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A Multi-product Humanitarian Supply Chain Network Design Problem: A Fuzzy Multi-objective and Robust Optimization Approach

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ABSTRACT

In today's dynamic and unpredictable world, the planning and management of humanitarian supply chains hold paramount importance. Efficient logistics management is crucial for effectively delivering essential aid and resources to affected areas during disasters and emergencies, ensuring timely support and relief to vulnerable populations. In this research, we addressed a novel humanitarian supply chain network design problem that considers product differentiation and demand uncertainty. Specifically, we simultaneously incorporate non-perishable, perishable, and blood products as critical components of the network. The problem is formulated as a multi-objective mixed-integer linear programming model aiming to minimize the total cost and total traveled distance of products by making location, allocation, and production decisions. To enhance realism, we account for demand uncertainty in affected areas. To tackle this challenging problem, we proposed a two-phase solution methodology. Firstly, we employed a robust optimization approach to establish a deterministic counterpart for the stochastic model. Subsequently, an efficient fuzzy programming-based approach reformulates the model into a single-objective form, effectively accommodating decision-makers' preferences. Numerical instances are solved to investigate the performance of the model and solution methodologies. The results demonstrate the effectiveness of our fuzzy approach in finding non-dominated solutions, enabling decision-makers to explore trade-offs. Also, sensitivity analyses were conducted to provide more insights. Finally, some suggestions are presented to extend the current work by feature researchers.

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NOMENCLATURE

Sets			
I	The set of suppliers for non-perishable relief products	O	The set of non-perishable relief products
S	The set of suppliers for perishable relief products	M	The set of perishable relief products
D	The set of donor groups	Q	The set of quality levels for perishable relief products
P	The set of fixed blood collection centers	G	The set of blood products
A	The set of mobile blood collection centers	J	The set of potential warehouses
C	The set of capacity levels for mobile blood collection centers	N	The set of packages
L	The set of blood processing centers	K	The set of affected regions
Parameters			
CNS_i	The fixed contract cost of non-perishable relief products supplier i	WLC_j	The establishment cost of warehouse j
CPS_s	The fixed contract cost of perishable relief products supplier s	BEW_{gj}	The equipment cost of warehouse j for blood product g
NCP_i	The capacity of supplier i to supply non-perishable relief products	CRW_j	The capacity of warehouse j
PCP_s	The capacity of supplier s to supply perishable relief products	WMN	The maximum number of warehouses
MNS	The maximum number of suppliers for non-perishable relief products	NNP_{qno}	The number of non-perishable relief product o at quality level q in package n

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MPS	The maximum number of suppliers for perishable relief products	NPP_{nm}	The number of perishable relief product m in package n
TPW_{ijm}	The transportation cost of perishable relief product m from supplier i to warehouse j	NBP_{ng}	The quantity of blood product g in package n
TNW_{sjoq}	The transportation cost of non-perishable relief product o at quality level q from supplier s to warehouse j	PPW_{jn}	The production cost of package n in warehouse j
BDC_d	The blood donation capacity of donor group d	TWA_{jkn}	The transportation cost of package n from warehouse j to affected region k
MLC_{ac}	The location cost of mobile blood collection center a at capacity level c	DMN_{kn}	The demand of package n in affected region k
NRM	The number of required mobile blood collection centers	DST	The minimum percentage of demand satisfaction
BDF_{dp}	The donation cost of donor group p in fixed blood collection center d	PCW_o	The perishability cost of product o
BDM_{da}	The donation cost of donor group p in mobile blood collection center a	PRL_{oq}	The perishability rate of product o at quality level q
FBC_p	The capacity of fixed blood collection center p	ECA_{nk}	The cost of a packaging error for package n in affected region k
FBM_{ac}	The capacity of mobile blood collection center a at capacity level c	ERP_{nj}	The package production fault for package n in warehouse j
CUS	The wastage rate of blood in collection centers	DNW_{ij}	The distance between the non-perishable relief products supplier i and warehouse j
TMP_{al}	The transportation cost of blood from mobile blood collection center a to blood processing center l	DPW_{sj}	The distance between the perishable relief products supplier s and warehouse j
TFP_{pl}	The transportation cost of blood from the fixed blood collection center p to the blood processing center l	DMR_{al}	The distance between the mobile blood collection center a and the blood processing center l
CBP_l	The capacity of blood processing center l	DLR_{pl}	The distance between the fixed blood collection center p and blood processing center l
PRC_{lg}	The production cost of blood product g in blood processing center l	DRW_{lj}	The distance between the blood processing center l and warehouse j
PUS	The wastage rate of blood in blood processing centers	DWA_{jk}	The distance between the warehouse j and affected region k
TBW_{lgj}	The transportation cost of blood product g from blood processing center l to warehouse j	ϕ	A big number
Variables			
qnw_{ijm}	The quantity of transported non-perishable relief product m from supplier i to warehouse j	sps_s	A binary decision variable; 1 if supplier s for perishable products is selected and 0, otherwise
qpw_{sjoq}	The quantity of transported perishable product o at level q from supplier s to warehouse j	lmc_{ac}	A binary decision variable; 1 if mobile blood collection center a at capacity level c is located and 0, otherwise
qsw_{jo}	The quantity of spoiled product o in warehouse j	lwh_j	A binary decision variable; 1 if warehouse j is established and 0, otherwise
qbm_{da}	The quantity of blood donation by donor group d in mobile collection center a	ecw_{gj}	A binary decision variable; 1 if warehouse j is equipped to holding infrastructures of product g and 0, otherwise
qbf_{dp}	The quantity of blood donation by donor group d in fixed collection center p	pbv_{jn}	A binary decision variable; 1 if warehouse j produce the package type n and 0, otherwise
qmp_{al}	The quantity of transported blood from mobile blood collection center a to blood processing center l	dam_{da}	A binary decision variable; 1 if donor group d is assigned to mobile blood collection center a and 0, otherwise
qfp_{pl}	The quantity of transported blood from fixed blood collection center p to blood processing center l	daf_{dp}	A binary decision variable; 1 if donor group d is assigned to fixed blood collection center p and 0, otherwise
qbw_{glj}	The quantity of transported blood product g from blood processing center l to warehouse j	amp_{al}	A binary decision variable; 1 if mobile blood collection center a is assigned to blood processing center l and 0, otherwise
qpp_{jn}	The quantity of produced packages of type n in warehouse j	apf_{pl}	A binary decision variable; 1 if fixed collection center p is assigned to blood processing center l and 0, otherwise
tqa_{jkn}	The number of transported package type n from warehouse j to affected region k	bsw_{glj}	A binary decision variable; 1 if blood processing center l is assigned to warehouse j for transformation of product g and 0, otherwise
sns_i	A binary decision variable; 1 if supplier i for non-perishable relief products is selected and 0, otherwise		

1. INTRODUCTION

Disaster events have always been on human life paths. Various crises, such as earthquakes, floods, storms, terrorist attacks, etc., have impacted people's lives in the past years (1). Since the beginning of 21st century, around 22,000 natural and man-made disasters have occurred worldwide (2). The September 11th terrorist attack, the Kermanshah earthquake in Iran, the Japan Tsunami, and the Pakistan flood are some of the disasters in the recent century. Regarding the severity, the possible consequences of disaster events might be catastrophic. Physical injuries and economic and environmental problems are examples of such negative results of disasters (3). During the terrorist attack of September 11th, almost 3,000 people lost their lives, and more than 6,000 were injured. The 2010 flood in Pakistan left over 300,000 dead and missing people, billions of lost property, and more than 20 millions homeless (4). According to the reports on Japan's tsunami, more than 24,000 people were dead or missing, more than 76,000 houses were destroyed, and people suffered a lot of damage. In 2017, during the Kermanshah earthquake in Iran, more than 10,000 people were injured, 600 people died, and many others became homeless (5). Also, a list of recent statistic shown in Figure 1 indicates that about 24.5 million people have been displaced due to disasters worldwide during the past 15 years[1]. In this situation, governments and humanitarian organizations must be prepared for the crisis events and respond to them efficiently by providing medical aid, food, and shelter to the victims (6). Here, humanitarian supply chain (HSC) planning is of great importance. HSC planning is defined as a process of planning, implementation, efficient control, and managing flows in the storage of crisis-related goods and services to reduce the suffering of vulnerable people (7, 8). The importance of HSC planning prompted researchers to focus on this problem in recent years.

