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A new stochastic location-allocation emergency medical services healthcare system model during major disaster

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Abstract

One of the most important subjects in designing the large scale logistics network in crisis time is providing a timely quick reaction for treating injured people and rapid distribution of medicines and medical equipment. In this paper, a multi-objective model is presented that aims to determine the location of transfer points and hospitals to provide timely quick reaction for treating injured people as well as to determine unreliable and reliable depots for the distribution of medicines and medical equipment. Because the dynamic nature of great crises, the parameters of the model are uncertain and dynamic. To solve the model, a hybrid meta-heuristic algorithm is proposed which is composed of simulated annealing algorithm and CPLEX. By comparing the results, the proposed meta-heuristic hybrid algorithm shows a good and efficient performance.

Keywords: Location-allocation, emergency medical services logistics, hybrid meta-heuristic algorithm, major crises

1- Introduction

Large scale emergencies event such as man-made or natural inflict tremendous damages on human, for instance in 2015, 341 natural disasters happened which have left 213 million victims and 8421 deaths and billions of loss in assets (Guha-Sapir et al., 2015). In the same year, 152 man-made disasters are happened which killed more than 10000 people (Swiss, R., 2015). In the light of such events and their impacts on human life, it is necessary that decision makers of disaster management prevent casualties and destructions using scientific methods. Relief logistics is an essential part of operation research which is recently being used as techniques and analytical tools to provide efficient relief to affected people who need help in affected areas with optimized functions and constraints. It is essential to consider the disaster characteristics for planning in time of disaster. One of the main characteristics of disasters is a large number of injured people who must be treated immediately. Therefore, for treating injured people a quick reaction has an important role in a disaster plan (Hashzemi et al., 2014). Regarding to aforementioned needs, relief logistics can help us for a good planning. One of the methods that can help us in relief

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logistics is the transfer point location problem (TPLP) (Berman et al., 2005). In this problem, some transfer points are considered to improve casualties transfer time to hospitals. These points have to be located in a manner that ambulances pass the predefined routes through transfer points or directly.

With regards to the fact that most fatalities occur in early hours of disasters, one of the most significant methods is accelerating the casualty transfer to hospitals, recognized as transfer point location. With respect to the fact that many injured people need medicine, drug and other medical equipments and usually these volumes of equipment do not exist at affected areas; another important characteristic in time of disaster is rapid distribution of drug and medicine to affected areas (Dessouky et al., 2006). For overcoming this problem, some medicine depots in or out of affected area must be considered. These depots distribute large amounts of medicine, drug and medical equipment during the disaster. For approaching to the real world, these depots are classified into two categories: 1) reliable depot.

2) unreliable depot.

The main contributions of this paper are as follows:

- Presenting a model which contemplates the different sources of uncertainty.
- Proposing a new bi-objective dynamic stochastic model to tackle the disaster relief problem.
- Considering disruption in facility under disaster condition.
- Considering good medicine distribution to certain affected areas in the relief distribution process.
- Designing a hybrid metaheuristic algorithm for the proposed model.

The rest of the paper is organized as follows: Section 2 shows a brief literature review on the topic. Section 3 describes the investigated problem and mathematical modeling. The solution method, numerical example and conclusion are stated in 3, 4 and 5 sections, respectively.

