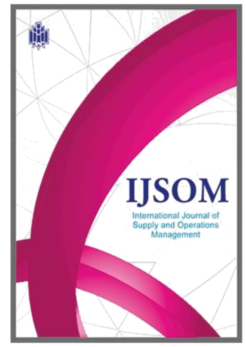
International Journal of Supply and Operations Management

IJSOM

2023, Volume 10, Issue 3, pp. 271-294
ISSN-Print: 2383-1359
ISSN-Online: 2383-2525
www.ijsom.com



A Robust-Stochastic Optimization Approach for Designing Relief Logistics Operations under Network Disruption

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Abstract

After a natural disaster, medical supplies will be in high demand in the disaster-affected communities. Providing prompt and high-quality rescue resources is critical to the emergency relief network's overall quality. This study presents a mathematical optimization model for constructing a multi-period emergency relief system that minimizes the system's overall expected costs. The model considers location, allocation, and distribution decisions as well as flow of medical supplies and injured people. Medical supply distribution centers and roads are vulnerable to failure in the suggested model. Since certain parameters in the real world are unknown, the model parameters' uncertainty is explored. There are four sources of uncertainty regarding the number of injured people, demand, costs, and the probability of failure. To cope these uncertainties, a robust-stochastic optimization approach is used. Also, a case study focused on an earthquake in southern and western cities of Fars province is discussed to assess the efficacy of the suggested model. The findings demonstrate that the robust-stochastic approach is capable of effectively controlling cost and demand uncertainty, and that failing to account for uncertainty when planning relief logistics would be extremely deceptive. The planned relief system has the highest cost at the highest level of uncertainty, but it will offer a better protected solution to uncertainty with a greater level of robustness. The stochastic model has the lowest cost, but it is unable to produce the most conservative solution with the best uncertainty protection when there is a great deal of uncertainty in the system.

Keywords: Relief logistics planning; Preparedness and response phases; Disruption; Uncertainty; Robust programming.

1. Introduction

Natural and man-made disasters have been growing at an exponential rate since around the 1950s. A disaster is a massive event that results in damage, environmental degradation, loss of lives, social distress, or worsening of health care and requires outside assistance. Disaster is characterized by the International Federation of Red Cross and Red Crescent Societies (IFRC) as an abrupt, catastrophic event which severely interrupts a community's functioning and causes human, financial, or ecological casualties that surpasses the community's capacity to adapt with the use of its

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DOI: 10.22034/IJSOM.2023.109855.2694

own resources (IFRC, 2012). Natural hazards such as fires, flooding, hurricanes, and winds, as well as man-made accidents such as nuclear or chemical blasts, which may strike with little notice, pose significant risks to human health and safety, resulting in the largest number of deaths and property destruction. In 2017, for example, there were 301 disasters around the world, killing or missing over 11000 people and causing $337 billion in damage (Sigma, 2018). Robust crisis planning is necessary to reduce risks and adjust in the case of an occurrence due to the unpredictable nature of catastrophes and their unintentional presence. Reduce, prepare, response, and recover are the four stages of disaster management. Pre-disaster (planning and reduction) and post-disaster (response and recovery) are the two stages of disaster scenarios. Coppola (2006) describes reduction as a decrease in the likelihood of a disaster occurring and the severity of the risk. Preparation is the set of actions that improve the chances of recovery when carried out following a disaster, thus lowering financial and other casualties. Reducing disaster impact during post-disaster incidents to prevent further distress is often known as part of the response; Finally, recovery is characterized as returning impacted areas to their previous state.

Generally, the major goal of humanitarian logistics problems would be to save human lives and get them help as quickly as possible (Rahmani et al., 2018). Determining the best strategies for transferring injured individuals between disaster areas and care centers and providing relief supplies for them can have a significant impact on saving people's lives. As a result, designing an effective logistical network for emergency medical services (EMS) is critical for solving challenges in disasters (Boonmee et al., 2017). Facility location planning is a key strategy for pre- and post-disaster activities that has a large effect on disaster management planning efficiency. Facility location problem is known as an important scientific method in EMS for reducing disaster repercussions (Jia et al., 2007). Infrastructure destruction after a disaster, particularly on highways and bridges, is a fundamental and essential concern that has a substantial negative effect on relief to impacted areas and should be considered when deciding on a relief facility.

Even if crisis plans are only effective for a little period of time, it is still important to assess their key components in order to be ready and avoid being caught off guard while dealing with disasters (Goli et al. 2017). Time is extremely important since catastrophe response systems have a limited lifespan (Oloruntoba & Gray, 2006). Following a disaster, the injured must be transported to hospitals as soon as possible to ensure that the number of casualties and financial losses are kept to a minimum (Fereiduni & Shahanaghi, 2017). For a large number of people to survive, there must be little time between the incidence of the disaster and the response to it. Transportation planning is an important humanitarian logistics activity, that helps shorten response times (Tomasini & Van Wassenhove, 2004). Falasca and Zobel (2011) stated that a sizable portion of the costs associated with humanitarian logistics is attributable to transportation. Although the extent of the event will determine this, it is safe to assume that the number of accessible vehicles is restricted in comparison to the demand in a disaster situation (Repoussis et al., 2016). Therefore, preparing for vehicle allocation reduces system costs and delays.

According to Liberatore et al. (2013), demand and transportation network uncertainties are two of main sources of uncertainty on emergency logistics. The literature on disaster relief networks considers uncertainty in supply, cost, and demand parameters (Zokaee et al., 2016). Estimating the exact number of injured individuals and the quantity of demand for medical supplies in a disaster is difficult or impossible in many situations caused by a scarcity of information about the nature of disasters, such as the type, severity, and scale of the disaster. The cost uncertainty is generated by a variety of factors, including the suppliers' route accessibility (Zokaee et al., 2016), increased demand for medical supplies and increase in fuel demand. At the time of the disaster, there is no accurate information concerning the condition of communication networks (Rawls & Turnquist, 2010), which demonstrates the need of considering the uncertainty in the condition of the road. The destruction of roads between different nodes and the increase in fuel demand due to increased transportation are the factors that cause the increase in transportation costs at the time of disasters (Döyen et al., 2012).

Natural or man-made disasters disrupt the whole supply chain, having a significant impact on the whole distribution system (Elluru et al., 2019). It is impossible to rapidly adjust the network infrastructure to meet demand in the event of a disruption. Mitigation or recourse operations are often conducted in such a way that demand nodes are reassigned to other operational facilities far away from their normally allocated facilities in order to ensure system reliability (Zarrinpoor et al., 2018; An et al., 2015; Zarrinpoor et al., 2017). The cost of transportation may be overestimated, service quality may be inadequate, and lives and property may be lost if the disruption impact is neglected (An et al., 2015). For these reasons, decision-makers must see disruption as a key component of disaster planning, with specific emphasis on preparedness activities (Ukkusuri & Yushimito, 2008).

In light of the above discussion, the aim of this research is to identify the optimal location for facilities on a relief network, the optimal flow of injured people and medical supplies, and also optimal transportation system in order to

address the disaster needs. The initial inventory of medical supplies is prepositioned in hospitals before the occurrence of disaster. After the disaster, medical supplies are purchased by medical supply distribution centers (MSDCs) and transported to hospitals and injured people transferred between impacted regions and hospitals in two ways. In the first case, injured people are transported directly from the impacted regions to hospitals at normal speeds. In the second case, injured people are transported from impacted regions to transfer sites at normal speeds and then they are transported from transfer sites to hospitals by high-speed vehicles. The type of vehicle used is based on the number of factors, including the type of equipment being transported (medical equipment or injured people), the transportation route, and the volume and weight of the equipment or injured people. There are four sources of uncertainty in the suggested model that include the number of injured people, demand, costs, and the probability of failure. To cope these uncertainties, a robust-stochastic optimization approach is used. Also, a case study focused on an earthquake in southern and western cities of Fars province is discussed to assess the efficacy of the suggested model.
The remaining sections of the paper are structured as follows. Section 2 describes the relevant literature on relief logistics problems. The model description explains in Section 3. The mathematical formulation of the suggested network is presented in Section 4. Section 5 sets out an actual case study and the sensitivity analysis. Ultimately, in Section 6, the conclusions and future research opportunities are explored.

2. Literature review

This section reviews the facility location, EMS and transportation network failure models for relief logistics.

2.1. Facility location planning of relief logistics

Facility location problem in relief logistics for responding to natural disasters has been widely studied. In this section, some of the most current papers of this field are examined. Murali et al. (2012) investigated a facility location problem in order to find out where medicine should be distributed to the general public in a large city. To account for distance-sensitive demand, they devised a specific case of the maximum coverage location problem of capacitated facilities, as well as chance constraints to account for uncertainty of demand. In response to natural disasters, Afshar and Haghani (2012) developed a detailed model that represented integrated logistical operations. Their proposed mathematical supply chain model managed the transfer of a variety of humanitarian commodities from the suppliers to the hands of beneficiaries.

The three-level location-distribution relief chain model developed by Zokaee et al. (2016) took into account suppliers, aid distribution centers, and damaged areas. A robust optimization (RO) was used to handle the uncertainty related to demand, supply, and all cost parameters. Loree and Aros-Vera (2018) designed a mathematical model for locating distribution centers and allocating inventory in post-disaster relief operations, with the goal of reducing facility construction, logistics, and deprivation costs. They also devised a heuristic approach for solving larger examples of the mathematical model. Hallak et al. (2019) concentrated on finding shelter places in Idleb, Syria, during the Syrian crisis. The model includes capacitated maximum coverage, fixed-charge expenses, and specific humanitarian concerns. Vulnerability criteria, economic factors, portable water and sanitary facilities, and the potential to scale up the location in the future are all taken into consideration. A mixed-integer weighted-goal programming model was discussed considering all these goals and the model was accomplished using real data from the area. Cotes and Cantillo (2019) presented a model for locating facilities to aid in disaster preparation by prepositioning resources. The model aims to reduce system costs such as transportation, inventory, fixed facility costs, and deprivation costs. It also specified how much of each kind of goods should be stored in advance for initial supply of disaster-affected areas.

