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A socio-economic optimization model for blood supply chain network design during the COVID-19 pandemic: An interactive possibilistic programming approach for a real case study

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ABSTRACT

In uncertain circumstances like the COVID-19 pandemic, designing an efficient Blood Supply Chain Network (BSCN) is crucial. This study tries to optimally configure a multi-echelon BSCN under uncertainty of demand, capacity, and blood disposal rates. The supply chain comprises blood donors, collection facilities, blood banks, regional hospitals, and consumption points. A novel bi-objective Mixed-Integer Linear Programming (MILP) model is suggested to formulate the problem which aims to minimize network costs and maximize job opportunities while considering the adverse effects of the pandemic. Interactive possibilistic programming is then utilized to optimally treat the problem with respect to the special conditions of the pandemic. To validate the developed methodology, a real case study of a Blood Supply Chain (BSC) is analyzed, along with sensitivity analyses of the main parameters. According to the obtained results, the suggested approach can simultaneously handle the bi-objectiveness and uncertainty of the model while finding the optimal number of facilities to satisfy the uncertain demand, blood flow between supply chain echelons, network cost, and the number of jobs created.

1. Introduction

Strategic Supply Chain (SC) planning or Supply Chain Network Design (SCND) deals with finding the optimal facilities locations while considering other functions such as inventory control policy, transportation modes, storage and warehousing, and routing problem [1]. Today’s competitive market requires an SCND with the lowest possible cost that can meet the SC goals. In addition to costs, growing concerns about meeting environmental, social, and legal needs have made newer goals a priority in SCND and led the SC towards sustainability [2]. An important element of sustainability is social responsibility which deals with issues such as environmental protection, job creation, and workplace safety [3,4]. Therefore, an optimal SCND plays an important role in the performance of the SC [5] in any industry, including the field of blood products.

Human blood is different from regular commodities in two ways: (i) Its demand is highly random, and conditions such as health crises and humanitarian disasters significantly change the demand, and (ii) Blood is a vital item that is solely generated by human beings and cannot be substituted by other products. It is necessary to note that blood units are not only perishable but also limited in supply due to a small pool of donors. According to the American Blood Organization, only about 5% out of 60% eligible population of the United States (US) donate blood [6]. Besides, from all donated blood units, only a small amount is usable, and there is a time interval needed to be taken between blood donation and the next turn [7]. Considering these facts, it is clear that careful planning is necessary to configure an efficient Blood Supply Chain (BSC). Consequently, Blood Supply Chain Management (BSCM) is a critical task that has received considerable attention from researchers [8].

In terms of SCM, especially the BSCM, several disruptions threaten the network. Low-impact operational risks (e.g., uncertain demand,
employee strike, operational failure in a part of SC, and excessive inflation) are managed through several mitigation strategies. In contrast, high-impact disruptions (e.g., natural disasters, terrorist attacks, and pandemics) can fail the SC functions and leave unprecedented adverse impacts. The World Health Organization (WHO) announced a pandemic status for COVID-19 on March 11, 2020. The pandemic has changed the entire world as billions of people are under quarantine and at risk of serious illness. It has also significantly interrupted the healthcare SCs and logistics [9]. During the COVID 19 pandemic, WHO estimated a reduction of 20–30% in blood supply in all affected countries. Additionally, the donation rate has decreased by 10–30% in Washington, USA, and by 30% at Canadian Blood Services [10]. Hospitals not only must treat an overwhelming number of COVID-19 patients but also keep the capacity for non-COVID-19 patients. The continued availability of safe blood is essential to both of these missions [11]. The blood banks have to add the COVID-19 test to the standard tests they perform on the given blood by donors. This additional test causes a delay in product flow and additional cost to the entire SC. According to the research, the COVID-19 virus will be around for at least a few years. Therefore, Blood Supply Chain Network Design (BSCND) decisions should be made considering the cost and operations effects of the pandemic. Additionally, healthcare systems provide a great deal of socioeconomic opportunity for the region. Different partners are included in the blood network, which could raise the number of job opportunities in the SC as a social responsibility. In 2018, one in seven new jobs were created by the healthcare sector, according to the Bureau of Labor Statistics. As a matter of fact, this sector outpaced all other major sectors of the economy, including food services, construction, and manufacturing. It is evident from these statistics that healthcare SC plays a remarkable role in the social and economic dimensions of society.

This study develops a new optimal BSCND model for this new trend in the market. Many researchers have worked on the BSCND optimization problem under disaster implications [12]. A major concern in the BSCND-related works is demand and the other relevant parameters’ uncertainty, i.e. capacity, and blood disposal rate uncertainty. Several Operations Research (OR) approaches such as fuzzy logic, queuing theory, simulation, and stochastic programming can be employed to capture uncertainty [13]. A preferred way to tackle dubious decisions and visualize the ambiguity in human thinking is to use fuzzy theory [14]. Fuzzy sets or fuzzy numbers can demonstrate and deal with inaccurate parameters appropriately and in different ways [15].

This study develops a novel fuzzy optimization model for the BSCND problem under uncertainty. The demand, disposal rate, and the minimum amount of demand allocated to deploy a facility as well as its capacity are uncertain. A four-echelon BSC, including Blood Donation Centers (BDCs), blood banks, regional hospitals, and demand points (local hospitals and clinics), is considered in the study. The model is formulated according to a fuzzy Mixed-Integer Linear Programming (MILP) model to maximize job opportunities and minimize SC costs. The decision variables are facilities design, transportation modes, allocation, and capacity of facilities. The COVID-19 test is added to the regular tests conducted in the blood banks. After the problem formulation and solution technique, a real case study is analyzed to show the efficacy of the developed model. Sensitivity analyses are also carried out to explore different aspects of the problem. Concerning the above introduction, here are the main research questions:

1) How do job opportunities incorporate into the problem of BSCND?
2) What would be the efficient capacity and transportation modes for blood transshipment in the Blood Supply Chain (BSC) in the existence of COVID-19?
3) How does the fuzzy theory apply to the problem of BSCND?
4) What implications do the decision-makers consider during the practical implementation of the BSCND decision?

The contributions of the research to the existing literature can be summarized as follows.

1) Introducing a new fuzzy optimization model to indicate the optimal BSCND variables considering the real uncertain nature of the effective parameters.
2) Taking into account the COVID-19 impact on the BSCND problem. More particularly, the research adds the cost of the COVID-19 test to the SC’s operational cost and adjusts the SCND to minimize the cost and maximize the socio-economy implications.
3) Incorporating increasing job opportunities as an objective to the problem of BSCND. This idea will provide more in-favor justification to invest in the healthcare SC for local and national decision-makers and investors.
4) Conducting the proposed model in a real case study, which is rare in the current works.

The rest of this study is structured as follows. The background of the study is reviewed in Section 2. The research problem is defined in Section 3. Section 4 formulates the optimization model. The solution methodology is described in Section 5. A real case study with extensive numerical illustration is investigated in Section 6. Section 7 provides comprehensive sensitivity analyses, and Section 8 concludes the research and provides an outlook.

2. Literature review

The BSC has been investigated by many researchers. This section briefly reviews the notable works based on the following streams: 1) BSCND problem, 2) BSC functions including inventory, allocation, location, transportation, etc., and 3) BSCND under uncertainty.

