Addressing a Humanitarian Relief Chain Considering Uncertain Demand and Deprivation Costs by a Hybrid LP-GA Method: An Earthquake in Kermanshah

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Addressing a humanitarian relief chain considering uncertain demand and deprivation costs by a hybrid LP-GA method: An earthquake in Kermanshah

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Abstract

Today, a great deal of attention to numerous disasters such as earthquakes, floods and terrorist attacks is motivated by humanitarian logistics. A comprehensive plan for relief logistic items under uncertainty is a challengeable concern for both academic and logistics practitioners. This study contributes another robust plan for the humanitarian logistics for the earthquake disaster in Kermanshah, Iran. The proposed framework evaluates both operational and disruption risks simultaneously to study the Humanitarian Relief Chain (HRC) network after an earthquake. The main novelty is the simultaneous consideration of the deprivation costs and demand under uncertainty. The deprivation cost leads to a reduction in high social costs for the decision-makers of the HRC. The proposed HRC also guarantees the delivery of the essential supplies to beneficiaries under both operational and disruption risks. As an optimization model, it seeks to minimize total costs consisting of inventory holding cost, shortage cost, deprivation costs and transportation cost and maximizes each facility's weighted resilience level as the second objective. A robust optimization model is established to deal with uncertain levels of the transport network paths, supply condition, amount of demand and deprivation costs which are assumed uncertain. The resilience parameters used for the second objective are obtained by a Best Worst Method (BWM). Another significant contribution was a hybrid approach combining the LP-metric method and Genetic Algorithm (GA) as the LP–GA approach for optimizing large-scale instances. Regarding the analyses, including tuning, validation and comparison of the proposed approach, its performance is showed by several standard multi-objective assessment metrics. As a final point, the achieved outcomes demonstrate that the suggested model is highly sensitive to uncertain parameters. This encourages further development and application of the proposed HRC with the use of a hybrid LP-GA approach as a strong technique for solving optimization problems.

Keywords: Robust Optimization; Relief logistic; Humanitarian Relief Chain (HRC); Operational and Disruptive risk; Hybrid LP–GA approach; Best worst method (BWM).

1. Introduction

Humanitarian logistics is an important aspect of relief operations when natural and/or manmade disasters occur. In general, and in common terms, humanitarian logistics deals with providing and transferring the required resources and goods to the injured individuals. However, this is only one aspect of humanitarian logistic and there is in fact more aspects to be considered, such as resource dope, optimization, inventory management and information exchange. Thus, a broader definition of humanitarian logistics which includes planning process, execution and control the resource flow, and accessibility to the relevant information at different stages of operation, is required to provide a successful performance for the injured individual (Behl and Dutta 2018). So most of the keywords used in the humanitarian supply chain are shown below (see Fig. 1).

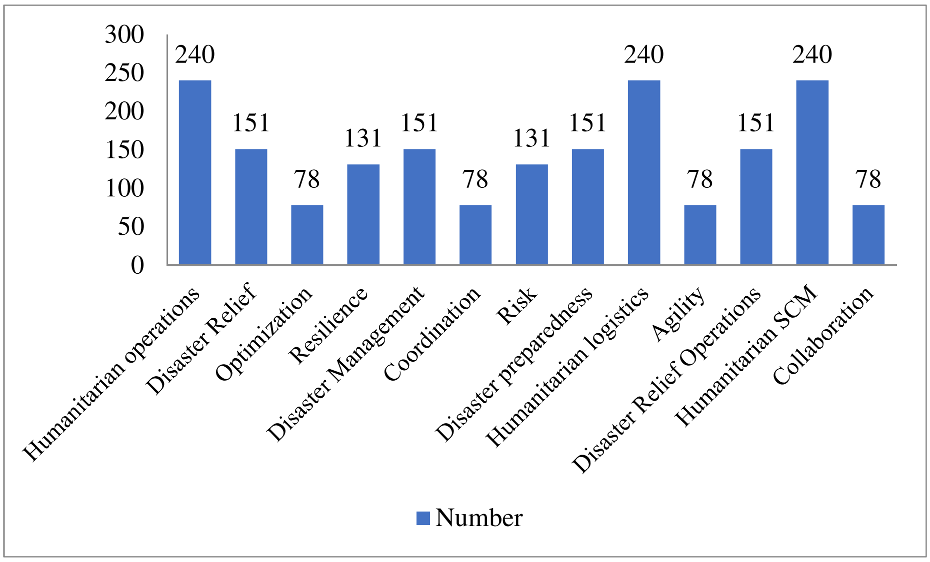


Fig. 1. Distribution of clustered keywords used in the humanitarian supply chain

Since one of the effective measures to reduce the effects of disaster has been the humanitarian supply chain, it has interested the researchers. It has also made it extremely difficult to determine effective measures for logistics operations due to the risks and uncertainties of complex events and operations in the humanitarian supply chain. Plus, due to the short duration and the unpredictable changes in supply and demand (Elluru et al., 2017), humanitarian aid chains are much more efficient than the commercial supply chain. Lack of resources in a disaster situation can have direct consequences, so focusing on HRC is more efficient in the supply chain, which plays an important role in countering uncertain demand (Kaur and Singh 2016). To respond to emergency needs, distribution, etc. at specific times and conditions that have been defined as a flexible response when an unexpected event occurs as a humanitarian supply chain capability (Kunz and Gold (2017). Supply disturbances occur during or after a disaster when the HRC is not very reliable. Also, supply disruptions lead to high increase social costs, which also worsening supply delays. Since the collection and production of adequate relief resources in the short term are cases where humanitarian assistance to it is needed, thus increasing the demand for emergency production. As a result, humanitarian supply chain capacity will be close to its peak (Galindo and Batta 2013). Therefore**,** this research designs a humanitarian logistics network consisting of central warehouses (CWs) and local distribution centers (LDCs) and some parameters such as availability level of the transport network paths, supply condition, amount of demand, and deprivation costs are assumed under uncertainty.

Therefore, the problem uses a novel robust optimization approach to manage the recommended model under uncertain conditions. The main aims of this research's model are optimizing the total costs of the relief chain and the weighted resilience level of each facility (CW/LDC). The resilience parameters are studied by the Best Worst Method (BWM) in the second objective for weighting parameters and making decisions. Moreover, another main novelty of this paper is a hybrid approach combining the LP-metric method and the Genetic Algorithm (GA) as one of the well-known evolutionary algorithms. The proposed hybrid LP–GA is used to verify the model for solving a case study in an earthquake of Iran. Generally, the main highlights are:

- ✓ A bi-objective robust optimization model for the humanitarian relief logistics considering uncertain deprivation costs and demand is developed.
- ✓ The BWM studies the resilience parameters and a hybrid LP-GA measure is created to manage the recommended model.
- ✓ A real-life case study of an earthquake in Kermanshah, Iran, is proposed to validate our methods.

2. Literature review

Every year, natural disasters affected many areas, including the world and injury, death, property destruction, and disruption of daily activities caused by these events. Generally, the disasters are divided into two key groups consist of natural (for example, earthquake, famine, tsunami, cyclone, hurricane, flood, etc.), disease (like plague or malaria), manmade disasters and extreme poverty situations (Galindo and Batta 2013).

By way of example, Mohasel afshar (2011) reports that in 2005 near 489 disasters in 127 countries all-over the world occurred, leading to 160 million injuries and the death of 104,698 people. Following the reports of the Natural Disaster Database, only earthquakes have killed over seventy thousand people in the last two decades. Due to the inevitability of the devastating effects of the disaster, these effects can be alleviated by a preventive measure and the formulation of an appropriate preparation plan. Therefore, it is essential to take proper action for such disasters. Also, since Iran's geographical situation has made it a disaster-prone country in the world, each year causing devastating earthquakes and the resulting crisis, resulting in huge harm to the individuals and the country's economy, hence, the creation of an integrated humanitarian relief chain will strengthen the management of natural disasters, especially earthquakes (Zokaee et al. 2016).

Several key components in relief operations are that crisis managers should consider them and Humanitarian Relief Logistics as the most important element. Logistics planning in disaster relief includes sending numerous parts, including rescue equipment, medicine, food, and rescue teams, from several supply sources to many distribution points in damaged fields by a chain structure (Caunhye et al., 2012).

Lately, a three-level model of relief chain that includes distribution centers, suppliers, and damaged regions is recommended by Zokaee et al. (2016). They offered a MILP deterministic model applying strong optimization. Their offered problem efforts to optimize the relief chain's costs and consider a penalty for shortages of commodities to optimize the satisfactory level of people in the affected regions. Also, Sahebjamnia et al. (2016) recommended a hybrid system based on decision support to design an HRC with three echelons. They made a clear analysis to show the exchange between reactionary and performance of the planned HRC using several key performance criteria consist of cost, coverage, and reaction time. Also, to verify the model, a case study is demonstrated using stochastic data. Fahimnia et al. (2017), designed a stochastic bi-objective blood supply chain (BSC) to lower the total cost and delivery time of BSC in catastrophes. They combined the Lagrangian relaxation and Ɛ-constraint methods to address the suggested model. Maharjan and Hanaoka (2017), had the intention to define the optimal location and warehouse number to be constructed for an HRC in different areas of Nepal. Simplex algorithm with branch and bound is applied to solve their proposed model. Moreover, developed two bi-level models in their two recent types of research; that the first model, Safaei et al. (2018), seeks to minimize operational costs and to use the TOPSIS method choose the suppliers with lower risk and by KKT method is solve; while the second research Safaei et al. (2018), attempt to minimize operational costs and unsatisfied demand and to use goal programming approach and KKT method is solved. Cao et al. (2018) presented a multi-objective mathematical model to raise the lowest victims' perceived moral and lower respectively the largest deviation on victims' perceived satisfaction for all demand points and sub-phases. Their model is solved using a genetic algorithm. A multi-echelon MILP is suggested by Tavana et al. (2018), to design a humanitarian logistic network that considers pre-and post-disaster management. Their proposed model was solved by using an Ɛ- constraint method, NSGA-II, and a modified NSGA-II. Nikkhoo et al. (2018), proposed a multi-echelon supply chain by utilizing a quantity flexibility contract (QFC) consist of a relief organization, one supplier, and affected areas to coordinate sequence activities. Ghatreh Samani et al. (2018), designed the blood supply chain network by a multi-objective mixed-integer linear programming model in order to minimize total cost, the maximum unsatisfied demand, and time span. They demonstrated the applicability of their model to a real study in Mashhad, Iran. A bi-objective mixed-integer mathematical programming model under uncertainty is proposed by Ghasemi et al. (2019), to minimize the location-allocation total cost of facilities and the amount of relief supplies shortage. Sarma et al. (2019) preset two new mathematical models for humanitarian logistic under uncertainty. In the first study, Sarma et al. (2019) aim to minimize the total cost and the redistribution total time. Then, three different approaches are used to solve the model: Neutrosophic programming approach, goal programming, and Pareto optimal solution approach; in the second study, Sarma et al. (2019), seeks to minimize the total cost and total time of the operation of relief logistic in association with a non-governmental organization (NGO), Then, the model solved using a different method. Shin et al. (2019) proposed a MILP mathematical model to provide optimal scheduling considering reconstruction and delivery. An ant Colony Optimization algorithm is utilized to resolve the model. Some studies proposed a humanitarian supply chain network to minimize total costs and consider location-allocation costs of facilities, operating costs of active facilities, Transportation costs, and shortage costs as a cost of the supply chain (e.g., Charles et al. (2016)). In general, mentioned researches considered variables like location of facilities, inventory, demand shortage, allocation and production line. Also, some studies aimed to maximize the covered demand and they considered location-allocation, the flow of product or material, and demand shortage as variables (see Ransikarbum and Mason (2016)). In this field, some researchers developed multi-objective mathematical models in order to follow different goals simultaneously. For example, Tavana et al. (2018), put forward a multi-objective mixed-integer programming model to lower total costs of relief logistics and minimize the operational relief time. They considered location-allocation, demand shortage, unused material or product and amount of wasted material or product as decision variables. Nezhadroshan et al. (2020) proposed an HRC with the use of a stochastic-possibilistic programming approach. They used a hybrid of DEMATEL and ANP methods to solve the model for a case study of the Mazandaran earthquake. A summary of several relevant papers in HRC is illustrated in Table 1.