Abazari et al. (2021) suggested a mathematical model for relief logistics to make location and distribution decisions. They considered a variety of vehicle types, perishable and imperishable relief commodities, and vehicle loading and unloading times. Vieira et al. (2021) presented a two-step process that helps in water distribution to drought-stricken areas. In the first step, an assignment problem is addressed, followed by a capacitated vehicle routing problem. The large-scale model is solved using a hybrid ant colony optimization. Shokr et al. (2021) suggested a relief chain consisting of a humanitarian organization and third-party logistics providers to assist decision-making in humanitarian logistics. A Benders decomposition algorithm is developed to solve large-scale problems. Demirbas and Ertem (2021) proposed a mixed-integer programming model for the location-reallocation problem to evaluate the benefits of operating equivalent warehouses and utilize existing warehouses efficiently. Shokr et al. (2022) suggested a relief logistics network in which several humanitarian organizations are worked concurrently to share resources and information properly in the network. Vosooghi et al. (2022) suggested a scenario-based location-allocation model for supplying relief goods to demand sites in an unpredictable environment with the goals of reducing total cost, minimizing the maximum unfulfilled demand, and minimizing the maximum response time. Mahtab et al. (2022) proposed a multi-objective robust-stochastic humanitarian logistics model for pre- and post-disaster regarding the uncertainty of demand, node reachability by a particular mode of transportation, and condition of pre-positioned supplies. The proposed model determined the location of facilities, the amount of pre-positioned commodities, distribution planning of commodities and the dispatch of vehicles. Sheikholeslami and Zarrinpoor (2023) presented a humanitarian logistics network design that determines the location of distribution centers and shelters, inventory management of perishable relief products, and the flow of afflicted and injured individuals in the lead-up to and following a disaster. They used two metaheuristic algorithms to solve their suggested model, and a real-world case study to validate it.

2.2. EMS for relief logistics

To overcome obstacles associated with disasters, an efficient logistical network for EMS must be developed. In this regard, Najafi, et al. (2013) suggested a stochastic model for managing the transportation of relief items and injured people after the earthquake. Zhang and Jiang (2014) provided a robust mathematical design for designing a cost-responsive EMS system under uncertainty. Integer programming and network-based partitioning were proposed by Chen and Yu (2016) to establish temporary locations for on-post EMS facilities, with the goal of improving EMS efficacy after a disaster. They used the Lagrangian relaxation to solve larger scale instances. Repoussis et al. (2016) presented a mathematical model for the integrated ambulance routing, patient-to-hospital allocation, and treatment schedualing. Their purpose was to make the most of the limited resources available during the response.

Kamali et al. (2017) studied a mathematical model that incorporates prioritizing into the triage procedure. They demonstrated how the magnitude of the disaster and the availability of resources influenced the outcome of the triage operation. Their goal was to increase the number of expected survival as much as possible. Leknes et al. (2017) suggested a problem of ambulance location and allocation in heterogeneous areas, with the goal of maximizing the overall value of station installation and ambulance distribution. In order to overcome the problem of designing a hierarchy health-care network considering three levels, Mousazadeh et al. (2018) presented a model to minimize the overall construction cost and the total weighted distance between affected regions and medical facilities at the same time. To address the problem of evacuation in the event of an emergency, Dulebenets et al. (2019) created a mathematical model to reduce evacuees' overall trip time by taking into account main social and demographical aspects of drivers, features of the evacuation route, driving circumstances, and congestion features. Under various scenarios, Oksuz and Satoglu (2020) suggested a mathematical model for locating temporary health facilities/ field hospitals by considering the existing hospitals' locations, injury categorization, health facility capacities, and the likelihood of road and hospital damage, as well as associated costs.

Depending on the outcomes of disaster effect modelling and forecasting, Yang et al. (2020) suggested a location model considering multi-coverage for EMS facilities. According to their findings, optimizing EMS locations reduced disaster-related delays in emergency responses while also significantly increasing the number of people rescued and demand point coverage. Babaee Tirkolaee et al. (2020) proposed a mathematical model that takes into consideration the learning impact when assigning and planning disaster rescue units. To cope with the problem's intrinsic uncertainty, they employed an uncertainty-set based RO approach.

2.3. Failure in relief logistics networks

When natural disasters damage facilities, aid delivery is disrupted, and response time is lost. Any disruption in relief activities would result in the loss of lives due to the short response time to disasters. Disruptions in transportation networks have gotten a lot of attention in the field of relief logistics because they cause delays in relief operations. Bozorgi-Amiri et al. (2013) devised a location-allocation robust-stochastic programming method for emergency relief operations. The model minimizes the total expected value and variation of the overall cost of the logistics network, and the maximum shortfalls in the damaged areas. In terms of damaged infrastructure and its impact on disaster accessibility, Salman and Yücel (2015) modelled the disaster's effect on network connections using randomized failure, with the purpose of optimizing the predicted demand covering within given distance throughout the whole network. In order to locate of transfer points and MSDCs, Mohamadi and Yaghoubi (2017) proposed a stochastic mathematical model. To approach the model to the actual case, they considered the system of triage, and probabilities of MSDC and routes malfunction. Cheraghi and Hosseini-Motlagh (2017) proposed a fuzzy-stochastic optimization model to design a blood supply chain network for disaster response, with the goal of minimizing overall supply chain. The disruption of facilities and routes is factored into their model. Rahmani et al. (2018) proposed a reliable and robust mathematical model for the humanitarian aid supply system to cope the hazards of facility disruptions after an earthquake. To enhance the model's reliability, they considered backup supplies for damaged populated areas. A stochastic approach was employed by Elçi and Noyan (2018) to introduce a relief procurement system in pre-disaster phase. In the model, the responding facilities' capacities and locations, as well as their stocks of humanitarian supplies are considered in the face of uncertainty of demand and the state of the transport system in post-disaster phase.

With the uncertainty in demand and required time for transportation, Liu et al. (2018) addressed a stochastic model for relief logistics activities in post-disaster following a disastrous earthquake in a region with mountains. They applied a RO approach to develop the robust counterpart (RC) of the suggested model. In an uncertain context, Alizadeh et al. (2019) used a two-stage robust-stochastic model to address an injured people collection points location problem. The number of injured individuals and the available transportation capacity were thought to be uncertain parameters. To develop relief logistics networks, Yahyaei and Bozorgi-Amiri (2019) presented a robust and reliable model. The suggested model's goal was to open facilities in preparation of a disaster, as well as to transport relief supplies and estimate disruption costs. Nezhadroshan et al. (2021) developed a robust and resilient humanitarian aid network that could provide critical commodities to disaster victims under both operational and disruptive risks. Their suggested network consists of numerous warehouses and distribution centers with varying levels of resilience. Akbari and Sayarshad (2022) presented a mathematical model in order to determine the schedule for a road restoration team and relief distribution and validated their model by real data from Hurricane Harvey in Harris County at Texas.

2.4 Motivation, research gap and contribution

It can be concluded from the related literature that just few studies have been taken into account the flow of relief supplies and injured people. The majority of extant models tend to concentrate on the preparation and response activities, while pre-disaster actions influencing post-disaster choices. Relief supplies are either pre-positioned during the preparation phase or purchased during the response period, according to most studies. Pre-positioning commodities increases warehousing and maintenance expenses, while buying commodities after a disaster causes a delay in disaster response time. A combination of these two strategies has two advantages. The first is to avoid wasting time in responding to the disaster, since relief activities begin immediately after the disaster. The second advantage is to keep prices down as well as saving storage space by avoiding pre-positioning a significant amount of relief items needed to respond to the disaster. Therefore, both pre-disaster and post-disaster decision-making must be considered. Although natural disasters might destroy roads, routes or facilities, most studies ignore the potential of communication networks deteriorating. To fill the mentioned gaps, this paper represents a multi-period, multi-commodity relief logistics mathematical model in two pre- and post-disaster phases. The proposed model considers four levels including impacted regions, distribution centers, transfer points and hospitals. A robust- stochastic approach is employed to handle a mixture of uncertain input data. The following are the study's contributions:

- Proposing a multi-period relief logistics plan that accounts for decisions made on the location of transfer points and MSDCs, the allocation of injured people, the distribution of medical supplies, and the planning of transportation.
- Both pre-disaster and post-disaster decision-making are considered.
- Evaluating the probability of distribution centers and routes failing under various scenarios.
- Considering two ways for transporting injured people by normal speed and high-speed vehicles.
- Proposing a robust-stochastic method to cope with different sources of uncertainty.

3. Model description

In this study, a multi-period four level relief logistics problem is used to illustrate the interaction between different levels and time periods of the relief logistics network under various scenarios. A variety of medical supplies and vehicles are included in the model. The model's main goal is to figure out the optimal locations for emergency facilities, as well as the best flow of medical supplies and injured individuals between them, so that the cost of construction of facilities, transportation, pre-positioned inventory and penalty costs is minimized. The schematic representation of the relief system structure is shown in Figure 1.

