



A robust reverse pharmaceutical supply chain design considering perishability and sustainable development objectives

Fatemeh Shekoohi Tolgari¹ · Naeme Zarrinpoor¹ 

Received: 21 November 2021 / Accepted: 26 January 2024 / Published online: 22 May 2024

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Abstract

The pharmaceutical supply chain (PSC) is a highly important strategic issue in the health-care domain because of its significant effect on human wellbeing and healthcare costs. This paper provides a mathematical optimization model to design a PSC by considering the drug's corruption. Given the importance of the sustainable development goals, three objectives are considered: economic, social, and environmental. The cost of fixed installation, transportation, holding, collection, distribution, recycling and disposal is reduced by the economic objective. A reduction in greenhouse gas emissions, water use, and nonrenewable energy consumption is achieved by the environmental objective. Based on the social objective, the number of employment opportunities, economic growth, job satisfaction, and national self-sufficiency are all increased, while the number of days lost due to work-related accidents decreases. To achieve the weight of elements in environmental and social objectives, the fuzzy best–worst method is used. Due to the inherent uncertainty in the PSC, its main parameters are referred to as unpredictable, which calls for a robust optimization approach to eliminate the model parameters' uncertainty. A fuzzy programming approach is used to solve the developed model. Numerical evidence drawn from a practical case shows that the suggested model is efficacious and valid. We suggest that the priorities and challenges of sustainable growth contribute to the determination of the PSC's managerial and operational characteristics.

Keywords Perishable pharmaceutical supply chain · Sustainable development goals · Uncertainty · Robust optimization · Fuzzy best–worst method

1 Introduction

The supply chain (SC) is a network of suppliers, manufacturers, and distribution centers (DCs) that manage the flow of goods before distributing them to customers. As a result,

✉ Naeme Zarrinpoor
zarrinpoor@sutech.ac.ir

Fatemeh Shekoohi Tolgari
F.Shokoohi@sutech.ac.ir

¹ Department of Industrial Engineering, Shiraz University of Technology, Shiraz, Iran

SC management (SCM) works for reliable, efficient, and dependable management of financial, information, and material flow in order to maximize total customer satisfaction via an effective corporate network (Sabouhi et al., 2018). The structure of the SC network (SCN) has a significant impact on the performance of its SC. This network has an impact on both quantitative and qualitative efficiency, as it influences the number of establishments and their locations, as well as their capacity and the distribution of information and material flows. In today's competitive environment, a SCN design is a critical subject in operational and financial choices in SCM to achieve strategic advantage and earnings (Eskandari-Khanghahi et al., 2018). The pharmaceutical industry, as a global industry, is defined as a set of processes, activities, and organizations involved in drug discovery, processing, and manufacture (Shah, 2004). This industry is critical to the environment, society, and public health in the majority of countries around the world (Chen et al., 2019). The pharmaceutical industry operates in an extremely competitive market. SCM is consequently required in order to modify costs and gain a competitive advantage (Yavari & Zaker, 2019). The pharmaceutical SC (PSC) has been viewed as one of the most serious geopolitical concerns in the SC due to its major impact on public health, and it has developed dramatically in recent decades as epidemic rates have risen (Weraikat et al., 2016a, b).

The PSC, being one of the most important sectors of the health industry, has numerous challenges. The following are some of the most significant challenges in this field:

- a. *Cost of health care* Medicines are used to diagnose, cure, prevent, and ultimately improve health. Since most health care costs are in the pharmaceutical industry, efficient medicines should be used to cut down on rising healthcare costs (Aghababaei et al., 2019). The healthcare industry is currently confronted with more strategic and cost-effective difficulties than ever before. For example, the cost of health care in the United States in 2014 was \$3.09 trillion, and it is predicted to reach \$3.57 trillion in 2017. According to US health statistics from 2014, the pharmaceutical industry accounts for approximately 12.9% of all large expenditures in the US (Zahiri et al., 2018).
- b. *Uncertainty* despite improvements in manufacturing, storage, and distribution, many pharmaceutical companies continue to fall short of fulfilling consumer expectations in a timely and dependable manner. The demand for each medicine is unpredictable, with regular seasonal fluctuations, and it is hard to estimate demand given the drug's corrupt existence. Emergency shortages are exceedingly expensive and might have a negative impact on the patient's recovery process (Kelle et al., 2012). Medication shortages have forced most clinics to postpone care and surgery. In such cases, hospitals are frequently forced to employ treatments with lower efficacy and greater pricing. PSC frequently requires successful optimization approaches to deal with uncertainty in order to improve their performance.
- c. *Perishability* the SC of perishable products, such as medicines, has lately become a significant human issue due to their effects on human lives. Their collection, distribution, and control require careful management and planning (Darestani & Hemmati, 2019). When the products are perishable, the distribution network design becomes more challenging and critical (Savadkoobi et al., 2018). Perishable products, on the other hand, generally have negative environmental impacts due to their fragile nature and particular packaging and shipping environments. As a result, the design of the SCN for perishable products is critical to meeting environmental and financial aims (Yavari & Zaker, 2019). The drug is also a perishable material with a limited shelf life that must be stored at specific temperatures and conditions. In order to effectively regulate and monitor the inventory and

- demand for perishable medicines, as well as to provide a suitable method to address the high expense of preserving perishable goods, PSC designs must be developed.
- d. *Drug recovery* in recent years, the pharmaceutical industry has seen significant changes. Governments also adopted new policies for dealing with unwanted pharmaceuticals in public places. Hospitals, as large consumers of drugs, are subjected to excessive demand. Because a lack of pharmaceuticals might have serious consequences for patients, consumers can apply a restrictive inventory management strategy and stock a large number of drugs. Because drugs are perishable, this strategy results in the medication expiring when the patient has no need for it. Improving the reverse SC is another strategy for gaining and maintaining market competition (Weraikat et al., 2016a, b). The reverse SC is explored for a variety of reasons, including sustainable development, environmental concerns, lack of energy, and decreased rates of return, which apply to procedures such as storing, recycling, and disposing of returned items from the final consumer.
 - e. *Environmental and social responsibility* in terms of regulatory policies, environmental concerns, and social responsibility, the design of a sustainable SCN has lately been embraced to address environmental and social challenges, as well as the economic impacts of the SC. Over the last two decades, as governments, corporations, and the general public have become more aware of the importance of sustainability, efforts have been made all over the world to incorporate environmental issues into municipal-industrial projects, and the medical profession has not been left behind (Zahiri et al., 2017). All SC operations have an environmental impact, which must be mentioned. Greenhouse gas (GHG) emissions from SC transportation operations, for example, play a substantial role in the development of environmental pollution. However, in recent years, the presence of pharmaceutical waste and pollution, as well as its harmful influence on quality of life, has become noticeable, and many countries have been forced to implement new laws to address PSC recovery systems (Weraikat et al., 2019). Fossil fuels continue to be a major component of the world's energy consumption. The growth of the world's population and the corresponding rise in the rate of natural resource consumption have pushed extra pressure on the environment. According to the sustainable development goals, it is critical to reduce the use of nonrenewable energy in developing countries' SCs (Afkhani & Zarrinpoor, 2022). One of the most important aspects of social responsibility is social economic growth, because there is a notion that the working environment should be better economically and socially. More specifically, the key priorities of social responsibility are growing employment prospects and sustainable economic growth (Zahiri et al., 2017).

In relation to the aforementioned issues, the research questions to be answered are how to design an optimal multi-product, multi-period PSC under parameter uncertainty and mathematical modeling to achieve all of the sustainable development goals at the same time, while considering a variety of realistic factors such as facility capacity, demand limitations, production time, medicine shelf life, imports, transportation modes, and transportation capacity to define both strategic and operational decisions. These decisions consist of: (1) the location of production, distribution, collection, recycling, and disposal centers; (2) determining the product distribution between various layers of the PSC; (3) determining optimum inventory levels for drugs according to shelf life and production time; (4) the quantity of recycled and disposed drug; (5) the number of vehicles used to deliver drugs, and (6) the amount of employee support. In this research, an attempt has been made to answer these cases by proposing a multi-product, multi-period, multi-stage mathematical optimization model to construct a PSC. We consider all aspects of the sustainable development goals. The social

and environmental effects of the SC decisions have been measured by GRI guideline indicators (GRI, 2016). The economic objective minimizes fixed installation, shipping, processing, distribution, recycling and disposal costs. The amount of GHG emissions, water use and nonrenewable energy use in the SC is reduced on the basis of the environmental goal. The number of employment openings, levels of economic growth, job satisfaction and national self-sufficiency are maximized and the number of labor days missed as a result of a workplace accident is reduced, depending on the social purpose feature. The fuzzy best–worst method (FBWM) is used to measure the weight of environmental and social elements. The intrinsic uncertainty of PSC designs, such as capacity, demand, fixed and operational costs, and social and environmental considerations, is taken into account. The uncertainty of model parameters is managed using a robust optimization approach. An interactive fuzzy programming method has been applied to solve the proposed model. A practical case has been proposed as a means of testing the results and determining the viability of the solution process.

The research framework is as follows: the linked literature is discussed in the next section. Section 3 provides the description and formulation of the model. To cope with uncertainty, Sect. 4 provides a robust optimization approach. Section 5 discusses how to solve the model. Section 6 denotes a practical case and the numerical findings. Discussion and policy implications are provided in Sect. 7. Finally, findings and possible study directions are explored in Sect. 8.

2 Literature review

In this section, the studies in the field of PSC design are reviewed, and after that, the contributions of this work are discussed.

2.1 Related works

Hansen et al., (2011) suggested a stochastic mixed integer linear programming (MILP) model to prepare a new PSC to increase profits. Chen et al., (2012) established a simulation–optimization tactic for a prescription SC with one pharmaceutical company and one pharmacy. They looked at how price limit legislation impacts pricing choices taken by pharmaceutical firms and assessed the PSC’s financial efficiency. Hansen et al. (2015) proposed a two-stage stochastic PSC model to help pharmaceutical industry start-up decisions and to minimize time-to-market in order to make greater use of patent rights. Their model has been generalized to a case based on an observational analysis. Stecca et al., (2016) explored optimizing the inventory costs of a hospital where the hospital’s central pharmacy plays a role as a key decision-maker (DM) for the procurement of medications and their distribution to internal wards. To reduce medication storage procurement prices, inventory management techniques such as combination-based mechanisms and conventional inventory monitoring have been implemented. The role of consumer benefits was discussed by Weraikat et al., (2016a, b) in order to promote left-over returns and boost the viability of a true reverse PSC. The effect of ensuring a proper method of communication between a manufacturer and third-party logistics firms responsible for receiving unnecessary medication from consumer zones was studied. An optimization-simulation strategy to solve the problem of redesigning the wholesaler network, matching running costs and customer service levels was proposed by Martins et al., (2017). Using a real case study, Weraikat et al., (2019) designed a PSC to analyze the effects

of introducing a vendor-managed inventory scheme in hospitals with the goal of lowering costs and medication wastage.

The uncertainty of the data has not been examined in the publications cited above, despite the fact that it is unavoidable in the actual world. If the inherent uncertainty of data in the design of the SC is ignored, the designed system with deterministic parameters will result in solutions that are neither optimal nor practicable. Since uncertainty presents a challenge to planning and operating procedures, it should be captured as quickly as possible (Zarrinpoor & Pishvaei, 2021). The uncertainty of parameters has been taken into consideration in certain PSC design works. Mousazadeh et al., (2015) generated a MILP model with two objectives for the implementation of a PSC network. Their model aims to make a number of business choices, such as the opening of pharmaceutical production facilities and DCs along with optimum inventory movement across the mid-term planning period as operational decisions. Their model simultaneously minimizes overall costs and unfulfilled demands. To deal with uncertain parameters, they employed a robust possibilistic programming approach. Imran et al., (2018) created a multi-period, multi-objective PSC model for an interconnected public health system with the goal of decreasing time and expense while increasing efficiency. They found an uncertain number of manufacturers' medication concerns and recommended a fuzzy programming approach to manage the uncertainty. For a three-level PSC, Savadkoobi et al., (2018) developed an inventory-location model. Their suggested model requires logistical and operational choices that include the opening of manufacturing and DCs, network content flows, and an optimum commodity perishability inventory strategy. To deal with uncertain conditions, they suggested a possibilistic programming approach. To build a resilient SC, Sabouhi et al., (2018) proposed a fuzzy data envelopment analysis model to evaluate the competitiveness of potential vendors. Then, a two-stage possibilistic-stochastic programming model is designed to integrate supplier selection and SC design under disruption and operating threats. Zahiri et al., (2018) presented a methodology for developing a PSC that took into account the commodity shelf-life, substitutability, and organization discount. The provided model's target functions aim to reduce overall costs and anticipated unmet demand. They took into account the ambiguity of demand and costs and used a robust possibilistic strategy to deal with it. By incorporating uncertainty conditions into a multi-objective model, Singh and Goh (2019) optimized the PSC network. In that model, qualitative performance in model decisions such as after-sales service, and network costs as objective functions were maximized and minimized, respectively. To deal with the uncertainty of the model parameters, they applied fuzzy optimization. Aghababaei et al., (2019) adopted a MILP model for the scarce drug rationing problem that represents conflicts of interest among SC participants. The maximization of minimal supplier benefit and the minimization of maximum scarcity are seen as the objective features of the first and second level models, respectively. To deal with uncertain factors like the exchange rate and demand, they created a credibility-based robust possibilistic programming approach. Using a multi-objective, multi-product model, Goodarzian et al., (2020) optimized the PSC network with the objectives of minimizing network costs and drug delivery time and maximizing the quality of the transportation system. To manage the uncertainty of factors like costs and capacities, they developed a robust fuzzy programming approach. Taleizadeh et al., (2020) proposed a reverse SCN for the pharmaceutical industry under uncertainty, and optimized it economically. They used robust optimization to examine the impact of demand uncertainty. Using an optimization and simulation-based approach, Franco & Lizarazo (2020) developed two single-objective and bi-objective mixed integer programming (MIP) models for designing and optimizing the PSC in hospital that account for uncertainty. The single-objective model minimizes network costs, whereas the bi-objective model minimizes the number of expired drugs and maximizes their

expiration date. Uncertainty has been dealt with using the stochastic optimization technique. Zandkarimkhani et al., (2020) created a bi-objective MILP model to optimize a PSC with the goals of reducing network costs and shortages. A strategy based on fuzzy theory and chance constraint programming is utilized to cope with the demand parameter's uncertain nature. Nasrollahi and Razmi (2021) developed a bi-objective four-level PSC network taking into account patients' priorities based on their disease type with the objectives of reducing network costs and increasing demand coverage. They developed a fuzzy method for dealing with demand uncertainty and tested their model using actual data from Iran.

Although past research focused on the economic goal of designing a PSC, it is critical that not only economic optimization but also environmental or social effect, or both, be taken into consideration in order to develop an ecologically friendly and socially responsive PSC networks. In this regard, Zahiri et al., (2017) proposed a multi-objective sustainable-resilient MILP model for creating a PSC network in the presence of uncertainty. Their model's goals were to reduce expenses, increase employment possibilities and balanced economic growth, reduce CO₂ emissions, and lessen network non-resiliency. A two-level PSC model with a drug dealer and a distributor with uncertain demand was discussed by Nematollahi et al., (2018). They took into account both the social goal of improving customer service and the economic goal of increasing profit. Roshan et al., (2019) tackled crisis management in the PSC with the aim of reducing total network costs, reducing unmet requirements, and increasing employment and regional economic growth as a social goal. With the aim of reducing costs, maximizing customer service as a social purpose, and limiting environmental effect, Ahmad et al., (2021) designed a PSC design with uncertainty of parameters and employed fuzzy optimization techniques to cope with the uncertainty. In order to examine how a competitive pharmaceutical market is affected by uncertain demand, Sazvar et al., (2021) designed a closed-loop SCN for drugs. Their suggested model seeks to maximize economic gain, reduce harmful environmental consequences, and increase employment possibilities.

