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Solving an Emergency Resource Planning Problem with Deprivation Time by a Hybrid MetaHeuristic Algorithm

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Abstract *– Every year, natural disasters (e.g., floods and earthquakes) threaten people's lives and finances. To cope with the damage of natural disasters, emergency resources (e.g., rescue teams) must be planned efficiently. Therefore, designing a decision support model to allocate and schedule rescue teams is necessary for the response phase of disaster management. The literature review shows that social aspects of disaster management have less been addressed by researchers, whereas this phenomenon must be incorporated into decision-making processes. The lack of timely relief implies a loss in people's welfare, which leads to social costs called deprivation cost or time. This study proposes a multi-objective mixed-integer programming model to assign and schedule the rescue teams considering different rescuers' capabilities, fatigue effects, and deprivation time. Due to the NP-Hardness of the proposed model, a hybrid approach based on the Lp-metric method and meta-heuristic algorithms are applied to solve the given problem. The results show that the developed algorithm can obtain high-quality solutions in a reasonable time.*

Keywords *– Disaster management, Deprivation time, Fatigue effect, Genetic algorithm, Particle swarm optimization.*

I. INTRODUCTION

A natural disaster is a major adverse event resulting from natural processes of the earth that have caused enormous harms yearly and threaten many people and infrastructures in the world. The reduction of casualties and economic losses is an essential issue in Natural Disaster Management (NDM). Due to the limited ability of the rescue units and time pressure, NDM is very complicated, especially when the incidents spread geographically. Hence, rescue teams' planning in a response phase of disaster management is one of the most critical emergency operation centers (Karimi Movahed et al., 2020; Mohamadi et al., 2020). In the real world, no rescuer can process all types of incidents (i.e., there are a specific unit for medical services and another distinct unit for fire stations), so it is necessary capacities of the rescuers and required ability of incidents is considered in allocating process, in which this point makes the problem harder.

Recently, an Allocation and Scheduling of Rescue Teams (ASRT) problem is likened to an Unrelated Parallel Machines Scheduling (UPMS) problem (Wex et al., 2014). In this regard, rescue teams are considered as machines, and incidents are considered as jobs. On the other hand, we can consider relief and traveling times as processing and setup

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times. Also, if the rescuers are considered salespeople, incidents considered as nodes (i.e., cities), and the sum of processing and travel times are considered traveling time, the ASRT problem is similar to the multiple-traveling salesman problem (Wex et al., 2014).

Usually, a population's needs involving a demand for relief services and goods are increased in a critical condition. On the other hand, emergency resources have limitations in time, quantity, and ability fields. In this stage, when providing humanitarian assistance, there are several difficulties, such as the short time horizon for helping people in need and the vast travel distances between distribution centers and the demand points. The situation described above may lead to a phenomenon, namely deprivation time. Deprivation time is the period in which the lack of needed goods and essential emergency relief leads to a loss in people's welfare (Cotes and Cantillo, 2019). To the best of our knowledge, there is no study to consider the mentioned phenomenon in the ASRT problem.

Regarding the literature, a few studies have dealt with the assignment of the rescue teams in disasters. Falasca et al. (2009) proposed a multi-objective model to assist in the assignment of volunteers to tasks. Rolland, Patterson, Ward, and Dodin (2010) proposed a decision support model to allocate the incidents to the relief teams and schedules them. They applied a hybrid heuristic algorithm based on the neighborhood search and adaptive reasoning technique to solve the proposed model. Wex et al. (2014) and Wex et al. (2011, 2012, 2013) studied the disaster management problem in the allocation and scheduling approach. They examined the problem under the certainty and uncertainty and solved the proposed models by a heuristic method based on Monte Carlo simulation. Rauchecker and Schryen (2018) developed a branch-and-price algorithm to handle the relief teams' scheduling in a disaster response problem in a reasonable time. Cunha et al. (2018) developed a biased random-key genetic algorithm for the allocation and scheduling of the relief teams in the natural disaster. They considered fuzzy processing times for the incidents and showed the proposed algorithm could obtain high-quality solutions. Molladavoodi et al. (2018) proposed a mathematical model for a disaster relief operation with uncertain demand and developed a hybrid LP-GA to solve the research problem.

Nayeri et al. (2018a) introduced a fatigue effect in disaster management and proposed a Mixed-Integer Programming (MIP) model to design the decision support model for an emergency operation center. They developed a hybrid meta-heuristic algorithm to solve the proposed model and showed their algorithm obtained high-quality solutions. Nayeri et al. (2018b) developed a goal programming-based decision support model for a multi-objective ASRT problem with time-windows for incidents. Santoso et al. (2019) developed a non-linear model for the assignment and scheduling of relief teams in a disaster under uncertainty and solved the proposed model with a GRASP algorithm. Kumar and Zaveri (2019) used queuing theory to study a resource scheduling problem in post-disaster management. Shavarani et al. (2019) proposed a non-linear model and developed three meta-heuristics to solve medical staff allocation to operating rooms in a disaster problem. Xu et al. (2019) proposed a Mixed-Integer Non-Linear Programming (MINLP) model with a multi-stage construction of rescue teams in disaster management and used an accelerated bi-level decomposition algorithm to solve it. Bodaghi et al. (2020) proposed an MIP model to design a decision support model for the ASRT problem under uncertainty considering different vehicle types. Zahedi et al. (2020) developed a multi-objective decision-making model to determine the optimal routing of vehicles in an emergency condition considering dynamic demand. The authors selected a real-case study and applied a genetic algorithm to solve the research problem. Wang et al. (2020) studied the allocation of the emergency resource planning problem. They proposed a multi-objective programming model and developed a cellular genetic algorithm to solve the proposed model. The results showed the efficiency of the developed algorithm. Hu et al. (2016) proposed a bi-objective robust optimization model to study emergency resource allocation problems under uncertainty to maximize efficiency and fairness under different sources of uncertainties. Then, the authors developed a heuristic-based multi-objective particle swarm optimization algorithm to solve the proposed model. Ghasemi et al. (2019) offered a multi-objective programming model for investigating location, allocation, and distribution of relief commodities. They applied scenario-based programming to tackle uncertainty and used the ε-constraint method to solve the research problem. Farahani et al. (2020) conducted a review research for investigating humanitarian operations, especially an application of operations research. One of the suggestions for future studies that the authors provided, is to incorporate time windows for incident in the mathematical model.

Table I categorizes some of the related papers and compares them with the current study. As can be seen in this table, for the allocation and the scheduling of the rescue teams problem, there are few multi-objective models. Also, in this field, a time window for incidents has been less addressed by the researchers. On the other side, deprivation time did not investigate by researchers in the allocation and the scheduling of the rescue teams problem.

Table I. Categorizing some of the essential related studies

Paper	*Type of problem*	*Mathematical model*		*Deprivation time*	*Time windows*	*Fatigue effect*	*Solution methodology*
		Single-objective	*Multi-objective*				
Fiedrich et al., 2000	Assignment of resources	×					Simulated Annealing (SA)
Tamura et al. , 2000	Disaster decision making problem	×					Value function under risk
Rolland et al., 2010	Allocation and scheduling	×					Tabu search
Wex et al., 2014	Allocation and scheduling	×					Monte Carlo-based heuristic
C. Zhang et al., 2016	Allocation and scheduling	×					Heuristic algorithm
Visheratin et al., 2017	Early warning systems	×					Hybrid algorithm
S. Zhang et al., 2017	Allocation and scheduling		×				NSGA-II and C-METRIC
Cunha et al, 2018	Allocation and scheduling	×					GA
Rauchecker & Schryen, 2018	Allocation and scheduling	×					Branch & Price
Nayeri et al., 2018	Allocation and scheduling	×				×	Hybrid metaheuristic
Nayeri et al., 2018	Allocation and scheduling		×		×		Multi-choice Goal programming
Sabouhi et al., 2018	Routing and scheduling	×					Memetic algorithm
Santoso et al., 2019	Allocation and scheduling	×			×		GRASP algorithm
Kumar et al., 2019	Scheduling	×					Heuristic algorithm
Cotes et al., 2019	Humanitarian logistic	×		×			GAMS
Xu et al. 2019	construction of rescue units	×					PSO
Bodaghi et al., 2020	Allocation and scheduling	×					Stochastic frequency approach
This research	Allocation and scheduling		×	×	×	×	GA-Lp and PSO-Lp

The literature review shows that the ASRT problem has attracted researchers' attention in the last decade. However, there are also some research gaps, which are listed below:

1. There is no study related to the ASRT problem considering the deprivation time, whereas this is an essential point in disaster management.

