International Journal of Industrial Engineering & Production Research (2018)

March 2018, Volume 29, Number 1
pp. 65- 78

DOI: 10.22068/ijiepr.29.1.65 http://IJIEPR.iust.ac.ir/

Goal Programming-Based Post-Disaster Decision-Making for Allocation and Scheduling of the Rescue Units in Natural Disasters with Time Windows

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KEYWORDS

Natural disaster management,
Decision support model,
Multi-choice goal programming,
parallel machine scheduling problem.

ABSTRACT

Natural disasters, such as earthquakes, tsunamis, and hurricanes, result in enormous harm during each year. To reduce casualties and economic losses in the response phase, rescue units must be allocated and scheduled efficiently so as to be prepared for any emergency responses. In this paper, a bi-objective mixed integer linear programming model (BOMILP) is proposed to minimize the sum of weighted completion times of relief operations and makespan, considering time window for the incidents. The rescue units also have different capabilities, and each incident must be allocated to a rescue unit that has the ability to do it. By considering incidents and rescue units as jobs and machine, respectively, the research problem can be formulated as a parallel machine-scheduling problem with unrelated machines. To handle the bi-objective model, a Multi-Choice Goal programming (MCGP) approach is applied to solve the research problem. The experimental results show the efficiency of the proposed approach to allocate and schedule the rescue units during natural disasters.

1. Introduction

Natural disasters, such as earthquakes, tsunamis, floods, hurricanes, and volcanic eruptions, caused tremendous harm in the past and continue to threaten infrastructure and the lives of millions of people in each year. The particular importance concerning reduction of casualties and economic losses is the response phase in natural disaster management, during which a large number of geographically dispersed incidents, such as fires and collapsed buildings, require immediate processing by the rescue units in the presence of severe resource scarcity and time pressure. Thus, one of the most critical emergency response tasks is to allocate and schedule rescue units efficiently [1]. As there is no any rescue unit that can prevent all kinds of incidents in the real world and each incident must be allocated only to the rescue units capable of handling it (i.e., there is a specific unit for the medical services and another distinct unit for quenching the fires), the

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Received 7 June 2017; revised 27 Janury 2018; accepted 5 February 2018

allocation and scheduling of the rescue units is extremely difficult and taxing. In traditional methods of disaster management, the incidents are usually allocated to the rescue units in descending order of their severity level, in which the incidents are assigned to the rescue units that have the ability to handle. In other words, the incidents with higher levels of destruction are assigned to the capable units and, then, incidents with lower severity levels will be allocated to them. This process is done manually without any decision support model.

This research is aimed at developing a decision support model to help the managers to make better decisions when facing the problems. According to the literature, this challenge has been addressed very rarely; therefore, in this paper, we propose a decision support model for emergency operation centers that allocate available rescue units to the emerging incidents. The model is formulated as a mixed integer optimization problem, where the objective functions are to minimize the sum of completion times of incidents weighted by their severity and makespan.

With respect to the general aspects of the research problem, it can be demonstrated that the research problem can be modelled as a modification of the Multiple Traveling Salesman Problem (mTSP) [2] as well as the parallel-machine scheduling problem with unrelated machines and sequence-dependent setup times [3]. In the routing domain, the problem is related to the mTSP. To prove the relationship with mTSP, one needs to map rescue units to salesmen and incidents to cities/nodes. In this analogy, the traveling time between the incidents is identical to the traveling time between two cities or nodes. This problem is also related to problems in the scheduling literature. By considering rescue units, incidents and traveling time as machines, jobs and sequence-dependent setup times, respectively, the natural disaster management problem is similar to the unrelated parallel-machine scheduling problem with sequence-dependent setup times.

In practice, some incidents must be prevented at a certain time interval. For example, lateness in rescuing people during earthquake phenomenon can lead to casualties, or starting relief operation for a fire accident will not be effective with lateness. To the best of our knowledge, the aforementioned point has not been considered in previous related researches. In this paper, to deal with this challenge, time windows are considered for the incidents. Time window means that the relief operation of an incident must be started at a certain time interval. It is an important issue in the earthquake, especially when humans are buried alive and require to be saved, quickly.

According to the importance of emergency response tasks in the natural disasters and their complexities, it is necessary to develop a decision support model for the emergency centers. Hence, we propose such a system where the decision support model allocates incidents to the available rescue units and schedules these incidents by considering different capabilities of each rescue unit and time window.

The remainder of the paper is organized as follows. The relevant literature is introduced in section 2. Section 3 defines research aims and contributions. Section 4 defines the research problem and presents a mathematical model and goal programming approach. Section 5 gives the experimental results, and section 6 presents discussion and some suggestions for the future works.

