Dual-Objective Scheduling of Rescue Vehicles to Distinguish Forest Fires via Differential Evolution and Particle Swarm Optimization Combined Algorithm

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***Abstract*—It is complex and difficult to perform the emergency scheduling of forest fires in order to reduce the operational cost and improve the efficiency of extinguishing fire services. A new research issue arises when: 1) decision-makers want to minimize the number of rescue vehicles (or fire-fighting ones) while minimizing the extinguishing time; and 2) decision-makers prefer to complete this task given limited vehicle resources. To do so, this paper presents a novel multiobjective scheduling model to handle forest fires subject to limited rescue vehicle (fire engine) constraints, in which a fire-spread speed model is introduced into this problem to better describe practical forestry fire. Moreover, a Multiobjective Hybrid Differential-Evolution Particle-Swarm-Optimization (MHDP) algorithm is proposed to create a set of Pareto solutions for this problem. This approach is applied to a real-world emergency scheduling problem of the forest fire in Mt. Daxing'anling, China. Its effectiveness is verified by comparing it with a genetic algorithm and particle swarm optimization algorithm. Experimental results show that the proposed approach is able to quickly produce satisfactory Pareto solutions.**

***Index Terms*—Forest fires, differential evolution (DE), particle swarm optimization (PSO), emergency scheduling, multi-objective optimization, modeling and simulation.**

NOMENCLATURE

$A(g)$	Archive set used to store the Pareto solutions at the gth generation.
$a(b, c)$	The factor related with the terrain for the spread model.
$c_1(c_2)$	Acceleration factor of PSO.
d_{ij}	Distance between points i and j.
F	Scaling factor of DE.
$f_1(f_2)$	Value of objective function 1 (2).
G_{best}	Global best.
$g_{\max}$	The maximum number of iterations.
U_i	Upper bound of the number of fire engines to the ith fire point, $i = 1, 2, \ldots, N$.
i, j	The index of a point/area, $i, j = 0, 1, 2, \ldots, N$.
K	Lower bound of the total number of vehicles required for forest fire emergency scheduling.
k_s	Correction factor of fuel types.
k_w	Correction factor of wind force.
k_φ	Correction factor of terrain slope.
L_i	Lower bound of the number of fire engines to the ith fire point, $i = 1, 2, \ldots, N$.
M	Upper bound of the total number of fire engines in the fire emergency scheduling centre.
m	The index of a fire engine, $m = 1, 2, \ldots, M$.
N	The number of starting and fire points. Note that 0 represents the starting point and others represent fire points.
P_{best}	Personal best.
P_c	Crossover probability of DE.
P_t	The particle's position at instant t.
$Q(g)$	Population in the gth generation.
$r_1(r_2, r_3)$	Random number from uniform distribution over [0, 1].
T	Temperature of a fire point.
t_{Ai}	The arrival time of fire engines to the ith fire point, $i = 1, 2, \ldots, N$.
t_{Ei}	The extinguishing time of the ith fire point, $i = 1, 2, \ldots, N$.
V_t	The particle's velocity at instant t.
v_0	The initial spread speed of a fire point.
v_m	The extinguishing speed offered by the mth fire engine.
v_{ij}	Average speed of the motorcade from point i to j, $i, j = 1, 2, \ldots, N$.
v_S	The spread speed of a fire point.
v_{Si}	Average fire spread speed of the ith fire point, $i = 1, 2, \ldots, N$.
v_w	The wind speed of a fire point.
ω	The wind force of a fire point.

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X	Individual.
$X_i(g)$	The ith individual in $Q(g)$, $i = 1, 2, \ldots, \text{PopSize}$.
x_i	The ith gene in X.
$x_{ij}(g)$	The ith gene in $X_i(g)$.
Φ	A mathematical function that rounds its variable to the nearest integer.
τ	Inertia factor of PSO.
z_{0i}^m	Binary variable (1 if the mth fire engine is sent from point 0 to i; 0 otherwise).

I. Introduction

EMERGENCY management problems are concerned with information collection, scheduling, transportation, damage, time response, material resources and accurately tracking disaster-hit area in all kinds of emergency events. Since it is initiated, there have been many advances in their solution methods, variants and applications, e.g., earthquake relief, traffic incident response, personnel evacuation, and flood emergency. Related main works include relief distribution, e.g., [1]–[6]; emergency response management, e.g., [7]–[13]; and logistics management following urban disasters, e.g., [14]–[17]. Many different models have been formed, e.g., integer linear program [18], dynamic program [19], and goal program [20]. Meanwhile, a large number of solution approaches for different models have been proposed, e.g., genetic, greedy search, metaheuristic and immune algorithms [21]–[25]. Also, complete surveys of various emergency operations can be found in [26]–[30].

Since emergency rescue and relief operations depend on surface transportation, a working roadway network after a disaster is essential. Thus many studies on emergency rescue planning are performed. For example, Ozdamar *et al.* construct a vehicle routing model in emergency logistics for natural disaster [16]. Zhang *et al.* present an optimal path model to minimize the travel distance in an emergency logistics network [31]. Yuan and Wang establish a single-objective path selection model with the minimum response time and use a Dijkstra algorithm to solve it [32]. Chang *et al.* propose an optimal model to minimize the travel time, resource demand and transport cost with resource constraints, and use a greedy-search-based genetic algorithm to solve it [33]. Wilson *et al.* describe a routing planning model for the medical emergency service of mass casualty incidents [34]. Yi and Kumar adopt an ant colony optimization method to solve a logistics scheduling problem arising in disaster relief activities [35]. Yan *et al.* present an earthquake emergency scheduling model to minimize the operating cost [36]. Wex *et al.* develop an emergency decision support model to minimize the sum of completion time of incidents due to natural disasters, e.g., earthquakes, tsunamis and hurricanes [37]. Bruni *et al.* establish a scheduling model characterizing the arrival of emergency patients and the duration of surgery [38]. Hu *et al.* propose an allocation model of earthquake emergency shelters to minimize the total rescue time and use a particle swarm optimization (PSO) algorithm to solve it [39].

