A Genetic Algorithm for Forest Firefighting Optimization*

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Abstract. In recent years, a large number of fires have ravaged planet Earth. A forest fire is a natural phenomenon that destroys the forest ecosystem in a given area. There are many factors that cause forest fires, for example, weather conditions, the increase of global warming and human action. Currently, there has been a growing focus on determining the ignition sources responsible for forest fires. Optimization has been widely applied in forest firefighting problems, allowing improvements in the effectiveness and speed of firefighters' actions. The better and faster the firefighting team performs, the less damage is done. In this work, a forest firefighting resource scheduling problem is formulated in order to obtain the best ordered sequence of actions to be taken by a single firefighting resource in combating multiple ignitions. The objective is to maximize the unburned area, i.e., to minimize the burned area caused by the ignitions. A problem with 10 fire ignitions located in the district of Braga, in Portugal, was solved using a genetic algorithm. The results obtained demonstrate the usefulness and validity of this approach.

Keywords: Forest Fires, Single-objective Optimization, Scheduling, Genetic Algorithm

1 Introduction

The incidence of forest fires has been high and worrying over the last few years. They represent high risk situations for the health of living beings and forests. Forest fires damage the ecosystem with negative consequences for wildlife and the atmosphere. Australia, between 2019 and early 2020, was devastated by several forest fires caused by record high temperatures, making it the biggest fire recorded in Australian history. About 19 million hectares were burned, killed 33 people and several animals and destroyed 3000 houses [6,11]. In 2018, more than 1.5 million hectares of forest were destroyed in the United States of America,

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where it was considered the second largest area burned since 1984, also caused by the high temperatures that were felt. California faced, in 2017, the deadliest and most destructive fires recorded in its history, with a total of 88 people dead and nearly 9000 lost structures [17,28]. In 2017, Portugal faced several forest fires, which was also a record year (temperatures, dry thunderstorms and deaths). This year was a critical year, with 117 deaths, 254 injuries, major damage to structures (houses and warehouses) and loss of biodiversity in a large forest area [8,18]. There were many other forest fires that caused great damage to our planet, affecting living beings, the planet and the world economy.

To protect and avoid major catastrophes such as forest fires, studies are needed to support firefighting professionals (firefighters, civil protection, etc.). Firefighting is a very important topic in optimization, since improvements in resources and quick actions are crucial requirements for professionals working in this area. Fighting forest fires depends on the number, skills and level of preparedness of firefighting teams [14]. The better and faster the firefighting team performs, the less damage is caused. Some of the challenges also include determining how many and what resources are available to act on a given forest fire and where and when to act [2].

Several works have been presented applying optimization to forest firefighting problems. Resource management in forest fire fighting can be modeled as a scheduling problem, where the machines correspond to resources and the jobs correspond to the fires. Rachaniotis and Pappis [20,21,22] studied the problem of scheduling a fire fighting resource when there are several fires at the same time, using a specific model for the fire propagation rate. Their objective was to maximize the unburned area, in order to reduce the damage caused. When controlling a forest fire, there must be no delays on the part of the firefighting team, because the shorter the delay, the faster and more effective the fire suppression becomes. A scheduling problem of a single firefighting resource when there are multiple wildfires to be suppressed is considered in [23]. In this work, the objective was to minimize the total delay of arrival at the forest fire site. An illustrative example was solved by a heuristic algorithm and the branch and bound algorithm.

Wu et al. [29] developed an integer linear programming model to determine the optimal routes for forest firefighting. The problem was addressed as an emergency scheduling problem for fires with limited rescue team resources and priority disaster areas. The objective was to minimize the total travel distance of all rescue teams. Araya-Córdova and Vásquez [1] studied the scheduling optimization problem of the disaster emergency unit for the control of forest fires. The objective was to determine a schedule and working times for firefighting, in order to minimize the sum of the total damage and the total cost of waiting for the firefighting teams.

