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Balancing quality, cost, and uncertainty in pharmaceutical supply chain: A robust possibilistic flexible programming approach

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A B S T R A C T

The pharmaceutical supply chain (PSC) plays a crucial role in ensuring the timely and reliable availability of essential drugs while maintaining high-quality standards. Balancing the triad of cost, time, and quality is paramount in optimizing the complexities of this supply chain. In this research, a multi-objective PSC optimization model is developed to maximize the key business factors. The dynamic nature of the PSC can significantly compromise the effectiveness of the decision making process. To deal with this challenge, a robust possibilistic flexible programming approach (RPFPA) solution methodology is proposed. This methodology provides a robust and flexible framework to tackle the uncertainties within the supply chain. To validate the proposed model and methodology, a computational analysis of a case study is conducted. The results of the analysis demonstrate the effectiveness of the model and methodology in addressing the uncertainties and complexities of the PSC. Specifically, the findings reveal that by accepting a 23.8% increase in costs, decision-makers can achieve a desirable level of robustness in their decisions. Moreover, the study identifies that the assignment of higher priority to cost objectives leads to more centralized decisions within the supply chain, while a greater emphasis on quality objectives results in a more decentralized approach. By employing the proposed approach, decision-makers can efficiently deal with the complexities and uncertainties inherent in the PSC, making well-informed choices that balance cost, time, and quality.

1. Introduction

The pharmaceutical supply chain (PSC) is a complex network of players and processes that is responsible for getting drugs from the manufacturer to the patient (Jaberidoost, Nikfar, Abdollahiasl, & Dinarvand, 2013). It is a critical aspect of ensuring the availability of high-quality medicines at the right time and at an optimum price (Kaufmann, Thiel, & Becker, 2005). The pharmaceutical supply chain is unique in that it is subject to a high degree of regulation and is characterized by urgency, importance, storage, transportation, and other specific considerations. The well-organized PSC contributes drugs in the righteous amount to the buyers with sustainable quality, at the right time, and with the minimum possible price to produce satisfaction for all the shareholders (Shah, 2004). In a PSC, the cost must be minimized, delivery is made in the shortest possible time, and the best quality medicine is delivered to the end customer. The increasing competition in the pharmaceutical industry has prompted policymakers to employ supply chain (SC) network design optimization models to minimize overall costs and improve efficiency. Effective PSC network design requires centralized planning at the strategic, tactical, and operational levels in order to reduce cost and ensure the timely distribution of high-quality medicine (Enyinda, Mbah, & Ogbuehi, 2010; Kanan, Habib, Shahbaz, et al., 2022). In this regard, the development of a comprehensive decision-making system that may assist managers in achieving both commercial success and quality assurance goals is critical. In this aspect, this study presents a

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model based on mixed integer linear programming (MILP) formulation to design a robust network for the PSC. The objective of the suggested model is to design the PSC by minimizing costs, and delivery time while maintaining the desired level of drugs quality.

Compared to other types of SC models, the PSC has to face a significant level of unpredictability which arises due to diverse factors including governmental regulations and fluctuations in the global market and other external factors (Imran, Kang, & Babar Ramzan, 2018). For example, a sudden rise in the demand for a particular drug can disrupt the supply chain of that drug. Also, any changes in the regulations of a specific drug represent another source of uncertainty. Furthermore, delays in the supply of raw materials can also result in production delays(Al-Rawashdeh, Jawabreh, & Ali, 2023; Ali, 2022). In the background, uncertainty can significantly impact the efficiency of the SC which can compromise the commercial feasibility. Therefore, the PSC needs to have a robust system in order to minimize the impact of these uncertainties. According to (Pishvaee & Torabi, 2010) possibilistic programming (PP) is an effective technique to deal with such uncertain environments. Moreover, by using the flexible programming (FP) approach, the model can also integrate "soft constraints" in order to account for variations in supply, demand, and capacity (Abusaq, Habib, Shehzad, Kanan, & Assaf, 2022). In this background, to assure the resilience and robustness of the results, a technique known as robust possibilistic flexible programming approach (RPFPA) is provided. This technique combines the qualities of flexible programming (FP) and robust possibilistic programming (RPP) to effectively deal with uncertain environments (Kanan, Habib, Habib, et al., 2022).

The subsequent sections of this study are outlined in the following manner: In Section 2, a comprehensive review of related research is given, covering previous studies and research in the related field. Section 3 presents the problem definition and the proposed MILP-based model for designing the PSC network, including details on how the model addresses uncertainty in factors such as ingredient sourcing, demand for medication, and regulatory compliance. In Section 4, the FRPP technique is elaborated in more detail, including how it is used to ensure the robustness of the final solution. Section 5 proceeds with the presentation of a case study, offering an in-depth analysis. Lastly, in Section 6 the research conclusion and the key findings are reported.

2. Literature Review

The PSC is a complex network of activities that includes sourcing raw materials, manufacturing, distribution, and delivery of medicines to patients. Recently, there has been a growing focus on optimizing this SC to improve efficiency, reduce costs, and increase the availability of medicines to those who need them. In this background, (Imran et al., 2018). presented a model for an integrated healthcare system that incorporates the uncertainty of product complaints. The model is based on a multi-echelon inventory system, where inventory is managed at various levels of SC, including suppliers, distributors, (Alhaj et al., 2023) and hospitals(Zandieh, Janatyan, Alem-Tabriz, & Rabieh, 2018). Employing a mathematical framework, the model optimizes inventory levels, while simulations are utilized to assess performance across various scenarios(Kanan, Habib, Habib, et al., 2022; Khouj et al., 2022). The authors employed a possibilistic programming approach to address uncertainty within PSC operations. However, this approach solely provides an average estimation of uncertain parameters, which may lead to significant penalties in real-time scenarios. Therefore, adopting more efficient techniques to manage operational uncertainty would enhance the effectiveness of solutions (Hassan, Aldoseri, Saeed, Khder, & Ali, 2022; Shan et al., 2022). proposed a dynamic SC resilience model for the medical equipment industry. The model aims to improve resilience under uncertainty and disruptions by considering factors such as inventory management, production planning, and logistics. Case results indicate that it can effectively identify key vulnerabilities and provide recommendations for improving system resilience. (Jafarnejad, Momeni, Hajiagha, & Khorshidi, 2019) suggested a model for the optimization of the PSC in hospitals, considering factors such as demand uncertainty, lead times, and safety stock levels. Results depict that the proposed model is effective in reducing inventory costs while maintaining a high level of customer service.

Ahmad et al. (2022) suggested a model to optimize the socio-economic performance of a PSC. The model considers factors such as inventory management, production planning, and logistics to optimize multiple objectives, such as cost, service level, and environmental impact. A genetic algorithm is employed to get the solution, taking into account trade-offs between objectives. Study findings show that the model is effective in finding solutions that balance cost, service level, and environmental impact. A neuromorphic optimization approach was proposed by (Ahmad, 2022)for solving multi-objective programming problems in PSC by considering the objectives of cost, service level, and environmental impact. In addition, (Ershadi & Ershadi, 2022; Shakouhi, Tavakkoli-Moghaddam, Baboli, & Bozorgi-Amiri, 2022)proposed a PSC model that considers objectives such as minimizing costs, maximizing service level, and reducing environmental impact. A hybrid approach employing multi-objective MILP and six sigma for optimizing the performance of a competitive PSC is provided by(Shakouhi et al., 2022; Zandieh et al., 2018). The authors considered the factors such as cost, service level, and environmental impact, and used the six sigma approach to identify and eliminate sources of variability and waste in the supply chain. (Zandieh et al., 2018)provided a case study of designing a sustainable PSC distribution network. The factors of demand forecasting, inventory management, logistics, and environmental impact were considered in their model.(Goodarzian, Wamba, Mathiyazhagan, & Taghipour, 2021) suggested a model for designing a green medicine SC network using a combination of fuzzy environment and hybrid metaheuristic algorithms as a solution approach. The objectives of environmental impact and cost minimization were considered. In addition, (Goodarzian, Taleizadeh, Ghasemi, & Abraham, 2021) provided a model for designing a sustainable medical SC network during the COVID-19 pandemic. The model takes into account multiple objectives such as cost, service level, and environmental impact. The model uses a multi-objective optimization approach to find the optimal decisions and it is designed considering sustainability factors. Further, Goodarzian et al. (2021) suggested a model for designing a new

medicine SC network that considers production technology policy. The model considered the factors of production technology policy, inventory management, logistics, and transportation to design the SC network. In this research, the authors used a genetic algorithm and particle swarm optimization algorithm to optimize the system under consideration.

In the PSC, blockchain technology can enhance transparency, efficiency, and traceability. In this background, Jamil et al. (2019)provided a medical blockchain model for drugs SC integrity management in a hospital. The proposed blockchain model combines blockchain technology, internet of things devices, and smart contracts, to monitor and track the drugs over the entire supply chain. In this background, Munir et al. (2022) highlighted the challenges in adoption of the blockchain technology to grab the relevant opportunities in the areas of the latest areas of SC. For the traceability optimization perspective, (Kumar & Tripathi, 2019)provided a blockchain-based model for medicine SC. To deal with the fake drugs circulation the authors suggested a blockchain-based system that enhances the transparency, traceability, and security of the drugs SC. The authors also propose a consensus algorithm for the blockchain network, which ensures that the data stored on the blockchain is accurate and tamper-proof.

A few authors have also discussed the opportunities and hindrances while adopting blockchain in the healthcare sector. The authors have also proposed frameworks to align the working of PSC with blockchain technology. For example, Liu et al. (2021)presented a blockchain-based tracing system for drugs SC. The authors explain how their proposed platform can be used to improve the traceability of drugs and reduce the risk of counterfeit drugs. Clauson et al. (2018) explored the potential use of blockchain technology to enhance SC management in healthcare to provide a detailed assessment of the potential advantages and opportunities that arise from implementing blockchain in SCM within the healthcare domain. Niu et al. (2021) outlined a framework for the implementation of blockchain technology by incentivizing the stakeholders and claimed that blockchain can enhance SC effectiveness and transparency, but its adoption is hindered by a lack of alignment between the various participants in the SC.

A summary of the research in PSC is provided in Table 1.

- A PSC network design (P-SCND) mathematical model is proposed that optimizes the cost efficiency of the PSC by considering factors such as ingredient sourcing, production, transportation, and storage. The model also minimizes overall costs while ensuring the timely delivery of high-quality medication to the hospitals.
- Using a technique named RPFPA to deal with uncertainty in the optimization model parameters and provide flexibility in the constraints of the model. The RPFPA aims to improve the decision-making process for managing PSC projects by generating robust solutions.
- An interactive fuzzy programming technique is suggested to adapt the model to the specific needs of the decision-makers and local dynamics.