2. The majority of the related papers proposed a single-objective model, and the multi-objective programming approach has less been addressed by researchers in this field.
3. Considering time windows as one of the most critical issues in a disaster management problem has less been addressed in the related studies.

Due to the above discussions, the main contributions of this research can be summarized as follows:

1. To the best of our knowledge, this is the first study incorporating the deprivation time in the ASRT problem.
2. This research proposes a multi-objective MIP model to design a decision support model for the response phase of disaster management
3. This study considers time windows for incidents in the proposed model.
4. Because time is a crucial issue in disaster management, a hybrid algorithm is developed to solve the considered problem in reasonable computational time in this study.

The remainder of this study is structured as follows. In section II, the presented problem and the mathematical model are demonstrated. The solution methodology is described in Section III. Numerical experiments are presented in Section IV. Finally, conclusions and future research suggestions are provided in Section V.

II. MATHEMATICAL MODEL

In this research, the assigning and scheduling of the rescue teams in a response phase of disaster management are investigated. Suppose a condition in which some disasters occur and emergency operation centers should be assigned the available rescuers to the incidents. All rescue teams must start the relief operation from the emergency operation center and travel between locations of the incidents for processing the corresponding tasks. Since every incident need a different ability, and every rescuer has a different capability, each incident should be assigned to a rescue team that can do it. On the other side, a fatigue effect is considered in the research problem, and the physical power of the rescue teams diminishes after successive operations, their performance is decreased gradually, and it may increase the relief time (i.e., processing time). Also, because the relief operations should be started in a specific time interval, we consider time windows for the incidents. Fig. 1 shows the schematic of the research problem.

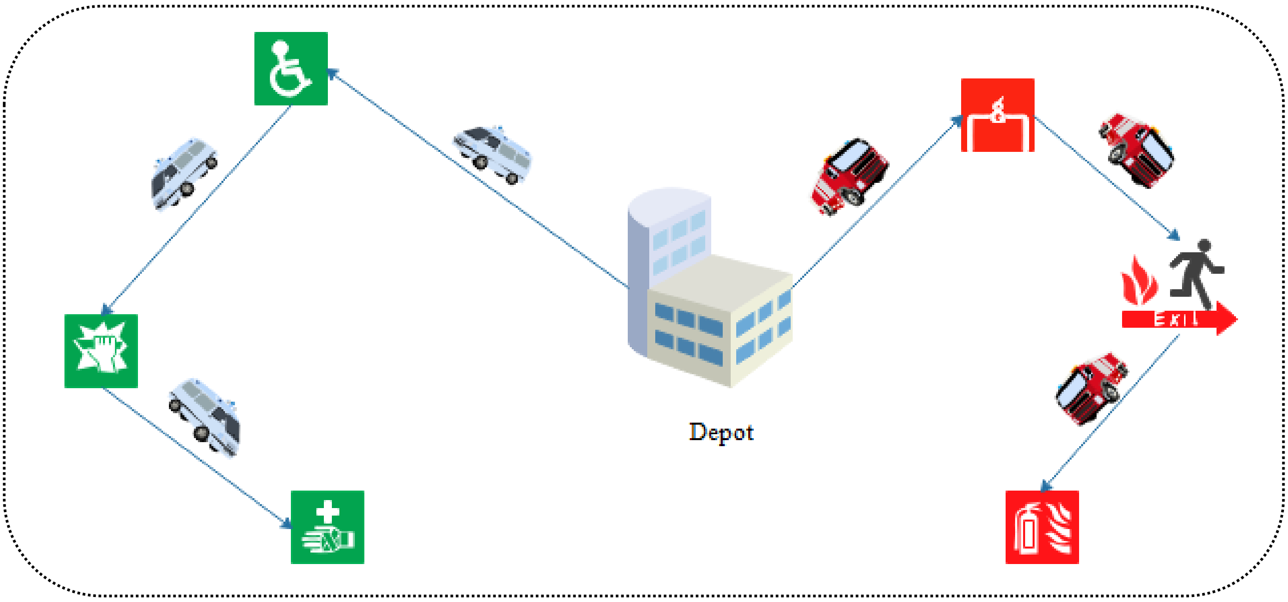


Fig. 1. Schematic of the research problem

Consider a critical condition where n incidents occur and the emergency operation center with m rescue teams responsible for relieving incidents. Let w_i and L_i denote the severity level and time windows of incident i, respectively. S_{ij}^k shows the required time for traveling between incidents i and j. P_i^k denotes the processing time (i.e., relief time) of the incident i by rescue team k. Cap_i^k is a binary parameter that equals one if rescue team k is capable of relieving incident i. Also, α represents the fatigue effect. $PT_{[r]}^k$ denotes the actual processing time of the incident (due to the fatigue effect), which is scheduled in the r-th position of rescue team k. $ST_{[r]}^k$ is the start time of the incident, which is scheduled in the r-th position on rescue unit k. $S_{[r]}^k$ shows the travel time of rescue team k for traveling to the location of the incident, which is scheduled in position r. DT_i^k and C_i^k show the deprivation time and completion time of the incident i, which is allocated to rescue team k, respectively. Also, $X_{i[r]}^k$ is a binary variable, which is equal to 1 if incident i is scheduled in the r-th position of rescue team k. Furthermore, we consider one dummy incident was given by 0, in addition to n incidents, to show the starting point (depot), and it does not require any processing time and destruction factor; however, the rescue team needs a travel time to move from its starting point to the first incident that should have relief it. Also, in this research, we calculate the deprivation time using the following formula:

$$Deprivation\ Time(i) = Completion\ Time(i) - Time\ window(i) \tag{1}$$

According to Relation (1), in this study, the deprivation time is equal to the difference value between the completion time of the incident and the specific time windows of the incident. It should be noted that if the value of the time-window is greater than the completion time of the incident (deprivation time<0), the deprivation time is set to 0.

A. Assumptions

In this research, the following assumptions are considered.

- The number of relief teams is less than the number of incidents
- Processing times are not fixed due to the fatigue effect.
- Each relief team has different capabilities (one relief team can have more than one capability) and each incident needs a specific ability to rescue.
- No interruption is allowed for the relief operations.

B. Mathematical model

According to the above definitions, the considered problem can be formulated by:

$$Min \sum_i \sum_k W_i . C_i^k \tag{2}$$

$$Min \sum_i DT_i \tag{3}$$

s.t.

$$\sum_{k=1}^{m} \sum_{r=1}^{R} X_{i[r]}^{k} = 1 \qquad i = 1,...,n \tag{4}$$

$$\sum_{i=1}^{n} X_{i[r]}^{k} \le 1 \qquad k = 1...,\text{m}; \text{r} = 1,...,R \tag{5}$$

$$X_{0[0]}^{k} = 1 \qquad k = 1, \dots, m \tag{6}$$

$$\sum_{i=1}^{n} X_{i[r+1]}^{k} \leq \sum_{i=1}^{n} X_{i[r]}^{k} \qquad r = 1, 2, \dots, R-1; k = 1, 2, \dots, m \tag{7}$$

$$PT_{[r]}^{k} = \sum_{i=0}^{n} P_{i}^{k} (1+\alpha)^{r-1} . X_{i[r]}^{k} \qquad k = 1, \dots, m; r = 0, 1, \dots, R \tag{8}$$

$$S_{[r]}^{k} \geq S_{ij}^{k} - BigM . (2 - X_{i[r]}^{k} - X_{j[r+1]}^{k}) \qquad \forall_{\{(i,j)|i \neq j\}} ; \forall_{k, r=1,2,\dots,R-1} \tag{9}$$

