

A Fuzzy Bi-objective Mathematical Model for Perishable Medical Goods Supply Chain Network Considering Crisis Situations: An Empirical Study

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ABSTRACT: In case of crisis, the salvation of injuries depends on the timely provision of medical goods, relief supplies, and equipment. The aim of this study is to present a mathematical model for the supply chain network of perishable medical goods in crisis situation considering the uncertain environment. In this paper, a three-level supply chain including suppliers, intermediate warehouses, and final customers is developed for perishable medical items. The uncertainty of customer demand for service and the spent time in the intermediate warehouses are considered using the exponential distribution functions. Also, it is assumed that the life-cycle of perishable medical goods follow the Weibull distribution function. The model attempts to minimize the total costs of the supply chain and total presence time of perishable items in the whole chain. The LP-Metric method is employed for solving small-sized problems. Due to the NP-Hardness of the problem, the modified Multi-objective Particle Swarm Optimization (MOPSO) and Non-dominated Sorting Genetic Algorithm (NSGA-II) are utilized as 2 well-known and efficient meta-heuristic algorithms for solving large-sized problems. The findings indicate that the meta-heuristic algorithms are efficient in achieving close to the optimal solution for large-size problems in a reasonable time. Also, the results demonstrate that NSGA-II outperforms MOPSO in terms of the high quality solution. Finally, the applicability of the model to real-world problems is demonstrated using a real case study. This paper can assist the planners and decision-makers of perishable drugs supply chain networks in crisis conditions with on-time supplying and distributing the required emergency items.

KEYWORDS: Supply chain network, perishable medical goods, crisis, relief, uncertainty, meta-heuristic algorithm

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Introduction

A disaster may occur at any time and place and this is often without prior warning. Several natural disasters, which cause mass casualties, occur in the world every year. Crisis is a natural or synthetic event that occurs suddenly or over the time and imposes hardship on society, and urgent and emergency actions are needed to overcome these hardships.¹ Events and disasters can be categorized as follows:

- Natural and sudden disasters such as avalanches, earthquakes, floods, dam destruction, storms, tornadoes, droughts and so on.
- Man-made and sudden events such as building collapse, chemical explosions, nuclear explosions, fires and chemical pollution.
- Man-made and long lasting events, including internal conflicts, international wars, and so on.

To deal with natural disasters and crises, there is a need for crisis management that is a set of specific operations and

processes that are designed to prevent and mitigate the effects of the crisis in the 3 stages of pre-crisis, during the crisis and post-crisis.² There are different approaches to dividing the phases of disaster management operations.³ One of these approaches divides the phases of disaster management operations into 4 phases: prevention, preparation, response, and recovery.⁴ Figure 1 shows the order of these phases starting from disasters. The duration of each phase is different depending on the type and severity of disasters. It should be noted that the above steps are repeated in a cycle.⁵

In the event of a crisis, the need for medical goods and relief products is well felt due to injuries and damage caused by it and rescue of many injuries and victims is dependent on the timely provision of relief supplies and equipment. Therefore, there should be a valid and reasonable planning for such critical situation which by timely supplying and distributing the required items, to create the opportunities to be used in urgent and emergency situation. Providing health and medical items that are needed by healthcare centers such as hospitals and health centers and managing them in normal and critical situation is a



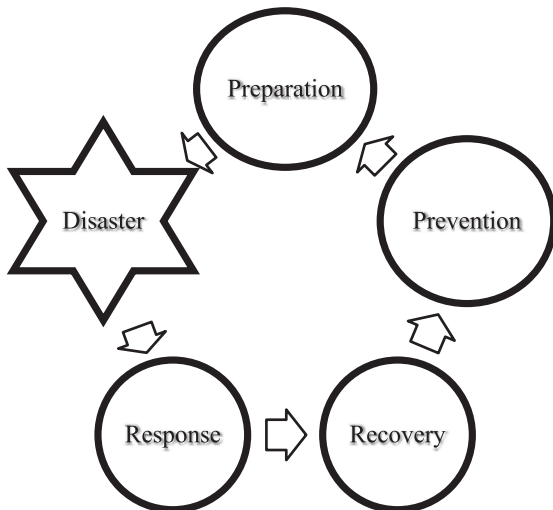


Figure 1. Four phases of crisis management cycle.

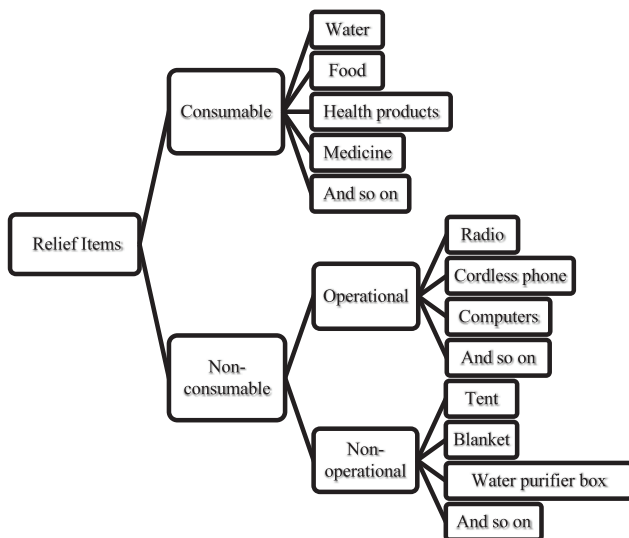


Figure 2. Classification of relief items.

challenge that the health systems are faced with it. There is always a demand for medical items, but the demand for these products is somewhat erratic. In other words, the demand for these items is often random and is not the same in different conditions.² Several studies have considered uncertainty in the supply chain (SC) problems. In addition, due to the nature of crisis, which often occurs all of a sudden, crisis is associated with some uncertainty parameters. Parameters such as demand and travel time are usually non-deterministic that should be dealt with an appropriate approach.

In a classification, relief items are divided into 2 main categories of consumable and non-consumable. Figure 2 shows the classification of relief items.

Consumable relief items are delivered to the affected people several times, while non-consumable relief items are delivered one time. Non-consumable operational relief items are required to set up an operation, while non-operational ones are required to meet the essential needs of the affected population.⁶ The

equilibrium of supply and demand for these products is difficult in an efficient way because most of the medical products are perishable and this makes it harder to manage such strategic products. If the perishable medical products are not delivered properly and timely to the demand centers, they are exposed to corruption and are no longer usable and this makes it difficult to plan for medical items, and it is necessary to consider the special sensitivity to supply and distribute these goods. In addition, unlike some other goods in the supply chain, that the shortage of them is allowed with a penalty, the shortage of medical and relief supplies is not acceptable at all since it leads to death and crisis. For all of the above reasons, designing an appropriate SC for supplying and distributing the medical products for crisis situation is a matter to take special care and consider all its components. One of the necessary and urgent actions in crisis management is the provision of adequate blood for the victims. As a result, in this study, a fuzzy bi-objective mixed-integer programming (MIP) model is proposed for the appropriate planning of transportation of perishable goods in crisis situation. The main goals of the current study are mentioned as follows:

- Investigating the impact of demand uncertainty in the supply chain network,
- Planning facility locations and assigning demand points to these locations,
- Detailed planning for transportation of perishable goods,
- Considering the perishability threshold of perishable medical goods,
- Presenting different approaches to solve problems in different dimensions

One of the significant contributions of the current research is to consider the uncertainty in the demand of service recipients (customers) and also the duration of the presence of medical goods in intermediate warehouses with an exponential probability distribution function to make the presented model close to real-world conditions. In addition, the important characteristics of medical goods and relief items that are usually perishable and have a certain life span are taken into account.

The rest of the paper is organized as follows: In Section 2, the relevant literature is reviewed. The problem description, model formulation, and solution methods are described in Section 3. In Section 4, numerical experiments, interpretation of results of the 3 methods and sensitivity analysis of the model's main parameters are presented. In addition, the application of the proposed model to an actual case study is provided. Eventually, the conclusions and suggestions for future research are presented in Section 5.

Literature Review

Fahimnia et al⁷ presented a comprehensive literature review of transportation problems and classified integrated production

and distribution planning models into 7 general chapters. Since these models have a lot of abundance, all of them are not mentioned here, and only a variety of these models are mentioned. The general models for designing the production and transportation network include the following categories. An article is presented as an example for each of the following categories.

- Transportation model for a product,⁸
- Multi-product transportation model with a production unit,⁹
- Multi-product with several units, with or without a warehouse,¹⁰
- Multi-product with several units, with several warehouses, with or without a final consumer,^{11,12}
- Multi-product with several units, with several warehouses, with several final consumers, with a single transportation route,^{13,14}
- Multi-product with several production units, with several warehouses, with several final consumers, with several transportation routes, and single-period,^{15,16}
- Multi-product with several production units, with several warehouses, with several final consumers, with several transportation routes, and multi-period.¹⁷

The category above is the classification of the models presented in the field of goods transportation based on the type of model used. Another approach that often exists in research classification is classification based on the model solution method. The solution models include 4 general categories: mathematical methods,¹⁸ heuristic algorithms,¹⁹ simulation methods,²⁰ and meta-heuristic algorithm.¹⁷

On the other hand, various approaches have been used in dealing with uncertainty.²¹ In some papers, the researchers presented a robust optimization model with regard to uncertainty in demand. This model integrates the entire supply, production, and distribution processes of a company, and all of these were identified in a comprehensive model by considering demand uncertainty in different parts.^{22,23} In these papers, a probabilistic and scenario-based approaches were used to address these uncertainties. In addition to the probabilistic and scenario-based approaches, the fuzzy approach has also been used by researchers to address the uncertainty. For example, Torabi and Hassini²⁴ provided an integrated fuzzy goal programming model for supplying, distributing and transporting the goods.

Rezaei-Malek et al.²⁵ designed a robust SC model for transportation of perishable commodities in crisis situation. The authors could bring the proposed model closer to the real-world conditions by considering the time windows and various scenarios for the severity of disasters. Cheraghi et al.²⁶ modeled the blood SC in crisis situation. The proposed model is a multi-objective mixed integer programming. Tavana et al.²⁷ presented a hybrid location, inventory, and routing model for the relief and

rescue SC in pre and post-crisis situation. They provided 2 models for planning before and after a crisis. Noham and Tzur²⁸ explored a model for a humanitarian SC to determine the post-crisis decisions. In this research, they provided a hybrid location, inventory, and routing model for a rescue and relief supply chain. Zahraee et al.²⁹ aimed at improving the efficiency of the blood SC system using the Taguchi method and dynamic simulation. They also implemented their model on the Iranian Blood Transfusion Organization. Habibi-Kouchaksaraei et al.³⁰ presented a bi-objective, multi-echelon robust model for the blood SC in crisis situation. In this chain, three levels include the supplier, processing, and distribution. The problem objectives include minimizing total cost, as well as satisfying blood needs. Table 1 shows a summary of the literature review of the research. Also, Zahiri et al.³¹ developed a bi-objective mathematical programming model to design the pharmaceutical SCN. Goodarzian et al.³² proposed a fuzzy mixed-integer non-linear programming (MINLP) model for the pharmaceutical SC problem and solved it using the meta-heuristic algorithms. Sinha and Anand³³ employed a meta-heuristic algorithm to solve the SCN of perishable products. Zandkarimkhani et al.³⁴ introduced a bi-objective optimization model for the perishable pharmaceutical SCN design considering the uncertainty of demand. Franco and Alfonso-Lizarazo³⁵ proposed a MIP model for the pharmaceutical SCN problem and solved it with the epsilon-constraint method. Goodarzian et al.³⁶ introduced a MIP model for the medicine SCN problem considering uncertainty and applied the meta-heuristic algorithms to solve the problem. In addition, Goodarzian et al.³⁷ addressed multiple objectives, multiple periods, multiple levels, and multiple products for a sustainable medical supply chain network. Fatemi et al.³⁸ developed a multi-objective mathematical programming model for the pharmaceutical SCN and solved it using the GAMS optimization software. Khalili-Damghani et al.³⁹ developed a mathematical model considering 2 levels and 2 echelons for minimizing the costs of pre-disaster and maximizing the coverage areas of post-disaster relief. They employed a geographic information system (GIS) to categorize the disaster areas and identify the location and optimal number of distribution centers provided keeping the inventory costs of relief supplies' as minimum as possible. They also exploited a simulation model for estimating the demands of relief supplies. Lotfi et al.⁴⁰ suggested a multi-objective nonlinear model for designing the pharmaceutical SCN and solved it using the LP-metric method with the GAMS software. Kochakkashani et al.⁴¹ proposed a MIP model for the pharmaceutical SCN clustering with K-means. Goodarzian et al.⁴² introduced a Fuzzy Inference System for forecasting medical wastes related to the COVID-19. They also proposed a fuzzy sustainable model for minimizing supply chain costs and the environmental consequences of medical waste while establishing detoxification centers ensuring effective management of social responsibility initiatives during the COVID-19 epidemic.

Table 1. A summary of the related studies.

