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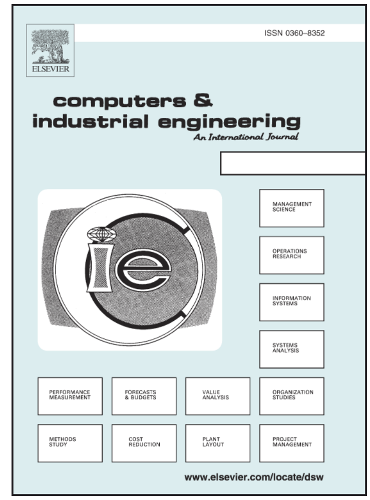

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A Robust Neutrosophic Fuzzy-based Approach to Integrate Reliable Facility Location and Routing Decisions for Disaster Relief under Fairness and Aftershocks Concerns

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Abstract

Relief distribution and victim evacuation are the crucial emergency relief operations after sudden-onset disasters to alleviate the repercussions of catastrophes in the concerned areas, although aftershocks and unfair distribution of relief items can affect these planning and beget plenty of undesirable reflections. In this paper, a new multi-objective reliable optimization model to organize a humanitarian relief chain is rendered to make a broad range of decisions, including reliable facility location-allocation, fair distribution of relief items, assignment of victims, and routing of trucks. For this purpose, the first objective function is to minimize the total logistics costs, the second one is to minimize the total time of relief operations, and the third one minimizes the variation between upper and lower bounds of transportation cost of distribution centers to regulate the workload of them. What is more, due to the fact that the uncertain essence of catastrophes, such as demand, the capacity of facilities, miscellaneous costs and transportation times, a novel uncertainty approach, including robust optimization and the neutrosophic set, is proposed to surmount these obstacles. Ultimately, a real case study is examined to illustrate the validity of the proposed model and solution method. The obtained results reveal that via increasing the capacity of the emergency centers by 30%, the total cost of the humanitarian relief network is reduced by 18%, and the operating time is reduced by 9%. What is more, if the probability of disruption in one of the distribution centers reaches zero, the logistics costs will be reduced to approximately 20%, and also the distance between the maximum and minimum distance traveled will be reduced by 30%, and the workload between distribution centers will be more balanced.

Keywords: Humanitarian logistics; Reliability; Facility Location; Equitable allocation; Vehicle routing; Uncertainty

1. Introduction

Year after year, a broad range of miscellaneous catastrophes such as natural or human-made calamities typically murders plenty of human beings, threatens manifold of the remnants, and beget titanic repercussions in terms of economic criteria. More importantly, the alteration of these calamities has manifested a considerable trend recently. In the literature, catastrophes were classified into slow and sudden onsets (Van Wassenhove, 2006) such that an earthquake, which falls out unexpectedly and unanticipatedly, is an instance of a sudden-onset catastrophe. Obviously, a broad range of repercussions would be brought about for disaster regions by a vigorous earthquake in the 100-km vicinity from the epicenter (Setiawan et al., 2019). In this study, the proposed framework is to deal with the challenges of this kind of catastrophe via providing a reliable tailor-made humanitarian logistics network (HLN).

In an attempt to mitigate the fatalities and enhance survivors' endurance, comprehensive cooperation must be implemented right after any catastrophes. In this regard, the inauguration of provisional facilities such as distribution and emergency centers, the distribution of relief items among survivors, and the evacuation of injured people to create an HLN, are the crucial considerations of vital measures. In retrospect, this cooperation could be encountered with varied obstacles (Balcik et al., 2010; Coppola, 2007; Nolte et al., 2012), such as the restriction of resources, aftershocks, varied types of injuries, unfair relief distribution (RD), accessibility of resources, increasing planning time, and uncertain and dynamic essence of catastrophes (e.g., Martinez et al., 2011; Jotshi et al., 2009).

One of the above-mentioned main obstacles is aftershocks and their concerns. Indeed, most vigorous earthquakes are followed by supplementary earthquakes, namely aftershocks. They are typically weaker and smaller than mainshock and could continue in the course of weeks, months, or years. Generally, the larger mainshock can beget larger and frequent aftershocks. In this way, almost all of the studies in the field of humanitarian logistics planning in pre-and post-disaster phases have assumed that the earthquake occurred and then necessitated planning is conducted and have not reflected the repercussions of aftershocks such as destruction of provisional facilities in their investigations. In this circumstance, the emergency relief chain possibly encounters substantial losses. Hence, in order to mitigate these repercussions, creating a reliable relief logistics network is one of the crucial measures. In this regard, with the intention of reflecting the facility disruption in a mathematical model, two major methods were proposed in the literature. The first method considers the failure probability as a constant parameter, and the second one endeavors to compute customer assignment probabilities through introducing a set of decision variables (Yu et al., 2017). Needless to say, the second one is complicated, but it is more accurate and reliable.

Another obstacle concerns the fairness manner of relief items distribution. Obviously, offering a fair and equitable scheme to distribute relief items among survivors, which have been stored in warehouses or distribution centers, is a vital measure and undeniable truth. For this purpose, there is a limited range of policies in the literature, including maximizing the minimum rate of demand satisfaction, minimizing the latest arrival time, minimizing the inequality in demand satisfaction, and considering a service level gap as a constraint. In the latest one, which is a new and efficient approach, the equity level could be adjusted by a maximal ratio to ascertain the best allocation of relief items with respect to the accessible supply. It should be noted that this gap could be considered for the disaster units with dissimilar facility providers, so it to be zero among disaster units that have similar service providers (Noham and Tzur, 2018).

Last but not least of the obstacles is the uncertain nature of calamities. In this regard, the reflection of uncertain conditions in the organizing and managing miscellaneous challenges is staggering, no more so than in the emergency relief supply chain. As a consequence, programming under uncertainty has been gaining prestige in the designing, planning and managing operations in this area (Liu et al., 2019; Tirkolaee et al., 2019, 2020a,b; Hematian et al., 2020). As a matter of fact, uncertain parameters can affect the performance of the humanitarian logistics planning to large scale, and disregarding this concern inevitably can beget ineffectual solutions. In the literature of humanitarian logistics, a broad range of parameters has been considered under an uncertain environment, including demand, the capacity of facilities, cost, transportation time and etc. In this regard, the supply factors could be encountered with uncertainty due to the unknown amount of resource availability and vibrational contributions from suppliers and responsible entities. In addition, the availability level of vehicles such as trucks, ambulances, and the accessibility of infrastructures can beget uncertainty in cost parameters. Also, the fluctuation of relief items or the number of injuries, and inaccurate estimations can beget uncertainty in demand parameters. In the literature, so as to surmount these challenges, there are two substantial solution approaches, including robust optimization (RO) and stochastic programming (SP). On the one hand, now that there are historical and meteorological information concerning short-notice calamities such as flooding and hurricanes, and prediction method can render a suitable projection about these disasters, the SP solution approaches have been widely employed for them (Mete and Zabinsky, 2010). On the other hand, when decision-makers (DMs) encounter the shortage of information, the RO approaches have been utilized to optimize the performance of the system under worst-case situation (Balcik and İhsan, 2019). Subsequently, the RO approaches might be reasonable in response to tsunamis and earthquakes, which are known as no-notice catastrophes or quick-onset. What is more, in a similar circumstance, DMs may favor employing the other uncertainty approaches such as inexact programming or miscellaneous fuzzy programming approaches, in order to surmount these uncertainties. However, the attitude of DMs and the availability level of data can ascertain the type of uncertain approach.

Accordingly, this paper investigates a multi-echelon relief logistics network problem. With the intention of planning this problem, a new multi-objective reliable optimization model is proposed. The offered model involves a number of simultaneous decisions concerning facilities location, equitable allocation, assignment probability, routing of vehicles, RD, and victim evacuation (VE). Also, a novel uncertainty approach, which is included neutrosophic fuzzy programming and RO, is rendered. Ultimately, a real case study is examined to illustrate the validity of the proposed model and solution method. Concisely, the unprecedented features of this research compared to its counterparts are abridged as bellows:

- Rendering a reliable synchronized framework to distribute relief items and evacuate victims in an HLN.
- Developing a novel multi-objective model to integrate reliable locating and routing under fairness in distribution relief items.
- Mitigating the repercussions of aftershocks by considering an efficient reliability approach.
- Proposing an uncertain approach based on neutrosophic fuzzy programming and RO

The remnant of this paper is structured as follows: Section2 investigates the literature in the related research area. A framework of the proposed model is provided in Section 3. The details of the development and implementation of the hybrid uncertainty approach are explained in Sections 4 and 5, respectively. The multi-objective solution approach is addressed in Section 6. The case study and numerical results are provided in Section 7, and Section 8 renders sensitivity analysis and management insights. Lastly, the paper is concluded in Section 9.

2. Literature review

Now that there are plenty of studies in the scope of emergency relief logistics (ERL), this section concentrates on the location routing (LR) models, which are comprehensively related to the main goal of the current study. What is more, a comparative table of the examined studies is rendered at the end of this section, in order better to demonstrate the research gaps and contributions of this study. Meanwhile, there are a significant number of studies concerning LR models in the ERL, but the scrutiny of these studies manifests that merely a limited number of them have been reflected the considerations of vehicle routing problem in their models, and the most of which have been reflected transmission considerations.

Yi and Ozdamar (2007) investigated a multi-period LR optimization model for synchronized RD and VE problems in an ERL network to minimize the waiting time of injuries and the unfulfilled demand of survivors. Also, the best locations of emergency centers were determined without introducing binary variables for this aim. Additionally, the pickup and delivery considerations were reflected in the phase of the vehicle routing problem (VRP) to determine the flow amount of various relief items. Another novelty of this research was to consider varied types of injuries in the planning. Also, a heuristic algorithm (HA) was introduced to solve the proposed model. The maximum number of disaster units considered in their study was 60, which required 140.3 seconds of computational time on a PC with 3.2 GHz CPU and 512 MB RAM to solve by CPLEX. A mobile healthcare management problem was considered to develop a multi-objective LR model by (Doerner et al., 2007), such that three criteria, including coverage, the effectiveness of workforce employment and average accessibility were examined to assess the tours of vehicles. Also, after completing the mission, the vehicles should have returned to the starting point, which was called closed VRP. More importantly, three meta-heuristic algorithms (MHAs) were proposed to solve the proposed model. As a matter of fact, the above-mentioned criteria to assess vehicle tours were the major contributions of this study. The maximum number of disaster units considered in their study was 500, which required 12 minutes of computational time on a Pentium III with 1400 MHz CPU to solve by MHA. Mete and Zabinsky (2010) presented an LR optimization model to minimize the total costs of the RD network, in which the parameters of the optimization model were considered under an uncertain state. In an attempt to overcome these uncertainties, they employed an SP approach. The main novelties of this research were to consider the dissimilar kinds of potential calamities and their magnitudes and to reflect on inventory management considerations. The maximum number of disaster units considered in their study was 10, which required 60 seconds of computational time on a PC with 1.8 GHz CPU to solve by CPLEX. A bi-level LR optimization model was proposed to design an HLN by (Oran et al., 2012). The location-allocation facilities' decisions were determined in the upper level, and the routing decisions of vehicles were ascertained in the lower-level by a VRP model. The objective function of the upper-level minimized the unfulfilled emergency demand, and the objective function of the lower-level maximized the priorities of emergency types. Moreover, the proposed framework, upper and lower objective functions, and the considerations of time windows constraints in the lower-level model were the contributions. Also, they proposed a tabu search based MHA to solve the presented models. The maximum number of disaster units considered in their study was 100, which required 5 minutes of computational time to solve by MHA. Afshar and Haghani (2012) addressed an LR model to plan a humanitarian supply chain, and the pickup and delivery considerations were reflected to determine the flow amount of various relief items. In this study, the total amount of weighted unsatisfied demand was minimized as the objective function. The main novelty of this research was the constraint of the minimum percentage of demand that should have been fulfilled. They opined that this model could offer a suitable opportunity to efficiently utilize resources and eliminate the delays. The maximum number of disaster units considered in their study was 500, which required 231035 seconds of computational time on a PC with 3 GHz CPU and 2 GB RAM to solve by CPLEX.

Wang et al., (2014) investigated a non-linear model with multiple objectives to plan a relief supply chain. The first objective minimized the maximum traveling time of vehicles, the second one minimized the costs of RD, and the third one maximized the minimum accessibility of routes. The main novelties of this research were to reflect split delivery considerations in the delivery process of relief items and to define the first and third objective functions. Also, two MHAs were applied to solve the addressed model. The maximum number of disaster units considered in their study was 120, which required 3989 seconds of computational time on a PC with 2.67 GHz CPU and 512 MB RAM to solve by MHA. In an attempt to maximize the recipient demand satisfaction and residual budget, a multi-level LR model under an uncertain state was proposed by (Rennemo et al., 2014). Also, they employed an SP approach, in order to overcome the uncertainties of demand, supplies, availability of vehicles and infrastructure. The location decisions of local distribution centers and the quantity of supply were determined at the first level. In what follows, the distribution decisions of last-mile routes and the resource arrangements were ascertained at the second and third levels, respectively. Moreover, presenting a synchronized configuration for discussed decisions, the types of objective functions, improvising adequate linkage between consecutive stages, and developing a set of efficiency constraints were the novelties of this study. The maximum number of disaster units considered in their study was 250, which required 3500 seconds of computational time on a PC with 3.40 GHz CPU and 16 GB RAM to solve by CPLEX. Abounacer et al., (2014) investigated a multi-objective LR optimization model to minimize traveling time, aid distribution facilities and unfulfilled demand. The main novelty of this study was related to the solution methodology, which was comprehended from the epsilon-constraint method. The maximum number of disaster units considered in their study was 45, which required 30038 seconds of computational time on a PC with 3.2 GHz CPU and 4 GB RAM to solve by CPLEX.

A non-linear LR optimization model to minimize the total evacuated time under considerations of traffic assignment was proposed by (Bayram et al., 2015). Computation of traffic flow on each arc and the restriction concerning maximum route length was the main novelties of this research. In the phase of location problem, the purpose was to determine the best locations of provisional shelters. What is more, they utilized order cone programming techniques to solve the proposed model. The maximum number of disaster units considered in their study was 416, which required 1907.59 seconds of computational time on a PC with 2.4 GHz CPU and 16 GB RAM to solve by CPLEX. In order to formulate an HLN by considering the uncertainties of demand, supply capacity, availability of roads and inventory level, two multi-period LR models were proposed by (Moreno et al., 2016). Moreover, they employed an SP approach to surmount the challenges of these uncertainties. The opportunity of reusing vehicles to cover additional routes, and ascertaining the fleet sizing of them were the main novelties of this research. Moreover, relax-and-fix and fix-and-optimize were offered as two HAs, in order to solve the proposed model. The maximum number of disaster units considered in their study was 10, which required 3600 seconds of computational time on a PC with 2.4 GHz CPU and 16 GB RAM to solve by CPLEX. Bozorgi-Amiri and Khorsi (2016) presented a multi-objective multi-period HLN model under an uncertain state, where the objective functions were to minimize the maximum unfulfilled demand, the vehicle traveling time and total costs. Also, they employed an SP approach in order to overcome the uncertainties of demand, cost and travel time. Considering the constraints of inventory balance among facilities was the main noticeable aspect of this study. Additionally, an ε-constraint method was utilized to solve the proposed model. The maximum number of disaster units considered in their study was 6, and numerical studies were implemented by CPLEX on a PC with 2.3 GHz CPU and 4 GB RAM. A multi-period multi-objective HLN was proposed by (Tavana et al., 2018) to minimize the total relief time and costs. Even though they reflected the considerations of perishable commodities, there was not any unique constraint to manage the requirements of this type of commodities. The noticeable feature of this research was to propose a reference point based non-dominated sorting genetic algorithm-II to solve the proposed model. The maximum number of disaster units considered in their study was 60, which required 64.84 seconds of computational time on a PC with 3.6 GHz CPU and 16 GB RAM to solve by MHA.

