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A Stochastic Optimization Model for Designing a Humanitarian Relief Chain Considering Operational and Disruption Risk

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ABSTRACT

Due to the increasing the number of natural disasters such as earthquakes and floods and unnatural disasters such as war and terrorist attacks, Humanitarian Relief Chain (HRC) is taken into consideration of most countries. Besides, this paper aims to contribute humanitarian relief chains under uncertainty. In this paper, we address a humanitarian logistics network design problem including local distribution centers (LDCs) and multiple central warehouses (CWs) and develop a scenario-based stochastic programming (SBSP) approach. Also, the uncertainty associated with demand and supply information as well as the availability of the transportation network's routes level after an earthquake are considered by employing stochastic optimization. While the proposed model attempts to minimize the total costs of the relief chain, it implicitly minimizes the maximum travel time between each pair of facility and the demand point of the items. Additionally, a data set derived from a real disaster case study in the Iran area, and to solve the proposed model a exact method called ε-constraint in low dimension along with some well-known evolutionary algorithms are applied. Also, to achieve good performance, the parameters of these algorithms are tuned by using Taguchi method. In addition, the proposed algorithms are compared via four multi-objective metrics and statistically method. Based on the results it was shown that: NSGA-II shows better performances in terms of SNS and CPU time, meanwhile, for NPS and MID, MRGA has better performances. Finally, some comments for future researches are suggested.

Keywords: Humanitarian supply chain, Stochastic programming, Evolutionary algorithms, Disruption risk

Introduction

In recent years, many areas around the world have been affected by natural disasters. These events are leading to the death, injury and destruction of property and disruption of daily activities that these unpleasant experiences are considered as natural disasters [1]. Moreover, disasters can be natural (such as earthquake, famine, tsunami, cyclone, hurricane, flood, etc.), manmade disasters (such as terrorism, war, civil disorder, etc.), disease (like HIV/aids or malaria) or extreme poverty situation.

The rate of natural disasters is increasing intensely due to population growth, global inclination in urbanism, land use and stressing of ecosystems. From global perspective, the number of natural disasters is increasing every year. For example, in 2005, there was 489 country-level disasters affecting 127 countries around the globe resulting in 104,698 people killed and 160 million people affected. According to Natural Disaster Database, earthquakes alone have killed more than 700,000 people in the past 20 years. Destructive effects of disasters, although inevitable, could be decreased by a proactive approach and the development of appropriate preparedness plans.

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Hence, necessity of appropriate measures to consider such disasters is needed extremely. Despite major contextual differences between commercial and humanitarian supply chains, in humanitarian operations, profit maximization that is the main objective in commercial supply chains is replaced by timely and appropriate provision of aid to beneficiaries. Besides, the high scale of these crises, has increased the need for efficient management of the relief supply chain.

Also, Iran is one of the most disaster-prone countries in the world due to its geographical conditions, that destructive earthquakes and the crisis that occurred after its occurrence, every year causing irreparable damage to people and the economy of the country. Existence of an integrated chain of all components and Humanitarian Relief, will be facilitate the disaster management in natural disasters, especially earthquakes that offered to the people involved in the events [2].

Humanitarian Relief Logistics is one of the most important elements of the relief operation in crisis management. Logistics planning in disaster relief is included sending of several items (such as medicine, rescue equipment, rescue teams, food, etc.) from a number of sources of supply to multiple points of distribution in damaged areas through a chain structure. Also, the transfer of goods should be done quickly and efficiently so that the survival rate of affected people, and the cost of operations are maximized and minimized respectively [3].

There are some review articles showing the state of the art in area of HRCs from various viewpoints consisting a general review on HRCs to identify suitable measures in various phases or steps of disasters which are pre-disaster, during-disaster and post-disaster [4-6]. For instance, Caunhye et al. [7] reviewed proposed models for post and pre-disaster operations. In addition, they mentioned proposed models for traffic control and lifeline rehabilitation. More recently, Özdamar and Ertem [8] presented a survey that focused on the response and recovery planning steps of the disaster lifecycle.

Recently, a three-level relief chain model include suppliers, distribution centers, and affected areas is proposed by Zokaee et al. [9]. They proposed a MILP deterministic model by using stochastic optimization and they considered uncertainty for demand, supply, and all of the cost parameters, where the uncertain parameters are independent and bounded random variables. Their offered model attempts to minimize the total costs of the relief chain, it implicitly maximizes people's satisfaction level in the affected areas through applying a penalty to shortages of relief commodities. Moreover, a real disaster case study in the Iran for earthquakes, is applied to test the efficiency of the suggested model. Also, Sahebjamnia et al. [10] proposed a Hybrid Decision Support System (HDSS) include a simulator, a rule-based inference engine, and a knowledge-based system in order to design a three level HRC. Three main performance measures including the coverage, total cost, and response time are considered to make an explicit trade-off analysis between cost efficiency and responsiveness of the designed HRC. Also, a real case study in Tehran demonstrates using stochastic data. Moreover, some researches paid to humanitarian supply chain using mathematical programming model or metaheuristic algorithms (see [11-14]).

As is clear, some of these researches paid to disaster issues and try to minimize total costs via exact method. Also, some of them used heuristic and meta- heuristic approaches and report the efficiency of these algorithms in their works.

Here, a humanitarian logistics network design problem including local distribution centers (LDCs) and multiple central warehouses (CWs) and a scenario-based stochastic programming (SBSP) approach is offered. Also, the uncertainty associated with demand and supply information as well as the availability of the transportation network's routes level after an earthquake are considered by employing stochastic optimization. As one of this paper contribution, we consider two objective functions include minimizing costs and minimizing maximum travel time that to the best our knowledge simultaneous combination of them is not reported yet. Moreover, we developed two well-known meta-heuristics along with ε-constraint method to solve proposed framework that it is another contribution of this paper. Additionally, a data set derived from a real disaster case study in the Iran area.

The structure of this paper is planned as follows: Section 2 and Section 3 presents the problem definition and model formulation, respectively. Section 4 presents Solution approach include encoding and decoding, employed evolutionary algorithms description, and performance measures. In Section 5, parameter tuning process is performed. In Section 6 a computational result is presented. Finally, future research and conclusion are given in Section 7.

