemented as regards environmental conservation, economic growth, and social effects (Allaoui et al., 2018; Ghasemzadeh et al., 2021). Some works have been done to identify the sustainable features of the SAPSCN, but there has been little attempt to present a comprehensive framework.

Sustainable innovations in organisations can be reached on the operational, tactical, and strategic levels. The relevant decisions may consist of selecting sustainable suppliers, the design of a sustainable supply chain network (SCN), i.e. purchase, transportation, production, and information technology. Meanwhile, the main contribution of the current study is to merge two significant topics: optimisation of the sustainability function impacts and sustainable supplier selection in designing the SAPSCN. Since a few studies have been done so far, the current paper can be considered as a primary effort in this regard. Therefore, the main subjects addressed by our paper have been classified under the rubrics of 'agricultural products supply chain', 'sustainability in the SCN', and concerning the problems of designing the

CONTACT Fariba Goodarzian Fariba.Goodarzian@mirlabs.org Machine Intelligence Research Labs (MIR Labs), Scientific Network for Innovation and Research Excellence, 11, 3rd Street NW, P.O. Box 2259. Auburn, WA 98071, USA

agricultural products network. Here, some of the relevant studies are evaluated.

Agricultural products including Orange, Lemon, Pomegranate, etc. are the most important subtropical and tropical fruits worldwide. Annually, in the gardens, sorting facilities, and also fruit markets, large amounts of citrus become inedible because of decay and cause huge losses for farmers, distributors, and customers. The costs include but are not confined to transportation costs, purchasing costs, and production costs. In addition, fixed water consumption of closing/maintaining/opening of carrier location (distribution centre), water pressure index, location efficiency rating, and other implicit costs and parameters should be added to the mentioned parameters and costs. Due to these gigantic costs, the necessity of SAPSCN implementation in agriculture supply chains is inevitable. To the best of our knowledge, this is the first study considering SAPSCN implementation in the proposed network. For this purpose, at first, a network for a sustainable agricultural product supply chain is developed.

Ferrer et al. (2008) formulated a model for decision-making as regards the amount of harvest production in each period, the means of transportation to the final product processing location and the planning of product processing and packing in the factory in a framework of an MILP model for red grape. Their model considers product harvesting cost and product quality decrease cost due to the delay in the objective function. Ahumada and Villalobos (2009) employed one of the first evaluations related to model programming in the agricultural SCN. They presented their research based on existing papers by concentration on various agricultural products, including perishable and non-perishable products and most vegetables. Audsley and Sandars (2009) carried out their research using the operation research model in the agriculture section, but it was limited to changes in Great Britain only. Zhang and Wilhelm (2011) proposed a formulation for the industry of products such as vegetables, grapes, fruits, tree-borne dried fruit, ornamental plants, various kinds of berries, and dried fruits. Ahumada et al. (2012) tried to find a balance between product cost and its quality by managing worker costs and by considering product value and means of transportation in the form of a dynamic MILP formulation. The goal of their formulation was to maximise the farmer's gain in proportion to product quality. Also, Shukla and Jharkharia (2013) summarised the existing literature in producing fresh commodities, such as fruits, vegetables, and flowers. The main feature of their study is that it concentrates on the evaluation of published studies on the production of perishable, non-perishable, and fresh products. To concentrate more on SCN specifications, Farahani et al. (2014) presented samples of decision making in a general SCN, while Tsolakis et al. (2014) developed a decision-making type in the agriculture product SCN. González-Araya et al. (2015) offered an MILP model to support the programming of decision making in a garden, with the purpose of decreasing the amount of used sources and ensuring fruit production with the best quality. Nadal-Roig and Plà-Aragonés (2015) extended a linear formulation for designing daily fruit transportation from warehouses to processing companies. Allaoui et al. (2018) suggested a sustainable Agri-Food SCN design employing a hybrid multi-objective two-stage decision-making approach due to the ordered weighted averaging (OWA) and analytic hierarchy process (AHP) approaches.

In mathematical optimisation and artificial intelligence, heuristic methods or meta-heuristic algorithms are designed techniques for efficient practical problem solving in which the exact solution methods are very slow or cannot offer an optimal or even near-optimal solution. Meta-heuristic algorithms are shortcuts for obtaining solutions. Amorim et al. (2012) formulated a multi-objective formulation for perishable commodity scheduling. They represented a hybrid NSGA-II algorithm with suitable efficiency. Asgari et al. (2013) developed an optimisation problem of transportation and storage of wheat in Iran, in which they proposed a mixed-integer programming (MIP) formulation. The objective function was to decrease wheat transportation and storage costs. They suggested memetic algorithm (MA) and tabu search (TS) algorithm to solve it. Uu Pauls-Worm et al. (2014) proposed a stochastic formulation for product programming for goods transported from a food producer. They considered the services level and non-seasonal demand for perishable commodities. Arigoni (2016) offered a production scheduling integrated planning model for the diary SCN. Also, they presented a hybrid approach of MIP and constraint programming to solve their model. Mogale et al. (2016) developed an mixed integer non-linear programming (MINLP) to minimise the transportation, inventory, and operational cost of shipping food grains from the cluster of procurement centres of producing states to the consuming state warehouses. Then, they used the chemical reaction optimisation (CRO) algorithm. Finally, they considered a real case study in Indian Public Distribution System (PDS) to validate their model. Bortolini et al. (2016) presented a sustainable distribution network for operational costs optimisation, total diffusion of carbon dioxide gas, and product delivery time. Mogale et al. (2017) formulated a multi-period transportation problem for weighted wheat in a two-level version of the SCN of the general distribution system. They developed a MINLP formulation after considering the wheat SCN scenario of India, for which they aimed to minimise operation, warehouse, and transportation costs. Besides, to solve their model, they used the chemical reaction optimisation (CRO), and TS algorithms, and developed a hybrid CROTS algorithm. Mogale, Kumar, Kumar et al. (2018) presented a new integrated multi-period, multi-model, and multi-objective formulation for the location allocation problem of seed silos. Also, they presented a mathematical model in the form of MINLP. Therefore, a non-dominated sorting chemical reaction optimisation (NCRO) algorithm was presented. Cheraghalipour et al. (2018) developed a novel model for a citrus closed-loop supply chain (CLSC) to maximise responsiveness to customer demands and minimise total costs; they also developed a multi-objective Keshtel algorithm (MOKA).

Sahebjamnia et al. (2020) extended a multi-period, multi-objective, and three-echelon citrus SCN. They developed an MINLP formulation to plan the chain's network. The goal of the formulation was to minimise waste, transportation, and holding inventory costs and to maximise benefit on the network level. To solve the model on a large-scale basis, three meta-heuristic algorithms, i.e. multi-objective particle swarm optimisation (MOPSO), non-dominated sorting genetic algorithm II (NSGA-II), and multi-objective imperialist competition algorithm (MOICA) were used. Cheraghalipour et al. (2019) suggested a bi-level formulation for a rice SCN using an algorithm constituted by a hybrid of the PSO and GA, and a modified version of the GPA meta-heuristic algorithms. Roghanian and Cheraghalipour (2019) presented a set of meta-heuristic algorithms for a multi-objective closed-loop citrus SCN regarding CO_2 emissions, which sought to maximise demand responsiveness and minimise total costs and CO_2 emissions. Besides, they developed a new tree growth algorithm (TGA) and used the non-dominated ranking genetic algorithm (NRGA), NSGA-II, multi-objective simulated annealing (MOSA), and MOKA algorithms to solve the model. The Taguchi method was used to tune these algorithms. Bottani et al. (2019) extended a new resilient food SCN and formulated a new bi-objective MILP mathematical model. Thus, they attempted to minimise the total SC lead time and maximise the total profit. Besides, they utilised an adapted ant colony optimisation (ACO) algorithm to find the Pareto solutions. Manna et al. (2019) investigated an imperfect production–reproduction inventory model for two types of quality items (item-I and item-II) produced in two different plants (plant-I and plant-II). They considered a single management system over a known-finite time horizon with consideration of environment pollution control through industrial waste management. Accordingly, two conflicting objectives were proposed of which one is the maximisation of the total profit out of two plants and the other is the minimisation of greenhouse gas emission from industrial waste over the finite time horizon.

Fakhrzad and Goodarzian (2021) developed a new bi-objective multi-level Citrus SCN. Also, an MINLP model is formulated. Their main aims are including to minimise the total costs and to maximise the profit. To solve their model, multi-objective meta-heuristic algorithms including ACO and SA are used so that the results of the multi-objective ACO are shown better than SA. Dwivedi et al. (2020) suggested a new two-echelon agro-food grain SCN with carbon emissions as well formulated a new MINLP model. Their goals are to minimise the total transportation costs and carbon emissions. Hence, quantum-based genetic and genetic algorithms are utilised to find Pareto solutions. Rabbani et al. (2020) developed a multi-objective multi-period sustainable location-allocation SCN model under uncertainty considering CO_2 emissions. To handle uncertainty parameters, a novel approach of uncertainty named hybrid robust possibilistic programming-II (HRPP-II) was suggested. Finally, a case study was solved by the improved augmented ε-constraint method (AUGMECON2) to attain Pareto solutions. Delfani et al. (2020) investigated a multi-objective mathematical model to address a new version of the hazardous waste location-routing problem under uncertainty. Another contribution of their research is the development of a basic possibilistic chance-constrained programming (BPCCP) method. To cope with the uncertainty parameters, a robust possibilistic programming was considered.

Goodarzian and Hosseini-Nasab (2021) applied a fuzzy multi-objective model for a production-distribution network design under uncertainty for a four-echelon SCN considering a set of transportation modals with different reliability rates. They formulated an MILP model for their network. To solve their model, a hybrid two-phase solution procedure was suggested according to the possibilistic programming, fuzzy multi-objective programming, and an efficient algorithm called self-adaptive differential evolution algorithm. Aloui et al. (2021) studied the integrated planning problem of location, inventory, distribution, and routing to design two-echelon green logistics networks in collaborative and non-collaborative scenarios. They proposed a bi-objective MILP for their network. First of all, a resolution of the several scenarios with a single objective and a comparison of the results was conducted. After that, a multi-objective optimisation utilising an aggregation approach was performed to attain a good trade-off between the economic objectives and environmental ones. Manna, Akhtar, et al. (2021) developed a hybrid tournament differential evolution algorithm on a two-warehouse inventory control problem of deteriorating items with the objective of determining the lot-size, maximum shortage level, and cycle length of the concerned system. Finally, they performed analysis of variance, Wilcoxon rank-sum test, and Friedman test. Ghosh et al. (2021) proposed a single manufacturer, multi retailers' green supply chain model. Also, they considered the green level of the product, selling price, and sales efforts dependent on customer demand. In addition, the effects of various payment strategies during the purchase of the product were compared. Hence, the Stackelberg game method was employed to maximise the average profits of supply chain members. Manna, Benerjee, et al. (2021) developed a two-plant production model in a single manufacturing system with the warranty period of the product and carbon emission level dependent demand. Their main aims were to determine the optimal values of the product's warranty period and the production period in each plant in order to maximise the average profit of the manufacturer based on some constraints. Finally, two numerical examples were proposed and solved by four meta-heuristic algorithms to show and validate their model.

Finally, the results of their proposed methods are compared together. The details of the examined studies are reported in Table 1.

1.1. Contributions and motivations

According to the mentioned gaps in the sustainable supply chain network design (SCND) problem, the current study considers sustainable agriculture SCND considering CO_2 emissions and water consumption that are a four-level SCN involving suppliers (farmers), transportation locations, distribution centres, and retailers. The main goal is finding the most efficient network according

Table 1. The summary of the examined studies

		The type of the problem							The type of the model	
References	Mathematical model	Production	Distribution	Routing	Solution methodology	Water consumption	CO2 emissions	Case study	Sustainable	Optimization
Ferrer et al. (2008)	MILP	*			Decision-making method					*
Ahumada and Villalobos (2009)	Review paper									
Audsley and Sandars (2009)	Review paper									
Zhang and Wilhelm (2011)	Review paper									
Amorim et al. (2012)	MILP	*	*		CPLEX					*
Ahumada et al. (2012)	MILP	*	*		Simulation approach					*
Shukla and Jharkharia (2013)	Review paper									
Asgari et al. (2013)	MIP			*	MA, TS			*		*
Farahani et al. (2014)	Review paper									
Pulse-Worm et al. (2014)	MILP	*			Simulation approach					*
Tsolakis et al. (2014)	Review paper									
González-Araya et al. (2015)	MILP				CPLEX			*		*
Nadal-Roig and Plà-Aragonés (2015)	MILP			*	CPLEX			*		*
Arigoni (2016)	MILP	*			Heuristic method					*
Bortolini et al. (2016)	MILP	*			CPLEX		*	*	*	*
Mogale et al. (2016)	MINLP	*			CRO			*		*

(*continued*).

Table 1. Continued.

References	Mathematical model	The type of the problem: Production	Distribution	Routing	Solution methodology	Water consumption	CO2 emissions	Case study	The type of the model: Sustainable	Optimization
Mogale et al. (2017)	MINLP	*			CRO, TS, hybrid CROTS			*		*
Allaoui et al. (2018)	MILP	*	*		OWA and AHP		*	*	*	*
Mogale, Kumar, and Tiwari (2018)	MINLP				NSRO, NSGA-II			*		*
Cheraghalipour et al. (2018)	MILP	*			MOKA, MOSA, NSGA-II, NRGA			*		*
Sahebjamnia et al. (2020)	MINLP	*	*		MOPSO, NSGA-II, MOICA					*
Manna et al. (2019)	MILP	*			MOGA, MOPSO					*
Cheraghalipour et al. (2019)	MILP	*			GA, PSO			*		*
Roghanian and Cheraghalipour(2019)	MILP	*	*		TGA, NRGA, MOSA, NSGA-II, MOKA		*	*		*
Bottani et al. (2019)	MILP	*			ACO			*		*
Fakhrzad and Goodarzian (2021)	MINLP	*	*		ACO, SA					*
Dwivedi et al. (2020)	MINLP	*		*	Guantum-based genetic and genetic algorithms		*	*		*
Rabbani et al. (2020)	MILP				AUGMECON2		*	*		*
Delfani et al. (2020)	MILP			*	CPLEX					*
Goodarzian and Hosseini-Nasab (2021)	MILP	*	*		Self-adaptive differential evolution algorithm					*
Aloui et al. (2021)	MILP		*	*	Aggregation approach		*			*
Manna, Beberje, et al. (2021)	MILP	*			Meta-heuristic algorithms		*			*
Ghosh et al. (2021)	MILP				Stackelberg game method		*			*
Manna, Akhtar, et al. (2021)	MILP				a hybrid tournament differential evolution algorithm					*
This paper	MILP	*	*	*	SA, TS, PSO, GA, Hybrid SA-PSO, Hybrid GA-TS	*	*	*	*	*

to the three pillars of sustainability. The main contributions that specify from current ones are:

- Formulating a new MILP model to design a SAPSCN considering CO_2 emissions and water consumption whose goals are to minimise total costs (economic impacts), environmental impacts, and social effects simultaneously.
- Integrating production, distribution, and routing decisions in the SAPSCN model.
- Considering sustainability in the suggested model.

• Suggesting four meta-heuristic algorithms including TS, PSO, SA, and GA to solve the proposed model.

• Developing two new hybrid meta-heuristic algorithms, namely, hybrid simulated annealing and particle swarm optimisation (HSA-PSO) and hybrid genetic algorithm and tabu search (HGA-TS) to find the optimal solutions for the first time.

• Demonstrate the effectiveness of the developed algorithms over the other proposed algorithms.

• Providing a real case study in Iran/Mazandaran to validate the proposed model.

The paper is structured as follows: In Section 3, the description of the problem and the formulation of the mathematical modelling will be presented. Solution methodologies, for model validation, along with several numerical examples are discussed in Section 4. Eventually, in Section 5, conclusions, managerial insights, and future studies are provided.