2. Literature Review

In the literature, challenges and activities in a natural disaster are classified into the preparation phase (the period before the disaster), the response phase (the period during and shortly after the disaster), and the recovery phase (the long time period after the disaster) [4,5,6]. More specifically, the preparation phase addresses tasks related to planning, training, early warning, and establishment of the necessary emergency services [7,8,9,10,11]. The primary aims during the response phase are to rescue one from an immediate danger and stabilize survivors' conditions. The main tasks of the response phase in the disaster include relief, emergency shelter, and settlement, emergency health, water, sanitation, tracing and restoring family links [6]. In the recovery phase, the tasks are related to person finding, data analysis, intelligent infrastructure repair, and provision of the various emergency services as well as resources in order to recover the most important infrastructure facilities [12,13,14]. According to Chen [15], these phases are arranged in a life cycle sometimes.

Many researchers proposed some decision support systems to manage the challenges and activities in a disaster. The combination of the applied statistical methods and probability theory with mathematical programming approaches can help commanders in the critical minutes of the decision-making [16,17,18,19]. Fiedrich et al. [20] introduced application of the optimization models to the natural disaster management problem. Furthermore, artificial intelligence is used to cover the research gap between designing the information system and decision support model architectures [21,22]. In continuation, researchers have used empirical investigations of past decision-making conclusions to establish innovative courses of action [23]. Another research stream also focuses on the decision-making process based on either decentralized agents or a centralized authority [17,24]. Beheshtinia et al. [25,26] studied the vehicle routing problem in the natural disaster management. Setak et al. [27] provided a dynamic vehicle routing model for emergency logistics operations in the occurrence of natural disasters. Some researchers also developed single and multi-objective mathematical models for designing a post-disaster logistics operations [28,29,30,31].

Rolland [32] promoted centralized coordination by applying a mathematical programming model for scheduling the distributed rescue units and the assignments of the incidents to these rescue units. In the proposed model, he considered the fixed time periods. Wex [3,33,34,35] suggested mathematical formulations and a Monte Carlo-based heuristic for the centralized scheduling and allocation of the rescue units under certainty and under uncertainty. Zhang et al. [36] formulated the resource allocation model (RAM) as a two-stage mixed integer linear programing Model (MILP). In the first stage, the total loss is minimized, and the second stage problem aims to optimize the resource allocation for the rescue service in the rescue time horizon by a heuristic algorithm which has polynomial complexity. Visheratin et al. [37] applied a hybrid algorithm to schedule some components of the early warning system (EWS).

Some of the important studies in the natural disaster management are categorized in Table 1.

Tab. 1. Some of the important studies related to this research

Paper	Mathematical modeling		Allocation & scheduling	Time-windows	Methodology
	Single objective	Multi objective			
Fiedrich et al. [20]	✓				Simulated Annealing
Tamura et al. [19]	✓				Value function under risk
Rolland et al. [32]	✓		✓		Hybrid heuristics
Wex et al. [34]	✓		✓		Monte Carlo simulation
Wex et al. [35]	✓		✓		Mont Carlo simulation
Wex et. al [3]	✓		✓		Mont Carlo simulation
Zhang et al. [36]	✓				Heuristic algorithm
Visheratin et al. [37]	✓				Hybrid scheduling algorithm
Present research		✓	✓	✓	Multi-choice goal programming

According to the literature, it can be concluded that the allocation and scheduling of the rescue unit in the natural disaster are rarely studied in the literature. The proposed models in all of the previous researches are a single-objective, aimed especially at minimizing sum of the weighted completion times. In this study, we consider a bi-objective model by inserting the makespan minimization as the second objective function. In addition, unlike the previous researches, in this study, a time window is considered for starting time of the incidents, and relief operation of every incident should be started in a certain time interval.

In this paper, a bi-objective mixed integer non-linear model is proposed by considering time window for the incidents to allocate and schedule the rescue units in the natural disaster. Note that the non-linear proposed model after some changes will be converted into a linear form, and a goal programming approach with utility function is applied to solve the mathematical model.

3. Research Aims and Contributions

According to the literature, allocation and scheduling of the rescue units is one of the important issues in the response phase of the natural disaster management, which is considered as post-disaster actions [1,3,32]. Designing an efficient decision support model to allocate and schedule the rescue units in the natural disasters can help reduce casualties and losses, substantially. This research is aimed at developing a decision support model to help managers make better decisions in the natural disasters.

According to the literature, allocation and scheduling of the rescue units in the natural disaster management have been rarely studied. In the entire previous researches, there is no restriction about the starting time of the relief operations at a certain time interval. This point in this research is considered as time window. Furthermore, the studied objective function by Rolland [32] and Wex et al. [3,33,34,35] only minimizes the weighted sum of the completion times; however, in addition to weighted sum of the completion times, we also add the makespan as the second objective function and propose a bi-objective mixed integer programming model.

As a result, a decision support model is developed to allocate and schedule the rescue units in the natural disaster by considering the time window for incidents in this research. With respect to bi-objective model, minimizing the sum of weighted completion times and makespan, we use the multi-choice goal programming, considering a utility function, to solve the proposed bi-objective model.