By analyzing the existing results, we conclude that the prior researches mainly focused on emergency planning/scheduling issues with a single target, i.e., emergency time or operational cost. However, in an actual emergency process, a decision-maker may want to minimize the number of rescue resources, as well as minimize the emergency processing time. Consequently, a multi-objective scheduling issue needs to be addressed. Also, in a practical emergency process, the resources, e.g., vehicles, have large impact on its efficiency. Thus resource availability should be considered when an optimal schedule is determined. In addition, researchers concentrate on the issues including earthquake, traffic incident and personnel evacuation, but they pay little attention to forest fire problems. Some authors have proposed the spread mechanism problem of forest fires [40], [41], and provide basic theory for the fire spread control. To our best knowledge, there are no studies on devising an emergency scheduling scheme to solve any realistic case of forest fires. To do so, this work proposes to establish a multi-objective scheduling model to cope with forest fires subject to rescue vehicle (fire engine) constraints for the first time. Namely, this work aims to find a new way to determine a schedule by taking multi-objectives and limited resources into full account. In addition, a Multi-objective Hybrid Differential-evolution and Particle-swarm-optimization (MHDP) algorithm is designed to solve the proposed model based on its characteristics. Compared with existing researches [1]–[57], we have the following contributions: (1) In order to describe actual forest fires, this work proposes a multi-objective scheduling model such that both extinguishing time and the number of scheduling fire engines can be minimized. (2) In an actual rescue process, since fire spread mechanisms have a large impact on emergency scheduling of forest fires, the proposed model considers fire spread speed as a crucial and important factor. (3) To solve a multi-objective scheduling problem, a multi-objective hybrid algorithm integrating differential evolution (DE) and PSO is designed to improve the quality of the solutions, which makes full use of the population diversity of DE and the convergence ability of PSO. (4) By performing experiments on multi-group instances and comparing with NSGA-II [56] and particle swarm optimization [58], [59], this work validates the effectiveness and feasibility of the proposed model and algorithm in solving a multi-objective scheduling problem.

The rest of this paper is organized as follows: Section II describes an emergency scheduling problem of forest fires and establishes its mathematical model. Section III describes a hybrid algorithm. Section IV presents the solutions to several cases. Finally, Section V concludes our work and describes some future research issues.

II. Problem Statement

A. Problem Statement

This work proposes a new emergency scheduling problem for forest fires involved with multiple fire areas/points and limited fire engines. As we all know, when dealing with major fire disasters especially like multiple fire points occurring in one region simultaneously, time is an indispensable and primary factor for each decision-maker. For this problem, the rescue time is composed of arrival time and extinguishing time. The former is generally constant since it is determined by distance and velocity if they are known, while the latter is highly related with fire spread. Thus, to minimize extinguishing time of forest fires is one optimization goal. Meanwhile decision-makers have to take existing rescue resources into consideration. Only in this way can we obtain a feasible and efficient scheme to solve this problem. A multi-objective program containing the firefighting time to extinguish forest fires and the number of fire engines sent is therefore designed. Its aim is to determine an optimal emergency schedule such that a certain number of fire engines are dispatched to different fire points to minimize the firefighting time, as well as need to save rescue expenditure as much as possible, i.e., minimizing the number of vehicles and their usage.

B. Fire Spread Model

Fire spread speed has a large impact on practical forest fires. To build an emergency scheduling optimization model, this section presents a fire spread model associated with natural conditions, e.g., wind force, initial spread speed, fuel types, temperature and the terrain slope [41], [42]. It is described as follows:

$$v_S = v_0 k_s k_\varphi k_w = v_0 k_s k_\varphi e^{0.1783 v_w} \tag{1}$$

where v_S and v_0 represent the fire spread speed and initial spread speed, respectively; k_s, k_w and k_φ are correction factors of fuel types, wind force and terrain slope, respectively. Also,

$$v_0 = aT + bw + c \tag{2}$$

where T is the temperature; w is the wind force; 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 obtained by related investigation and measurement, and listed in Tables VIII–X, respectively, in the Appendix.

C. Mathematical Model

Based on the above description, by considering two goals of minimizing extinguishing time and the number of fire engines, we formulate a dual-objective emergency scheduling optimization model with multi-resource constraints as follows:

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

$$\text{Min} \quad f_2 = \sum_{j=1}^{N} \sum_{m=1}^{M} z_{0j}^m \tag{4}$$

s.t.

$$K \le \sum_{j=1}^{N} \sum_{m=1}^{M} z_{0j}^m \le M \tag{5}$$

$$L_i \le \sum_{m=1}^{M} z_{0i}^m \le U_i, i = 1, 2, \ldots, N \tag{6}$$

$$z_{0i}^m \in \{0, 1\}, m = 1, 2, \ldots, M, i = 1, 2, \ldots, N. \tag{7}$$

Objective function f_1 in (3) aims to minimize the extinguishing time of fires. In this work, it is related with fire engines' arrival time to each fire point and described next. The arrival time of vehicles to the ith fire point t_{Ai} is computed as:

$$t_{Ai} = \frac{d_{0i}}{v_{0i}}, \ i = 1, 2, \ldots, N \tag{8}$$

where d_{0i} and v_{0i} are the distance between points 0 and i, and the average speed of the motorcade from point 0 to i, respectively. Note that point 0 represents the starting point.

Then, the extinguishing time of all fire points is given next. Note that according to the actual fire situation, a mathematic relation among v_{Si}, v_m and t_{Ei} is described as follows:

$$(t_{Ai}+t_{Ei}).v_{Si} = \left(\sum_{m=1}^{M} z_{0i}^m.v_m - v_{Si}\right).t_{Ei}, \ i=1,2,\ldots,N \tag{9}$$

where v_{Si}, v_m, and t_{Ei} are the fire spread speed of the ith fire point, the extinguishing speed offered by the mth fire engine and the extinguishing time of the ith fire point, respectively; $\sum_{m=1}^{M} z_{0i}^m$ means the total number of vehicles reaching the ith fire point from point 0. Note that v_{Si} is obtained via Eqs. (1) and (2). The left side of (9) represents the fire spread area of the ith fire point, which consists of two parts: the fire spread area of the ith fire point before fire engines' arrival, i.e., $t_{Ai} \cdot v_{Si}$, and the fire spread area of the ith fire point after their arrival, i.e., $t_{Ei} \cdot v_{Si}$; and the right side represents the firefighting area of the ith fire point. Thus, the extinguishing time of the ith fire point t_{Ei} is:

$$t_{Ei} = \frac{v_{Si} \cdot t_{Ai}}{\left(\sum_{m=1}^{M} z_{0i}^m \cdot v_m - 2v_{Si}\right)} \tag{10}$$

Thus we have:

$$f_1 = \sum_{i=1}^{N} \left[\frac{v_{Si} \cdot t_{Ai}}{\left(\sum_{m=1}^{M} z_{0i}^m \cdot v_m - 2v_{Si}\right)} \right]. \tag{11}$$

Objective function f_2 in (4) aims to minimize the number of dispatched vehicles; Constraint (5) ensures that the total number of fire engines sent to each fire point cannot be greater than M vehicles, and the total number of fire engines sent to each fire point cannot be less than K vehicles such that fires are extinguished in time. Constraint (6) limits the number of vehicles sent to the ith fire point, where L_i and U_i are its low and upper bounds, respectively. Constraint (7) defines decision variables that can take 1 or 0.