2. Mathematica formulation

2.1. Problem statement

In this section, a new multi-echelon SAPSCN, including suppliers (farmers), transportation locations, distributer centres, and customers (retailers), is considered. A multi-objective SAPSCN has been designed with the aims of selecting effective suppliers from a candidate collection of suppliers and locating a number of efficient carriers and distributer centres to meet customer demands. The proposed SAPSCN tries to minimise economic and environmental effects and to maximise social aspects and supplier (farmer) satisfaction, concerning distribution capacity and transportation constraints. The structure of the SAPSCN problem is indicated in Figure 1.

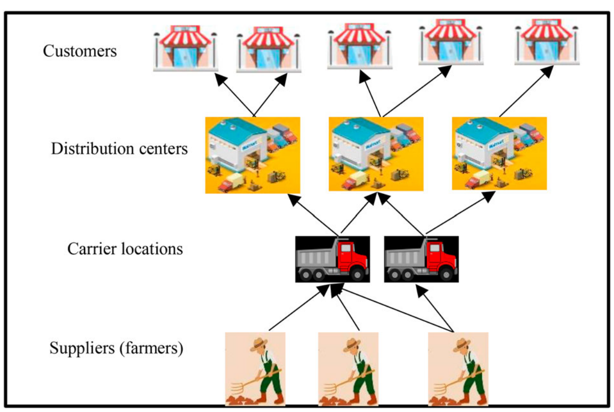

Figure 1. The framework of the studied SAPSCN.

In this paper, three objective functions are considered: the economic, environmental, and social impacts. The related indices are presented in Table 2.

As a significant point, the water amount in this formulation is assessed by multiplying the amount of used water by the water pressure index which is computed according to the freshwater of the location. Essential boundary conditions have been considered for the SCN aimed at meeting customer needs. Therefore, the SCN is drawn inversely, i.e. it is defined by what the consumer wants through a raw material supplier.

Customer demand is the foremost in the proposed model. Potential suppliers, transportation locations and distribution centres, and their capacities have been determined. Furthermore, for each selected supplier, decisions should be made concerning the total number of product units which should be produced by the transporter and transferred to the distributor; all units of raw material that require to be bought and transported from the selected supplier, and the total number of commodity units which should be distributed from the distribution centre to the customer.

The total cost of SCN consists of production, raw material purchasing, distribution, closing and opening fixed transportation, inventory holding, and changing location capacity costs. Also, it is supposed that the carbon emission and water consumption of the three sources are as follows:

Table 2. The used indices in the objective functions.

Objective functions / Main players	Economic	Environmental	Social
Supplier	Transportation cost, Raw material cost, and emission tax Transportation	Transportation emission	–
Transportation	Operational cost, Closing and opening cost, Production and transportation costs, Capacity change cost, Emission tax Transportation, and Energy cost	Production emission, operation emission, Production water consumption, operational water consumption, and Transportation emission	Number of created works
Distribution	Closing and opening cost, Capacity change cost, Emission tax, Operational cost, Transportation cost, Transportation, and Energy cost	operation emission, operational water consumption, and Transportation emission	Number of created works

(1) From suppliers: transportation to the carrier and raw material production.
(2) From carriers: established locations, commodity production, and transportation to distribution centres.
(3) From distribution centres: established locations and product delivery to customers.

Finally, created jobs are related to opening and closing locations.

2.2. Mathematical modelling

According to the problem descriptions and its assumptions, the mathematical formulation is designed with the aim of minimising the sustainability, economic, environmental, and social objective functions and maximising the SCN efficiency by using the calculated efficiency for each of the carrier, distributer centre, and supplier locations. Before engaging in the model, introducing its variables, indices, and parameters is necessary.

2.2.1. Indices

p	Product $p = \{1 \dots P\}$
i	Suppliers $i = \{1 \dots I\}$
e	The type of energy $e = \{1 \dots E\}$
j	Carrier location $j = \{1 \dots J\}$
k	Distributer centre $k = \{1 \dots K\}$
m	Raw material $m = \{1 \dots M\}$
l	Customer $l = \{1 \dots L\}$
s	Transportation system $s = \{1 \dots S\}$
t	Period $t = \{1 \dots T\}$

2.2.2. Parameters

ω_{pl}^{t}	Product order p by customer l during period t
ϵ_m	Number of units of m needed to make a unit of raw material
λ_{mp}	Number of units of m needed to make a unit of product p
ϕ_{im}^{t}	Capacity of supplier i for the supply of m during period t
$\mu(\mathrm{E})_j$	Lower bound of carrier place capacity j (distribution centre)
$\mu'(\mathrm{E})_j$	Higher bound of carrier place capacity j (distribution centre)
$\kappa(\mathrm{E})_j$	Initial capacity of carrier location j (distribution) at the beginning of the first period (opening = 1, closing = 0)
$\varphi(\mathrm{E})_j$	Initial position of carrier location j (distribution) at the beginning of the first period (opening = 1, closing = 0)
$\eta(\varepsilon, o)T(\mathrm{E})_{je}^{t}$	Fixed cost of closing/maintaining /opening carrier location j (distributor) using energy type e during period t
θ_j^t	The amount of work created by the location of opening j during period t
$\eta'(\varepsilon, o)CT(\mathrm{E})_j^t$	Fixed cost of reducing/maintaining/increasing a unit of capacity at carrier location j (distribution centre) during period t
$\vartheta(T,\mathrm{E})T(\mathrm{E},C)_{mijs}^{t}$	Transportation cost of a unit of m or product from supplier (carrier, distribution centre) i to carrier (distribution centre, customer) j using Transportation type s during period t
$\sigma(\varsigma)_{pje}^{t}$	Production cost of a unit of product p in carrier location j using energy type e during period t
ρ_{mi}^{t}	Purchasing cost of a unit of m from supplier i during period t
$\tau(T,\mathrm{E})T(\mathrm{E},C)_{mijs}^{t}$	Transportation emission of a unit of m or product from supplier (transportation, distribution centre) $i$to carrier (distribution centre, customer) j using transportation type s during period t
$\gamma(\varsigma)_{pje}^{t}$	Production output of a unit of product p in carrier location j using energy type e during period t
$\gamma'(\varsigma)_{pje}^{t}$	The amount of water produced by a unit of product p at carrier location j using energy type e during period t
Γ_{mi}^{t}	Output generated to produce raw material unit m from supplier i during period t
$\Gamma'^{t}{}_{mi}$	Water consumption for the production of a unit of m from supplier $i$during period t
$\ell(\varepsilon, o)T(\mathrm{E})_{je}^{t}$	Fixed water consumption of closing/maintaining /opening of carrier location (distribution centre) j by using energy type e during period t
β_j	Water pressure index of location j
$\alpha(\varepsilon, o)T(\mathrm{E})_{je}^{t}$	The fixed output created by closing/maintaining/opening carrier (distribution centre) j using energy type e during period t
ψ_j	Location efficiency rating j
a, b, c	CO_2 emission weights, water utilisation, and work done

2.2.3. Decision variables

$\Pi(\Lambda,\Omega)t(e)_j^t$ The binary decision variable represents the current state (closing, opening) of carrier location (distribution centre) j during period t (opening $=1$, closing $=0$)

$\Pi'(\upsilon,\Omega)t(e)_j^t$ The integer decision variable represents the increase (present, decrease) of the capacity of carrier location j (distribution) during period t

$\Pi''(t,e)t(e,c)_{mijs}^t$ The quantity of m or product from the supplier (carrier, distribution centre) i to carrier j (distribution centre, customer) using transportation type s during period t

$\Omega(\nu)_{pje}^t$ The amount of product p produced at carrier location j using energy type e during period t

2.2.4. Objective functions

$$
\begin{aligned}
1 = min(&\sum_{s\hat{I}S}\sum_{t\hat{I}T}\sum_{p\hat{I}P}\sum_{k\hat{I}K}\sum_{l\hat{I}L} JEC_{pkls}^t\,\Pi''ec_{pkls}^t \\
&+\sum_{s\hat{I}S}\sum_{t\hat{I}T}\sum_{p\hat{I}P}\sum_{j\hat{I}J}\sum_{k\hat{I}K} CTE_{pjks}^t\,\Pi''te_{pjks}^t \\
&+\sum_{s\hat{I}S}\sum_{t\hat{I}T}\sum_{m\hat{I}M}\sum_{j\hat{I}J}\sum_{j'\hat{I}J\ddot{E}j} JTT_{mjj'^ts}\,\Pi''tt_{mjj'^ts} \\
&+\sum_{s\hat{I}S}\sum_{t\hat{I}T}\sum_{m\hat{I}M}\sum_{i\hat{I}I}\sum_{j\hat{I}J} JT_{mijs}^t\,\Pi''t_{mijs}^t) \\
&+(\sum_{e\hat{I}E}\sum_{t\hat{I}T}\sum_{j\hat{I}J}(\eta T_{je}^t\,\Lambda t_{je}^t+\eta'\varepsilon T_j^t\,\Pi't_j^t \\
&+\eta o T_{je}^t\,\Omega t_{je}^t) \\
&+\sum_{e\hat{I}E}\sum_{t\hat{I}T}\sum_{j\hat{I}J}(\eta \mathrm{E}_{ke}^t\,\Lambda e_{ke}^t+\eta'\varepsilon \mathrm{E}_k^t\,\Pi'\mathrm{E}_k^t \\
&+\eta' o\mathrm{E}_{ke}^t\,\Omega e_{ke}^t)) \\
&+(\sum_{t\hat{I}T}\sum_{j\hat{I}J}(\eta' CT_j^t\Pi't_j^t+\eta' CT_j^t\,\Pi'\upsilon t_j^t \\
&+\eta' oCT_j^t\,\Pi'\Omega t_j^t) \\
&+\sum_{t\hat{I}T}\sum_{k\hat{I}K}(\eta' CE_k^t\,\Pi'e_k^t+\eta'\varepsilon CE_k^t\,\Pi'\upsilon e_k^t \\
&+\eta' oCE_k^t\,\Pi'\Omega e_k^t)) \\
&+(\sum_{e\hat{I}E}\sum_{t\hat{I}T}\sum_{p\hat{I}P}\sum_{j\hat{I}J}\sigma_{pje}^t\,\Omega_{pje}^t \\
&+\sum_{e\hat{I}E}\sum_{t\hat{I}T}\sum_{m\hat{I}M}\sum_{j\hat{I}J}\varsigma_{mje}^t\,\upsilon_{mje}^t) \\
&+\sum_{t\hat{I}T}\sum_{m\hat{I}M}\sum_{i\hat{I}I}\sum_{j\hat{I}J}\rho_{mij}^t\,\Pi''t_{mij}^t
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
obj2 = \min\ a(&\sum_{s\in S}\sum_{t\in T}\sum_{p\in P}\sum_{k\in K}\sum_{l\in L}\tau \mathrm{E}C_{pkls}^t\,\Pi''ec_{pkls}^t \\
&+\sum_{s\in S}\sum_{t\in T}\sum_{p\in P}\sum_{j\in J}\sum_{k\in K}\tau T\mathrm{E}_{pjks}^t\,\Pi''te_{pjks}^t \\
&+\sum_{s\in S}\sum_{t\in T}\sum_{m\in M}\sum_{j\in J}\sum_{j'\in J\not\subset j}\tau TT_{mjj'^ts}\Pi''tt_{mjj'^ts} \\
&+\sum_{s\in S}\sum_{t\in T}\sum_{m\in M}\sum_{i\in I}\sum_{j\in J}\tau T_{mijs}^t\Pi''t_{mijs}^t \\
&+(\sum_{e\in E}\sum_{t\in T}\sum_{j\in J}(\alpha T_{je}^t\,\Lambda t_{je}^t+\alpha\varepsilon T_j^t\,\Pi''t_j^t \\
&+\alpha o T_{je}^t\,\Omega t_{je}^t) \\
&+\sum_{e\in E}\sum_{t\in T}\sum_{j\in K}(\alpha \mathrm{E}_{ke}^t\,\Lambda e_{ke}^t+\alpha\varepsilon \mathrm{E}_k^t\,\Pi''e_k^t \\
&+\alpha o\mathrm{E}_{ke}^t\,\Pi e_{ke}^t) \\
&+\sum_{e\in E}\sum_{t\in T}\sum_{p\in P}\sum_{j\in J}\gamma_{pje}^t\,\Omega_{pje}^t \\
&+\sum_{e\in E}\sum_{t\in T}\sum_{m\in M}\sum_{j\in J}\varsigma_{mje}^t\,\nu_{mje}^t \\
&+\sum_{t\in T}\sum_{m\in M}\sum_{i\in I}\sum_{j\in J}\Gamma_{mij}^t\,\Pi''t_{mij}^t) \\
&+b(\sum_{e\in E}\sum_{t\in T}\sum_{p\in P}\sum_{j\in J}\beta_j\,\gamma'^{t_{pje}}\,\Omega_{pje}^t \\
&+\sum_{e\in E}\sum_{t\in T}\sum_{m\in M}\sum_{j\in J}\beta_j\gamma'\varsigma_{mje}^t\,\Omega\nu_{mje}^t \\
&+\sum_{e\in E}\sum_{t\in T}\sum_{j\in J}\beta_j(\ell T_{je}^t\,\Lambda t_{je}^t+\ell\varepsilon T_j^t\,\Pi t_j^t \\
&+\ell o T_{je}^t\,\Pi t_{je}^t) \\
&+\sum_{e\in E}\sum_{t\in T}\sum_{j\in K}\beta_k(\ell \mathrm{E}_{ke}^t\,\Lambda e_{ke}^t+\ell\varepsilon \mathrm{E}_k^t\,\Pi e_k^t \\
&+\ell o\mathrm{E}_{ke}^t\,\Omega e_{ke}^t) \\
&+\sum_{t\in T}\sum_{m\in M}\sum_{i\in I}\sum_{j\in J}\beta_i\,\Gamma'^{t_{mij}}\,\Pi''t_{mij}^t) \\
&+\sum_{e\in E}\sum_{t\in T}\sum_{k\in K}(\theta_k^t\,\Lambda e_{ke}^t-\theta_k^t\,\Omega e_{ke}^t))
\end{aligned} \tag{2}
$$

$$
\begin{aligned}
obj3 = \max &\sum_{e\in E}\sum_{t\in T}\sum_{j\in J}\psi_j(\Lambda t_{je}^t+\Pi t_j^t) \\
&+\sum_{e\in E}\sum_{t\in T}\sum_{k\in K}\psi_k(\Lambda e_{ke}^t+\Pi e_k^t) \\
&+\sum_{t\in T}\sum_{s\in S}\zeta_s\Pi''e_s^t
\end{aligned}
$$

$$with\ \Pi''t_s^t = 1\ if \sum_{m\in M}\sum_{i\in I}\sum_{j\in J}\Pi''t_{mijs}^t > 0, else\ \Pi''t_s^t = 0 \tag{3}$$

The three objective functions have been shown in Equations (1)–(3), respectively. As is shown in Equation (1), the objective function (1) represents objective function minimisation concerning the sustainability economy index given in Table 2. Therefore, the sum of transportation costs related to transferring from distribution centres to customers, from carriers to distribution centres, from carriers to carriers, and from suppliers to carriers are shown in the first objective function. In addition, the fixed costs (opening, holding, and closing) related to carrier locations and distribution centres, increase in the fixed costs (holding and decreasing) of carrier location capacity and distribution centres, and supply costs and production and distribution costs are indicated, respectively. As is shown in Equation (2), the objective function (2) is a minimisation of the sum of the social and environmental objectives. The environmental function is the sum of all CO_2 emissions and overall water consumption. The total amount of CO_2 emissions is the sum of released fixed CO_2 emissions during the opening, holding, and closing of carrier locations and distribution centres as well as the released CO_2 emissions by transportation, i.e. from distribution centres to customers, from carriers to distribution centres, from carriers to carriers, and from suppliers to carriers are provided. Total CO_2 emission is calculated due to the energy state in the carrier locations and the total emission of raw material production by the suppliers. The overall amount of consumed water is the sum of the fixed amount of consumed water during the opening, closing, and holding of carrier locations and distribution centres. The consumed water variable relates to suppliers, carriers, and distribution centres. The social objective function accords with the number of created or spoiled works during the opening or closing of carrier locations and distribution centres.

