

# Discrete event simulation in a firefighting resource scheduling problem

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## Abstract

Every year the world is faced with a natural and human-caused catastrophe: forest fires. Firefighting depends on quick and efficient decision-making. Delays can lead to large areas being devastated and many lives at risk. On the other hand, when there are simultaneous ignitions, prioritization criteria must be used to minimize this phenomenon's impacts. Decision-making in this context of urgency and effectiveness has led to the use of Operations Research techniques, both in the optimization process and in the simulation of possible scenarios. In this work, the Genetic Algorithm (GA) is used to optimize the firefighting resource scheduling problem. A case study is addressed, whose main objective is to determine the scheduling of two available resources to extinguish ten fire ignitions while minimizing the total burned area (TBA). Two distinct GA population sizes are used in the optimization procedure in order to assess the one that produces better results. Then, a Discrete Event Simulation model is generated in Flexsim software, considering three scenarios. The first one is based on the best solution obtained by the GA and the other two adding uncertainty to the processing and travel time. The simulation results validated the GA's optimal scheduling and allowed evaluating the impact of the TBA when considering uncertainty.

**Keywords:** Firefighting, Scheduling, Optimization, Simulation

# 1 Introduction

Forest fires occur in areas of vegetation and are often caused by natural factors, such as lightning, or human activities. They can cause significant damage to the environment, affecting both flora and fauna, as well as posing risks to human life and property. The increase in forest fires has been rising globally. In Portugal, for example, there was a significant increase in fires resulting in fatalities and substantial property damage. In 2017, Portugal experienced a record number of forest fires, driven by extreme temperatures and dry thunderstorms [1]. In September 2024, more than 100 wildfires in Portugal stretched thousands of firefighters to their limits, resulting in seven deaths. The European Copernicus satellite reported that more than 15000 hectares were burned, with 13 kilometers of fire fronts detected and an area that is home to 210000 people exposed to the risk [2]. Fire suppression is important to reduce this type of phenomenon. It involves strategic planning, adequate resources and firefighting techniques, including the use of fire trucks and the implementation of containment and control measures. Effective management and prevention, such as creating firebreaks, are essential to minimizing impacts and protecting ecosystems.

In various domains, such as project management, production or emergency response (such as firefighting), scheduling ensures that resources are allocated effectively to complete tasks within constraints such as deadlines or availability. Scheduling problems can involve making complex decisions, often requiring methods such as optimization algorithms or simulations to find the most efficient solution. The job shop scheduling problem is a fundamental and widely studied combinatorial optimization problem in operational research. Due to its vast range of engineering and social applications, it has attracted significant attention from the scientific community [3].

Currently, there are several studies on fire suppression strategies based on scheduling problems, for example on the scheduling of forest firefighting vehicles [4, 5]. Jemmali et al. [6] focused on scheduling monitoring tasks for drones in a forest monitoring system. Several algorithms were developed to minimize the total task completion time and 990 instances in three classes were used to evaluate the algorithms. The results obtained showed the effectiveness of the algorithms, in which the random iterative drone algorithm performed best, achieving a success rate of 90.3% with an execution time of 0.088 seconds. The paper by Wang et al. [7] addressed an emergency scheduling problem for forest firefighting in priority areas, to minimize transport distance and rescue time. A multi-objective mixed-integer linear programming model was used to solve the problem, along with an iterative decision approach based on the  $\epsilon$ -constraint method and fuzzy logic. The computational results demonstrated the effectiveness and feasibility of the model and methodology developed. Matos et al. [8] studied a forest firefighting resource scheduling problem to determine the optimal sequence of actions for a single team fighting multiple fires. The objective was to maximize the unburned area while minimizing the damage caused by ignitions. A scenario with ten ignitions in the district of Braga, Portugal, was solved using a genetic algorithm (GA). The results demonstrated the effectiveness and validity of this approach.

Zhou et al. [9] analyzed firefighting cycles and the water refilling process for fire trucks, comparing different scheduling strategies using the eM-plant simulation tool.