3. Modelling of the PSC optimization

3.1 Problem statement

The focus of this research is to address the problem of designing a PSC network that involves balancing three key tradeoffs: cost, time, and quality objectives. By considering the interdependencies and interactions between cost, time, and quality, this research seeks to provide a PSC network designing support system for managers. The PSC network consists of drug producers and hospitals. The proposed model is a multi-objective optimization model and gives the following answers to decision-makers (DMs).

- How many no. of units of a specific drug is to be manufactured at a selected manufacturing site?
- Which hospital's demand will be fulfilled by a specific drug manufacturer in a specific planning period?
- What are the most suitable locations to locate the drug distribution centers while considering the conflicting objectives of the optimization model?

Fig. 1 provides the working framework of the pharmaceutical supply chain network design model (P-SCND). In the P-SCND model drugs demand is generated through an integrated information system of the hospitals and communicated to the drugs manufacturing companies. The drugs manufactured by the companies are evaluated and approved by the government health department. After the approval from the health department a drug manufacturer qualifies as a drug supplier. Hospitals issue a tender notice to purchase a specific drug, and drug manufacturers submit their expression of interest against it. Finally, hospitals evaluate these tenders based on quality, time, and cost and allocate purchase orders for a specific drug using the proposed P-SCND model.

Table 1
An overview of studies on PSC.

Author	Nature of decisions/findings			Solution/Analysis approach	Consideration of uncertainty		Objectives of the model	Supply chain decisions considered				
	Operational	tactical	strategic		Stochastic	Fuzzy		ID	LD	MD	MP	CD
(Imran et al., 2018)	✓	✓		Interactive fuzzy programming		✓	Minimization of cost, Minimisation of time, Maximization of quality level		✓	✓	✓	
(Jafarnejad et al., 2019)			✓	Hesitant fuzzy Delphi method		✓	Identification of key factors to enhance resilience of medical SC					
(Franco & Alfonso-Lizarazo, 2020)	✓	✓		Simulation-optimization approach	✓		Minimization of cost	✓		✓	✓	
(Ahmad, 2022)	✓	✓	✓	TOPSIS, robust optimization techniques		✓	Tripple bottom line (sustainability) objectives	✓	✓	✓		✓
(Ershadi & Ershadi, 2022)	✓	✓	✓	Neutrosophic optimization methods		✓	Minimization of cost		✓	✓	✓	✓
(Ershadi & Ershadi, 2022)	✓	✓	✓	NSGA, particle swarm optimization	✓		Minimization of cost Minimization of unsatisfied requests Minimization of total transportation		✓	✓	✓	✓
(Shakouhi et al., 2022)	✓	✓	✓	Game theory, six sigma	✓		Minimization of environmental pollution Maximize profit, Maximize consumer health level		✓	✓	✓	
(Zandieh et al., 2018)	✓	✓	✓	NSGA-II algorithm	✓		Minimization of costs Maximization of the welfare of society Minimization of environmental impact	✓	✓	✓	✓	✓
(Goodarzian, Taleizadeh, et al., 2021)	✓	✓	✓	Firefly algorithm & simulated annealing,		✓	Minimization of environmental impact	✓	✓	✓	✓	✓
(Goodarzian, Hoseini-Nasab, et al., 2021)	✓	✓	✓	Ant colony, fish swarm, and firefly algorithm	✓		Tripple bottom line (sustainability) objectives	✓	✓	✓	✓	✓
(Goodarzian, Wamba, et al., 2021)	✓	✓	✓	Simulated annealing, harmony search, ant colony optimization	✓		Minimization of cost, Minimization of time	✓	✓	✓	✓	✓
(Jamil et al., 2019)		✓	✓	Blockchain-based hyperledger fabric approach			Safety of the pharmaceutical supply chain (counterfeit drugs)					
	✓	✓	✓				Drug safety in the pharmaceutical supply chain (counterfeit drugs), traceability					
(Kumar & Tripathi, 2019)	✓	✓	✓	Robust possibilistic flexible programming approach (RPFPA)		✓	Minimization of cost, Minimization of time, Maximization of quality level	✓	✓	✓	✓	✓

ILD – Inventory level decision, LAD—Location allocation decision, MD—Materials flow decision, MP—Multi-product, CD—Capacity decision

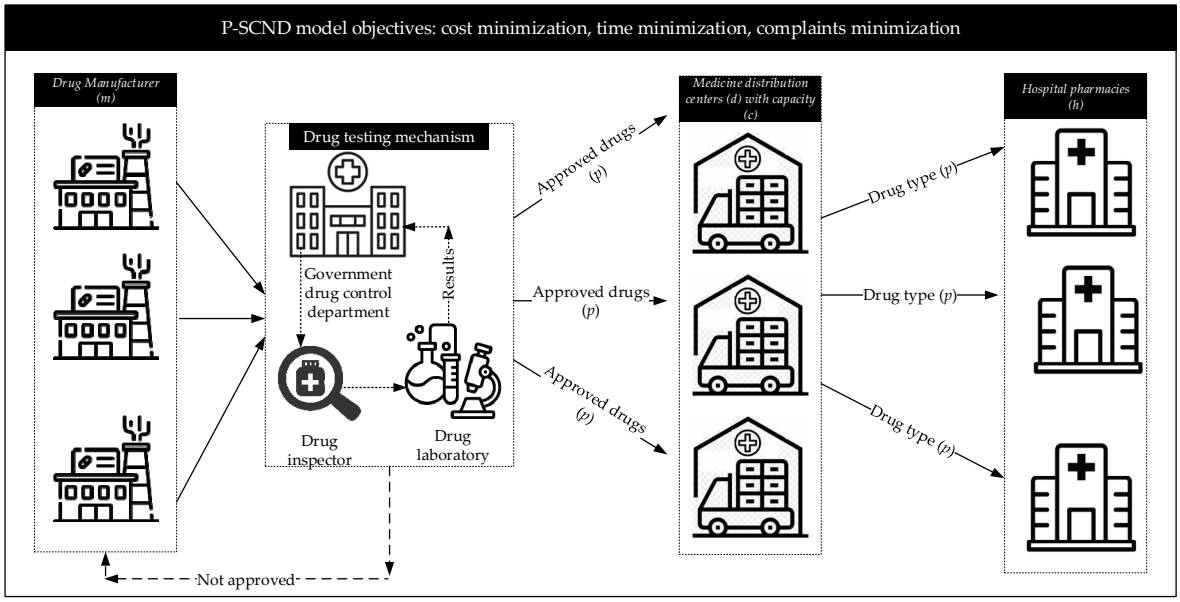


Figure 1. P-SCND optimization model working framework.

3.2 Assumptions

- Medications are transported directly from the drug plant to the hospital pharmacy.
- A uniform fleet of trucks is utilized, allowing for less-than-truckload shipments.
- The logistics cost depends on the distance and is determined by the price per kilometer.
- All supplied drugs have a minimum shelf life of two years.
- The logistic cost is dependent on the distance and is calculated by the cost per kilometer.
- The demand for drugs is considered uncertain which follows a trapezoidal possibility distribution (TPD).
- Multiple deliveries within a planned period are prohibited.

3.1.1 Indices

m	drugs manufacturing sites
h	hospitals
d	drugs distribution center
c	capacity level of the drugs distribution center
p	drugs type
t	planning duration

3.1.2 Parameters

$\tilde{\lambda}_{mpt}^{prod}$	production cost of drug type p at drug manufacturing site m in planning duration t
$\tilde{\lambda}_{p}^{insp}$	inspection cost of drug type p
$\tilde{\lambda}_{dc}^{inst}$	installation cost of drug storage center d with capacity c
$\tilde{\lambda}_{md}^{tran}$	transference cost of drugs from drug plant m to drug distribution center d
$\tilde{\lambda}_{dh}^{tran}$	transference cost of drugs from center d to hospital h
$\tilde{\lambda}_{dp}^{stor}$	storage cost for drug type p at distribution center p
$\tilde{\tau}_{md}^{time}$	duration required to transport drugs from manufacturer m to distributor d
$\tilde{\tau}_{p}^{inspt}$	inspection time required for drug type p
τ_{dh}^{time}	duration required to transport drugs from distributor d to hospital h

$\tilde{\tau}_{mp}^{prot}$	production time required to produce one batch of drug type p at drug manufacturer m
$\tilde{\eta}_{mp}$	number of drug rejections for drug type p sent by drug manufacturer m
δ_{mp}	Total units of drug type p manufactured at location m
μ	drug rejection scaling parameter
q_{mp}	average complaints level for the drug type p manufactured by manufacturer m
Q	established acceptance criteria for the drugs
$Pcap_{mp}$	processing capacity of drug manufacturing site m for product type p
$D\tilde{e}m_{hpt}$	the demand for drug p in hospital h during period t
$Scap_{dc}$	the capacity of center d with capacity c

Decision variables

y_{mpdt}	If drug manufacturer d supplies drugs to distributor d of type p in planning duration t then 1; otherwise 0
z_{dc}	If the drug distribution center at d with a capacity of c is located then 1; otherwise 0
Q_{mpdt}	Quantity of drug type p sent to drug distribution center d from drug manufacturer m in planning duration t
Q_{pdht}	Quantity of drugs type p is sent from center d to hospital pharmacy h in planning duration t

3.2 Mathematical model

a. Total cost minimization objective

$$\min \quad f^{\text{total cost}} = \sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\tilde{\lambda}_{mpt}^{prod}Q_{mpdt} + \sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\tilde{\lambda}_{p}^{insp}y_{mpdt} + \sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\tilde{\lambda}_{dp}^{stor}Q_{mpdt} + \sum_{d}^{D}\sum_{c}^{C}\tilde{\lambda}_{dc}^{inst}z_{dc} + \sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\tilde{\lambda}_{md}^{tran}Q_{mpdt} + \sum_{d}^{D}\sum_{h}^{H}\sum_{t}^{T}\tilde{\lambda}_{dh}^{tran}Q_{pdht} \tag{1}$$

The foremost component of the objective function specified in Eq. (1) serves to minimize the cost of drug production in the manufacturing process. The next term tries to minimize the overall cost associated with drug inspections. The third term signifies the cumulative cost of storing drugs at distribution centers. The fourth term aims to reduce the total expense incurred in establishing distribution centers. Lastly, the last two components work towards minimizing the overall cost of drug transportation.

b. Total time minimization objective

$$\min \quad f^{\text{total time}} = \sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\tilde{\tau}_{mp}^{prot}Q_{mpdt} + \sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\tilde{\tau}_{md}^{time}y_{mpdt} + \sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\tilde{\tau}_{p}^{inspt}y_{mpdt} + \sum_{d}^{D}\sum_{h}^{H}\sum_{p}^{P}\sum_{t}^{T}\tau_{dh}^{time}Q_{pdht} \tag{2}$$

The objective function pertaining to time, as outlined in Eq. (2), encompasses the product of production time and the quantity of product families transferred to distribution centers across all time periods. Additionally, it includes the inspection time at manufacturing sites, as well as the transportation time from manufacturing sites to drugs distribution centers and subsequently from distribution centers to hospital pharmacies.

c. Drugs complaints minimization objective

$$\min \quad f^{\text{total complaints}} = \sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\frac{\tilde{\eta}_{mp}}{\delta_{mp}}\times\mu\right)y_{mpdt} \tag{3}$$

In the context of measuring quality, it is assessed by considering the number of complaints received for a particular drug type p. Given this context, Eq. (3) aims to minimize the highest count of rejections received for drug type p that is manufactured by manufacturing site m. The objective is to reduce the occurrence of rejected products and enhance overall product quality

by minimizing the maximum number of rejections observed for a specific drug type produced at a particular manufacturing site.