The third objective function, overall CO_2 emissions, overall amount of consumed water, and the number of generated or spoiled works are weighted by the *a*, *b*, and *c* factors. It is used to maximise SCN efficiency by using the calculated efficiency for any location of carriers, distributors, and suppliers.

$$\sum_{s\in S}\sum_{k\in K}\Pi''ec_{pkls}^t = \omega_{pl}^t (t \in T,\ p \in P,\ l \in L) \tag{4}$$

$$\sum_{s\in S}\sum_{j\in J}\Pi''t_{mijs}^t = \phi_{mi}^t (t \in T,\ m \in M,\ i \in I) \tag{5}$$

$$\Pi'\nu t_j^1 = \kappa_j + \Pi' t_j^1 - \Pi'\Omega t_j^1 (j \in J) \tag{6}$$

$$\Pi'\nu t_j^1 = \Pi'\nu t_{jj}^{t-1} + \Pi' t_j^1 - \Pi'\Omega t_j^1 (j \in J,\ t \geq 2) \tag{7}$$

$$\mu_j\, \Pi t_j^t \leq \Pi'\nu t_j^t \leq \mu_j'\, \Pi t_j^t\ (j \in J,\ t \in T) \tag{8}$$

$$\sum_{e\in E}\sum_{m\in M}\Omega\nu_{mje}^t + \sum_{e\in E}\sum_{p\in P}\Omega_{pje}^t \leq \Pi'\nu t_j^t (j \in J,\ t \in T) \tag{9}$$

$$\Pi'\nu e_k^1 = \kappa \mathrm{E}_k + \Pi' e_k^1 - \Pi'\Omega e_k^1 (k \in K) \tag{10}$$

$$\Pi'\nu e_k^t = \Pi'\nu e_k^{t-1} + \Pi' e_k^t - \Pi'\Omega e_k^t (k \in K,\ t \geq 2) \tag{11}$$

$$\mu \mathrm{E}_k\, \Pi e_k^t \leq \Pi'\nu e_k^t \leq \mu' \mathrm{E}_k\, \Pi e_k^t\ (k \in K,\ t \in T) \tag{12}$$

$$\sum_{s\in S}\sum_{p\in P}\sum_{l\in L}\Pi''ec_{pkls}^t \leq \Pi\nu t_k^t (k \in K,\ t \in T) \tag{13}$$

$$\sum_{s\in S}\sum_{j\in J}\Pi''te_{pjks}^t = \sum_{s\in S}\sum_{l\in L}\Pi''ec_{pkls}^t (k \in K,\ t \in T,\ p \in P) \tag{14}$$

$$\sum_{e\in E}\Omega\nu_{mje}^t + \sum_{s\in S}\sum_{i\in I}\Pi''t_{mijs}^t + \sum_{s\in S}\sum_{j'\in J\ddot{E}j}\Pi''tt_{mj'^tjs} \geq \sum_{s\in S}\sum_{j'\in J\ddot{E}j}\Pi''tt_{mjj'^ts} + \sum_{m'\in M\ddot{E}m}\varepsilon_{mm'}\sum_{e\in E}\Omega\nu_{m'je}^t + \sum_{p\in P}\lambda_{mp}\sum_{e\in E}\Omega_{pje}^t\ (j \in J, t \in T, m \in M) \tag{15}$$

$$\sum_{e\in E}\Omega_{pje}^t = \sum_{s\in S}\sum_{k\in K}\Pi''te_{pjks}^t\quad (j \in J, t \in T, p \in P) \tag{16}$$

$$M \times \Pi t_j^t - \left(\sum_{e\in E}\sum_{m\in M}\Omega\nu_{mje}^t + \sum_{e\in E}\sum_{p\in P}\Omega_{Pje}^t\right) \geq 0\ (t \in T,\ j \in J) \tag{17}$$

$$M \times \Pi t_j^t - \left(\sum_{s\in S}\sum_{m\in M}\sum_{i\in I}\Pi''t_{mijs}^t\right) \geq 0\ (t \in T,\ j \in J) \tag{18}$$

$$M \times \Pi t_j^t - \left(\sum_{s\in S}\sum_{m\in M}\sum_{j'\in J\not\subset j}\Pi''tt_{mj'^tjs}\right) \geq 0\ (t \in T,\ j \in J) \tag{19}$$

$$M \times \Pi t_j^t - \left(\sum_{s\in S}\sum_{p\in P}\sum_{k\in K}\Pi''te_{pjks}^t\right) \geq 0\ (t \in T,\ j \in J) \tag{20}$$

$$M \times \Pi e_k^t - \left(\sum_{s \in S} \sum_{p \in P} \sum_{j \in J} \Pi'' te_{pjks}^t \right) \geq 0 \, (t \in T, \, k \in K) \tag{21}$$

$$M \times \Pi e_k^t - \left(\sum_{s \in S} \sum_{p \in P} \sum_{l \in L} \Pi'' ec_{pkls}^t \right) \geq 0 \, (t \in T, \, k \in K) \tag{22}$$

$$\Pi t_j^t + \sum_{e \in E} \Omega t_{je}^t \leq 1 \, (t \in T, \, j \in J) \tag{23}$$

$$\Pi t_j^t - \sum_{e \in E} \Lambda t_{je}^t \geq 0 \, (t \in T, \, j \in J) \tag{24}$$

$$\Pi e_k^t + \sum_{e \in E} \Omega e_{ke}^t \leq 1 \, (t \in T, \, k \in K) \tag{25}$$

$$\Pi e_k^t - \sum_{e \in E} \Lambda e_{ke}^t \geq 0 \, (t \in T, \, k \in K) \tag{26}$$

$$\Pi t_j^1 \leq \varphi_j + \sum_{e \in E} \Lambda t_{je}^1 \leq 1 \;\; (j \in J) \tag{27}$$

$$\Pi t_j^t \leq \Pi t_j^{t-1} + \sum_{e \in E} \Lambda t_{je}^t \leq 1 \;\; (t \geq 2, \;\; j \in J) \tag{28}$$

$$\Pi e_k^1 \leq \varphi \mathrm{E}_k + \sum_{e \in E} \Lambda e_{ke}^1 \leq 1 \;\; (k \in K) \tag{29}$$

$$\Pi e_k^t \leq \Pi e_k^{t-1} + \sum_{e \in E} \Lambda e_{ke}^t \leq 1 \;\; (t \geq 2, \;\; k \in K) \tag{30}$$

$$1 - \Pi t_j^1 \leq (1 - \varphi_j) + \sum_{e \in E} \Omega t_{je}^1 \leq 1 \;\; (j \in J) \tag{31}$$

$$1 - \Pi t_j^t \leq (1 - \Pi t_j^{t-1}) + \sum_{e \in E} \Omega t_{je}^t \leq 1 \;\; (t \geq 2, \;\; j \in J) \tag{32}$$

$$1 - \Pi e_k^1 \leq (1 - \varphi \mathrm{E}_k) + \sum_{e \in E} \Omega e_{ke}^1 \leq 1 \;\; (k \in K) \tag{33}$$

$$1 - \Pi e_k^t \leq (1 - \Pi e_k^{t-1}) + \sum_{e \in E} \Omega e_{ke}^t \leq 1 \;\; (t \geq 2, \;\; k \in K) \tag{34}$$

$$\Pi t_j^t, \Lambda t_{je}^t, \Omega t_{je}^t, \Pi e_k^t, \Lambda e_{ke}^t, \Omega e_{ke}^t \in \{0, 1\} \tag{35}$$

$$\Pi' t_j^t, \Pi' v t_j^t, \Pi' \Omega t_j^t, \Pi'' tt_{mj'^t js}, \Pi'' t_{mijs}^t, \Pi'' te_{pjks}^t, \Pi'' ec_{pkls}^t, \Omega_{Pje}^t, \Omega v_{mje}^t, \Pi' e_k^t, \Pi' v e_k^t, \Pi' \Omega e_k^t \geq 0 \tag{36}$$

Constraint (4) shows that all customer orders should be delivered. Constraint (5) establishes that the amount of raw material supplied by a supplier has a permitted capacity. Constraints (6) and (7) guarantee the relationship between the existing capacity and the increase and decrease of a carrier location. Constraint (8) ensures the capacity (upper and lower bounds) of a carrier location. Constraint (9) indicates that the produced amount cannot be more than that accommodated by the existing capacity in a carrier location. Constraints (10) and (11) state the relationship between the existing capacity and the increase and decrease of a distribution centre. Constraint (12) shows the capacity (upper and lower bounds) of a distribution centre. Constraints (13) and (14) ensure that the delivered amount cannot be more than that accommodated by the existing capacity in a distribution centre. Constraints (15) and (16) indicate raw material capacity or deformed products. Constraints (17)–(22) show the opening and closing locations when M is too high. Constraints (23)–(34) ensure the continuous constraints of the opening and closing locations. Constraints (35) and (36) define decision variables.

3. Solution methods

The presented model is NP-hard for medium and large-scale problems and solving them is time consuming using exact methods. Accordingly, four suitable meta-heuristics are applied for comparing the model in test problems with various sizes. Moreover, two efficient hybrid meta-heuristics are developed.

In a hybrid algorithm, two or more algorithms are collectively and cooperatively solve a predefined problem (Talbi, 2015). In some hybrids, one algorithm may be incorporated as a sub-algorithm to locate the optimal parameters for another algorithm, while in other cases, different components of algorithms such as mutation and crossover are used to improve another algorithm in the hybrid structure (Blum & Roli, 2008). With regards to this nature, hybrid meta-heuristic algorithms can loosely be divided into two categories:

(i) Unified objective hybrids. Under this category, all sub-algorithms are utilised to solve the same problem directly; and different sub-algorithms are used indifferent search stages. Hybrid metaheuristic algorithms with the local search are an atypical example. The global search explores the search space, while the local search is utilised to refine the areas that may contain the global optimum.
(ii) Multiple objective hybrids. One primary algorithm is used to solve the problem, while the sub-algorithm is employed to tune the parameters for the primary algorithm. In this paper, this category is used for the hybridisation of the meta-heuristic algorithms.

Our reason for using the hybrid meta-heuristic algorithms is to combine the advantages of each algorithm to form a stronger algorithm, while simultaneously trying to minimise any substantial disadvantage. All in all, the result of hybridisation can usually make some improvements in terms of either computational speed or accuracy. In addition, the hybrid meta-heuristic algorithms provide the great advantages of increasing the diversity in a population and hence enhancing the search capability of the developed hybrid algorithm. Also, the hybrid meta-heuristic algorithms are said to be superior in giving optimal or at least sub-optimal outcomes within a specific time period. Higher flexibility and efficient behaviour are the reported key advantages when a clever combination of optimisation techniques with that of suitable meta-heuristic algorithms are made (Muthuraman & Venkatesan, 2017). Finally, the last reason for the hybridisation of meta-heuristic algorithms is technically to enhance the results, improving the outcomes, or decreasing the computational time, or both.

3.1. Multi-objective optimisation

The SAPSCN problem has three objectives. The interactions among the solutions are represented by the Pareto optimal set. This set involves the non-dominated solutions (Sahebjamnia et al., 2020). To clarify, consider three solutions: solution A, B, and C. Solution A dominates solutions B and C when all objective functions of A are not worse than those of B and C and there is available at least one objective of A that is better than those of B and C. According to the Pareto optimum set, the current study uses four metrics to evaluate the quality of Pareto fronts as do many recent researches. In this regard, the solution representation of the utilised multi-objective meta-heuristics is explained.

3.2. Solution representation

A scheme should be designed to encode the problem to implement meta-heuristic algorithms. Accordingly, a two-stage method called Random-Key is employed (Sahebjamnia et al., 2020). Furthermore, this method converts an unfeasible solution to a feasible one using a set of strategies in two stages.

To encode the solution representation, a numerical example is indicated as follows: suppose that there are four suppliers (i), five carrier locations (j), three distribution locations (k), five customers (l) with three sorts of vehicles (s), and 10 products (p). First, the type of vehicle used to transfer each product to the customers should be designated. In this process, an array by a length of l is created by uniform distribution: $U(0, l)$. Hence, the types

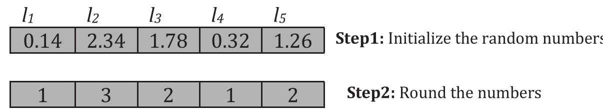

Figure 2. The proposed procedure to allocate a sort of vehicle for customers.

of vehicle allocation to transfer products to customers should be specified. A set of procedures has been displayed in Figure 2. Furthermore, the third sort of vehicle is employed for customers l_2. The first and second sorts of the vehicles are applied to customers l_1, $l_4$and l_3, l_5, respectively.

3.3. Genetic algorithm

The GA is a common optimisation instrument in engineering calculation. First, GA was suggested by Holland (1992). It is a special kind of evolutionary algorithm that uses biological evolutionary techniques such as heredity and mutation. Indeed, it uses Darwin's natural selection principle to find optimisation equations to predict or match the pattern. Two search operators, i.e. crossover and mutation are defined in this algorithm. In mutation, a neighbourhood of a generator array is created; and at the crossover, two solutions are selected as the parents and after combining, two children are composed such that the algorithm searches the possible solution space. It blindly performs the two phases of concentration and diversity in a meta-heuristic algorithm in the solution space. More information and details are given in Mirjalili (2019), Nasr et al. (2021), and Lamiae et al. (2021).

3.4. Simulated annealing

One of the most successful single-solution algorithms is called SA. This uses a mathematical rationale and is simple for searching. Its efficiency is appreciated in various operational research problems and engineering sciences. It uses the rationale of cooling crystallised metal at high temperatures. It was introduced by Kirkpatrick et al. (1983). It starts searching using a random solution at a high temperature. In each stage of the algorithm, a neighbourhood is created for the solution of the previous stage. If the mentioned solution is improved, the new solution is accepted; otherwise, the mentioned solution is accepted with a probability; it is controlled by current temperature and using the Boltzmann function. This logic helps the algorithm to initially accept bad solutions with high probability and thereafter with lower probability and to escape a local optimisation (Chouhan et al., 2021 Fakhrzad & Goodarzian, 2021; and Yadav et al., 2021).

3.5. Tabu search

This algorithm was introduced by Glover and Taillard (1993). The overall structure of the algorithm is such that it begins an initial solution and thereafter the best neighbour solution among current neighbour solutions is selected. According to the aspiration criteria, if the neighbour solution is better than the found solutions, the algorithm will move to it, even if it is in the Tabu list. The movement of the current solution to neighbour solutions continues until the stop condition is reached. For more details, Punyim et al. (2018), Camacho-Vallejo et al. (2021) and Kresnanto et al. (2021) can be read.

3.6. Particle swarm optimisation

One of the efficient optimisation algorithms is the PSO that was presented by Eberhart and Kennedy (1995). It was inspired by the social behaviour and food finding habits of groups of birds. Initially, it was applied for discovering patterns of simultaneous flight in birds and their sudden change of route and the optimised deformation of a group in which particles flow in the search space. The location change of the particles is affected by their experience, knowledge, and neighbourhood. Therefore, the mass situation of other particles influences how a particle is searched. For more information, refer to Salem and Haouari (2017), Goodarzian et al., (2021), and Fatemi Ghomi et al. (2021).

