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Integrated design of sustainable supply chain and transportation network using a fuzzy bi-level decision support system for perishable products

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ABSTRACT

This study introduces a fuzzy bi-level Decision Support System (DSS) to optimize a sustainable multi-level multi-product Supply Chain (SC) and co-modal transportation network for perishable products distribution. To this end, two integrated multi-objective Mixed Integer Linear Programming (MILP) models are proposed to formulate the problem. On-time delivery is taken into account as the main factor that determines model performance due to perishability of products. Optimizing the design of SC network using the first level of the proposed DSS, the transportation network configuration is provided optimally in the second level considering different modes and options. In order to contribute to the literature, mainly by addressing uncertainty and perishability, a hybrid solution technique based on possibilistic linear programming and Fuzzy Weighted Goal Programming (FWGP) approach is developed to accommodate our suggested bi-level model. This technique can deal with problem uncertainty while also ensuring the sustainability of the overall system. Lp-metric method is implemented along with three well-known quality indicators to assess the performance of the proposed solution method and quality of obtained solutions. Finally, three illustrative numerical examples are provided using the CPLEX solver to showcase the applicability of the proposed methodology and discuss the complexity of the model. Results demonstrate the efficiency of the proposed methodology in finding optimal solutions compared to Lp-metric method, such that it is able to treat a problem with more than 2.2 million variables and 1.3 million constraints in 1093.08 s.

1. Introduction

The rising demand for perishable products (e.g., fresh food, meat and vaccines) around the world has rendered Supply Chain (SC) performance a critical factor in determining the security of global production, logistics and consumption. A product is regarded as perishable if at least one of the following three conditions holds (Biuki et al., 2020): (*i*) its quality deteriorates progressively and significantly, (*ii*) its monetary value decreases over time, and (*iii*) its decreased functionality leads to undesired and even fatal outcomes. These inherent features add to the complexity of perishable products SC management. Therefore, different decision-making layers should be considered in managing perishable product SCs with a view to coping with the time constraints and other dynamic risks posed by the perishability.

Recently, increasing awareness about environmental and social issues have forced industries to consider the environmental and social effects of their activities – along with the economic effects – and address the three pillars of sustainability as a whole (Sherafati et al., 2019). Perishable items require exceptional handling measures which may have social and environmental aspects along with their popular economic impacts. In the recent decades, the sustainability of SCs has proceeded forward, but the sustainability of perishable product SCs is not yet a fully-addressed topic in the literature. Therefore, SC catered for perishable products have become a key aspect of sustainable development of industries, as the latter issue should be incorporated into different levels of the decision-making processes, including strategic, tactical as well as operational.

Dairy industry deals with one of high-consumption items in human food chains in which products are perishable at all levels of the SC (Jouzdani & Govindan, 2021). In fact, the perishability is taken into account when the main raw material — the milk is produced and enters the production facilities until the final dairy products are produced and delivered to the final customer. Sustainable development studies in the dairy industry need a comprehensive standpoint in order to efficiently address three pillars of sustainability, particularly the social aspect that has been less emphasized in previous research works (Feil et al., 2020).

Against this background, this study aims to develop a possibilistic optimization model for identifying the most favorable SC setup and design a cost-efficient transportation network that is suitable for the

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perishable products SC and has minimal environmental impact. In order to properly address the main decisions in this SC at, a bi-level design architecture needs to be taken into account. The first level is used to decide on the optimal supply structure (i.e., which location, production and inventory strategy should be chosen under the given constraints). The second level is then to deal with the optimal transportation of supplies from source to target nodes. Therefore, the strategic and tactical decisions are treated in the first level, while the second level deals with the operational decisions. The peculiarity of the model comes from its reflection of not only economical but also environmental and sustainability-related concerns in the objective function. To address the uncertainty in parameters, a possibilistic linear programming approach is applied, which is then hybridized with the Fuzzy Weighted Goal Programming (FWGP) technique to tackle the multi-objectiveness of the model and reach the option solution. Finally, the performance of the suggested FWGP is benchmarked against the Lp-metric method as one of the most well-known techniques in the literature. In addition, the complexity of the proposed DSS is examined in terms of the number of variables and constraints.

Given the fact that the perishable product SCs are challenged by the pertinent need for continuous improvement to enhance their performances, our research aims to answer the following critical questions:

(i) How can we facilitate the optimization of a perishable product SC network using a bi-level DSS?
(ii) What are the key factors affecting the perishability, sustainability and uncertainty of such a SC and how can they be incorporated in to the design phase?
(iii) How can we evaluate the validity, complexity and applicability of the proposed DSS?

The rest of the paper is organized as follows. Section 2 offers a review of literature related to the design of sustainable SCs. Section 3 describes different sections given in the proposed bi-level DSS. Section 4 explains the problem, main assumptions and mathematical models as well as the proposed possibilistic linear programming approach is presented. FWGP, Lp-metric and quality indicators are represented in Section 5. Section 6 presents the computational results of the study using three different numerical examples to validate the proposed methodology. Section 7 discusses the main achievements and practical implications, and finally, the conclusion and outlook of the research are expressed in Section 8.

2. Related work

In traditional SC management, decision makers aim solely to find a cost-effective way to meet the customer demand while omitting the possible environmental impacts. With the increasing pressure on the environment, sustainable SC network design models and methods have been the subject of recent research. Eskandarpour et al. (2015) reviewed 87 papers related to SC network design, covering mathematical models that accommodate economic factors as well as environmental and/or social dimensions. The authors report the narrow scope of environmental and social measures in SC network design models and also point out the need for a more effective inclusion of uncertainty and risk in models with multiple objectives. Zhu et al. (2018) conducted a comprehensive review of related scientific papers that employed mathematical modeling methods to tackle issues in Sustainable Food Supply Chain (SFSC).

On the other hand, the number of research works that feature multi-modal transportation in the design of perishable product SCs – let alone a comprehensive transportation network model – is scarce. Stochastic programming and fuzzy set theory seem to be two main methods for handling uncertainty in such models. The former requires the availability of large amounts of high-quality historical data for parameter estimation whereas the latter leverages on fuzzy definition of real data which would otherwise be hard to obtain in large amounts.

In particular, Boukherroub et al. (2015) proposed a model that incorporates sustainability (i.e., economic, environmental and social) footprint into SC decisions through multi-objective mathematical programming as well as weighted goal programming technique as the solution method. On the other hand, Pishvaee and Razmi (2012) offered a multi-objective fuzzy mathematical programming model for designing an environmentally conscious SC that is able to consider the minimization of multiple environmental impacts beside the traditional cost minimization objective, and a fuzzy solution approach for the model. Besides, Soleimani et al. (2017) investigated a multi-objective design problem for a closed-loop SC, including suppliers, manufacturers, distribution centers, customers, warehouse centers, return centers, and recycling centers, and employ a genetic algorithm to solve the model.

Tsai and Hung (2009) proposed a fuzzy goal programming approach that integrates Activity-Based Costing (ABC) and performance evaluation in a value-chain structure for the optimal selection of suppliers in a green SC which features flexible goals, financial and non-financial measures, a multi-layer structure, multiple criteria and multiple objectives. Selim et al. (2008) developed a multi-objective linear programming model for collaborative production–distribution planning problem in SC systems where uncertain priority levels of the goals for decision makers are incorporated into the model using fuzzy goal programming approach. The results favor the effectiveness of fuzzy goal programming approach in different SC structures. Selim and Ozkarahan (2008) suggested a SC distribution network design model using fuzzy programming which aims to select the optimum numbers, locations and capacity levels for plants and warehouses to deliver products to retailers while minimizing the cost and satisfying desired service level to retailers. Mokhtari and Hasani (2017) designed a multi-objective optimization model towards a cleaner production–transportation planning in manufacturing plants which incorporates various environmental effects such as generated wastes, gas emissions, noise disturbance, workers injuries, and energy consumption, and adopt fuzzy goal programming as well as heuristics as the solution approach.

Liu et al. (2019) proposed a novel two-stage multi-objective optimization method for a SC design problem with uncertain demand that combines fuzzy and stochastic modeling. The problem was treated using a Multi-Objective Particle Swarm Optimization (MOPSO) approach. Su and Sun (2019) developed a mathematical model for a closed-loop SC network with uncertain demand that maximizes total profit and minimizes environmental pollution. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) was used to generate and analyze the approximated Pareto solutions of the proposed model. Transportation of Hazardous Materials (HAZMAT) as well as associated risk models for protecting lives, property, environment and supporting sustainable development were studied by Hu et al. (2020). Balaman et al. (2018) proposed a mathematical programming based optimization technique to design sustainable SCs along with transportation networks for biomass products. To attain optimal solutions from the proposed models, the authors presented a hybrid solution tool that combines fuzzy set theory and ϵ-constraint method. Sherafati et al. (2019) designed a robust SC network considering sustainable development paradigm for a cable industry. They applied the ϵ-constraint method to deal with their multi-objective Mixed-Integer Linear Programming (MILP) model.

Sazvar et al. (2014) and some other authors; e.g., Paksoy et al. (2010) and Zhao et al. (2012) focused on Greenhouse Gas (GHG) emissions to develop mathematical models for designing sustainable SCs. Sazvar et al. (2014) proposed multi-stage stochastic programming under uncertain and partially back-ordered demands for developing a green two-echelon centralized SC model by determining an eco-efficient frontier for costs vis-a-vis GHG emissions.

Daryanto et al. (2019) investigated an integrated three-echelon SC with disposing of the deteriorated products as well as carbon emissions from transportation and warehousing processes. Their suggested model simultaneously optimized the delivery size and the number of deliveries

Table 1
Tabular literature.

Author(s)	Year	Main features								Objectives			Case	Product type	Solution approach	Solver
		f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	o_1	o_2	o_3				
Selim & Ozkarahan	2008					*				*		*			Fuzzy GP	CPLEX
Selim et al.	2008				*	*	*	*	*	*		*			Fuzzy GP	CPLEX
Pishvaee & Razmi	2012				*					*	*		*	End-of-life	Fuzzy solution	LINGO
Sazvar et al.	2014		*		*		*	*	*	*	*		*	Pharmaceutical	Compromise programming	CPLEX
Boukherroub et al.	2015			*			*	*	*	*	*	*	*	Wood	Weighted GP	CPLEX
Mokhtari & Hasani	2017				*	*	*	*	*	*	*	*			Fuzzy GP & SA-based Heuris.	LINGO
Farrokh et al.	2018				*		*	*	*	*					Robust fuzzy Stoch. Prog.	CPLEX
Balaman et al.	2018	*		*	*	*		*		*	*	*	*	Bio	Fuzzy ϵ-constraint method	CPLEX
Su & Sun	2019	*			*				*	*	*				NSGA-II	MATLAB
Liu et al.	2019			*	*	*	*		*	*	*		*	Light Emitting Diode	Equilibrium Opt. model & Hybrid MOPSO	CPLEX, C++
Onggo et al.	2019		*		*		*	*	*	*				Agro-food	MC simulation & Iterated local search	Java app.
Daryanto et al.	2019		*				*		*	*	*				Heuristic algorithm	MAPLE
Sherafati et al.	2019			*		*	*	*	*	*		*	*	Cable	ϵ-constraint method	CPLEX
Sinha & Anand	2020		*				*		*	*			*	Perishable	IBFA	MATLAB
Li et al.	2020		*			*			*	*			*	Grape	Global solution method	Baron
Jouzdani & Govindan	2021		*	*		*	*	*	*	*	*	*	*	Dairy	GP	LINGO
This study	2021	*	*	*	*	*	*	*	*	*	*	*	*	Perishable	FWGP and Lp-metric	CPLEX

Main features: f_1: Bi-level DSS, f_2: Perishability, f_3: Sustainability, f_4: Uncertainty, f_5: Multiple materials/products, f_6: Multiple periods, f_7: Multimodal transportation, f_8: Inventory. **Objectives:** o_1: Economic, o_2: Environmental, o_3: Social.

from a supplier to a Third-Party Logistics (3PL) service provider, and from the 3PL to a buyer. Li et al. (2020) developed a Mixed-Integer Non-Linear Programming (MINLP) model for the food SC configuration problem in a general multi-echelon food SC. Mogale et al. (2019), on the other hand, suggested a model that covers several features such as multi-echelon, multi-modal transportation, multi-period, multi-sourcing and multi-distribution, emissions, capacitated warehouses and heterogeneous fleet of capacitated vehicles with limited availability. An improved bacteria foraging algorithm was implemented by Sinha and Anand (2020) to optimize a three-stage multi-period SC network for perishable products. The objective was to minimize the total cost.