3.3 Constraints of the P-SCND optimization model

Constraint (4) stipulates that the total quantity of a drug manufactured at a manufacturing plant and transferred to a distribution center must not exceed the effective production capacity of the manufacturing plant. By adhering to this constraint, the model ensures that the manufacturing site's capabilities are not exceeded, enabling efficient production planning and allocation of resources.

$$\sum_{d}^{D} Q_{mpdt} \tilde{\leq} Pc\tilde{a}p_{mp} \times y_{mpdt} \qquad \forall m, p, t \tag{4}$$

Constraint (5) states that the cumulative quantity of each drug supplied from a distribution center to a hospital pharmacy must be at least higher than the total demand for each drug in that specific hospital pharmacy during each planned duration. By enforcing this constraint, the model guarantees that enough drugs are available at the hospital pharmacies to fulfill the needs of patients and healthcare providers, ensuring a consistent and reliable supply of medications.

$$\sum_{d}^{D} Q_{pdht} \tilde{\geq} D\tilde{e}m_{hpt} \qquad \forall p, h, t \tag{5}$$

Constraint (6) impost that the number of drugs supplied to each distribution center in each planning duration must be less than the total storage capacity of the distribution center. Constraint (6) requires that the number of drugs supplied to each distribution center during each planning duration must be strictly less than the total storage capacity of the respective distribution center. This constraint ensures that the quantity of drugs received and stored at each distribution center remains within its storage capacity limits.

$$\sum_{d}^{D}\sum_{p}^{P} Q_{mpdt} \leq \sum_{c}^{C} Scap_{dc} \times z_{dc} \qquad \forall m, t \tag{6}$$

Constraint (7) guarantees the equilibrium between the quantity of each drug type supplied from manufacturers to the storage center and the quantity supplied from the storage center to the hospital pharmacies. By maintaining this equilibrium, the constraint facilitates a smooth and consistent supply chain operation, preventing any imbalances or discrepancies between the supply of drugs from manufacturers and their subsequent distribution to hospital pharmacies.

$$\sum_{m}^{M} Q_{mpdt} - \sum_{h}^{H} Q_{pdht} = 0 \qquad \forall d, p, t \tag{7}$$

Constraint (8) imposes a limitation within the P-SCND optimization model, requiring that only a single capacity level be selected for each operational drug distribution center. By constraining the capacity selection to one level per distribution center, the optimization model aims to streamline resource allocation and facilitate efficient planning for the operational drug distribution network.

$$\sum_{c}^{C} z_{dc} \leq 1 \qquad \forall d \tag{8}$$

Constraint (9) specifies that the acceptance level for the actual production of drug type *p*, manufactured by drug manufacturer *m*, must be lower than the predefined acceptance level. Following this constraint, the manufacturer aims to maintain the desired level of product quality and ensure that the actual production process consistently meets the established acceptance criteria.

$$q_{mp} \times y_{mpdt} \leq Q \quad \forall m, p, d, t \tag{9}$$

Eq. (10) and Eq. (11) provide the drugs inventory levels for each type of drug *p* at each drug distribution center in specific planning durations.

$$IL_{dpt} = \Gamma_{dpt} - \sum_{h}^{H} Q_{pdht} \quad \forall d.p, t \mid t = 1 \tag{10}$$

$$IL_{dpt} = IL_{d,p,t-1} + \Gamma_{dpt} - \sum_{h}^{H} Q_{pdht} \quad \forall d.p, t \mid t \geq 2 \tag{11}$$

Eq. (12) and Eq. (13) impose binary and non-negativity constraints on the P-SCND model.

$$y_{mpdt}, z_{dc} \in \{0,1\} \tag{12}$$

$$Q_{mpdt}, Q_{pdht} \geq 0 \tag{13}$$

4. Solution methodology to solve the P-SCND optimization model

The integration of possibilistic programming, robust possibilistic programming, and flexible programming culminates in the formation of RPFPA. Each of them contributes a unique advantage in tackling uncertainty, which is as follows:

Possibilistic programming allows for the representation and handling of uncertainty in a flexible manner (Habib, Tayyab, Zahoor, & Sarkar, 2020). It employs possibility distributions to quantify the degree of possibility for different outcomes, accommodating imprecise and incomplete information. While robust programming enhances decision-making under uncertainty by considering multiple scenarios or variations in the uncertain parameters. Lastly, flexible programming introduces adaptability within the constraints of the model, enabling adjustments and modifications based on changing circumstances or evolving requirements. Using the combination of all these three techniques the DM can harness the benefits of each approach to effectively handle and manage uncertainty, leading to more robust and flexible solutions.

4.1 Generic formulation of RPFPA

To understand the working of RPFPA, Eq.n (14) presents a simplified version of an optimization model that consists of imprecise parameters. This formulation enables a deeper understanding of the composition of RPFPA and its application in handling uncertainty.

$$\begin{aligned} \min \quad & Z = \tilde{K} \times c + \tilde{R} \times o \\ \text{subject to} \quad & F \times c \leq \tilde{T}, \\ & D \times c = 0, \\ & Q \times o \leq \tilde{V} \times c, \\ & W \times o \geq 1, \\ & o \geq 0, \qquad c \in \{0,1\}, \end{aligned} \tag{14}$$

By employing the *ExpV* (Expected value) and *Me*-measure (for details of *ExpV* and *Me*-measure please see: (Abusaq et al., 2022; Pishvaee, J. Razmi, & Torabi, 2012; Rabbani, Zhalechian, & Farshbaf-Geranmayeh, 2018), uncertain parameters in Eq. (14) undergo a transformation, resulting in their conversion from an uncertain form to a certain form, as illustrated below:

$$\begin{aligned} \min \quad & ExpV[Z] = \left[\frac{1-\Im}{2} \times (K_1 + K_2) + \frac{\Im}{2} \times (K_3 + K_4)\right] \times c + \left[\frac{1-\Im}{2} \times (R_1 + R_2) + \frac{\Im}{2} \times (R_3 + R_4)\right] \times o \\ \text{subject to} \quad & F \times c \leq \left[\frac{(\Phi_1 - \Im) \times T_1 + (1-\Phi_1) \times T_2}{1-\Im}\right], \\ & D \times c = 0, \\ & Q \times o \leq \left[\frac{(\Phi_2 - \Im) \times V_1 + (1-\Phi_2) \times V_2}{1-\Im}\right] \times c, \\ & W \times o \geq 1, \\ & o \geq 0,\ c \in \{0,1\},\ 0.5 \leq \Phi_1, \Phi_2 \leq 1,\ 0 \leq \Im \leq 1 \end{aligned} \tag{15}$$

During the following phase, the PP equivalent form, as illustrated in Eq. (15), is subject to modifications that involve the integration of flexibility within its constraints. This adaptation results in a revised formulation called FPP, which is outlined in Eq. (16) provided below:

$$\begin{aligned} \min \quad & ExpV[Z] = \left[\frac{1-\Im}{2} \times (K_1 + K_2) + \frac{\Im}{2} \times (K_3 + K_4)\right] \times c + \left[\frac{1-\Im}{2} \times (R_1 + R_2) + \frac{\Im}{2} \times (R_3 + R_4)\right] \times o \\ \text{subject to} \quad & F \times c \tilde{\leq} \left[\frac{(\Phi_1 - \Im) \times T_1 + (1-\Phi_1) \times T_2}{1-\Im}\right], \\ & D \times c = 0, \\ & Q \times o \tilde{\leq} \left[\frac{(\Phi_2 - \Im) \times V_1 + (1-\Phi_2) \times V_2}{1-\Im}\right] \times c, \\ & W \times o \geq 1, \\ & o \geq 0,\ c \in \{0,1\},\ 0.5 \leq \Phi_1, \Phi_2 \leq 1,\ 0 \leq \Im \leq 1 \end{aligned} \tag{16}$$

In the above Equation, the parameter $\Im$ represents the pessimistic-optimistic parameter, while Φ_1 and Φ_2 are indicative of the SC manager's level of confidence. Besides, the symbol $\tilde{\leq}$ signifies the integration of flexibility into the target values of uncertain constraints.

$$
\begin{aligned}
\min \quad & ExpV[Z] = \left[\frac{1-\Im}{2}\times(K_1+K_2)+\frac{\Im}{2}\times(K_3+K_4)\right]\times c+\left[\frac{1-\Im}{2}\times(R_1+R_2)+\frac{\Im}{2}\times(R_3+R_4)\right]\times o \\
\text{subject to} \quad & F\times c \leq \left[\frac{(\Phi_1-\Im)\times T_1+(1-\Phi_1)\times T_2}{1-\Im}\right]+\left[\frac{v_1+v_2+v_3+v_4}{4}\right](1-\beta_1) \\
& D\times c = 0, \\
& Q\times o \leq \left[\frac{(\Phi_2-\Im)\times V_1+(1-\Phi_2)\times V_2}{1-\Im}\right]\times c+\left[\left\{\frac{j_1+j_2+j_3+j_4}{4}\right\}(1-\beta_2)\right]\times c \\
& W\times o \geq 1, \\
& o\geq 0,\ c\in\{0,1\},\ \ 0.5\leq\Phi_1,\Phi_2\leq 1,\ \ 0\leq\Im\leq 1,\ 0\leq\beta_1,\beta_2\leq 1
\end{aligned}
\tag{17}
$$