2.2 Contributions of this research

The essential elements of the relevant studies are categorized in this subsection. Table 1 reports a more detailed classification of the literature. Robust optimization, fuzzy optimization, stochastic optimization, and combined methods are, determined by RO, FO, SO, and CM in this table, respectively. Only Zahiri et al., (2017), Ahmad et al., (2021) and Sazvar et al., (2021) have studied the three elements of sustainability in PSC, despite the increasing relevance of sustainable development in other industries, particularly the pharmaceutical business. In papers that examined the environmental side of sustainability, CO₂ emissions received lots of attention, but other factors like the use of nonrenewable energy and trash production were not considered. Additionally, any air pollutants that are harmful to human health when emitted into the atmosphere during transportation, including CO₂, SO_x, and NO_x, are not taken into account. The number of new job openings and regional expansion were taken into consideration in articles that examined the social aspect of sustainability; worker satisfaction, national self-sufficiency and the number of days lost due to unavoidable calamity received less attention. There is no published research that examines the role of drug recycling. However, a considerable portion of pharmaceuticals can be recycled and reused during the manufacturing process. Only Aghababaei et al., (2019) incorporated drug imports in the mathematical model, despite the fact that they are crucial in many countries to satisfy consumer demand. The perishability of the medication has also not been taken into account in most research, despite the fact that it is one of the fundamental characteristics of the medicine that cannot be

Table 1 A classification of similar literature articles

Reference	Function		Function type					Problem type		
	Single-objective	Multi-objective	Economic	Social	Environmental	Demand	Time	Quality	Problem type	
Hansen et al. (2011)	✓		✓							MILP
Chen et al. (2012)	✓		✓							MILP
Hansen and Grunow (2015)	✓									MILP
Mousazadeh et al. (2015)		✓	✓			✓				MILP
Stecca et al. (2016)	✓		✓							MILP
Weraikat et al., (2016a, 2016b)	✓		✓							LP
Martins et al. (2017)	✓		✓							MIP
Zahiri et al. (2017)		✓	✓		✓					MILP
Imran et al. (2018)		✓	✓							MILP
Nematollahi et al. (2018)		✓	✓							NLP
Zahiri et al. (2018)		✓	✓		✓					MILP
Savadkoohi et al. (2018)	✓		✓					✓		MINLP
Sabouhi et al. (2018)	✓		✓							MILP
Singh and Goh (2019)		✓	✓							MILP
Aghababaei et al. (2019)	✓		✓							NLP
Weraikat et al. (2019)	✓		✓							MINLP
Roshan et al. (2019)		✓	✓		✓					MINLP

Table 1 (continued)

Reference	Function		Function type				Problem type				
	Single-objective	Multi-objective	Economic	Social	Environmental	Demand	Time	Quality			
Goodarzian et al. (2020)		✓	✓				✓	✓			MINLP
Taleizadeh et al. (2020)	✓		✓					✓			LP
Franco and Lizarazo (2020)		✓	✓				✓	✓			MIP
Zandkarimkhani et al. (2020)		✓	✓						✓		MILP
Ahmad et al. (2021)		✓	✓	✓					✓		MILP
Sazvar et al. (2021)		✓	✓	✓					✓		MILP
Nasrollahi and Razmi (2021)		✓	✓						✓		MILP
Current study		✓	✓	✓					✓		MILP
Reference	Uncertainty	Approach to dealing with uncertainty	Reverse SC	Multi-product	Multi-period	Inventory management	Import	Transportation mode	Drug recovery	Perishability	
Hansen et al. (2011)	✓	FO, CM		✓							
Chen et al. (2012)				✓		✓					
Hansen and Grunow (2015)	✓	FO, CM		✓		✓					

Table 1 (continued)

Reference	Uncertainty	Approach to dealing with uncertainty	Reverse SC	Multi-product	Multi-period	Inventory management	Import	Transportation mode	Drug recovery	Perishability
Mousazadeh et al. (2015)	✓	SO, CM		✓		✓		✓		
Stecca et al. (2016)				✓		✓				
Weraikat et al., (2016a, 2016b)			✓	✓						
Martins et al. (2017)				✓		✓		✓		
Zahiri et al. (2017)	✓	CM		✓		✓		✓		
Imran et al. (2018)	✓	RO, CM	✓	✓		✓				
Nematollahi et al. (2018)				✓						
Zahiri et al. (2018)	✓	CM		✓		✓				✓
Savadkoochi et al. (2018)	✓	RO, CM		✓		✓				✓
Sabouhi et al. (2018)	✓	FO, CM		✓						
Singh and Goh (2019)	✓	FO		✓		✓				

Table 1 (continued)

Reference	Uncertainty	Approach to dealing with uncertainty	Reverse SC	Multi-product	Multi-period	Inventory management	Import	Transportation mode	Drug recovery	Perishability
Aghababaei et al. (2019)	✓	SO, CM		✓		✓	✓			
Weraikat et al. (2019)	✓	FO, CM	✓	✓	✓					
Roshan et al. (2019)	✓	RO, CM		✓	✓	✓				✓
Goodarzian et al (2020)	✓	RO		✓	✓	✓		✓		
Taleizadeh et al. (2020)	✓	RO	✓	✓	✓					
Franco and Lizarazo (2020)	✓	SO		✓	✓	✓				✓
Zandkarimkhani et al. (2020)	✓	CM		✓	✓	✓		✓		✓
Ahmad et al. (2021)	✓	FO								
Sazvar et al. (2021)	✓	CM	✓	✓	✓	✓		✓		
Nasrollahi and Razmi (2021)	✓	CM		✓	✓	✓				
Current study	✓	MPFRP	✓	✓	✓	✓	✓	✓	✓	✓

disregarded. There are articles that address the uncertainty of parameters in the PSC design, but none of them take into account mixed possibilistic flexible robust programming (MPFRP) to deal with the uncertainty. According to the literature, this article presents a PSC problem in which the network is created with the aims of sustainable development and the perishability of medications in consideration while also analyzing the effect of drug imports on the chain. Furthermore, the proposed problem is reversed in the SC category to examine the role of drug recycling and disposal, as well as other essential chain components. The last row of Table 1 shows the features of the desired problem.

The following are the key contributions of this study, as determined by the research gaps:

1. Introducing a multi-product, multi-period optimization model for a PSC design that simultaneously examines economic, environmental, and social sustainability.
2. Taking into account the drug's lifespan and shelf life in the mathematical model with respect to the perishability of the drugs.
3. Creating recycling and disposal facilities as part of the proposed reverse PSC to handle environmental issues with produced waste and medications that can be recycled and put them back into the production cycle or be disposed of.
4. Considering drug imports as one of the most important elements impacting the economy of developing nations to satisfy domestic drug demand for which adequate production is not possible.
5. Taking into account the uncertainty of main issue parameters, and providing a MPFRP method to manage it.
6. Verify the model by providing a real-world case study for diabetes drugs in Iran.

3 Problem definition and proposed model

The strategic importance of medicine in health systems is growing daily. Because medicine affects people's health and quality of life, it is produced, distributed, and maintained with scientific consideration, and if it is not correctly addressed, it will have a negative impact on both quantitative and qualitative public health indicators. The expense of healthcare makes up a considerable portion of the national income in developed nations. The pharmaceutical sector in Iran is also affected by issues including inefficient drug distribution and timing, which prevent medications from reaching patients on time, or, on the other hand, a significant volume of expired medications (Shahbahrami et al., 2020). Increased efficiency of supply and distribution networks and infrastructures is a critical component in reorganizing the nation's SC and distribution of goods. This is because of the sector's position and importance in the gross domestic product as well as the major goals established in the country's major programs in this area (Abedini et al., 2019). Additionally, Iran's pharmaceutical sector faces unique and challenging circumstances as a result of the existence of two critical factors: the global health crisis and the country's rate of financial growth and profitability. In this business, an ineffective distribution network causes issues which include adding significant costs to the SC, decreasing distributors' efficiency, lengthening wait times, decreasing the safety of drugs, raising the cost of hospital inventory, decreasing the effectiveness of hospital operations, increasing patient dissatisfaction, and late delivery of medication (Sepahi et al., 2020).

Medicines are typically regarded as perishable due to the fact that their quality is known to rapidly deteriorate not only during the manufacture and storage procedures but also throughout the distribution. Delivering drugs to consumers before the expiration date is crucial for

the survival and success of PSCs. In this context, the design of a supply network for perishable goods is critical (Yakavenka et al., 2020). Additionally, during the past few years, the market for medicines has grown in both scope and diversity in addition to being on the rise. More focus is now necessary due to the importance of the multi-product SC. In order to best meet consumer expectations, optimization techniques have been applied voraciously to these kinds of networks (Goodarzian et al., 2021a, 2021b).

Imports are essential for every country because they make it possible to obtain goods that are both in high demand and unable to be produced in sufficient numbers to meet domestic demand (Trishna & Gupta, 2019). In Iran, the internal market for supplying the medicine needed by the country can eliminate internal imbalances by adapting to the world market. As a result, imports are one of the most significant factors influencing the economies of developing countries like Iran. In essence, Iran is one of the countries with high rates of drug use. Number-wise, roughly 96% of the pharmaceuticals consumed in Iran are supplied by domestic pharmaceutical factories, and just about 4% of the drugs are imported into the nation’s healthcare system through drug importers. With these interpretations, it’s crucial to take into account how imports fit into the overall PSC in Iran (Barouni et al., 2016).

In accordance with the points above, a mathematical model for developing a multi-product, multi-objective perishable PSC network is described in this section. Different levels of production, importer, distributor, supplier, consumer, collection, recycle and disposal are all included in the model. Figure 1 shows the structure of proposed PSC network. According to Fig. 1, raw material suppliers provide the raw ingredients used for finished products production. Manufacturers move manufactured goods to DCs due to the unpredictability of consumer demand for each form of medication. Some medicines are moved from importers to manufacturers as well. Based on the time of manufacture and the expiry date of the medicines, the DCs will store some of the goods for distribution in the next period, if necessary, while others will be transported to the consumer region. In the reverse SCN, recycling centers (RCs) receive waste goods and certain recyclable or recycled products are returned to production

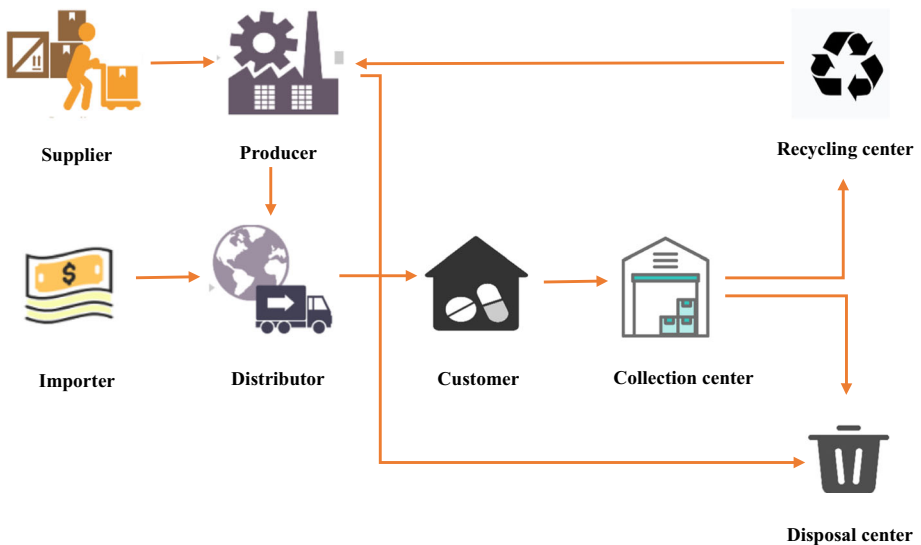


Fig. 1 The proposed network of PSC

centers (PCs) following inspection. In this study, the spoilage of pharmaceutical goods is known to be a period of time and the medicines are shipped to the patient until they are spoiled. Proper control of the storage and distribution of pharmaceutical products in the DCs is therefore the main goal of the study.

Sustainability is an important concept in the process of SCN design (Sarkis, 2020). In this paper, it was decided that the proposed mathematical model be presented as a multi-objective model, since like many other SCs, it contains activities that have their own economic, environmental, and social implications and it is better to examine them comprehensively. As multi-objective models play a significant role in long-term SCNs networks (Tautenhain et al., 2021), it is clear that concentrating solely on the economic aspect of SC activities cannot provide health managers with benefits that are acceptable. In the long run, although the network's economic dimension will reach the optimal level, the environmental and social dimensions of the suggested network will not be under control. Using a multi-objective model, allows for the examination and evaluation of the components of each objective as well as the analysis of the interactions between the objectives and any probable contradictions. Also, it gives the decision-makers the opportunity to express their viewpoints on each objective during the problem-solving process and select the best solution (Tautenhain et al., 2021).

It is more practical to establish a planning horizon in which different strategic and operational decisions for the PSC design are made based on the lifetime and time of drug production. Moreover, since the perishability and short shelf life of medication represent one of the PSC's biggest concerns, taking the planning horizon into account becomes even more crucial. The number of expired drugs and drugs that can be returned to the chain will be determined based on the drug's life and production period. Furthermore, the inventory management policy in distribution centers is time-dependent. As a result, all of the time-dependent decisions are made over different time periods in order to account for the biggest challenge in the PSC, namely, the restricted life duration.

In the designing of the model, the assumptions mentioned below are taken into consideration:

1. The problem is multi-period and multi-product.
2. The capacity of the PCs, DCs, collection centers (CCs), RCs, and disposal centers (DICs) is limited.
3. Different means of transportation are considered, between the levels of the SC.
4. Vehicle capacity is limited.
5. The model's main parameters, such as fixed costs, operational costs, facility capacity, demand, social factors, and environmental factors, are uncertain.
6. Medications have a limited shelf life.
7. Deficits in arrears are permitted, and customer demand must be met up to the last time period.

3.1 Notation

The notation used in this study includes:

Sets

- I Importers
- S Suppliers for raw materials
- J PCs
- K DCs

C	Customers
M	CCs
R	RCs
D	DICs
P	Drugs
Q	Raw materials
T	Time periods
E	Production times
V	Vehicles
H	Employee support types
G	Emission types to the air

Parameters

\widetilde{F}_j	Annualized expense of setting up PC j
\widetilde{F}_k	Annualized expense of setting up DC k
\widetilde{F}_m	Annualized expense of setting up CC m
\widetilde{F}_r	Annualized expense of setting up RC r
\widetilde{F}_d	Annualized expense of setting up DIC d
\widetilde{F}_v	Annualized expense of setting up vehicle type v
\widetilde{h}_{pk}	Expense of holding one unit of drug p in DC k
\widetilde{C}_{pj}	Expense of making one unit of drug p in PC j
\widetilde{CD}_{pk}	Expense of distributing one unit of drug p by DC k
\widetilde{CC}_{pm}	Expense of collecting one unit of drug p by CC m
\widetilde{CR}_{pr}	Expense of recycling one unit of drug p by RC r
\widetilde{Cd}_{pd}	Expense of disposing one unit of drug p by DIC d
\widetilde{CB}_{qs}	Expense of purchasing raw material q from supplier s
\widetilde{CM}_{pi}	Expense of purchasing drug p from importer i
\widetilde{CH}_{ht}	Expense of employee support type h in period t
\widetilde{cw}_{pd}	Expense of disposal of the waste generated per unit of drug p by DIC d
\widetilde{TC}_{vt}	Transportation cost of vehicle v in period t
d_{ik}	Distance between importer i and DC k
d_{sj}	Distance between supplier s and PC j
d_{jk}	Distance between PC j and DC k
d_{kc}	Distance between DC k and customer c
d_{cm}	Distance between customer c and CC m
d_{mr}	Distance between CC m and RC r
d_{md}	Distance between CC m and DIC d
d_{rj}	Distance between RC r and PC j
d_{jd}	Distance between PC j and DIC d

\widetilde{CE}_{gpik}	Amount of emission type g produced by transporting one unit of drug p from importer center i to DC k
\widetilde{CE}_{gqsj}	Amount of emission type g produced by transporting one unit of raw material q from supplier s to PC j
\widetilde{CE}_{gpjk}	Amount of emission type g produced by transporting one unit of drug p from PC j to DC k
\widetilde{CE}_{gpkc}	Amount of emission type g produced by transporting one unit of drug p from DC k to customer c
\widetilde{CE}_{gpcm}	Amount of emission type g produced by transporting one unit of drug p from customer c to CC m
\widetilde{CE}_{gpmr}	Amount of emission type g produced by transporting one unit of drug p from CC m to RC r
$\widetilde{CE}_{gpm d}$	Amount of emission type g produced by transporting one unit of drug p from CC m to DIC d
\widetilde{CE}_{gpjd}	Amount of emission type g produced by transporting the waste generated per unit of drug p from PC j to DIC d
\widetilde{CE}_{gqrj}	Amount of emission type g produced by transporting one unit of recycled raw material q from RC r to PC j
α	Percentage of recyclable drug in CCs
β_{qp}	Amount of raw material q obtained from recyclable drug p
l_{qp}	Amount of raw material q required to produce each unit of drug p
LF_p	Life time of drug p
\widetilde{D}_{cpt}	Demand of customer c for drug p in period t
\widetilde{ca}_{ip}	Capacity of importer i for drug p
\widetilde{ca}_{sq}	Capacity of supplier s for raw material q
\widetilde{ca}_{jp}	Capacity of PC j for drug p
\widetilde{ca}_{kp}	Capacity of DC k for drug p
\widetilde{ca}_{mp}	Capacity of CC m for drug p
\widetilde{ca}_{rp}	Capacity of RC r for drug p
\widetilde{ca}_{dp}	Capacity of DIC d for drug p
ca_v	Capacity of vehicle type v
$\widetilde{F}o_j$	Fixed number of employees provided as a result of the establishment of PC j
$\widetilde{v}o_j$	Variable number of employees provided as a result of the establishment of PC j
$\widetilde{I}D_j$	Number of days dropped due to a job accident at PC j
$\widetilde{F}o_k$	Fixed number of employees provided as a result of the establishment of DC k
$\widetilde{v}o_k$	Variable number of employees provided as a result of the establishment of DC k
$\widetilde{I}D_k$	Number of days dropped due to a job accident at DC k
$\widetilde{F}o_m$	Fixed number of employees provided as a result of the establishment of CC m
$\widetilde{v}o_m$	Variable number of employees provided as a result of the establishment of CC m
$\widetilde{I}D_m$	Number of days dropped due to a job accident at CC m