Abedi and Zhu (2017) employed a MILP model to maximize the total profit in a fish SC based on a real case study. Onggo et al. (2019) investigated an agri-food SC with stochastic demands and developed a multi-period Inventory-Routing Problem (IRP) to address the perishability of products. They applied a Mixed-Integer Programming (MIP) and a simheuristic algorithm to minimize the expected overall cost. An integrated model was developed by Biuki et al. (2020) for the Location-Routing-Inventory (LRI) Problem for perishable products distribution. They designed a sustainable SC network under demand uncertainty using possibilistic programming method and meta-heuristic algorithms. Tirkolaee, Mahdavi et al. (2020) introduced a robust green traffic-based routing problem for perishable products distribution considering fuel consumption of vehicles within a two-echelon SC network. They formulated the problem using a MILP model and validate it through a real case study problem. Recently, Jouzdani and Govindan (2021) suggested a multi-objective mathematical model to configure a perishable SC network for the dairy industry. The objectives were to concurrently minimize the total cost, total energy consumption an traffic congestion. They employed a revised multi-choice goal programming method to investigate a real case study in Iran. A fuzzy bi-objective MILP model was proposed by Goodarzian et al. (2021) to design a green medicine SC network using hybrid meta-heuristic algorithms. They included perishability cost in the first objective function to minimize the total cost. Total environmental impact was also defined as the second objective function. Abbasi et al. (2021) introduced a reliable SC network of perishable products for 3PL providers using consolidation hubs. Disruption risks of pharmaceutical distribution network were incorporated to the suggested MILP model to strike a balance between total cost and total time. They utilized Weighted Sum Method (WSM) and credibility-based possibilistic programming in order to cope with bi-objectiveness and uncertainty of the model. A systematic summary of the most relevant research works is given in Table 1 which highlights the main contributions of the present study.

Referring to the tabular summary of literature presented in Table 1, it is clear that most of the studies addressed the problem in combination and there are only 2 research works that applied bi-level models. In other words, the other studies just conducted the strategic, tactical and operational decisions in one level. Moreover, there is only 1 research work addressing sustainability and perishability at the same time — the two main factors which cannot be considered individually nowadays. Therefore, our proposed bi-level DSS has two purposes. First, it makes us plan much better in a specific time horizon. Moreover, it makes a dynamic and periodic strategic plan. Possibilistic linear programming approach and FWGP are implemented to tackle the uncertainty and multi-objectiveness of the problem, respectively. Furthermore, Lp-metric method is implemented to test the performance of FWGP in terms of three well-known quality indicators. In summary, the main novelties and contributions of the paper can be outlined as follows:

- *Decision system*: The developed integrated model features a bi-level Decision Support System (DSS) to design the Supply Chain Design (SCD) and Transportation Network Configuration (TNC) parts of the problem,
- *Sustainability*: It is investigated through the SCD and TNC models by analyzing the economic, environmental and social objective functions,
- *Perishability*: The perishability feature of products is explicitly taken into account by the deterioration rate of in-stock products at manufacturing plants and Distribution Centers (DCs),
- *Uncertainty*: The uncertainty of the key parameters in the models is treated using possibilistic linear programming approach,
- *Multi-criteria decision-making*: The required decisions are made based on the trade-offs between multiple competing criteria including cost, GHG emission, job opportunity, delay and confidence levels of the system,
- *Solution algorithm*: The FWGP approach is designed to efficiently deal with the multi-objectiveness of the mathematical model and provide the most preferable compromise solution. Furthermore, Lp-metric is applied to evaluate the performance of the proposed FWGP in terms of several quality indicators.

3. Bi-level decision support system

In this section, the proposed methodology of the research as a bi-level DSS is described. In the first and second levels, novel MILP models are proposed to design SC and transportation networks, respectively. Moreover, possibilistic linear programming, as one of the efficient approaches (Günay et al., 2021; Ismail, 2021), is applied to both

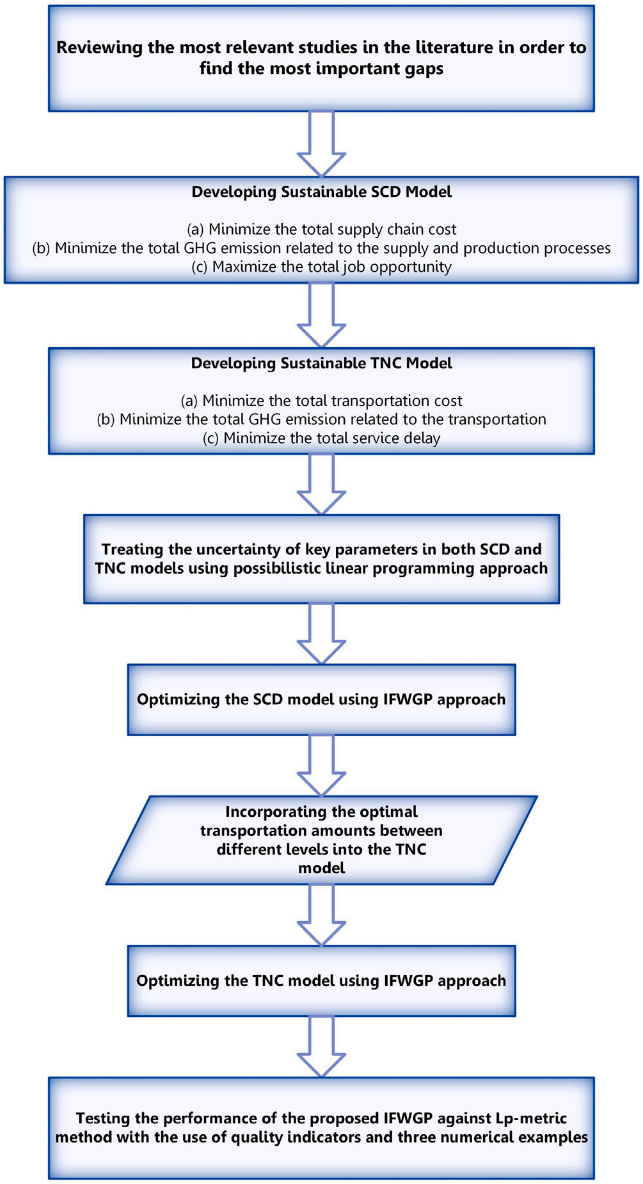


Fig. 1. Proposed methodology of the research.

models in order to cope with the uncertainty of key parameters. Next, FWGP is implemented to deal with multi-objectiveness of the models which has been employing in the literature as a well-known method to examine the uncertainty of objective functions (Javid et al., 2020; Kilic & Yalcin, 2020). Finally, the performance of the suggested methodology is evaluated using quality indicators against Lp-metric technique. Fig. 1 presents a visual representation of the methodology used in this study.

4. Mathematical models

This section describes the main characteristics and assumptions of the model and proposes alternative solution models. Consider a three-echelon SC including four levels of actors: suppliers, manufacturing plants, DCs and retailers. At the first level of decision-making, the aim is to meet the required demands of customers for multiple perishable products over a planning horizon. Due to the perishability of the products, it is assumed that a fixed rate of remaining products is deteriorated at manufacturing plants and DCs. Transportation planning is incorporated into the decision-making processes at the second level.

Table 2
Indices for the SCD model variables and parameters.

Index	Description	Index	Description
$s \in \mathcal{S}$	Suppliers	$t \in \mathcal{T}$	Production technologies
$p \in \mathcal{P}$	Manufacturing plants	$g \in \mathcal{G}$	Raw materials
$d \in \mathcal{D}$	Distribution centers	$m \in \mathcal{M}$	Products
$r \in \mathcal{R}$	Retailers	$h \in \mathcal{H}$	Time periods

The schematic view of the problem is depicted by Fig. 2 for better understanding. It shows the flow of perishable items between different levels of the SC, starting from suppliers and ending at retailers within a given set of planning periods. Raw materials are only transported from suppliers to manufacturing plants, and then, final products are transported from manufacturing plants to DCs, and eventually, retailers receive their required final products from DCs. Accordingly, two MILP models are designed that accommodate sustainable development effects by incorporating economic, environmental and social aspects into their objective functions. These two MILP models are aimed to optimize the SCD and TNC concurrently.

The main assumptions of the SCD model are as follows:

1. Four levels of actors: suppliers, manufacturing plants, DCs and retailers,
2. Location decisions are made at the levels of manufacturing plants and DCs, whereas each type of facility has a unique establishment cost and capacity,
3. Location decisions are made at the beginning of the time horizon based on input data during the planning periods,
4. Different types of manufacturing technologies are taken into account,
5. Multiple perishable items are regarded as final products to be delivered to the retailers,
6. Multiple raw materials are needed to be supplied by potential suppliers and have unique consumption rates for each product,
7. A planning horizon including multiple planning periods is taken into account,
8. Demand for each product in each period is uncertain,
9. Shortages and back-ordering are not allowed and the initial inventory at the beginning of the time horizon is zero,
10. An uncertain percent of in-stock products remained in each period at manufacturing plants and DCs deteriorates until the start of the next period,
11. GHG emissions are related to: (i) the production processes of suppliers and manufacturing plants and (ii) the deterioration of products at manufacturing plants and DCs,
12. Establishment of manufacturing plants and DCs leads to the provision of new job opportunities.

Moreover, the main assumptions of the TNC model are as follows:

1. Transportation activities should be carried out between suppliers and manufacturing plants, manufacturing plants and DCs and DCs and retailers,
2. Multi-modal transportation is taken into account for different echelons of the SC,
3. Each transportation is defined by its own variable and fixed costs, and capacity,
4. Variable and fixed costs are defined for each transportation mode,
5. Transportation time depends on the distance and transportation mode,
6. Delivery time is directly dependent on the procurement time at suppliers, production time at manufacturing plants, processing time at DCs and transportation time between different levels where these parameters are uncertain,

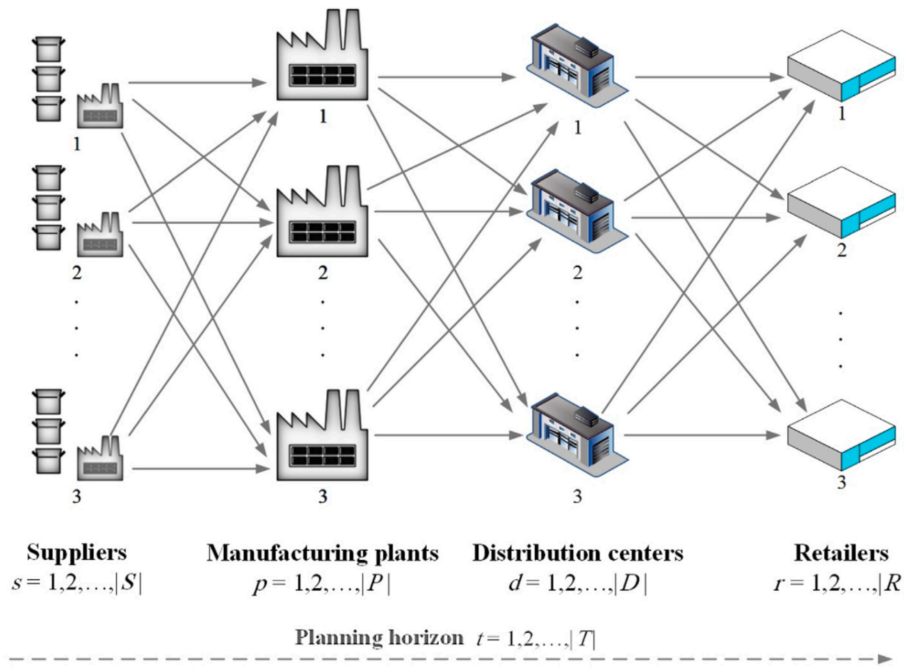


Fig. 2. Schematic view of the proposed SC.

Table 3
SCD model parameters.

Parameter	Description	Unit
$\tilde{Dem}_{rmh}$	Demand of retailer r for product m in period h	kg
A_{gm}	Raw material g required to produce one unit of product m (consumption coeff.)	kg
Hc_{mpth}	Inventory holding cost of product m at manufacturing plant p with production technology t in period h	\$/kg
Hc'_{dmh}	Inventory holding cost of product m at DC d in period h	\$/kg
$\tilde{\Psi}_{mpth}$	Deterioration percent of in-stock product m at manufacturing plant p with production technology t in period h	%
$\tilde{\psi}'_{dmh}$	Deterioration percent of in-stock product m at DC d in period h	%
Cap_{gs}	Capacity of supplier s for raw material g in each period	kg
Cap'_{mpt}	Capacity of manufacturing plant p to produce product m with production technology t in each period	kg
Cap''_{dm}	Capacity of DC d to process product m in each period	kg
CF_{pt}	Fixed establishment cost of manufacturing plant p with production technology t	\$
CF'_{d}	Fixed establishment cost of DC d	\$
CV_{gsh}	Unit variable processing cost of raw material g by supplier s in period h	\$/kg
CV'_{mpth}	Unit variable processing cost of manufacturing plant p with production technology t for product m in period h	\$/kg
CV''_{dmh}	Unit variable processing cost of DC d for product m in period h	\$/kg
CV'''_{rmh}	Unit variable processing cost of product m by retailer r in period h	\$/kg
PC_{mpth}	Unit deterioration cost imposed by the deterioration of product m at manufacturing plant p with production technology t in period h	\$/kg
PC'_{dmh}	Unit deterioration cost imposed by the deterioration of product m at DC d in period h	\$/kg
GHG_{gs}	GHG emission level related to the production processing of raw material g by supplier s	(kg CO2-eq)/ kg product weight
GHG'_{mpt}	GHG emission level related to the production processing of product m in manufacturing plant p with production technology t	(kg CO2-eq)/ kg product weight
GHG''_{mpt}	GHG emission level related to the deteriorated product m at manufacturing plant p with production technology t	(kg CO2-eq)/ kg product weight
GHG'''_{dm}	GHG emission level related to the deteriorated product m at DC d	(kg CO2-eq)/ kg product weight
J_{pt}	Number of job opportunities created by establishing manufacturing plant p with production technology t	
J'_{d}	Number of job opportunities created by establishing DC d	

Table 4
Decision variables for the SCD model.