$$S_{[r]}^{k} \leq S_{ij}^{k} + BigM . (2 - X_{i[r]}^{k} - X_{j[r+1]}^{k}) \qquad \forall_{\{(i,j)|i \neq j\}} ; \forall_{k, r=1,2,\dots,R-1} \tag{10}$$

$$S_{[r]}^{k} \leq BigM . (\sum_{i=1}^{n} X_{i[r]}^{k}) \qquad k = 1, \dots, m; r = 1, \dots, R \tag{11}$$

$$C_{i}^{k} \geq (ST_{[r]}^{k} + PT_{[r]}^{k}) . X_{i[r]}^{k} \qquad i = 0, 1, \dots, n; k = 1, \dots, m; r = 0, 1, \dots, R \tag{12}$$

$$ST_{[r]}^{k} = (ST_{[r-1]}^{k} + PT_{[r-1]}^{k} + S_{[r-1]}^{k}) . (\sum_{i=1}^{n} X_{i[r]}^{k}) \qquad k = 1, \dots, m; r = 1, \dots, R \tag{13}$$

$$\sum_{r} X_{i[r]}^{k} \leq Cap_{i}^{k} \qquad i = 1, \dots, n; k = 1, \dots, m \tag{14}$$

$$DT_{i}^{k} \geq C_{i}^{k} - L_{i} . X_{i[r]}^{k} \qquad i = 1, \dots, n;\ j = 1, \dots, n;\ k = 1, \dots, m;\ v = 1, \dots, V \tag{15}$$

$$ST_{[r]}^{k} \leq \sum_{i} L_{i} X_{i[r]}^{k} \qquad k = 1, \dots, m; r = 1, \dots, R \tag{16}$$

$$X_{i[r]}^{k} \in \{0,1\};\ ST_{[r]}^{k}, P_{[r]}^{k}, S_{[r]}^{k}, C_{i}^{k}, DT_{i}^{k} \geq 0 \qquad i = 0, \dots, m; k = 1, \dots, m; r = 0, \dots, R \tag{17}$$

'

Equation (2) is the first objective function that minimizes the sum of the weighted completion time of the relief operation. Relation (3) denotes the second objective function that minimizes the sum of deprivation times. Constraint (4) indicates that each incident must be assigned to one of the rescue team's existing positions. Relation (5) guarantees that in each position of a rescue team, at most, one incident can be assigned. That's mean in each available position of the reduce team, either one incident be allocated, or this position remains empty (no incident assigned). Constraint (6) shows that the relief operation begins from the starting point (depot). Relation (7) is the flow balance constraint, which indicates that the positions of each relief team must be occupied in ascending order. Relation (8) calculates the actual processing time of incident *i*, which is scheduled in the *r*-th position of rescue team *k* due to the fatigue effect. Equations (9) to (11) measure the required travel time to go from the location of the incident in position *r* to incidents in position *r+1* by rescue team *k*. Relations (12) and (13) calculate the start and completion times in the relief operation. Constraint (14) indicates that rescue team *k* is only assigned to incident *i* if rescue team *k* is capable to serve incident *i*.

deprivation time is calculated in constraint (15). Relation (16) shows the time-windows constraint that indicates relief operation of the incident must be started before this corresponding time-window. Finally, constraint (17) shows a range of variables.

Number 2, which exists in Relations (9) and (10), balances these inequalities. To better understanding, we give an example below. Let $X^1_{2[1]}$ and $X^1_{4[1]}$ are equal to 1. Thus, rescue unit 1 should be traveled between the locations of incidents 2 and 4 with travel time S^1_{24}. Now, we have the following relations.

$$S^1_{[2]} \geq S^1_{24} - BigM.(2-1-1) \rightarrow S^1_{[2]} \geq S^1_{24} \tag{18}$$

$$S^1_{[2]} \leq S^1_{24} + BigM.(2-1-1) \rightarrow S^1_{[2]} \leq S^1_{24} \tag{19}$$

$$(18)\ \&\ (19) \rightarrow S^1_{[2]} = S^1_{24} \tag{20}$$

C. Linearization

Due to Relations (12) and (13), the proposed model is non-linear. To reduce the complexity of the proposed model and the computational time, these expressions can be converted to a linear one through Property 1.

Property 1: Suppose $C = A \times B$ is the multiplication of two decision variables so that A is a binary variable, and B is a continuous variable. The following equations can be used to linearize the non-linear terms (Glover & Woolsey, 1974):

$$C \leq B \tag{21}$$

$$C \leq BigM.A \tag{22}$$

$$C \geq B - BigM.(1-A) \tag{23}$$

The non-linear relation (12) is linearized using this property as follows:

$$Q^k_{[r]} = ST^k_{[r-1]} + PT^k_{[r-1]} + S^k_{[r]} \tag{24}$$

$$H^k_{[r]} = \sum_{i=1}^{n} X^k_{i[r]} \tag{25}$$

$$ST^k_{[r]} = Q^k_{[r]}.H^k_{[r]} \tag{26}$$

$$ST^k_{[r]} \leq Q^k_{[r]} \tag{27}$$

$$ST^k_{[r]} \leq M.H^k_{[r]} \tag{28}$$

$$ST^k_{[r]} \geq Q^k_{[r]} - M.(1-H^k_{[r]}) \tag{26}$$

Moreover, the relation (13) is converted to a linear form in the same method.

III. METHODOLOGY

This section is devoted to describing the solution method of this research. Based on the literature review, the ASRT problem, known as an NP-Hard one (Wex et al., 2014). Hence, the exact method cannot solve this problem in a reasonable time. This study develops a hybrid approach based on an Lp-metric method and meta-heuristic algorithms to handle this issue. The proposed hybrid algorithm is described below.

A. Lp-metric method

This paper applies the Lp-metric method to convert the proposed multi-objective model to a single one (Mirzapour Al-E-Hashem et al., 2011). In the mentioned method, the problem segregated into sub-problems that each problem is solved with the corresponding objective function separately. The problem is then reformulated as a single-objective programming model to minimize normalized differences between each objective function and its optimal value (Mirzapour Al-E-Hashem et al., 2011). Suppose that Z_1 and Z_1 denote the first and second objective functions, respectively. On the other side, Z_1^* and Z_2^* are optimal values for the first and second objective function. Under these conditions, the Lp-metric method considers the objective function formulated in Relation (27), where w shows the weight of the objective function (Mirzapour Al-E-Hashem et al., 2011).

$$Z_3 = [\mathrm{w}.\frac{Z_1 - Z_1^*}{Z_1^*} + (1-\mathrm{w}).\frac{Z_2 - Z_2^*}{Z_2^*}] \tag{27}$$

B. Genetic algorithm

The Genetic Algorithm (GA) introduced by Holland (1975) is a population-based algorithm widely applied to solve optimization problems. It starts by generating an initial population (a set of chromosomes). Then, each chromosome's fitness function is calculated, and chromosomes with higher fitness values will receive more chances to be selected for reproducing the next generation. Afterward, crossover and mutation operators are performed, and a new population is created. Then, a new population's fitness function is evaluated, and this loop continues until the stopping criterion is met. The structure of a chromosome is designed for this research, as described below:

Designing an efficient solution representation is essential in running algorithms (Mir & Rezaeian, 2016). In this section, we explain the chromosome that is designed in this paper. Our solution representation is divided into two parts. Assume there are *n* incidents and *m* rescue teams. The first part is composed of incidents symbols, from 1 to *n*, and the second section is composed of *m*-1 symbols, represented by "#", from 1 to *m*-1, to divide the relief operations to assign the relief teams. For instance, with *n* incidents and *m* relief teams, a solution includes (*n*+*m*-1) gens (Mir & Rezaeian, 2016). For example, Fig. 2 depicts an example with three rescue teams and seven incidents. Based on this figure, incidents 3 and 5 are allocated to rescue team 1, incidents 4, 2, and 1 are assigned to rescue team 2, and incidents 6 and 7 are assigned to rescue team 3.

