Resource Dispatch Optimization for Firefighting using a Differential Evolution Algorithm*

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Abstract. The incidence of forest fires has shown an upward trend in recent years. This increase can be attributed to rising ambient temperatures and population growth, which act as the primary catalysts for these disasters. The application of optimization techniques has significantly contributed to addressing forest firefighting challenges, enabling improvements in the efficiency and promptness of firefighting operations. This study focuses on a specific resource dispatch problem to combat forest fires, which involves assigning 7 resources to extinguish 20 ignitions. The main objective is to minimize the total area burned by these ignitions in a minimum period of time. To solve this problem, the differential evolution algorithm adapted to this context was applied. Furthermore, a statistical analysis was performed to evaluate the performance of differential evolution when different selection and crossover operators are tested. The preliminary results show that the current-to-best selection and exponential crossover operators are the most suitable to solve the resource dispatch problem for forest firefighting.

Keywords: Forest Fires, Single-objective Optimization, Resource Dispatch Problem, Differential Evolution

1 Introduction

In recent years, forest fires have been increasingly frequent on our planet. This is due to the fact that ambient temperatures have been rising over the years, leading to high-risk situations for the health of living beings and forests. In 2017 fire season, there were several fires around the world. Canada, United States, Chile, Portugal, Spain, South Africa, Ireland and Greenland were the most affected countries in this catastrophic year. In turn, in 2018 the total burned area

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exceeded 1 million hectares, thus surpassing the year 2017. In this year, the most affected regions were Greece, England, Sweden and North America [6]. Australia also experienced a series of severe wildfires due to unusually high temperatures between 2019 and early 2020 [4].

Unfortunately, every year around 4 million square kilometers of land (roughly the size of the European Union) burn around the world [15]. In Europe, more than 5500 square kilometers of land burned in 2021 [18]. According to the Global Forest Fire Information System, between 2012 and 2021 an average of 448 million hectares of land burned each year, with 1.4 million hectares corresponding to the European Union and the United Kingdom [20].

With the increase in the number of forest fires in recent years, more and more decision-support strategies for fighting forest fires have been studied. The main objectives of firefighting decisions are to reduce the burned area, protect living beings, structures and the environment. The number, skills, and level of preparedness of firefighting teams are relevant factors. The performance of the fighting team is a very important factor in firefighting, and the better and faster it is, the less damage will be caused [1]. Fire suppression management involves identifying how many and which combat resources need to be deployed for each forest fire in order to best and quickly extinguish the fire.

Several optimization strategies have been used in the engineering area to solve fire suppression problems aiming to find the best trajectory and position of fighting vehicles, find the shortest route, decide the number of resources to dispatch, among others. In Zeferino et al. [22], a mathematical optimization model was developed to identify the optimal location of various aircraft in order to maximize the coverage of high-risk areas. The research focused on a case study conducted in Portugal. Chan et al. [5] introduced the Firefly algorithm in their study as a means to allocate a limited number of drones and firefighters across multiple zones. The performance of the Firefly algorithm was evaluated under various configurations. Their findings demonstrated that when a relatively small percentage of drones, ranging from 10% to 20% of the total number of zones, were deployed, the algorithm achieved optimal performance levels of 80% to 95% in the majority of cases. In the study conducted by Granberg et al. [9], a mathematical model was developed to address the problem of dispatching firefighting and rescue services. This problem involved determining the optimal allocation of firefighters to vehicles and devising an efficient dispatch strategy for emergency situations. The researchers employed both exact and heuristic solution methods to solve the developed model, using data from the Skåne region in Sweden. The results showed that the exact solution method was time-consuming in certain scenarios, while the heuristic approach generally produced fast and near-optimal solutions in the majority of cases. The study demonstrated the effectiveness of different solution techniques for addressing the firefighting and rescue service dispatch problem.

To effectively mitigate forest fires, it is imperative to develop decision-support systems for forest fire management that use advanced techniques for monitoring, detection and control. These initiatives aim to improve the understanding

of forest fire dynamics and implement measures to minimize their occurrence and impact [1]. The strategic planning of forest firefighting resources, including determining the appropriate quantity and type of resources required to suppress a specific fire, is a highly significant field of study. These research efforts have the potential to minimize the damage caused by forest fires and to provide valuable support to decision makers involved in firefighting operations. By understanding the optimal allocation and utilization of firefighting resources, decision-makers can make informed choices and take effective actions to combat forest fires, ultimately reducing the overall impact and devastation caused by these incidents.