AUTHOR(S)	YEAR	DESCRIPTION	FUZZY	SCENARIO	PROBABILISTIC	OBJECTIVE FUNCTION(MINIMIZING)	SOLLUTION APPROACH	NETWORK DESIGN
Nagurney et al. ⁴³	2010	Providing a blood SC model, including collection centers, laboratory facilities, storage facilities and distribution centers			P	costs	Euler algorithm	Location-allocation
Alfonso et al. ⁴⁴	2012	Studing the blood collection problems by considering different blood collection processes, blood donor behaviors and required human resources		P		costs	Simulation technique	Location-allocation
Salehi et al. ⁴⁵	2019	Developing a robust stochastic model for designing a blood SCN in a crisis			P	costs	Stochastic programing	Location-allocation
Khalilpourazari and Arshadi Khamseh and Khamseh ⁴⁶	2019	Bi-objective emergency blood SCN design in earthquake considering earthquake magnitude				costs	Exact method	Location-allocation
Diabat et al. ⁴⁷	2019	A perishable product SCN problem with reliability and disruption considerations			P	costs	Exact method	Location-allocation
Safaei et al. ⁴⁸	2020	Emergency logistics planning under supply risk and demand uncertainty				uncovered demand and total cost	Exact method	Location-allocation
Goodarzian et al. (2020)	2020	A fuzzy robust multi-objective model for the pharmaceutical SCN	P			costs	Meta-heuriscst algorithm	;Location-allocation
Fatemi et al. ³⁸	2022	A multi-objective mathematical model for the pharmaceutical SCN	P			costs, unmet demands, and waiting time	Exact method and meta-heuriscst algorithm	Location-allocation
Kochakkashani et al. ⁴¹	2023	A single-objective mathematical model for the SCN design of vaccine and pharmaceutical clusters		P		costs	Stochastic programing	Location-allocation

According to the literature review, few studies have considered the SCN problem of perishable medical goods in crisis situation. In other words, the particular characteristics and conditions of crisis have been neglected. For example, in the event of a crisis, some parameters such as time and demand are uncertain. Moreover, the features of medical goods and relief items that are often perishable and have a certain lifespan have

been overlooked in numerous research works. In addition, the relevant studies have focused solely on locating or routing problems. To this end, in the current study, a fuzzy bi-objective MIP model is presented for the SCN of perishable medical goods in crisis situation taking the uncertainty into account. In this model, the practical and real-world conditions such as the uncertainties associated with the customer demand and the

presence duration of medical goods and relief items in intermediate warehouses are considered using the exponential probability distribution. In addition, it is assumed that the perishable medical goods follow the Weibull distribution function to improve the accuracy of the model.^{49–54} The perishable medical goods SC is accompanied by high uncertainty. This uncertainty in demand can be in terms of the place and time of demand as well as the amount and type of demand. Since facilities and distribution networks might be partially or completely interrupted by disaster, access to the transportation network, required time to pass through each route of the network, and transportation costs are associated with uncertainty. In addition, it should be noted that the generosity of donors cannot be predicted. Also, in case of a disaster occurrence, the capacity of suppliers and the stock stored in permanent medical goods distribution centers may be partially or completely disrupted. Hence, there is a high degree of uncertainty in the supply of medical goods and relief items.

Modeling

Problem description

In this paper, a fuzzy bi-objective mathematical programming model is developed for the three-level SCN problem of the perishable medical goods assuming that the corruption of medical products follows the Weibull probability distribution.

The Weibull random variable is a random variable with continuous values based on non-negative real numbers. As a result, in cases where the random variable is related to life span, this distribution can be used.⁵⁰ The Weibull distribution is a continuous probability distribution used to model lifetime and failure time. This distribution has high flexibility and can model a wide range of failure behaviors, including premature failures, wear-out, and random failures. The Weibull distribution parameters include the shape and scaling parameters. The shape parameter determines the shape of the distribution and the scaling parameter determines the scale of the distribution.^{52,53} The Weibull distribution can model a wide range of failure behaviors. Weibel distribution is easy to understand and use, which makes it useful in various fields. Weibel distribution is used in various sciences and in many fields, including medical sciences. Weibel distribution can be used in survival time modeling to check the life of patients, check the life of medical parts and analyze errors.⁵⁴ In engineering sciences, the Weibull distribution is used as a useful tool in modeling the lifetime of pipelines, electrical and mechanical systems, electronic components, and manufacturing and assembly systems. This distribution can help to analyze the behavior of parts reduction and predict their life. Weibel distribution can be used in buyer behavior modeling, product and project performance analysis, delivery time modeling and supply chain management. In general, the Weibel distribution with its diverse properties is a powerful tool for modeling complex behaviors and analyzing data that simultaneously has the property of reducing the

exponential distribution function and the shape of the Weibel distribution. It should be noted that this distribution has been used in many articles related to the life of the product and the results presented are acceptable and close to reality.⁵¹ In addition, Chołodowicz and Orłowski and Orłowski⁴⁹ demonstrated that the accuracy of modeling can be increased by the application of the Weibull distribution function to perishability. That is, the higher the presence of each relief item in the SC, the higher the probability of its corruption. The SC levels include: (1) suppliers of items, (2) intermediate warehouses, and (3) final customers.

The present supply includes three main levels, the customers for medical goods and relief items are at the first level of chain that are denoted by set $I: \{i=1, 2, 3, \dots, |I|\}$, and the amount of each customer's demand (\tilde{d}_i) is considered as a triangular fuzzy number. Zadeh⁵⁵ introduced the fuzzy sets theory for displaying the verbal assessment and linguistic judgment associated with the decision-making processes as well as dealing with ambiguity and uncertainty corresponding with the real-world decision-making processes. Fuzzy set theory has been broadly applied to deal with the uncertainty because of its several advantages that can be briefly explained as follows⁵⁶:

(a) Fuzzy sets theory can be exploited when there is no historical data for the parameter and no probability distribution function can be attributed to that parameter. (b) Unlike the probabilistic method, in which the dimensions of the problem increase significantly with transforming the non-deterministic model into its deterministic equivalent, the crisp equivalent of a fuzzy model, which is the same as the deterministic equivalent, does not change the dimensions of the problem.

At the second level, there are potential intermediate warehouses displayed by set $J: \{j=1, 2, 3, \dots, |J|\}$ that receive, store, and transfer relief items from suppliers at the third level, and play the role of interface between 2 levels. The proposed model seeks to select the optimal intermediate warehouses as well as the optimal amount of flow from suppliers to intermediate warehouses, and from intermediate warehouses to each of the customers, with the minimum total costs and shortest possible time for the items to be received by the customers. Finally, at the third level, there are suppliers denoted by set $K: \{k=1, 2, 3, \dots, |K|\}$. The medical items are displayed with set $M: \{m=1, 2, 3, \dots, |M|\}$. Figure 3 shows the structure of the problem network. It should be noted that the capacity of the intermediate warehouses is limited and is shown with parameter C_j . It is assumed that the time of the presence of the medical items in the intermediate warehouses follows an exponential distribution with the parameter λ_j , which, in fact, the average time of presence of each medical item is equal to $\frac{1}{\lambda_j}$. The corruption of items has a probability function of Weibull with the parameters μ and ρ from the time of presentation (t) in the chain as follows:

$$f(t) = \rho\mu^\rho t^{\rho-1} e^{-(\mu t)^\rho} \quad t \geq 0 \quad (1)$$

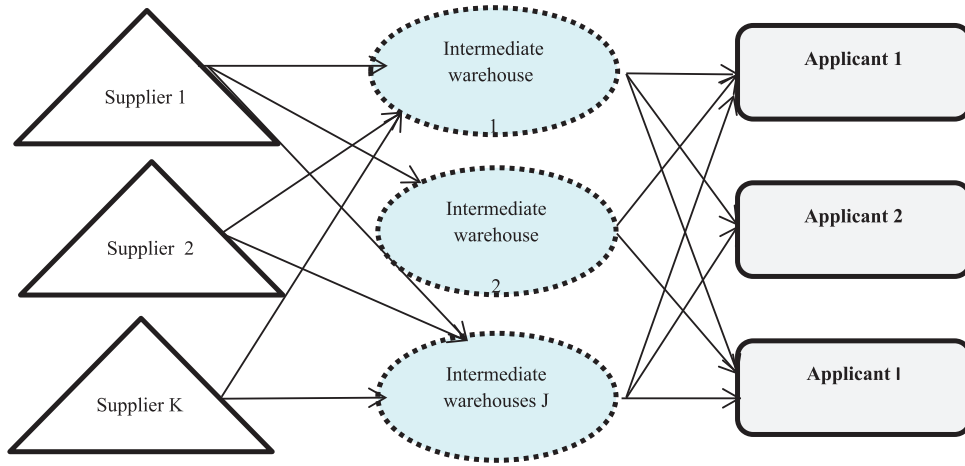


Figure 3. Supply chain network (SCN).

In order to make the proposed model closer to real-world conditions, uncertainty in the parameters of customer demand for service and spent time in the intermediate warehouses is taken into account using the exponential distribution function.^{57,58}

Parameters

C_j	Capacity of intermediate warehouse j
F_j	Fixed cost of opening intermediate warehouse j
d_{ij}	Distance between customer i and intermediate warehouse j
d_{jk}	Distance between intermediate warehouse j and supplier k
t_{ij}	Time interval between customer i and intermediate warehouse j
t_{jk}	Time interval between intermediate warehouse j and supplier k
\tilde{Q}_i^m	Demand of node i for item m is given as a triangular fuzzy number $(Q_i^{m1}, Q_i^{m2}, Q_i^{m3})$
$\frac{1}{\lambda_j}$	Average time of presence of each medical item in intermediate warehouse j
μ	Scale parameter of the Weibull probability distribution indicating probability of corruption of each medical item in the supply chain
ρ	Shape parameter of the Weibull probability distribution indicating probability of corruption of each medical item in the supply chain
R_{ij}	Cost of transferring a unit of medical product from warehouse j to customer i per unit of distance
R_{jk}	Cost of transferring a unit of medical product from supplier k to warehouse j per unit of distance
β	Feasibility coefficient of fuzzy constraints
BN	A big number

Variables

Y_{ij}^m	A binary variable determines whether medical item m required by customer i is provided by warehouse j or not
W_{jk}^m	A binary variable determines whether medical item m from supplier k is transferred to intermediate warehouse j or not
X_j	A binary variable determines whether intermediate warehouse j is open for storage and transfer of medical items or not
D_{ij}^m	Number of product m sent from intermediate warehouse j to customer i
D_{jk}^m	Number of item m sent from supplier k to intermediate warehouse j

Mathematical model.

$$\min Obj1 = \sum_i \sum_j \sum_m D_{ij}^m * d_{ij} * R_{ij} + \sum_j \sum_k \sum_m D_{jk}^m * d_{jk} * R_{jk} + \sum_j F_j * X_j \quad (2)$$

$$\min Obj2 = \sum_i \sum_j \sum_m D_{ij}^m * \left[t_{ij} + \frac{1}{\lambda_j} \right] + \sum_j \sum_k \sum_m D_{jk}^m * t_{jk} \quad (3)$$

$$Y_{ij}^m \leq X_j; \forall i, j, m \quad (4)$$

$$W_{jk}^m \leq X_j; \forall j, k, m \quad (5)$$

$$D_{ij}^m \geq Y_{ij}^m * \tilde{Q}_i^m * \left[1 + \mu * \left(t_{ij} + \frac{1}{\lambda_j} + t_{jk} \right)^\rho \right]; \forall i, j, m \quad (6)$$

$$D_{jk}^m \geq \sum_i D_{ij}^m - BN * (1 - W_{jk}^m); \forall j, k, m \quad (7)$$

$$\sum_j Y_{ij}^m = 1; \forall i, m \quad (8)$$

$$\sum_k W_{jk}^m \leq X_j; \forall j, m \quad (9)$$

$$\sum_i \sum_m D_{ij}^m \leq C_j; \forall j \quad (10)$$

$$Y_{ij}^m, W_{jk}^m, X_j \in \{0 \text{ or } 1\}; \forall i, j, k, m \quad (11)$$

$$D_{ij}^m, D_{jk}^m \geq 0; \forall i, j, m \quad (12)$$

$$Obj1, Obj2 \in R \quad (13)$$

Constraint (2) expresses the first objective function of the model (*Obj1*) that attempts to minimize the total costs including the total transportation costs from suppliers to intermediate warehouses and from intermediate warehouses to customers as well as the construction costs of intermediate warehouses. Constraint (3) states the second objective function of the model (*Obj2*) that seeks to minimize the total time of the presence of the medical goods in the supply chain, in which the total transportation time from suppliers to intermediate warehouse, the transportation time from intermediate warehouses to customers and the average time of the presence of each medical item in intermediate warehouse are taken into account. Constraints (4) and (5) ensure that entry to and exit from the present intermediate warehouse depends on its openness.

Constraint (6) ensures providing the demand of each customer, taking into account the initial amount of demand and the amount of corrupted medical items along the supply chain. Constraint (7) shows that the input of each intermediate warehouse is at least equal to its output (since the first objective function is to minimize the flow of input and output of intermediate warehouse, the left side value of the constraint cannot be greater than its right side value). Constraint (8) indicates that each medical item required by each customer is supplied by exactly 1 intermediate warehouse. Constraint (9) states that any medical item can be entered into an intermediate warehouse from only 1 supplier. Constraint (10) mandates the capacity of intermediate warehouses. Constraint (11) exhibits the binary variables. Constraint (12) specifies the nonnegative variables, and constraint (13) shows that the objective functions are free variables.