Variable	Description	Unit
x_{pt}	Binary: 1 if manufacturing plant p with production technology t is established; 0 otherwise	
x'_d	Binary: 1 if DC d is established; 0 otherwise	
y_{gspth}	Amount of raw material g provided by supplier s for manufacturing plant p with production technology t in period h	kg
y'_{mpth}	Amount of product m produced by manufacturing plant p with production technology t in period h	kg
y''_{dmpth}	Amount of product m received by DC d from manufacturing plant p with production technology t in period h	kg
y'''_{drmh}	Amount of product m at DC d to be delivered to retailer r in period h	kg
I_{mpth}	Inventory level of product m at manufacturing plant p with production technology t in period h	kg
I'_{dmh}	Inventory level of product m at DC d in period h	kg

7. Similar to the SCD model, a planning period is taken into account,
8. Transportation systems are equipped with coolers to maintain the freshness of perishable products; therefore, no deterioration in quality would occur during the transportation processes,
9. GHG emissions are related to transportation mode, distance and amount of products to be shipped,
10. Since perishable products have a close expiration date, these products should be delivered timely with minimum delay, accordingly, the satisfaction level of the SC is taken into account to address the social aspect of sustainable development.

4.1. The SCD model

The mathematical notations of the suggested SCD model including indices, model parameters and decision variables are given in Tables 2–4. Now, the proposed MILP model is as follows:

$$\begin{aligned}
\text{minimize } \tilde{Z}_1 f \;=\; & \sum_{(p,t)} CF_{pt}\, x_{pt} + \sum_{d} CF'_d\, x'_d \\
& + \sum_{(g,p,t,s,h)} CV_{gsh}\, y_{gspth} \\
& + \sum_{(p,t,m,h)} CV'_{mpth}\, y'_{mpth} + \sum_{(d,t,p,m,h)} CV''_{dmh}\, y''_{dmpth} \\
& + \sum_{(d,r,m,h)} CV'''_{rmh}\, y'''_{drmh} + \sum_{(p,t,m,h)} Hc_{mpth}\, I_{mpth} \\
& + \sum_{(d,m,h)} Hc'_{dmh}\, I'_{mdh} \\
& + \sum_{(p,t,m,h)} PC_{mpth}\, \tilde{\Psi}_{mpth}\, I_{mpth} \\
& + \sum_{(d,r,m,h)} PC'_{dmh}\, \tilde{\Psi}'_{dmh}\, I'_{dmh}
\end{aligned} \tag{1}$$

and

$$\begin{aligned}
\text{minimize } \tilde{Z}_2 \;=\; & \sum_{(g,s,p,t,h)} GHG_{gs}\, y_{gspth} \\
& + \sum_{(g,s,p,t,h)} GHG'_{mpt}\, y'_{mpth} \\
& + \sum_{(p,t,m,h)} GHG''_{mpt}\, \tilde{\Psi}_{mpth}\, I_{mpth} \\
& + \sum_{(d,m,h)} GHG'''_{dm}\, \tilde{\Psi}'_{dmh}\, I'_{dmh}
\end{aligned} \tag{2}$$

and

$$\text{maximize } Z_3 = \sum_{(p,t)} J_{pt}\, x_{pt} + \sum_{(d)} J'_d\, x'_d \tag{3}$$

such that

$$\sum_{t} x_{pt} \le 1 \quad \forall p \in \mathcal{P}, \tag{4}$$

Table 5
Indices for the TNC model variables and parameters.

Index	Description
$\alpha \in \mathcal{A}$	Transportation modes between suppliers and manufacturing plants
$\beta \in \mathcal{B}$	Transportation modes between manufacturing plants and DCs
$\gamma \in \Gamma$	Transportation modes between DCs and retailers

$$\sum_{p\in\mathcal{P}} \sum_{t\in\mathcal{T}} y_{gspth} \le Cap_{gs} \quad \forall g \in \mathcal{G}, s \in \mathcal{S}, h \in \mathcal{H}, \tag{5}$$

$$y'_{mpth} \le Cap'_{mpth}\, x_{pt} \quad \forall m \in \mathcal{M}, p \in \mathcal{P}, t \in \mathcal{T}, h \in \mathcal{H}, \tag{6}$$

$$\sum_{p\in\mathcal{P}} \sum_{t\in\mathcal{T}} y''_{dmpth} \le Cap''_{dm}\, x'_d \quad \forall d \in \mathcal{D}, m \in \mathcal{M}, h \in \mathcal{H}, \tag{7}$$

$$\sum_{d\in D} y'''_{drmh} \ge \tilde{Dem}_{rmh} \quad \forall r \in \mathcal{R}, m \in \mathcal{M}, h \in \mathcal{H}, \tag{8}$$

$$\sum_{s\in S} \sum_{g\in\mathcal{G}} y_{gspth}\, A_{gm} = y'_{mpth} \forall p \in \mathcal{P}, t \in \mathcal{T}, m \in \mathcal{M}, h \in \mathcal{H}, \tag{9}$$

$$y'_{mpth} \ge \sum_{d\in D} y''_{dmpth} \quad \forall p \in \mathcal{P}, t \in \mathcal{T}, m \in \mathcal{M}, h \in \mathcal{H}, \tag{10}$$

$$\sum_{p\in\mathcal{P}} \sum_{t\in\mathcal{T}} y''_{dmpth} \ge \sum_{r\in\mathcal{R}} y'''_{drmh} \quad \forall d \in \mathcal{D}, m \in \mathcal{M}, h \in \mathcal{H}, \tag{11}$$

$$\begin{aligned} I_{mpth} &= \left(1 - \tilde{\Psi}_{mpth-1}\right) I_{mpth-1} + y'_{mpth} \\ &- \sum_{d\in D} y''_{dmpth} \; \forall m \in \mathcal{M}, p \in \mathcal{P}, t \in \mathcal{T}, h \in \mathcal{H}, \end{aligned} \tag{12}$$

$$\begin{aligned} I'_{dmh} &= \left(1 - \tilde{\Psi}'_{dmh-1}\right) I'_{dmh-1} + \sum_{p\in\mathcal{P}} \sum_{t\in\mathcal{T}} y''_{dmpth} \\ &- \sum_{r\in\mathcal{R}} y'''_{drmh} \quad \forall d \in \mathcal{D}, m \in \mathcal{M}, h \in \mathcal{H}, \end{aligned} \tag{13}$$

$$I_{mpt0} = 0 \quad \forall m \in \mathcal{M}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{14}$$

$$I'_{dm0} = 0 \quad \forall d \in \mathcal{D}, m \in \mathcal{M}, \tag{15}$$

$$\begin{aligned} & x_{pt}, x'_d \in \{0, 1\} \quad \forall p \in \mathcal{P}, t \in \mathcal{T}, d \in \mathcal{D}, \\ & y_{gspth}, y'_{mpth}, y''_{dmpth}, y'''_{drmh}, I_{mpth}, I'_{dmh} \ge 0 \\ & \quad \forall m \in \mathcal{M}, p \in \mathcal{P}, t \in \mathcal{T}, d \in \mathcal{D}, g \in \mathcal{G}, s \in \mathcal{S}, h \in \mathcal{H}. \end{aligned} \tag{16}$$

Objective function (1) minimizes the total cost of the SCD including 10 terms. The 1st and 2nd terms denote the fixed establishment costs of manufacturing plants and DCs, respectively. The 3rd-6th terms represent the processing costs of suppliers, manufacturing plants, DCs and retailers, respectively. The 7th and 8th terms stand for the inventory holding costs at manufacturing plants and DCs, respectively. Eventually, the 9th and 10th terms show the deterioration costs of products at manufacturing plants and DCs, respectively. Objective function (2) minimizes the total GHG emission including 4 terms. The 1st and 2nd terms represent the GHG emissions by suppliers and manufacturing plants, respectively. The 3rd-4th terms show the GHG emissions by

Table 6
TNC model parameters.

Parameter	Description	Unit
dis_{sp}	Distance between supplier s and manufacturing plant p	km
dis'_{pd}	Distance between manufacturing plant p and DC d	km
dis''_{dr}	Distance between DC d and retailer r	km
Tc_{α}	Capacity of transportation mode α	kg
Tc'_{β}	Capacity of transportation mode β	kg
Tc''_{γ}	Capacity of transportation mode γ	kg
$Fx_{\alpha h}$	Fixed cost of using transportation mode α in period h	$
$Fx'_{\beta h}$	Fixed cost of using transportation mode β in period h	$
$Fx''_{\gamma h}$	Fixed cost of using transportation mode γ in period h	$/kg
$Vx_{\alpha h}$	Variable cost of transportation mode α in period h	$/kg
$Vx'_{\beta h}$	Variable cost of transportation mode β in period h	$/kg
$Vx''_{\gamma h}$	Variable cost of transportation mode γ in period h	$/kg
GT_{α}	Amount of GHG emissions related to the transportation mode α	kg CO2-eq/kg-km
GT'_{β}	Amount of GHG emissions related to the transportation mode β	kg CO2-eq/kg-km
GT''_{γ}	Amount of GHG emissions related to the transportation mode γ	kg CO2-eq/kg-km
ET_{gpth}	Maximum expected time to receive raw material g by manufacturing plant p with production technology t in period h	h
ET'_{dmh}	Maximum expected time to receive product m by DC d in period h	h
ET''_{rmh}	Maximum expected time to receive product m by retailer r in period h	h
$\tilde{PT}_{gs}$	Procurement time of unit raw material g by supplier s	h/kg
$\tilde{PT'}_{mpt}$	Production time of unit product m by manufacturing plant p with production technology t	h/kg
$\tilde{PT''}_{md}$	Processing time of unit product m by DC d	h/kg
UT_{α}	Unit transportation time by transportation mode α	h/km
UT'_{β}	Unit transportation time by transportation mode β	h/km
UT''_{γ}	Unit transportation time by transportation mode γ	h/km

deteriorated products at manufacturing plants and DCs, respectively. Objective function (3) maximizes the total job opportunity created at manufacturing plants and DCs, respectively. Constraint (4) indicates that at most one technology level should be considered for establishing each manufacturing plant at the beginning of the time horizon. Constraint (5) restricts the raw materials procurement amount by the available capacity of suppliers. Constraint (6) and (7) represent the capacity limitations of manufacturing plants and DCs in each period, respectively. Moreover, these equations state the requirement of establishing manufacturing plants and DCs, respectively. Constraint (8) guarantees that all the demands for perishable products are met at retailers in each period. Constraint (9) shows that raw materials are turned into products based on their consumption coefficients. Constraint (10) ensures that the products receiving by DCs should not exceed the production amounts at manufacturing plants. Constraint (11) guarantees that the products receiving by retailers should not exceed the amount of products at DCs. Constraints (12) and (13) calculate the inventory levels of the products at manufacturing plants and DCs at the end of each period, respectively. These values are calculated by summing the inventory level of fresh products at the end of the last period (the start of the current period) and the amount of input products where the amount of output products is subtracted then. Constraints (14) and (15) state that the initial inventory level (at the beginning of the time horizon) is zero at manufacturing plants and DCs, respectively. Constraint (16) displays the domain of the variables.

4.2. The TNC model

Here, the mathematical notations of the proposed TNC model including indexes, parameters and variables are listed in Tables 5–7. It should be noted that the notations identical to the SCD model are not presented again.

Now, the proposed MILP model is as follows:

$$\begin{aligned} \text{minimize } W_1 = & \sum_{(s,p,t,g,\alpha,h)} \left(Fx_{\alpha h}\ \omega_{\alpha sph}\right) + \left(Vx_{\alpha h}\ dis_{sp}\ \varphi_{gspt\alpha h}\right) \\ & + \sum_{(d,p,m,t,\beta,h)} \left(Fx'_{\beta h}\ \omega'_{\beta pdh}\right) + \left(Vx'_{\beta h}\ dis'_{pd}\ \varphi'_{mptd\beta h}\right) \\ & + \sum_{(d,r,m,\gamma,h)} \left(Fx''_{\gamma h}\ \omega''_{\gamma drh}\right) + (Vx''_{\gamma h}\ dis''_{dr}\varphi''_{mdr\gamma h}) \end{aligned} \tag{17}$$

and

$$\begin{aligned} \text{minimize } W_2 = & \sum_{(s,p,t,g,\alpha,h)} GT_{\alpha}\ dis_{sp}\ \varphi_{gspt\alpha h} \\ & + \sum_{(d,p,m,t,\beta,h)} GT'_{\beta}\ dis'_{pd}\ \varphi'_{mptd\beta h} \\ & + \sum_{(d,r,m,\gamma,h)} GT''_{\gamma}\ dis''_{dr}\ \varphi''_{mdr\gamma h} \end{aligned} \tag{18}$$

and

$$\begin{aligned} \text{minimize } \tilde{W_3}f = & \sum_{(g,p,t,s,\alpha,h)} \tilde{DT}_{gspt\alpha h} \\ & + \sum_{(d,p,m,t,\beta,h)} \tilde{DT'}_{mptd\beta h} \\ & + \sum_{(d,r,m,\gamma,h)} \tilde{DT''}_{mdr\gamma h} \end{aligned} \tag{19}$$

such that

$$\sum_{g\in\mathcal{G}}\sum_{t\in\mathcal{T}} \varphi_{gspt\alpha h} \le Tc_{\alpha}\omega_{\alpha sph} \quad \forall p\in\mathcal{P}, s\in\mathcal{S}, \alpha\in\mathcal{A}, h\in\mathcal{H}, \tag{20}$$

$$\sum_{m\in\mathcal{M}}\sum_{t\in\mathcal{T}} \varphi'_{mptd\beta h} \le Tc'_{\beta}\omega'_{\beta pdh} \quad \forall p\in\mathcal{P}, d\in\mathcal{D}, \beta\in\mathcal{B}, h\in\mathcal{H}, \tag{21}$$

$$\sum_{m\in\mathcal{M}} \varphi''_{mdr\gamma h} \le Tc''_{\gamma}\omega''_{\gamma drh} \quad \forall d\in\mathcal{D}, r\in\mathcal{R}, \gamma\in\gamma, h\in\mathcal{H}, \tag{22}$$

Table 7
Decision variables for the TNC model.