Planning the amount and type of resources needed to fight a given forest fire is also one of the most studied problems. Veiga et al. [26] proposed an integer linear programming model, which addresses the allocation of resources in different time periods during the planning period for extinguishing a fire. A second part of this work involved carrying out a simulation of the problem studied, where they showed that the solution can be obtained quickly up to a planning period of five hours. In fighting forest fires, the longer it takes to fight these fires, the longer they become and the more difficult it is to control them. In [13], a single forest fire suppression processor for simultaneous ignitions was introduced. The aim was to find the optimal sequence of actions in firefighting, minimizing the total fire damage in the burned areas when all fires are suppressed. They proposed a stochastic formulation to solve the problem concluding that the approach was effective and efficient.

This work aims to find an optimal schedule actions to be taken by a single firefighting resource in combating several ignitions. The objective function of the problem is to maximize the unburned area, i.e., to minimize the burned area caused by the ignitions. A problem with 10 forest fires ignitions located in the district of Braga, in Portugal, will be solved using the genetic algorithm.

This article is organized as follows. Section 2 describes the management and suppression of wildfires. The formulation of the scheduling optimization problem and the genetic algorithm are described in Sect. 3. In Sect. 4 the results are presented and discussed. Finally, the conclusions of this study and future work are exposed in Sect. 5.

2 Forest Fires Suppression

The increase in forest fires is currently a worrying factor for society and for planet Earth. Some of them were catastrophic, leading to deaths, pollution, damage to homes and businesses, among other negative aspects. Around 400 million hectares are burned every year worldwide, where only 100 million hectares are forest areas [3,16,25]. A forest fire is based on the combustion of combustible materials existing in forest areas and its main causes are due to human action (most common), climate change and natural agents [9,10]. The spread of a fire depends on the type of fuel, slope of the area, wind strength and direction, weather conditions, ambient humidity and temperature [25].

Forest fires suppression is based on planning what type and amount of suppression resources are needed and where they should be located to best and quickly extinguish the fire [15]. When fighting forest fires, factors, such as wind intensity and ambient temperature, influence the propagation of fire, which makes the suppression problem difficult. Therefore, studying in advance ways to fight fires before they happen is mandatory, in order to obtain safe, effective and fast solutions to reduce the spread of forest fires.

Recently, fire suppression has been the focus of many studies. Cardil et al. [7] developed an analysis of the influence of suppression objectives (fire detection, initial attack and fire control), where fire intensity, fuel type, fire ignition cause, year and homogeneous fire regime areas were also included. This study was designed using data from the Quebec Forest Fire Protection Agency from fires that occurred between 1994 and 2015. They obtained an improvement of 88% in fire suppression and also improved fire detection and control. Overall, this paper has contributed to helping wildfire protection agencies better understand their wildfire suppression systems to better adapt to future changes in the fire regime. A fire management system based on deep reinforcement learning was developed in [19]. This work aimed to simulate a trajectory where agents are trained to select the areas to be treated in order to minimize the spread of fire. An algorithm based on centralized training with decentralized execution was used and the applied approach had a good performance when compared to traditional approaches.

Resource scheduling is one of the main studies that has been addressed in the area of firefighting. A target scheduling model was presented by Zhou and Erdogan [31], where two phases were addressed, the allocation of firefighting resources and the evacuation of residents. This strategy made it possible to optimize resource preparation before the start of the fire and resource allocation decisions during the fire event. The main objectives were to minimize the total cost of operations and property losses and to reduce the number of people at risk of being evacuated. Thus, the type and amount of resources needed are critical to firefighting. An integer linear programming model was proposed by Rodriguez-Veiga et al. [26] in which a problem of resource allocation in different periods of time during the management of a given fire was studied. Zeferino et al. [30] developed a mathematical optimization model to find the optimal location solution for different aircraft that maximizes the coverage of risk areas. Its application was used in a case study in Portugal.