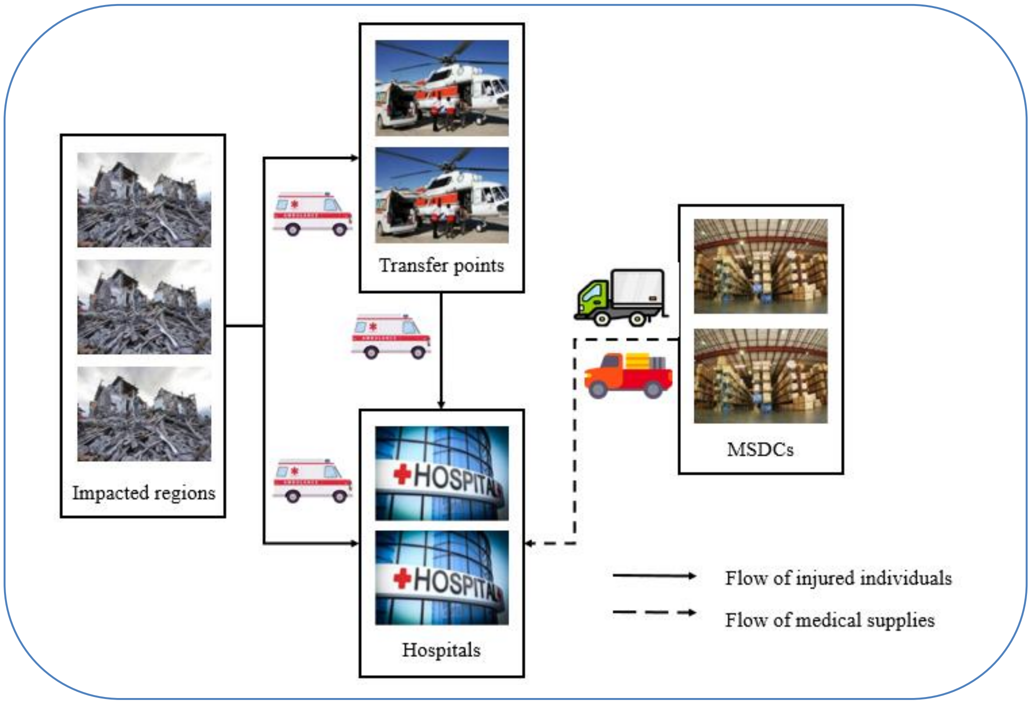


Figure 1. The schematic view of the network

As shown in this figure, the set of nodes is categorized into four subsets in this model: the impacted regions, the transfer points, the MSDCs, and the hospitals. Some medical equipment is pre-positioned in hospitals in pre-disaster phase in the model. Hospitals receive medical supplies from MSDCs. People who have been injured are taken to hospitals from the impacted regions in one of two ways: by vehicles driving at normal speeds directly from impacted regions to hospitals, or by vehicles driving at normal speeds from impacted regions to transfer points and subsequently by high-speed vehicles from transfer points to hospitals. The type of vehicle used depends on a variety of criteria, such as the type of commodities being delivered (medical supplies or injured people), the route used, and the volume and weight of commodities or injured people. The number of vehicles that may be rented and the amount of supplies that may be purchased as initial inventory both have upper limits. In both the pre-disaster and post-disaster stages, the model assists the planning team in making the optimal decisions. In the preparedness phase, the suggested model determines the best locations for MSDCs and transfer points, as well as the best quantity of initial medical supply inventory. After disaster, the model determines optimal transportation plans, flow of medical supplies and injured people, and response time for treating injured people in response phase. The assumptions are as follows:

- High-speed vehicles and nursing teams are available at the transfer points to provide first aid.
- The number of impacted regions and potential locations for MSDCs and transfer points are known.
- As there are hospitals in every city, hospital locations are considered fixed.
- Each impacted regions' injured people can only be allocated to one hospital.
- Several MSDCs can supply each hospital with the medical supplies.
- All routs are prone to damage and may become inaccessible in the event of a disaster.

4. Model formulation

4.1. Notations

The sets, parameters, and decision variables are described below.

Sets

H	Hospitals
I	Impacted regions
J	Potential locations for MSDCs
K	Types of medical supplies
M	Transfer points
Z	Transportation modes ($z, z' \in Z$)
S	Scenarios
T	Time periods

Parameters

$\boldsymbol{A_{it}^s}$	Number of individuals who have been injured at impacted region *i* in period *t* under scenario *s*
$\boldsymbol{B_z}$	Renting cost of transportation mode *z*
$\boldsymbol{Ba_{z'}}$	Renting cost of transportation mode z'
$\boldsymbol{C_h}$	Capacity of hospital *h* to treat injured people
$\boldsymbol{C_m}$	Capacity of transfer point *m* to transport injured people
$\boldsymbol{C_{jk}}$	Capacity of MSDC *j* for medical supply *k*
$\boldsymbol{d_{hkt}^s}$	Required demand of hospital *h* for medical supply *k* in period *t* under scenario *s*
$\boldsymbol{F_m}$	Establishment cost of transfer point *m*
$\boldsymbol{Fa_j}$	Establishment cost of MSDC *j*
$\boldsymbol{g_{kj}}$	Unit cost of procurement medical supply *k* by MSDC *j*
$\boldsymbol{g_{kj}^{max}}$	Maximum amount of medical supply *k* that can be procured by MSDC *j*
$\boldsymbol{l_{kh}}$	Unit cost of pre-positioned medical supply *k* in hospital *h*
$\boldsymbol{o_z^{max}}$	Number of accessible transportation mode *z*
$\boldsymbol{o_{z'}^{max}}$	Number of accessible transportation mode z'
$\boldsymbol{p_k^{max}}$	Maximum limitation of medical supply *k* that can be pre-positioned
$\boldsymbol{P^s}$	Occurrence probability of scenario *s*
$\boldsymbol{q_{iht}^s}$	Likelihood that the route between point *i* and point *h* fails in period *t* under scenario *s*
$\boldsymbol{q_{ihmt}^s}$	Likelihood that the route between point *i* and point *h* through transfer point *m* fails in period *t* under scenario *s*
$\boldsymbol{q_{jht}^s}$	Likelihood that the route between point *j* and point *h* fails in period *t* under scenario *s*
$\boldsymbol{V_i}$	Average number of individuals injured at impacted region *i*
$\boldsymbol{V_k}$	Volume of a unit of medical supply *k*
$\boldsymbol{W_i}$	Average weight of injured individuals at impacted region *i*
$\boldsymbol{W_k}$	Unit weight of medical supply *k*
$\boldsymbol{CV_z}$	Volumetric capacity of transportation mode *z*
$\boldsymbol{CV_{z'}}$	Volumetric capacity of transportation mode z'
$\boldsymbol{CW_z}$	Carrying weight capacity of transportation mode *z*
$\boldsymbol{CW_{z'}}$	Carrying weight capacity of transportation mode z'
$\boldsymbol{Tc_{ihzt}^s}$	Transportation cost for an injured between point *i* and point *h* using transportation mode *z* in period *t* under scenario *s*
$\boldsymbol{Tc_{ihmzt}^s}$	Transportation cost for an injured between point *i* and point *h* through transfer point *m* using transportation mode *z* in period *t* under scenario *s*
$\boldsymbol{Tc_{kjhz't}^s}$	Transportation cost for a unit medical supply *k* from point *j* to point *h* using transportation mode z' in period *t* under scenario *s*
$\boldsymbol{T_{ihzt}^s}$	The time required to transport between point *i* and point *h* using transportation mode *z* in period *t* under scenario *s*
$\boldsymbol{T_{ihmzt}^s}$	The time required to transport between point *i* and point *h* through transfer point *m* using transportation mode *z* in period *t* under scenario *s*
$\boldsymbol{\beta_t^s}$	Available budget for procurement of medical supplies in period *t* under scenario *s*
$\boldsymbol{\mu_k}$	Consumption rate of medical supply *k* for each injured person
$\boldsymbol{\pi_{kht}^s}$	Unit cost for shortage of medical supply *k* in hospital *h* in period *t* under scenario *s*

$\boldsymbol{\tau}$	Penalty cost for infraction of maximum time limitation per minute for treating injured individuals
$\boldsymbol{\Phi}$	Maximum time limitation for treating injured people
$\boldsymbol{\Psi_{jt}^{s}}$	Likelihood of having access to MSDC *j* in period *t* under scenario *s*

Variables

$\boldsymbol{Y_{kjhz't}^{s}}$	Number of medical supply *k* transported between point *j* and point *h* using transportation mode z' in period *t* under scenario *s*
$\boldsymbol{I_{kht}^{s}}$	Quantity of unmet medical supply *k* at hospital *h* in period *t* under scenario *s*
$\boldsymbol{T_{SH}}$	Amount of infraction of time limitation for treating injured individuals
$\boldsymbol{P_{kh}^{0}}$	Amount of pre-positioned medical supply *k* in hospital *h*
$\boldsymbol{R_{z}}$	Number of in contract transportation mode *z*
$\boldsymbol{R_{z'}}$	Number of in contract transportation mode z'
$\boldsymbol{G_{kjt}^{s}}$	Amount of medical supply *k* procured by MSDC *j* in period *t* under scenario *s*
$\boldsymbol{N_{ziht}^{s}}$	Number of transportation mode *z* in road between point *i* and point *h* in time *t* under scenario *s*
$\boldsymbol{N_{zihmt}^{s}}$	Number of transportation mode *z* in road between point *i* and point *h* through transfer point *m* in period *t* under scenario *s*
$\boldsymbol{N_{z'jht}^{s}}$	Number of transportation mode z' in road between point *j* and point *h* in period *t* under scenario *s*
$\boldsymbol{E_{m}}$	1 if a transfer point is constructed at potential location *m*; otherwise 0;
$\boldsymbol{U_{j}}$	1 if a MSDC is constructed at potential location *j*; otherwise 0
$\boldsymbol{X_{ihzt}^{s}}$	1 if injured people at impacted region *i* is allocated to hospital *h* using transportation mode *z* in period *t* under scenario *s*; otherwise 0
$\boldsymbol{X_{ihmzt}^{s}}$	1 if injured people at impacted region *i* is allocated to hospital *h* through transfer point *m* using transportation mode *z* in period *t* under scenario *s*; otherwise 0

4.2. Mathematical model

The proposed mixed-integer programming model is expressed as follows, using the aforementioned notation.