Parameter	Description	Unit
$\omega_{\alpha sph}$	Binary: 1 if transportation mode α is used to transport raw materials from supplier s to manufacturing plant p in period h; 0 otherwise	
$\omega'_{\beta pdh}$	Binary: 1 if transportation mode β is used to transport products from manufacturing plant p to DC d in period h; 0 otherwise	
$\omega''_{\gamma drh}$	Binary: 1 if transportation mode γ is used to transport products from DC d to retailer r in period h; 0 otherwise	
$\varphi_{gspt\alpha h}$	Amount of raw material g transported from supplier s to manufacturing plant p with production technology t by transportation mode α in period h	kg
$\varphi'_{mptd\beta h}$	Amount of product m transported from manufacturing plant p with production technology t to DC d by transportation mode β in period h	kg
$\varphi''_{mdr\gamma h}$	Amount of product m transported from DC d to retailer r by transportation mode γ in period h	kg
$\tilde{DT}_{gspt\alpha h}$	Delivery time of raw material g from supplier s to manufacturing plant p with production technology t by transportation mode α in period h	h
$\tilde{DT}'_{mptd\beta h}$	Delivery time of product m from manufacturing plant p with production technology t DC d by transportation mode β in period h	h
$\tilde{DT}''_{mdr\gamma h}$	Delivery time of product m from DC d to retailer r by transportation mode γ in period h	h

$$\sum_{\alpha\in\mathcal{A}} \varphi_{gspt\alpha h} = y^{*}_{gspth} \quad \forall g\in\mathcal{G}, s\in\mathcal{S}, p\in\mathcal{P}, t\in\mathcal{T}, h\in\mathcal{H}, \tag{23}$$

$$\sum_{\beta\in\mathcal{B}} \varphi'_{mptd\beta h} = y''^{*}_{dmpth} \quad \forall p\in\mathcal{P}, d\in\mathcal{D}, m\in\mathcal{M}, t\in\mathcal{T}, h\in\mathcal{H}, \tag{24}$$

$$\sum_{\gamma\in\gamma} \varphi''_{mdr\gamma h} = y'''^{*}_{drmh} \quad \forall d\in\mathcal{D}, r\in\mathcal{R}, m\in\mathcal{M}, h\in\mathcal{H}, \tag{25}$$

$$\omega_{\alpha sph}, \omega'_{\beta pdh}, \omega''_{\gamma drh} \in \{0,1\} \quad \forall p\in\mathcal{P}, d\in\mathcal{D}, s\in\mathcal{S},$$
$$\alpha\in\mathcal{A}, \beta\in\mathcal{B}, \gamma\in\gamma, r\in\mathcal{R}, h\in\mathcal{H}, \tag{26}$$

$$\varphi_{gspt\alpha h},\ \varphi'_{mptd\beta h}, \varphi''_{mdr\gamma h} \geq 0 \quad \forall p\in\mathcal{P}, d\in\mathcal{D}, t\in\mathcal{T}, g\in\mathcal{G},$$
$$s\in\mathcal{S}, m\in\mathcal{M}, \alpha\in\mathcal{A}, \beta\in\mathcal{T}, \gamma\in\Gamma, r\in\mathcal{R}, h\in\mathcal{H}. \tag{27}$$

Objective function (17) minimizes the transportation cost including the fixed and variable transportation costs between suppliers and manufacturing plants, manufacturing plants and DCs and DCs and retailers, respectively. Objective function (18) minimizes the total GHG emission related to the transportation activities between suppliers and manufacturing plants, manufacturing plants and DCs and DCs and retailers, respectively. Objective function (19) minimizes the total delay in delivery throughout the SC. It is calculated by summing the total processing time and total transportation time and deducting the expected delivery time. The first, second and third terms correspond to the delays in the first, second and third echelons, respectively. The delays DT, DT' and DT'' are formulated as follows:

$$\tilde{DT}_{gspt\alpha h} = \max\{0, \left(\tilde{PT}_{gs}\ \varphi_{gspt\alpha h} + UT_{\alpha}\ dis_{sp}\ \omega_{\alpha sph}\right) - ET_{gpth}\}$$

$$\forall g\in\mathcal{G}, s\in\mathcal{S}, p\in\mathcal{P}, t\in\mathcal{T}, \alpha\in\mathcal{A}, h\in\mathcal{H}, \tag{28}$$

$$\tilde{DT}'_{mptd\beta h} = \max\{0, \left(\tilde{PT}'_{mpt}\ \varphi'_{mptd\beta h} + UT'_{\beta}\ dis'_{pd}\ \omega'_{\beta pdh}\right) - ET'_{dmh}\}$$

$$\forall m\in\mathcal{M}, p\in\mathcal{P}, t\in\mathcal{T}, d\in\mathcal{D}, \beta\in\mathcal{B}, h\in\mathcal{H}, \tag{29}$$

$$\tilde{DT}''_{mdr\gamma h} = \max\{0, \left(\tilde{PT}''_{md}\ \varphi''_{mdr\gamma h} + UT''_{\gamma}\ dis''_{dr}\ \omega''_{\gamma drh}\right) - ET''_{rmh}\}$$

$$\forall m\in\mathcal{M}, d\in\mathcal{D}, r\in\mathcal{R}, \gamma\in\Gamma, h\in\mathcal{H}. \tag{30}$$

Constraints (20), (21) and (22) express the capacity limitations of the transportation modes for the transportation processes between suppliers and manufacturing plants, manufacturing plants and DCs, and DCs and retailers, respectively. Moreover, these equations state the requirement of choosing a unique transportation mode for each transportation process in each echelon. Constraint (23) indicates that the amount of raw materials transported between suppliers and manufacturing plants is equal to the optimal amount determined by the SCD model in the first level of the DSS. Constraint (24) guarantees that the amount of products transported between manufacturing plants and DCs is equal to the optimal amount determined by the SCD model in the first level of the DSS. Constraint (25) states that the amount of products transported between DCs and retailers should be equal to the optimal amount determined by the SCD model in the first level of the DSS. Constraint (26) represents the domain of the variables.

4.3. Possibilistic linear programming

In order to treat the imprecise coefficients in the first and second objective functions of the SCD model, and also in the third objective function of the TNC model, one cannot ensure an ideal solution to the problem. The same problem occurs for the imprecise parameters in the constraints. To this end, the proposed possibilistic linear programming model by Lai and Hwang (1992) is employed to deal with this issue and provide an equivalent auxiliary crisp model.

4.3.1. Treating the uncertain objective functions

In the SCD model, since $\tilde{\psi}_{mpth}$ and $\tilde{\psi}'_{dmh}$ are uncertain, triangular possibility distributions are taken into account and, then, $\tilde{Z}_1$ and $\tilde{Z}_2$ would also have triangular possibility distributions. Geometrically, these fuzzy objective functions can be denoted by three points. Accordingly, $(Z_1^a, 0)$, $(Z_1^b, 1)$ and $(Z_1^c, 0)$ are applied for $\tilde{Z}_1$ and $(Z_2^a, 0)$, $(Z_2^b, 1)$ and $(Z_2^c, 0)$ are used for $\tilde{Z}_2$. Now, minimizing the imprecise $\tilde{Z}_1$ and $\tilde{Z}_2$ is in need of minimizing Z_1^a, Z_1^b and Z_1^c and Z_2^a, Z_2^b and Z_2^c, respectively. According to Lai and Hwang (1992), we just need to concurrently minimize Z_1^b, maximize $(Z_1^b - Z_1^a)$ and minimize $(Z_1^c - Z_1^b)$ to deal with $\tilde{Z}_1$. The same procedure is taken to deal with $\tilde{Z}_2$. Therefore, Constraints (1) and (2) are replaced with Constraints (31)–(33) and Constraints (34)–(36) below, where $\tilde{\psi}_{mpth} = (\psi^a_{mpth}, \psi^b_{mpth}, \psi^c_{mpth})$ and $\tilde{\psi}'_{mpth} = (\psi'^a_{mpth}, \psi'^b_{mpth}, \psi'^c_{mpth})$ are regarded as triangular fuzzy numbers:

$$\text{minimize } Z_1^b = \sum_{(p,t)} CF_{pt}\ x_{pt} + \sum_{d} CF'_d\ x'_d + \sum_{(g,p,t,s,h)} CV_{gsh}\ y_{gspth} + \sum_{(p,t,m,h)} CV'_{mpth}\ y'_{mpth} + \sum_{(d,t,p,m,h)} CV''_{dmh}\ y''_{dmpth} \tag{31}$$

$$+ \sum_{(d,r,m,h)} CV'''_{rmh}\ y'''_{drmh} + \sum_{(p,t,m,h)} Hc_{mpth}\ I_{mpth}$$
$$+ \sum_{(d,m,h)} Hc'_{dmh}\ I'_{mdh}$$
$$+ \sum_{(p,t,m,h)} PC_{mpth}\ \psi^{b}{}_{mpth}\ I_{mpth}$$
$$+ \sum_{(d,m,h)} PC'_{dmh}\ \psi'^{b}_{dmh}\ I'_{dmh}$$

$$\text{maximize}\ (Z_1^b - Z_1^a) = \sum_{(p,t)} CF_{pt}\ x_{pt} + \sum_{d} CF'_d\ x'_d + \sum_{(g,p,t,s,h)} CV_{gsh}\ y_{gspth} + \sum_{(p,t,m,h)} CV'_{mpth}\ y'_{mpth} + \sum_{(d,t,p,m,h)} CV''_{dmh}\ y''_{dmpth} + \sum_{(d,r,m,h)} CV'''_{rmh}\ y'''_{drmh} + \sum_{(p,t,m,h)} Hc_{mpth}\ I_{mpth} + \sum_{(d,m,h)} Hc'_{dmh}\ I'_{mdh} + \sum_{(p,t,m,h)} PC_{mpth}\ (\psi^{b}{}_{mpth} - \psi^{a}{}_{mpth})\ I_{mpth} + \sum_{(d,m,h)} PC'_{dmh}\ (\psi'^{b}{}_{dmh} - \psi'^{a}{}_{dmh})\ I'_{dmh} \tag{32}$$

$$\text{minimize}\ (Z_1^c - Z_1^b) = \sum_{(p,t)} CF_{pt}\ x_{pt} + \sum_{d} CF'_d\ x'_d + \sum_{(g,p,t,s,h)} CV_{gsh}\ y_{gspth} + \sum_{(p,t,m,h)} CV'_{mpth}\ y'_{mpth} + \sum_{(d,t,p,m,h)} CV''_{dmh}\ y''_{dmpth} + \sum_{(d,r,m,h)} CV'''_{rmh}\ y'''_{drmh} + \sum_{(p,t,m,h)} Hc_{mpth}\ I_{mpth} + \sum_{(d,m,h)} Hc'_{dmh}\ I'_{mdh} + \sum_{(p,t,m,h)} PC_{mpth}\ (\psi^{c}{}_{mpth} - \psi^{b}{}_{mpth})\ I_{mpth} + \sum_{(d,m,h)} PC'_{dmh}\ (\psi'^{c}{}_{dmh} - \psi'^{b}{}_{dmh})\ I'_{dmh} \tag{33}$$

and,

$$\text{minimize}\ Z_2^b = \sum_{(g,s,p,t,h)} GHG_{gs}\ y_{gspth} + \sum_{(g,s,p,t,h)} GHG'_{mpt}\ y'_{mpth} + \sum_{(p,t,m,h)} GHG''_{mpt}\ \psi^{b}{}_{mpth}\ I_{mpth} + \sum_{(d,r,m,h)} GHG'''_{dm}\ \psi'^{b}{}_{dmh}\ I'_{dmh} \tag{34}$$

$$\text{maximize}\ (Z_2^b - Z_2^a) = \sum_{(g,s,p,t,h)} GHG_{gs}\ y_{gspth} + \sum_{(g,s,p,t,h)} GHG'_{mpt}\ y'_{mpth} + \sum_{(p,t,m,h)} GHG''_{mpt}\ (\psi^{b}{}_{mpth} - \psi^{a}{}_{mpth})\ I_{mpth} + \sum_{(d,r,m,h)} GHG'''_{dm}\ (\psi'^{b}{}_{dmh} - \psi'^{a}{}_{dmh})\ I'_{dmh} \tag{35}$$

$$\text{minimize}\ (Z_2^c - Z_2^b) = \sum_{(g,s,p,t,h)} GHG_{gs}\ y_{gspth} + \sum_{(g,s,p,t,h)} GHG'_{mpt}\ y'_{mpth} + \sum_{(p,t,m,h)} GHG''_{mpt}\ (\psi^{c}{}_{mpth} - \psi^{b}{}_{mpth})\ I_{mpth} + \sum_{(d,r,m,h)} GHG'''_{dm}\ (\psi'^{c}{}_{dmh} - \psi'^{b}{}_{dmh})\ I'_{dmh} \tag{36}$$