Table 1. A concise review on related researches

Authors/Year	Objectives	Disaster type	Solution approach	Case study
Barzinpour and Esmaeili (2014)	Population, Costs	Earthquake	Goal programming	Tehran
Hu et al. (2014)	Opening cost, travel evacuation distance	Earthquake	Genetic algorithm	Chaoyang District of Beijing
Jabbarzadeh et al. (2014)	Costs	Earthquakes	Branch and bound	Iran (IBTO)
Akgün et al. (2015)	Risk	Earthquakes	Exact algorithm	Turkey
Kedchaikulrat and Lohatepanont (2015)	Structure cost and AHP score	General	Pareto dominance	Thai Red Cross
Khayal et al. (2015)	Costs	General	Exact algorithm	South Carolina, USA
Kilci et al. (2015)	Weight of operating candidate shelter	Earthquakes	Exact algorithm	Kartal, Istanbul, Turkey
Moeini et al. (2015)	Warehouse operation, transportation time	General	Exact algorithm	Val-de-Marene, France
Verma and Gaukler (2015)	Weight distance, Un-weight distance	Earthquakes	Weiszfeld algorithm, heuristics	California
Salman and Yücel (2015)	Transportation, Unmet demand, Holding	Earthquakes	Lagrangian, L-shaped method	Istanbul
Manopiniwes and Irohara (2016)	Opening cost, shipping cost, response time	Flood	Goal Programming	Chiang Mai, Thailand
Marcelin et al. (2016)		Hurricane		Leon country, Florida
Ransikarbum and Mason (2016)	Transportation, Shortage, Delay	Hurricane	Exact algorithm	South Carolina
Fahimnia et al. (2017)	Cost, delivery time	general	hybrid solution	Numerical experiments
Cao et al. (2018)	victims' perceived	Earthquake	Genetic algorithm	Wenchuan

	satisfaction, deviation on perceived satisfaction			Earthquake, China
Tavana et al. (2018)	Costs, Time	General	Ɛ-constraint, NSGA-II, modified NSGA-II	Numerical experiments
Ghatreh Samani et al. (2018)	Cost, Unsatisfied demand, Time span	Earthquakes	interactive fuzzy solution approach	Mashhad, Iran
Ghasemi et al. (2019)	Costs, Shortage	Earthquake	MMOPSO, NSGA-II, Ɛ-constraint	Tehran- Iran
Deepshikha et al. (2019)	Costs, Time	General	Neutrosophic programming, goal programming, Pareto optimal solution	Numerical experiments
Nezhadroshan et al. (2020)	Costs, Time	Earthquakes	Hybrid of DEMATEL and ANP	Mazandaran-Iran
This study/2020	Cost, weighted resilience level	Earthquakes	LP-GA, Robust-Heuristics , LP-metric	Kermanshah - Iran

To show the contributions of this research in comparison with the aforementioned works in the literature, some points can be highlighted. First, this paper considers a designation of humanitarian logistics network consisting of central warehouses (CWs) and local distribution centers (LDCs) and some parameters assumed under uncertainty. Second, the model is formulated by a novel robust optimization as a bi-objective model to minimize the total cost and maximize resiliency. Third, the BWM is used to assess the resilience parameters and then a hybrid LP-GA method is developed to obtain a flexible and more trustworthy output. Finally, a real-life case study of Kermanshah, Iran for an earthquake is employed to show the applicability of our framework.

Due to the nature of the problem and the proposed mathematical model, also the lack of response in large-size problems, the solution to this problem is to use a heuristic approach as a combination of LP-metric and GA. Moreover, according to the relevant literature explored in Table 1, the employment of a robust optimization approach would result in a resilience relief logistic. The objectives of the previous studies investigated in Table 1 mostly consider the minimization of the total cost. Also, the resilience parameters are used by the approach of Best Worst Method (BWM). In this regard, this goal is also presented in this paper as a special contribution. Regarding the nature of the problem expressed in this paper, the simultaneous consideration of deprivation costs and demand under uncertainty expresses the special contribution of this study.

All in all, as given in Table 1 and the comparison of recent literature and discussion above of our contributions, the main highlights are:

- ✓ Because of the presence of nonlinear constraints, including uncertain parameters in the suggested model as a Mixed Integer Non-Linear Programming (MINLP), an innovative, robust optimization model is employed heuristically to reduce the computational time against uncertainty's different levels.
- ✓ Besides, uncertainty in some parameters such as availability level of the transport network paths, supply condition, amount of demand, and deprivation costs.
- ✓ This study, among the first papers, considers deprivation costs as the uncertain parameters in the literature.
- ✓ A novel hybrid approach combining LP-metric and GA is developed to solve our real case study.
- ✓ A real-life case study as a recent earthquake in Kermanshah, Iran, is introduced.

3. Problem description

Here, as illustrated in Fig. 2, three stages for the proposed disaster relief logistics network are considered. These stages contain CWs and strategic stocks, the suppliers set, and the final stage includes local distribution centers (LDCs) in the areas damaged by a disaster. Therefore, suppliers (e.g., governments, aid organizations, etc.) may play a serious role in the network and ready the essential supplies of individuals in dilapidated regions; these individuals can consider as the main customers of a normal distribution. CWs include airports, warehouses, and train and bus stations. The application of LDCs is completely admissible because several inactive CWs in the absence of the crises are impossible. Indeed, the use of available public places could be a proper choice to deal with a crisis situation (Görmez et al., 2011).

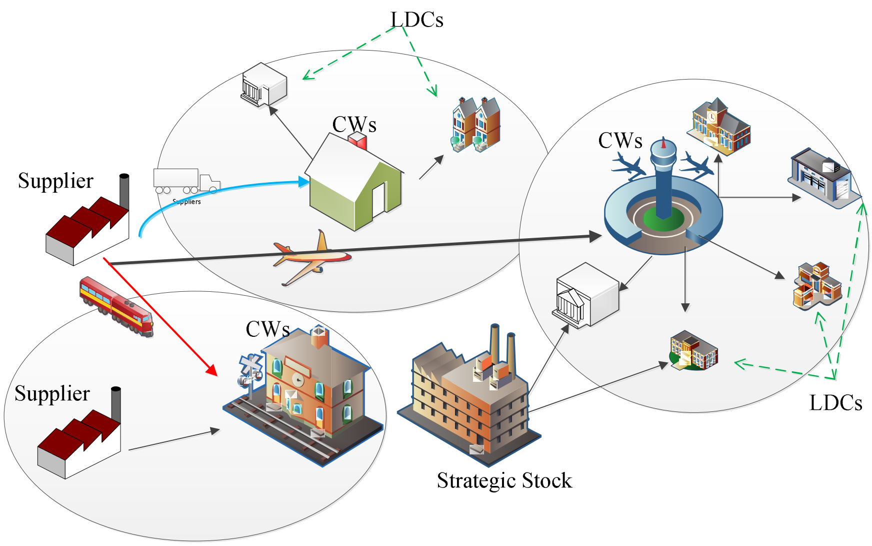


Fig. 2. Overall structure of HRC (Nezhadroshan et al. 2020).

3.1. Resilience parameter

Here, we consider resilience measure by determining facility's resilience level (Suppliers, LDCs, and CWs). Table 2 indicates the focus of literature in each criterion.

Table 2. Provides these means with their helpful references for each one

No. Criteria																
C_1	Interchangeable people	×	×	×	×	×	×	×	×							
C_2	Flexible facilities	×	×	×	×				×	×	×					
C_3	Profound relation with major suppliers	×	×	×		×										
C_4	Distributed power, enabled to take needed measures	×	×	×	×	×	×	×	×			×	×			
C_5	Continued Communication amongst well-informed employees	×	×	×	×	×	×	×	×			×	×			
C_6	Information-sharing with suppliers and customers			×		×	×	×		×	×	×	×	×		
C_7	Auto-ID technology such as RFID	×	×			×	×	×		×		×	×	×	×	×
C_8	Process improvement	×	×	×	×		×	×				×	×			

Source: (Pettit et al. 2010; Tang 2006; Pettit et al. 2013).

3.2. Modelling

Here, the main assumptions are provided, and then using them and a description of model notations, the proposed bi-objective resilience HRC model is formulated. The main utilized components and assumptions to formulate the resilience HRC model are reported as below.

- ✓ Sometimes, a disaster may lead to the destruction of facilities and disturbances in the routes. Therefore, these can cause a disruption in the ability of candidate CWs and suppliers. To this end, the facilities damages are considered by combining different consumable inventory ratios to deal with supply uncertainty.
- ✓ Each CW is provided by suppliers (with limited capacity).
- ✓ LDCs are provided by either CWs or multiple CWs or strategic stocks.
- ✓ Strategic stock is placed in a secure location and beyond the anticipated disaster areas.
- ✓ Each strategic stock ships the things immediately, not to all the LDCs, yet most proximate ones.
- ✓ Transportation among suppliers and CWs or strategic stock and LDCs is thought multi-mode (Truck, Motorcycle, Helicopter, Train, and Plane).
- ✓ The level of resiliency is measured for each facility.
- ✓ The various disasters or following minor disasters are thought for modeling.

- ✓ There are several essential relief commodities that must be distributed. Therefore, to distribute these, various costs are raised associated with shipping, procurement, and inventory.
- ✓ Each supplier and LDC is able to deliver a provided number of relief commodities, and it is on the basis of suppliers' flexibility level. Based on several effective factors such as the impact of the disaster, and the designed scenarios, some parameters are assumed uncertain (e.g., transportation time, demand, cost, etc.).
- ✓ Here, we consider several capacity levels for which potential CW which suitable capacity must be identified.

Based on the aforementioned assumptions, the following components are utilized in developing proposed resilient HRC model.