Problem Description

In this paper, we suppose that the network of disaster relief logistics includes of three stages, Figure 1. The stages are the set of suppliers, the contain CWs and strategic stocks, and the last stage include of local distribution centers (LDCs) in the areas, which are affected by disaster. Hence, suppliers (e.g., aid agencies, private sector, governments, etc.) could play as a critical role in the relief chain and prepare the required commodities to people in devastated areas; those people could play a main role of the customers in the physical distribution. CWs contain warehouses, airports, train station and bus stations. The location of LDCs can be determined on the facilities of fortified existing public as health centers, schools, and mosques which are distributed in all over the city. Using of LDCs is completely justifiable since according to the response agency representatives it is not practical to found a large number of CWs that remain inactive until a disaster strikes. Indeed, using some existing public facilities could be a better alternative for disaster response purposes.

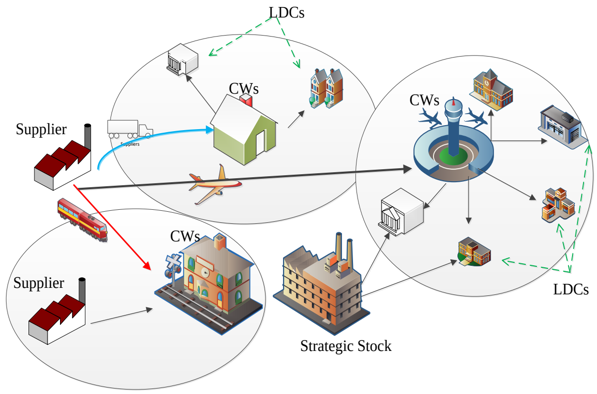

Figure 1. Overall structure of HRC

Model Formulation

In this section, the model elements including indices, parameters, and variables are introduced as follows:

Indices

l Index of potential suppliers
i Index of potential *CWs*
j Index of potential *LDCs*
k Index of affected areas; demand points
h Index of potential strategic stocks
m Index of potential transportation mode
s Index of potential disaster scenarios
q Index of relief items
c Index for storage capacity levels of CWs
g Index of potential sub-sequent disasters

Parameters

F_i^c Establishing cost of ith CW at capacity level c
G_j Establishing cost of jth LDC
E_h Establishing cost of hth strategic stocks
IH_q Inventory holding cost of item q
UC_q^{is} Unit inventory cost of unused item q at each CWs i in disaster scenario s
UL_q^{js} Unit inventory cost of unused item q at each LDCs j in disaster scenario s
λ_{qs}^i Usable inventory ratio of the qth item at the ith CW under scenario s
μ_{qs}^j Usable inventory ratio of the qth item at the jth LDC under scenario s
ξ_l^s Usable capacity ratio of the lth supplier under scenario s
US_q^s Unit shortage cost of item q in disaster scenario s
TA_{ijm}^s Transportation time between the ith CW and jth LDC via mode m to reflect the road and traffic conditions in disaster scenario s
TB_{lim}^s Transportation time between the lth supplier and the ith CW via mode m to reflect the road and traffic conditions in disaster scenario s
ζ_{ijm}^s 1, if mode m is available under scenario s between the ith CW and jth LDC; 0 otherwise

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ω_{lim}^{s}	1, if mode *m* is available under scenario *s* between the *l*th supplier and *i*th CW; 0 otherwise
D_{qk}^{s}	Demand level for the *q*th item at the *k*th demand point under scenario *s*
V^{c}	Storage capacity of each CW established at capacity level *c*
CA_{j}	Storage capacity of the *j*th LDC
SA_{h}^{q}	Storage capacity of the *h*th strategic stock for *q*th item
CS_{ql}	Storage capacity of the *l*th supplier for the *q*th item
CAP_{ijm}	Capacity of transportation mode between *i*th CW and *j*th LDC via mode *m*
ccp_{lim}	Capacity of transportation mode between the *l*th supplier and the *i*th CW via mode *m*
CT_{qlim}	Cost of transportation mode between the *l*th supplier and the *i*th CW via mode *m* for *qth* item
CTR_{qijkm}	Cost of transportation mode between *i*th CW and *j*th LDC to demand point *k* via mode *m* for *qth* item
A_{q}	Required unit storage capacity of the *q*th item
P_{s}	Probability of occurring the scenario *s*
ϕ_{s}^{g}	Sub-sequent disasters effects on demands after the major disaster in scenario *s* (*g* is the number of minor disasters in scenario *s*)
φ_{s}^{g}	Sub-sequent disasters effects on delivery time after major disaster scenario *s* (*g* is the number of minor disasters in scenario *s*)
ρ_{ql}	1, if supplier *lth* capable to deliver *qth* item

Decision variables

Y_{i}^{c}	1, if the ith candidate CW is opened at capacity level c; 0, otherwise
O_{j}	1, if the jth candidate LDC is opened; 0, otherwise
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}	Inventory level of the qth item at the ith CW
U_{qj}	Inventory level of the qth item at the jth LDC
UI_{qi}^{s}	Unused inventory level of the qth item at the ith CW under disaster scenario s
UR_{qj}^{s}	Unused inventory level of critical item q at the jth LDC under disaster scenario s
N_{ijm}^{s}	1, if transportation mode m is selected between ith CW and jth LDC under scenario s
C_{lim}^{s}	1, if transportation mode m is selected between lth supplier and ith CW under scenario s
x_{qjk}^{s}	Amount of the qth critical item to be delivered from the jth LDC to demand point k under disaster scenario s
z_{qijkm}^{s}	Amount of the qth item to be delivered from CW i to demand point k via jth LDC and transportation mode m under disaster scenario s
v_{qhjk}^{s}	Amount of the qth item to be delivered from strategic stock h to demand point k via jth LDC under disaster scenario s
w_{qlim}^{s}	Amount of the qth item to be delivered from supplier l to the ith CW via transportation mode m under disaster scenario s
η_{qk}^{s}	Amount of unfulfilled demand for the qth item in demand point k under disaster scenario s
$T^{\max}$	Maximum travel time between each pair of facility and the demand point of the items

In this section, we aim to present a bi-objective mixed integer linear programming to specify the location of CWs and LDCs, simultaneously and the corresponding inventory quantities for relief items, and the distribution quantities from supplier to CWs, from CWs to the affected areas (LDC) and from strategic stock to LDC. The presented model seeks to minimize the cost variability, expected total cost. In the second stage, a relief distribution plan is extended based on different disaster scenarios by goals of minimizing the