2- Literature review

Transfer point location problem is a new concept that is proposed in relief logistics area by Berman et al. (2005), investigated the location of a facility and several transfer points to serve as collector points for customers who need the services of this facility. They considered demand for emergency services, generated at a set of points that need the services of a central facility. In the next work, they (Berman et al., 2007a) introduced the transfer point location problem. In this problem, they assumed that the location of the facility is known and so, they sought the best location for one transfer point that can serve a set of demand points. Berman et al. (2007b) suggested a multiple location of transfer points while locating was allowed from several transfer points as an extension of transfer point location. Mahmudian et al., (2008) presented two heuristic algorithms for TPLP problem. The first algorithm clustered affected areas and the next one located transfer points places. Furuta et al., (2013) utilized mini-sum and mini-max methods in their model. Casualties had to be carried by ambulances or helicopters which met each other in a place called Rendezvous Points. They selected japan for case study and acquired good results. Hosseinijou and Bashiri (2011) considered the case in which demand points were weighted and their coordinates had bivariate uniform distribution. Hence, they used a different conceptual view and different distance measures to make their models more applicable to real world situations. Kalantary et al., (2013) developed a new TPLP with weighted demand points and fuzzy coordinates. They developed their model as a fuzzy unconstrained nonlinear one where decision variables are fuzzy numbers. Mohamadi et al., (2015a) presented a model for mini-sum TPLP, which was different from former works. They had a comprehensive attitude to the problem and with combination of VRP and TPLP attempted for creating a new view in this topic. Their model was bi-objective and uncertain. Ebrahimi Zade and Lotfi (2015) proposed a facility and transfer point model considering uncertainty in parameters. This model is based on a given service time which targeted by a decision maker. They considered a soft capacity constraint for the facilities and a second objective to minimize the overtime in the facility with highest assigned demand proposed (Ebrahimi Zade et al., 2015). Mohmadi et al., (2015b) presented a model for blood products to respond the need for blood products in disaster situations. Their model was a bi-objective mixed integer one and with respect to unstable conditions during the disaster, uncertain parameters are modeled by fuzzy numbers (Kohneh et al., 2016). Also, there exist other works in this topic such as Sasaki et al., (2008), Jabal Ameli et al., (2012), Araste et al., (2012).

Considering transfer point, hospitals and medicine depots at the same time are an important contribution in this paper using this idea with regard to aforementioned characteristics arising during disaster. Also, we consider reliable depots and unreliable depots that can be disrupted in disaster. For approaching to the real world, we consider the probability of shortage occurrence in the model. With regard the literature, we focused on limitation of facility numbers and capacity of using facility. Also, another point that has not been attentive by researchers in the literature is lack of an efficiency optimization algorithm for large scale problems. Therefore, we proposed a hybrid metaheuristic algorithm for the proposed model. Uncertainty in various parameters is considered for more flexibility of the model. Also, disruption in the route is considered.

3- Problem description

The relief logistic system investigated in this study is based on characteristics arising during disaster which are: 1) Quick reaction for treating injured people. 2) Rapid distribution of drug and medicine to affected areas. Hospitals, transfer points and medicine depots must be located in optimal potential locations. Demand for emergency service is generated at a set of affected points which need the services of hospitals. Injured people are transferred to a transfer point at normal speed, and from there to the hospital at increased speed. With gathering the demand of hospitals, it is necessary that medicine depots satisfy these demands. With respect to the existing disruption in medicine depots, the demand can be satisfied from reliable or unreliable medicine depots. In the other hand, the shortage in satisfying the demand has considered. Whole the decisions on this network are based on the disruption on the routes between facilities. Also, due to the difference in nature disasters, we considered two objectives including 1) minimization of the weighted distances between facilities considering disruption in routes, and 2) minimization of shortage cost. The model has formulated as a two stage stochastic approach that in its first stage, the strategic decisions are made (the model aims to select optimum location of facilities) and in its second stage, the tactical decisions must be made (transportation routes between facility locations and demand points are explored). Therefore, in this paper, a stochastic multi-objective model is proposed which considers vital needs in the time of disaster.

3-1 Assumptions

- The developed model is a p-median LTPT and multi-period.
- Uncertainty on the model is assumed to be a two stage stochastic.
- In this problem, several points are candidate for establishing hospitals and transfer points; also, several points are candidate for establishing reliable and unreliable depots.
- Shortage is allowed.
- Each affected area can be served by to several hospitals or transfer points.
- Each transfer point has a limit capacity.
- Each hospital has limited capacity.
- Each reliable and unreliable facility has limited capacity.
- Each facility has limited capacity.
- Uncertainty on parameters id considered in the model.

3-2 Sets and parameters and decision variables

Sets, parameters and decision variables are as follows.

