Information Sciences 608 (2022) 578–596

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Multi-objective scheduling of priority-based rescue vehicles to extinguish forest fires using a multi-objective discrete gravitational search algorithm

Guangdong Tian [a,b], Amir M. Fathollahi-Fard [c], Yaping Ren [d], Zhiwu Li [e,f,*], Xingyu Jiang [b]

[a] School of Mechanical-Electrical and Vehicle Engineering, Beijing University of Civil Engineering and Architecture, Beijing 100044, China
[b] School of Mechanical Engineering, Shenyang University of Technology, Shenyang 110870, China
[c] Department of Electrical Engineering, École de Technologie Supérieure, University of Quebec, 1100 Notre-Dame St. W., Montreal, Quebec, Canada
[d] School of Intelligent Systems Science and Engineering, Jinan University, Zhuhai 509070, China
[e] Institute of Systems Engineering, Macau University of Science and Technology, Taipa 999078, Macau
[f] School of Electro-Mechanical Engineering, Xidian University, Xi'an 710071, China

ARTICLE INFO

Article history:
Received 28 May 2020
Received in revised form 12 June 2022
Accepted 12 June 2022
Available online 27 June 2022

Keywords:
Forest fire
Emergency management
Rescue priority
Gravitational search algorithm
Optimization algorithms

ABSTRACT

The implementation of emergency scheduling of priority-based rescue vehicles for extinguishing forest fires is a complex optimization problem facing with many challenges and difficulties to optimize the operational costs and to improve the efficiency to make robust decisions. The main challenges are to minimize the number of fire engines while minimizing firefighting time and firefighting delay time, simultaneously. The main difficulties to make these decisions are to consider the severity of each fire point with regards to the limited resources of vehicles. Hence, this paper motivates to develop a new multi-objective scheduling model for extinguishing the fire of forests considering rescue priority with the limited rescue resources. To make an efficient and robust solution for the proposed problem, another novelty is to propose a hybrid optimization algorithm which is a modified discrete gravitational search algorithm. To confirm the applicability of the proposed problem, an actual forest fire emergency scheduling in Heilongjiang Province, China, is simulated. The proposed hybrid optimization algorithm is tested to check the feasibility the Pareto solutions and it is compared with a set of well-known and recent algorithms to show its efficiency. Finally, after a comprehensive discussion, the results prove that this work provides an accurate and effective tool for performing the emergency scheduling for extinguishing the forest fire.

1. Introduction

Nowadays, our world is faced with many types of disasters in nature like earthquake, famine, tsunami, cyclone, hurricane, flood, and forest fire as well as man-made disasters like terrorist attacks and wars in addition to disease like COVID-19 [1–5]. They have become a significant research topic and have been growing and gaining public attention [6–7]. With regards to the global warming and climate changes around the world, China scrimmages a grand challenge for controlling the forest fire in the summer. For example, in April 2021, a very big forest fire was occurred in the southwest of China and more than 2000

* Corresponding author at: Institute of Systems Engineering, Macau University of Science and Technology, Taipa 999078, Macau.
E-mail address: zhwli@xidian.edu.cn (Z. Li).

https://doi.org/10.1016/j.ins.2022.06.052
0020-0255/

Nomenclature

PSO	Particle swarm optimization
MOPSO	Multi-objective particle swarm optimization
MDGSA	Multi-objective discrete gravitational search algorithm
GSA	Gravitational search algorithm
MOABC	Multi-objective artificial bee colony
SPEA2	Enhanced strength of Pareto evolutionary algorithm
MOEA/D	Multi-objective evolutionary algorithm based on decomposition
CPU time	Central processing unit of time
MID	Mean ideal distance for Pareto solutions
HV	Hypervolume of Pareto solutions
MORDA	Multi-objective red deer algorithm
$M_{pk}(t)$	The passive gravitational mass of particle k in GSA
$M_{ik}(t)$	The inertia mass of particle k at time t in GSA
$M_{aq}(t)$	The active gravitational mass of particle q in GSA
NFL	No free lunch theory
NPS	Number of Pareto solutions
MS	Maximum spread of Pareto solutions
RSM	Response surface methodology
NSGA-III	Non-dominated sorting genetic algorithm III
PoC	Percentage of crossover operator in NSGA-III
PoM	Percentage of mutation operator in NSGA-III
CG	Coefficient of the global optimum in MOPSO
CL	Coefficient of the local optimum in MOPSO
MND	Maximum number of non-dominated solutions in SPEA2 and MOEA/D
PopSize	The population size in all algorithms
G_0	An initial value in MDGSA
I_M	The maximum number of iterations in all algorithms
RDI	Relative deviation index
NoD	Number of times to decompose solutions
nOnlooker	Number of onlooker bees in MOABC
Gamma	Percentage of male commanders in MORDA
Beta	Percentage of mating in each harem
Alpha	Percentage of mating out of each harem
Kbest	The set of the first K agents with the biggest mass and the best fitness value in MDGSA
i	Index of fire nodes
m	Index of firefighting equipment
t_{Ei}	The extinguishing time of the ith fire node
v_{Si}	The fire spreading speed of the ith fire node
v_m	The extinguishing speed using the mth firefighting equipment
r_q	A random number between [0, 1]
λ	A constant term of iterations
$G(t)$	A monotonically decreasing function
$[y]$	A rounding function taking the nearest integer value
k_w	Wind force
v_S	Fire speed
v_0	Initial speed of wind
v_w	Wind speed
k_s	Correction factors of fuel types
k_w	Wind force
k_φ	Terrain slope
d_{0i}	The distance between nodes 0 and i
v_{0i}	The average velocity of the fleet from node 0 to i
$\sum_{m=1}^{M} z_{0i}^{m}$	The total number of rescue vehicles arriving the ith point from node 0
P_i	The rescue priority of the ith point

firefighters and volunteers were battling the forest fire[1]. Such accidents are occurred yearly. This becomes a big problem for preserving the forests in China. This motivates the use of emergency management with optimization tools to address such disaster events. The needs and benefits from the optimization of emergency management are very effective to create a plan when a disaster occurs. A robust plan should comprise the information collection, damage assessment, scheduling of operations, time response, transportation, and accurate tracking of disaster areas and other emergencies [1–2].

This study proposes a robust plan to address the forest fire problem in China. The proposed plan needs a multi-objective optimization model to minimize the number of fire engines while minimizing firefighting time and firefighting delay time, simultaneously. Feasibility requires the real-life constraints such as the consideration of severity of each fire point with regards to the limited resources of vehicles. Efficiency needs an optimization algorithm like the proposed discrete gravitational search algorithm which is robust and manageable computationally. To approve our contributions to the field of emergency rescue planning problem, the following relevant articles are reviewed.

The earliest studies confirm that a valid road network is an important content for the emergency management [8–9]. For example, Yi and Özdamar proposed the construction of a vehicle routing model using a greedy neighborhood search algorithm for the emergency logistics after a natural disaster [9]. Yuan and Wang formulated a routing-inventory model to minimize emergency handling time [10]. In [11], the authors considered the varying travel time of ambulance with regards to the changes on ambulance network conditions during the day, and continuously optimized the traffic volume at the same time point while planning vehicle routing optimization problem via a variable neighborhood search algorithm. To increase the total operational efficiency while improving the satisfaction degree, Tzeng et al. proposed a fuzzy optimization model [12]. The work in [13] developed a path optimization model for the emergency management of large casualties. Schmid presented an approximate dynamic programming method to formulate the vehicle scheduling with the possibility of redistribution to minimize the rescue time [14]. The authors in [15] solved the vehicle dispatching problem by a heuristic method. Their model minimizes the time taken to arrive at the last rescue point with the minimum average rescue time. In [16], a decision-support system was built to reduce the handling time of natural disaster events. The work in [17] graded the entire wounded first, and then provided the assignment of different rescue methods for different types of injuries, as well as the number of ambulances the capacity limitation in hospitals. At the end, an improved large-scale neighborhood algorithm to obtain the optimized scheme was proposed. As on the first multi-objective models in this research area, Chiu et al. [18] proposed a representation model and solution method for multi-objective group objectives, e.g., transportation dispatch schedule for the real-time response of no-notice warning. In conclusion, these studies confirm the needs of more multi-objective frameworks using efficient optimization algorithms [18–19].

Since the emergency rescue planning problem for the application of forest fire, is newly studied, the previous studies mostly concentrate on the single-objective emergency planning/scheduling problems, such as operational cost or emergency time. Nevertheless, in practical emergency processes, decision-makers regularly intend to reduce the number of rescue resources and the emergency time. Simultaneous consideration of these criteria requires to solve a multi-objective scheduling model. Meanwhile, for the forest fire emergencies, the number of rescue resources and different requirements of each fire point have a great influence on the efficiency for extinguishing the forest fires. Therefore, the priority of rescue is important to be considered, and the delay time of fire extinguishing should be minimized along with the extinguishing time and the number of rescue vehicles.

Another research gap is that researchers mostly contributed to well-known disaster types like earthquakes and traffic incidents, while a little attention is paid to forest fire issues. The mechanism of forest fire spreading is put forward [20], and the basic theory for the fire spreading control is proposed in our prior works [21–24]. Although our previous research is to propose a dual-objective scheduling of rescue vehicles to distinguish forest fires, it is insufficient without considering the fire situation and rescue priority of each fire point and fails to handle the extinguishing delay time of fires. To overcome this deficiency, this work aims to build a multi-objective scheduling model to consider the priority of forest fires for each fire point and constraints of the fire engines. In conclusion, the purpose of this work is to find an approach to fix a schedule subject to multiple objectives with resource constraints.

