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Assignment of Medical Staff to Operating Rooms in Disaster Preparedness: A Novel Stochastic Approach

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Abstract

Following a large-scale disaster in a highly populated city, one can expect a large number of injured people to need urgent operation. If it can be assumed that the city in question is likely to experience a disaster (although the time of its occurrence is unknown), pre-disaster measures should be taken to mitigate the consequences of the disaster. This study aims to minimize the fatality rate through the proper assignment of operating room personnel to hospitals, such that both the expected value of the functioning operating rooms and the expected value of the service level are maximized. Service level is defined as a variable that has a negative relationship to the distance a patient is expected to travel in order to receive the required medical services. The probability of survival, for both personnel and operating rooms, depends on several stochastic factors. A bi-objective mixed integer nonlinear model is proposed for the problem. A simulated annealing algorithm, particle swarm and a genetic algorithm are developed to solve the model using a weighted metric method. The model is applied to a

possible worst-case earthquake scenario in Tehran. The results show that the proposed approach significantly improves the performance of post-disaster emergency relief.

Keywords: medical staff; assignment; simulated annealing; particle swarm optimization; disaster preparedness

Managerial Relevance Statement

An effective Disaster Management (DM) system is necessary to mitigate the consequences of a large-scale disaster. This study combines DM and Human Resource Management (HRM), as one of the most important branches of Management Science, to realize the most important objectives of DM.

The aim is to maximize the expected number of functioning operating rooms and minimize the total travel distance for transferring patients to the functioning hospitals, which translates to the minimization of the response time and the fatality rate. All of the objectives are achieved by a novel stochastic formulation for the problem of assigning the resource-intensive medical staff to operating rooms, with respect to an acceptable distance, in the preparedness phase. An operating room works under two conditions: (a) it is undamaged, and (b) it has key personnel. The uncertainty of these conditions and other parameters of the model is addressed by the utilization of probabilistic variables and stochastic models. City clustering makes the computational time affordable.

The method of weighted metrics provides the decision maker with non-dominated solutions. The decision maker can direct the search by setting the appropriate weight vector. Different weights result in different non-dominated solutions. The proposed innovative approach to solutions yields significantly better results than other conventional methods.

1. Introduction

Human beings are always jeopardized by different types of disasters. The significance of this hazard is highlighted when the future occurrence of a disaster at a specific location is almost

certain, but the time of this disaster is unknown. DM plays a vital role in decreasing the fatality rate caused by large-scale disasters. Thus, many studies have scrutinized different aspects of DM[1]–[6].

DM aims to determine the best assignment of limited resources to different units, to establish the right conditions in order for the system to run [7]. Disaster management is categorized into three phases [8]: In the preparedness phase, the infrastructures that are needed to cope with the disaster are constructed. In the response phase, shortly after the incident, the emergency response and relief distribution is addressed and during the recovery phase, a long-term plan is developed to address issues such as finding lost victims and repairing infrastructures [9], [10].

Resource allocation is one of the most prominent categories of emergency logistics [11]–[13]. Generally, the purpose of resource allocation is to assign certain items, such as jobs, vehicles or resources, to other items, such as machines or operations [14], [15]. Logistics planning for an emergency includes the assignment of human resources and equipment to facilities, with the aim of accelerating relief distribution to affected areas. Categorizing the victims in need of medical care contributes to an optimized resource utilization [16] and proper allocation of rescue units to different categories decreases the rate of casualties [17]–[19]. Martí et al.(2009) addressed this issue using mobile electronic triage tags to collect information from victims and allocate medical resources to them in real time. Özdamar et al. (2004) proposed a hybrid model to locate distribution centers and assign demand and vehicles to facilities in a periodic manner. Özdamar and Demir (2012) studied a hierarchical cluster-and-route method to provide vehicle routes for large-scale relief distribution. They proposed a mathematical model to minimize travelling time by assigning the optimal number of vehicles to warehouses and hospitals. Ng et al. (2010) suggested a bi-level mathematical model for the shelter assignment problem in an emergency evacuation. The upper level determines the optimal assignment of evacuees to shelters. In the lower level, evacuees find the shortest routes to the shelters they are assigned to. Considering secondary disasters, Zhang et al. (2012) formulated the problem of assigning emergency resources from multiple emergency depots to multiple disaster locations.