One of the main features of HSCs is the demand for multiple product types, which are totally different in their nature. In general, there are three categories of items in HSCs: non-perishable, perishable, and blood products (9, 10). As the first category, the non-perishable relief products include the prevailing items such as tents, blankets, sleeping bags, etc. The main feature of these products is that they do not lose their properties over time and can be stored long, and there is no special storage requirement. Perishable products are the second category of products in HSCs. Unlike non-perishable products, they require special storage infrastructures, such as air circulation systems or low-temperature environments, to maintain quality. The lack of these types of equipment and conditions results in the degradation of the products. Alcohol, medicine, etc., are some examples of perishable products. Finally, blood products are the third category of products in HSCs. Although, blood products are inherently perishable, several factors distinguish blood from other products, even similar perishable products. While non-perishable and perishable products can be purchased from companies and retailers at a purchasing cost, humans are the suppliers of blood, and blood donation is a volunteer activity. Therefore, the blood supply is very limited. In addition, the donated blood can not be directly used in the affected region. The whole blood should be tested, processed, and decomposed into subproducts, including red blood cells, platelets, and plasma. The resulting subproducts are also different in their properties; each has a particular shelf life and storage condition, which are totally different. Finally, the results of blood shortage in HSCs differ from other products and may cause human death (11).

To the best of the authors' knowledge, no paper in the literature addresses the HSC design problem considering these products and the related features. More specifically, the recent work by Abazari, Aghsami (9) is one of the closest works to this research, which addresses the non-perishable and perishable products in an HSC. However, they ignored the presence of blood products in the HSC system. This research aims to design an HSC network considering three types of non-perishables, perishables, and blood products. In this problem, total cost and total traveled distance were considered objective functions to cover the network's economic and emergency response goals. As the first part of the solution methodology, we present an efficient fuzzy programming approach to establish a trade-off between these conflictive objectives and establish the single-objective counterpart model. Since the demand of affected regions in HSCs is violated during the crisis period, the product demand uncertainty is also considered to present a more realistic framework. In this direction, a robust optimization approach will be provided in the second part of the solution methodology to consider the demand uncertainty. The performance of the developed model and proposed methodologies will be investigated through extensive analysis of numerical examples. Briefly, the main contribution of this work can be summarized as follows:

- Developing a multi-objective HSC design problem considering three categories of non-perishable, perishable, and blood products under demand uncertainty.
- Developing a mixed-integer linear programming (MILP) mathematical model for the problem.
- Presenting an efficient fuzzy programming approach to deal with the conflicts of objectives.
- Presenting a robust optimization approach to deal with the demand uncertainty.
- Solving several numerical examples to investigate the performance of the developed model and solution methodologies.

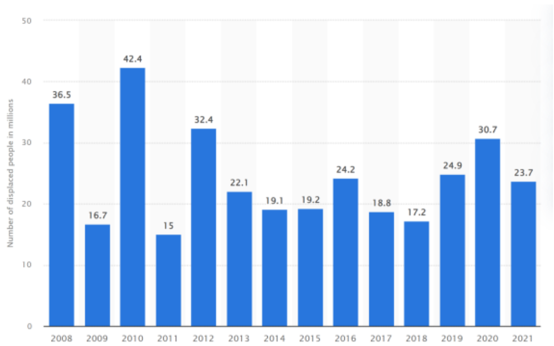

Figure 1. Number of people displaced from 2008 to 2021

[1] www.statistia.com

The rest of the paper is organized as follows. Section 2 provides a review of the related studies in the literature. Section 3 provides the problem definition and a multi-objective mixed-integer linear mathematical model for the defined problem. Section 4 presents a two-part solution methodology for the problem. First, a fuzzy-programming approach is proposed to handle the objectives' conflicts. Then, a robust optimization approach is discussed to address the uncertainty. Section 5 explores the performance model of the model and solution methodologies by solving several numerical examples. Section 6 presents managerial insights based on the computational results. Finally, section 7 provides a conclusion to the paper and some direction for future works.

2. RELATED STUDIES

As pointed out before, the proper planning of operations is very important in disaster conditions. Therefore, the HSC planning problems have been investigated from different viewpoints in recent years. Researchers have tried to define several strategic, tactical, and operational problems for HSC networks. In these problems, optimal decision-making frameworks for various decisions, such as facility location, flow allocation, inventory planning, production, etc., have been addressed. In this section, we reviewed the relevant studies to this paper in the literature. Interested readers can study the review papers in the literature, such as the works by Kovács and Spens (12) and Balcik, Bozkir (13).

A significant portion of studies in the field of HSC planning has been focused on network design problems with location-allocation decisions. Zhan and Liu (14) studied a multi-objective HSC design problem that simultaneously minimizes the unmet demand and service time. They utilized a goal programming approach to address the conflict of objectives. Murali, Ordóñez (15) developed a new model to determine the optimal location of facilities in an HSC. In this paper, the goal is to maximize the number of served people. Bozorgi-Amiri, Jabalameli (16) addressed the uncertainty in the HSC design problem by considering uncertainty in demand, capacities, and cost parameters. The model was solved using a PSO algorithm. Khayal, Pradhananga (17) studied a location planning problem for impermanent distribution centers of HSC. A dynamic resource allocation approach for these facilities was also presented. Hasani and Mokhtari (18) presented some strategies for designing and redesigning an HSC. In this paper, a rolling horizon planning method was used to address the uncertainty and dynamics of the network. In another research, Hasani and Mokhtari (19) studied a multi-objective HSC and employed the fault tree analysis (FTA) method for risk assessment of the network. The objective functions were the minimization of total cost and risk and the maximization of population coverage. Wang and Nie (20) tried to improve the transportation operations of an HSC and developed a location-allocation model considering traffic congestion. Aghajani, Torabi (21) utilized the option contract for coordination in an HSC. The results prove that this contract can improve the responsiveness and cost-efficiency of the network. Mansoori, Bozorgi-Amiri (22) considered evacuating injured people from the affected region. They proposed a multi-objective model to minimize unmet demand and the number of non-evacuate homeless people. Nezhadroshan, Fathollahi-Fard (23) focused on a robust humanitarian logistics problem for disaster response, aiming to address operational and disruption uncertainties. They introduced a novel scenario-based possibilistic-stochastic programming approach to address uncertainty in a network with central warehouses and distribution centers. Recently, Mahtab, Azeem (24) proposed a multi-objective robust-stochastic model for humanitarian logistics, focusing on pre- and post-disaster decisions. The authors addressed facility location, pre-positioning, distribution scheduling, and equity in supply distribution. Their model incorporated uncertainties in demand, transportation, and supply condition, with a real flood case study. Akbari, Valizadeh (25) developed a model for integratig service provider collaboration in HSC. The authors used cooperative game theory approaches to solve this problem. Foroughi, Moghaddam (26) presented a resilient HSC with multiple disasters in their paper. The resilience parameters were obtained using the best-worst multi-criteria decision-making method.

The importance of transportation and inventory decisions in HSCs motivated researchers to develop models focusing on these problems. Ukkusuri and Yushimito (27) suggested inventory preposition as an effective strategy for increasing the responsiveness of HSC. They presented the idea as a location-routing problem. Kutanoglu and Mahajan (28) developed a model for inventory management of an HSC. The network included a central warehouse and several local warehouses. The authors also considered the possibility of transshipment between the local warehouses. Campbell and Jones (29) developed a new model to determine the location of HSC suppliers in predisaster conditions. Their model also incorporated inventory decisions. Ahmadi, Seifi (30) developed a multi-depot vehicle routing-location problem for an HSC network. They considered the failure of the network and stochastic travel times. Bozorgi-Amiri and Khorsi (31) developed a multi-objective location-routing problem for an HSC under the risk of disruption. The model aimed to minimize unsatisfied demand, total cost, and travel time. Sabouhi, Bozorgi-Amiri (32) presented a transportation planning problem for an HSC that included location, routing, and scheduling decisions. The authors formulated the disruption of routes, and the objective function was minimizing the expected arrival time of relief vehicles. Tofighi, Torabi (33) worked on a two-level HSC network, which included warehouses and distribution centers. The uncertainty in supply, demand, and availability levels of the transportation routes were taken into account, and the problem was formulated using a two-stage stochastic programming model.