3.7. Hybrid simulated annealing and particle swarm optimisation (HSA-PSO)

Studies confirm that the PSO is considered as a robust method, with a performance able to handle several types of optimisation problems (Che, 2012). Likewise, if the local best and global best positions are equal to the particle's position over a number of iterations, it could be trapped into a local optimum. Hence, to decrease this drawback, we have combined the SA with the PSO algorithm. In this hybrid algorithm, new generation members are generated at each iteration by utilising the SA algorithm. Also, PSO's movement rule is used for these new members and provides a better chance of exploring new locations. The pseudo-code of the HSA-PSO algorithm is displayed in Figure 3.

```
%%Hybrid SA-PSO Parameters
MaxIt=1000; % Maximum Number of Iterations
MaxSubIt=10; % Maximum Number of Sub-iterations
T0=10; % Initial Temp.
alpha=0.99; % Temp. Reduction Rate
nPop=50; % Swarm (Population) Size
%Definition of Constriction Coefficients
phi1=2.05;
phi2=2.05;
phi=phi1+phi2;
chi=2/(phi-2+sqrt(phi^2-4*phi));
w=chi;
c1=phi1*chi;
c2=phi2*chi;
%Initialize Temp.
T=T0;
%%Initialization
%Empty Structure to Hold Individuals Data
empty_ individual. Position= [];
empty_ individual. Velocity= [];
empty_ individual. Cost= [];
empty_ individual. Best. Position= [];
empty_ individual. Best. Cost= [];
%Create Population Matrix
pop=repmat(empty_individual,nPop,1);
%Global Best
Best Sol. Cost=inf;
%Initialize Positions
for i=1:nPop
    pop(i). Position=unifrnd(VarMin,VarMax,VarSize);
    pop(i).Velocity=zeros(VarSize);
    pop(i). Cost=Cost Function(pop(i).Position);
    pop(i).Best. Position=pop(i).Position;
    pop(i).Best.Cost=pop(i).Cost;
    if pop(i). Best. Cost<Best Sol. Cost
        Best Sol=pop(i).Best;
    end
end
%Vector to Hold Best Cost Values
Best Cost=zeros(MaxIt,1);
%%HAS-PSO Main Loop
for it=1:MaxIt
  for subit=1:MaxSubIt
    for i=1:nPop
      %Update Velocity
       pop(i).Velocity=w*pop(i).Velocity ...
       +c1*rand(Var Size).*(pop(i).Best.Position-pop(i).Position) ...
       +c2*rand(Var Size).*(Best Sol. Position-pop(i).Position);
      %Apply Velocity Bounds
       pop(i).Velocity=min(max(pop(i).Velocity,VelMin),VelMax);
      %Update Position
       pop(i). Position=pop(i). Position+ pop(i).Velocity;
      %Velocity Reflection
       flag=(pop(i). Position<Var Min | pop(i). Position>Var Max);
       pop(i). Velocity(flag)=-pop(i).Velocity(flag);
      %Apply Position Bounds
       pop(i). Position=min(max(pop(i). Position, VarMin), VarMax);

      %Evaluation
       pop(i). Cost=Cost Function(pop(i).Position);
      %Update Personal Best
       if pop(i). Cost<pop(i).Best.  Cost
           pop(i).Best.Position=pop(i).Position;
           pop(i).Best.Cost=pop(i).Cost;
           %Update Global Best
           if pop(i).Best.Cost<BestSol.Cost
               Best Sol=pop(i).Best;
           end
       end
    end
    %Store Best Cost
    Best Cost(it)=Best Sol. Cost;
   %Show Iteration Information
   disp (['Iteration ' num2str(it) ': Best Cost = ' num2str(BestCost(it))]);
   %Temp. Reduction
   T=alpha*T;
  end
end
```

Figure 3. The pseudo-code of the HSA-PSO.

3.8. Hybrid genetic algorithm and Tabu search (HGA-TS)

For the SAPSCN problem, this research developed a novel hybrid genetic algorithm in connection with Tabu search (HGA-TS), which merges GA's global optimisation and parallel computing with fast local search and the TS search skill. The pseudo-code of HGA-TS is given in Figure 4.

4. Experimental results

4.1. Data generation

Here, the parameters of the meta-heuristic algorithms as well as the parameters of the problem model are set. Therefore, to evaluate the efficiency of the suggested algorithms, several test instances in different sizes, shown in Table 3, were carried out. We ran the proposed meta-heuristics in MATLAB 2020b environment on PCs with 2.5 GHz CPU 6 CORE i5.

```
%%Hybrid GA-TS Parameters

MaxIt=50; % Maximum Number of Iterations
MaxSubItGA=1; % Maximum Number of Sub-Iterations for GA
MaxSubItTS=2; % Maximum Number of Sub-Iterations for TS
TL=round (0.5*n Action); % Tabu Length
nPop=50; %Population Size
pCrossover=0.7; % Crossover Percentage
nCrossover=round(pCrossover*nPop/2) *2; % Number of Parents (Off springs)
pMutation=0.2; % Mutation Percentage
nMutation=round(pMutation*nPop); % Number of Mutants

 %%Initialization
 %Create Empty Individual Structure
 empty_ individual. Position= [];
 empty_ individual. Cost= [];
 %Create Initial Solution
 sol=empty_ individual;
 sol. Position=randperm(n Queen);
 sol. Cost=Cost Function (sol. Position);
 %Initialize Best Solution Ever Found
 Best Sol=sol;
 %Array to Hold Best Costs
 Best Cost=zeros(MaxIt,1);
 %Initialize Action Tabu Counters
  TC=zeros(nAction,1);
 %%HGA-TS  Main Loop
for it=1:MaxIt
 %TS Operators
     Best new sol. Cost=inf;
     %Apply Actions
     for i=1:nAction
         if TC(i)==0
             new sol. Position=Do Action (sol.  Position, Action List{i});
             new sol.  Cost=Cost Function (new sol. Position);
             new sol. Action Index=i;

             if new sol. Cost<=best new sol. Cost
                 best new sol=new sol;
             end
         end
     end
    %Update Current Solution
     sol=best new sol;
    %Update Tabu List
     for i=1:n Action
         if i==best new sol. Action Index
             TC(i)=TL; % Add To Tabu List
         else
             TC(i)=max(TC(i)-1,0); % Reduce Tabu Counter
         end
     end
     %Update Best Solution Ever Found
     if sol. Cost<=Best Sol. Cost
         Best Sol=sol;
     end
     %Save Best Cost Ever Found
     Best Cost(it)=Best Sol. Cost;
```

Figure 4. The pseudo-code of HGA-TS.

```
%GA Operators
for gait=1: MaxSubItGA
   %Crossover
    popc=repmat(empty_individual, nCrossover/2,2);
    for k=1: nCrossover/2
        i1=randi([1 nPop]);
        i2=randi([1 nPop]);
        p1=pop(i1);
        p2=pop(i2);
        [popc(k,1).Position popc(k,2).Position]=Crossover(p1.Position,p2.Position,VarRange);
        popc(k,1). Cost=Cost Function(popc(k,1). Position);
        popc(k,2). Cost=Cost Function(popc(k,2).Position);
        if p1. Best. Cost <p2. Best. Cost
            popc(k,1). Best=p1.Best;
            popc(k,2). Best=p1.Best;
        else
            popc(k,1). Best=p2.Best;
            popc(k,2). Best=p2.Best;
        end
        if rand<0.5
            popc(k,1). Velocity= p1. Velocity;
            popc(k,2). Velocity= p2. Velocity;
        else
            popc(k,1). Velocity=p2.Velocity;
            popc(k,2). Velocity=p1.Velocity;
        end
    end
    popc=popc(:);
    %Mutation
    popm=repmat(empty_ individual, nMutation,1);
    for k=1:nMutation
        i=randi([1 nPop]);
        p=pop(i);
        popm(k). Position=Mutate (p. Position, Var Range);
        popm(k). Cost=Cost Function(popm(k). Position);
        popm(k). Velocity=p. Velocity;

        popm(k). Best=p.Best;
    end
   %Merge Population
    pop= [pop
          popc
          popm];
   %Sort Population
    pop=Sort Population (pop);
   %Delete Extra Individuals
    pop=pop(1:nPop);
    for i=1:nPop
   %Update Personal Best
        if pop(i). Cost<pop(i).Best. Cost
            pop(i).Best. Position=pop(i). Position;
            pop(i).Best. Cost=pop(i).Cost;
          %Update Global Best
            if pop(i).Best. Cost<Best Sol. Cost
                Best Sol=pop(i). Best;
            end
        end
    end
end
%Store Best Cost
Best Cost(it)=Best Sol. Cost;
%  Show Iteration Information
disp(['Iteration ' num2str(it) ': Best Cost = ' num2str (Best Cost(it))]);
End
```

Figure 4. Continued.

Table 3. Different sizes of test instances.

Size	No.	I	J	K	L	P	M	S	E	T
Small	1	2	2	3	2	2	1	2	2	2
	2	2	3	2	1	3	2	3	3	2
	3	3	2	4	3	2	2	4	4	2
edium	4	5	6	6	7	6	2	7	6	3
	5	4	7	7	8	5	2	8	6	4
	6	6	8	6	9	6	2	9	8	5
Large	7	9	8	8	7	7	2	10	9	5
	8	10	9	10	9	7	2	11	12	6
	9	12	8	13	10	9	2	9	12	7

The convergence quality of the evolutionary algorithm solution is mainly influenced by the set parameters of the meta-heuristic algorithms. Accordingly, efficient parameters for the algorithms are necessary to obtain efficient simulation results. Scientific approaches of meta-heuristic parameters are rare in literature reviews and depend more on the researcher's experience. Hence, the appropriate parameters that yield reasonable performance are determined by performing multiple runs and analysing different sizes of the problem using the proposed algorithms. The performances of the proposed algorithms are evaluated in each of the nine instances with ten different parameters according to several values for each parameter. The performance of parameter tunning test instances is represented in Table 4.

The efficiency of meta-heuristic algorithms is directly related to the setting of its parameters and operators,

Table 4. Final tunned parameters of suggested algorithms.

		Parameter tuning				
Algorithm	Parameter	1	2	3	4	5
GA	P_c	0.2	0.3	0.4	0.45	0.5
	P_m	0.05	0.1	0.15	0.25	0.3
	n-pop	50	100	150	200	250
	Max-iteration	50	100	150	200	250
SA	T	25	30	35	40	45
	α	0.2	0.3	0.4	0.45	0.5
	Max-iteration and sub-iteration	50	100	150	200	250
TS	*Breathing period*	5	15	20	25	30
	Max-iteration	50	100	150	200	250
PSO	C_1, C_2	0.25	0.5	0.75	1	1.25
	W	0.25	0.5	0.75	1	1.25
	W_{damp}	0.2	0.25	0.3	0.35	0.4
	n-pop	50	100	150	200	250
	Max-iteration	50	100	150	200	250
HSA-PSO	C_1, C_2	0.25	0.5	0.75	1	1.25
	W	0.25	0.5	0.75	1	1.25
	W_{damp}	0.2	0.25	0.3	0.35	0.4
	n-pop	50	100	150	200	250
	Max-iteration	50	100	150	200	250
	T	25	30	35	40	45
	α	0.2	0.3	0.4	0.45	0.5
	Max-sub iteration	50	100	150	200	250
	P_c	0.2	0.3	0.4	0.45	0.5
	P_m	0.05	0.1	0.15	0.25	0.3
	n-pop	50	100	150	200	250
	Max-iteration	50	100	150	200	250
HGA-TS	*Breathing period*	5	15	20	25	30
	Max Sub iteration GA	1	2	3	4	5
	Max Sub iteration TS	2	3	4	5	6
		Parameter tunning				
Algorithm	Parameter	6	7	8	9	10
GA	P_c	0.6	0.7	0.8	0.85	0.9
	P_m	0.35	0.4	0.45	0.5	0.55
	n-pop	300	350	400	450	500
	Max-iteration	300	350	400	450	500
SA	T	50	55	60	65	70
	α	0.6	0.7	0.8	0.85	0.9
	Max-iteration& sub-iteration	300	350	400	450	500
TS	*Breathing period*	35	40	45	50	55
	Max-iteration	300	350	400	450	500
PSO	C_1, C_2	1.5	1.75	2	2.25	2.5
	W	1.5	1.75	2	2.25	2.5
	W_{damp}	0.45	0.5	0.55	0.6	0.65
	n-pop	300	350	400	450	500
	Max-iteration	300	350	400	450	500
HSA-PSO	C_1, C_2	1.5	1.75	2	2.25	2.5
	W	1.5	1.75	2	2.25	2.5
	W_{damp}	0.45	0.5	0.55	0.6	0.65
	n-pop	300	350	400	450	500
	Max-iteration	300	350	400	450	500
	T	50	55	60	65	70
	α	0.6	0.7	0.8	0.85	0.9
	Max-sub iteration	300	350	400	450	500
	P_c	0.6	0.7	0.8	0.85	0.9
	P_m	0.35	0.4	0.45	0.5	0.55
	n-pop	300	350	400	450	500
HGA-TS	*Max-iteration*	300	350	400	450	500
	Breathing period	35	40	45	50	55
	Max Sub iteration GA	1	2	3	4	5
	Max Sub iteration TS	2	3	4	5	6

Table 5. CPU time for suggested algorithms.

		Performance CPU time (s)					
Test instance size	Test instance dimension	TS	SA	GA	PSO	HSA-PSO	HGA-TS
Small	S1	0.1334	0.156	0.567	3.5761	0.056	0.1334
	S2	5.6781	2.522	2.566	8.334	1.322	4.2456
	S3	8.6709	3.738	10.302	6.0054	1.788	7.6709
Medium	M4	10.3221	4.893	11.62	10.273	2.433	8.8799
	M5	78.586	16.566	14.082	13.480	3.566	67.586
	M6	185.521	17.907	28.00	26.489	19.907	78.521
Large	L7	234.459	58.544	50.85	45.065	44.544	89.459
	L8	432.322	81.707	97.18	76.912	53.707	94.322
	L9	561.98	91.899	118.9	93.489	71.899	145.98

so the incorrect selection of the parameters of the successful meta-heuristic algorithm will make it ineffective. In this paper, the Taguchi method is used to set up the algorithm's parameters (Mosallanezhad et al., 2021). For more information about this method, interested readers can refer to Goodarzian, Kumar, and Abraham (2021) and Mosallanezhad et al. (2021). In this paper, six meta-heuristic algorithms including SA, TS, GA, PSO, HSAPSO, and HGATS are presented. The algorithms' parameters are the terminology of factors for each meta-heuristic algorithm. Then, the proposed factors and levels are shown in Table 4. Hence, a maximum of ten levels is provided to algorithms' factors.

These algorithms were evaluated from the perspective of running time. The computational (CPU) time of the proposed algorithms are implemented on a PC with CPU6, CORE i5, 5GB of RAM and 8 GHz and are represented in Table 5.

As Table 5 emphasises, due to the used parameters, the lowest CPU time belongs to the SA algorithm; so, for problems with larger sizes, e.g. problem 9, the effect of these times can easily be seen such that TS needs a CPU time 576 times bigger than SA and despite the best-obtained solution from TS in six implementations, TS is slightly better than SA, but has a higher average and standard deviation than the latter. Therefore, if it is desirable to evaluate the algorithms in terms of average, standard deviation, and needed CPU time, SA is definitely better than TS for larger sizes.

Figure 5 displays the time needed to solve different test instances with the help of the suggested algorithms. In these figures, it is clear that the CPU times of SA and PSO are very similar. Accordingly, the trend of TS is shown without change but by growing the size, it increases.

4.2. The evaluation metrics for pareto optimal solutions

Here, in terms of multi-objective programming, the comparison of meta-heuristic algorithms is hard and difficult. Hereupon, a number of criteria to evaluate the quality

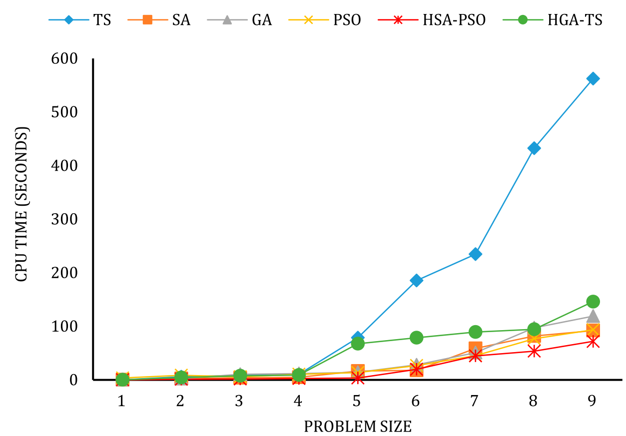

Figure 5. Behaviour of CPU time for proposed algorithms.

of Pareto fronts for the meta-heuristics are developed by some studies. Hence, in this paper, three evaluation metrics are utilised.