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total distribution time, the maximum weighted distribution time of critical items, total cost of unused inventories, and the shortage cost of unmet demands. The model considers uncertainty in the locations where the demands might increase like as the possibility that some of the pre-arranged supplies at CWs or suppliers might be destroyed partially regarding to the disaster (i.e., supply uncertainty). To demonstrate the imprecise parameters, we make utilize of discrete scenarios from set *S* of potential disaster conditions. We suppose that the probability distribution of each scenario can be computed based on historical data. The proposed bi-objective mixed integer linear programming model of HRC is as follows:

$$\begin{aligned} Min\ TC =& \sum_i \sum_c F_i^c . Y_i^c + \sum_j G_j . O_j + \sum_h E_h . \gamma_h + \sum_q \sum_k \sum_i IH_q . R_{ki} \\ &+ \sum_s P_s . \left\{ \begin{aligned} &\sum_q \sum_i UC_q^{is} . UI_{qi}^s + \sum_q \sum_j UL_q^{js} . UR_{qj}^s + \sum_q \sum_k US_q^s . \eta_{qk}^s \\ &+ \sum_q \sum_l \sum_i \sum_m CT_{qlim} . w_{qlim}^s + \sum_q \sum_i \sum_j \sum_k \sum_m CTR_{qijkm} . z_{qijkm}^s \end{aligned} \right\} \\ &+ \sum_q \sum_k \sum_j IH_q . U_{kj} \end{aligned} \tag{1}$$

$$Min = T^{\max} \tag{2}$$

Subject to:

$$\sum_q A_q . R_{qi} \le \sum_c V^c . Y_i^c \qquad \forall i \in I \tag{3}$$

$$\sum_c Y_i^c \le 1 \qquad \forall i \in I \tag{4}$$

$$\sum_q A_q . U_{qj} \le CA_j . O_j \qquad \forall j \in J \tag{5}$$

$$\sum_j x_{qjk}^s + \sum_i \sum_j \sum_m z_{qijkm}^s + \sum_h \sum_j v_{qhjk}^s = D_{qk}^s \sum_g (1 + \phi_s^g) - \eta_{qk}^s \tag{6}$$
$$\forall k \in K, q \in Q, s \in S$$

$$\sum_k x_{qjk}^s + UR_{qj}^s = \mu_{qs}^j . U_{qj} \qquad \forall j \in J, q \in Q, s \in S \tag{7}$$

$$\sum_j \sum_k \sum_m z_{qijkm}^s + UI_{qi}^s = \lambda_{qs}^i . R_{qi} \qquad \forall i \in I, q \in Q, s \in S \tag{8}$$

$$\sum_q \sum_k z_{qijkm}^s \le \zeta_{ijm}^s . CAP_{ijm} . N_{ijm}^s \quad \forall i \in I, j \in J, m \in M, s \in S \tag{9}$$

$$\sum_i \sum_m w_{qlim}^s \le \rho_{ql} . \xi_l^s . CS_{ql} . \tau_l \quad \forall q \in Q, l \in L, s \in S \tag{10}$$

$$\sum_q w_{qlim}^s \le \omega_{lim}^s . CCP_{lim} . C_{lim}^s \quad \forall l \in L, i \in I, m \in M, s \in S \tag{11}$$

$$\sum_k \sum_j v_{qhjk}^s \le SA_h^q . \gamma_h \qquad \forall h \in H, q \in Q, s \in S \tag{12}$$

$$\left[TA_{ijm}^s . \sum_g (1 + \varphi_s^g) \right] . N_{ijm}^s \le \zeta_{ijm}^s . T^{Max} \tag{13}$$
$$\forall i \in I, j \in J, m \in M, g \in G, s \in S$$

$$\left[TB_{lim}^s . \sum_g (1 + \phi_s^g) \right] . C_{lim}^s \le \omega_{lim}^s . T^{\max} \tag{14}$$
$$\forall l \in L, i \in I, m \in M, g \in G, s \in S$$

$$w_{qlim}^s \le M . C_{lim}^s . \omega_{lim}^s \quad \forall l \in L, i \in I, m \in M, q \in Q, s \in S \tag{15}$$

$$z_{qijkm}^s \le M . N_{ijm}^s . \zeta_{ijm}^s \quad \forall k \in K, j \in J, i \in I, m \in M, q \in Q, s \in S \tag{16}$$

$$z_{qijkm}^s, x_{qjk}^s, \eta_{qk}^s, w_{qlim}^s, T^{\max}, v_{qhjk}^s, UR_{qj}^s, U_{qj}, R_{qi}, UI_{qi}^s \ge 0 \tag{17}$$
$$\forall i \in I, j \in J, l \in L, k \in K, h \in H, q \in Q, s \in S$$

$$O_j, Y_i^c, \tau_l, \gamma_h, N_{ijm}^s, C_{lim}^s \in \{0,1\} \tag{18}$$
$$\forall i \in I, l \in L, m \in M, c \in C, j \in J, h \in H, s \in S$$

Objective function (1) minimizes the total operating costs of selected CWs and LDCs, and their inventory costs. The last part of objective function (1), minimize total cost of unused inventories and shortage cost of

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unmet demands and transportation cost of items. Objective function (2) minimizes the maximum travel time between each pair of CW/LDC and demand point for the items.

Constraint (3) enforce restrictions on the available capacity of CWs. Constraint (4) implies that maximum number of CW with specified capacity level which could be constructed at each candidate site is one. Constraint (5) enforces restrictions on the available capacity of LDCs. Constraint (6) determines the unsatisfied demands for critical items. The right hand of equation (6), determines initial demand plus demands added after sub-sequent minor disasters. Constraints (7) and (8) ensure that the distributed quantity of each item plus regarded unused inventory is equal to their corresponding inventory levels in respective CW/LDCs. Constraint (9) enforce restrictions on the available capacity of transportation system between pair of CW/LDCs. Constraint (10) enforces restrictions on the available capacity of suppliers. Each supplier can deliver a given number or set of critical items which is depend on suppliers' flexibility level. Also, each supplier may loss its capacity partially or totally and right hand of constraint (10) guarantees these conditions. Constraint (11) ensures restrictions on the available capacity of transportation system between pair of supplier/CWs. Constraint (12) enforce restrictions on the available capacity strategic stock. Constraint (13) and (14) calculate the maximum travel time. Constraint (15) and (16) ensures that the quantity of each item will be shipped if the transportation system is available. Constraint (17) and (18) determine the type of decision variables.