As pointed out, several types of products are in demand in HSCs. Some of the previous studies aimed to address these products and their features in disasters. Zhang and Jiang (34) investigated the pharmacy management problem in an HSC as a perishable product and tried simultaneously minimizing the system's total cost and servicing time. Akbarpour, Torabi (35) also presented a model for pharmacy supply chain planning during disasters. In this research, an option contract is proposed for coordination with suppliers. Some other works investigated the planning of blood flow in the outbreak of crisis events. Jabbarzadeh, Fahimnia (36) proposed a new problem for blood supply chain design under disaster scenarios. In this paper, the demand uncertainty was addressed by a robust optimization approach. Khalilpourazari, Soltanzadeh (10) presented a blood supply chain planning problem to respond to the earthquake disaster. They considered the possibility of helicopter usage to transport blood and injured people. Fallahi, Mousavian Anaraki (37) developed a new model for supply chain planning of regular and convalescent plasma during the COVID-19 pandemic. The authors suggested using motivational programs and a transshipment strategy to increase the efficiency of the supply chain. Haghjoo, Tavakkoli-Moghaddam (38) suggested a reliable approach to address the disruption of the blood supply chain during the disaster. In this study, the impact level of disruption on facilities depends on the initial investment level. Kamyabniya, Noormohammadzadeh (39) presented an integrated model for the flow management of platelet blood products. They assumed ABO/Rh(d)-compatibility and difference in age of products to establish a more realistic problem. Recently, Hong (40) introduced a weighted goal programming model to optimize an HSC configuration while accounting for emergency response facility disruptions. By employing a two-stage network data envelopment analysis (DEA) approach, the proposed method consistently identifies efficient configurations, offering valuable insights for disaster response planning. Modarresi and Maleki (41) developed a two-stage stochastic model for efficient humanitarian relief supply chain design, integrating pre- and post-disaster decisions to enhance disaster management. The model encompasses quantity flexibility contracts, equitable relief goods distribution, warehouse location, inventory planning, and various post-disaster activities. The approach effectively reduces inventory levels pre-disaster and mitigates supply risks post-disaster, as demonstrated in the context of a potential earthquake in Iran.

Table 1 presents a comprehensive comparison of the key features and contributions of our current work in contrast to previous research efforts. This table serves as a valuable reference to highlight the distinct advantages and novel aspects of our study compared to the prior state-of-the-art. As can be seen in the literature, there are several papers on optimizing HSCs. Also, some papers in other research areas studied the supply chain planning of particular perishable products such as blood and pharmacy in disaster situations. However, none of the previous papers investigated an HSC design problem considering three types of non-perishable, perishable, and blood products. This research aims to cover this gap by developing a new MILP multi-objective model for the problem. The total cost and total traveled distance of products are considered as the objective functions to provide flexibility for decision-makers to make trade-offs between economic and emergency response aspects. The conflicts of these objectives will be handled by presenting an efficient fuzzy programming approach. Moreover, the uncertainty in product demand is another assumption of this research, which will be addressed by a robust optimization approach.

3. PROBLEM DEFINITION AND MODELING

In this section, we describe the new problem for designing an HSC network under three categories of non-perishable, perishable, and blood relief products. First, the problem definition is presented. Then, the MILP mathematical model is developed by presenting notations, objective functions, and constraints.

3. 1. Problem Definition Natural and human disasters have always been a part of human life. Today, crisis management is very effective in preventing damage from these disasters. One of the crisis management mechanisms is the design of the HSC network, which greatly reduces the damages after the disaster. This paper considers a multi-echelon HSC that includes perishable, non-perishable, and blood products as three types of relief items (9, 10). The main echelons are the suppliers of perishable and non-perishable relief products, the blood donor groups, fixed and mobile blood collection centers, blood processing centers, warehouses, and affected regions. The perishable and non-perishable relief products are purchased from a set of available suppliers and directly transported into warehouses. The location of warehouses should be determined from a set of potential locations. Regarding the perishable nature, we assumed that perishable relief products are available

TABLE 1. The novelties of the current research against the previous work in the literature

Research	**Year**	**Product types**			**Objective numbers**		**Uncertainty**	**Solution approach**		**Case study**
		Non-perishable	**Perishable**	**Blood**	**Single**	**Multiple**		**Exact**	**(Meta) heuristic**	
Zhan and Liu (14)	2011	✓	✗	✗	✗	✓	✓	✓	✗	✗
Murali, Ordóñez (15)	2012	✓	✗	✗	✓	✗	✓	✓	✗	✓
Bozorgi-Amiri, Jabalameli (16)	2012	✓	✗	✗	✓	✗	✓	✗	✓	✗
Zhang and Jiang (34)	2014	✗	✓	✗	✗	✓	✓	✓	✗	✓
Jabbarzadeh, Fahimnia (36)	2014	✗	✗	✓	✓	✗	✓	✓	✗	✓
Ahmadi, Seifi (30)	2015	✓	✗	✗	✓	✗	✓	✓	✓	✓
Khayal, Pradhananga (17)	2015	✓	✗	✗	✓	✗	✗	✓	✗	✓
Bozorgi-Amiri and Khorsi (31)	2016	✓	✗	✗	✗	✓	✓	✓	✗	✓
Tofighi, Torabi (33)	2016	✓	✗	✗	✗	✓	✓	✓	✓	✓
Hasani and Mokhtari (18)	2018	✓	✗	✗	✗	✓	✓	✓	✗	✓
Wang and Nie (20)	2019	✓	✗	✗	✓	✗	✓	✓	✗	✓
Aghajani, Torabi (21)	2020	✓	✗	✗	✗	✓	✓	✓	✓	✓
Khalilpourazari, Soltanzadeh (10)	2020	✗	✗	✓	✓	✗	✗	✓	✗	✓
Akbarpour, Torabi (35)	2020	✗	✓	✗	✗	✓	✓	✓	✗	✓
Mansoori, Bozorgi-Amiri (22)	2020	✓	✗	✗	✗	✓	✓	✓	✗	✓
Haghjoo, Tavakkoli-Moghaddam (38)	2020	✗	✗	✓	✓	✗	✓	✓	✓	✓
Nezhadroshan, Fathollahi-Fard (23)	2021	✓	✗	✗	✗	✓	✓	✓	✗	✓
Kamyabniya, Noormohammadzadeh (39)	2021	✗	✗	✓	✗	✓	✓	✓	✗	✓
Sabouhi, Bozorgi-Amiri (32)	2021	✓	✗	✗	✓	✗	✓	✓	✗	✓
Mahtab, Azeem (24)	2022	✓	✗	✗	✗	✓	✓	✓	✗	✓
Akbari, Valizadeh (25)	2022	✓	✗	✗	✓	✗	✓	✗	✓	✓
Fallahi, Mousavian Anaraki (37)	2022	✗	✗	✓	✗	✓	✗	✓	✗	✓
Foroughi, Moghaddam (26)	2022	✓	✗	✗	✗	✓	✗	✗	✓	✓
Modarresi and Maleki (41)	2023	✓	✗	✗	✓	✗	✓	✓	✗	✓
Hong (40)	2023	✓	✗	✗	✗	✓	✗	✓	✗	✓
This paper	2023	✓	✓	✓	✗	✓	✓	✓	✗	✗

in different quality levels. There is a set of donor groups who volunteer to donate blood. We consider a set of fixed blood collection centers and mobile blood collection centers to receive the whole blood from these volunteer groups. The location of fixed blood collection centers is prespecified. However, mobile blood collection centers should be located in the network.

Also, each mobile blood collection center has a set of collection capacity levels, and the optimal capacity level for each center should be determined. The collected whole blood should be transported into processing centers for testing and production of subproducts. A portion of blood in collection and processing centers cannot be used and is lost.

After processing, different subproducts, e.g. red blood cells, platelets, and plasma, are obtained from whole blood. Then, the produced blood subproducts are sent to the warehouses. Different blood products need different holding equipment. Therefore, the decisions for inventory holding equipment of warehouses are also taken into account in the problem. The received non-perishable, perishable, and blood products are packaged and grouped in the warehouse to transport to affected regions (42). A portion of perishable relief products may expire or spoil based on a perishability rate while being stored in warehouses and cannot be included in relief packages. Each type of package contains a prespecified amount of each product. We consider the possibility of human fault in the packaging of products, and a portion of packages may not be used in affected regions due to these faults (42). Depending on the package type, these faults impose a cost in each affected region.

Note that each facility can service another facility if they are within servicing distance. There is a service level constraint, and a minimum level of demand for each affected region should be satisfied (43). The goal is to determine the optimal location, allocation, blood production, and packaging decisions so that the objective functions are optimized. The economic aspects are considered in the first objective, where the goal is to minimize the total cost of the HSC. To improve the responsiveness of the network, the second objective function aims to minimize the total traveled distance of products in the network. Figure 1 demonstrates the structure of the studied HSC network.