The two objectives of the proposed model are in conflict with each other because $\sum_{i=1}^{N} t_{Ei}$ in objective functions (3) and (4) is inversely proportional. To minimize the extinguishing time f_1, we require more vehicles such that f_2 increases. If a small number of vehicles is used, more extinguishing time is needed to extinguish fires such that f_1 becomes greater.

Based on the above description, the formulated model is a complex non-linear issue since: (a) Equation (11) is a non-linear function and equation (4) indicates that it is 0-1 integer programming problem; (b) forest fires are multiple and as the number of forest fires increases, the emergency scheduling becomes more complex and a rapidly growing number of scheduling solutions can be produced; and (c) two objectives which we have proposed can impact each other. Thus we propose a metaheuristic method to solve this problem next.

III. Hybrid Algorithm

Differential Evolution (DE), as an effective stochastic evolutionary algorithm proposed by Storn and Price including differential mutation operator, crossover and selection [43], has gained popularity in evolutionary algorithm research, which is used to successfully solve some optimization problems due to its strong optimization ability [44]–[49]. As one of swarm intelligence algorithms, PSO simulates the social behavior of bird flocking to a desired place. It starts by initializing a population of random solutions and searches for optima by updating generations. Compared to analytical or general heuristic methods, PSO is computationally efficient and can escape from local optima. In addition, PSO is easy to implement and there are few parameters to adjust [50]–[55]. To make full use of their advantages, an MHDP integrating DE and PSO is designed to solve the proposed problem. In MHDP, we introduce two differential evolutionary operators into PSO, i.e., mutation and crossover. Mutation is to increase the diversity of individuals and avoid PSO's being trapped into local optima. Crossover is exchanging some genes of the current individual with another in the same generation. Also, the velocity of particles is removed from PSO to reduce the impact of setting more parameters on the algorithm, e.g., ω, c_1, c_2, r_1, and r_2 as shown as in the following equations:

$$V_{t+1} = \tau V_t + c_1.r_1.(P_{\text{best}} - V_t) + c_2.r_2.(\text{G}_{\text{best}} - V_t) \quad (12)$$

$$P_{t+1} = P_t + V_{t+1} \quad (13)$$

where V_t and P_t are the particle's velocity and position at instant t, τ is an inertia factor, used to control the amount of a particle's current velocity, c_1 and c_2 are acceleration factors used to determine the relative influence of the self knowledge and global knowledge. r_1 and r_2 are two random numbers from the uniform distribution over interval [0, 1]. $\text{P}_{\text{best}} - V_t$ represents the exchange degree with reference to the personal best particle and $\text{G}_{\text{best}} - V_t$ represents the exchange degree with reference to the global best particle. The position of particle P_t is updated as P_{t+1} by exchanging the element order based on the updated velocity V_{t+1}.

The proposed hybrid algorithm contains five tasks: individual (solution) coding, generating initial population, calculating fitness values and screening Pareto solutions, mutation and crossover, and updating an archive set.

A. Solution (Individual) Coding

The encoding form of a solution directly affects the efficiency of the proposed algorithm. We first devise an initial multi-constraint-based coding scheme that has low decoding complexity and can conveniently execute the mutation and crossover operations. According to our problem's feature, a solution is encoded as an integer-valued vector, each gene of which corresponds to the number of fire engines sent to a fire point. As shown in Fig. 1, gene $x_i = \sum_{m=1}^{M} z_{0i}^m, i \in \{1, 2, \ldots, N\}$, of solution X, indicates the number of vehicles sent to the ith fire point from the starting point and x_i is ranged from L_i to U_i to satisfy constraint (6). For example, $X = \{2, 5, 3, 2, 4, 3\}$, the first element is 2, denoting that 2 vehicles are assigned to the first fire point, the second one is 5, meaning that 5 vehicles is assigned to the second fire point, and so on.

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

Fig. 1. Coding scheme of a solution.

B. Generating Initial Population Q(0)

The population size is denoted by PopSize. The values of initial individuals are generated randomly under multi-constraints. The number of vehicles f_2 in an individual is set as a random integer and $f_2 \in \{K, K+1, \ldots, M\}$. For a solution, each vehicle z_{0j}^m has a state, which is 1 if the scheduling solution contains the mth fire engine from point 0 to point j, and 0 otherwise. Usually, as the number of fire points increases, the number of scheduling solutions does so drastically. Clearly, some solutions/individuals among them are infeasible, namely they cannot meet specific constraints, e.g., (5) and (6). They need to be adjusted and a common method to do so is re-generation or re-construction. To make the algorithm quickly produce feasible solutions and converge to quality solutions, we initialize each individual in the initial population via Algorithm 1.