Sets

I : Set of demand points indexed by i

J : Set of transfer points indexed by j
K : Set of hospitals indexed by k
H : Set of unreliable depots indexed by h
R : Set of reliable depots indexed by r
T : Set of periods indexed by t
S : Set of scenarios indexed by s

Parameters

d_i : Number of injured people at each demand points
K : Number of hospitals which must be established
t_{ij} : Transportation time between demand point i and transfer point j
t_{jk} : Transportation time between transfer point j and hospital k
t_{ik} : Transportation time between demand point i and hospital k
t_{kh} : Transportation time between hospital k and unreliable depot h
t_{kr} : Transportation time between hospital k and reliable depot r
π_{ij}^{s} : The probability that the route is reliable between demand point i and transfer point j
π_{jk}^{s} : The probability that the route is unreliable between transfer point j and hospital k under scenario s
π_{ik}^{s} : The probability that the route is reliable between demand point i and hospital k under scenario s
Cap_j : Capacity of transfer point j
Cap_k : Capacity of hospital k
Cap_h : Capacity of unreliable medicine depot h
Cap_r : Capacity of reliable medicine depot h
η_h^s : Capacity of unreliable medicine depot h under scenario s
L : Number of transfer points which should be established
M : Number of hospitals which should be established
N : Number of unreliable medicine depots which should be established
O : Number of reliable medicine depots which should be established
μ_i : Shortage cost at demand point i
λ_k : Shortage cost at hospital k
p_s : The probability of occurrence of the scenario s

Decision variables

Z_j : A binary variable equal 1 if new transfer point established in location j; 0, otherwise
W_k : A binary variable equal 1 if new hospital established in location k; 0, otherwise

E_h : A binary variable equal 1 if new unreliable medicine depot established in location h; 0, otherwise

Q_r : A binary variable equal 1 if new reliable medicine depot established in location r; 0, otherwise

ϕ_{ij}^{st} : Flow between demand point I and transfer point j in period t

ψ_{jk} : Flow between transfer point j and hospital k in period t

δ_{ik}^{st} : Flow between demand point I and hospital k in period t

x_{kh}^{st} : Flow between hospital k and unreliable medicine depot h in period t

G_{kr}^{st} : Flow between hospital k and reliable medicine depot h in period t

f_i^{st} : Flow at demand point I which do not meet in period t

q_k^{st} : Flow at hospital k which do not meet in period t

3-3- Mathematical modeling

With regard to notations mentioned in the previous section, mathematical model for designing the network logistics is as follows.

$$\text{Min} \sum_s p_s \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} t_{ij}(1-\pi_{ij}^s)\phi_{ij}^{st} + \sum_{j\in J}\sum_{k\in K}\sum_{t\in T} t_{jk}(1-\pi_{jk}^s)\psi_{jk}^{st} + \sum_{i\in I}\sum_{k\in K}\sum_{t\in T} t_{ik}(1-\pi_{ik}^s)\delta_{ik}^{st} \tag{1}$$

$$+\sum_{k\in K}\sum_{h\in H}\sum_{s\in S}\sum_{t\in T} X_{kh}^{st}(1-\pi_{kh}^s)t_{kh}\left(\eta_h^s\right) + \sum_{k\in K}\sum_{r\in R}\sum_{s\in S}\sum_{t\in T} G_{kr}^{st}(1-\pi_{kr}^s)t_{kr}$$

$$\text{Min} \sum_s p_s \sum_{t\in T}\sum_{i\in I} \mu_i f_i^{st} + \sum_{t\in T}\sum_{k\in K} \lambda_k q_k^{st} \tag{2}$$

$$\sum_{i\in I}\phi_{ij}^{st} = \sum_{k\in K}\psi_{jk}^{st} \quad \forall\, j\in J,\, s\in S,\, t\in T \tag{3}$$

$$\sum_{j\in J}\phi_{ij}^{st} + \sum_{k\in K}\delta_{ik}^{st} + f_i^{st} = d_i^{st} \quad \forall\, i\in I,\; s\in S,\; t\in T \tag{4}$$

$$\sum_{i\in I}\phi_{ij}^{st} \le Cap_j Z_j \quad \forall\; j\in J, s\in S, t\in T \tag{5}$$

