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

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***Abstract*—With the increasing issue of global warming, the problem of forest fires during the summer season is becoming more severe every year. For this reason we decided to focus our attention on a project that could possibly deal with this problem. Our attention landed on the paper *"Dual-Objective Scheduling of Rescue Vehicles to Distinguish Forest Fires via Differential Evolution and Particle Swarm Optimization Combined Algorithm"* written by *Guangdong Tian, Yaping Ren, and MengChu Zhou, Fellow, IEEE*. In this paper the authors presented a method to optimize the deployment of vehicles used to distinguish a set of fire points with the objectives of minimize the disinguishing time and the number of motorcade used.**

Interestingly, to test this approach, it has been applied to a real-world scenario in Mt. Daxing'anling, China.

***Index Terms*—PSO, DE, NSGA-II, Pareto Solutions, Genetic Operators, MHDP**

I. Introduction

The problem of forest fires is becoming a big issue all around the world. With the continuous rise in temperature and with the less frequent rains in summer, the number of forest fires is increasing every year. However, the number of rescue vehicles is limited and, in case of multiple fire points, deciding how many vehicles to use for each fire point is a difficult scheduling task that has to be solved very quickly. In particular, different fire points may have different weather characteristics (e.g. the temperature and the wind speed) and/or varying terrain characteristics such as different slopes and terrain types; these parameters have to be taken into account during the decision making to achieve a proper solution. Finally, other aspects to consider are : the distance of a fire point from the fire department and the time that each vehicle takes to extinguish a fire.

In the paper *Dual-Objective Scheduling of Rescue Vehicles to Distinguish Forest Fires via Differential Evolution and Particle Swarm Optimization Combined Algorithm* [1], by Tian, G., Ren, Y. & Zhou, M., the authors present a Multi-objective Hybrid Differential-evolution and Particle-swarm-optimization (MHDP) algorithm to minimize the time spent to extinguish all the fires while minimizing the total number of vehicles used. The proposed algorithm integrates differential evolution (DE) and particle swarm optimization (PSO) into a multi-objective optimization algorithm in order to increase the population diversity with DE and improving the convergence ability with PSO.

This paper is organized as follows: Section II describes the problem and the objectives that has to be minimized. Section III describes the MHDP algorithm. Section IV discuss implementation aspects. Section V shows and analyzes the results. Finally, Section VI concludes our work with ending considerations.

II. Problem Statement

A. Problem Statement

In this work, an implementation of an emergency scheduling algorithm to solve a scheduling problem in organizing the deployment of fire engines is proposed.

In particular, the considered scenario focuses on forest fires whose location points may be dislocated in several areas/points even far away from each other. As it is possible to imagine, under emergency conditions the time factor is a key aspect to consider. Indeed, when dealing with major disasters, time is an indispensable and primary factor for each decision-maker to contain risks and damages.

In the context of this work, the rescue time is considered to be given by the sum of the arrival time of a motorcade to a specific fire point and the extinguishing time needed to put out the flames. Since the first is related just to a matter of distance and velocity, it is reasonable to consider arrival time as a constant if pace and distance are known. On the other hand, the extinguishing time is highly related to several fire factors such as type of fuel, wind force, terrain slope, so it requires to be carefully modelled.

Fire modelling is not the only concern we have in formulating this scheduling problem since it would result unrealistic to assume infinite amount of resources. Indeed, a multi-objective optimization problem has been devised in order to take into account also the number of resources (fire engines) available in the fire station. In light of this, as a result we get an optimal emergency policy such that a certain number of fire engines are dispatched to different fire points to minimize the firefighting time and, at the same time, it tries to minimize the number of vehicle deployed and their usage.

B. Fire Spread Model

In the purposes of this work, a fire spread model associated with natural phenomena, i.e. wind force, initial spread speed, fuel types, temperature and terrain slope is used.
Mathematically, it is defined 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 : fire spread speed
- v_0 : initial fire spread speed
- k_s : fuel correction factor
- k_w : wind correction factor
- k_φ : terrain slope correction factor

Furthermore :

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

where :

- T : fire point internal temperature
- w : wind force
- a, b, c : these are terrain related factors and depends on the actual fire point location

The reference values for k_s, k_w, k_φ can be found respectively, in Tables II, III, IV.