Defuzzification method

In order to defuzzify the fuzzy parameters of the proposed model, a well-known defuzzification method introduced by Jiménez et al.⁵⁹ is employed to transform the triangular fuzzy numbers into the crisp numbers. It should be noted that the selection of the appropriate defuzzification method pertains to the context and type of the decision-making.⁶⁰

The steps of this approach are as follows:

Step 1: Determine a minimum constraint feasibility degree: This is, in fact, determination of the minimum possibility of fuzzy numbers in the constraints, which, constraint feasibility is met.

Step 2: Determine the values for feasibility of constraints based on the minimum specified parameter in the first step: Based on the methodology proposed by Kaufman and Gupta,⁶¹ which states that for every 0.1 changes in the value of the possibility of a fuzzy number, the value of the number also changes, so the values for feasibility of constraints are started from the minimum value and 0.1, 0.1 is added to reach 1.

If β_{min} is the minimum constraint feasibility degree that the DM is willing to admit, the feasibility interval is as follows:

$$M = \left\{ \beta_k = \beta_{min} + 0.1 * k \mid k = 0, 1, \dots, \frac{1 - \beta_{min}}{0.1} \right\} \subset [0, 1] \quad (14)$$

Step 3: Solving the model with the objective function equals to the middle value of the fuzzy number of the objective function and feasibility of constraints for each feasibility value: We start from the minimum feasibility value and, make the constraints crisp for the different feasibility values, and solve the model, for all constraints and with the objective function equals to the middle value (probable value) of the fuzzy number and determine the values of decision variables and objective functions. Note that after determining the value of decision variables for the probable value of the fuzzy objective, we set the values of the variables in the fuzzy objective and determine the fuzzy value of the fuzzy objective.

Define a fuzzy goal number for the fuzzy objective: In fact, at this stage, 1 goal is defined as a fuzzy number for a given fuzzy objective value. In other words, the minimum and the maximum satisfactory value for the fuzzy objective are respectively \underline{G} and \bar{G} , then the goal is expressed by means of a fuzzy set \tilde{G} whose membership function is as follows:

$$\mu_{\tilde{G}}(z) = \begin{cases} 1; z \leq \underline{G} \\ \frac{\bar{G} - z}{\bar{G} - \underline{G}}; \underline{G} < z \leq \bar{G} \\ 0; z > \bar{G} \end{cases} \quad (15)$$

Step 5: Determine the degree of satisfaction of the fuzzy goal by each obtained value for the fuzzy objective: If the value of the fuzzy objective for the feasibility value of β_k for the constraints equals to $\tilde{z}^0(\beta_k)$, the degree of satisfaction of the fuzzy goal ($K_{\tilde{G}}$) is as follows:

$$K_{\tilde{G}}(z^0(\beta_k)) = \frac{\int_{-\infty}^{+\infty} \mu_{z^0(\beta_k)}(z) * \mu_{\tilde{G}}(z) dz}{\int_{-\infty}^{+\infty} \mu_{z^0(\beta_k)}(z) dz} \quad (16)$$

Determine the fuzzy decision set: The members of the mentioned set are the vector of $x^0(\beta_k)$ and the membership function is equal to $\mu_{\tilde{D}}$ which is calculated according to the following equation:

$$\mu_{\tilde{D}}(x^0(\beta_k)) = \beta_k * K_{\tilde{G}}(z^0(\beta_k)) \quad (17)$$

Determine the decision vector and the crisp objective value for the problem: Among the decision vectors, the vector that has the highest membership in the set is chosen as the final vector of the decision and its associated objective value as the final value of the fuzzy objective. In simpler terms:

$$\mu_{\tilde{D}}(x^*) = \max_{\beta_k \in M} \left\{ \beta_k * K_{\tilde{G}}(z^0(\beta_k)) \right\} \quad (18)$$

Consider the following example to better understand the defuzzification method of Jimenez et al.⁵⁹:

$$\begin{aligned} & \text{Min } (19, 20, 21) x_1 + (29, 30, 31) x_2 \\ & \text{S.t.} \\ & (4.5, 5, 5.5) x_1 + (2.5, 3, 4) x_2 \geq (194, 200, 206) \\ & (3, 4, 5) x_1 + (6.5, 7, 7.5) x_2 \geq (230, 240, 250) \\ & x_1, x_2 \geq 0 \end{aligned} \quad (19)$$

Now we have to calculate the acceptable solutions of the following ordinary α -parametric linear program:

$$\begin{aligned} & \text{Min } 20x_1 + 30x_2 \\ & \text{S.t.} \\ & ((1-\alpha) 5.25 + \alpha 4.75) x_1 + ((1-\alpha) 3.5 + \alpha 2.75) x_2 \geq 203 \\ & \alpha + (1-\alpha) 197 \\ & ((1-\alpha) 4.5 + \alpha 3.5) x_1 + ((1-\alpha) 7.25 + \alpha 6.75) x_2 \geq 245 \\ & \alpha + (1-\alpha) 235 \\ & x_1, x_2 \geq 0 \end{aligned} \quad (20)$$

Different values of the coefficient α from 0 to 1 can be considered depending on the level of conservatism or the risk appetite of the decision maker. Then solve the model based on this assigned coefficients. Assume that the value of α is considered to be 0.5 according to the manager's view. According to this coefficient, the value of x_1 is 28.89, the value of x_2 is 17.78, and the objective function value is equal to (1064.53, 1111.20, 1157.87).

The crisp equivalent of the sixth constraint according to the defuzzification method of Jimenez is in the form of relation (21):

$$D_{ij}^m \geq Y_{ij}^m * \left[\beta * Q_i^{m1} + Q_i^{m2} + (1-\beta) * Q_i^{m3} \right] * \left[1 + \mu * \left(t_{ij} + \frac{1}{\lambda_j} + t_{jk} \right)^p \right]; \forall i, j, m \quad (21)$$

Solution methods

Since the SC problems are NP-hard, the solution time increases exponentially by increasing the dimensions of the problem. Hence, it is not possible to apply the exact methods to find the optimal solutions for large-sized real-world problems within a reasonable computational time. Hence, the need arises to use meta-heuristic algorithms to solve large-size problems. As the proposed optimization model is NP-hard, it is necessary to solve large-size problems with heuristic and meta-heuristic algorithms. In the present study, the LP-Metric exact method is employed to solve the proposed model for small-sized problems. In addition, due to the NP-Hardness of the problem in hand, the modified multi-objective particle swarm optimization (MOPSO) and Non-dominated Sorting Genetic Algorithm (NSGA-II) are utilized as the 2 of the most efficient and frequently used meta-heuristic algorithms to solve the large-size problems since the LP-Metric exact method is not capable in finding the optimal solutions in a reasonable computational time.

In the last decade, many multi-objective evolutionary algorithms have been proposed. Among these algorithms, the MOPSO, MOSA, MOGWO, and NSGA algorithms can be mentioned.⁶² The NSGA-II algorithm has characteristics that make its use in multi-objective problems easier compared to other algorithms.⁶³ NSGA-II uses binary codes for coding the decision variables and also uses the probability cycle to select the parents and this itself causes getting close to the optimal solution.⁶⁴ On the other hand, the speed of reaching the optimal solution is lower than the MOPSO algorithm, also, it reaches convergence later.⁶⁵ The NSGA-II algorithm is one of the most powerful algorithms that has been widely used in the literature and has shown several times that it works well for solving various multi-objective optimization problems, for this reason, this algorithm is considered as the basic and accepted algorithm in this research.^{66,67}

The MOPSO algorithm is one of the frequently-used efficient population-based and multi-objective algorithms that was chosen for comparison with the NSGA-II algorithm.⁶⁸ The MOPSO algorithm has a memory in such a way that the knowledge of good solutions is kept by all particles.⁶⁹ In other words, in MOPSO, each particle benefits from its past information, while there is no such behavior and feature in other evolutionary algorithms, for example, there is no such memory in GA. The previous knowledge of the problem is lost once the population

changes. The PSO algorithm shows more flexibility compared to other optimization strategies by using a large number of crowding particles against the local optimal problem. The main problem of MOPSO is premature convergence. In this algorithm, the particles gradually travel in the search space near the best global optimal solution and do not explore the rest of the space, and in other words, the particles converge and during the search process, some particles in the population may get caught in the local optimum and do not participate in the next discoveries. The MOPSO algorithm has several advantages and disadvantages. The use of memory, high convergence speed, better dealing with the local optimal solutions, and ease of implementation can be mentioned as some its main advantages. Some of its disadvantages are premature convergence, getting stuck in the local optimum, and reducing the diversity of the population.⁷⁰

The results indicate that the proposed meta-heuristic algorithms are efficient in achieving the optimal solution for small-size problems and close to the optimal solution for the large-size problems in a quite short computational time.

LP-metric method. The goal of this approach is to arrive at a response that minimizes the deviation between the values of objective functions and ideal value derived from the individual optimization of them in problems with more than one goal.⁷¹ At first, each of goals is considered separately in the problem and the optimal value of each of them is obtained, regardless of the other goals, and this is considered as the ideal value of the objective. In the next step, the objective function of the deviation, equation (22), is considered as the new objective of the problem and the optimization of the problem is performed with that goal. It should be noted that in the first step, the goals should be maximized in order to individual optimization, that is, minimization functions should be converted to maximization with a multiplication in a negative. For a better understanding, assume that the objective functions of the problem and their individual optimal values in maximization case are respectively $(f_g; g = 1, 2, 3, \dots, p)$ and $(f_g^*; g = 1, 2, 3, \dots, p)$. Now the deviation objective function used in the second step is calculated as the equation (22) (in this case r is a constant parameter):

$$\min D = \left(\sum_{g=1}^p \left(\frac{f_g^* - f_g}{f_g^*} \right)^r \right)^{\frac{1}{r}} \quad (22)$$

In this research, the value of the parameter r is assumed to be 1 to retain the linearity of the proposed MIP model for using the CPLEX solver. Therefore, the limitations of the CPLEX solver were the main motivation for the parameter setting.

Multi-objective particle swarm optimization (MOPSO). Particle swarm optimization was first introduced by Eberhart and

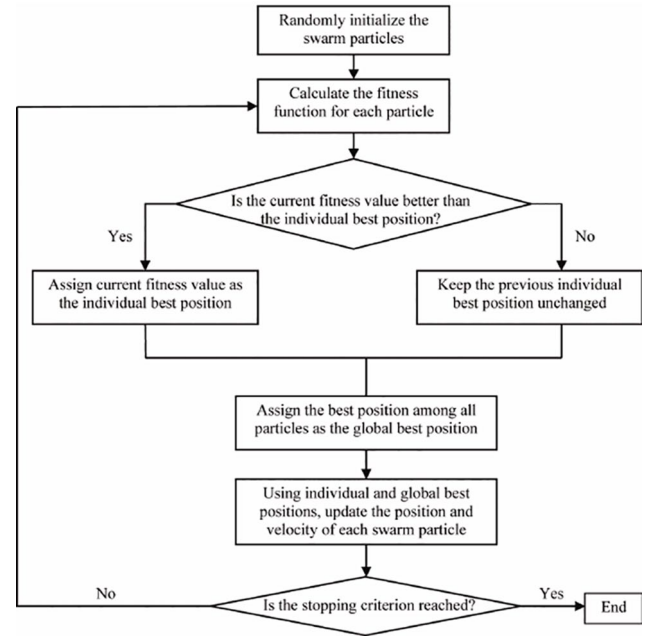


Figure 4. Flowchart of PSO.

Kennedy in 1955 as a stochastic optimization technique for functional optimization. This algorithm is a social search algorithm inspired by social behavior of bird flocking or fish schooling. The PSO algorithm is based on an initial population (swarm) containing the candidate solutions (particles) which move around the search space. The particles' movements are directed by their best position so far in the search space together with the entire swarm's best position so far.⁷² Each particle has a fitness value calculated by a fitness function. If a particle is closer to the food-goal in the search space (in the model of the movement of birds), its fitness value is greater. Each particle also has a velocity that controls the movement of the particle. The agent moves in the problem space by continuing to pursue the optimal particles in the present state. PSO initializes with a group of random particles (solutions) and tries to find an optimal solution by updating the generations. At each step, each particle is updated using 2 best values. The first one (pbest) has been the best situation ever achieved by the particle.⁷³ The flowchart of this algorithm is shown in Figure 4. In this algorithm, the convergence test is updating the best position found by each particle and best position found by the best particle of the particle group. The execution of the algorithm continues, until the stop condition (execution of the algorithm's iterations, reaching the predetermined time for the algorithm execution, reaching the predetermined tolerance in the best value of the particle target, etc.) is met.