$$\sum_{j\in J}\psi_{jk}^{st} + \sum_{i\in I}\delta_{ik}^{st} \le Cap_k W_k \quad \forall\; k\in K,\; s\in S,\; t\in T \tag{6}$$

$$\sum_{k\in K}\psi_{jk}^{st} \le MZ_j \quad \forall\; j\in J, s\in S, t\in T \tag{7}$$

$$\beta\sum_{j\in J}\psi_{jk}^{st} + \sum_{i\in I}\delta_{ik}^{st} = \varphi_k^{st} \forall k\in K, s\in S, t\in T \tag{8}$$

$$\sum_{k\in K}\sum_{t\in T} X_{kh}^{st} \le Cap_h E_h \quad \forall\; h\in H,\; s\in S \tag{9}$$

$$\sum_{k\in K}\sum_{t\in T} G_{kr}^{st} \le Cap_r Q_r \quad \forall\; r\in R, s\in S \tag{10}$$

$$\sum_{h\in H} E_h = N \tag{11}$$

$$\sum_{r\in R} Q_r = O \tag{12}$$

$$\sum_{h\in H} X_{kh}^{st} + q_{k}^{st} = \varphi_{k}^{st} \quad \forall\ k\in K, s\in S, t\in T \tag{13}$$

$$\sum_{j\in J} Z_{j} = L \tag{14}$$

$$\sum_{k\in K} W_{k} = M \tag{15}$$

$$\sum_{r\in R} G_{kr}^{st} = \sum_{h\in H} X_{kh}^{st}(1-\eta_{h}^{s}) \quad \forall k\in K, s\in S, t\in T \tag{16}$$

$$\phi_{ij}^{st}, \psi_{jk}^{st}, \delta_{ik}^{st}, \varphi_{k}^{st}, f_{i}^{st}, q_{k}^{st} \geq 0, \tag{17}$$

$$\forall k\in K, i\in I, j\in J, s\in S, t\in T$$

$$W_{k}, Z_{j}, E_{h}, Q_{r} \in \{0,1\} \quad \forall\ k, j, h, r \tag{18}$$

Objective function **Error! Reference source not found.** shows the minimization of the total demand-weighted time transportation between facilities considering disruption on routes. This term includes travel time between demand point to transfer point or hospital, travel time between hospitals to medicine depots. Objective function (2) shows the cost of lost demand in demand points and hospitals. Equation (3) is the flow conservation constraint at transfer point j. Equation (4) shows the requirement that all demand must be satisfied considering shortage allowance. Equations (5) and (6) are capacity constraints of transfer points and hospitals. Equation (7) ensures that no injured people travel to other transfer points and facilities. Equation (8) is the flow conservation constraint at hospital k. Equations (9) and (10) are capacity constraints of unreliable and reliable medicine depots. Equations (11) and (12) exhibit the number of established unreliable and reliable medicine depots. Equation (13) requires all hospital demand to satisfy considering allowed shortage. Equations (14) and (15) exhibit the number of established transfer points and hospitals. Equations (16) show how much flow should be met from reliable medicine depot. Equations (17) and (18) enforce the binary and non-negativity restrictions on the corresponding decision variables.

4- Solution method

In this section a multi objective approach in addition with a hybrid meta-heuristic algorithm is presented for solving the model.

4-1- Compromise programming method

The presented bi-objective model can be changed into a single-objective one using compromise programming method. With respect to the nature of the problem, in this paper, the method of compromise programming is used for changing of bi-objective problem to single- objective one. Minimization of the distance between the ideal solution and the expected solution is the important idea of current method. For this purpose, first the nadir and ideal value are calculated for every objective function (Cochrane and Zeleny, 1973). The best value is obtained through optimizing model along each of the objective functions regardless another function and nadir value is obtained through optimizing in the opposite direction of any objective function. The following equations show how to implement the calculations.