✓ Inverted Generational Distance (IGD) (Goodarzian, Taleizadeh, et al., 2021)
✓ Hyper Volume (HV) (Goodarzian, Taleizadeh, et al., 2021)
✓ Number of Pareto Solution (NPS) (Goodarzian, Kumar, et al., 2021)

In this regard, the proficiency of suggested algorithms is inspected by evaluation criteria, i.e. the IGD, HV, and NPS, as the comparison criteria for generated Pareto sets under each experiment problem. Moreover, the outcomes are presented in Tables 6–8.

In addition, two test instances of non-dominated solutions of proposed methods in two test instances (M6 and L8) are displayed in Figure 6. Accordingly, it can be concluded that the HSA-PSO algorithm demonstrated high efficiency but PSO shows the worst efficiency. TS and SA performances are close to each other.

Moreover, this paper conducted a set of statistical comparisons among proposed algorithms due to the Pareto optimal analyses taken by measurement metrics to obtain the best method. Hence, the outcomes which

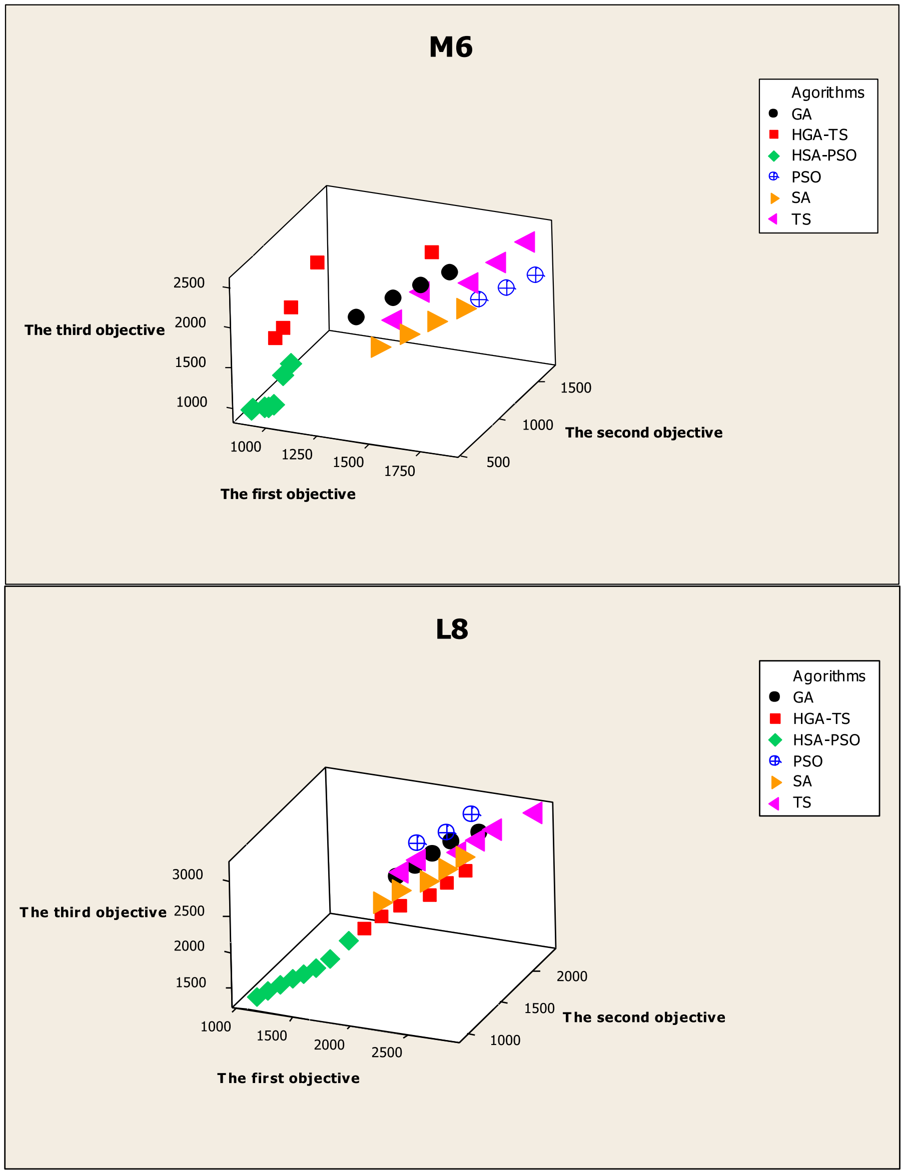

Figure 6. The Pareto frontier of suggested algorithms in M6 and L8 samples.

Table 6. The outcomes of the IGD of the suggested methods.

Example no.	SA	TS	PSO	GA	HSA-PSO	HGA-TS
S1	4.17	3.25	7.45	5.21	1.45	1.67
S2	4.34	3.56	7.21	5.74	1.17	1.56
S3	4.49	3.76	7.89	5.95	2.32	2.79
M4	4.86	3.86	8.34	6.56	3.28	3.24
M5	4.93	4.53	8.59	6.49	3.59	3.93
M6	4.98	5.45	9.27	7.27	4.12	4.58
L7	5.78	5.67	9.34	7.88	4.91	5.73
L8	5.94	5.88	9.59	7.97	5.17	5.82
L9	6.71	6.32	10.14	8.44	5.31	6.18

Table 7. The outcomes of the HV of the suggested methods.

Example no.	SA	TS	PSO	GA	HSA-PSO	HGA-TS
S1	3.35	6.52	2.18	4.27	8.35	7.45
S2	16.67	11.39	4.32	9.03	18.63	16.31
S3	18.32	16.31	5.19	11.12	27.31	22.65
M4	49.53	56.34	5.45	31.35	69.17	65.19
M5	52.12	68.67	17.21	35.56	82.82	76.56
M6	123.23	99.31	21.27	88.25	182.32	176.23
L7	155.29	119.17	32.39	89.22	194.31	189.72
L8	168.29	156.34	76.76	96.71	298.19	292.18
L9	212.53	169.61	92.31	108.32	326.34	287.24

were represented in Tables 6–8 are transformed into a well-known metric, namely, Relative Deviation Index (RDI) as the following formula:

$$\mathrm{RDI} = \frac{|Alg_{sol} - Best_{sol}|}{\mathrm{Max}_{sol} - \mathrm{min}_{sol}} \times 100 \tag{37}$$

It is evident that a lower value of RDI shows a higher quality of methods. Hence, the confidence interval of 95% for the performance metrics in all algorithms is conducted to statistically analyse the effectiveness of algorithms. Then, the least significant difference (LSD) and means a plot for the suggested methods have indicated. The outcomes

Table 8. The outcomes of the NPS of the suggested methods.

Example no.	SA	TS	PSO	GA	HSA-PSO	HGA-TS
S1	2	3	1	1	5	4
S2	2	2	1	1	4	3
S3	3	3	2	2	5	4
M4	3	4	2	3	6	5
M5	7	6	3	5	10	8
M6	4	5	3	4	7	5
L7	4	5	4	5	7	5
L8	5	6	3	5	8	6
L9	8	7	5	6	12	10

run by Minitab 16 Statistical software are indicated in Figure 7. In terms of the IGD, HV, and SNS, and based on Figure 7, the extended HSA-PSO and HGA-TS algorithms are more than the other suggested methods, and both of them are close to each other. All in all, first, the HSA-PSO and then HGA-TS show the best efficiency in all metrics. Based on Figure 7, PSO and GA display poor performance, but PSO has the worst efficiency than the GA in IGD, HV, and SNS criteria. Besides, TS and SA are close to each other, and also TS is more powerful than SA in all criteria. As a result, the HSA-PSO is more successful than other provided methods, but PSO indicates the worst behaviour in terms of the IGD, HV, and SNS criteria.

4.3. The performance of the convergence of the proposed algorithms

The efficiency of the suggested algorithms relevant to their convergence is performed by the plots of the convergence. Thus, the plots of the convergence for six suggested algorithms (SA, TS, GA, PSO, HSA-PSO, and HGA-TS) according to the objective functions are indicated in Figures 8–13, respectively. It is evident that HAS-PSO is fixed after 54 iterations and HGA-TS is fixed after 67 iterations with a steady line. But, the SA, TS, GA, and PSO algorithms are converging in 100 iterations. Accordingly, the HAS-PSO has the best quality and performance and high convergence compared to the proposed algorithms.

4.4. Case study

In this sub-section, to validate the developed mathematical model and consider its applicability in real-life conditions, a real pragmatic case in North of Iran farmlands (in Mazandaran Province) is investigated. The considered agricultural land cultivates three products including Orange, Lemon, and Pomegranate. Moreover, agricultural land has 10 main customers which are different in terms of the product order and purchasing costs. Table 9 presents the purchasing costs.

Table 10 lists the agricultural land regions that are all located in Mazandaran Province. Then, the considered agricultural land regions (suppliers/farmlands) are placed into two cities including Sari and Ghaemshahr, which is indicated in Figure 14. Besides, two suppliers have three main distribution centres in Babol, Babolsar, and Amol cities of Mazandaran Province, which is represented in Figure 14.

The amount of the used water by a unit of product and water consumption for the production of a unit of the

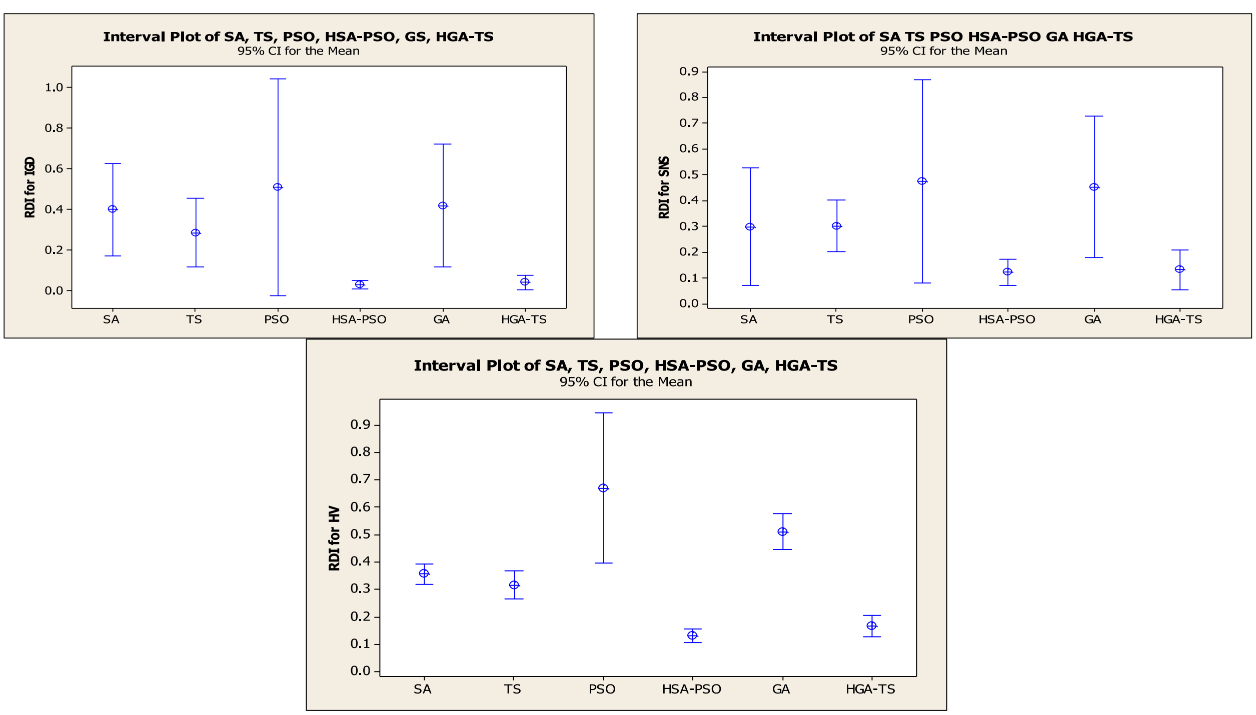

Figure 7. ANOVA plots for the three evaluation criteria in term of RDI for the proposed algorithms.

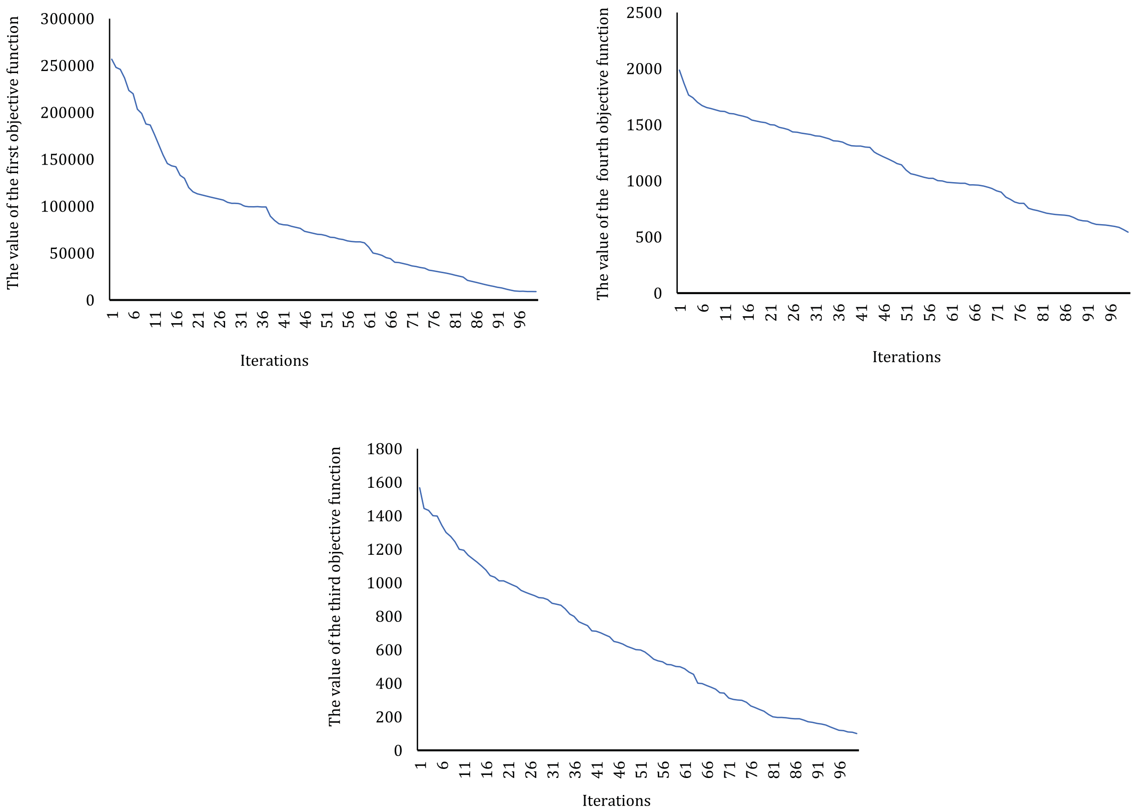

Figure 8. The trend of the convergence based on SA.