C. Mathematical model

Considering what has been said before, the dual-objective emergency scheduling optimization model with multi-resource constraints is formulated as follows :

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

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

s.t.

$$\begin{cases} K \leq \sum_{j=1}^{N} \sum_{m=1}^{M} z_{0j}^m \leq M & (5) \\ L_i \leq \sum_{m=1}^{M} z_{0i}^m \leq U_i, i = 1, \dots, N & (6) \\ z_{0i}^m \in \{0, 1\}, m = 1, \dots, M, i = 1, \dots, N & (7) \end{cases}$$

where:

- K : Lower bound of the total number of vehicles required for forest fire emergency scheduling
- M : Upper bound of the total number of fire engines in the fire emergency scheduling center
- z_{0i}^m : Binary variable (1 if the $m-th$ fire engine is sent from point 0 to i; 0 otherwise)
- L_i : Lower bound of the number of fire engines to the $i-th$ fire point, $i = 1, 2, \dots, N$
- U_i : Upper bound of the number of fire engines to the $i-th$ fire point, $i = 1, 2, \dots, N$

1) Objective f_1:

The objective f_1 in (3) aims to minimize the extinguishing time of fires which is given by the following expression :

$$t_{E_i} = \frac{v_{S_i} \cdot t_{A_i}}{\left(\sum_{m=1}^{M} z_{0i}^m \cdot v_m - 2v_{S_i} \right)} \tag{8}$$

where:

- t_{A_i} is the arrival time of vehicles to the ith fire point and it is defined as:

  $$t_{A_i} = \frac{d_{0i}}{v_{0i}}, i = 1, 2, \dots, N \tag{9}$$

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

Thus, composing (3) and (8) we have:

$$f_1 = \sum_{i=1}^{N} \frac{v_{S_i} \cdot t_{A_i}}{\left(\sum_{m=1}^{M} z_{0i}^m \cdot v_m - 2v_{S_i} \right)} \tag{10}$$

2) Objective f_2:

Objective f_2 in (4) aims to minimize the number of deployed vehicles.
The (5) constraint ensures that the number of motorcades sent to a specific fire point is at most M and, at the same time, ensures that some fire engines are sent to each fire point such that fires are extinguished (at least K).
The second constraint (6) limits the number of vehicles sent to the i-th fire point and, finally, the last constraint defines that the z variables can only assume binary values.
It is worth to mention that the **two objective are in conflict with each other**, that's because conceptually, the first objective would require a higher number of motorcades in order to faster extinguishing the fire but this is in contrast with what we are trying to do with f_2.
Based on this, the formulated model turns out to be highly non-linear since :

a. Equation 3 is a non-linear function and (4) indicates an integer programming problem
b. fire points are multiple so as this number increases, the emergency scheduling becomes more complex.

III. MHDP Algorithm

The Multi-objective Hybrid Differential-evolution and Particle-swarm-optimization algorithm combines DE and PSO into a multi-objective optimization algorithm. This algorithm is composed of 5 tasks : Solution Coding, Population Initialization, Evaluation of individuals, Mutation and Crossover.

A. Solution Coding

Each solution is encoded into a vector of N elements whose $i-$th element indicates the number of vehicles sent to the fire point at location i.

B. Generating the initial population

Each individual is created by generating N random integer values, where the random values are chosen in the range $[L_i, U_i]$ to comply with constraint (5). This procedure is repeated until the individual comply also with constraint (6). $PopSize$ individuals are generated.

C. Calculating Fitness Values and Screening Pareto Solutions

After having generated the initial population we compute the fitness value of each solution and we update the personal best (P_{best}) value of each individual and the global best value (G_{best}). Subsequently, we seek for Pareto non-dominated solutions (based on fitness value) and we insert the first front in an archive $A(g)$ responsible for containing the best solutions found until generation g. Finally, we screen again the Pareto front in the archive because after the insertion of the new individuals there may be new domination relations between the fresh Pareto Solutions and $A(g-1)$.