In Eq. (17), $\tilde{v}$ and $\tilde{j}$ are the uncertain flexibility margins for uncertain constraints, while β_1,β_2 are the confidence level of DM for the flexibility margin. Subsequently, by utilizing the concept of RPP presented by Pishvaee et al. (2012), the resultant RPFPA form is as below:

$$
\begin{aligned}
\min \quad & ExpV[Z]+\Theta\left(Z_{\max}-ExpV[Z]\right)+\Xi_1\left[\left[\frac{(\Phi_1-\Im)\times T_1+(1-\Phi_1)\times T_2}{1-\Im}\right]-\Phi_1\right]+ \\
& \Xi_2\left[\left[\frac{(\Phi_2-\Im)\times V_1+(1-\Phi_2)\times V_2}{1-\Im}\right]-\Phi_2\right]\times c+o_1\left[\left[\frac{v_1+v_2+v_3+v_4}{4}\right](1-\beta_1)\right]+ \\
& o_2\left[\left[\left\{\frac{j_1+j_2+j_3+j_4}{4}\right\}(1-\beta_2)\right]\times c\right] \\
\text{subject to} \quad & ExpV[Z] = \left[\frac{1-\Im}{2}\times(K_1+K_2)+\frac{\Im}{2}\times(K_3+K_4)\right]\times c+\left[\frac{1-\Im}{2}\times(R_1+R_2)+\frac{\Im}{2}\times(R_3+R_4)\right]\times o \\
& F\times c \leq \left[\frac{(\Phi_1-\Im)\times T_1+(1-\Phi_1)\times T_2}{1-\Im}\right]+\left[\frac{v_1+v_2+v_3+v_4}{4}\right](1-\beta_1) \\
& D\times c = 0, \\
& Q\times o \leq \left[\frac{(\Phi_2-\Im)\times V_1+(1-\Phi_2)\times V_2}{1-\Im}\right]\times c+\left[\left\{\frac{j_1+j_2+j_3+j_4}{4}\right\}(1-\beta_2)\right]\times c \\
& W\times o \geq 1, \\
& o\geq 0,\ c\in\{0,1\},\ \ 0.5\leq\Phi_1,\Phi_2\leq 1,\ \ 0\leq\Im\leq 1,\ 0\leq\beta_1,\beta_2\leq 1
\end{aligned}
\tag{18}
$$

4.2 Conversion of uncertain P-SCND model into RPFPA form

The systematic conversions described in Section 4.1 are employed to transform the uncertain generic model into an equivalent RPFPA form. As a result of these conversions, the P-SCND model can be represented in the following RPFPA format:

$$
\begin{Bmatrix}
\textit{Minimize} \quad ExpV\left[f^{\textit{total cost}}\right]+\chi^{\textit{cost}}\left[f^{\textit{total cost,MAX}}-ExpV\left[f^{\textit{total cost}}\right]\right]+ \\
pen^{\textit{pcap,cost}}\times\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left[\left\{\frac{(\partial^{\textit{sup}}-\hat{\lambda})Pcap_{mp(1)}+(1-\partial^{\textit{sup}})Pcap_{mp(2)}}{1-\hat{\lambda}}\right\}-Pcap_{mp(1)}\right]y_{mpdt}+ \\
pen^{\textit{dem,cost}}\times\sum_{h}^{H}\sum_{p}^{P}\left[Dem_{hp(4)}-\left\{\frac{(\partial^{\textit{dem}}-\hat{\lambda})Dem_{hp(4)}+(1-\partial^{\textit{dem}})Dem_{hp(3)}}{1-\hat{\lambda}}\right\}\right] \\
\\
ExpV\left[f^{\textit{total cost}}\right]=\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\left\{\frac{1-\Lambda^{\textit{cost}}}{2}\left(\lambda_{mpt(1)}^{\textit{prod}}+\lambda_{mpt(2)}^{\textit{prod}}\right)+\frac{\Lambda^{\textit{cost}}}{2}\left(\lambda_{mpt(3)}^{\textit{prod}}+\lambda_{mpt(4)}^{\textit{prod}}\right)\right\}\times Q_{mpdt}\right)+ \\
\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\left\{\frac{1-\Lambda^{\textit{cost}}}{2}\left(\lambda_{p(1)}^{\textit{insp}}+\lambda_{p(2)}^{\textit{insp}}\right)+\frac{\Lambda}{2}^{\textit{cost}}\left(\lambda_{p(3)}^{\textit{insp}}+\lambda_{p(4)}^{\textit{insp}}\right)\right\}\times y_{mpdt}\right)+ \\
\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\left\{\frac{1-\Lambda^{\textit{cost}}}{2}\left(\lambda_{dp(1)}^{\textit{stor}}+\lambda_{dp(2)}^{\textit{stor}}\right)+\frac{\Lambda^{\textit{cost}}}{2}\left(\lambda_{dp(3)}^{\textit{stor}}+\lambda_{dp(4)}^{\textit{stor}}\right)\right\}\times Q_{mpdt}\right)+ \\
\sum_{d}^{D}\sum_{c}^{C}\left(\left\{\frac{1-\Lambda^{\textit{cost}}}{2}\left(\lambda_{dc(1)}^{\textit{inst}}+\lambda_{dc(2)}^{\textit{inst}}\right)+\frac{\Lambda^{\textit{cost}}}{2}\left(\lambda_{dc(3)}^{\textit{inst}}+\lambda_{dc(4)}^{\textit{inst}}\right)\right\}\times z_{dc}\right)+ \\
\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\left\{\frac{1-\Lambda^{\textit{cost}}}{2}\left(\lambda_{md(1)}^{\textit{tran}}+\lambda_{md(2)}^{\textit{tran}}\right)+\frac{\Lambda^{\textit{cost}}}{2}\left(\lambda_{md(3)}^{\textit{tran}}+\lambda_{md(4)}^{\textit{tran}}\right)\right\}\times Q_{mpdt}\right)+ \\
\sum_{d}^{D}\sum_{h}^{H}\sum_{t}^{T}\left(\left\{\frac{1-\Lambda^{\textit{cost}}}{2}\left(\lambda_{dh(1)}^{\textit{tran}}+\lambda_{dh(2)}^{\textit{tran}}\right)+\frac{\Lambda^{\textit{cost}}}{2}\left(\lambda_{dh(3)}^{\textit{tran}}+\lambda_{dh(4)}^{\textit{tran}}\right)\right\}\times Q_{pdht}\right) \\
\\
f^{\textit{total cost,MAX}}=\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\left\{\left(\lambda_{mpt(4)}^{\textit{prod}}\right)\right\}\times Q_{mpdt}\right)+\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\left(\lambda_{p(4)}^{\textit{insp}}\right)\times y_{mpdt}\right)+\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\left(\lambda_{dp(4)}^{\textit{stor}}\right)\times Q_{mpdt}\right)+ \\
\sum_{d}^{D}\sum_{c}^{C}\left(\left(\lambda_{dc(4)}^{\textit{inst}}\right)\times z_{dc}\right)+\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\left(\lambda_{dh(4)}^{\textit{tran}}\right)\times Q_{mpdt}\right)+\sum_{d}^{D}\sum_{h}^{H}\sum_{t}^{T}\left(\left(\lambda_{dh(4)}^{\textit{tran}}\right)\times Q_{pdht}\right)
\end{Bmatrix}
\tag{19}
$$

$$
\begin{Bmatrix}
\textit{Minimize} \quad ExpV\left[f^{\textit{total complain}}\right]+\chi^{\textit{complain}}\left[f^{\textit{totalcomplain,MAX}}-ExpV\left[f^{\textit{total complain}}\right]\right]+ \\
pen^{\textit{pcap,complain}}\times\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left[\left\{\frac{(\partial^{\textit{sup}}-\hat{\lambda})Pcap_{mp(1)}+(1-\partial^{\textit{sup}})Pcap_{mp(2)}}{1-\hat{\lambda}}\right\}-Pcap_{mp(1)}\right]y_{mpdt}+ \\
pen^{\textit{dem,tcomplain}}\times\sum_{h}^{H}\sum_{p}^{P}\left[Dem_{hp(4)}-\left\{\frac{(\partial^{\textit{dem}}-\hat{\lambda})Dem_{hp(4)}+(1-\partial^{\textit{dem}})Dem_{hp(3)}}{1-\hat{\lambda}}\right\}\right] \\
ExpV\left[f^{\textit{total complain}}\right]=\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\frac{\left\{\frac{1-\Lambda^{\textit{complain}}}{2}\left(\eta_{mp(1)}+\eta_{mp(2)}\right)+\frac{\Lambda^{\textit{complain}}}{2}\left(\eta_{mp(3)}+\eta_{mp(4)}\right)\right\}}{\delta_{mp}}\times\mu\right)y_{mpdt} \\
f^{\text{total complaints, MAX}}=\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\frac{\eta_{mp(4)}}{\delta_{mp}}\times\mu\right)y_{mpdt}
\end{Bmatrix}
\tag{20}
$$

$$
\begin{Bmatrix}
Minimize \quad ExpV\left[f^{total\,time}\right]+\chi^{time}\left[f^{total\,time,MAX}-ExpV\left[f^{total\,time}\right]\right]+ \\
pen^{pcap,time}\times\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left[\left\{\frac{(\partial^{sup}-\lambda)Pcap_{mp(1)}+(1-\partial^{sup})Pcap_{mp(2)}}{1-\lambda}\right\}-Pcap_{mp(1)}\right]y_{mpdt}+ \\
pen^{dem,time}\times\sum_{h}^{H}\sum_{p}^{P}\left[Dem_{hp(4)}-\left\{\frac{(\partial^{dem}-\lambda)Dem_{hp(4)}+(1-\partial^{dem})Dem_{hp(3)}}{1-\lambda}\right\}\right] \\
\\
ExpV\left[f^{total\,time}\right]=\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\left\{\frac{1-\Lambda^{time}}{2}\left(\tau_{mp(1)}^{prot}+\tau_{mp(2)}^{prot}\right)+\frac{\Lambda^{time}}{2}\left(\tau_{mp(3)}^{prot}+\tau_{mp(4)}^{prot}\right)\right\}\times Q_{mpdt}\right)+ \\
\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\left\{\frac{1-\Lambda^{time}}{2}\left(\tau_{md(1)}^{time}+\tau_{md(2)}^{time}\right)+\frac{\Lambda^{time}}{2}\left(\tau_{md(3)}^{time}+\tau_{md(4)}^{time}\right)\right\}\times y_{mpdt}\right)+ \\
\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\left\{\frac{1-\Lambda^{time}}{2}\left(\tau_{p(1)}^{inspt}+\tau_{p(2)}^{inspt}\right)+\frac{\Lambda^{time}}{2}\left(\tau_{p(3)}^{inspt}+\tau_{p(4)}^{inspt}\right)\right\}\times y_{mpdt}\right)+ \\
\sum_{d}^{D}\sum_{h}^{H}\sum_{p}^{P}\sum_{t}^{T}\left(\left\{\frac{1-\Lambda^{time}}{2}\left(\tau_{dh(1)}^{time}+\tau_{dh(2)}^{time}\right)+\frac{\Lambda^{time}}{2}\left(\tau_{dh(3)}^{time}+\tau_{dh(4)}^{time}\right)\right\}\times Q_{pdht}\right) \\
\\
f^{total\,time,MAX}=\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\tau_{mp(4)}^{prot}\times Q_{mpdt}\right)+\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\tau_{md(4)}^{time}\times y_{mpdt}\right)+ \\
\sum_{m}^{M}\sum_{p}^{P}\sum_{d}^{D}\sum_{t}^{T}\left(\tau_{p(4)}^{inspt}\times y_{mpdt}\right)+\sum_{d}^{D}\sum_{h}^{H}\sum_{p}^{P}\sum_{t}^{T}\left(\tau_{dh(4)}^{time}\times Q_{pdht}\right)
\end{Bmatrix} \tag{21}
$$

$$
\sum_{d}^{D}Q_{mpdt}\le\left[\frac{(\partial^{sup}-\lambda)Pcap_{mp(1)}+(1-\partial^{sup})Pcap_{mp(2)}}{1-\lambda}\right]\times y_{mpdt}+\left[\left(\frac{\upsilon_1+\upsilon_2+\upsilon_3+\upsilon_4}{4}\right)\left(1-\hbar^{\sup}\right)\right]\times y_{mpdt}\quad\forall m,p,t\,|0.5\le\partial^{sup}\le 1 \tag{22}
$$

$$
\sum_{d}^{D}Q_{pdht}\ge\left[\frac{(\partial^{dem}-\lambda)Dem_{hp(4)}+(1-\partial^{dem})Dem_{hp(3)}}{1-\lambda}\right]-\left[\left(\frac{\mu_1+\mu_2+\mu_3+\mu_4}{4}\right)\left(1-\hbar^{dem}\right)\right]\qquad\forall p,h,t\,|0.5\le\partial^{dem}\le 1 \tag{23}
$$

and constraints (6) – (13).