The crossover operator used in this paper is a single-point crossover that is illustrated in Fig. 3. In this operator, as shown in Fig. 3, two parents are randomly selected from the population (i.e., parents 1 and 2) at the outset. Afterward, a cut point for parent strings is selected randomly. When a crossover point is determined, all elements before the crossover point are copied from the parent 1 to the first segment of the direct offspring 1. The second segment of the primary offspring one is made up of copying all elements after the crossover point from parent 2. The primary offspring two is made using a similar way. Due to some of the elements in the created offspring being repetitive, which leads to generating illegal solutions, the primary offspring must be reformed by applying a modification mechanism. Thus, to modify generated offspring, we reconnoiter the location of repeated elements, which appear in direct offspring before the crossover point.

Also, the mutation operator designed for this research is depicted in Fig. 4. In this operator, the following operations are performed.

- Swap: two genes of a solution are selected, and their positions are substituted.
- Inversion: two genes of a solution are selected, and the positions of every gens between them are reversed.

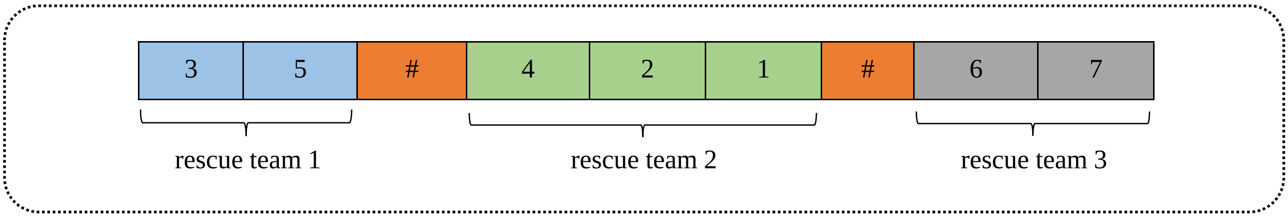


Fig. 2. Solution representation

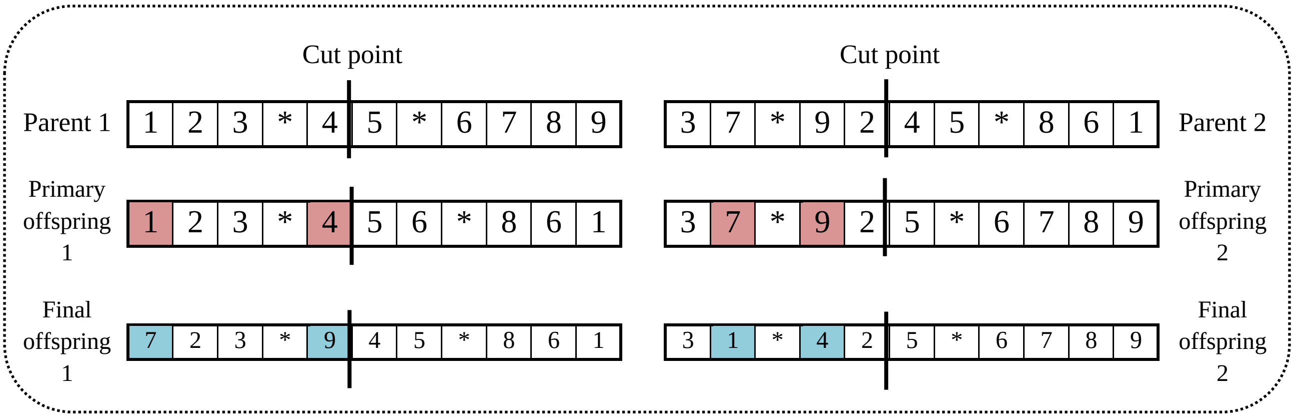


Fig. 3. Example of a crossover mechanism

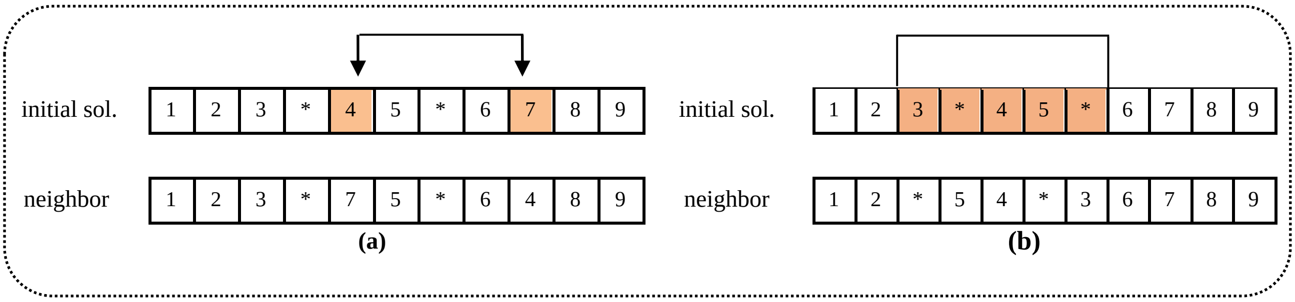


Fig. 4. Example of the mutation mechanism: (a) swap; (b) inversion

C. PSO algorithm

PSO introduced by (Eberhart & Kennedy, 1995) is a standard population-based random search method, which is designed to solve the optimization problems. In this algorithm, the position and velocity vectors of the particles are updated in each iteration, according to Eqs. (28) and (29).

$$x_i(\mathrm{k}+1) = x_i(\mathrm{k}) + v_i(\mathrm{k}+1) \tag{28}$$

$$v_i(\mathrm{k}+1) = w.v_i(\mathrm{k}) + \mathrm{c}_1.r_1.(pbest_i - \mathrm{x}_i(\mathrm{k})) + c_2.r_2.(gbest - x_i(\mathrm{k})) \tag{29}$$

where $X_i(k)$ shows the position vector of particle i in the k-th iteration and $v_i(k)$ represents the velocity vector of particle i in iteration k. $pbest_i$ is the best particle i obtained until iteration k, and $gbest$ is the global best position vector among the population in the k-th iteration, which is achieved so far. w shows Inertia weight, c_1 and c_2 denoted acceleration coefficients. r_1 and r_2 are random numbers between [0 1].

This paper uses a random key (RK) technique to transform a vector in continuous space to one in discrete space. In this approach, a position in RK continuous space is converted to discrete space. Every position in RK virtual space is indicated by a vector of real numbers, while a vector of integers indicates every position in the problem-solution space.

In this method, if there are m relief teams and n incidents. We generate $n+m$-1 random numbers in the interval [0, 1). Afterward, the random numbers are sorted in ascending order. The position of the sorted numbers considered as a solution structure. For example, consider a problem with seven elements, in which Fig. 4 shows an implementation of the RK method. The allocation of incidents to the rescue units is similar to the one mentioned for the GA.

D. Hybrid algorithm

This section devotes to explain the proposed hybrid algorithm. At first, in the Lp-metric method, the ideal solution must be determined as given in Table II. To do this, the values of both objective function are calculated for the initial population (or swarm). Here, the value of the first and second objectives represent by $f1_i$ and $f2_i$. Then, the best value of each objective function in an initial population (or swarm) is determined to utilize in used in GA and PSO as the fitness value obtained by the Lp-metric method. For example, the flow diagram of the Lp–GA algorithm is shown in Fig. 6.

0.3	0.75	0.42	0.1	0.68	0.05	0.55

Random numbers

1	2	3	4	5	6	7

Position of numbers

0.05	0.1	0.3	0.42	0.55	0.68	0.75

Sorted random numbers

6	4	1	3	7	5	2

Sorting based on the position of numbers

Fig. 5. An example of the RK method

As can be seen in Fig. 6, at first, the initial population is generated randomly. Then, the objective functions for each solution are measured. The *Fmin* is calculated by using the previous step results. Afterward, the fitness function related to Lp-Metric method is evaluated for solutions. Eventually, if the stopping criterion is satisfied, the algorithm is terminated. Otherwise, a new population is generated by applying crossover and mutation operators, and the loop is made again.

IV. COMPUTATIONAL EXPERIMENTS

This section presents the results obtained by the proposed methods. At first, necessary data is estimated, then parameters of the algorithms are tuned, and next, the proposed model is solved using the developed algorithms, and obtained results are reported.