3. 2. Mathematical Modelling Considering the above-described components, the total cost objective can be expressed as follows:

$$Min\ Z_1 = \sum_{i=1}^{I} CNS_i sns_i + \sum_{s=1}^{S} CPS_s sps_s + \sum_{a=1}^{A}\sum_{c=1}^{C} MLC_{ac} lmc_{ac} + \sum_{d=1}^{D}\sum_{p=1}^{P} BDF_{dp} qbf_{dp} + \sum_{d=1}^{D}\sum_{a=1}^{A} BDM_{da} qbm_{da} + \sum_{a=1}^{A}\sum_{l=1}^{L} TMP_{al} qmp_{al} + \sum_{a=1}^{A}\sum_{l=1}^{L} TMP_{al} qmp_{al} + \sum_{g=1}^{G}\sum_{l=1}^{L}\sum_{j=1}^{J} PRC_{gl} qbw_{glj} + \sum_{g=1}^{G}\sum_{l=1}^{L}\sum_{j=1}^{J} TBW_{glj} qbw_{glj} + \sum_{j=1}^{J} WLC_j lwh_j + \sum_{g=1}^{G}\sum_{j=1}^{J} BEW_{gj} ecw_{gj} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M} TPW_{ijm} qnw_{ijm} + \sum_{o=1}^{O}\sum_{q=1}^{Q}\sum_{s=1}^{S}\sum_{j=1}^{J} TNW_{sjoq} qpw_{sjoq} + \sum_{p=1}^{P}\sum_{l=1}^{L} TFP_{pl} qfp_{pl} + \sum_{j=1}^{J}\sum_{n=1}^{N} PPW_{jn} qpp_{jn} + \sum_{j=1}^{J}\sum_{n=1}^{N} PPW_{jn} qpp_{jn} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N} TWA_{jkn} tqa_{jkn} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N} ECA_{nk} ERP_{nj} tqa_{jkn} + \sum_{o=1}^{O}\sum_{j=1}^{J} PCW_o qsw_{jo} \quad (1)$$

The total cost of the presented HSC network includes the fixed contract cost of non-perishable relief products, the fixed contract cost of perishable products, the location cost of mobile blood collection centers, the blood donation cost at fixed blood collection centers, the blood donation cost at mobile blood collection centers, the blood transportation cost from mobile blood collection centers to blood processing facilities, the blood transportation cost from fixed blood collection centers to blood processing facilities, the production cost of blood products in blood processing facilities, the establishment cost of warehouses, the equipment cost of warehouses for blood products, the transportation cost of non-perishable relief products from suppliers to warehouses, the transportation cost of perishable products from suppliers to warehouses, the transportation cost of blood products from blood processing centers to warehouses, the production cost of packages in warehouses, the transportation cost of packagers from warehouses to affected regions, the exceed cost, and the total perishability cost.

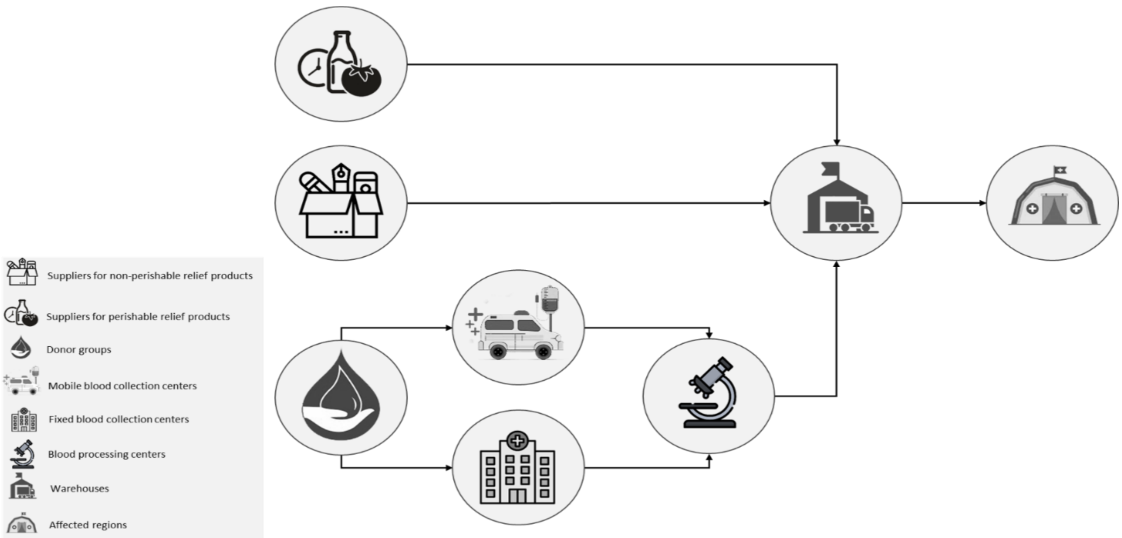

Figure 1. A schematic illustration of the studied network

$$Min\ Z_2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M} DNW_{ij} qnw_{ijm} + \sum_{o=1}^{O}\sum_{q=1}^{Q}\sum_{s=1}^{S}\sum_{j=1}^{J} DPW_{sj} qpw_{sjoq} + \sum_{p=1}^{P}\sum_{l=1}^{L} DLR_{pl} qfp_{pl} + \sum_{a=1}^{A}\sum_{l=1}^{L} DMR_{al} qmp_{al} + \sum_{g=1}^{G}\sum_{l=1}^{L}\sum_{j=1}^{J} DRW_{lj} qbw_{glj} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N} DWA_{jk} BP_{jk}^{n} \quad (2)$$

In addition, the second objective function minimizes the total traveled distance of products, including non-perishable relief products, perishable products, whole blood, blood subproducts, and the produced packages. The objective functions is subjected to the following constraints:

Establishment constraints

$$\sum_{m=1}^{M}\sum_{i=1}^{I} qnw_{ijm} \le \phi lwh_j \quad \forall j \in J \quad (3)$$

$$\sum_{m=1}^{M}\sum_{j=1}^{J} qnw_{ijm} \le \phi sns_i \quad \forall i \in I \quad (4)$$

$$\sum_{j=1}^{J}\sum_{o=1}^{O}\sum_{q=1}^{Q} qpw_{sjoq} \le \phi sps_s \quad \forall s \in S \quad (5)$$

$$apm_{al} \le \sum_{c=1}^{C} lmc_{ac} \quad \forall a \in A, \forall l \in L \quad (6)$$

$$\sum_{n=1}^{N} pbv_{jn} = lwh_j \quad \forall j \in J \quad (7)$$

$$\sum_{n=1}^{N}\sum_{k=1}^{K} tqa_{jkn} \le \phi lwh_j \quad \forall j \in J \quad (8)$$

$$qpp_{jn} \le \phi pbv_{jn} \quad \forall j \in J, \forall n \in N \quad (9)$$

Constraints 3 to 5 limit product flow to the established warehouses and selected suppliers. Constraints 6 limit the flow of blood between the established mobile blood collection centers and blood processing centers. Constraints 7 guarantee that one package type is produced in each established warehouse. Constraints 8 limit the outflow of packages to the established warehouses. Constraints 9 limit the production of package types to the determined facilities for each package type.

Capacity constraints

$$\sum_{j=1}^{J}\sum_{m=1}^{M} qnw_{ijm} \le NCP_i \quad \forall i \in I \quad (10)$$

$$\sum_{o=1}^{O}\sum_{q=1}^{Q}\sum_{j=1}^{J} qpw_{sjoq} \le PCP_s \quad \forall s \in S \quad (11)$$

$$\sum_{a=1}^{A} qbm_{da} + \sum_{p=1}^{P} qbf_{dp} \le BCD_d \quad \forall d \in D \quad (12)$$

$$\sum_{d=1}^{D} qbf_{dp} \le FBC_p \quad \forall p \in P \quad (13)$$

$$\sum_{d=1}^{D} qbm_{da} \le \sum_{c=1}^{C} FBM_{ac} lmc_{ac} \quad \forall a \in A \quad (14)$$

$$\sum_{c=1}^{C} lmc_{ac} \le 1 \quad \forall a \in A \quad (15)$$

$$\sum_{a=1}^{A} qmp_{al} + \sum_{p=1}^{P} qfp_{pl} \le CBP_l \quad \forall a \in A, \forall l \in L \quad (16)$$

$$\sum_{n=1}^{N} qpp_{jn} \le CRW_j \quad \forall j \in J \quad (17)$$

Constraints 10 and 11 are the limitations on suppliers' capacity for non-perishable and perishable relief products. Constraints 12 consider the donation capacity of each donor group. Constraints 13 and 14 are the capacity constraints of fixed and mobile collection centers, respectively. Constraints 15 guarantee that each mobile blood collection center is worked with one capacity level. The capacity limitation of blood processing centers is considered by Constraints 16. Constraints 17 consider the package production capacity of the warehouses.