The resource dispatch problem refers to a simulation that determines resource utilization, including when, where, and what resources will be used in a given scenario. In the context of forest firefighting, this problem involves making decisions about which methods to apply and which firefighting resources should be deployed to fight a specific fire and at what time they should be used. By addressing the resource dispatch problem, authorities can optimize their response strategies, ensuring the timely and appropriate allocation of firefighting resources to effectively manage and extinguish forest fires [2].

Several algorithms have been applied to solve the resource dispatch problem, such as particle swarm optimization, genetic algorithm, among others. Baisravan et al. [11, 12] have proposed several decision support strategies to minimize the total burned area using the Genetic Algorithm (GA). The GA developed an ideal line of fire in order to reduce the total area burned, also providing the best places to attack the firefighting teams. In addition, homogeneous and heterogeneous environmental conditions were considered. Monte-Carlo simulations were used to develop robust strategies under uncertain conditions. Naziris et al. [16] developed a model to protect historic buildings from fires, where they presented a generic model of resource selection and allocation. For this, they applied the differential evolution and particle swarm optimization algorithms. The case study was based on the monasteries of Mount Athos, where good results were obtained, showing the efficiency of the presented model. Zhou and Zhang [24] proposed a model event response tree-based method for dispatching different types of firefighting assets based on the fire suppression index. This index evaluates the effect of fire suppression considering time, cost and dispatch effect resources. To validate this method, historical fire data from Nanjing Laoshan National Forest Park was used and the results were compared to a mixed integer programming (MIP) method. The results showed that both methods were effective. In addition, the proposed model was clear and intuitive for firefighters to make decisions regarding the various dispatch processes of forest firefighting vehicles.

This paper focuses on solving the resource dispatch problem for forest firefighting. The objective function to be minimized is the extent of burned area, using a Differential Evolution (DE) algorithm, implemented in the *Python* programming language. Taking advantage of the DE algorithm, the study aims to improve the decision-making process in the dispatch of resources for forest firefighting operations. A resource dispatch problem involving 7 firefighting resources to extinguish 20 ignitions of a forest fire is used to evaluate the perfor-

mance of DE in solving this type of problem. Furthermore, several DE variants were tested, followed by a statistical analysis to determine the most suitable operators to achieve the best results in this particular problem. In addition, a comparison of solutions between DE and GA is made.

This paper is organized as follows. The differential evolution algorithm is described in Sect. 2 and in Sect. 3 the problem definition is presented. The implementation details, the testing of DE variants, the best solution found and the comparison of solutions between DE and GA are presented in Sect. 4. Finally, the conclusions of this study and future work are shown in Sect. 5.

2 Differential Evolution

Differential evolution is a widely adopted evolutionary algorithm that has become popular for its effectiveness in solving complex optimization problems. It was first proposed by Storn and Price [19] and is known for its simplicity and efficiency. This stochastic search algorithm is population-based and uses mutation, crossover and selection operators to iteratively guide the population towards the global optimum [21]. DE is specifically designed to optimize real-valued functions with real parameters. The algorithm starts by randomly initializing a population of candidate solutions for a given optimization problem. By applying crossover and mutation operators, new individuals are created in each generation of the evolutionary process. The crossover operator combines the target individual with a mutated individual, resulting in an experimental individual that incorporates successful solutions from the previous generation. The experimental individual is then compared with the target individual, and the one with the lowest function value is selected to move on to the next generation. The mutation, crossover and selection processes continue until a stopping criterion is reached, such as reaching the maximum number of generations, reaching the maximum number of function evaluations, reaching a specific fitness value or reaching a predetermined computation time. By improving the population based on the successful individuals and favoring those with the lowest function values, differential evolution aims to converge to the optimal solution of the optimization problem at hand [10].