The DM decision makers must deal with the complications and uncertainties faced in the process of scheduling and assigning staff and resources to different missions [25]. The personnel assignment problem is that of determining the best assignment of staff to jobs, assuming that the performance of each worker on a specific task is known [26]. The performance of a relief supply chain is heavily determined by the proper allocation of scarce

emergency resources [27]. Kwak and Lee (1997) used goal programming to assign human resources to different shifts at health centers in order to minimize costs and preserve patient satisfaction. Barbarosoğlu et al. (2002) proposed a bi-level hierarchical multi-criteria methodology for planning helicopter missions during disaster relief operations. The higher level deals with the fleet composition, pilot assignment, and determination of tour numbers for each helicopter. The lower level considers concomitant operational decisions, such as refueling, scheduling and routing problems. Stolletz and Brunner (2012) considered a tour-scheduling problem to assign shifts and off days to a given number of physicians in such a manner that demand is completely met. Falasca and Zobel (2012) developed a multi-criteria optimization model for assigning volunteers to humanitarian organizations. Balasubramanian et al. (2014) developed a stochastic dynamic model for a same-day allocation of patients to physicians. In order to accommodate the actual surgical demand, Hosseini and Taaffe (2015) presented an algorithm to allocate blocks to surgeons by considering the over-time and under-time restrictions. Liang and Turkcan (2016) developed two bi-objective optimization models concomitant to the nurse assignment and patient scheduling problems in oncology clinics. Based on the multiple phases in the patient-provider interaction, Vahdat et al. (2017) studied a dynamic exam room assignment policy in ambulatory care clinics and presented a new taxonomy of room sharing policies. Feng et al. (2017) constructed a multi-objective mathematical model for medical resource allocation in emergency departments to simultaneously minimize both the average patient's length of stay and the wasted costs. Bastian et al. (2017) introduced a stochastic multi-objective auto-optimization model for resource allocation decision-making in a fixed-input health system. The introduced model accounts for the re-allocation of resources at hospital level for optimizing the overall system performance.

This paper is devoted to the assignment of personnel to operating rooms in the post-disaster period. The injuries incurred during a disaster may call for a special knowledge of surgery, and, therefore, an expert in a special discipline. However, for the sake of simplicity and without the loss of generality, this study only considers two types of medical staff: surgeons (general surgeons) and anesthetists. These two specialties are assumed to be the most critical resources and the extension of the proposed model to consider other types of personnel should be straightforward. This assignment problem is part of the preparedness phase of DM. It is a low-cost activity that can be carried out and repeated during the pre-disaster period. It is independent of other functions and services of the relief system, although it can be considered part of the relief system.

The structure of the paper is as follows: Section 2 provides a description of the problem and its mathematical model. The algorithms used as the solution methods are discussed in Section 3. The case study on Tehran and its special circumstances are laid out in Section 4. The results are discussed in Section 5. And finally, the last chapter presents conclusions.

2. Problem Definition

If a disaster is expected at a location, it is possible to organize, maintain, and train a relief system, which can have many different subsystems, to mitigate the suffering of the victims in the aftermath of the disaster. The population of the city must be well informed of the services offered. People must also know where and how they can access these services. One such subsystem is the healthcare system. Its functions go beyond the scope of disasters and even under normal conditions is considered a resource-intensive unit. However, the healthcare system has special functions in the post-disaster period. After a major disaster, namely an earthquake, a large number of injured people need urgent medical help; those with serious injuries need operations. Such injuries call for surgeons with special knowledge and skills, and such surgeons are available in limited numbers. Therefore, an appropriate assignment of these surgeons to operating rooms in the case of an earthquake or any other disaster is of great importance. In the post-disaster period, special emergency rules can be introduced, such as the assignment of operating personnel to hospitals other than the ones in which they normally work in the pre-disaster period.

Different parts of a city will be hit by an earthquake to different degrees. The greatest destruction will take place in the vicinity of seismic faults. The probability of survival for both people and buildings is at its lowest in these regions. Also, movement is restricted in a shocked and chaotic city where some streets are not usable and personnel may not reach their assigned position if the distance is too long.

The collapse of a building depends on many factors, such as the magnitude of the earthquake, the closeness of the epicenter, the design and age of the building and the quality of materials used in construction. Therefore, the probability of survival for neighboring buildings is not completely independent and the value of the factors determining them can be very different from one building to the other, except the ones depending on geographical properties. Since there is no way to observe this interdependence, the best possible assumption is that the survival probabilities of both people and buildings are independent of one another. However, the probability of survival depends on the region of the city.