$\widetilde{F}o_r$	Fixed number of employees provided as a result of the establishment of RC r
$\widetilde{v}o_r$	Variable number of employees provided as a result of the establishment of RC r
$\widetilde{I}D_r$	Number of days dropped due to a job accident at RC r
$\widetilde{F}o_d$	Fixed number of employees provided as a result of the establishment of DIC d
$\widetilde{v}o_d$	Variable number of employees provided as a result of the establishment of DIC d
$\widetilde{I}D_d$	Number of days dropped due to a job accident at DIC d
$\widetilde{v}ot_v$	Variable number of employees provided using vehicles v
$\widetilde{e}v_j$	Regional economic value for opening a PC at potential location j
$\widetilde{e}v_k$	Regional economic value for opening a DC at potential location k
$\widetilde{e}v_m$	Regional economic value for opening a CC at potential location m
$\widetilde{e}v_r$	Regional economic value for opening a RC at potential location r
$\widetilde{e}v_d$	Regional economic value for opening a DIC at potential location d
$\widetilde{d}l_j$	Level of regional growth at potential location j
$\widetilde{d}l_k$	Level of regional growth at potential location k
$\widetilde{d}l_m$	Level of regional growth at potential location m
$\widetilde{d}l_r$	Level of regional growth at potential location r
$\widetilde{d}l_d$	Level of regional growth at potential location d
$\widetilde{J}S_h$	Level of workplace satisfaction attained as a result of employee support type h
$M B_t$	Highest budget allocated to employee support at period t
ψ	Impact of production on self-sufficiency
$g w_{pj}$	Amount of the waste generated per unit of drug p in PC j
$\widetilde{e}c_{pj}$	Amount of the nonrenewable energy consumed per unit of drug p in PC j
W^j	Importance of the job satisfaction
W^s	Importance of the self-sufficiency
W^o	Importance of employment creation
W^d	Importance of days dropped due to a job accident
W^e	Importance of regional growth
W^c	Importance of GHG emissions
W^{ec}	Importance of the nonrenewable energy consumption
W^w	Importance of the waste generation

Decision variables

I_{pikt}	Quantity of purchased drug p transferred from importer i to DC k in period t
S_{qpsjt}	Quantity of purchased raw material q for drug p that is passed from supplier s to PC j in period t
Y_{pjkt}	Quantity of drug p that is passed from PC j to DC k in period t
V_{pkct}	Quantity of drug p that is passed from DC k to customer c in period t
O_{pcmt}	Quantity of drug p that is passed from customer c to CC m in period t
R_{pmrt}	Quantity of recyclable drug p that is passed from CC m to RC r in period t
N_{pmdt}	Quantity of unrecyclable drug p that is passed from CC m to DIC d in period t

M_{qprjt}	Quantity of recycled raw material q for drug p that is passed from RC r to PC j in period t
Q_{pekt}	Quantity of inventory drug p that had been produced at production time e which is kept in DC k in period t
gd_{pjdt}	Amount of waste generated per unit of drug p that is transferred from PC j to DIC d in period t
nv_{vsjt}	Number of vehicle v used to deliver raw materials from supplier s to PC j in period t
nv_{vikt}	Number of vehicle v used to deliver the drug from importer i to DC k in period t
nv_{vjkt}	Number of vehicle v used to deliver the drug from PC j to DC k in period t
nv_{vkct}	Number of vehicle v used to deliver the drug from DC k to customer c in period t
nv_{vcmt}	Number of vehicle v used to deliver the drug from customer c to CC m in period t
nv_{vmdt}	Number of vehicle v used to deliver the drug from CC m to DIC d in period t
nv_{vmrt}	Number of vehicle v used to deliver the drug from CC m to RC r in period t
nv_{vrjt}	Number of vehicle v used to deliver the drug from RC r to PC j in period t
nv_{vjdt}	Number of vehicle v used to deliver the waste generate per unit of drug from PC j to DIC d in period t
ES_{ht}	1 If employee support type h is considered in period t , 0 otherwise
x_j	1 If PC j is installed, 0 otherwise
x_k	1 If DC k is installed, 0 otherwise
x_m	1 If CC m is installed, 0 otherwise
x_r	1 If RC r is installed, 0 otherwise
x_d	1 If DIC d is installed, 0 otherwise

3.2 Formulation

The mathematical model is described in this subsection. The cost of designing the PSC network is reduced by objective (1). The fixed expenses of opening PCs, DCs, CCs, RCs, and DICs are included in the first to fifth terms of this objective. The fixed expense of vehicles is displayed from the sixth to the fourteenth terms. Transportation costs between SC levels are shown from the fifteenth to the twenty-third terms. The cost of holding drugs in distributor’s warehouses is addressed in the twenty-fourth phrase. The remaining terms cover costs associated with producing, purchasing raw materials and imported drugs, distribution, collection, recycling, and disposal. The employee support cost is the final phrase.

$$\begin{aligned}
 \text{Min } Z_1 = & \sum_{j=1}^J \tilde{F}_j x_j + \sum_{k=1}^K \tilde{F}_k x_k + \sum_{m=1}^M \tilde{F}_m x_m + \sum_{r=1}^R \tilde{F}_r x_r + \sum_{d=1}^D \tilde{F}_d x_d \\
 & + \sum_{v=1}^V \sum_{t=1}^T \tilde{F}_v \left[\sum_{j=1}^J \sum_{k=1}^K nv_{vjkt} + \sum_{k=1}^K \sum_{c=1}^C nv_{vkct} + \sum_{i=1}^I \sum_{k=1}^K nv_{vikt} \right]
 \end{aligned}$$

$$\begin{aligned}
 & + \sum_{s=1}^S \sum_{j=1}^J n v_{vsjt} + \sum_{c=1}^C \sum_{m=1}^M n v_{vcmt} + \sum_{m=1}^M \sum_{r=1}^R n v_{vmrt} \\
 & + \sum_{m=1}^M \sum_{d=1}^D n v_{vmdt} + \sum_{r=1}^R \sum_{j=1}^J n v_{vrjt} + \sum_{j=1}^J \sum_{d=1}^D n v_{vjdt} \Big] \\
 & + \sum_{v=1}^V \sum_{t=1}^T \widetilde{TC}_{vt} \left[\sum_{j=1}^J \sum_{k=1}^K d_{jk} n v_{vjkt} + \sum_{k=1}^K \sum_{c=1}^C d_{kc} n v_{vckt} \right. \\
 & + \sum_{i=1}^I \sum_{k=1}^K d_{ik} n v_{vikt} + \sum_{s=1}^S \sum_{j=1}^J d_{sj} n v_{vsjt} + \sum_{c=1}^C \sum_{m=1}^M d_{cm} n v_{vcmt} + \sum_{m=1}^M \sum_{r=1}^R d_{mr} n v_{vmrt} \\
 & \left. + \sum_{m=1}^M \sum_{d=1}^D d_{md} n v_{vmdt} + \sum_{r=1}^R \sum_{j=1}^J d_{rj} n v_{vrjt} + \sum_{j=1}^J \sum_{d=1}^D d_{jd} n v_{vjdt} \right] \\
 & + \sum_{p=1}^P \sum_{e=1}^E \sum_{k=1}^K \sum_{t=1}^T \widetilde{h}_{pk} Q_{pekt} + \sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T \widetilde{C}_{pj} Y_{pjkt} \\
 & + \sum_{q=1}^Q \sum_{p=1}^P \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T \widetilde{CB}_{qs} S_{qpsjt} + \sum_{p=1}^P \sum_{i=1}^I \sum_{k=1}^K \sum_{t=1}^T \widetilde{CM}_{pi} I_{pikt} \\
 & + \sum_{p=1}^P \sum_{k=1}^K \sum_{c=1}^C \sum_{t=1}^T \widetilde{CD}_{pk} V_{pkct} + \sum_{p=1}^P \sum_{c=1}^C \sum_{m=1}^M \sum_{t=1}^T \widetilde{CC}_{pm} O_{pcmt} \\
 & + \sum_{p=1}^P \sum_{m=1}^M \sum_{r=1}^R \sum_{t=1}^T \widetilde{CR}_{pr} R_{pmrt} + \sum_{p=1}^P \sum_{m=1}^M \sum_{d=1}^D \sum_{t=1}^T \widetilde{Cd}_{pd} N_{pmdt} \\
 & + \sum_{p=1}^P \sum_{j=1}^J \sum_{d=1}^D \sum_{t=1}^T \widetilde{c}w_{pd} g d_{pjdt} + \sum_{h=1}^H \sum_{t=1}^T C H_{ht} E S_{ht} \tag{1}
 \end{aligned}$$

Objective (2) minimizes the amount of GHG emissions caused by transportation at either stage of the SC (CE), as well as the nonrenewable energy use (EE) or waste created during drug producing (WG).

$$\text{Min}Z_2 = W^c CE + W^{ec} EE + W^w WG \tag{2}$$

The main cause of climate change is GHG emissions. The total direct and indirect GHG is one of the environmental indicators that have a substantial impact on global warming, per GRI305 criteria (GRI, 2016). The total quantity of GHG emissions brought on by the shipping throughout all time periods to generate the first component of the environmental goal function.

$$\begin{aligned}
 CE = & \sum_{g=1}^G \sum_{p=1}^P \sum_{i=1}^I \sum_{k=1}^K \sum_{t=1}^T \widetilde{CE}_{gpi} d_{ik} I_{pikt} + \sum_{g=1}^G \sum_{q=1}^Q \sum_{p=1}^P \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T \widetilde{CE}_{gqsj} d_{sj} S_{qpsjt} \\
 & + \sum_{g=1}^G \sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T \widetilde{CE}_{gpj} d_{jk} Y_{pjkt} + \sum_{g=1}^G \sum_{p=1}^P \sum_{k=1}^K \sum_{c=1}^C \sum_{t=1}^T \widetilde{CE}_{gpk} d_{kc} V_{pkct}
 \end{aligned}$$

$$\begin{aligned}
 &+ \sum_{g=1}^G \sum_{p=1}^P \sum_{c=1}^C \sum_{m=1}^M \sum_{t=1}^T \widetilde{CE}_{gpcm} d_{cm} O_{pcmt} + \sum_{g=1}^G \sum_{p=1}^P \sum_{m=1}^M \sum_{r=1}^R \sum_{t=1}^T \widetilde{CE}_{gpmr} d_{mr} R_{pmrt} \\
 &+ \sum_{g=1}^G \sum_{p=1}^P \sum_{m=1}^M \sum_{d=1}^D \sum_{t=1}^T \widetilde{CE}_{gpm d} d_{md} N_{pmdt} \\
 &+ \sum_{g=1}^G \sum_{q=1}^Q \sum_{p=1}^P \sum_{r=1}^R \sum_{j=1}^J \sum_{t=1}^T \widetilde{CE}_{gqrj} d_{rj} M_{qprjt} + \sum_{g=1}^G \sum_{p=1}^P \sum_{j=1}^J \sum_{d=1}^D \sum_{t=1}^T \widetilde{CE}_{gpjd} d_{jd} g d_{pjdt}
 \end{aligned} \tag{3}$$

Energy use may be used as an environmental indicator to gauge how efficiently people use energy according to the GRI302 section (GRI, 2016). The quantity of nonrenewable energy spent, which relies on the number of products, to create the second component of the environmental objective function.

$$EE = \sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T \widetilde{ec}_{pj} Y_{pjkt} \tag{4}$$

According to the GRI306 section of the GRI report (GRI, 2016), the waste generation and disposal including its improper transportation can also pose harm to human health and the environment. This is of particular concern if waste is transported to zones lacking the infrastructure and regulations to handle it. Another environmental indicator that pertains to waste is the third part of this paper’s environmental goal function, which indicates the waste generated during the creation of medications.

$$WG = \sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T gw_{pj} Y_{pjkt} \tag{5}$$

Employment creation (EC), number of days dropped due to a job accident (ED), economic growth (RG), job satisfaction (JS), and national self-sufficiency (SS) are all social factors that objective (3) maximizes.

$$Max Z_3 = W^o EC - W^d ED + W^e RG + W^j JS + W^s SS \tag{6}$$

The topic of employment, which is concerned with companies’ approaches to employment and its specific arrangements in the SC, is covered in the GRI401 section of the GRI report (GRI,2016). A number of work possibilities will be created with the establishment of centers. On the other hand, depending on how the centers’ capacity is utilized, a variety of variable job opportunities will be produced in the centers. In addition, depending on the volume of transportation, a number of work possibilities are available for the movement of materials and goods between the levels of the chain. Fixed and variable work possibilities provided by establishment of centers and transportation over the time are included in the first portion of the social aim, which is written as follows:

$$\begin{aligned}
 EC = & \sum_{j=1}^J \widetilde{FO}_j x_j + \sum_{k=1}^K \widetilde{FO}_k x_k + \sum_{m=1}^M \widetilde{FO}_m x_m + \sum_{r=1}^R \widetilde{FO}_r x_r + \sum_{d=1}^D \widetilde{FO}_d x_d \\
 & + \sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T \widetilde{vo}_j \frac{Y_{pjkt}}{CA_{jp}} + \sum_{p=1}^P \sum_{k=1}^K \sum_{c=1}^C \sum_{t=1}^T \widetilde{vo}_k \frac{V_{pkct}}{CA_{kp}}
 \end{aligned}$$

$$\begin{aligned}
 & + \sum_{p=1}^P \sum_{m=1}^M \sum_{r=1}^R \sum_{d=1}^D \sum_{t=1}^T \widetilde{vO}_m \frac{R_{pmrt} + N_{pmdt}}{ca_{mp}} + \sum_{q=1}^Q \sum_{p=1}^P \sum_{r=1}^R \sum_{j=1}^J \sum_{t=1}^T \widetilde{vO}_r \frac{M_{qprjt}}{ca_{rp}} \\
 & + \sum_{p=1}^P \sum_{m=1}^M \sum_{d=1}^D \sum_{t=1}^T \widetilde{vO}_d \frac{N_{pmdt}}{ca_{dp}} + \sum_{v=1}^V \sum_{t=1}^T \widetilde{vO}_t v \left[\sum_{j=1}^J \sum_{k=1}^K nv_{vjkt} + \sum_{k=1}^K \sum_{c=1}^C nv_{vckt} \right. \\
 & + \sum_{i=1}^I \sum_{k=1}^K nv_{vikt} + \sum_{s=1}^S \sum_{j=1}^J nv_{vsjt} + \sum_{c=1}^C \sum_{m=1}^M nv_{vcmt} + \sum_{m=1}^M \sum_{r=1}^R nv_{vmrt} \\
 & \left. + \sum_{m=1}^M \sum_{d=1}^D nv_{vmdt} + \sum_{r=1}^R \sum_{j=1}^J nv_{vrjt} + \sum_{j=1}^J \sum_{d=1}^D nv_{vjdt} \right] \tag{7}
 \end{aligned}$$

The physical safety and comfort of workers should be seen as a significant social feature, where the workers’ health and safety is a social indicator, according to GRI standards (GRI, 2016). The number of working days lost as a result of employee illnesses and accidents is utilized in this study as a proxy for workplace health and safety. The second component of the social function calculates the total number of lost days in places indicated for the establishment of PCs, DCs, CCs, RCs, and DICs.

$$ED = \sum_{j=1}^J \widetilde{ID}_j x_j + \sum_{k=1}^K \widetilde{ID}_k x_k + \sum_{m=1}^M \widetilde{ID}_m x_m + \sum_{r=1}^R \widetilde{ID}_r x_r + \sum_{d=1}^D \widetilde{ID}_d x_d \tag{8}$$

The GRI report’s GRI405 section (GRI, 2016) addresses the topic of balance opportunities. When a company promotes equality, it has the potential to benefit society significantly. In light of this, the third component of the social objective determines the level of balanced economic growth by taking into account the economic value of facilities and regional development in places indicated for the establishment of PCs, DCs, CCs, RCs, and DICs:

$$\begin{aligned}
 RG = & \sum_{j=1}^J \widetilde{ev}_j (1 - \widetilde{dl}_j) x_j + \sum_{k=1}^K \widetilde{ev}_k (1 - \widetilde{dl}_k) x_k + \sum_{m=1}^M \widetilde{ev}_m (1 - \widetilde{dl}_m) x_m \\
 & + \sum_{r=1}^R \widetilde{ev}_r (1 - \widetilde{dl}_r) x_r + \sum_{d=1}^D \widetilde{ev}_d (1 - \widetilde{dl}_d) x_d \tag{9}
 \end{aligned}$$

Employee support is a social metric that is included in section GRI401 of the GRI standards (GRI, 2016) and is treated as job satisfaction in this article. The GRI guidelines state that one of the indicators with social consequences on companies is employee support, which includes things like interest-free loans, redundancy compensation, housing assistance, educational grants, etc. Following is a calculation of the employees’ degree of job satisfaction:

$$JS = \sum_{h=1}^H \sum_{t=1}^T \widetilde{JS}_h ES_{ht} \tag{10}$$

According to the GRI report’s GRI401 section (GRI, 2016), the fifth component of the social function is how production affects self-sufficiency. Undoubtedly, increased output

increases a nation’s self-sufficiency and results in a less dependent economy.