Vahdani et al., (2018a) formulated a bi-level multi-objective multi-period HLN under an uncertain state, where the objective function of the upper-level was to minimize the total costs and objective functions of lower-level were to minimize the traveling costs, traveling time, and to maximize the reliability of routes with respect to the hard time windows constraints. As a matter of fact, the upper-level ascertained the facilities' locations, the levels of capacity and inventory of them, and the lower-level model determined the routes of vehicles. The noticeable feature was related to the vehicle scheduling considerations. Also, they employed an RO approach, in order to overcome the uncertainties of travel time, capacities of facilities and route reliability. What is more, an extension of this model under a split delivery assumption was introduced. Also, they applied two MHAs to solve the proposed model. The maximum number of disaster units considered in their study was 200, which required 634.58 seconds of computational time on a PC with 3.6 GHz CPU and 8 GB RAM to solve by MHA. Veysmoradi al., (2018) formulated an HLN under an uncertain state in terms of the multi-objective optimization model, where the objective functions were to minimize the total costs, the vehicle traveling time, and to maximize the minimum route reliability. The noticeable features were comprehended two dissimilar transportation modes, including helicopter and vehicle for the VRP stage. Also, they utilized an RO approach in order to overcome the uncertainties of costs and aids. In this study, likewise to the studies, which were proposed by (Wang et al., 2014) and (Vahdani et al., 2018a), the assumption of split delivery was also reflected. The maximum number of disaster units considered in their study was 11, which required 14 minutes and 37 seconds of computational time on a PC with 3.6 GHz CPU and 8 GB RAM to solve by BARON. Vahdani et al., (2018b) formulated a multi-objective multi-period relief logistics network, where the objective functions were similar to previous research. The noticeable aspect of this study was related to the possibility of repairing the emergency roadway. Also, they employed two MHAs to solve the proposed model. The maximum number of disaster units considered in their study was 65, which required 655.781 seconds of computational time on a PC with 3.6 GHz CPU and 8 GB RAM to solve by MHA.

Moreno et al., (2018) formulated an HLN under an uncertain environment in terms of the multi-objective multi-period optimization model, where the objective functions were to minimize the human suffering and total costs. Also, they utilized a two-stage SP approach to surmount the uncertainties of demand, supply and availabilities of roads. The novelties of this research were to consider the possibility to reuse vehicles for multi-trip planning and to reflect social concerns considerations. Furthermore, a heuristic algorithm was offered to solve the presented model. The maximum number of disaster units considered in their study was 5, which required 571.3 seconds of computational time on a PC with 3.2 GHz CPU and 32 GB RAM to solve by CPLEX. Çankaya et al., (2018) formulated an HLN in terms of a bi-level optimization model, where the upper-level objective function was to minimize total costs, and the lower-level one was to maximize the minimum safety stock level. The location decisions were to determine at the upper level, and the routing and scheduling decisions were ascertained at the lower level. The novelty of this research was to reflect the considerations of slack. More importantly, a multi-stage HA was sketched to solve the different phased of the proposed model, ranging from clustering to routing. The maximum number of disaster units considered in their study was 100, which required 215.14 seconds of computational time on a PC with 2.4 GHz CPU and 24 GB RAM to solve by CPLEX. With the intention of distributing reliefs and evacuating survivors, three mathematical models were formulated by (Setiawan et al. 2019). The objective functions of these models minimized the victim's suffering. The first model formulated in terms of bi-level programming, and the second one rendered an integrated model. Also, the third model offered a synchronized framework to share the necessitated vehicles between RD and VE. The noticeable constraints were related to the computation of vehicle resources and combinations of trips. What is more, a heuristic algorithm was also rendered to solve the proposed model. The maximum number of disaster units considered in their study was 47, and numerical studies were implemented by Xpress MP on a PC with 3 GHz CPU and 4 GB RAM. Another study concerning synchronizing RD and VE under an uncertain environment in terms of multi-objective multi-period mathematical mode was proposed by (Ghasemi et al., 2019), where the objective functions were to minimize total costs and the amount of the shortage of relief commodities. The noticeable features were to consider different types of injuries and different types of facilities, including destroyable and indefectible. Moreover, two MHAs were proposed to solve the model. The maximum number of disaster units considered in their study was 10, which required 139 seconds of computational time on a PC with 2.5 GHz CPU and 8 GB RAM to solve by MHA.

As can be seen in the above-mentioned description, in these valuable studies have been endeavored to organize a number of necessitated items such as facilities and means of transport to managing the repercussions of disaster in an HLN. Although, a number of critical and practical concerns have not been considered due to the expansion of the subject, which this research has tried to take care of a limited number of them. The first one concerns aftershocks after the mainshock, which could have a significant negative influence on the determined decisions in the whole of these studies. The second one relates to synchronizing location and routing decisions under aftershocks' concerns. Although there are a number of magnificent research studies in the literature of reliable facility location to driving down the negative impacts of disruptions, there is a lack of a framework to integrate location and routing decisions, especially where the customer assignment probabilities should be computed. The third one concerns the fair distribution of relief items, which could have significant impacts on survivors, both psychologically and helpfully. In this regard, organizing several decisions, including supply, equitable assignment, and distribution in the same as the quota, are momentous. Last but not least, in most of these studies, RO has been employed to surmount the challenges of uncertainties. Meanwhile, some estimations could be provided for a limited number of uncertain parameters under inconsistent, imprecise, and vague information. Hence, providing a hybrid approach to simultaneously consider the lack of information alongside inconsistent, imprecise, and vague information is indispensable. So as to demonstrate the research gap and our contributions, a comparative table of the investigated studies on location-routing models in relief logistics network design is offered in **Table 1**.

Table 1. A comparative literature review

Authors and Year	Objective Function		Type of Research		Condition		Uncertain Approach		Planning system		Fairness in Distribution	Aftershock/ Reliable Location	Transportation Mode		Solver	Maximum number of disaster units
	Single	Multiple	Theoretical	Case Study Based	Certain	Uncertain	Singular	Mixed	Victim Evacuation	Relief Distribution			Single	Multiple		
Yi and Ozdamar (2007)	✓			✓	✓				✓	✓				✓	CPLEX	60
Doerner et al., (2007)		✓		✓	✓								✓		MHA	500
Mete and Zabinsky (2010)		✓		✓		✓	✓			✓			✓		CPLEX	10
Oran et al., (2012)		✓	✓		✓					✓				✓	MHA	100
Afshar and Haghani (2012)	✓			✓	✓					✓				✓	CPLEX	500
Wang et al., (2014)		✓		✓	✓					✓			✓		MHA	120
Rennemo et al., (2014)	✓			✓	✓		✓			✓				✓	CPLEX	250
Abounacer et al., (2014)		✓	✓		✓					✓				✓	CPLEX	45
Bayram et al., (2015)	✓		✓		✓				✓				✓		CPLEX	416
Moreno et al., (2016)	✓			✓		✓	✓			✓				✓	CPLEX	10
Bozorgi-Amiri and Khorsi (2016)		✓		✓		✓	✓			✓				✓	CPLEX	6
Tavana et al., (2018)		✓	✓		✓					✓			✓		MHA	60
Vahdani et al., (2018a)		✓	✓			✓	✓			✓			✓		MHA	200
Veysmoradi al., (2018)		✓		✓		✓	✓			✓				✓	BARON	11
Vahdani et al., (2018b)		✓	✓		✓					✓			✓		MHA	65
Moreno et al., (2018)		✓		✓		✓	✓			✓				✓	CPLEX	5
Çankaya et al., (2018)		✓	✓		✓					✓			✓		CPLEX	100
Setiawan et al., (2019)	✓		✓		✓				✓	✓				✓	Xpress MP	47
Ghasemi et al., (2019)		✓		✓		✓	✓		✓	✓			✓		MHA	10
Current research		✓		✓		✓		✓	✓	✓	✓	✓		✓	BARON	10

3. Problem definition and formulation

In this paper, a multi-echelon HLN, including suppliers, distribution centers, disaster units, emergency centers, and hospitals, is considered. Suppliers could provide the essentials needed and relief items for distribution centers by vehicles such as trucks, trailers, and aircraft. In the following, distribution centers allocate these relief items among disaster units. Also, with the intention of improving service recipients, enhancing the accuracy of plans, reducing planning time, and increasing utilization of resources, truck routing between distribution centers and disaster units is considered. It is worth noting that after completing the mission, these trucks should return to the starting point.

Moreover, in an attempt to provide a fairness distribution of relief items among survivors, which have been stored in distribution centers, a service level gap as a constraint is considered to ascertain the best allocation of relief items with regard to the available supply. This gap could be considered for the disaster units with dissimilar facility providers, and it to be zero among disaster units that have similar facility providers. Meanwhile, so as to mitigate the repercussions of aftershocks and design a reliable relief logistics network, the possibility of failure of distribution centers is considered, and an efficient approach, which was proposed by Aboolian et al., (2012), is utilized to overcome this challenge. With the intention of evacuating injured people, there are two alternatives, including transferring them from disaster units to hospitals and transferring them through emergency centers as transitional points to hospitals. In fact, in the real situation of a disaster, a number of injured people are taken to emergency centers, and after examining their physical condition, the decision of transferring them to the hospitals would be made. Needless to say, people with serious injuries are transported to hospitals directly. The decisions which are made in this problem are included setting up suppliers, opening provisional locations of distribution centers and emergency centers, determining assignment probability, routing of trucks between disaster units and distribution centers, and a number of allocations, including classical and equitable allocations concerning evacuating injured people and distributing relief items. What is more, **Fig. 1** provides a road map for better illustrating the connections among the comprehensive, decision, and mathematical visions. **Fig. 2** depicts a graphic demonstration of the investigated problem. The main assumptions, which are considered in this research, are as follows:

- Distribution centers could be encountered with disruption due to the aftershocks.
- There is not any connection between distribution centers.
- The locations of suppliers, distribution centers, and emergency centers are undefined.
- A number of influential parameters such as demand, costs, transportation time, the capacity of supply, the percentage of injured people who should be dispatched from the emergency center to hospital, and the capacity of facilities are uncertain.

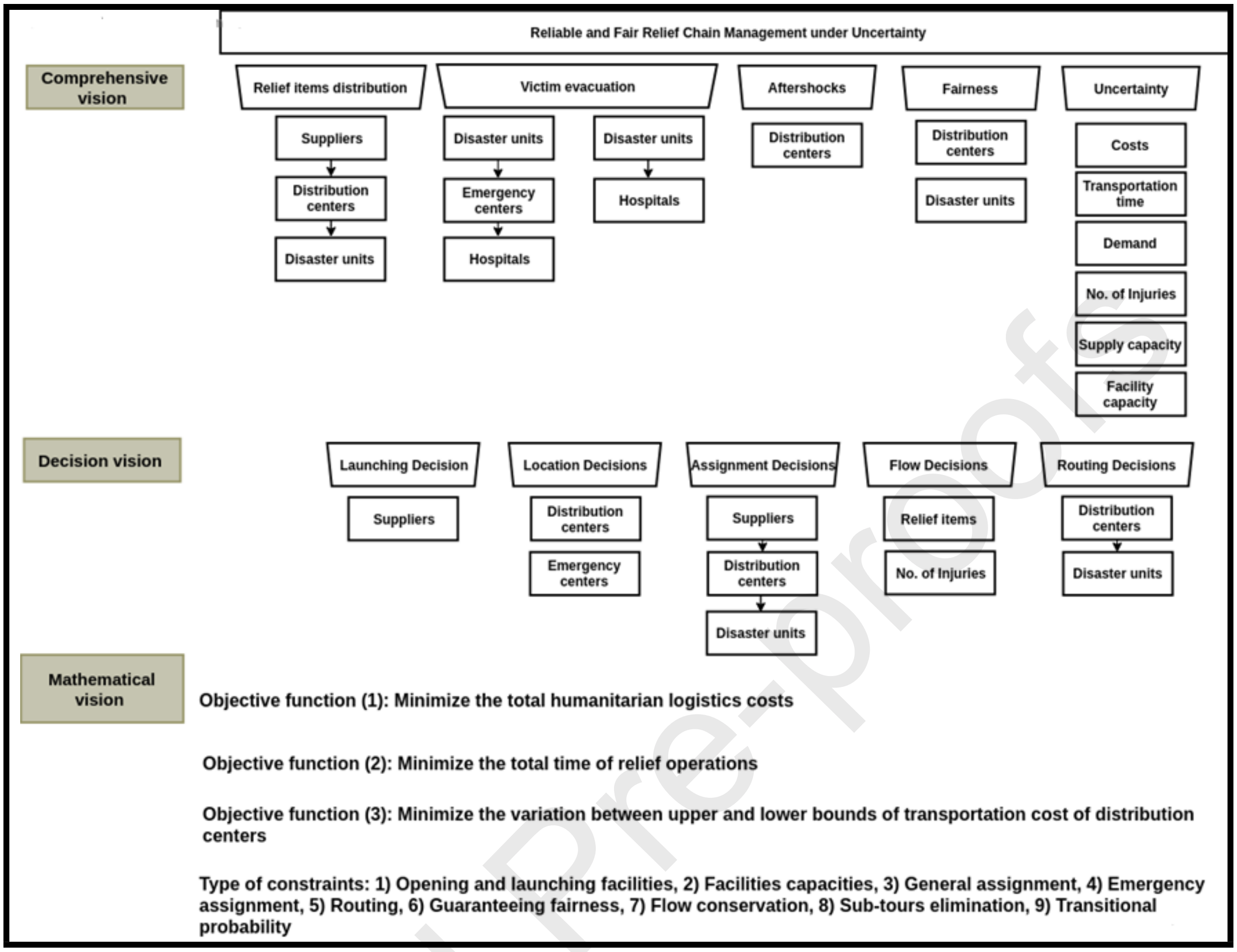

Fig 1. A road map for illustrating the various levels of planning

3.1. Sets and indices

(k,j,i,l,r,s,n,h,v): Indices for nodes
K: Set of potential suppliers
J: Set of potential distribution centers
E: Set dummy distribution centers
I: Set of disaster units
R: Assignment levels
N: Set of potential emergency centers
H: Set of hospitals
V: Set of vehicles
M: Set of all nodes $\{I,J,E\}$

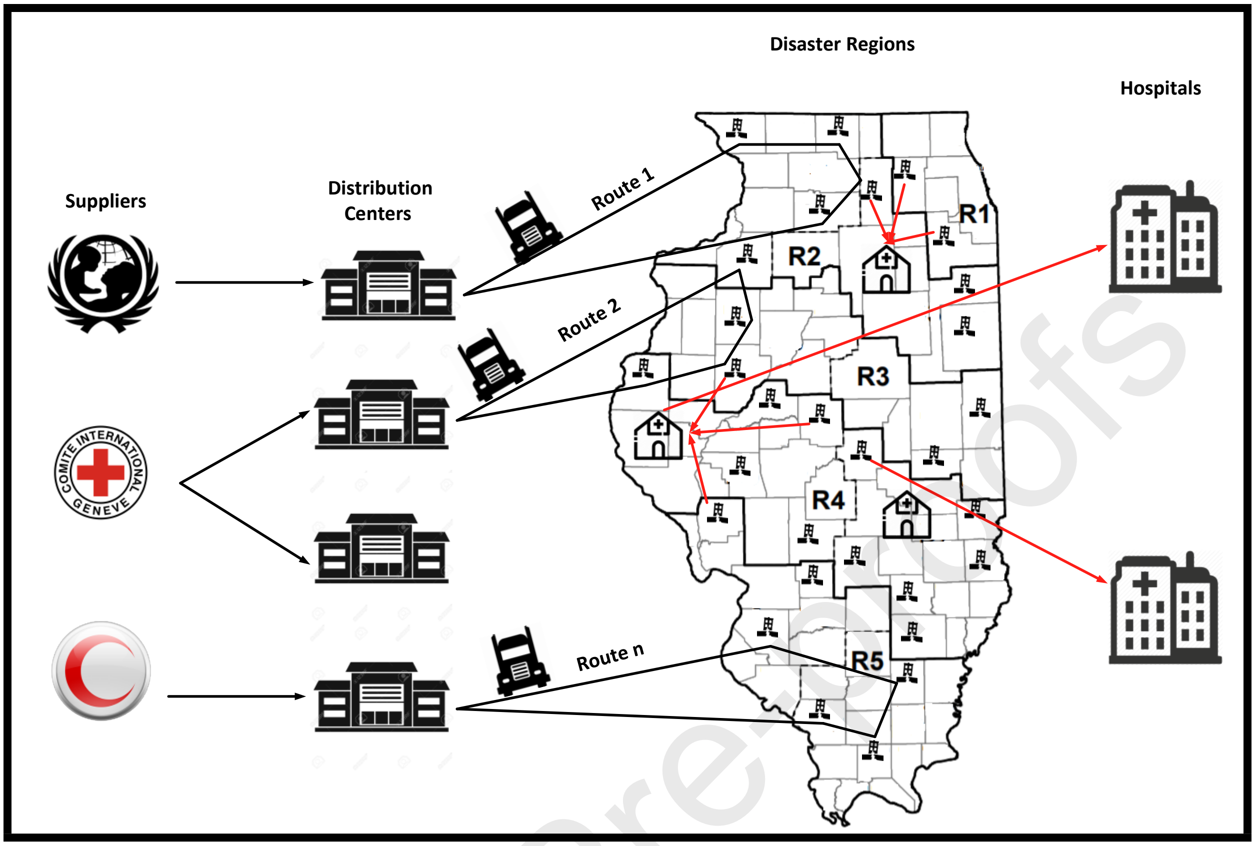

Fig.2. The graphic demonstration of the investigated problem

3.2. Parameters

$\tilde{d}_i$: Demand of disaster unit i

ρ: Service level gap ($\rho \leq 1$)