Facility numbers constraints

$$\sum_{i=1}^{I} sns_i \le MNS \quad (18)$$

$$\sum_{s=1}^{S} sps_s \le MPS \quad (19)$$

$$\sum_{a=1}^{A}\sum_{c=1}^{C} lmc_{ac} \le NRM \quad (20)$$

$$\sum_{j=1}^{J} lwh_j \le WMN \quad (21)$$

Constraints (19) and (19) limit the number of suppliers to the specified threshold. Constraints (20) limit the number of mobile blood collection centers to the specified threshold. The maximum number of located warehouses is taken into account by constraints (21).

Network balance constraints

$$(1 - CUS)\sum_{d=1}^{D} qbf_{dp} = \sum_{l=1}^{L} qfp_{pl} \quad \forall p \in P \quad (22)$$

$$(1 - CUS)\sum_{d=1}^{D} qbm_{da} = \sum_{l=1}^{L} qmp_{al} \quad \forall a \in A \quad (23)$$

$$(1 - PUS)\left(\sum_{a=1}^{A} qmp_{al} + \sum_{p=1}^{P} qfp_{pl}\right) = \sum_{g=1}^{G}\sum_{j=1}^{J} qbw_{glj} \quad \forall l \in L \quad (24)$$

$$qpp_{jn} NPP_{mn} \le \sum_{i=1}^{I} qnw_{ijm} + \phi(1 - pbv_{jn}) \quad \forall n \in N, \forall m \in M, \forall j \in J \quad (25)$$

$$qpp_{jn}NNP_{qno} \leq \sum_{s=1}^{S}\left(\left(1-PRL_{oq}\right)qpw_{sjoq}\right)+\phi\left(1-pbv_{jn}\right) \quad \forall j \in J, \forall o \in O, \forall q \in Q, \forall n \in N \quad (26)$$

$$qpp_{jn}NBP_{ng} \leq \sum_{l=1}^{L} qbw_{glj} + \phi\left(1-pbv_{jn}\right) \quad \forall j \in J, \forall g \in G, \forall n \in N \quad (27)$$

$$qsw_{jo} = \sum_{s=1}^{S}\sum_{q=1}^{Q} PRL_{oq}qpw_{sjoq} \quad \forall j \in J, \forall o \in O \quad (28)$$

$$\sum_{k=1}^{K} tqa_{jkn} \leq qpp_{jn} \quad \forall j \in J, \forall n \in N \quad (29)$$

The flow constraints of blood in fixed collection centers, mobile collection centers, and processing centers are formulated in constraints (22) to (24), respectively. Constraints (25) to (27) ensure that each warehouse produces one type of package and limit the inflow and outflow of facilities based on the production quantity. Constraints (28) determine the quantity of spoiled perishable products in warehouses. Constraints (29) ensure that the total flow of packages from the warehouses to affected regions is less than or equal to the quantity of produced packages.

Facilities assignment constraints

$$\sum_{a=1}^{A} dam_{da} + \sum_{p=1}^{P} daf_{dp} \leq 1 \quad \forall d \in D \quad (30)$$

$$qbm_{da} \leq \phi dam_{da} \quad \forall d \in D, \forall a \in A \quad (31)$$

$$qbm_{da} \geq dam_{da} \quad \forall d \in D, \forall a \in A \quad (32)$$

$$qbf_{dp} \leq \phi daf_{dp} \quad \forall d \in D, \forall p \in P \quad (33)$$

$$qbf_{dp} \geq daf_{dp} \quad \forall p \in P, \forall d \in D \quad (34)$$

$$qmp_{al} \leq \phi apm_{al} \quad \forall a \in A, \forall l \in L \quad (35)$$

$$qmp_{al} \geq apm_{al} \quad \forall a \in A, \forall l \in L \quad (36)$$

$$qfp_{pl} \leq \phi apf_{pl} \quad \forall p \in P, \forall l \in L \quad (37)$$

$$qfp_{pl} \geq apf_{pl} \quad \forall p \in P, \forall l \in L \quad (38)$$

$$qbw_{glj} \leq \phi bsw_{glj} \quad \forall l \in L, \forall g \in G, \forall j \in J \quad (39)$$

$$qbw_{glj} \geq bsw_{glj} \quad \forall l \in L, \forall g \in G, \forall j \in J \quad (40)$$

$$\sum_{l=1}^{L} qbw_{glj} \leq \phi ecw_{gj} \quad \forall g \in G, \forall j \in J \quad (41)$$

Each donor group should be assigned to a fixed or mobile blood collection center, and constraints (30) ensure this. Constraints (31) to (40) limit the flow of products only to the assigned facilities. Constraints (41) limit blood product flow to warehouses with the required holding equipment.

Demand stisfaction consrtains

$$\sum_{j=1}^{J}\left(1-ERP_{nj}\right)tqa_{jkn} \geq DMN_{kn}DST \quad \forall k \in K, \forall n \in N, \forall m \in M, \forall j \in J \quad (42)$$

Constraints (42) ensure the minimum level of demand satisfaction in each affected region.

4. SOLUTION APPROACH

The section addresses the presented two-phase solution methodology for the problem. The goal is to simultaneously handle the objectives conflicts and the models's uncertainty. First, a robust optimization approach is presented to deal with the demand uncertainty of the HSC system. Afterward, a fuzzy programming approach is described that handles the conflicts of the objective functions and provides a single-objective counterpart of the MILP model.

4. 1. Robust Optimization Approach Considering the above-described components, the total cost objective can be expressed as follows:

Several approaches have been presented in the literature to address the uncertainty in optimization problems. A well-known way to deal with uncertainty is stochastic programming. However, this approach needs historical data to estimate probability mass/density functions. In addition, constraint violation may occur in stochastic programming. Therefore, a robust optimization approach was developed in the literature to address these problems. Robust optimization aims to develop a feasible solution for all realizations of unknown parameters. Unlike stochastic programming, the robust optimization approach can deal with both hard constraints and interval uncertainty. In this procedure, an interval uncertainty is considered for the stochastic parameters.

As mentioned, we considered the uncertainty in demand for packages in affected regions. It is difficult to estimate the demand of the HSC systems using a probability distribution function. We use the proposed approach by Bertsimas and Sim (44) as one of the most well-known approaches in the literature (45). Consider the following optimization problem:

$$\begin{aligned} & Max\ cx \\ & S.t \\ & \sum_{j\in J_i}\tilde{a}_{ij}x_j+\sum_{j\in N\{J_i\}}\tilde{a}_{ij}x_j\le \mu_i(x) && \forall i\in I \\ & x\epsilon F(x) && \forall \tilde{a}_{ij}\in J_i \end{aligned} \tag{43}$$

where $\tilde{a}_{ij}$ is the uncertain parameter of the system and is in the interval $[\bar{a}_{ij}-\hat{a}_{ij},\bar{a}_{ij}+\hat{a}_{ij}]$. In this interval, $\bar{a}_{ij}$ and $\hat{a}_{ij}$ are the nominal value and deviation. In addition, J_i is the set of uncertain parameters in row i. This approach considers a parameter, denoted by Γ_i, for each i, which is referred to as the budget of uncertainty. This parameter allows for control over the level of conservatism in the solution and can take on integer values in the range of $(0,|J_i|)$. The budget of uncertainty ensures that the solution remains feasible even when multiple parameters are changed simultaneously. The reformulation of the problem using the budget of uncertainty is as follows:

$$\begin{aligned} & Max\ cx \\ & S.t \\ & && \forall i\in I, \\ & \sum_{j\in N}a_{ij}x_j+\max_{\{S_i|S_i\epsilon J_i,|S_i|=\Gamma_i\}}\{\sum_{j\in S_i}\widehat{a_{ij}}x_j\}\le b_i && \forall \tilde{a}_{ij}\in J_i \\ & x\epsilon F(x) && \forall \tilde{a}_{ij}\in J_i \end{aligned} \tag{44}$$