$$SS = \psi \sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T Y_{pjkt} \tag{11}$$

The flow balance between SC levels is defined in constraints (12–16).

$$\sum_{s=1}^S S_{qpsjt} + \sum_{r=1}^R M_{qprjt} = \sum_{k=1}^K Y_{pjkt} I_{qp}, \forall p, j, q, t \tag{12}$$

$$(1 - \alpha) \sum_{c=1}^C O_{pcmt} = \sum_{d=1}^D N_{pmdt}, \forall p, m, t \tag{13}$$

$$\alpha \sum_{c=1}^C O_{pcmt} = \sum_{r=1}^R R_{pmrt}, \forall p, m, t \tag{14}$$

$$\sum_{m=1}^M R_{pmrt} \beta_{qp} = \sum_{j=1}^J M_{qprjt}, \forall q, p, r, t \tag{15}$$

$$\sum_{j=1}^J \sum_{k=1}^K gw_{pj} Y_{pjkt} = \sum_{j=1}^J \sum_{d=1}^D gd_{pjdt}, \forall p, t \tag{16}$$

Constraints (17–19) reflect the inventory level of drugs for a distributor at all times depending on their shelf life. Constraint (17) states that in the first time period, the inventory level is calculated by comparing the amount of pharmaceuticals imported and generated with the quantity of drugs sent to DCs. The amount of drug inventory produced in the prior time periods will be added to these amounts if the time period is shorter than the drug’s shelf time in accordance with constraint (18). According to constraint (19), when the time period is higher than or equal to the life time of drugs, the inventory of drugs had been created in the time period from $e = t + 1 - LF_p$ to before t is taken into consideration.

$$\sum_{e=1}^t Q_{pekt} = \sum_{i=1}^I I_{pikt} + \sum_{j=1}^J Y_{pjkt} - \sum_{c=1}^C V_{pkct}, \forall p, k, t = 1 < LF_p \tag{17}$$

$$\sum_{e=1}^t Q_{pekt} = \sum_{e=1}^{t-1} Q_{pekt-1} + \sum_{i=1}^I I_{pikt} + \sum_{j=1}^J Y_{pjkt} - \sum_{c=1}^C V_{pkct}, \forall p, k, 1 < t < LF_p \tag{18}$$

$$\sum_{e=t+1-LF_p}^t Q_{pekt} = \sum_{e=t+1-LF_p}^{t-1} Q_{pekt-1} + \sum_{i=1}^I I_{pikt} + \sum_{j=1}^J Y_{pjkt} - \sum_{c=1}^C V_{pkct}, \forall p, k, t \geq LF_p \tag{19}$$

The volume of drug transported to the final customer must be less than the inventory warehouse level in DCs, according to constraints (20).

$$\sum_{c=1}^C V_{pkct} \leq Q_{pekt}, \forall p, k, e, t \tag{20}$$

Constraint (21) ensures that the overall consumer demand for each drug is fulfilled.

$$\sum_{k=1}^K V_{pkct} \geq \widetilde{D}_{cpt}, \forall p, c, t \tag{21}$$

Constraint (22) suggests that the cost of job supports should be smaller than the maximum budget allotted to job support.

$$\sum_{h=1}^H CH_{ht} ES_{ht} \leq MB_t, \forall t \tag{22}$$

Constraints (23–30) signify the capacity of the centers of distribution, production, importing, supplying, collection, recycling and disposal. Full capacity should be used when a center is built. It is important to highlight that manufacturers may generate the required pharmaceuticals in accordance with overall demand based on the production capacity restriction, and importation centers can import drugs in accordance with capacity and drug purchase costs. If the cost of importing pharmaceuticals is greater than the cost of producing drugs, the manufacturers will, in accordance with their capability, meet consumer demand first. Pharmaceutical importing firms can fill any unmet demand from customers if a producer’s capacity is insufficient to supply the entire demand. When the cost of producing a medicine is more than the cost of importing it, the importer initially meets customer demand in accordance with their capacity before the remaining demand is handled by the PCs.

$$\sum_{c=1}^C V_{pkct} \leq \widetilde{ca}_{kp} x_k, \forall p, k, t \tag{23}$$

$$\sum_{k=1}^K Y_{pjkt} \leq \widetilde{ca}_{jp} x_j, \forall p, j, t \tag{24}$$

$$\sum_{j=1}^J Y_{pjkt} \leq \widetilde{ca}_{kp} x_k, \forall p, k, t \tag{25}$$

$$\sum_{k=1}^K I_{pikt} \leq \widetilde{ca}_{ip}, \forall p, i, t \tag{26}$$

$$\sum_{j=1}^J S_{qpsjt} \leq \widetilde{ca}_{sq}, \forall q, p, s, t \tag{27}$$

$$\sum_{c=1}^C O_{pcmt} \leq \widetilde{ca}_{mp} x_m, \forall p, m, t \tag{28}$$

$$\sum_{m=1}^M R_{pmrt} \leq \widetilde{ca}_{rp} x_r, \forall p, r, t \tag{29}$$

$$\sum_{m=1}^M N_{pmdt} \leq \widetilde{ca}_{dp} x_d, \forall p, d, t \tag{30}$$

Constraints (31–39) indicate the vehicle capacity.

$$\sum_{v=1}^V Ca_v n v_{vsjt} \geq S_{qpsjt}, \forall q, p, s, j, t \tag{31}$$

$$\sum_{v=1}^V Ca_v n v_{vikt} \geq I_{pikt}, \forall p, i, k, t \tag{32}$$

$$\sum_{v=1}^V Ca_v n v_{vjkt} \geq Y_{pjkt}, \forall p, j, k, t \tag{33}$$

$$\sum_{v=1}^V Ca_vnv_{vkct} \geq V_{pkct}, \forall p, k, c, t \tag{34}$$

$$\sum_{v=1}^V Ca_vnv_{vcmt} \geq O_{pcmt}, \forall p, c, m, t \tag{35}$$

$$\sum_{v=1}^V Ca_vnv_{vmrt} \geq R_{pmrt}, \forall p, m, r, t \tag{36}$$

$$\sum_{v=1}^V Ca_vnv_{vmdt} \geq N_{pmdt}, \forall p, m, d, t \tag{37}$$

$$\sum_{v=1}^V Ca_vnv_{vrjt} \geq M_{qprjt}, \forall q, p, r, j, t \tag{38}$$

$$\sum_{v=1}^V Ca_vnv_{vjdt} \geq gd_{pjdt}, \forall p, j, d, t \tag{39}$$

Constraints (40–42) identify the decision variables’ boundaries.

$$Y_{pjkt}, V_{pkct}, Q_{pekt}, I_{pikt}, S_{qpsjt}, O_{pcmt}, R_{pmrt}, N_{pmdt}, M_{qprjt}, gd_{pjdt} \geq 0, \forall p, q, j, k, i, s, c, m, r, d, t, e \tag{40}$$

$$nv_{vsjt}, nv_{vikt}, nv_{vjkt}, nv_{vkct}, nv_{vcmt}, nv_{vmdt}, nv_{vmrt}, nv_{vrjt}, nv_{vjdt} \text{ integer}, \forall v, s, j, i, k, c, m, r, d, t \tag{41}$$

$$x_j, x_k, x_m, x_r, x_d, ES_{ht} \in \{0, 1\}, \forall j, k, m, r, d, h, t \tag{42}$$

4 Accounting for data uncertainty

There are two types of fuzzy programming methods: (1) possibilistic programming and (2) flexible programming (Mousazadeh et al., 2018). Flexible programming tackles the soft constraint and flexibility on the target value of objectives. Possibilistic programming is useful where the input parameters are undefined or the exact value of the parameters is unclear (Pishvae & Khalaf, 2016). According to the real-world nature of the proposed model, all methods must be implemented together to handle inherent ambiguity in input data and the elasticity of constraints. This article employs the MPFRP method proposed by Pishvae and Khalaf (2016) to handle uncertainty in input parameters and flexibility in objectives and constraints.

A concise overview of this method is provided below. Find the fuzzy model mentioned below, which contains both uncertain parameters and flexible constraints:

$$\begin{aligned} \text{Min}Z &= \tilde{c}x + \tilde{f}y \\ \text{s.t.} \\ Ax &\tilde{\geq} \tilde{d} \\ Sx &\tilde{\leq} \tilde{N}y \\ y &\in \{0, 1\}, x \geq 0 \end{aligned} \tag{43}$$

where \tilde{c} and \tilde{f} are objectives' coefficients, A and S represent constraints' coefficients, \tilde{d} and \tilde{N} are triangular fuzzy parameters, $\tilde{d} = (d^p, d^m, d^o)$ and $\tilde{N} = (N^p, N^m, N^o)$, x is a positive variable and y is a binary variable. Symbol $\tilde{\geq}$ is known to be a fuzzy variant of \geq that indicates the constraint's right side is slightly less than or equal to the constraint's left side. The violation of soft constraints can be represented by two fuzzy numbers (\tilde{t} and \tilde{r}). The following is how the model can be described:

$$\begin{aligned}
 \text{Min}Z &= \tilde{c}x + \tilde{f}y \\
 \text{s.t.} \\
 Ax &\geq \tilde{d} - \tilde{t}(1 - \alpha) \\
 Sx &\leq \tilde{N}y + [\tilde{r}(1 - \beta)]y \\
 y &\in \{0, 1\}, x \geq 0
 \end{aligned}
 \tag{44}$$

Parameters α and β are a measure of the minimum degree of satisfaction of flexible constraints. Two triangular fuzzy numbers (\tilde{t} and \tilde{r}) are employed to display the violation of soft constraints. These fuzzy numbers can be represented by their three influential points ($\tilde{t} = (t^p, t^m, t^o)$ and $\tilde{r} = (r^p, r^m, r^o)$). \tilde{t} and \tilde{r} can be defuzzified with the fuzzy ranking system proposed by Yager (1979, 1981) as follows:

$$\left(t^m + \left(\frac{\varphi_t - \varphi_{t'}}{3} \right) \right),
 \tag{45}$$

$$\left(r^m + \left(\frac{h_r - h_{r'}}{3} \right) \right),
 \tag{46}$$

where parameters φ_t and $\varphi_{t'}$ (h_r and $h_{r'}$) are the lateral margins of triangular fuzzy number \tilde{t} (\tilde{r}) and are given as:

$$\varphi_t = t^o - t^m,
 \tag{47}$$

$$\varphi_{t'} = t^m - t^p.
 \tag{48}$$

Centered on the possibilistic programming method set out in Jimenez et al., (2007) and Pishvae and Torabi (2010), the mixed possibilistic flexible programming model is stated as follows:

$$\begin{aligned}
 \text{Min}Z &= \left(\frac{c^p + c^m + c^o}{3} \right)x + \left(\frac{f^p + f^m + f^o}{3} \right)y \\
 \text{s.t.} \\
 Ax &\geq \left[\delta \left(\frac{d^m + d^o}{2} \right) + (1 - \delta) \left(\frac{d^p + d^m}{2} \right) \right] - \left(t^m + \left(\frac{\varphi_t - \varphi_{t'}}{3} \right) \right) (1 - \alpha) \\
 Sx &\leq \left[\rho \left(\frac{N^p + N^m}{2} \right) + (1 - \rho) \left(\frac{N^m + N^o}{2} \right) \right] y + \left[\left(r^m + \left(\frac{h_r - h_{r'}}{3} \right) \right) (1 - \beta) \right] y \\
 y &\in \{0, 1\}, x \geq 0
 \end{aligned}
 \tag{49}$$

The present objective function, which is based on expected value, ignores the possibility of objective function violation due to parameter uncertainty. The aforementioned factors render the resulting outcomes untrustworthy, which could result in DM incurring huge unanticipated

expenditures. The MPFRP model proposed by Pishvae and Khalaf (2016) is as follows:

$$\begin{aligned}
 \text{Min}Z = & \left(\frac{c^p + c^m + c^o}{3}\right)x + \left(\frac{f^p + f^m + f^o}{3}\right)y \\
 & + \pi \left[[c^o x + f^o y] - \left[\left(\frac{c^p + c^m + c^o}{3}\right)x + \left(\frac{f^p + f^m + f^o}{3}\right)y \right] \right] \\
 & + \omega \left[d^m - \delta \left(\frac{d^m + d^o}{2}\right) - (1 - \delta) \left(\frac{d^p + d^m}{2}\right) \right] \\
 & + \mu \left[\rho \left(\frac{N^p + N^m}{2}\right) + (1 - \rho) \left(\frac{N^m + N^o}{2}\right) - N^p \right] y + \gamma \left[\left(t^m + \frac{\varphi_t - \varphi'_t}{3}\right)(1 - \alpha) \right] \\
 & + \theta \left[\left(r^m + \left(\frac{h_r - h'_r}{3}\right)\right)(1 - \beta) \right] y,
 \end{aligned}$$

s.t.

$$\begin{aligned}
 Ax & \geq \left[\delta \left(\frac{d^m + d^o}{2}\right) + (1 - \delta) \left(\frac{d^p + d^m}{2}\right) \right] - \left(t^m + \left(\frac{\varphi_t - \varphi'_t}{3}\right) \right) (1 - \alpha) \\
 Sx & \leq \left[\rho \left(\frac{N^p + N^m}{2}\right) + (1 - \rho) \left(\frac{N^m + N^o}{2}\right) \right] y + \left[\left(r^m + \left(\frac{h_r - h'_r}{3}\right) \right) (1 - \beta) \right] y \\
 y & \in \{0, 1\}, x \geq 0.
 \end{aligned}$$

(50)

The first and second terms of objective function represent the system’s average performance based on the predicted values of uncertain parameters. The third term modifies the robustness of optimality and reduces the maximum deviation of objective function from its predicted value ($Z_{max} - E(Z)$). The relevance of this phrase in comparison to other terms is determined by the parameter π . The remaining terms focus on minimizing overall penalty costs resulting from any soft constraint violations. Furthermore, parameters ω and μ reflect the penalty cost for each unit of constraint violation caused by uncertain parameters’ imprecision. Parameters δ and ρ denote the confidence level of the constraint encompassing uncertain parameters ($0.5 \leq \rho, \delta \leq 1$). Parameters α and β are the degree of satisfaction of flexible constraints ($0 \leq \alpha, \beta \leq 1$). Although these values may be treated as variables and obtained by solving the model, the DMs should rank the significance of the aforementioned parameters in this study in order to account for their preferences.

It should be noted that the robustness cost is added as a virtual penalty to the economics objective function, which typically includes real costs such as fixed costs and transportation costs, in all previous studies that have used the robust fuzzy programming approach. However, because robustness costs are not a real part of operating costs, they cannot logically be summed into a single goal in line with the other operating costs. However, if these virtual costs are to be integrated by the real costs, the DM will be unable to distinguish the shares of real and virtual costs when the model is solved using a multi-objective approach. As a result, in this paper, a separate objective function (i.e., the robustness cost) is used to address the deficiencies mentioned above according to Boronoos et al., (2021). Consequently, the proposed MPFRP model can be formulated as follows:

$$\text{Min}Z_1 = \sum_{j=1}^J \left(\frac{F_j^p + F_j^m + F_j^o}{3}\right)x_j + \sum_{k=1}^K \left(\frac{F_k^p + F_k^m + F_k^o}{3}\right)x_k$$