Suppose that equation (19) is a linear programming with several objective functions as follows.

$$Min\left[Z_1,...,Z_3\right] \tag{19}$$

$$g_i(x) \geq 0$$

Using the compromise programming method we will have:

$$Min\ Z_T^* = \left[\sum_i \lambda_i \left(\frac{Z_i - Z_i^*}{Z_m - Z_i^*} \right)^r \right]^{\frac{1}{r}} \tag{20}$$

$$g_i(x) \geq 0$$

4-2- A hybrid metaheuristic algorithm

In this section, a hybrid metaheuristic algorithm by combining Simulated Annealing (SA) and Cplex approache is developed to solve the proposed model. Simulated annealing is a technique which has been applied to problems that are both difficult and important. The simulated annealing begins its search from a random initial solution. The iteration loop that characterizes the main procedure randomly generates in each iteration only one neighbor s' of the current solution s. The variation ∆ for the value of the objective function $f(x)$ is tested for each neighbor generation (Hwang, 1988) and (Barzinpour et al., 2014). To test this variation, $\Delta = f(s) - f(s)$ is obtained. If the value of ∆ is less than zero, then the new solution s' will be automatically accepted to replace s. Otherwise, accepting the new solution s' will depend on the probability established by the Metropolis criteria, which is given by $e\Delta/T$, where T is a temperature parameter, a key variable for the method. Therefore we have:

$$P(Acceptance) = e^{-\frac{\Delta f}{T}} \tag{21}$$

Figure 1 shows the simulated annealing pseudo code.

```
Input: Cooling schedule.
s = s0 ; /* Generation of the initial solution */
T = Tmax ; /* Starting temperature */
Repeat
   Repeat /* At a fixed temperature */
     Generate a random neighbor s' ;
     ΔE = f(s') − f(s) ;
     If ΔE ≤ 0 Then s = s' /* Accept the neighbor solution */
     Else Accept s' with a probability e^(−ΔE/T) ;
   Until Equilibrium condition
   /* e.g. a given number of iterations executed at each temperature T */
   T = g(T) ; /* Temperature update */
 Until Stopping criteria satisfied /* e.g. T < Tmin */
Output: Best solution found.
```

Figure 1. Simulated annealing pseudo code

Now, for decreasing solution time as well as increasing the accuracy and improvement of the solution, we applied a mechanism based on exact method in generation of the initial solutions and production of neighborhood solution. This approaches applied as follows.

4-2-1- Solution Representation

To show the binary variables, we use 8 matrices; the first matrix is related to transfer point location. Its dimension is $1\times|I|$ in which columns are potential locations for establishing the transfer point. This matrix's elements are zero and one in a way that zero and one correspond to inactiveness and activeness of the transfer point location.

$$Z_j = \begin{bmatrix} Z_1 & Z_2 & .... & Z_j \end{bmatrix}$$

For example, the solution representation for this matric can be written as Figure 2 if four candidate locations' exist for establishing the transfer points.

Transfer point			
0	0	0	1

Figure 2. Solution representation for initial solution

As shown Figure 2, transfer point is not located at location 1, 2 and 3 and only located at location 4. Also, the matrices related to hospitals and depots location are as follows.

$$W_k = [W_1 \quad W_2 \quad .... \quad W_k]$$

$$E_h = [E_1 \quad E_2 \quad .... \quad E_h]$$

$$Q_r = [Q_1 \quad Q_2 \quad .... \quad Q_r]$$

Similarly, the allocation of variables can also be represented by the matrices. For example, the next matrix is related to δ_{ik}^{st} variable and to represent this, we use 4 dimension matrix in a way that the first index is the number of demand points and the second index is for hospitals and the third and fourth indexes are related to the scenarios and the periods, respectively.

4-2-2- Generating Initial Population

After determining a technique to assign a chromosome to each solution, one can create an initial population. In this process, as shown in Figure 3, we generate a random number in the range (0, 1) then this number is multiplied by the number of elements. In Figure 3 and matrix before mutation, we know four transfer points, three hospitals and two reliable depots and two unreliable depots. It is assumed that the random number is 0.65, therefore, this number is multiplied by 11 and 6.05. So 7 is achieved by round off of 6.05. Then, the 7^{th} column which is related to hospital is changed from 0 to 1. With respect to the limitation of numbers in establishing each facility, two columns related to hospital should be changed from 1 to 0 randomly. According to this approach, we generate a feasible neighborhood solution.