4. Problem Description

This section is devoted to proposing a mathematical model for allocation and scheduling of the rescue units. The problem size is determined by the number of available rescue units (*m*) and the number of incidents (*n*) that needs to be processed. In addition to the existing *n* incidents, we add two dummy incidents given by 0 as the starting point (named depot) and n+1 as the ending point. These require no processing time, yet unit *k* needs a given traveling time to move from its starting location to incident *j*. In addition to that, we set the travelling time between incident *i* and dummy incidents n+1 equal to zero.

Furthermore, we account the following assumptions and properties:

- The number of available rescue units is smaller than that of incidents.
- A weighted factor, named destruction factor or severity, is assigned to each incident.
- The incident with lower destruction factor has less severity.
- A time window is considered for the start time of the incidents.

In addition, some unique properties, which are considered in this research, are as follows:

Property 1: No rescue unit can process any incident; thus, we consider both specific requirements of the incidents and different capabilities of the rescue units.

Property 2: Processing times are dependent on the incidents and rescue units (incident-specific and unit-specific).

Property 3: traveling times moving between the locations of the incidents are different for the rescue units.

Property 4: All the rescue units begin their relief operations from the depot.

Property 5: Processing of an incident cannot be interrupted.

4-1. Relation between the research problem and the mTSP problem

As mentioned before, the research problem is closely related to the mTSP. At first, the processing and travel times are aggregated as overall traveling times in this research. To consider **Property 1**, we can set the corresponding decision variables to 0 in the mTSP. Based on **Properties 2** and **3**, the traveling time requires being salesman specific, and these properties must be modelled as salesman-specific traveling times between two cities. Furthermore, **Property 4** (starting from depot) and **Property 5** (non-preemption) are inherently included in the mTSP. As a result, we conclude that the research problem can be considered as mTSP with salesman-specific traveling times.

4-2. Relation between the research problem and unrelated parallel machine scheduling problem

The research problem is also related to problems in the scheduling literature. If we consider the rescue units as machines, the incidents as jobs, and traveling times as sequence-dependent setup times, then the research problem is also similar to the parallel machine scheduling problem with unrelated machines and sequence-dependent setup times [3]. **Property 1** can be modelled by setting the corresponding decision variables to 0. In the general scheduling problems, the setup time is only dependent on the jobs; however, with respect to **Property 3**, not only the travel time (setup time) is dependent on the incidents (jobs), but also it depends on the rescue unit (machine). Thus, any formulation of the unrelated parallel machine scheduling problem with sequence-dependent setup times can be applied to the research problem, such that properties 3 and 4 must be held, only.

4-3. Indices, parameters and decision variables

The necessary indices, parameters, and decision variables to develop the mathematical model are as follows:

i,j,l: Index of incidents (i,j,l=1,2,…,n)

k: Index of rescue unit (k=1,2,…,m)

PT_i^k: The necessary time to process incident i by rescue unit k; if rescue unit k is able to process incident i

T_{ij}^k: Traveling time from the location of incident i to the location of incident j by rescue unit k

W_i: Destruction factor (severity level) of incident i

Cap_i^k: 1 if rescue unit k is capable to address incident i; 0 otherwise.

$[e_i, l_i]$: The time window of incident i

Y_{ij}^k: 1 if incident i is processed by rescue unit k (at any time) before processing incident j; 0 otherwise

X_{ij}^k: 1 if incident i is processed by rescue unit k immediately before processing incident j; 0 otherwise

ST_i^k: Starting time of the incident i by rescue unit k.

FT_i^k: Completion time of incident i which is scheduled on rescue unit k.

$FT_{\max}$: Makespan

4-4. Model formulation

The proposed mixed integer programming model is as follows:

$$\text{Min} \sum_i \sum_k W_i . FT_i^k \qquad (1)$$

$$\text{Min } FT_{\max} \qquad (2)$$

$$\sum_{i=0}^{n} \sum_{k=1}^{m} X_{ij}^k = 1 \qquad j=1,\dots,n \qquad (3)$$

$$\sum_{j=1}^{n+1} \sum_{k=1}^{m} X_{ij}^k = 1 \qquad i=1,\dots,n \qquad (4)$$

$$\sum_{j=1}^{n+1} X_{0j}^k = 1 \qquad k=1,..,m \qquad (5)$$

$$\sum_{i=1}^{n} X_{i(n+1)}^k = 1 \qquad k=1,..,m \qquad (6)$$

$$Y_{il}^k + Y_{lj}^k - 1 \le Y_{ij}^k \qquad i=0,..,n;\ j=1,...,n+1;\ k=1,\dots,m \qquad (7)$$

$$\sum_{i=0}^{n} X_{il}^k = \sum_{j=1}^{n+1} X_{lj}^k \qquad l=1,\dots,n;\ k=1,\dots,m \qquad (8)$$

$$X_{ij}^k \le Y_{ij}^k \qquad i=0,..,n;\ j=1,...,n+1;\ k=1,\dots,m \qquad (9)$$

$$Y_{ii}^k = 0 \qquad i=0,..,n+1 \qquad (10)$$

$$Y_{ij}^k \le Cap_{ki} \qquad i=0,..,n;\ j=1,...,n+1;\ k=1,\dots,m \qquad (11)$$