$$Min\ obj = \sum_{m} F_m E_m + \sum_{j} Fa_j U_j + \sum_{k}\sum_{h} l_{kh} P_{kh}^{0} + \sum_{z} B_z R_z + \sum_{z'} Ba_{z'} R_{z'} \quad (1)$$

$$+ \sum_{s} P_s \Bigg[\sum_{i}\sum_{h}\sum_{z}\sum_{t} A_{it}^{s} Tc_{ihzt}^{s} q_{iht}^{s} X_{ihzt}^{s}$$

$$+ \sum_{i}\sum_{m}\sum_{h}\sum_{z}\sum_{t} A_{it}^{s} Tc_{ihmzt}^{s} q_{ihmt}^{s} X_{ihmzt}^{s}$$

$$+ \sum_{k}\sum_{j}\sum_{h}\sum_{z'}\sum_{t} Tc_{kjhz't}^{s} q_{jht}^{s} \Psi_{jt}^{s} Y_{kjhz't}^{s} + \sum_{k}\sum_{h}\sum_{t} \pi_{kht}^{s} I_{kht}^{s} \Bigg] + \tau T_{SH}$$

$$\sum_{h}\sum_{z} X_{ihzt}^{s} + \sum_{m}\sum_{h}\sum_{z} X_{ihmzt}^{s} = 1, \qquad \forall i \in I, t \in T, s \in S \quad (2)$$

$$\sum_{h}\sum_{z} X_{ihzt}^{s} \leq 1, \qquad \forall i \in I, t \in T, s \in S \quad (3)$$

$$X_{ihmzt}^{s} \leq E_m, \qquad \forall i \in I, m \in M, h \in H, z \in Z, t \in T, s \in S \quad (4)$$

$$\mu_k \sum_{i}\sum_{m}\sum_{z} (X_{ihmzt}^{s} + X_{ihzt}^{s}) A_{it}^{s} \geq d_{hkt}^{s}, \qquad \forall k \in K, h \in H, s \in S, t \in T \quad (5)$$

$$\sum_{m}\sum_{h}\sum_{z} T_{ihmzt}^{s} X_{ihmzt}^{s} + \sum_{h}\sum_{z} T_{ihzt}^{s} X_{ihzt}^{s} \leq \Phi + T_{SH}, \qquad \forall i \in I, s \in S, t \in T \quad (6)$$

$$\sum_{i}\sum_{m}\sum_{z} (X_{ihmzt}^{s} + X_{ihzt}^{s})\, A_{it}^{s} \leq C_h, \qquad \forall h \in H, s \in S, t \in T \quad (7)$$

$$\sum_{i}\sum_{h}\sum_{z} A_{it}^{s} X_{ihmzt}^{s} \leq C_m E_m, \quad \forall m \in M, s \in S, t \in T \tag{8}$$

$$\sum_{h}\sum_{z\prime} Y_{kjhz\prime t}^{s}\, \Psi_{jt}^{s} \leq C_{jk} U_j, \quad \forall j \in J, k \in K, s \in S, t \in T \tag{9}$$

$$d_{hkt}^{s} - \sum_{j}\sum_{z'} Y_{kjhz't}^{s} = I_{kht}^{s}, \quad \forall k \in K, h \in H, s \in S, t \in T \tag{10}$$

$$\sum_{h} P_{kh}^{0} \leq p_k^{max}, \quad \forall k \in K \tag{11}$$

$$R_z \leq o_z^{max}, \quad \forall z \in Z \tag{12}$$

$$R_{z\prime} \leq o_{z'}^{max}, \quad \forall z' \in Z \tag{13}$$

$$\sum_{t} G_{kjt}^{s} \leq g_{kj}^{max} U_j, \quad \forall k \in K, j \in J, s \in S \tag{14}$$

$$N_{z'jht}^{s} \geq \sum_{k} \frac{W_k}{CW_{z'}} Y_{kjhz't}^{s}, \quad \forall\, j \in J, h \in H, z' \in Z, s \in S, t \in T \tag{15}$$

$$N_{ziht}^{s} \geq \frac{W_i}{CW_z} A_{it}^{s} X_{ihzt}^{s}, \quad \forall i \in I, h \in H, z \in Z, s \in S, t \in T \tag{16}$$

$$N_{zihmt}^{s} \geq \frac{W_i}{CW_z} A_{it}^{s} X_{ihmzt}^{s}, \quad \forall i \in I, m \in M, h \in H, z \in Z, s \in S, t \in T \tag{17}$$

$$N_{z'jht}^{s} \geq \sum_{k} \frac{V_k}{CV_{z'}} Y_{kjhz't}^{s}, \quad \forall j \in J, h \in H, z' \in Z, s \in S, t \in T \tag{18}$$

$$N_{ziht}^{s} \geq \frac{V_i}{CV_z} A_{it}^{s} X_{ihzt}^{s}, \quad \forall i \in I, h \in H, z \in Z, s \in S, t \in T \tag{19}$$

$$N_{zihmt}^{s} \geq \frac{V_i}{CV_z} A_{it}^{s} X_{ihmzt}^{s}, \quad \forall i \in I, m \in M, h \in H, z \in Z, s \in S, t \in T \tag{20}$$

$$\sum_{i}\sum_{h}\sum_{t} N_{ziht}^{s} \leq R_z, \quad \forall z \in Z, s \in S \tag{21}$$

$$\sum_{i}\sum_{m}\sum_{h}\sum_{t} N_{zihmt}^{s} \leq R_z, \quad \forall z \in Z, s \in S \tag{22}$$

$$\sum_{j}\sum_{h}\sum_{t} N_{z'jht}^{s} \leq R_{z'}, \quad \forall z' \in Z, s \in S \tag{23}$$

$$\sum_{k}\sum_{j} g_{kj} G_{kjt}^{s} \leq \beta_t^{s}, \quad \forall s \in S, t \in T \tag{24}$$

$$I_{kht}^{s}, T_{SH}, P_{kh}^{0}, G_{kjt}^{s} \geq 0, \quad \forall k \in K, h \in H, j \in J, s \in S, t \in T \tag{25}$$

$$R_z, R_{z\prime} \geq 0, integer \quad \forall z \in Z, z' \in Z \tag{26}$$

$$N_{ziht}^{s}, N_{zihmt}^{s}, N_{z'jht}^{s}, Y_{kjhz't}^{s} \geq 0, integer \quad \forall z \in Z, z' \in Z, i \in I, m \in M, j \in J, h \in H, k \in K, s \in S, t \in T \tag{27}$$

$$X_{ihmzt}^{s}, X_{ihzt}^{s}, E_m, U_j \in \{0,1\}, \quad \forall z \in Z, i \in I, m \in M, j \in J, h \in H, s \in S, t \in T \tag{28}$$

The goal is to reduce overall network costs, including the fixed costs of opening transfer points and MSDCs, pre-positioned inventory costs, vehicle rental prices, transportation costs, the shortage costs per medical supplies, and penalty costs for response time violation. Constraint (2) shows that injured individuals in each impacted region are allocated to a hospital, either directly or through a transfer point. Constraint (3) ensures that at most one hospital is assigned to each impacted region. Constraint (4) permits one hospital to be assigned to each impacted region through a transfer point, only when the transfer point exists. Constraint (5) shows the quantity of each hospital's medical supply demand. Constraint (6) ensures that injured individuals are transported to hospitals in a reasonable time. Constraints (7) to (9) are capacity limitation of hospitals, transfer points and MSDCs, respectively. Constraint (10) calculates the quantity of unsatisfied medical supply demands. Constraint (11) limits the amount of pre-positioned inventory of medical supplies. Constraints (12) and (13) ensure that the number of vehicles under contract does not surpass a specific threshold of transportation modes for transporting injured people and transportation modes for transporting medical supplies, respectively. It should be noted that index z shows transportation modes for transferring injured individuals between impacted regions and hospitals and index $\boldsymbol{z'}$ shows transportation modes for transporting medical supplies from MSDCs to hospitals. Constraint (14) limits the amount of medical supplies that can be purchased from each MSDC. Constraints (15) to (20) determine the type and number of transportation vehicles in network routs regarding to the volume and weight of supplies and volumetric capacity and weight capacity of vehicles. Constraints (21) to (23) guarantee that the total number of rented vehicles does not surpass the total number of vehicles under contract. Constraint (24) shows the budget limitations and the variables domains are specified by constraints (25) to (28).

4.3. Robust-stochastic approach

Numerous strategies, including stochastic programming, fuzzy optimization, and robust optimization, have been used in the literature to cope the uncertainty of mathematical models. When there is enough historical data for the uncertain parameters to determine their probability distributions, stochastic programming is a useful technique (Zarrinpoor et al., 2018). Robust programming that looks for risk-averse result decisions is another method for managing uncertainty. Decision-makers can alter the level of conservatism of output results in response to parameter uncertainty by using this method (Fazli-Khalaf et al., 2017). When there is no historical data on the value of a parameter and no conceivable function can be linked to the parameter, fuzzy optimization can be used. In fuzzy planning, uncertainty or a lack of understanding about parameters is expressed using fuzzy confidence coefficients and membership functions (Pishvaee and Torabi, 2010; Liu and Iwamura, 1998). In the previous section, we have considered a number of disruption scenarios for the operational decisions of the suggested model. Each of these scenarios describes a disruptive condition with a specific probability. In real-world scenarios, logisticians desire not just to establish cost-effective plans, but also to have less fluctuating expenses in the future (Darvishi et al., 2020). Although stochastic programming can efficiently generate solutions based on various disruption scenarios, the optimal solutions cannot be immunized for any realization of the uncertainty in a specific bounded set. In this research, a hybrid uncertainty handling approach is utilized. This approach benefits from both stochastic programming and RO method as it provides more immunized optimal solutions against uncertainty with a higher degree of resilience in disruption scenarios. With the help of stochastic programming, this approach effectively takes into account the best course of action for each disruptive situation that can cause the system to malfunction. Additionally, with the help of the RO technique, it provides more resilient optimal solutions that are more immune to uncertainty.

In this section, a hybrid approach based on a RO method presented by Ben-tal and Nimrovsky (1999) and Pishvaee et al. (2011) is used to address the uncertainty. The RO approach is briefly described in the following, after that, the proposed model's RC is presented. To describe this approach, the linear optimization model with deterministic parameters is considered as follows:

$$\begin{aligned} &\min \;\; cx + d \\ &s.t. \;\; Ax \le b \end{aligned} \tag{29}$$

The following is a definition of the uncertain linear optimization problem:

$$\begin{aligned} &\min \;\; cx + d \\ &s.t. \;\; Ax \le b \\ &c, d, A, b \in U \end{aligned} \tag{30}$$

In which the parameters c, d, A, and b change in an uncertainty set U. A robust feasible solution to model (30) is one that satisfies all realizations of the constraints from the uncertainty set U. The RC structure of the mathematical model (30) is defined in the following way:

$$min\left\{\hat{c}(x) = \underset{(c,d,A,b\in U)}{sup}[cx + d]: Ax \le b \;\; \forall c, d, A, b \in U\right\} \tag{31}$$

Optimal solution of model (31) is the optimal robust solution of model (30). To generate the optimal robust solution for the suggested model presented in the previous subsection, the compact form of the model is written as follows:

$$\begin{aligned} &\min fy + cx \\ &s.t. \\ &Ax \ge d, \\ &Hx = r, \end{aligned} \tag{32}$$

$$Nx = 0,$$
$$Mx \leq 0,$$
$$Bx \leq Cy,$$
$$y \epsilon \{0,1\}, \;\; x \in R^+.$$