Algorithm 1 Generation of initial population $Q(0)$

Input: X_i
Output: $Q(0)$
While ($i \leq$ PopSize) Do
  Flag = 0;
  While (Flag == 0) Do
    Randomly generate an integer-valued vector including N elements and satisfying (6);
    Construct an individual X_i;
    If X_i is feasible, i.e., meeting (5), then
      $Q(0) = Q(0) \cup \{Xi\}$;
      Flag = 1;
    Else
      Flag = 0;
  End While;
  $i++$;
End While;

C. Calculating Fitness Values and Screening Pareto Solutions

It is essential to evaluate each individual (solution) by comparing their fitness values. The formulation consists of two objectives. An emergency scheme for our proposed model can be decoded into a solution X. The initial value of each individual is taken as its initial personal best ($\mathrm{P_{best}}$). The initial global best of the population ($\mathrm{G_{best}}$) is chosen from all the initial personal best values. Apparently, the number of vehicles f_2 can be easily obtained via (4) when X is known. However f_1 cannot be calculated directly and need to be derived via (8)–(10). Also, from (10), we have:

$$\sum_{m=1}^{M} z_{0i}^{m} \cdot v_m > 2v_{si}, \text{ i.e., } \sum_{m=1}^{M} z_{0i}^{m} \cdot > \frac{2v_{Si}}{v_m} \tag{14}$$

and according to (6): $L_i \leq \sum_{m=1}^{M} z_{0i}^{m} \leq U_i$. Thus

$$L_i > \frac{2v_{Si}}{v_m}. \tag{15}$$

In addition, U_i can be determined and evaluated by the actual fire spread speed of fire point i and the actual number of fire engines. 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 fire engines and it is a given parameter as U_i.

After the calculation of fitness values, the next key task is to search Pareto solutions from population $Q(g)$. Pareto optimality means there is no other solution that in every objective evaluation is equal or better than the solutions in the Pareto optimal solution set. Solutions are selected by comparing their every objective to ensure that they are Pareto optimal solutions. Algorithm 2 describes how to obtain Pareto ones via screening all solutions.

Algorithm 2 The process of screening Pareto solutions

Input: $Q(g-1)$, $Q(g)$
Output: $Q(g)$, $A(g)$
(1) Calculate the fitness values of each individual in the current population $Q(g)$ via (4), (11);
(2) For $i = 1$ to PopSize
(3) If $X_i(g)$ is feasible, i.e., meeting (5) and (6), and $X_i(g)$ dominates $X_i(g-1)$, then
(4) $\mathrm{P_{best}}(i) = X_i(g)$;
(5) End If;
(6) If $X_i(g)$ is feasible, and $X_i(g)$ and $X_i(g-1)$ are non-dominated each other, then
(7) Randomly choose one of them as $\mathrm{P_{best}}(i)$;
(8) End If;
(9) End For;
(10) Then the new Perato solutions in $Q(g)$ are merged into $A(g-1)$;
(11) Again screen the Pareto solutions because domination relations may exist between the new Perato solutions and $A(g-1)$;
(12) Produce $A(g)$;
(13) Randomly choose one of individuals in $A(g)$ as $\mathrm{G_{best}}$;

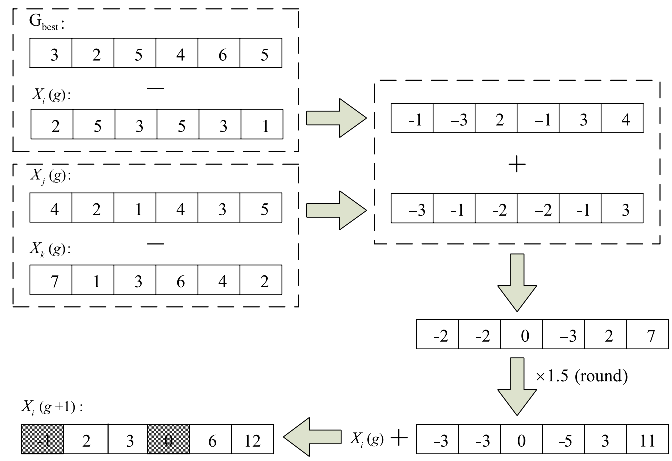

Fig. 2. Schematic of mutation operation.

D. Mutation and Crossover

As an evolutionary algorithm for solving optimization problems, DE uses a 3-parent mutation strategy in the current generation $Q(g)$ as given as follows:

$$X_i(g+1) = X_i(g+1) + F \cdot (X_j(g) - X_k(g)) \tag{16}$$

where F is the scaling factor and $F \in (0, 2), X_i(g)$ represents the ith individual in the current population, $i, j, k = 1, 2, \ldots, \text{PopSize}$, and $i \neq j \neq k$.

MHDP is an integration of DE and PSO. The main improvement of a mutation operator is that $\mathrm{G_{best}}$ and (16) are incorporated into PSO instead of (12) and (13), yielding:

$$X_i(g+1) = X_i(g+1) + \Phi\left[r_1(G_{\text{best}} - X_i(g)) + r_2(P_{\text{best}} - X_i(g)) + F(X_j(g) - X_k(g))\right] \tag{17}$$

where Φ represents a mathematical function that rounds its variable to the nearest integer.

Mutation probability is removed from the mutation operator [43], i.e., each mutation operation must be performed. In this way, the feasible solutions have preferable diversity and can avoid prematurity effectively. Its construction procedure is illustrated in Fig. 2 and F is set as 1.5.

According to Fig. 2, each individual in $Q(g)$ performs a differential mutation operation with G_{best} and another two randomly chosen individuals, and then, a new individual is created. All new individuals produced by the mutation operation form population $Q(g)$. All individuals, including mutated genes, are added into new $Q(g)$. The devised coding scheme ensures that crossover and mutation operations cannot create any infeasible solution. Notice that each gene of $X_i(g)$ must satisfy (6), otherwise, some genes will be adjusted to meet it via Algorithm 3. From Fig. 2, it is obvious that the first and fourth genes marked in shadow are unable to satisfy (6) and need to be adjusted. The adjustment process is given in Algorithm 3.

Each gene of individuals in $Q(g)$ carries out a crossover operation with probability P_c. A random real number r_3 is produced between 0 and 1, and if $r_3 < P_c$, gene $x_i, i = 1, 2, \ldots, N$, crosses; otherwise the crossover cannot be performed.

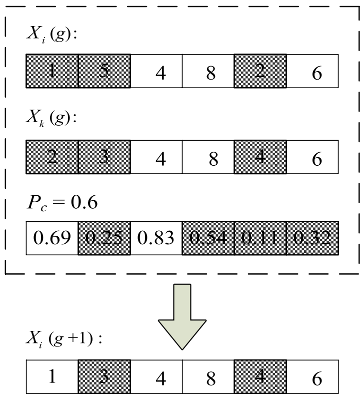

Fig. 3. Schematic of crossover operation.

The crossover operation is described in Algorithm 4. Also, an example is given in Fig. 3 and $P_c = 0.6$ [56].