3 Forest Firefighting Optimization

Optimization is widely used in engineering, such as finding the optimal vehicle trajectory, obtaining the shortest route, allocating resources or services among various activities to maximize benefit, controlling wait times on production lines to minimize costs, among others [24]. In this section, the forest firefighting scheduling problem formulation and the Genetic Algorithm (GA) used to solve this problem are described. The firefighting scheduling problem has a combinatorial nature and GA are particularly adequate to explore this kind of search spaces [4].

3.1 Optimization Model

In this paper, a forest firefighting resource scheduling problem is formulated, based on the works of Rachaniotis and Pappis [20,21,22,23] who developed and solved several resource scheduling problems in the area of forest fires. Therefore, the resource management in forest firefighting is modeled as a scheduling problem, where the machines correspond to resources and the jobs correspond to the fires. Firefighting resource travel times and fire suppression times correspond to machine setup times and job processing times, respectively. The propagation of fires always depends on the moment when they start to be suppressed by the firefighting resource, that is, the sooner the firefighting starts, the faster and easier it will be to extinguish, minimizing the damage caused.

This paper aims to find an optimal schedule of actions to be taken by a single firefighting resource in combating multiple ignitions that maximizes the unburned area, i.e., minimizes the burned area caused by the ignitions. The forest firefighting scheduling problem to be solved in this paper can be mathematically formulated as follows:

$$\text{Maximize } \sum_{i=1}^{k} V_{[i]} \tag{1}$$

subject to

$$V_{[i]} = V_{[i]0} - a_{[i]} C_{[i]}^2 \geq 0 \qquad \forall i = 1, \ldots, k \tag{2}$$

where the completion time and the processing time for each ignition fire $F_{[i]}$ $(i = 1, \ldots, k)$ are given by

$$C_{[i]} = \sum_{j=1}^{i} P_{[j]}(t) + \sum_{j=1}^{i} T_{[j-1],[j]} \tag{3}$$

$$P_{[i]}(t) = \begin{cases} \alpha_{[i]} t^{\beta_{[i]}} + \gamma_{[i]} t + \delta_{[i]}, & \text{if } t \leq d_{[i]} \\ X_{[i]}, & \text{if } t > d_{[i]} \end{cases} \tag{4}$$

where k is the number of fire ignitions; (1) is the unburned area to be maximized; (2) gives the unburned area of each fire ignition i; (3) is the completion time of each fire ignition; and (4) is the processing time for each fire ignition.

The notation used in the mathematical formulation is described in Table 1.

3.2 Genetic Algorithm

Genetic Algorithms are, probably, the best known and most widely used evolutionary algorithms applied to optimization and became popular with the work of John Holland in 1975 [12]. GA is a global optimization method inspired by the evolutionary theory of the species, namely the natural selection, the survival of the fittest and the inheritance of characteristics from parents to offspring by reproduction. The main components of a GA are the population of chromosomes, the fitness function, the selection, the crossover and the mutation (Figure 1). GA work with a population of chromosomes that represent potential solutions of the optimization problem. The initial population is generated at random. Different chromosome representations can be used according to the search space of the optimization problem. The fitness function measures the quality of chromosomes and it is related with the objective function. Each generation, the fittest chromosomes in population are more likely to be selected to generate offspring by means of the crossover and the mutation genetic operators. This cycle is repeated until a given stopping criterion is satisfied.

Table 1. Notation used in the forest firefighting scheduling problem formulation.

Variable	Description
$F_{[i]}$	Fire ignition ($i = 1, 2, \ldots, k$)
$C_{[i]}$	Completion time of $F_{[i]}$ suppression effort
$d_{[i]}$	Containment escape time limit
$V_{[i]}$	Remaining area value (unburned) in fire $F_{[i]}$
$V_{[i]0}$	Value of the area at the time when the overall containment effort begins in fire $F_{[i]}$
$a_{[i]}$	Deterioration rate in each fire $F_{[i]}$
$P_{[i]}(t)$	Processing time elapsed from ignition of fire $F_{[i]}$
t	Time elapsed since ignition of fire $F_{[i]}$
$T_{[i-1],[i]}$	Time required for the processor to travel from suppressed fire $F_{[i]}$ to fire $F_{[i+1]}$
$\alpha_{[i]}$, $\beta_{[i]}$, $\gamma_{[i]}$, $\delta_{[i]}$	Constant parameters depending on the area that $F_{[i]}$ burns (the meteorological conditions, the processor's water, the processor's water capacity and the fire's containment strip width)
$X_{[i]}$	Value that depends on the additional resources that will be dispatched to the specific area