Solution Approach

In low dimension problem an exact method called ε-constraint is used and due to NP-*hardness* of the proposed model, exact methods are not proper for large-size problem. Besides, non-dominated sorting genetic algorithm (NSGA-II), non-dominated ranking genetic algorithm (NRGA) are applied to discover Pareto solutions. The mentioned algorithms are used in the same way in recent literature. Moreover, encoding and decoding procedures are illuminated in the following section.

Encoding and decoding

Diverse methods have been established to encode the solutions in different models, such as: Michalewicz matrix, Prufer numbers, and priority-based technique. In this paper the priority-based method is applied. To present the offered array or chromosome, a small-size example is shown in this sector to show the procedure of satisfying all the constraints by the suggested form. In this example, amounts of indices as *i=3, l=3, h=2, j=3, c=3, q=2,* and *k=2* is assumed. The offered chromosome is a matrix with two rows for each item and (*l+2i+h+2j+k*) columns that it has three sectors. These sectors are considered according to the flows shown in Figure 1. Also, the plan of suggested chromosome is shown in Figure 2.

Item	node	Segment 1						Segment 2								Segment 3				
		l			*i*			*h+i*					*j*			*j*			*k*	
1	Priority	0.072	0.132	0.786	0.958	0.799	0.641	0.385	0.650	0.897	0.674	0.115	0.243	0.122	0.490	0.986	0.218	0.516	0.026	0.346
	Capacity level	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	Priority	0.099	0.332	0.034	0.383	0.339	0.431	0.997	0.350	0.792	0.313	0.852	0.512	0.391	0.382	0.472	0.304	0.894	0.471	0.635
	Capacity level	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

Figure 2. Plan of offered random key chromosome

In low dimension problem an exact method called ε-constraint is used and due to NP-hardness of the proposed model, exact methods are not proper for large-size problem. Besides, non-dominated sorting genetic algorithm (NSGA-II), non-dominated ranking genetic algorithm (NRGA) are applied to discover Pareto solutions. The mentioned algorithms are used in the same way in recent literature. Moreover, encoding and decoding procedures are illuminated in the following section.

The matrix shown in Figure 2 is randomly generated and all elements of first row of this matrix are set to

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random numbers in the interval [0, 1], and all elements of second row of this matrix 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 of each segment, for each sub-segment, is done separately. The plan of suggested priority-based chromosome is shown in Figure 3.

Segment one presents the amount of shipped goods from suppliers (*l*) to CWs (*i*). Segment two presents the amount of shipped goods from CWs and strategic stocks (*h+i*) to LDCs (*j*). Also, segment three presents the amount of shipped goods from LDCs (*j*) to affected areas *(k)*. Moreover, Capacity level of each CWs (*i*) is presented in second row of proposed chromosome. Furthermore, allocation procedure is presented in Figure 4 which for each segment can be used from needed steps of it.

		Segment 1						Segment 2								Segment 3				
Item	*node*	*l*			*i*			*h+i*					*j*			*j*			*k*	
1	Priority	1	2	3	3	2	1	2	3	5	4	1	2	1	3	3	1	2	1	2
	Capacity level	*	*	*	2	2	3	*	*	3	2	1	*	*	*	*	*	*	*	*
2	Priority	3	2	1	2	1	3	5	2	3	1	4	3	2	1	2	1	3	1	2
	Capacity level	*	*	*	2	1	1	*	*	2	1	2	*	*	*	*	*	*	*	*

Figure 3. Plan of priority-based chromosome for each scenario

NRGA and NSGA-II

Usually, the real world issues and decisions are often complex, hence they cannot be solved by the exact methods in a proper time and cost [15]. NSGA-II and NRGA as two strong well-known multi-objective algorithms are utilized to evaluate the performance of solutions. The chromosome structure and the function evaluation procedure in NSGA-II and NRGA algorithms are similar to each. The only difference between these algorithms is in their selection mechanism. NSGA-II uses binary tournament selection strategy while NRGA uses Roulette wheel selection strategy. Moreover, four types of mutation operators including reversion mutation, insertion mutation, continuous mutation, and swap mutation are used in local search sector of these algorithm. Furthermore, three types of crossover operators including single-point crossover, double-point crossover, and uniform crossover are utilized in these algorithms to enhance their performances. The main structure of these two algorithms is provided in [16, 17].

For s=1:S
For q=1:Q

Inputs:
I: set of source
J: set of applicant
D_{js}*: demand of applicant j under scenario s*
Ca_{is}*: capacity of source i under scenario s*
V(I+J): Encode solution of item q for scenario s

Outputs:
$Xaloc_{ijs}$*: amount of shipment between nodes under scenario s*
Y_j*: binary variable shows the opened applicant*
U_{qis}*: amount of unused item q of source i under scenario s*
U_{qjs}*: amount of unused item q of applicant j under scenario s*

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While $\sum_i Ca_{is} \geq 0 \,\&\&\, \sum_j D_{js} \geq 0$
Step1: $Xaloc_{ijs} = 0 \quad \forall i \in I, j \in J$
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: $Xaloc_{ijs}=min(Ca_{is}, D_{js})$
Update demands and capacities
$Ca_{is}= Ca_{is} - Xaloc_{ijs} \quad D_{js}= D_{js} - Xaloc_{ijs}$
Step4: if $Ca_{is}=0$ *then* $V(1,I)=0$
if $D_{js}=0$ *then* $V(1,J)=0$
End while
Step5: $U_{ais}=Ca_{is} \quad U_{ajs}=D_{js}$
End for
Step6: for j= 1 to J
if $\sum_s \sum_j Xaloc_{ijs} > 0$ *then* $Y_j=1$
End for
End for

Figure 4. The allocation procedure

Performance metrics

Four performance measures are used in this sector to evaluate the performance of the above-mentioned multi-objective evolutionary algorithms.