Transfer points				hospitals			depots		Reliable depots	
0	1	0	1	1	1	0	1	0	0	1

Before mutation

Transfer points				hospitals			depots		Reliable depots	
0	1	0	1	0	1	1	1	0	0	1

After mutation

Figure 3. Mutation operator

4-3- Tuned values of the Hybrid-SA algorithm parameters

The proposed hybrid algorithm includes parameters that affect the proper functioning and final results and algorithm efficiency. With regard to merits of the Taguchi method, it is used for the configuration of parameters.

4-3-1- Taguchi method

Before calibration of the proposed algorithm, some preliminary tests are used to obtain appropriate parameter levels. The four following configuration parameters are considered in the presented algorithm for achieving more accurate results: A (initial temperature), B (cooling rate), C (number of repetitions in each temperature), and D (final temperature). The parameters and their levels are shown in Tables 1 and 2. Also, for using Taguchi method, we used the square matrix with 4 parameters in 3 levels which are L9. In this method, we have two output results which are 1) the variation of the output results measured by means of signal-to-noise (S/N) ratio where the value of S/N ratio is computed as the following.

$$S/N \; ratio = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \tag{22}$$

And mean of means.

It is noted that the larger value of S/N ratio leads to the smaller variation of the response variable. The S/N ratio and mean of means have calculated and has shown as Figures 4 and 5. Also, the characteristics of sample problems that have been used for Taguchi method has obtained as Table 3.

Table 1. Proposed Hybrid-SA algorithm parameters and their levels

Problem size	Levels	Initial temperature (A)	Cooling rate (B)	Number of repetitions in each temperature (C)	Final temperature (D)
Large scale	1	2000	0.95	40	0.00001
	2	3000	0.96	50	0.0001
	3	4000	0.97	60	0.005

Table 2. Orthogonal array *L*9

Experiments	Factor A	Factor B	Factor C	Factor D	Experiments	Factor A	Factor B	Factor C	Factor D
1	A(1)	B(1)	C(1)	D(1)	6	A(2)	B(3)	C(1)	D(2)
2	A(1)	B(2)	C(2)	D(2)	7	A(3)	B(1)	C(3)	D(2)
3	A(1)	B(3)	C(3)	D(3)	8	A(3)	B(2)	C(1)	D(3)
4	A(2)	B(1)	C(3)	D(3)	9	A(2)	B(3)	C(2)	D(1)
5	A(2)	B(2)	C(3)	D(1)					

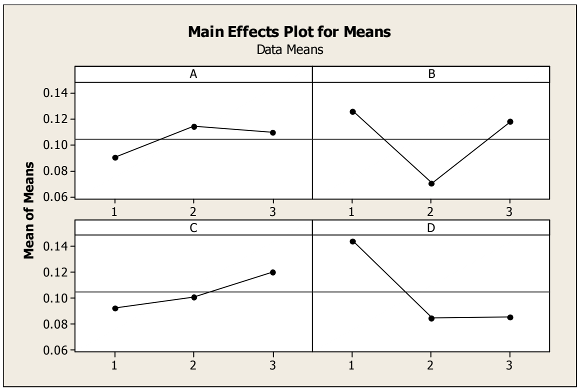

Figure 4. Diagram of mean effect of means for large problem in hybrid-SA algorithm

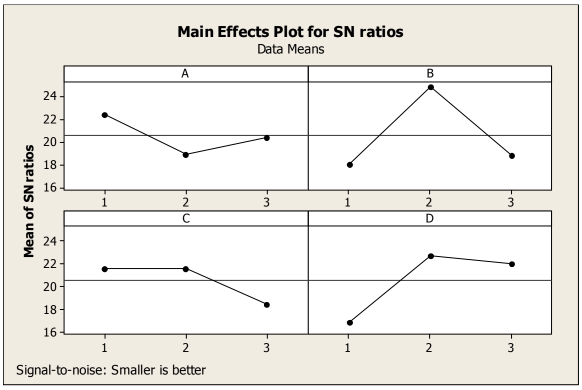

Figure 5. Diagram of mean effect of the S/N ratio for large problem in hybrid-SA algorithm

Table 3. Characteristics of sample problems that have been used for Taguchi method

Algorithm	Factor A	Factor B	Factor C	Factor D
Hybrid-SA	2000	0.96	40	0.0001

4-4- Stopping criterion

We consider a maximum number of iterations for stopping the algorithm. In addition, another stopping criterion is considered as the maximum number of iterations with no improvement for the increasing the efficiency and decreasing waste time.