4.3 Membership functions formulation for P-SCND model objectives

After obtaining the P-SCND model's uncertain formulation, a pay-off table is developed for model objectives. Based on which membership function for each model objective is developed as below in Equation (24) – (26).

$$
\kappa^{cost}=\begin{cases}1 & if\ f^{total\,cost}\le f_{PS}^{total\,cost}\\ \dfrac{f_{NS}^{total\,cost}-f^{total\,cost}}{f_{NS}^{total\,cost}-f_{PS}^{total\,cost}} & if\ f_{PS}^{total\,cost}<f^{total\,cost}<f_{NS}^{total\,cost}\\ 0 & if\ f^{total\,cost}\ge f_{NS}^{total\,cost}\end{cases} \tag{24}
$$

$$
\kappa^{time}=\begin{cases}1 & if\ f^{total\,time}\le f_{PS}^{total\,time}\\ \dfrac{f_{NS}^{total\,time}-f^{total\,time}}{f_{NS}^{total\,time}-f_{PS}^{total\,time}} & if\ f_{PS}^{total\,time}<f^{total\,time}<f_{NS}^{total\,time}\\ 0 & if\ f^{total\,time}\ge f_{NS}^{total\,time}\end{cases} \tag{25}
$$

$$\kappa^{complain} = \begin{cases} 1 & if \ \ f^{total\ complain} \le f_{PS}^{total\ complain} \\ \dfrac{f_{NS}^{total\ complain} - f^{total\ complain}}{f_{NS}^{total\ complain} - f_{PS}^{total\ complain}} & if \ \ f_{PS}^{total\ complain} < f^{total\ complain} < f_{NS}^{total\ complain} \\ 0 & if \ \ f^{total\ complain} \ge f_{NS}^{total\ complain} \end{cases} \tag{26}$$

where, κ^{cost}, κ^{time} ,and $\kappa^{complain}$ are the attainment degrees for respective objective functions.

4.4 Transforming the P-SCND model into a single objective form

In the last stage of the proposed methodology, the proposed model is transformed into a single objective. In this research, the TH method is employed. TH method is employed in many research studies (Habib & Sarkar, 2018)Its formulation is as follows:

$$\begin{aligned} \text{max} \quad & \aleph\, \ell + \left\{ (1-\ell)\left(w^{cost}\kappa^{cost} + w^{time}\kappa^{time} + w^{complain}\kappa^{complain} \right) \right\} \\ \text{such that} \quad & \kappa^{cost} \ge \aleph \\ & \kappa^{time} \ge \aleph \\ & \kappa^{complain} \ge \aleph \\ & \aleph \in [0,1] \end{aligned} \tag{27}$$

System constraints (6) – (13) and (19) – (23).

where ℓ and $\aleph$ represent the compensation coefficient and the minimum possible objective target, in the P-SCND model. On the other hand, w^{cost}, w^{time}, and $w^{complain}$ denote the priority weights assigned to the objectives of the model.

5. Case problem

In this portion, we present the implementation of the P-SCND model in practical scenarios. To validate its effectiveness, we provide a numerical example that serves as an illustration of the model discussed in the previous section. The SC network under consideration is a three-tiered system, handling multiple types of drugs. It includes eight drug manufacturing sites, four drug distribution centers (with two different capacity levels), and four hospitals. In this network, the manufacturing sites are located on the left side, representing the supply echelon, while the hospitals are positioned on the right side, representing the demand echelon. The model has been analyzed within a three planning horizon, enabling the identification of the most favorable balance among cost, time, and quality factors. The demand of each hospital is fulfilled through a group of distribution centers, and decisions regarding their location and capacity are treated as binary variables.

The transportation cost between different tiers of the supply chain facilities is calculated by multiplying the distances between individual facilities with the unit transportation cost specific to each tier. This unit transportation cost is determined based on data obtained from regional logistics firms. Additionally, the model assumes that a fleet of homogeneous drug supply vehicles with a capacity of 10 tons is responsible for transporting feedstock from supply terminals to distributors. Similarly, vehicles, each with a capacity of 5 tons, have been utilized to transport drugs from distribution centers to the respective demand zones (hospitals). The decision-makers (DMs) engaged in the PSC are focused on procuring drugs to fulfill the hospitals' requirements for the upcoming three months. The procurement department is responsible for the purchasing process. Within a 300-kilometer radius, there are eight suppliers available. The network of healthcare centers, in collaboration with the health department, aims to assess each supplier's performance based on criteria such as time, quality, and cost. The P-SCND model involves the following decisions:

- *Selection of suppliers*: The model determines the number of suppliers to be chosen based on their ability to meet the evaluation criteria of cost, time, and quality.
- *Capacity planning for drug distribution centers*: The model determines the operational capacity levels of drug distribution centers, considering factors such as demand and logistical requirements.
- *Allocation of drugs from suppliers to distribution centers*: The model calculates the optimal quantity of each type of drug to be allocated from selected suppliers to specific locations within the drug distribution centers.
- *Allocation of drugs from distribution centers to demand points*: The model determines the quantity of each type of drug to be allocated from the selected locations within the drug distribution centers to the respective demand points.

- *Cost for robustness*: The model helps evaluate the need for additional investments by decision-makers to guarantee the reliability of the chosen SC configuration, even in an uncertain environment.

These decisions, made on strategic and tactical fronts, aim to optimize the supply chain operations while considering cost-effectiveness, timely delivery, quality assurance, and risk against an uncertain environment. In the P-SCND model, uncertain input parameters are represented as fuzzy parameters. The tables presented in Appendix A, specifically Tables A1 to A11, offer a comprehensive compilation of the most probable values for the data utilized in this research.

5.1 Results and computational analysis

In the subsequent phase, the data that was gathered, along with the P-SCND model represented in Equations (5) -(18) and (19) -(27) are encoded in the LINGO software to obtain optimized results. Since the provided RPFPA approach is interactive, the managers are required to select the values of interactive parameters under real-time dynamics. These parameters include the CL (confidence level) of the manager, the scaling parameter, the penalty for violating uncertain constraints, and the penalty for violating flexible constraints. The scaling parameter value plays a crucial role in improving the robustness and optimality of the P-SCND model. The scaling parameter helps to balance the trade-offs between different objectives and ensure that the model's solution remains robust in the face of uncertain or variable durations. By minimizing the maximum deviation of the objective, the scaling parameter contributes to achieving a more desirable and consistent outcome for the P-SCND model. Furthermore, the values for the penalty associated with uncertain constraint violation and soft constraint violation are determined based on the DMs confidence level. If the DM is facing a higher level of uncertain environment, then the confidence level is low hence, higher values of penalty violation constraints are more suitable. Assuming a CL of 90% of DM for the uncertain constraints, the RPFPA equivalent form was used to develop the payoff table of the P-SCND model objectives which is given below in Table 2.

Table 2
Best and worst case values for the objectives of the P-SCND model.

P-SCND model objectives	Cost minimization ($)	Time minimization (hours)	Complaint minimization (quality)
Cost minimization	21,058,669	9,748	35,498
Time minimization	30,044,300	8,490	66,549
Complaint minimization (quality)	29,065,440	11,540	18,659

The decision acquired from the proposed model depicts a conflicting nature between the P-SCND model objectives. For instance, when considering the cost objective, the best solution yields the lowest value of $21,058,669, while the worst-case solution provides a value of $30,044,300. Alternatively, when addressing the time objective independently, the resulting value is 8,490. However, when it is considered in conjunction with the cost minimization objective, the time minimization objective increases to 9,748. Similarly, the quality objective, when solved independently, achieves a minimum value of 18,659. Yet, when combined with the time minimization objective, the quality minimization objective yields a value of 66,549. The reason for this contradiction is that when the quality objective is addressed independently, it consumes more inspection time to uplift the value of the quality objective satisfaction level. Conversely, when the time minimization objective is pursued in isolation, it aims to minimize the overall system while still meeting the minimum acceptable level of quality set by the constraints of the model. These outcomes clearly illustrate the trade-offs among the P-SCND model objectives.

$$\kappa^{cost} = \begin{cases} 1 & if\ \ f^{total\ cost} \le 21,058,669 \\ \dfrac{30,044,300 - f^{total\ cost}}{30,044,300 - 21,058,669} & if\ \ 21,058,669 < f^{total\ cost} < 30,044,300 \\ 0 & if\ \ f^{total\ cost} \ge 30,044,300 \end{cases} \tag{28}$$

$$\kappa^{time} = \begin{cases} 1 & if\ \ f^{total\ time} \le 8,490 \\ \dfrac{11,540 - f^{total\ time}}{11,540 - 8,490} & if\ \ 8,490 < f^{total\ time} < 11,540 \\ 0 & if\ \ f^{total\ time} \ge 11,540 \end{cases} \tag{29}$$

$$\kappa^{complain} = \begin{cases} 1 & if\ \ f^{total\ complain} \le 18,659 \\ \dfrac{66,549 - f^{total\ complain}}{66,549 - 18,659} & if\ \ 18,659 < f^{total\ complain} < 66,549 \\ 0 & if\ \ f^{total\ complain} \ge 66,549 \end{cases} \tag{30}$$

By applying Equation (28) to Equation (30) in the TH formulation, the results for the P-SCND model can be derived. It is worth mentioning that the proposed solution is interactive in nature. Therefore, it allows for obtaining scenario-specific results tailored to specific scenarios. Fig. 2 has been provided to visually depict the optimized decision. It represents the decisions made during the first planning duration only, where the values of $\ell = 0$ and equal preference for w^{cost}, w^{time}, and $w^{complain}$ are considered. In this specific case scenario, the objectives of minimization of cost, time, and quality have achieved goals of 70.2%, 67.3%, and 62.8%, respectively. These values represent the level of accomplishment (κ^{cost}, κ^{time}, $\kappa^{complain}$) for each objective based on the optimization process within the model.