$\widetilde{CAS}_k$: Capacity of supplier k

$\widetilde{CAE}_n$: Capacity of emergency center n

$\widetilde{CAH}_h$: Capacity of hospital h

CAV_v: Capacity of vehicle v

$\tilde{T}_j^{max}$: Maximum supply capacity of distribution center j

$\widetilde{cw}_k$: Constant setting up cost of supplier k

$\tilde{f}_j$: Constant opening cost of distribution center j

$\widetilde{cf}_n$: Constant opening cost of emergency center n

$\widetilde{cu}_{kj}$: Transportation cost of relief items from supplier k to distribution center j

$\widetilde{fv}_v$: Transportation cost per distance traveled by vehicle v

$\widetilde{cq}_{ij}$: Preparation cost of relief items based on the demand of disaster unit i at distribution center j

$\widetilde{ct}_{1in}$: Dispatching cost per injured person from disaster unit i to emergency center n

$\widetilde{ct}_{2nh}$: Dispatching cost per injured person from emergency center n to hospital h

$\widetilde{ct}_{3ih}$: Dispatching cost per injured person from disaster unit i to hospital h

$\widetilde{wd}_i$: Number of injuries at disaster unit i
$\tilde{\tau}_{1in}$: Transportation time per injured person from disaster unit i to emergency center n
$\tilde{\tau}_{2nh}$: Transportation time per injured person from emergency center n to hospital h
$\tilde{\tau}_{3ih}$: Transportation time per injured person from disaster unit i to hospital h
q_j: Probability of failure of distribution center j
dis_{ji}: Distance between node$j$ and node i
δ_v: Speed of vehicle v
γ: Capacity of dispatching injured people
$\tilde{\mu}$: The percentage of injured people who should be dispatched from the emergency center to hospital
$\mathcal{M}$: A sufficient big number

3.3. Decision variables

w_k: 1 if supplier k is selected for setting up; 0 otherwise
Z_j: 1 if the distribution center is opened at location j; 0 otherwise
φ_n: 1 if the emergency center is opened at location n; 0 otherwise
kh_{kj}: 1 if distribution center j is assigned to supplier k; 0 otherwise
y_{jir}: 1 if distribution center j is assigned to disaster unit i at level r
vr_{jivr}: 1 if node j is on the route of the vehicle v before node i at assignment level r; 0 otherwise
x_{jvr}: 1 if distribution center j is on the route of the vehicle v at assignment level r; 0 otherwise
u_{kj}: Number of relief items transported from supplier k to distribution center j
T_{ji}: Number of relief items transported from distribution center j to disaster unit i
gd_i: Number of relief items allocated to disaster unit i
P_{ijr}: The probability that distribution center j serves disaster unit i at assignment level r
fx_{in}: Number of injuries dispatched from disaster unit i to emergency center n
mx_{nh}: Number of injuries dispatched from emergency center n to hospital h
hx_{ih}: Number of injuries dispatched from disaster unit i to hospital h
uu_{ivr}: Subtour elimination variable

3.4. Mathematical model

$$\min z_1 = \sum_{k\epsilon K}\tilde{cw}_k\, w_k + \sum_{j\epsilon J}\tilde{f}_j\, Z_j + \sum_{n\epsilon N}\tilde{cf}_n\, \varphi_n + \sum_{i\epsilon I}\sum_{n\epsilon N}\tilde{ct}_{1in}\, fx_{in} + \sum_{n\epsilon N}\sum_{h\epsilon H}\tilde{ct}_{2nh}\, mx_{nh} + \sum_{i\epsilon I}\sum_{h\epsilon H}\tilde{ct}_{3ih}\, hx_{ih} + \sum_{j\epsilon J\cup E}\sum_{k\epsilon K}\tilde{cu}_{kj}\, u_{kj} + \sum_{i\epsilon I}\sum_{j\epsilon J\cup E}\sum_{r=1}^{J+1}\tilde{cq}_{ij}\, P_{ijr}\, y_{jir} + \sum_{j\epsilon M}\sum_{i\epsilon M}\sum_{v\epsilon V}\sum_{r=1}^{J+1}\tilde{fv}_v\, dis_{ji}\, vr_{jivr} \quad (1)$$

$$\min z_2 = \sum_{i\epsilon M}\sum_{j\epsilon M}\sum_{v\epsilon V}\sum_{r=1}^{J+1}\frac{dis_{ji}\, vr_{jivr}}{\delta_v} + \sum_{i\epsilon I}\sum_{n\epsilon N}\sum_{h\epsilon H}\left(\frac{\tilde{\tau}_{1in}\, fx_{in} + \tilde{\tau}_{2nh}\, mx_{nh} + \tilde{\tau}_{3ih}\, hx_{ih}}{\gamma}\right)$$

(2)

$$\min z_3 = \underset{j\epsilon J\cup E}{\arg max}\left\{\sum_{i\epsilon M}\sum_{j\epsilon M}\sum_{v\epsilon V}\sum_{r=1}^{J+1}\widetilde{fv}_v\, dis_{ji}\, vr_{jivr}\right\} - \underset{j\epsilon J\cup E}{\arg min}\left\{\sum_{i\epsilon M}\sum_{j\epsilon M}\sum_{v\epsilon V}\sum_{r=1}^{J+1}\widetilde{fv}_v\, dis_{ji}\, vr_{jivr}\right\}$$

(3)

The first objective function (1) minimizes the total humanitarian logistics costs, in which the first to third terms calculate the setting up and opening costs of suppliers, distribution centers and emergency centers, respectively. The fourth to sixth terms calculate the dispatching cost of injured people among facilities, including disaster units, emergency centers, and hospitals. The seventh term computes the transportation costs between suppliers and distribution centers. The eighth term calculates preparation costs of relief items, and the ninth term computes the transportation costs of vehicle routing among distribution centers and disaster units. The second objective function (2) minimizes the total time of relief operations, in which the first term computes the time of distributing relief, and the second term calculates the time of dispatching injured people. The third objective function (3) minimizes the variation between upper and lower bounds of transportation cost of distribution centers to regulate the workload of them.

S.t.:

$$\sum_{n\epsilon N} fx_{in} + \sum_{h\epsilon H} hx_{ih} = \widetilde{wd}_i \qquad \forall\ i\epsilon I$$

(4)

$$\sum_{h\epsilon H} mx_{nh} \le \mathcal{M}.\varphi_n \qquad \forall\ n\epsilon N$$

(5)

$$\sum_{h\epsilon H} mx_{nh} \le \tilde{\mu}\,.\sum_{i\epsilon I} fx_{in} \qquad \forall\ n\epsilon N$$

(6)

$$\sum_{i\epsilon I} fx_{in} \le \widetilde{\mathcal{CA}E}_n\, \varphi_n \qquad \forall\ n\epsilon N$$

(7)

$$\sum_{i\epsilon I} hx_{ih} + \sum_{n\epsilon N} mx_{nh} \le \widetilde{\mathcal{CA}H}_h \qquad \forall\ h\epsilon H$$

(8)

Constraint (4) ensures that the number of injured people transferred from each disaster unit to emergency centers and hospitals is equal to the number of injuries in that disaster unit. Constraint (5) ensures that emergency centers have been opened by the time they could provide transmission service. Constraint (6) ensures that the flow of injured people between disaster units and hospitals through emergency centers. Constraints (7) to (8) signify the restriction capacities of emergency centers and hospitals. Also, constraint (7) ensures that emergency centers have been opened by the time they could provide related service.

$$\sum_{k\epsilon K} u_{kj} = \sum_{i\epsilon I} \sum_{r=1}^{J+1} T_{ji}\, y_{jir} \qquad \forall\ j\epsilon J \cup E \tag{9}$$

$$\sum_{j\epsilon J \cup E} u_{kj} \le \widetilde{\mathcal{CAS}}_k\, w_k \qquad \forall\ k\epsilon K \tag{10}$$

$$kh_{kj} \le w_k \qquad \forall\ j\epsilon\, J \cup E\ , \forall\ k\epsilon K \tag{11}$$

$$\sum_{k\epsilon K} kh_{kj} = 1 \qquad \forall\ j\epsilon\, J \cup E \tag{12}$$

Constraint (9) guarantees that the amount of relief items transferred from suppliers to each distribution center is equal to the amount of supplied relief items to the whole of disaster units, which have been assigned to that distribution center. Constraint (10) signifies the restriction capacity of suppliers. Also, constraints (10) and (11) ensure that suppliers have been launched by the time they could provide related service and could assign to a distribution center. Constraint (12) guarantees that a distribution center could be assigned to only one supplier.

$$T_{ji} \le \tilde{T}_j^{max} \sum_{r=1}^{J+1} y_{jir} \qquad \forall\ j\epsilon\, J \cup E\ \ , i\epsilon I \tag{13}$$

$$\sum_{i\epsilon I} T_{ji} \le \tilde{T}_j^{max}\, Z_j \qquad \forall\ j\epsilon J \tag{14}$$

Constraints (13) to (14) signify the restriction capacities of distribution centers. Also, constraint (13) ensures that a distribution center could send relief items to disaster units only if it serves those demand units. Constraint (14) guarantees that the distribution center has been opened by the time they could provide related service.

$$gd_i = \sum_{j\epsilon J \cup E} T_{ji} \qquad \forall\ i\epsilon I \tag{15}$$

$$gd_i \le \tilde{d}_i \qquad \forall\ i\epsilon I \tag{16}$$

$$\frac{gd_i}{\tilde{d}_i} \le \frac{gd_l}{\tilde{d}_l} . \rho \qquad \forall\ i\, , l\epsilon\, I\ \ , \ i \ne l \tag{17}$$

$$\frac{gd_i}{\tilde{d}_i} \le \frac{gd_l}{\tilde{d}_l} + \left(2 - \sum_{r=1}^{J+1} y_{jir} - \sum_{r=1}^{J+1} y_{jlr}\right) \qquad \forall\ i\, , l\epsilon\, I\ \ , i \ne l\ \ ,\ \ j\epsilon J \cup E \tag{18}$$

Constraint (15) specifies the number of relief items received by each disaster unit. Constraint (16) restricts the number of allocated relief items to disaster units. Constraint (17) defines the service gap, that is to say, the maximal ratio between the proportions of fulfilled demand at all disaster units. Constraint (18) states that all disaster units that are served by the identical distribution center will receive equal proportions of their demand. Constraints (17) and (18) denote an equitable allocation policy.

$$\sum_{r=1}^{J} y_{jir} \leq Z_j \qquad \forall\, j\epsilon J \;, i\epsilon I \tag{19}$$

$$\sum_{r=1}^{J+1} \sum_{j\epsilon E} y_{jir} = 1 \qquad \forall\, i\epsilon I \tag{20}$$

$$\sum_{j\epsilon J \cup E} y_{jir} + \sum_{j\epsilon E} \sum_{s=1}^{r-1} y_{jis} = 1 \qquad \forall\, i\epsilon I \,,\; 1 \leq r \leq J+1 \tag{21}$$

$$\sum_{r=1}^{J+1} y_{jir} \leq 1 \qquad \forall\, i\epsilon I \;, j\epsilon J \cup E \tag{22}$$

$$P_{ij1} = 1 - q_j \qquad \forall\; i\epsilon I \;, j\epsilon J \cup E \tag{23}$$

$$P_{ijr} = (1 - q_j) \sum_{l\epsilon J} \frac{q_l}{1 - q_l}\, P_{i,l,r-1}\, y_{i,l,r-1} \qquad \forall\; i\epsilon I \,, j\epsilon J \cup E \;, 2 \leq r \leq J+1 \tag{24}$$

Constraint (19) guarantees that disaster units are only allocated to the established distribution centers, and constraint (20) signifies that each disaster unit to be allocated to the dummy distribution center at a specified level. Constraint (21) guarantees that for each disaster unit i and each assignment level r, either i is allocated to a distribution center at assignment level r or it is allocated to the dummy distribution center at a specified level $s < r$. Constraint (22) restricts the allocation of each disaster unit to each distribution center on more than one assignment level. Constraints (23) and (24) are transitional equations of probability.

$$Z_j \geq x_{jvr} \qquad \forall\, j\epsilon J \cup E \;, v\epsilon V \,,\; 1 \leq r \leq J+1 \tag{25}$$

$$y_{jir} \geq vr_{jivr} \qquad \forall\, j\epsilon J \cup E \,,\; \forall i\epsilon I \,, v\epsilon V \,,\; 1 \leq r \leq J+1 \tag{26}$$

$$x_{jvr} \geq vr_{jivr} \qquad \forall\, j\epsilon M \,,\; \forall v\epsilon V \,,\; \forall i\epsilon I \,,\; 1 \leq r \leq J+1 \tag{27}$$

Constraint (25) ensures that a distribution center has been opened by the time it could be on the route of a vehicle to provide the required service. Constraint (26) ensures that a distribution center has been assigned to a disaster unit by the time it could be on the route of a vehicle to provide the required service. Constraint (27) ensures that a distribution center should have been on a route by the time it could provide related service.

$$\sum_{j\epsilon J\cup E}\sum_{r=1}^{J+1} x_{jvr} \leq 1 \qquad \forall\, v\epsilon V \tag{28}$$

$$\sum_{j\epsilon M}\sum_{v\epsilon V}\sum_{r=1}^{J+1} vr_{jivr} = 1 \qquad \forall\, i\epsilon I \tag{29}$$

$$\sum_{j\epsilon J\cup E}\sum_{i\epsilon I}\sum_{r=1}^{J+1} vr_{jivr} \leq 1 \qquad \forall\, v\epsilon V \tag{30}$$

Constraint (28) ensures that each vehicle could be assigned to only one distribution center. Constraint (29) ensures that each disaster unit is met only once. Constraint (30) ensures that each vehicle could be dispatched from only one distribution center.

$$\sum_{j\epsilon M} vr_{ijvr} + \sum_{j\epsilon M} vr_{ljvr} - y_{lir} \leq 1 \qquad \forall\, l\epsilon J\cup E,\ i\epsilon I,\ v\epsilon V,\ 1 \leq r \leq J+1 \tag{31}$$

$$\sum_{v\epsilon V}\sum_{r=1}^{J+1} vr_{jivr} \leq 1 \qquad \forall\, i,j\ \epsilon\ I,\ i \neq j \tag{32}$$

$$\sum_{i\epsilon M} vr_{jivr} - \sum_{i\epsilon M} vr_{ijvr} = 0 \qquad \forall\, j\epsilon M,\ v\epsilon V,\ 1 \leq r \leq J+1 \tag{33}$$

$$uu_{jvr} - uu_{ivr} + |M| * vr_{jivr} \leq |M| - 1 \qquad \forall\, i,j\ \epsilon I,\ v\epsilon V,\ 1 \leq r \leq J+1 \tag{34}$$

$$\sum_{j\epsilon M}\sum_{i\epsilon I}\sum_{r=1}^{J+1} \tilde{d}_i\, vr_{jivr} \leq \mathcal{CAV}_v \qquad \forall\, v\epsilon V \tag{35}$$

$$\sum_{r=1}^{J+1} vr_{jivr} = 0 \qquad \forall\ i,j\ \epsilon\ J\cup E,\ v\epsilon V \tag{36}$$

$$\varphi_n,\ w_k, z_j, kh_{kj}, y_{jir}, vr_{jivr}, x_{jvr} \in (0,1) \tag{37}$$

$$u_{kj}, T_{ji}, gd_i, p_{ijr}, fx_{in}, mx_{nh}, hx_{ih}, uu_{jvr} \geq 0 \tag{38}$$

Constraint (31) ensures that a disaster unit could be assigned to a distribution center if both are on the same route. Constraint (32) states that at most one vehicle could be selected for each route.