The DE has only three control parameters that need to be adjusted: mutation, crossover and selection [8]. As with all evolutionary algorithms, the DE starts with an initial set of potential solutions (initialization), which are evolved (using mutation, crossover and selection operators) until a stopping criterion (termination) is achieved [7, 17]. In each iteration, for each parent x_i, $i = 1, \ldots, NP$, a mutant vector v_i is created by means of a differential mutation operator. Then, the mutant is crossed-over with the parent and yields an offspring u_i. The selection is based on a competition between x_i and u_i.

Initialization

In the initialization of the algorithm, an initial population of NP individuals is generated in the search space to be evaluated by the DE operators, usually with random values.

Mutation

In the mutation phase, individuals with better fitness are selected and modified by introducing more genetic material into the population to create new individuals. Mutation aims to add diversity and avoid getting stuck in local optima. In the case of DE, a new individual is created by adding a scaled differential term to a base vector (individual). In addition, another aspect that influences the mutation and performance of the algorithm is the mutation factor F, usually a range between 0 and 2 is considered. This factor controls the rate of evolution of the population by determining the size of the perturbation of the differential term. The higher the value of F, the greater the probability of escaping from local optimum.

Mutation has several variants, and the mutant vector v_i used in this paper is presented below [23].

- **DE/rand/1:**

$$v_i = x_{r_1} + F\left(x_{r_2} - x_{r_3}\right)$$

- **DE/best/1:**

$$v_i = x_{\text{best}} + F\left(x_{r_1} - x_{r_2}\right)$$

- **DE/current-to-best/1:**

$$v_i = x_i + F_1\left(x_{\text{best}} - x_i\right) + F_2\left(x_{r_1} - x_{r_2}\right)$$

where $x_{r_1}, x_{r_2}, x_{r_3}$ are randomly selected individuals from the current population $\{1, \ldots, NP\}$, distinct from each other and also from individual x_i (i.e. $r_1 \neq r_2 \neq r_3 \neq i$) and F, F_1 and F_2 are real constants, $F, F_1, F_2 \in [0, 2]$.

Crossover

The crossover phase intends to improve the diversity of the population. Two populations (current and mutated) are used and a new experimental population is created. There are several crossover operators, the most commonly used being the binomial and the exponential. In binomial crossover a random number is generated between 0 and 1 in which, if it is less than the crossover control parameter (CR, crossover probability), the element is removed from the mutated individual. Otherwise, the element from the current individual is copied to the experimental individual. On the other hand, in the exponential crossover procedure an initial starting point is generated, and the opposite of binomial crossover occurs.

Thus, the offspring vector u_i is computed either from the elements of target vector $x_i = x_{i,1}, \ldots, x_{i,n}$ or the elements of the mutant vector $v_i = v_{i,1}, \ldots, v_{i,n}$ as follows:

$$u_{i,j} = \begin{cases} v_{i,j}, \text{ if } \text{rand}_{i,j} \leq \text{CR} \text{ or } j = j_{\text{rand}} \\ x_{i,j}, \text{ otherwise} \end{cases}$$

where $i = \{1, \ldots, NP\}$, $j = \{1, \ldots, n\}$, n is the dimension of a single vector, $\text{rand}_{i,j} \sim U(0, 1)$ is a uniformly distributed random number which is generated for each j and $j_{\text{rand}} \in \{1, \ldots, n\}$ is a random integer used to ensure that $u_i \neq x_i$ in all cases.

Selection

In the selection phase of the algorithm, a mechanism is used to select the individuals who will form the next generation. A comparison is made based on their objective values between the experimental and current individuals. The individuals with the lowest function value (when considering a minimization problem) are selected to form the next generation. This survival criterion can also be called "objective function based criterion" or "greedy criterion".

Thus, the new target vector is obtained and its value is computed as follows:

$$x_i = \begin{cases} u_i, \text{ if } f(u_i) < f(x_i) \\ x_i, \text{otherwise} \end{cases}$$

where $f(u_i)$ is the objective function value of the trial vector and $f(x_i)$ is the objective value of the parent vector.

Termination

In the termination phase, the algorithm stops when a stopping condition is reached. Typically, this can be the maximum number of generations or the maximum number of function evaluations, for example.

The DE steps are presented in Algorithm 1.