Algorithm 3 Adjustment of genes unsatisfying (6)

Input: $Q(g)$
Output: $Q(g)$
(1) While $(i \leq \text{PopSize})$ Do
(2) For $j = 1$ to N
(3) If $(x_{ij}(g) < L_i)$Then
(4) $x_{ij}(g) = L_i$;
(5) Else if $(x_{ij}(g) > U_i)$Then
(6) $x_{ij}(g) = U_i$;
(7) End If;
(8) End for;
(9) End While;

Algorithm 4 The process of crossover

Input: $Q(g)$
Output: $Q(g)$
(1) While $(i \leq \text{PopSize})$ Do
(2) For $j = 1$ to N
(7) Randomly select neighboring individual $x_k(g), k \in \{1, 2, \ldots, \text{PopSize}\}$ and $k \neq i$;
(3) If $(r_3 < P_c \ \&\&\ x_{ij}(g) \neq x_{kj}(g))$ Then
(4) $x_{ij}(g) = x_{kj}(g)$;
(7) End If;
(8) End for;
(9) End While;

E. Multi-Objective Optimizer

This work uses a non-dominated sort algorithm [56] to divide the population solutions into several levels according to their dominated solutions. In addition, archive set $A(g)$ is used to store the top solutions found during the search process. In each generation, all nondominated solutions in the current population are regarded as candidate solutions to update $A(g)$. If each of the two objective values of a candidate solution satisfies a given threshold, the solution is added into A(g). Meanwhile, all dominated solutions are removed from $A(g)$.

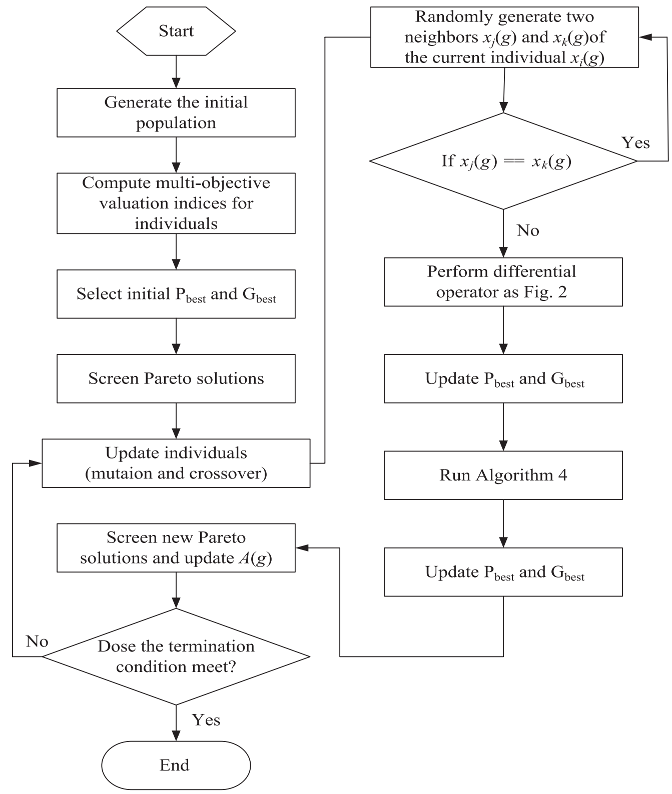

Fig. 4. The MHDP algorithm.

F. MHDP Procedure

The proposed MHDP adopts the maximum iteration count $g_{\max}$ as a termination criterion, i.e., if it is reached, output the Pareto solutions and terminate the algorithm. Pareto optimality means there is no other solution that in every objective evaluation is equal or better than the solutions in the Pareto optimal solution set $A(g)$. Based on the above discussion, the proposed algorithm is shown in Fig. 4.

IV. Experimental Results and Analysis

The proposed approach is applied to real-life emergency scheduling of forest fires in Mt. Daxing'anling of Heilongjiang Province, China.

The fires occurred in Huzhong region located in Mt. Daxing'anling at 10:40 local time on June 29, 2010. The distance information is given in Table I. According to Table I, point 0 represents the starting point of fire engines and other seven points represent fire locations as shown in Fig. 5, i.e.,

1. 1231 highland in Hubin,
2. No. 311 line in Huxi,
3. No. 59 line in Xigou,
4. No. 59 line in Hubin,
5. No. 12 line in Mt. Xiaobai,
6. No. 3 line in Mt. Xiaobai, and
7. No. 6 line in Mt. bishuitiyang. The coding length is 7, i.e., $N = 7$. The extinguishing speed of each fire engine is mainly dependent on its firefighting configuration, and each fire engine is assigned with an identical

TABLE I
THE DISTANCE OF EACH FIRE POINT (km)

Point No. (N)	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

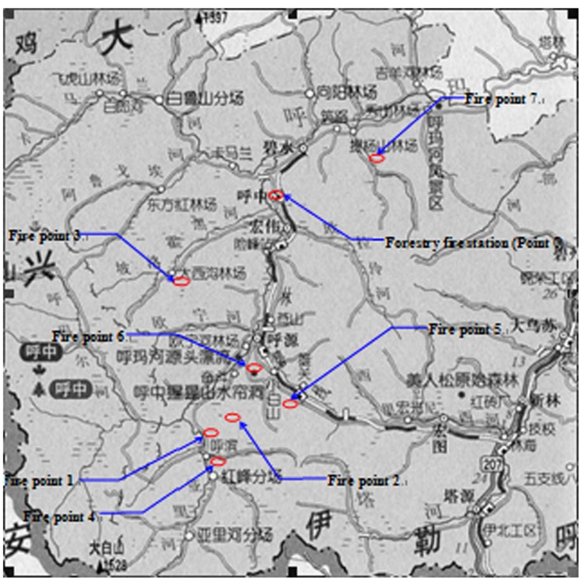

Fig. 5. Schematic diagram of Huzhong region in China.

TABLE II
METEOROLOGICAL DATA 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

quantity of personnel and equipment. Hence, its extinguishing speed can be considered to be identical, which is set to be 2.5 m/min, i.e., $v_m = 2.5$ m/min, $m = 1, 2, \ldots M$. For this region, $a = 0.053$, $b = 0.048$ and $c = 0.275$. Meteorological data and geographic information of each point are listed in Tables II and III.

According to the fire spread model in Section II-B, the spread speed of each fire point is obtained in Table IV.