Similarly, in the TNC model, since $\tilde{PT}_{gs}$, $\tilde{PT'}_{mpt}$ and $\tilde{PT''}_{md}$ are uncertain, Objective function (19) is replaced with Constraints (37)–(39).

$$\min\ W_3^b = \sum_{(g,p,t,s,\alpha,h)} \{0 \vee (PT^{b}{}_{gs}\ \varphi_{gspt\alpha h} + UT_\alpha\ dis_{sp}\omega_{\alpha sph} - ET_{gpt})\} + \sum_{(d,p,m,t,\beta,h)} \left\{0 \vee \left(PT'^{b}_{mpt}\ \varphi'_{mptd\beta h} + UT'_\beta\ dis'_{pd}\ \ \omega'_{\beta pdh} - ET'{}_{dm}\right)\right\} + \sum_{(d,r,m,\gamma,h)} \left\{0 \vee \left(PT''^{b}_{md}\ \varphi''{}_{mdr\gamma h} + UT''{}_\gamma\ dis''{}_{dr}\omega''_{\gamma drh} - ET''{}_{rm}\right)\right\} \tag{37}$$

$$\max\ (W_3^b - W_3^a) = \sum_{(g,p,t,s,\alpha,h)} \left\{0 \vee \left((PT^b_{gs} - PT^a_{gs})\ \varphi_{gspt\alpha h} + UT_\alpha\ dis_{sp}\omega_{\alpha sph} - ET_{gpt}\right)\right\} + \sum_{(d,p,m,t,\beta,h)} \left\{0 \vee \left((PT'^b_{gs} - PT'^a_{gs})\ \varphi'_{mptd\beta h} + UT'_\beta\ dis'_{pd}\ \ \omega'_{\beta pdh} - ET'_{dm}\right)\right\} + \sum_{(d,r,m,\gamma,h)} \left\{0 \vee \left((PT''^b_{gs} - PT''^a_{gs})\ \varphi''_{mdr\gamma h} + UT''{}_\gamma\ dis''_{dr}\ \omega''_{\gamma drh} - ET''{}_{rm}\right)\right\} \tag{38}$$

$$\min\ (W_3^c - W_3^b) = \sum_{(g,p,t,s,\alpha,h)} \left\{0 \vee \left((PT^c_{gs} - PT^b_{gs})\ \varphi_{gspt\alpha h} + UT_\alpha\ dis_{sp}\omega_{\alpha sph} - ET_{gpt}\right)\right\} + \sum_{(d,p,m,t,\beta,h)} \left\{0 \vee \left((PT'^c_{gs} - PT'^b_{gs})\ \varphi'_{mptd\beta h} + UT'_\beta\ dis'_{pd}\ \ \omega'_{\beta pdh} - ET'_{dm}\right)\right\} + \sum_{(d,r,m,\gamma,h)} \left\{0 \vee \left((PT''^c_{gs} - PT''^b_{gs})\ \varphi''_{mdr\gamma h} + UT''_\gamma\ dis''_{dr}\ \omega''_{\gamma drh} - ET''_{rm}\right)\right\} \tag{39}$$

where $\tilde{PT}_{gs} = (PT^a_{gs}, PT^b_{gs}, PT^c_{gs})$, $\tilde{PT'}_{mpt} = (PT'^a{}_{mpt}, PT'^b{}_{mpt}, PT'^c{}_{mpt})$ and $\tilde{PT''}_{md} = (PT''^a{}_{md}, PT''^b{}_{md}, PT''^c{}_{md})$.

4.3.2. Treating the uncertain constraints

To treat the imprecise demands and deterioration percentages in Constraints (8), (12) and (13), the weighted average method proposed by Lai and Hwang (1992) is employed to defuzzify these parameters and provide crisp values. Hence, if the minimum acceptable possibility (or minimum acceptable degree of feasibility), η, is given, then the corresponding crisp constraints can written as follows:

$$\sum_{d \in D} y'''_{drmh} \geq \zeta\ Dem^a_{rmh,\eta} + \zeta'\ Dem^b_{rmh,\eta} + \zeta''\ Dem^c_{rmh,\eta} \quad \forall r \in \mathcal{R}, m \in \mathcal{M}, h \in \mathcal{H}, \tag{40}$$

$$I_{mpth} = (\zeta\ (1 - \psi^a_{mpt,h-1,\eta}) + \zeta'\ (1 - \psi^b_{mpt,h-1,\eta}) + \zeta''\ (1 - \psi^c_{mpt,h-1,\eta}))I_{mpth-1} + y'_{mpth} - \sum_{d \in D} y''_{dmpth} \quad \forall m \in \mathcal{M}, p \in \mathcal{P}, t \in \mathcal{T}, h \in \mathcal{H}, \tag{41}$$

$$I'_{dmh} = (\zeta\ (1 - \psi'^a{}_{dm,h-1,\eta}) + \zeta'\ (1 - \psi'^b{}_{dm,h-1,\eta}) + \zeta''\ (1 - \psi'^c{}_{dm,h-1,\eta}))I'_{dmh-1}$$

$$+\sum_{r\in\mathcal{R}} y'''_{drmh} - \sum_{p\in\mathcal{P}}\sum_{t\in\mathcal{T}} y''_{dmpth} \qquad \forall d\in\mathcal{D}, m\in\mathcal{M}, h\in\mathcal{H}, \quad (42)$$

where ζ, ζ' and ζ'' stand for the weights of the most pessimistic, most possible and most optimistic value of the fuzzy parameters, respectively. Here, the decision-maker determine appropriate values for these weights and η. We set these values as $\zeta = \zeta' = 1/6$, $\zeta'' = 4/6$ and $\eta = 0.5$ according to the concept of most likely values defined by Lai and Hwang (1992).

5. Solution method: Fuzzy weighted goal programming

This section presents a hybrid solution approach based on fuzzy set theory and Weighted Goal Programming (WGP), or, FWGP in short. The aim is to obtain the most preferable compromise solution for the proposed mathematical models in the previous two sub-sections. On the other hand, this approach transforms the fuzzy model into a crisp one. The execution steps of the suggested solution approach are given for the SCD model as follows. Similarly, this procedure can be applied to the TNC model.

Step (1): Determine all uncertain variables and obtain the related distribution functions.

Step (2): Validate the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) (Nadir) for each objective function. To acquire the PISs; i.e., (Z_1^{PIS}, X_1^{PIS}), (Z_2^{PIS}, X_2^{PIS}) and (Z_3^{PIS}, X_3^{PIS}), the equivalent crisp SCD model should be solved separately for each objective function. Here, Z and X stand for the objective function and solution vector, respectively. Furthermore, the NIS for each objective function is calculated by Eqs. (43)–(45):

$$Z_1^{NIS} = Z_1\left(X_2^{PIS}\right) \ or\ Z_1\left(X_3^{PIS}\right), \quad (43)$$

$$Z_2^{NIS} = Z_1\left(X_1^{PIS}\right) \ or\ Z_1\left(X_3^{PIS}\right), \quad (44)$$

$$Z_3^{NIS} = Z_3\left(X_1^{PIS}\right) \ or\ Z_3\left(X_2^{PIS}\right). \quad (45)$$

Step (3): Validate a linear membership function for all objective functions based on Eqs. (46)–(48):

$$\mu_1(X) = \left\{\begin{array}{ll} 1, & Z_1 < Z_1^{PIS}, \\ \frac{Z_1^{NIS}-Z_1}{Z_1^{NIS}-Z_1^{PIS}}, & Z_1^{PIS} \le Z_1 \le Z_1^{NIS}, \\ 0, & Z_1 > Z_1^{NIS}. \end{array}\right\}, \quad (46)$$

$$\mu_2(X) = \left\{\begin{array}{ll} 1, & Z_2 < Z_2^{PIS}, \\ \frac{Z_2^{NIS}-Z_2}{Z_2^{NIS}-Z_2^{PIS}}, & Z_2^{PIS} \le Z_2 \le Z_2^{NIS}, \\ 0, & Z_2 > Z_2^{NIS}. \end{array}\right\}, \quad (47)$$

$$\mu_3(X) = \left\{\begin{array}{ll} 1, & Z_3 > Z_3^{PIS}, \\ \frac{Z_3-Z_3^{NIS}}{Z_3^{PIS}-Z_3^{NIS}}, & Z_3^{NIS} \le Z_3 \le Z_3^{PIS}, \\ 0, & Z_3 < Z_3^{NIS}. \end{array}\right\}. \quad (48)$$

where $\mu_k(X)$ represents the satisfaction level of objective function k. Figs. 3 and 4 depict the membership functions.

Now, the Crisp Mixed-Integer Linear Goal Programming (CMILGP) model is provided as follows:

$$\begin{aligned} &\text{maximize } \theta && (49)\\ &\text{s.t. } \mu_{z_k}\left(x_i\right) \ge \theta \quad (k=1,2,3; i=1,2,\ldots,n),\\ &\theta \in [0,1],\\ &x_i \in Q(X) \quad (i=1,2,\ldots,n). \end{aligned}$$

In Model (49), the goal is to obtain the maximum satisfaction level; i.e., Î,-value, such that the constraints are satisfied. Here, $Q(X)$ stands for the feasible region related to the constraints of the equivalent crisp model. The above model can be re-written for the SCD model using Eqs. (46)–(48):

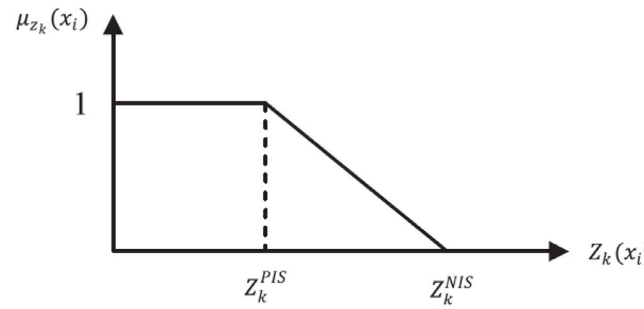


Fig. 3. Membership function corresponds to minimization-type objective functions.

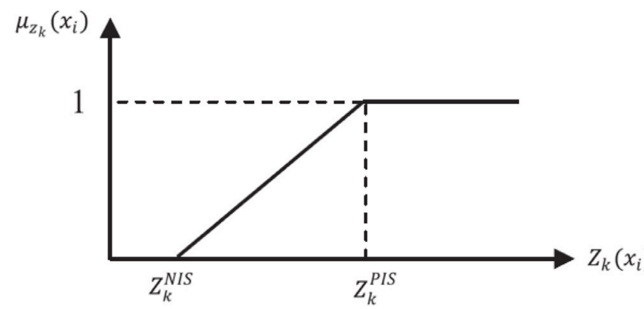


Fig. 4. Membership function corresponds to maximization-type objective functions.

$$\begin{aligned} &\text{maximize } \theta && (50)\\ &\text{s.t. } Z_k\left(x_i\right) \le Z_k^{NIS} - \theta\left(Z_k^{NIS} - Z_k^{PIS}\right) \quad (k=1,2; i=1,2,\ldots,n),\\ &Z_3\left(x_i\right) \ge Z_3^{NIS} + \theta\left(Z_3^{PIS} - Z_3^{NIS}\right) \quad (i=1,2,\ldots,n),\\ &\theta \in [0,1],\\ &x_i \in Q(X) \quad (i=1,2,\ldots,n). \end{aligned}$$

Step (4): Create the equivalent CMILGP formulation of the Fuzzy Mixed-Integer Linear Goal Programming (FMILGP) considering the importance of each objective function as follows:

$$\begin{aligned} &\text{maximize } \sum_{k=1}^{3} \vartheta_k\theta_k && (51)\\ &\text{s.t. } Z_k\left(x_i\right) \le Z_k^{NIS} - \theta_k\left(Z_k^{NIS} - Z_k^{PIS}\right)\\ &\qquad (k=1,2; i=1,2,\ldots,n),\\ &Z_3\left(x_i\right) \ge Z_3^{NIS} + \theta_3\left(Z_3^{PIS} - Z_3^{NIS}\right)\\ &\qquad (i=1,2,\ldots,n),\\ &\theta_k \in [0,1] \quad (k=1,2,3),\\ &x_i \in Q(X) \quad (i=1,2,\ldots,n). \end{aligned}$$

where ϑ_k shows the importance weight parameter of objective function k that takes value based on the decision-maker's attitude, such that $\sum_{k=1}^{3}\vartheta_k = 1$. Accordingly, we can introduce a Crisp Mixed-Integer Linear WGP (CMILWGP) model for both the SCD and TNC phases. The corresponding CMILWGP model for the SCD phase is given below:

$$\begin{aligned} &\text{maximize } \ Conf = \sum_{k=1}^{3} \vartheta_k\theta_k && (52)\\ &\text{s.t. } Z_1 \le Z_1^{NIS} - \theta_1\left(Z_1^{NIS} - Z_1^{PIS}\right),\\ &Z_2 \le Z_2^{NIS} - \theta_2\left(Z_2^{NIS} - Z_2^{PIS}\right),\\ &Z_3 \ge Z_3^{NIS} + \theta_3\left(Z_3^{PIS} - Z_3^{NIS}\right), \end{aligned}$$

$$\text{Constraints (4)–(16)},$$
$$\theta_k \in [0, 1] \quad (k = 1,2,3).$$

Here, *Conf* denote the total confidence level of the SCD model. Similarly, the final CMILWGP model of the TNC phase is obtained as follows:

$$\begin{aligned}
\text{maximize} \quad & Conf' = \sum_{k=1}^{3} \vartheta'_k \theta'_k \\
\text{s.t.} \quad & W_1 \le W_1^{NIS} - \theta'_1 \left(W_1^{NIS} - W_1^{PIS}\right), \\
& W_2 \le W_2^{NIS} - \theta'_2 \left(W_2^{NIS} - W_2^{PIS}\right), \\
& W_3 \le W_3^{NIS} - \theta'_3 \left(W_3^{NIS} - W_3^{PIS}\right), \\
& \text{Constraints (20)–(27)}, \\
& \theta'_k \in [0, 1] \quad (k = 1,2,3).
\end{aligned} \tag{53}$$

where ϑ'_k and θ'_k represent the importance weight parameter and satisfaction level of objective function k in the TNC model, respectively. Here, again, ϑ'_k takes value based on the decision-maker's attitude and satisfies $\sum_{k=1}^{3} \vartheta'_k = 1$. Moreover, $Conf'$ denotes the total confidence level of the TNC model.