Also, connectivity constraints and sub tour elimination are guaranteed by constraints (33) to (34), respectively. Constraint (35) signifies the restriction capacities of vehicles, and constraint (36) guarantees that there is not any connection between distribution centers. Constraints (37) to (38) denote the types of decision variables.

4. Proposed uncertainty approach

Among the various uncertainty approaches, RO can be conducted, once DMs encounter the shortage of information, so this approach can be employed to optimize the system's performance under a worst-case situation. What is more, in a similar circumstance, DMs may favor employing the other uncertainty approaches such as miscellaneous fuzzy programming approaches, in order to surmount these uncertainties. Indeed, so as to surmount the challenges of ambiguity and uncertainty, the fuzzy set theory was presented by Zadeh (1965). In the course of time, different extensions of fuzzy sets have been developed in the related literature, including type 2, multi-sets, hesitant, intuitionistic, neutrosophic, Pythagorean fuzzy sets (Otay et al., 2017). The goal of these propagations is to render a better interpretation of imprecise and vague information. Since the intuitionistic fuzzy set (IFS) includes membership, non-membership and hesitancy functions, it is popular to surmount the vagueness and impreciseness (Ye, 2010). However, it cannot simulate the process of human decision making. With the intention of overcoming the obstacles of IFS, and handling inconsistent, imprecise and vague information, neutrosophic set (NS) was proposed by (Broumi et al., 2016a). Hence, NS theory can simulate the process of human decision making with respect to the entire features of the decision-making process. Indeed, NS is an extension of fuzzy and IFS such that each element of the set has the truth, indeterminacy and falsity membership functions, so NS can adapt vague, inaccurate and incompatible information effectively and efficiently (Deli and Şubaş, 2017a,b).

In the literature of HLN, a broad range of parameters have been considered under an uncertain environment, including demand, the capacity of facilities, cost, transportation time and etc. In this regard, the supply factors could be encountered with uncertainty due to the unknown amount of resource availability and vibrational contributions from suppliers and responsible entities. In addition, the availability level of vehicles such as trucks, ambulances, and the accessibility of infrastructures can beget uncertainty in cost parameters. Also, the fluctuation of relief items or the number of injuries, and inaccurate estimations can beget uncertainty in demand parameters. Therefore, in an attempt to overcome the challenges of uncertain humanitarian logistics environment, a new approach by integrating NS and RO is provided in this section, in which the uncertainty of cost and time parameters are handled by NS, and the other ones such as demand and supply, including the capacity of facilities, the number of injuries are handled by RO approach. Fig 3 illustrates an overview of the proposed uncertainty approach.

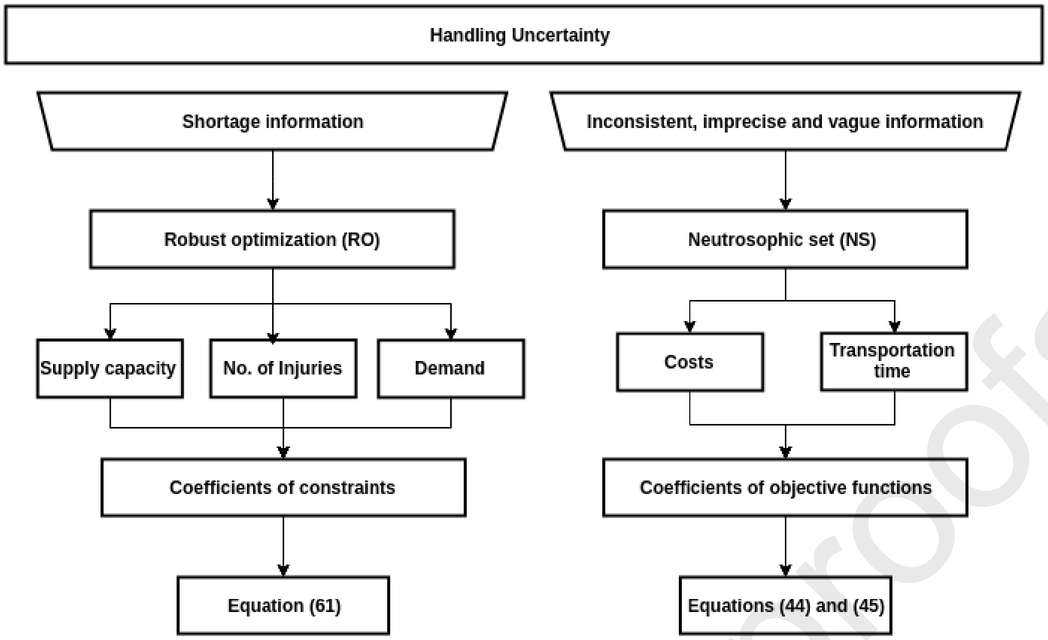

Fig 3. An overview of the proposed uncertainty approach

4.1. Mathematical Programming with Neutrosophic Number

4.1.1. Preliminaries of Trapezoidal Neutrosophic Number

Definition 1. Let $K = [a_1,a_2,a_3,a_4]$ be a trapezoidal fuzzy number (TFN) on R, which is the real number set, such that $a_1 \leq a_2 \leq a_3 \leq a_4$, and its membership function μ_K:$R \rightarrow [0,1]$ is described as follows (Broumi et al., 2016a):

$$\mu_K(x) = \begin{cases} \mu_K\left(\dfrac{x-a_1}{a_2-a_1}\right) & a_1 \leq x \leq a_2 \\ \mu_K & a_2 \leq x \leq a_3 \\ \mu_K\left(\dfrac{a_4-x}{a_4-a_3}\right) & a_3 \leq x \leq a_4 \\ 0 & \text{otherwise.} \end{cases} \quad (39)$$

when $a_2 = a_3$, the TFN is converted to a triangular fuzzy number.

Definition 2. Consider that X be a set of points or objects, with a common component in X signified by x. A single-valued neutrosophic set (SVNS) V in X is defined by three separate segments, including truth (T_V), indeterminacy (I_V), and falsity(F_V) membership functions, so that T_V:$X \rightarrow [0,1]$, I_V :$X \rightarrow [0,1]$, and F_V:$X \rightarrow [0,1]$. For notational ease, V is regularly signified as $V = \{< x,(T_V(x), I_V(x), F_V(x)) > |x \in X\}$ and satisfies $0 \leq T_V(x) + I_V(x) + F_V(x) \leq 3$.

A component in an SVNS, which is named single-valued neutrosophic number (SVNN), is represented by crisp numbers; it is comprehended to a discrete set and cannot truly describe fuzzy information. So as to surmount this obstacle, a continuous set was extended by (Ye, 2015) with integrating the concepts of TFNs and SVNS to introduce the single-valued neutrosophic trapezoidal numbers (SVTNNs).

Definition 3. Let $T_{\tilde{a}}, I_{\tilde{a}}, F_{\tilde{a}} \in [0,1]$; a SVTNN $\tilde{a} =< [a_1,a_2,a_3,a_4],(T_{\tilde{a}}, I_{\tilde{a}}, F_{\tilde{a}}) >$ be a special NS on R, whose truth $(\mu_{\tilde{a}})$, indeterminacy $(v_{\tilde{a}})$, and falsity$(\lambda_{\tilde{a}})$ membership functions are defined as follows (Broumi et al., 2016a):

$$\mu_{\tilde{a}}(x) = \begin{cases} (x-a_1)T_{\tilde{a}}/(a_2-a_1) & a_1 \le x \le a_2 \\ T_{\tilde{a}} & a_2 \le x \le a_3 \\ (a_4-x)T_{\tilde{a}}/(a_4-a_3) & a_3 \le x \le a_4 \\ 0 & \text{otherwise.} \end{cases} \tag{40}$$

$$v_{\tilde{a}}(x) = \begin{cases} (a_2-x+I_{\tilde{a}}(x-a_1))/(a_2-a_1) & a_1 \le x \le a_2 \\ I_{\tilde{a}} & a_2 \le x \le a_3 \\ (x-a_3+I_{\tilde{a}}(a_4-x))/(a_4-a_3) & a_3 \le x \le a_4 \\ 0 & \text{otherwise.} \end{cases} \tag{41}$$

$$\lambda_{\tilde{a}} = \begin{cases} (a_2-x+F_{\tilde{a}}(x-a_1))/(a_2-a_1) & a_1 \le x \le a_2 \\ I_{\tilde{a}} & a_2 \le x \le a_3 \\ (x-a_3+F_{\tilde{a}}(a_4-x))/(a_4-a_3) & a_3 \le x \le a_4 \\ 0 & \text{otherwise.} \end{cases} \tag{42}$$

Once $a_1 > 0$, $\tilde{a} =< [a_1,a_2,a_3,a_4],(T_{\tilde{a}}, I_{\tilde{a}}, F_{\tilde{a}}) >$ is termed a positive SVTNN, signified by $\tilde{a} > 0$. Likewise, once $a_4 \le 0$, $\tilde{a} =< [a_1,a_2,a_3,a_4],(T_{\tilde{a}}, I_{\tilde{a}}, F_{\tilde{a}}) >$ is termed a negative SVTNN, signified $\tilde{a} < 0$. Once $0 \le a_1 \le a_2 \le a_3 \le a_4 \le 1$and $T_{\tilde{a}}, I_{\tilde{a}}, F_{\tilde{a}} \in [0,1]$, $\tilde{a}$ is termed a normalized SVTNN (Broumi et al., 2016a).

Once $I_{\tilde{a}} = 1 - T_{\tilde{a}} - F_{\tilde{a}}$, the SVTNN is converted to a trapezoidal intuitionistic fuzzy number (TIFN). Once $a_2 = a_3$, $\tilde{a} =< [a_1,a_2,a_3,a_4],(T_{\tilde{a}}, I_{\tilde{a}}, F_{\tilde{a}}) >$ converts to a single-valued triangular neutrosophic number (SVTrNN). Once $I_{\tilde{a}} = 0$,$F_{\tilde{a}} = 0$, an SVTNN is converted to a generalized TFN, $\tilde{a} =< [a_1,a_2,a_3,a_4],T_{\tilde{a}} >$.

Definition 4. Let R:$N(R)$→R be a ranking function of neutrosophic numbers (NNs), where $N(R)$ is a set of NNs defined on set of real numbers, which converts each NN into the crisp value. Let $\tilde{A} =< [a_1,a_2,a_3,a_4],(T_{\tilde{a}}, I_{\tilde{a}}, F_{\tilde{a}}) >$ and $\tilde{B} =< [b_1,b_2,b_3,b_4],(T_{\tilde{b}}, I_{\tilde{b}}, F_{\tilde{b}}) >$ are two SVTNNs, hence (Abdel-Basset, 2019):

- If $R(\tilde{A}) > R(\tilde{B})$ then $\tilde{A} > \tilde{B}$,
- If $R(\tilde{A}) < R(\tilde{B})$ then $\tilde{A} < \tilde{B}$,
- If $R(\tilde{A}) = R(\tilde{B})$ then $\tilde{A} = \tilde{B}$.

4.1.2. Mathematical Programming with SVNNs

Consider the following mathematical programming model, in which its parameters are SVNNs:

$$
\begin{aligned}
& Max\sum_{j=1}^{n}\tilde{c}_j x_j \\
& \text{S.t.:}\sum_{j=1}^{n}\tilde{a}_{ij}x_j \le \tilde{b}_i \quad \forall i=1,2,\ldots,m \\
& x_j \ge 0 \;\; \forall j=1,2,\ldots,n
\end{aligned} \tag{43}
$$

where $\tilde{c}_j = < [c_{j1},c_{j2},c_{j3},c_{j4}],(T_{\tilde{c}_j}, I_{\tilde{c}_j}, F_{\tilde{c}_j}) >$, $\tilde{a}_{ij} = < [a_{ij1},a_{ij2},a_{ij3},a_{ij4}],(T_{\tilde{a}_{ij}}, I_{\tilde{a}_{ij}}, F_{\tilde{a}_{ij}}) >$ and $\tilde{b}_i = < [b_{i1},b_{i2},b_{i3},b_{i4}],(T_{\tilde{b}_i}, I_{\tilde{b}_i}, F_{\tilde{b}_i}) >$ are SVNNs. By utilizing the ranking function R, the equivalent crisp model of the model (43) is provided as follows (Abdel-Basset, 2019):

$$
\begin{aligned}
& Max\sum_{j=1}^{n}\left[\left(\frac{c_{j1}+c_{j4}+2(c_{j2}+c_{j3})}{2}\right)+\left(T_{\tilde{c}_j}-I_{\tilde{c}_j}-F_{\tilde{c}_j}\right)\right]x_j \\
& \text{S.t.:}\sum_{j=1}^{n}\left[\left(\frac{a_{ij1}+a_{ij4}+2(a_{ij2}+a_{ij3})}{2}\right)+\left(T_{\tilde{a}_{ij}}-I_{\tilde{a}_{ij}}-F_{\tilde{a}_{ij}}\right)\right]x_j \le \left[\left(\frac{b_{i1}+b_{i4}+2(b_{i2}+b_{i3})}{2}\right)\right. \\
& \qquad\qquad \left.+\left(T_{\tilde{b}_i}-I_{\tilde{b}_i}-F_{\tilde{b}_i}\right)\right] \quad \forall i=1,2,\ldots,m \\
& x_j \ge 0 \;\; \forall j=1,2,\ldots,n
\end{aligned} \tag{44}
$$

In what follows, if a mathematical model is a minimization problem, the equivalent crisp model is provided as bellows (Abdel-Basset, 2019):

$$
\begin{aligned}
& Min\sum_{j=1}^{n}\left[\left(\frac{c_{j1}+c_{j4}-3(c_{j2}+c_{j3})}{2}\right)+\left(T_{\tilde{c}_j}-I_{\tilde{c}_j}-F_{\tilde{c}_j}\right)\right]x_j \\
& \text{S.t.:}\sum_{j=1}^{n}\left[\left(\frac{a_{ij1}+a_{ij4}-3(a_{ij2}+a_{ij3})}{2}\right)+\left(T_{\tilde{a}_{ij}}-I_{\tilde{a}_{ij}}-F_{\tilde{a}_{ij}}\right)\right]x_j \le \left[\left(\frac{b_{i1}+b_{i4}-3(b_{i2}+b_{i3})}{2}\right)\right. \\
& \qquad\qquad \left.+\left(T_{\tilde{b}_i}-I_{\tilde{b}_i}-F_{\tilde{b}_i}\right)\right] \quad \forall i=1,2,\ldots,m \\
& x_j \ge 0 \;\; \forall j=1,2,\ldots,n
\end{aligned} \tag{45}
$$

4.2. Robust Optimization (RO)

In this section, with respect to the modern achievements in the field of RO, the definitions of the set-induced RO approach for the box polyhedral uncertainty set are presented. In this kind of RO, the uncertain parameters are changed in a specified uncertainty set, and the model attempts for those feasible solutions that protect the investigated system for the whole possible realizations from uncertainty set (Ben-Tal and Nemirovski, A., 2000). The main features of this kind of RO approach are 1) The independence of the statistical distribution of uncertain parameters, 2) maximum robustness of feasibility, 3) highly conservative and risk-averse, 4) providing the maximum degree of confidence.