3.2.1. Indices

l	Potential suppliers, $l = 1, 2, 3, \ldots, L$
i	Candidate CWs, $i = 1, 2, 3, \ldots, I$
j	Candidate LDCs, $j = 1, 2, 3, \ldots, J$
k	Demand zones, $k = 1, 2, 3, \ldots, K$
h	Potential strategic stocks, $h = 1, 2, 3, \ldots, H$
m	Potential transportation mode, $m = 1, 2, 3, \ldots, M$
s	Potential disaster scenarios, $s = 1, 2, 3, \ldots, S$
q	Relief commodities, $q = 1, 2, 3, \ldots, Q$
c	Capacity levels of CWs, $c = 1, 2, 3, \ldots, C$
g	Potential sub-sequent disasters, $g = 1, 2, 3, \ldots, G$

3.2.2. Parameters

F_i^c	Cost of creating ith CW at capacity level c
G_j	Cost of creating jth LDC
E_h	Cost of creating hth strategic stocks
IH_q	Inventory saving cost of item q
UC_q^i	Unit inventory cost of unused item q at each CWs i
UL_q^j	Unit inventory cost of unused item q at each LDCs j
λ_q^i	Consumable rate of inventory for item q at CW i
μ_q^j	Consumable rate of inventory for item q at LDC j
ξ_l	Consumable rate of capacity for supplier l
US_q	Shortage cost for each unit of commodity q

ζ_{ijm}	1, if mode m is available between the ith CW and jth LDC; 0 otherwise
ω_{lim}	1, if mode m is available between the lth supplier and ith CW; 0 otherwise
D_{qk}	Demand of the commodity q by demand zone k
V^{c}	Storing capacity of the established CW at capacity level c
CA_{j}	Storing capacity of the LDC j
SA_{h}^{q}	Storage capacity of the hth strategic stock for qth item
CS_{ql}	Storage capacity of the lth supplier for the qth item
CAP_{ijm}	Capacity of shipping approach between ith CW and jth LDC by mode m
CCP_{lim}	Capacity of shipping approach between the supplier l and the CW i by mode m
CT_{qlim}	Cost of transportation mode between the lth supplier and the ith CW via mode m for qth item
CTR_{qijkm}	Cost of transportation mode between ith CW and jth LDC to demand point k via mode m for qth item
A_{q}	Needed unit storing capacity of the commodity q
P_{s}	Possibility of occurring the scenario s
α_{i}	Resiliency level of the ith CWs
θ_{j}	Resiliency level of the jth LDCs
ϕ_{g}	Sub-sequent disasters effects on demands after the major disaster (g is the number of minor disasters)
ρ_{ql}	1, if supplier lth capable to deliver qth item
$Capl_{\max}$	Maximum deprivation capacity levels so that there are no life losses.
ψ_{k}	Deprivation cost function, which depends on the deprivation capacity levels in demand zones, K
BigM	upper bound demand

3.2.3. Decision variables

Y_{i}^{c}	=1, when the nominee CW i is established at capacity level c; otherwise = 0
O_{j}	=1, when the nominee LDC j is established; otherwise = 0
γ_{h}	=1, if the hth candidate strategic stock is opened; 0, otherwise
τ_{l}	=1, if the lth candidate supplier is selected; 0, otherwise

R_{qi}	The amount of inventoried part q in the CW i
U_{qj}	The amount of inventoried part q in the LDC j
UI_{qi}	The amount of unused inventoried part q in the CW i
UR_{qj}	The amount of unused inventoried part q in the LDC j
N_{ijm}	=1, if shipping type m is selected between ith CW and jth LDC
C_{lim}	=1, if shipping type m is selected between lth supplier and ith CW
x_{qjk}	Amount of the distributed part q from the LDC j to demand zone k
z_{qijkm}	Amount of the shipped part q from the CW i to demand zone k via LDC j and transportation mode m
v_{qhjk}	Amount of the shipped part q from the strategic stock h to demand zone k via LDC j
w_{qlim}	Amount of the shipped part q from the supplier l to the CW i via transportation mode m
η_{qk}	Amount of the unsatisfied demand part q in demand zone k

Finally, the proposed MINLP model is established as follows:

$$\begin{aligned} Min\ TC = & \sum_{i}\sum_{c} F_i^c.Y_i^c + \sum_{j} G_j.O_j + \sum_{h} E_h.\gamma_h + \sum_{q}\sum_{k}\sum_{i} IH_q.R_{ki} \\ & + \sum_{q}\sum_{k}\sum_{j} IH_q.U_{kj} + \sum_{q}\sum_{i} UC_q^i.UI_{qi} + \sum_{q}\sum_{j} UL_q^j.UR_{qj} \\ & + \sum_{q}\sum_{k} US_q.\eta_{qk} + \sum_{q}\sum_{l}\sum_{i}\sum_{m} CT_{qlim}.w_{qlim} \\ & + \sum_{q}\sum_{i}\sum_{j}\sum_{k}\sum_{m} CTR_{qijkm}.z_{qijkm} + \sum_{q}\sum_{i}\sum_{j}\sum_{k}\sum_{m} \psi\left(CAP_{ijm}\right).z_{qijkm}.N_{ijm} \\ & + \sum_{q}\sum_{l}\sum_{i}\sum_{m} \psi\left(CCP_{lim}\right).w_{qlim}.C_{lim} \end{aligned} \tag{1}$$

$$Max = \sum_{i}\sum_{c} \alpha_i.Y_i^c + \sum_{j} O_j.\theta_j \tag{3}$$

Subject to:

$$\sum_{q} A_q.R_{qi} \le \sum_{c} V^c.Y_i^c \qquad \forall i \in I \tag{4}$$

$$\sum_{c} Y_i^c \le 1 \qquad \forall i \in I \tag{5}$$

$$\sum_{q} A_q.U_{qj} \le CA_j.O_j \qquad \forall j \in J \tag{6}$$

$$\sum_{j} x_{qjk} + \sum_{i}\sum_{j}\sum_{m} z_{qijkm} + \sum_{h}\sum_{j} v_{qhjk} = D_{qk}\sum_{g}(1+\phi_g) - \eta_{qk} \qquad \forall k \in K, q \in Q \tag{7}$$

$$\sum_{k} x_{qjk} + UR_{qj} = \mu_{qs}^{j}.U_{qj} \qquad \forall j \in J, q \in Q \tag{8}$$

$$\sum_{j}\sum_{k}\sum_{m} z_{qijkm} + UI_{qi} = \lambda_{qs}^{i}.R_{qi} \qquad \forall i \in I, q \in Q \tag{9}$$

$$\sum_{q}\sum_{k} z_{qijkm} \leq \zeta_{ijm}.CAP_{ijm}.N_{ijm} \qquad \forall i \in I, j \in J, m \in M \tag{10}$$

$$\sum_{i}\sum_{m} w_{qlim} \leq \rho_{ql}.\xi_{l}.CS_{ql}.\tau_{l} \qquad \forall q \in Q, l \in L \tag{11}$$

$$\sum_{q} w_{qlim} \leq \omega_{lim}.CCP_{lim}.C_{lim} \qquad \forall l \in L, i \in I, m \in M \tag{12}$$

$$\sum_{k}\sum_{j} v_{qhjk} \leq SA_{h}^{q}.\gamma_{h} \qquad \forall h \in H, q \in Q \tag{13}$$

$$w_{qlim} \leq M.C_{lim}.\omega_{lim} \qquad \forall l \in L, i \in I, m \in M, q \in Q \tag{14}$$

$$z_{qijkm} \leq M.N_{ijm}.\zeta_{ijm} \qquad \forall k \in K, j \in J, i \in I, m \in M, q \in Q \tag{15}$$

$$CAP_{ijm}.N_{ijm} \leq Capl_{\max} \qquad \forall j \in J, i \in I, m \in M \tag{16}$$

$$CCP_{lim}.C_{lim} \leq Capl_{\max} \qquad \forall l \in L, i \in I, m \in M \tag{17}$$

$$\begin{aligned} & z_{qijkm}, x_{qjk}, \eta_{qk}, w_{qlim}, v_{qhjk}, UR_{qj}, U_{qj}, R_{qi}, UI_{qi} \geq 0 \\ & \forall i \in I, j \in J, l \in L, k \in K, h \in H, q \in Q \end{aligned} \tag{18}$$

$$O_{j}, Y_{i}^{c}, \tau_{l}, \gamma_{h}, N_{ijm}, C_{lim} \in \{0,1\} \qquad \forall i \in I, l \in L, m \in M, c \in C, j \in J, h \in H \tag{19}$$

The objective function (1) efforts to minimize the total operational and holding costs of chosen CWs and LDCs. The part two of objective function (1) minimized the shortage cost of unsatisfied demands and cost of unused inventories and transportation cost of items. The last part of objective function (1) minimized the deprivation costs. Objective function (2) seeks to maximize the weighted resilience level of each facility, CW/LDC.

Constraint (4) execute limitation on the accessible capacity of CWs. Constraint (5) shows that the maximum one CW with a determined capacity level should be opened in any nominated location. Constraint (6) enforces limitations on the accessible capacity of LDCs. Constraint (7) defines the unfavorable demands for critical items. The right hand of equation (7), defines first demand as well as demands added after sub-sequent minor disasters. Constraints (8) and (9) certify that the transferred amount of each commodity plus its unused inventoried quantity is equal to their related inventory levels for each CW/LDCs. Constraint (10) shows boundaries on the accessible capacity of the transportation system between pairs of CW/LDCs. Constraint (11) imposes limits over the suppliers' available capacity. Each supplier can transfer a specific number or set of critical items which is dependent upon suppliers' flexibility level.

Furthermore, each supplier might lose its capacity partially or totally, and constraint right hand (11) ensures these circumstances. Constraint (12) guarantees confines on the available transportation system capacity between pair of supplier/CWs. Constraint (13) imposes limits on the available capacity strategic stock. Constraints (14) and (15) guarantee that the quantity of each item will be shipped if the transportation system is available. Constraints (16) and (17) guarantee that the Capacity of shipping from either the between CW and LDC or supplier to the CW is less than or at most equal to a maximum deprivation capacity level so that there are no life losses. Constraint (18) and (19) determine the type of decision variables.

3.3. Model Linearization

According to Section 3.3, the multiplication of a binary variable with a continuous variable in objective one has led to the proposed model being nonlinear. Using the change of the traditional variable, the proposed model turns into a linear model to solve this problem. Hence, the constraint of linearization is defined for each variable as follows: Gholizadeh et al. (2020):

$$\sum_{q}\sum_{k} z_{qijkm} \leq N_{ijm}.BigM \qquad \forall j \in J, i \in I, m \in M \qquad (20)$$

$$\sum_{q}\sum_{k} HH_{qijkm} \leq \sum_{q}\sum_{k} Z_{qijkm} \qquad \forall j \in J, i \in I, m \in M \qquad (21)$$

$$\sum_{q}\sum_{k} HH_{qijkm} \geq \sum_{q}\sum_{k} Z_{qijkm} - \left(1 - N_{ijm}\right) * BigM \qquad \forall j \in J, i \in I, m \in M \qquad (22)$$

For the last statement of the objective function 1, we do the same.

3.4. Proposed robust optimization model

This section considers a heuristic solution for a sustainable supply and delivery model with respect to uncertainty data. Since the computational time for each model MILNP and MILP increases with increasing variables and levels of uncertainty. This has caused the model to be unacceptable at some time.

Therefore, we need an innovative method based on the binaries variable refinement that is the nonlinear factor of the proposed model. Proposed discoveries were tested for all samples of medium and large experiments, including large data, used for MINLP and MILP. The suggested heuristics are shown in the flowchart below (see Fig. 3).