Focusing on emergency response to chemical fires, the study evaluated strategies like assigning fire trucks based on proximity to hydrants and distributing them according to hydrant numbers. The results indicated that a uniform distribution of fire trucks performs well but can be optimized further. The study offered guidelines for improving fire truck scheduling in emergency situations. The study presented in [8] was extended and validated using a Discrete Event Simulation model. Subsequently, a simulation-optimization approach was developed incorporating uncertainty in certain parameters [10].

This paper presents a firefighting scheduling problem with two resources to extinguish ten fires. The main objective is to determine the optimal resource schedule while spending the least completion time (i.e., the shortest possible processing and travel time), in order to minimize the burned area. To do this, the problem is first optimized through GA, using two different population sizes. Then, the best solution given by the optimization process is modeled in a FlexSim simulator software. Therefore, a simulation-based optimization approach is then developed to validate the solution found. Additionally, different scenarios are generated by applying uncertainty to some problem variables.

This paper is organized as follows. The overview of the firefighting resource scheduling problem is presented, along with the results obtained from the optimization process is described in Sect. 2. The description of the discrete event simulation model and the results obtained by the scenarios are shown in Sect. 3. Finally, Sect. 4 rounds up the paper with conclusions and presents the future work.

## 2 Firefighting resource scheduling

This section addresses the problem of scheduling in different domains, including its use in forest fire suppression. The scheduling problem refers to the challenge of organizing tasks, resources, or events in a way that optimizes performance or efficiency. It involves determining the best sequence or allocation of activities to meet specific goals, such as minimizing time, costs, or conflicts. This problem arises in various fields, from manufacturing and transportation to computing and emergency response, like forest fire suppression. The GA is one of the stochastic optimization algorithms that has been widely used in this type of problem [11].

Ren and Tian [12] proposed a new fire emergency scheduling model that prioritizes disaster areas, taking into account the limited resources of rescue teams. The objective of the model is to minimize the total travel distance for rescue operations. To solve the proposed model, the authors used a hybrid intelligent algorithm that combines GA with Particle Swarm Optimization. Both the theoretical analysis and the simulation results demonstrate that the model can effectively conduct a quantitative analysis of forest fire emergencies, helping decision-makers to make more informed decisions during fire emergencies. The work by Wu et al. [13] presented forest fire emergency scheduling, optimizing routes for limited firefighting teams, giving priority to critical areas. An integer linear programming model was developed and computational tests showed that the model was efficient with different instances, outperforming existing methods in speed and quality of solution. A new mixed integer programming model is

also introduced to reduce the total recovery time under resource constraints. Another resource-constrained emergency scheduling problem for priority disaster areas can be found in [7]. The emergency response is crucial to mitigating the damage caused by large-scale fires and preventing them from getting worse. During firefighting efforts, multiple fire trucks can be involved simultaneously, and their scheduling impacts the efficiency of firefighting and consequently the overall capacity. Skorin-Kapov et al. [14] developed a Mixed Integer Linear Programming model to schedule daily aerial operations for large-scale forest fires, prioritizing water flow over areas and periods. Secondary objectives included minimizing completion time and maximizing water production. For larger instances, a scalable heuristic was proposed that combines a randomized greedy method and simulated annealing. Tests showed that the heuristic provided near-optimal solutions for small instances and effective results for larger instances, making it suitable for night and morning planning in fire emergencies.

## 2.1 Firefighting Resource Scheduling Problem

This paper deals with a firefighting resource scheduling problem. In the case study under consideration, ten different ignition points (representing different fronts of the same forest fire) are ignited simultaneously, detected and reported, and two resources are assigned for their containment. A resource could be a fire truck, modeled as a forest firefighting vehicle equipped with a water tank. All the fires evolve independently and no constraint is assumed which impose the order in which fires must be suppressed. As time elapses, the fire expands and the processing time of a fire increases if the beginning of fire containment effort is delayed. The main goal is to minimize the total burned area after the completion of the containment operation of all ignitions. That is, the optimization approach aims to determine the optimal schedule of two resources to extinguish all the ignitions considering the completion time (travel time and processing time).