The total number of vehicles in the initial individuals is a random integer from $\{29, 30, \ldots, 40\}$, i.e., $K = 29$ and $M = 40$ according to formulation (15). In the phase of calculating fitness values, v_{ij} is set to be 54 km/h based on the real-road driving

TABLE III
GEOGRAPHIC DATA 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 IV
FIRE SPREAD SPEED OF EACH FIRE POINT

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

conditions, and parameter F is set as 1.5. The parameters of the multi-objective hybrid algorithm are set as PopSize $= 50$, and $P_c = 0.6$.

A. Realistic Instance

1) Experimental Results: The proposed approach is implemented in MATLAB 7.14 and runs on an Intel(R) Core(TM) i3 CPU (2.53 GHz/4.00 G RAM) PC with a Windows 7 operating system. Four independent runs of the proposed algorithm are done, and in each run, the algorithm is executed for $g_{\max} = 100$ generations to adequately converge.

The Pareto solutions found in the four runs are given in Table V. The first column lists the number of runs, and the second one is the number of the Pareto solutions obtained in each run. The third one represents the scheduling schemes obtained in each run. The fourth and fifth ones show f_1 and f_2 values of the Pareto solutions, respectively. The sixth one gives the computational time to find the solutions. We can see that total time and the number of vehicles sent in those obtained Pareto solutions fall into [6.08, 39.60] and $\{29, 30, \ldots, 40\}$, respectively.

The Pareto solutions obtained in the four runs are also illustrated in Fig. 6. Each run is able to produce highly similar Pareto solutions, which indicates that the algorithm performance is stable.

2) Comparison With NSGA-II and MOPSO: To further test the proposed method, we use the same case to execute NSGA-II [56] and MOPSO [58], [59]. Table VI shows their experimental results. It is noted that the same encoding method, decoding rules, assessment of objective functions, screening Pareto solutions and updating $A(g)$ operator are adopted when running them. Also, mutation probability $p_m = 0.3$ when executing NSGA-II and other parameters in NSGA-II and MOPSO are the same as MHDP. The results with different $PopSize$ and $g_{\max}$ to run the case for three algorithms are given in Table IV.

From Table VI, the following conclusions can be drawn:

1) We obtain more non-dominated solutions from the proposed algorithm than NSGA-II and MOPSO; and
2) The proposed algorithm yields a result superior to those from NSGA-II and MOPSO and has competitive computational time.

Hence the proposed method is preferred to solve the proposed problem. In addition, to test the effectiveness of the proposed algorithm, their obtained Pareto solutions resulting

TABLE V
PRODUCED PARETO SOLUTIONS OF THE PROPOSED ALGORITHM

Runs	No.	The scheduling schemes	f_1 (h)	f_2	Used time (ms)
1	1	{5, 2, 3, 6, 6, 5, 3}	24.32	30	284.38
	2	{6, 3, 3, 8, 7, 6, 4}	7.60	37	
	3	{5, 2, 3, 6, 6, 4, 3}	39.60	29	
	4	{6, 3, 4, 8, 8, 6, 5}	6.08	40	
	5	{5, 3, 3, 7, 6, 5, 3}	15.55	32	
	6	{5, 2, 3, 7, 6, 5, 3}	18.61	31	
	7	{5, 3, 3, 7, 7, 5, 4}	10.54	34	
	8	{6, 3, 3, 7, 7, 5, 4}	9.56	35	
	9	{5, 3, 3, 7, 6, 5, 3}	12.38	33	
	10	{6, 3, 3, 8, 7, 5, 4}	8.57	36	
	11	{6, 3, 4, 8, 8, 6, 4}	6.47	39	
2	1	{5, 2, 3, 7, 6, 5, 3}	18.61	31	259.19
	2	{6, 3, 3, 8, 8, 6, 4}	7.10	38	
	3	{5, 3, 3, 7, 7, 5, 3}	13.70	33	
	4	{5, 3, 4, 8, 7, 6, 4}	7.95	37	
	5	{5, 3, 3, 7, 6, 5, 3}	15.55	32	
	6	{5, 2, 3, 6, 6, 4, 3}	39.60	29	
	7	{6, 3, 3, 8, 8, 7, 5}	6.36	40	
	8	{5, 2, 3, 6, 6, 5, 3}	24.32	30	
	9	{5, 3, 3, 7, 7, 5, 3}	10.54	34	
	10	{5, 3, 3, 8, 7, 5, 4}	9.56	35	
3	1	{6, 3, 3, 8, 8, 6, 6}	6.56	40	249.88
	2	{5, 3, 3, 7, 6, 5, 3}	15.55	32	
	3	{5, 2, 3, 7, 6, 5, 3}	18.61	31	
	4	{6, 3, 3, 8, 7, 5, 6}	8.04	38	
	5	{5, 3, 3, 7, 7, 5, 3}	13.70	33	
	6	{6, 3, 3, 8, 7, 5, 4}	8.57	36	
	7	{6, 3, 3, 8, 8, 7, 4}	6.75	39	
	8	{5, 2, 3, 6, 6, 4, 3}	39.60	29	
	9	{5, 2, 3, 6, 6, 5, 3}	24.32	30	
4	1	{5, 3, 3, 7, 6, 5, 3}	15.55	32	297.37
	2	{5, 2, 3, 7, 6, 5, 3}	18.61	31	
	3	{5, 3, 4, 8, 8, 6, 4}	7.45	38	
	4	{5, 2, 3, 6, 6, 4, 3}	39.60	29	
	5	{6, 4, 3, 9, 7, 6, 4}	6.87	39	
	6	{5, 3, 4, 8, 7, 6, 4}	7.95	37	
	7	{6, 3, 4, 8, 8, 6, 5}	6.08	40	
	8	{5, 3, 3, 7, 6, 5, 3}	12.38	33	
	9	{5, 3, 3, 8, 7, 6, 4}	8.59	36	
	10	{5, 3, 3, 8, 7, 5, 4}	9.56	35	

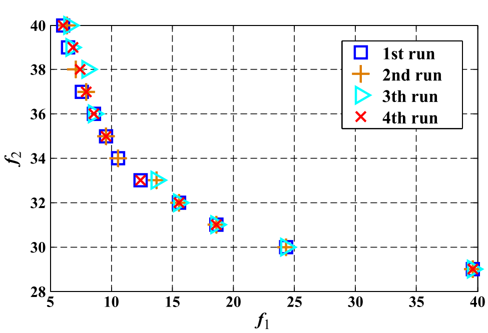

Fig. 6. Pareto solutions in the objective space.

from the same population size and maximum iteration count are compared as shown in Fig. 7.