2.1. Blood supply chain network design problem

BSCND is classified as a strategic decision in SC that needs a considerable cost and is planned for a long-term period. Though, some researchers consider tactical and even operational decisions along with the BSCND. Osorio et al. [16] provided a comprehensive review of BSC research works. They categorized the articles according to the main criteria such as blood component, facility design decisions (operational, tactical, and strategic), and solution techniques. Several works have considered deterministic demand in the BSCND. As an instance, Arvan, Tavakkoli-Moghaddam [17] used a deterministic model to study the network optimization model for the BSC. The network includes demand points, distribution sites, storage, laboratories, and collection centers. An exact approach using GAMS/Cplex was applied to solve the suggested model. Sha and Huang [18] used the Lagrangian relaxation technique to solve a multi-period location-allocation problem in BSC where minimizing the costs (inventory, transportation, and shortage) was considered the objective function.

Researchers have paid much attention to the uncertain supply and demand. Ramezanian and Behboodi [19] designed a BSCN using MILP where the blood donors’ decisions are impacted by several social factors such as experiences, advertising costs, and distance. Zahiri and Pishvaee [20] studied BSCND under blood group compatibility. They offered a bi-objective mathematical model to minimize the network cost and unmet demand. Nagurney et al. [21] also developed an optimization approach for BSN in which minimizing blood wastage is considered a primary goal. Abbasi et al. [22] focused on the computational concern of a large-scale optimization model for the BSCN problem and introduced a novel machine learning methodology to treat the problem more efficiently. Osorio et al. [23] provided a generic model that optimizes the BSCN configuration. They used an optimization approach to minimize the costs and maximize the performance of the entire SC. Ghandforoush and Sen [24] proposed a non-linear integer programming model to minimize the cost of producing platelet in a blood center that serves...
Several researchers have also examined the social implications of the BSC. Hsieh [25] designed a bi-objective optimization model for the blood location inventory problem in the BSC. The author tried to minimize the system costs (maximize the efficiency) and maximize the SC responsiveness. Eskandari-Khanghahi, Tavakkoli-Moghaddam [7] employed the ε-constraint method, fuzzy possibilistic programming approach, Simulated Annealing (SA) algorithm, and Harmony Search (HS) algorithm to treat a multi-objective BSCND problem. The objectives were to simultaneously minimize the total cost and environmental impacts while maximizing the social impacts. Fahimnia et al. [26] also studied the SCND to minimize the cost and blood delivery time using ε-constraint and Lagrangian relaxation. Haghjoo et al. [5] studied the same model, however, they used Invasive Weed Optimization (IWO) and Self-Adaptive Imperialist Competitive (SAIC) algorithms to find the best solution. Şahinyazan et al. [27] studied the BSC under disruption events when the survival rate follows a known probability function. The study was formulated to optimize resource allocation and delivery to the patients. Likely, a BSCND problem in a disaster time is formulated by Kohneh et al. [28] according to bi-objective mathematical programming. The objectives were to minimize the cost and maximize the coverage of the donor individuals.

The simulation approach is also applied in some works to treat the high uncertainty in the BSCND problem [29–31]. Hajjema et al. [32] combined simulation methods with Markov dynamic programming to minimize the costs related to inventory and production functions in the SC. Afterward, the proposed model was tested on actual blood banks in the Netherlands. A simulation optimization model was developed by Duan and Liao [8] to manage a single-hospital single-blood center SC aimed at minimizing the rate of blood waste.

2.2. Blood supply chain functions

Inventory control models in BSC have been extensively investigated in the literature. Periodical methods such as (R, s, S), (R, S), and (R, Q) where R, s, S, and Q stand for the review periodically, reorder point, target inventory level, and order quantity, respectively, are more common in the existing works [33,34]. Dehghani et al. [6] developed two-stage stochastic programming to determine the optimal ordering and transshipment policies in the context of blood inventory management. Kendall and Lee [35] studied the blood allocation problem in hospitals intending to minimize wastage. A location-allocation decision problem is investigated by Şahin et al. [36] to optimize blood distribution at a regional level. The validity of the model was examined through the Turkish Red Crescent blood service. Rajendran and Ravindran [37] introduced a single hospital inventory control model when the demand is uncertain. Minimizing the costs, shortages, and blood wastage is considered the objective function. Puranam et al. [38] introduced an integer programming approach to inventory management in a blood network under a blood unit sharing policy among hospitals. Khalipourazari et al. [39] considered transportation planning in BSC under natural disasters such as an earthquake. They adopted several transportation modes, including helicopters, to carry the blood. It was also assumed that the model should minimize the unfulfilled demand. A hybrid optimization-neural learning approach was applied to treat the problem. Hemmelmayr et al. [40] studied the allocation and routing problem in BSC and examined recourse actions in hospitals to mitigate the impact of blood demand uncertainty.

2.3. Blood supply chain network design under uncertainty

The demand function is a great deal in BSC that significantly changes the results of the models. Therefore, different types of this function are studied by the researchers. The uncertain demand function, random demand with a known distribution [8], fuzzy numbers [41], and worst scenario bounded [42], to name a few. Several researchers have used Robust Optimization (RO) technique to cope with the uncertainty. Hamdan and Diabet [43] offered a bi-objective RO model for BSCND where the SC is resilient to disasters. The objective was to minimize the time and blood delivery cost to the hospitals. A Lagrangian relaxation method was employed to treat the complexity of the model. Wang and Chen [12] used a two-stage RO approach for BSCN problems during disaster events. It is assumed that only a small number of historical data exists, and a moment-based ambiguous set defines the uncertain demand. A real case study in China was analyzed to validate the proposed approach. A five-echelon BSC was studied by Fazli-Khalaf et al. [44], in which the robust probabilistic chance constraint programming method was considered to handle uncertainties. Salehi et al. [45] also formulated a robust stochastic optimization model for the BSCND problem with the assumptions of different blood types and blood compatibilities. A RO model for emergency BSCND problems was developed by Rahmani [46] where a Lagrangian relaxation approach was applied to solve the model.

The fuzzy approach is another technique that has been applied in a few research works. Shokouhifar, Sabbaghi [47] studied the SC of age-differentiated platelets as a blood product to minimize the costs, shortages, and blood wastages. A fuzzy supply/demand uncertainty is assumed to formulate and solve the problem. Besides, a real case study was evaluated to demonstrate the efficacy of the suggested model. Haeri, Hosseini-Motlagh [48] first, defined several resiliency metrics to evaluate the performance of BSC. Then, they suggested a multi-objective BSC fuzzy optimization model that incorporates the resiliency metrics into the objective function. An interesting implication of the study is introducing multiple motivational social actions to stimulate blood donors and boost the SC’s blood flow. Seyfi-Shishavan et al. [49] studied the BSCND during natural disasters using a fuzzy multi-period optimization model. The trapezoidal fuzzy numbers and spherical fuzzy membership degrees are assumed to convert the mathematical model into a fuzzy optimization model. Mousavi et al. [50] considered a stochastic programming technique to design a Blood Supply Chain Network (BSCN) under social and environmental factors. Recently, Larimi et al. [51] addressed the application of Geographic Information System (GIS) in recognizing BSCN using a robust-stochastic method to tackle demand uncertainty and disruption damages. The objective was to minimize the total cost in a real case study in Tehran, Iran. On other hand, several recent research works can be found on the SCND problems under uncertainty considering COVID-19 Pandemic; for example, please see Hosseinia et al. [52] and Zahedi et al. [53].