Now, in order to incorporate the parameters uncertainty into the above models, the modifications presented in Section 4.3 are applied. To this end, the final models are as follows:

$$\begin{aligned}
\text{maximize} \quad & Conf = \sum_{k=1}^{3} \vartheta_k \theta_k \\
\text{s.t.} \quad & Z_1^b \le Z_1^{b,NIS} - \frac{\theta_1}{3} \left(Z_1^{b,NIS} - Z_1^{b,PIS}\right), \\
& (Z_1^b - Z_1^a) \ge (Z_1^{b,NIS} - Z_1^{a,NIS}) \\
& + \frac{\theta_1}{3} \left((Z_1^{b,PIS} - Z_1^{a,PIS}) - (Z_1^{b,NIS} - Z_1^{a,NIS})\right), \\
& (Z_1^c - Z_1^b) \le (Z_1^{c,NIS} - Z_1^{b,NIS}) \\
& - \frac{\theta_1}{3} \left((Z_1^{c,NIS} - Z_1^{b,NIS}) - (Z_1^{c,PIS} - Z_1^{b,PIS})\right), \\
& Z_2^b \le Z_2^{b,NIS} - \frac{\theta_2}{3} \left(Z_2^{b,NIS} - Z_2^{b,PIS}\right), \\
& (Z_2^b - Z_2^a) \ge (Z_2^{b,NIS} - Z_2^{a,NIS}) \\
& + \frac{\theta_2}{3} \left((Z_2^{b,PIS} - Z_2^{a,PIS}) - (Z_2^{b,NIS} - Z_2^{a,NIS})\right), \\
& (Z_2^c - Z_2^b) \le (Z_2^{c,NIS} - Z_2^{b,NIS}) \\
& - \frac{\theta_2}{3} \left((Z_2^{c,NIS} - Z_2^{b,NIS}) - (Z_2^{c,PIS} - Z_2^{b,PIS})\right), \\
& Z_3 \ge Z_3^{NIS} + \theta_3 \left(Z_3^{PIS} - Z_3^{NIS}\right), \\
& \text{Constraints (4)–(7), (9)–(11),(14)–(16), (40)–(42)}, \\
& \theta_k \in [0, 1] \quad (k = 1,2,3).
\end{aligned} \tag{54}$$

$$\begin{aligned}
\text{maximize} \quad & Conf' = \sum_{k=1}^{3} \vartheta'_k \theta'_k \\
\text{s.t.} \quad & W_1 \le W_1^{NIS} - \theta'_1 \left(W_1^{NIS} - W_1^{PIS}\right), \\
& W_2 \le W_2^{NIS} - \theta'_2 \left(W_2^{NIS} - W_2^{PIS}\right), \\
& W_3^b \le W_3^{b,NIS} - \frac{\theta'_3}{3} \left(W_3^{b,NIS} - W_3^{b,PIS}\right), \\
& (W_3^b - W_3^a) \ge (W_3^{b,NIS} - W_3^{a,NIS}) \\
& + \frac{\theta'_3}{3} \left((W_3^{b,PIS} - W_3^{a,PIS}) - (W_3^{b,NIS} - W_3^{a,NIS})\right), \\
& (W_3^c - W_3^b) \le (W_3^{c,NIS} - W_3^{b,NIS}) \\
& - \frac{\theta'_3}{3} \left((W_3^{c,NIS} - W_3^{b,NIS}) - (W_3^{c,PIS} - W_3^{b,PIS})\right), \\
& \text{Constraints (20)–(27)}, \\
& \theta'_k \in [0, 1] \quad (k = 1,2,3).
\end{aligned} \tag{55}$$

5.1. Lp-metric

In this subsection, the LP-metric technique is applied to our DSS model as one of the widely-used approach in the literature (Branke et al., 2008). The main aim is to evaluate the performance of the proposed FWGP. First, we just need to individually solve the model with each objective function and acquire the ideal values of $(Z_1^{b^*}, (Z_1^b - Z_1^a)^*, (Z_1^c - Z_1^b)^*)$, $(Z_2^{b*}, (Z_2^b - Z_2^a)^*, (Z_2^c - Z_2^b)^*)$ and Z_3^* in the SCD model. For the TNC model, the ideal values of W_1^*, W_2^* and $(W_3^{b*}, (W_3^b - W_3^a)^*, (W_3^c - W_3^b)^*)$ are obtained likewise. Finally, the single-objective models of both SCD and TNC are given as follows:

$$\begin{aligned}
\min \quad Z_{Lp} = {} & \tau_1 \left(\frac{Z_1^b - Z_1^{b*}}{Z_1^{b*}} + \frac{(Z_1^b - Z_1^a)^* - (Z_1^b - Z_1^a)}{(Z_1^b - Z_1^a)^*} \right. \\
& \left. + \frac{(Z_1^c - Z_1^b) - (Z_1^c - Z_1^b)^*}{(Z_1^c - Z_1^b)^*} \right) + \tau_2 \left(\frac{Z_2^b - Z_2^{b*}}{Z_2^{b*}} \right. \\
& \left. + \frac{(Z_2^b - Z_2^a)^* - (Z_2^b - Z_2^a)}{(Z_2^b - Z_2^a)^*} + \frac{(Z_2^c - Z_2^b) - (Z_2^c - Z_2^b)^*}{(Z_2^c - Z_2^b)^*} \right) \\
& + \tau_3 \left(\frac{Z_3^b - Z_3^{b*}}{Z_3^{b*}} \right) \\
& \text{subject to} \\
& \text{Constraints (4)–(7), (9)–(11),(14)–(16), (40)–(42)}.
\end{aligned} \tag{56}$$

$$\begin{aligned}
\min \quad W_{Lp} = {} & \tau'_1 \left(\frac{W_1^b - W_1^{b*}}{W_1^{b*}} \right) + \tau'_2 \left(\frac{W_2^b - W_2^{b*}}{W_2^{b*}} \right) \\
& + \tau'_3 \left(\frac{W_3^b - W_3^{b*}}{W_3^{b*}} + \frac{(W_3^b - W_3^a)^* - (W_3^b - W_3^a)}{(W_3^b - W_3^a)^*} \right. \\
& \left. + \frac{(W_3^c - W_3^b) - (W_3^c - W_3^b)^*}{(W_3^c - W_3^b)^*} \right) \\
& \text{subject to} \\
& \text{Constraints (20)–(27)}.
\end{aligned} \tag{57}$$

It should be noted that $\tau_1 + \tau_2 + \tau_3 = 1$ and $\tau'_1 + \tau'_2 + \tau'_3 = 1$. In this study, (τ_1, τ_2, τ_3) and $(\vartheta_1, \vartheta_2, \vartheta_3)$ take the same values. This also makes sense for $(\tau'_1, \tau'_2, \tau'_3)$ and $(\vartheta'_1, \vartheta'_2, \vartheta'_3)$.

5.2. Quality indicators

Quality indicators are utilized in order to test the performance of a solution method or the quality of solutions in multi-objective optimization. Moreover, to provide a comprehensive performance measure, several metrics should be taken into account (Zitzler et al., 2003). Here, we employ three metrics including Diversification Metric (DM), Mean Ideal Distance (MID) and Rate of Achievement Simultaneously to Two Objectives (RAS). The formulations of these metrics are given by Eqs. (58)–(60), respectively, which can be easily extended based on the objective functions of both models.

$$DM = \left[\left(\frac{\max_i f_{1,i} - \min_i f_{1,i}}{F_1^{\max} - F_1^{\min}} \right)^2 + \left(\frac{\max_i f_{2,i} - \min_i f_{2,i}}{F_2^{\max} - F_2^{\min}} \right)^2 + \left(\frac{\max_i f_{3,i} - \min_i f_{3,i}}{F_3^{\max} - F_3^{\min}} \right)^2 \right]^{0.5}, \tag{58}$$

$$MID = \frac{\sqrt{\sum_{i=1}^{n} \left(\frac{f_{1,i} - f_1^{\text{best}}}{F_1^{\max} - F_1^{\min}} \right)^2 + \left(\frac{f_{2,i} - f_2^{\text{best}}}{F_2^{\max} - F_2^{\min}} \right)^2 + \left(\frac{f_{3,i} - f_3^{\text{best}}}{F_3^{\max} - F_3^{\min}} \right)^2}}{n}, \tag{59}$$

where n is the number of solutions (Pareto points), $f_{1,i}$, $f_{2,i}$ and $f_{3,i}$ represents the values of the 1st, 2nd and 3rd objective function for the ith solution, respectively. Moreover, $(F_1^{\max}, F_2^{\max}, F_3^{\max})$ and $(F_1^{\min}, F_2^{\min}, F_3^{\min})$ show the maximum and minimum values of

Table 8
Results for the PIS and NIS values of the different objective functions.

Criteria	Values	Criteria	Values
$Z_1^{a,PIS}$	557 395.33	W_1^{PIS}	1 532 932.66
$Z_1^{b,PIS}$	648 517.21	W_1^{NIS}	2 002 270.65
$Z_1^{c,PIS}$	746 423.85	W_2^{PIS}	0.41
$Z_1^{a,NIS}$	4 302 819.54	W_2^{NIS}	0.46
$Z_1^{b,NIS}$	4 903 234.98	$W_3^{a,PIS}$	95.61
$Z_1^{c,NIS}$	5 555 757.49	$W_3^{b,PIS}$	122.17
$Z_2^{a,PIS}$	58.03	$W_3^{c,PIS}$	145.75
$Z_2^{b,PIS}$	69.59	$W_3^{a,NIS}$	157.50
$Z_2^{c,PIS}$	81.35	$W_3^{b,NIS}$	204.75
$Z_2^{a,NIS}$	219.38	$W_3^{c,NIS}$	244.90
$Z_2^{b,NIS}$	269.71	$Z_2^{c,NIS}$	338.52
Z_3^{PIS}	338	Z_3^{NIS}	83

the 1st, 2nd and 3rd objective functions, again, respectively. Finally, $(f_1^{\text{best}}, f_2^{\text{best}}, f_3^{\text{best}})$ stand for the ideal points for the 1st, 2nd and 3rd objective functions, respectively.

$$RAS = \frac{\sum_{i=1}^{n} \frac{f_{1,i}-F_i}{F_i} + \frac{f_{2,i}-F_i}{F_i} + \frac{f_{3,i}-F_i}{F_i}}{n}, \tag{60}$$

where $F_i = \min\{f_{1,i}, f_{2,i}, f_{3,i}\}$.

Lower MID and RAS as well as higher DM are more desirable.

6. Computational results

This section presents three numerical examples in small, medium and large sizes to validate the proposed methodology and investigate the complexity of the proposed model. To do so, CPLEX solver/GAMS software is employed to run the model as one of the most commonly used tools in optimization problems (Farrokh et al., 2018; Mohammed & Duffuaa, 2020; Tirkolaee et al., 2021; Tirkolaee, Goli et al., 2020).

6.1. Model validation

At the first stage, the small example is just solved step by step in order to represent the applicability of the methodology where the scale of the example is designed as $|\mathcal{S}| = 3$, $|\mathcal{P}| = 5$, $|\mathcal{D}| = 10$, $|\mathcal{R}| = 20$, $|\mathcal{T}| = 3$, $|\mathcal{G}| = 2$, $|\mathcal{M}| = 3$, and $|\mathcal{H}| = 3$ for the SCD model and $|\mathcal{A}| = |\mathcal{B}| = |\Gamma| = 3$ for the TNC model. Moreover, the values of the parameters in both models are given in Tables 11 and 12. For this example, $(\tau_1, \tau_2, \tau_3) = (\vartheta_1, \vartheta_2, \vartheta_3) = (\tau_1', \tau_2', \tau_3') = (\vartheta_1', \vartheta_2', \vartheta_3') = (0.5, 0.3, 0.2)$. The required parameters are generated randomly using uniform distributions. It should be noted that most of the assigned values to the parameters are adapted from the literature such as Sazvar et al. (2014) and Hill et al. (2018). The proposed methodology is implemented on a laptop computer with core Intel i7 2.60 GHz CPU and 12 GB RAM. Table 8 displays the output results of the single-objective optimization to determine the values of PIS and NIS for each objective function.