Since our scheduling model is more complex than previous studies, existing optimization algorithms may be not efficient for solving the proposed model. Based on the theory of No Free Lunch (NFL) [4], a modified optimization algorithm is able to better solve an optimization problem in comparison with the original algorithms and the rest of state-of-the-art ones. This motivates this research to devise a Multi-objective Discrete Gravitational Search Algorithm (MDGSA) to address the proposed model. As a recently-developed but effective solution approach, the Gravitational Search Algorithm (GSA), presented in 2009 [24], is used to settle a dispute. It is notable that the GSA was applied to numerous optimization problems in diverse fields. However, this is the first attempt to apply this algorithm in the emergency rescue planning problem [25–26]. In this algorithm, agents are regarded as its targets and their ability is reflected via agent's masses. These targets affect each other through the gravity force, according to Newton's law of gravity. The given initial velocity causes an overall motion of all targets towards the heaviest targets. The rules of mass and gravity lead to a fact that good solutions owning heavy masses shift tardily than gentler ones. Hence, it has a great potential in this study to produce effective search operators. Using this concept, we propose a modified MDGSA and compared it with the state-o-the-art algorithms like Non-dominated Sorting Genetic Algorithm III (NSGA-III) [27–28], Multi-Objective Particle Swarm Optimization (MOPSO) [29–30], SPEA2 [31], and MOEA/D [32], and other recent algorithms like Multi-Objective Artificial Bee Colony (MOABC) [33–34], and Red deer algorithm (RDA) [35].

Having a conclusion about the main novelties of this research in comparison with the existing works, following highlights are made:

- A novel multi-objective scheduling model is presented which aims to minimize the fire extinguishing time, delay time, and number of fire rescue vehicles.

- Since the fire spreading mechanism has a great influence on the forest fire emergency scheduling, the factor of fire spreading speed is firstly considered in our optimization model.
- A revised multi-objective discrete gravitational search algorithm is designed to produce Pareto solutions.
- An empirical case study in Heilongjiang Province, China is applied to show the applicability of this research.

The remainder of the paper is structured as follows: Section 2 presents the problem description and builds an optimization scheme. Section 3 proposes the solution approach, while the results for different cases are listed in Section 4. In the last section, we reach a conclusion for the present work and point out findings and recommendations for future studies.

2. Proposed multi-objective scheduling model

2.1. Problem description

This study proposes a robust plan against the forest fire emergency scheduling and this needs a multi-objective optimization model and new constraints to make our plan more practical and efficient. All notations for our optimization model are defined in the nomenclature section. Our proposed model determines the rescue priority of each fire point with regards to its actual fire condition. Contrary to most of the previous studies [20–22], our model is able to simulate multiple fire points at the same time. In this practical situation, the rescue time comprises rescue arrival time and fire extinguishing time. The former is usually regarded as a constant because it is determined by the distance and velocity that are usually known. The latter is closely related to the speed of fire spreading. It should be noted that it is one of the foremost indexes for each decision-maker. To address this challenge, our scheduling model is able to reduce the extinguishing time of forest fires. This issue is addressed by the first objective function in our optimization model.

Additionally, to describe different priorities of multiple fire points, we introduce another time target—the extinguishing delay time that can be computed by extinguishing time windows, where the latest extinguishing time t_{Li} of each fire point is recorded. Meanwhile, decision-makers have to consider the actual limited rescue resources. Considering the practical situation is a crucial factor to acquire feasible scheme and to tackle the problem.

Overall, a multi-objective scheme, including the firefighting time and the firefighting delay time to extinguish forest fires as well as the number of deployed rescue vehicles, is designed in this work. Its objective is to obtain the best schedule such that certain numbers of rescue vehicles are arranged to each fire points so as to minimize the firefighting time and the firefighting delay time. At the same time, the number of deployed rescue vehicles and their wage are minimized as much as possible, thus reducing cost.

2.2. Rescue priority

For complex emergency scheduling problems, due to different urgency degrees, each fire should be assigned corresponding rescue resources, which can reduce losses as well as scheduling cost. P_i, $i = 1, 2, \ldots, N$, is therefore considered in this work. The extinguishing delay time is introduced into our emergency scheduling model to depict the priority of each fire point, and the extinguishing delay time can be obtained via time windows in which the latest extinguishing time of each fire point is given based on different fire situations. Note that P_i is greater if fire point i has higher priority.

Different from a regular time window with a lower and upper bound [25], the extinguishing time window in this work contains only an upper bound, i.e., the latest extinguishing time, without a specified lower bound since the extinguish time should be as short as possible for the emergency scheduling problem. To further highlight the priority, each fire point is given a corresponding weighting factor η_i, $i = 1, 2, \ldots, N$, whose value is set between (0,1]. Note that η_i is smaller if fire point i has higher priority.

2.3. Fire spreading model

Our optimization model aims to simulate the emergency scheduling after a disaster event occurs. It is stressed that emergency scheduling for forest fires differs from other emergency scheduling problems, e.g., earthquakes, traffic accidents, and medical rescue. It is greatly influenced by the fire condition, in addition to the travel time. The fire situation can be measured by fire spreading speed; thus, we need to discuss a fire spreading model that calculates fire spreading speed.

The speed of fire spreading has a great influence on an actual forest fire situation. In order to establish an emergency scheduling optimization model, a fire spreading model related to natural conditions is proposed in this subsection, including wind speed, initial propagation velocity, fuel types, temperature and terrain gradient [22–23]. The expressions are as follows:

$$\mathrm{v_s = v_0 k_s k_\varphi k_w = v_0 k_s k_\varphi e^{0.1783}} \tag{1}$$

$$\mathrm{v_0 = aT + bw + cv_0} \tag{2}$$

where, as explained in our previous work [19], a, b and c are factors related with the terrain and they are determined by the actual location of forest fires. The reference data of correction factors k_s, k_w and k_φ are acquired through the related surveys and measurement, as listed in Appendix A.

2.4. Mathematical model

Having the above definition of the proposed problem, three objectives, i.e., to minimize extinguishing time (Eq. (3)), extinguishing delay time (Eq. (4)) and the number of rescue vehicles (Eq. (5)), creates our multi-objective emergency scheduling optimization scheme as follows:

$$\mathrm{Min} f_1 = \sum_{i=1}^{N} t_{Ei} \tag{3}$$

$$\mathrm{Min}\, f_2 = \sum_{i=1}^{N} (\max(0, t_{Ei} - \eta * t_{Li})) \tag{4}$$

$$\mathrm{Min} f_3 = \sum_{j=1}^{N} \sum_{m=1}^{M} z_{0j}^{m} \tag{5}$$

s.t.

$$K \leqslant \sum_{j=1}^{N} \sum_{m=1}^{M} z_{0j}^{m} \leqslant M \tag{6}$$

$$L_i \leqslant \sum_{m=1}^{M} z_{0j}^{m} \leqslant U_i, i = 1, 2, \ldots, N \tag{7}$$

$$z_{0j}^{m} \in \{ 0, 1\}\ m = 1, 2, \ldots, M; i = 1, 2, \ldots, N \tag{8}$$

The purpose of objective function f_1 in Eq. (3) is to minimize the extinguishing time of fires. The value of f_1 consists of the arrival time of rescue vehicles to each fire point, and the arrival time to the ith fire point t_{Ai} can be calculated as:

$$t_{Ai} = d_{0i}/v_{0i},\ i = 1,\ 2,\ \cdots,\ N \tag{9}$$

where point/node 0 is regarded as the starting point.

Furthermore, the extinguishing time of each fire point is given next. According to the practical fire situation, the relationship among v_{Si}, v_m and t_{Ei} is described as follows:

$$(t_{Ai} + t_{Ei}) * v_{Si} = \left(\sum_{m=1}^{M} z_{0j}^{m} * v_m \text{-} v_{Si}\right),\ \ i = 1, 2, \ldots, N \tag{10}$$

Note that v_{Si} is obtained via Eqs. (1) and (2). The left side of Eq. (10) means that the fire spreading area of the ith fire node relates to two parts: the area before the arrival of rescue vehicles and that after their arrival, i.e., $t_{Ai*}v_{Si}$ and $t_{Ei*}v_{Si}$, respectively. Its right side means the firefighting area of the ith fire point. Therefore, its extinguishing time t_{Ei} can be calculated as:

$$t_{Ei} = v_{Si} * t_{Ai} / \left(\sum_{m=1}^{M} z_{0i}^{m} * v_m \text{-} 2v_{Si}\right) \tag{11}$$

Hence,

$$f_1 = \sum_{i=1}^{N} t_{Ei} \tag{12}$$

The purpose of objective function f_2 in Eq. (4) is to reduce the fire extinguishing delay time, which involves t_{Ei} and t_{Li}. t_{Ei} can be obtained via Eq. (11); t_{Di} is a special "t_{Ei}", which means its largest firefighting time, i.e., fire point i has the smallest number of rescue vehicles L_i at the time that can just put out the fire. Hence its tolerant latest extinguishing time t_{Li} is calculated by:

$$t_{Li} = v_{Si} * t_{Ai} / (L_i * v_m - 2v_{Si}) \tag{13}$$

The purpose of objective function f_3 in (5) is to reduce the number of dispatched vehicles. Constraint (6) guarantees that the total number of rescue vehicles sent to each fire point is between K to M, which means that K is the lower bound and M is the upper bound. Constraint (7) restricts the number of vehicles sent to the ith fire point, which means that L_i is the lower bound and U_i is the upper bound. Constraint (8) defines decision variables with values of 1 or 0.