For the sake of simplicity, only two professions are considered necessary for each operating room: surgeons and anesthetists. An operating room works in the post-disaster period if the operating room survives the earthquake, i.e. it does not collapse, and the assigned personnel also survive and reach the operating room. If the number of personnel assigned to an operating room is only one of each type, then the probability that the operating room works is:

$$P(\text{The operating room survived}) \times P(\text{Its surgeon survived}) \\ \times P(\text{Its anesthetist survived}).$$

The probability of survival for individuals, i.e. for surgeons and anesthetists, depends on the region of the city in which they stay. Therefore, their probability of survival is equal to that of the region where they live, which implies that people from the same region have equal probability of survival. However, the model can be formulated in a simpler way if every person has his or her individual probability. This still allows buildings and persons from the same region to have the same probability of survival.

Personnel must reach the operating room as soon as possible. Therefore, they can only be assigned to operating rooms located within a limited distance of their domicile, but not necessarily to the closest one.

2.1. Formulation

The index sets, parameters, scalars and variables defined to develop the mathematical model are as follows:

Sets:

- I^S, I^A : The sets of existing surgeons and anesthetists, ($i \in I^S$) and ($k \in I^A$), respectively
- J : The set of existing operating rooms ($j \in J$)
- V^S, V^A : The valid pairs of operating rooms and staff (surgeons and anesthetist) based on the distance criteria ($V^S \subseteq I^S \times J$ and $V^A \subseteq I^A \times J$)
- R : The set of partitions of the city ($r, l \in R$)

Scalar:

182 • U^d : The maximum allowed distance between an operating room and its assigned
 183 personnel

184 Parameters:

- 185 • sur_l : The survival probability of region l
- 186 • π_i^s : The survival probability of surgeon i ($\pi_i^s = sur_l$ if surgeon i lives in region l)
- 187 • π_k^a : The survival probability of anesthetist k ($\pi_k^a = sur_l$ if anesthetist k lives in region
 188 l)
- 189 • π_j^o : The survival probability of the j^{th} operating room
- 190 • d_{qr} : The distance between locations q and r
- 191 • w_r : The weight of region r , which is proportional to the population of the region.

192 Decision variables:

- 193 • x_{ij} : $\begin{cases} 1 & \text{if surgeon } i \text{ is assigned to the operating room } j \\ 0 & \text{otherwise} \end{cases}$
- 194 • y_{kj} : $\begin{cases} 1 & \text{if anesthetist } k \text{ is assigned to operating room } j \\ 0 & \text{otherwise} \end{cases}$
- 195 • p_j^s : The probability that at least one of the surgeons assigned to the j^{th} operating room
 196 survives
- 197 • p_j^a : The probability that at least one of the anesthetists assigned to the j^{th} operating
 198 room survives
- 199 • p_j^f : The functioning probability of the j^{th} operating room

200 The pairs of members of personnel and operating rooms that have a distance of less than the
 201 upper limit (U^d) are considered to be valid pairs. Thus, the set of valid pairs V , is defined as

202 $V^S = \{(i, j) | (i, j) \in I^S \times J, d_{ij} \leq U^d\}$ and $V^A = \{(k, j) | (k, j) \in I^A \times J, d_{kj} \leq U^d\}$.

203 The model has two objective functions. The first objective function maximizes the expected
 204 number of functioning operating rooms. It is well known that the expected value of a random
 205 binary variable is the probability of value 1. This implies that the first objective function is

$$\max \sum_j p_j^f \quad (1)$$

206 The second objective function minimizes the expected value of the distance that a person, more
 207 precisely the emergency vehicle that transports the person, must travel until it finds a
 208 functioning operating room.

209 To solve the problem, the city is divided into regions. The regions are represented by their
 210 center points. The distance to a hospital, which also lies at a point, is the distance between the
 211 two points. In the case of a reliable communication system, after picking up the patients, the
 212 Disaster Command Center will navigate the emergency vehicles to the nearest functioning
 213 operating room. In that case, let $p(r, j)$ be the permutation of hospitals in increasing order of
 214 their distance to region r , i.e.

$$d_{rp(r,1)} \leq d_{rp(r,2)} \leq \dots \quad (2)$$

215 The probability that the j^{th} operating room works, but the first $j - 1$ operating rooms before
 216 that do not, is:

$$p_{p(r,j)}^f \prod_{q=1}^{j-1} (1 - p_{p(r,q)}^f) \quad (3)$$

217 Therefore, the form of the objective function that minimizes the expected value of the total
 218 distance travelled would be:

$$\min \sum_r w_r \sum_k p_{p(r,k)}^f d_{rp(r,k)} \prod_{l=1}^{k-1} (1 - p_{p(r,l)}^f) \quad (4)$$