D. Mutation and Crossover

A 3-parent mutation strategy is used:

$$X_i(g+1) = X_i(g) + F \cdot (X_j(g) - X_k(g)) \tag{11}$$

where F is the scaling factor ($F \in (0, 2)$), $X_i(g)$ is the $i-th$ individual in the current population, $i, j, k = 1, 2, ..., PopSize$ and $i \neq j \neq k$.

MHDP integrates (11) into PSO:

$$\begin{aligned} X_i(g+1) = X_i(g) + \Phi[r_1(G_{best} - X_i(g)) \\ +r_2(P_{best} - X_i(g)) + F(X_j(g) - X_k(g))] \end{aligned} \tag{12}$$

where Φ is the $round$ function and r_1, r_2 are two random numbers from a uniform distribution over $[0, 1]$. Here each individual takes a small step towards G_{best} and a small step towards P_{best}. The mutation contribution is given by $F(X_j(g) - X_k(g))$ where $X_j(g)$ and $X_k(g)$ are randomly selected.

The crossover operation is applied to each individual X_i by selecting another random individual X_k in the population and performing the operation $X_{ij} = X_{kj}$ with probability P_c for each $j = 1, 2, ..., N$.

After mutation and crossover we adjust the new individuals to meet constraints (5) and (6).

E. Updating the archive set

After mutation and crossover we evaluate again the solutions, we update P_{best} for each individual, G_{best} and the archive $A(g)$.

The loop of mutation - crossover - evaluation is repeated until a termination condition is met.

IV. Implementation of MHDP

The code for the implementation has been written in Python. Concerning the implementation of the MHDP algorithm, we followed the pseudocodes present in the paper for : the generation of the initial population, the crossover operator and

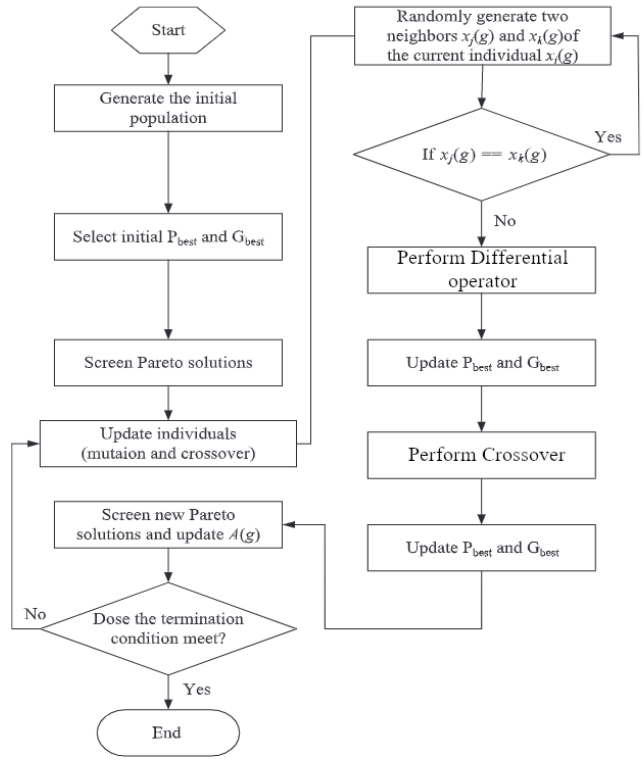

Fig. 1. MHDP algorithm

the adjustment of infeasible solutions. The mutation operation was easy to implement, we only needed to select two different random individuals from the pool of possible solutions and apply (12). Regarding the evaluation procedure, we had to implement also the *fast non-dominated sort* algorithm to find the Pareto fronts.

V. Results and analysis

The algorithm has been tested upon the same data used by the researchers in [1]. More precisely, the used data correspond to the fire occurred in Huzhong, region located in Mt. Daxing'anling, at $10:40$ local time on June 29, 2010. The flames hit a total of 7 fire points in that specific area.