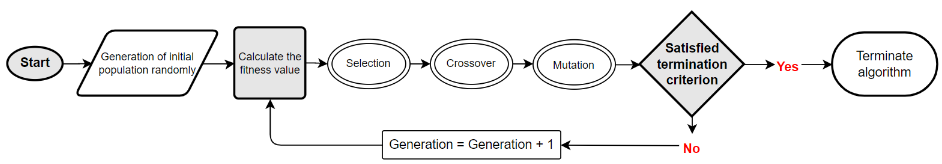

Fig. 1. Genetic algorithm process.

The forest firefighting scheduling problem is a combinatorial problem. GA are particularly adequate to explore this kind of search spaces since different chromosome representations can be used, namely permutation based representations [4]. Therefore, a permutation representation was adopted to represent a potential solution of this scheduling problem. In this representation, each chromosome is a sequence of integer values that can occur only once. Thus, each chromosome indicates the order each fire ignition is combated by the firefighting resource. The recombination plays an important role since genetic material of the chromosomes is combined to ensure that new promising regions of the search space are explored. However, the genetic operators have to guarantee that feasible permutations are maintained during the search. Several specialized genetic operators have been developed that fulfill this requirement such as the order-based crossover or the inverse mutation [4,27].

In this paper, each chromosome has dimension k (number of fire ignitions) and represents the sequence order of combat of each fire ignition $F_{[i]}$, $i = 1, 2, \ldots, k$.

4 Experimental Results

In this section, the numerical results for the scheduling of a single firefighting resource to fight ten forest fire ignitions located in the district of Braga in Portugal is presented.

4.1 Implementation Details

The optimization problem and the GA were coded in *Python* language using the *pymoo*: Multi-objective Optimization in Python framework [5]. After some preliminary experiments, the population size was set to 20 and a limit of 200 was imposed in the maximum number of generations. Permutation representation was used to represent solutions of the firefighting problem. Tournament selection, order-based crossover and inverse mutation was used to generate new chromosomes. The default values for the remaining parameters of the GA were used. Since GA is stochastic algorithm, 30 independent runs were performed in order to statistically analyze its performance.

In this forest firefighting scheduling problem, there is a single firefighting resource and 10 fire ignitions located in the district of Braga in Portugal. These fire locations are large forest areas, prone to major fires, chosen using *Google Maps* software. Figure 2 shows the location of Braga fire station (in red) which is where the firefighting resource departs, and the 10 fire ignitions (in light blue).

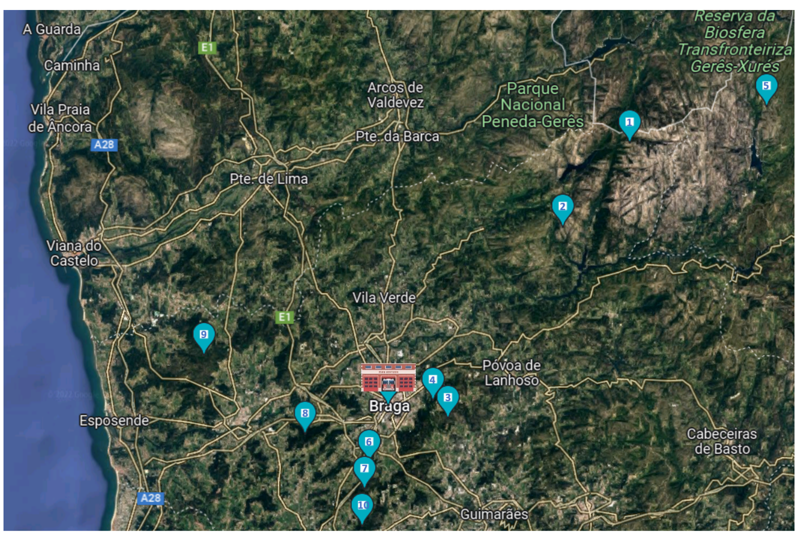

Fig. 2. Location of the Braga fire station and the 10 fire ignitions.