4.2.1. Robust Mixed Integer Linear Optimization (MILP)

Regularly, consider the subsequent MILP problem

$$\max \sum_{m} c_m x_m + \sum_{k} d_k y_k$$

S.t.:

$$\sum_{m} \tilde{a}_{im} x_m + \sum_{k} \tilde{b}_{ik} y_k \leq \tilde{p}_i \quad \forall i \tag{46}$$

In this model, the continuous and integer decision variables are presented by x and y, respectively, and $\tilde{a}_{im}$, $\tilde{b}_{ij}$, $\tilde{p}_i$ exhibit uncertain parameters. With respect to the ith constraint of this model, these uncertain parameters can be defined as follows (Ben-Tal and Nemirovski, A., 2000; Bertsimas et al., 2012):

$$\tilde{a}_{im} = a_{im} + \xi_{im} \hat{a}_{im} \quad \forall m \in M_i \tag{47}$$

$$\tilde{b}_{ik} = b_{ik} + \xi_{ik} \hat{b}_{ik} \quad \forall k \in K_i \tag{48}$$

$$\tilde{p}_i = p_i + \xi_{i0} \hat{p}_i \tag{49}$$

where M_i and K_i exhibit the subsets that involve the continuous and integer decision variable indices whose equivalent technological coefficients and right-hand sides (RHSs) are susceptible to uncertainty, respectively; the nominal value of them are represented by a_{im}, b_{ik} and p_i; the positive constant perturbations are represented by $\hat{a}_{im}$, $\hat{b}_{ik}$ and $\hat{p}_i$; and the random variables which are susceptible to uncertainty are represented by ξ_{im}, ξ_{ik} and ξ_{i0}. With respect to the above-mentioned description, Eq. (46) can be reformulated as follows (Ben-Tal and Nemirovski, A., 2000):

$$\sum_{m \notin M_i} a_{im} x_m + \sum_{k \notin K_i} b_{ik} y_k + \sum_{m \in M_i} \tilde{a}_{im} x_m + \sum_{k \in K_i} \tilde{b}_{ik} y_k \leq \tilde{p}_i \tag{50}$$

In what follows, by classifying the uncertain parts, Eq. (50) can be rewritten as follows:

$$\sum_{m} a_{im} x_m + \sum_{k} b_{ik} y_k + \left\{ -\xi_{i0} \hat{p}_i + \sum_{m \in M_i} \xi_{im} \hat{a}_{im} x_m + \sum_{k \in K_i} \xi_{ik} \hat{b}_{ik} y_k \right\} \leq p_i \tag{51}$$

With regard to a predetermined uncertainty set U for $\xi = \{\xi_{i0}, \xi_{im}, \xi_{ik}\}$; the objective function attempts solutions that stay feasible for each ξ, in an attempt to protect against infeasibility, that is to say:

$$\sum_{m} a_{im} x_m + \sum_{k} b_{ik} y_k + \max_{\xi \in U} \left\{ -\xi_{i0} \hat{p}_i + \sum_{m \in M_i} \xi_{im} \hat{a}_{im} x_m + \sum_{k \in K_i} \xi_{ik} \hat{b}_{ik} y_k \right\} \leq p_i \tag{52}$$

Afterward, by substituting Eq. (52) for the original MILP problem, the set induced robust counterpart of Eq. (46) is as follows (Zhang et al., 2016):

$$\max \sum_m c_m x_m + \sum_k d_k y_k$$

S.t.:

$$\sum_m a_{im} x_m + \sum_k b_{ik} y_k + \max_{\xi \in U} \left\{ -\xi_{i0} \hat{p}_i + \sum_{m \in M_i} \xi_{im} \hat{a}_{im} x_m + \sum_{k \in K_i} \xi_{ik} \hat{b}_{ik} y_k \right\} \le p_i \tag{53}$$

It is worth noting that the formulation (53) pertains to the type of uncertainty set U.

4.2.2. Uncertainty Sets

In this section, the definitions of box, polyhedral and box polyhedral uncertainty sets are described. For simplicity's sake, we remove the index of constraint i in the random vector ξ.

Definition 5. The box uncertainty set can be defined utilizing the ∞-norm of the vector of uncertain data as follows (Ben-Tal and Nemirovski, A., 2000):

$$U_\infty = \{\xi | \|\xi\|_\infty \le \Psi\} = \{\xi | |\xi_j| \le \Psi, \forall j \in J_i\} \tag{54}$$

In Eq. (54), with the intention of regulating the size of uncertainty set, the adjustable parameter (Ψ) is considered. In the sequel, the configuration of box uncertainty set for the parameter $\tilde{a}_j$ is depicted in Fig 4. If the uncertain parameters can be recognized to be bounded in specified intervals $\tilde{a}_{ij} \in [a_{ij} - \tilde{a}_{ij}, a_{ij} + \tilde{a}_{ij}]\ \forall j \in J_i$, next, it can be described by $\tilde{a}_{ij} = a_{ij} + \xi_{j\tilde{a}_{ij}}$ and this derives in the interval uncertainty set, which is a particular state of box uncertainty set, when $\Psi = 1$ (i.e., $U_\infty = \{\xi | |\xi_j| \le 1, \forall j \in J_i\}$).

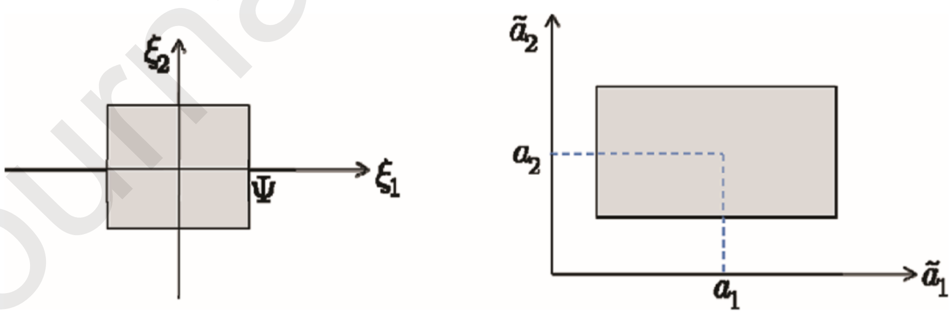

Fig. 4. Configuration of box uncertainty set.

Definition 6. The polyhedral uncertainty set can be defined utilizing the 1-norm of the vector of uncertain data as depicted in Fig. 5 (Ben-Tal and Nemirovski, A., 2000),

$$U_1 = \{\xi | \|\xi\|_1 \le \Gamma\} = \left\{\xi | \sum_{j \in J_i} |\xi_j| \le \Gamma,\ \forall j \in J_i \right\} \tag{55}$$

In Eq. (55), with the intention of regulating the size of uncertainty set, the adjustable parameter (Γ) is considered. It should be noted that for bounded uncertainty $\xi_j \in [-1,1]$, when $\Gamma \geq |J_i|$, this set covers the whole uncertain space.

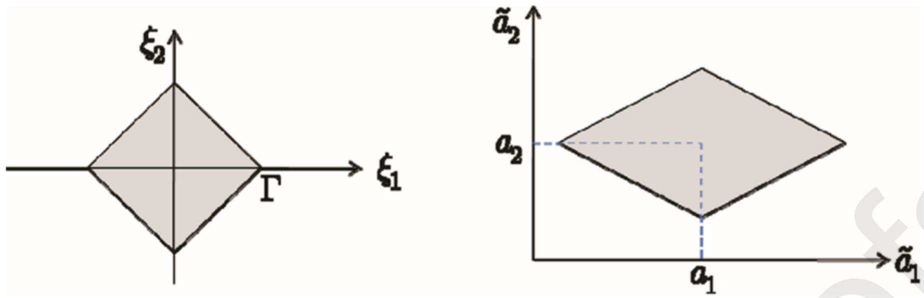

Fig. 5. Configuration of polyhedral uncertainty set.

Definition 7. Interval Polyhedral Uncertainty Set. The combination of the interval and polyhedral sets with respect to the both1 and ∞ norms can introduce the interval polyhedral uncertainty set as follows (Ben-Tal and Nemirovski, A., 2000):

$$U_{1\cap\infty} = \left\{ \xi | \sum_{j \in J_i} |\xi_j| \leq \Gamma,\ |\xi_j| \leq \Psi \qquad \forall j \in J_i \right\} \tag{56}$$

It is worth noting that by satisfying Eq. (57), which is the relationship between these two sets, the combination of them does not diminish to any one of them.

$$\Psi \leq \Gamma \leq \Psi |J_i| \tag{57}$$

Once $\Psi = 1$, this set describes the combination between these two sets, which is termed interval polyhedral uncertainty set. In this case, once $\Gamma = 1$, the polyhedron is precisely inscribed by the box and the combination of them is absolutely the polyhedron; once $\Gamma = |J_i|$, this combination is absolutely the box, as depicted in Fig. 6.

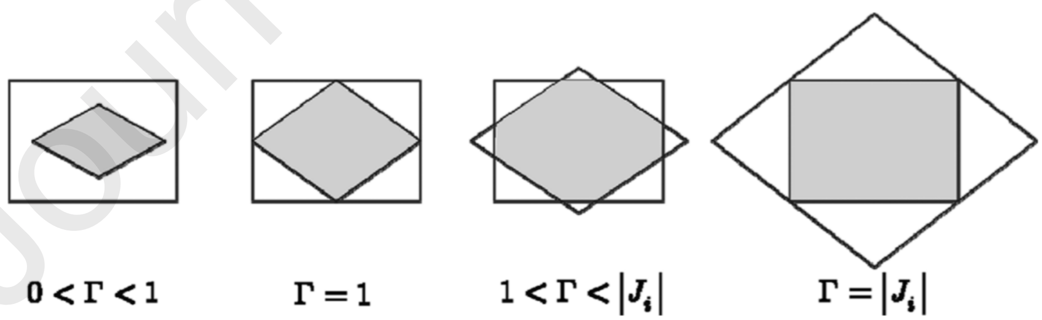

Fig. 6. Configuration of combined interval and polyhedral uncertainty set.

4.2.3. Robust Counterpart Formulation for MILP Based on the Interval Polyhedral Uncertainty Set

In an attempt to obtain robust solutions, we seek those solutions, which are feasible for any realization of the uncertain data with respect to the determined uncertainty set. In the sequel, a derivation approach is represented based on Eq. (53). So as to remove the interior maximization function in the ith constraint of Eq. (53), it is transformed into its conic dual, next the dual problem is incorporated into the original constraint. What is more by defining an auxiliary variable x_0, and extra constraint $x_0 = -1$, the initial ith constraint of Eq. (53) can be rewritten as follows (Ben-Tal and Nemirovski, A., 2000; Zhang et al., 2016):

$$p_i x_0 + \sum_m a_{im} x_m + \sum_k b_{ik} y_k + \max_{\xi \in U} \left\{ \xi_{i0} \hat{p}_i x_0 + \sum_{m \in M_i} \xi_{im} \hat{a}_{im} x_m + \sum_{k \in K_i} \xi_{ik} \hat{b}_{ik} y_k \right\} \leq 0 \tag{58}$$

where $\xi_i = [\xi_{i0};\{\xi_{im}\};\{\xi_{ik}\}]$, $A_i = [p_i;\{a_{im}\};\{b_{ik}\}]$, $\hat{A}_i = [\hat{p}_i;\{\hat{a}_{im}\};\{\hat{b}_{ik}\}]$, $X = [x_0;\{x_m\};\{y_k\}]$ and $j \in J_i = \{0\} \cup M_i \cup K_i$, so Eq. (58) can be rewritten as follows:

$$\sum_j A_{ij} X_j + \max_{\xi_i \in U} \left\{ \sum_{j \in J_i} \xi_{ij} \hat{A}_{ij} X_j \right\} \leq 0 \tag{59}$$

With respect to the above-mentioned description and removing the maximization function of Eq. (59), if the uncertainty set U is considered as Eq. (56) with $\Psi = 1$, the equivalent robust counterpart Eq. (59) is as follows:

$$\begin{aligned}
&\sum_m a_{im} x_m + \sum_k b_{ik} y_k + \left[z_i \Gamma_i + \sum_{m \in M_i} w_{im} + \sum_{k \in K_i} w_{ik} + w_{i0} \right] \leq p_i \\
&z_i + w_{im} \geq \hat{a}_{im} |x_m| \quad \forall m \in M_i \\
&z_i + w_{ik} \geq \hat{b}_{ik} |y_k| \quad \forall k \in K_i \\
&z_i + w_{i0} \geq \hat{p}_i
\end{aligned} \tag{60}$$

It should be noted that when the decision variables are positive, the absolute operator can be straightly eliminated. If not, the Eq. (60) can be rewritten as follows:

$$\begin{aligned}
&\sum_m a_{im} x_m + \sum_k b_{ik} y_k + \left[z_i \Gamma_i + \sum_{m \in M_i} w_{im} + \sum_{k \in K_i} w_{ik} + w_{i0} \right] \leq p_i \\
&z_i + w_{im} \geq \hat{a}_{im} u_m \quad \forall m \in M_i \\
&z_i + w_{ik} \geq \hat{b}_{ik} v_k \quad \forall k \in K_i \\
&z_i + w_{i0} \geq \hat{p}_i \\
&-u_m \leq x_m \leq u_m \quad \forall m \in M_i \\
&-v_k \leq y_k \leq v_k \quad \forall k \in K_i
\end{aligned} \tag{61}$$

5. Robust neutrosophic model

This section aims to develop the proposed deterministic HLN model to a robust neutrosophic counterpart model in which demand, costs, transportation time, the capacity of supply, the percentage of injured people who should be dispatched from the emergency center to hospital and capacity of facilities are uncertain. Based on the above-mentioned descriptions, the robust neutrosophic is conducted to the objective functions and uncertain constraints.

5.1. Objective functions

There are nine, three, and two uncertain coefficients in the first, second, and third objective functions, respectively, by utilizing model (45) it is transformed to the following neutrosophic counterpart objective functions:

$$\begin{aligned}
\min z_1 = &\sum_{k\epsilon K}\left[\left(\frac{cw_{k1}+cw_{k4}-3(cw_{k2}+cw_{k3})}{2}\right)+\left(T_{\tilde{cw}_k}-I_{\tilde{cw}_k}-F_{\tilde{cw}_k}\right)\right]w_k+\sum_{j\epsilon J}\left[\left(\frac{f_{j1}+f_{j4}-3(f_{j2}+f_{j3})}{2}\right)+\left(T_{\tilde{f}_j}-I_{\tilde{f}_j}-F_{\tilde{f}_j}\right)\right]Z_j\\
&+\sum_{n\epsilon N}\left[\left(\frac{cf_{n1}+cf_{n4}-3(cf_{n2}+cf_{n3})}{2}\right)+\left(T_{\tilde{cf}_n}-I_{\tilde{cf}_n}-F_{\tilde{cf}_n}\right)\right]\varphi_n\\
&+\sum_{i\epsilon I}\sum_{n\epsilon N}\left[\left(\frac{ct_{1in1}+ct_{1in4}-3(ct_{1in2}+ct_{1in3})}{2}\right)+\left(T_{\tilde{ct}_{1in}}-I_{\tilde{ct}_{1in}}-F_{\tilde{ct}_{1in}}\right)\right]fx_{in}\\
&+\sum_{n\epsilon N}\sum_{h\epsilon H}\left[\left(\frac{ct_{2nh1}+ct_{2nh4}-3(ct_{2nh2}+ct_{2nh3})}{2}\right)+\left(T_{\tilde{ct}_{2nh}}-I_{\tilde{ct}_{2nh}}-F_{\tilde{ct}_{2nh}}\right)\right]mx_{nh}\\
&+\sum_{i\epsilon I}\sum_{h\epsilon H}\left[\left(\frac{ct_{3ih1}+ct_{3ih4}-3(ct_{3ih2}+ct_{3ih3})}{2}\right)+\left(T_{\tilde{ct}_{3ih}}-I_{\tilde{ct}_{3ih}}-F_{\tilde{ct}_{3ih}}\right)\right]hx_{ih}\\
&+\sum_{j\epsilon J\cup E}\sum_{k\epsilon K}\left[\left(\frac{cu_{kj1}+cu_{kj4}-3(cu_{kj2}+cu_{kj3})}{2}\right)+\left(T_{\tilde{cu}_{kj}}-I_{\tilde{cu}_{kj}}-F_{\tilde{cu}_{kj}}\right)\right]u_{kj}\\
&+\sum_{i\epsilon I}\sum_{j\epsilon J\cup E}\sum_{r=1}^{J+1}\left[\left(\frac{cq_{ij1}+cq_{ij4}-3(cq_{ij2}+cq_{ij3})}{2}\right)+\left(T_{\tilde{cq}_{ij}}-I_{\tilde{cq}_{ij}}-F_{\tilde{cq}_{ij}}\right)\right]P_{ijr}y_{jir}\\
&+\sum_{j\epsilon M}\sum_{i\epsilon M}\sum_{v\epsilon V}\sum_{r=1}^{J+1}\left[\left(\frac{fv_{v1}+fv_{v4}-3(fv_{v2}+fv_{v3})}{2}\right)+\left(T_{\tilde{fv}_v}-I_{\tilde{fv}_v}-F_{\tilde{fv}_v}\right)\right]dis_{ji}\,vr_{jivr}
\end{aligned} \tag{62}$$

$$\begin{aligned}
\min z_2 = &\sum_{i\epsilon M}\sum_{j\epsilon M}\sum_{v\epsilon V}\sum_{r=1}^{J+1}\frac{dis_{ji}\,vr_{jivr}}{\delta_v}+\sum_{i\epsilon I}\sum_{n\epsilon N}\sum_{h\epsilon H}\left(\frac{\left[\left(\frac{\tau_{1in1}+\tau_{1in4}-3(\tau_{1in2}+\tau_{1in3})}{2}\right)+\left(T_{\tilde{\tau}_{1in}}-I_{\tilde{\tau}_{1in}}-F_{\tilde{\tau}_{1in}}\right)\right]fx_{in}}{\gamma}\right.\\
&+\frac{\left[\left(\frac{\tau_{2nh1}+\tau_{2nh4}-3(\tau_{2nh2}+\tau_{2nh3})}{2}\right)+\left(T_{\tilde{\tau}_{2nh}}-I_{\tilde{\tau}_{2nh}}-F_{\tilde{\tau}_{2nh}}\right)\right]mx_{nh}}{\gamma}\\
&\left.+\frac{\left[\left(\frac{\tau_{3ih1}+\tau_{3ih4}-3(\tau_{3ih2}+\tau_{3ih3})}{2}\right)+\left(T_{\tilde{\tau}_{3ih}}-I_{\tilde{\tau}_{3ih}}-F_{\tilde{\tau}_{3ih}}\right)\right]hx_{ih}}{\gamma}\right)
\end{aligned} \tag{63}$$

$$\begin{aligned}
\min z_3 = &\arg\max_{j\epsilon J\cup E}\left\{\sum_{i\epsilon M}\sum_{j\epsilon M}\sum_{v\epsilon V}\sum_{r=1}^{J+1}\left[\left(\frac{fv_{v1}+fv_{v4}-3(fv_{v2}+fv_{v3})}{2}\right)+\left(T_{\tilde{fv}_v}-I_{\tilde{fv}_v}-F_{\tilde{fv}_v}\right)\right]dis_{ji}\,vr_{jivr}\right\}\\
&-\arg\min_{j\epsilon J\cup E}\left\{\sum_{i\epsilon M}\sum_{j\epsilon M}\sum_{v\epsilon V}\sum_{r=1}^{J+1}\left[\left(\frac{fv_{v1}+fv_{v4}-3(fv_{v2}+fv_{v3})}{2}\right)+\left(T_{\tilde{fv}_v}-I_{\tilde{fv}_v}-F_{\tilde{fv}_v}\right)\right]dis_{il}\,vr_{jivr}\right\}
\end{aligned} \tag{64}$$