The mathematical formulation of the total burned area is based on the works of Rachaniotis and Pappis [15, 16], that takes into account several factors, such as weather conditions, topography, fuel type. Thus, the mathematical formulation of the total burned area to be minimized is given by

$$\text{Minimize } \sum_{i=1}^k a_{[i]} C_{[i]}^2 \quad (1)$$

where  $k$  is the number of fires and  $a_{[i]}$  is the deterioration rate in each fire  $F_{[i]}$ . The completion time (2) and the processing time  $P_{[i]}(t)$  in (3) for fire  $F_{[i]}$  at time elapsed  $t$  ( $i = 1, \dots, k$ ) are given by

$$C_{[i]} = \sum_{j=1}^i P_{[j]}(t) + \sum_{j=1}^i T_{[j-1],[j]} \quad (2)$$

$$P_{[i]}(t) = \begin{cases} \alpha_{[i]} t^{\beta_{[i]}} + \gamma_{[i]} t + \delta_{[i]}, & \text{if } t \leq d_{[i]} \\ X_{[i]}, & \text{if } t > d_{[i]} \end{cases} \quad (3)$$

where  $T_{[i-1],[i]}$  is the travel time required for the processor to travel from suppressed fire  $F_{[i]}$  to fire  $F_{[i+1]}$ . The notation used in the forest firefighting scheduling problem formulation also includes  $d_{[i]}$  that is the containment escape time limit,  $\alpha_{[i]}$ ,  $\beta_{[i]}$ ,  $\gamma_{[i]}$ ,  $\delta_{[i]}$  are 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), and  $X_{[i]}$  is the value that depends on the additional resources that will be dispatched to the specific area.

Figure 1 shows the selected study area located in Braga (Portugal), the fire ignitions and routes generated from Geographic Information System (GIS) that connect these locations. In the center of the figure, the fire station is represented in dark blue,



**Fig. 1** Fire locations in the study area

while the ignition points are marked with red circles, with numbers inside the red circles so they can be referenced. The brown circles represent the two firefighting resources. The existing routes to reach these locations are outlined in black. There are 11 interconnected sites: the fire station and 10 forest fire ignition points. The total area represented by Fig. 1 is 16124.78 hectares. The values of the travel times between the ignitions and from the base to each ignition, can be found in [10]. The model proposed by Rachaniotis and Pappis [15, 16] is used to determine the completion time, i.e. the time required for fire suppression. Additionally, the data used for computing the TBA are available in [8].

An adapted Genetic Algorithm from the “Pymoo” online framework [17], implemented in *python* (version 3.12.6) using *VScode* (Version 1.93.1) was used. Firstly, the GA was adapted with a permutation-based representation 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. GA is a metaheuristic optimization technique inspired by the theory of evolution, where the “fittest” individuals are more likely to survive. This process is driven by biologically based operators like mutation, crossover and selection [18].

The default GA parameters from the “Pymoo” framework were used, such as the number of function evaluations set to 100000, and the maximum number of generations of 1000. The initial population size was 20, which was also a default value. In addition to this, another initial population size, 50, was tested to see if a larger population was required to obtain better solutions. The genetic operators used were tournament selection (by default), order crossover and reverse mutation. Since GA is a stochastic algorithm, 30 runs were executed for the problem under study. More details on the initial data and the application of GA to this scheduling problem can be found in [8, 10].

## 2.2 Scheduling Results

As mentioned above, two population sizes (pop= 20 and pop= 50) were used in the GA, 20 and 50. Table 1 shows the average, best and worst solutions obtained over 30 runs, when using the two population sizes. Each row of the table shows the solutions for each population size, and the first column refers to that value. The next five columns are related to the average values of the TBA, number of function evaluations (nfe) and number of generations (gen), and the corresponding standard deviation values. Columns 7 to 9 present the best solution obtained in terms of TBA among the 30 runs. The last three columns correspond to the worst solutions obtained.

**Table 1** Average, best and worst solutions obtained over 30 runs

| pop | TBA <sub>avg</sub> | TBA <sub>std</sub> | nfe <sub>avg</sub> | nfe <sub>std</sub> | gen <sub>avg</sub> | TBA <sub>b</sub> | nfe <sub>b</sub> | gen <sub>b</sub> | TBA <sub>w</sub> | nfe <sub>w</sub> | gen <sub>w</sub> |
|-----|--------------------|--------------------|--------------------|--------------------|--------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| 20  | 9.77               | 1.3                | 774                | 213.7              | 38                 | 8.31             | 680              | 33               | 12.46            | 580              | 28               |
| 50  | 9.35               | 1.1                | 1943               | 477.6              | 10                 | 8.31             | 1450             | 28               | 12.19            | 2050             | 40               |

With a population of 50, lower TBA<sub>avg</sub> values were obtained compared to the population of 20, the same applying to the standard deviation (TBA<sub>std</sub>). Although fewer iterations were done, there is a higher value of nfe<sub>avg</sub>, which is obvious, since the population size is larger. Note that, the number of function evaluations is given by nfe=pop(gen+1), where gen represents the generations number.