$$\sum_{l=1}^{n+1} X_{il}^k \ge Y_{ij}^k \qquad i=0,..,n;\ j=1,...,n+1;\ k=1,\dots,m \qquad (12)$$

$$\sum_{l=0}^{n} X_{lj}^{k} \geq Y_{ij}^{k} \qquad i=0,..,n \quad j=1,...,n+1 \quad k=1,\dots,m \tag{13}$$

$$e_i \leq ST_i^k \leq l_i \qquad i=0,..,n+1 \quad k=1,\dots,m \tag{14}$$

$$ST_j^k = (ST_i^k + PT_i^k + T_{ij}^k).X_{ij}^k \qquad i=0,..,n \quad j=1,...,n+1 \quad k=1,\dots,m \tag{15}$$

$$FT_i^k \geq (ST_i^k + PT_i^k).X_{ij}^k \qquad i=0,..,n \quad j=1,...,n+1 \quad k=1,\dots,m \tag{16}$$

$$FT_{\max} \geq FT_i^k \qquad i=0,..,n+1 \quad k=1,\dots,m \tag{17}$$

$$X_{ij}^k, Y_{ij}^k \in \{0,1\}$$
$$ST_i^k, FT_i^k, FT_{\max} \geq 0 \qquad i=0,..,n \quad j=1,...,n+1 \quad k=1,\dots,m \tag{18}$$

Expression (1) represents the first objective function which minimizes the weighted sum of completion times of all the incidents. The second objective function is presented in expression (2) that aims to minimize makespan. Constraint set (3) ensures that there is exactly one incident that is processed immediately before each of *n* non-dummy incidents. Similarly, constraint set (4) ensures that there is exactly one incident that is processed immediately after each of *n* non-dummy incidents. Constraint sets (5) and (6) guarantee that each rescue unit starts processing the dummy incident 0 (the depot) and each rescue unit ends processing the dummy incident *n+1*. Constraint set (7) accounts for the transitivity in predecessor relationships. If an immediate predecessor for a specific incident *j* exists, there has to be a successor as given by constraint set (8). Constraint set (9) indicates that an immediate predecessor is also considered a general predecessor. Constraint set (10) prohibits a reflexive, direct or indirect predecessor relationship. Constraint set (11) ensures that rescue unit *k* is not assigned to incident *i* if rescue unit *k* has not the capability to process incident *i*. Constraint sets (12) and (13) ensure that Y_{ij}^k is set to 0 if rescue unit *k* does not process incident *i* before incident *j*. Time window is incorporated into the model by constraint set (14), and constraint set (15) calculates starting time of incidents *i* on rescue unit *k*. Constraint set (16) defines the completion time of each incident and constraint set (17) measures the makespan. Finally, constraint set (18) defines the range of the decision variables.

4-5. Linearization

With respect to constraint sets (15) and (16), the proposed model is obviously non-linear. Since the non-linear models are very time-consuming to achieve the optimal solution, and it be cannot guaranteed that the generated solution is the global optimal solution, it is necessary to convert it into the linear form. Hence, we try to convert the proposed model into a linear form by using proposition 1.

Proposition 1: Suppose that $Z = X_1 \times X_2$ is multiplication of binary variable (X_1) and a continuous variable (X_2). In this case, when the binary variable is equal to one, variable Z gives value equals to continuous variable. The following equations can be used for linearization [38]:

$$Z \leq X_2 \tag{19}$$

$$Z \leq M.X_1 \tag{20}$$

$$Z \geq X_2 - M.(1-X_1) \tag{21}$$

Therefore, the linearized form of constraint set (15) is as follows:

$$ST_j^k = ST_i^k.X_{ij}^k + (PT_i^k + T_{ij}).X_{ij}^k \qquad \forall_{i,j,k} \tag{22}$$

$$L_{ij}^{k} = ST_i^k . X_{ij}^k \Rightarrow ST_j^k = L_{ij}^k + (PT_i^k + T_{ij}) . X_{ij}^k \quad \forall_{i,j,k} \quad (23)$$

$$L_{ij}^{k} \le ST_i^k \quad \forall_{i,j,k} \quad (24)$$

$$L_{ij}^{k} \le M . X_{ij}^k \quad \forall_{i,j,k} \quad (25)$$

$$L_{ij}^{k} \ge ST_i^k - M.(1 - X_{ij}^k) \quad \forall_{i,j,k} \quad (26)$$

In addition, the linearized form of constraint set (16) is presented below:

$$FT_i^k \ge ST_i^k . X_{ij}^k + PT_i^k . X_{ij}^k \quad \forall_{i,j,k} \quad (27)$$

$$Q_{ij}^{k} = ST_i^k . X_{ij}^k \Rightarrow FT_i^k \ge Q_{ij}^k + PT_i^k . X_{ij}^k \quad \forall_{i,j,k} \quad (28)$$