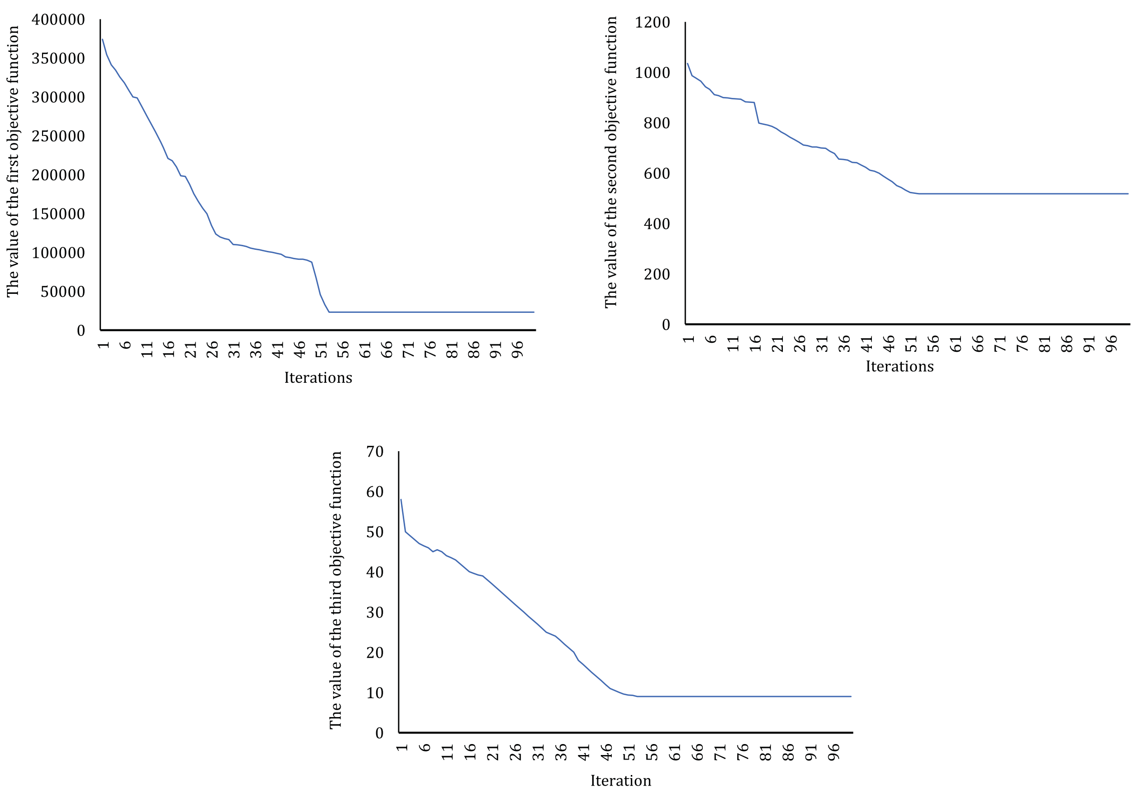

Figure 9. The trend of the convergence based on HSA-PSO.

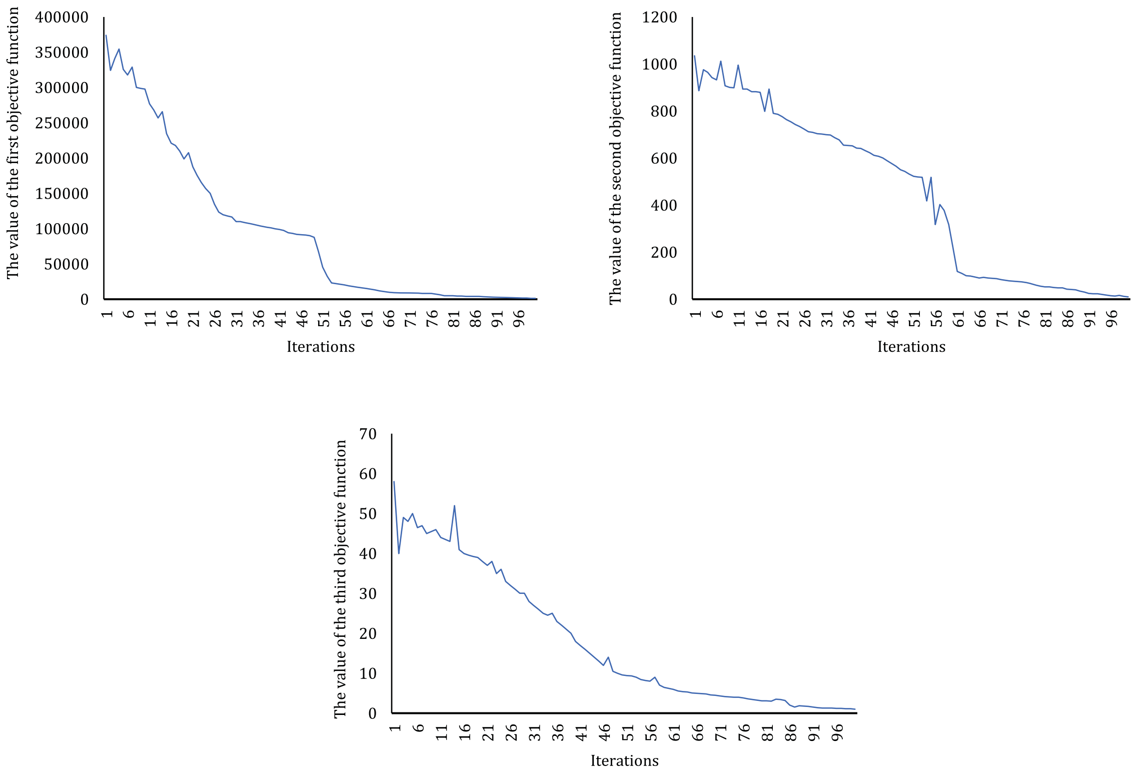

Figure 10. The trend of the convergence based on TS.

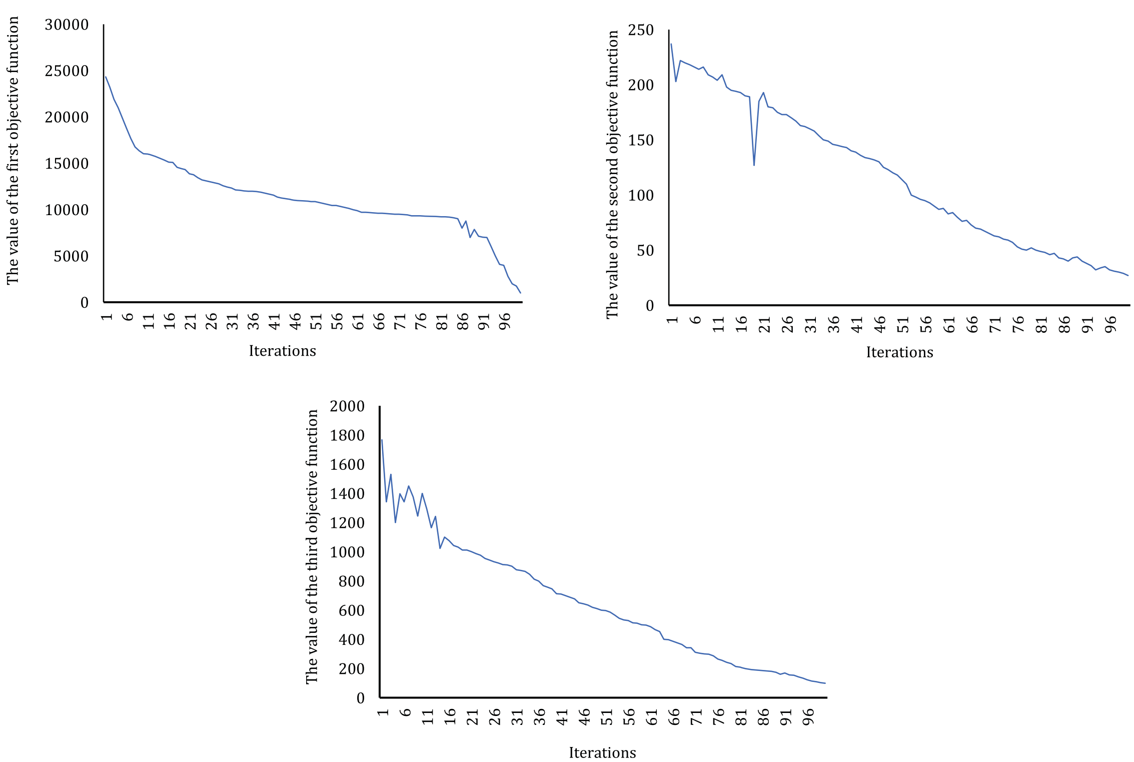

Figure 11. The trend of the convergence based on PSO.

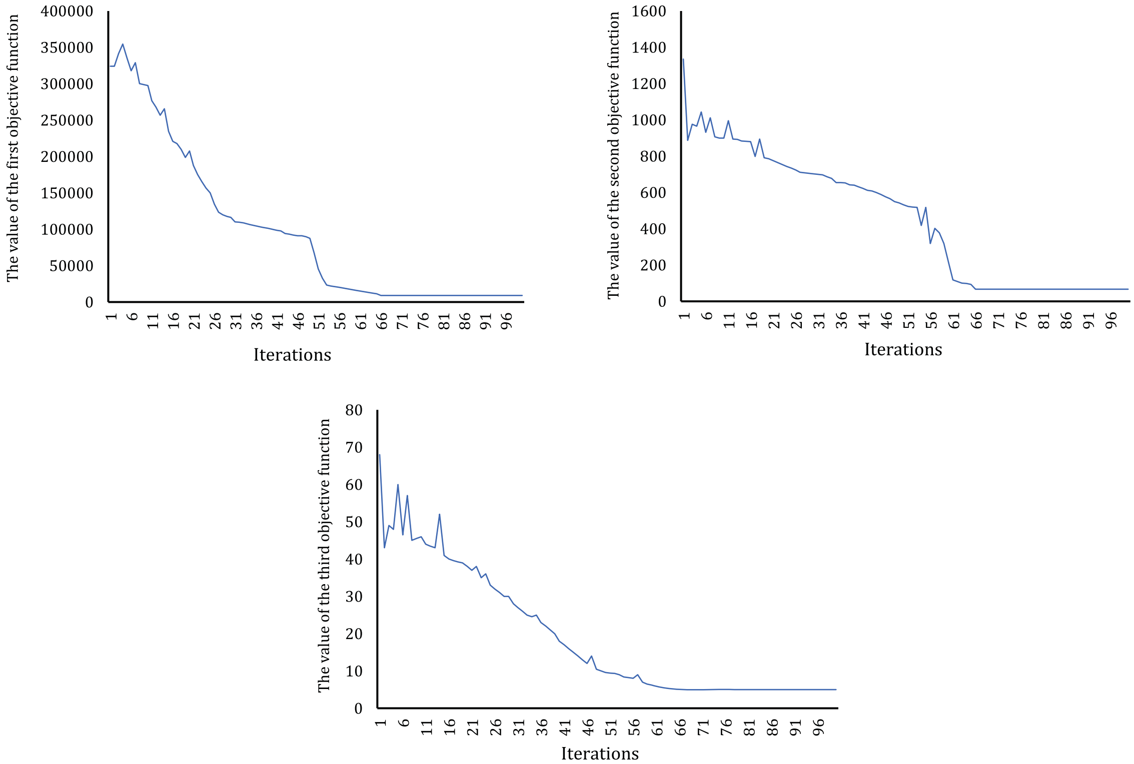

Figure 12. The trend of the convergence based on HGA-TS.

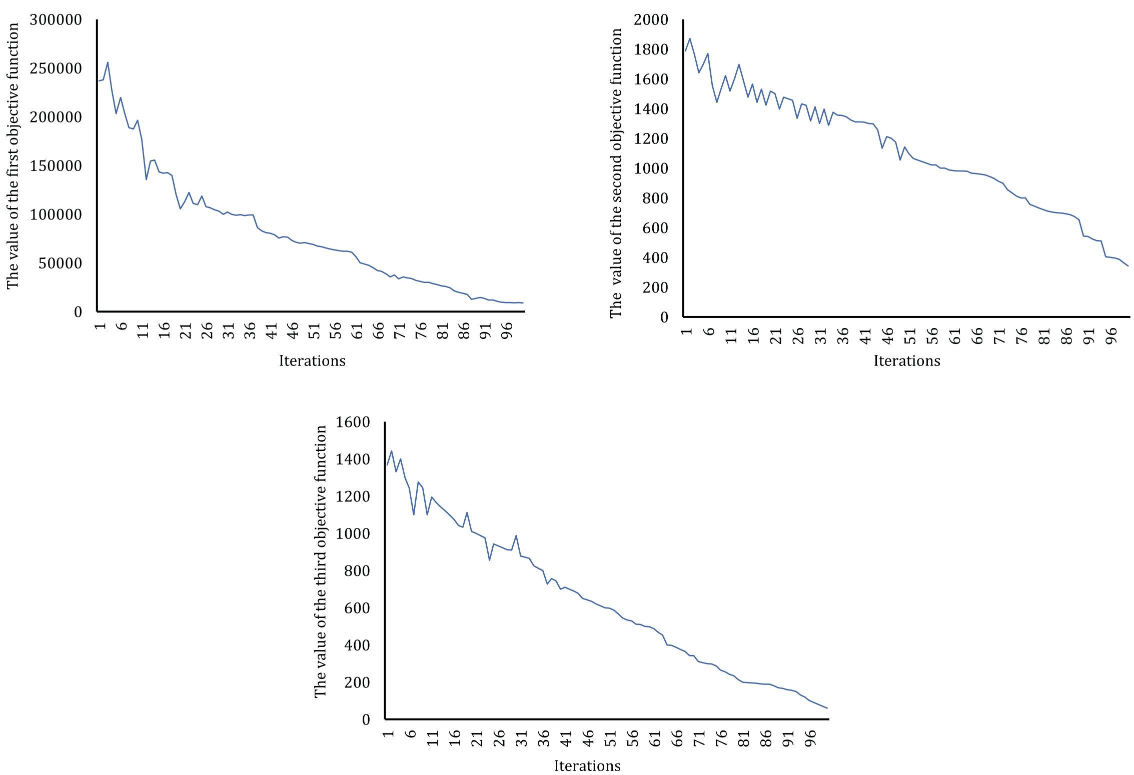

Figure 13. The trend of the convergence based on GA.

Table 9. Purchasing costs ($) of the three products in each customer zone.

Product	Customers									
	1	2	3	4	5	6	7	8	9	10
Orange	30	30	40	40	40	50	50	60	60	60
Lemon	40	40	40	45	45	50	60	70	75	75
Pomegranate	40	45	45	45	50	55	60	80	80	80

Table 10. Space and production costs ($) of the two agricultural land regions.

Province	Agricultural land regions	Space (ha^2)	Production cost
	Sari	3500	10
Mazandaran	Ghaemshahr	6000	10

Table 11. The amount of the used water/water consumption for the production of a unit of the product (m^3/ha).

Product	Sari	Ghaemshahr
Orange	4000	6000
Lemon	5000	8000
Pomegranate	6000	9000

Table 12. The transportation costs between suppliers and distribution centres ($).

		Distribution centre		
Supplier	Product type	Babol	Amol	Babolsar
Sari	Orange	5	8	4
	Lemon	6	9	5
	Pomegranate	7	10	7
Ghaemshahr	Orange	4	12	5
	Lemon	5	16	7
	Pomegranate	5	14	8

product depends on the location of the agricultural land is reported in Table 11.

Table 12 lists the transportation costs between supplier/farmlands and distribution centres in dollars. The considered location of the customers with black colour is shown in Figure 15 as well as the transportation costs between supplier/farmlands and customers are reported in Table 13. Additionally, Table 14 shows the transportation costs between distribution centres and customers. For example, transportation cost between Babol and Isfahan is 20 dollars for Orange product. Here, only one vehicle type is used to transport.

The capacity of supplier/farmland for the supply of raw material is shown in Table 15. Then, the water pressure index of location *j* is listed in Table 16.