As shown in Figure 5, the red node (p_k^g) represents the best position found by the best particle in the group in the k -th repetition of the algorithm's execution. The blue and black nodes p^i , x_k^i and x_{k+1}^i , respectively, are the best position found for the i -th particle and the positions of this particle in the k -th and $k+1$ -th repetition of that particle. Also, the green, blue

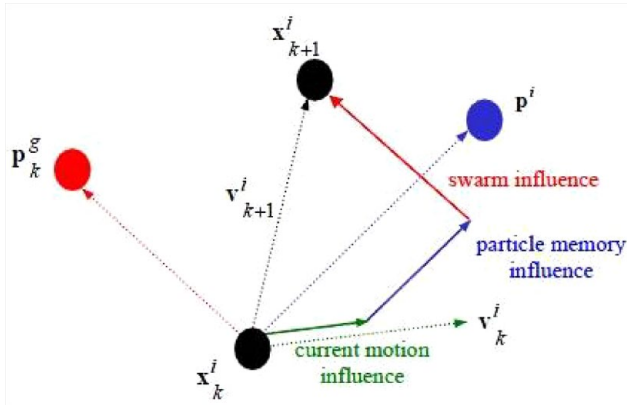


Figure 5. Particle motion view in PSO.

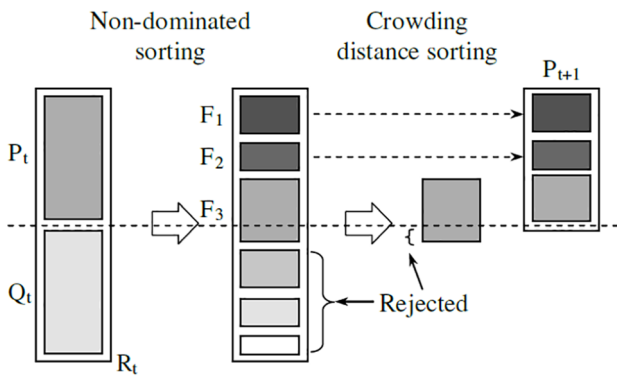


Figure 6. Schematic of the NSGA-II procedure.

and red vectors show the current motion influence, particle memory influence and swarm influence, what PSO formalizes is how to combine these tendencies in order to be globally efficient.

Non-dominated sorting genetic algorithm (NSGA-II). The non-dominated sorting genetic algorithm (NSGA-II) has been broadly employed to solve numerous multi-objective optimization problems.⁷⁴⁻⁷⁸ In the NSGA-II algorithm, the fast non-dominated-sorting operator is exploited to insert the dominance concept via searching the first goal known as convergence. The schematic representation of the NSGA-II procedure and flow diagram are displayed in Figures 6 and 7.

Structure of the solution in the algorithms. The proposed problem is a complete delivery, so that all demand for each medical item required by each customer must be provided by a supplier and an intermediate warehouse. For validation of the model as well as the solution approach, a SC is considered that includes 3 suppliers, 6 intermediate warehouses and 3 customers, each of them requires a specified amount of 3 medical items with the assumption of complete delivery. Since this algorithm works only with numbers in the interval 0 and 1, then consider the structure of the solution as a matrix with 3 rows and 9 columns. (The number of rows equals to the number of drug items and each of the first to third lines of each row represents

the number of intermediate warehouses supplying that drug item to the first to third customers, and the fourth-ninth lines of each row determine that an intermediate warehouse providing the medical item for each customer is served by which supplier, but if the intermediate warehouse is not used to supply the medical item, the value of the number associated with the supplier is considered to be zero). First, fill all matrix strings with the random numbers in the interval 0 and 1, which we call it the position of the solution. The position designed for this problem is shown in Table 2. Figure 8 shows the schematic presentation of the designed solution for $r = .74$.

As described above, the first 3 lines of all rows indicate that the corresponding demand node (first, second, or third) is provided by which of the first, second, third, . . . , sixth warehouses. Suppose that a random number in one of those strings is equal to r . The intermediate warehouse is calculated by the following equation:

$$a = \min((1 + 6 * r), 6) \quad (23)$$

In equation (23), sign $\lceil \cdot \rceil$ means the rounding of the inner phrase is downward and number 6 indicates the number of intermediate warehouses. Same relationship is also used for the second part of the solution structure, since the second part of each row indicates the intermediate warehouse supplier number and in this example, the number of suppliers is equal to 3, so, number 6 in the above relationship changes to 3. The positions of solutions are used in all stages of the algorithm, except for calculating the objective functions.

Parameter tuning. The efficiency of metaheuristic algorithms significantly depends on the values of structural factors of the algorithm. Hence, there are many approaches to tune the control parameters of the metaheuristic algorithms in order to create a powerful solving method. Here the Taguchi approach is used because of its positive features.⁷⁹ Hajipour et al.⁸⁰ states that the Taguchi method leads to the proper and effective adjustment of the parameters of the algorithm based on statistical evaluations and sensitivity analysis. In this technique, the S/N ratio implies the amount of variation present in the response variable.⁸¹ Some of these parameters values are presented in Tables 3 and 4. The optimal levels of parameters are displayed in Tables 5 and 6.

Numerical Experiments and Results

Sample generation

To generate the sample problems, assume that customers, intermediate warehouses, and suppliers are distributed uniformly on a 2-dimensional page, respectively, with dimensions $[10,100]$, $[0,100]$, and $[20,120]$. Also, their distance is considered as Euclidean intervals (rounded to the nearest integer) and the delivery times are calculated by dividing these intervals

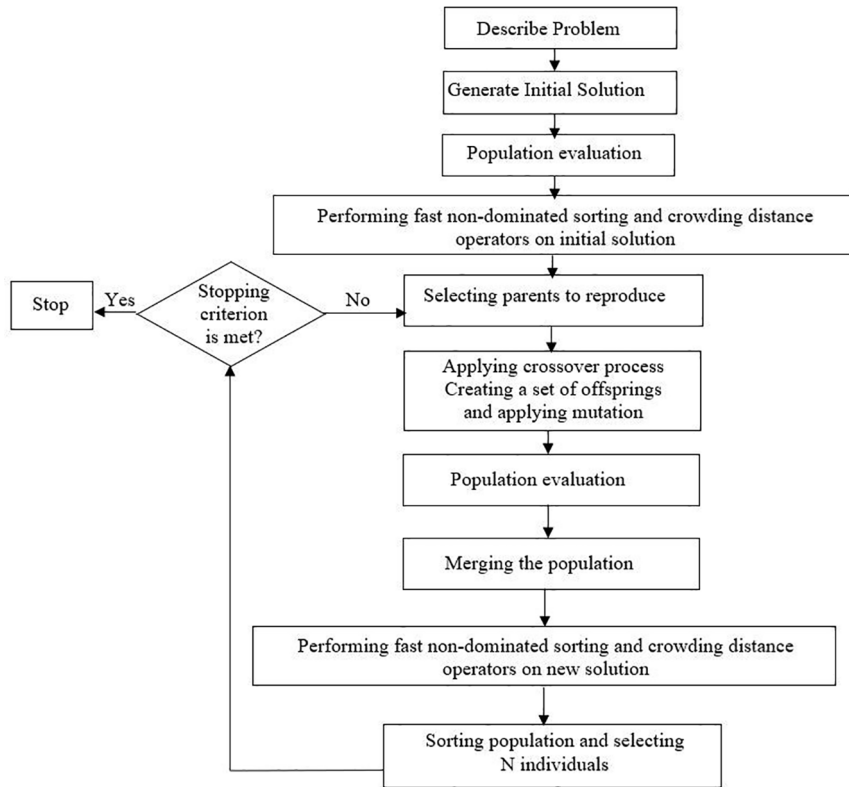


Figure 7. Flowchart of NSGA-II.

Table 2. An initial position designed for the problem.

0.23	0.19	0.83	0.27	0.58	0.91	0.88	0.86	0.77
0.44	0.31	0.66	0.12	0.58	0.08	0.48	0.66	0.96
0.74	0.28	0.31	0.91	0.77	0.68	0.79	0.37	0.05

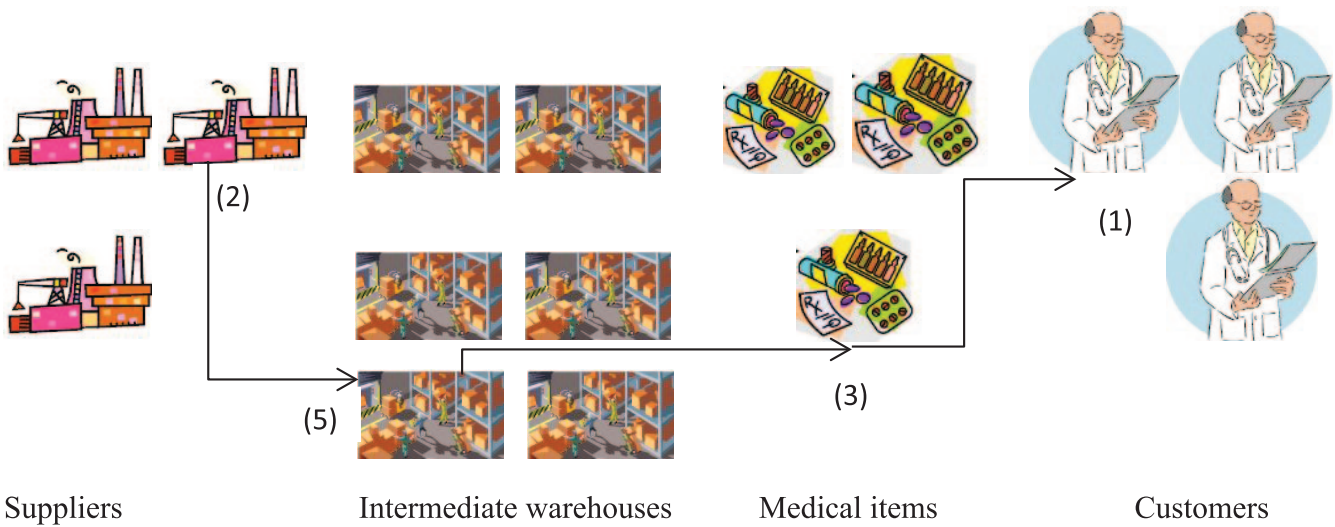


Figure 8. Schematic presentation of the designed solution for $r = .74$.

Table 3. Parameters of MOPSO.

PARAMETERS	LEVELS	DESCRIPTION
$MaxIt$	100,200,300	Maximum number of iterations
$nPop$	100,150,200	Number of population
$nRep$	10,20,30	Number of members of the Pareto Front in each iteration
$\varphi_1 = \varphi_2$	2.05	—
$\varphi = \varphi_1 + \varphi_2$	4.1	—
W	$\frac{2}{\varphi - 2 + \sqrt{\varphi^2 - 4\varphi}}$	Inertia Weight
$Wdamp$	0.99	Inertia weight loss ratio
$C1$	$W * \varphi_1$	Individual learning factor
$C2$	$W * \varphi_2$	Collective learning factor
$nGrid$	20,30,40	Number of networks in each dimension
α	0.1,0.2,0.3	Inflation rate to create a positioning network of the members of Rep
β	5,7,9	Pressure of selecting a leader
γ	5,7,9	Pressure of selecting the additional member of Rep to remove
μ	0.1,0.2,0.3	Mutation rate

Table 4. Parameters of NSGA-II.

PARAMETERS	LEVELS	DESCRIPTION
$MaxIt$	50,75,100	Stopping condition for the algorithm
$nPop$	50,75,100	Number of population
P_m	0.1,0.2,0.3	Mutation rate
P_c	0.7,0.8,0.9	Crossover rate

into 80 (with one decimal). The values of the parameters $Q1_{im}$ and $Q3_{im}$ are determined as the random integers with uniform distributions in the intervals [20, 40] and [30,60] which the value of the parameter $Q2_{im}$ is equal to the average of 2 other values. Table 7 shows how to generate the data.

Table 5. The best factor level combination for MOPSO.

PARAMETERS	LEVELS
$MaxIt$	100
$nPop$	100
$nRep$	20
$\varphi_1 = \varphi_2$	2.05
$\varphi = \varphi_1 + \varphi_2$	4.1
W	$\frac{2}{\varphi - 2 + \sqrt{\varphi^2 - 4\varphi}}$
$Wdamp$	0.99
$C1$	$W * \varphi_1$
$C2$	$W * \varphi_2$
$nGrid$	30
α	0.1
β	7
γ	7
μ	0.3

Table 6. The best factor level combination for NSGA-II.

PARAMETERS	BEST LEVELS
$MaxIt$	100
$nPop$	100
P_m	0.3
P_c	0.7

Numerical examples

In this section, various test problems with different sizes (small, medium, and large) are considered and solved to evaluate the efficiency and performance of the proposed solution methods. The computational experiments are performed on a personal PC with Intel, Core i5 CPU, 1 GHz Processor and 4 GB of RAM. Achieving the optimal solution is possible for a problem with 4 customers, 3 medical items, 6 intermediate warehouses and 3 suppliers at a time less than 3600 seconds (small size problems) due to the length of the solution time in the LP-Metric method. Because the GAMS Software is incapable of solving large size problems and needs long time runs for

Table 7. The function of generating the random numbers.

PARAMETER	RANDOM DISTRIBUTION FUNCTION
$Q1_{im}$	U [20,40]
$Q3_{im}$	U [30,60]
R_{ij}	U [10,24]
R_{kj}	U [3,10]
F_j	U [5000,10000]
C_j	U [600,650]

large size problems. Therefore, meta-heuristic algorithms were used in large-size problems. The results indicate that the algorithms are efficient in achieving the optimal solution for small-sized problems and close to the optimal solutions for large-sized problems within a very short time. In the LP-Metric method, it is only possible to obtain a solution that has the minimum difference of the individual optimal value of each objective, while MOPSO and NSGA-II find a set of non-dominated members in the population (Pareto front solutions).