For both population sizes, the same best solution was found with TBA<sub>b</sub> = 8.31, although at the expense of a smaller number of function evaluations. This solution corresponds to the following ignition extinction order for resource 1 ( $R_1$ ) of  $I_4$ ,  $I_3$ ,  $I_6$ ,  $I_7$ ,  $I_{10}$ ,  $I_8$  and  $I_9$ , and for resource 2 ( $R_2$ ) to extinguish ignitions  $I_2$ ,  $I_1$  and  $I_5$ . This same solution was obtained in 9 out of 30 runs (30%) for population 20, and for 6 out of 30 runs (20%) for population 50. For the worst solution, the TBA<sub>w</sub> values were 12.457 and 12.187 for pop 20 and 50, respectively. When pop is 20, the solution found selected  $R_1$  to extinguish ignitions  $I_2$ ,  $I_9$  and  $I_5$ , and  $R_2$  to extinguish ignitions  $I_4$ ,  $I_3$ ,  $I_7$ ,  $I_6$ ,  $I_8$ ,  $I_{10}$  and  $I_1$ , in that order. As for the solution found when pop is 50,

$R_1$  extinguished ignitions  $I_3, I_6, I_7, I_{10}, I_8$  and  $I_5$ , and  $R_2$  was assigned to extinguish ignitions  $I_2, I_1, I_4$  and  $I_9$ .

A statistical analysis was also performed for the average TBA values between the two populations used in this study, where it was found that there were no significant differences since the  $p$ -value was of 0.1071 greater than 0.05.

### 3 Discrete event simulation

As defined by Robinson [19], simulation is the imitation of a system, wherein a model is generated to represent the dynamic behavior of that system. Discrete-event simulation, according to Banks [20], denotes the imitation of a system wherein the state of the system undergoes change at discrete, potentially random, time points.

To validate the empirical results obtained from the GA optimization, a discrete event simulation model was generated using the parameters described in [10]. FlexSim was chosen for the modeling because it includes the GIS module, version 24.0.2, which is capable of generating realistic models taking into account the geographical coordinates (latitude and longitude) of the defined ignition points and the road distances between them.

As can be seen in Figure 1, the 10 ignition points were defined, their geographical coordinates configured and two resources (firefighting trucks) allocated to meet the optimal schedule generated by GA. The road routes available to connect the fire station and all the ignition points are shown in black. The generated model was identified as “Exp1”, an experiment with deterministic data. As posited by Kelton [21], a deterministic model is predicated on the assumption that there are no random or uncontrollable elements and that the inputs are exact values, devoid of any uncertainty.

Running the simulation model showed a TBA result of 8.31, which is consistent with the empirical result obtained by the GA, which on the one hand confirms the GA result and on the other hand validates the model, allowing it to be used in planned experiments. Validating the simulation model based on this criterion of comparison with empirical data is one of the types of validation proposed by Sargent [22].

#### 3.1 Adding uncertainty

Once the computer simulation model had been generated and validated, an experimental procedure was carried out in which the combat data, which were deterministic (exact) in Exp1, were replaced by probability distributions in order to introduce randomness into the ignition point combat process. To this end, it was decided to assign normal distributions to all the ignition points, and a Monte Carlo simulation procedure was carried out for each of them to more accurately determine the parameters (denoted by “Mean” and “St.Dev.”) of this distribution. Table 2 shows the parameters defined for the Normal Distribution for each ignition point.