However, the above model is in a nonlinear form, which can be linearized as follows:

$$\begin{aligned} & Max\ cx \\ & S.t \\ & z_i\Gamma_i+\sum_{j\in J_i}p_{ij}+\sum_{j\in N}a_{ij}x_j\le b_i && \forall i\in I \\ & z_i+p_{ij}\ge \tilde{a}_{ij}x_j && \forall i\in I,\ j\in J_i \\ & z_i,p_{ij}\ge 0 && \forall i\in I,\ \forall j\in J \\ & x\epsilon F(x) && \forall \tilde{a}_{ij}\in J_i \end{aligned} \tag{45}$$

where z_i and p_{ij} are two auxiliary variables. Considering the explained procedure, the robust formulation of the presented problem substitutes Equation (42) with the following constraints:

$$\sum_{j=1}^{J}(1-ERP_{nj})tqan_{jk}\ge (\widehat{DMN}_{kn}+P_k^n+Z_k^n\Gamma)DST \qquad \forall k\in K\quad \forall n\in N \tag{46}$$

$$P_k^n+Z_k^n\ge \widehat{DMN}_{kn} \qquad \forall k\in K,\quad \forall n\in N \tag{47}$$

4. 1. Fuzzy Programming Multi-objective Approach Several approaches have been developed in the literature to address the conflicts of objectives in multi-objective optimization problems. Among these approaches, fuzzy techniques are becoming more popular due to their ability to determine the satisfaction level of any objective function directly (46, 47). This allows decision-makers to calculate Pareto solutions depending on their choices (i.e., the relative degree of importance of objectives). Zimmermann (48) developed the first approach for multi-objective based on fuzzy theory, which was the max-min method. The main deficiency of this method is that it does not ensure the calculation of Pareto solutions. Considering this problem, Lai and Hwang (49) developed the augmented max-min method. The SO and LZL methods were some other approaches that were developed in subsequent years by Selim and Ozkarahan (50) and Li, Zhang (51), respectively. In this paper, we utilize the TH method, which was developed by Torabi and Hassini (52), to handle the conflict between total cost and total traveled distance of products. This approach guarantees the calculation of Pareto solutions and includes the following phase:

Phase I: In this phase, the positive ideal solution and negative ideal solutions of each objective function are calculated. Consider a bi-objective problem. The positive best solutions (PBS) of each objective function, PBS_{Z1} and PBS_{Z2} are obtained through the separate optimization of the model for each objective function. In addition, the negative best solution (NBS) is obtained as follows:

$$NBS_{Z1} = Z_1\left(x_{PBS_{Z2}}\right) \tag{48}$$

$$NBS_{Z2} = Z_2\left(x_{PBS_{Z1}}\right) \tag{49}$$

Phase II: In this phase, for each objective function, a linear membership function is established as follows:

$$\mu_1(x) = \begin{cases} 1 & Z_1 \le PBS_{Z1} \\ \frac{NBS_{Z1}-Z_1}{NBS_{Z1}-PBS_{Z1}} & PBS_{Z1} \le Z_1 \le NBS_{Z1} \\ 0 & Z_1 \ge NBS_{Z1} \end{cases} \tag{50}$$

$$\mu_2(x) = \begin{cases} 1 & Z_2 \le PBS_{Z2} \\ \frac{NBS_{Z2}-Z_2}{NBS_{Z2}-PBS_{Z2}} & PBS_{Z2} \le Z_2 \le NBS_{Z2} \\ 0 & Z_2 \ge NBS_{Z2} \end{cases} \tag{51}$$

Phase III: In this phase, the single-objective equivalent problem is established using the aggregation function of TH method as below:

$$\begin{aligned} & Min\ \lambda(x) = \beta\lambda_0 + (1-\beta)\textstyle\sum_i w_i\, \mu_i(x) \\ & S.t: \\ & \lambda_0 \le \mu_i(x) \qquad \forall i = 1,2 \\ & x \in F(x) \\ & \lambda_0, \lambda \in [0,1] \end{aligned} \tag{52}$$

5. COMPUTATIONAL EXPERIMENTS

In this section, we validate the developed model and provide insights by solving several numerical examples. The data of numerical examples are mostly adopted from the works by Abazari, Aghsami (9) and Khalilpourazari, Soltanzadeh (10). Table 2 presents the details of the data.

To explore the performance of the problem, the model is coded in GAMS programming software, and the CPLEX solver is used to solve each problem. The examples are randomly generated and run on a personal laptop with 8 GB of RAM, Intel Core i7, and CPU 2.6 GHz. As previously highlighted, there exist inherent conflicts between the objectives, making it challenging to optimize both objective functions simultaneously. This inherent trade-off implies that enhancing one objective may come at the expense of the other. Table 3 provides a comprehensive summary of our findings. The values presented in the third and fourth columns of the table quantitatively illustrate the nature of these conflicts. When efforts are made to improve the total traveling distance, the optimization process tends to favor the selection of closer facilities. However, this preference may lead to increased costs for the healthcare system. Consequently, in this scenario, the model tends to allocate less attention to minimizing the location cost of the facilities. Conversely, when the focus is on improving the total cost, the optimization process shifts towards selecting facilities that minimize location costs and other cost components.

TABLE 2. The considered ranges for the data of numerical examples

Parameter	Value	Parameter	Value
NCP_i	Rand(40000,7000)	PRL_{oq}	Rand(0.1,0.2)
PCP_s	Rand (2000,3000)	MLC_{ac}	Rand(5000,50000)
BDC_d	Rand (100,3000)	BDF_{dp}	Rand(0.5,3)
WLC_j	Rand(1000,3000)	BDM_{da}	Rand(0.05,3)
CNS_i	Rand (20000,40000)	TMP_{al}	Rand(0.05,2)
CRW_j	Rand(7000,18000)	TFP_{pl}	Rand(0.25,2)
CPS_s	Rand (20000,50000)	TBW_{lgj}	Rand(0.02,1.5)
PCW_o	Rand(200,500)	PRC_{lg}	Rand(0.05,1.75)
FBC_p	Rand(500,2000)	FBM_{ac}	Rand(100,1000)
CBP_l	Rand(500,2000)	DPW_{sj}	Rand(10,350)
MNS	RandI(1,3)	DNW_{ij}	Rand(10,1000)
WMN	RandI(2,5)	DMR_{al}	Rand(1,600)
MPS	RandI(1,3)	DLR_{pl}	Rand(50,550)
NRM	RandI(1,5)	DRW_{lj}	Rand(8,1000)
CUS	Rand(0.1,0.2)	DWA_{jk}	Rand(50,600)
PUS	Rand(0.05,0.15)	BEW_{gj}	Rand(20,700)
DST	Rand(0.85,0.95)	PPW_{jn}	Rand(0.15,1.5)
TPW_{ijm}	Rand(0.2,2)	ERP_{nj}	Rand(0.05,2)
TWA_{jkn}	Rand(0.01,2)	NNP_{qno}	RandI(0,40)
$\overline{DMN}_{kn}$	RandI(0,10)	NPP_{nm}	RandI(0,50)
$\widehat{DMN}_{kn}$	Rand(0.05,0.2)	NBP_{ng}	RandI(0,50)
TNW_{sjoq}	Rand(0.05,1.5)		

In this continuing, the analysis of sensitivity is performed to provide more insights into the behavior of the model. Sensitivity analysis is a systematic approach to investigate the impact of variation on the input of parameters to the outputs of the model. We carry out the sensitivity analysis on model parameters and problem parameters. First, we are going to analyze the sensitivity of results based on variations in the price of robustness, as the main parameter of the proposed robust optimization methodology. The obtained computational results in different levels of price of robustness are summarized in Table 3. The conducted sensitivity analysis on the price of robustness provides crucial and illuminating findings for the multi-objective optimization problem in HSC planning. The results reveal that both the total cost and total traveled distance objectives are highly responsive to changes in the price of robustness. As the price of robustness increases, there is a clear and significant upward trend in both cost and distance metrics, highlighting the trade-off between achieving cost efficiency and ensuring robustness in the network design.

This pivotal insight emphasizes the necessity of carefully selecting an appropriate price of robustness, as it directly impacts the delicate balance between minimizing expenses and guaranteeing a robust supply chain in unpredictable contexts. Understanding the trade-off allows decision-makers to make informed choices that align with their priorities and strategic objectives. Moreover, the analysis demonstrates that CPU time remains stable and unaffected by variations in the price of robustness. This stability is of immense practical importance, as it enables decision-makers to explore a diverse range of robustness values without compromising the optimization process's computational speed. The ability to efficiently examine different robustness levels empowers planners to make timely and well-informed decisions even under time constraints.