- Number of Pareto solution (NPS): The number of Pareto optimal solutions is offered by this metric. The greater number of Pareto solutions in an algorithm is better performance.
- Mean ideal distance (MID): this metric is used to compute the distances between the Pareto fronts and the ideal point. The value of this metric is calculated by Eq. (19):

$$MID = \frac{\sum_{i=1}^{n} \sqrt{\left(\frac{f1_i - f1_{best}}{f1_{total}^{max} - f1_{total}^{min}}\right)^2 + \left(\frac{f2_i - f2_{best}}{f2_{total}^{max} - f2_{total}^{min}}\right)^2}}{n} \tag{19}$$

In this equation, n is the number of non-dominated solutions, and $f1_i$ and $f2_i$ are the value of i^{th} non-dominated solution for each objective function, respectively. ($f1_{best}$, $f2_{best}$) is the ideal point that characterizes the point (0,0) in this problem. fj_{total}^{max}, fj_{total}^{min} are the smallest and the biggest values of every fitness function among all non-dominated solutions resulted from an algorithm, respectively. The less the value of MID, the better algorithm's performance.

- Spread of non-dominance solution (SNS): To assess the diversity of Pareto solutions this metric is applied and is framed as Eq. (20) [18]:

$$SNS = \sqrt{\frac{\sum_{i=1}^{n} (MID - C_i)^2}{n-1}} \tag{20}$$

Where, $C_i = \sqrt{f1_i^2 + f2_i^2}$

- Computational time (CPU time): The speed of running the algorithms to find near optimum solutions is one of the most important indices to evaluate the performance of an algorithm.

Parameters Setting

Here, the parameter tuning process is performed both on the parameters of the algorithms and on the model parameters in the following two subsections, respectively.

Parameter Tuning

Here, in order to tuning the values of the algorithms' parameters, the Taguchi method is applied [19]. This effective method proposed by Taguchi and this method is utilized instead of the full factorial experimental design. In this method a statistical measure named the signal to noise ratio (S/N), is considered to evaluate the performance. As multi-objective algorithms are assessed according to multi-objective measures. Also, Eq. (21) presents the selected response of Taguchi method in this study. The advantage of this response is that it considers both of the two main features of multi-objective algorithms entitled diversity and convergence. First, the *MID* metric measures the convergence rate of the algorithm and second, the diversity of Pareto solutions is obtained by the *SNS* metric.

$$MCOV = \frac{MID}{SNS} \tag{21}$$

The first step to produce a Taguchi design is identify the levels of each factor of algorithms. This step is shown in Table 1 where each factor has three levels [20-22]. Then, by using Minitab software and applying the Taguchi method the L_9 orthogonal array for NRGA, NSGA-II algorithms are designated. The orthogonal arrays of each algorithm along with the achieved results are displayed in Table 2.

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For each algorithm, the related S/N ratio chart obtained by the Minitab® software is shown in Figure 5-6. In this figure, the best level of each factor is selected to be the one with the highest S/N ratio. Besides, {Pc=0.7, Pm=0.1, N-pop=100, Max-iteration =100} are the selected parameters for NSGA-II and {Pc=0.7, Pm=0.15, N-pop=50, Max-iteration =200} are the selected parameters for NRGA by using the Figures 5-6. Moreover, it should be notice that the Taguchi experiment is perform for the first test problem of Table 2 and for other test problems these tuned parameters are utilized. Also, in performing of Taguchi experiment, the "smallest response is better" as a selected response for identifying of parameters is used.

Table 1
Algorithm parameter ranges along with their levels [20-22].

Algorithms	Parameters	Parameter level		
		Level 1	**Level 2**	**Level 3**
NSGA-II	Pc	0.7	0.8	0.9
	Pm	0.05	0.1	0.15
	N-pop	50	100	150
	Max-iteration	100	200	300
NRGA	Pc	0.7	0.8	0.9
	Pm	0.05	0.1	0.15
	N-pop	50	100	150
	Max-iteration	100	200	300

Table 2
The orthogonal array L9 and Computational results for the NRGA and NSGA-II

Run	Pc	Pm	N_{pop}	Max-iter	NRGA	NSGA-II
1	1	1	1	1	1.5426e-011	1.7548e-011
2	1	2	2	2	2.3523e-011	2.3432e-011
3	1	3	3	3	1.8792e-011	2.7898e-011
4	2	1	2	3	3.4582e-011	3.1347e-011
5	2	2	3	1	3.1835e-011	1.7458e-011
6	2	3	1	2	1.7481e-011	5.5568e-011
7	3	1	3	2	2.5756e-011	4.2356e-011
8	3	2	1	3	2.9625e-011	2.8796e-011
9	3	3	2	1	2.7452e-011	1.5143e-011

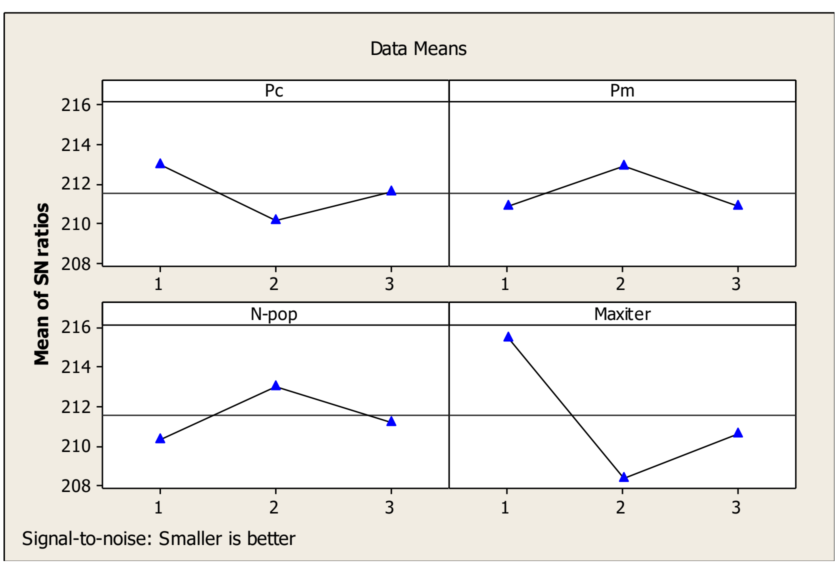

Figure 5. Signal to noise plot of NSGA-II.