Table 2 presents the data concerning this problem. In this table, $\alpha_{[i]}$, $\beta_{[i]}$, $\gamma_{[i]}$, $\delta_{[i]}$, $d_{[i]}$ and $X_{[i]}$ are the parameters related to the computation of processing times of each fire $F_{[i]}$. The parameter $a_{[i]}$ is the deterioration rate of fire $F_{[i]}$. The initial area, in hectares, where each coordinate is located and the travel time, in hours, that the firefighting resource takes from the fire station until each ignition are given by $V_{[i]0}$ and $T_{[0],[i]}$, respectively.

Table 2. Data for the forest firefighting scheduling problem in Braga.

$F_{[i]}$	$\alpha_{[i]}$	$\beta_{[i]}$	$\gamma_{[i]}$	$\delta_{[i]}$	$X_{[i]}$	$d_{[i]}$ (h)	$a_{[i]}$	$V_{[i]0}$ (ha)	$T_{[0],[i]}$ (h)
1	0.46	3.20	0.22	0.005	0.20	0.10	0.10	201.25	1.20
2	0.39	3.00	0.24	0.006	1.80	0.80	0.10	791.47	0.98
3	1.51	2.70	0.28	0.008	1.40	0.70	0.10	320.42	0.32
4	1.50	2.50	0.28	0.009	1.00	0.50	0.10	740.19	0.22
5	0.51	3.52	0.24	0.006	1.40	0.70	0.10	8479.81	1.70
6	0.43	3.30	0.26	0.007	0.20	0.10	0.10	354.14	0.25
7	1.66	2.97	0.31	0.009	0.10	0.05	0.10	499.96	0.35
8	1.65	2.75	0.31	0.010	0.60	0.30	0.10	809.45	0.42
9	0.56	3.87	0.27	0.006	0.80	0.40	0.10	3148.38	0.62
10	0.39	2.97	0.24	0.006	1.20	0.60	0.10	779.71	0.48

The travel time matrix of the firefighting resource between each forest fire ignition, in hours, is given by $T_{[i],[j]}$.

$$T_{[i],[j]} = \begin{pmatrix} 0.00 & 0.60 & 1.27 & 1.17 & 1.22 & 1.35 & 1.45 & 1.60 & 1.95 & 1.58 \\ 0.60 & 0.00 & 1.12 & 1.03 & 1.57 & 1.15 & 1.05 & 1.12 & 1.32 & 1.20 \\ 1.27 & 1.12 & 0.00 & 0.18 & 1.77 & 0.40 & 0.53 & 0.73 & 1.07 & 0.60 \\ 1.17 & 1.03 & 0.18 & 0.00 & 1.67 & 0.30 & 0.40 & 0.50 & 0.87 & 0.53 \\ 1.22 & 1.57 & 1.77 & 1.67 & 0.00 & 1.68 & 1.95 & 2.08 & 2.47 & 2.10 \\ 1.35 & 1.15 & 0.40 & 0.30 & 1.68 & 0.00 & 0.27 & 0.50 & 0.85 & 0.43 \\ 1.45 & 1.05 & 0.53 & 0.40 & 1.95 & 0.27 & 0.00 & 0.50 & 0.85 & 0.30 \\ 1.60 & 1.12 & 0.73 & 0.50 & 2.08 & 0.50 & 0.50 & 0.00 & 0.60 & 0.67 \\ 1.95 & 1.32 & 1.07 & 0.87 & 2.47 & 0.85 & 0.85 & 0.60 & 0.00 & 0.93 \\ 1.58 & 1.20 & 0.60 & 0.53 & 2.10 & 0.43 & 0.30 & 0.67 & 0.93 & 0.00 \end{pmatrix}$$