$$\begin{aligned}
 & + \sum_{m=1}^M \left(\frac{F_m^p + F_m^m + F_m^o}{3} \right) x_m + \sum_{r=1}^R \left(\frac{F_r^p + F_r^m + F_r^o}{3} \right) x_r \\
 & + \sum_{d=1}^D \left(\frac{F_d^p + F_d^m + F_d^o}{3} \right) x_d + \sum_{v=1}^V \sum_{t=1}^T \left(\frac{F_v^p + F_v^m + F_v^o}{3} \right) \\
 & \left[\sum_{j=1}^J \sum_{k=1}^K n v_{vjkt} + \sum_{k=1}^K \sum_{c=1}^C n v_{vckt} + \sum_{i=1}^I \sum_{k=1}^K n v_{vikt} \right. \\
 & + \sum_{s=1}^S \sum_{j=1}^J n v_{vsjt} + \sum_{c=1}^C \sum_{m=1}^M n v_{vcmt} + \sum_{m=1}^M \sum_{r=1}^R n v_{vmrt} \\
 & \left. + \sum_{m=1}^M \sum_{d=1}^D n v_{vmdt} + \sum_{r=1}^R \sum_{j=1}^J n v_{vrjt} + \sum_{j=1}^J \sum_{d=1}^D n v_{vjdt} \right] \\
 & + \sum_{v=1}^V \sum_{t=1}^T \left(\frac{TC_{vt}^p + TC_{vt}^m + TC_{vt}^o}{3} \right) \left[\sum_{j=1}^J \sum_{k=1}^K d_{jk} n v_{vjkt} + \sum_{k=1}^K \sum_{c=1}^C d_{kc} n v_{vckt} \right. \\
 & + \sum_{i=1}^I \sum_{k=1}^K d_{ik} n v_{vikt} + \sum_{s=1}^S \sum_{j=1}^J d_{sj} n v_{vsjt} + \sum_{c=1}^C \sum_{m=1}^M d_{cm} n v_{vcmt} + \sum_{m=1}^M \sum_{r=1}^R d_{mr} n v_{vmrt} \\
 & \left. + \sum_{m=1}^M \sum_{d=1}^D d_{md} n v_{vmdt} + \sum_{r=1}^R \sum_{j=1}^J d_{rj} n v_{vrjt} + \sum_{j=1}^J \sum_{d=1}^D d_{jd} n v_{vjdt} \right] \\
 & + \sum_{p=1}^P \sum_{e=1}^E \sum_{k=1}^K \sum_{t=1}^T \left(\frac{h_{pk}^p + h_{pk}^m + h_{pk}^o}{3} \right) Q_{pekt} \\
 & + \sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T \left(\frac{C_{pj}^p + C_{pj}^m + C_{pj}^o}{3} \right) Y_{pjkt} \\
 & + \sum_{q=1}^Q \sum_{p=1}^P \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T \left(\frac{CB_{qs}^p + CB_{qs}^m + CB_{qs}^o}{3} \right) S_{qpsjt} \\
 & + \sum_{p=1}^P \sum_{i=1}^I \sum_{k=1}^K \sum_{t=1}^T \left(\frac{CM_{pi}^p + CM_{pi}^m + CM_{pi}^o}{3} \right) I_{pikt} \\
 & + \sum_{p=1}^P \sum_{k=1}^K \sum_{c=1}^C \sum_{t=1}^T \left(\frac{CD_{pk}^p + CD_{pk}^m + CD_{pk}^o}{3} \right) V_{pkct} \\
 & + \sum_{p=1}^P \sum_{c=1}^C \sum_{m=1}^M \sum_{t=1}^T \left(\frac{CC_{pm}^p + CC_{pm}^m + CC_{pm}^o}{3} \right) O_{pcmt} \\
 & + \sum_{p=1}^P \sum_{m=1}^M \sum_{r=1}^R \sum_{t=1}^T \left(\frac{CR_{pr}^p + CR_{pr}^m + CR_{pr}^o}{3} \right) R_{pmrt}
 \end{aligned}$$

$$\begin{aligned}
 & + \sum_{p=1}^P \sum_{m=1}^M \sum_{d=1}^D \sum_{t=1}^T \left(\frac{Cd_{pd}^p + Cd_{pd}^m + Cd_{pd}^o}{3} \right) N_{pmdt} \\
 & + \sum_{p=1}^P \sum_{j=1}^J \sum_{d=1}^D \sum_{t=1}^T \left(\frac{cw_{pd}^p + cw_{pd}^m + cw_{pd}^o}{3} \right) gd_{pjdt} + \sum_{h=1}^H \sum_{t=1}^T CH_{ht}ES_{ht} \tag{51}
 \end{aligned}$$

$$\begin{aligned}
 MinZ_2 = & W^c \left(\sum_{g=1}^G \sum_{p=1}^P \sum_{i=1}^I \sum_{k=1}^K \sum_{t=1}^T \left(\frac{CE_{gpik}^p + CE_{gpik}^m + CE_{gpik}^o}{3} \right) d_{ik}I_{pikt} \right. \\
 & + \sum_{g=1}^G \sum_{q=1}^Q \sum_{p=1}^P \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T \left(\frac{CE_{gqsj}^p + CE_{gqsj}^m + CE_{gqsj}^o}{3} \right) d_{sj}S_{qpsjt} \\
 & + \sum_{g=1}^G \sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T \left(\frac{CE_{gpjk}^p + CE_{gpjk}^m + CE_{gpjk}^o}{3} \right) d_{jk}Y_{pjkt} \\
 & + \sum_{g=1}^G \sum_{p=1}^P \sum_{k=1}^K \sum_{c=1}^C \sum_{t=1}^T \left(\frac{CE_{gpkc}^p + CE_{gpkc}^m + CE_{gpkc}^o}{3} \right) d_{kc}V_{pkct} \\
 & + \sum_{g=1}^G \sum_{p=1}^P \sum_{c=1}^C \sum_{m=1}^M \sum_{t=1}^T \left(\frac{CE_{gpcm}^p + CE_{gpcm}^m + CE_{gpcm}^o}{3} \right) d_{cm}O_{pcmt} \\
 & + \sum_{g=1}^G \sum_{p=1}^P \sum_{m=1}^M \sum_{r=1}^R \sum_{t=1}^T \left(\frac{CE_{gpmr}^p + CE_{gpmr}^m + CE_{gpmr}^o}{3} \right) d_{mr}R_{pmrt} \\
 & + \sum_{g=1}^G \sum_{p=1}^P \sum_{m=1}^M \sum_{d=1}^D \sum_{t=1}^T \left(\frac{CE_{gpmd}^p + CE_{gpmd}^m + CE_{gpmd}^o}{3} \right) d_{md}N_{pmdt} \\
 & + \sum_{g=1}^G \sum_{q=1}^Q \sum_{p=1}^P \sum_{r=1}^R \sum_{j=1}^J \sum_{t=1}^T \left(\frac{CE_{gqrj}^p + CE_{gqrj}^m + CE_{gqrj}^o}{3} \right) d_{rj}M_{qprjt} \\
 & + \sum_{g=1}^G \sum_{p=1}^P \sum_{j=1}^J \sum_{d=1}^D \sum_{t=1}^T \left(\frac{CE_{gpjd}^p + CE_{gpjd}^m + CE_{gpjd}^o}{3} \right) d_{jd}gd_{pjdt} \Big) \\
 & + W^{ec} \left(\sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T \left(\frac{ec_{pj}^p + ec_{pj}^m + ec_{pj}^o}{3} \right) Y_{pjkt} \right) \tag{52} \\
 & + W^w \left(\sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T gw_{pj}Y_{pjkt} \right)
 \end{aligned}$$

$$\begin{aligned}
Max Z_3 = & W^o \left(\sum_{j=1}^J \left(\frac{Fo_j^p + Fo_j^m + Fo_j^o}{3} \right) x_j \right. \\
& + \sum_{k=1}^K \left(\frac{Fo_k^p + Fo_k^m + Fo_k^o}{3} \right) x_k + \sum_{m=1}^M \left(\frac{Fo_m^p + Fo_m^m + Fo_m^o}{3} \right) x_m \\
& + \sum_{r=1}^R \left(\frac{Fo_r^p + Fo_r^m + Fo_r^o}{3} \right) x_r + \sum_{d=1}^D \left(\frac{Fo_d^p + Fo_d^m + Fo_d^o}{3} \right) x_d \\
& + \sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T \left(\frac{vo_j^p + vo_j^m + vo_j^o}{ca_{jp}^p + ca_{jp}^m + ca_{jp}^o} \right) Y_{pjkt} \\
& + \sum_{p=1}^P \sum_{k=1}^K \sum_{c=1}^C \sum_{t=1}^T \left(\frac{vo_k^p + vo_k^m + vo_k^o}{ca_{kp}^p + ca_{kp}^m + ca_{kp}^o} \right) V_{pkct} \\
& + \sum_{p=1}^P \sum_{m=1}^M \sum_{r=1}^R \sum_{d=1}^D \sum_{t=1}^T \left(\frac{vo_m^p + vo_m^m + vo_m^o}{ca_{mp}^p + ca_{mp}^m + ca_{mp}^o} \right) (R_{pmrt} + N_{pmdt}) \\
& + \sum_{q=1}^Q \sum_{p=1}^P \sum_{r=1}^R \sum_{j=1}^J \sum_{t=1}^T \left(\frac{vo_r^p + vo_r^m + vo_r^o}{ca_{rp}^p + ca_{rp}^m + ca_{rp}^o} \right) M_{qprjt} \\
& + \sum_{p=1}^P \sum_{m=1}^M \sum_{d=1}^D \sum_{t=1}^T \left(\frac{vo_d^p + vo_d^m + vo_d^o}{ca_{dp}^p + ca_{dp}^m + ca_{dp}^o} \right) N_{pmdt} \\
& + \sum_{v=1}^V \sum_{t=1}^T \left(\frac{vot_v^p + vot_v^m + vot_v^o}{3} \right) \left[\sum_{j=1}^J \sum_{k=1}^K nv_{vjkt} + \sum_{k=1}^K \sum_{c=1}^C nv_{vckt} \right. \\
& + \sum_{i=1}^I \sum_{k=1}^K nv_{vikt} + \sum_{s=1}^S \sum_{j=1}^J nv_{vsjt} + \sum_{c=1}^C \sum_{m=1}^M nv_{vcmt} + \sum_{m=1}^M \sum_{r=1}^R nv_{vmrt} + \sum_{m=1}^M \sum_{d=1}^D nv_{vmdt} \\
& \left. + \sum_{r=1}^R \sum_{j=1}^J nv_{vrjt} + \sum_{j=1}^J \sum_{d=1}^D nv_{vjdt} \right] \\
& - W^d \left(\sum_{j=1}^J \left(\frac{ID_j^p + ID_j^m + ID_j^o}{3} \right) x_j + \sum_{k=1}^K \left(\frac{ID_k^p + ID_k^m + ID_k^o}{3} \right) x_k \right. \\
& + \sum_{m=1}^M \left(\frac{ID_m^p + ID_m^m + ID_m^o}{3} \right) x_m + \sum_{r=1}^R \left(\frac{ID_r^p + ID_r^m + ID_r^o}{3} \right) x_r \\
& + \sum_{d=1}^D \left(\frac{ID_d^p + ID_d^m + ID_d^o}{3} \right) x_d \left. \right) \\
& + W^e \left(\sum_{j=1}^J \left(\frac{ev_j^p + ev_j^m + ev_j^o}{3} \right) \left(1 - \left(\frac{dl_j^p + dl_j^m + dl_j^o}{3} \right) \right) x_j \right. \\
& \left. + \sum_{k=1}^K \left(\frac{ev_k^p + ev_k^m + ev_k^o}{3} \right) \left(1 - \left(\frac{dl_k^p + dl_k^m + dl_k^o}{3} \right) \right) x_k \right)
\end{aligned}$$

$$\begin{aligned}
 & + \sum_{m=1}^M \left(\frac{ev_m^p + ev_m^m + ev_m^o}{3} \right) \left(1 - \left(\frac{dl_m^p + dl_m^m + dl_m^o}{3} \right) \right) x_m \\
 & + \sum_{r=1}^R \left(\frac{ev_r^p + ev_r^m + ev_r^o}{3} \right) \left(1 - \left(\frac{dl_r^p + dl_r^m + dl_r^o}{3} \right) \right) x_r \\
 & + \sum_{d=1}^D \left(\frac{ev_d^p + ev_d^m + ev_d^o}{3} \right) \left(1 - \left(\frac{dl_d^p + dl_d^m + dl_d^o}{3} \right) \right) x_d \\
 & + W^j \left(\sum_{h=1}^H \sum_{t=1}^T \left(\frac{JS_h^p + JS_h^m + JS_h^o}{3} \right) ES_{ht} \right) + W^s \left(\Psi \sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K \sum_{t=1}^T Y_{pjkt} \right) \tag{53}
 \end{aligned}$$

$$\begin{aligned}
 \text{Min} Z_4 = & \pi * \left[[Z_{1max} - E(Z_1)] + [Z_{2max} - E(Z_2)] + [E(Z_3) - Z_{3min}] \right] \\
 & + \omega * \left(\sum_{c=1}^C \sum_{p=1}^P \sum_{t=1}^T \left[D_{cpt}^m - \delta \left(\frac{D_{cpt}^m + D_{cpt}^o}{2} \right) - (1 - \delta) \left(\frac{D_{cpt}^p + D_{cpt}^m}{2} \right) \right] \right) \\
 & + \mu * \left(\sum_{k=1}^K \sum_{p=1}^P \left[\rho \left(\frac{ca_{kp}^p + ca_{kp}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{kp}^m + ca_{kp}^o}{2} \right) - ca_{kp}^p \right] x_k \right. \\
 & + \sum_{j=1}^J \sum_{p=1}^P \left[\rho \left(\frac{ca_{jp}^p + ca_{jp}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{jp}^m + ca_{jp}^o}{2} \right) - ca_{jp}^p \right] x_j \\
 & + \sum_{i=1}^I \sum_{p=1}^P \left[\rho \left(\frac{ca_{ip}^p + ca_{ip}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{ip}^m + ca_{ip}^o}{2} \right) - ca_{ip}^p \right] \\
 & + \sum_{s=1}^S \sum_{q=1}^Q \left[\rho \left(\frac{ca_{sq}^p + ca_{sq}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{sq}^m + ca_{sq}^o}{2} \right) - ca_{sq}^p \right] \\
 & + \sum_{m=1}^M \sum_{p=1}^P \left[\rho \left(\frac{ca_{mp}^p + ca_{mp}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{mp}^m + ca_{mp}^o}{2} \right) - ca_{mp}^p \right] x_m \\
 & + \sum_{r=1}^R \sum_{p=1}^P \left[\rho \left(\frac{ca_{rp}^p + ca_{rp}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{rp}^m + ca_{rp}^o}{2} \right) - ca_{rp}^p \right] x_r \\
 & + \sum_{d=1}^D \sum_{p=1}^P \left[\rho \left(\frac{ca_{dp}^p + ca_{dp}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{dp}^m + ca_{dp}^o}{2} \right) - ca_{dp}^p \right] x_d \\
 & + \gamma * \left(\sum_{t=1}^T \sum_{c=1}^C \sum_{p=1}^P \left(\vartheta_{cpt}^m + \frac{\varphi_{cpt} - \varphi_{\vartheta_{cpt}}}{3} \right) (1 - \alpha) \right) \\
 & + \theta * \left(\sum_{k=1}^K \sum_{p=1}^P \left[\left(r_{kp}^m + \frac{h_{r_{kp}} - h_{r_{kp}}}{3} \right) (1 - \beta) \right] x_k \right. \\
 & + \sum_{j=1}^J \sum_{p=1}^P \left[\left(r_{jp}^m + \frac{h_{r_{jp}} - h_{r_{jp}}}{3} \right) (1 - \beta) \right] x_j
 \end{aligned}$$

$$\begin{aligned}
& + \sum_{i=1}^I \sum_{p=1}^P \left[\left(r_{ip}^m + \frac{h_{rip} - h'_{rip}}{3} \right) (1 - \beta) \right] \\
& + \sum_{s=1}^S \sum_{q=1}^Q \left[\left(r_{sq}^m + \frac{h_{rsq} - h'_{rsq}}{3} \right) (1 - \beta) \right] \\
& + \sum_{m=1}^M \sum_{p=1}^P \left[\left(r_{mp}^m + \frac{h_{rmp} - h'_{rmp}}{3} \right) (1 - \beta) \right] x_m \\
& + \sum_{r=1}^R \sum_{p=1}^P \left[\left(r_{rp}^m + \frac{h_{rrp} - h'_{rrp}}{3} \right) (1 - \beta) \right] x_r \\
& + \sum_{d=1}^D \sum_{p=1}^P \left[\left(r_{dp}^m + \frac{h_{rdp} - h'_{rdp}}{3} \right) (1 - \beta) \right] x_d \quad (54)
\end{aligned}$$

s.t. (12) – (20), (22), (31) – (42)

$$\begin{aligned}
\sum_{k=1}^K V_{pkct} \geq & \left[\delta \left(\frac{D_{cpt}^m + D_{cpt}^o}{2} \right) + (1 - \delta) \left(\frac{D_{cpt}^p + D_{cpt}^m}{2} \right) \right] \\
& - \left(\vartheta_{cpt}^m + \frac{\varphi_{cpt} - \varphi'_{cpt}}{3} \right) (1 - \alpha), \forall p, c, t \quad (55)
\end{aligned}$$

$$\begin{aligned}
\sum_{c=1}^C V_{pkct} \leq & \left[\rho \left(\frac{ca_{kp}^p + ca_{kp}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{kp}^m + ca_{kp}^o}{2} \right) \right] x_k \\
& + \left[\left(r_{kp}^m + \frac{h_{rkp} - h'_{rkp}}{3} \right) (1 - \beta) \right] x_k, \forall p, k, t \quad (56)
\end{aligned}$$

$$\begin{aligned}
\sum_{k=1}^K Y_{pjkt} \leq & \left[\rho \left(\frac{ca_{jp}^p + ca_{jp}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{jp}^m + ca_{jp}^o}{2} \right) \right] x_j \\
& + \left[\left(r_{jp}^m + \frac{h_{rjp} - h'_{rjp}}{3} \right) (1 - \beta) \right] x_j, \forall p, j, t \quad (57)
\end{aligned}$$

$$\begin{aligned}
\sum_{j=1}^J Y_{pjkt} \leq & \left[\rho \left(\frac{ca_{kp}^p + ca_{kp}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{kp}^m + ca_{kp}^o}{2} \right) \right] x_k \\
& + \left[\left(r_{kp}^m + \frac{h_{rkp} - h'_{rkp}}{3} \right) (1 - \beta) \right] x_k, \forall p, k, t \quad (58)
\end{aligned}$$

$$\sum_{k=1}^K I_{pikt} \leq \left[\rho \left(\frac{ca_{ip}^p + ca_{ip}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{ip}^m + ca_{ip}^o}{2} \right) \right] + \left[\left(r_{ip}^m + \frac{h_{rip} - h_{rip}}{3} \right) (1 - \beta) \right], \forall p, i, t \quad (59)$$

$$\sum_{j=1}^J S_{qpsjt} \leq \left[\rho \left(\frac{ca_{sq}^p + ca_{sq}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{sq}^m + ca_{sq}^o}{2} \right) \right] + \left[\left(r_{sq}^m + \frac{h_{rsq} - h_{rsq}}{3} \right) (1 - \beta) \right], \forall q, p, s, t \quad (60)$$

$$\sum_{c=1}^C O_{pcmt} \leq \left[\rho \left(\frac{ca_{mp}^p + ca_{mp}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{mp}^m + ca_{mp}^o}{2} \right) \right] x_m + \left[\left(r_{mp}^m + \frac{h_{rmp} - h_{rmp}}{3} \right) (1 - \beta) \right] x_m, \forall p, m, t \quad (61)$$

$$\sum_{m=1}^M R_{pmrt} \leq \left[\rho \left(\frac{ca_{rp}^p + ca_{rp}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{rp}^m + ca_{rp}^o}{2} \right) \right] x_r + \left[\left(r_{rp}^m + \frac{h_{rrp} - h_{rrp}}{3} \right) (1 - \beta) \right] x_r, \forall p, r, t \quad (62)$$

$$\sum_{m=1}^M N_{pmdt} \leq \left[\rho \left(\frac{ca_{dp}^p + ca_{dp}^m}{2} \right) + (1 - \rho) \left(\frac{ca_{dp}^m + ca_{dp}^o}{2} \right) \right] x_d + \left[\left(r_{dp}^m + \frac{h_{rdp} - h_{rdp}}{3} \right) (1 - \beta) \right] x_d, \forall p, d, t \quad (63)$$

Note that Z_{1max} , Z_{2max} , and Z_{3min} are calculated using the optimistic values of the first and second and pessimistic value of the third objectives' unknown parameters, and their formulae have been omitted for brevity. Moreover, $E(Z_1)$, $E(Z_2)$, and $E(Z_3)$ are the expected value values of the first, second, and third objectives as they are stated in constraints (51) to (53).