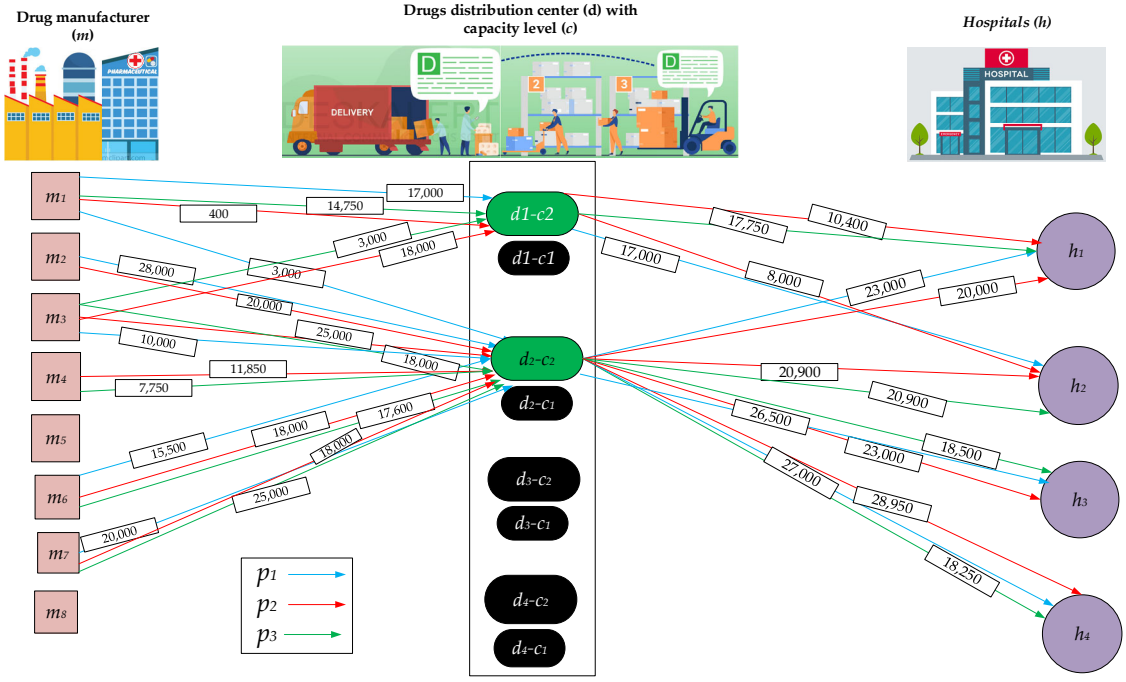


Fig. 2. Optimized decisions for the P-SCND optimization using the RPFPA approach

Based on the graphical representation in Fig. 2, the optimized decision for the first planning duration of the P-SCND model reveals that six out of the eight drug manufacturing sites have been selected as suppliers. Moving forward to the second tier of the P-SCND model, out of the four available drug distribution and storage centers, two have been designated as operational. Additionally, the capacity decision is also made for drug distribution centers. It has been determined that the optimization model has chosen distribution centers with high processing capacities for both operational locations. By opting for distribution centers with larger processing capacities, the optimization model takes advantage of economies of scale. This means that as the scale of operations increases, the average cost per operation decreases. The model recognizes that by leveraging economies of scale, it becomes more cost-effective to process a higher quantity of drugs in a single operation, rather than distributing them through multiple smaller operations. This approach optimizes the utilization of resources, minimizes costs, and enhances operational efficiency within the pharmaceutical supply chain. By prioritizing distribution centers with high processing capacities and benefiting from the economies of scale factor, the optimization model aims to streamline operations, maximize cost savings, and ultimately improve the overall performance of the distribution process within the pharmaceutical industry.

5.2 Impact on the total cost for integration of robustness factor

Assuming a confidence level of 90% of DM for the uncertain constraints of the P-SCND model a minimum of total $21,058,669 is obtained. According to Equation (27), Figure 3 illustrates the relative contributions, expressed as percentages, of the three components of the cost minimization objective in the RPFPA formulation. Specifically, the ExpV cost, and robustness cost, 76.2%, and 23.8%, respectively.

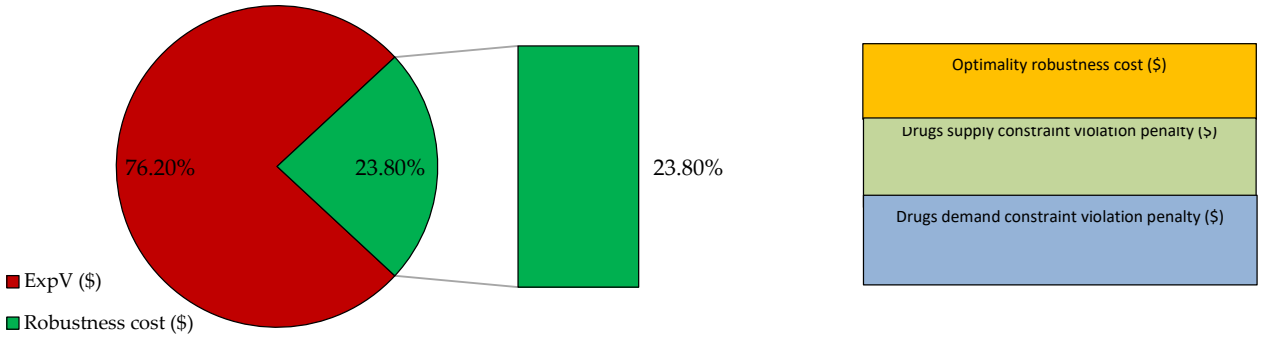


Fig. 3. Contribution of the different types of cost in the robust objective formulation of the P-SCND model.

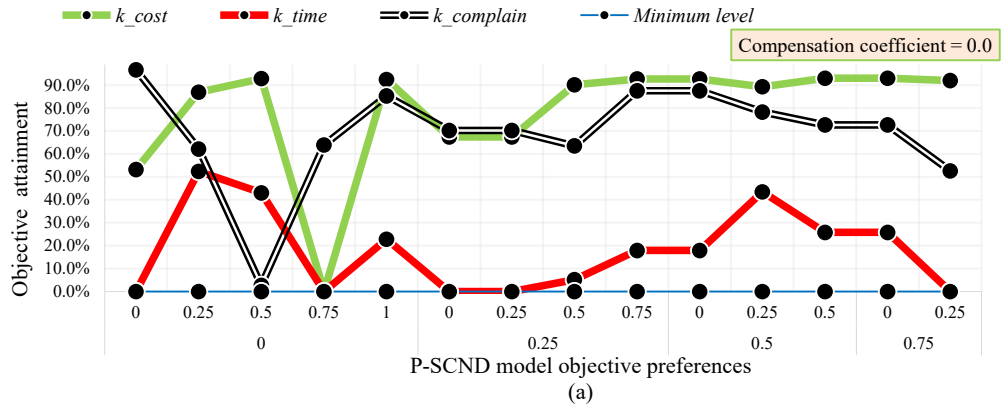
The drugs SC achieves a minimum cost of $21,058,669. Within this total cost, the ExpV cost component amounts to $16,046,706. The ExpV cost solely takes into account the average values of the uncertain parameters in the model. The reliability of findings based on the ExpV cost, which considers uncertain parameters obtained from TPD and can take on various values, is questionable. Due to the inherent uncertainty related to these parameters, the reliability and accuracy of the results may be compromised. Given the aforementioned background and the inherent limitations associated with uncertain parameters obtained from TPD, the RPFPA formulation presented in Equation (19) - (21) is utilized. RPFPA approach, in addition to considering the ExpV, also enhances the robustness, optimality, and feasibility of the optimization model. By incorporating the uncertainties and their associated penalties, the FRPP formulation aims to achieve a more stable and reliable solution. In the P-SCND model, a penalty cost of $1,503,589 is incurred to enhance the optimality of the obtained results. Additionally, there are constraint violation penalties associated with supply and demand which are $1,002,392 and $2,505,982, respectively. Table 2 provides a detailed breakdown of the total SC system cost, illustrating the individual components and their respective contributions to the overall cost.

Table 2
Total cost minimization composition in RPFPA formulation of P-SCND model.

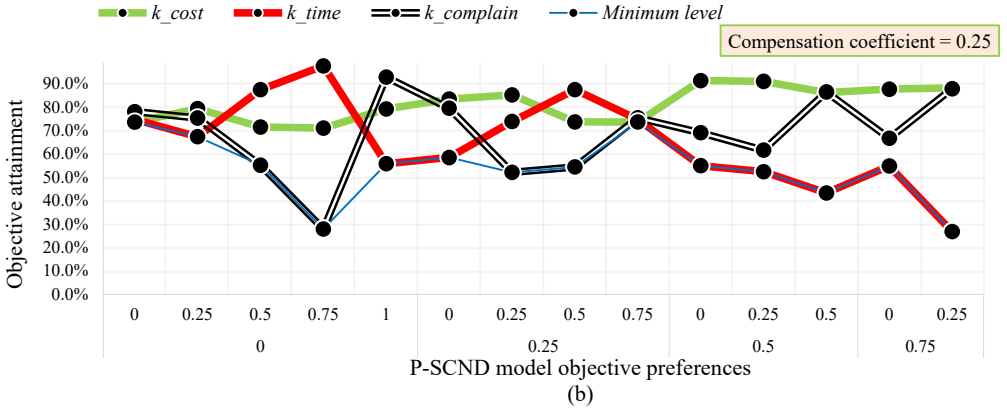
ExpV ($)	Objective function optimality robustness cost ($)	Drugs supply constraint violation penalty ($)	Drugs demand constraint violation penalty ($)	Total cost ($)
16,046,706	1,503,589	1,002,392	2,505,982	21,058,669