Algorithm 1 DE algorithm

Require: NP, F, CR
  $\{x_1, x_2, \ldots, x_{NP}\} \longleftarrow$ **Initialization**
  while stopping criterion is not met **do**
    for each point x_i of the population **do**
      Mutation(F)
      Crossover(CR)
      Selection
    end for
  end while

Several approaches have been proposed to solve optimization problems using DE. Researchers continue to explore and develop DE variants and hybrid algorithms that better handle constraints and improve DE performance in constrained optimization scenarios. According to the literature, DE has been widely applied in resource dispatching problems, however, as far as we know, no application of this algorithm to forest firefighting resource dispatching problems has been done. Naziris et al. [16] present an optimization-based metaheuristic approach to solve the budget dispatch problem related to fire safety improvement for a group of historic buildings. The motivation behind this research is the development of a generic resource selection and allocation (SRA) model specifically tailored to the improvement of fire protection measures in historic buildings. The model is formulated as a variant of the knapsack problem and is solved using metaheuristics. The proposed approach is evaluated and compared using two metaheuristic optimization algorithms, namely particle swarm optimization and

differential evolution. Real test cases are used to evaluate the effectiveness of the approach, focusing on updating the fire protection measures in the 20 monasteries of Mount Athos. The study demonstrates the efficiency and applicability of the approach based on metaheuristic optimization in solving the SRA model for various budget scenarios. The results show the adaptability and suitability of the approach in optimizing the selection and allocation of resources for different networks of historic buildings and cultural heritage structures. In the article by Li et al. [13], an effective three-layer DDE structure with adaptive resource allocation that increases search efficiency and improves computational efficiency has been proposed. Three methods (general performance indicator, fitness evaluation allocation and load balance strategy) were applied to obtain the results. In addition, theoretical analyzes were carried out to show how this structure can be effective. With the results obtained, they verified the efficiency of the proposed structure.

3 Problem Definition

In this paper, the resource dispatch problem for fighting forest fires is described. The problem involves 7 resources, denoted as A, B, C, D, E, F and G, which are dispatching to extinguish 20 ignitions of a forest fire, identified as I_i (where i ranges from 1 to 20). The considered time ranges from 0 to 100 minutes, with 10 minute intervals spanning multiple instants of time. At time 0, resources are stationed at the base or fire station and need to be strategically dispatched to fight the fires over this time interval. Resources for fighting forest fires are vehicles equipped with water tanks. These vehicles have a total water capacity of 9000 liters. The specific capacities of each resource water tank, measured in liters (l), are given in Table 1. At the beginning of the time interval, all resources are fully charged with water, so their tanks are at maximum capacity.

Table 1. Resource capacity

Resource	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Capacity	500	1000	3000	1500	1000	500	1500

The locations of the ignitions and the base (fire station) are known, as well as the travel times between the base and each ignition point. Additionally, the travel time between each ignition point is also known. It is important to note that the travel times remain constant regardless of the capacity of the firefighting means used. However, the fire spreads over time causing the burned area to increase. The burned area (in ha) of each ignition is known for each instant of time and, increasing over time, with some ignitions growing at a slower rate than others. Similarly, the amount of water (in liters) required to extinguish each ignition varies with time and is related to the burned area. That is, at each instant of time, the larger the burnt area, the greater the amount of water needed to

extinguish an ignition. The data used for the problem were generated for the simulation of a real situation of 20 ignitions and are fully described in [14].

To solve the resource dispatch problem, several assumptions need to be considered. Some ignition and resource assumptions are considered. The following ignition assumptions are considered: each ignition can only be extinguished once; a given ignition can be extinguished by one or more resources; if the water capacity of the assigned resources is sufficient to extinguish a given ignition, it will be extinguished immediately. Regarding the resources, it is assumed that, each resource has a maximum capacity of water in its tank, which can be used until it runs out; each resource can only be assigned to one ignition at a time, during each instant of time. Given these assumptions, the resource dispatch problem can be effectively addressed and optimized to dispatch available firefighting resources for maximum efficiency and effectiveness in fighting forest fires.

The objective of this problem is to minimize the total burned area (TBA) by effectively extinguishing the ignitions. To solve the resource dispatch problem, the differential evolution algorithm is used as the chosen solution methodology.