$$Q_{ij}^{k} \le ST_i^k \quad \forall_{i,j,k} \quad (29)$$

$$Q_{ij}^{k} \le M . X_{ij}^k \quad \forall_{i,j,k} \quad (30)$$

$$Q_{ij}^{k} \ge ST_i^k - M.(1 - X_{ij}^k) \quad \forall_{i,j,k} \quad (31)$$

4-6. Goal Programming approach

In the general goal programming approach, the decision-maker (DM) determines a specific goal for every objective and, then, tries to achieve the goal as much as possible. Charnes and Cooper [39] introduced the weighted goal programming. In real situations, however, the DMs may not always have precise data and information related to their criteria. Therefore, it may be difficult for them to specify an exact goal for every objective. Thus, the general goal programming approach becomes less favorable unless the DMs are allowed to choose more than one goal or aspiration level for each objective. This can be done either by choosing multiple aspiration levels for each objective or by specifying a range of values instead of a single aspiration level. Chang [40] extended a Multi-Choice Goal Programming (MCGP). Thereupon Chang developed the previous model and proposed revised MCGP [41]. In continuation, he added a general utility function to the revised approach in order to maximize the DMs expected utility. Chang [42] considered linear and *S* shape utility functions. The proposed approach is as follows:

$$Min \sum_k [\beta_k^d (d_k^+ + d_k^-) + \beta_k^\delta \delta_k^-] \quad (32)$$

S.t.

$$\lambda \le \frac{U_{k,\max} - y_k}{U_{k,\max} - U_{k,\min}} \quad \forall_k \quad (33)$$

$$f_k(X) + d_k^- - d_k^+ = y_k \quad \forall_k \quad (34)$$

$$\lambda_k + \delta_k^- = 1 \quad \forall_k \quad (35)$$

$$U_{k,\min} \le y_k \le U_{k,\max} \quad \forall_k \quad (36)$$

$$d_k^- . d_k^+ = 0 \quad \forall_k \quad (37)$$

$$d_k^-, d_k^+, \delta_k^-, \lambda_k \ge 0 \quad \forall_k \quad (38)$$

Model constraints sets (39)

where $U_{k,\min}$ and $U_{k,\max}$ are the range of the *k*th aspiration level, and y_k is the continuous decision variable. d_k^+ and d_k^- are respectively the positive and negative deviations of $f_k(X)$ from y_k and β_k^d is the relative importance connecting (d_k^+, d_k^-). δ_k^- is the normalized deviation of y_k from $U_{k,\min}$. β_k^d represents the weight of δ_k^-, and λ_k is the utility value.

As the range for each aspiration level [$U_{k,\min}$; $U_{k,\max}$] must be decided by the decision-makers, we propose that the lower bound of the range, $U_{k,\min}$, be set equal to U_k^+, while the upper bound, $U_{k,\max}$, can be less than or equal to U_k^-, where $U_k^+ = \min\{f_k(X)\}$ and $U_k^- = \max\{f_k(X)\}$. The rationalization for this suggestion is that, in a minimization problem, the decision-makers would normally prefer the lowest value for the objective. Therefore, the MCGP approach considering the utility function for the research problem is formulated as follows:

$$\text{Min } \beta_1^d(d_1^+ + d_1^-) + \beta_2^d(d_2^- + d_2^+) + \beta_1^\delta \delta_1^- + \beta_2^\delta \delta_2^- \quad (40)$$

$$\lambda_1 \le \frac{U_{1,\max} - y_1}{U_{1,\max} - U_{1,\min}} \quad (41)$$

$$\lambda_2 \le \frac{U_{2,\max} - y_2}{U_{2,\max} - U_{2,\min}} \quad (42)$$

$$\sum_i \sum_k W_i . FT_i^k + d_1^- - d_1^+ = y_1 \quad (43)$$

$$FT_{\max} + d_2^- - d_2^+ = y_2 \quad (44)$$

$$\lambda_1 + \delta_1^- = 1 \quad (45)$$

$$\lambda_2 + \delta_2^- = 1 \quad (46)$$

$$U_{1,\min} \le y_1 \le U_{1,\max} \quad (47)$$

$$U_{2,\min} \le y_2 \le U_{2,\max} \quad (48)$$

Constraint sets of (3)-(14),(17),(18),(23)-(31) (49)

5. Computational Results

5-1. Data generation

As mentioned before, the factor of destruction of an incident indicates the level of severity. According to the classification which is introduced by the U.S. Department of Homeland Security (2008), the severity of an incident has five levels as follows: low (1), guarded (2), elevated (3), high (4), and severe (5) harm. Hence, we select a discrete uniform distribution for the severity levels at the interval [1, 5]. We also consider five different rescue units, such as policemen, fire brigades, paramedics, search and rescue units, and special casualty access teams in this research. The incidents require exactly one of these multi-faceted skilled rescue units. The ratio of capabilities and the personnel required for an incident is generated randomly using a discrete uniform distribution. The processing times of the incidents are generated based on a normal distribution with average value 20 and variance value 10. The travelling times are generated based on a normal distribution with average value 5 and variance value 2. The number of rescue units (*m*) varies from 5 to 11 and the number of incidents (*n*) varies from 10 to 20. In addition, the weights of the objective functions are considered equal.