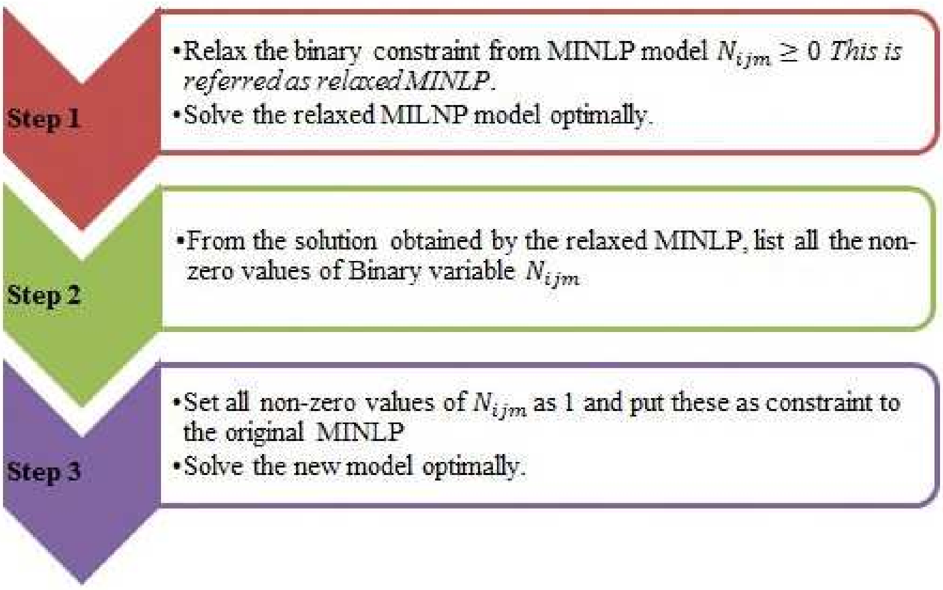


Fig. 3. steps for proposed heuristics

3.5. Robust optimization

In order to solve optimization problems with data uncertainty, a robust technique was put forward in the early 1970s and has lately been widely studied and developed. Under this approach tends to adopt an optimal answer to the nominal values of data to ensure that the justified and optimal response when the data is changed is guaranteed (Gholizadeh et al. 2020).

In the robust optimization model, there are two types of variables: design variables and control variables. Design variables have been decided before the potential parameters are realized and cannot be adjusted after realization. Time control variables are subject to tuning to trigger a particular occurrence of potential parameters.

x vector of design variables and y vector of control variables. A, B and C are the parameter coefficients, b and e are the parameter vectors (right side values). A and b are certain values; While B, C and e are uncertain. A special understanding of the parameter is called the uncertainty of the scenario, which is assigned s symbol and its probability is determined byp_s. The Ω symbol is used to represent a set of scenarios. The coefficients of uncertainty are e_s and C_s، B_s for each scenarios $\in \Omega$. Also, the control variable y is modified after understanding the scenario; it can be assigned the $y_s$the symbol for the scenario s. Because of the uncertainty of the parameters, the model may not be justified for a number of scenarios. Because of the uncertainty of the parameters, the model may not be justified for a number of scenarios; therefore, $\eta_s$show the models unjustified ness under any scenario s. If the model is justified, η_s is equal to zero; otherwise, it will receive a positive result from the following equations. The model is based on the method of (Mulvey et al. 1995) as follows:

$$
\begin{aligned}
&Min \quad \sigma\left(x, y_1, y_2, \ldots, y_s\right)+\gamma\rho\left(\eta_1, \eta_2, \ldots, \eta_s\right) \\
&s.t. \\
&\qquad Ax = B, \\
&\qquad B_S x + C_S y_S + \eta_S = e_S, \\
&\qquad x \geq 0,\ y_S \geq 0,\ \eta_S \geq 0,\ \forall s \in \Omega.
\end{aligned} \tag{23}
$$

There can be observed 2 parts in the objective function above: the first is a steady-state solution and shows the second equilibrium of the model by weightγ. The following two terms are discussed below for the Array of f(x, y)the symbolξ, which is a cost and utility function, is used. And for each scenario$\xi_s = f(x, y_s)$ the high variance for $\xi_s = f(x, y_s)$indicates that the decision has a high risk. In other words, a small change in the parameters with uncertainty can lead to large changes in the value of the function of measurement. Mulvey et al. (1995) used the following to illuminate the stability of solution δ is the weight assigned to the solution variance.

$$
\sigma(o) = \sum_{s\in\Omega} p_S \xi_S + \delta \sum_{s\in\Omega} p_S \left(\xi_S - \sum_{s\in\Omega} p_S{}' \xi_S{}'\right)^2 \tag{24}
$$

As you can see a second-order phrase $\sum_{s\in\Omega} p_S \left(\xi_S - \sum_{s\in\Omega} p_S{}'\xi_S{}' \right)^2$ there is in the phrase. Yu,C.S. et al. (2000) use a value of absolute deflection to use a second-order expression to reduce the operation of the computer time for solving the problem, as shown below:

$$\sigma(o) = \sum_{s\in\Omega} p_S \xi_S + \delta \sum_{s\in\Omega} p_S \left| \xi_S - \sum_{s\in\Omega} p_S{}'\xi_S{}' \right| \tag{25}$$

Although the above equation contains absolute values, however, two additional variables Q_s^+ and Q_s^- can be used to linear the objective function.

If $\sum_{s\in\Omega} p_S{}'\xi_S{}'$ it is more thanξ_s, Q_s^-it is interpreted, whereas $Q_s^+$is equal to $\sum_{s\in\Omega} p_S{}'\xi_S{}'$ the value smaller than ξ_S . The formulation above changes as follows:

$$\begin{aligned} &\sigma(o) = \sum_{s\in\Omega} p_S \xi_S + \delta \sum_{s\in\Omega} p_S \left(Q_s^+ + Q_s^- \right) \\ &s.t. \\ &\qquad \xi_S - \sum_{s\in\Omega} p_S{}'\xi_S{}' = Q_s^+ + Q_s^-, \; s \in \Omega, \\ &\qquad Q_s^+, Q_s^- \geq o, \; s \in \Omega. \end{aligned} \tag{26}$$

According to the linear programming theory, it is clear that one of the values of Q_s^+ and Q_s^- is always zero for $\delta \geq 0$ (Maharjan and Hanaoka 2017). Notice what it $\left| \xi_S - \sum_{s\in\Omega} p_S{}'\xi_S{}' \right| = \left(Q_s^+ + Q_s^- \right)$ is.

The second phrase above objective function $\gamma\rho(\eta_1, \eta_2, \ldots, \eta_s)$ that is for being unjustified the model is used and shows the stability of the model. Theγ weight is allocated for non-justification and illustrates the cost-benefit analysis between a robust model and a solution. Here, the η_s an unjustified model shows that for an uncertainty parameter under the scenario s has been created due to capacity constraints. According to the above discussion, the function of the final goal is formulated as follows.

$$Min \quad \sum_{s\in\Omega} p_S \xi_S + \delta \sum_{s\in\Omega} p_S \left(Q_s^+ + Q_s^- \right) + \gamma \sum_{s\in\Omega} p_S \eta_S \tag{27}$$

3.6. Robust model

In this section, owing to the demand uncertainties and cost of deprivation in the proposed model, robust optimization is applied to tackle this issue, as stated in Section 3.5. The robust optimization model of the proposed problem and index and parameters and decision variables of the model is demonstrated below.

3.6.1. Index

s Demand and cost of deprivation Scenario (Low, Average, Much) $s = 1, \dots, s$

3.6.2. Parameters

P_s Probability of scenario s

ω_j infeasibility weight being set experimentally j

λ The weight of risk

3.6.3. Decision variables

θ_s The linearization coefficient under the scenario s

δ_s The surplus variables in the scenario s

$$\mathrm{MinZF} = \sum_s P_s \mathrm{OBJ1}_s + \lambda \sum_s P_s \left(\mathrm{OBJ1}_s - \sum_{s'} P_{s'} \mathrm{OBJ1}_{s'} + 2\theta_s \right) + \omega \sum_s P_s \delta_s \tag{28}$$

$$\mathrm{MaxRF} = \sum_s P_s \mathrm{OBJ2}_s - \lambda \sum_s P_s \left(\left(\mathrm{OBJ2}_s - \sum_{s'} P_{s'} \mathrm{OBJ2}_{s'} \right) + 2\theta_s \right) \tag{29}$$

$$\mathrm{OBJ1}_s - \sum_{s'} P_{s'} \mathrm{OBJ1}_{s'} + \theta_s \geq 0 \qquad \forall s \tag{30}$$

$$\mathrm{OBJ2}_s - \sum_{s'} P_{s'} \mathrm{OBJ2}_{s'} + \theta_s \geq 0 \qquad \forall s \tag{31}$$

$$\theta_s \geq 0 \tag{32}$$

The first and second terms in Eqs. (28) and (29) indicated the mean value and objective functions' variance, in turn. The final terming (29) of the objective function is to assess the robustness of the model based on the control constraints' infeasibility values under each scenario. The constraints (31-31) are auxiliary constraints added to the model for linearization. And a constraint (32) is non-negative variables.

4. Solution approach

At first, the resilience parameters used for second objective are obtained using a strong MCDM approach entitled Best Worst Method (BWM). Moreover, the suggested bi-objective model is including several integer decision variables along with some binary variable which it leads to NP-hardness of it. Due to this concern, exact methods cannot be proper especially for large-size problem. Thus, three well-known metaheuristic algorithms are utilized to discover Pareto solutions. Moreover, metaheuristics procedures are illustrated in the next section.

4.1. BWM

Before solving the model, the values of resilience parameters, based on the selected criteria of Table 2 should be obtained. To do this, the BWM as a strong MCDM method is applied. The BWM is developed by Rezaei et al (2015), and ease of procedure and less computational table as two key features of it are reported. Also, several researchers in various fields, such as (Rezaei et al. 2015) report the efficiency of this method. The main steps of BWM are provided as follows.

Step 1. Propose criteria based on the expert opinions $\{c_1, c_2 \ldots c_n\}$.

Step 2. Select the worst and the best indicators.

Step 3. Find **the** "Best-to-Others" vector. Do pairwise judgment between the best indicator and other criteria via a number from 1 to 9 as follows:

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn}) \tag{33}$$

here a_{Bj} indicates the dominance of the best indicator B than the indicator j, and $a_{BB}=1$.

Step 4. Find "Others-to-Worst" vector. Do pairwise judgment between the other indicators and the worst indicator as follows:

$$A_W = (a_{1W}, a_{2W}, \ldots, a_{nW})^T \tag{34}$$

here, a_{jW} demonstrates the superiority of the criterion j than the worst indicator W, and $a_{WW}=1$.

Step 5. Compute the optimum values of $(\omega_1^*, \omega_2^*, \ldots, \omega_n^*)$ using the following optimization problem (Rezaei 2015).

$$\begin{aligned}
&\min \xi \\
&s.t. \\
&\left| \frac{\omega_j}{\omega_W} - a_{jW} \right| \le \xi \quad for\ all\ j \\
&\left| \frac{\omega_B}{\omega_j} - a_{Bj} \right| \le \xi \quad for\ all\ j \\
&\sum_j \omega_j = 1 \\
&\omega_j \ge 0 \quad for\ all\ j
\end{aligned} \tag{35}$$

After running the problem (20), the optimum values of $(\omega_1^*, \omega_2^*, \ldots, \omega_n^*)$ and ξ^* are achieved.