4 Experimental Results

4.1 Implementing Details

In this study, the differential evolution algorithm is implemented in the *Python* programming language. The implementation is based on the adaptation of the DE algorithm from the pymoo framework [3], which is a *Python* library providing several single-objective optimization algorithms. To solve the resource dispatch problem, a permutation representation is used (more details in [14]). This representation consists of ordering a sequence of forest firefighting actions, indicating the order in which resources must be dispatched to extinguish the ignitions. The permutations, which represent potential solutions of the problem, were generated in an array of dimension equal to the number of resources multiplied by the number of ignitions. This array indicates the order each resource must combat the ignitions, i.e., defines the combat priority of each resource. After implementing the DE algorithm and adapting it to the resource dispatch problem for fighting forest fires, different variants of the DE algorithm are tested. The objective is to identify the configuration that presents the best performance in solving the problem of dispatching firefighting vehicles effectively. Variants of the DE algorithm involve exploring various combinations of algorithm parameters, such as population size, mutation rate, crossover rate, and selection strategy, where considered to identify the most effective configuration that can help decision makers to make informed choices and improve dispatching resources strategies for forest firefighting.

In this work, the DE algorithm was configured with specific parameters. The population size was set to 20, the maximum number of generations was set to 1000 and the maximum number of function evaluations was 100000. The crossover probability, which determines the probability of mating occurring during crossover, was fixed at 0.3 and the mutation factor was 0.5. Several crossover

operators were tested, including binomial/uniform, exponential, hypercube and linear crossovers. For selection, three different strategies were tested, random selection, best selection and current-to-best selection. These selection strategies determine how individuals are chosen from the population for the next generation based on their fitness values. The type of mutation applied was the polynomial mutation (default) and the mutation probability was 0.1. To ensure robustness and reliability of the results, the experiment was conducted with 30 independent runs. This statistical analysis allows a comprehensive evaluation of the performance of different DE variants and provides significant information about the effectiveness of the algorithm in solving the problem of dispatching resources to combat forest fires.

The numerical experiments were carried out on a PC 11th Gen Intel(R) Core(TM) i7-1165G7 @ 2.80GHz, 2803 Mhz, 4 Nucleus(s), 8 Processor(s) Logic(s), 16 Gb RAM. The code was implemented in *python* (version 3.9.13) using *VScode* (Version 1.79.1).

4.2 Testing DE Variants

In this section, the strategy used to test the different DE variants is described. The DE variants were obtained by combining Random, Best and Current-to-best selection with Binomial, Exponential, Hypercube and Line crossover. The mutation operator in all test was the polynomial mutation. All DE variants were assessed in terms of total burned area. First, the selection operator was varied, keeping the binomial crossover (DE/Selection/1/Crossover) and polynomial mutation. From the three different selections, the current-to-best selection performed the best. Afterwards, the four different crossover operators were tested, maintaining the polynomial mutation and the current-to-best selection. It turns out that the crossover operator with the best performance was the exponential crossover. Table 2 summarizes the statistics for 30 independent runs of the several DE variants assessed. The total burned area (TBA_{av}), in ha, the number of generations (ngen_{av}), the number of objective function evaluations (nfe_{av}), the total used water (UW_{av}), in l, and the execution time (Time_{av}), in s, are presented. In addition, the standard deviation of the total burned area ($\mathrm{TBA}_{\mathrm{sd}}$) is also reported.

Table 2. Statistics for different variants of DE

DE/Selection/1/Crossover		$\mathbf{TBA_{av}}$	$\mathbf{TBA_{sd}}$	$\mathbf{UW_{av}}$	$\mathbf{ngen_{av}}$	$\mathbf{nfe_{av}}$	$\mathbf{Time_{av}}$
Selection	**Crossover**						
Random	Binomial	1279.5	21.4	5319.9	59.2	1164.0	69.7
Best	Binomial	1268.3	15.2	5268.8	66.7	1314.0	74.0
Current-to-best	Binomial	1267.1	20.9	5305.5	70.4	1388.7	35.2
Current-to-best	**Exponential**	**1266.5**	**32.9**	**5250.1**	**98.2**	**1944.7**	**46.3**
Current-to-best	Hypercube	1270.6	25.9	5293.8	70.3	1386.7	35.9
Current-to-best	Line	1273.7	22.6	5332.6	59.8	1176.0	31.0

Based on these performance data statistics, a statistical analysis was conducted. The one-tailed t-student test for was used and the p-values computed. A significance level of 5% was considered, meaning that if the p-value is less than 0.05, the differences between the TBA values are considered statistically significant. This statistical analysis provides a rigorous evaluation of the performance of the different DE operators, allowing for a comprehensive comparison and identification of the operators that yield the most significant improvements in solving the resource dispatch problem for forest firefighting.