5-2. Analysis of the results

This section is devoted to present the experimental results of the research problem. The proposed model is implemented in *ILOG.Cplex 12.6* software and all the required procedures are run on a PC with 2 GHz CPU and 2 GB RAM. The experimental results are shown in Table 2, in which T.P represents the number of test problem, *n* is the number of incidents, *m* shows the number of rescue units, and OF_1 and OF_2 are values of the first and second objective functions, respectively.

Tab. 2. Results of the computational experiments

T.P	(n,m)	OF_1	OF_2	δ_1^-	δ_2^-
1	(8,5)	826	51	0.000	0.000
2	(10,5)	1042	55	0.000	0.000
3	(12,5)	1372	68	0.011	0.026
4	(12,6)	1167	57	0.000	0.014 0
5	(13,6)	1265	62	0.050	0.031

6	(13,7)	1159	55	0.036	0.025
7	(14,7)	1358	68	0.064	0.055
8	(14,8)	1285	61	0.051	0.047
9	(14,9)	1103	55	0.044	0.032
10	(15,8)	1512	81	0.093	0.058
11	(15,9)	1380	74	0.077	0.050
12	(15,10)	1260	74	0.065	0.043
13	(16,9)	1772	85	0.153	0.086
14	(16,10)	1565	78	0.125	0.08
15	(17,9)	1818	86	0.210	0.102
16	(17,10)	1705	72	0.174	0.096
17	(18,10)	1894	88	0.253	0.140
18	(18,11)	1788	75	0.228	0.100
19	(19,11)	1866	82	0.277	0.170
20	(20,11)	1952	91	0.291	0.196

To show the applicability of the solution approach, 20 test problems are generated with different sizes. Table 1 only contains the test problems, which can achieve the optimal solutions in the time limit. Each test problem is run five times, four times are used to generate $U_{1,\min}$, $U_{2,\min}$, $U_{1,\max}$, $U_{2,\max}$ and the last one is applied to solve the MCGP. As can be seen in Table 2, by increasing the number of incidents and fixing the number of rescue units, both objective functions are increased.

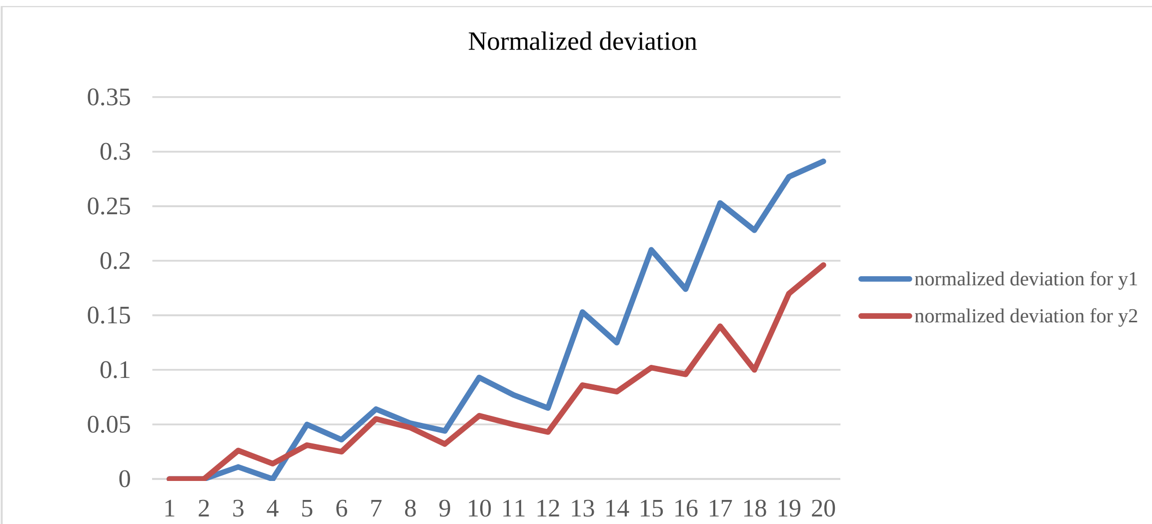
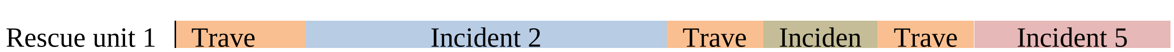


Fig. 1. Different values of δ_1^- and δ_2^- in test problems

Fig. 1 shows values of δ_1^- and δ_2^- in the test problems. We can see an ascending order of the δ_1^- and δ_2^- by increasing of the problem size. Also, δ_2^- is lower than δ_2^- in the entire test problems. Furthermore, if the number of incident is considered fixed, by increasing of the number of rescue units, δ_1^- and δ_2^- are decreased.