5- Numerical Results

In this section, 12 numerical examples in accordance with the proposed model are presented to validate the model and algorithm. Computational results and analysis of the developed model are presented. All of numerical examples include 50 demand points, 15 hospitals, 15 transfer points, 25 unreliable medicine depots and 5 reliable medicine depots. At the same time, the number of periods and scenarios are changed. For sensitivity analysis, the number of depots that should be established is changed between 8 and 12 and the number of periods is changed among 6, 9 and 12, also, the number of scenarios is changed between 6 and 12. To examine efficiency of this algorithm and model, the value objective function is compared between Hybrid-SA and CPLEX. The results are shown in Table (4) and Table (5)
The parameters of the numerical example are considered as follows:
The distance between each demand point from the others is assumed to have uniform distribution (1000, 1500). The speed of vehicles between the transfer points and hospitals has uniform distribution between (50, 60). The speed of vehicles to go to the hospital has uniform distribution between (20, 30).

Table 4. The result for first case

Scenarios	Depots	Periods	Objective function			The diversion between HAS and Cplex	Time (second)	
			Cplex	Hybrid-SA	Best solution		Cplex	HSA
6	8	6	210839852	212354148	212336814	0.71	274.463	223.280
				212342147				
				212364123				
				212347820				
				212336814				
6	8	9	226910100	229784235	229769167	1.26	840.760	317.624
				229770413				
				229767167				
				229769412				
				229776472				
6	8	12	25314923	257347845	257343062	1.47	2450.610	547.327
				257350471				
				257349872				
				257352423				
				257343062				
6	14	6	169526619	171935672	171933897	1.42	6845.123	913.266
				171937412				
				171938452				
				171933897				
				171942537				
6	15	9	179277978	182214727	18200209	1.63	17923.292	1505.795
				182200209				
				182224203				
				182251237				
				182209754				
6	14	12	19999291.7	207552650	207552650	3.78	52468.601	2360.735
				207567412				
				207570145				
				207561423				
				207564123				

The times are calculated by dividing the distance and speed. The time between hospitals and unreliable depots has uniform distribution between (10, 30). The time between hospitals and reliable depots has uniform distribution between (40 and 50). The number of injured people is conserved between (1000 and 4000) uniformly.

To compare the results between the Hybrid-SA and CPLEX, the proposed algorithm is performed in 5 times and the best answer among them is compared with the exact solution. As shown table 5, the value of objective functions in the case of 6 scenarios, 8 depots and 6 periods have been increased compared with case of 6 scenarios, 8 depots and 9 periods. It is why the dimension and volume of the parameters such as the number of injured people and disruptions have been increased. Increasing the number of scenarios leads to increasing the size of the problem and thus increasing the value of the objective function. If the number of depots increases, with regard to the fact that the solution space is wider, this can cause a variety of allocation and, therefore, the answer will not be worse even better.

Table 5. The result for second case

Scenarios	Depots	Periods	Objective function			The diversion between HSA and Cplex	Time (second)	
			Cplex	Hybrid-SA	Best solution		Cplex	HSA
12	8	6	272159633.4	279872485 279861751 279869741 279868752 279864752	279861751	2.83	113404.487	2723.573
12	8	9	*	284965472 284969412 284967412 284962741 284956318	284956318	*	*	3274.689
12	8	12	*	304754713 304757412 304749875 304749872 305758015	304748015	*	*	3582.983
12	14	6	*	255087412 255081472 255073193 255083472 255074123	255073193	*	*	4386.439
12	14	9	*	267145741 267149975 267142179 267144120 267151403	267142179	*	*	5205.695
12	14	12	*	279864721 279867412 278972310 279861751 279882163	279861751	*	*	6439.943

If the number of facilities increase, it can be realized that the value of objective function intend to a fixed measure. As can be seen in the tables (4) and (5), improvement occurs in solutions obtained by the exact algorithm in comparison with Hybrid-SA. But the solution time in Hybrid-SA is better than exact approach in all these cases.