A. Data generation

In this study, the problem size is determined by the number of incidents (n), which varies from 6 to 40, and the number of rescue units (m), which varies from 2 to 20. According to Wex et al. (2014), the processing times of the incidents are generated based on a normal distribution with average value 20 and variance value 10 and the travel time has a normal distribution with average value 1 and variance value 0.3.

Table II. Maximum and minimum values for hybridization of the GA (PSO) and Lp-metric

Population (swarm) number	*First objective function*	*Second objective function*
*P*1 (*S*1)	f_{11}	f_{21}
*P*2 (*S*2)	f_{12}	f_{22}
*P*3 (*S*3)	f_{13}	f_{23}
…	…	…
Pn (*Sn*)	f_{1n}	f_{2n}
fmin	f_{1min}	f_{2min}

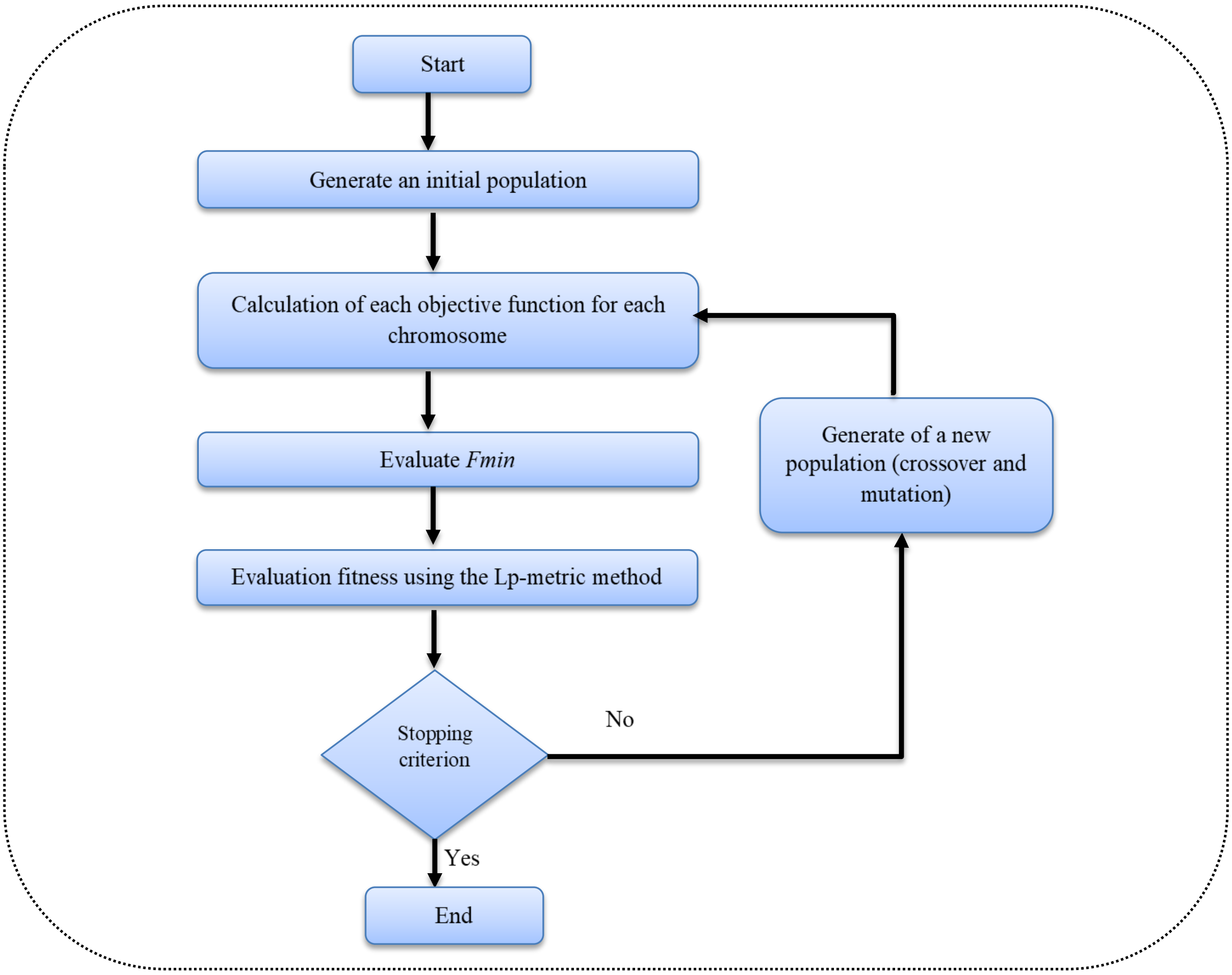


Fig 6. Flow diagram of the Lp-GA algorithm

The factor of the destruction of an incident shows the severity level of the incidents, as introduced by the U.S. Department of Homeland Security (2008): low (1), guarded (2), elevated (3), high (4), and severe (5) harm. Hence, we select a discrete uniform distribution for the severity levels in the interval of $[1, 5]$. Capabilities of rescue units are created in a zero-one matrix, and the fatigue effect is equal to 0.15.

B. Parameter setting

Each meta-heuristic algorithm has some parameters, whose values of these parameters dramatically impact the performance of the algorithm. There are various methods to tune the parameters of the algorithms, in which the Taguchi method (Taguchi, 1986) is used to caliber the parameters. This approach tune the parameter based on the signal-to-noise ratio. In this paper, the maximum iteration ($MaxIt$), number of population ($Npop$), rate of crossover (Pc) and rate of mutation (Pm) are considered as the GA parameters, and $MaxIt$, $swarm\ size$, w, $C1$, and $C2$ are considered as PSO parameters. Table III shows the parameters and their levels for the Taguchi design. The S/N ratio charts obtained by implementing the Taguchi method in MINITAB software are given in Fig. 7. In the Taguchi method, whatever the S/N ratio is at the highest level, the parameter value is better. Hence, according to this figure, the best value for each parameter of the algorithms are given in Table IV.

C. Report on the results

In this section, the obtained results are reported and analyzed. Table II shows the results of solving the considered problem using the proposed algorithms. In this research, 15 test problems of various sizes are designed, and these problems solve with the proposed algorithms. Then, the values of the first objective function, second objective function, Lp-metric objective function, and CPU time are reported in Table V. It should be noted that the algorithms run each test problem 10 times, and the best value obtained for objective functions is reported. It should be noted that the values for the parameters of the algorithms are selected based on some related papers in the literature (e.g., Nayeri et al. (2018a) and Mir & Rezaeian (2016)).

Table III. Parameters and their levels in the GA and PSO algorithms

Algorithm	Parameter	Level		
		1	2	3
GA	*MaxIt*	300	400	500
	Npop	50	60	70
	Pc	0.6	0.7	0.8
	Pm	0.1	0.2	0.3
PSO	*MaxIt*	300	400	500
	Swarm-Size	50	60	70
	C1	1	1.5	2
	C2	1	1.2	2
	W	0.4	0.9	1.2

Table IV. Best values for parameters

Algorithm	*Parameter*	*Best level*	*Value*
GA	*MaxIt*	1	300
	Npop	1	50
	Pc	1	0.6
	Pm	1	0.1
PSO	*MaxIt*	1	300
	Swarm-size	2	60
	C1	3	2
	C2	3	2
	W	3	1.2