In the above model, vectors y and x contain all binary and continuous decision variables, respectively. The parameters d, r, and c are used to represent uncertain parameters. The parameters f, and matrices *A* and *H* are definite parameters. Each of the uncertain parameters should fluctuate inside a closed delimited box. This box's overall shape can be written as follows:

$$U_{Box} = \left\{ \xi \in R^n : \left| \xi_t - \overline{\xi_t} \right| \leq \rho G_t, \;\; t = 1, \dots, n \right\} \tag{33}$$

where $\overline{\xi_t}$ is the nominal amount of ξ_t, parameter t of n-dimension vector ξ. The positive number G_t expresses uncertainty scale while $\rho > 0$ indicates the level of uncertainty. As previously indicated, the compact model's RC is as follows:

$$\min z$$
$$s.t.$$
$$fy + cx \leq z, \qquad \forall c \in U^c_{Box} \tag{34}$$
$$Ax \geq d, \qquad \forall d \in U^d_{Box} \tag{35}$$
$$Hx = r, \qquad \forall r \in U^r_{Box} \tag{36}$$
$$Nx = 0, \tag{37}$$
$$Mx \leq 0, \tag{38}$$
$$Bx \leq Cy, \tag{39}$$
$$y \epsilon \{0,1\}, \;\; x \in R^+. \tag{40}$$

The RC model can then be turned to a tractable equivalent one by replacing with a finite set of the extreme points of U_{box}. For this purpose, Eqs. (34) to (36) should be transformed to tractable equivalents. For Eq. (34), we have:

$$cx \leq z - fy, \forall c \in U^c_{Box} | U^c_{Box} = \{c \in R^{n_c} : |c_t - \overline{c_t}| \leq \rho_c G^c_t, t = 1, \dots, n_c\}. \tag{41}$$

The left-hand side of Eq. (41) contains uncertain parameters, whereas the right-hand side contains all certain parameters. The following is the tractable form of the aforementioned inequality:

$$\sum_t (\overline{c_t} x_t + \eta_t) \leq z - fy, \tag{42}$$
$$\rho_c G^c_t x_t \leq \eta_t, \qquad \forall t \in \{1, \dots, n_c\}$$
$$\rho_c G^c_t x_t \geq -\eta_t, \qquad \forall t \in \{1, \dots, n_c\}.$$

Similarly, for Eqs. (35) and (36) we have:

$$a_i x \geq \bar{d}_i + \rho_d G^d_i, \qquad \forall i \in \{1, \dots, n_d\}, \tag{43}$$
$$h_j x \geq \overline{r_j} - \rho_r G^r_j, \qquad \forall j \in \{1, \dots, n_r\}, \tag{44}$$
$$h_j x \leq \overline{r_j} + \rho_r G^r_j, \qquad \forall j \in \{1, \dots, n_r\}.$$

Finally, the robust compact model is expressed in tractable form as follows:

$$\min z \tag{45}$$
$$\sum_t (\overline{c_t} x_t + \eta_t) \leq z - fy$$
$$\rho_c G^c_t x_t \leq \eta_t \qquad \forall t \in \{1, \dots, n_c\}$$
$$\rho_c G^c_t x_t \geq -\eta_t \qquad \forall t \in \{1, \dots, n_c\}$$
$$a_i x \geq \bar{d}_i + \rho_d G^d_i \qquad \forall i \in \{1, \dots, n_d\}$$
$$h_j x \geq \overline{r_j} - \rho_r G^r_j \qquad \forall j \in \{1, \dots, n_r\}$$
$$h_j x \leq \overline{r_j} + \rho_r G^r_j \qquad \forall j \in \{1, \dots, n_r\}$$

$Nx = 0,$

$Mx \leq 0,$

$Bx \leq Cy,$

$y \in \{0,1\}, \;\; x, \eta_t \in R^+.$

According to the above specifications, the RC of the suggested model with uncertain costs and demand provided by uncertainty box set can be stated as follows:

$$\min \zeta$$

$$s.t. (2)-(4), (6)-(9), (11)-(23), (25)-(28),$$

$$\sum_m (\bar{F}_m E_m + \mu_m^F) + \sum_j (\overline{Fa}_j U_j + \mu_j^{Fa}) + \sum_k \sum_h (\bar{l}_{kh} P_{kh}^0 + \mu_{kh}^l) + \sum_z (\bar{B}_z R_z + \mu_z^B) + \sum_{z'} (\overline{Ba}_{z'} R_{z'} + \mu_{z'}^{Ba}) + (\bar{\tau} T_{SH} + \mu^\tau) + \sum_s P_s \Bigg[\sum_i \sum_h \sum_z \sum_t A_{it}^s Tc_{ihzt}^s q_{iht}^s X_{ihzt}^s + \sum_i \sum_m \sum_h \sum_z \sum_t A_{it}^s Tc_{ihmzt}^s q_{ihmt}^s X_{ihmzt}^s + \sum_k \sum_j \sum_h \sum_{z'} \sum_t Tc_{kjhz't}^s q_{jht}^s \Psi_{jt}^s Y_{kjhz't}^s + \sum_k \sum_h \sum_t (\bar{\pi}_{kht}^s I_{kht}^s + \mu_{khts}^\pi) \Bigg] \leq \zeta \quad (46)$$

$\rho_F G_m^F E_m \leq \mu_m^F, \quad \forall m \in M, \quad (47)$

$\rho_F G_m^F E_m \geq -\mu_m^F, \quad \forall m \in M, \quad (48)$

$\rho_{Fa} G_j^{Fa} U_j \leq \mu_j^{Fa}, \quad \forall j \in J, \quad (49)$

$\rho_{Fa} G_j^{Fa} U_j \geq -\mu_j^{Fa}, \quad \forall j \in J, \quad (50)$

$\rho_l G_{kh}^l P_{kh}^0 \leq \mu_{kh}^l, \quad \forall k \in K, h \in H, \quad (51)$

$\rho_l G_{kh}^l P_{kh}^0 \geq -\mu_{kh}^l, \quad \forall k \in K, h \in H, \quad (52)$

$\rho_B G_z^B R_z \leq \mu_z^B, \quad \forall z \in Z, \quad (53)$

$\rho_B G_z^B R_z \geq -\mu_z^B, \quad \forall z \in Z, \quad (54)$

$\rho_{Ba} G_{z'}^{Ba} R_{z'} \leq \mu_{z'}^{Ba}, \quad \forall z' \in Z, \quad (55)$

$\rho_{Ba} G_{z'}^{Ba} R_{z'} \geq -\mu_{z'}^{Ba}, \quad \forall z' \in Z, \quad (56)$

$\rho_\tau G^\tau T_{SH} \leq \mu^\tau, \quad (57)$

$\rho_\tau G^\tau T_{SH} \geq -\mu^\tau, \quad (58)$

$\rho_\pi G_{khts}^\pi I_{kht}^s \leq \mu_{khts}^\pi \quad \forall k \in K, h \in H, t \in T, s \in S \quad (59)$

$\rho_\pi G_{khts}^\pi I_{kht}^s \geq -\mu_{khts}^\pi \quad \forall k \in K, h \in H, t \in T, s \in S \quad (60)$

$$\mu_k \sum_i \sum_m \sum_z (X_{ihmzt}^s + X_{ihzt}^s) A_{it}^s \geq \bar{d}_{hkt}^s + \rho_d G_{hkts}^d, \quad \forall k \in K, h \in H, s \in S, t \in T \quad (61)$$

$$\sum_j \sum_{z'} Y_{kjhz't}^s \leq \bar{d}_{hkt}^s + \rho_d G_{hkts}^d - I_{kht}^s, \quad \forall k \in K, h \in I, s \in S, t \in T \quad (62)$$

$$\sum_j \sum_{z'} Y_{kjhz't}^s \geq \bar{d}_{hkt}^s - \rho_d G_{hkts}^d - I_{kht}^s, \quad \forall k \in K, h \in I, s \in S, t \in T \quad (63)$$

$$\sum_k \sum_j g_{kjt}^s G_{kjt}^s \leq \bar{\beta}_t^s - \rho_\beta G_{ts}^\beta \quad \forall s \in S, t \in T \quad (64)$$

$\mu_m^F, \mu_j^{Fa}, \mu_{kh}^l, \mu_z^B, \mu_{z'}^{Ba}, \mu^\tau, \mu_{khts}^\pi \geq 0, \quad \forall m \in M, j \in J, k \in K, h \in H, z \in Z, z' \in Z, s \in S, t \in T. \quad (65)$

5. Case study

A case study focused on the southern and western cities of Fars province is provided in this section to demonstrate the effectiveness of the suggested model in the real world. Fars province is Iran's fourth most populated province, with a total area of 120608 km^2 and a population of 5130927 people according to the 2022 Shiraz City Annual Report (SCAR, 2022).

In terms of earthquake engineering, deep earthquakes have a focal depth greater than 70 kilometers, whereas surface earthquakes have a focal depth less than 70 kilometers. It is worth noting that surface-type earthquakes have always been more destructive. The focal depths of most earthquakes in Fars province have been between 10 and 15 kilometers, making them destructive earthquakes. Another aspect to consider is earthquakes' non-compliance with fault lines. The majority of earthquakes have occurred at a distance from fault lines. As indicated in Figure 2, the province's southern and western parts have the highest number of earthquakes.

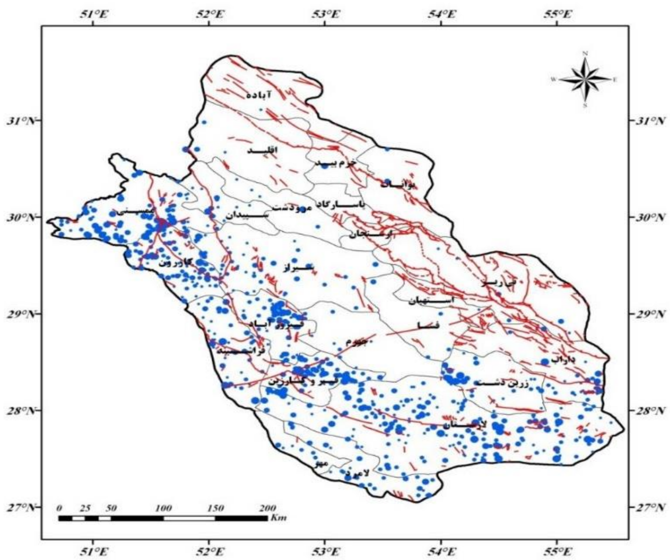


Figure 2. The map of distribution of earthquake centers relative to fault lines

The study region is containing 15 cities of Fars province as impacted regions. Its population is more than 3 million people and its area is about 56000 km^2. The cities are listed in Table 1. Note that I, FH, and H stand for intermediate, fairly high, and high risks. Study and planning in this area for earthquake disasters and possible breakdowns, as well as the establishment of adequate disaster facilities can assist in making decisions throughout both the preparedness and response processes, reducing disaster impacts. Several active faults, including as Kazerun, Karebas, Sarvestan, and Sabzpoushan, threaten the region. Figure 3 illustrates the map of impacted regions and potential locations for facilities.