Despite extensive research on BSCND in the past, there are still several research gaps. As far as we are aware, there has been no significant research on BSCND and COVID-19 pandemic. It is important to take into account the impact of the pandemic on the flow of products in BSC as part of the planning process. Secondly, the creation of jobs is an important aspect of the social responsibility of SCN that is rarely discussed in the literature. The majority of research on BSCN has assumed deterministic approaches. Lastly, real case studies are not very common in this field.

Unlike previous works, the research at hand introduces a new fuzzy optimization model that will determine the BSCN decision variables (i.e., facility design, allocation, capacity, and transportation) during the COVID-19 pandemic in such a way the SC cost is minimized while maximizing job opportunities. This work combines the economic aspect of BSCN with the job opportunities index as a social factor to reflect the real situation better. It also formulates and solves the model according to a fuzzy MILP identified as a strong approach in BSC problems. Finally, this work includes a real case study that validates the proposed approach.

3. Problem definition

The first echelon of a BSC is blood collection centers or BDCs where the blood donors voluntarily give blood to blood donation facilities or
mobile blood centers. Then, blood banks receive and process the collected blood units. Several bacterial and other mandatory tests such as West Nile Virus (WNV), Human Immunodeficiency Virus (HIV), and Hepatitis are conducted at the blood banks [47]. In some cases, additional tests will be requested upon need and exaggerate the uncertainty. COVID-19 is among the additional tests that are required during the pandemic in 2020. We assume that the antibody test is the main COVID test in blood banks. Blood banks keep the processed blood units until they distribute them to healthcare clinics and hospitals. Finally, patients in need will receive blood at the hospitals and other healthcare centers [43].

This section presents the BSCND problem to be socio-economically optimized, considering the impact of the COVID-19 pandemic. A four-echelon BSC is considered, including BDCs, blood banks, hospitals, and local hospitals and clinics (demand points). Blood is collected either through mobile or fixed blood centers from the blood donors. The convenience of blood donors is very important, and they should have access to the best option according to their desire. Then the collected blood is transferred to the blood banks. Three transportation modes, including motorcycle, helicopter, and vehicle, are considered to dispatch the blood from the BDCs to the blood banks and also from blood banks to the hospitals. At the blood banks, required tests such as HIV, Hepatitis, etc., are conducted. It is also assumed that the COVID-19 test is added to the lab work and aggravates the uncertainty. Blood banks will complete the tests and determine the blood type to be ready for distribution in hospitals. Lastly, hospitals will deliver the blood to the needed patients at demand points. Fig. 1 shows the proposed BSC.

It is noteworthy that two separate echelons for regional hospitals and local hospitals are considered in this research based on the real case that has been studied in the research. The small hospitals and clinics in the area lack the necessary equipment and staff to maintain the blood for an extended period. When the blood is needed, they will be able to receive it without having to maintain an inventory for a long time. It is also facilitating the management of blood flow in local clinics, based on our discussions with local hospital administrators. Furthermore, the hospitals in our model are more like distribution centers that officially receive blood products from the blood banks and distribute them to the demand points. Generally speaking, there are two types of demand points. 1) Internal demand points: these are clinics and healthcare centers within the hospital that require blood products. 2) External demand points: these are small clinics and hospitals outside the hospital that do not have long-term blood inventory systems. The products will be delivered to them when they are required.

The problem is formulated as an uncertain multi-objective MILP. The model assumes an extra cost for the COVID-19 test within the blood processing costs at the blood banks. The model determines the facility location, blood allocation, transportation mode, and blood processing capacities at blood banks to minimize the total costs and maximize the SC’s job opportunities. BSCND is very costly, and minimizing the cost is extremely important for decision-makers. Besides, BSCND is a great way to boost local job opportunities and improve healthcare centers’ social and economic impacts. Therefore, maximizing the job opportunities within the SC is another crucial goal in the SCND problem. It is assumed that the blood demand, supply, and disposal rate are uncertain.

The following additional assumptions are also considered:

1) Collected blood units have a known disposal rate.
2) The BDC has a limited, unknown capacity.
3) The population and the ratio of blood groups will determine the volume of donor blood units.
4) The number of medical personnel and donation stations will determine the BDCs’ capacity.
5) Due to the pandemic conditions, all the collected types of blood are immediately sent to hospitals and blood banks and then to local hospitals/clinics (markets). Moreover, just a single-level demand is taken into account.
6) The possibility of shortages is considered at hospitals.
7) The uncertain parameters are treated as triangular fuzzy numbers.

4. Mathematical formulation

This section presents the optimization model, including the notation, objective function, and constraints.

Notations

Sets and indices:

\[ d \in \{1, \ldots, D\} \quad \text{Index of BDCs}, \]
\[ f,f \in \{d,h,i\} \quad \text{Index of facilities}, \]
\[ b \in \{1, \ldots, B\} \quad \text{Index of blood banks (blood transfusion organization)}, \]
\[ t \in \{1, \ldots, T\} \quad \text{Index of blood types}, \]
\[ h \in \{1, \ldots, H\} \quad \text{Index of regional hospitals}, \]
\[ i \in \{1, \ldots, I\} \quad \text{Index of local hospitals and clinics (markets)}, \]
\[ o \in \{1, \ldots, O\} \quad \text{Index of transportation modes}. \]

Parameters:

\[ c_d^F \quad \text{Fixed deployment cost of facilities } f \in \{d,h\}, \]
\[ c_o^{b,D} \quad \text{Cost of supplying raw blood from BDC d to blood bank b with transportaion mode o}, \]
\[ c_b^n \quad \text{Unit disposal cost of blood}, \]
\[ c_b^l \quad \text{Unit laboratory cost at the blood bank b}, \]
\[ c_f^{b,D} \quad \text{Unit transportation cost from BDC d to blood bank b with transportation mode o}, \]
\[ c_f^{h,H} \quad \text{Unit transportation cost from blood bank b to hospital h with transportation mode o}, \]
\[ c_i^{b,h} \quad \text{Unit subsidy cost of the market i from hospital h}, \]
\[ c_h \quad \text{Unit shortage cost of blood type r at hospital h}, \]
\[ j_f \quad \text{Number of fixed job opportunities created by deploying facility } f \in \{d,h\}, \]
\[ j_o \quad \text{Number of variable job opportunities created by deploying facility } f \in \{d,h\}, \]
\[ C_f \quad \text{Capacity of facility } f \in \{b,h\}. \]

(continued on next page)
minimize $\tilde{Z}_{\text{cost}} = \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} j_{d}^{T} x_{d} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} j_{b}^{T} y_{b} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} t_{d}^{T} \bar{x}_{d}^{T} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} t_{b}^{T} \bar{y}_{b} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} c_{d}^{T} \bar{v}_{d} y_{d}^{T} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} c_{b}^{T} \bar{v}_{b} y_{b}^{T} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} c_{d}^{T} x_{d}^{T} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} c_{b}^{T} y_{b}^{T}$

$= \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} j_{d}^{T} x_{d} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} j_{b}^{T} y_{b} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} t_{d}^{T} \bar{x}_{d}^{T} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} t_{b}^{T} \bar{y}_{b} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} c_{d}^{T} \bar{v}_{d} y_{d}^{T} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} c_{b}^{T} \bar{v}_{b} y_{b}^{T} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} c_{d}^{T} x_{d}^{T} + \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} c_{b}^{T} y_{b}^{T}$

(1)

maximize $Z_{\text{obj}} = \frac{1}{\alpha} \sum_{b=1}^{B} \sum_{t=1}^{T} \bar{x}_{b} y_{b}^{T} - \sum_{b=1}^{B} \sum_{t=1}^{T} t_{b}^{T} \bar{y}_{b} - \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} c_{d}^{T} \bar{v}_{d} y_{d}^{T}$

$+ \frac{1}{\alpha} \left( 1 - \alpha \right) \sum_{b=1}^{B} \sum_{t=1}^{T} \bar{x}_{b} y_{b}^{T} - \sum_{b=1}^{B} \sum_{t=1}^{T} t_{b}^{T} \bar{y}_{b} - \sum_{d=1}^{B} \sum_{b=1}^{O} \sum_{t=1}^{T} c_{d}^{T} \bar{v}_{d} y_{d}^{T}$

where $\alpha$ is a triangular fuzzy number and $\alpha \in (0, 1)$.