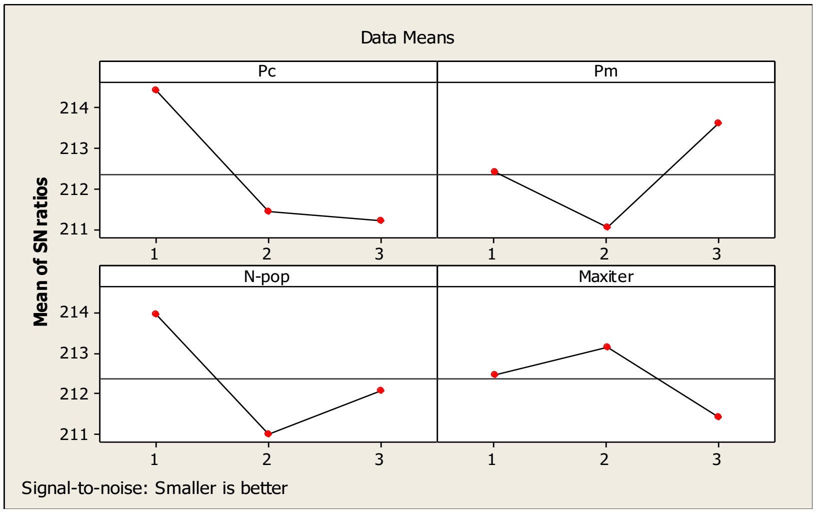

Figure 6. Signal to noise plot of NRGA.

Case study

In this section, to accumulation of the proposed model's parameters, a case study in Iran is applied. In this respect, the proposed model is applied on the case study to demonstrate the correctness and appropriateness of the results. In fact, this research is stimulate regarding to the complex issue of designing a HRC in Mazandaran province in Iran. Accordingly, we provide details of the case study for the design of HRC in one of the northern provinces of Iran, Mazandaran; aiming at better response to a potential disaster.

The province covers a region of 23,842 km². In addition, Mazandaran is one of the most thickly populated provinces in Iran and has various natural resources, especially large reservoirs of oil and natural gas. The population of the province was 2,922,432 regarding to the census of 2006, in which 46.82% villagers, 53.18% were urban dwellers, and remaining were non-residents.

Increasing the number of disruption scenarios represented that the leads to computational time could be increase. Meanwhile, the number of scenarios which is considered for the network design problems is 3 disruption scenarios in our case study.

Since, the level of a disaster scenario depends on the occurrence time are separately presented in the Table 3.

The proposed mathematical model is coded in the MATLAB™ 2010 software and regarding to a Pentium dual-core 2.5 GHz computer with 4 GB RAM is solved.

Moreover, other parameters of proposed model such as: the general data of the test problems and other parameters are presented in Tables 4 and 5.

Table 3
Probabilities of different earthquake scenarios

Disaster scenarios	Probability	Number
Scenario 1	0.453	3
Scenario 2	0.345	2
Scenario 3	0.202	1

Table 4
Other model parameters tuning

Parameter	Values
F_i^c	Uniform ~ [10, 16]
G_j	Uniform ~ [3, 6]
E_b	Uniform ~ [9, 14]
IH_q	Uniform ~ [10000, 40000]
UC^{si}_q	Uniform ~ [10000, 35000]
UL^{sj}_q	Uniform ~ [10000, 35000]
λ^i_{qs}	Uniform ~ [0, 1]

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μ_{qs}^{j}	Uniform ~ [0, 1]
ξ_{l}^{s}	Uniform ~ [0, 1]
US_{q}^{s}	Uniform ~ [100000, 185000]
TA_{ijm}^{s}	$Uniform \sim \left[\frac{distance\,(km)}{60(km\,/\,h)}, \frac{distance\,(km)}{600(km\,/\,h)}\right]$
TB_{lim}^{s}	$Uniform \sim \left[\frac{distance\,(km)}{60(km\,/\,h)}, \frac{distance\,(km)}{600(km\,/\,h)}\right]$
ζ_{ijm}^{s}	0 or 1
ω_{lim}^{s}	0 or 1
D_{qk}^{s}	Uniform ~ [50, 300]
V^{c}	Uniform ~ [80, 250]
CA_{j}	Uniform ~ [20, 100]
SA_{h}^{q}	Uniform ~ [10, 150]
CS_{ql}	Uniform ~ [3, 10]
CAP_{ijm}	Uniform ~ [10, 50]
CCP_{lim}	Uniform ~ [4, 10]
CT_{qlim}	$Uniform \sim \left[distance\,(km)\times 10000(R), distance\,(km)\times 100000(R)\right]$
CTR_{qijkm}	$Uniform \sim \left[distance\,(km)\times 10000(R), distance\,(km)\times 100000(R)\right]$
A_{q}	Uniform ~ [0.01, 0.4]
P_{s}	[0.2, 0.5, 0.3]
ϕ_{s}^{g}	Uniform ~ [0, 1]
φ_{s}^{g}	Uniform ~ [0, 1]
ρ_{ql}	0 or 1

Table 5

The general data of the test problems

Test	***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

Computational Results

In this section, the performances of the offered tuned multi-objective algorithms are evaluated and compared using the multi-objective metrics given in Section 4.3. Table 6 contains the computational results of employing the algorithms on the 10 test problems introduced in Section 5.2. Moreover, to validate proposed approaches, ε-constraint method is used in low dimension problems. As is clear, two developed metaheuristics have a near behavior with ε-constraint method that it refers to efficiency of these two algorithms.

In order to compare the obtained metrics, analysis of variance (ANOVA) is used. The results prove that there is a clear statistically significant difference between performances of the algorithms. The intervals plot (at the 95% confidence level) for these algorithms

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for each metric are shown in Figures 7-10. Each interval plot has three points for each algorithm in each metric.

Table 6
The obtained results of algorithms

Ex.	NPS ↑			CPU Time↓			MID↓			SNS↑		
	NSGA-II	NRGA	EC	NSGA-II	NRGA	EC	NSGA-II	NRGA	EC	NSGA-II	NRGA	EC
1	10	9	10	42.48	48.42	480.55	1.47	2.47	1.22	2.8475e011	2.7586e011	2.9712e011
2	12	10	10	105.43	114.24	828.70	1.15	1.19	1.05	3.9973e011	4.0173e011	4.2493e011
3	11	8	10	188.81	209.13	1750.6	2.76	2.12	1.86	6.8714e011	4.9314e011	6.5741e011
4	9	12	-	302.75	342.87	-	3.75	3.11	-	7.4586e011	6.2486e011	-
5	10	7	-	843.28	924.24	-	3.46	3.61	-	9.2345e011	8.7521e011	-
6	11	14	-	1092.76	2096.75	-	3.75	2.81	-	1.1247e012	9.7547e011	-
7	8	9	-	2257.45	2379.99	-	5.01	5.02	-	1.2632e012	1.0086e012	-
8	10	13	-	3978.62	4271.47	-	4.42	5.14	-	1.3478e012	1.1456e012	-
9	12	15	-	4675.63	4215.52	-	4.15	3.97	-	1.4125e012	1.4896e012	-
10	14	15	-	5104.43	4902.48	-	3.45	3.74	-	1.7236e012	1.8452e012	-
Sum	107	112	-	18591.63	19505.12	-	33.39	33.23	-	9.913E+12	9.135E+12	-