In this part, we evaluate the impact of changes in some parameters on the objective functions of the studied HSC. The supplier's capacity, demand, and blood wastage rate are selected as three important parameters for sensitivity analysis. The sensitivity analysis of the objective functions to variations in the nominal value of the demand rate has been thoroughly investigated, and the findings are depicted in Figure 2. Understanding the sensitivity of the objective functions to demand variations offers invaluable insights for supply chain decision-makers. By recognizing the intricate relationship between demand rates and cost and distance metrics, planners can proactively adapt their strategies to cope with dynamic demand scenarios effectively.

TABLE 3. The results of the problem based on the degree of importance of objective functions

(w_1, w_2)	Γ	β	z_1	z_2	μ_{z_1}	μ_{z_2}	%Gap	CPU time (S)
(0.0,1.0)	0.5	0.3	242267.64	322693.05	0.441	0.965	0.00	1.41
(0.2,0.8)	0.5	0.3	242382.33	282957.99	0.724	0.832	0.00	1.62
(0.4,0.6)	0.5	0.3	242382.96	282957.99	0.724	0.832	0.00	1.40
(0.2,0.8)	0.5	0.3	242382.96	282957.99	0.780	0.731	0.00	1.52
(1.0,0.0)	0.5	0.3	251491.01	222314.23	0.780	0.731	0.00	1.44

TABLE 4. The results of the problem based on the variation in the price of robustness

(w_1, w_2)	Γ	β	z_1	z_2	μ_{z_1}	μ_{z_2}	%Gap	CPU time (S)
(0.8,0.2)	0.00	0.3	239863.75	272809.46	0.736	0.792	0.00	1.47
(0.8,0.2)	0.10	0.3	240367.59	274844.88	0.736	0.791	0.00	1.53
(0.8,0.2)	0.20	0.3	240871.44	276880.31	0.736	0.791	0.00	1.52
(0.8,0.2)	0.30	0.3	241375.28	278915.73	0.735	0.791	0.00	1.49
(0.8,0.2)	0.40	0.3	241879.12	280951.15	0.735	0.791	0.00	1.53
(0.8,0.2)	0.50	0.3	242382.96	282986.58	0.735	0.791	0.00	1.47
(0.8,0.2)	0.60	0.3	242886.81	285022.00	0.735	0.791	0.00	1.47
(0.8,0.2)	0.70	0.3	243390.65	287057.42	0.734	0.791	0.00	1.48
(0.8,0.2)	0.80	0.3	243894.49	289092.85	0.734	0.791	0.00	1.49
(0.8,0.2)	0.90	0.3	244398.34	291128.27	0.734	0.791	0.00	1.45
(0.8,0.2)	1.00	0.3	244902.18	293163.69	0.734	0.792	0.00	1.46

Implementing appropriate demand management and response mechanisms can lead to more resilient and cost-efficient supply chain networks, ensuring timely and optimal delivery of humanitarian aid and resources to those in need. As expected, the results reveal a clear and consistent negative impact of increasing demand rates on both objective functions. This behavior is intuitively understandable, as higher demand necessitates a greater flow of products within the supply chain network. Consequently, an increase in product flow leads to a rise in both the total cost and total traveled distance objectives. The amplified demand significantly affects the overall transportation and distribution processes, resulting in higher costs incurred and longer distances traveled. These observations underscore the critical importance of managing and responding to fluctuating demand patterns in HSC planning. Notably, the sensitivity analysis highlights that the total traveled distance objective exhibits a higher degree of sensitivity compared to the total cost. This finding suggests that changes in demand rates have a more pronounced impact on the transportation aspect of the supply chain network, which directly influences the total distance traveled by products.

In the investigation of the second parameter, we analyzed the sensitivity of the objective functions concerning the wastage rate of blood products, as illustrated in Figure 3. Understanding the sensitivity of the objective functions to the wastage rate of blood products empowers supply chain decision-makers to design more robust and cost-effective networks. By strategically managing blood product utilization and implementing waste reduction measures, organizations can enhance their responsiveness to emergencies and humanitarian crises, ensuring a reliable supply of blood products to those in need. As anticipated, the results exhibit a clear and consistent negative correlation between increasing wastage rates of blood products and the performance of the objective functions. This negative impact is expected, as higher wastage rates imply a higher percentage of blood products that become unsuitable for use or are discarded, resulting in inefficiencies in the supply chain network. To mitigate the adverse effects of increased wastage rates, the network's donation and processing of blood must be strategically increased to satisfy demand efficiently. By bolstering the blood flow through the network, the system can better meet the demand for blood products. However, the analysis reveals that such increases in blood flow come at a cost, as they lead to higher total cost and total traveled distance objectives. These findings underscore the significance of minimizing wastage rates and optimizing the blood supply facilities to ensure efficient allocation and utilization of blood products. Effective waste management strategies and enhanced processing and distribution procedures can play a pivotal role in reducing wastage rates and associated costs while improving overall supply chain performance.

In our latest phase of investigation, we are delving into a sensitivity analysis of the objective functions, regarding variations in supplier capacity, as vividly depicted in Figure 4. This critical analysis serves as a powerful tool for supply chain decision-makers, providing them with valuable insights for making informed and strategic choices. This strategic approach to supplier capacity planning ensures the timely and efficient delivery of essential goods and resources; thus, enhancing the network's responsiveness in effectively addressing humanitarian crises and emergency scenarios.

Our sensitivity analysis has unveiled intriguing and contrasting behaviors exhibited by the objective functions in response to changes in supplier capacity. One noteworthy revelation is that increases in supplier capacity do not significantly impact the overall performance of the supply chain network. This finding suggests that the network is inherently equipped to

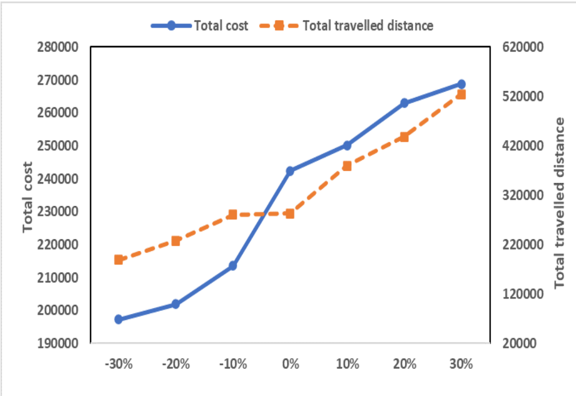

Figure 2. Sensitivity analysis of objectives with respect to the demand for packages

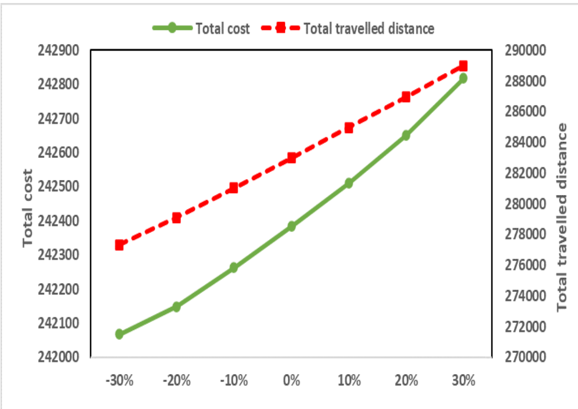

Figure 3. Sensitivity analysis of objectives with respect to blood wastage rate

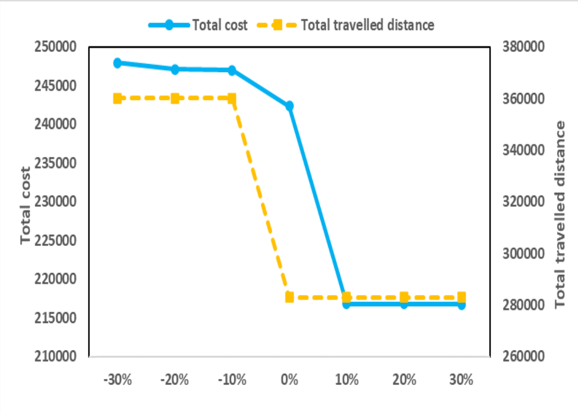

Figure 4. Sensitivity analysis of objectives with respect to the capacity of suppliers

accommodate higher supplier capacities without incurring substantial adverse effects on the total cost and total traveled distance objectives. On the flip side, when supplier capacity experiences reductions, it triggers a remarkable and noteworthy ripple effect throughout the network's performance. This leads to a substantial increase in both the total cost and total traveled distance, emphasizing the critical role of prudent supplier capacity management in optimizing supply chain performance.