Based on these new processing time variables, the model was adjusted and ten replicates were generated to test whether the average results compared to the empirical values of this process would show statistically significant differences. This procedure was called “Exp2”. Table 3 illustrates the values for the random variable Processing Time obtained for each of the ten ignition points in the ten replicates. The mean

**Table 2** Parameters of the distributions for Processing Time

|          | Hours |         | Seconds |         |
|----------|-------|---------|---------|---------|
|          | Mean  | St.Dev. | Mean    | St.Dev. |
| $I_1$    | 0.20  | 0.02    | 720     | 70      |
| $I_2$    | 1.80  | 0.18    | 6480    | 654     |
| $I_3$    | 1.40  | 0.14    | 5040    | 507     |
| $I_4$    | 1.00  | 0.10    | 3600    | 373     |
| $I_5$    | 1.40  | 0.14    | 5040    | 512     |
| $I_6$    | 0.20  | 0.02    | 720     | 73      |
| $I_7$    | 0.10  | 0.01    | 360     | 37      |
| $I_8$    | 0.60  | 0.05    | 2160    | 194     |
| $I_9$    | 0.80  | 0.08    | 2880    | 281     |
| $I_{10}$ | 1.20  | 0.13    | 4320    | 457     |

value and standard deviation were calculated for each replication and subsequently included in the statistical test. The resulting  $p$ -values indicate the test results for each ignition point. A review of the  $p$ -values indicates that none of the replications

**Table 3** Replicate results for Exp2

| Repl.      | $I_1$  | $I_2$  | $I_3$  | $I_4$  | $I_5$  | $I_6$  | $I_7$  | $I_8$  | $I_9$  | $I_{10}$ |
|------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|----------|
| 1          | 0.21   | 1.64   | 1.34   | 0.99   | 1.36   | 0.20   | 0.09   | 0.56   | 0.75   | 1.07     |
| 2          | 0.19   | 1.73   | 1.40   | 0.93   | 1.45   | 0.18   | 0.12   | 0.54   | 0.85   | 1.16     |
| 3          | 0.20   | 1.76   | 1.45   | 1.07   | 1.42   | 0.22   | 0.10   | 0.60   | 0.65   | 1.09     |
| 4          | 0.18   | 1.84   | 1.49   | 1.17   | 1.57   | 0.20   | 0.09   | 0.54   | 0.80   | 1.23     |
| 5          | 0.19   | 1.63   | 1.12   | 0.97   | 1.48   | 0.16   | 0.10   | 0.63   | 0.87   | 1.32     |
| 6          | 0.20   | 1.76   | 1.26   | 0.96   | 1.31   | 0.16   | 0.08   | 0.59   | 0.65   | 1.24     |
| 7          | 0.18   | 1.80   | 1.60   | 0.83   | 1.40   | 0.20   | 0.09   | 0.73   | 0.84   | 1.15     |
| 8          | 0.22   | 1.78   | 1.54   | 1.15   | 1.24   | 0.20   | 0.10   | 0.61   | 0.76   | 1.21     |
| 9          | 0.22   | 1.95   | 1.09   | 1.08   | 1.44   | 0.19   | 0.11   | 0.63   | 0.77   | 1.13     |
| 10         | 0.21   | 1.53   | 1.18   | 0.86   | 1.42   | 0.19   | 0.09   | 0.51   | 0.85   | 1.14     |
| Average    | 0.200  | 1.742  | 1.347  | 1.001  | 1.409  | 0.190  | 0.097  | 0.594  | 0.779  | 1.174    |
| Std        | 0.0149 | 0.1185 | 0.1790 | 0.1148 | 0.0911 | 0.0189 | 0.0116 | 0.0628 | 0.0796 | 0.0759   |
| $p$ -value | 1.000  | 0.156  | 0.374  | 0.979  | 0.762  | 0.129  | 0.435  | 0.769  | 0.426  | 0.307    |

exhibited statistically significant discrepancies from the reference data.

Furthermore, in order to guarantee greater precision in the model, the journey time was substituted with randomly generated values derived from the data set presented in [10]. According to the methodology employed for the processing time, the normal distribution's average and standard deviation parameters were determined for each ignition point. In this instance, random values that were less than the average journey times were excluded, thus requiring the average values to be adopted. It is postulated that the journey times for the resources used could not be less than those initially defined.

The experiment, which involved the introduction of a new random variable, was designated "Exp3". Table 4 illustrates the average and standard deviation parameters of journey times for each ignition point, which were organized according to the optimal scheduling generated by GA for each resource.