(2)

$\sum_{b=1}^{B} \sum_{t=1}^{T} \bar{x}_{b} y_{b}^{T} \leq \alpha \sum_{b=1}^{B} \sum_{t=1}^{T} \bar{x}_{b} y_{b}^{T}$

(3)

$\sum_{b=1}^{B} \sum_{t=1}^{T} \bar{x}_{b} y_{b}^{T} = \bar{v}_{b}$

(4)

$\sum_{b=1}^{B} \sum_{t=1}^{T} \bar{x}_{b} y_{b}^{T} \leq \bar{v}_{b}$

(5)

$\sum_{b=1}^{B} \sum_{t=1}^{T} \bar{x}_{b} y_{b}^{T} = \bar{v}_{b}$

(6)

$\sum_{b=1}^{B} \sum_{t=1}^{T} \bar{x}_{b} y_{b}^{T} \leq \bar{v}_{b}$

(7)

$\sum_{b=1}^{B} \sum_{t=1}^{T} \bar{x}_{b} y_{b}^{T} \leq \bar{v}_{b}$

(8)

$\sum_{b=1}^{B} \sum_{t=1}^{T} \bar{x}_{b} y_{b}^{T} \leq \bar{v}_{b}$

(9)

(3) sets the balance of the blood units received from the BDCs to the blood banks and from the blood banks to the regional hospitals. In the constraint, $\bar{\alpha}$ is a triangular fuzzy number and works independently and just affects the flow of blood within the network coming in and out of blood banks. Constraint (4) represents the balance of blood demand and processed blood units. Constraint (5) specifies the fulfillment of the demand considering the possibility of shortages. In other words, the amount of blood transferred from the regional hospitals to the final markets is equal to the demand minus the positive shortage. If the amount of supply at regional hospitals is larger than the total demand at final markets, there will be no shortage and the amount of blood flow will be exactly equal to the total demand. Otherwise, there will be a shortage of blood. Each demand point should be served only by a regional hospital as shown in Constraint (6). Constraint (7) sets a balance between received and processed blood units. Constraints (8) and (9) represent the capacity of BDCs and blood banks. Constraint (10) implies that the blood bank capacity is a portion of BDCs. Constraint (11) assures that the hospital’s capacity is less than or equal to the processed blood units in blood banks. Finally, Constraints (12) and (13) show the domain of decision variables.

5. Solution methodology: interactive possibilistic programming

This section describes the solution methodology such that a fuzzy method is applied to reformulate the developed model and solve it. The decision-making process in such a complicated BSC network requires taking into account conflicting objectives as well as various constraints imposed by donation centers and markets. Furthermore, in real-world situations, most of the parameters incorporated in BSCN are mainly fuzzy due to the imperfection or unavailability of the data, which can be only attained subjectively [54]. Furthermore, during the COVID-19 pandemic, the amount of blood demand and blood donation cannot be estimated easily, and thus, assigning crisp values for such vague
parameters is not proper. Therefore, a non-deterministic technique is required to reflect real-world conditions. The possibility theory can model this fuzziness by employing possibility distributions to tackle the inherent vague phenomenon of the parameters \[55\].

Several possible distributions have been developed by the researchers. However, the triangular possibility distribution is the most applicable and common tool to treat the imprecise nature of the vague parameters because of its computational efficiency and ease in data attainment \[54\]. Typically, a possibility distribution can be expressed as the occurrence degree of an event with imprecise data. Fig. 2 illustrates the triangular possibility distribution of a hypothetical fuzzy number \(\tilde{q} = (q_p, q_m, q_o)\) where \(q_p, q_m\) and \(q_o\) represent the most pessimistic, the most possible, and the most optimistic values of \(\tilde{q}\) that are estimated by a decision-maker.

In the proposed model, uncertainty can be found in Eq. (1), as well as Constraints (3), (5), (8), and (10). Therefore, it is necessary to treat the imprecise total cost and constraints using an auxiliary bi-objective MILP model.

A two-phase method is implemented in which the initial problem is formulated as an equivalent auxiliary crisp bi-objective MILP model in the first phase to deal with the problem uncertainty. In the second phase, an interactive fuzzy programming technique is utilized to provide a preferred compromise solution considering the interaction between the model-analyzer and decision-maker. This phase deals with the multi-objectiveness of the auxiliary crisp bi-objective MILP model built up in the first phase.

Details related to the first and second phases can be found in Appendices A and B, respectively. Fig. 3 gives an overview of the

| Table 1: Input data used in the problem. |
| Parameters | Values | Units | Parameters | Values | Units |
| c_{i}^{a} | Unif (20000, 60000) | $ | c_{i}^{a} | 160000 | $ |
| c_{i}^{a} | 24000000 | $ | c_{i}^{a} | 40000000 | $ |
| c_{i}^{a} | 25600000 | $ | c_{i}^{a} | 40000000 | $ |
| c_{i}^{a} | 16000000 | $ | c_{i}^{a} | 10520000 | $ |
| c_{i}^{a} | 1.28 | $ | c_{i}^{a} | 8 | $ |
| c_{i}^{a} | 0.04 | $ | c_{i}^{a} | 0.1024 | $ |
| c_{i}^{a} | 60 | $ | c_{i}^{a} | 550 | $ |
| c_{i}^{a} | 100 | $ | c_{i}^{a} | 1500 | $ |
| c_{i}^{a} | 600 | $ | c_{i}^{a} | 450 | $ |
| c_{i}^{a} | 1500 | $ | c_{i}^{a} | 10 | $ |
| c_{i}^{a} | 400 | $ | c_{i}^{a} | 150 | $ |
| c_{i}^{a} | 55 | $ | c_{i}^{a} | 150 | $ |
| c_{i}^{a} | 60 | $ | c_{i}^{a} | 40 | $ |
| c_{i}^{a} | 45 | $ | c_{i}^{a} | 10 | $ |

Fig. 2. Triangular possibility distribution of fuzzy parameter \(\tilde{q}\).

Fig. 3. Representation of the developed solution methodology.
suggested interactive possibilistic programming method.

6. Case study

This section tries to validate the performance of the developed methodology using a real case study in Tehran, Iran. It is noteworthy that, due to the lack of permission to enter names, although the data is real, the names of centers and network components are not included. The MILP model is coded in GAMS software and implemented by the CPLEX solver. Table 1 indicates the input data for BSCN in Tehran. This city has 19 main BDCs, 2 blood banks (it is assumed that the Tehran Blood Transfusion Organization will be divided into two banks in the northern and southern regions for better services), 6 main regional hospitals related to blood activities, and 23 urban areas for local hospitals and clinics (markets) according to the official Tehran district map. Furthermore, 3 transportation modes are taken into account.