For the purposes of this work, the researchers reported all the necessary parameters to calculate the objective functions. The only element that's missing is the upper bound to the number of vehicles for each fire point (U_i). Since in the paper it was presented as a given parameters, we used a representative number 10 for all the points.

In table I we reported the results obtained after running the algorithm 4 consecutive times. The lowest calculated time to extinguish all the fires is 6.17 hours, using all the vehicles, while the lowest number of vehicles used is 29, that is the lower bound given by the authors. In the latter case, the extinguish time is 40.04 hours. In figure 2 these solutions are plot on a 2D graph with f_1 on the x axis and f_2 on the y axis. We can see that most of the solutions are concentrated between 5 and 20 hours for f_1 and these solutions cover almost all the values in f_2, so the results are satisfying. Our results are very

TABLE I
PRODUCED PARETO SOLUTIONS

Runs	Solution Number	Scheduling schemes	f_1 (h)	f_2
1	1	$\{5,4,3,8,7,6,4\}$	8.25	37
	2	$\{7,3,4,8,8,6,4\}$	6.17	40
	3	$\{5,3,3,7,6,5,6\}$	11.83	35
	4	$\{5,3,3,7,7,6,3\}$	12.76	34
	5	$\{5,2,3,8,6,4,3\}$	33.38	31
	6	$\{5,3,3,7,8,6,4\}$	9.06	36
	7	$\{7,3,3,8,7,6,4\}$	7.31	38
	8	$\{5,2,3,6,7,5,4\}$	19.33	32
	9	$\{6,2,3,7,7,5,3\}$	15.87	33
2	1	$\{6,4,3,8,7,6,4\}$	7.28	38
	2	$\{6,3,3,8,8,6,5\}$	6.71	39
	3	$\{6,3,3,9,7,7,5\}$	6.46	40
	4	$\{5,2,3,6,6,4,3\}$	40.04	29
	5	$\{5,2,3,7,6,5,3\}$	18.68	31
	6	$\{5,3,4,7,6,6,4\}$	10.76	35
	7	$\{5,2,3,7,6,5,4\}$	15.48	32
	8	$\{5,3,3,7,8,6,5\}$	8.67	37
	9	$\{5,2,3,6,6,5,3\}$	24.36	30
	10	$\{5,2,3,7,7,5,5\}$	13.26	34
	11	$\{5,2,3,7,7,5,4\}$	13.65	33
	12	$\{5,3,3,7,7,5,6\}$	10.00	36
3	1	$\{6,4,3,8,7,6,5\}$	6.89	39
	2	$\{5,3,3,7,7,5,3\}$	13.74	33
	3	$\{5,2,3,6,6,5,3\}$	24.36	30
	4	$\{5,3,4,7,7,6,4\}$	8.93	36
	5	$\{5,2,3,8,7,5,4\}$	12.66	34
	6	$\{5,3,3,9,7,7,4\}$	7.82	38
	7	$\{5,2,4,6,6,5,3\}$	23.73	31
	8	$\{5,2,3,8,8,5,4\}$	12.16	35
	9	$\{6,3,5,8,7,6,5\}$	6.38	40
	10	$\{5,4,4,7,7,6,4\}$	8.60	37
4	1	$\{5,2,3,7,6,5,3\}$	18.68	31
	2	$\{5,3,3,7,6,6,3\}$	14.60	33
	3	$\{5,3,3,8,7,5,4\}$	9.56	35
	4	$\{6,3,4,8,8,5,4\}$	7.45	38
	5	$\{5,4,3,7,7,7,4\}$	8.88	37
	6	$\{6,3,3,7,8,5,4\}$	9.06	36
	7	$\{6,4,3,7,8,6,5\}$	7.37	39
	8	$\{6,3,3,9,8,6,5\}$	6.31	40
	9	$\{5,2,3,7,7,5,5\}$	13.26	34
	10	$\{5,2,3,7,6,5,4\}$	15.48	32

similar to the ones found by the authors, however the pareto front in their experiment (Fig. 3) is very well distributed and all the runs produce very similar solutions.