In the next step, the final CMILWGP model is implemented by using the values shown in Table 8. The obtained results are reported in Table 9. It should be noted that the most likely values of $\tilde{Z}_1$, $\tilde{Z}_2$ and $\tilde{W}_3$ are reported.

Now, to analyze the effect of the decision-making process, 10 different combinations are taken into account for the weights assigned to the sustainability aspects of the proposed DSS. In other words, 10 different combinations of importance weights of the objective functions are tested and the behavior of the objective functions is analyzed. Table 10 and Figs. 5 and 6 present these combinations as well as the obtained results for the required criteria.

As can be seen in Table 10 and Figs. 5 and 6, different combinations of importance weights yield various values for the objective functions in both models. The aim is to analyze each combination and to choose the best based on the decision-maker attitude. However, there may be some systematic limitations based on the real-world situation; e.g., the budget limitation or available resources, which can make the decision-maker to define the best policy only among a few possible solutions. Therefore, by analyzing these trade-offs, one can set the best possible values for the importance weights to approach the sustainable development of the SC.

Table 9
Final results for the 1st numerical example.

Criteria	Values	Criteria	Values
Z_1^{b*}	726 196.59	W_3^{b*}	122.68
Z_2^{b*}	75.84	$Conf$	0.98
Z_3^{*}	136	$Conf'$	0.79
W_1^{*}	1 645 158.66	Run time (s)	24.56
W_2^{*}	0.45	–	–

6.2. Model complexity

In this section, the performance of the proposed CMILWGP model is investigated for problems of different scales. It should be noted that the model contains

$$\begin{aligned} &|\mathcal{P}|\,|\mathcal{T}|\,|\mathcal{H}|(|\mathcal{G}|\,|\mathcal{S}| + 2|\mathcal{M}| + 2|\mathcal{D}|\,|\mathcal{M}| \\ &\quad + |\mathcal{G}|\,|\mathcal{S}|(2|\mathcal{A}| + 1) + 2|\mathcal{M}|\,|\mathcal{D}|\,|\mathcal{B}|) \\ &+ |\mathcal{P}|\,|\mathcal{T}|(|\mathcal{M}| + 1) + |\mathcal{D}|(1 + |\mathcal{R}|\,|\mathcal{M}|\,|\mathcal{H}| + |\mathcal{M}|\,|\mathcal{H}|) \\ &\quad + |\mathcal{D}|\,|\mathcal{R}|\,|\mathcal{H}|(|\Gamma| + 2|\mathcal{M}|\,|\Gamma|) \\ &\quad + |\mathcal{P}|\,|\mathcal{H}|(|\mathcal{A}|\,|\mathcal{S}| + |\mathcal{B}|\,|\mathcal{D}|) \end{aligned}$$

variables, of which

$$|\mathcal{P}||\mathcal{T}||\mathcal{H}|(|\mathcal{G}||\mathcal{S}| + 2|\mathcal{M}| + |\mathcal{D}||\mathcal{M}|) + |\mathcal{P}||\mathcal{T}| + |\mathcal{D}|(1 + |\mathcal{R}||\mathcal{M}||\mathcal{H}| + |\mathcal{M}||\mathcal{H}|)$$

are related to the SCD model, and

$$\begin{aligned} &|\mathcal{P}||\mathcal{T}||\mathcal{H}|(2|\mathcal{G}||\mathcal{S}||\mathcal{A}| + 2|\mathcal{M}||\mathcal{D}||\mathcal{B}|) + |\mathcal{G}||\mathcal{S}| + |\mathcal{M}||\mathcal{P}||\mathcal{T}| + |\mathcal{M}||\mathcal{D}| \\ &\quad + |\mathcal{D}||\mathcal{R}||\mathcal{H}|(|\Gamma| + 2|\mathcal{M}||\Gamma|) + |\mathcal{P}||\mathcal{H}|(|\mathcal{A}||\mathcal{S}| + |\mathcal{B}||\mathcal{D}|) \end{aligned}$$

related to the TNC model. Moreover, a total of

$$\begin{aligned} &|\mathcal{M}|\,|\mathcal{P}|\,|\mathcal{T}|\,|\mathcal{H}|(6 + |\mathcal{D}| + |\mathcal{D}|\,|\mathcal{B}|) + |\mathcal{D}|\,|\mathcal{M}|\,|\mathcal{H}|(4 + |\mathcal{P}|\,|\mathcal{T}| \\ &\quad + 2|\mathcal{R}| + |\mathcal{P}|\,|\mathcal{T}|\,|\mathcal{B}| + 2|\mathcal{R}|\,|\Gamma|) \\ &\quad + |\mathcal{G}|\,|\mathcal{S}|\,|\mathcal{H}|(1 + 2|\mathcal{P}|\,|\mathcal{T}| + 2|\mathcal{P}|\,|\mathcal{T}|\,|\mathcal{A}|) \\ &\quad + |\mathcal{R}|\,|\mathcal{H}|(|\mathcal{M}| + 2|\mathcal{D}|\,|\Gamma|) \\ &+ |\mathcal{P}|(1 + |\mathcal{M}|\,|\mathcal{T}| + |\mathcal{T}| + 2|\mathcal{S}|\,|\mathcal{A}|\,|\mathcal{H}| + 2|\mathcal{B}|\,|\mathcal{D}|\,|\mathcal{H}|) + |\mathcal{D}| \end{aligned}$$

constraints are defined for the CMILWGP model, of which

$$\begin{aligned} &|\mathcal{M}|\,|\mathcal{P}|\,|\mathcal{T}|\,|\mathcal{H}|(6 + |\mathcal{D}|) + |\mathcal{D}|\,|\mathcal{M}|\,|\mathcal{H}|(4 + |\mathcal{D}|) + |\mathcal{P}|(1 + |\mathcal{T}| + |\mathcal{M}|\,|\mathcal{T}|) \\ &\quad + |\mathcal{G}|\,|\mathcal{S}|(|\mathcal{H}| + |\mathcal{P}|\,|\mathcal{T}|\,|\mathcal{H}|) + |\mathcal{D}| \end{aligned}$$

are related to the SCD model, and

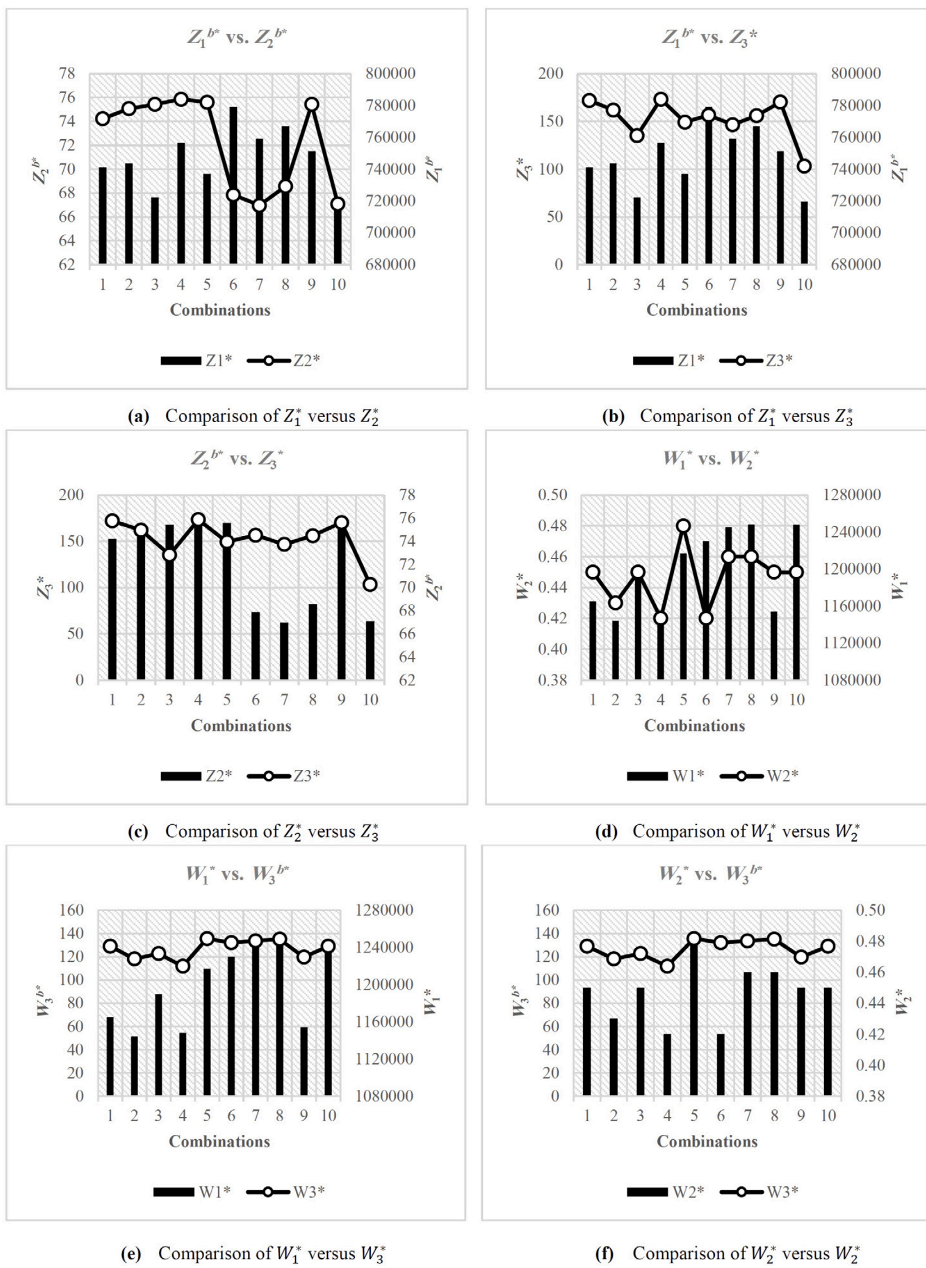
$$\begin{aligned} &|\mathcal{P}|\,|\mathcal{S}|\,|\mathcal{H}|(|\mathcal{A}| + |\mathcal{G}|\,|\mathcal{T}| + |\mathcal{A}| + 2|\mathcal{G}|\,|\mathcal{T}|\,|\mathcal{A}|) \\ &\quad + |\mathcal{D}|\,|\mathcal{R}|\,|\mathcal{H}|(2|\Gamma| + |\mathcal{M}| + 2|\mathcal{M}|\,|\Gamma|) \\ &+ |\mathcal{D}|\,|\mathcal{H}|(2|\mathcal{P}|\,|\mathcal{B}| + |\mathcal{P}|\,|\mathcal{M}|\,|\mathcal{T}| + 2|\mathcal{M}|\,|\mathcal{P}|\,|\mathcal{T}|\,|\mathcal{B}|) \end{aligned}$$

to the TNC model.

In the following, we generate two additional numerical examples whose sizes are larger than the 1st one and report the solutions to three problems together in terms of their runtime and objective function values. The parameters used to solve these problems are already given in Tables 11 and 12. Tables 13 and 14 represent the information of different problems and their obtained results, respectively. As can be seen, the number of variables and constraints grow exponentially as well as the reported run time by CPLEX solver. Moreover, CPLEX solver was not able to solve Problem 3 within 3600 s. This runtime limitation is just set to evaluate the performance and viability of CPLEX solver.

Table 10
Results for 10 different FWGP weights in the 1st numerical example.

	$(\vartheta_1, \vartheta_2, \vartheta_3)$	$(\vartheta'_1, \vartheta'_2, \vartheta'_3)$	**(Criteria)**							
			Z_1^{b*}	Z_2^{b*}	Z_3^*	W_1^*	W_2^*	W_3^{b*}	$Conf$	$Conf'$
1	(0.4, 0.3, 0.3)	(0.4, 0.3, 0.3)	741 169.76	74.22	172	1 165 055.39	0.45	129.06	0.98	0.81
2	(0.4, 0.2, 0.2)	(0.4, 0.2, 0.2)	743 742.64	75.07	162	1 144 007.18	0.43	118.12	0.98	0.59
3	(0.5, 0.3, 0.2)	(0.5, 0.3, 0.2)	722 248.99	75.43	135	1 189 816.20	0.45	122.68	0.98	0.77
4	(0.5, 0.2, 0.3)	(0.5, 0.2, 0.3)	756 569.33	75.86	173	1 147 901.45	0.42	111.78	0.98	0.51
5	(0.5, 0.4, 0.1)	(0.5, 0.4, 0.1)	737 086.56	75.60	149	1 216 734.58	0.48	135.64	0.98	0.90
6	(0.5, 0.1, 0.4)	(0.5, 0.1, 0.4)	779 206.57	67.86	157	1 230 075.74	0.42	132.06	0.98	0.90
7	(0.6, 0.2, 0.2)	(0.6, 0.2, 0.2)	759 164.53	66.97	147	1 244 872.87	0.46	133.64	0.98	0.95
8	(0.6, 0.1, 0.3)	(0.6, 0.1, 0.3)	766 968.29	68.57	156	1 248 124.83	0.46	135.09	0.98	0.97
9	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	751 248.91	75.43	170	1 154 120.19	0.45	119.64	0.98	0.71
10	(0.7, 0.1, 0.2)	(0.7, 0.1, 0.2)	719 714.21	67.09	103	1 248 001.61	0.45	128.97	0.97	0.88



(a) Comparison of Z_1^* versus Z_2^*

(b) Comparison of Z_1^* versus Z_3^*

(c) Comparison of Z_2^* versus Z_3^*

(d) Comparison of W_1^* versus W_2^*

(e) Comparison of W_1^* versus W_3^*

(f) Comparison of W_2^* versus W_2^*

Fig. 5. Comparison of the objective functions for 10 different FWGP weights in the 1st numerical example.