From Fig. 6, it is seen that the distribution uniformity of Pareto solutions of MHDP is better than that of NSGA-II and MOPSO, thereby showing that the proposed algorithm has strong solution ability. In a word, the proposed algorithm is feasible and efficient to solve a multi-objective emergency scheduling problem for forest fires.

B. Stochastic Instances

To further show the performance of the proposed algorithm, we perform several comparison tests with a different number of fire points, i.e., 10, 15, 20, and 50 respectively. Note that the distance among these points, $d_{ij} \in [50, 100]$, and the fire spread speed $v_{Si} \in [2, 6]$. PopSize $= 50$ and $g_{\max} = 100$. Other parameters are same as the first case. After different algorithms are executed, the results are obtained and shown in Table VII.

It can be seen from Table VII that MHDP is competitive in comparison with two other known algorithms. Its obtained solutions dominate those of NSGA-II due to the following reasons: MHDP can obtain richer non-dominated solutions and search superior results with competitive computational efficiency. Also, compared to MOPSO, MHDP obtains near Pareto solutions. But it still outperforms MOPSO since it has more non-dominated solutions and shorter execution time; especially the last test shows the great superiority of MHDP in terms of both quantity and quality over NSGA-II and MOPSO. Thus, MHDP can obtain both superior solutions and richer non-dominated solutions than its two peers. It should be noted that MHDP can obtain non-dominated solutions in short time, i.e., its average computational time is 15711 ms, while NSGA-II and MOPSO's are 29946 ms and 21997 ms, respectively; and the execution time is rapidly growing with the increase of the number of forest fires, i.e., N, which indicates the complexity of our problem is related with N. In summary, the results show

TABLE VI

COMPARISON OF OPTIMIZATION RESULTS AMONG THE PROPOSED ALGORITHM, NSGA-II AND MOPSO

PopSize	g_{max}	The Pareto solutions						Running time (*ms*)		
		NSGA-II		MOPSO		The proposed method		NSGA-II	MOPSO	The proposed method
		f_1	f_2	f_1	f_2	f_1	f_2			
20	20	26.65 8.60 12.26 7.57 6.51	34 37 36 39 40	8.58 12.72 10.42 14.56 30.74 8.23 27.67	36 34 35 33 31 37 32	9.05 14.48 14.06 10.04 23.35 8.08 6.62 6.26 7.60	36 33 34 35 31 37 39 40 38	82.08	55.62	30.92
30	50	32.91 11.75 8.08 7.30 11.36 6.67 13.70	31 34 37 38 35 39 33	7.60 8.57 9.56 11.40 17.63 14.47 23.34 38.62	37 36 35 34 32 33 31 30	18.61 9.05 17.63 24.32 6.97 39.60 11.40 8.07 10.42 12.38	31 36 32 30 38 29 34 37 35 33	248.92	172.20	99.57
50	100	14.2351 6.07712 6.64082 7.9528 9.55839 18.6136 14.4782 7.0979	34 40 39 37 35 31 33 38	6.96937 24.3189 10.5408 9.55733 18.6136 15.4514 12.3849 6.07712 39.603	38 30 34 35 31 32 33 40 29	18.61 9.56 39.60 15.45 24.32 6.47 6.08 12.38 10.54 8.08 8.57	31 35 29 32 30 39 40 33 34 37 36	725.06	333.14	220.07

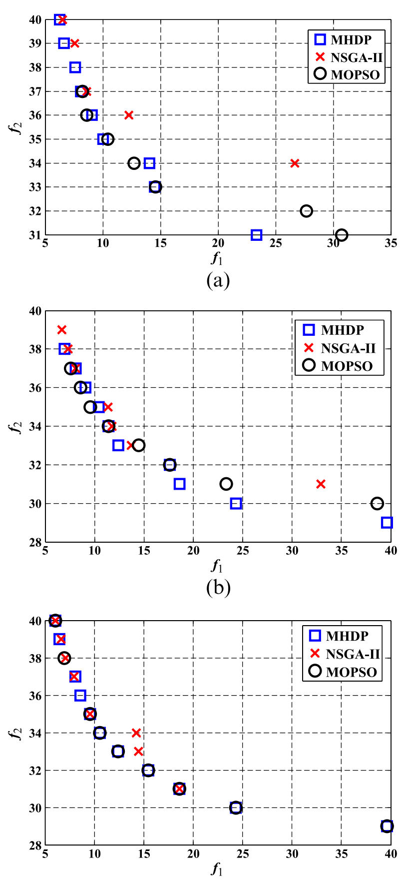

Fig. 7. Comparison of Pareto solutions from MHDP, DE and PSO. (a) PopSize $= 20$, $g_{\max} = 20$. (b) PopSize $= 30$, $g_{\max} = 50$. (c) PopSize $= 50$, $g_{\max} = 100$.

the efficiency and effectiveness of the proposed algorithm in solving a dual-objective scheduling problem of rescue vehicles to distinguish forest fires.

Considering the particularity of emergency scheduling, it is necessary to discuss the impact of the quantity of rescue resources, i.e., the number of fire engines, to our problem. Hence we run NSGA-II, MOPSO and the proposed method, respectively by adjusting the maximum number of fire engines M and the results are shown in Table XI of Appendix.

From Table XI, we conclude that:

1) The proposed method obtains more non-dominated solutions from the proposed algorithm than NSGA-II and MOPSO. Also, it yields a better result than those of the latter and has competitive computational time;
2) The number of non-dominated solutions is basically ascending with the increase of M, namely, if M is adjusted, the corresponding scheduling solutions change accordingly. In addition, even if N and the value of objective function f_2 are the same, non-dominated solutions can be distinguished, e.g., for $N = 20$, $f_2 = 81$, three different non-dominated solutions are produced, i.e., {62.33, 81}, {57.97, 81} and {60.11, 81}. They in part explain the complexity of the scheduling problem of rescue vehicles to distinguish forest fires.
3) The execution time is falling dramatically as M increases when the number of fire points is constant, and this reflects the characteristics of meta-heuristic: the number of feasible solutions is decreasing with the reduction of M, i.e., the space of feasible solutions is compressed. Thus the computational time to search feasible solutions varies with M.