4.5. The results of the case study

According to the obtained results of solution methods in the previous sections, the HSA-PSO was the best algorithm, which is used to solve the case study. The results of the proposed model are provided based on the applied data in the previous section. The value of the first, second, and third objective functions are 2532.98,

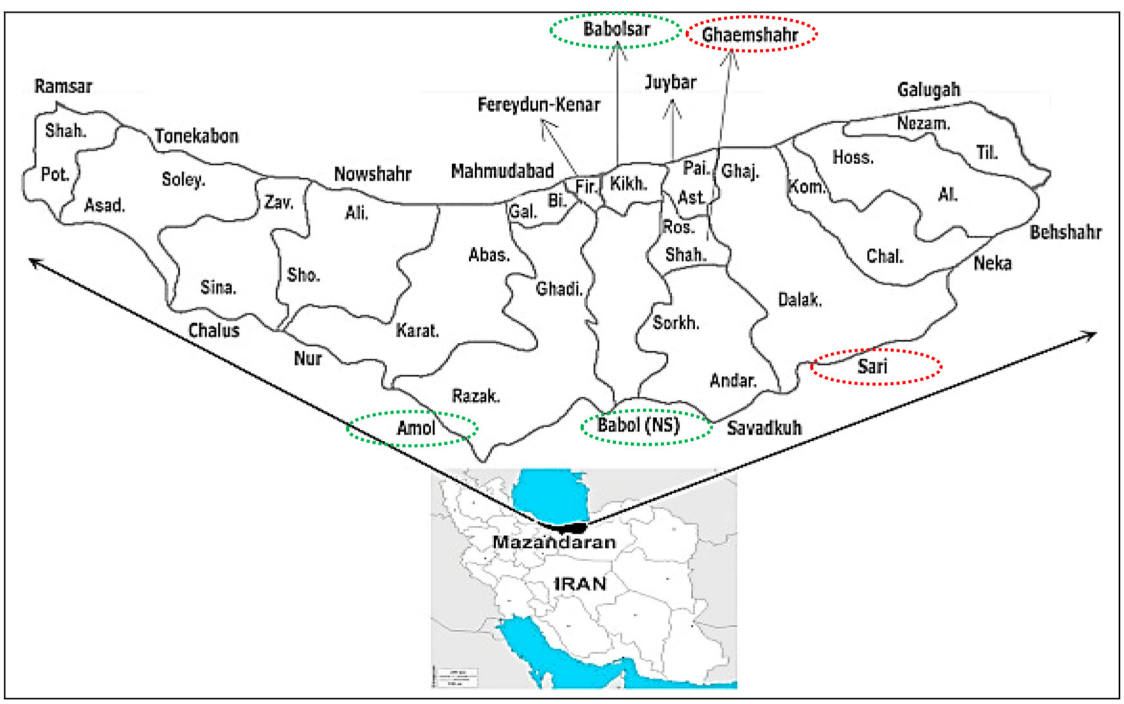

Figure 14. The considered two cities as suppliers/farmlands in Mazandaran Province.

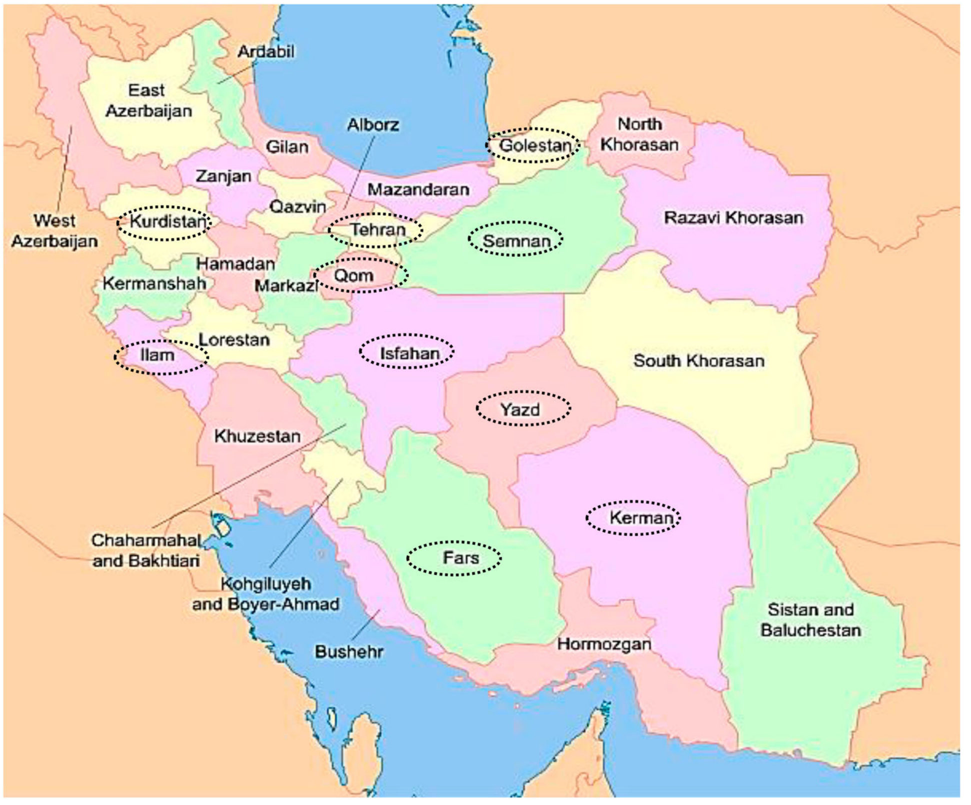

Figure 15. The map of the considered 10 cities as customers.

Table 13. The transportation costs between suppliers and customers ($).

		Customer									
Supplier	Product type	Isfahan	Yazd	Semnan	Tehran	Kurdistan	Golestan	Qom	Fars	Kerman	Ilam
Sari	Orange	30	40	20	15	25	28	17	65	60	55
	Lemon	35	45	25	18	35	32	19	70	66	60
	Pomegranate	40	50	30	20	45	38	21	75	73	65
Ghaemshahr	Orange	25	35	25	17	35	30	20	70	65	60
	Lemon	30	40	30	20	45	36	25	75	70	65
	Pomegranate	35	45	35	25	55	48	30	80	75	70

3421.45, and 1802.34, respectively. Only one of the products (Orange) is cultivated in the near-optimal solutions. Therefore, all existing land is utilised for the product. Table 17 presents the results of the used products and land. Then, 91% of the capacity of supplier/farmland for the supply of raw material is applied in the optimal solution.

The optimal flows of Orange between suppliers and distribution centres, between suppliers and customers, and between distribution centres and customers are

Table 14. The transportation costs between distribution centres and customers ($).

		Customer									
Distribution centre	Product type	Isfahan	Yazd	Semnan	Tehran	Kurdistan	Golestan	Qom	Fars	Kerman	Ilam
Babol	Orange	20	25	15	12	30	18	28	54	45	35
	Lemon	23	30	17	14	32	19	30	58	50	37
	Pomegranate	31	35	19	15	35	20	33	65	53	40
Amol	Orange	22	26	17	8	28	15	20	45	50	30
	Lemon	25	34	20	10	30	16	22	48	53	32
	Pomegranate	28	42	25	12	32	18	24	52	58	36
Babolsar	Orange	32	35	32	10	35	20	18	55	56	28
	Lemon	38	40	36	14	38	22	23	60	58	32
	Pomegranate	41	42	38	16	40	25	26	65	60	36

Table 15. The capacity of suppliers/farmlands (tons).

Supplier	Product type	Capacity of raw material
Sari	Orange	4000
	Lemon	8000
	Pomegranate	12,000
Ghaemshahr	Orange	7000
	Lemon	10,000
	Pomegranate	15,000

Table 16. The water pressure index of carrier location in suppliers/farmlands.

Supplier	Product type	Water pressure index (Bar)
Sari	Orange	2
	Lemon	3
	Pomegranate	4
Ghaemshahr	Orange	2
	Lemon	3
	Pomegranate	4

Table 17. Optimal planting region (ha^2).

Product	Sari	Ghaemshahr
Orange	3000	5500
Lemon	0	0
Pomegranate	0	0

Table 18. The optimal flows of orange (tons) between suppliers and distribution centres.

	Oranges Distribution centre		
Supplier	Babol	Amol	Babolsar
Sari	5000	7000	1000
Ghaemshahr	0	12,000	6000

provided in Tables 18–20. The amount of the used water/water consumption for the production of a unit of the product (m^3/ha) in each area is listed in Table 21. It is clear that the amount of the used water is adequate for the production of a unit of the product.

Table 21. The results of the amount of the used water/water consumption for the production of a unit of the product (m^3).

Area	Used water/water consumption
Sari	256,787
Ghaemshahr	3,456,700

4.6. Sensitivity analysis

This section is demonstrated to analysing the impact of product order (ω_{pl}^t), fixed costs ($\eta(\varepsilon, o)T(\mathrm{E})_{je}^t$and $\eta'(\varepsilon, o)CT(\mathrm{E})_j^t$), transportation cost ($\vartheta(T, \mathrm{E})T(\mathrm{E}, \mathrm{C})_{mijs}^t$), production cost ($\sigma(\varsigma)_{pje}^t$), purchasing cost ($\rho_{mi}^t$), the production output of a unit of product ($\gamma(\varsigma)_{pje}^t$), water pressure index (β_j), and the rate of the location efficiency (ψ_j) on the objective functions. Here, a number of test instances are carried out to prove how economic, environmental, and social impacts would change in accordance with the HSA-PSO algorithm based on the M4 test problem. Since the HSA-PSO algorithm is the best method in this paper, it is used to analyse the suggested model. According to Table 22, the parameters related to the proposed network in the current model are analysed. In Figures 16–18, the results and behaviour of the objective functions based on analysis of the suggested parameters are represented.

According to Figure 16, increasing the suggested costs leads to a raise in the three objective functions. The reasons for this behaviour may be hidden in growing the transportation, purchasing, and production costs. As expected, Figure 17 shows that a rise in the production output of a unit of product and water pressure index leads to an increase in the third and first objective functions and a decrease in the second objective function. According to Figure 18, a rise in the rate of location efficiency leads to an increase in the first and third objective functions. But, the second objective function is decreased between −20% and +20%.

Table 19. The optimal flows of orange (tons) between suppliers and customers.

	Orange Customer									
supplier	Isfahan	Yazd	Semnan	Tehran	Kurdistan	Golestan	Qom	Fars	Kerman	Ilam
Sari	2000	0	1500	7500	0	3700	1700	1200	0	0
Ghaemshahr	0	3400	2500	8000	3500	2000	25,000	7000	0	6000

Table 20. The optimal flows of orange (tons) between distribution centres and customers.

	Orange Customer									
Distribution centre	Isfahan	Yazd	Semnan	Tehran	Kurdistan	Golestan	Qom	Fars	Kerman	Ilam
Babol	500	0	0	2500	0	0	1000	1000	0	0
Amol	1000	2000	2000	7000	1500	1500	2000	2000	0	0
Babolsar	0	0	1500	3000	0	1500	1000	0	0	0

Table 22. Sensitivity analysis of parameters related to the supplier system.

Cases	Product	ω_{pl}^{t}	$\eta(\varepsilon,o)T(E)_{je}^{t}$	$\eta'(\varepsilon,o)CT(E)_{j}^{t}$	$\vartheta(T,E)T(E,C)_{mijs}^{t}$	$\sigma(\varsigma)_{pje}^{t}$	ρ_{mi}^{t}	$\gamma(\varsigma)_{pje}^{t}$	β_j	ψ_j
−20%	1	200	2	3	300	250	250	500	10	1.5
−10%	2	250	3	4	400	300	300	600	12	2
0	3	300	4	5	500	350	350	700	14	1.5
10%	4	350	5	6	600	400	400	800	16	3
20%	5	400	6	7	700	450	450	900	18	3.5

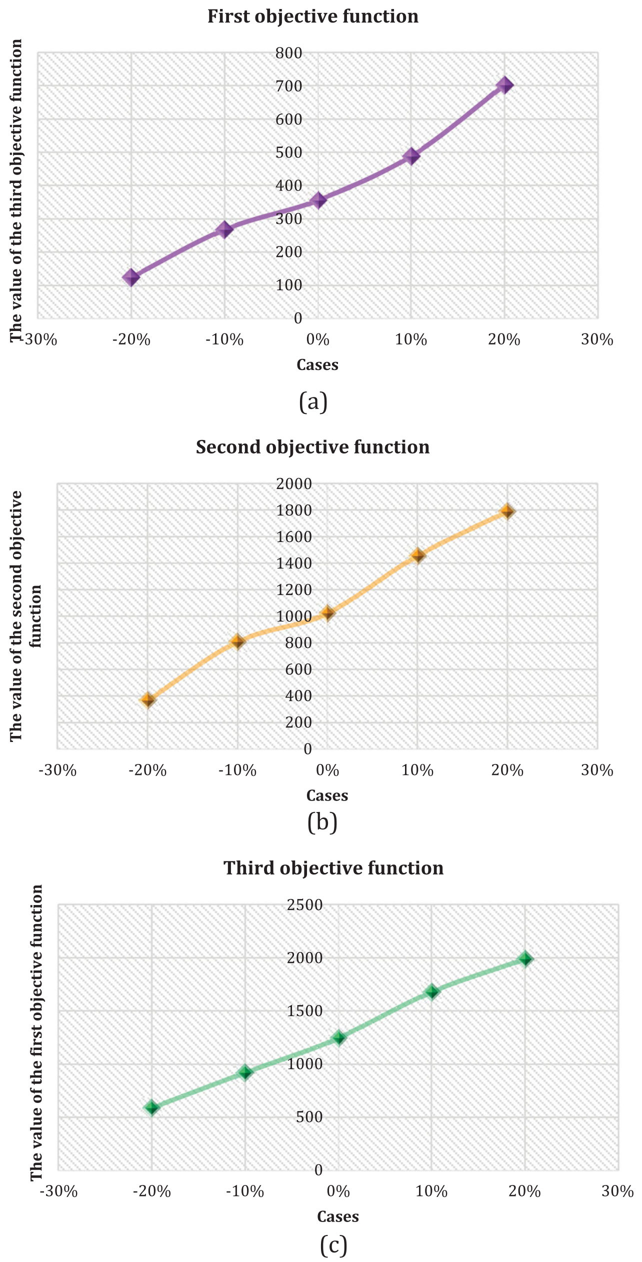

Figure 16. The trend of the objective functions based on changing $\eta(\varepsilon,o)T(E)_{je}^{t}$, $\eta'(\varepsilon,o)CT(E)_{j}^{t}$, $\vartheta(T,E)T(E,C)_{mijs}^{t}$, $\sigma(\varsigma)_{pje}^{t}$, ρ_{mi}^{t}.

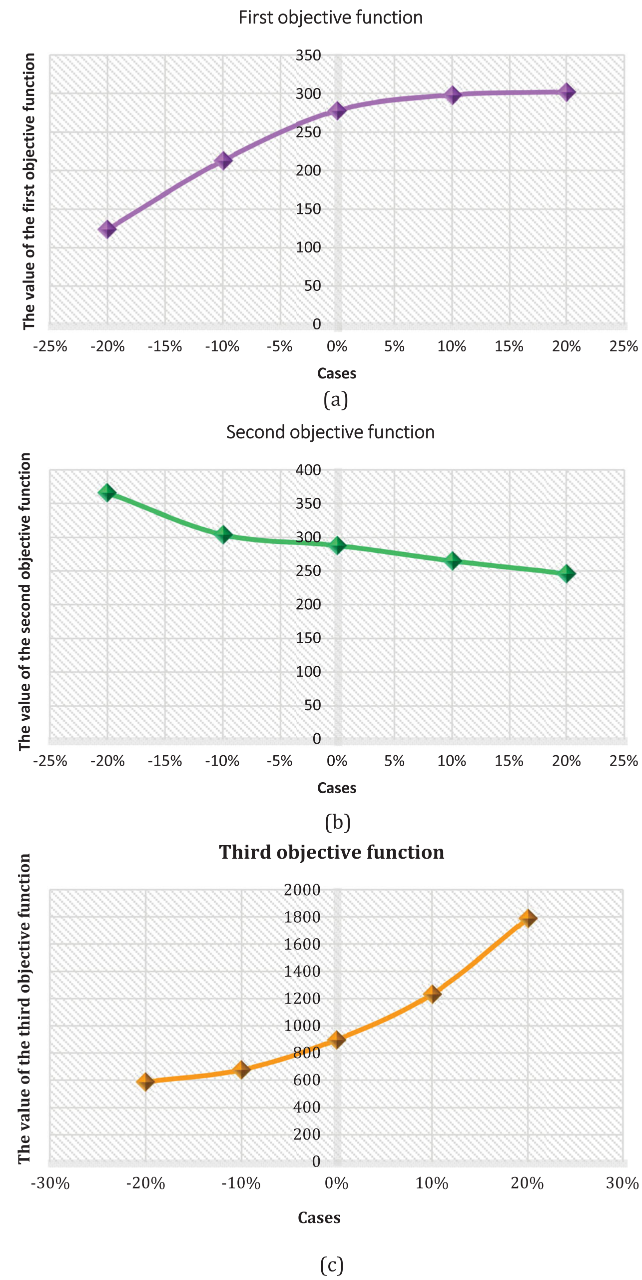

Figure 17. The trend of the objective functions based on changing $\gamma(\varsigma)_{pje}^{t}$ and β_j.