The three goals of the presented model are in conflict: a) f_1 and f_3 are in conflict with each other because $\sum_{i=1}^{N} t_{Ei}$ in Eqs. (3) and (5) is inversely proportional, so do f_2 and f_3; additionally, it is obvious that a nonlinear relationship exists between f_1 and f_2 according to Eqs. (3) and (4); and b) In fact, we usually require more vehicles to minimize the extinguishing time f_1 and the extinguishing delay time f_2 such that f_3 increases; reversely, if less rescue vehicles are used, more extinguishing time is spent, which increases f_1 and f_2.

According to the above instruction, the proposed model is complex and non-linear since the forest fires are multiple and emergency dispatch becomes more complex with the increased number of forest fires, and the number of scheduling solutions may also increase rapidly. Our model targets three different goals which can influence each other. Therefore, our model is more complex than all similar models [20–22]. This motivates an efficient optimization algorithm which should be more efficient than previous and other algorithms in the literature review.

3. Proposed algorithm

As mentioned before, although many optimization algorithms were developed in this research area, none of them may be not efficient for our optimization problem as it is more complex than the existing studies. Based on the NFL theory [4], an improvement to an optimization algorithm is more effective than the use of existing algorithms. Therefore, this study proposes a modified GSA which is multi-objective to handle three objectives and it is a discrete version to find an optimal schedule for forest fire emergency decisions. The proposed MDGSA is compared with the traditional algorithms including NSGA-III [27–28], MOPSO [29–30], SPEA2 [31], and MOEA/D [32] as well as recent algorithms like MOABC [33–34] and MORDA [35].

Rashedi *et al.* have proposed the GSA in [24] for the first time, where, agents are presented by objects and their performance is calculated via their masses. The objects attract mutually by the gravity. During the process, the objects with light masses move towards the ones with heavy masses. In the GSA, the objects with light masses move fast, representing bad solutions and that with heavy masses move slowly, representing good solutions.

In the algorithm, each agent has four parameters: inertial mass, position, active gravitational mass, and passive gravitational mass. In addition, by computing each agent's acceleration based on the law of motion, their velocity and position can be updated simultaneously. Note that a solution is represented by the position of an agent, and the fitness value of a solution is represented by the gravitational and inertial masses of an agent.

So far, comparisons have been made between the GSA and some common heuristic algorithms, which show the advantages of the GSA in addressing nonlinear problems [24]. Note that the GSA is initially developed to resolve continuous functions instead of such presented integer planning schemes. In addition, the three objectives in the proposed model require a multi-objective optimization framework based on Pareto solutions, which differ from the single-objective version of the GSA. Hence, a modified GSA, called MDGSA, is designed to suit the multi-objective discrete problem as contributed to this paper. A non-dominated approach as presented in NSGA-III [27–28] is adopted to produce the Pareto solution set and update an external Pareto solution archived in this work. Meanwhile, local search and greedy selection operations are introduced into the proposed algorithm to accelerate the solution process.

The proposed approach contains seven tasks: Representation of the initial population, fitness evaluation of agents, calculation of the masses of each agent, calculation of acceleration, updating of the agents' velocity and position, local search and greedy selection, and finally the multi-objective version of the proposed algorithm.

3.1. Representation of the initial population

For all *meta*-heuristic algorithms, the representation of a feasible solution for the proposed optimization problem is essential. The original GSA uses a continuous search space and therefore, it is not applicable for our proposed model. To encode the proposed model, an efficient representation technique with no need to repair the solutions is designed. Based on the characteristics of the considered problem, a scheduling scheme is coded as an integer-valued vector, and each dimension corresponds to the number of rescue vehicles. This procedure creates a feasible solution for the proposed optimization problem. As illustrated in Fig. 1, the ith dimension $x_i = \sum_{m=1}^{M} z_{0i}^{m}$, $i \in \{1, 2,..., N\}$, of solution X_k^i, $k \in \{1, 2,..., PopSize\}$, illustrates the number of rescue vehicles and x_i means that its range is from L_i to U_i to meet constraint (7). For instance, $X_k^i = \{2, 5, 3, 2, 4, 3\}$.

2	5	3	2	4	······	x_N
x_1	x_2	x_3	x_4	x_5	······	x_N

Fig. 1. The coding example for a solution.

Note that, initial element x_1 is equal to 2, which means that two rescue vehicles are allocated to the 1st point; x_2 = 5 means that five rescue vehicles are sent to the 2nd point and so on.

The values of initial *PopSize* individuals are produced randomly in multiple constraints. The number of individual vehicles f_3 is taken a stochastic integer and $f_2 \in [K, M]$. Each vehicle z_{0j}^m has two cases: 1 or 0, where the value 1 means that the solution includes the *m*th rescue vehicle from point 0 to *j*, and 0 otherwise. Generally, with the increase of the fire points, the number of solutions increases even drastically. Obviously, a few solutions/individuals may not be viable. It means that they cannot satisfy designated constraints, such as constraints (6) or (7). Thus, they need to be adjusted and an effective method for adjusting them is to re-generate or re-construct.

3.2. Fitness evaluation of agents

The formulation of the proposed optimization model contains three objectives. Certainly, it is important to assess each agent via computing their fitness values [24 36–37]. Our proposed model of emergency response could be coded into a solution *X*. Let Pbest (primary personal best) be the primary value of each agent and Gbest (the primary global best of the population) be the best of entire primary personal best values, respectively. Obviously, the number of rescue vehicles f_3 can be acquired easily via Eq. (3) as soon as *X* is known. Nevertheless, f_1 and f_2 cannot be computed directly and need to be derived from Eqs. (7)–(11). From Eq. (19), we have:

$$\sum_{m=1}^{M} z_{0j}^{m} * v_m - 2v_{Si} > 0, \text{ i.e., } \sum_{m=1}^{M} z_{0j}^{m} > 2v_{Si}/v_m \tag{14}$$

and $L_i \le \sum_{m=1}^{M} z_{0j}^m \le U_i$, according to Eq. (4). Thus:

$$L_i > 2v_{Si}/v_m, \text{i.e.,} L_i - 2v_{Si}/v_m > 0 \tag{15}$$

Since L_i represents the smallest number of vehicles to the *i*th fire point, we have:

$$0 < L_i - 2v_{Si}/v_m \leqslant 1 \tag{16}$$

where Eq. (14) indicates that each fire point has a lowest demand for rescue vehicles. In other words, fire point *i* can be extinguished only if at least L_i vehicles can reach them as soon as possible.

In addition, U_i can be determined and evaluated by the actual fire spread speed of fire point *i* and the actual number of rescue vehicles. It is a given parameter in this work. Note that *K* is determined based on the sum of L_i of each fire point and *M* can be obtained by the actual number of rescue vehicles and it is a given parameter as U_i.

3.3. Calculation of the masses of an agent

Gravitational and inertia masses are simply calculated by the fitness evaluation according to the encoding plan [38–40]. Assuming the equality of the gravitational and inertia masses, i.e., $M_{ak}(t) = M_{pk}(t) = M_{ik}(t) = M_k(t)$, $k = 1, 2, \ldots, \Omega$, the values of masses are calculated by using the map of fitness. The mass of agent *k* is updated by the following equations [41–44]:

$$m_k(t) = \frac{fit_k(t)\text{-}worst(t)}{best(t)\text{-}worst(t)} \tag{17}$$

$$M_k(t) = \frac{m_k(t)}{\sum_{q=1}^{popsize} m_q(t)} \tag{18}$$

where $fit_k(t)$ represents the fitness value of agent *k* at time *t*, $best(t)$ and $worst(t)$ are defined as follows (for a minimization problem):

$$best(t) = \min_{q=\{1,2,\ldots,\Omega\}} fit_q(t) \tag{19}$$

$$worst(t) = \min_{q=\{1,2,\ldots,\Omega\}} fit_q(t) \tag{20}$$

However, the above calculation of $M_k(t)$ is based on a single objective model [24] and cannot be directly applied to solve our multi-objective problem. Thus a weighting method is adopted to deal with our problem [36–37], and three weighting factors w_1, w_2 and w_3 are introduced. We have:

$$M_k(t) = \sum_{n=1}^{3} \frac{w_n * m_k^n(t)}{\sum_{q=1}^{popsize} m_q(t)} \tag{21}$$

where w_n, $n \in \{1, 2, 3\}$ is a random number between (0,1], and m_k^n is m_k of the *n*th objective.