Numerical results for the small-sized test problems. Five test problems in small size were generated and solved with 3 approaches. The results are shown in Table 8.

It should be noted that, as a sample, the expression $3 \times 6 \times 2 \times 3$ in the specification column of Table 8 means 3 customers, 6 intermediate warehouses, 2 suppliers and 3 items. Error percentage of first and second objective function of mentioned algorithms was calculated for the comparison of each algorithm's results with the results of GAMS software. According to Table 8, the results of proposed algorithms are similar to the results of LP-Metric method for small-sized problems. Figures 9 to 11 show the Pareto front for problems 1 to 3.

According to Figures 9 to 11, it can be said that while the value of the first objective function (economic goal) decreases, the value of the second objective function, which seeks to minimize the total time of the presence of the medical goods in the supply chain, increases gradually. On the contrary, if the decision of the managers is to reduce the total time of the presence of the medical goods in the supply chain, more costs should be incurred.

In order to analyze the sensitivity on the parameters that follow the Weibel distribution, the problem s_1 defined in the previous section is examined. As mentioned in the previous section, the value of the first objective function of the problem is equal to 667590.385 and the value of the second objective function is equal to 4231.628. Now, we consider the increase and decrease of the value of this parameter by 20% while

Table 8. Comparison of the results of LP-Metric method, MOPSO, and NSGA-II.

PROBLEM SPECIFICATIONS	LP-METRIC APPROACH			MOPSO			NSGA-II			ERROR PERCENTAGE		
	FIRST OBJECTIVE FUNCTION	SECOND OBJECTIVE FUNCTION	CPU (IN SECONDS)	FIRST OBJECTIVE FUNCTION	SECOND OBJECTIVE FUNCTION	CPU (IN SECONDS)	FIRST OBJECTIVE FUNCTION	SECOND OBJECTIVE FUNCTION	CPU (IN SECONDS)	FIRST OBJECTIVE FUNCTION	SECOND OBJECTIVE FUNCTION	CPU (IN SECONDS)
S1 $3 \times 6 \times 2 \times 3$	667590.385	4231.628	28.44	667590.385	4231.628	28.44	0	0	28.5	0	0	0
S2 $3 \times 6 \times 2 \times 4$	846415	5123.087	313.45	846415	5123.087	45.81	0	0	56.52	0	0	0
S3 $4 \times 6 \times 3 \times 3$	7598200	3940.9	1800	7598200	3940.9	56.11	0	0	69.21	0	0	0
S4 $3 \times 7 \times 3 \times 3$	76253	4151.08	712.51	75481	4126.44	53.12	0.01	0.006	63.18	0	0	0
S5 $4 \times 6 \times 4 \times 4$	98218	5823	1964.3	95217	5711	64.11	0.03	0.0196	71.12	0.033	0.0374	0.0374

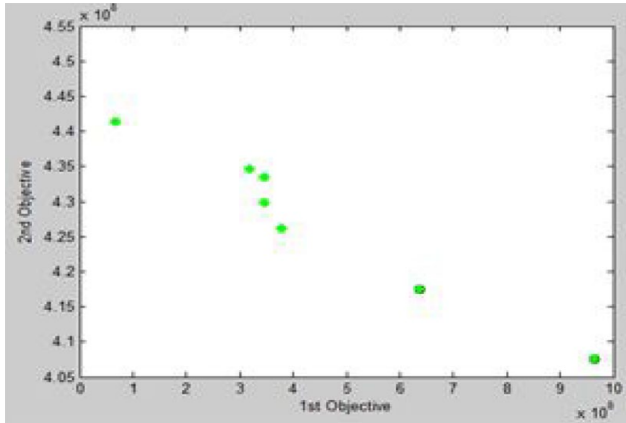


Figure 9. Pareto front for problem S_1 .

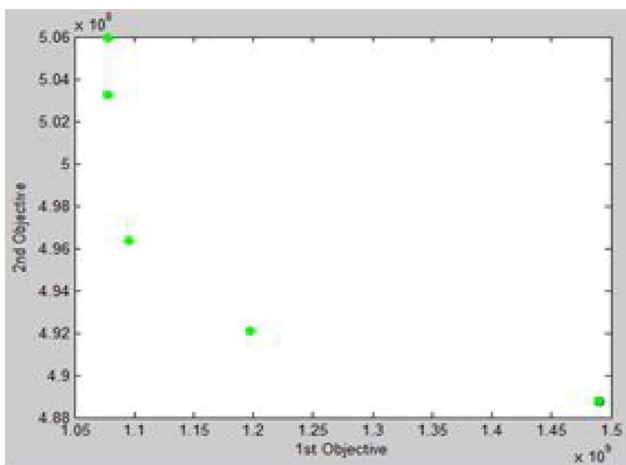


Figure 10. Pareto front for problem S_2 .

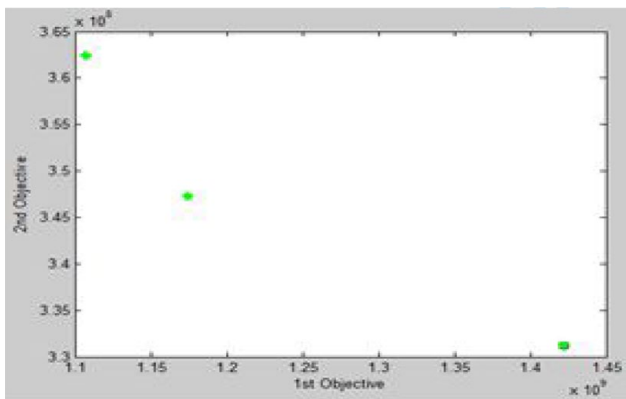


Figure 11. Pareto front for the problem S_3 .

keeping the other parameters constant to analyze its effect on the objective functions. Table 9 shows the values of the objective functions in the current, increased, and decreased situations of the above parameter.

As can be seen in Table 9, the increase in the parameter significantly reduces the value of the first objective function. Also, the decrease in this parameter increases the value of the first objective function significantly. The effect of these changes on the value of the second objective function is completely

Table 9. The values of the objective functions corresponding with decreasing and increasing of the values of the Weibel distribution parameters.

PARAMETER	1.2ρ	ρ	0.8ρ
Objective function value 1	623841.79	667590.385	701983.2
Objective function value 2	4379.91	4231.628	4153.39

opposite, so that the increase of this parameter in the Weibel distribution causes an increase in the value of the second objective function, and its decrease causes a decrease in the value of the second objective function.

Numerical results for the medium and large-sized test problems. In this section, several test problems with different sizes (medium and large) are solved to evaluate the performance of 2 presented meta-heuristic algorithms. Totally, ten test problems were randomly generated and solved with the algorithms. The results are shown in Table 10. Figures 12 and 13 are shown to evaluate and compare the performance, objective function values (OFVs) and CPU times of the mentioned parameter tuned algorithms. As shown in Figures 12 and 13, NSGA-II achieves the more suitable solutions for the first and second objective functions than the MOPSO. Also, as shown in Table 10, meta-heuristic algorithms achieve the best quality solutions for medium and large-size problems at a very good time that the LP-Metric did not achieve them at a time less than 1 hour. Also, these algorithms, despite the LP-Metric method, which was only able to achieve an appropriate response, was able to obtain a set of good responses. Figures 14 to 16 show the Pareto front for problems 1 to 3.

Sensitivity analysis. Sensitivity analysis is performed on several important parameters to assess the impact of various factors on the objective function values.

Sensitivity analysis on R_{ij} (the cost of transferring the items from the warehouses to the customers). Problem S_1 , which is defined in the previous section, is examined in order to do the sensitivity analysis on the cost of transferring the items from the warehouses to the customers. As mentioned in the previous section, the first objective function value is 667590.385 and the second objective function value is 4231.628. We are investigating the effect of reducing and increasing of this parameter on the objective functions while the other parameters are constant, so we reduce the value of this parameter by 20% and increase 20%. Table 11 shows the value of the objective functions in the current, increased and decreased state of the mentioned parameter.

As can be seen, the increase in the parameter R_{ij} significantly increases the first objective function. The decrease in this parameter also significantly reduces the first objective cost ve

Table 10. Numerical results in medium and large dimensions.

PROBLEM	SPECIFICATIONS	NSGA-II			MOPSO		
		FIRST OBJECTIVE FUNCTION (*10 ⁹)	SECOND OBJECTIVE FUNCTION (*10 ⁴)	CPU (IN SECONDS)	FIRST OBJECTIVE FUNCTION (*10 ⁹)	SECOND OBJECTIVE FUNCTION (*10 ⁴)	CPU (IN SECONDS)
M1	4 × 7 × 4 × 3	1.2546	10.825	78	1.4623	11.837	66.92
M2	4 × 7 × 4 × 4	0.8954	7.0032	89	1.6102	7.2035	64.62
M3	5 × 8 × 5 × 4	0.2897	4.7875	77	0.66012	5.0646	53.80
M4	5 × 7 × 5 × 4	1.1589	5.7125	84	1.7246	6.114	58.23
M5	6 × 8 × 6 × 5	1.0789	6.0548	95	1.9621	7.513	78.20
M6	7 × 6 × 4 × 3	1.7968	7.3515	102	2.0545	8.3521	84
M7	7 × 7 × 6 × 3	1.2485	7.1458	109	2.4214	8.2154	94
M8	8 × 5 × 4 × 5	1.1562	5.7895	108	1.9654	6.1148	102
M9	9 × 7 × 5 × 6	2.7985	6.4578	113	3.4578	7.4589	101
M10	9 × 8 × 7 × 7	2.5894	5.6478	114	3.6584	8.3546	104

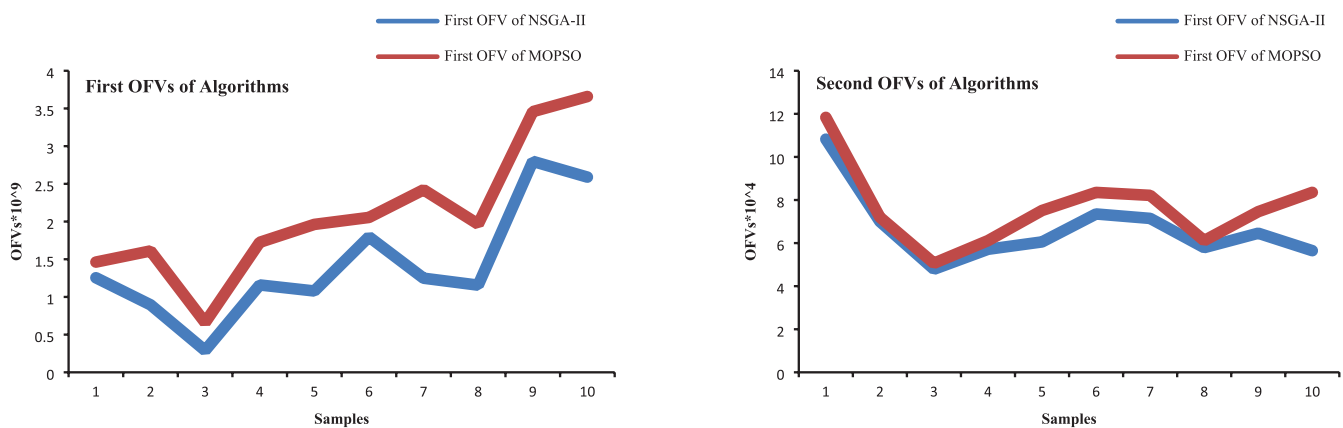


Figure 12. Comparison of the OFVs of the proposed algorithms.

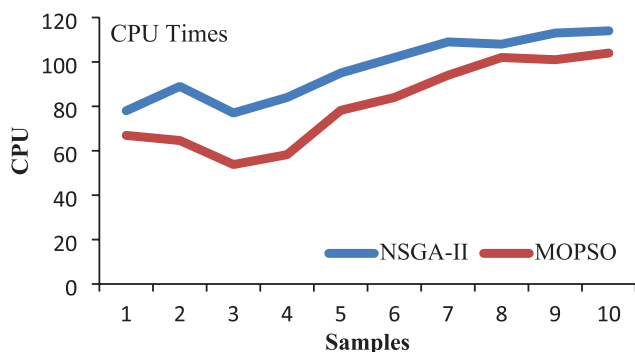


Figure 13. Comparison of the CPU times of the proposed algorithms.

function. The effect of these changes is not significant on the second objective function.

Sensitivity analysis on R_{jk} (the cost of transferring a medical item from the supplier to the intermediate warehouse). Problem s_1 , which is defined in the previous section, is examined in order to do the sensitivity analysis on the cost of transferring a medical item from the supplier to the intermediate warehouse. As mentioned in the previous section, the first objective function value is 667590.385 and the second objective function value is 4231.628. We are investigating the effect of reducing and increasing of this parameter on the objective functions while the other parameters are constant, so we reduce the value of this parameter by 20% and increase 20%. Table 12 shows the value of the objective functions in the current, increased and decreased state of the mentioned parameter.