For the sake of better understanding, Gantt chart of test problem 3 is illustrated in Fig. 2. As can be seen in Fig.2, rescue unit 1 goes to prevent incident 2 from the emergency operation center, and then it will go to incident 4; finally, the relief operation of rescue unit 1 finishes in incident 5. The relief operation of rescue unit 2 is started from the emergency operation center and is finished after preventing incidents 1 and 3. Rescue unit 3 starts the relief operation from incident 7 and, then, travels to incidents 6 and 8. Rescue unit 4 also starts the relief operation from emergency operation center and its work finishes after preventing incidents 12 and 11. Finally, the relief operation of rescue unit 5 starts from emergency center and operation finishes after preventing incidents 9 and 10.



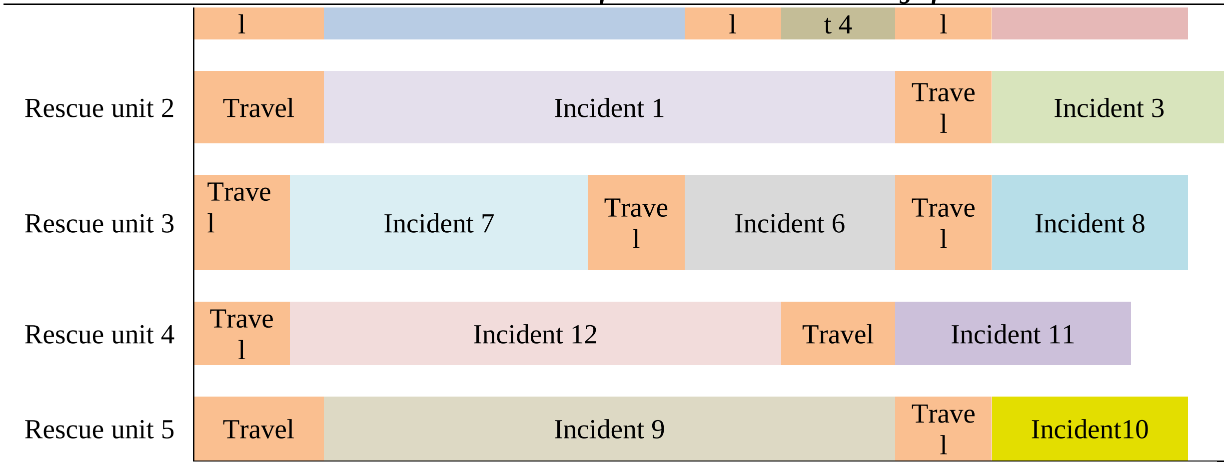


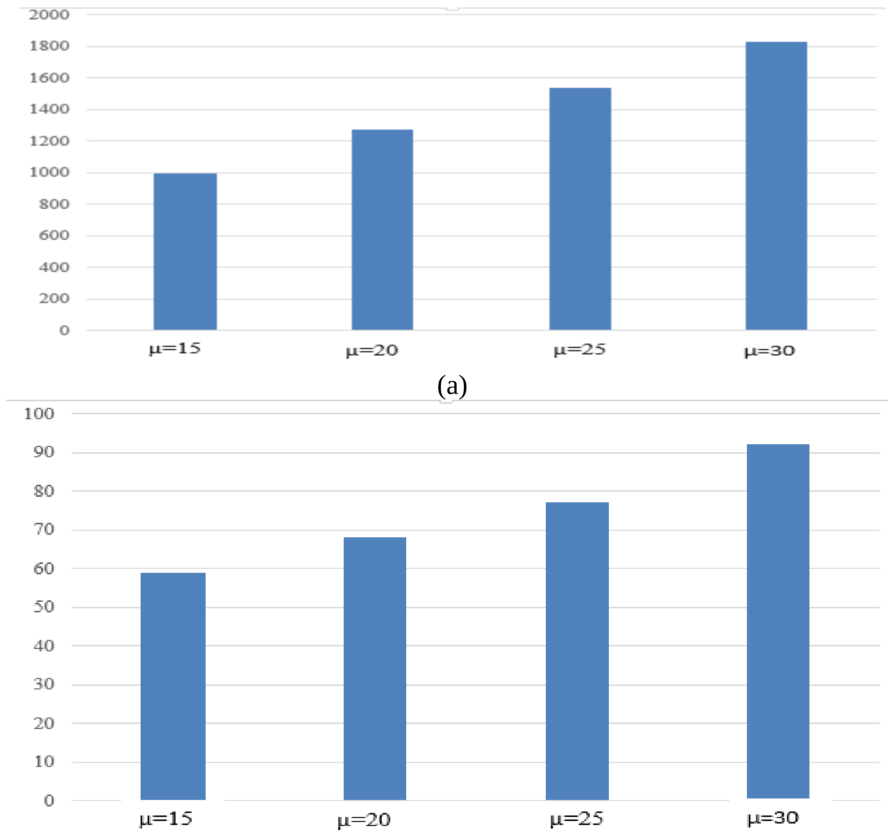
Fig. 2. The Gantt chart of test problem 3

5-3. Sensitivity analysis

In this section, we try to analyze impact of the processing time and traveling time on the both objective functions. For this purpose, a new test problem is generated and solved with different scenarios.