Table 1. The list of cities.

Number	City	Risk	Number	City	Risk	Number	City	Risk
1	Zarindasht	I	6	Sarvestan	H	11	Mamasani	H
2	Jahrom	FH	7	Mohr	H	12	Larestan	H
3	Kazerun	H	8	Farashband	H	13	Khonj	H
4	Firuzabad	H	9	Ghir va Karzin	H	14	Gerash	H
5	Kavar	H	10	Shiraz	H	15	Lamerd	H

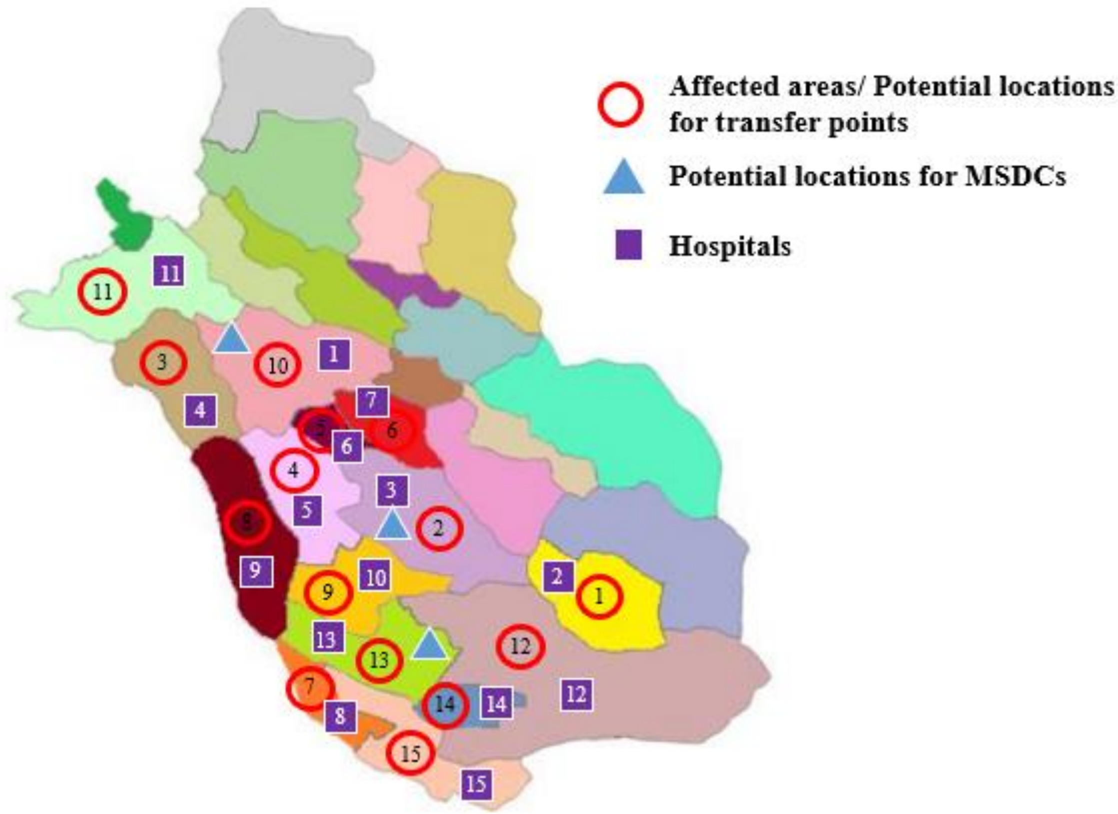


Figure 3. The map of impacted regions and potential locations for facilities

The activity of each of Kazerun, Karebas, Sarvestan, and Sabzpoushan faults has been considered as a scenario. Expert judgement and historical data have determined that the probabilities for these scenarios are 0.4, 0.3, 0.2, and 0.1, respectively. Three cities, Shiraz, Jahrom, and Khonj, were chosen as potential MSDC locations based on accessibility and safety factors and each MSDC has the ability to serve its own city as well as any city with a common boundary. There is an active hospital in each city. Each hospital's demand for medical equipment is equal to 30% of the population that can be given to the hospital.

There are considered two types of medical equipment including medicines and medical devices. It should be noted that food and clothes are examples of relief supplies that might be included in this category. Prepositioning capacity is zero for medicines since they are regarded perishable. A medical kit can serve up to 100 individuals. Each medical equipment's penalty cost for unmet demand is 100 times more than its purchase price. To determine the time and distance of each route, the shortest path (highway or freeway) is considered. State ambulances, private ambulances, and bus ambulances for transferring injured individuals, as well as trucks and pickup trucks for delivering medical equipment are considered.

5.1. Numerical results

The numerical results obtained from solving the suggested model are provided in this subsection. The proposed model was coded in *GAMS 23.4* on a *Pentium Core i5* computer with *2GB RAM*. The proposed model might be seen as a complex version of the capacitated facility location problem. In its most basic form, the capacitated facility location problem is an NP-Hard problem (Mirchandani and Francis, 1990). This problem becomes more difficult as it is expanded by the addition of aspects like allocation and distribution decisions, the flow of injured people and medical supplies, failure of distribution centers for medical supplies and roadways, and uncertainty factors. Since only some regions of Fars province are considered for the studied case, the results are generated within a reasonable amount of

CPU time. The objective value and facility deployment for different uncertainty levels are presented in Table 2. Note that the reported values are rounded to the nearest integer.

Table 2. Robust-stochastic model results.

Uncertainty level	Objective function value	Transfer points	MSDCs
0.2	12705841	3, 10, 12 and 13	1,2 and 3
0.5	13337841	2, 4, 10, 13 and 15	1,2 and 3
0.7	13485221	4, 7, 10, 11 and 12	1,2 and 3
0.9	13691810	4, 5, 10,12 and 15	1,2 and 3

By comparing the results, it is observed that varying levels of uncertainty result in various solutions for optimum number and position of facilities and also the allocation of injured individuals to the hospitals. For example, for $\rho = 0.5$, five cities 2, 4, 10, 13 and 15 are selected as the optimal location for transfer points, while for $\rho = 0.9$ five cities 4, 5, 10, 12 and 15 are selected. It's also been found that raising the level of uncertainty raises the network's total cost. As expected, the results of stochastic model are completely different from the results of the hybrid robust-stochastic model. Figures 4 and 5 show the flow of injured people from impacted region 5 under scenario 1, for stochastic and hybrid robust-stochastic models. According to the results given by stochastic model, the injured people in time period 1 are allocated to transfer point 5 and after that to hospital 7. In time periods 2 and 3, they are allocated to the same transfer point and after that to hospital 6, and they are allocated to hospital 6 directly in time period 4. While according to the hybrid model, the injured people in time periods 1 and 2 are transferred to transfer point 10 and from there to hospitals 7 and 4, respectively, and in time periods 3 and 4 they are allocated to hospitals 3 and 6, respectively.

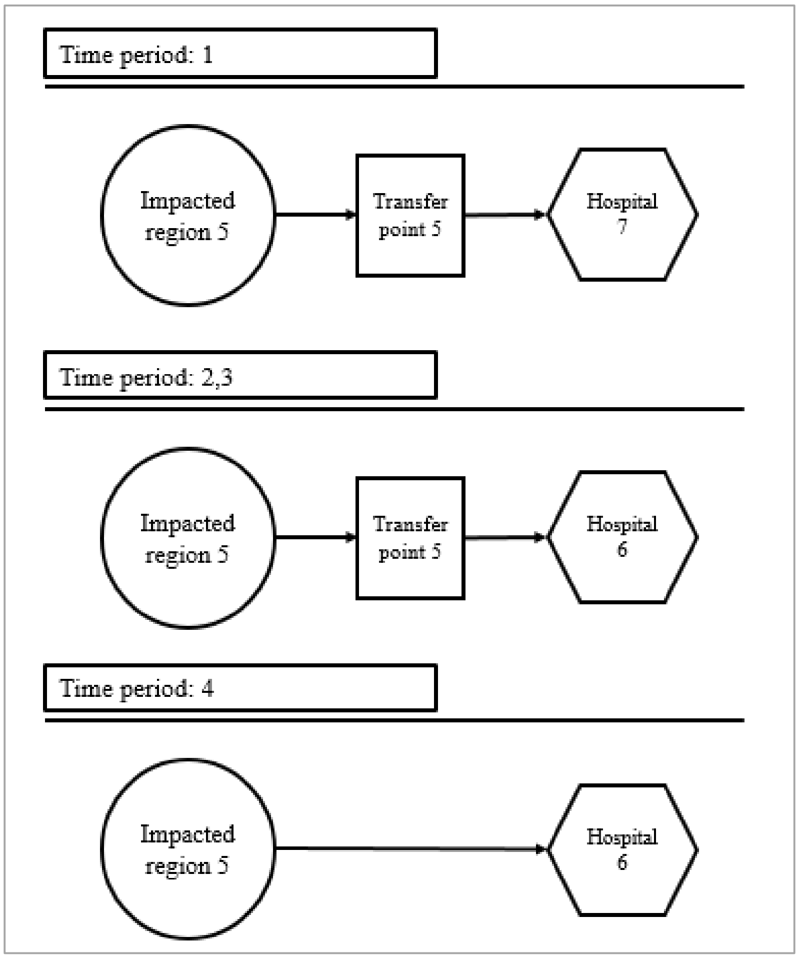


Figure 4. The flow of injured individuals from impacted region 5 under scenario1 using the stochastic model