5 Solution approach

This section presents a two-phase solution technique. Using the FBWM, the first phase assesses the significance of environmental and social indicators. The suggested multi-objective model is solved in the second phase using the TH approach.

5.1 FBWM

In this study, the social and environmental goals are broken down into a number of parts, each of which has a different weight and should be chosen depending on the advice of

Table 2 Rules on the transition of DM’s linguistic terms (Guo & Zhao, 2017)

Linguistic terms	Membership function
Equally important (EI)	(1, 1, 1)
Weakly important (WI)	(2/3, 1, 3/2)
Fairly important (FI)	(3/2, 2, 5/2)
Very important (VI)	(5/2, 3, 7/2)
Absolutely important (AI)	(7/2, 4, 9/2)

specialists. A reductive difficulty is determining the importance of the criteria in a decision-making problem. Rezaei (2015) has more recently offered the best–worst method (BWM) as a solution to this issue and a sensible way to perform pairwise comparisons. In this process, the DM determines the best and worst criteria first, and then specifies the efficiency of the best criterion relative to the other criteria, as well as the efficiency of the other criteria relative to the worst criterion. The BWM needs less pairwise comparisons than other multi-criteria decision-making approaches, such as AHP. In the case of a decision problem with n parameters, $\frac{(n \times (n-1))}{2}$ pairwise comparisons are needed in the AHP process, while the number of comparisons is $(2 \times n) - 3$ in the BWM (Omrani et al., 2020). The crisp values of criteria might not be sufficient to accurately represent multi-criteria decision-making in real life because uncertainty and doubt are commonly present in human judgments. To determine the weights of the criteria in this research, the FBWM developed by Guo and Zhao (2017) is applied. This technique takes into account the fuzziness of human mind and the ambiguity of objective things, enabling DMs to produce outcomes that are more congruent with real-world settings. According to Guo and Zhao (2017), the phases of the FBWM are as follows.

Phase 1. Evaluate the best and worst criteria. This can be achieved with the expert opinion or the Delphi process.

Phase 2. The best criteria is compared to other criteria, and other criteria are compared to the worst criterion. In this stage, any fuzzy spectrum can be used for pairwise comparisons, but the most common spectrum for this approach is the following five fuzzy spectra as seen in Table 2.

The comparison of fuzzy preferences contains two parts: first, the most important and least important criteria, which is best and worst, should be determined. After that, the best criterion must be compared to other criteria, and other criteria must be compared to the worst criterion. The obtained fuzzy best-to-others vector is:

$$\widetilde{A}_B = (\widetilde{a}_{B1}, \widetilde{a}_{B2}, \dots, \widetilde{a}_{Bn})$$

where \widetilde{A}_B is a fuzzy best-to-others vector; \widetilde{a}_{Bj} is a fuzzy choice of the best criteria over criterion j , $j = 1, 2, \dots, n$. It is possible to realize that $\widetilde{a}_{BB} = (1, 1, 1)$. The fuzzy others-to-worst vector can be obtained as follows:

$$\widetilde{A}_W = (\widetilde{a}_{1W}, \widetilde{a}_{2W}, \dots, \widetilde{a}_{nW})$$

where \widetilde{A}_W is a fuzzy others-to-worst vector; \widetilde{a}_{jW} is a fuzzy criterion j choice over the worst criterion. It is possible to realize that $\widetilde{a}_{WW} = (1, 1, 1)$.

Phase 3. Build a model of FBWM. In this phase, the weight of the criteria is determined using the following nonlinear model.

$$\begin{aligned}
 & \min \max_j \left\{ \left| \frac{\widetilde{w}_B}{\widetilde{w}_j} - \widetilde{a}_{Bj} \right|, \left| \frac{\widetilde{w}_j}{\widetilde{w}_W} - \widetilde{a}_{jW} \right| \right\} \\
 & \text{s.t} \\
 & \sum_{j=1}^n R(\widetilde{w}_j) = 1 \tag{64} \\
 & l_j^w \leq m_j^w \leq u_j^w \forall j = 1, 2, \dots, n \\
 & l_j^w \geq 0 \forall j = 1, 2, \dots, n
 \end{aligned}$$

where $\widetilde{w}_B = (l_B^w, m_B^w, u_B^w), \widetilde{w}_j = (l_j^w, m_j^w, u_j^w), \widetilde{w}_W = (l_W^w, m_W^w, u_W^w), \widetilde{a}_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj})$ and $\widetilde{a}_{jW} = (l_{jW}, m_{jW}, u_{jW})$.

The nonlinear model below can be made from the latter model.

$$\begin{aligned}
 & \min \widetilde{\xi} \\
 & \left| \frac{\widetilde{w}_B}{\widetilde{w}_j} - \widetilde{a}_{Bj} \right| \leq \widetilde{\xi}, \forall j = 1, 2, \dots, n \\
 & \left| \frac{\widetilde{w}_j}{\widetilde{w}_W} - \widetilde{a}_{jW} \right| \leq \widetilde{\xi}, \forall j = 1, 2, \dots, n \tag{65} \\
 & \sum_{j=1}^n R(\widetilde{w}_j) = 1 \\
 & l_j^w \leq m_j^w \leq u_j^w \forall j = 1, 2, \dots, n \\
 & l_j^w \geq 0 \forall j = 1, 2, \dots, n
 \end{aligned}$$

where $\widetilde{\xi} = (l^\xi, m^\xi, u^\xi)$. Suppose $l^\xi \leq m^\xi \leq u^\xi, \widetilde{\xi}^* = (k^*, k^*, k^*), k^* \leq l^\xi$, then the model can be transferred as follows:

$$\begin{aligned}
 & \min \widetilde{\xi}^* \\
 & \left| \frac{(l_B^w, m_B^w, u_B^w)}{(l_j^w, m_j^w, u_j^w)} - (l_{Bj}, m_{Bj}, u_{Bj}) \right| \leq (k^*, k^*, k^*) \forall j = 1, 2, \dots, n \\
 & \left| \frac{(l_j^w, m_j^w, u_j^w)}{(l_W^w, m_W^w, u_W^w)} - (l_{jW}, m_{jW}, u_{jW}) \right| \leq (k^*, k^*, k^*) \forall j = 1, 2, \dots, n \tag{66} \\
 & \sum_{j=1}^n R(\widetilde{w}_j) = 1 \\
 & l_j^w \leq m_j^w \leq u_j^w \forall j = 1, 2, \dots, n \\
 & l_j^w \geq 0, \forall j = 1, 2, \dots, n
 \end{aligned}$$

Phase 4. Solve the model using one of the optimization tools, such as GAMS, and achieve optimum weights.

5.2 TH method

The suggested model can be viewed as a more intricate variation of the capacitated facility location problem. In its simplest form, the capacitated facility location problem is an NP-Hard problem (HO, 2015). The suggested model contains economic, environmental, and social aims, hence multi-objective problem solving techniques must be applied to find solutions. Multi-objective model solution approaches may be broadly classified into three categories: priori methods, posteriori methods, and interactive methods. Priori techniques frequently include asking the DM their preference first, then choosing the response that comes the closest to their choice. The model is initially solved using the posteriori approach, and the DM then chooses the best result (Joneghani et al., 2022). One of the most commonly used posteriori strategies is the Epsilon constraint method (Hwang & Masud, 2012). Through interactive techniques that regularly repeat the solution process, the DM constantly engages with the solution process to determine the optimal solution (Miettinen, 2012). Among all the methods for solving multi-objective models, fuzzy approaches, which determine the degree of membership for each objective function, have attracted the greatest interest recently. One of the interactive fuzzy methods of solving multi-objective models is the TH method (Torabi & Hassini., 2008), which is also used in this paper due to its simple implementation and ability to deliver a Pareto optimum solution in a short processing time. Fuzzy approaches can be used to determine the appropriate solution based on the preferences of the DM (Zahiri et al., 2014). The DM may choose the optimal value for each goal function from the set of best-produced solutions by using the membership degree and weight specified for each objective. In contrast to the weighted sum approach, which can only create inefficient solutions, the use of the TH method yields a robust set of efficient solutions (Zahiri et al., 2014). The TH approach is comprised of the following steps:

1. Evaluate the positive ideal solution (PIS) and the negative ideal solution (NIS) for each objective as follows:

$$Z_1^{PIS} = \text{Min}Z_1 \quad Z_1^{NIS} = \text{Max}Z_1$$

$$Z_2^{PIS} = \text{Min}Z_2 \quad Z_2^{NIS} = \text{Max}Z_2$$

$$Z_3^{PIS} = \text{Max}Z_3 \quad Z_3^{NIS} = \text{Min}Z_3$$

2. Evaluate each objective's linear membership function as follows:

$$\mu_1(Z_1) = \begin{cases} 1 & \text{if } Z_1 < Z_1^{PIS} \\ \frac{Z_1^{NIS} - Z_1}{Z_1^{NIS} - Z_1^{PIS}} & \text{if } Z_1^{PIS} \leq Z_1 \leq Z_1^{NIS} \\ 0 & \text{if } Z_1 > Z_1^{NIS} \end{cases} \quad (67)$$

$$\mu_2(Z_2) = \begin{cases} 1 & \text{if } Z_2 < Z_2^{PIS} \\ \frac{Z_2^{NIS} - Z_2}{Z_2^{NIS} - Z_2^{PIS}} & \text{if } Z_2^{PIS} \leq Z_2 \leq Z_2^{NIS} \\ 0 & \text{if } Z_2 > Z_2^{NIS} \end{cases} \quad (68)$$

$$\mu_3(Z_3) = \begin{cases} 1 & \text{if } Z_3 > Z_3^{PIS} \\ \frac{Z_3 - Z_3^{NIS}}{Z_3^{PIS} - Z_3^{NIS}} & \text{if } Z_3^{NIS} \leq Z_3 \leq Z_3^{PIS} \\ 0 & \text{if } Z_3 < Z_3^{NIS} \end{cases} \quad (69)$$

3. Use the following formulation to convert the multi-objective model into a single-objective one:

$$\begin{aligned} \text{Max } \lambda(v) &= \gamma \lambda_0 + (1 - \gamma) \sum_h \theta_h \mu_h(v) \\ \text{s.t. } \lambda_0 &\leq \mu_h(v), h = 1, 2, 3 \\ v &\in F(v), \lambda_0 \text{ and } \gamma \in [0, 1] \end{aligned} \quad (70)$$

In cases where $F(v)$ represents a feasible area, $\mu_h(v)$ and $\lambda_0 = \min_h(\mu_h(v))$ denotes the level of satisfaction of objective h and the minimum level of satisfaction of objectives. In addition, the relative importance of objective h and the coefficient of compensation are shown by θ_h and γ . θ_h is calculated by the DM ($\sum_h \theta_h = 1, \theta_h > 0$).

4. Solve a single-objective model on the basis of the compensation coefficient (γ) and the relative importance of the objectives (θ_h). If the DM is comfortable with the solution obtained, stop; otherwise, change the values of the parameters specified to achieve a new solution.

6 Computational results

In this section, the performance of the suggested model is assessed using an actual case study focused on data gathered by Iran's National Organization of Food and Drug 2021. Diabetes drugs are regarded to verify the proposed model as the real case study in Iran. It should be noted that the proposed model takes perishability, recyclability, and disposal of drugs into account. To this aim, major diabetes drugs using in Iran have been considered, which have the characteristics of perishability, recyclability, and disposal. Although the suggested model is generally relevant to all sorts of perishable and recyclable medications, it can also be used to build SCs for medications with longer shelf lives or that are not recyclable. In this situation, it is possible to choose the model's input parameters in a way that best fits the key traits of the chosen medications. For instance, the layers of CCs, DICs, and RCs might be deleted if the drug is not recyclable, or the planning horizon could be determined by the drug's life expectancy. The following parts detail the case description and data collection, the findings of the experimental research, and the sensitivity analysis.

6.1 Case description and data collection

The World Health Organization (WHO) estimates that 422 million people worldwide have diabetes, with low- and middle-income nations having a higher incidence of the illness than high-income nations. 8.5% of persons who were 18 and older had diabetes in 2014. 1.5 million fatalities in 2019 were directly related to diabetes, which also contributed to 48% of all deaths occurring before the age of 70. Premature diabetes-related mortality (deaths occurring before the age of 70) increased by 5% between 2000 and 2016. From 2000 to 2010, the rate of early death from diabetes in high-income nations fell; however, from 2010 to 2016, it rose. Premature diabetes mortality has increased in both low- and middle-income countries during the past few decades, as both the prevalence and incidence of the disease have gradually grown (WHO, 2020). In Iran, 11 percent of people over the age of 25, more than 5 million, have diabetes (Ministry of Health, Treatment and Medical Training, 2020). Study by the Iranian Diabetes Society (2020) shows that Yazd province with 16.2%, Semnan with 14.1%, Khuzestan with 14%, Golestan with 13.6%, Alborz with 13.2%, Bushehr with

Table 3 Diabetes prevalence for each province

No	Provinces	Diabetes percentage	Population	Number of patients
1	Yazd	16.2	549,147	88,961.8
2	Semnan	14.1	360,073	50,770.3
3	Khozestan	14	2,656,347	371,888.6
4	Golestan	13.6	1,086,361	147,745.1
5	Alborz	13.2	1,767,558	233,317.7
6	Bushehr	13	783,764	101,889.3
7	Tehran	12.8	8,803,806	1,126,887.2
8	Azerbaijan-e Gharbi	10.13	3,265,219	330,766.7
9	Azerbaijan-e Sharghi	10	3,909,652	390,965.2
10	Fars	10	3,420,640	342,064.0
11	Hormozgan	10	1,109,839	110,983.9
12	Kermanshah	10	1,952,434	195,243.4

13%, and Tehran with 12.8% have the highest incidence of diabetes in Iran. Azerbaijan-e Gharbi, Azerbaijan-e Sharghi, Fars, Hormozgan and Kermanshah are ranked next to the national average (about 10%) with diabetes statistics. The SC of 5 major diabetes drugs for these 12 provinces has been designed and validated in this study. Table 3 indicates the number of people living with diabetes in each province.

All 12 provinces may be considered as demand areas. Figure 2 indicates the possible and existing locations of the network nodes. Due to the value of sustainable growth and social responsibility, 3 provinces of Sistan and Baluchestan, Khorasan-e Jonobi and Ardabil, which are among the least established economic provinces, have also been suggested as candidates for the establishment of PCs. The diabetes medical network involves PCs, DCs, suppliers, importers, customers, CCs, DICs and RCs (see Fig. 2 for locations). A planning horizon of 24 periods is considered. As the medication is a perishable substance and the lifetime of the medicines typically ranges from 24 to 36 months, 24 months are assumed to be lifespan. The time horizon is divided into 24 month intervals over 2 years. Every month is seen as a time period. According to the Iran's National Organization of Food & Drug, the major medicines for diabetes are considered, including Metformin, Acarbose, Ziptin, Pioglitazone and Glibenclamide.

The provided parameters are obtained from database websites such as Iran's Statistical Center, Iran's National Organization of Food and Drug, expert assessments, and certain investigations 2021. The capacity of centers are considered based on internal estimates and prior feasibility assessments conducted in Iran. Table A.1 displays these characteristics.