**Table 4** Parameters for Travel Time distributions

|       |          | Hours |         | Seconds |         |
|-------|----------|-------|---------|---------|---------|
|       |          | Mean  | St.Dev. | Mean    | St.Dev. |
| $R_1$ | $I_2$    | 0.78  | 0.08    | 2808    | 280     |
|       | $I_1$    | 0.42  | 0.04    | 1512    | 150     |
|       | $I_5$    | 1.29  | 0.13    | 4644    | 460     |
| $R_2$ | $I_4$    | 0.21  | 0.02    | 756     | 75      |
|       | $I_3$    | 0.11  | 0.01    | 396     | 40      |
|       | $I_6$    | 0.35  | 0.04    | 1260    | 130     |
|       | $I_7$    | 0.20  | 0.02    | 720     | 70      |
|       | $I_{10}$ | 0.19  | 0.02    | 684     | 60      |
|       | $I_8$    | 0.53  | 0.05    | 1908    | 190     |
|       | $I_9$    | 0.54  | 0.06    | 1944    | 200     |

It should be noted that the average journey times from points  $I_2$  and  $I_4$  reflect the time taken to travel the stretch between the fire station and the respective initial ignition points for each resource. As in Exp2, the data for the random variable “Travelling Time” were entered into the simulation model and ten replicates were run. Table 5 presents the data obtained from each replicate, which was also organized according to the optimal scheduling for each resource. In contrast to the findings of Exp2, Exp3

**Table 5** Replicate data for Exp3

| Repl.   | $R_1$  |        |        | $R_2$  |        |        |        |          |        |        |
|---------|--------|--------|--------|--------|--------|--------|--------|----------|--------|--------|
|         | $I_2$  | $I_1$  | $I_5$  | $I_4$  | $I_3$  | $I_6$  | $I_7$  | $I_{10}$ | $I_8$  | $I_9$  |
| 1       | 0.88   | 0.43   | 1.37   | 0.21   | 0.13   | 0.35   | 0.26   | 0.19     | 0.58   | 0.54   |
| 2       | 0.78   | 0.45   | 1.29   | 0.21   | 0.14   | 0.36   | 0.20   | 0.20     | 0.53   | 0.69   |
| 3       | 0.78   | 0.42   | 1.29   | 0.21   | 0.11   | 0.35   | 0.22   | 0.19     | 0.53   | 0.54   |
| 4       | 0.79   | 0.42   | 1.30   | 0.21   | 0.11   | 0.37   | 0.20   | 0.19     | 0.68   | 0.56   |
| 5       | 0.78   | 0.42   | 1.29   | 0.22   | 0.11   | 0.40   | 0.20   | 0.22     | 0.53   | 0.68   |
| 6       | 0.78   | 0.51   | 1.50   | 0.21   | 0.16   | 0.35   | 0.26   | 0.19     | 0.57   | 0.64   |
| 7       | 0.83   | 0.42   | 1.52   | 0.27   | 0.12   | 0.35   | 0.21   | 0.19     | 0.58   | 0.59   |
| 8       | 0.78   | 0.42   | 1.29   | 0.21   | 0.12   | 0.35   | 0.23   | 0.19     | 0.53   | 0.55   |
| 9       | 1.00   | 0.44   | 1.38   | 0.21   | 0.11   | 0.42   | 0.20   | 0.19     | 0.53   | 0.69   |
| 10      | 0.78   | 0.58   | 1.57   | 0.21   | 0.12   | 0.35   | 0.20   | 0.19     | 0.55   | 0.54   |
| Average | 0.818  | 0.451  | 1.380  | 0.217  | 0.123  | 0.365  | 0.218  | 0.194    | 0.561  | 0.602  |
| Std     | 0.0719 | 0.0532 | 0.1101 | 0.0189 | 0.0164 | 0.0251 | 0.0244 | 0.0097   | 0.0470 | 0.0660 |
| p-value | 0.129  | 0.099  | 0.029  | 0.271  | 0.033  | 0.091  | 0.045  | 0.223    | 0.067  | 0.016  |

yielded statistically significant results regarding  $R_1$  and  $R_2$ .