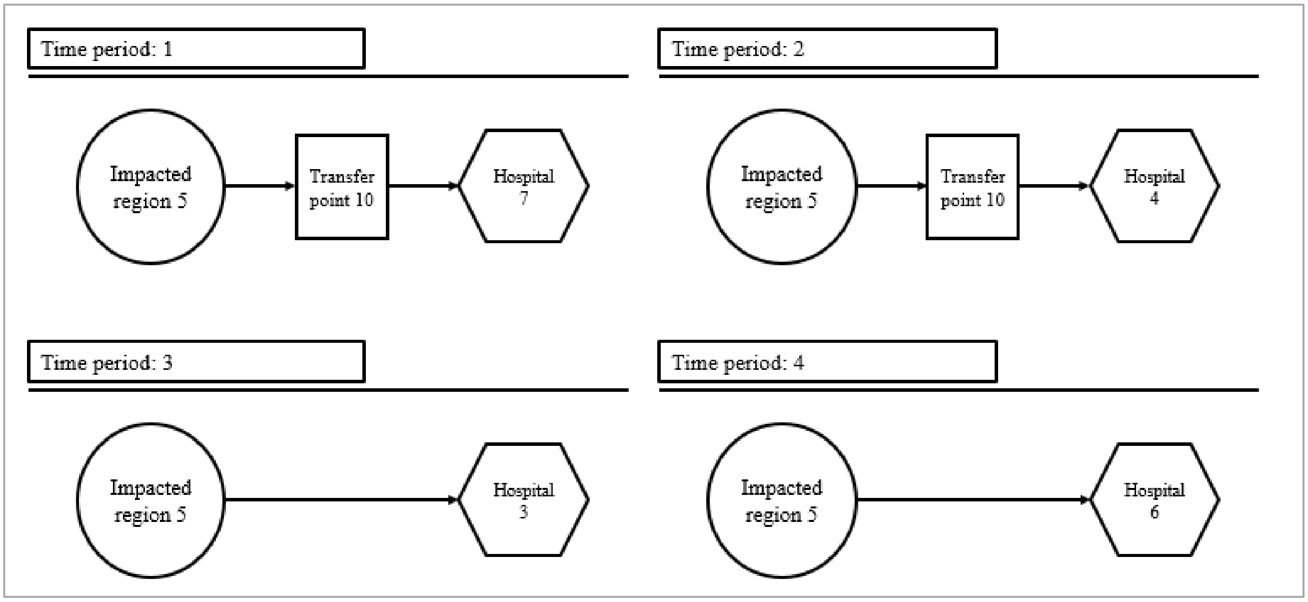


Figure 5. The flow of injured individuals from impacted region 5 under scenario1 using the hybrid robust-stochastic model

As we have seen, by applying assumptions, variables and realistic constraints the proposed model is able to provide appropriate strategic activities for locating of facilities as well as appropriate operational decisions of allocation of injured people and distribution of medical equipment after a disaster to experts and decision-makers.

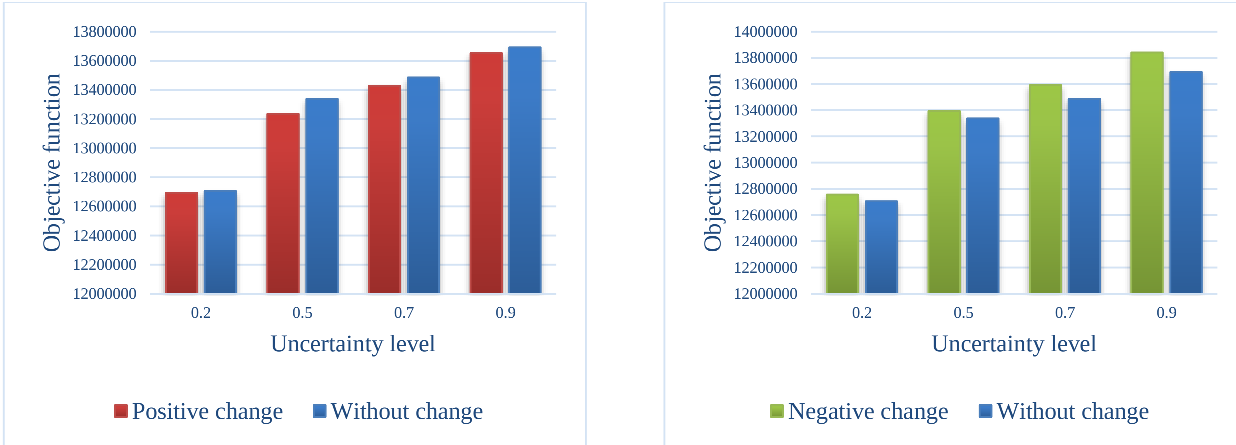
5.2. Sensitivity analysis

In this section, some of the main parameters, such as demand and capacity parameters, have been subjected to sensitivity analysis. These sensitivity analyses are carried out by adjusting the values of main parameters for positive and negative changes in the four different uncertainty levels 0.2, 0.5, 0.7, and 0.9 while keeping other parameters constant. Table 3 summarizes the results for various change levels.

Table 3. The results of sensitivity analysis.

Parameter	**Stochastic**		**Robust-stochastic**							
			ρ =0.2		ρ =0.5		ρ =0.7		ρ =0.9	
	Positive change	Negative change	Positive change	Negative change	Positive change	Negative change	Positive change	Negative change	Positive change	Negative change
C_h	12427835	12584058	12691901	12756543	13234109	13393518	13428587	13591342	13651331	13840903
C_m	12210738	12514612	12685751	12753372	13300062	13393160	13450496	13538303	13672573	13805673
C_{jk}	12038799	12394271	12629553	12719398	12970392	13537022	13449447	13655112	13625737	13862698
d^s_{hkt}	65294169	12426059	65320747	12671264	69042922	12889541	72988239	13051314	75997502	13197474

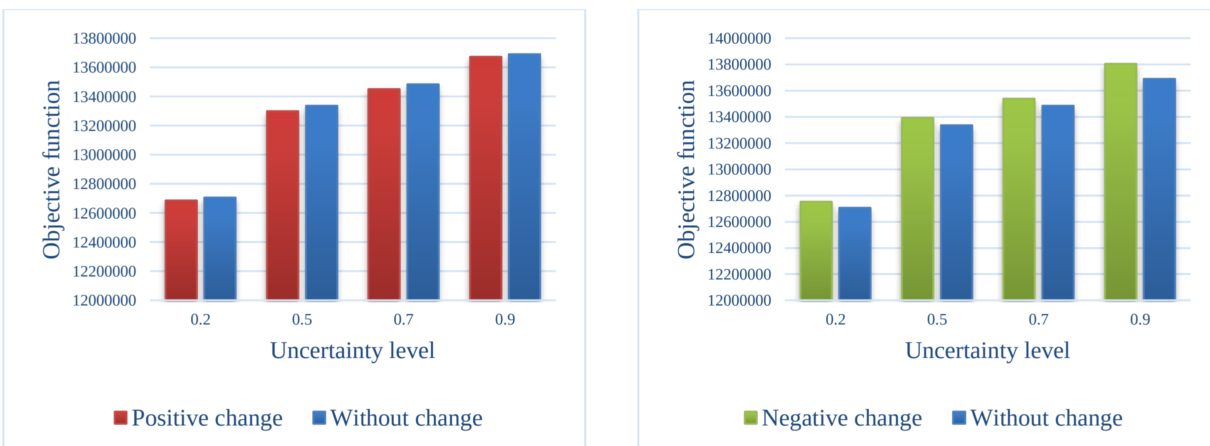
As shown in Figure 6, changing the positive or negative hospital capacity alters the objective's value, which reflects the sensitivity of the response to the hospital capacity parameter. As can be observed, by expanding hospital capacity, the system cost will go down as more patients may be treated at closer facilities. However, when hospital capacity is reduced, injured patients must be sent to hospitals further away, and transportation costs will soar, increasing the overall cost of the system.



a) Positive change level *b) Negative change level*

Figure 6. The impact of hospitals capacity C_h on the robust-stochastic model

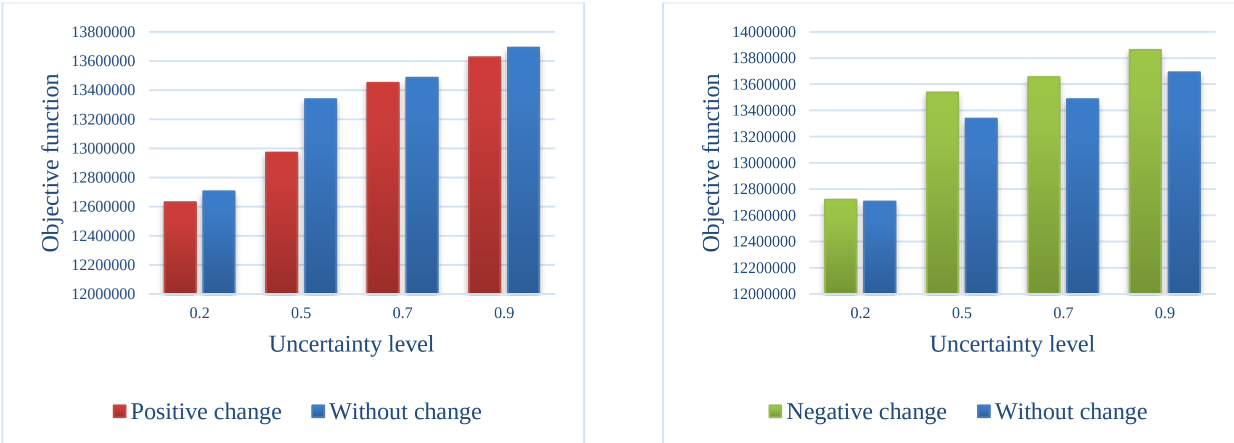
Changing the capacity level for the transfer points capacity parameter, as illustrated in Figure 7, changes the objective value. When transfer points' capacity falls, the system cost rises; conversely, when it rises, the system cost drops because more injured persons can be sent to transfer points that are closer to them.



a) Positive change level *b) Negative change level*

Figure 7. The impact of transfer points capacity $C_m$on the robust-stochastic model