Light, mid-size, and heavy-duty trucks are three different types of vehicles that are used as a mode of transportation between different centers. The cost of transportation between two locations is determined by the product of the unitary transportation cost and the distance between them. The unit transportation costs per kilometer via three different vehicle types are supported and assisted through consultation with shipping organizations. Table A.2 displays vehicle types and capacity and Table A.3 shows the estimated distance between each pair of 15 provinces using Google Maps.

The use of fossil fuels produces a large quantity of GHG, which has negative hygienic and environmental consequences. Clearly, all of the intended SC processes emit far too

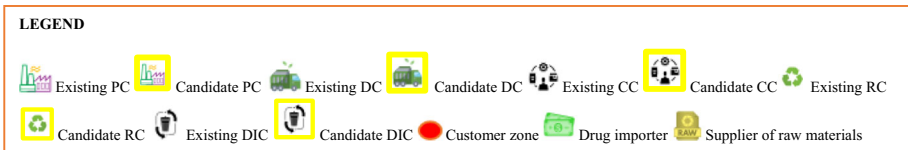
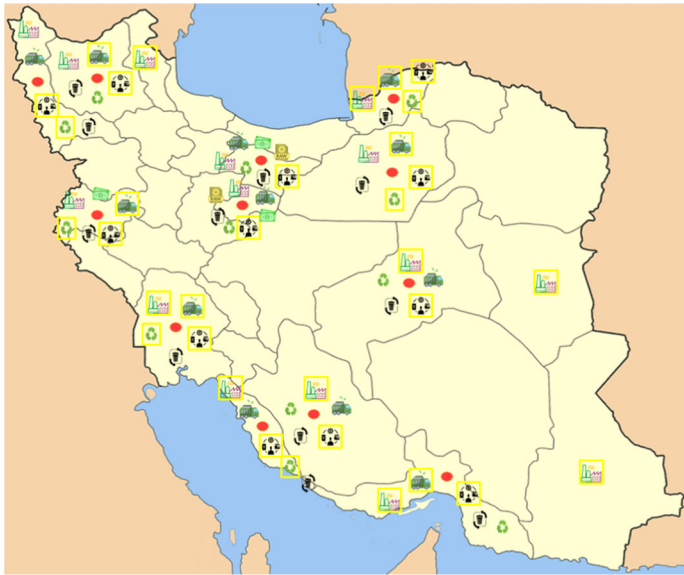


Fig. 2 Possible and existing locations of PSC nodes

many hazardous gases into the atmosphere. In this paper, we consider CO₂, NO_x, and SO_x emissions of transporting in PSC. Table A.4 indicates the amount of these parameters based on some papers such as Fattahi and Govindan (2018).

Because Iran has a high unemployment rate throughout the country, creating job opportunities is a top concern right now. Job creation is especially important in provinces with low income and geographical relevance. Data from numerous studies are utilized to compute the number of new fixed and variable jobs and the number of days lost due to occupational accidents that is seen in Table A.5. Table A.6 displays data obtained from the Statistical Center of Iran on the region’s economic worth. Self- sufficiency per unit of product is estimated to be 0.00005. Employee satisfaction is determined by the company’s lending to employees, the degree of flexibility in working hours, workplace regulation, the number of rest hours, the amount of salary, and job security, according to GRI, (2016). Because providing employee welfare services incurs expenses on the SC, the cost of implementing welfare services is factored into the economic goal.

Since it is assumed that some constraints and the goal’s target value are flexible, the robust model defines various parameters that relate to the potential violation of the objectives and soft restrictions. According to Pishvae and Khalaf (2016), the maximum deviation from the goal is set to 75% of the expected level. The maximum flexibility of soft constraints is also set at 30% of the corresponding right-hand sides (i.e., the demand and capacity of facilities). Uncertain parameters’ optimistic and pessimistic values differ by 15% from their probable value.

6.2 Experimental results

This section presents experimental results based on an actual case. The model is coded by GAMS 24.1.3 and solved by the CPLEX 12.1 solver. All tests are conducted on an INTEL Core i7 CPU with 3.5 GHz and 8 GB RAM.

The second and third goals are environmental factors and social concerns. Thus, the GRI indicators are utilized for the social and environmental implications, as was previously noted. To evaluate the relative weight of each criterion's importance, these criteria should be compared. Here, the FBWM is used to achieve this goal. A fuzzy priority of the better criterion over all criteria and a fuzzy priority of all criteria over the worst criterion are established based on expert opinion. The FBWM model from subSect. 6.3 is then solved after that. Table 4 illustrates the significance of environmental and social factors. The experimental results are stated on the basis of the formulation of the MPFRP model provided in Sect. 5.2. The model size is presented in Table 5.

Table 6 presents the results after the TH approach was implemented in a deterministic and robust model under nominal data. It should be highlighted that, Z_1 , Z_2 and Z_3 demonstrated values for economic, environmental and social objective functions, respectively and

Table 4 The importance of social and environmental variables

Factors	W^o	W^d	W^e	W^j	W^S	W^c	W^{ec}	W^w
Weight	0.286	0.193	0.204	0.204	0.113	0.44	0.36	0.2

Table 5 The model size

Set	Size	Set	Size
Importers	3	Drugs	5
Suppliers for raw materials	2	Raw materials	10
PCs	15	Time periods	24
DCs	12	Production times	12
Customers	12	Vehicles	3
CCs	12	Employee support types	3
RCs	12	Emission types to the air	3
DICs	12	Constraints	436,084
Variables	556,411		

Table 6 Value of objectives

Objective functions	Z_1	Z_2	Z_3	Z_4	CPU time (second)
Deterministic model	2.09488E + 11	6.203024E + 7	178,313.713	–	698.12
Robust model	2.39007E + 11	6.563092E + 7	190,338.890	1.20994E + 11	722.16

Z_4 demonstrated robustness cost. Moreover, the MPFRP model is identified with the robust model in this subsection for the sake of brevity. As shown by Table 6, when the uncertainty is taken into account, the value of objective functions has gotten worse when compared to the deterministic model, and it has really had an impact on all three objective functions. The findings demonstrate that uncertainty has a major impact on chain costs as well as social and environmental goals and that it cannot be ignored. Given the uncertainty, the values of the objectives deviate from their optimal value relative to the deterministic state, and the network cost rises by 14.09%, the environmental objective rises by 5.8%, and the social objective increases by 6.74%. As can be shown, the deterministic model is less expensive than the robust approach in terms of objective values. Table 7 summarizes the outcomes of solving the deterministic and robust model with a confidence and satisfaction level of 0.8. Figure 3 depicts the best network for the deterministic and robust models under nominal data. When uncertainty is not factored into the modeling, 4 PCs, 3 DCs, 12 CCs, 2 DICs, and 3 RCs are created; however, when uncertainty is factored into the modeling, 5 PCs, 4 DCs, 12 CCs, 2 DICs, and 3 RCs are created. In order to meet demand and lower costs related to model uncertainty, 1 more PC and DC are actually being constructed in the robust model. It is also noteworthy that the TH technique can solve both deterministic and robust models in a reasonable amount of CPU time. The robust model takes longer to solve than the deterministic model because it offers a more resilient and immunized response to uncertainty, whereas the deterministic approach ignores parameter uncertainty.

To evaluate the suitability and robustness of the suggested models' solutions under nominal data, 10 random realizations are created uniformly and the performance of the resultant solutions is examined under each realization. The model's uncertain parameters are produced at random in accordance with the range of corresponding triangular fuzzy numbers. To compare the suggested models, the average and standard deviation of objective function values under random realizations are employed as performance measurements. Table 8 summarizes the findings of these experiments. The mean of the first and second objective functions in the robust model is greater than the mean of the first and second objective functions in the deterministic model, as shown in Table 8. Increasing center construction and transportation development, which boost average costs in each realization, are to blame for the increased economic function. When demand uncertainty is taken into account, the model must produce solutions that are protected against uncertainty in order to fulfill all anticipated demands. As a result, more transportation is required, which increases GHG emissions. The mean of third objective functions in the robust model is higher than the mean of third objective functions in the deterministic model. This is due to the fact that a robust model encourages the construction of more centers, which increases the number of fixed work possibilities. In addition, more production is required to meet the demand in conditions of great uncertainty, and the system's transportation must be expanded as well. All of these factors enhance the variety of work prospects and raise the social objective. The main benefit of the robust model over the deterministic model is that it has a lower standard deviation for all three economic, environmental, and social objective functions, which means that using the robust method can reduce the risks that uncertainty imposes on the system. This lowers the system's result dispersion and predictive risks.

In the majority of the reviewed publications in the field of PSC, the objective is to reduce the costs in the network. In this part, two views have been examined: (1) network optimization only taking into account the economic objective while neglecting the environmental and social objective functions and (2) network optimization in accordance with sustainable development objectives. The weights for the economic, environmental, social, and robust cost objectives are, in accordance with the experts' assessments, 0.3, 0.25, 0.25, and 0.2, respectively.

Table 7 The Location of the facilities

Number	Province	PC		DC		CC		DIC		RC	
		Deterministic	Robust	Deterministic	Robust	Deterministic	Robust	Deterministic	Robust	Deterministic	Robust
1	Yazd			*		✓	✓			*	*
2	Semnan	*		✓		✓	✓			✓	✓
3	Khozestan		*			✓	✓				
4	Golestan	✓		✓		✓	✓	✓		✓	✓
5	Alborz	*		*		✓	✓	*		*	*
6	Bushehr		✓	*		✓	✓			*	*
7	Tehran	*		*		✓	✓	*		*	*
8	Azerbaijan-e-Gharbi	*		*		✓	✓	*		✓	✓
9	Azerbaijan-e-Sharghi	*				✓	✓			*	*
10	Fars			*		✓	✓	*		*	*
11	Hormozgan	✓				✓	✓			*	*
12	Kermanshah	*				✓	✓			*	*
13	Sistan and Baluchestan			✓		✓	✓	✓		✓	✓
14	Ardabil	✓									
15	Khorasan-e-Jonobi	✓									

*Existing facility
 ✓New facility.

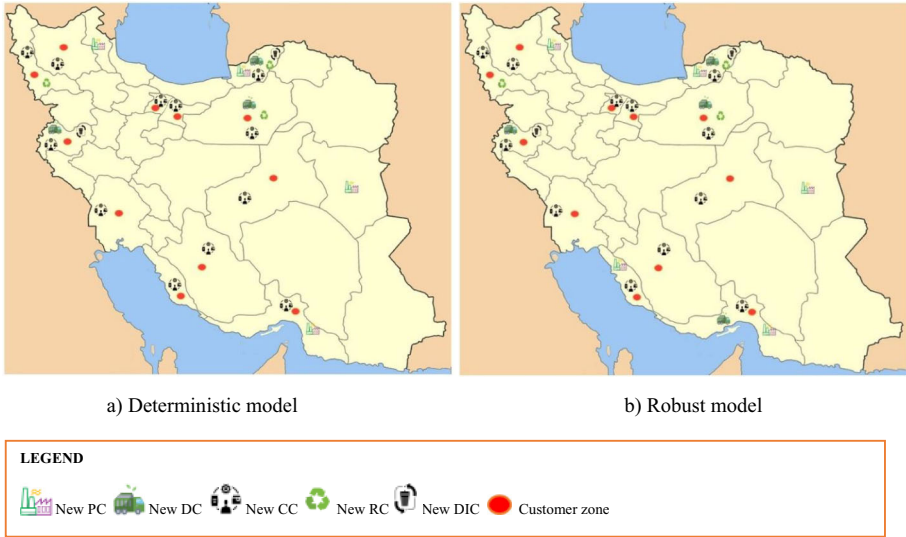


Fig. 3 The proposed PSC for deterministic and robust models under nominal data

Table 8 The performance of the proposed models under different realizations

Realization	Deterministic model			Robust model		
	Z ₁	Z ₂	Z ₃	Z ₁	Z ₂	Z ₃
1	2.10E + 11	6.19E + 07	1.69E + 05	2.32E + 11	6.50E + 07	1.93E + 05
2	2.13E + 11	6.14E + 07	1.74E + 05	2.30E + 11	6.52E + 07	1.91E + 05
3	2.13E + 11	6.18E + 07	1.71E + 05	2.35E + 11	6.57E + 07	1.90E + 05
4	2.10E + 11	6.21E + 07	1.74E + 05	2.30E + 11	6.49E + 07	1.96E + 05
5	2.15E + 11	6.11E + 07	1.78E + 05	2.34E + 11	6.53E + 07	1.89E + 05
6	2.05E + 11	6.13E + 07	1.78E + 05	2.28E + 11	6.55E + 07	1.97E + 05
7	2.08E + 11	6.19E + 07	1.73E + 05	2.37E + 11	6.56E + 07	1.93E + 05
8	2.12E + 11	6.11E + 07	1.70E + 05	2.39E + 11	6.48E + 07	1.95E + 05
9	2.08E + 11	6.09E + 07	1.77E + 05	2.29E + 11	6.58E + 07	1.92E + 05
10	2.03E + 11	6.20E + 07	1.69E + 05	2.34E + 11	6.60E + 07	1.88E + 05
Average	2.10E + 11	6.15E + 07	1.73E + 05	2.33E + 11	6.54E + 07	1.93E + 05
Standard deviation	3.69E + 09	4.20E + 05	3.24E + 03	3.43E + 09	3.84E + 05	2.84E + 03

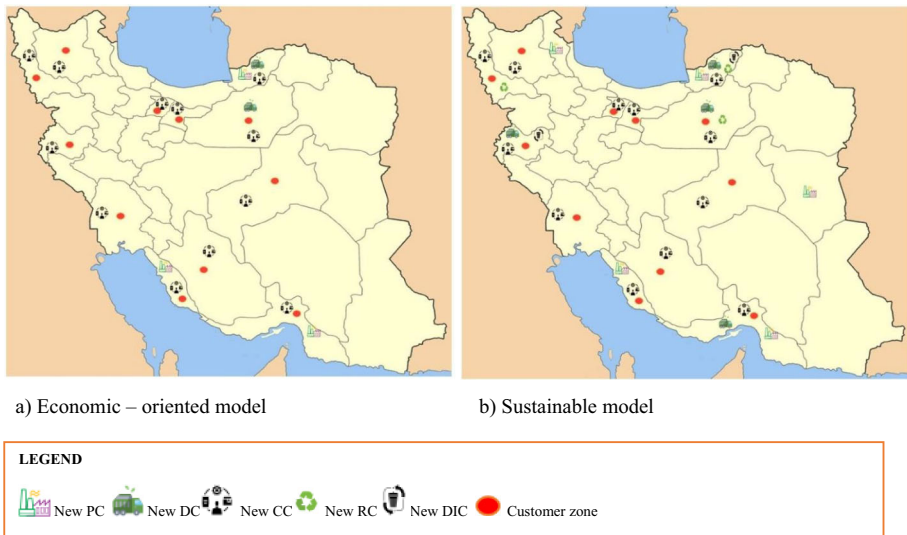


Fig. 4 The optimal network design under different perspectives

Figure 4a shows the optimal locations for construction centers when the economic-oriented model is taken into account. In this situation, 3 PCs, 2 DCs and 12 CCs will be constructed among the prospective locations for facilities; however, in the sustainable model 5 PCs, 4 DCs, 12 CCs, 2 DICs, and 3 RCs are created. Fewer centers are developed under the economic-oriented model. In fact, in this model, in order to reduce fixed and operational expenses, the number of centers will be reduced while capacity is increased. According to Fig. 4b in the sustainable model, in addition to the centers established in the first model, two PCs will also be constructed in the province of Ardabil and Khorasan-e-Jonobi. In addition to DCs created in first state, new DCs will be established in the Hormozgan and Kermanshah. There will be a CC in each of the 12 provinces. In the provinces of Semnan, Golestan and Azerbaijan-e-Gharbi, new RCs will be built. Two DICs will be established in the provinces of Golestan and Kermanshah.

The detailed findings for the optimal network designs are shown in Table 9. Considering sustainability has enhanced the social objective and lowered environmental objective by 18.54% and 34.03%, respectively, while increasing network cost by 19.54%. It is obvious that a solution developed by taking into account just economic objective could not be successful in other circumstances. It may be deduced that the established model delivers solutions that are successful in all dimensions at once because all objectives are satisfactorily met in the sustainable solution.

6.3 Sensitivity analysis

This subsection discusses the sensitivity analysis of key parameters of the problem, such as demand, confidence level, the capacity of PCs and the parameters of the TH process.