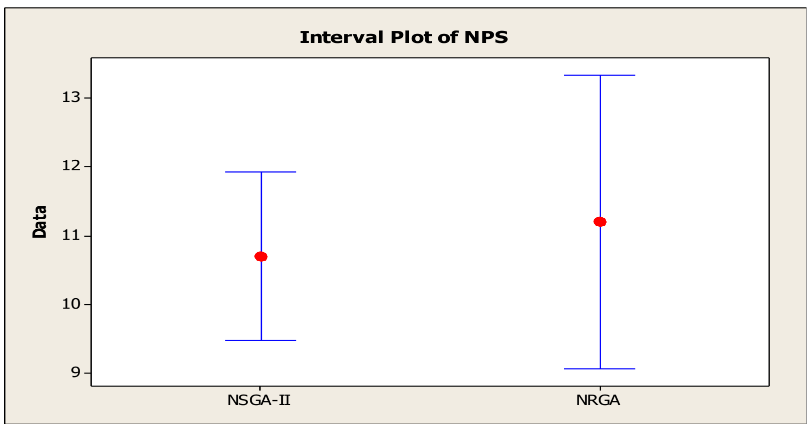

Figure 7. The intervals plot of NPS (at the 95% confidence level)

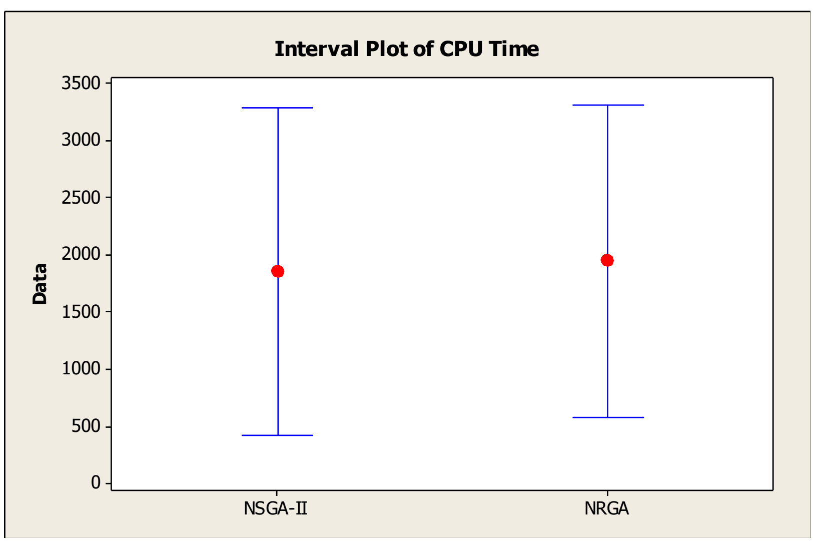

Figure 8. The intervals plot of CPU Time (at the 95% confidence level)

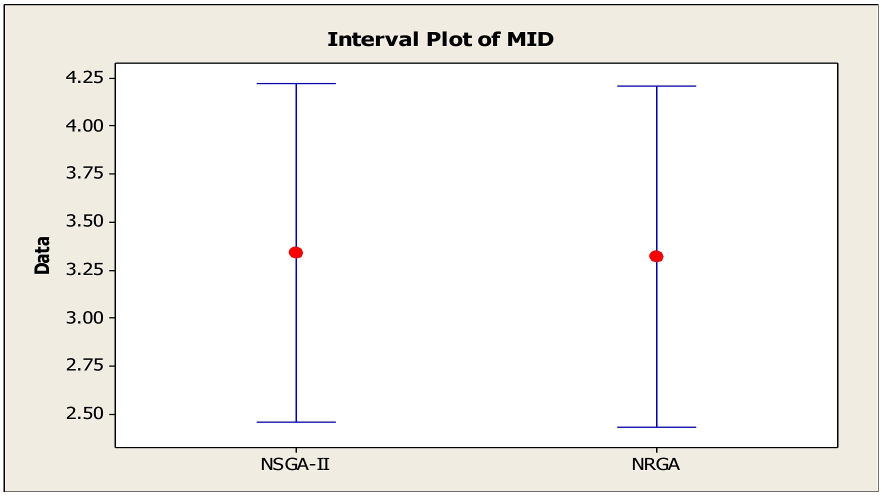

Figure 9. The intervals plot of MID (at the 95% confidence level)

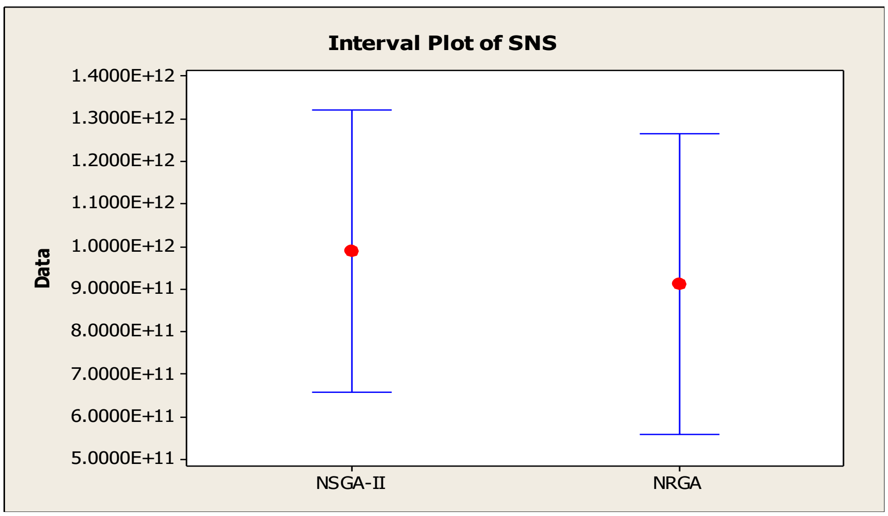

Figure 10. The intervals plot of SNS (at the 95% confidence level)

We note that while in terms of the SNS and NPS metrics, bigger values are desired, for spacing, MID and CPU time, smaller values are better. Then, in general, based on the outputs in the last row of Table 6, it is clear that NSGA-II shows better performances in terms of SNS and CPU time. Meanwhile, for other two metrics, NPS and MID, MRGA has better performances. Besides, to clarify better performance of the proposed Pareto-based algorithms, the obtained Pareto solutions of all algorithms on four test problem 1, 5, 9, and 10 are presented in Figures 11-14.