4.7. Managerial insights

This section investigates the outcomes to give fruitful managerial insights. According to the importance of agriculture in Mazandaran province as a case study, these results will be valuable and will help to improve the efficiency of the outcomes of the proposed model. The related findings are stated in the areas of cost, water consumption, optimal production, and CO_2 emissions.

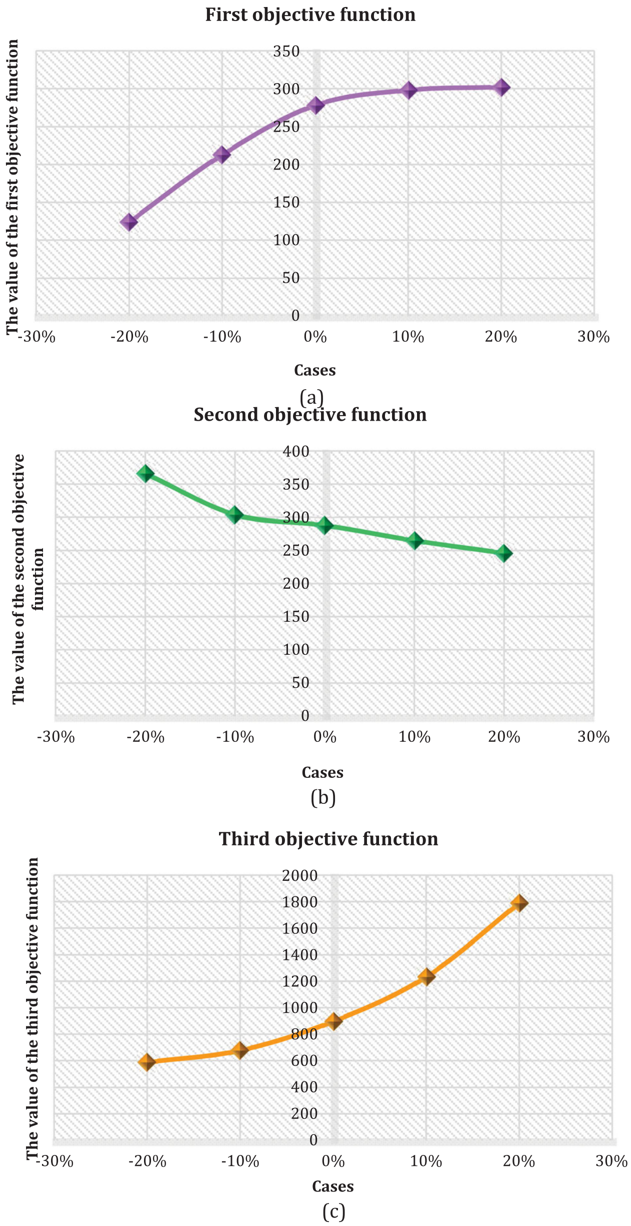

Figure 18. The trend of the objective functions based on changingψ_j.

The proposed results can be used in various ways to help practitioners. Firstly, managers are able to utilise the formulation for existing and new markets to find cost-efficient contract terms. Secondly, suppliers can exploit their current resources efficiently based on the upper and lower bounds of carrier and distribution location capacities. They can ascertain the amount of each raw material, water consumption, and production to stay within a CO_2 emission limit while consuming all their available resources. Thirdly, suppliers may apply a sensitivity analysis to compare spending on production improvement, total CO_2 emission, total water consumption, and the possible long-term benefits. This sort of analysis will present essential and more reliable information for strategic research and development planning.

Cost in the agriculture supply chain has always been one of the most significant factors in planning. In most cases, decreasing costs is the main priority in optimisation modelling. This factor is effective in all levels of the chain. The proposed model computes the optimal solutions by considering the cost minimisation objective. Paying attention to optimum production levels decreases transportation and purchasing costs appropriately results in reducing the costs of the chain. The amount of water consumption in each farm and each cultivation mode has been reported according to the water demand of the area, the available resources, and the specified water cost, which decreases supply chain costs. Accordingly, raising farmers' awareness in how using these water consumptions and considering the cost of water, optimal consumption, and appropriate management of the proposed chain can help.

Optimised water consumption, which is one of the most important and urgent energy sources, has received more attention in recent years. Due to the depletion of water resources, most countries seek to manage water resources used in industry and agriculture, similar to the proposed model which tries to decrease the utilisation of water consumption.

According to the sensitivity analysis, the economic, environmental, and social impacts increase significantly by raising the parameters of costs related to the supplier system. This type of sensitivity analysis states the trade-off between economic, environmental, social impacts to decrease emissions, fixed, production, purchasing, and transportation costs and to increase water pressure and production output. The sensitivity analysis of the presented model can help to find a cost-efficient level of spending for production process enhancement and decrease pollution during product transportation, and decrease water consumption.

5. Conclusions, limitations, and future works

According to the significance of agricultural product supply and the production of agricultural products, it is imperative to study the proposed supply chain that can affect many factors in society. Additionally, taking into account the sustainability dimensions of the supply chain will help to enhance its efficiency.

In the this paper, a new SAPSCN has been developed, which is the first novelty. The suggested multi-product, multi-period, and multi-echelon multi-objective model is proposed. The main aims have been included to minimising the objective function concerning the sustainability economic index, minimising the total of the social and environmental objective functions, and maximising the efficient supply chain by applying calculated efficiencies for each location of carriers, distribution centres, and suppliers. In addition, the proposed model based on an MILP model has been formulated. To solve the suggested model, four well-known meta-heuristic algorithms include genetic algorithm (GA), PARTICLE SWARM OPTIMISATION (PSO), TS, and simulated annealing (SA) are used. Also, two hybrid algorithms based on GA and TS as well as SA and PSO were developed, the second novelty of this paper. Finally, to obtain better efficiency of the proposed algorithms, the corresponding parameters were tuned by the Taguchi method.

After solving the suggested model by the proposed algorithms, the results have been evaluated and analysed, using analysis of variance (ANOVA) through interval plots at the 95% confidence level. Utilising ANOVA, the statistically major difference between efficiencies of the algorithms was clear. Also, different assessment metrics have been used to evaluate the performance of the proposed algorithms. In addition, to evaluate further the proposed model, sensitivity analysis under some of the key parameters has been conducted for the M4 test problem. Hence, a real case study was performed on the agricultural products including Orange, Lemon, and Pomegranate in Mazandaran province/Iran, and the results were proposed to appraise the validity of the model. In order to improve the suggested network performance, several directions about managerial implications were discussed. These obtained results can be useful for agricultural organisations or managers of this field.

This research, like other cases, has its own limitations and assumptions, which are expressed as follows:

- As there was no official database for some parts of cost elements, the farmers' experiences and sellers of agricultural products in fruit markets were used for information related to the costs. The questions about the transportation costs for each route have been categorised and the estimated costs have been entered into the mathematical model. In addition, the information related to water consumption and the capacity of suppliers/farmlands has been received by farmers.
- Additionally, the recent high inflation rate and the rising transportation, production, and purchasing costs in Iran make it more difficult to estimate the relevant costs.
- The final solution obtained using the proposed algorithms depends on the coder's skill in defining the initial value of its parameters.
- In order to implement the presented solution approach for the real case study, high RAM and CPU hardware facilities and software facilities are required, which are the limitations of the proposed paper.

Also, several directions and suggestions for future works are listed below.

- Utilise realistic assumptions related to the agricultural product chains in other countries, and also consider their various production approaches.
- Employing the robust, fuzzy, or stochastic version of the proposed model and considering the uncertainty of some parameters such as costs.
- Using the exact methods such as the Benders decomposition or the Lagrangian relaxation methods.
- Using some new meta-heuristic algorithms or developing a novel heuristic.

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

Data availability statement

Data available on request authors

Notes on contributors

Dr Fariba Goodarzian is a Postdoc at the Machine Intelligence Research Labs (MIR Labs), Scientific Network for Innovation and Research Excellence, Washington, D.C., United States, and the University of Tehran, Department of Industrial Engineering, Tehran, Iran. She earned her Ph. D. degree in Industrial Engineering from Yazd University, Yazd, Iran from 2017 to 2020, M. Sc. degree in Industrial Engineering from the University of Science and Technology of Mazandaran, Behshar from 2014 to 2016, and also she graduated B. Sc. degree in Industrial Engineering from Mazandaran University of Science and Technology, Babol from 2020 to 2014. Her publications are in Applied Soft Computing, Engineering Applications and Artificial Intelligence, Journal of Computational Design and Engineering, Computers and Industrial Engineering, Annals of Operations Research, Soft Computing, RAIRO-Operations Research, International Journal of Systems Science: Operations & Logistics, International Journal of Logistics Management, etc. Her main research interests are in the area of Supply Chain Management, Health Care Management, Network Design, Big Data Analytics, Uncertainty Programming, as well as proposing novel heuristic methods and metaheuristic algorithms. Dr. Fariba Goodarzian is a Postdoc at the Machine Intelligence Research Labs (MIR Labs), Scientific Network for Innovation and Research Excellence, Washington, D.C., United States, and the University of Tehran, Department of Industrial Engineering, Tehran, Iran. She earned her Ph.D. degree in Industrial Engineering from Yazd University, Yazd, Iran, from 2017 to 2020, M.Sc. degree in Industrial Engineering from the University of Science and Technology of Mazandaran, Behshar from 2014 to 2016, and also she graduated B.Sc. degree in Industrial Engineering from Mazandaran University of Science and Technology, Babol from 2020 to 2014. Her publications are in *Applied Soft Computing*, *Engineering Applications and Artificial Intelligence*, *Journal of Computational Design and Engineering*, *Computers and Industrial Engineering*, *Annals of Operations Research*, *Soft Computing*, *RAIRO-Operations Research*, *International Journal of Systems Science: Operations & Logistics*, *International Journal of Logistics Management*, etc. Her main research interests are in the area of supply chain management, health care management, network design, big data analytics, uncertainty programming, as well as proposing novel heuristic methods and metaheuristic algorithms.

Dr. Davood Shishebori is an associate professor of Industrial Engineering Department at Yazd University. Also, he is the director of quality and productivity research centre in Yazd University. Dr. Shishebori works in a stochastic optimisation and risk management, especially for supply chain management and logistics, applied to various real-world problems. Another research area is quality control and productivity management. In these areas, he has authored/coauthored more than 50+ research publications. His main highlighted publications are in *Computers and Industrial Engineering*, *European Journal of Industrial Engineering*, *Transportation Research*: *Part E*, *Journal of Manufacturing Systems*, *Journal of Ambient Intelligence and Humanized Computing*, *RAIRO-Operations Research*, *International Journal of Systems Science: Operations & Logistics*, *Journal of Cleaner Production*, *International Journal of Logistics Management*, etc. Dr. Shishebori received Ph.D. degree from Iran University of Science and Technology (IUST), Tehran, Iran (2013); Ph.D. Sabbatical course in Lehigh University, USA (2012), a Master of Science Degree from Isfahan University of Technology (IUT), Isfahan, Iran (2008), and bachelor degree in Yazd University, Yazd, Iran (2005).

Dr. Farzad Bahrami is an assistant professor of Industrial Management Department in the Faculty of Administrative Sciences & Economics at Arak University. He has been the senior advisor of well-known Iranian companies in the area of hub location and allocation, supply chain network design and truck routing. As the commercial manager of the Ofoq Kourosh chain stores, the largest online and brick-and-mortar Iranian discount chain stores, he has led an elite and result-oriented team to work on many related subject areas such as payment optimisation, category optimisation, budgeting, demand forecasting, pricing, assortment planning, shelf space optimisation and planogram design with data science and machine learning methods. Dr. Bahrami's main competence is linear and non-linear mathematical modelling of all kinds of problems which companies encounter in real word. His interest is in developing novel heuristics and meta-heuristics methods to solve the proposed mathematical models. In these areas, he has authored/coauthored more than 10+ unclassified research publications. Dr. Bahrami received Ph.D. degree in Industrial Management from Tehran University (UT), Tehran, Iran (2016) and a Master of Science Degree in Industrial Engineering from Isfahan University of Technology (IUT), Isfahan, Iran (2007).

Prof. Ajith Abraham is the Director of Machine Intelligence Research Labs (MIR Labs), a Not-for-Profit Scientific Network for Innovation and Research Excellence connecting Industry and Academia. The Network with HQ in Seattle, USA has currently more than 1000 scientific members from over 100 countries. As an Investigator/Co-Investigator, he has won research grants worth over 100+ Million US$ from Australia, USA, EU, Italy, Czech Republic, France, Malaysia and China. Dr. Abraham works in a multi-disciplinary environment involving machine intelligence, cyber-physical systems, Internet of things, network security, sensor networks, Web intelligence, Web services, data mining and applied to various real-world problems. In these areas he has authored/coauthored more than 1400+ research publications out of which there are 100+ books covering various aspects of computer science. One of his books was translated to Japanese and a few other articles were translated to Russian and Chinese. About 1200+ publications are indexed by Scopus and over 1000+ are indexed by Thomson ISI Web of Science. Some of the articles are available in the Science Direct Top 25 hottest articles. He has 1100+ co-authors originating from 40+ countries. Dr. Abraham has more than 43,000+ academic citations (h-index of 97 as per google scholar). He has given more than 150 plenary lectures and conference tutorials (in 20+ countries). For his research, he has won seven best paper awards at prestigious International conferences held in Belgium, Canada Bahrain, Czech Republic, China and India. Since 2008, Dr. Abraham is the Chair of IEEE Systems Man and Cybernetics Society Technical Committee on Soft Computing (which has over 200+ members) and served as a Distinguished Lecturer of IEEE Computer Society representing Europe (2011-2013). Currently, Dr. Abraham is the Editor-in-Chief of Engineering Applications of Artificial Intelligence (EAAI) and serves/served the editorial board of over 15 International Journals indexed by Thomson ISI. He is actively involved in the organisation of several academic conferences, and some of them are now annual events. Dr. Abraham received Ph.D. degree in Computer Science from Monash University, Melbourne, Australia (2001) and a Master of Science Degree from Nanyang Technological University, Singapore (1998).

Dr. Andrea Appolloni is Professor in Operations Management and Sustainability at Tor Vergata University in Rome, Italy. In the same university, he completed his Ph.D in Business Administration. He is a permanent visiting fellow at Cranfield University (UK) and Research Associate at the Italian Research Council. His teaching areas focused on operations, supply chain and procurement management and sustainability courses at undergraduate and executive levels. He was visiting several universities in the last few years. He has published and presented articles in several international journals and conferences. He is the coordinator of the European Project Marie Curie Hosrizon 2020 on Sustainable Public Procurement. He is an expert member in Sustainability at the Global SCP. Clearinghouse is a unique one-stop hub dedicated to Sustainable Consumption and Production (SCP) and he is part of the10 Year Framework of Programmes on SCP (10YFP on SCP), convened by the United Nations Environment Programme (UNEP). He was a visiting scholar at Tianjin University (China), at the University of Tennessee in Knoxville (USA) and ETH Zurich (CH).

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