Table 9 The detailed solutions under different perspectives

Model	Solution	Value
Economic-oriented model	Z_1	1.99942E + 11
	Z_2	8.796661E + 7
	Z_3	160,566.973
	Z_4	9.84401E + 10
	PC	Golestan- Bushehr- Hormozgan
	DC	Semnan- Golestan
	CC	All province
	DIC	–
	RC	–
	CPU time (second)	878.50
	Sustainable model	Z_1
Z_2		6.563092E + 7
Z_3		190,338.890
Z_4		1.20994E + 11
PC		Golestan- Bushehr- Hormozgan- Ardabil- Khorasan-e-Jonobi
DC		Semnan- Golestan- Hormozgan- Kermanshah
CC		All provinces
DIC		Golestan-Kermanshah
RC		Semnan-Golestan-Azerbaijan-e-Gharbi
CPU time (second)		722.16

6.3.1 Impact of demand change

Customer demand is one of the key and critical network factors that has a substantial impact on the optimal values of the objective functions in the model. As illustrated in Fig. 5, all four objective functions rise when customer demand rises, while all four objective functions fall when demand falls. When demand increases, production and the flow of goods and inventory through the network increase. This results in an increase in network transportation, which increases operational costs like holding and transportation costs. As a result, the cost of uncertainty will grow. On the other hand, expanding the network's transportation would result in higher energy use and GHG emissions. Additionally, as demand rises, production rises as well, adding to the overall amount of waste in the system. They all lead to an improvement in the environmental objective function. To fulfill increased demand, more facility capacity must be used in the network, and as capacity is added, new job opportunities will emerge. On the other hand, increased network production corresponds to rising national self-sufficiency. These changes will also increase the significance of social objectives.

6.3.2 Impact of confidence level change

Figure 6 displays how objectives performed as a result of varying confidence levels and the

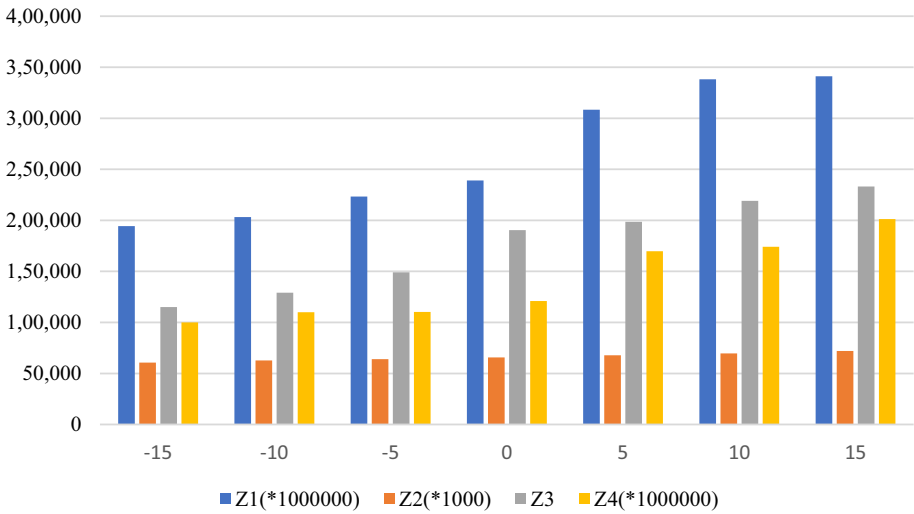


Fig. 5 Impact of variations in demand on objectives

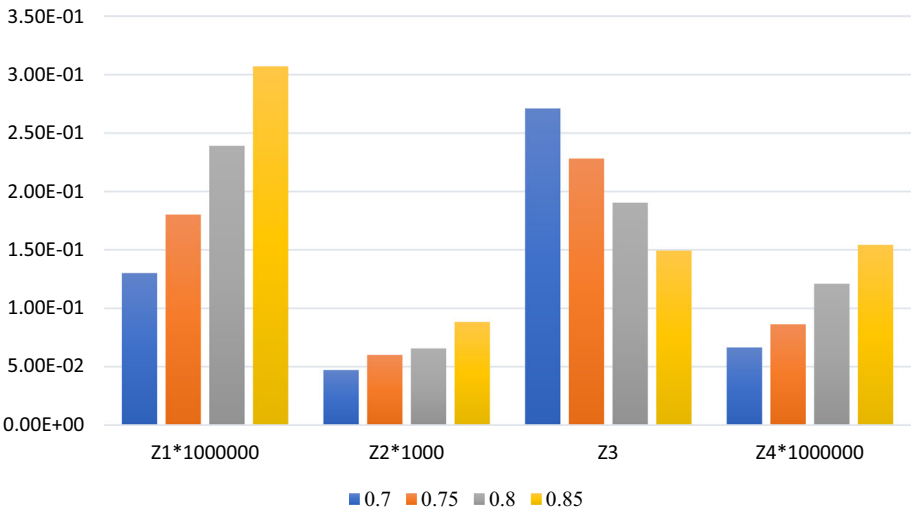


Fig. 6 Values of objectives under variations of confidence level value

degree of satisfaction of flexible constraints in the robust model. As can be seen, for the value of $\alpha = \beta = \delta = \gamma = 0.7$, all four objectives are at their best, whereas for the value of $\alpha = \beta = \delta = \gamma = 0.85$, they are at their worst. The feasible problem area decreases as confidence levels and the degree of satisfaction of flexible constraints in the robust model increase, while the values of economic and environmental objectives increase and the values of social objectives decrease.

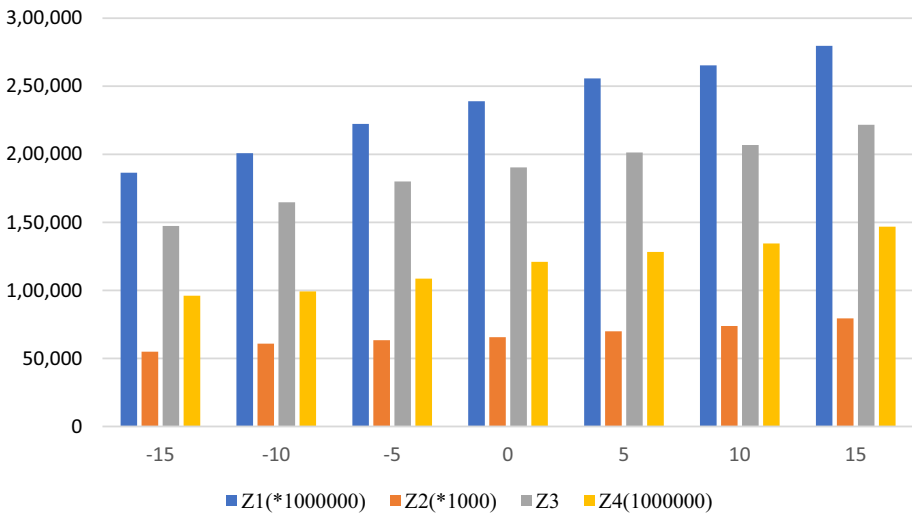


Fig. 7 Impact of capacity changes on objectives

6.3.3 Impact of production capacity change

In this part, changes to the SC’s production capacity have been used to investigate changes in the objective functions. The diagrams in Fig. 7 clearly show that all of the objective functions’ amounts increased as capacity rose, and their values decreased as capacity fell. A capacity expansion has led to an increase in production and material flow in the SC, which has boosted network cost, as can be seen by examining the model’s output. Growing production is associated with rising non-renewable energy demand, waste production, and GHG emissions. As a result, the environmental objective function expands. Additionally, as capacity is increased, the production and transportation will increase, leading to the increase in variable work possibilities.

6.3.4 Impact of TH method parameters

The results of sensitivity analysis on TH parameters, including the relative importance of the objectives and the compensation coefficient, are shown in Tables 10 and 11. Table 10 indicates that increasing the value of θ_h would result in a reduction in the first, second, and fourth objectives, while decreasing the value of θ_h would result in a reduction in the third

Table 10 Results of changing θ_h on objectives ($\gamma = 0.7$)

θ_h				Z_1	Z_2	Z_3	Z_4
0.3	0.3	0.15	0.25	2.38106E+11	6.30102E+07	188,340	1.18395E+11
0.3	0.25	0.25	0.2	2.39007E+11	6.56309E+07	190,339	1.20994E+11
0.4	0.2	0.25	0.15	2.34312E+11	6.66416E+07	193,004	1.23370E+11
0.4	0.15	0.3	0.15	2.18005E+11	6.70896E+07	194,307	1.24068E+11

Table 11 Impact of changing parameter γ on the TH method ($\theta_h = (0.3, 0.25, 0.25, 0.2)$)

γ	Z_1	Z_2	Z_3	Z_4
0.4	2.39007E + 11	6.56309E + 07	190,339	1.20994E + 11
0.5	2.39007E + 11	6.56309E + 07	190,339	1.20994E + 11
0.6	2.39007E + 11	6.56309E + 07	190,339	1.20994E + 11
0.7	2.39007E + 11	6.56309E + 07	190,339	1.20994E + 11
0.8	2.32841E + 11	6.48607E + 07	196,024	1.18832E + 11
0.9	2.29446E + 11	6.41870E + 07	197,963	1.16934E + 11

objective. The effect of modifying parameter γ on the TH method is shown in Table 11. Table 11 demonstrates that the value of objectives does not change from $\gamma = 0.4$ to $\gamma = 0.7$, but when the compensation coefficient is raised ($\gamma = 0.8$ to $\gamma = 0.9$), the value of Z_1, Z_2 and Z_4 drops while the value of Z_3 rises.

7 Discussion and policy implications

The present study includes the concepts of SCN of diabetes drugs in Iran, which by considering a scientific approach can analyze the obstacles and challenges in this field. The following are some of the most significant challenges in the PSC: (1) the role of drugs in health care costs, (2) the perishability of drugs and their special storage conditions, (3) the uncertainty and facing drug shortages, (4) the presence of pharmaceutical waste in the environment, (5) drug recycling, (6) environmental pollution and (7) social responsibility. The output of this study can help and support the government and policymakers of pharmaceutical companies in solving current challenges. Some most significant managerial insights of the results of the presented paper are listed below to help decision-makers to optimally decide during the planning horizon of the designed network:

- A solution that is developed with simply economic objectives in mind may not work successfully in other circumstances. When sustainability is taken into account, network costs have increased by 19.54%. But, it will bring significant benefits to the environmental and social aspects, simultaneously. There has been a 34.03% decrease in the environmental aim and an 18.54% increase in the social target by considering sustainable development goals in the model.
- When compared to the deterministic model, the network cost in the robust model rises by 14.09%, the environmental objective by 5.8%, and the social objective by 6.74%. Additionally, a different network structure with more created facilities will be obtained in the robust model to fulfill unknown demands. Policymakers cannot ignore uncertainty in their assessments since the robust model will defend against a high level of uncertainty even if it will be much more expensive.
- The feasible problem area decreases as confidence levels and the degree of satisfaction of flexible constraints in the robust model increase, while the values of economic and environmental objectives increase and the values of social objective decrease. Higher confidence levels will increase system costs, but the created solutions will still function properly even in the presence of high levels of uncertainty, and the likelihood of breaching constraints with uncertain parameters will be reduced.

- According to the results, the model experiences significant changes from uncertainty in demand parameters rather than other uncertain parameters such as capacity levels of facilities. In this regard, the costs incurred due to the uncertain nature of demands must be reduced by predicting demand parameters more accurately. Moreover, health managers can provide a safety stock, through production or importing, in order to fulfill the uncertain demand.
- Expanding the production capacity leads to a more significant increase in the environmental objective. While SC's production capacity is boosted by 15%, the environmental objective is increased by 21%. On the other hand, capacity expansion of facilities, will less considerably affect the economic and social aims, while a 15% growth in production capacity of SC, leads to 17% and 16% increase in economic and social objectives, respectively. In such situation, managers can select to import drugs from foreign suppliers to control destructive effects of producing more drugs through boosting capacity level of SC's production.
- Finally, the TH technique can offer the chance to achieve the most desirable trade-off between different aspects of sustainability, and DMs can achieve the desired results by adjusting the coefficients taken into account for each sustainable target.

8 Conclusion

This study describes a multi-product, multi-period mathematical optimization model for designing a PSC network. The proposed network considers producers, importers, retailers, suppliers, consumers, collection, recycling and disposal facilities. The importance of sustainable development goals in SC design is influenced by three economic, environmental, and social objectives. The social and environmental effects of the SC decisions have been measured by GRI guideline indicators (GRI, 2016). The economic objective minimizes fixed installation costs and operational costs, including transport, holding, ordering, production, purchasing of raw materials, distribution, disposal and recycling. Based on the environmental objective, the amount of GHG emitted by transportation, as well as the amount of nonrenewable energy and waste generation in the SC are minimized. The social objective is to consider the number of job opportunities, economic development, job satisfaction, self-sufficiency and the number of days lost due to accidents at work. In view of the fact that the social and environmental objectives consist of many components, the FBWM is used to calculate the coefficient of importance of each component. Due to the inherent uncertainty of SC parameters, capacity, demand, fixed and operating costs, environmental and social factors have been considered to be uncertain. The MPFRP method is used to cope with uncertainties. The proposed multi-objective model is solved using the TH technique. The efficiency and validity of the proposed model are then assessed by presenting numerical results and sensitivity analysis from a specific case study involving diabetes drugs in Iran.

The main outcomes based on numerical results and sensitivity analysis are; (a) the deterministic model costs less than the robust model. This is reasonable because more facilities are actually being constructed in the robust model, which is employed to protect the system against uncertainty but is ignored in the deterministic model; (b) achieving sustainable development goals leads to an increase in the economic aspect, but environmental and social aspects will improve noticeably; (c) as drug demand grows during the planning horizon, the amount of the economic, environmental and social objective also increases; (d) the feasible problem area decreases as confidence levels and the degree of satisfaction of flexible constraints in the robust model increase, while the values of economic and environmental

objectives increase and the values of social objective decrease; (e) the overall cost of the network is increased by increasing the maximum production capacity; the increase in capacity increases production and material flow, which has raised network cost. Growth in production is associated with a rise in nonrenewable energy use, waste generation, and GHG emissions. As a result, the environmental objective function expands. Additionally, as capacity grows, more employment possibilities will become available, raising the social goal, and (f) the TH approach provides the opportunity to obtain the most desirable trade-off between different aspects of sustainability based on the importance of each sustainable objective.

Several recommendations are made for future studies. Economic indicators such as inflation and interest rate may be included in the economic objective in future studies. Another idea is to use stochastic optimization and fuzzy optimization to deal with uncertainty. Other issues to be studied in future research include raising the issue as a large-scale problem and using heuristic and meta-heuristic methods to solve the model. Another alternative is to develop model for disaster situations. Future research can take into account an equitable distribution of pharmaceuticals among all study sites in the event of uncertainty that could result in a drug shortage.

Declarations

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

Appendix

See Tables [A.1](#), [A.2](#), [A.3](#), [A.4](#), [A.5](#) and [A.6](#).

Table A.1 The capacity of centers

Parameter	Value
$\tilde{c}a_{jp}$	[200, 300]
$\tilde{c}a_{kp}$	[150, 250]
$\tilde{c}a_{mp}$	[200, 350]
$\tilde{c}a_{rp}$	[120, 250]
$\tilde{c}a_{dp}$	[180, 250]
$\tilde{c}a_{sq}$	[200, 270]
$\tilde{c}a_{ip}$	[170, 260]

Table A.2 The capacity of vehicles

Vehicle type	ca_v (Kg)
Light truck	3000
Mid-size truck	6000
Heavy duty truck	10,000

Table A.3 The distance between each pair of 15 provinces

Provinces	Yazd	Semnan	Khozestan	Golestan	Alborz	Bushehr	Tehran	Azerbaijan-e Gharbi	Azerbaijan-e Sharghi	Fars	Hormozgan	Kermanshah	Sistan and Baluchestan	Khorasan-e Jonobi	Ardabil
Yazd		751	797	1003	644	717	624	1293	1152	434	654	870	852	625	1162
Semnan			921	336	264	1161	222	974	833	1038	1404	699	1360	913	794
Khozestan				1159	787	446	780	1050	1150	520	1126	518	1581	1352	1202
Golestan					425	1411	381	1135	994	1288	1654	882	1378	932	753
Alborz						1030	47	709	568	933	1298	501	1497	1180	529
Bushehr							1035	1492	1497	287	727	960	1348	1346	1481
Tehran								753	612	910	1276	497	1474	1135	573
Azerbaijan-e Gharbi									146	1506	1935	541	2134	1886	356
Azerbaijan-e Sharghi										1368	1797	580	1995	1748	217
Fars											580	1019	1063	1063	1362
Hormozgan												1467	719	1043	1818
Kermanshah													1717	1404	675
Sistan and Baluchestan														450	2017
Khorasan-e Jonobi															1594
Ardabil															

Table A.4 GHG emissions of transporting

GHG	Emission from transporting (kg per ton-kilometer)
CO ₂	0.2002
NO _x	0.031
SO _x	0.00011

Table A.5 Social parameters

Parameters	Amount
The number of created fixed job opportunities	[30, 200]
The number of created variable job opportunities	[0.02, 0.06]
Job opportunities are created in transportation activities	[10, 15]
The number of lost days due to occupational accidents	[10, 22]

Table A.6 The regional economic value

Provinces	Regional economic value
Yazd	1.8
Semnan	0.9
Khozestan	14.8
Golestan	1.2
Alborz	2.8
Bushehr	6
Tehran	22.1
Azerbaijan-e Gharbi	2
Azerbaijan-e Sharghi	3.5
Fars	4.7
Hormozgan	2
Kermanshah	1.5
Sistan and Baluchestan	1.4
Khorasan-e Jonobi	0.5
Ardabil	1

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