To calculate the consistency level of the judgments, the value of ξ^* and reported consistency index in Table 3 are utilized as equation (21):

$$Consistency\ \ Ratio = \frac{\xi^*}{Consistency\ \ Index} \tag{36}$$

Table 3. Information about consistency index (Rezaei 2015)

a_{BW}	1	2	3	4	5	6	7	8	9
Consistency Index	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

Moreover, based on (Rezaei 2015) the final score of alternative i due to the indicators is computed as:

$$S^{i} = \sum_{n=1}^{N} \omega_n \times C_{in} \quad \forall i \tag{37}$$

here ω_n represent the final weight of indicator n, C_{in} is the allocated score of ith supplier based on indicator n, and N shows the number of indicators. Also, the normalized score of suppliers can be formulated as bellow:

$$Normalized\ Score_k = \frac{S_k}{\sum_i S_i} \tag{38}$$

4.2. Encoding and decoding

Up to now, various approaches have been proposed to convert mathematical model to a chromosome or solution manner, such as priority-based method and Prufer numbers (Prüfer 1918; Gen et al. 2006). Here, to present the proposed chromosome using the priority-based method, a small-size example is given. In this example, i=3, l=3, h=2, j=3, c=3, q=2, and k=2 are supposed. The presented solution matrix has two rows for each item and (l+2i+h+2j+k) columns that it has three sections. Fig. 2 shows that all of these sections are consistent with the flows. Moreover, the designed solution matrix is displayed in Fig. 4. In this figure, CL and Pri represents the capacity level and priority, respectively.

		Segment 1						Segment 2								Segment 3				
Item	node	l			i			h+i					j			j			k	
1	Pri	0.07	0.13	0.78	0.95	0.79	0.64	0.38	0.65	0.89	0.67	0.11	0.24	0.12	0.49	0.98	0.21	0.51	0.02	0.34
	CL	1.526	1.268	1.209	1.562	2.123	2.544	2.738	1.726	2.783	1.860	1.168	1.469	2.989	1.716	2.289	1.239	2.457	2.723	1.199
2	Pri	0.09	0.33	0.03	0.38	0.33	0.43	0.99	0.35	0.79	0.31	0.85	0.51	0.39	0.38	0.47	0.30	0.89	0.47	0.63
	CL	2.738	1.726	2.783	1.860	1.168	1.469	2.989	1.716	2.289	1.239	2.457	2.723	1.199	1.526	1.268	1.209	1.562	2.123	2.544

Fig. 4. Design of proposed random key chromosome.

The matrix presented in Fig. 4 is created randomly and all genes of first row of this chromosome are filled by numbers between [0, 1], and all genes of second row of this chromosome are filled by uniform~ [1, c]. After sorting the values of first row and rounding the values of second row, the priority-based matrix is achieved. Also sorting for each sub-section, is performed separately. The design of proposed priority-based chromosome is exposed in Fig. 5.

		Segment 1						Segment 2								Segment 3				
Item	node	l			i			h+i					j			j			k	
1	Pri	1	2	3	3	2	1	2	3	5	4	1	2	1	3	3	1	2	1	2
	CL	-	-	-	2	2	3	-	-	3	2	1	-	-	-	-	-	-	-	-
2	Pri	3	2	1	2	1	3	5	2	3	1	4	3	2	1	2	1	3	1	2
	CL	-	-	-	2	1	1	-	-	2	1	2	-	-	-	-	-	-	-	-

Fig. 5. Design of proposed priority-based chromosome.

Segment 1 presents the sequence of allocation from suppliers (l) to CWs (i). Segment 2 presents the sequence of allocation from CWs and strategic stocks (h+i) to LDCs (j). Also, segment 3 presents the sequence of allocation from LDCs (j) to affected areas (k). Moreover, each CWs (i) capacity level is presented in the second row of the suggested chromosome. Additionally, the allocation procedure is shown in Fig. 6, which can be used from needed steps of each segment.

```
For q=1 to Q
Inputs:     I: set of source
            J: set of applicant
            Dj: demand of applicant j
            Cai: capacity of source i
            V(I+J): Encode solution of item q
Outputs:    Xalocij: quantity of distribution between nodes
            Yj: binary variable displays the active applicant
            Uqi: amount of unused item q of source i
            Uqj: amount of unused item q of applicant j
while ∑i Cai ≥ 0 && ∑j Dj ≥ 0
Step1: Xalocij = 0  ∀i ∈ I, ∀j ∈ J
Step2: select value of first column of sub-segment I for i index
       select value of first column of sub-segment J for j index
Step3: Xalocij=min(Cai , Dj)
        Update demands and capacities
        Cai= Cai - Xalocij          Dj= Dj - Xalocij
Step4: if Cai=0 then V(1,I)=0
        if Dj =0 then V(1,J)=0
End while
Step5:  Uqi=Cai    Uqj =Dj
Step6:  for j= 1 to J
          if ∑j Xalocij > 0 then Yj=1
End for
End for
```

Fig. 6. The allocation procedure of proposed model.

4.3. LP-metric method

The method of LP-metric attempts to lower the objective functions' deviation from its desired solution. That is to say; the most desirable and possible solution is the one that has the shortest distance from the ideal point. In the lp-metric method to measure the proximity of a solution to the ideal solution, metric distance is used. This condition is described as a consistent function.

For "the less the better" problems, the compatibility function is defined as follows:

$$LP = \left[\sum_{i=1}^{n} w_i \left(\frac{f_i(x_i) - f_i(x_i^{\min})}{f_i(x_i^{\max}) - f_i(x_i^{\min})} \right)^p \right]^{1/p} \tag{39}$$

For "the more the better" problems, the compatibility function are defined as follows:

$$LP = \left[\sum_{i=1}^{n} w_i \left(\frac{f_i(\mathrm{x}_i^{\max}) - f_i(x_i)}{f_i(\mathrm{x}_i^{\max}) - f_i(\overline{x_i^{\min}})} \right)^p \right]^{1/p} \quad (40)$$

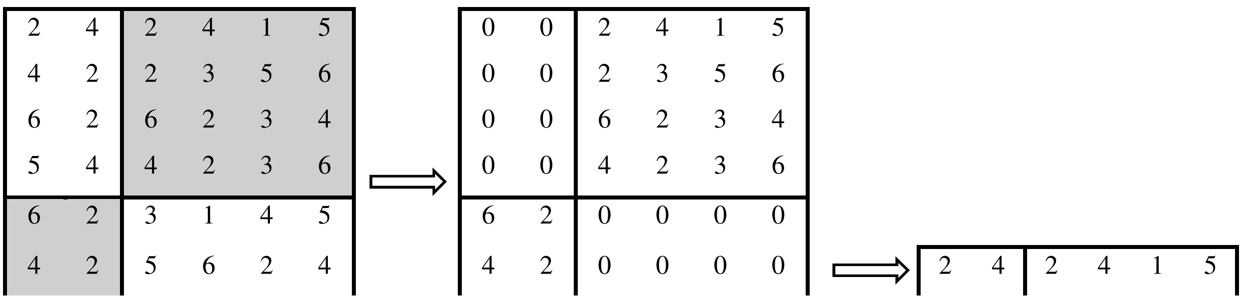
Where $f_i(\overline{x_i^{\max}})$ and $f_i(\overline{x_i^{\min}})$ represent the ideal counter-solution to i-th goal optimization

In the above equations $X^{\min}$ and $X^{\max}$ represent the ideal solution in optimizing the objective function i-th and X_i represent the available solution. w_i denotes the degree of importance for i-th purpose.

P indicates the degree of emphasis on the existing deviations, so the higher the P value, the greater the emphasis on the largest deviations. The value of P depends on the decision-makers' opinion and is usually of values of $\{P=1, P=2, P=\infty$. Also which $\overline{x_i^{\max}}$ and $\overline{x_i^{\min}}$ 2 represent an ideal solution in optimizing the i-th objective function.

4.4. GA

One of the solutions to large-scale resilience relief logistic problems is the use of heuristic algorithms such as genetic algorithms, which are used in this section to resolve the suggested large-scale model. Since genetic algorithms are a random search method. Many studies have been used in the field that can be found here (Diabat & Deskoores 2016; Kannan et al. 2010). The first step in solving a metaheuristics method is to create an appropriate structure for the desired problem (Fathollahi-Fard et al. 2020). In this algorithm, the chromosome comprises three parts representing the LDC–demand zone, CW/LDC and supplier–CW, respectively. The possibility of any chosen chromosome is based on its adaptability value and corresponding indices, and chromosomes with preferable possibilities of greater adaptability are designed; for example, the first part determines the Quantity from each LDC to each demand zone for all relief commodities under scenarios. This operator is a hybrid operator, which consists of three steps. In the initial step, a pair of preferred chromosomes r randomly selects between [k*s, q (i+j)]. In the second step, the locality is randomly selected for integration between [1, q (i+j)] and [1, S+k-1] along the chromosome strand. Eventually, in step three, the value of the two strings, which is determined based on the location of the merger, is specified. The intersection operator used in this research is shown in Fig. 7. Next, the population is populated with mutation operations. A multi-spot mutation operation is deployed for population resumption. Two rows or two columns are randomly selected so as to mutate in each chromosome portion, and the interstices between them are displaced inverted. In the mutation operator used in this study is shown in Fig. 8.



3	1	6	2	3	5

3	1	0	0	0	0

2	2	2	3	5	6
6	1	6	2	3	4
5	4	4	2	3	6
6	2	4	3	4	6
4	2	4	3	5	3
3	1	2	2	6	5

5	6	5	4	3	6
2	4	2	1	4	4
6	5	5	1	2	3
4	6	3	4	3	2
4	2	3	4	5	6
4	2	3	1	3	6
2	1	2	1	5	5

$\Rightarrow$

0	0	5	0	3	0
2	0	0	0	0	4
6	0	0	0	0	3
0	6	0	0	3	0
4	0	3	4	5	0
4	0	3	0	3	0
2	0	2	0	5	5

Fig.7. Crossover operator display

2	4	2	4	1	5
4	2	2	3	5	6
6	2	6	2	3	4
5	4	4	2	3	6
6	2	3	1	4	5
4	2	5	6	2	4
3	1	6	2	3	5

$\Rightarrow$

2	1	2	4	4	5
4	5	2	3	2	6
6	3	6	2	2	4
5	3	4	2	4	6
6	4	3	1	2	5
4	2	5	6	2	4
3	3	6	2	1	5

Fig. 8: mutation operator display

4.5. Hybrid LP-GA

In this section, we combine the LP-metric method with a reliable GA to solve multi-objective optimization problems. As mentioned in the previous section, GA is a population-based algorithm that finds the best solution with respect to a target function. However, the proposed model has two objectives, so for each primitive population and the model variables, two variables are considered relevant to the objectives. This method is formulated according to the objective function of the LP-metric method of the GA algorithm. As you know, the objective of LP-metric method is minimization. We can show optimal values for all purposes. The algorithm steps are demonstrated in Fig. 9.