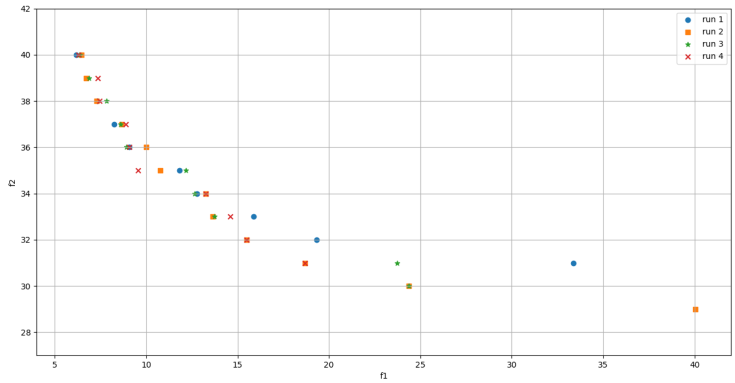

Fig. 2. Our Pareto solutions

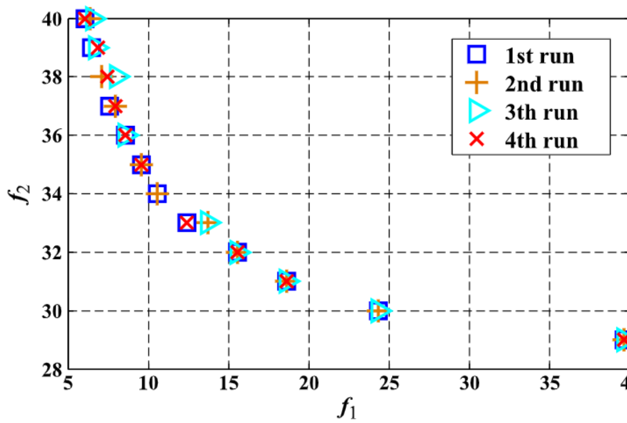

Fig. 3. Authors' Pareto solutions

VI. Conclusion

During the development of the project we had the opportunity to apply evolutionary computation on a real world scenario and to implement evolutionary algorithms by hand. Moreover we implemented something that may be useful for others and make the work of firefighters more efficient. While reading the paper we found some explanations that were not clear, however, after reading the papers referenced by the authors, we were able to understand better what to do.

VII. Contributions

Davide and Matteo worked together to implement the algorithm. Usually, for each section of the paper [1], we decided by chat or by a video call, what function to implement. Then, depending on the available time, each of us worked on the code when the other member couldn't. In this way we were able to review what the other did and correct possible errors or bugs.
Following the above procedure, Davide implemented most part of the crossover, mutation and fast non-dominated sort algorithms, while Matteo implemented most part of the population generation, fitness computation and evaluation algorithms.

VIII. Appendix

TABLE II
k_S VALUES OF DIFFERENT FUEL TYPES

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

TABLE III
v_w ($k_w = e^{0.1783 v_w}$) VALUE OF DIFFERENT WIND FORCE

Wind force leve l	$v_w(m/s)$
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 IV
k_φ VALUE OF DIFFERENT TERRAIN SLOPES

Slope range	k_φ
$-42° \sim -38°$	0.007
$-37° \sim -33°$	0.13
$-32° \sim -28°$	0.21
$-27° \sim -23°$	0.32
$-22° \sim -18°$	0.46
$-17° \sim -13°$	0.63
$-12° \sim -8°$	0.83
$-7° \sim -3°$	0.90
$-2° \sim 2°$	1.00
$3° \sim 7°$	1.20
$8° \sim 12°$	1.60
$13° \sim 17°$	2.10
$18° \sim 22°$	2.90
$23° \sim 27°$	4.10
$28° \sim 32°$	6.20
$33° \sim 37°$	10.10
$38° \sim 42°$	17.50

References

[1] Tian, G., Ren, Y. & Zhou, M. Dual-Objective Scheduling of Rescue Vehicles to Distinguish Forest Fires via Differential Evolution and Particle Swarm Optimization Combined Algorithm. *IEEE Transactions On Intelligent Transportation Systems*. **17**, 3009-3021 (2016)