5-3-1. Processing time (PT)

To analyze the impact of the processing time on the objective functions, we solve the test problem with different values of *PT*. We change the average of processing time to 15, 20, 25, and 30, and the obtained results are illustrated in Fig. 3. As shown in Fig. 3, by increasing the processing time, both objective functions increase almost linearly.

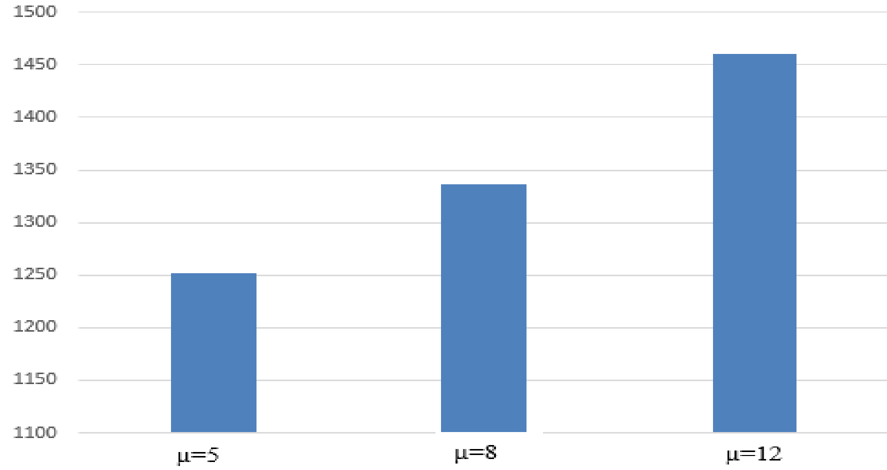


(b)

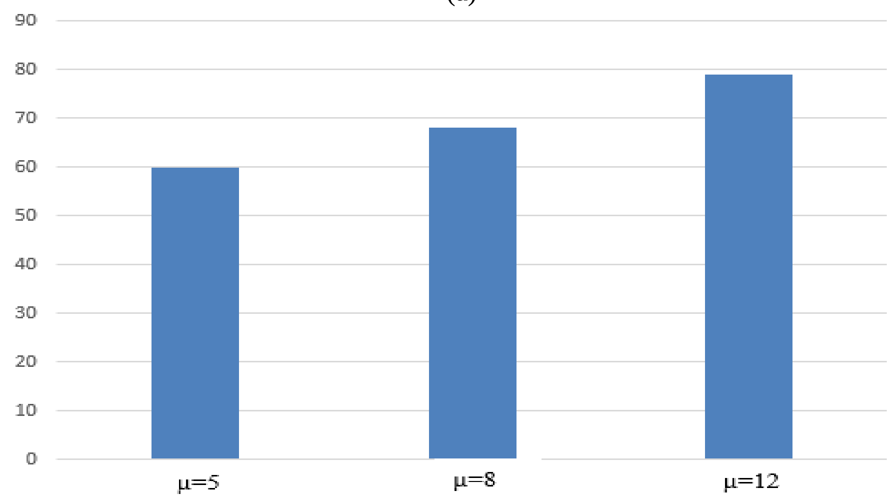
Fig. 3. Sensitivity analysis of objective functions based on different processing times; (a): First objective function, (b): Second objective function

5-3-2. Traveling time (T)

We also change the average of travelling time from 5 to 8 and 12, and the results are presented in Fig. 4. The obtained results show that impact of the travel time is significant on the first objective function rather than the second one.



(a)



(b)

Fig. 4. Sensitivity analysis of objective functions based on different travelling times; (a): First objective function, (b): Second objective function

6. Conclusions

In this paper, allocation and scheduling of the rescue unit, which is a key issue in the emergency response management, was considered. Due to some constraints, such as limited resources and time, planning to deal with natural disasters is so difficult. Hence, some researchers likened the natural disaster problem to routing and scheduling problem in recent years. In this paper, a bi-objective mixed integer linear programming model (BOMILP) was proposed to allocate and schedule the rescue in the natural disaster. The first objective minimizes the sum of the weighted completion times of relief operations, and the second one aims to minimize makespan. The proposed model was solved as a single-objective mixed integer programming model by applying the Multi-Choice Goal Programming (MCGP) with the linear utility function method. The experimental results show the efficiency of the proposed approach to achieve high-quality solutions.

Suggestions for future studies include considering uncertainly processing time, traveling time, and level of severity. Using metaheuristic algorithms to solve the research problem in large-sized instances is another avenue for the future research.

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