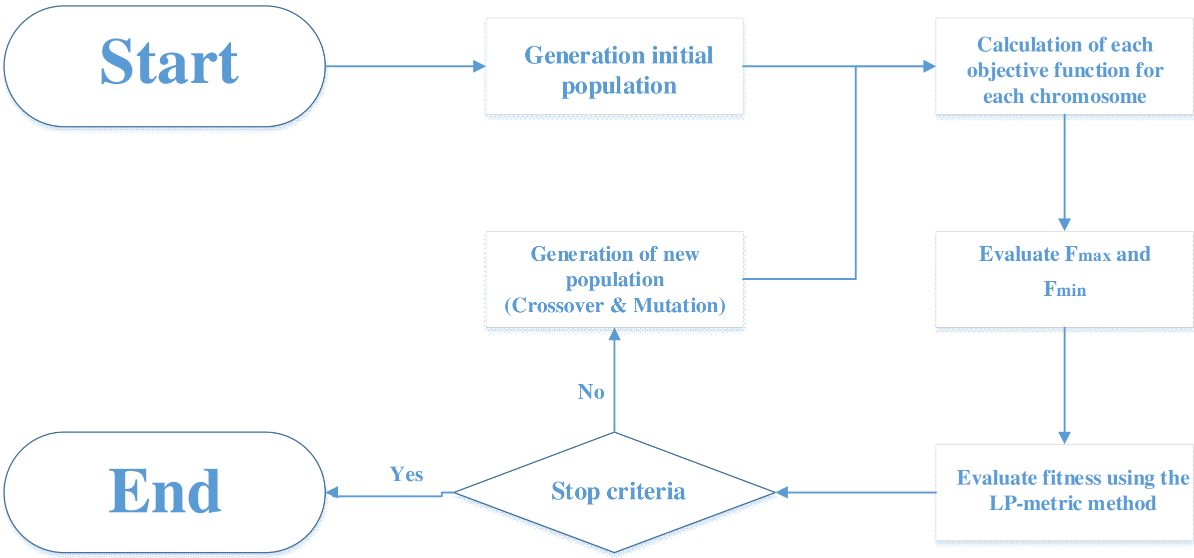


Fig. 9. The steps of the algorithm

5. Case study

Here, to set the developed model's parameters, a real case located in Iran is reported. In that regard, the suggested model is used in the survey to show the accuracy and consistency of the outcomes. Indeed, this study is stimulating concerning designing a humanitarian relief chain in Kermanshah province in Iran. Hence, to deals with potential disasters, detailed information about a real disaster case in one of the western provinces of Iran, Kermanshah, is provided. The earthquake's epicenter occurred 17 km from Sar Pol-e Zahab, 18 km from the Qasr Shirin and 33 km from Guilan-e Gharb. And the closest centers of the province to the Ilam earthquake center were with 106 km and Kermanshah with 127 km distance.

The province covers a region of 25,009 km². Furthermore, this province is enriched by many natural resources and it as one of the most thickly populated regions of Iran is raised. The population of the region was 1,945,227 regarding to the census of 2011, in which 46.82% were the villagers, 53.18% were related to the urban residents, and rest of them were emigrant. Also, this province is divided into 15 counties and Sari city as its capital is raised as shown in Fig. 10.

Fig. 10. A schematic map of Kermanshah (adopted from (Wikipedia))

As is clear, the computational time holds a positive association with the number of disruption scenarios, so CPU time will be increased by an increment of the scenarios' numbers. Therefore, three disruption scenarios are considered in our survey. Here, the disaster scenario level dependent upon the occurrence time, and these are exhibited in the Table 4.

Table 4. Different earthquake scenarios' probabilities

Disaster scenarios	Probability	Number
Scenario 1	0.443	3
Scenario 2	0.344	2
Scenario 3	0.213	1

Furthermore, to illustrate the effect of increasing the size of the problem on the performance of the solutions and the mathematical model, 10 test problems have been designed in different dimensions in Table 5. Other parameters of proposed model are presented in Table 6-7.

Table 5. The detailed information about the test problems.

# of problem	L	I	J	K	H	M	S	Q	C	G
1	3	2	3	2	2	2	3	4	2	1
2	5	3	5	3	2	3	3	6	3	2
3	7	4	7	5	3	3	3	9	3	3

4	9	6	9	6	5	3	3	10	5	5
5	11	7	11	8	6	3	3	15	6	5
6	12	9	14	10	7	3	3	18	8	6
7	13	10	16	13	9	3	3	20	10	7
8	16	12	19	14	10	3	3	22	12	8
9	17	15	21	18	11	3	3	25	15	9
10	18	18	23	20	13	3	3	30	20	10

Table 6. Set values for the rest of the model parameters

Parameter	**Values**	**Unit**	**Parameter**	**Values**	**Unit**
F_i^c	U ~ [10, 16]	Billion Rial (BR)	ω_{lim}^s	0 or 1	-
G_j	U ~ [3, 6]	Billion Rial (BR)	D_{qk}^s	U ~ [50, 300]	Set, Kg, Pair, or Box
E_h	U ~ [9, 14]	Billion Rial (BR)	V^c	U ~ [80, 250]	Pallet
IH_q	U ~ [10000, 40000]	Rial (R)	CA_j	U ~ [20, 100]	Pallet
UC_q^i	U ~ [10000, 35000]	Rial (R)	SA_h^q	U ~ [10, 150]	Pallet
UL_q^j	U ~ [10000, 35000]	Rial (R)	CS_{ql}	U ~ [3, 10]	Pallet
λ_{qs}^i	U ~ [0, 1]	Percentage	CAP_{ijm}	U ~ [10, 50]	Pallet
μ_{qs}^j	U ~ [0, 1]	Percentage	CCP_{lim}	U ~ [4, 10]	Pallet
ξ_l^s	U ~ [0, 1]	Percentage	A_q	U ~ [0.01, 0.4]	Pallet
US_q^s	U ~ [100000, 185000]	Rial (R)	ϕ_s^g	U ~ [0, 1]	Percentage
ζ_{ijm}^s	0 or 1	-	ρ_{ql}	0 or 1	-
CT_{qlim}	U ~ [$distance\ (km) \times 10000 (R), distance\ (km) \times 100000 (R)$]				Rial (R)
CTR_{qijkm}	U ~ [$distance\ (km) \times 10000 (R), distance\ (km) \times 100000 (R)$]				Rial (R)

Table 7. The pairwise distance of the candidate cities used in the case study (KM)

City	Qasr-e shirin	Guilan-e Gharb	Kerned-e	Sarvpol-e	Tazeh Abad	Paveh	Javanrud	Ravansar	Eslam-Abad	kermanshah	Harsin	Sahneh	Sonqor	Kangavar	Ilam	Sanandaj
Qasr-e shirin	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Guilan-e Gharb	23	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Kerned-e	46	23	*	*	*	*	*	*	*	*	*	*	*	*	*	*

Gharb																
Sarvpol-e Zahab	66	37	20	*	*	*	*	*	*	*	*	*	*	*	*	*
Tazeh Abad	62	43	20	20	*	*	*	*	*	*	*	*	*	*	*	*
Paveh	116	93	70	70	50	*	*	*	*	*	*	*	*	*	*	*
Javanrud	110	90	65	65	45	10	*	*	*	*	*	*	*	*	*	*
Ravansar	106	83	60	34	40	90	86	*	*	*	*	*	*	*	*	*
Eslam-Abad Gharb	82	63	40	43	20	70	65	20	*	*	*	*	*	*	*	*
kermanshah	135	112	89	75	69	119	110	41	49	*	*	*	*	*	*	*
Harsin	115	92	69	72	49	99	96	39	29	20	*	*	*	*	*	*
Sahneh	160	137	114	129	94	144	142	66	74	25	45	*	*	*	*	*
Sonqor	209	186	163	135	163	193	190	115	123	74	14	49	*	*	*	*
Kangavar	210	187	164	150	144	194	191	116	124	75	95	50	5	*	*	*
Ilam	271	248	225	211	190	255	250	177	184	132	156	107	62	57	*	*
Sanandaj	296	269	246	253	230	280	274	202	210	157	181	132	87	82	25	*

6. Computational results

Here, the computational results of solving proposed model is reported. To this end, at first the resilience parameters used for second objective should be obtained using BWM. Then, other parameters of the model must be generated. Besides, to gain better execution, the method of Taguchi is employed for tuning the metaheuristics' parameters. Finally, the results and discussion are provided.

The proposed mathematical model is coded in the GAMS 2017 and MATLAB™ 2013 software. All of the program runs are performed on a PC with Intel(R) Core (TM) i5-5200U CPU @2.20 GHz under Windows 10. Besides, each test problem was calculated utilizing the advanced algorithms based on the most favorable parameters according to Taguchi experiments.

6.1. Finding the resilient parameters

In the proposed bi-objective mathematical model, two resilient parameters include α_i and θ_j are existed which to find them values the BWM method is applied. To perform this MCDM method, two components include the alternatives and criteria are needed. Here, for α_i, the i CWs are the alternatives and for θ_j, the j LDCs are the alternatives. Also, the criteria of Table 2 are utilized. For instance, in first test problem, i=2 and j=3, so the α_1, α_2, θ_1, θ_2, and θ_3 should be obtain.

Based on experts' and DMs opinions, Flexible facilities (C2) and Distributed power empowered to take necessary action (C4) as the best criterion and worst criterion are selected, respectively. So, the Best-to-Others vector, and Others-to-Worst vector are provided in Table 8-9, respectively. Then, solving the presented problem in equation (20), the global weights of indicators result. The problem (20) is coded in Lingo software and finally values of (0.06, 0.03, 0.31, 0.18, 0.11, 0.15, 0.12, 0.04, 1.228) are obtained for (ω_1, ω_2, ω_3, ω_4, ω_5, ω_6, ω_7, ω_8, ξ), respectively.

Table 8. Best-to-Others vector.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Best criterion C_2	5	1	2	9	4	2	3	8

Table 9. Others-to-Worst vector**.**

Criteria	**Worst criterion C_4**
C_1	3
C_2	9
C_3	7
C_4	1
C_5	4
C_6	6
C_7	4
C_8	2

Finally, to calculate the score of CWs and LDCs, at first, the experts give the score to the alternatives based on each indicator (Table 120-11). Then, the final scores and normalized manner of alternatives are resulted in Table 12 using the formulas (22) and (23). Similarly, for other test problems the values of α_i and θ_j can be found.

Table 10. The scoring of the CWs based on the criteria**.**

Alternatives	Criteria							
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
α_1	4	6	3	5	3	4	2	2
α_2	5	6	5	4	4	2	2	3

Table 11. The scoring of the LDCs based on the criteria**.**

Alternatives	Criteria							
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
θ_1	6	4	6	6	3	3	2	2
θ_2	5	7	9	6	2	4	3	4
θ_3	2	7	5	6	5	5	4	2

Table 12. The attained score of alternatives based on the criteria

Alternatives	S_i	Normalized $Scor_k$
α_1	4.049	**0.486**
α_2	4.285	**0.514**
θ_1	3.943	**0.207**
θ_2	5.601	**0.293**
θ_3	9.544	**0.500**

As discussed earlier, the LP-metric method was used in this study. The input parameters of the LP-metric method for 10 test problem are shown in Table 13. According to opinion experts, the weight for the first, second objective function is, respectively 0.6, 0.4.

Table 13. The input parameters of the LP-metric method

# of problem	objective function	f_{min}	f_{max}
1		11877527.09	3322312.07
2		10438337.11	7287586.14
3		9544569.07	10581393.00
4		3822361.23	1726815.07

5	Z_1	3616425.56	1689415.72
6		3581580.87	2792851.63
7		10694586.95	6815366.09
8		3121933.12	6041184.15
9		8715152.01	2427395.82
10		10130420.07	7424848.33
1		236	1154
2		350	927
3		265	864
4		228	1327
5	Z_2	260	1345
6		358	1156
7		339	1456
8		207	1289
9		232	1450
10		262	1605

The outcomes of the suggested model solution are exhibited in Table 14. As you can see, the optimal LP-Metric model is tested in three types (MINLP, MILP, and Heuristic) and two modes (Deterministic, Robust) and the optimal GAP is shown.

Table 14. Comparison among MINLP, MILP, heuristic and robust LP-Metric model solutions for problems possessing are solved under uncertain characteristics.