5.3 Impact of coefficient of compensation (TH method) on P-SCND model objectives attainment levels

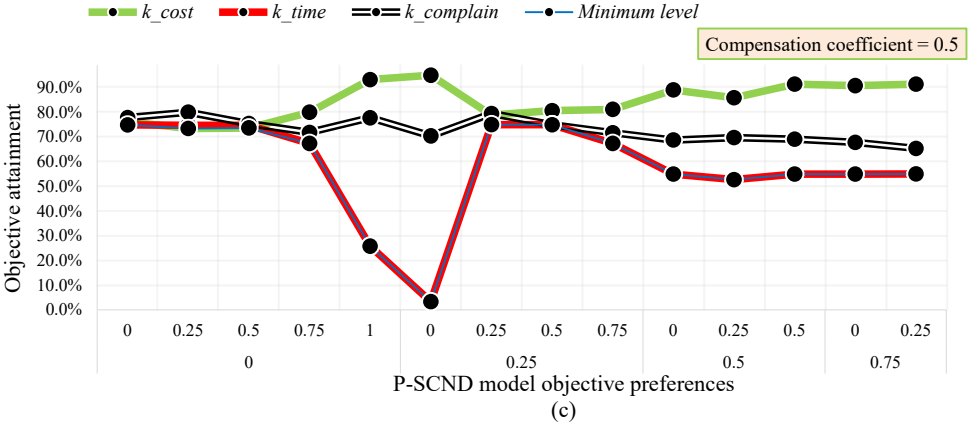
The P-SCND model undergoes conversion into a single objective through the utilization of the TH approach. Given the interactive nature of the TH method, decision-makers can obtain multiple global optimal solutions by adjusting the values of interactive parameters in response to real-time circumstances. The TH method encompasses two categories of interactive parameters: the coefficient of compensation (ℓ) and the preference weights (w^{cost}, w^{time}, and $w^{complain}$) assigned to the model objectives. By adjusting the values of the interactive parameters, it is possible to obtain multiple global optimal solutions for the model objectives (κ^{cost}, κ^{time}, $\kappa^{complain}$). Figure 4 provided displays the P-SCND model, where the levels of objective attainment are depicted on the vertical axis, and the preference weights assigned to each objective are represented on the horizontal axis. Upon careful examination of the results, an intriguing pattern becomes apparent: as the compensation coefficient (ℓ) increases, a balanced solution emerges for the P-SCND model objectives. This occurrence can be attributed to the TH method's behavior when utilizing higher values of the compensation coefficient. In such cases, the TH method focuses on elevating the minimum level of satisfaction across all goals, resulting in a more equitable and well-rounded solution. This implies that decision-makers, by adjusting the compensation coefficient, can achieve a desirable balance among the various objectives of the P-SCND model. As a result, there exists a relationship among the compensation coefficient (ℓ), objective preference weights, and the dispersion of objective attainment levels in the P-SCND model which is shown in Figure 4 (a)–(e). In Figure 4(a), the attainment levels display the highest dispersion, indicating a wider variation among the objectives' levels of attainment. Conversely, in Figure 4(e), the dispersion is the least, providing a highly uniform and consistent attainment level across the P-SCND model objectives irrespective of priority weights. This implies that the combination of appropriate preference weights and an optimal compensation coefficient (ℓ) can reduce the dispersal of satisfaction levels, resulting in a more balanced solution.


k_cost
k_time
k_complain
Minimum level
Compensation coefficient = 0.0
Objective attainment
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
0 0.25 0.5 0.75 1 0 0.25 0.5 0.75 0 0.25 0.5 0 0.25
0 0.25 0.5 0.75
P-SCND model objective preferences

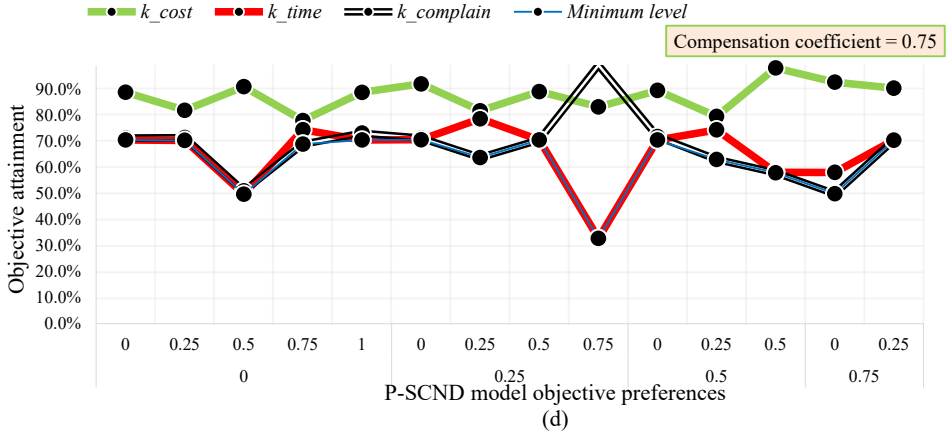
(a)


k_cost
k_time
k_complain
Minimum level
Compensation coefficient = 0.25
Objective attainment
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
0 0.25 0.5 0.75 1 0 0.25 0.5 0.75 0 0.25 0.5 0 0.25
0 0.25 0.5 0.75
P-SCND model objective preferences

(b)


k_cost
k_time
k_complain
Minimum level
Compensation coefficient = 0.5
Objective attainment
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
0 0.25 0.5 0.75 1 0 0.25 0.5 0.75 0 0.25 0.5 0 0.25
0 0.25 0.5 0.75
P-SCND model objective preferences

(c)


k_cost
k_time
k_complain
Minimum level
Compensation coefficient = 0.75
Objective attainment
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
0 0.25 0.5 0.75 1 0 0.25 0.5 0.75 0 0.25 0.5 0 0.25
0 0.25 0.5 0.75
P-SCND model objective preferences

(d)

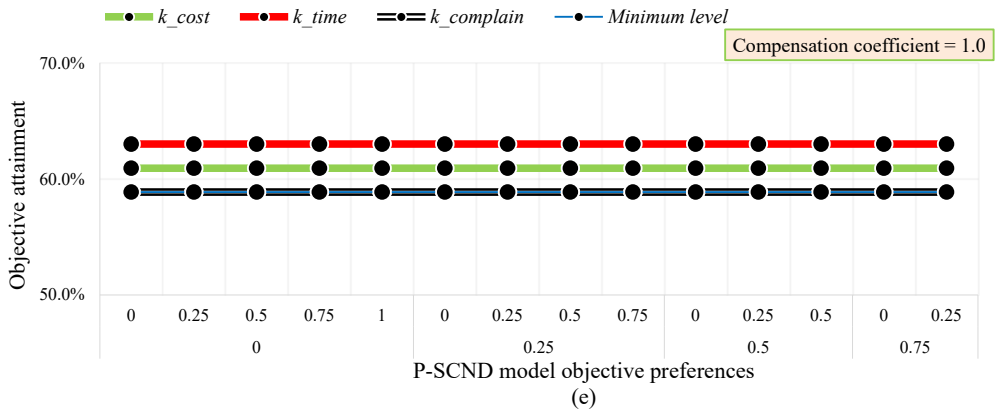


Fig. 4. Impact of coefficient of compensation (TH method) on P-SCND model objectives attainment levels. (a) $\ell = 0$, (b) $\ell = 0.25$, (c) $\ell = 0.50$, (d) $\ell = 0.75$, (e) $\ell = 1.0$.

6. Conclusions and future research directions

This research addresses the complexities of the PSC and aims to achieve a balance among quality, cost, time, and uncertainty. This research provides a decision-making system that assists managers in achieving commercial success while maintaining quality assurance goals in a PSC. Since the PSC faces considerable unpredictability due to factors such as governmental regulations and market fluctuations, it requires a robust system to minimize uncertainties and provide high-quality medicine to hospital pharmacies. For this purpose, this research provides a P-SCND optimization model. Additionally, to ensure resilience and robustness in the results of the P-SCND model, the research introduces the RPFPA solution approach. Research results demonstrate that the proposed model offers a promising approach to optimize allocation planning in the medicine SC. The results underscore the advantages of utilizing the proposed model to optimize allocation planning, meet customer demands, and mitigate system complaints. Additionally, by employing the RPFPA methodology, decision-makers gain the ability to strategically allocate investments within the PSC to enhance its resilience and mitigate the effects of inherent uncertainties.

Overall, the study contributes to the advancement of decision-making systems in the PSC, facilitating improved efficiency, cost-effectiveness, and quality assurance in the delivery of medicine to end customers. While the research provides valuable insights into optimizing the PSC, it also has a few limitations. These limitations can serve as future research directions to further enhance the understanding and effectiveness of PSC optimization. Two limitations and potential areas for future research are as follows:

- The research primarily focuses on internal factors within the pharmaceutical supply chain, such as production costs, transportation times, and quality parameters. However, the external factors that impact the PSC, such as market demand fluctuations, regulatory requirements, and geopolitical considerations, are not fully addressed. This research can be further extended by integrating external factors into the optimization model to provide a more comprehensive and realistic representation of the PSC dynamics.
- The research predominantly emphasizes the triad of cost, time, and quality, but does not extensively address sustainability and environmental factors. As the pharmaceutical industry is increasingly concerned with sustainability and environmental impact, future research could delve into incorporating green and sustainable practices into the PSC optimization model. This could involve considering factors such as carbon footprint reduction, waste management, and the use of eco-friendly materials. By integrating sustainability objectives into the optimization model, the PSC can become more environmentally responsible and aligned with global sustainability goals.

By extending research in these directions, scholars and practitioners can further enhance the understanding of PSC optimization, making it more comprehensive, adaptable, and sustainable. These future research directions have the potential to contribute to the development of more robust and holistic approaches for managing the complexities of the PSC, leading to improved operational efficiency, cost-effectiveness, and environmental sustainability.

References

Abusaq, Z., Habib, M. S., Shehzad, A., Kanan, M., & Assaf, R. (2022). A Flexible Robust Possibilistic Programming Approach Toward Wood Pellets Supply Chain Network Design. *Mathematics, 10*(19), 3657.

Ahmad, F. (2022). Interactive neutrosophic optimization technique for multiobjective programming problems: an application to pharmaceutical supply chain management. *Annals of Operations Research, 311*(2), 551-585.

Ahmad, F., Alnowibet, K. A., Alrasheedi, A. F., & Adhami, A. Y. (2022). A multi-objective model for optimizing the socio-economic performance of a pharmaceutical supply chain. *Socio-economic planning sciences, 79*, 101126.

Al-Rawashdeh, O. M., Jawabreh, O., & Ali, B. J. (2023). Supply Chain Management and Organizational Performance: The Moderating Effect of Supply Chain Complexity. *Information Sciences Letters, 12*(3), 1673-1684. doi:http://dx.doi.org/10.18576/isl/120351

Alhaj, A., Zanoon, N., Alrabea, A., Alnatsheh, H., Jawabreh, O., Abu-Faraj, M., & Ali, B. J. (2023). Improving the Smart Cities Traffic Management Systems using VANETs and IoT Features. *Journal of Statistics Applications & Probability, 12*(2), 405-414. doi:http://dx.doi.org/10.18576/jsap/120207

Ali, B. J. (2022). Integration of Supply Chains and Operational Performance: The Moderating Effects of Knowledge. *Information Sciences Letters, 11*(04), 1069-1076. doi:10.18576/isl/110407

Clauson, K. A., Breeden, E. A., Davidson, C., & Mackey, T. K. (2018). Leveraging Blockchain Technology to Enhance Supply Chain Management in Healthcare:: An exploration of challenges and opportunities in the health supply chain. *Blockchain in healthcare today*.