The cost-related parameters listed in Table 1 are in dollars. On average, each bed in a hospital has a fixed cost of $40,000 where the first (600 beds), the second (1000 beds), the 3rd (640 beds), the 4th (1000 beds), the 5th (400 beds) and the 6th (263) hospitals have fixed costs of $24,000,000, $40,000,000, $25,600,000, $40,000,000, $16,000,000 and $10,520,000, respectively. The fixed deployment cost in a BDC is between $20,000 and $60,000. The fixed deployment cost of a blood transfusion organization (blood bank) is 4 times the average fixed deployment cost of a BDC, which is $160,000. Furthermore, the cost of blood collection (blood supply) is $1.28, the shipping cost is 8% of the blood sampling; i.e., $0.1024, and laboratory and extermination costs are $8, $0.04, respectively. The cost of government subsidy is 30% of the treatment cost where the average treatment cost is estimated at $200 and the subsidy cost is equal to $60. Finally, the unit penalty cost for shortages at regional hospitals is set to $100.

There are 20 permanent job opportunities for each BDC and 100 for each blood bank. According to the statistics, the hospitals have a fixed number of staff including 550, 1500, 600, 1500, 450, and 400 people, respectively. The variable job opportunities are considered 10% of the fixed-job opportunities for each facility. The capacity of the facilities is also given in Table 2 (in 1000ml/1000 cc or 1lit).

In 2019, the total blood demand was 3000 ± 500 blood units, of which 33%, 25%, 27%, 8%, and 7% are O+, B+, A+, AB+ types, and negative blood groups, respectively. Accordingly, the amounts of demands for different blood groups are based on the mentioned percentages; i.e., \((d^i_t, d^o_t, d^e_t)\) Percentage of demand for blood type \(i \times (2500, 3000, 3500)\). The other treated fuzzy parameters are given in Table 3 (in 1000ml/1000 cc or 1lit).

Now, given all the required data and information to deal with the model, using the suggested solution algorithm results in the values of the objective functions presented in Table 4. The most possible value of the 1st objective function \((Z^1_{\text{opt}})\) and the optimal value for the 2nd objective function \((Z_{\text{opt}})\) are also equal to 1.585453E+8 and 26284, respectively.

Tables 5 and 6 illustrate the decision variable values.

Table 5 shows that 5 hospitals and 2 blood banks need to be deployed. Besides, all the BDCs are deployed to supply the required amount of blood. The amount of blood conducted for 8 blood types is 27384 and 26284, respectively. On the other hand, the confidence level of the model should not be neglected since the pandemic conditions require an acceptable confidence level as much as possible. Here, increasing the parameter leads to neglecting the pandemic conditions \((\phi)\), which can be the center of attention. It seems that the best trade-off between the 1st and 2nd objective functions is the –20% change interval of the unit subsidy cost in the pandemic conditions. However, a 20% increase in the parameter leads to a better result for the 1st and 2nd objective functions against a 0% change in the unit subsidy cost. On the other hand, the confidence level of the model should not be neglected since the pandemic conditions require an acceptable confidence level as much as possible. Here, increasing the parameter leads to a worse confidence level where the least confidence level is obtained for a 20% decrease.

Based on Fig. 5, it can be concluded that by increasing the compensation coefficient, the total cost also increases. It occurs to Obj1, Obj2, and Obj3 wherein we can observe approximately the same behaviors. These objective functions have the lowest and highest values against the change intervals of –20% and +20%, respectively. On the other hand, the number of job opportunities, as well as the confidence level, follow a downward trend by raising the parameter.

### Table 2: The capacity of the facilities.

| Parameters  | Values     | Parameters  | Values     |
|-------------|------------|-------------|------------|
| Cap(h)      | Unif(60000,80000) | Cap(h)      | Unif(5000,6000) |
| Cap(h)      | 24500      | Cap(h)      | 40000      |
| Cap(h)      | 26000      | Cap(h)      | 40000      |
| Cap(h)      | 16500      | Cap(h)      | 11500      |

### Table 3: Values of the treated fuzzy parameters.

| Treated fuzzy parameters | Values          | Other parameters | Values          |
|--------------------------|-----------------|-----------------|-----------------|
| \((\alpha^i_t, \beta^i_t, \gamma^i_t)\) | (0.15, 0.2, 0.3) | \((\tau_1, \tau_2, \tau_3, \tau_4)\) | (0.5, 0.15, 0.15, 0.2) |
| \((\varphi^i_t, \varphi^o_t, \varphi^e_t)\) | (80, 100, 130) | \(\gamma\) | 0.4 |
| \((\text{Cap}^i_{\text{AB}}, \text{Cap}^o_{\text{AB}}, \text{Cap}^e_{\text{AB}})\) | (7500, 9000, 10500) | – | – |

### Table 4: Values of the objective functions.

| Variables | Values | Variables | Values |
|-----------|--------|-----------|--------|
| \(y_{i, j}\) | 1      | \(y_{i, j}\) | 1      |
| \(y_{i, j}\) | 1      | \(y_{i, j}\) | 1      |
| \(y_{i, j}\) | 1      | \(y_{i, j}\) | 1      |
| \(y_{i, j}\) | 1      | \(y_{i, j}\) | 1      |

### Table 5: Deployment decisions of regional hospitals and blood banks.

| Variables | Values | Variables | Values |
|-----------|--------|-----------|--------|
| \(y_{i, j}\) | 1      | \(y_{i, j}\) | 1      |
| \(y_{i, j}\) | 1      | \(y_{i, j}\) | 1      |
| \(y_{i, j}\) | 1      | \(y_{i, j}\) | 1      |

7. Sensitivity analysis

To investigate the effects of controllable parameters on the objective functions, a sensitivity analysis is carried out on the following parameters: (1) compensation coefficient \(\gamma\), (2) relative significance of objective function \(\alpha\), (3) unit subsidy cost during the pandemic conditions \(\phi\).

To conduct the analysis, the change intervals of compensation coefficient \(\gamma\), relative significance of objective function \(\alpha\), and unit subsidy cost during the pandemic conditions \(\phi\) are considered for \(-20\%\), \(-10\%\), \(0\%\), \(+10\%\), and \(+20\%\) are regarded for \(\gamma\) and \(\phi\), and also five different combinations are regarded for \(\alpha\). The results are given in Table 7, as well as Figs. 4–6.