While our analysis indicates that augmenting supplier capacity may not necessarily yield substantial improvements, it underscores the paramount importance of maintaining adequately calibrated capacities. This proactive approach helps mitigate the risk of cost escalations and operational inefficiencies. Additionally, addressing reductions in supplier capacity in a timely and proactive manner is crucial to preempt potential disruptions and ensure the seamless operation of the supply chain.

6. MANAGERIAL INSIGHTS

Our computational experiments offer valuable insights for supply chain decision-makers in the context of HSC management. By analyzing various scenarios and conducting sensitivity analyses, we unveil critical considerations for optimizing HSC networks. Here are the key managerial insights:

Balancing conflicting objectives: In HSC planning, there exists a fundamental trade-off between minimizing total cost and reducing total traveled distance. As demonstrated in Table 3, varying the importance of each objective function affects the network's performance. When prioritizing one objective, such as minimizing total traveling distance, it results in selecting nearer facilities but potentially increases costs. Conversely, minimizing total costs involves selecting facilities that reduce location costs and other cost components, which may lead to longer distances traveled. Managers must carefully consider this trade-off to align network design with specific priorities and operational constraints.

- **Robustness of network:** The sensitivity analysis of the price of robustness, as depicted in Table 4, highlights a critical managerial decision. Both total cost and total traveled distance objectives are highly responsive to changes in the price of robustness. Decision-makers should strategically select an appropriate price of robustness, as it directly impacts the balance between cost efficiency and network robustness. This choice influences the network's ability to adapt to uncertainties without incurring substantial cost increases. Moreover, the stability of CPU time allows planners to explore different robustness levels efficiently, even under time constraints, enabling informed decisions in dynamic environments.
- **Managing demand variations:** Understanding the sensitivity of objective functions to demand variations, as shown in Figure 2, is pivotal for HSC managers. Higher demand rates significantly impact both total cost and total traveled distance, necessitating proactive demand management strategies. To enhance network resilience and cost-effectiveness, managers should implement demand forecasting and response mechanisms. This enables the efficient allocation of resources and ensures timely aid delivery during fluctuating demand scenarios.
- **Minimizing Blood Wastage:** The sensitivity analysis related to blood wastage rates, which is provided in Figure 3, emphasizes the importance of waste reduction strategies in blood product supply chains. Increasing wastage rates negatively affect both cost and distance objectives. To mitigate these effects, organizations should focus on optimizing blood supply facilities, enhancing processing and distribution procedures, and minimizing waste. Efficient waste management strategies can lead to cost savings while improving overall supply chain performance.
- **Supplier Capacity Management:** Analyzing the sensitivity of objective functions to changes in supplier capacity, which is presented in Figure 4, reveals the significance of prudent supplier capacity management. Increasing supplier capacity does not substantially impact overall network performance, indicating room for accommodating higher capacities without incurring significant cost or distance penalties. However, reducing supplier capacity has a noteworthy negative impact. To optimize supply chain performance, managers should maintain well-calibrated capacities, proactively address reductions, and ensure smooth operations, particularly in humanitarian crises and emergency situations.

This paper can be extended in several ways by future research. From the problem development viewpoint, resiliency is of great importance for HSCs. One of the potential directions is to consider the resiliency objectives and improve the power of the network in facing disruptions (26). Furthermore, some other important decisions, such as the inventory and routing decisions, also have the potential to be incorporated in the presented model by considering proper coordination agreements such as VMI (53). From the solution methodology perspective, we employed the CPLEX commercial solver, a powerful optimization tool known for its ability to handle MILP mathematical models. CPLEX allowed us to find non-dominated solutions for the studied multi-objective HSC network design problem. However, it's essential to acknowledge that as the problem size scales up, the computational costs associated with solving it can become quite substantial regarding the NP-hard complexity of the problem. Researchers and practitioners should be mindful of these computational challenges Therefore, the exact or metaheuristic algorithms such as can be designed in future research to consider this issue. Some examples are different variants of Lagrangian relaxation, fast fireworks (54), memetic (55-57), hybrid multi-objective evolutionary (58), tabu search (59-61), differential evolution (62, 63), ant-based (64), multi-objective profitable severity and delay reduction (65), particle swarm optimization (66) algorithms. In addition, the machine learning approaches, such as unsupervised learning methods, can be used to cluster the packages, and improve the performance of the system (67).

7. CONCLUSION

In this research, we developed a new humanitarian supply chain network design problem under product differentiation and demand uncertainty. For the first time, non-perishable, perishable, and blood products were simultaneously considered as three important products of the network. The problem was formulated using a MILP multi-objective mathematical model. The model aims to minimize the total cost and total traveled distance of products by determining location, allocation, and production decisions. To provide a more realistic problem, the uncertainty in demand of affected areas was also taken into account.

A two-phase solution methodology was suggested to solve this problem. First, a robust optimization approach was presented to establish the deterministic counterpart of the stochastic model. Next, an efficient fuzzy programming-based approach was designed to reformulate the model in a single-objective form. The model's performance and solution methodologies were investigated by solving numerical instances. The results showed that the proposed fuzzy approach can successfully find non-dominated solutions for the problem considering the decision-maker's preferences. The choice of the price of robustness significantly influences the balance between cost efficiency and network robustness, highlighting the importance of strategic decision-making for this parameter. Sensitivity analyses reveal the impact of demand variations on both cost and distance objectives, emphasizing the need for proactive demand management strategies. Furthermore, minimizing blood wastage rates and prudent supplier capacity management emerge as crucial factors for cost savings and network responsiveness.

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Persian Abstract

چکیده

در محیط پویا و غیرقابل پیش‌بینی دنیای امروز، برنامه‌ریزی و مدیریت زنجیره‌های تامین بشردوستانه از اهمیت بسیار بالایی برخوردار است. در این راستا مدیریت لجستیک کارا سبب می‌شود تا کالاها و منابع ضروری در شرایط قابل قبول و در زمان مناسب به نواحی بحران‌زده تحویل گردند و در نهایت پشتیبانی لازم از جمعیت آسیب‌دیده به عمل آید. در این پژوهش، یک مسئله‌ی طراحی شبکه‌ی زنجیره تامین بشردوستانه با در نظرگرفتن تمایز میان اقلام و هم‌چنین شرایط عدم قطعیت تقاضا مورد بررسی قرار می‌گیرد. به‌صورت دقیق‌تر، سه دسته‌ی کلی کالاهای فسادناپذیر، کالاهای فسادپذیر و خون به عنوان سه دسته کالای اساسی در شبکه‌ی زنجیره تامین بشردوستانه در مسئله‌ی طراحی شبکه لحاظ می‌شوند. مسئله در قالب یک مدل برنامه‌ریزی ریاضی چندهدفه عددصحیح–خطی فرموله می‌شود. اهداف مسئله‌ی ارائه‌شده، حداقل‌سازی مجموع هزینه و مجموع مسافت طی شده‌ی کالاها می‌باشند. به‌منظور نزدیک‌تر نمودن فرضیات پژوهش به شرایط دنیای واقعی، عدم قطعیت در پارامتر تقاضای محصولات نیز لحاظ می‌گردد. یک متدولوژی دو مرحله‌ی به عنوان روش حل مسئله ارائه می‌شود. در ابتدا، یک رویکرد بهینه‌سازی استوار جهت فرموله‌سازی مدل هم‌ارز قطعی مسئله مورد بحث قرار می‌گیرد. در مرحله‌ی دوم، یک روش کارای مبتنی بر برنامه‌ریزی فازی جهت تبدیل مسئله‌ی دوهدفه به یک مسئله‌ی تک‌هدفه تشریح می‌شود. عملکرد مدل ریاضی توسعه‌داده شده و متدولوژی پیشنهادی از طریق حل مثال‌های عددی مختلف مورد تجزیه و تحلیل قرار می‌گیرند. نتایج محاسباتی بیانگر این هستند که روش فازی پیشنهادی قادر است تا مجموعه جواب‌های نامغلوب برای مسئله را با در نظر گرفتن ترجیحات تصمیم‌گیرنده ایجاد نماید. هم‌چنین تحلیل حساسیت بر روی پارامترهای ورودی مسئله با هدف ایجاد بینش بیشتر انجام می‌شود. در انتها پیشنهاداتی برای تحقیقات آتی جهت توسعه‌ی پژوهش فعلی ارائه می‌شود.