Table V. Results of the solving algorithms

TP	*(m,n)*	*GAMS*			*Hybrid GA-Lp*				*Hybrid PSO-Lp*			
		FOF	*SOF*	*CPUT (s)*	*FOF*	*SOF*	*PRE/RPD*	*CPUT (s)*	*FOF*	*SOF*	*PRE/RPD*	*CPUT (s)*
1	(2,6)	1640.8	0	17.3	1640.8	0	0.0	31.2	1640.8	0	0.0	29.8
2	(3,7)	1758.3	3.1	28.8	1758.3	3.1	0.0	35.5	1758.3	3.1	0.0	30.1
3	(3,8)	1997.5	8	40.5	1997.5	8	0.0	37.3	1997.5	8	0.0	31.5
4	(4,8)	1908.1	4.5	57.3	1908.1	4.5	0.0	37.8	1932.7	6.3	1.3	33.5
5	(5,9)	2275.6	13.2	72.8	2394.8	16.4	5.2	40.2	2402.8	18.5	5.6	35.4
6	(5,10)	2518.2	20.5	184.1	2605.7	23.2	3.5	45	2695.1	23.2	7.0	41.8
7	(6,10)	2393.5	15.7	256.5	2500	17.9	4.4	51.8	2577.3	19.3	7.7	46.2
8	(6,12)	2671.8	21.1	481.6	2818.5	29.5	5.5	66.9	2895.7	33.6	8.4	60.5
9	(7,12)	2867.1	18.9	657	2976.3	25.2	3.8	72.5	3092.1	25.2	7.8	66.8
10	(7,15)	3196.5	34.6	903.7	3375.8	42.1	5.6	80.3	3448.5	46.5	7.9	73.3
11	(10,20)	N/A	N/A	>10000	5108.3	73.8	0.0	145.7	5170.9	81.1	1.2	126.1
12	(11,20)	N/A	N/A	>10000	4983.1	66.5	0.0	145.8	5038.3	74.8	1.1	129.5
13	(11,25)	N/A	N/A	>10000	6682.6	87.2	0.0	151.3	6758.5	95.4	1.1	136.7
14	(12,25)	N/A	N/A	>10000	6437.5	79.8	0.0	158.1	6510.1	88.5	1.1	141.2
15	(12,30)	N/A	N/A	>10000	7815.9	112.3	0.0	167.2	7955.6	125.1	1.8	150.6
16	(14,30)	N/A	N/A	>10000	7534.2	92.5	0.0	166.5	7610	100.8	1.0	155.3
17	(15,30)	N/A	N/A	>10000	7375.6	83.4	0.0	168.3	7452.9	91.2	1.0	153.1
18	(18,35)	N/A	N/A	>10000	8856.3	100.8	0.0	171.3	8975.2	110.6	1.3	156.8
19	(19,35)	N/A	N/A	>10000	8275.5	91.4	0.0	178.8	8380.7	101.7	1.3	161.7
20	(20,40)	N/A	N/A	>10000	9578.4	115.6	0.0	182.4	9688.5	130.2	1.1	163.5

TP: Test Problem; FOF: First Objective Function; SOF: Second Objective Function; LP: LP-metric objective function; CPUT: Computational Time

To validate the results obtained by the proposed algorithms, test problems in small sizes (problems 1-10) are solved with the exact method (i.e., GAMS software), and the Percentage Relative Error (PRE) is used for examining the algorithms. The PRE is computed by:

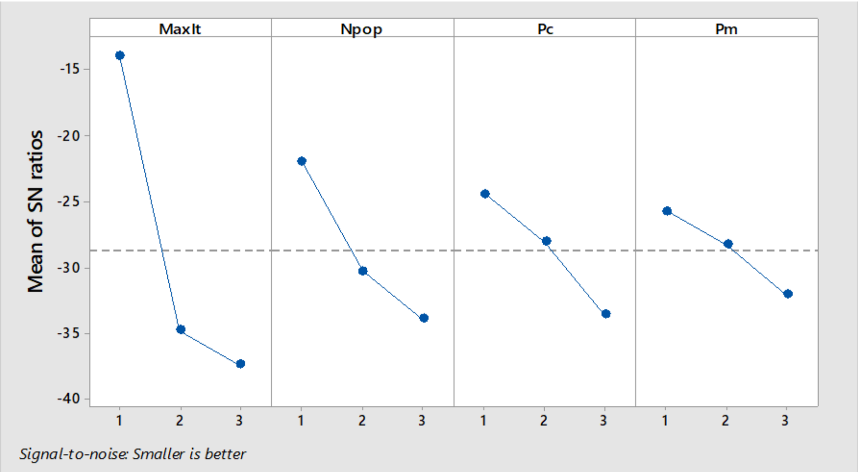
$$PRE = \frac{ALG_{sol} - OPT_{sol}}{OPT_{sol}} \times 100 \qquad (28)$$

Where, OPT_{Sol} and ALG_{Sol} are the optimum value obtained by GAMS software and the objective value obtained by each proposed meta-heuristic algorithm, respectively.

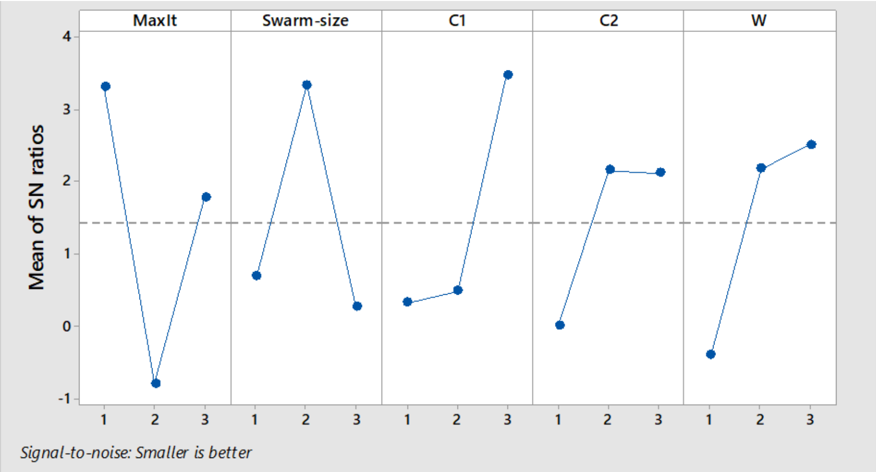
For large-sized test problems (problems 11-20), the solution obtained by algorithms compared using the Relative Percentage Deviation (RPD) criteria, which is measured by:

$$RPD = \frac{ALG_{sol} - Best_{sol}}{Best_{sol}} \times 100 \qquad (29)$$

The ALG_{sol} is the solution obtained by the algorithm, and the $Best_{sol}$ is the best solution of all algorithms.