3.4. Calculation of acceleration

At a specific time t, the force acting on mass k from mass q in the ith dimension can be expressed as:

$$F_{kq}^{i}(t) = G(t)\frac{M_{aq}(t) \times M_{pk}(t)}{R_{kq}(t) + \varepsilon} \times \left(X_q^i - X_k^i\right) \tag{22}$$

where ε is a very small constant to ensure the denominator is non-zero, and the acceleration can be calculated as:

$$a_k^i(t) = \frac{F_{kq}^i(t)}{M_k(t)} \tag{23}$$

It should be stressed that Eqs. (22) and (23) are obtained from only agents k and q, while there are a set of agents (Ω agents) in the whole space. Thus, we compare the total force that acts on agent k as a randomly weighted sum of the forces exerted from other agents:

$$F_k^i(t) = \sum_{q=1, q\neq k}^{popsize} r_q \times F_{kq}^i(t) \tag{24}$$

The acceleration of agent k is represented as:

$$a_k^i(t) = \frac{F_k^i(t)}{M_k(t)} \tag{25}$$

Additionally, $R_{kq}(t)$ is the Euclidian distance between two agents k and q,

$$R_{kq}(t) = \left|\left|X_k^i, X_q^i\right|\right|_2 \tag{26}$$

Meanwhile, the gravitational constant $G(t)$ is not a constant differing from the Law of universal gravitation and continually adjusted with the iteration count in order to control the search accuracy. It is presented as follows:

$$G(t) = G(G_0, t) = G_0 e^{-\lambda t/IM} \tag{27}$$

In the basic GSA [24], to keep a good tradeoff between exploration and exploitation is to reduce the number of agents with the lapse of time in Eq. (22), in which only the $K_{best}(t)$ agents attract the others, with the initial value K_0 at the beginning and decreasing with time. Hence, Eq. (22) is adjusted as:

$$F_k^i(t) = \sum_{q=1, q\neq k}^{K_{best}(t)} rand_q \times F_{kq}^i(t) \tag{28}$$

where $K_{best}(t)$ is the number of the first K agents with the best fitness value.

The $K_{best}(t)$ agents are conveniently obtained in a single objective model, but difficult to obtain in our multi-objective optimization problem. Therefore, it is necessary to establish a mechanism to determine the agents. The non-dominated sorting is introduced into this work to distinguish different levels of Pareto solutions [27–28]. Meanwhile, we propose the P_{best} agents, which are the highest level of Pareto solutions and stored in an external archive $A(g)$, g = 1, 2, . . ., I_M. Note that P_{best} is equal to the number of the highest level of Pareto solutions. We have the following procedure:

1) If $P_{best} \geq K_{best}(t)$, $K_{best}(t)$of the P_{best} agents are randomly selected from $A(g)$;
2) Otherwise, $K_{best}(t) - P_{best}$ agents should be chosen from Pareto solutions at the second highest level for m $K_{best}(t)$ agents. If the number of the second highest level of Pareto solutions at the second highest level is less than $K_{best}(t) - P_{best}$, continue to select agents from Pareto solutions at the next highest level, and so on, until $K_{best}(t)$ agents are determined.

The above approach contributes to improve the performance of the GSA by controlling the exploration and exploitation ability since $K_{best}(t)$ can be decreased linearly as iterations proceed.

3.5. Update/renew agent velocity and position

The updating of velocity is regarded as the sum of its current velocity and acceleration. Thus, its velocity and position can be computed as follows:

$$v_k^i(t+1) = rand_k \times v_k^i(t) + a_k^i(t+1) \tag{29}$$

$$x_k^i(t+1) = x_k^i(t) + v_k^i(t+1) \tag{30}$$

Clearly, Eqs. (28) and (29) involve the real arithmetic issue, while our work is devised for a discrete optimization problem. Hence, Eq. (30) should be adjusted into:

$$x_k^i(t+1) = [y] * [x_k^i(t) + v_k^i(t+1)] \tag{31}$$

3.6. Local search and greedy selection

To generate good quality and diverse neighboring agents, a local search approach is used in this work. The local search operation is easy and simple to be implemented, where a swap operation is commonly applied. The swap operation is to interchange two digital symbols of an agent at the different dimensions [45–48]. Then a new agent produced by the local search is assessed and compared with the old one, and the one with a heavier mass is kept in the population, which is a greedy selection procedure.

3.7. Multi-objective framework

We have applied the multi-objective version of the proposed algorithm. According to the Pareto solutions, the non-dominated sorting algorithm is used to distribute the population solutions into different levels in this work [35–40]. In addition, archive set $A(g)$ is applied to store the top solutions found in the search process. All non-dominated solutions in the current population are seen as a candidate to update $A(g)$ in each generation. Each of the three target values of a candidate meets a given threshold; then the solution can be added into $A(g)$. At the same time, all dominated solutions are removed from $A(g)$.

3.8. Proposed MDGSA

To have the final algorithm, the maximum iteration count g_{max} can be used as a termination criterion in the presented MDGSA. If it is reached, then the algorithm is terminated and outputs are the Pareto solutions. In any objective evaluation, Pareto optima means that no any solution is superior to or even equal to the solution of Parent optimal set $A(g)$. On the basis of the above description, the final flowchart of the proposed MDGSA is shown in Fig. 2.

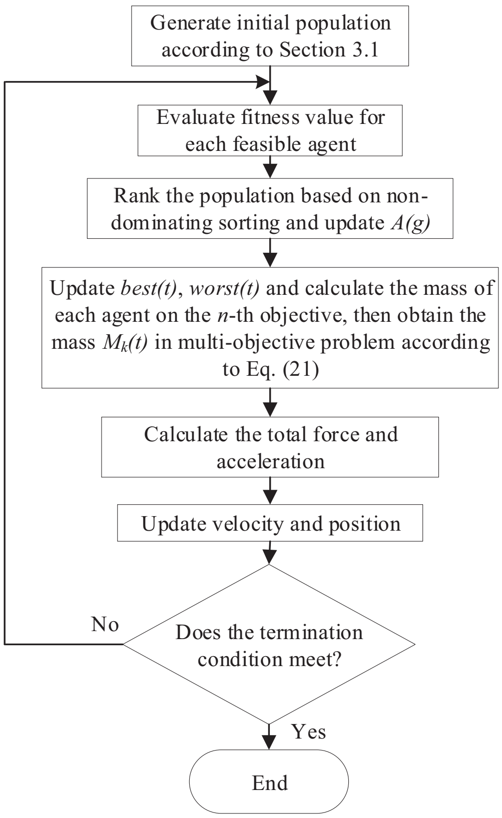


Fig. 2. Flowchart of the proposed MDGSA algorithm.

4. Results and comparison

Here, we firstly tune the algorithms' parameters and then our case study to show the applicability of this research is explained in details. The sensitivity analyses on the performance of the proposed algorithm for solving the case study are done accordingly. To approve its performance in a comprehensive way, our algorithm is compared with many other algorithms in the literature review and statistical tests are done. Finally, the discussion of the results is provided to show the findings of this research and to recommend the managerial insights. It goes without saying that all our computations were done on a laptop with 1.7 GB CPU and 6.0 GB RAM.

4.1. Tuning of algorithms

To assess our algorithms, we have different criteria as our optimization algorithms are multi-objective [35]. Similar to the evaluation of single-objective models, the computational time for running the algorithms, i.e., CPU time is one of the criteria. In addition, the Number of Pareto Solutions (NPS), Mean Ideal Distance (MID), Maximum Spread (MS) and Hypervolume (HV) are our multi-objective metrics. For the CPU and MID criteria, a lower value would be efficient and conversely, for the NPS, MS and HV criteria, a higher value brings a better quality for solutions. To see the computations of NPS, MID and MS, please, see [49] and to see the simulation method of HV, please, see [48].

Before implementation of our optimization algorithms, it is essential to tune their parameters efficiently. If the algorithms are not tuned well, their comparison would be unbiased. The tuning of algorithms is done by the Response Surface Methodology (RSM) [50]. The RSM uses a regression model and considers each parameter as a factor. The RSM transforms the value of each factor from -1 to 1. The goal is to find the maximum desirability for each algorithm. For interested readers, the mathematic of RSM for tuning an optimization algorithm can be referred to [50].

In this regard, the test problem is our case study for running our algorithms, i.e., NSGA-III [27–28], MOPSO [29–30], SPEA2 [31], MOEA/D [32], MOABC [33–34], MORDA [35] and the proposed MDGSA. The range of parameters for each algorithm is adopted by the previous works [38–40,46–49]. The emphasis to evaluate the desirability in the RSM model is valued to be 1, 1, 2 and 3 for NPS, MID, MS and HV metrics respectively. Finally, the tuned parameters of each algorithm using the calculation of the R-squared (R^2) for each multi-objective metric and the total desirability (D) are given in Table 1. The desirability is between zero and 1 and a higher value shows a better performance of the algorithm. The definition of each algorithm's notations, is reported in the nomenclature section. Our results confirm the high performance of the MDGSA in comparison with other algorithms for solving our case study.

4.2. Solving our case study

As mentioned earlier, one of grand challenges in China is addressing the forest fire in the summer. This study models a multi-objective plan and develops the MDGSA to address this challenge. The applicability of this research is tested on an actual forest fire emergency scheduling at Huzhong region located in Mt. Daxing'anling of Heilongjiang Province, China, as shown in Fig. 3.

The fires broke out in Huzhong region at 10:40 local time on June 29, 2010 [23]. Table 2 shows the details of distance. As listed in Table 1, point 0 means the location of rescue vehicles and the remaining seven points indicate fire points. The details of the remaining seven points are shown in Table 3, i.e., the 2nd row indicates "Fire point No.1 means 1231 highland located in Hubin". Then, the coding length of the algorithm is $N = 7$.

The fire extinguishing speed of each rescue vehicle mostly depends on its firefighting configuration. Suppose that the capacities of rescue vehicles are the same. Thus its fire extinguishing speed can be considered the same, which can assumed to be 2.5 m/min, implying that the value of v_m is equal to 2.5 m/min, $m = 1, 2, \ldots M$. As for the area, *a is* set to be 0.053, *b* is 0.048 and *c* is 0.275 [22–23]. Meteorological information and geographic data of each point are shown in Tables 4 and 5.