5.2. Constraints

There are thirteen uncertain coefficients in the constraints, including technological coefficients and RHSs, by utilizing model (60), they are transformed to the following robust counterpart constraints. Since the decision variables of the proposed model are positive, the absolute value operator can be directly removed.

$$\sum_{n\epsilon N}fx_{in}+\sum_{h\epsilon H}hx_{ih}+\left[z_i^1\Gamma_i+w_i^1\right]\le wd_i\ \ \forall\ i\epsilon I$$

$$z_i^1 + w_i^1 \geq \widehat{wd}_i \quad \forall\, i \epsilon I$$
$$\sum_{n \epsilon N} fx_{in} + \sum_{h \epsilon H} hx_{ih} - [z_i^1 \Gamma_i + w_i^1] \geq wd_i \;\; \forall\, i \epsilon I$$
$$z_i^1 + w_i^1 \leq \widehat{wd}_i \quad \forall\, i \epsilon I$$
(65)

$$\sum_{h \epsilon H} mx_{nh} - \mu . \sum_{i \epsilon I} fx_{in} + [z_n^1 \Gamma_n^1 + w_\mu] \leq 0 \qquad \forall\, n \epsilon N$$
$$z_n^1 + w_\mu \geq \hat{\mu}\, fx_{in} \quad \forall i \in I, n \in N$$
(66)

$$\sum_{i \epsilon I} fx_{in} - \mathcal{CAE}_n\, \varphi_n + [z_n^2 \Gamma_n^2 + w_n] \leq 0 \qquad \forall\, n \epsilon N$$
$$z_n^2 + w_n \geq \widehat{\mathcal{CAE}}_n \varphi_n \quad \forall\, n \epsilon N$$
(67)

$$\sum_{i \epsilon I} hx_{ih} + \sum_{n \epsilon N} mx_{nh} + [z_h \Gamma_h + w_h] \leq \mathcal{CAH}_h \qquad \forall h \in H$$
$$z_h + w_h \geq \widehat{\mathcal{CAH}}_h \quad \forall h \in H$$
(68)

$$\sum_{j \epsilon J \cup E} u_{kj} - \mathcal{CAS}_k\, w_k + [z_k \Gamma_k + w_k] \leq 0 \qquad \forall\, k \epsilon K$$
$$z_k + w_k \geq \widehat{\mathcal{CAS}}_k w_k \quad \forall\, k \epsilon K$$
(69)

$$T_{ji} - T_j^{max} \sum_{r=1}^{J+1} y_{jir} + [z_{ji} \Gamma_{ji} + \sum_{r=1}^{J+1} w_{jir}] \leq 0 \qquad \forall\, j \epsilon J \cup E \;\;, i \epsilon I$$
$$z_{ji} + w_{jir} \geq \hat{T}_j^{max} y_{jir} \quad \forall\, j \epsilon J \cup E \;\;, i \epsilon I, \forall r$$
(70)

$$\sum_{i \epsilon I} T_{ji} - T_j^{max} Z_j + [z_j \Gamma_j + w_j] \leq 0 \qquad \forall\, j \epsilon J$$
$$z_j + w_j \geq \hat{T}_j^{max} Z_j \quad \forall\, j \epsilon J$$
(71)

$$gd_i + [z_i^2 \Gamma_i + w_i^2] \leq d_i \qquad \forall\, i \epsilon I$$
$$z_i^2 + w_i^2 \geq \hat{d}_i \quad \forall\, i \epsilon I$$
(72)

$$\frac{gd_i}{\tilde{d}_i} - \frac{gd_l}{\tilde{d}_l} . \rho + [z_{il}^1 \Gamma_{il} + w_i^3 + w_l^1] \leq 0$$
$$z_{il}^1 + w_i^3 \geq \frac{gd_i}{\hat{d}_i} \quad \forall\, i, l \epsilon I \;,\; i \neq l$$
$$z_{il}^1 + w_l^1 \geq \frac{gd_l}{\hat{d}_l} \quad \forall\, i, l \epsilon I \;,\; i \neq l$$
(73)

$$\frac{gd_i}{\tilde{d}_i} - \frac{gd_l}{\tilde{d}_l} + [z_{il}^2 \Gamma_{il} + w_i^4 + w_l^2] \leq \left(2 - \sum_{r=1}^{J+1} y_{jir} - \sum_{r=1}^{J+1} y_{jlr}\right) \qquad \forall\, i, l \epsilon I \;, i \neq l \;,\; j \epsilon J \cup E$$
$$z_{il}^2 + w_i^4 \geq \frac{gd_i}{\hat{d}_i} \quad \forall\, i, l \epsilon I \;,\; i \neq l$$
$$z_{il}^2 + w_l^2 \geq \frac{gd_l}{\hat{d}_l} \quad \forall\, i, l \epsilon I \;,\; i \neq l$$
(74)

$$\sum_{j\epsilon M}\sum_{i\epsilon I}\sum_{r=1}^{J+1} d_i\, vr_{jivr} + [z_v\Gamma_v + \sum_{j\epsilon M}\sum_{i\epsilon I}\sum_{r=1}^{J+1} w_{jivr}] \leq \mathcal{CAV}_v \qquad \forall\, v\epsilon V$$
$$z_v + w_{jivr} \geq \hat{d}_i vr_{jivr} \quad \forall\, j\epsilon J,\, i \in I, \forall r, \forall\, v\epsilon V \tag{75}$$

6. Multi-objective solution approach

In a multi-objective optimization problem, DMs are typically encountered with Pareto-optimal solutions instead of optimal solution(s), and the solution space should be explored to find them. As a matter of fact, if a solution cannot enhance any objective function without diminishing at least one other objective function, it is termed a Pareto optimal solution (Mavrotas, 2009). Subsequently, these solutions establish the Pareto front whence DMs can select final favored compromise solution. There is a broad range of approaches in the literature to solve a multi-objective optimization problem. One of the efficient approaches among them is AUGMECON2, which was proposed by (Mavrotas and Florios, 2013). Indeed, it is an improved version of the ε-constraint method, in which one of the objective functions (typically the objective with utmost priority) is optimized while the other ones are considered in terms of constraints as follows:

$$\max\left(f_1(x) + eps \times \left(\frac{s_2}{r_2} + 10^{-1} \times \frac{s_3}{r_3} + \ldots + 10^{-(p-2)} \times \frac{s_p}{r_p}\right)\right)$$

S.t.:

$$f_k(x) - s_k = e_k \quad k = 2,3,\ldots,p; \quad x \in S; \quad s_k \in R^+ \tag{76}$$

where S, x and $f_k(x)$ are the solution space, decision vector and objective function, respectively. Also, the ranges of objective functions and the RHS values of these objectives are signified by r_2,r_3,…, r_p and e_k; respectively. Moreover, a sufficiently small number, which is typically between10^{-3} and 10^{-6}, and a surplus variable are indicated by eps and s_k, respectively. Ehrgott and Wiecek (2005) articulated that the optimal solution of the model (76) can be efficient if each of $(p-1)$ objective functions' constraints is mandatory i.e., $(s_k = 0$ for $k = 2,3,\ldots,p)$. In the primary ε-constraint approach, the entire of objective functions are classified to specified equal intervals and the optimization model is solved utilizing the whole compounds of RHS values. Although an acceleration scheme was considered in AUGMECON2, so as to extrude those combinations that produce infeasible or weakly efficient solutions.

In what follows, Mousazadeh et al., (2018) proposed a modified AUGMECON2, in which a Tabu list that contains some combinations of RHS values is considered. Although, this list at the initialization stage is empty, it is gradually updated after solving the model using each combination of RHS values to improve the acceleration of AUGMECON2. As a result, the model is solved utilizing a specified compound, except that one exists on the Tabu list. The major superiority of this version that of other acceleration approaches is that this method is not concentrated merely on interior loop combinations, and surcharges some exterior loop ones to the Tabu list in each iteration. This modification outstandingly decreases the number of combinations required to be solved in order to achieve all the efficient Pareto optimal solutions. Because of the aforementioned reasons, this method is employed to solve the proposed optimization model.

7. Case study

The Kermanshah province earthquake in the western region of Iran occurred in 2017, with a magnitude of 7.3 on the Richter scale at the border region of Ezgeleh that killed about 1,000 people and left 10,000 injured and 70,000 homeless (Ahmadi and Bazargan-Hejazi, 2018; Hosseini et al., 2019). It was the deadliest earthquake in the world in 2017 that was felt in most of the western provinces of Iran and Iraq. It should be noted that this earthquake has had more than 1000 aftershocks so far, with 45 aftershocks ranging between 4 and 6.5 on the Richter scale, causing more severe damage in some areas (Ahmadi and Bazargan-Hejazi, 2018). In this case study, Kermanshah Red Crescent Center and the other ones in different provinces have been employed to assist disaster regions to provide them with basic supplies. In this regard, the air fleet has been used to expedite the transportation of shipment of relief items from other provinces, and these items have been stored in airport warehouses, and after that, they have been distributed to various disaster regions.

Hence, in this case study, Kermanshah Red Crescent Center and Kermanshah airport are considered as potential suppliers. Also, ten disaster regions between Sarpol-e Zahub and eslamabad-e gharb cities are considered to plan relief operations, due to the fact that they were available in the early hours of the crisis. In an attempt to coordinate and facilitate the distribution of relief items among disaster regions, distribution centers should be established as intermediaries to receive these items from suppliers and then send them to the disaster regions. Subsequently, Sarpol-e Zahub Red Crescent Center and Central Mosque, and eslamabad-e gharb Red Crescent Center are considered as potential distribution centers, such that these centers can distribute the relief items by trucks. Because of aftershocks, there is a possibility of failure of each distribution center, so Kerend-e gharb Red Crescent Center is considered as the emergency distribution center, which could provide required services to disaster units assigned to the disrupted distribution centers. As a matter of fact, the emergency centers would be established in near disaster regions to provide primary treatment for injured people. Additionally, there are two specialized hospitals, including Emam Reza and Bisotun to provide necessitated services for injured people. The main information on issues such as the capacities of facilities, the opening costs of potential facilities, demand of disaster units and failure probabilities of distribution centers are shown in Tables 2 to 5. Also, the proposed model was solved using GAMS software, version 23.6.2 by using the BARON optimization solver in a PC with core i3, 2.1 GHz CPU and 4 GB RAM for both deterministic and an uncertain condition. Moreover, the variation domain/perturbation level $(\hat{a}_{ij} = 15\%)$ and budget parameter $(\Gamma_i = 99\%)$. In order to determine the values of two significant parameters in RO, including perturbation and budget, if there is much lack of information, the higher values should be considered for them. This is especially important in relation to the perturbation level since it considers the dispersion in estimating the uncertain parameters. In the case study, the earthquake happened and investigated in the past, and the information about the uncertain parameters has a relatively good estimate, so the perturbation level is considered lower. However, if the model is employed immediately after a crisis, this parameter should be considered at a high level due to the lack of information. Regarding the budget parameter, since the current problem belongs to disaster relief, it is better to consider this parameter at the highest possible level to prevent the repercussions due to the unsuitable estimation of uncertain parameters.

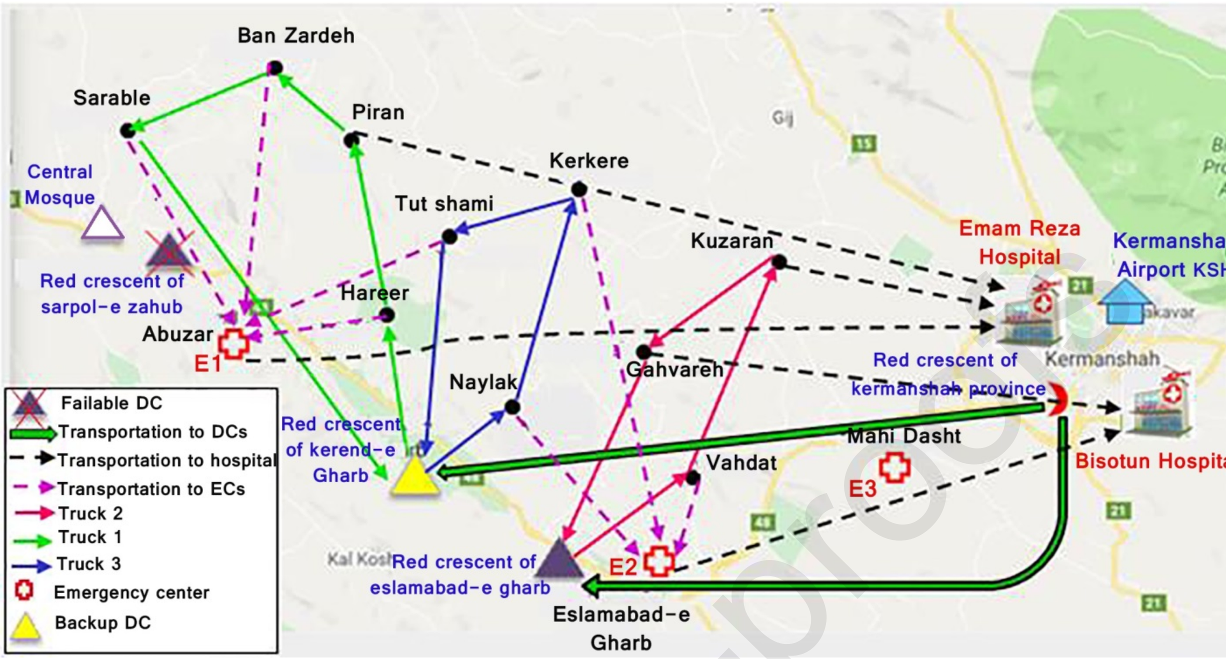

Fig 7. A demonstration of distributing and evacuating operations under deterministic state

Table 2. Parameters related to suppliers

Potential suppliers	Constant setting up cost of supplier $\widetilde{cw}_k$ ($)	Capacity of supplier $\widetilde{CAS}_k$
Kermanshah Red Crescent Center	$\widetilde{20000} =<[17500,19850,20100,21150],(1, 0.5, 0.2)>$	10000
Kermanshah airport	$\widetilde{22000} =<[19500,20150,22100,22300],(1, 0.5, 0.2)>$	8000

Table 3. Parameters related to distribution centers

Distribution centers	Probability of failure of distribution center q_j	Constant opening cost of distribution center $\tilde{f}_j$	Maximum supply capacity of distribution center $\tilde{T}_j^{max}$
Sarpol-e Zahub Red Crescent Center	0	$\widetilde{8000} =<[6500,7100,8150,8250],(1, 0.5, 0.2)>$	4000
Sarpol-e Zahub Central Mosque	0.8	$\widetilde{5000} =<[4580,4800,5200,5400],(1, 0.5, 0.2)>$	3500
eslamabad-e gharb Red Crescent Center	0.9	$\widetilde{7000} =<[6500,6800,7200,7500],(1, 0.5, 0.2)>$	4000

Table 4. Parameters related to emergency centers

Emergency centers	Constant opening cost of emergency center $\widetilde{cf}_n$ ($)	Capacity of emergency center $\widetilde{CAE}_n$
E_1	$\widetilde{12000}$ =< [10400,11100,12250,12600],(1, 0.5, 0.2) >	50
E_2	$\widetilde{15000}$ =< [13500,14000,15300,15800],(1, 0.5, 0.2) >	55
E_3	$\widetilde{11000}$ =< [9800,10500,11600,12300],(1, 0.5, 0.2) >	45

Table 5. Parameters related to disaster units

Disaster units	Demand of disaster unit $\tilde{d}_i$	Number of injuries $\widetilde{wd}_i$
Piran	910	15
Ban Zardeh	860	14
Kerkere	845	11
Sarable	1000	13
Tut Shami	870	14
Hereer	800	13
Naylak	916	10
Vahdat	980	12
Kuzaran	832	11
Gahvareh	900	10

Fig. 7 demonstrates the solution of problem-solving in the deterministic state. As can be seen in this figure, only Kermanshah Red Crescent Center is selected as a supplier. Also, among three potential distribution centers, Sarpol-e Zahub Red Crescent Center and eslamabad-e gharb Red Crescent Center are established. As it is noticeable, truck 2 is assigned to the eslamabad-e gharb Red Crescent Center such that this truck is responsible for distributing relief items to Gahvareh, Kuzaran and Vahdat disaster units. Moreover, the other disaster units are assigned to the Sarpol-e Zahub Red Crescent Center at the first level of assignment, but due to the aftershocks, it cannot serve them.