As can be seen, the increase in the parameter R_{jk} significantly increases the first objective function. The decrease in this

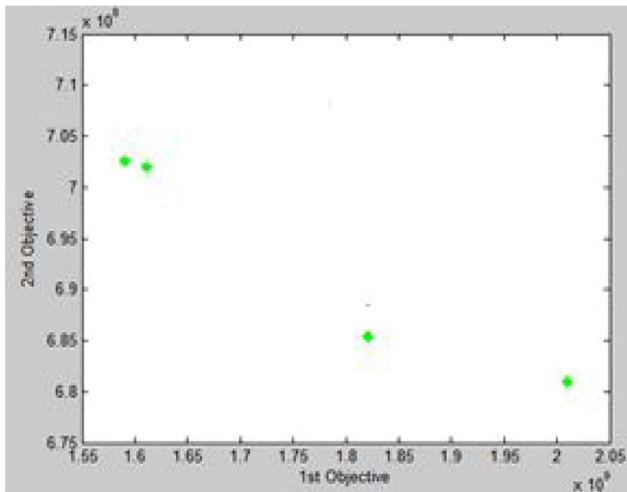


Figure 14. Pareto front for the problem M_1 .

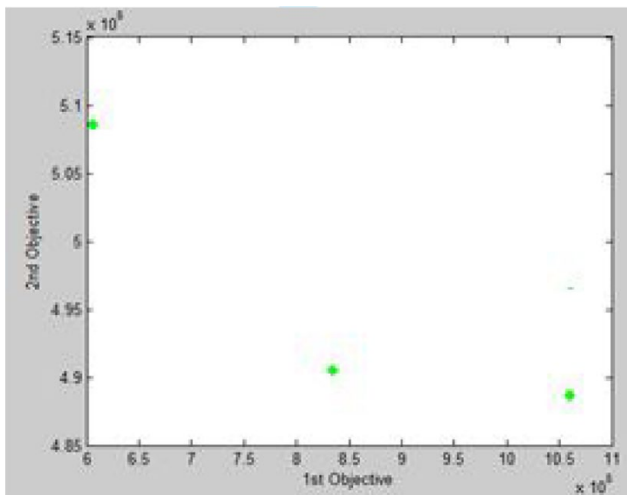


Figure 15. Pareto front for the problem M_2 .

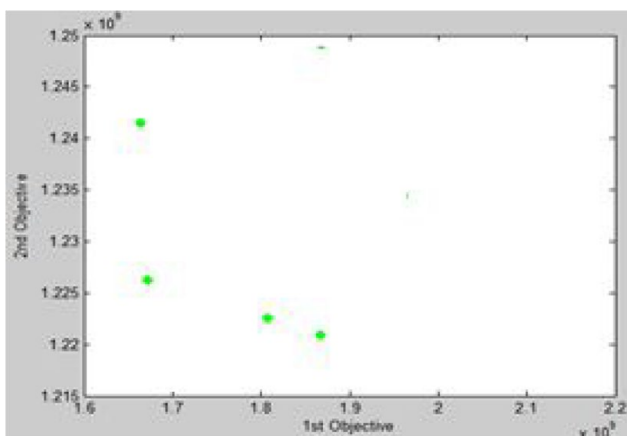


Figure 16. Pareto front for the problem M_3 .

parameter also significantly reduces the first objective function. The effect of these changes on the second objective function is that by increasing this parameter, the second objective function

Table 11. The effect of reducing and increasing of R_{ij} on the objective function values.

PARAMETER	0.8 R_{ij}	R_{ij}	1.2 R_{ij}
First objective function	631256.14	667590.385	697210.1
Second objective function	4286.12	4231.628	4198.5

Table 12. The effect of reducing and increasing of R_{jk} on the objective function values.

PARAMETER	0.8 R_{jk}	R_{jk}	1.2 R_{jk}
First objective function	621218.4	667590.385	758 236
Second objective function	4278.2	4231.628	4208.13

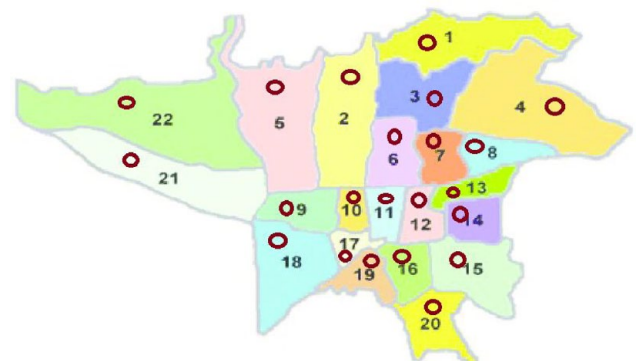


Figure 17. Location of the pharmacies in the geographical districts of Tehran.

decreases slightly. Also, by decreasing this parameter, the second objective function shows a slight increase.

The case study

In this section, the usefulness and practicality of the proposed model as well as the solution method are evaluated based on a real case study. The model was applied to design an effective and efficient perishable medical product SCN in Tehran (the capital city of Iran). The Tehran metropolitan city contains 22 geographically dispersed districts. The customers are allocated based on these districts. Figure 17 shows the location of the pharmacies (customers) in 22 geographical districts of Tehran. This SC involves ten pharmaceutical companies as suppliers, 5 pharmaceutical distribution companies as intermediate warehouses, and pharmacies in 22 districts of Tehran as the final customers for the pharmaceutical products. Six types of widely used drugs in Iran were taken into account as the medical items

Table 13. Pharmaceutical companies of the drug items.

	ASPIRIN	METFORMIN	ATORVASTATIN	LOSARTAN	METORAL	PANTOPRAZOLE
Pars Darou Co.	✓				✓	
Tehran Chemie Co.	✓		✓			
Aburaihan Co.			✓	✓		
Tolid Daroo Co.	✓		✓		✓	
Osveh Co.		✓				✓
Dr. Abidi Co.						✓
Razak Co.		✓				
Darou Pakhsh Co.	✓					
Tehrandarou Co.	✓					
Chemidarou Co.		✓				✓

in this study. A brief description of these drugs and their applications are given below:

Aspirin (acetylsalicylic acid (ASA)) is used to relieve pain, fever, and inflammation in various conditions such as lower back and neck pain, the flu, common cold, and so on. Metformin is an oral diabetes medicine that helps control blood sugar levels. Metformin works by helping to restore your body's proper response to the insulin you naturally produce. Atorvastatin is used along with a proper diet to help lower bad cholesterol and fats (such as LDL, triglycerides) and raise good cholesterol (HDL) in the blood. Losartan is used to treat high blood pressure (hypertension) and to help protect the kidneys from damage due to diabetes. Metoral (Metoprolol) is a drug called a beta-blocker. It's used to treat conditions such as high blood pressure, heart failure, and angina (chest pain). Pantoprazole is used to treat certain stomach and esophagus problems (such as acid reflux). It works by decreasing the amount of acid your stomach makes. Table 13 shows the companies that produce these drugs. It is obvious that all drugs are distributed by all pharmaceutical distribution companies.

The required data of our case is collected according to valid sources and published studies and travel distances and travel times are obtained from *Google maps*. Demand of each pharmacy for each drug item is given as a triangular fuzzy number $(Q_i^{m1}, Q_i^{m2}, Q_i^{m3})$ which the value of the parameter Q_{2im} is shown in Table 14, and the values of the parameters Q_{1im} and Q_{3im} are determined based on the parameter Q_{2im} , $(0.8 * Q_i^{m2}, Q_i^{m2}, 1.2 * Q_i^{m2})$.

Traveling distance between pharmacies and pharmaceutical distribution companies is shown in Table 15. Traveling distance between pharmaceutical distribution companies and pharmaceutical companies is shown in Table 16. The cost of transferring a unit of medical product from pharmaceutical distribution companies to pharmacies and cost of transferring a unit of medical product from pharmaceutical companies to pharmaceutical distribution companies are supposed to be proportional to the

traveling distances between nodes (Tables 15 and 16). Travel time between pharmacies and pharmaceutical distribution companies is shown in Table 17. Travel time between pharmaceutical distribution companies and pharmaceutical companies is given in Table 18. Set up cost of intermediate warehouses depends on its storage capacity, if the capacity of distribution companies is supposed to be 16000 m³ (medium); the opening cost of local hospitals is equal to \$800000.⁸² The average life of each drug is estimated to be 300 minutes $\left(\frac{1}{\lambda_j}\right)$. Scale and Shape parameters of the Weibull probability distribution are estimated to be .3 and .1, respectively.

Tables 18 and 19 summarize the numerical results of the problem. Distribution companies of Alborz and Exir are chosen to be open for storage and transfer of medical items to pharmacies with the goal of minimizing the total cost of the chain and total time of the presence of the items in the supply chain. Table 19 shows that which distribution company provides the medical items required by pharmacies and the quantity of medical products transferred from distribution companies to pharmacies and Table 20 shows the transmission of medical items from pharmaceutical distribution companies to distribution companies.

Conclusion

In this paper, a fuzzy bi-objective MIP model for the SCN of perishable medical goods in crisis situation was proposed considering uncertainty. The present problem was the design of a three-level SC for corruptible items, which the corruption of items has a probability function of Weibull. It means whatever the presence of any relief item is more in the chain, the probability of corruption is even greater. The customers are at the first level of chain that are customers for relief items, and the amount of demand for each of them is considered as a triangular fuzzy number. At the second level, there are potential intermediate

Table 14. Demand of each drugstore for drug items.

DISTRICT		ASPIRIN	METFORMIN	ATORVASTATIN	LOSARTAN	METORAL	PANTOPRAZOLE
1	Taleghani Pharmacy	532 100	412356	401 265	347 446	78962	215 895
2	Dr. Pasbin Pharmacy	428 256	258 996	358 974	78 562	86 952	245 895
3	Dr. Entekhabi Pharmacy	100 326	473 353	125 896	98 521	98 562	87 562
4	Omid Pharmacy	99 856	423 678	401 598	101 259	145 896	99 856
5	Dr. Adib Hashemi Pharmacy	88 546	321 589	398 752	254 120	245 895	125 963
6	13 Aban Pharmacy	520 728	198 756	378 562	125 964	278 952	150 253
7	Dr. Shirzadi Pharmacy	398 234	248 978	345 895	145 895	289 563	178 955
8	Armaghan Pharmacy	256 556	225 689	268 954	245 896	158 963	214 589
9	Dr. Shahrooz Saremi Pharmacy	357 438	158 965	400 259	345 895	178 952	276 512
10	Aryan Pharmacy	425 256	99 479	417 088	321 589	48 952	258 964
11	Nezaja 29 Farvardin Pharmacy	500 451	148 975	256 988	285 652	75 689	156 335
12	Shahid Abedini Pharmacy	128 318	256 987	195 230	325 955	154 123	202 566
13	Bu Ali Pharmacy	298 819	321 598	98 562	345 891	189 562	278 812
14	Abyaneh Pharmacy	438 514	414 569	78 953	125 985	285 623	101 259
15	Dr. Bazargani Pharmacy	523 392	325 879	398 561	145 985	278 955	85 662
16	Omid-e-No Pharmacy	89 996	245 987	158 965	178 532	169 665	245 895
17	Isar Pharmacy	56 534	254 897	245 895	278 562	65 896	271 236
18	Dr. Esfandiari Pharmacy	265 943	158 698	389 562	344 789	215 698	68 955
19	Dr. Biabanaki Pharmacy	351 556	456 899	289 541	321 589	299 972	78 956
20	Sama Drugstore	256 666	358 974	401 256	258 963	201 568	158 965
21	Ghavamin Pharmacy	295 531	258 997	125 986	269 852	102 598	254 689
22	Shahab Pharmacy	432 321	459 872	245 698	289 522	136 984	189 663

Table 15. Traveling distance between pharmacies and pharmaceutical distribution companies (Co.).

	HEJRAT CO.	FERDOWS CO.	ALBORZ CO.	RAZI CO.	EXIR CO.
Taleghani Pharmacy	17.5	29.1	14	13.6	18.1
Dr. Pasbin Pharmacy	4.2	8.1	12.5	9.8	17.2
Dr. Entekhabi Pharmacy	18.2	17.9	14.7	14.3	16
Omid Pharmacy	16.5	16.2	13.2	12.9	8
Dr. Adib Hashemi Pharmacy	6.2	11.3	17.1	17.5	21.8
13 Aban Pharmacy	2.9	6.5	4	3.6	3.4
Dr. Shirzadi Pharmacy	15.5	8.4	3.8	3.4	0.12
Armaghan Pharmacy	18.4	18.1	10.5	10.2	7.1
Dr. Shahrooz Saremi Pharmacy	7.9	7.4	11.3	11.6	13.6
Aryan Pharmacy	10.9	6.2	7.7	8	11.2
Nezaja 29 Farvardin Pharmacy	12	7.3	3.6	3.8	6.9
Shahid Abedini Pharmacy	20.3	9.2	3	2.6	2.1
Bu Ali Pharmacy	21.7	11.9	7.3	6.9	5.1
Abyaneh Pharmacy	26.8	17.2	9.6	9.3	8.3
Dr. Bazargani Pharmacy	40.6	41.6	35.1	52.6	54.6
Omid-e-No Pharmacy	17.4	9.7	6.9	7.1	11.1
Isar Pharmacy	3.4	8.6	4.4	4.1	5
Dr. Esfandiari Pharmacy	7	13.8	8.1	7.8	12.8
Dr. Biabanaki Pharmacy	15	14.4	11.7	11.9	15
Sama Drugstore	24	31.9	11.8	11.4	11.8
Ghavamin Pharmacy	12.6	6.7	5.8	15.5	17.5
Shahab Pharmacy	12.3	6.4	10.8	23.3	24.2

Table 16. Traveling distance between pharmaceutical distribution companies and pharmaceutical companies.