Based on the above fire spreading model proposed in Section 2.3, the fire speed data of each point are shown in Table 6. The number of initial individual vehicles is set as a random integer as in [15], i.e., $K = 29$ based on Eq. (17), and $M = 35$ based on the total number of rescue vehicles in the forestry fire station (point 0) marked in Fig. 3. In the calculation of fitness value

Table 1
Results of tuning of algorithms.

Algorithm	Parameters	R^2 (%)				D
		NPS	MID	MS	HV	
NSGA-III	$I_M = 100$, $PopSize = 50$, $PoC = 0.7$; $PoM = 0.2$;	66	76	58	54	0.6
MOPSO	$I_M = 100$, $PopSize = 50$, $CG = 2$, $CL = 2$;	72	56	68	62	0.6428
SPEA2	$I_M = 100$, $PopSize = 50$, $MND = 50$;	68	66	54	68	0.6371
MOEA/D	$I_M = 100$, $PopSize = 50$, $MND = 50$; $NoD = 20$;	71	66	58	62	0.6428
MOABC	$I_M = 100$, $PopSize = 50$, $nOnlooker = 50$;	69	66	72	56	0.6385
MORDA	$I_M = 100$, $PopSize = 50$, $Gamma = 0.7$, $Beta = 0.5$, $Alpha = 0.5$;	66	78	59	62	0.64
MDGSA	$G_0 = 10$, $\lambda = 10$, $I_M = 100$, $PopSize = 50$;	87	75	69	83	0.7842

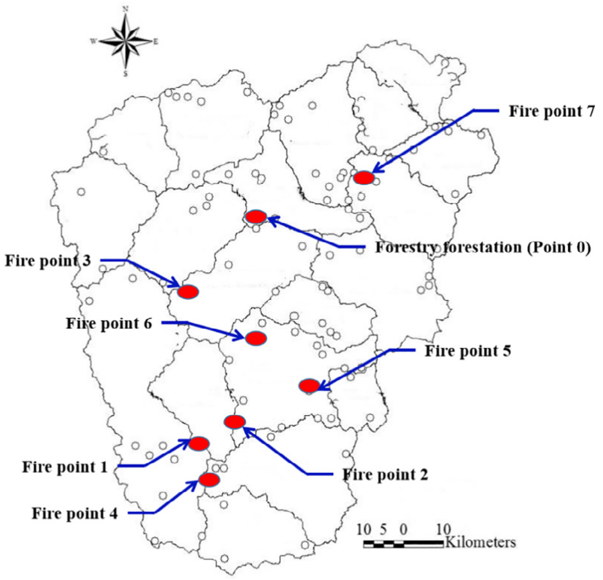


Fig. 3. Schematic diagram of Huzhong region in China.

stage, v_{ij} can be assumed to be 54 km/h considering the actual conditions of road driving, and parameters w_1, w_2 and w_3 are of the same value.

In addition, the rescue priority sequence for this emergency scheduling is $P_4 > P_5 > P_1 > P_6 > P_7 > P_3 > P_2$, decided by the spreading speed of each fire point in Table 5. Thus, the weighting factor η_{i} of each fire point can be given in Table 7.

Our analyses in the previous sub-section confirm that the proposed MDGSA is more efficient than other algorithms. Hence, our case study is analyzed by the proposed algorithm. Having a sensitivity analysis, the population sizes are changed from 20 to 50 [39–40]. For each value of population size, the values of G_0 and λ increase as shown in Table 8. According to the total Pareto solutions, with different values of parameters given in Table 8, both population sizes of 20 and 50, G_0 = 10 and λ = 10 are seen to give best Pareto solutions shown in bold; and only a group of best Pareto solutions is obtained if *PopSize* = 20, but more than one for population size of 50, which means that *PopSize* = 50 is adequate to search the space.

Based on the tuned parameters given in Table 1, the specific emergency scheduling schemes produced by the proposed algorithm using the above parameters are shown in Table 9, where the priority of fire point *i* is higher and more vehicles are assigned to the point, which testifies that the MDGSA is able to cope with the rescue priority of each fire point effectively. Our results confirm that the proposed algorithm is highly efficient for solving our case study.

4.3. Comparison of algorithms

To clearly illustrate the extraordinary performance of the proposed method, random tests are generated in three different complexity levels, i.e., small, medium and large scales. In this regard, the range of parameters given in the case study, is simulated by uniform functions. For example, we note that the distance between these points is $d_{ij}\, f_3 = \sum_{j=1}^{N}\sum_{m=1}^{M} z_{0j}^{m}[50, 100]$, the fire spreading speed $v_{Si}\, K \leqslant \sum_{i=1}^{N}\sum_{m=1}^{M} z_{0j}^{m} \leqslant M[2,6]$, and $\eta_{\mathrm{i}}\, L_i \leqslant \sum_{m=1}^{M} z_{0j}^{m} \leqslant U_i[0, 10]$. Meanwhile, the other parameters are set to be identical with the first case as given in Section 4.2. In each scale, three random tests are generated to compare the algorithms including NSGA-III, MOPSO, SPEA2, MOEA/D, MOABC, MORDA and the proposed MDGSA. These algorithms are evaluated by five criteria including, NPS, MID, MS, HV and the CPU time. The results are given in Table 10. It should be noted

Table 2
The distance of each fire point (km).

Point No.	0	1	2	3	4	5	6	7
0	0	42	56	63	65	50	66	45
1	42	0	20	33	45	35	48	64
2	56	20	0	46	53	44	42	58
3	63	33	46	0	60	55	52	54
4	65	45	53	60	0	62	64	56
5	50	35	44	55	62	0	65	66
6	66	48	42	52	64	65	0	63
7	45	64	58	54	56	66	63	0

Table 3
The site details of each fire point.

Fire point No.	1	2	3	4	5	6	7
Site Location	1231 highland Hubin	No. 311 line Huxi	No. 59 line Xigou	No. 59 line Hubin	No. 12 line Mt. Xiaobai	No. 3 line Mt. Xiaobai	No. 6 line Mt. Bishuitiyang

Table 4
Meteorological information of each fire point.

Point No. (N)	Average temperature (°C)	Average wind speed (m/s)	Average wind force (level)
1	25	3.6	2
2	23	2	1
3	22	2	1
4	26	3.6	2
5	24	3.6	2
6	23	3.6	2
7	22	2	1

Table 5
Geographic information of each fire point.

Fire point No.	1	2	3	4	5	6	7
Slope (°)	10	2	5	15	13	8	8
Fuel types	I	I	I	I	I	I	I

Table 6
The fire spreading speed of each fire point.

Fire point No.	1	2	3	4	5	6	7
v_{Si} (m/min)	5.16	2.20	2.55	6.98	6.56	4.83	3.40

Table 7
The weighting factor of each fire point.

Fire point No.	1	2	3	4	5	6	7
η_i	0.48	0.80	0.76	0.30	0.34	0.51	0.67

that since our optimization algorithms are stochastic, we run them 10 times and the average of outputs is considered by our results.

To identify which algorithm is the best in each criterion, statistical tests are done. In this regard, the results given in Table 10 are first normalized by the Relative Deviation Index (RDI) as follows:

$$RDI = \frac{|Alg_{sol} - Best_{sol}|}{Max_{sol} - Min_{sol}} \tag{32}$$

where Alg_{sol} is the optimal solution for each algorithm by each assessment metric, Max_{sol} and Min_{sol} are the maximum and minimum solution among the three algorithms by each assessment metric. $Best_{sol}$ is the optimal solution among the three algorithms by each assessment metric which is one of Max_{sol} orMin_{sol}. For the NPS, MS and HV metrics, $Best_{sol}$ is theMax_{sol}. A lower value for the RDI brings a better capability of the algorithm. For the MID and CPU time, $Best_{sol}$ is theMin_{sol}. Using the range of values from RDI, the means plot with 95 % confidence level is drawn as given in Fig. 4. The lowest interval plot which is more accurate, shows a better performance of algorithms in each criterion.

As can be seen in Fig. 4(a), the proposed MDGSA is highly different from other algorithms based on the NPS metric. Except MORDA, the performance of other algorithms is the same in this criterion. Based on the MID metric (Fig. 4(b)), there is a competition between all algorithms. However, it is evident that the proposed MDGSA shows the best performance and the NSGA-III is the weakest algorithm in this criterion. This competition is very close for the evaluation of the MS metric as can be seen in Fig. 4(c). However, it should be noted the proposed MDGSA is still the best algorithm. For the evaluation of HV metric (Fig. 4(d)), both MDGSA and MORDA are the best algorithm in this metric. However, the performance of other algorithms is the same. Finally, as can be seen in Fig. 4(e), the proposed MDGSA is faster than all algorithms except MORDA and MOPSO methods.

Table 8
The produced Pareto solutions of the proposed algorithm in solving our case study (the best values are shown in bold).