According to the results, different behaviors are observed by the objective functions against different change intervals of the key parameters. As can be seen in Fig. 4, Obj1, Obj2, and Obj3 approximately reflect similar behaviors since they imply the total cost. As one of the interesting outputs in this sensitivity analysis, there are symmetrical behaviors for the increase and decrease change intervals of the unit subsidy cost during the pandemic conditions, which can be the center of attention. It seems that the best trade-off between the 1st and 2nd objective functions is the –20% change interval of the unit subsidy cost. However, a 20% increase in the parameter leads to a better result for the 1st and 2nd objective functions against a 0% change in the parameter. On the other hand, the confidence level of the model should not be neglected since the pandemic conditions require an acceptable confidence level as much as possible. Here, increasing the parameter leads to a worse confidence level where the least confidence level is obtained for a 20% decrease.
Furthermore, considering different combinations of relative significance for each objective function results in different solution points which can be evaluated by the decision-maker (cf. Fig. 6). The last two combinations seem to be of high interest since superior results are attained in terms of all objective functions. It is so critical that the decision-maker handle these conflicts to provide the best policy for blood supply under uncertain conditions. Hence, the decision-maker may take into account one of these points as

### Table 6

| \( v_k \) | \( t = 1 \) | \( t = 2 \) | \( t = 3 \) | \( t = 4 \) | \( t = 5 \) | \( t = 6 \) | \( t = 7 \) | \( t = 8 \) |
|---|---|---|---|---|---|---|---|---|
| \( b = 1 \) | 23310 | 0 | 18630 | 3360 | 13860 | 10500 | 4380 | 3360 |
| \( b = 2 \) | 0 | 19367 | 0 | 2160 | 8910 | 6750 | 14250 | 2160 |

### Table 7

Obtained results from the sensitivity analysis.

| Variables | Values of \( c_{SU}^{hi} \) |
|---|---|
| -20% | -10% | 0% | +10% | +20% |
| Obj1 | 1.515252E+8 | 1.522952E+8 | 1.585435E+8 | 1.538353E+8 | 1.546054E+8 |
| Obj2 | 1.463906E+8 | 1.466128E+8 | 1.521257E+8 | 1.467765E+8 | 1.469043E+8 |
| Obj3 | 1.463906E+8 | 1.466139E+8 | 1.521257E+8 | 1.467765E+8 | 1.469043E+8 |
| Obj4 | 26655 | 26655 | 26284 | 26655 | 26655 |
| Conf | 0.540 | 0.529 | 0.517 | 0.507 | 0.496 |

| Variables | Values of \( \gamma \) |
|---|---|
| -20% | -10% | 0% | +10% | +20% |
| Obj1 | 1.530653E+8 | 1.530653E+8 | 1.585435E+8 | 1.585435E+8 | 1.585435E+8 |
| Obj2 | 1.466473E+8 | 1.466473E+8 | 1.521257E+8 | 1.521257E+8 | 1.521257E+8 |
| Obj3 | 1.466476E+8 | 1.466476E+8 | 1.521257E+8 | 1.521257E+8 | 1.521257E+8 |
| Obj4 | 26655 | 26655 | 26284 | 26284 | 26284 |
| Conf | 0.582 | 0.550 | 0.517 | 0.507 | 0.496 |

| Variables | \((\tau_1, \tau_2, \tau_3, \tau_4)\) |
|---|---|
| \((0.4, 0.2, 0.2, 0.2)\) | \((0.4, 0.10, 0.10, 0.2)\) | \((0.5, 0.15, 0.15, 0.2)\) | \((0.6, 0.10, 0.10, 0.2)\) | \((0.6, 0.05, 0.05, 0.3)\) |
| Obj1 | 1.585453E+8 | 1.585453E+8 | 1.530653E+8 | 1.530653E+8 | 1.530653E+8 |
| Obj2 | 1.521257E+8 | 1.521257E+8 | 1.466473E+8 | 1.466473E+8 | 1.466473E+8 |
| Obj3 | 1.521256E+8 | 1.521256E+8 | 1.466476E+8 | 1.466476E+8 | 1.466476E+8 |
| Obj4 | 26283 | 26283 | 26284 | 26284 | 26284 |
| Conf | 0.518 | 0.501 | 0.517 | 0.531 | 0.528 |

**Fig. 4.** Sensitivity analysis of the unit subsidy cost \( c_{SU}^{hi} \).
8. Conclusion and future remarks

In this study, an efficient multi-echelon BSCN during the recent COVID-19 pandemic was designed to cope with the shortages of different blood types and the uncertainty of supply and demand. Accordingly, a novel bi-objective MILP model was developed to formulate the problem under socio-economic factors by minimizing the network cost and maximizing job opportunities at the same time. An interactive possibilistic programming technique was then utilized to concurrently deal with the bi-objectiveness and uncertainty of blood demand, capacity, and blood disposal rate. A real case study of a BSC in Iran was then investigated in terms of different criteria. The optimal policy was found by solving the problem and then discussed using a set of sensitivity analyses on the main parameters of compensation coefficient, the relative significance of objective function, and unit subsidy cost during the pandemic.

Based on the optimal policy, the confidence level of 51.7% is found where the objective functions have almost slight dispersions from their PIS values where the objective functions (1) and (2) represent the gaps of 3.64% (on average) and 4.02%, respectively. In the proposed network, 5 out of 6 hospitals as well as all 2 blood banks and 19 BDCs should be deployed. According to the results obtained from the sensitivity analysis, it is also revealed that objective functions show different behaviors against different change intervals where the unit subsidy cost is the most unpredictable parameter. In this regard, management needs to examine different change intervals to find the required level of resources and keep a high level of confidence during the pandemic.

Although this research tried to address the most significant aspects of the problem, there are some limitations to be taken into account wherein several recommendations can be given to extend the current study. Sustainable development was ignored in the problem which can be incorporated through considering the environmental impacts of transportation and processes at different facilities. Meanwhile, other objective functions such as reliability maximization of the system as another social criterion can be incorporated into the model to decrease the probability of failures. Other uncertainty handling techniques, as well as solution methods, can be employed and compared to the proposed interactive possibilistic programming technique (e.g., RO and goal programming method). Finally, meta-heuristic algorithms or decomposition-based algorithms can be employed to treat the problem in large-scale problems efficiently.

Research ethics

We further confirm that any aspect of the work covered in this manuscript that has involved human patients has been conducted with
the ethical approval of all relevant bodies and that such approvals are acknowledged within the manuscript.

Written consent to publish potentially identifying information, such as details or the case and photographs, was obtained from the patient(s) or their legal guardian(s).

**Intellectual property**

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

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**Conflicts of interest**

No conflict of interest exists.

Appendix A. First Phase: Auxiliary Bi-Objective MILP Model

Here, the extended variant of a well-known technique suggested in Lai and Hwang [56,57] is implemented to convert the bi-objective MILP model into an auxiliary crisp bi-objective MILP model. Accordingly, proper strategies should be applied to transform the fuzzy total cost as well as the set of soft constraints into their counterpart crisp formulations.

A1. Tackling the Imprecise Total Cost

Since the last term of the first objective function contains imprecise coefficients, no one can guarantee an ideal solution to the problem. Assume that the demand ($d_0$) and disposal rate ($\alpha_i$) follow a triangular possibility distribution. Accordingly, $Z_{Cost}$ would also have a triangular possibility distribution where it can be represented geometrically by three prominent points ($Z^p_{Cost}$, $Z^m_{Cost}$, and $Z^z_{Cost}$). Therefore, minimizing $Z_{Cost}$ means minimizing $Z^p_{Cost}$, $Z^m_{Cost}$ and $Z^z_{Cost}$ concurrently. However, a conflict during the concurrent minimization of these crisp objective functions should be encountered. Lai and Hwang [56] suggested minimizing $Z^p_{Cost}$, maximizing ($Z^m_{Cost} - Z^z_{Cost}$), and minimizing ($Z^z_{Cost} - Z^m_{Cost}$) instead of simultaneous minimization of $Z^p_{Cost}$, $Z^m_{Cost}$ and $Z^z_{Cost}$. Finally, Eq. (1) is replaced with the following crisp objective functions to attain a compromise solution:

$$\text{minimize } Z^p_{Cost} = \sum_{d=1}^{D} c^F_{d} y_d + \sum_{b=1}^{B} c^F_{b} y_b + \sum_{h=1}^{H} c^F_{h} y_h + \sum_{t=1}^{T} c^b_{bot} x_{bot} + \sum_{d=1}^{D} \sum_{b=1}^{B} \sum_{h=1}^{H} \sum_{t=1}^{T} c^b_{bot} x_{bot} + \sum_{d=1}^{D} \sum_{b=1}^{B} \sum_{h=1}^{H} \sum_{t=1}^{T} \alpha_i^p c^{bol} x_{bot}$$

$$\text{maximize } (Z^m_{Cost} - Z^z_{Cost}) = \sum_{d=1}^{D} c^F_{d} y_d + \sum_{b=1}^{B} c^F_{b} y_b + \sum_{h=1}^{H} c^F_{h} y_h + \sum_{t=1}^{T} c^b_{bot} x_{bot} + \sum_{d=1}^{D} \sum_{b=1}^{B} \sum_{h=1}^{H} \sum_{t=1}^{T} c^b_{bot} x_{bot} + \sum_{d=1}^{D} \sum_{b=1}^{B} \sum_{h=1}^{H} \sum_{t=1}^{T} \alpha_i^m c^{bol} x_{bot} - \sum_{d=1}^{D} \sum_{b=1}^{B} \sum_{h=1}^{H} \sum_{t=1}^{T} \alpha_i^z c^{bol} x_{bot}$$

$$\text{minimize } (Z^z_{Cost} - Z^m_{Cost}) = \sum_{d=1}^{D} c^F_{d} y_d + \sum_{b=1}^{B} c^F_{b} y_b + \sum_{h=1}^{H} c^F_{h} y_h + \sum_{t=1}^{T} c^b_{bot} x_{bot} + \sum_{d=1}^{D} \sum_{b=1}^{B} \sum_{h=1}^{H} \sum_{t=1}^{T} c^b_{bot} x_{bot} + \sum_{d=1}^{D} \sum_{b=1}^{B} \sum_{h=1}^{H} \sum_{t=1}^{T} \alpha_i^z c^{bol} x_{bot} - \sum_{d=1}^{D} \sum_{b=1}^{B} \sum_{h=1}^{H} \sum_{t=1}^{T} \alpha_i^m c^{bol} x_{bot}$$

A2. Tackling the Soft Constraints

Similarly, assume that $\bar{\text{Cap}_{d}}, \bar{\alpha}_i$, $\bar{\varphi}$ and $\bar{d}_0$ are uncertain and follow a triangular possibility distribution as $\bar{\text{Cap}_{d}} = (\text{Cap}^p_{d}, \text{Cap}^m_{d}, \text{Cap}^z_{d}), \bar{\alpha}_i = (\alpha_i^p, \alpha_i^m, \alpha_i^z), \bar{\varphi} = (\varphi^p, \varphi^m, \varphi^z)$ and $\bar{d}_0 = (d^p_0, d^m_0, d^z_0)$. Therefore, Constraints (3), (5), (8), and (10) are fuzzy constraints. The Weighted Average Method (WAM) is utilized to do the defuzzification and transform the uncertain parameters into crisp numbers. Thereupon, if the minimum acceptable possibility; i.e., a minimum acceptable degree of feasibility ($\beta$) is defined by the decision-maker, then the counterpart auxiliary crisp constraints can be written as follows:

$$\left(1 - \left[ \omega_1 \omega_2 \alpha_i^p + \omega_2 \alpha_i^m + \omega_3 \alpha_i^z \right] \right) \sum_{d=1}^{D} \sum_{b=1}^{B} \sum_{h=1}^{H} \sum_{t=1}^{T} x_{bot} = \sum_{h=1}^{H} \sum_{t=1}^{T} x_{bot} \quad \forall b, t,$$

$$x_{bot} + \delta_{\alpha} = y_{\alpha} \left( \alpha_1^p d^p_0 + \alpha_2^m d^m_0 + \alpha_3^z d^z_0 \right) \quad \forall h, i, t.$$

$$x_{bot} + \delta_{\alpha} = y_{\alpha} \left( \alpha_1^p d^p_0 + \alpha_2^m d^m_0 + \alpha_3^z d^z_0 \right) \quad \forall h, i, t.$$
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\[ \sum_{b=1}^{B} \sum_{o=1}^{O} x_{o,b} \leq \left( \omega_1 \text{Cap}_{d,b}^T + \omega_2 \text{Cap}_{d,b}^P + \omega_3 \text{Cap}_{d,b}^Q \right) y_b \quad \forall d, t. \]

\[ \left( \omega_1 \varphi_1 + \omega_2 \varphi_2 + \omega_3 \varphi_3 \right) \sum_{b=1}^{B} y_b \leq \sum_{d=1}^{D} \sum_{o=1}^{O} \sum_{t=1}^{T} x_{o,b}. \]

where \( \omega_1 = \omega_2 = \omega_3 = 1, \omega_1' + \omega_2' + \omega_3' = 1, \omega_1'' + \omega_2'' + \omega_3'' = 1 \) and \( \omega_1''' + \omega_2''' + \omega_3''' = 1 \). Moreover, the triple points of \((\omega_1, \omega_2, \omega_3), (\omega_1', \omega_2', \omega_3'), (\omega_1'', \omega_2'', \omega_3''), (\omega_1''', \omega_2''', \omega_3''')\) display the weights of the most pessimistic, the most possible, and the most optimistic values of \( \bar{\omega}_1, \bar{\omega}_2, \bar{\omega}_3, \bar{\omega}_1', \bar{\omega}_2', \bar{\omega}_3', \bar{\omega}_1'', \bar{\omega}_2'', \bar{\omega}_3'', \bar{\omega}_1''', \bar{\omega}_2''', \bar{\omega}_3''' \). The appropriate values of \( \bar{\beta} \) as well as the weights, are defined based on the knowledge and experience of the decision-maker. In this research, these weights and \( \beta \) are respectively set as \( \left( \bar{\beta}, \frac{1}{6}, \frac{1}{2} \right) \) and 0.5 in accordance with the concept of the most likely values suggested by Lai and Hwang [56].

Now, the auxiliary crisp bi-objective MILP model is given as follows:

\[
\begin{align*}
\text{minimize } & \text{Obj} = \{\text{Obj}_1, -\text{Obj}_2, \text{Obj}_3, -\text{Obj}_4\} \\
\text{Obj}_1 &= \text{Z}_{\text{Cap}}^m, \\
\text{Obj}_2 &= \left( \text{Z}_{\text{Cost}}^m - Z_{\text{Cost}}^{m^*} \right), \\
\text{Obj}_3 &= \left( \text{Z}_{\text{Cost}}^m - Z_{\text{Cost}}^{m^*} \right), \\
\text{Obj}_4 &= \text{Z}_{\text{lab}}, \\
\text{subject to } & \bar{\theta} \in F(\bar{\theta}).
\end{align*}
\]

where \( \bar{\theta} \) stands for a feasible solution vector including all the binary and continuous variables in the initial problem. Furthermore, \( F(\bar{\theta}) \) represents the feasible region including Constraints (4), (6), (7), (9), (11)–(13), and (17)–(20).

Appendix B. Second Phase: Interactive Fuzzy Programming Technique

The fuzzy programming methods are known as the most applicable tools to solve multi-objective programming models in which the possibility of measuring the satisfaction level of each objective function is regarded as the main advantage. This option selects a preferred efficient solution concerning the satisfaction level and relative importance of each objective function.