	PARS DAROU	TEHRAN CHEMIE	ABURAIHAN	TOLID DAROO	OSVEH	DR. ABIDI	RAZAK	DAROUPAKHSH	TEHRANDAROU	CHEMIDAROU
Hejrat Co.	21.1	15.2	32.6	12.9	14.6	16.5	23.6	25.5	15.4	32.2
Ferdows Co.	23.4	14.1	23.3	10.1	11.1	13.3	21.6	23.5	12.3	33.5
Alborz Co.	15.8	21.6	12.4	10.1	12.8	17.8	25.6	31	16.7	14.8
Razi Co.	16.6	18.2	13.2	11.2	15.2	17.3	25.2	26.2	16.3	15.6
Exir Co.	13.3	20.1	13.2	14.1	17.1	27.6	27.1	28.1	18.2	13.5

warehouses that receive, store and transfer relief items from suppliers at the third level, and play the role of interface between 2 levels. The selection of optimal intermediate warehouses and the optimal amount of flow from suppliers to them, and from them to each of the customers, with the minimum cost in the

chain and the shortest possible time for the items to be received by the customers, is the object of the problem. And finally, there are suppliers at the third level. In this research, we tried to make the problem as compliant as possible with the real world conditions. The proposed mathematical model can be applied to all

Table 17. Travel time between pharmacies and pharmaceutical distribution companies (minute).

	HEJRAT CO.	FERDOWS CO.	ALBORZ CO.	RAZI CO.	EXIR CO.
Taleghani Pharmacy	29	39	34	32	27
Dr. Pasbin Pharmacy	12	24	33	33	34
Dr. Entekhabi Pharmacy	30	33	28	28	22
Omid Pharmacy	35	40	26	24	16
Dr. Adib Hashemi Pharmacy	17	21	38	35	36
13 Aban Pharmacy	9	24	12	11	9
Dr. Shirzadi Pharmacy	30	33	12	11	1
Armaghan Pharmacy	32	36	23	21	12
Dr. Shahrooz Saremi Pharmacy	20	18	30	29	35
Aryan Pharmacy	22	16	26	26	32
Nezaja 29 Farvardin Pharmacy	24	17	14	14	22
Shahid Abedini Pharmacy	32	32	12	10	6
Bu Ali Pharmacy	35	34	17	15	10
Abyaneh Pharmacy	45	41	24	23	18
Dr. Bazargani Pharmacy	51	51	37	64	69
Omid-e-No Pharmacy	33	24	24	25	29
Isar Pharmacy	9	26	11	10	11
Dr. Esfandiari Pharmacy	19	22	21	20	22
Dr. Biabanaki Pharmacy	34	29	27	27	33
Sama Drugstore	41	32	32	31	27
Ghavamin Pharmacy	20	11	13	32	38
Shahab Pharmacy	19	10	15	41	45

Table 18. Travel time between pharmaceutical distribution companies and pharmaceutical companies (minute).

	PARS DAROU	TEHRAN CHEMIE	ABURAIHAN	TOLID DAROO	OSVEH	DR. ABIDI	RAZAK	DAROUPAKHSH	TEHRANDAROU	CHEMIDAROU
Hejrat Co.	63	35	65	36	33	28	33	32	27	56
Ferdows Co.	32	21	32	19	18	17	21	21	15	32
Alborz Co.	27	32	27	23	27	29	36	35	27	29
Razi Co.	28	31	29	23	28	28	34	35	26	31
Exir Co.	17	30	17	26	27	37	33	34	25	22

infrastructure or disaster types that are compatible with this model.

Three multi-objective approaches (LP-Metric, MOPS and NSGA-II) were utilized for the test problems to compare their performances based on the CPU run times and fitness function values and the results indicate the ability of the model and

algorithms to solve various problems. To demonstrate the validity and capability of the developed model, a case study of a SC of perishable medical goods in crisis situations in Iran's capital, Tehran was considered.

According to the obtained results, key managerial implications can be outlined as follows:

Table 19. The assignment of pharmacies to pharmaceutical distribution companies and the quantity of medical products transferred from pharmaceutical distribution companies to pharmacies.

		ASPIRIN	METFORMIN	ATORVASTATIN	LOSARTAN	METORAL	PANTOPRAZOLE
Taleghani Pharmacy	Alborz Co.	612 132	432 386		347 846		224 895
	Exir Co.			421 365		79 961	
Dr. Pasbin Pharmacy	Alborz Co.		274 996	421 574		87 552	257 195
	Exir Co.	512 256			81 662		
Dr. Entekhabi Pharmacy	Alborz Co.	110 316				101 256	
	Exir Co.		481 257	126 895	99 854		87 954
Omid Pharmacy	Alborz Co.	109 856	435 898		211 289		
	Exir Co.			523 598		215 796	120 268
Dr. Adib Hashemi Pharmacy	Alborz Co.	98 548			278 120		
	Exir Co.		345 689	421 852		314 595	215 463
13 Aban Pharmacy	Alborz Co.				215 874	321 852	158 253
	Exir Co.	541 228	215 656	421 762			
Dr. Shirzadi Pharmacy	Alborz Co.		324 978	358 995			
	Exir Co.	410 534			214 895	315 763	184 591
Armaghan Pharmacy	Alborz Co.	264 156	235 889				
	Exir Co.			315 854	316 096	178 568	348 189
Dr. Shahrooz Saremi Pharmacy	Alborz Co.				412 195		314 526
	Exir Co.	384 538	215 765	401 358		211 452	
Aryan Pharmacy	Alborz Co.	487 456		445 689	456 789	78 592	
	Exir Co.		112 579				328 964
Nezaja 29 Farvardin Pharmacy	Alborz Co.		214 935			84 589	178 735
	Exir Co.	623 451		278 956	295 752		
Shahid Abedini Pharmacy	Alborz Co.			211 356	345 855		
	Exir Co.	283 418	258 999			162 523	212 668
Bu Ali Pharmacy	Alborz Co.	308 489	348 598		378 591		
	Exir Co.			101 262		198 762	288 112
Abyaneh Pharmacy	Alborz Co.		478 596		129 855	299 213	125 250
	Exir Co.	485 714		79 853			
Dr. Bazargani Pharmacy	Alborz Co.	578 312	358 679			289 955	95 462
	Exir Co.			401 761	189 585		
Omid-e-No Pharmacy	Alborz Co.	89 999	278 956	189 635			289 558
	Exir Co.				187 132	178 658	
Isar Pharmacy	Alborz Co.	87 134	321 197		289 462		287 116
	Exir Co.			289 115		74 596	
Dr. Esfandiari Pharmacy	Alborz Co.	289 431	189 998	401 556			88 555
	Exir Co.				378 889	256 981	

(continued)

Table 19. (continued)

		ASPIRIN	METFORMIN	ATORVASTATIN	LOSARTAN	METORAL	PANTOPRAZOLE
Dr. Biabanaki Pharmacy	Alborz Co.	358 558		298 741	328 585		89 156
	Exir Co.		489 911			301 172	
Sama Drugstore	Alborz Co.		378 174	411 258		212 567	
	Exir Co.	266 866			299 967		179 465
Ghavamin Pharmacy	Alborz Co.		287 156		275 152		
	Exir Co.	353 151		185 110		158 501	259 856
Shahab Pharmacy	Alborz Co.	452 231		278 618	299 522		
	Exir Co.		488 721			178 596	201 565

Table 20. The quantity of transferred medical items from pharmaceutical companies to pharmaceutical distribution companies.

		ASPIRIN	METFORMIN	ATORVASTATIN	LOSARTAN	METORAL	PANTOPRAZOLE
Alborz Co.	Pars Darou						1 475 576
	Tehran Chemie						
	Aburaihan						
	Tolid Daroo				3 017 422		
	Osveh						
	Dr. Abidi						2 108 701
	Razak			3 417 156			
	Daroupakhsh	3 736 762					
	Tehrandarou						
	Chemidarou					3 969 135	
Exir Co.	Pars Darou						
	Tehran Chemie	3 861 156					
	Aburaihan				3 968 741		
	Tolid Daroo						2 825 924
	Osveh			2 608 577			
	Dr. Abidi						2 427 095
	Razak						
	Daroupakhsh						
	Tehrandarou					2 063 832	
	Chemidarou						

- Senior management should consider the issues of transportation and inventory of relief items in a coordinated and integrated framework.
- The collection for different situations and changes should be managed, and the planning should not be confined to a definite specific condition, anticipate the uncertainties should be foreseen and proper planning should be provided for them.
- The management of the rescue and relief chain should not consider merely the cost factors in the discussion of completing and supplying the network and should always consider qualitative factors in their decisions.

Although it has been tried to identify all the important parameters of the model, due to the abundance of these factors, some other unknown factors may also be effective that were not identified. Also, accessing the required data was challenging, and obtaining the necessary permits took considerable time. In addition, due to the NP-hardness of the problem, it was not possible to solve the problem with commercial softwares such as LINGO and GAMS.

The following suggestions are provided for further studies: The multi-objective model can be solved by other efficient meta-heuristic or heuristic algorithms and results should be compared with the results of this research. Also, other approaches may be considered to cope with the uncertainty of the parameters. In addition, the presented model should be implemented and evaluated on different types of crises and geographical regions.

Author Contributions

Conceptualization, F.S., H.K.; methodology, F.S., H.K., A.H., and M.K.; software, F.S.; validation, F.S., H.K., A.H., and M.K.; formal analysis, F.S., H.K., A.H., and M.K.; investigation, F.S., H.K., A.H., and M.K.; resources, F.S., H.K., A.H., and M.K.; data curation, F.S., H.K., A.H., and M.K.; writing—original draft preparation, F.S., and H.K.; writing—review and editing, H.K., and M.K.; visualization, F.S., H.K., A.H., and M.K.; supervision, H.K., and M.K.; project administration, F.S.; All authors have read and agreed to the published version of the manuscript.