PopSize	G_0	The Pareto solutions								
		10			50			100		
		f_1 (h)	f_2 (h)	f_3	f_1 (h)	f_2 (h)	f_3	f_1 (h)	f_2 (h)	f_3
20	0.1	33.90	13.99	30	19.31	7.96	32	33.90	13.99	30
		17.64	5.48	32	32.05	12.15	31	17.63	5.48	32
		21.16	9.80	31				30.83	13.23	31
	0.5	17.63	4.53	32	15.55	4.72	32	19.41	8.53	32
		15.55	4.72	32	21.16	9.80	31	36.44	18.31	30
		33.90	13.99	30	22.47	9.29	31	22.47	9.29	31
	10	24.32	11.14	30	16.77	3.64	32	17.98	5.19	32
		16.77	3.64	32	15.45	4.15	32	24.32	11.14	30
		15.45	4.15	32	18.61	5.48	31	39.60	19.65	29
		18.61	5.48	31	24.32	11.14	30	17.64	5.48	32
		39.60	19.65	29				18.61	5.48	31
	50	15.45	4.15	32	24.32	11.14	30	24.32	11.14	30
		24.32	11.14	30	15.45	4.15	32	17.64	5.48	32
		39.60	19.65	29	39.60	19.65	29	18.61	5.48	31
		18.61	5.48	31	18.61	5.48	31	39.6	19.65	29
	100	39.60	19.65	29	21.25	10.38	31	15.45	4.15	32
		18.61	5.48	31	17.63	4.53	32	18.61	5.48	31
		24.32	11.14	30	39.6	19.65	29	24.32	11.14	30
		15.45	4.15	32	24.32	11.14	30			
50	0.1	16.77	3.64	32	24.32	11.14	30	39.6	19.65	29
		24.32	11.14	30	15.45	4.15	32	33.90	13.99	30
		39.60	19.65	29	18.61	5.48	31	18.61	5.48	31
		18.61	5.48	31						
	0.5	16.77	3.64	32	24.32	11.14	30	39.6	19.65	29
		24.32	11.14	30	21.16	9.80	31	16.77	3.64	32
		15.45	4.15	32	16.77	3.64	32	33.90	13.99	30
		18.61	5.48	31	22.47	9.29	31	21.16	9.80	31
	10	24.32	11.14	30	24.32	11.14	30	15.45	4.15	32
		15.45	4.15	32	16.77	3.64	32	24.32	11.14	30
		16.77	3.64	32	15.45	4.15	32	16.77	3.64	32
		39.60	19.65	29	18.61	5.48	31	18.61	5.48	31
		18.61	5.48	31	39.60	19.65	29	39.60	19.65	29
	50	15.45	4.15	32	24.32	11.14	30	39.6	19.65	29
		24.32	11.14	30	39.60	19.65	29	33.90	13.99	30
		16.77	3.64	32	15.45	4.15	32	15.45	4.15	32
		39.60	19.65	29	16.77	3.64	32	18.61	5.48	31
		18.61	5.48	31	18.61	5.48	31			
	100	16.77	3.64	32	24.32	11.14	30	17.63	4.53	32
		15.45	4.15	32	16.77	3.64	32	15.55	4.72	32
		24.32	11.14	30	15.45	4.15	32	24.32	11.14	30
		18.61	5.48	31	39.6	19.65	29	18.61	5.48	31
					18.61	5.48	31			

Table 9
The produced Pareto solutions of the proposed algorithm.

No.	The scheduling schemes	f_1 (h)	f_2 (h)	f_3	Running time (*ms*)
1	{5, 2, 3, 7, 7, 5, 3}	16.77	3.64	32	1645.10
2	{5, 2, 3, 6, 6, 5, 3}	24.32	11.14	30	
3	{5, 2, 3, 7, 6, 5, 4}	15.45	4.15	32	
4	{5, 2, 3, 6, 6, 4, 3}	39.60	19.65	29	
5	{5, 2, 3, 7, 6, 5, 3}	18.61	5.48	31	

In conclusion, based on all multi-objective metrics, the proposed MDGSA reaches a high-quality of non-dominated solutions in comparison with all algorithms. However, it is not very fast.

4.4. Discussion of results and managerial insights

Academically, the scheduling problems are a very complex optimization problem and the development of an efficient solution algorithm is essential. The scheduling of emergency schemes when a forest fire occurs, not only needs a very quick solution, but also it must be optimal as the decisions are strategic. In China, the forest fire occurs yearly and this issue is a grand challenge for China government to preserve the natural resources and forest as much as possible. After the industrial revolution in China during the last century, the climate change is happened and such natural disasters are occurred rapidly.

Table 10
Comparison of the applied algorithms (the CPU time is based on seconds).

Complexity level	The number of fire points *N*	The maximum number of rescue vehicles *M*	NSGA-III					MOPSO					SPEA2					MOEA/D					MOABC					MORDA					MDGSA				
			NPS	MID	MS	HV	CPU	NPS	MID	MS	HV	CPU	NPS	MID	MS	HV	CPU	NPS	MID	MS	HV	CPU	NPS	MID	MS	HV	CPU	NPS	MID	MS	HV	CPU	NPS	MID	MS	HV	CPU
Small	10	42	5	4.55	37,066	2.89E+04	148.74	5	2.6428	42,715	2.38E+04	104.56	4	3.4267	33,800	2.76E+04	134.63	5	4.7602	40,950	2.57E+04	184.53	4	2.1239	43,901	4.63E+04	132.45	6	3.9062	40,112	4.54E+04	176.54	8	2.519	46,367	3.91E+04	116.54
	10	42	5	4.6661	33,662	3.76E+04	136.62	5	3.3217	49,825	1.87E+04	124.54	4	2.155	43,590	3.54E+04	129.66	6	4.2839	36,460	3.52E+04	162.12	5	3.5946	37,755	3.28E+04	126.54	7	3.3717	46,539	3.92E+04	145.73	8	2.0296	43,434	4.73E+04	94.72
	10	42	5	2.4964	46,154	2.54E+04	157.53	5	2.6988	30,560	2.65E+04	166.84	5	4.9658	40,795	2.85E+04	162.75	6	4.851	40,315	3.37E+04	192.64	5	3.9227	35,149	3.15E+04	172.83	6	3.1944	44,226	4.16E+04	184.28	9	1.5651	40,230	4.29E+04	121.54
Medium	15	70	6	4.5756	57,214	3.54E+05	278.43	7	2.163	59,676	4.28E+05	239.83	6	3.1448	54,585	3.28E+05	295.71	6	3.5057	49,251	3.91E+05	312.65	7	2.445	54,890	4.91E+05	254.67	8	2.3356	48,687	6.75E+05	284.42	10	2.4142	51,347	5.32E+05	245.63
	15	70	6	4.995	54,042	3.72E+05	289.75	7	4.5974	47,625	4.17E+05	269.43	6	4.4252	48,490	3.81E+05	312.83	6	3.383733	49,676	4.17E+05	296.54	7	3.8106	47,835	3.86E+05	272.67	8	3.9113	50,728	5.32E+05	291.78	10	1.2731	55,715	4.97E+05	276.62
	15	70	6	3.5275	46,401	4.18E+05	247.81	6	2.2383	47,942	3.96E+05	196.54	6	2.2356	52,185	3.79E+05	256.82	6	4.883176	59,529	3.28E+05	267.13	7	2.1541	44,940	4.17E+05	239.43	8	2.118	47,343	4.12E+05	256.53	10	2.224	54,859	4.12E+05	213.54
Large	50	260	6	3.6907	53,379	3.72E+07	480.25	8	2.969	53,890	3.81E+07	398.72	7	4.5698	55,068	4.17E+07	457.82	7	2.192947	62,248	5.73E+07	463.26	8	2.276	57,906	6.18E+07	445.72	9	3.202	53,542	1.54E+08	483.27	12	2.048	67,182	2.31E+08	436.54
	50	260	7	4.5851	68,848	5.46E+07	536.81	8	4.6236	63,575	5.38E+07	458.61	7	3.7785	52,862	5.73E+07	504.27	7	3.165635	64,365	5.16E+07	514.62	8	2.7239	52,855	5.24E+07	502.18	9	2.8111	56,249	1.62E+08	545.73	11	2.5164	64,731	1.97E+08	485.29
	50	260	7	4.0937	59,947	4.82E+07	497.15	8	2.5415	52,106	6.15E+07	427.91	7	4.4887	67,606	4.19E+07	482.17	7	3.086012	56,634	5.82E+07	499.27	8	3.082	54,262	4.91E+07	483.71	9	2.2664	53,808	1.85E+08	495.28	12	2.4773	68,181	2.14E+08	468.92