Problem No	MINLP						MILP						Heuristics					
	Deterministic	Time	optimal gap%	Robust	Time	optimal gap%	Deterministic	Time	optimal gap%	Robust	Time	optimal gap%	Deterministic	Time	optimal gap%	Robust	Time	optimal gap%
1	0.233	0:04:00	2.8	0.203	0:04:56	1.56	0.161	0:02:00	2.02	0.149	0:02:00	1.85	0.147	0:01:03	2.5	0.133	0:02:23	1.05
2	0.188	0:04:19	0.51	0.168	0:05:00	1.04	0.111	0:01:00	0.036	0.101	0:01:15	0.5	0.091	0:01:10	0.00	0.080	0:02:46	1.2
3	0.219	0:04:55	0.00	0.209	0:05:34	0.94	0.189	0:02:00	1.68	0.171	0:02:38	0.008	0.168	0:01:09	1.05	0.153	0:03:19	0.00
4	0.298	0:06:56	0.82	0.304	0:07:41	0.00	0.241	0:04:56	0.39	0.228	0:05:06	1.36	0.225	0:02:11	0.005	0.220	0:05:17	0.00
5	0.320	0:3:20	1.18	0.289	0:10:00	0.76	0.236	0:10:00	3.35	0.213	0:10:58	2.59	0.205	0:02:01	0.069	0.198	0:07:39	1.006
6	0.210	00:34:44	2.71	0.187	00:38:00	0.83	0.144	00:35:24	0.32	0.131	00:36:51	3.61	0.123	0:02:11	2.03	0.118	0:08:42	2.13
7	0.168	00:44:15	0.19	0.123	00:55:47	3.22	0.098	00:54:41	3.12	0.076	00:54:41	0.41	0.066	0:03:04	0.04	0.057	0:11:04	0.13
8	0.189	00:57:02	0.00	0.146	00:43:35	5.05	0.118	00:37:41	0.795	0.098	00:37:41	3.66	0.092	0:03:01	2.14	0.087	0:13:49	0.065
9	0.157	00:17:32	0.00	0.129	00:28:02	4.03	0.103	00:10:32	0.12	0.073	00:11:00	0.5	0.065	0:04:54	1.04	0.049	0:16:50	0.0085
10	0.288	00:41:05	1.15	0.210	00:33:00	2.33	0.147	00:33:00	0.1	0.139	00:33:39	0.24	0.135	0:04:56	0.06	0.129	0:17:36	0.3

As you can see, in optimal GAP three different cases, they are compared, which shows that the heuristic method is better and more optimistic in than the other two.

As you can see in Table 14, the model is on the basis of four kinds of problem-solving, and the outcomes are as below:

The objective function value was analyzed in 2 robust and deterministic cases, which were presented on the basis of differences in the confidence levels in the case of a robust, the targets' values in the deterministic are higher than the robust state, and the confidence levels of the uncertainty is raised. Still, the purposes are in robust mode will rise. The models' values rise respectively, which indicates that it gets its maximal value model in exploratory mode. Contrary to the targets' values in varied modes, the time to solve the models is decreased. Considering the targets' values in the robust are deterministic and firmly associated, it can be argued that the model is steady and integrated.

The objective function's values	$\mathrm{MINLP}_{\mathrm{Deterministic}} \leq \mathrm{MILP}_{\mathrm{Deterministic}} \leq \mathrm{Heuristics}_{\mathrm{Deterministic}}$ $\mathrm{MINLP}_{\mathrm{Robust}} \leq \mathrm{MILP}_{\mathrm{Robust}} \leq \mathrm{Heuristics}_{\mathrm{Robust}}$
Model's CPU Time values	$\mathrm{MINLP}_{\mathrm{Deterministic}} \geq \mathrm{MILP}_{\mathrm{Deterministic}} \geq \mathrm{Heuristics}_{\mathrm{Deterministic}}$ $\mathrm{MINLP}_{\mathrm{Robust}} \geq \mathrm{MILP}_{\mathrm{Robust}} \geq \mathrm{Heuristics}_{\mathrm{Robust}}$

In this study to set the parameter for the proposed algorithm, since the objective functions are considered as variables. The initial population size, crossover probabilities, mutation probabilities according to their definition in section 4.4 we use the slope linear regression method through the data points proposed by Shah et al. (2018). We use the method to discover the optimal levels of the problem. The highest slope linear regression method should be selected for the best level of each factor. Thus, using main excellence of this response points it can be found that, {Max-iteration =200, Pc=0.7, N-pop=150, Pm=0.05} are the chosen values for parameters of LP-GA. Since, the model has multiple objectives, so ideal response based on the multi-objective measure metrics is provided for the response of LP-metric technique in this examination.

Given the equation (41) relative error (PRE) for small samples of the problem is calculated as follows:

$$\mathrm{PRE} = \frac{\mathrm{ALG}_{\mathrm{sol}} - \mathrm{OPT}_{\mathrm{sol}}}{\mathrm{OPT}_{\mathrm{sol}}} \times 100 \tag{41}$$

where, $\mathrm{OPT}_{\mathrm{sol}}$ and $\mathrm{ALG}_{\mathrm{sol}}$ are the optimum value acquired by the GAMS software and the objective value acquired by each suggested GA, in turn.

Plus, utilizing formula (42), we are able to normalize the resulting data. In this formula RPD defined Related Percentage Deviation.

$$\mathrm{RPD} = |\text{ Every Experiment Sol } - \text{ Best Sol }| * 100 / |\text{Best Sol}| \tag{42}$$

6.2. Results and discussion

Here, the reaction of the developed metaheuristic algorithms is assessed by the standard metrics assumed in Section 6.1. To this end, after solving the proposed model using mentioned algorithms, the obtain results are provide in Table 15. These values are reported for 10 test problems introduced in Section 5.

Table 15. Results of computational for the problem

	GAMS		LP-GA				
	Optimal	CPU Time	Best	Avg.	RPD	PRE	CPU Time
1	0.133	0:02:23	0.136	0.145	0.00	1.26	0:30:21
2	0.080	0:02:46	0.085	0.115	1.30	0.38	0:35:11
3	0.153	0:03:19	0.168	0.189	1.10	1.26	0:38:25
4	0.220	0:05:17	0.243	0.268	1.30	3.11	0:42:28
5	0.198	0:07:39	0.111	0.205	1.50	1.17	0:49:41
6	0.118	0:08:42	0.152	0.175	1.80	0.26	0:47:23
7	0.057	0:11:04	0.097	0.105	1.60	2.89	0:53:18
8	0.087	0:13:49	0.024	0.109	1.90	1.26	0:52:36
9	0.049	0:16:50	0.056	0.085	2.10	3.27	0:57:17
10	0.129	0:17:36	0.165	0.179	2.00	3.10	01:05:28

According to Table 15 comparing the results of the proposed model solution for the Problem instances for Heuristics - Robust Model between LP model and LP-GA it has been shown. According to it we found that the effectiveness of the proposed solution was better at solving time and response quality. Also, the LP-GA approach was more stable under uncertainty, although the LP-GA-time solution is slightly longer than the GAMS solution time so the amount of time increase is justified.

6.3. The analysis of sensitivity

In the present part, the sensitivity examination of the objective function is contrasted with several model parameters to define the impact of the difference in the objective function value. For this purpose, a test problem is selected, and the value of all parameters other than demand is constant, and the problem is solved in different situations.
This section examines the changes made during the total cost (first objective function) and the weighted resilience level of each facility, CW/LDC (second objective function), regarding the change in the demand. For this purpose, a case study of the problem is considered, and all parameters other than fixed demand are considered, then the problem is solved with different demand values to determine its impact upon the problem's objective functions. The result demonstrates the objective functions' sensitivity analysis in relation to the amount of demand in Fig. 11 and 12.