219 Suppose that the opposite case is true, i.e. there is no reliable communication system. In that
 220 case, the driver of the vehicle must find an operating room. The logical behavior of the driver
 221 is as follows: The driver goes to the nearest hospital. If the operating room works, then the
 222 route is finished. Otherwise, the driver goes to the hospital that is nearest to the first one. If this
 223 operating room works, the route is terminated. Otherwise, the driver continues to the next
 224 operating room in a similar way, and so forth. This order of operating rooms determines the
 225 permutation $p(r, j)$. Let $p(r, 0) = r$. Hence, the second objective function is:

$$\min \sum_r w_r \sum_k p_{p(r,k)}^f \sum_{l=1}^k d_{p(r,l-1)p(r,l)} \prod_{q=1}^{k-1} (1 - p_{p(r,q)}^f) \quad (5)$$

226 The probability that at least one surgeon assigned to an operating room j survives is:

$$\forall j \in J: p_j^s = 1 - \prod_{i:(i,j) \in V} (1 - \pi_i^s x_{ij}) \quad (6)$$

227 Similarly, the probability that at least one anesthetist assigned to an operating room survives
228 is:

$$\forall j \in J: p_j^a = 1 - \prod_{i:(i,j) \in V} (1 - \pi_i^a x_{ij}) \quad (7)$$

229 The probability that an operating room functions is:

$$p_j^f = \pi_j^o p_j^s p_j^a \quad \forall j \quad (8)$$

230 Each surgeon and each anesthetist can be assigned to at most one operating room.

$$\forall j: \sum_{i:(i,j) \in V} x_{ij} \leq 1 \quad (9)$$

$$\forall k: \sum_{i:(k,i) \in V} y_{ki} \leq 1 \quad (10)$$

231 The final model consists of objective functions (1) and (5), subject to constraints (6)-(10) and
232 completed by describing the assignment variables as binary:

$$\forall i, j, k: x_{ij}, y_{kj} \in \{0,1\} \quad (11)$$

233

234 3. Solution Method

235 In order to solve the proposed problem, the developed mathematical model was coded using
236 the General Algebraic Modeling System (GAMS), which is one of the most prominent
237 optimization compilers [38]. Since the developed mathematical model is categorized as a
238 constrained mixed-integer nonlinear programming model, it is considered an NP-hard problem
239 and achieving the exact solution for such a problem is difficult, if not impossible, specifically
240 when the size of the problem is large [39]. Therefore, GAMS failed to solve even small
241 instances of the problem, with more than 50 areas and 12 hospitals, within a time limit of 72
242 hours. The small instances solved by GAMS are shown in Table 1. The proposed model is
243 supposed to serve as a decision support system for the DM of metropolitan cities with large
244 numbers of areas and hospitals, so the application of metaheuristic algorithms to solve the
245 problem is inevitable.

246 Table 1. The solutions found by GAMS

Instance No.	# areas	# hospitals	f_1^*	f_2^*	F^*	CPU time
1	20	8	3.959	1159.002	0.259	37 s
2	50	12	6.124	7998.014	0.406	9180 s
3	100	20	***	***	***	> 72 hours

Sign (***) denotes that GAMS cannot find the optimal solution

247

248 In this study, the simulated annealing algorithm (SA), Genetic Algorithm (GA), and Particle
 249 Swarm Optimization (PSO) are used to solve the model. Since the proposed mathematical
 250 model has more than one objective function formulated by (1) and (5), the method of weighted
 251 metrics is used for combining the objective functions and evaluating the solutions. As long as
 252 the weights are positive, this method is proven to produce Pareto optimal solutions [40]. By
 253 changing the weights, different points in the Pareto front can be achieved. The L_p -metric is
 254 used as the distance measure [41], [42]. This method uses equation (12) to minimize the
 255 differences between objective functions and their pertinent desired values ($f_i^* \in \mathbb{R}^Q$):

$$\text{Min } F(x) = \left[\sum_{i=1}^Q \left[w_i \left| \frac{f_i^* - f_i(x)}{f_i^*} \right| \right]^p \right]^{\frac{1}{p}} \quad (12)$$

Subject to:

$$x \in X \subseteq \mathbb{R}^Q \quad (13)$$

256 In (12), w_i is the weight of the objective function, defined by the decision maker. p is a positive
 257 integer. When $p = 1$, which is the case here, the distance measure is called the Manhattan
 258 metric. f_i^* is the optimum value of objective function i if considered alone.

259 Before evaluating the performance of the algorithms, the parameters are tuned using the
 260 Taguchi method. The Taguchi method reduces the size of the experiments by an orthogonal
 261 arrangement of factors, hence it is frequently used in tuning algorithm parameters [43]. This
 262 method finds the optimal combination of factors, by reducing the effect of noise, by evaluating
 263 the signal to noise ratio. The parameters, levels and the response of algorithms are discussed in
 264 3.4, while the results and the performance of tuned algorithms are discussed in the subsequent
 265 sections.