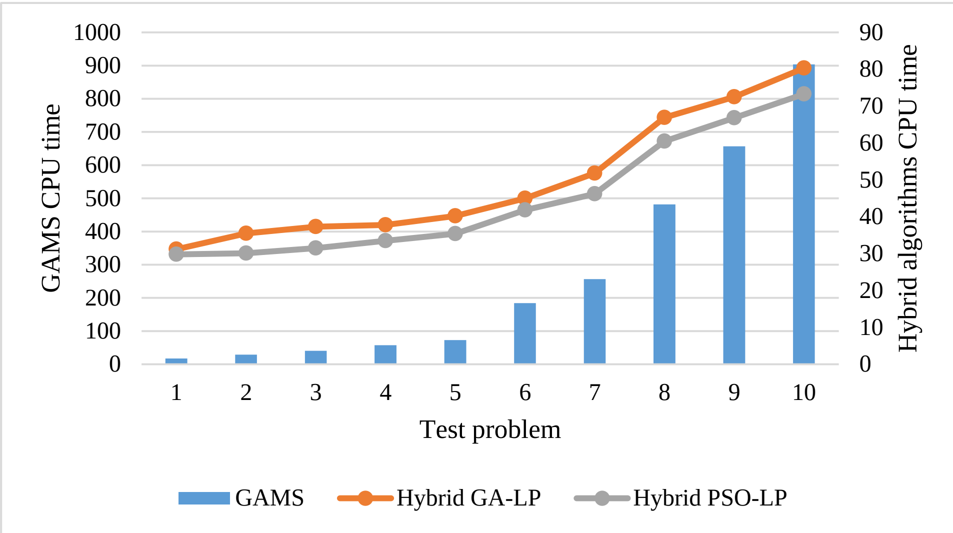
(a) GA



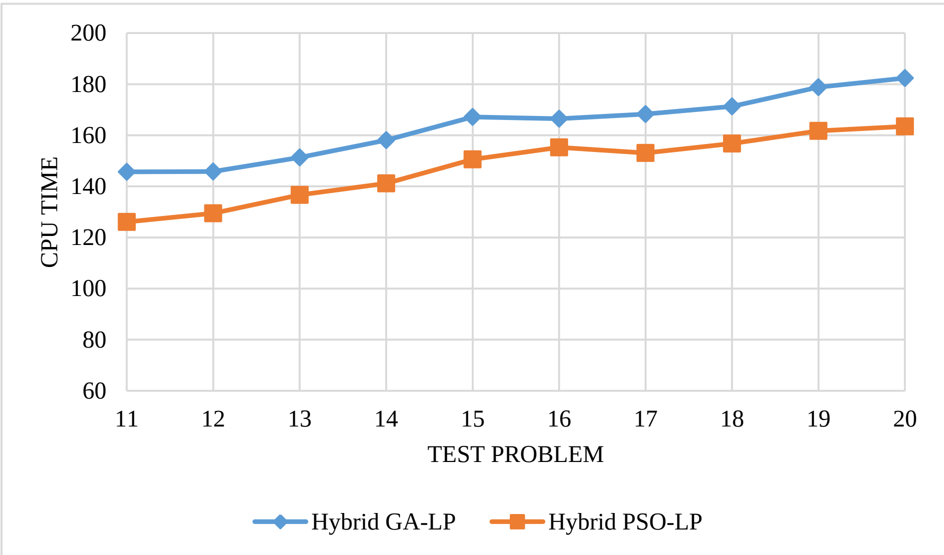
(b) PSO

Fig. 7. Taguchi ratios for the proposed algorithms

As shown in Table V, the proposed hybrid algorithms can obtain optimal/near-optimal solutions in a shorter CPU time than GAMS software. Fig. 8(a) shows the comparing between GAMS software and the proposed algorithms in small-sized test problems. Based on Fig. 8(a), the developed algorithms significantly have better performance than the exact method in terms of CPU time. Also, Fig. 8(b) presents the CPU times of the algorithms in solving large-sized instances. According to Fig. 8(b), in large-sized instances, the performance of the hybrid PSO-Lp algorithm is better performance of the GA-lp in terms of the CPU time metric.



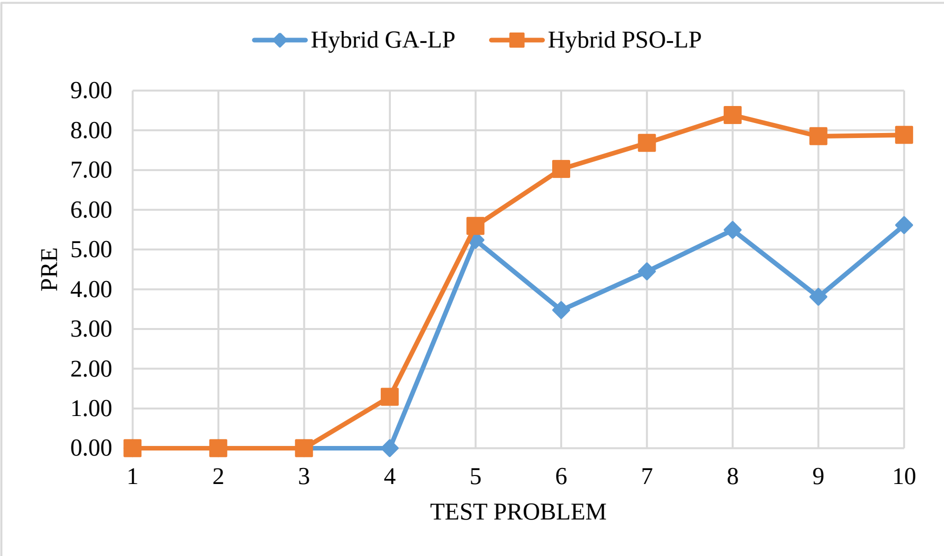
(a) Small-sized problems



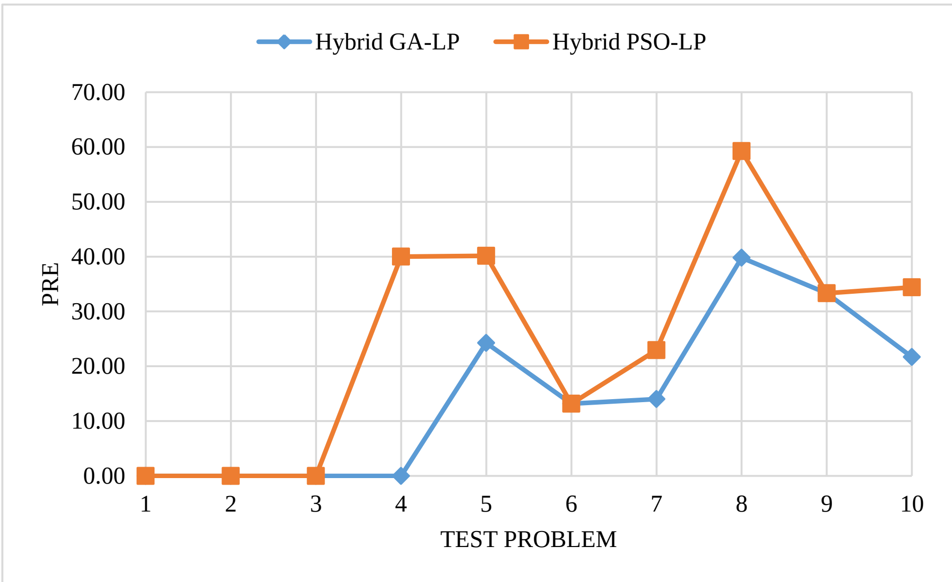
(b) Large-sized problems

Fig. 8. Comparing the CPU time of the algorithms

In association with the quality of solutions, the obtained results are compared in Figs. 9 and 10. Fig. 9 shows that the developed algorithms can obtain optimal/near-optimal solutions with low deviation. Moreover, based on Fig. 9(a), in small-sized instances, the hybrid GA-Lp performance is better than another algorithm in terms of solution quality for the first objective function. Also, as shown in Fig. 9(b), for the second objective function, the performance of the GA-Lp algorithm is better than another one. On the other side, an analysis of variance (ANOVA) is applied to evaluate the statistical validity of the obtained results according to the RPD criteria. Fig. 10 represents the LSD (least significant deviation) diagram for the metaheuristic approaches at the confidence level of 95%. According to Fig. 10, the GA-Lp has better performance than PSO-Lp in RPD criteria.