Enyinda, C. I., Mbah, C. H., & Ogbuehi, A. (2010). An empirical analysis of risk mitigation in the pharmaceutical industry supply chain: A developing-country perspective. *Thunderbird International Business Review, 52*(1), 45-54.

Ershadi, M. M., & Ershadi, M. S. (2022). Logistic planning for pharmaceutical supply chain using multi-objective optimization model. *International Journal of Pharmaceutical and Healthcare Marketing, 16*(1), 75-100.

Franco, C., & Alfonso-Lizarazo, E. (2020). Optimization under uncertainty of the pharmaceutical supply chain in hospitals. *Computers & Chemical Engineering, 135*, 106689.

Goodarzian, F., Hoseini-Nasab, H., Toloo, M., & Fakhrzad, M. B. (2021). Designing a new Medicine Supply Chain Network considering production technology policy using two novel heuristic algorithms. *RAIRO-Operations Research, 55*(2), 1015-1042.

Goodarzian, F., Taleizadeh, A. A., Ghasemi, P., & Abraham, A. (2021). An integrated sustainable medical supply chain network during COVID-19. *Engineering Applications of Artificial Intelligence, 100*, 104188.

Goodarzian, F., Wamba, S. F., Mathiyazhagan, K., & Taghipour, A. (2021). A new bi-objective green medicine supply chain network design under fuzzy environment: Hybrid metaheuristic algorithms. *Computers & Industrial Engineering, 160*, 107535.

Habib, M. S., & Sarkar, B. (2018). *A multi-objective approach to sustainable disaster waste management.* Paper presented at the Proc. Int. Conf. Ind. Eng. Oper. Manag.

Habib, M. S., Tayyab, M., Zahoor, S., & Sarkar, B. (2020). Management of animal fat-based biodiesel supply chain under the paradigm of sustainability. *Energy Conversion and Management, 225*, 113345.

Hassan, W. M., Aldoseri, D. T., Saeed, M. M., Khder, M. A., & Ali, B. J. (2022). *Utilization of Artificial Intelligence and Robotics Technology in Business.* Paper presented at the 2022 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS).

Imran, M., Kang, C., & Babar Ramzan, M. (2018). Medicine supply chain model for an integrated healthcare system with uncertain product complaints. *Journal of Manufacturing Systems, 46*, 13-28. doi:https://doi.org/10.1016/j.jmsy.2017.10.006

Jaberidoost, M., Nikfar, S., Abdollahiasl, A., & Dinarvand, R. (2013). Pharmaceutical supply chain risks: a systematic review. *DARU Journal of Pharmaceutical Sciences, 21*(1), 1-7.

Jafarnejad, A., Momeni, M., Razavi Hajiagha, S. H., & Faridi Khorshidi, M. (2019). A dynamic supply chain resilience model for medical equipment's industry. *Journal of Modelling in Management*, *14*(3), 816-840.

Jamil, F., Hang, L., Kim, K., & Kim, D. (2019). A novel medical blockchain model for drug supply chain integrity management in a smart hospital. *Electronics, 8*(5), 505.

Kanan, M., Habib, M. S., Habib, T., Zahoor, S., Gulzar, A., Raza, H., & Abusaq, Z. (2022). A Flexible Robust Possibilistic Programming Approach for Sustainable Second-Generation Biogas Supply Chain Design under Multiple Uncertainties. *Sustainability, 14*(18), 11597.

Kanan, M., Habib, M. S., Shahbaz, A., Hussain, A., Habib, T., Raza, H., . . . Assaf, R. (2022). A Grey-Fuzzy Programming Approach towards Socio-Economic Optimization of Second-Generation Biodiesel Supply Chains. *Sustainability, 14*(16), 10169.

Kaufmann, L., Thiel, C., & Becker, A. (2005). *Supply chain management in the Mexican pharmaceutical industry.* Paper presented at the 16th annual North American research/teaching symposium on purchasing and supply chain management.

Khouj, M., AlSharif, A., AlObaid, A., Omar, A., Aazam, F., AlGhamdi, M., . . . Kanan, M. (2022). *Assessing the Service, Information, and Website Quality of the Opera Student Information System at the University of Business and Technology (UBT).* Paper presented at the International Conference on Business and Technology.

Kumar, R., & Tripathi, R. (2019). *Traceability of counterfeit medicine supply chain through Blockchain.* Paper presented at the 2019 11th international conference on communication systems & networks (COMSNETS).

Liu, X., Barenji, A. V., Li, Z., Montreuil, B., & Huang, G. Q. (2021). Blockchain-based smart tracking and tracing platform for drug supply chain. *Computers & Industrial Engineering, 161*, 107669.

Munir, M. A., Habib, M. S., Hussain, A., Shahbaz, M. A., Qamar, A., Masood, T., . . . Hasan, M. (2022). Blockchain adoption for sustainable supply chain management: Economic, environmental, and social perspectives. *Frontiers in Energy Research, 10*, 899632.

Niu, B., Dong, J., & Liu, Y. (2021). Incentive alignment for blockchain adoption in medicine supply chains. *Transportation Research Part E: Logistics and Transportation Review, 152*, 102276.

Pishvaee, Razmi, J., & Torabi, S. A. (2012). Robust possibilistic programming for socially responsible supply chain network design: A new approach. *Fuzzy Sets and Systems, 206*, 1-20. doi:http://dx.doi.org/10.1016/j.fss.2012.04.010

Pishvaee, M. S., Razmi, J., & Torabi, S. A. (2012). Robust possibilistic programming for socially responsible supply chain network design: A new approach. *Fuzzy sets and systems, 206*, 1-20.

Pishvaee, M. S., & Torabi, S. A. (2010). A possibilistic programming approach for closed-loop supply chain network design under uncertainty. *Fuzzy sets and systems, 161*(20), 2668-2683.

Rabbani, M., Zhalechian, M., & Farshbaf-Geranmayeh, A. (2018). A robust possibilistic programming approach to multiperiod hospital evacuation planning problem under uncertainty. *International Transactions in Operational Research, 25*(1), 157-189.

Shah, N. (2004). Pharmaceutical supply chains: key issues and strategies for optimisation. *Computers & Chemical Engineering, 28*(6-7), 929-941.

Shakouhi, F., Tavakkoli-Moghaddam, R., Baboli, A., & Bozorgi-Amiri, A. (2022). Multi-objective programming and Six Sigma approaches for a competitive pharmaceutical supply chain with the value chain and product lifecycle. *Environmental Science and Pollution Research*, 1-21.

Shan, R., Xiao, X., Dong, G., Zhang, Z., Wen, Q., & Ali, B. (2022). The influence of accounting computer information processing technology on enterprise internal control under panel data simultaneous equation. *Applied Mathematics and Nonlinear Sciences, aop*(aop), 1–9. doi:10.2478/amns.2022.2.0157

Zandieh, M., Janatyan, N., Alem-Tabriz, A., & Rabieh, M. (2018). Designing sustainable distribution network in pharmaceutical supply chain: A case study. *International journal of supply and operations management, 5*(2), 122-133.

Appendix

Table A1

Production cost ($) of each drug per unit ($\tilde{\lambda}_{mpt}^{prod}$)

	p_1			p_2			p_3		
	t_1	t_2	t_3	t_1	t_2	t_3	t_1	t_2	t_3
m_1	1.2	1.26	1.32	2.1	2.205	2.31	3.2	3.36	3.52
m_2	1.8	1.89	1.98	2.3	2.415	2.53	3.1	3.255	3.41
m_3	1.4	1.47	1.54	2.5	2.625	2.75	3.2	3.36	3.52
m_4	1.5	1.575	1.65	1.9	1.995	2.09	3.1	3.255	3.41
m_5	1.4	1.47	1.54	1.9	1.995	2.09	3.3	3.465	3.63
m_6	1.5	1.575	1.65	2.12	2.10	2.2	3.4	3.57	3.74
m_7	1.6	1.68	1.76	2.1	2.205	2.31	3.12	3.15	3.35
m_8	1.2	1.26	1.32	2.2	2.31	2.42	2.9	3.045	3.19

Table A2

Inspection cost ($) of each drug type ($\tilde{\lambda}_{p}^{insp}$)

Drugs	($)
p_1	1.4
p_2	1.8
p_3	1.7

Table A3

The installation cost of drug distribution centers with capacity levels ($\tilde{\lambda}_{dc}^{inst}$)

	c_1	c_2
d_1	12,000	16,000
d_2	18,000	20,000
d_3	14,000	17,000
d_4	15,000	16,000

Table A4

Cost for transferring drugs from the drug manufacturing site to the drug distribution center ($\tilde{\lambda}_{md}^{tran}$)

	d_1	d_2	d_3	d_3
m_1	330	21	51	400
m_2	420	380	100	200
m_3	150	180	330	160
m_4	170	230	180	160
m_5	170	1100	150	360
m_6	180	110	250	350
m_7	490	210	330	450
m_8	350	250	190	150

Table A5
Time required to transport drugs from manufacture to distributor ($\tilde{\tau}_{md}^{time}$).

	d_1	d_2	d_3	d_3
m_1	33	21	51	40
m_2	42	38	10	20
m_3	15	18	33	16
m_4	17	23	18	16
m_5	17	11	15	36
m_6	18	11	25	35
m_7	49	21	33	45
m_8	35	25	19	15

Table A6
Time required to transport drugs from distributors to hospitals (τ_{dh}^{time}).

	h_1	h_2	h_3	h_3
d_1	12	7	12	20
d_2	14	10	20	18
d_3	17	13	19	21
d_4	20	18	12	10

Table A7
Complaints for each drug in last year's duration ($\tilde{\eta}_{mp}$)

	p_1	p_2	p_3
m_1	250	275	200
m_2	180	260	250
m_3	150	190	270
m_4	265	205	260
m_5	250	169	280
m_6	170	170	250
m_7	240	180	200
m_8	190	190	157

Table A8
Processing capacity of drug manufacturing sites for each drug type ($Pcap_{mp}$).

	p_1	p_2	p_3
m_1	25,000	25,000	20,000
m_2	30,000	21,000	15,000
m_3	27,000	28,000	20,000
m_4	30,000	26,000	25,000
m_5	25,000	35,000	24,000
m_6	20,000	30,000	20,000
m_7	24,000	20,000	28,000
m_8	30,000	20,000	21,000

Table A9
Estimated demand for drugs in hospitals

	p_1			p_2			p_3		
	t_1	t_2	t_3	t_1	t_2	t_3	t_1	t_2	t_3
h_1	21,500	23,650	24,725	28,400	31,240	32,660	15,000	16,500	17,250
h_2	14,500	15,950	16,675	26,900	29,590	30,935	18,900	20,790	21,735
h_3	24,800	27,280	28,520	21,500	23,650	24,725	16,500	18,150	18,975
h_4	25,000	27,500	28,750	27,500	30,250	31,625	17,500	19,250	20,125