### 3.2 Results and Discussion

A test for averages was conducted for the purpose of statistical analysis, with each column of Tables 3 and 5 treated as a distinct sample. Subsequently, the mean and standard deviation were calculated, and the Student’s t-test for equality versus difference was performed on each point, with a 95% confidence level. In conducting this assessment, the mean reference values for Processing Time and Travel Time ( $\mu_{H_0}$ ) were derived from the findings presented by Matos et al. [10].

Considering Exp2, as can be seen in Table 3, all the  $p$ -values are greater than the significance level of the test (5%), indicating that there were no significant differences between the averages of the replicates and the processing times of the Exp1 model. These results demonstrate that the TBA value did not change statistically for the distributions and parameters adopted, even considering random processing times.

Table 5, referring to Exp3, illustrates a contrasting pattern in the  $p$ -values when comparing the replication averages. The ignition points  $I_5$  ( $R_1$ ) and  $I_3$ ,  $I_7$ , and  $I_9$  ( $R_2$ ) exhibited statistically significant discrepancies. These discrepancies may signify a notable increase in TBA, thereby diminishing the efficiency observed in the preceding experiments.

Nevertheless, it can be argued that this approach offers a more reliable reflection of the results, as it accounts for a significant random variable that is susceptible to a range of unusual occurrences, including heavy traffic, mechanical breakdowns, and unanticipated stops.

To calculate TBA for Exp2 and Exp3, the average values obtained from the ten replicates were employed. Table 6 presents the findings of the three experiments, with a comparison to the results previously presented by Paiva et al. [10].

**Table 6** Comparison of results between the use of one and two Resources

|                   |                                  | TBA (ha) | Travel Time (h) | Processing Time (h) | Total Time (h) |
|-------------------|----------------------------------|----------|-----------------|---------------------|----------------|
| One Resource [10] | Deterministic Model              | 95.40    | 11.88           | 8.70                | 20.58          |
|                   | Uncertain Processing Time        | 178.58   | 11.00           | 8.38                | 19.38          |
|                   | Uncertain Travel Time            | 177.46   | 10.96           | 8.00                | 18.96          |
| Two Resources     | Deterministic Model (Exp1)       | 8.31     | 2.49            | 3.27                | 5.76           |
|                   | Uncertain Processing Time (Exp2) | 8.50     | 2.49            | 3.29                | 5.78           |
|                   | Uncertain Travel Time (Exp3)     | 11.42    | 2.49            | 3.20                | 5.69           |

The results are in accordance with the hypothesis that TBA is sensitive to the presence of uncertainty in process and travel times. The results indicate a slight increase in this variable as a result of Exp2 and a significant difference as a result of Exp3. However, this behavior is not observed with regard to completion time.

In comparison to the findings reported in [10], a notable decline was observed in all the responses, particularly when examining the TBA values. Regarding the completion time variable, the data indicate an improvement of approximately 70%.

## 4 Conclusions

Overall, the number of forest fires has increased in recent years. Since forest fires are difficult to fight due to the vast areas involved, the unpredictable nature of the fire's spread, and the sometimes remote and rugged terrain, fighting these fires poses significant challenges. Therefore, it is crucial to explore effective firefighting solutions by developing strategies, techniques, and tools to manage and contain them.

This paper introduces an optimization-based simulation approach with practical applications in crisis management, particularly in reducing response times to extreme

natural events and mitigating their impacts. The main goal is to optimize the firefighting resource scheduling problem, with two resources to extinguish ten fires, using GA. The objective is to determine the optimal resource allocation to minimize the total burned area while ensuring the shortest possible completion time. An optimization procedure was conducted using a genetic algorithm to generate an optimal sequence for combating 10 forest fire ignition points, attended by two resources, represented by two firefighting trucks. Two distinct initial populations were used in the optimization procedure. The total area was 16124.78 ha, and there was a reduction in the total burned area when comparing this article with [10]. It was found that only 8.31 ha burned for the deterministic model, 8.50 ha for the uncertain processing time and 11.42 for the uncertain travel time, thus proving that the more resources available to extinguish the various ignitions, the lower the TBA value. The study demonstrates that the availability of an additional resource would result in a notable reduction in the burned area, consequently reducing the completion time.

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