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REFERENCES

- Ergun O, Karakus G, Keskinocak P, Swann J, Villarreal M. Operations research to improve disaster supply chain management. *Wiley Encycl Oper Res Manag Sci*. 2010. <https://doi.org/10.1002/9780470400531.eorms0604>
- Tang CS. Robust strategies for mitigating supply chain disruptions. *Int J Logist Res Appl*. 2006;9:33-45.
- Kuruppu KKS. Management of blood system in disasters. *Biologicals*. 2010;38:87-90.
- Schmidt P, Bayer W. Transfusion support in a community disaster. In: *Supportive Therapy in Haematology*. Springer; 1985:371-377.
- Mete HO, Zabinsky ZB. Stochastic optimization of medical supply location and distribution in disaster management. *Int J Prod Econ*. 2010;126:76-84.
- Day JM, Melnyk SA, Larson PD, Davis EW, Whybark DC. Humanitarian and disaster relief supply chains: a matter of life and death. *J Supply Chain Manag*. 2012;48:21-36.
- Fahimnia B, Farahani RZ, Marian R, Luong L. A review and critique on integrated production–distribution planning models and techniques. *J Manuf Syst*. 2013;32:1-19.
- Demirli K, Yimer A. Production-distribution planning with fuzzy costs. *Fuzzy Information Processing Society, 2006. NAFIPS 2006. Annual meeting of the North American*; 2006:702-707.
- Pyke DF, Cohen MA. Performance characteristics of stochastic integrated production–distribution systems. *Eur J Oper Res*. 1993;68:23-48.
- Chen M, Wang W. A linear programming model for integrated steel production and distribution planning. *Int J Oper Prod Manag*. 1997;17:592-610.
- Liang T-F. Fuzzy multi-objective production/distribution planning decisions with multi-product and multi-time period in a supply chain. *Comput Ind Eng*. 2008;55:676-694.
- Bilgen B. Application of fuzzy mathematical programming approach to the production allocation and distribution supply chain network problem. *Expert Syst Appl*. 2010;37:4488-4495.
- Das K, Sengupta S. A hierarchical process industry production–distribution planning model. *Int J Prod Econ*. 2009;117:402-419.
- Yimer AD, Demirli K. A genetic approach to two-phase optimization of dynamic supply chain scheduling. *Comput Ind Eng*. 2010;58:411-422.
- Ferrio J, Wassick J. Chemical supply chain network optimization. *Comput Chem Eng*. 2008;32:2481-2504.
- Kim Y, Yun C, Park SB, et al. An integrated model of supply network and production planning for multiple fuel products of multi-site refineries. *Comput Chem Eng*. 2008;32:2529-2535.
- Fahimnia B, Luong L, Marian R. Genetic algorithm optimisation of an integrated aggregate production–distribution plan in supply chains. *Int J Prod Res*. 2012;50:81-96.
- Jordan D, Smith P, eds. *Mathematical Techniques: An Introduction for the Engineering, Physical, and Mathematical Sciences*. 3rd ed. OUP; 2002.
- Yeh W-C. A hybrid heuristic algorithm for the multistage supply chain network problem. *Int J Adv Manuf Technol*. 2005;26:675-685.
- Siprelle A, Parsons D, Clark R. Benefits of using a supply chain simulation tool to study inventory allocation. *Proceedings of the 2003 Winter Simulation Conference*. 2003;231:238-245.
- Gupta A, Maranas CD. Managing demand uncertainty in supply chain planning. *Comput Chem Eng*. 2003;27:1219-1227.
- Kanyalkar AP, Adil GK. A robust optimisation model for aggregate and detailed planning of a multi-site procurement–production–distribution system. *Int J Prod Res*. 2010;48:635-656.
- Kaya O, Urek B. A mixed integer nonlinear programming model and heuristic solutions for location, inventory and pricing decisions in a closed loop supply chain. *Comput Oper Res*. 2016;65:93-103.
- Torabi SA, Hassini E. Multi-site production planning integrating procurement and distribution plans in multi-echelon supply chains: an interactive fuzzy goal programming approach. *Int J Prod Res*. 2009;47:5475-5499.
- Rezaei-Malek M, Tavakkoli-Moghaddam R, Zahiri B, Bozorgi-Amiri A. An interactive approach for designing a robust disaster relief logistics network with perishable commodities. *Comput Ind Eng*. 2016;94:201-215.
- Cheraghi S, Hosseini-Motlagh SM, Ghatreh Samani M. Integrated planning for blood platelet production: a robust optimization approach. *J Ind Syst Eng*. 2017;10:55-80.
- Tavana M, Abtahi A-R, Di Caprio D, Hashemi R, Yousefi-Zenouz R. An integrated location–inventory–routing humanitarian supply chain network with pre- and post-disaster management considerations. *Socioecon Plann Sci*. 2018;64:21-37.
- Noham R, Tzur M. Designing humanitarian supply chains by incorporating actual post-disaster decisions. *Eur J Oper Res*. 2018;265:1064-1077.
- Zahraee SM, Rohani JM, Firouzi A, Shahpanah A. Efficiency improvement of blood supply chain system using Taguchi method and dynamic simulation. *Procedia Manuf*. 2015;2:1-5.
- Habibi-Kouchaksaraei M, Paydar MM, Asadi-Gangraj E. Designing a bi-objective multi-echelon robust blood supply chain in a disaster. *Appl Math Model*. 2018;55:583-599.
- Zahiri B, Julia P, Tavakkoli-Moghaddam R. Design of a pharmaceutical supply chain network under uncertainty considering perishability and substitutability of products. *Inf Sci*. 2018;423:257-283.
- Goodarzian F, Hosseini-Nasab H, Muñuzuri J, Fakhrazad MB. A multi-objective pharmaceutical supply chain network based on a robust fuzzy model: a comparison of meta-heuristics. *Appl Soft Comput*. 2020;92:106331.
- Sinha AK, Anand A. Optimizing supply chain network for perishable products using improved bacteria foraging algorithm. *Appl Soft Comput*. 2020;86:105921.
- Zandkarimkhani S, Mina H, Biuki M, Govindan K. A chance constrained fuzzy goal programming approach for perishable pharmaceutical supply chain network design. *Ann Oper Res*. 2020;295:425-452.
- Franco C, Alfonso-Lizarazo E. Optimization under uncertainty of the pharmaceutical supply chain in hospitals. *Comput Chem Eng*. 2020;135:106689.
- Goodarzian F, Wamba SF, Mathiyazhagan K, Taghipour A. A new bi-objective green medicine supply chain network design under fuzzy environment: hybrid metaheuristic algorithms. *Comput Ind Eng*. 2021;160:107535.
- Goodarzian F, Taleizadeh AA, Ghasemi P, Abraham A. An integrated sustainable medical supply chain network during COVID-19. *Eng Appl Artif Intell*. 2021;100:104188.
- Fatemi MS, Ghodrathnama A, Tavakkoli-Moghaddam R, Kaboli A. A multi-functional tri-objective mathematical model for the pharmaceutical supply chain considering congestion of drugs in factories. *Res Transp Econ*. 2022;92:101094.
- Khalili-Damghani K, Tavana M, Ghasemi P. A stochastic bi-objective simulation–optimization model for cascade disaster location–allocation–distribution problems. *Ann Oper Res*. 2022;309:103-141.
- Lotfi A, Shakouri M, Abazari SR, Aghsami A, Rabbani M. A multi-objective optimization for a closed-loop sustainable pharmaceutical supply chain network

- design: a case study. *J Adv Manag Res.* 2023;20:565-598. ahead-of-print No. Ahead-of-print. doi:10.1108/jamr-05-2022-0100
41. Kochakkashani F, Kayvanfar V, Haji A. Supply chain planning of vaccine and pharmaceutical clusters under uncertainty: the case of COVID-19. *Socioecon Plann Sci.* 2023;87:101602.
 42. Goodarzian F, Ghasemi P, Gunasekaran A, Labib A. A fuzzy sustainable model for COVID-19 medical waste supply chain network. *Fuzzy Optim Decis Mak.* 2024;23:93-127.
 43. Nagurney A, Masoumi AH, Yu M. Supply chain network operations management of a blood banking system with cost and risk minimization. *Comput Manag Sci.* 2012;9:205-231.
 44. Alfonso E, Xie X, Augusto V, Garraud O. Modeling and simulation of blood collection systems. *Health Care Manag Sci.* 2012;15:63-78.
 45. Salehi F, Mahootchi M, Husseini SMM. Developing a robust stochastic model for designing a blood supply chain network in a crisis: a possible earthquake in Tehran. *Ann Oper Res.* 2019;283:679-703.
 46. Khalilpourazari S, Arshadi Khamseh A. Bi-objective emergency blood supply chain network design in earthquake considering earthquake magnitude: a comprehensive study with real world application. *Ann Oper Res.* 2019;283:355-393.
 47. Diabat A, Jabbarzadeh A, Khosrojerdi A. A perishable product supply chain network design problem with reliability and disruption considerations. *Int J Prod Econ.* 2019;212:125-138.
 48. Safaei AS, Farsad S, Paydar MM. Emergency logistics planning under supply risk and demand uncertainty. *Oper Res Int J.* 2020;20:1437-1460.
 49. Cholodowicz E, Orłowski P. Development of new hybrid discrete-time perishable inventory model based on Weibull distribution with time-varying demand using system dynamics approach. *Comput Ind Eng.* 2021;154:107151.
 50. Gupta S, Chaudhary S, Chatterjee P, Yazdani M. An efficient stochastic programming approach for solving integrated multi-objective transportation and inventory management problem using goodness of fit. *Kybernetes.* 2022;51:768-803.
 51. Sugapriya C, Nagarajan D, Gobinath VM, Kuppulakshmi V. A multi-period optimization model for medicine supply chains using modified interactive multi-objective fuzzy programming. *Supply Chain Anal.* 2023;4:100048.
 52. Pooya A, Mansoori A. Neural network for solving disturbance optimal control model for production inventory system with stochastic deterioration in two-level supply chain. *Soft Comput.* 2024;1-16. <https://doi.org/10.1007/s00500-024-09868-9>
 53. Supakar P, Manna AK, Mahato SK, Bhunia AK. Application of artificial bee colony algorithm on a green production inventory problem with preservation for deteriorating items in neutrosophic fuzzy environment. *Int J Syst Assur Eng Manag.* 2024;15:672-686.
 54. Mamoudan MM, Mohammadnazari Z, Ostadi A, Esfahbodi A. Food products pricing theory with application of machine learning and game theory approach. *Int J Prod Res.* 2024;62:5489-5509.
 55. Zadeh LA. Fuzzy sets. *Inf Control.* 1965;8:338-353.
 56. Jabbarzadeh A, Fahimnia B, Seuring S. Dynamic supply chain network design for the supply of blood in disasters: a robust model with real world application. *Transp Res E Logist Transp Rev.* 2014;70:225-244.
 57. Lavenberg SS, Reiser M. Stationary state probabilities at arrival instants for closed queueing networks with multiple types of customers. *J Appl Probab.* 1980;17:1048-1061.
 58. Jose KP, Reshmi PS. A production inventory model with deteriorating items and retrieval demands. *OPSEARCH.* 2021;58:71-82.
 59. Jiménez M, Arenas M, Bilbao A, Rodríguez MV. Linear programming with fuzzy parameters: an interactive method resolution. *Eur J Oper Res.* 2007;177:1599-1609.
 60. Talon A, Curt C. Selection of appropriate defuzzification methods: application to the assessment of dam performance. *Expert Syst Appl.* 2017;70:160-174.
 61. Kaufman A, Gupta M. *Introduction to Fuzzy Arithmetic.* Van Nostrand Reinhold Company; 1991.
 62. Heidari A, Imani DM, Khalilzadeh M, Sarbazvatan M. Green two-echelon closed and open location-routing problem: application of NSGA-II and MOGWO metaheuristic approaches. *Environ Dev Sustain.* 2022;25:1-37.
 63. Hajghani M, Forghani MA, Heidari A, Khalilzadeh M, Kebriyaii O. A two-echelon location routing problem considering sustainability and hybrid open and closed routes under uncertainty. *Heliyon.* 2023;9:e14258.
 64. Ma H, Zhang Y, Sun S, Liu T, Shan Y. A comprehensive survey on NSGA-II for multi-objective optimization and applications. *Artif Intell Rev.* 2023;56:15217-15270.
 65. Hosseini Dehshiri SJ, Yousefi Hanoomarvar A, Amiri M. Comparative performance of the NSGA-II and MOPSO algorithms and simulations for evaluating time-cost-quality-risk trade-off in multi-modal PERT networks. *Soft Comput.* 2023;27:18651-18666.
 66. Kebriyaii O, Heidari A, Khalilzadeh M, Pamucar D. A green project scheduling with material ordering problem considering cost constraints and quality of materials. *Eng Construct Architect Manag.* 2024. doi:10.1108/ecam-01-2024-0004
 67. Ravandi F, Fathi Heli Abadi A, Heidari A, Khalilzadeh M, Pamucar D. A bi-objective model for location, dispatch and relocation of ambulances with a revision of dispatch policies. *Kybernetes.* 2024. doi:10.1108/k-11-2023-2491
 68. Kebriyaii O, Heidari A, Khalilzadeh M, Antucheviciene J, Pavlovskis M. Application of three metaheuristic algorithms to time-cost-quality trade-off project scheduling problem for construction projects considering time value of money. *Symmetry.* 2021;13:2402.
 69. Lalwani S, Singhal S, Kumar R, Gupta N. A comprehensive survey: applications of multi-objective particle swarm optimization (MOPSO) algorithm. *Trans Comb.* 2013;2:39-101.
 70. Aranha C, Camacho Villalón CL, Campelo F, et al. Metaphor-based metaheuristics, a call for action: the elephant in the room. *Swarm Intell.* 2022;16:1-6.
 71. Lee J, Naor A. Lp metrics on the Heisenberg group and the Goemans-Linial conjecture. In: Foundations of Computer Science. FOCS'06. 47th Annual IEEE Symposium, 2006:99-108
 72. Alvarez-Benitez J, Everson R, Fieldsend J. A MOPSO algorithm based exclusively on pareto dominance concepts. In: International Conference on Evolutionary Multi-Criterion Optimization, 2005:459-473
 73. Fallah-Mehdipour E, Haddad OB, Mariño MA. MOPSO algorithm and its application in multipurpose multireservoir operations. *J Hydroinformatics.* 2011;13:794-811.
 74. Goldberg D, Deb K. A comparative analysis of selection schemes used in genetic algorithms. In: *Foundations of Genetic Algorithms.* Elsevier; 1991; 1: 69-93.
 75. Deb K. *Genetic Algorithms in Multimodal Function Optimization. Clearinghouse for genetic Algorithms.* Department of Engineering Mechanics, University of Alabama; 1989.
 76. Deb K. *Multi-Objective Optimization Using Evolutionary Algorithms.* John Wiley & Sons; 2001.
 77. Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans Evol Comput.* 2002;6:182-197.
 78. Fonseca C, Fleming P. Genetic Algorithms for Multiobjective Optimization: Formulation Discussion and Generalization. In: *Icga.* 1993; 416-423.
 79. Ross P, Ross P. *Taguchi Techniques for Quality Engineering: Loss Function, Orthogonal Experiments, Parameter and Tolerance Design.* McGraw-Hill; 1988.
 80. Hajjipour V, Rahmati SHA, Pasandideh SHR, Niaki STA. A multi-objective harmony search algorithm to optimize multi-server location-allocation problem in congested systems. *Comput Ind Eng.* 2014;72:187-197.
 81. Phadke M. *Quality Engineering Using Robust Design.* Prentice Hall PTR; 1995.
 82. Bozorgi-Amiri A, Jabalameli MS, Mirzapour Al-e-Hashem SMJ. A multi-objective robust stochastic programming model for disaster relief logistics under uncertainty. *OR Spectr.* 2013;35:905-933.