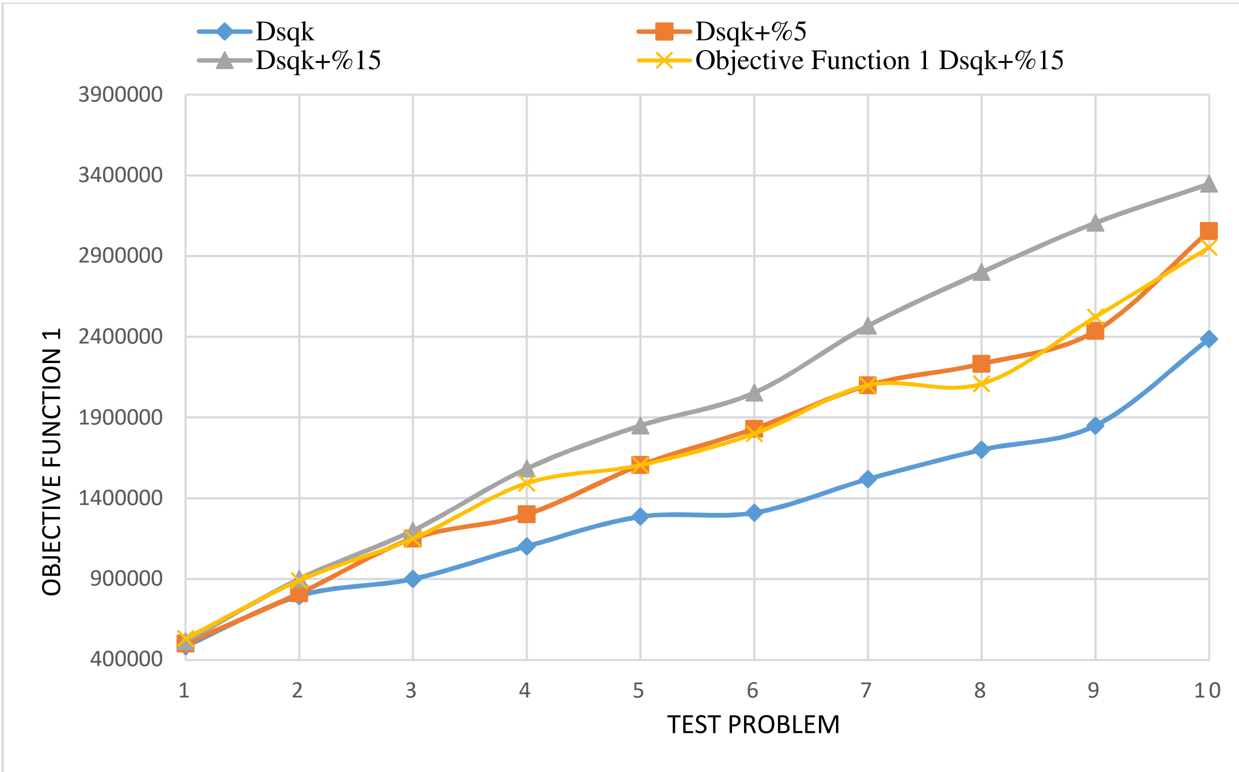


Fig. 11. To analyze the sensitivity of demand for the first objective function

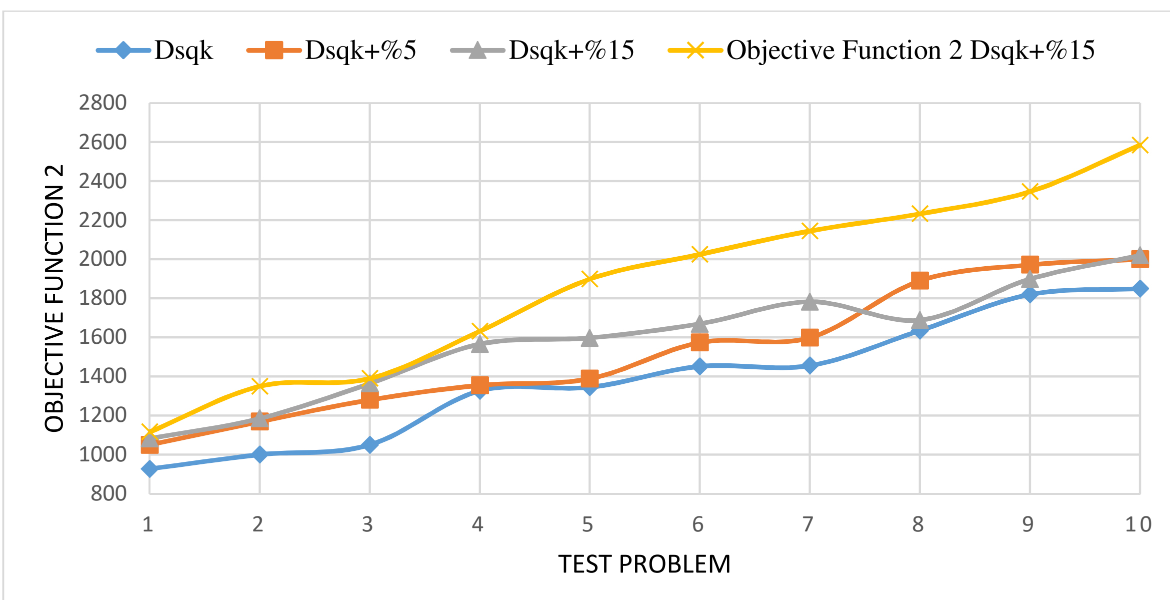


Fig. 12. To analyze the sensitivity of demand for the second objective function

As shown in Fig. 11 and 12, the objective functions represent a direct relationship with the parameters change. To put it another way, they rise by the development of the different amount of demand. Nevertheless, those fluctuations and increases are varied in several change intervals, and each objective holds its sensitivity against different change intervals.

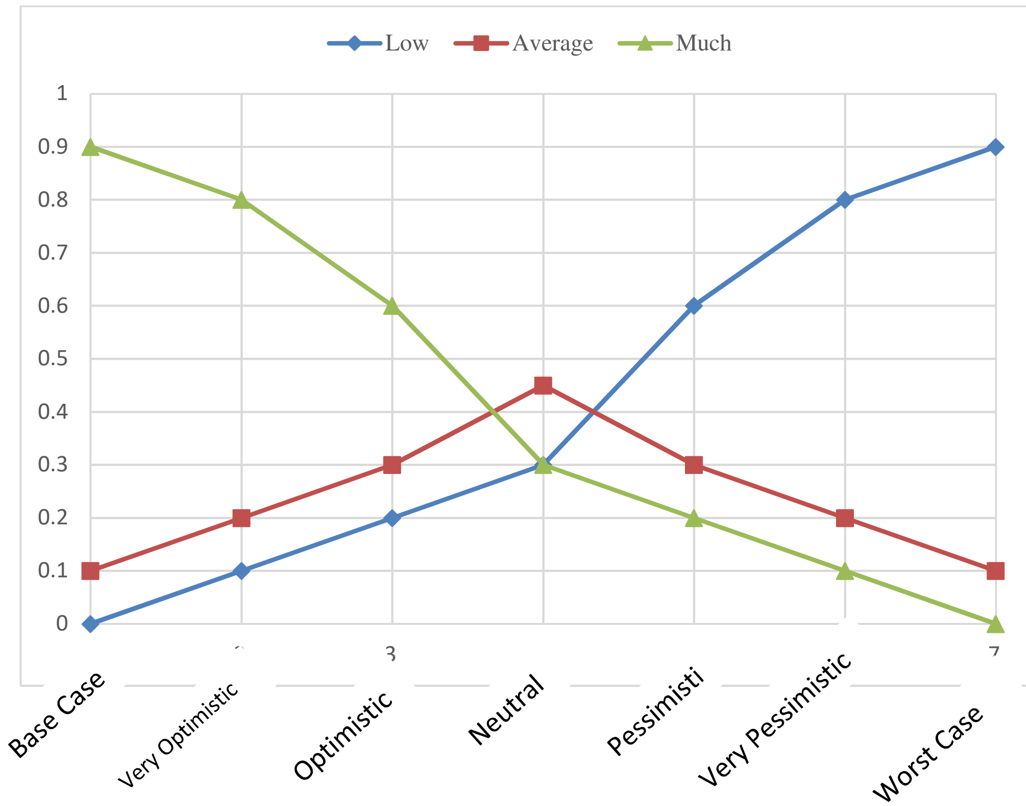


Fig. 13. The probability of each scenario for different modes

As given in Fig. 13, it illustrates the different changes and probabilities in different scenarios at the case study level.

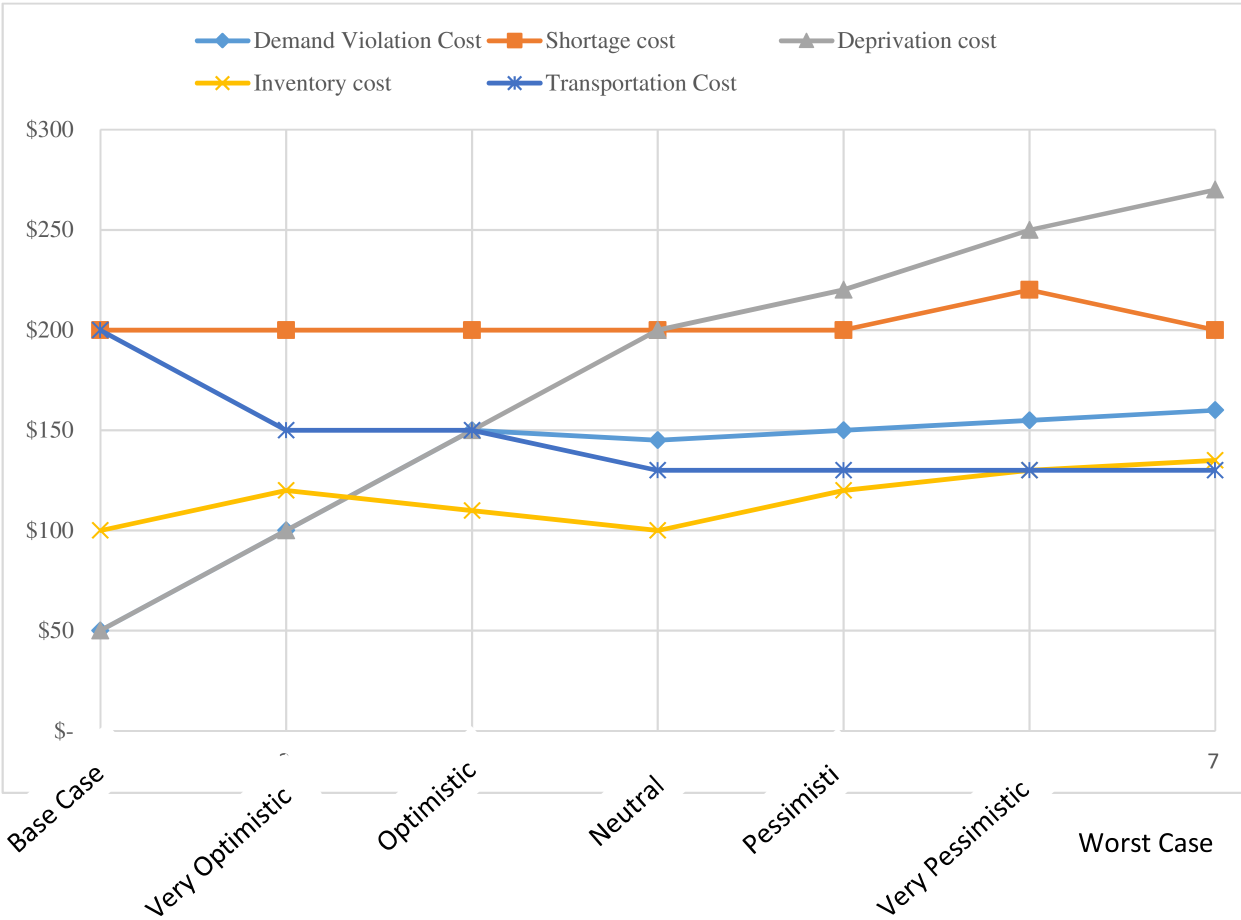


Fig. 14. The different scenarios effect on optimal supply chain cost parameters examined

The scenario possibilities effect on the optimal components of logistic relief costs is presented in Fig. 14. In the case described earlier, altering the conditions does not significantly affect optimal transportation costs and Short-term costs.

7. Conclusion

The present study provides a bi-objective MINLP model to identify the locations of LDCs and CWs, at the same time, and the corresponding inventoried relief commodities, and the distributed quantities to CWs from supplier, from CWs to the damaged regions (LDC), and from strategic stock to LDC. To this end, this paper provides a base scenario bi-objective model that seeks to reduce total cost consisting of inventory holding cost, shortage and transportation cost while maximizing the level of the weighted resilience of each facility (CW/LDC). Here, a novel robust optimization approach is employed to deal with the uncertainty level of the transport network paths, supply condition, amount of demand and deprivation costs are assumed. Also, based on historical data, several scenarios are defined which represent S disaster conditions. Also, the resilience parameters used for the second objective are obtained using BWM. Moreover, the multiple disasters (sub-sequent minor post disasters) which can increase the initial demand are considered. Furthermore, in view of the NP-Hardness of the model, the well-known metaheuristic algorithm LP–GA is employed, and their performance is compared per 10 test problems by several standard single-objective measure metrics. The present article has revealed that with the integration of LP-GA into models, the model calculating time is decreased. Due to the nonlinearity of the model, the solution time is raised; for solving this issue, the vast range for relaxation of the created model has been employed, which decreases the computing time by roughly 27%. Finally, according to the results, it was exposed that: LP–GA has better proficiency in terms of RPD, PRE; meanwhile, for CPU time, LP–GA has better performances. The achieved results prove that a statistically significant difference is observed among the performances of the metaheuristics. The results demonstrate the effectiveness of suggested model and framework and these results can be helpful for crisis managers. Finally, as management recommendations for future research and recommendations are as follows:

The lack of access to media after the disaster has prevented critical information from being released. That can be conducted through installing banners concerning the specific locations with more vulnerability informed.

Information on critical needs created after the disaster: Avoid unnecessary dispatch of goods to the affected areas. In the earthquake disaster of Kermanshah, 2018 in Iran, one of the major problems with overloading private vehicles such as clothing packs and blankets to the affected areas has been the disruption to assisting the injured. Therefore, the needs of the injured should be addressed with appropriate assistance and those of the army and the Red Crescent.

- The model can be formulated using a fuzzy set theory or another approach such as robust stochastic programming for formulating the model.
- Utilizing the suggested model in other sectors of logistics.
- Developing some hybrid meta-heuristics and heuristics to solve the model.
- Applying other MCDM methods such as TOPSIS, AHP, and DEMATEL to find resilient parameters.

8. Declarations

- Ethics approval and consent to participate: Not Applicable.
- Consent for publication: Not Applicable.
- Availability of data and materials: Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.
- Competing interests: The authors declare no competing interests.
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- Authors' contributions: AF, and BFM: planning of study; MHB, and FMS: statistical analysis and critical review; AF, BFM, MHB, and FMS: data discussion. All the authors approved the final version of the manuscript.

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