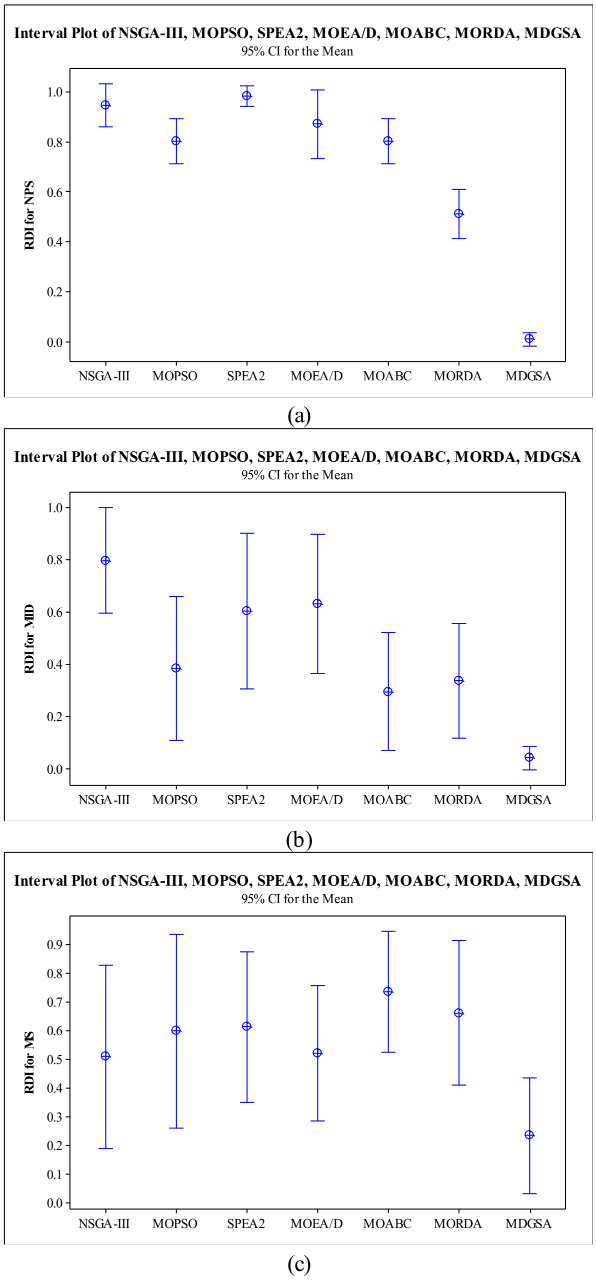
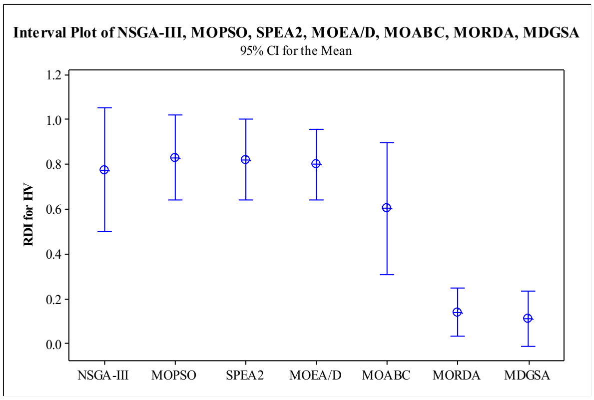


Fig. 4. Interval plot for algorithms' comparison, i.e., (a)NPS, (b)MID, (c)MS, (d) HV and (e)CPU time.

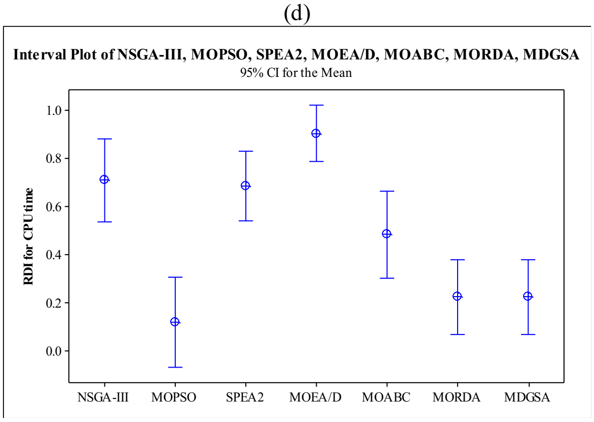
This motivates our attempts to propose a robust multi-objective plan to optimize the number of fire engines while minimizing firefighting time and firefighting delay time, simultaneously. Our model also includes real-life constraints like the severity of each fire point with regards to the limited resources of vehicles. The proposed model addresses an actual forest fire emergency scheduling at Huzhong region located in Mt. Daxing'anling of Heilongjiang Province, China. Due to high complexity for solving the proposed problem, this study develops an efficient solution algorithm as a modified MDGSA which is robust and efficient.

Based on the results of this paper, following findings are achieved. First, after tuning all algorithms, the proposed MDGSA was more efficient for solving our case study (Table 1). Then, our sensitivity analyses for evaluation of proposed MDGSA in solving our case study approve that our algorithm was successful for finding feasible and robust solutions (Table 8). Finally, based on different multi-objective metrics including NPS, MID, MS, HV and CPU time, the high performance of the proposed algorithm was shown (Fig. 4) against NSGA-III, MOPSO, SPEA2, MOEA/D, MOABC and MORDA.

In conclusion, from our results, some managerial insights can be concluded. First, the proposed multi-objective can help managers to take the necessary steps to expedite operations by having a comprehensive view of the emergency rescue plan-



(d)



(e)

Fig. 4 (*continued*)

ning problem to address the forest fire in China. Using our non-dominated solutions, the decision-maker is able to find an interaction between the number of fire engines, firefighting time and firefighting delay time. At last but not least, it goes without saying that the proposed MDGSA is robust and applicable to solve emergency scheduling of forest fire in China.

5. Conclusion and future works

Since emergency rescue and relief operations may have an impact to the surface transportation, a working roadway network is essential. This work formulated a multi-objective scheduling model to address the emergency services for the forest fire in China with regards to the rescue priority and limited rescue resources. A significant novelty of this research was to develop a modified GSA, so-called, MDGSA for solving our optimization model. An empirical application, i.e., an actual forest fire emergency scheduling in China, was used to verify this scheduling model and to show the applicability of proposed algorithm. In comparison with previous algorithms like MOPSO, NSGA-III, SPEA2 and MOEA/D as the traditional methods and MOABC and MORDA as the recent algorithms, the proposed algorithm was more productive to obtain the optimal solutions of a forest fire emergency scheduling problem. The results can be applied to help decision-makers for making better decisions when multiple forest fires occur and they present a new solution to determine the best rescue schedule to deal with forest fires.

Although this research was successful to propose a new multi-objective scheduling model and an efficient optimization algorithm, there are some limitations which can be considered for our future works. First, using a dynamic programming approach can better simulate the emergency scheduling for addressing the forest fire. Another future research direction is to develop a graphical user interface to visualize the proposed approach. Due to uncertainty for our schedules, a real-time optimization approach is another good alternative for the future. Finally, other novel optimization algorithms or efficient reformulation techniques like Lagrangian relaxation and Benders decomposition, can be suggested for further research.

CRediT authorship contribution statement

Guangdong Tian: Conceptualization, Methodology. **Amir M. Fathollahi-Fard:** . **Yaping Ren:** Investigation, Project administration. **Zhiwu Li:** Supervision, Writing – review & editing. **Jiangyu Jiang:** .

Data availability

No data was used for the research described in the article.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is supported in part by National Natural Science Foundation of China under Grant No. 52075303.

Appendix A

Table A1
Table A2
Table A3

Table A1
The k_s value of different fuel types.

Forest types	Meadow (I)	Secondary forest (II)	Coniferous forest (III)
k_s	1.0	0.7	0.4

Table A2
The v_w ($k_w = e^{0.1783 v_w}$) value of different wind force.

Wind force level	v_w (m/s)
1	2
2	3.6
3	5.4
4	7.4
5	9.8
6	12.3
7	14.9
8	17.7
9	20.8
10	24.2
11	27.8
12	29.8

Table A3
The k_φ value of different terrain slope.

Slope range	k_φ
$-42^\circ \sim -38^\circ$	0.07
$-37^\circ \sim -33^\circ$	0.13
$-32^\circ \sim -28^\circ$	0.21
$-27^\circ \sim -23^\circ$	0.32
$-22^\circ \sim -18^\circ$	0.46
$-17^\circ \sim -13^\circ$	0.63
$-12^\circ \sim -8^\circ$	0.83
$-7^\circ \sim -3^\circ$	0.90
$-2^\circ \sim 2^\circ$	1.00
$3^\circ \sim 7^\circ$	1.20
$8^\circ \sim 12^\circ$	1.60
$13^\circ \sim 17^\circ$	2.10
$18^\circ \sim 22^\circ$	2.90
$23^\circ \sim 27^\circ$	4.10
$28^\circ \sim 32^\circ$	6.20
$33^\circ \sim 37^\circ$	10.10
$38^\circ \sim 42^\circ$	17.50