266 3.1 Simulated Annealing (SA)

Inspired by the annealing procedure in metallurgy, SA was first introduced by Kirkpatrick et al. (1983) and Černý (1985) and has since frequently been used to provide near-optimal solutions to hard and large combinatorial optimization problems [46]–[48]. SA is a modified local search algorithm. In order to escape the local optima and in an effort to find the global optimum, this algorithm occasionally accepts a worse solution for neighborhood search according to a determined probability.

SA uses a parameter called temperature. Initially, the temperature (T) is fixed at the starting point (T_0) and the algorithm commences with a randomly generated solution. The structure of the solution is a $2 \times n$ matrix, where n is the number of existing regions. The allocation of surgeons or anesthetists in region (i) to operating room (j), such that $(i, j) \in V$, is illustrated in the first and second rows of the matrix, respectively. Figure 1 presents the encoding of the solution schematically. This encoding illustrates the complete assignment of the staff to the hospitals and, with given probabilities, the calculation of objective functions is at hand.

Fig. 1: Solution representation

First, the algorithm generates a random solution and the initial solution is considered to be the best solution ($\bar{S}$). At each iteration of the algorithm or, in other words, at each temperature, N neighborhood solutions (S') are generated by applying the mutation operation on the current solution (S). Let l be the number of regions. In the mutation operation, k ($k \in (1, \frac{l}{3})$) randomly selected regions are reallocated to alternative operating rooms (j') such that $((i, j') \in V, j \neq j')$. At each iteration, if $F(S') < F(\bar{S})$, $\bar{S}$ is replaced with S' . Furthermore, the objective function value of S' is compared with that of S and the neighborhood search continues with the superior solution. To escape the local optima, a solution that is not as good as the solution at hand is accepted as the current solution (S) with a probability equal to $e^{-\left(\frac{F(S')-F(S)}{T}\right)}$. At the end of each iteration, the temperature decreases by a predetermined

coefficient α . It is clear that by decreasing the value of α , the total number of iterations will increase. The algorithm continues until reaching the final temperature (T_f).

3.2 Genetic Algorithm (GA)

As described by Mangano [49], GAs provide large-scale problems with solutions that might not otherwise be achievable in a lifetime. Inspired by the evolution of a species through generations in nature, GA was developed by John Holland (1970's) and has been utilized in many studies since [50]–[54]. GA consists of several steps: generation of the initial population, selecting some individuals for creating children/offspring (new solutions), sorting the newly increased population based on their superiority, selection of a superior individual for survival (entering the next generation) and discarding the rest of the individuals and repeating the cycle.

The initial population consists of randomly generated solutions. Each solution is represented by an encoding structure called a chromosome. The structure of the chromosome is the same as the one used in SA. The superiority of each solution/individual is determined based on a fitness function (objective function). Then the roulette wheel selection process is used to select some individuals as parents to give birth to new children/offspring by mutation and crossover operators. According to this selection method, the better the solution fitness, the higher the chance of being selected. To perform the crossover operation, two parents are selected, a crossover point is generated randomly along the length of the chromosome and the second part of the chromosomes is interchanged, giving birth to two new solutions. In order to perform the mutation operation, one parent is selected, some genes of the chromosome are selected randomly and their values are altered. The crossover and mutation operators are illustrated in Fig 2.

Fig. 2. a) Crossover operation. b) Mutation Operation

3.3 Particle Swarm Optimization (PSO)

PSO is a biologically inspired algorithm introduced by Eberhart and Kennedy based on swarming/social habits of some animals like fish, birds and bees and evolutionary algorithms such as GA [55]. The performance of PSO is not highly sensitive to the nature of the objective function and it would not be trapped in local minima [56]. The advantages of PSO has made it a desirable solution method for many researchers [57]–[59]. PSO contains a population of particles each representing a solution. Each particle swarms to find a better fitness value in the solution space.