Testing Selection

Table 3 presents the results of the statistical analysis performed to evaluate the different selection operators used in the DE algorithm. In the lower triangular part of the table, the p-values corresponding to the comparisons between the selection operators are displayed. These p-values indicate the significance of the differences between the TBA values obtained with each selection operator. In the upper triangular part of the table, the average differences between the TBA values of the selection operators are displayed. These differences provide information about performance variations between selection operators. By examining the p-values and mean differences, it is possible to determine which selection operators have statistically significant differences in terms of their impact on TBA values. This analysis helps to identify the selection operators that contribute to better or worse performance in solving the resource dispatch problem for fighting forest fires using the DE algorithm. After the statistical analysis between the

Table 3. Statistical analysis for selection DE operator

	Random	**Best**	**Current-to-best**
Random	-	**11.165**	**12.384**
Best	0.012	-	1.218
Current-to-best	0.013	0.398	-

selection operators, it was verified that between the operators random and best, and random and current-to-best, there were significant differences (p-value $<$ 0.05). However, the combination of best selection and current-to-best selection obtained a p-value $>$ 5%. Therefore, the chosen operator was the current-to-best because it was the one that obtained a lower value of TBA (see Table 2) compared to the remaining selection operators.

Testing Crossover

A statistical analysis was performed to compare the DE crossover operators, maintaining the current-to-best selection and the polynomial mutation. The results of this analysis are shown in Table 4. The table shows the p-values corresponding to the paired comparisons of crossover operators in the lower triangle.

The p-values indicate whether there are statistically significant differences between the TBA values obtained with each crossover operator. In this case, as all p-values are greater than 0.05, no significant differences are observed between the crossover operators. However, based on the average TBA values shown in Table 2, the exponential crossover was chosen since it has the lowest average TBA value. The negative values presented in Table 4 indicate that the operators in the leftmost column obtained lower TBA values compared to the operators in the corresponding row.

Table 4. Statistical analysis for crossover DE operator

	Binomial	**Exponential**	**Hypercube**	**Line**
Binomial	-	0.557	-3.519	-6.568
Exponential	0.469	-	-4.076	-7.125
Hypercube	0.282	0.298	-	-3.048
Line	0.123	0.166	0.315	-

Overall, the statistical analysis allows for a comprehensive assessment of the performance of DE crossing operators, providing insights into their effectiveness in solving the problem of deploying resources to combat forest fires. After statistical analysis, it was found that the best operators for this problem were current-to-best selection and exponential crossover, that means DE/current-to-best/1/exp.

4.3 Best Result Analysis

The best solution found by the DE algorithm, based on the previously selected operators (current-to-best selection and exponential crossover), among the 30 independent runs, is presented in Table 5. This table includes the optimal value obtained for the total burned area (TBA = 1211.6 ha) and the amount of water used to extinguish the ignitions in the optimal solution (UW = 5088.3 l). Additionally, it presents the number of generations (ngen = 132), the number of function evaluations (nfe = 2620) performed by DE during the optimization process, and the execution time of the algorithm (Time = 46.8 s), indicating its efficiency in finding a high-quality solution within a reasonable time. Thus, this table offers a comprehensive view of the performance and efficiency of the DE algorithm in solving the resource dispatch problem for forest firefighting, considering the selected operators.

Table 5. Best solution found using current-to-best, exponential crossover and polynomial mutation operators (DE/current-to-best/1/exp)

TBA	**UW**	**ngen**	**nfe**	**Time**
1211.6	5088.3	132.0	2620.0	46.8

Table 6 presents the best solution found by DE, where at each instant of time the resource assigned to each ignition is shown. The symbol $\rightarrow$ represents that the resource of combat is traveling.