4.2 Results and Discussion

In this section, the results obtained are presented and discussed. Table 3 shows the results of the solutions obtained over the 30 runs. Each table row shows a solution found in a given number of runs (second column). Thus, the first column shows the optimal sequence order to combat the fire ignitions found and the last two columns present the value of the unburned and burned area for that solution, respectively. Among the 30 runs, GA got five different solutions, being one of them found 23 times. The average value of unburned area was 16027.576 hectares and the burned area was 97.204 hectares, over the 30 runs. In each run, 4020 function evaluations were performed by the algorithm.

The best solution found corresponds to the following order of action the firefighting resource: $FS \rightarrow F_5 \rightarrow F_9 \rightarrow F_1 \rightarrow F_{10} \rightarrow F_2 \rightarrow F_7 \rightarrow F_8 \rightarrow F_3 \rightarrow F_6 \rightarrow F_4$ where

Table 3. Solutions found among the 30 runs.

Solution	No. Runs	Unburned Area (ha)	Burned Area (ha)
$F_5 \to F_9 \to F_1 \to F_{10} \to F_2 \to F_7 \to F_8 \to F_3 \to F_6 \to F_4$	1	16029.383	95.397
$F_1 \to F_9 \to F_5 \to F_{10} \to F_2 \to F_8 \to F_3 \to F_7 \to F_4 \to F_6$	1	16028.506	96.274
$F_5 \to F_9 \to F_1 \to F_{10} \to F_2 \to F_3 \to F_8 \to F_7 \to F_4 \to F_6$	1	16028.414	96.366
$F_5 \to F_9 \to F_1 \to F_{10} \to F_2 \to F_8 \to F_3 \to F_7 \to F_4 \to F_6$	4	16028.080	96.700
$F_5 \to F_9 \to F_1 \to F_{10} \to F_2 \to F_6 \to F_8 \to F_3 \to F_7 \to F_4$	23	16027.333	97.447

FS denotes the Braga fire station, which is the depart location and F_1 to F_{10} are the fire ignitions. This solution corresponds to a maximum value of unburned area of 16029.383 hectares. Figure 3 depicts this solution, where the red circles denote the fire ignitions and the blue lines represent the path that the forest firefighting resource takes to suppress all fires. In the x and y axes the geographic coordinates of each fire ignition are shown.

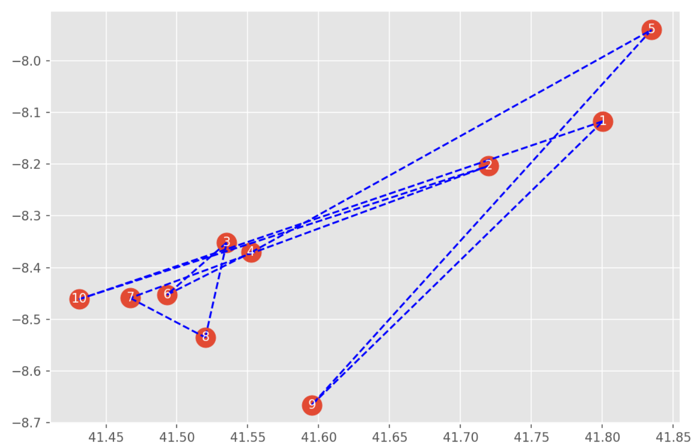

Fig. 3. Optimal Sequence.

In Table 4, detailed data for this solution is given. In this table, for each ignition, the unburned and burned areas, in hectares, and the travel and processing times, in hours, are given. The travel time (T) is the time required for the firefighting resource to move from one fire ignition to the next. The processing time (P) is the time needed to extinguish the fire ignition. The last column of Table 4 shows the percentage of saved area for each ignition.