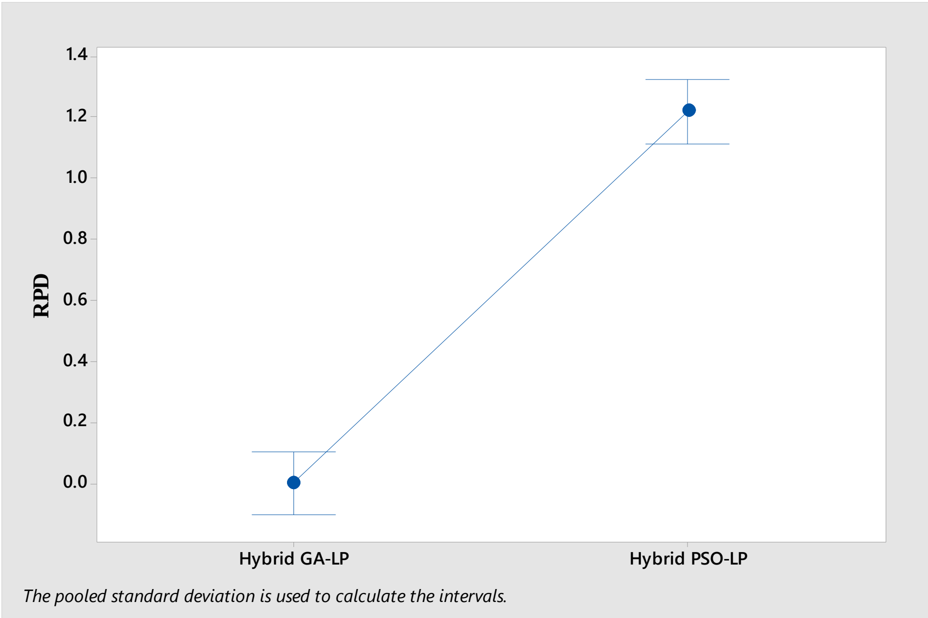


(a) Second objective function

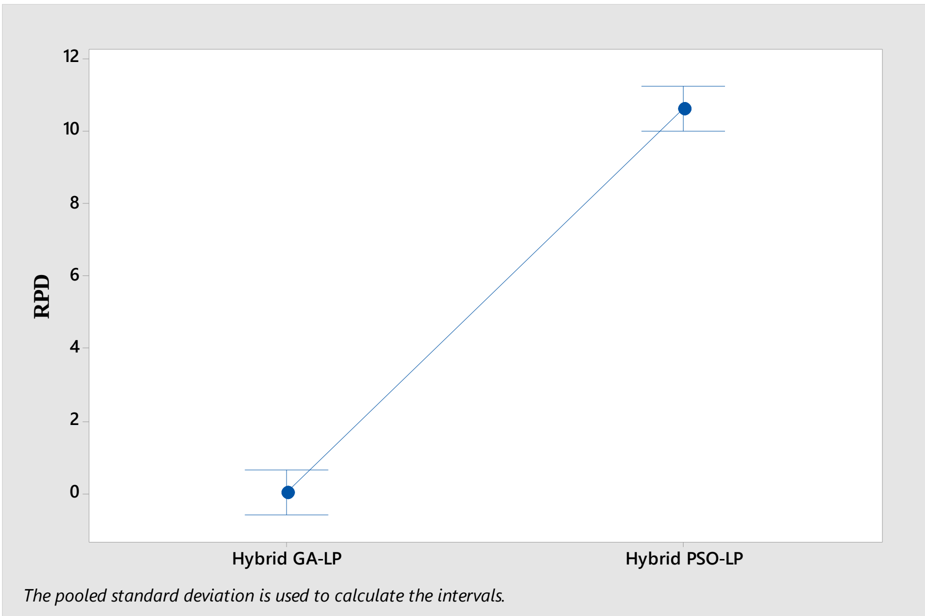


(b) First objective function

Fig. 9. Comparing the quality of solutions (PRE)



(a) Second objective function



(b) First objective function

Fig. 10. Comparing the quality of solutions (RPD)

D. Sensitivity analysis

This section devotes to examine the impact of changing the value of some parameters on both objective functions. Thus, a test problem is designed and solved in different modes, and results are reported. At first, the impact of the fatigue effect value on the objective function is investigated. The test problem is solved with different values of α, and the result is illustrated in Fig. 11. As can be seen in this figure, increasing the fatigue effect parameter leads to an increase in both objective functions. The results show that a 0.3 increase in the fatigue effect leads to a 41% increase in the first objective function and a 38% increase in the second objective function. These points show the significant effect of rescuers' physical power inefficiency of the operation relief.

The test problem was also solved with different values for the traveling time parameter (-20%, -10%, Base Case, +10%, and +20%). The sensitivity analysis results are depicted in Fig. 12, which shows that increasing the travel time leads to an increase in both objective function values almost linearly. Based on Fig. 12, a 20% decrease in travel time from the base case resulted in a 17% improvement in the first objective function and a 27% improvement in the second objective function. On the other side, a 20% increase in travel time than the base case leads to a 19% increase in the first objective function and a 33% increase in the second objective function.

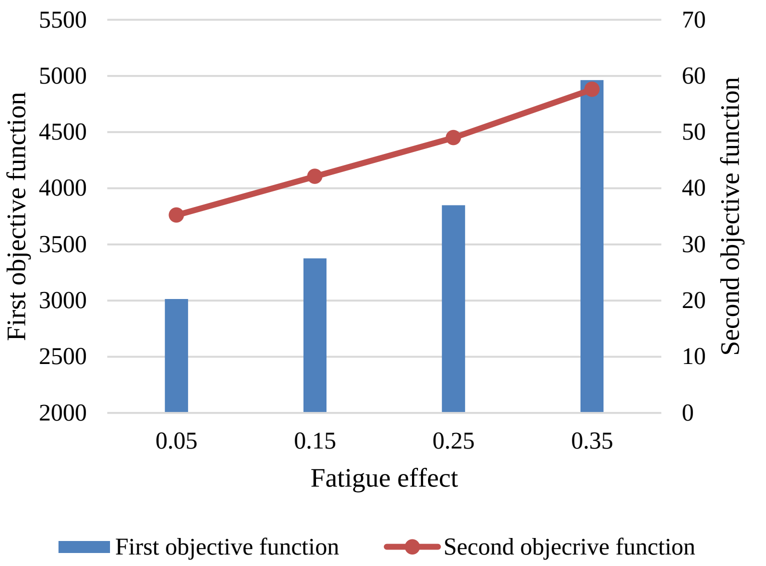


Fig. 11. The sensitivity of the objective function values to the fatigue effect

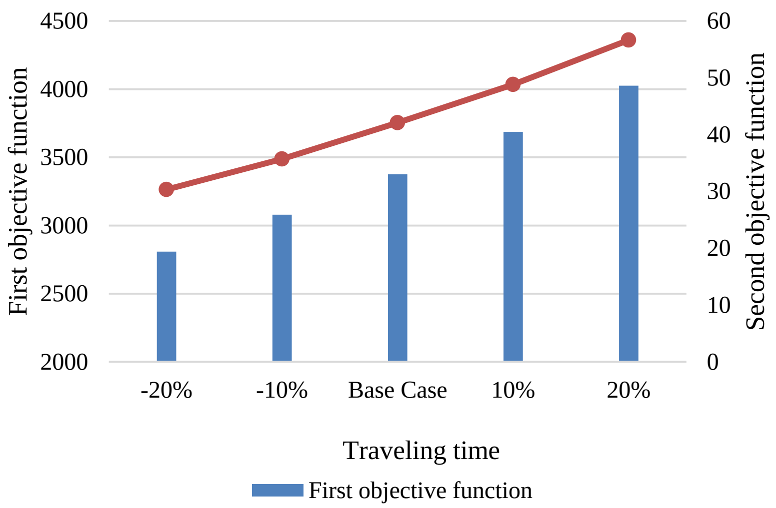


Fig. 12. The sensitivity of the objective functions to the traveling time

V. CONCLUSIONS

This paper addressed the ASRT problem, which played an essential role in the response phase of disaster management. The literature showed that the researchers had paid less attention to multi-objective programming models and social aspects (e.g., deprivation time) in this research field. In this study, a multi-objective MIP model was proposed to minimize the total weighted completion times and the sum of deprivation times. The deprivation time, known as one of the social concepts in disaster management problems according to this phenomenon, the lack of timely relief, implied a loss in people's welfare. In this paper, to more similarity to the real world, some features like different capabilities for rescue teams, different ability to process incidents, fatigue effect, and time windows were considered. Then, due to the complexity of the considered problem, two hybrid algorithms based on the Lp-Metric method and meta-heuristic algorithms were developed to solve the proposed model in a reasonable time. The results showed that the developed algorithms could obtain optimal/near-optimal solutions in a reasonable time. In detail, in terms of CPU time, the PSO-Lp algorithm has better performance than GA-Lp. On the other side, the GA-Lp algorithm has better performance than PSO-Lp in terms of the quality of the solutions. The sensitivity analyses showed that a 20% decrease in travel times could improve the first and the second objective functions by 16% and 27%, respectively. Also, the significant impact of the fatigue effect on the objective functions is observed from the results, so that 0.3 increase in the fatigue effect resulted in 41%. Eventually, some managerial insights are provided based on the obtained results to improve operation relief. We suggested to managers of emergency operations that try to increase the physical power of rescuers that leads to improve in the objective function drastically. Also, some strategies are used to reduce the travel time that leads to dramatically decrease in the total completion time and deprivation time.

Suggestions for future studies include considering assignments of the collaborative rescue teams (co-allocation) to each incident and considering different modes for travel the rescue teams. Researchers can also be considered uncertainty in the research problem and apply robust convex optimization methods, robust fuzzy optimization, to tackle uncertainty. Another direction for future research is to investigate the problem under multi-depot mode.

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