As a result, these disaster units are assigned to the Kerend-e gharb Red Crescent Center at the next assignment level as the emergency center, and relief items are distributed among disaster units by trucks 1 and 3. The route of each truck is shown in different colors. Furthermore, the first and second emergency centers are established, and the injured people of Sarable, Ban Zardeh, Tut Shami and Hereer disaster units are dispatched to emergency center 1 to receive primary treatment, and then dispatched to Emam Reza hospital, but the injured people of Piran and Kuzaran disaster units are directly dispatched to Emam Reza hospital. Likewise, the injured people of Kerkere, Naylak, and Vahdat are dispatched to emergency center 2 to receive primary treatment, and then dispatched to Bisotun hospital, but the injured people of Gahvareh is directly dispatched to Bisotun hospital. In this state, the values of the first to third objective functions are 2561792.3, 166.767 and 306, and the CPU time is 1001 seconds. Also, the number of constraints and variables are 18750 and 4569, respectively.

Fig. 8 demonstrates the solution of problem-solving in an uncertain state. Similar to the deterministic state, only Kermanshah Red Crescent Center is selected as a supplier. But, three potential distribution centers are established. As it is noticeable, at the first assignment level, Gahvareh, Kuzaran, Kerkere and Vahdat disaster units are assigned to the eslamabad-e gharb Red Crescent Center, and truck 3 is responsible for distributing relief items among these units. Similarly, Hereer, Tut Shami and Naylak disaster units are assigned to the Sarpol-e Zahub Red Crescent Center at the first level of assignment, and Sarable, Ban Zardeh and Piran disaster units are assigned to

Sarpol-e Zahub Central Mosque at the first level of assignment, but due to the aftershocks, they cannot serve these disaster units.

As a result, these disaster units are assigned to the Kerend-e gharb Red Crescent Center at the next assignment level as the emergency center, and relief items are distributed among disaster units by trucks 1 and 2. The route of each truck is shown in different colors. Moreover, the entire of potential emergency centers are established, and the injured people of Sarable, Piran, Hereer disaster units are dispatched to emergency center 1 to receive primary treatment, and then dispatched to Emam Reza hospital. Likewise, Naylak, Tut Shami and Gahvareh disaster units are dispatched to emergency center 2 to receive primary treatment and then dispatched to Bisotun hospital. Similarly, Kerkere and Vahdat disaster units are dispatched to emergency center 3 to receive primary treatment, and then dispatched to Emam Reza hospital, and the others are directly dispatched to related hospitals, which are shown in Fig 6. In this state, the values of the first to third objective functions are 2632185.87, 197.83 and 324, and the CPU time is 2540 seconds. The obtained results exhibit the validity of the proposed model and solution approach. Needless to say, all the goals of this research have been fulfilled. More importantly, the percentages of satisfied demands for each disaster unit under deterministic and uncertain states are provided in Table 6. Likewise, the number of injured people transported from disaster units to medical centers are presented in Table 7.

Table 6. Percentage of satisfied demands

Disaster units	**Satisfied demand (%)**	
	Deterministic state	**Uncertain state**
Piran	0.81	0.61
Ban zarde	0.65	0.68
Kerkere	0.87	0.85
Sarable	0.56	0.79
Tut shami	0.79	0.48
Hareer	0.90	0.85
Naylak	0.95	0.93
Vahdat	0.98	0.64
Kuzaran	0.87	0.72
Gahvareh	0.82	0.91
Average	**0.82**	**0.75**

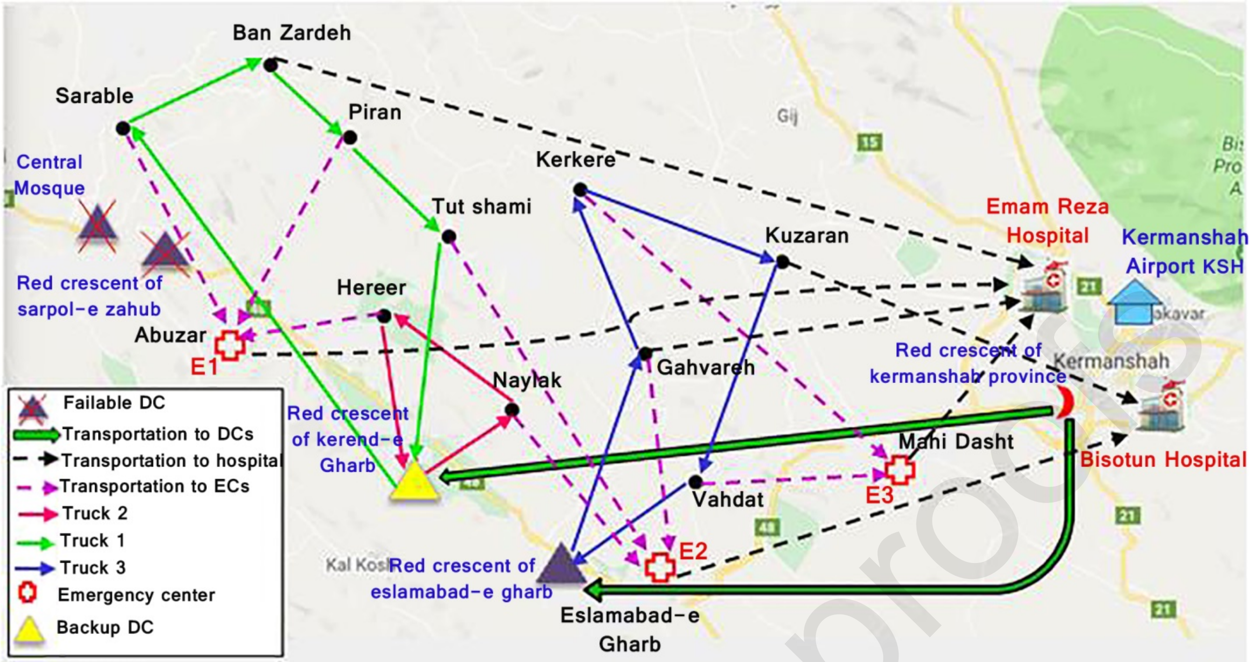

Fig 8. A demonstration of distributing and evacuating operations under uncertain state

Table 7. The number of injured people transferred to medical centers (Deterministic, Uncertain states)

Disaster units/ Emergency centers	Medical centers				
	Emergency Center 1	**Emergency Center 2**	**Emergency Center 3**	**Emam reza Hospital**	**Bisotun Hospital**
Piran	- ,15	_	_	15 , -	_
Ban zarde	14 , -	_	_	- ,14	_
Kerkere	_	11, -	- ,11	_	_
Sarable	13 , 13	_	_	_	_
Tut shami	14 , -	- ,14	_	_	_
Hareer	13 , 13	_	_	_	_
Naylak	_	10 , 10	_	_	_
Vahdat	_	12 ,-	- ,12	_	_
Kuzaran	_	_	_	11 , -	- , 11
Gahvareh	_	- ,6	_	- , 4	10 , -
Emergency Center 1	_	_	_	54 , 41	_
Emergency Center 2	_	_	_	_	33 , 30
Emergency Center 3	_	_	_	- , 23	_

8. Computational results and discussion

8.1. Sensitivity analysis

This section investigates the effectiveness of the recommended robust neutrosophic fuzzy model under uncertain state and compares the performance of it with that of the deterministic model. Firstly, the influences of uncertainty levels on objective functions are investigated via changing the conservatism level of the proposed model and the perturbation level of uncertain parameters. The perturbation domain is supposed to be 15%, 25%, and 35%, while the budget parameter, which represents reliability/conservatism level, is set to 70%, 85%, 99%. The obtained results which are presented in Table 8 manifest that the total cost of the robust neutrosophic model is higher than the deterministic one due to costs incurred for enhancing the stability of HLN. Once the reliability level or perturbation level increases, these trends become more perceptible. For case in a point, an extremely conservative version of the proposed robust neutrosophic model (i.e., perturbation level= 35% and reliability level=99%) under the optimistic attitude provides us solutions and decisions that lead to 42.3% $(100 \times ((568036.145 - 2561792.3)/2561792.3))$ higher total cost.

Moreover, these changes are much less for the second and third objective functions such that these increases are 15.6% and 22.5%, which the details of them are provided in Tables 9 and 10. Also, a healthy balance between robustness and its cost can be made under lower levels of uncertainty with the intention of enhancing the reliability of the solutions alongside a more sensible cost. Furthermore, the trends of computational time are provided in Table 11. Since a broad range of constraints and variables are augmented to the proposed model with the intention of transforming the proposed uncertain model to an equivalent crisp model, naturally this approach increases the problem size and its computational time.

Table 8. Comparison of total costs of deterministic and robust neutrosophic models

Perturbation level	Total humanitarian logistics costs ($)			
	Deterministic	Robust neutrosophic		
		Reliability level		
		99%	85%	70%
15%	2561792.3	2632185.8	2598267.5	2613144.1
25%		3156707.8	2804987.9	2655138.4
35%		3645430.4	3310932.6	3031450.8

Table 9. Comparison of total time of relief operations of deterministic and robust neutrosophic models

Perturbation level	Maximum overload			
	Deterministic	Robust neutrosophic		
		Reliability level		
		99%	85%	70%
15%	166.767	197.83	180.45	177.09
25%		205.13	197.14	187.32
35%		228.69	209.31	195.43

Table 10. Comparison of difference between maximum and minimum transportation cost of deterministic and robust neutrosophic models

Perturbation level	Maximum overload			
	Deterministic	Robust neutrosophic		
		Reliability level		
		99%	85%	70%

15%		324	314.5	309.1
25%	306	375.6	351.9	331.8
35%		397.2	371.2	355.6

Table 11. Comparison of computational times of deterministic and robust neutrosophic models

Perturbation level	**Computational times (second)**			
	Deterministic	**Robust neutrosophic**		
		Reliability level		
		99%	**85%**	**70%**
15%		2540.6	2315.4	2804.3
25%	1001	2656.5	2518.2	2561.8
35%		2844.9	2761.1	2799.6

In the following, the objective functions of the proposed model are compartmentalized among varied uncertain input parameters. In order to clarify the role of each of them in objective functions increases under various reliability and perturbation levels, it is supposed that only one specific kind of input-parameters are contained to uncertainty and the remnant are deterministic. After that, the levels of reliability and perturbation are gradually varied and the values of the objective functions are investigated by normalized deviation $(\mathbb{Z}^{RN} - \mathbb{Z}^{D})/\mathbb{Z}^{D}$, where $\mathbb{Z}^{RI}$ and $\mathbb{Z}^{D}$ are the robust neutrosophic and deterministic solutions, respectively. The obtained results of these investigations for different uncertain parameters are provided in **Figs**. **9** to **13**. What is more, the behavior of each objective function with respect to the changes of the failure probability of distribution centers, which are caused by aftershocks, is depicted in **Fig 14**.