PSO starts with randomly generated solutions called particles/individuals. PSO does not discard solutions through iterations but maintains the initial population and only changes the position of the particles. The position of particle i in iteration t is updated by this formula: $x_i^{t+1} = x_i^t + v_i^{t+1}$ where x_i^t is the current position of the particle, x_i^{t+1} is the new position, and v_i^{t+1} is the vector indicating the direction and the intensity of the movement, which is called velocity. The velocity is influenced by three factors: a) the current position of the particle, b) the best position found so far by the particle (individual's best) and c) the best position found so far by all the particles (global best). The velocity is calculated by the following equation:

$$v_i^{t+1} = wv_i^t + c_1r_1(\hat{x}_i^t - x_i^t) + c_2r_2(g_t - x_i^t) \quad (14)$$

v_i^t is the velocity of particle i at iteration t . wv_i^t is the tendency of the particle towards its current position and hence this term is called the inertial component. w (the inertia weight)

controls the level of exploitation and exploration. The value of w is generally reduced by a damping ratio as the algorithm proceeds. c_1 , is the personal learning coefficient, determines the tendency of the particle towards its individual best and the second term on the right-hand side of equation (14) is the individual/cognitive component. And finally, the last term indicates the tendency of the particle towards global best and, reasonably, is called the social component. r_1 and r_2 are random real numbers in the interval $[0,1]$. g_t indicates the global best found as of t^{th} iteration and $\hat{x}_i^t$ is the individual's best position. The flow chart of the developed PSO is presented in Fig 4.

The solution encoding consists of a vector with a length equal to two times that of the area. The first part indicates the assignment of surgeons and the second parts indicate the assignment of anesthetists. Each element of the vector is a real number between zero and one. This real number is used to select an operating room among the existing ones in the allowed radius using the roulette wheel selection process. To do so, the weight of all operating rooms is considered equal to $1/n$, with n being the number of hospitals in the allowed radius. The encoding of the solutions is depicted in Fig. 3.

Fig.3. PSO Encoding

Fig. 4. Flow chart describing the PSO algorithm

3.4. Parameter Tuning

It is incontrovertible that the efficiency and effectiveness of metaheuristics algorithms is affected by the applied parameter levels and, therefore, tuning the parameters prior to the implementation of algorithms is necessary [60]. Although in the majority of studies the parameters are fixed manually according to the reference values of previous similar researches, this study applies the Taguchi method to calibrate the parameters. In addition to reducing the computational effort of inefficient trial and error tuning methods [61], orthogonal arrays of the Taguchi method outperform the classical statistical optimization parameter tuning methods by investigating more decision variables in a smaller number of experiments [62]. Taguchi classifies the factors into two main categories: controllable and noise (those that cannot be controlled directly) factors. The method aims to minimize the effect of noise while determining the optimal level of controllable factors [63]. To do so, the signal-to-noise (S/N) ratio is calculated using equation (15), where the signal (S) represents the desirable value (mean response variable), noise (N) represents the undesirable value (standard deviation), (Y) denotes the response value, and (n) shows the number of orthogonal arrays [64].

$$S/N = 10 \times \log_{10}(S(Y)^2/n) \quad (15)$$

To use the Taguchi method for tuning the parameters of each algorithm, for each combination of parameters in Taguchi design, five problem instances are solved and the average objective value is used as the response value. The parameters and their levels are illustrated in Table 2. As a quick reminder, in PSO the parameter C1 is the personal learning coefficient, which regulates the movements towards individual's best, C2 is the social coefficient indicating the individual's tendency towards global best, w is the damping ratio, MaxIt is the total number of iterations and finally Npop is the total number of individuals. For GA, MaxIt is the total number of generations/iterations, Npop is the total number of genes/solutions, Pc is the crossover rate and Pm is the permutation rate. For SA, Tz indicates the initial temperature, Tf is the final temperature, Alpha is the temperature reduction coefficient and Nit is the number of neighborhood searches in each temperature. The different levels of the algorithms are selected based on preliminary test runs. The main effect plot for S/N ratios is also demonstrated in Fig. 5 for all the algorithms. The selected levels for each parameter are shown in bold in Table 2.

Table 2. Parameters, Levels, and results of Taguchi analysis

<u>PSO</u>				<u>GA</u>				<u>SA</u>			
Parameter	Levels			Parameter	Levels			Parameter	Levels		
C1	1.0	1.20	1.5	MaxIt	200	400	600	Tz	95	98	99
C2	1.5	1.75	2.0	Npop	40	75	100	Tf	0.50	0.75	1.00
w	0.8	1.00	1.2	Pc	0.60	0.75	0.90	Alpha	0.85	0.90	0.95
MaxIt	300	500	700	Pm	0.40	0.50	0.60	Nit	10	20	30
Npop	40	60	80								
wdamp	0.90	0.95	0.99

Fig. 5. Main Effects Plot for SN ratios

3.4. Performance Evaluation

To evaluate the performance of the algorithms, a problem was solved ten times by each tuned algorithm. Test results in Table 3 were used to determine if there is any significant difference between the performance of the three algorithms.