TABLE VII
COMPARISON OF OPTIMIZATION RESULTS AMONG THE PROPOSED ALGORITHM, NSGA-II AND MOPSO

The number of fire points N	The maximum number of fire engines M	The Pareto solutions						Running time (ms)		
		NSGA-II		MOPSO		The proposed method		NSGA-II	MOPSO	The proposed method
		f_1	f_2	f_1	f_2	f_1	f_2			
10	48	18.65 34.02 53.45 23.35 18.32 29.15	47 42 41 46 48 45	15.56 57.53 26.66 31.07 68.13 23.22 39.44 17.20	47 38 42 41 37 43 40 46	39.44 47.97 31.07 68.14 57.53 21.13 26.66 22.10 23.22 16.18	40 39 41 37 38 45 42 44 43 48	1549.86	687.79	525.12
15	72	45.80 61.09 38.60 37.68 33.72	67 66 69 70 71	35.94 46.56 33.63 60.60 52.56 68.99 79.54	66 63 67 61 62 60 59	60.60 46.56 68.99 52.56 79.54 40.79 30.25 29.49 45.43	61 63 60 62 59 65 71 72 64	8648.63	5926.31	4703.88
20	90	59.61 64.84 71.45 59.88 81.04	90 88 86 89 83	49.49 56.36 144.62 90.37 67.65 42.24 39.86	85 82 73 76 79 87 90	57.77 54.28 100.28 40.36 144.62 73.62 39.28 90.37	81 82 75 87 73 78 88 76	11432.05	8282.67	6090.68
50	250	148.72 119.80 142.96	248 249 246	226.52 142.19 121.95 140.32	225 230 248 246	194.36 195.31 156.11 115.19 101.43 130.32 96.90	231 226 235 241 246 238 248	98155.16	73092.92	51525.77

Hence it is necessary to take the number of rescue vehicles into account and the results reconfirm the better performance obtained by the proposed method than NSGA-II and MOPSO.

V. CONCLUSION

This work addresses a dual-objective emergency scheduling issue of forest fires for the first time. Its goal is to minimize the number of vehicles and the extinguishing time. MHDP is designed to solve the proposed model. Compared with NSGA-II and MOPSO, the proposed algorithm can solve the model effectively and efficiently, and generate the optimal solution of a dual-objective emergency scheduling problem. The results can be used to guide decision makers in making better decisions when multiple forest fires take place and provide a new method to determine a best rescue schedule to deal with them.

For a more practically orientated application a software package with a graphical user interface need to be developed. Furthermore, a robust system capable of real-time scheduling needs to be developed. The complexity of the proposed problem need to be further explored for some special cases. Other optimization methods, e.g., [60]–[66], should be tested.

APPENDIX

TABLE VIII
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 IX
THE v_w ($k_w = e^{0.1783 v_w}$) VALUE OF DIFFERENT WIND FROCE

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 X
THE k_φ VALUE OF DIFFERENT TERRAIN SLOPE

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

TABLE XI
COMPARISON OF OPTIMIZATION RESULTS AMONG THE PROPOSED ALGORITHM, NSGA-II AND MOPSO WITH DIFFERENT M VALUES

The number of fire points N	The maximum number of fire engines M	The Pareto solutions						Running time (ms)		
		NSGA-II		MOPSO		The proposed method		NSGA-II	MOPSO	The proposed method
		f_1	f_2	f_1	f_2	f_1	f_2			
10	40	59.60 49.00 44.59	38 39 40	57.53 47.97 43.57	38 39 40	57.53 47.97 68.14 39.60	38 39 37 40	108615.47	106636.03	96049.63
	42	33.55 56.77 38.47	42 40 41	47.97 68.14 57.53 29.94 43.57	39 37 38 42 40	47.97 39.44 35.20 68.14 57.53 27.68	39 40 41 37 38 42	10993.71	9549.503	8282.67
	45	45.01 53.04 31.44 21.99	41 40 43 45	25.98 47.97 23.11 39.60 57.53	43 39 45 40 38	25.20 47.97 21.14 39.60 68.14 57.53 27.62	43 39 45 40 37 38 42	1731.79	1181.54	1021.32
15	68	49.76 56.41 46.21 59.22	66 65 67 64	48.24 37.26 60.60 41.20 52.56	64 68 61 66 62	60.60 38.36 52.56 79.54 42.53 43.29 38.21	61 66 62 59 65 64 67	186957.15	177284.76	153578.05
	69	62.70 37.25 51.79 49.52	64 68 66 67	62.99 79.54 58.35 44.73 52.88 43.29	61 59 62 65 63 64	36.92 46.56 52.56 60.60 38.65 41.92 79.54 32.99	66 63 62 61 65 64 59 68	56805.00	52230.81	49972.05
	70	49.11 51.63 34.60 41.27	67 66 70 69	79.54 60.60 54.60 43.98 49.96 40.06 43.02	59 61 62 65 63 69 66	35.94 32.50 52.56 31.04 60.60 41.92 46.56 79.54	66 68 62 69 61 64 63 59	31789.15	24660.77	22368.81
20	86	123.83 81.04 96.84	82 83 85	74.33 110.99 80.16 52.60 68.85	80 77 79 86 81	50.20 144.62 59.05 73.62 100.28 62.33 81.26	86 73 82 78 75 81 77	147673.83	171931.67	136547.60
	87	77.31 105.47 61.81 80.31	85 84 86 83	121.52 57.99 64.74 83.92 64.58 65.57	75 87 83 78 84 82	57.97 53.42 61.81 51.10 52.07 144.62 50.37 121.10	81 84 80 86 85 73 87 74	89904.16	63078.36	45413.21
	89	47.28 104.70 91.96 100.03 66.10	89 84 87 86 88	71.04 62.67 144.14 54.94 99.81 121.52 65.80	81 83 74 87 76 75 82	144.62 60.11 52.26 54.28 100.28 49.18 48.83 90.37	73 81 84 82 75 87 88 76	18758.95	16083.97	15788.03

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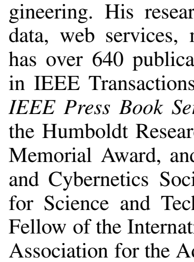

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