References

[1] W. Yi, L. Ozdamar, A dynamic logistics coordination model for evacuation and support in disaster response activities, Eur. J. Oper. Res. 179 (3) (2007) 1177–1193.
[2] M. Munoz-Guillermo, Image encryption using q-deformed logistic map, Inform. Sci. 552 (2021) 352–364.
[3] X. Qian, S. Fang, M. Yin, M. Huang, X. Li, Selecting green third party logistics providers for a loss-averse fourth party logistics provider in a multiattribute reverse auction, Inf. Sci. 548 (2021) 357–377.
[4] D.H. Wolpert, W.G. Macready, No free lunch theorems for optimization, IEEE Trans. Evolut. Comput. 1 (1) (1997) 67–82.
[5] R. Knott, Vehicle scheduling for emergency relief management: A knowledge-based approach, Disasters 12 (4) (1988) 285–293.
[6] H. Wang, P. Hu, H. Wang, A genetic timing scheduling model for urban traffic signal control, Inf. Sci. 576 (2021) 475–483.
[7] G.D. Tian, M.C. Zhou, J.W. Chu, T. Qiang, H.S. Hu, Stochastic cost-profit tradeoff model for locating an automotive service enterprise, IEEE Trans. Autom. Sci. Eng. 12 (2) (2015) 580–587.
[8] S.Y. Yan, J.C. Chu, Y.L. Shih, Optimal scheduling for highway emergency repairs under large-scale supply-demand perturbations, IEEE Trans Intell. Transp. 15 (6) (2014) 2378–2393.
[9] A. Haghani, S. Oh, Formulation and solution of a multi- commodity, multi-modal network flow model for disaster relief operations, Transp. Res. A. 30 (3) (1996) 231–250.
[10] Y. Yuan, D. Wang, Path selection model and algorithm for emergency logistics management, Comput. Ind. Eng. 56 (3) (2009) 1081–1094.
[11] V. Schmid, K. Doerner, Ambulance location and relocation problems with time-dependent travel times, Eur. J. Oper. Res. 207 (3) (2010) 1293–1303.
[12] G.H. Tzeng, H.J. Cheng, D.H. Tsung, Multi-objective optimal planning for designing relief delivery systems, Transport. Res. E-Log. 43 (6) (2007) 673–686.
[13] D.T. Wilson, G.I. Hawe, G. Coates, R.S. Crouch, A multi-objective combinatorial model of casualty processing in major incident response, Eur. J. Oper. Res. 230 (2013) 643–655.
[14] V. Schmid, Solving the dynamic ambulance relocation and dispatching problem using approximate dynamic programming, Eur. J. Oper. Res. 219 (3) (2012) 611–621.
[15] A.M. Campbell, D. Vandenbussche, W. Hermann, Routing for relief efforts, Transport. Sci. 42 (2) (2008) 127–145.
[16] F. Wex, G. Schryen, S. Feuerriegel, D. Neumann, Emergency response in natural disaster management: Allocation and scheduling of rescue units, Eur. J. Oper. Res. 235 (2014) 697–708.
[17] L. Talarico, F. Meisel, K. Sörensen, Ambulance routing for disaster response with patient groups, Comput. Oper. Res. 56 (2015) 120–133.
[18] Y. Chiu, H. Zheng, Real-time mobilization decisions for multi-priority emergency response resources and evacuation groups: Model formulation and solution, Transport. Res. E-Log. 43 (6) (2007) 710–736.
[19] G. Tian, Y. Ren, M.C. Zhou, Dual-objective scheduling of rescue vehicles to distinguish forest fires via differential evolution and particle swarm optimization combined algorithm, IEEE Trans. Intell. Transport. Syst. 17 (2016) 3009–3021.
[20] P. Wu, F. Chu, A. Che and M. C. Zhou, "Bi-objective scheduling of fire engines for fighting forest fires: new optimization approaches," *IEEE Trans. on Intelligent Transportation Systems*, 19(4) 1140–1151.
[21] J. Margerit, O. Séro-Guillaume, Modelling forest fires, Part II: reduction to two-dimensional models and simulation of propagation, Int. J. Heat Mass Transf. 45 (2002) 1723–1737.
[22] G. Wen, Y. Liu, A model of forest fires spread and itsapplication, J. Northeast Forestry Univ. 22 (2) (1994) 31–36.
[23] Z.F. Wang, The measurement method of the wildfire initial spread rate, Mt. Res. 1 (2) (1983) 42–51.
[24] E. Rashedi, H. Nezamabadi-pour, S. Saryazdi, GSA: a gravitational search algorithm, J. Inform. Sci. 179 (13) (2009) 2232–2248.
[25] T. Eiichi, S. Hiroshi, Intelligent transportation system based dynamic vehicle routing and scheduling with variable travel times, Transport. Res. C 12 (2004) 235–250.
[26] Y. Sun, C.Y. Zhang, L. Gao, X.J. Wang, Multi-objective optimization algorithms for flow shop scheduling problem: a review and prospects, Int. J. Adv. Manuf. Tech. 55 (2011) 723–739.
[27] Y. Hou, N. Wu, M.C. Zhou, Z. Li, Pareto-optimization for scheduling of crude oil operations in refinery via genetic algorithm, IEEE Trans. Syst. Man Cybern. Syst. 47 (3) (2017) 517–530.
[28] K.Z. Gao, Z.G. Cao, L. Zhang, Z.H. Chen, Y.Y. Han, Q.K. Pan, A review on swarm intelligence and evolutionary algorithms for solving flexible job shop scheduling problems, IEEE/CAA J. Autom. Sinica 6 (4) (2019) 875–887.
[29] Z. Lv, L. Wang, Z. Han, J. Zhao, W. Wang, Surrogate-assisted particle swarm optimization algorithm with Pareto active learning for expensive multi-objective optimization, IEEE/CAA J. Autom. Sin. 6 (3) (2019) 838–849.
[30] Q. Kang, S.W. Feng, M.C. Zhou, A.C. Ammari, K. Sedraoui, Optimal load scheduling of plug-in hybrid electric vVehicles via weight-aggregation multi-objective evolutionary algorithms, IEEE Trans. Intell. Transport. Syst. 18 (9) (2017) 2557–2568.
[31] E. Zitzler, M. Laumanns, L. Thiele, SPEA2: Improving the strength Pareto evolutionary algorithm, TIK-Report 103 (2001) 34–76.
[32] Q. Zhang, H. Li, MOEA/D: A multiobjective evolutionary algorithm based on decomposition, IEEE Trans. Evol. Comput. 11 (6) (2007) 712–731.
[33] G. Tian, Y. Ren, Y. Feng, M. Zhou, H. Zhang, J. Tan, Modeling and planning for dual-objective selective disassembly using and/or graph and discrete artificial bee colony, IEEE Trans. Indust. Inform. 15 (4) (2019) 2456–2468.
[34] H. Liu, M. Zhou, X. Guo, Z. Zhang, N. Bin, T. Tang, Timetable optimization for regenerative energy utilization in subway systems, IEEE Trans. Intell. Transp. Syst. 20 (9) (2019) 3247–3257.
[35] A.M. Fathollahi-Fard, M. Hajiaghaei-Keshteli, R. Tavakkoli-Moghaddam, Red deer algorithm (RDA): a new nature-inspired meta-heuristic, Soft. Comput. 24 (19) (2020) 14637–14665.
[36] F. Neri, J. Toivanen, G.L. Cascella, Y.-S. Ong, An adaptive multimeme algorithm for designing HIV multidrug therapies, IEEE ACM T. Comput. Bi. 4 (2) (2007) 264–278.
[37] S. Rostami, F. Neri, A fast hypervolume driven selection mechanism for many-objective optimisation problems, *Swarm*, Evol. Comput. 34 (2017) 50–67.
[38] X. Zuo, C. Chen, W. Tan, M.C. Zhou, Vehicle scheduling of an urban bus line via an improved multiobjective genetic algorithm, IEEE Trans Intell. Transp. 16 (2) (2015) 1030–1041.
[39] S. Mondal, A. Bhattacharya, S.H. Dey, Multi-objective economic emission load dispatch solution using gravitational search algorithm and considering wind power penetration, Int. J. Elec. Power 44 (2013) 282–292.
[40] Z.K. Li, G.D. Tian, G. Cheng, H.G. Liu, Z.H. Cheng, An integrated cultural particle swarm algorithm for multi-objective reliability-based design optimization, *Proc IMechE, Part C: J MEC*. 228 (7) (2014) 1185–1196.
[41] J. Li, J. Zhang, C. Jiang, M.C. Zhou, Composite Particle Swarm Optimizer with Historical Memory for Function Optimization, IEEE Trans. Cybernetics 45 (10) (2015) 2089–2099.
[42] M.B. Dowlatshahi, H. Nezamabadi-Pour, GGSA: a grouping gravitational search algorithm for data clustering, Eng. Appl. Artif. Intell. 36 (2014) 114–121.
[43] R. Jiao, S. Zeng, C. Li, Y. Ong, Two-type weight adjustments in MOEA/D for highly constrained many-objective optimization, Inf. Sci. 578 (2021) 592–614.
[44] G.D. Tian, M.C. Zhou, P.G. Li, Disassembly sequence planning considering fuzzy component quality and varying operational cost, IEEE T. Autom. Sci. Eng. 15 (2018) 748–760.
[45] H.H. Zhang, Y. Peng, L. Hou, G.D. Tian, Z.W. Li, A hybrid multi-objective optimization approach for energy-absorbing structures in train collisions, Inform. Sciences 481 (2019) 491–506.
[46] S. Gao, M. Zhou, Y. Wang, J. Cheng, H. Yachi, J. Wang, Dendritic neuron model with effective learning algorithms for classification, approximation and prediction, IEEE Trans. Neural Networks Learn. Syst. 30 (2) (2019) 601–614.

[47] G. Tian, Y. Ren, Y. Feng, M. Zhou, H. Zhang, J, Tan., Modeling and Planning for Dual-objective Selective Disassembly Using AND/OR Graph and Discrete Artificial Bee Colony, IEEE Trans. Ind. Inf. 15 (2019) 2456–2468.

[48] A.M. Fathollahi-Fard et al, An adaptive Lagrangian relaxation-based algorithm for a coordinated water supply and wastewater collection network design problem, Inf. Sci. 512 (2020) 1335–1359.

[49] A.M. Fathollahi-Fard, L. Woodward, O. Akhrif, Sustainable distributed permutation flow-shop scheduling model based on a triple bottom line concept, J. Indust. Inform. Integrat. 24 (2021) 100233.

[50] W.J. Hill, W.G. Hunter, A review of response surface methodology: a literature survey, Technometrics 8 (4) (1966) 571–590.