Table 3. Results of the tuned algorithms

	#run									
	1	2	3	4	5	6	7	8	9	10
PSO	0.518	0.522	0.515	0.518	0.515	0.513	0.514	0.510	0.512	0.511
GA	0.754	0.743	0.734	0.730	0.747	0.732	0.787	0.752	0.723	0.724
SA	0.790	0.805	0.787	0.793	0.789	0.820	0.800	0.798	0.796	0.765

The analysis of variance performed by Minitab indicates that the performance of the algorithms is significantly different. PSO results in better solutions and, therefore, is used to solve the case study in the next section.

Table 4. One way ANOVA for comparing the performance of the tuned algorithms

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	2	0.442043	0.221022	1144.64	0.000
Error	27	0.005213	0.000193		
Total	29	0.447257			

4. Case Study: Tehran

Tehran is the capital of Iran, with an area of 686.3 km² and a dense population of almost nine million [65]. The population is mostly distributed throughout the old part of the city, which has narrow streets and could experience calamitous consequences if exposed to a major disaster. There is a cycle length of 173 years between major earthquakes affecting Tehran. The last one was in 1830. Therefore, the occurrence of an earthquake is highly probable in the near future [66], [67]. There are three main earthquake faults surrounding Tehran. As studied by JICA and CEST (2000), the detriment rate caused by the Mosha, North Tehran, and Ray faults is estimated to be 13%, 36%, and 55%, respectively. The catastrophic consequences of a probable earthquake in Tehran and the measures required to confront it have been widely studied [13], [69], [70].

In order to apply the developed mathematical model to the case of an earthquake in Tehran, the map of Tehran and coordinates of 235 existing hospitals were obtained using the ArcGIS software. The topology of these hospitals is illustrated in Fig. 6. The area of the city is partitioned into 2500 areas, of which only 1657 are residential, and incorporated into the model. The probability of the survival of a person depends on the region and is calculated using the coordinates of the center point of each region. In order to calculate the survival probability for each region, the following formula, proposed by Salman and Yücel (2015), is used:

$$p_i = 1 - \beta_i PGA_i \quad (16)$$

β_i is the damage risk of region i , obtained from the JICA report. PGA_i , the peak ground acceleration at the center of region i , is formulated by Panoussis (1974) as:

$$PGA_i = \alpha \frac{e^{0.8\mu}}{(r_i+40)^2} \quad (17)$$

In (17), μ is the earthquake magnitude and r_i is the distance between the center of region i and the hypocenter of the earthquake in kilometers. Parameter α , used to determine the range of survival probabilities, is considered equal to 2 [69]. Equations (16) and (17) are calculated considering the worst-case scenario, which is the activation of the Ray fault model with magnitude 7.5.

To calculate equation (12), the optimum value of the objective functions (f_1^* and f_2^*) are acquired, corresponding to the situation where all the operating rooms function after the earthquake, in which case their value would be equal to 235 and 1683100, respectively. The

maximum allowable radius for the assignment of medical staff to a hospital is equal to three kilometers. Needless to say, the same radius is applied for the assignment of patients to the hospitals.

Fig. 6: Topography of Tehran hospitals

5. Results

The problem was run on an Intel Core i5 PC using MATLAB R2017a. The CPU time was equal to 3893 seconds. The value of the objective function (12) achieved by the algorithm is equal to 0.51207, the expected number of operating hospitals is equal to 181.358 and the expected total travelling distance is equal to 2,160,781 km. The total number of surgeons and anesthetists in the whole city is respectively equal to 964 and 945. The maximum, minimum, average and standard deviation of the number of surgeons assigned to one hospital are equal to 42, 0, 6.2, and 5.09 respectively, while for anesthetists these values change to 45, 0, 6.27, and 5.1. There are eight hospitals without any surgeons and the same number of hospitals without any anesthetists. These hospitals are the ones with a high probability of demolition.

It is very important to note that if the resources were simply assigned to the nearest hospital, the objective function would have increased to 0.95, with the expected number of operating hospitals and expected travel distance to equal to 124.76 and 2,504,768 km, respectively. Thus, the results obtained by the nearest neighborhood assignment are far worse in all aspects than the solution obtained by the proposed assignment method, regardless of the solution algorithms. The results obtained by PSO, SA, GA and nearest neighborhood assignment (NN) are compared in Table 5. It is clear that PSO outperforms the other algorithms, considering the problem at hand.