In this solution, the firefighting resource departs from the Braga fire station (FS) to the first fire ignition in the sequence (F_5). The travel time was 1.7 hours, the extinguishing time was 1.4 hours and 0.961 hectares burned. Then, the resource travels to F_9, taking 2.47 hours to arrive, 2.470 hectares of area was burned and fire was suppressed after 0.8 hours. This was followed by the extinguishing of the F_1 fire, the resource having traveled 1.95 hours to its position, it took 1.2 hours to suppress it and 3.994 hectares burned. Subsequently, the resource took 1.58 hours to arrive to F_{10}, took 1.2 hours to extinguish it, and 7.921 hectares were damaged. Then the fighting resource traveled to the F_2, extinguishing it in 1.8 hours and losing 11.449 hectares. This was followed by F_7, where the resource needed 1.05 hours to get to this one and 0.1 hours to extinguish it. The ignition identified as F_8 was the next fire to be suppressed, where 12.210 hectares were burned. In the fire F_3, 304.594 hectares of forest area were saved out of a total of 320.42 hectares. Subsequently, the fire F_6 was extinguished, taking 0.2 hours to extinguish and a trip to it of 0.4 hours. Finally, the resource moved to the last ignition of the sequence obtained, F_4, having burned 16.589 hectares, the travel time from the fire before this one was 0.30 hours and it took 1.0 hour to fight it.

At the end of the action to combat forest fires, 95.397 hectares of forest were destroyed, in a total of 16124.780 hectares, that is, 16029.383 hectares of forest area were saved, representing a total of 99.41% of area not destroyed by the 10 ignitions. The total travel time for the firefighting resource was 11.88 hours and a total of 8.7 hours were required to suppress all fire ignitions. Thus, a total of 20.58 hours were required to combat the 10 ignitions, plus 0.22 hours to return to Braga fire station.

Table 4. Solution Data.

Ignition	**Unburned Area**	**Burned Area**	T	P	**Saved area**
F_5	8478.849	0.961	1.70	1.4	99.99%
F_9	3145.910	2.470	2.47	0.8	99.92%
F_1	197.256	3.994	1.95	0.2	98.02%
F_{10}	771.789	7.921	1.58	1.2	98.98%
F_2	780.021	11.449	1.20	1.8	98.55%
F_7	489.860	10.100	1.05	0.1	97.98%
F_8	797.240	12.210	0.50	0.6	98.49%
F_3	304.594	15.826	0.73	1.4	95.06%
F_6	340.263	13.877	0.40	0.2	96.08%
F_4	723.601	16.589	0.30	1.0	97.76%
Total	16029.383	95.397	11.88	8.7	99.41%

5 Conclusions and Future Work

The occurrence of forest fires has increased in recent years due to natural factors such as the global warming or other factors caused by society. Forest fires endanger the health of all living beings, bringing negative impacts to planet Earth. Thus, optimizing firefighting actions is a very important topic and depends on the number, skills and level of preparation of firefighting teams.

In this work, a forest firefighting scheduling problem with 10 fire ignitions in the district of Braga in Portugal was studied. The aim was to find the best ordered sequence of actions of one firefighting resource. A genetic algorithm was used to seek the optimal solution of this problem. Thirty independent runs were performed. Five different solutions were obtained in the different runs. These solutions share similarities in terms of the order of suppression of fire ignitions and have close values of unburned area. The best solution found was $FS \to F_5 \to F_9 \to F_1 \to F_{10} \to F_2 \to F_7 \to F_8 \to F_3 \to F_6 \to F_4$, with an objective function value of 16029.383 hectares. These results show the usefulness and validity of this approach. Moreover, this approach can be applied to large instances of the problem providing good solutions.

In the future, we intend to formulate the problem with more than one firefighting resource; to study the effect of other permutation based genetic operators on the performance of the algorithm; to formulate and solve this problem as a multi-objective problem by introducing other objectives such as tardiness; to apply and compare the performance of other optimization algorithms.

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