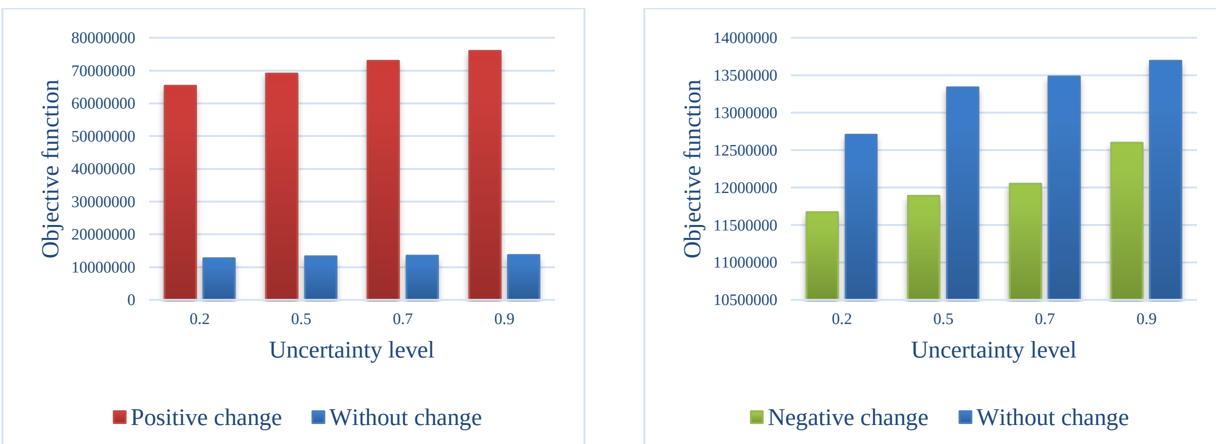
As shown in Figure 8, changing the MSDC's capacity level, alters the value of the objective in the same way that changing the two preceding parameters does. This parameter has a greater impact on the final result than the other capacity parameters.



a) Positive change level *b) Negative change level*

Figure 8. The impact of MSDCs capacity C_{jk} on the robust-stochastic model

The objective function optimal value increases rapidly as the amount of demand rises. When demand rises while other parameters remain constant, the amount of unmet demand rises and a significant penalty cost incurred in the network, resulting in an increase in overall cost. When the quantity of demand is reduced, the objective function value drops considerably, as predicted. This is apparent in Figure 9.



a) Positive change level *b) Negative change level*

Figure 9. The impact of demand d_{hkt}^{s} on the robust-stochastic model

Figures 10 and 11 show that, comparing to other factors, the demand parameter has a considerable impact on the final result. The objective function value is strongly influenced by demand parameter. It can be observed that when there is a negative change in demand, the projected network cost is 2.72% lower than when there is no change in demand. While the positive change leads to 5.32 times increase in overall network cost.

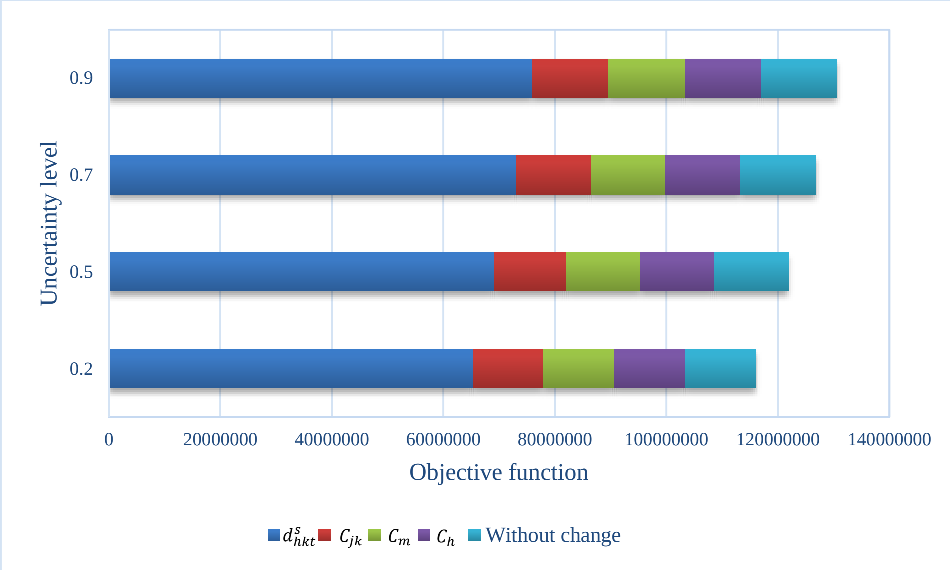


Figure 10. The impact of the positive change in the parameters on the objective

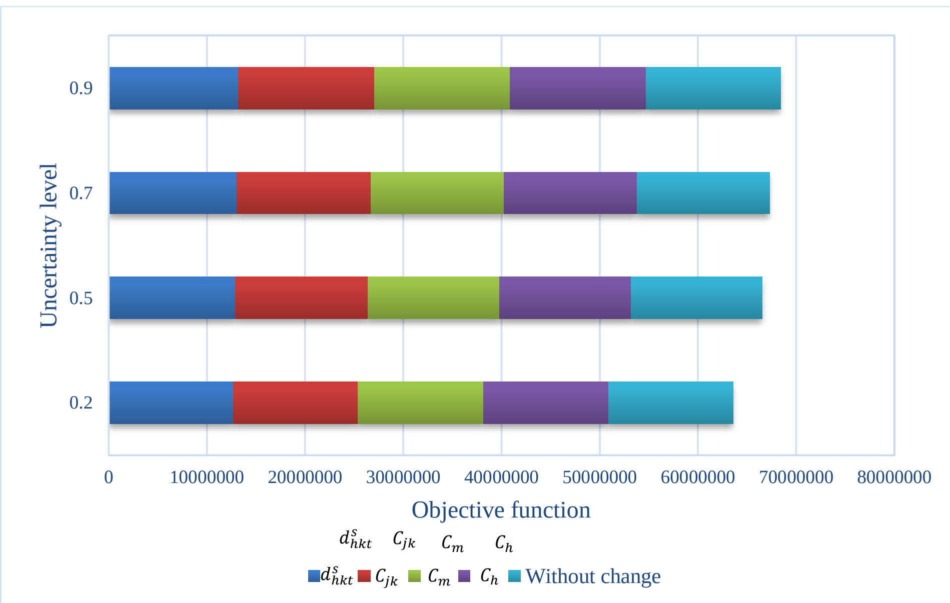


Figure 11. The impact of the negative change in the parameters on the objective.

5.3. Discussion and managerial insights

The effectiveness and application of the relief logistics model for setting up an EMS network are examined in this research utilizing a real-world case study in the Fars province of Iran. A multi-period emergency relief system is required for a rapid disaster response with fewer casualties. Governments must prepare reliable relief plans before a disaster strikes because of limited resources in the event of a disaster. At the same time, since there are many uncertain parameters at the time of disaster, the planning should also consider different disruptive scenarios.

This paper outlines a plan for disaster response that enables decision makers to make strategic and operational decisions about the location of relief facilities, the types and numbers of vehicles needed to transport and allocate relief goods and people. Additionally, it helps decision-makers deal with the uncertainty of real-world parameters in logistics problems for disaster relief. The findings of the case study and sensitivity analysis of this study can be summarized as follows. First, it is exceedingly misleading to plan relief logistics without taking uncertainty into account. Although the designed relief system has the highest cost under the highest uncertainty level, it will provide a more immunized solution to uncertainty with a higher degree of robustness. The stochastic model has the least cost, but it is unable to produce the most conservative solution with the highest uncertainty protection when the system is highly uncertain. Second, among the capacity parameters, the transfer point capacity, the hospital capacity and the MSDC capacity level parameters have the least to the greatest effect on the final result. As more patients may be treated at nearby facilities, the cost of the system will decrease as hospital and transfer point capacity is increased. However, as a result of the decreased capacity, injured patients will need to be transported to locations further away, which will result in higher transportation expenses and a rise in the system's overall cost. Examining the impact of these parameters is very important due to the limited budget and resources. Third, by increasing the demand while other parameters remain constant, the amount of unmet demand increases as a result of the significant penalty cost imposed on the network, thereby increasing the overall cost. This issue shows the lack of resources with increasing demand in the case study that should be considered by decision makers.

6. Conclusion

This study addresses a practical mathematical programming model for designing an emergency relief network in either preparedness and response phases, taking into consideration the failure likelihood of facilities and communication routes, as well as uncertainty in the input data, under different scenarios. The number of injured individuals, demand, costs, and failure probability were all regarded as the model's uncertain parameters. To tackle this problem, we devised a mixed integer robust stochastic programming model with two stages of decision-making, that the first stage selecting the best location for facilities and the second stage investigating transportation routes between those locations. The suggested model reduces the network's overall cost by identifying the optimal locations for transfer points and MSDCs, as well as the optimal allocations between facilities based on MSDC and route failure probabilities. To evaluate the suggested model's effectiveness in the actual world, we used it in a case study based on earthquake zones in Iran's Fars province. The obtained results demonstrate the model's applicability and effectiveness. The main parameters were also subjected to a sensitivity analysis, such as capacity and demand, to show the impact of changes in the key parameters on the model results. Changes in demand parameters had a significant impact on the final results when compared to other factors, according to the results. Considering the transfer points between the affected regions and the hospitals will help reduce casualties in the event of a disaster. Transfer points should be located in places where patients can be transferred from the affected regions to these points and from these points to hospitals in the shortest time. Due to a lack of resources at the moment of the disaster, it is impossible to transport all injured people to medical facilities quickly. Taking into account vehicles with various speeds and transporting persons with serious injuries at a faster speed has a significant impact on saving injured people.

The following recommendations for further study are made in order to better align the proposed model with real applications. Considering a queue system for treating injured people can be regarded for future research. Thus, casualty prioritization for transferring and treatment will be applied. In addition, backup facilities for MSDCs can be considered. This will guarantee that emergency services are more efficient in the event of a crisis. Only some parameters like demand and cost factors were regarded as sources of uncertainty. The uncertainty of transportation time and response time can be regarded as an interesting topic for further research. We employed a hybrid stochastic-robust programming approach to cope with the uncertainties; other mixed approaches, like fuzzy-possibilistic programming, can also be applied.

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