449 Table 5. Performance Evaluation and Comparison of Different Algorithms

	<u>PSO</u>	<u>GA</u>	<u>SA</u>	<u>NN</u>
Objective function	0.51	0.74	0.77	0.95
Expected value of functioning hospitals	181.35	149.11	147.19	124.76
Expected value of total travel distance	2,160,781	2,320,575	2,356,101	2,504,768

450

451 The trend of convergence of the PSO algorithm toward the best solution is illustrated in Fig. 7.
 452 The expected number of functioning operating rooms translates to more than 77% of the total
 453 number of existing operating rooms. Furthermore, it should be mentioned that only 104
 454 operating rooms have a functioning probability of more than 80%. The solutions acquired by
 455 the PSO can be justified by the fact that only 131 hospital buildings (55%) have a survival
 456 probability greater than 0.8 and there is no hospital with a survival probability greater than 0.9.
 457 The remaining hospitals have a survival probability that is less than 0.8. Thus, the expected
 458 number of 181 functioning operating rooms (77%) acquired by the PSO algorithm can be
 459 considered an acceptable result and an effective performance.

460 The division of regions is depicted in Fig. 8. In this figure, the dimmer the color of a region,
 461 the greater the expected travelling distance for patients. The residential regions of the city are
 462 located in 1657 regions. Among these regions, only 1473 have at least one hospital in their
 463 allowable radius. The mean expected travel distance for all the areas is equal to 1304 meters
 464 and the maximum is equal to 3820. Table 6 illustrates the total number of regions at different
 465 intervals of expected travel distance and compares the results acquired by PSO by that of other
 466 algorithms. Table 7 lays out the total number of hospitals in different categories of functioning
 467 probability.

Fig. 7: The convergence of the objective function

Fig. 8: The coverage of different regions

Table 6. Number of regions in different intervals of expected travelling distance

<u>Expected travel distance (meters)</u>	<u>PSO</u>	<u>GA</u>	<u>SA</u>	<u>NN</u>
0< Expected travel distance<=1000	670	565	557	507
1000< Expected travel distance<=2000	601	668	666	660
2000< Expected travel distance<=3000	343	369	371	399
3000< Expected travel distance<=5000	43	54	60	84
5000< Expected travel distance	0	1	3	7

Table 7. The total number of hospitals in different categories of functioning probability

<u>functioning probability</u>	<u>PSO</u>	<u>GA</u>	<u>SA</u>	<u>NN</u>
$0.0 < p \leq 0.4$	8	32	52	66
$0.4 < p \leq 0.6$	0	31	26	22
$0.6 < p \leq 0.8$	123	101	87	86
$0.8 < p \leq 1.0$	104	71	70	61

It should be mentioned that the performance of the algorithms depends highly on the structure of the model and the smoothness of the feasible space. In many problems, GA had beaten other algorithms and provided a significantly better solution than other algorithms. However, in this study, the performance of the PSO was better. All these algorithms were tuned using the Taguchi method before comparison. Thus, all of them were in their best state and had the best parameter configurations for this specific problem. It is the nature of heuristic methods that none of them is the winner in all cases and this study is by no means intended to specify a specific algorithm as the preferred one for all the problems. This study proposes a probabilistic model for assigning medical staff to hospitals, which would lead to a higher rate of saved lives by maximizing the expected number of functioning operating rooms. Such an approach is unprecedented in the literature. The solution methods used here are only selected to illustrate the efficiency of the model by comparing the results to a classic nearest neighborhood assignment. In practice, and in real life, considering the existence of the decision maker, other solution methods can be selected to solve the problem. A good approach would be the application of an interactive evolutionary algorithm which would exploit the preferences and knowledge of the decision maker to direct the optimization process towards the most preferred solution.

6. Conclusion

The problem of assigning personnel to operating rooms in a metropolitan city that faces a serious disaster, like an earthquake, was defined. Disasters leave a great number of injured people behind; the survival of these patients depends heavily on medical services. To reduce the number of casualties, this paper provides a model to increase both the service level and the expected number of functional operating rooms. This problem and its solutions are part of the preparedness phase, according to humanitarian logistics. The mathematical model is a highly nonlinear binary programming problem. Three algorithms are suggested as solution methods

and, after tuning the parameters using the Taguchi method, their performance is compared to determine the best solution algorithm for this specific problem. The fact that this model outperforms the simple nearest neighborhood assignment with any solution method indicates the importance of the proposed model and suggests that assignment of personnel should be carried out accordingly. The contribution of this study is the introduction of a novel comprehensive macro perspective and policy for the assignment of scarce and resource-intensive medical staff to hospitals and operating rooms in order to significantly improve the performance of the system. For future studies, one could consider hospital capacity and/or patients' waiting time in the hospital.

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