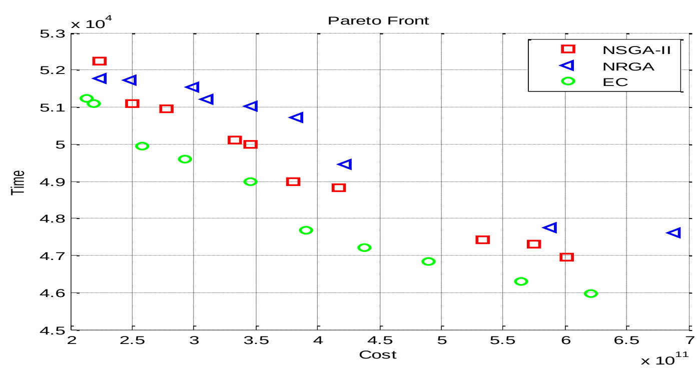

Figure 11. Pareto front of test problem (1)

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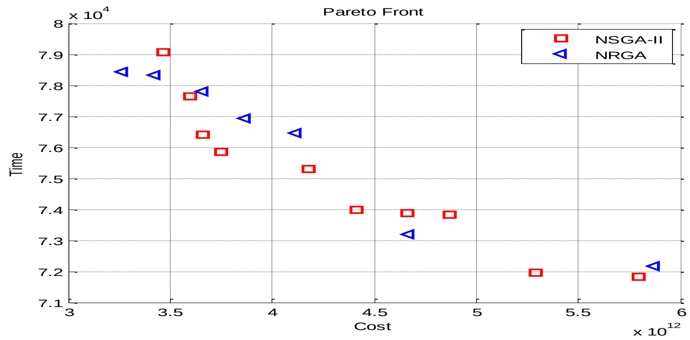

Figure 12. Pareto front of test problem (5)

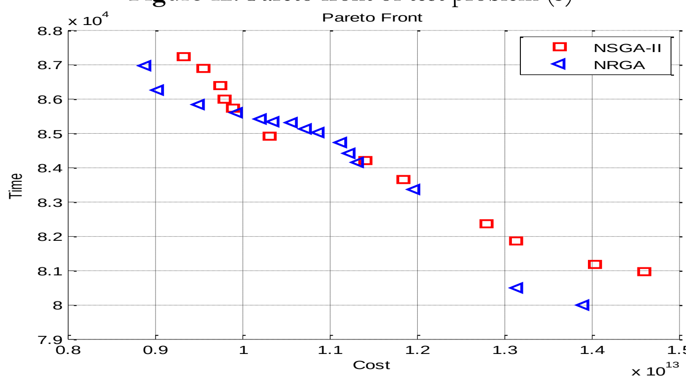

Figure 13. Pareto front of test problem (9)

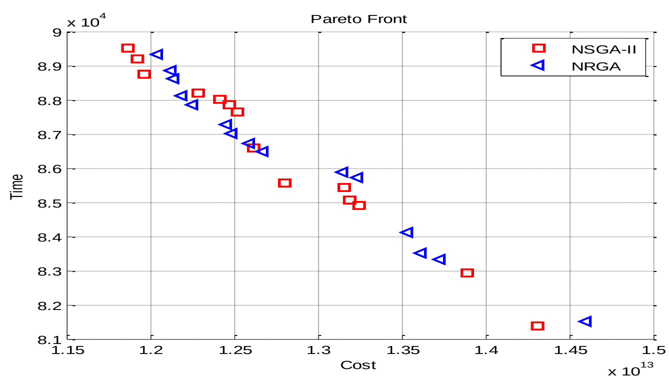

Figure 14. Pareto front of test problem (10)

Conclusion

In this paper a bi-objective mixed integer linear programming to specify the location of CWs and LDCs, simultaneously and the corresponding inventory quantities for relief items, and the distribution quantities from supplier to CWs, from CWs to the affected areas (LDC) and from strategic stock to LDC. The presented model seeks to minimize the cost variability, expected total cost. In the second stage, a relief distribution plan is extended based on different disaster scenarios by goals of minimizing the total distribution time, the maximum weighted distribution time of critical items, total cost of unused inventories, and the shortage cost of unmet demands. The model considers uncertainty in the locations where the demands might increase like as the possibility that some of the pre-arranged supplies at CWs or suppliers might be destroyed partially regarding to the disaster (i.e., supply uncertainty). To demonstrate the imprecise parameters, we make utilize of discrete scenarios from set S of potential disaster conditions. Then, in view of the NP-Hardness of proposed model, two tuned Pareto-based multi-objective meta-heuristic algorithms, called NSGA-II and NRGA were proposed to solve the problem.

Moreover, to achieve better performance these algorithms are tuned by Taguchi method. The proposed algorithms were compared using 10 test problems via four multi-objective metrics. Also, to

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validate proposed framework, ε-constraint method is used in low dimension problems. Moreover, the performance of two algorithms for each metric via statistically method called the intervals plot are analyzed. As is shown in Figure 11 and Table 6, two developed metaheuristics have a close behavior with ε-constraint method that it refers to efficiency of these two algorithms. Finally, based on the results it was shown that: NSGA-II shows better performances in terms of SNS and CPU time, meanwhile, for NPS and MID, MRGA has better performances. Finally, managers by using this comprehensive framework and solution approaches can achieve the best performance includes minimum total costs and minimum of maximum travel time, and based on their organization directions can choose best solution among pareto fronts. As a limitation it should be noted that the proposed framework and data are related to the selected case study and we cannot be sure that these outcomes will be efficient for other areas.

As future research, the model can be extended to have multiple fuzzy-objective. In addition, different methods for solving the proposed model can be developed. Applying the proposed model in similar fields can be one of the research areas for the future studies. The proposed solution approaches can also be used for the aforementioned cases.

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