This research uses an interactive solution approach adapted from Ref. [54]. The solution technique considers the bi-objective characteristic of the model and finds the optimal solution.

**Step 1:** Find the positive ideal solution (PIS) and negative ideal solution (NIS) values for each objective function according to Model (22):

\[
\begin{align*}
\text{Obj}_1^{\text{PIS}} &= \text{minimize } \text{Z}_{\text{Cost}}^m, \quad \text{Obj}_1^{\text{NIS}} = \text{maximize } \text{Z}_{\text{Cost}}^m, \\
\text{Obj}_2^{\text{PIS}} &= \text{maximize } (\text{Z}_{\text{Cost}}^m - \text{Z}_{\text{Cost}}^{m^*}), \quad \text{Obj}_2^{\text{NIS}} = \text{minimize } (\text{Z}_{\text{Cost}}^m - \text{Z}_{\text{Cost}}^{m^*}), \\
\text{Obj}_3^{\text{PIS}} &= \text{minimize } (\text{Z}_{\text{Cost}}^m - \text{Z}_{\text{Cost}}^{m^*}), \quad \text{Obj}_3^{\text{NIS}} = \text{maximize } (\text{Z}_{\text{Cost}}^m - \text{Z}_{\text{Cost}}^{m^*}), \\
\text{Obj}_4^{\text{PIS}} &= \text{maximize } \text{Z}_{\text{lab}}, \quad \text{Obj}_4^{\text{NIS}} = \text{maximize } \text{Z}_{\text{lab}}.
\end{align*}
\]

subject to \( \bar{\theta} \in F(\bar{\theta}). \)

**Step 2:** Determine a linear membership function for each objective function based on Eqs. (23)–(26):

\[
\mu_1(\bar{\theta}) = \begin{cases} 
1, & \text{if } \text{Obj}_1 < \text{Obj}_1^{\text{PIS}}, \\
\frac{\text{Obj}_1 - \text{Obj}_1^{\text{NIS}}}{\text{Obj}_1^{\text{PIS}} - \text{Obj}_1^{\text{NIS}}}, & \text{if } \text{Obj}_1^{\text{PIS}} < \text{Obj}_1 \leq \text{Obj}_1^{\text{NIS}}, \\
0, & \text{if } \text{Obj}_1 > \text{Obj}_1^{\text{NIS}}.
\end{cases}
\]

(23)

\[
\mu_2(\bar{\theta}) = \begin{cases} 
1, & \text{if } \text{Obj}_2 < \text{Obj}_2^{\text{PIS}}, \\
\frac{\text{Obj}_2 - \text{Obj}_2^{\text{NIS}}}{\text{Obj}_2^{\text{PIS}} - \text{Obj}_2^{\text{NIS}}}, & \text{if } \text{Obj}_2^{\text{PIS}} < \text{Obj}_2 \leq \text{Obj}_2^{\text{NIS}}, \\
0, & \text{if } \text{Obj}_2 > \text{Obj}_2^{\text{NIS}}.
\end{cases}
\]

(24)

\[
\mu_3(\bar{\theta}) = \begin{cases} 
1, & \text{if } \text{Obj}_3 < \text{Obj}_3^{\text{PIS}}, \\
\frac{\text{Obj}_3 - \text{Obj}_3^{\text{NIS}}}{\text{Obj}_3^{\text{PIS}} - \text{Obj}_3^{\text{NIS}}}, & \text{if } \text{Obj}_3^{\text{PIS}} < \text{Obj}_3 \leq \text{Obj}_3^{\text{NIS}}, \\
0, & \text{if } \text{Obj}_3 > \text{Obj}_3^{\text{NIS}}.
\end{cases}
\]

(25)
\[ \mu_i(\theta) = \begin{cases} 1, & \text{if } \text{Obj}_i > \text{Obj}_i^{\text{PIS}}, \\ \frac{\text{Obj}_i - \text{Obj}_i^{\text{NIS}}}{\text{Obj}_i^{\text{PIS}} - \text{Obj}_i^{\text{NIS}}}, & \text{if } \text{Obj}_i^{\text{NIS}} \leq \text{Obj}_i \leq \text{Obj}_i^{\text{PIS}}, \\ 0, & \text{if } \text{Obj}_i < \text{Obj}_i^{\text{NIS}}. \end{cases} \] (26)

\( \mu_i(\theta) \) (\( i = 1, 2, 3, 4 \)) stands for the satisfaction degree of objective function \( o \) for the feasible solution vector \( \theta \). Furthermore, Figures B1 and B2 depict the linear membership functions corresponding to \( \text{Obj}_1 (\text{Obj}_3) \) and \( \text{Obj}_2 (\text{Obj}_4) \), respectively.

![Fig. B1. Linear membership function of \( \text{Obj}_1 (\text{Obj}_3) \).](image1)

![Fig. B2. Linear membership function of \( \text{Obj}_2 (\text{Obj}_4) \).](image2)

- **Step 3:** Convert the auxiliary multi-objective MILP Model (22) into an equivalent single-objective MILP model according to Model (27):

\[
\begin{align*}
\text{maximize } & \xi(\theta) = \gamma \xi_0 + (1 - \gamma) \sum_{o=1}^{4} \tau_o \mu_o(\theta) \\
\text{subject to } & \xi_0 \leq \mu_o(\theta) \quad (o = 1, 2, 3, 4), \\
& \theta \in \mathcal{F}(\theta), \\
& \xi_0 \in [0, 1].
\end{align*}
\] (27)

where \( \mu_o(\theta) \) and \( \xi_0 = \min_o \{ \mu_o(\theta) \} \) represent the satisfaction degree of objective function \( o \) and the minimum satisfaction degree of objective functions, respectively. Furthermore, \( \tau_o \in [0, 1] \) and \( \gamma \in [0, 1] \) stand for relative significance of objective function \( o \) and compensation coefficient, respectively. It should be noted that \( \sum_{o=1}^{4} \tau_o = 1 \), \( \tau_o > 0 \), each of \( \tau_o \) takes value concerning the decision maker’s preferences. The compensation coefficient \( \gamma \) handles the minimum satisfaction degree of objective functions along with the compromise level among them implicitly. A higher value of \( \gamma \) leads to more concentration on a higher lower bound for \( \xi_0 \) and also more balanced compromise solutions.

- **Step 4:** Solve the developed auxiliary crisp Model (28) in which the objective function represents the total confidence level (Conf). If the decision-maker accepts the current compromise solution, then stop. Otherwise, find another solution by changing the initialization of controllable parameters, such as \( \gamma \) and \( \beta_i \), and then go to Step 1.
maximize $\gamma \phi + (1 - \gamma)$

subject to

$\xi_0 \leq \frac{Obj^{PIS}_1 - Obj_1}{Obj^{PIS}_1 - Obj_1}$

$\xi_0 \leq \frac{Obj^{NIS}_2 - Obj_2}{Obj^{NIS}_2 - Obj_2}$

$\xi_0 \leq \frac{Obj^{PIS}_3 - Obj_3}{Obj^{PIS}_3 - Obj_3}$

$\xi_0 \leq \frac{Obj^{NIS}_4 - Obj_4}{Obj^{NIS}_4 - Obj_4}$

Constraints (4), (6), (7), (9), (11) – (13), (17) – (20),

$\xi_0 \in [0, 1]$
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