Table 6. The best resource dispatch solution found by DE (TBA = 1211.6)

R \ t		**10**	**20**	**30**	**40**	**50**
A	Base	$\rightarrow$	I_{14}	I_{13}	I_{16}	
B	Base	$\rightarrow$	I_4	$\rightarrow$	I_3	
C	Base	$\rightarrow$	I_6	I_{12}	I_{16}	
D	Base	I_9	$\rightarrow$	I_{17}	I_{18}	I_{15}
E	Base	$\rightarrow$	I_{20}	$\rightarrow$	I_{10}	I_2
F	Base	$\rightarrow$	I_8	I_5		
G	Base	I_7	I_{19}	I_{11}	$\rightarrow$	I_1

In the beginning, all the resources are at the Base. At $t = 10$, the resources D and G are assigned to ignitions I_9 and I_7, respectively. At $t = 20$ resources A, B, C, E, F and G are assigned to extinguish ignitions I_{14}, I_4, I_6, I_{20}, I_8 and I_{19}, respectively. In addition, resource D is traveling. The ignitions I_{13}, I_{12}, I_{17}, I_5 and I_{11} are extinguished at the instant of time $t = 30$. At the instant of time $t = 40$, resources B, D and E are dispatched to ignitions I_3, I_{18} and I_{10}, respectively, extinguishing them. Resources A and C are assigned to ignition I_{16}. Resource A ran out of water in its tank, so resource C is needed to finish extinguishing this ignition. From this instant of time, resource F was not assigned to any more ignitions, as it did not have enough water to extinguish any other remaining ignitions. Finally at instant of time $t = 50$, the ignitions I_{15}, I_2 and I_1 were extinguished by the resources D, E and G, respectively. In this solution, it took only 5 instants of time for the 7 resources to extinguish all ignitions.

4.4 Comparison between DE and GA

In this section, the performance between DE and GA algorithms is analyzed. The comparison is based on the average values, among 30 runs, obtained by DE and GA. Table 7 presents the performance of the algorithms in terms of the average values of TBA, UW, nfe and Time, where the lower values are indicated in bold. The optimization results when solving this problem by GA can be found in [14].

Table 7. Comparison between DE and GA average results

$\mathbf{TBA_{av}}$		$\mathbf{UW_{av}}$		$\mathbf{nfe_{av}}$		$\mathbf{Time_{av}}$	
DE	GA	DE	GA	DE	GA	DE	GA
1266.5	**1249.9**	**5250.1**	5891.2	1944.7	**1584.7**	46.3	**16.1**

It can be seen that in terms of average TBA, GA outperformed DE. In contrast, the average value of UW was lower in DE than in GA. However, it should be noted that UW was not being optimized. DE obtained the highest average nfe value while GA was the least time-consuming. The difference between the average TBA values achieved by DE and GA is 16.6. A statistical analysis was performed between the TBA values for both algorithms, which showed that the p-value for the TBA mean difference test was greater than 0.05, meaning that there were no significant differences between the performance of the two algorithms.

5 Conclusions

The occurrence of forest fires has increased in recent years. Therefore, the importance of studying new decision-making approaches for forest firefighting means is very significant.

In this paper a problem of dispatching forest firefighting resources was studied. The effective dispatch of firefighting resources plays a vital role in forest firefighting management. In order to control the fire in the shortest possible time, resources must be dispatched efficiently and effectively. The goal was to minimize the TBA by assigning 7 combat resources to extinguish 20 ignitions. For this, the differential evolution algorithm was applied. The DE algorithm is a powerful optimization technique that can be used to efficiently and effectively dispatch firefighting resources, leading to a reduction in the total burned area caused by ignitions. Furthermore, a statistical analysis was performed between the variants of DE (DE/selection/1/crossover) for the forest firefighting resource dispatch problem. This analysis revealed that the best DE variant for this particular problem was DE/current-to-best/1/exp. These operators showed superior performance and effectiveness in minimizing the total burned area and obtaining optimal solutions. An optimal solution value of TBA = 1211.6 ha was found. Additionally, a statistical analysis and comparison of the average solutions between the DE and GA algorithms was performed, where it was found that there were no significant differences, although GA had a lower average TBA value when compared to DE.

In the future, it is intended to solve this type of problems using a multi-objective strategy, for example, minimizing the total burned area and the used used simultaneously. Moreover, to validate this strategy, a problem with real data will be solved.

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