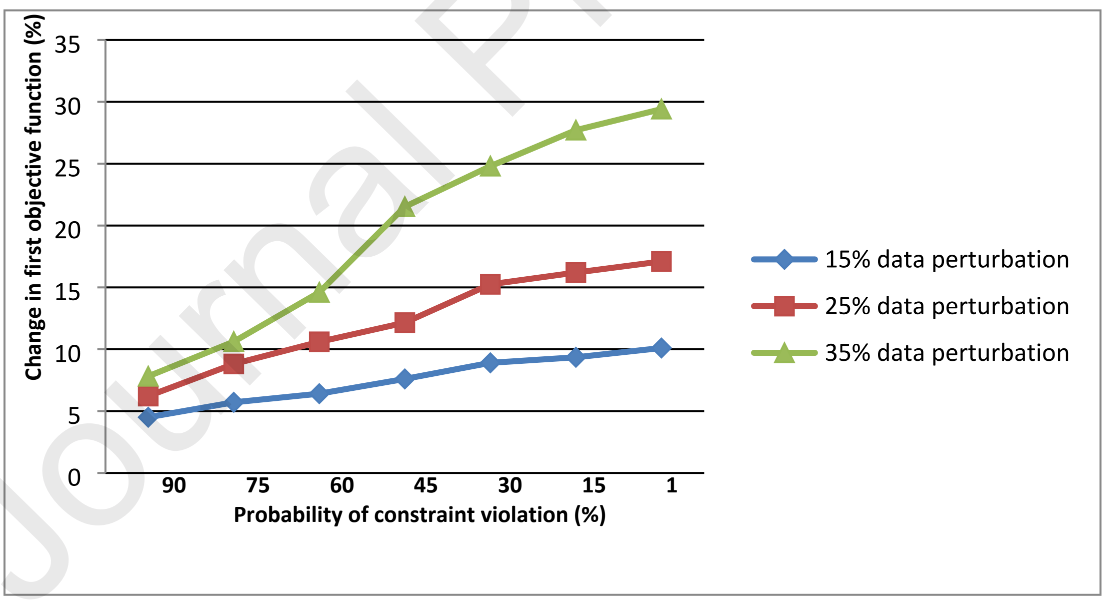

Fig 9. The impact of variations in demand in the first objective function

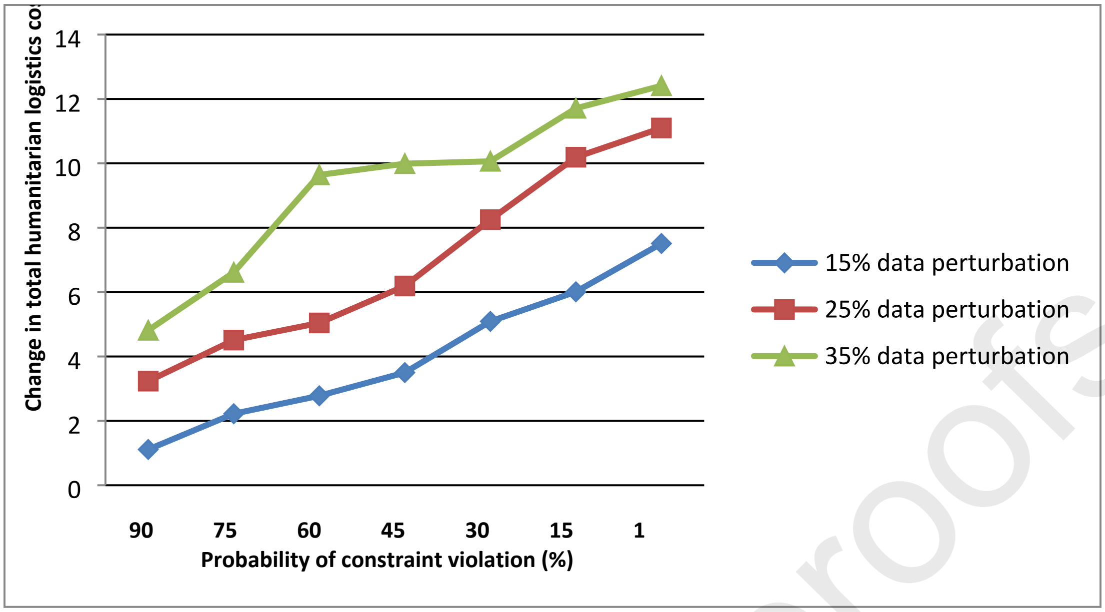

Fig 10. The impact of variations in demand in the second objective function

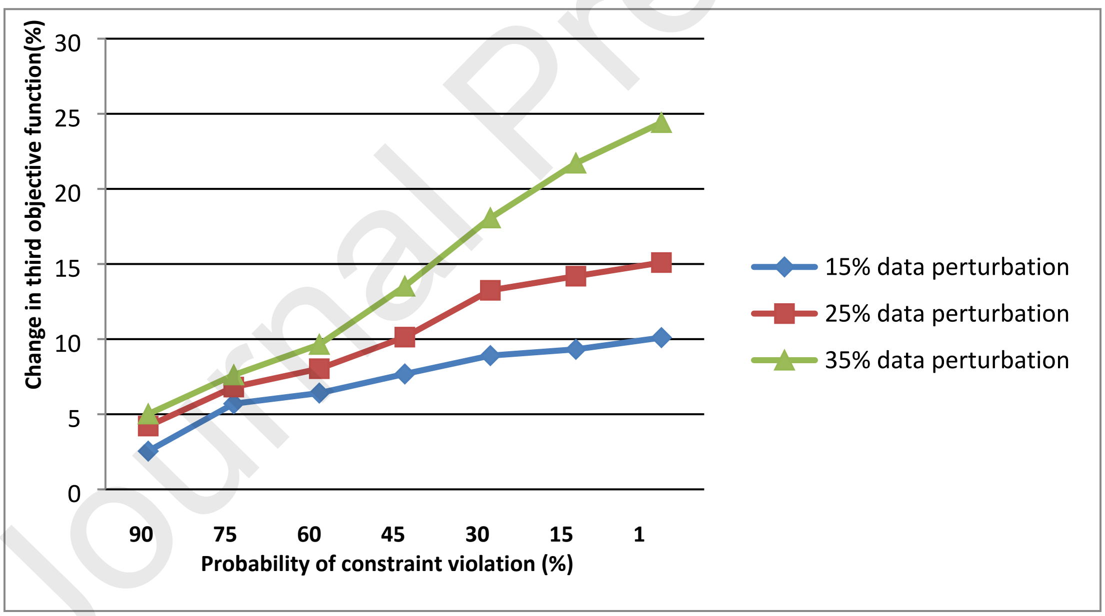

Fig 11. The impact of variations in demand in the third objective function

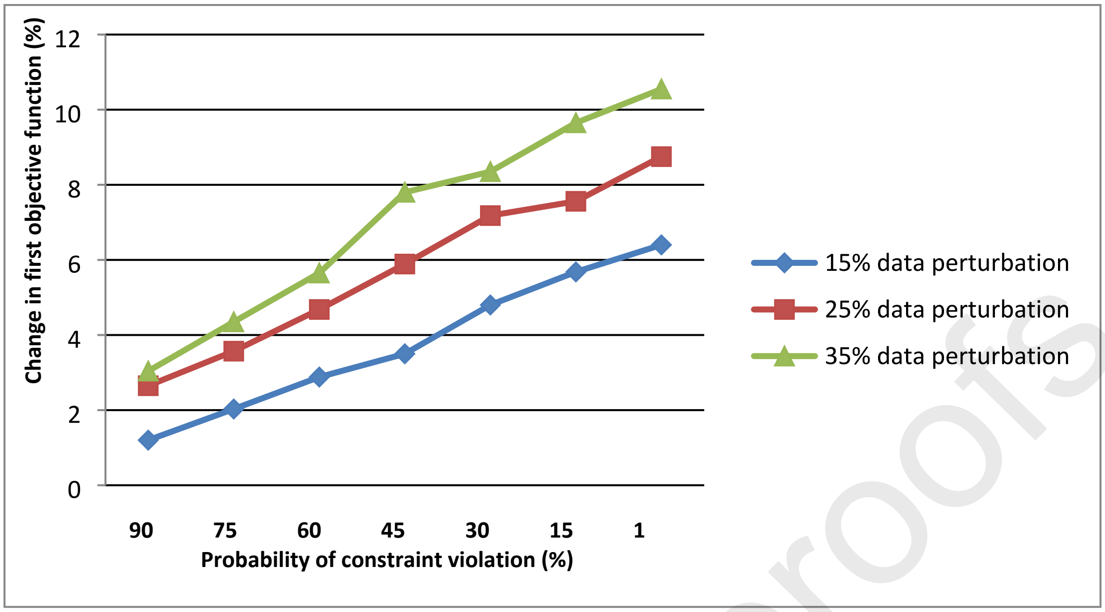

Fig 12. The impact of variations in the number of injuries in the first objective function

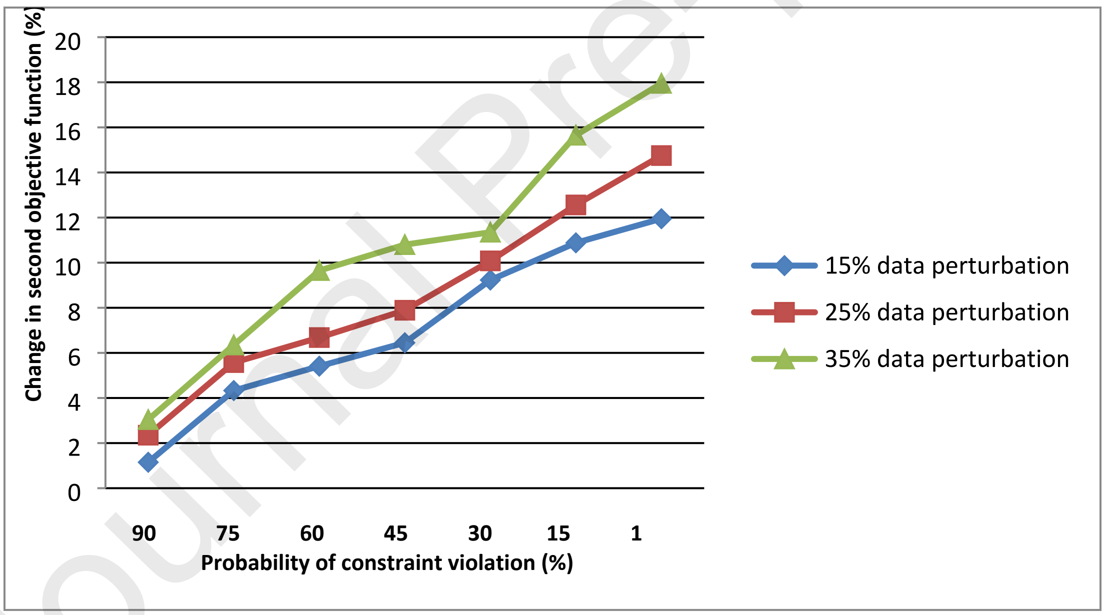

Fig 13. The impact of variations in the number of injuries in the second objective function

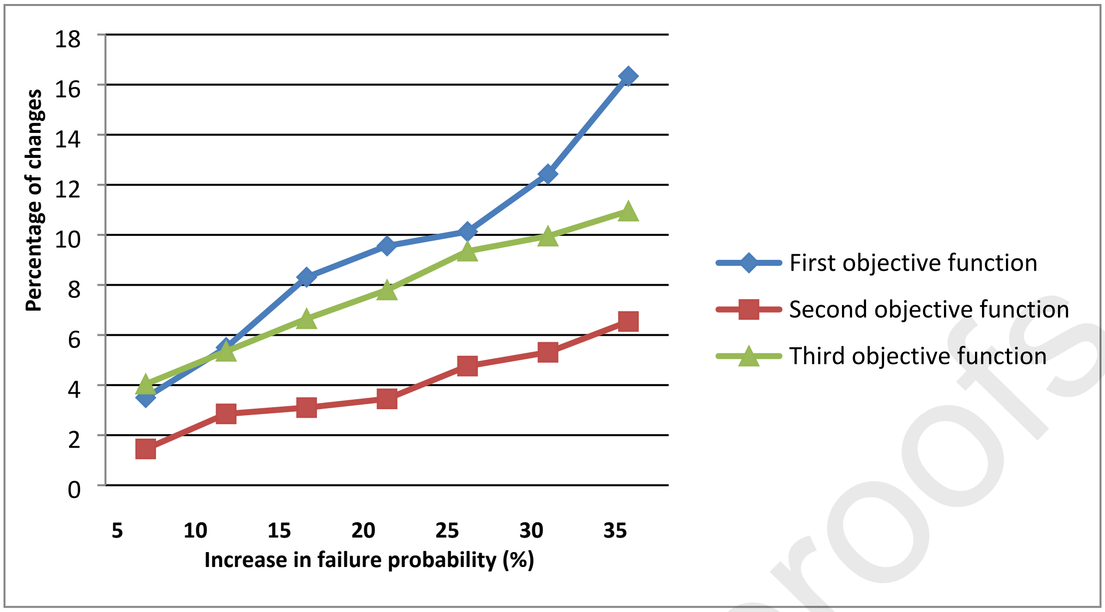

Fig 14. The impact of variations in failure probability in objective functions

As can be seen, with the increase in the demand for relief items, most changes occur in the first objective function, while the increase in the number of injuries has the most changes in the second objective function. In addition, the percentage of changes in the total humanitarian logistics costs is higher than in the total time of relief operations, so it is suggested that more endeavors and measures should be made to better approximate demand because it is are more sensitive to changing perturbation level. Furthermore, it is clear that the reliability approach considered in this study has been able to provide a suitable solution to mitigate the effects of aftershocks. Although this method creates a reliable network, it also imposes additional costs on the system. Therefore, it is suggested that in the construction of distribution centers to provide the relief items needed for the disaster units, there should be no mere time considerations and that more durable distribution centers be built to avoid additional system costs.

8.2. Managerial insights

With respect to the obtained results from investigated case study and explorative analysis, three helpful managerial insights are provided as follows:

Insight 1: Inequality in demand is a crucial issue in times of crisis. The high volume of demand in critical points from distribution centers dramatically affects the quality of service, which is a vital challenge in the relief logistics and services. The high volume of demand increases the cost, which is due to the insufficient capacity of the service facilities. This will lead to the creation of more distribution centers to meet the demand, while this also requires cost and results in economic decline. Additionally, aid distribution centers may have sufficient capacity to meet all demand. Nevertheless, there is usually an unequal volume of demand and, therefore, unequal access to service, and this inequality often stems from statistical changes and geographical issues. Obviously, one of the desired goals in relief logistics is to meet the maximum volume of demand in the fastest possible time. Therefore, if there are no specific constraints on the management and planning of this issue, the model will endeavor to meet the demand of the nearest critical areas to the distribution centers first, and only after fully fulfilling them will send the remaining units to the farthest points of demand. It is clear that the allocation of relief assistance in this way is not desirable and unequal, so it is necessary to add the limits of fair allocation to the model. One of the measures that reflect the quality of allocation is the ratio of $\frac{gd_i}{d_i}$, which expresses the level of service at a point of demand. What is more, the high volume of demand in some distribution centers compared to other ones makes the level of service to the demand points, which have been allocated to these centers, lower than planned. Consequently, the low values of service levels, in this case, may result in maximum service to other points of demand and thus affect the entire system. Hence, the ratio between the maximum and minimum service levels has been calculated, which is limited by the ρ parameter. However, this ratio may be less than ρ in actual application, in which case the allocation of assistance is fairer. Therefore, in the case study, the value of this parameter was initially considered to be 2, but after the necessary analysis, the value of this ratio was determined to be 1.75 in the deterministic case and 1.92 in the uncertain case.

Insight 2: The speed of transporting the injured from critical areas to the hospital plays a crucial role in ensuring the effectiveness and efficiency of emergency services. During a crisis, the number of casualties is usually higher than the capacity of the hospitals, and many of the injured only need first aid and outpatient treatment, or some of the victims have died. In these cases, they do not need to be transferred to the hospital. Therefore, to prevent overcrowding in the hospital and also to maintain the effectiveness of emergency services, emergency centers as the transfer points are designed to screen the injured. Therefore, the transfer of the injured from critical areas can be done directly to the hospital or indirectly through the transfer points. In other words, if the distance between the critical areas and the hospital is such that it does not worsen the condition of the injured, the transfer will be made directly to the hospital. Otherwise, the injured will first be sent to the nearest transfer point, and medical teams will take the initial treatment according to the type of injury to be sent to the hospital so that the transfer of the injured to the hospital is done quickly by using the equipped medical equipment and the rescue team. This provides the best chance of survival for those affected by the crisis and provides emergency services as soon as possible. What is more, due to screening in transmission points, it has been neglected over long distances and transportation. Therefore, the rate of displacement of the injured in the system is reduced, which not only increases the efficiency of the system but also reduces the total cost of the system. Moreover, congestion in the network also negatively affects the operation time. According to the analysis of the case study, it was found that by increasing the capacity of the transmission points by 30%, the total cost of the network is reduced by 18% and the operating time is reduced by 9%. Furthermore, by increasing the capacity of the transfer points, many problems that arise due to the influx of the injured to the hospital will be prevented, and the treatment and rescue process will be done correctly and with the desired efficiency.

Insight 3: Given the nature of natural disasters that can disrupt facilities, designing a reliable network is critical and dramatically reduces unmet demand. Considering emergency facilities is one of the ways to increase reliability, and if the primary distribution center is not able to provide services, it will send relief goods to the demand points. When a distribution center is completely disrupted, that center is not available, and the critical areas that were originally allocated to it must be redistributed to other distribution centers, and this redesign often results in higher costs. In the case study, it was found that if the probability of disruption in one of the distribution centers reaches zero, the costs will be reduced to approximately 20%, and also the distance between the maximum and minimum distance traveled will be reduced by 30% and the workload between distribution centers will be more balanced. Therefore, locating distribution centers in places with a lower probability of disruption is highly recommended.

9. Conclusions

In this paper, a novel reliable humanitarian logistics network was investigated to synchronize relief distribution and victim evacuation, distribute relief items in a fair manner, and mitigate the repercussions of aftershocks. For this purpose, a framework for the planning of reliable location-allocation of facilities, fair distribution of relief items and vehicle routing was proposed. The proposed framework was a multi-objective optimization model, in which the first objective minimizes the total costs of planning, the second one minimizes the total time of relief operations, and the third one minimizes the difference between the maximum and minimum transportation cost of distribution centers and balances the workload of distribution centers. Moreover, due to the uncertain nature of the disaster, including demand, supply, time, capacities of facilities and costs, a hybrid robust optimization approach which involves robust optimization and the neutrosophic set was proposed to overcome this challenge. The main obtained results from the investigated case study and sensitivity analysis revealed that (1) increasing the capacity of the emergency centers by 30%, the total cost of the humanitarian relief network is reduced by 18% and the operating time is reduced by 9%; (2) if the probability of disruption in one of the distribution centers reaches zero, the logistics costs will be reduced to approximately 20%, and also the distance between the maximum and minimum distance traveled will be reduced by 30% and the workload between distribution centers will be more balanced, so locating distribution centers in places with a higher probability of confidence is highly recommended. A number of future directions could be considered including (1) reflecting the type of injuries, which is the main shortcoming of the current research; (2) proposing exact solution methods, heuristic and meta-heuristic algorithms to solve the proposed model in a large-scale; (3) conducting spatial filtering by utilizing GIS to recognize the most appropriate candidates' locations to establish facilities.

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Highlights

- Rendering a reliable synchronized framework to distribute relief items and evacuate victims in a humanitarian logistics network.
- Developing a novel multi-objective model to integrate reliable locating and routing under fairness in distribution relief items.
- Mitigating the repercussions of aftershocks by considering an efficient reliability approach.
- Proposing an uncertain approach based on neutrosophic fuzzy programming and robust optimization.

Author Contribution Statement

S. Mohammadi: Conceptualization, Methodology, Software, Writing- Original draft preparation, Data curation

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