By examining the time in the exact algorithm, the results show that the solution time increases exponentially with increasing size. With regard to the very high solution time, the exact approach has been stopped in gap 31, 73% in case of 12 scenarios, 8 unreliable depots and 9 periods in time of 49 hours. But, based on the results in Table (4) and (5), the Hybrid-SA is reached to near optimal solution in less time than the exact approach.

Also due to the consideration of the shortage costs, the model in the normal state is not willing to allow shortage, this causes an increasing in total cost, but when demand increases suddenly, hospitals and medicine depots in case of cost-effectiveness will allow shortage. It is noted that the proposed hybrid algorithm is widely used generally for problems with large size and in the case of small-scale loses its effectiveness.

It can be realized from Tables (4) and (5) that both the methods are much more sensitive to the number of scenarios than the number of depots and periods. We can illustrate the iteration process in figure 6. The value of the objective function is obtained and drawn versus iterations.

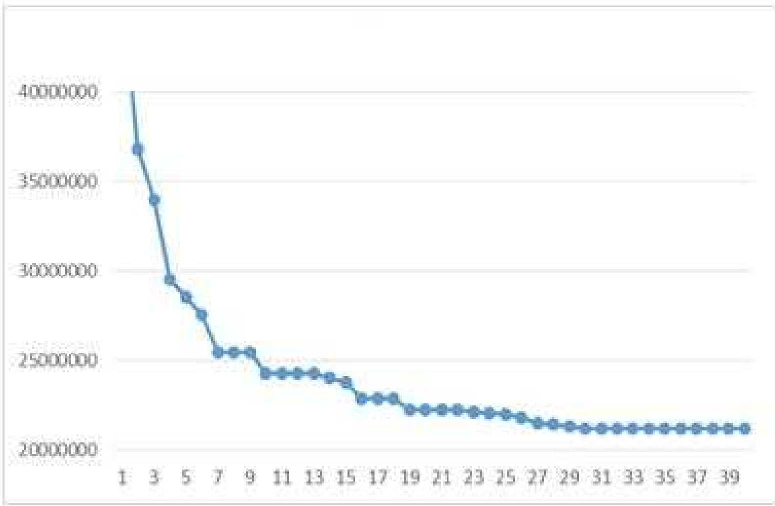

Figure 6. Convergence diagram

6- Conclusion

In this paper, a relief logistics network is considered including transfer points, hospitals and medicine depots. Also, disruption in routes and facilities was applied. The proposed model was multi-period, bi-objective and uncertain. Due to the difference in nature of disasters, we considered two objectives including 1) minimization of the weighted distances between facilities considering disruption in routes and 2) minimization of shortage cost. The decisions were consisted of locating the facility and allocations among them. Also, another point that has not been attentive by researchers in the literature is lack of an efficiency optimization algorithm for the large scale problems. Therefore, we propose a hybrid-SA algorithm for the proposed model. And to examine the efficiency of this algorithm and the model, the value of the objective function is compared between Hybrid-SA and CPLEX. The results show that Hybrid-SA obtains a near optimal solution in shorter time than the exact method. Also due to the shortage costs, the model in the normal state is not willing to allow shortage. This cause increase the total cost, but when demand increases suddenly, hospitals and medicine depots in the case of cost-effectiveness will allow shortage. In this paper, we try to approach real world conditions, for example the large scale emergencies such as man-made and natural disasters. When these disasters happens, we are faced a large number of injured people who need quick help. Therefore, this model can help the DM for reduction the consequences of such events. Future research could investigate the application of the model and solution method presented in this paper to manage actual relief supply chain challenges. Also, robust optimization can enhance the proposed model.

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