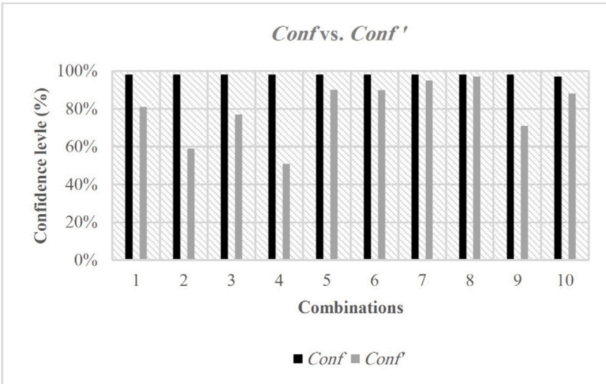


Fig. 6. Comparison of $Conf$ versus $Conf'$ in the 1st numerical example.

Table 11
Parameter values of the SCD model (U:Uniform).

Parameters	Values	Parameters	Values
Dem^{a}_{rmh}	U(100,130)	Dem^{b}_{rmh}	U(130,160)
Dem^{c}_{rmh}	U(160,200)	A_{gm}	U(2,4)
Hc_{mpth}	U(1,2)	Hc'_{dmh}	U(2,3)
Ψ^{a}_{mpth}	U(0.05,0.07)	Ψ'^{a}_{dmh}	U(0.1,0.12)
Ψ^{b}_{mpth}	U(0.07,0.09)	Ψ'^{b}_{dmh}	U(0.12,0.15)
Ψ^{c}_{mpth}	U(0.09,0.1)	Ψ'^{c}_{dmh}	U(0.15,0.2)
Cap_{gs}	U(10000,20000)	Cap'_{mpt}	U(8000,10000)
Cap''_{dm}	U(1000,2000)	CF_{pt}	U(5000,6000)
CF'_{d}	U(5000,6000)	CV_{gsh}	U(1,2)
CV'_{mpth}	U(1,2)	CV''_{dmh}	U(0.5,1)
CV'''_{rmh}	U(0.5,1)	PC_{mpth}	U(5,8)
PC'_{dmh}	U(10,12)	GHG_{gs}	U(1,2)10^{-4}
GHG'_{mpt}	U(3,4)10^{-4}	GHG''_{mpt}	U(1.5,1.8)10^{-4}
GHG'''_{dm}	U(2, 2.5)10^{-4}	J_{pt}	Round(U(50, 100))
J_{pt}	Round(U(5, 10))	–	–

Table 12
Parameter values of the TNC model (U:Uniform).

Parameters	Values	Parameters	Values
dis_{sp}	U(10,60)	dis'_{pd}	U(5,30)
dis''_{dr}	U(10,100)	Tc_{α}	U(300000,400000)
Tc'_{β}	U(200000,300000)	Tc''_{γ}	U(100000,200000)
$Fx_{\alpha h}$	U(5,10)	$Fx'_{\beta h}$	U(4,6)
$Fx''_{\gamma h}$	U(3,5)	$Vx_{\alpha h}$	U(0.005,0.008)
$Vx'_{\beta h}$	U(0.004,0.006)	$Vx''_{\gamma h}$	U(0.003,0.005)
GT_{α}	U(5(10^{-8}), 6(10^{-8}))	GT'_{β}	U(4(10^{-8}), 5(10^{-8}))
GT''_{γ}	U(3(10^{-8}), 4(10^{-8}))	ET_{gpth}	U(35,45)
ET'_{dmh}	U(45,63)	ET''_{rmh}	U(63,82)
PT^{a}_{gs}	U(0.01,0.014)	PT^{b}_{gs}	U(0.014,0.018)
PT^{c}_{gs}	U(0.018,0.020)	PT'^{a}_{mpt}	U(0.020,0.024)
PT'^{b}_{mpt}	U(0.024,0.028)	PT'^{c}_{mpt}	U(0.028,0.030)
PT''^{a}_{md}	U(0.005,0.006)	PT''^{b}_{md}	U(0.006,0.007)
PT''^{c}_{md}	U((0.007,0.008)	UT_{α}	U(0.5,1)
UT'_{β}	U(0.3,0.8)	UT''_{γ}	U(0.2,0.6)

Fig. 7 depicts the growing rate of runtime values for Problems 1–3. It took 24.56 and 1093.08 s to run the 1st and 2nd numerical examples, respectively. Accordingly, CPLEX solver cannot be regarded as an efficient solution tool to tackle large-sized problems. With regard to Fig. 8, it is obvious that the number of variables and constraints follow an exponential increase where the slope is much steeper in the number of variables.

Table 13
Information on different numerical examples.

Problem	(Criteria)										
	$\|\mathcal{S}\|$	$\|\mathcal{P}\|$	$\|\mathcal{D}\|$	$\|\mathcal{R}\|$	$\|\mathcal{T}\|$	$\|\mathcal{G}\|$	$\|\mathcal{M}\|$	$\|\mathcal{H}\|$	$\|\mathcal{A}\|$	$\|\mathcal{B}\|$	$\|\Gamma\|$
1	3	5	10	20	3	2	3	12	3	3	3
2	6	10	15	40	5	5	5	12	5	5	5
3	9	15	25	60	7	8	8	24	7	7	7

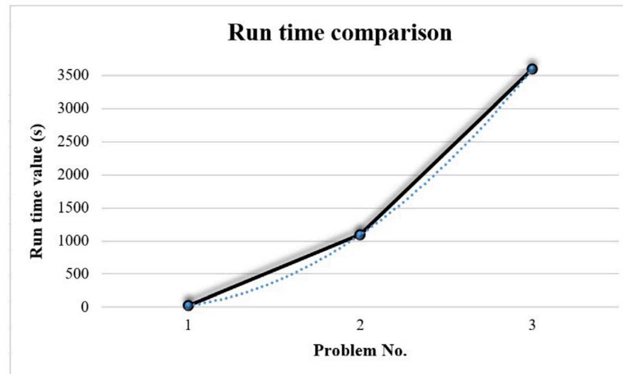


Fig. 7. Runtime comparison of different numerical examples.

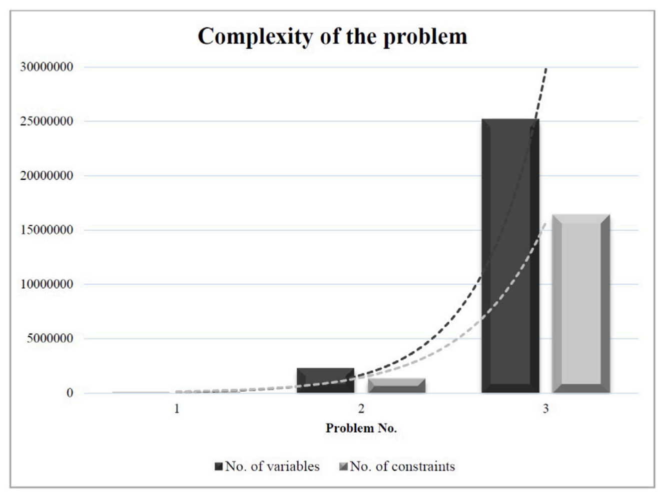


Fig. 8. Complexity comparison in terms of the number of variables and constraints.

6.3. Evaluation of the proposed solution method

In this section, the performance of our solution method is compared to the Lp-metric approach discussed in Section 5.1. To this end, the 1st and 2nd numerical examples are employed to test both solution methods in terms of the quality indicators described in Section 5.2. To generate 10 different solutions in each numerical example, different combinations of weights (cf. Table 10) are taken into account for both methods. The output results are given by Table 15 and Fig. 9.

As can be inferred from the results, FWGP has an obvious superiority in terms of all indicators. The proposed FWGP could achieve lower MID and RAS values as well as higher DM value against Lp-metric.

7. Discussion

As one of the main differences of our research with other relevant ones in the literature, we developed a novel optimization methodology to favorably design a SC configuration and planning its transportation network for supplying and delivering perishable products SC

Table 14
Results obtained from 3 different numerical examples.

Prob.	(Criteria)									
	Variables	Constraints	Z_1^{b*}	Z_2^{b*}	Z_3^{*}	W_1^{*}	W_2^{*}	W_3^{b*}	$Conf$	$Conf'$
1	76 734	134 067	722 248.99	75.43	135	1 189 816.20	0.45	122.68	0.98	0.77
2	2 295 965	1 309 885	4 404 129.86	237.59	1291.20	2 986 283.99	1.31	748.73	0.63	0.92
3	25 193 032	16 404 793	–	–	–	–	–	–	–	–

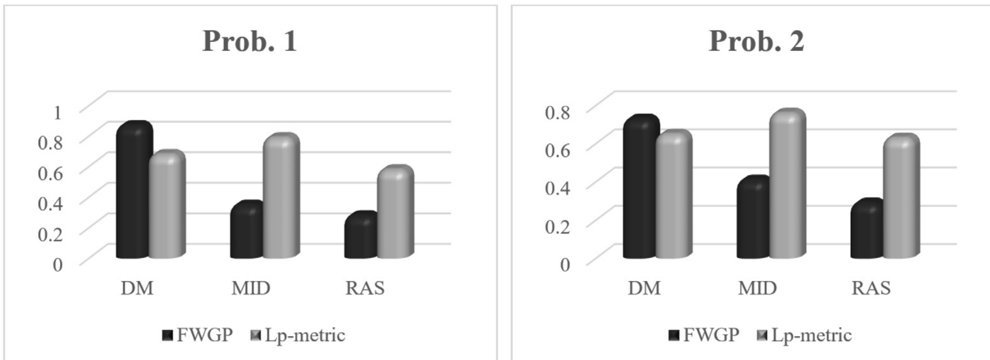


Fig. 9. Comparison of two proposed solution methods based on quality indicators.

Table 15
Comparison of FWGP and Lp-metric.

Prob.	(FWGP)			(Lp-metric)		
	DM	MID	RAS	DM	MID	RAS
1	0.87	0.35	0.28	0.68	0.79	0.58
2	0.73	0.41	0.29	0.65	0.76	0.63

considering sustainable development paradigm. In other words, this paper addressed a sustainable bi-level DSS to formulate and optimize a multi-level multi-product SC and co-modal transportation network for perishable products distribution, integrating two multi-objective mathematical models. On-time delivery was taken into account as the main factor that determines model performance due to perishability of products. Optimizing the design of SC network using the first level of the proposed DSS, the transportation network configuration was provided optimally in the second level considering different modes and options. To solve the suggested bi-level model, a hybrid solution technique was developed based on possibilistic linear programming and FWGP approach. The main reason was to provide an efficient technique which could concurrently deal with model uncertainty of parameters and objective functions while ensuring the sustainability of the system in terms of economic, environmental and social aspects. Moreover, the perishability of items was also examined through the DSS affecting the amount of fresh products to be delivered. Numerical examples were then generated to evaluate the validity, applicability and complexity of the proposed DSS. Meanwhile, Lp-metric method and well-known quality indicators were applied to demonstrate the superiority of the FWGP. Based on the findings, FWGP excelled Lp-metric in terms of DM, MID and RAS. Furthermore, sensitivity analyses were performed to provide managerial insights and support decisions related to the design of perishable product SCs based on the resulting impact on the optimum SC design and performance indicators of changing controllable parameter values. All in all, the results demonstrated the efficiency of the proposed methodology to solve the problem and provide optimal solution. Accordingly, our proposed methodology gives the managers required flexibility and efficiency to utilize and customize it in order to include main characteristics of the target SC.

8. Conclusion and outlook

As was discussed, this study sought to build up a useful DSS for integrated design of sustainable SC and transportation network for perishable products under uncertain environment. The main reason was to take into account the probable shortage of required resources in real world; e.g., the capacity limitations of the multimodal transportation system to meet the total demand by retailers. On the other hand, key factors of sustainability, perishability of products and uncertainty that directly influence the potentials were also incorporated into the suggested DSS. This implies that managers should investigate different aspects of the system, consider possible fluctuations in the weights given to objective functions, and review the level of the available resources in order to prevent potential system failures. To achieve this goal throughout this research, there were some limitations which can be tackled through the following suggestions for future research directions. As the first suggestion, other uncertainty methods, such as robust optimization (Goli et al., 2019; Khalilpourazari et al., 2020), stochastic optimal control (Savku & Weber, 2018) and grey systems (Roy et al., 2017), can be applied to the model in order to test the performance of the proposed fuzzy DSS. Furthermore, to make the model closer to real-world conditions, the reverse logistics of perishable products can be taken into account in the problem, which results in a closed-loop SC. Accordingly, the reverse flow of products and its consequent effects on the model can be studied. From the computational perspective, the proposed solution tool applied in this study is limited to tackle the large-scale problem. Real-life problems may include more number of facilities and customers such that there is definitely a need to develop an effective heuristic or meta-heuristic algorithm to provide optimal solutions within a reasonable run time.

CRediT authorship contribution statement

Erfan Babaee Tirkolaee: Writing – original draft, Conceptualization, Methodology, Supervision, Data curation, Software. **Nadi Serhan Aydin:** Reviewing and editing, Validation, Visualization, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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