A Simulation-Based Optimization Approach to the Firefighting Resource Scheduling Problem

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Abstract. In recent years, the number of forest fires has increased significantly. The main factors behind these disasters are rising temperatures and population growth. Optimization and simulation have been widely applied to forest firefighting problems, making it possible to improve the effectiveness and speed of firefighting actions. This work presents a forest firefighting resource scheduling problem, where a single firefighting resource is fighting 10 ignitions. A Genetic Algorithm (GA) is used to find the near-optimal sequence of actions, taking into account the maximization of the total unburned area. The solution found by the GA is evaluated using a Discrete-Event Simulation model developed in FlexSim software, thus validating the solution. Then, a simulation-based optimization approach is developed, involving uncertainty in some parameters.

Keywords: Forest Fires · Scheduling Problem · Optimization · Discrete-Event Simulation

1 Introduction

Forest fires are uncontrolled phenomena that can spread rapidly if no containment measures are put in place. They have been increasing in recent years, due to the rise in the ambient temperature and the increase in the world population. This is why viable strategies are needed to combat forest fires. Optimization is one of the most applied techniques in forest firefighting problems, allowing improvements in the effectiveness and speed of firefighter actions. Every year, around 4 million square kilometers of land are burned worldwide [17,21]. In the last 7 years (2016–2023) there has been a large number of fires in the countries

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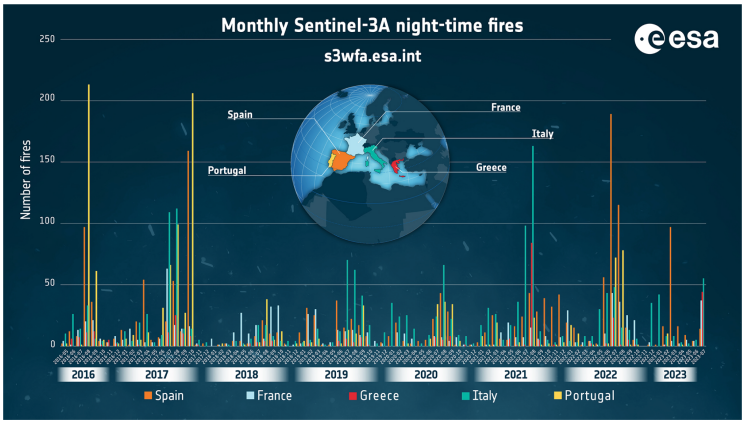

Fig. 1. Forest fires in 2016–2023 (https://www.esa.int/Space_in_Member_States/Portugal/Contagem_dos_incencios_florestais_no_mundo)

of Southern Europe: Spain, France, Greece, Italy and Portugal, as can be seen in Fig. 1. In 2016 and 2017, Portugal faced a large number of forest fires, both record years for the number of fires that occurred, where 2017 was the deadliest year in Portuguese history [1].

Firefighting is a very important field that has been studied in the literature. It is therefore necessary to find solutions to improve the fight against forest fires and, consequently, reduce the damage caused by them. Protecting and preventing fires is an important issue, and studies have been carried out to support the decisions of forest firefighting professionals (firefighters, civil protection, etc.). The characteristics of firefighting teams are defined as their number, their skills and their level of preparation, making them very important for the fight. The better and faster the firefighting team acts, the smaller the total burned area, which can save lives and reduce the impact on the ecosystem [2]. In order to manage forest fire suppression, it is necessary to know how many and which firefighting resources should be sent to each forest fire, to extinguish the fire as quickly as possible.

In engineering, optimization techniques have been applied to solve fire suppression problems, with the aim of finding the best trajectory and location for firefighting vehicles, obtaining the shortest route, determining the number and resources to send, among others. The work by Wu et al. [23] studied a forest firefighting vehicle scheduling problem. A multi-objective approach was applied to minimize the total time to extinguish the fire and the number of firefighting vehicles sent to the same fire. To do this, an integer programming model was developed, which is an improved and simplified version of an existing program. In addition, an exact dynamic programming algorithm and a fast, greedy heuristic method were applied to this problem. The effectiveness and efficiency of the proposed model and algorithms were confirmed using a real instance and randomly generated large reference instances.

A genetic algorithm (GA) is one of the most used metaheuristics to solve this type of problem, where several works have been presented using it in forest firefighting problems. HomChaudhuri et al. [12,13] used GA to minimize the total burned area, where homogeneous and heterogeneous meteorological conditions with uncertainty were considered. To deal with uncertainty, Monte-Carlo simulations were used, verifying the effectiveness of sending resources to combat complex forest fires in uncertain and dynamic conditions. There was a significant reduction in damage caused. In the work carried out by Matos et al. [16], the optimal scheduling of a forest firefighting resource to combat multiple ignitions was studied. The objective was to minimize the total burned area using GA in a problem with ten forest fire ignitions and one resource to extinguish these ignitions. Chan et al. [6] used the Firefly algorithm for a firefighting resource allocation problem. The algorithm used a combination of the maximum set coverage formulation and a new utility estimation technique, and used a knapsack formulation to calculate the allocation of resources. They found, with real data, that the strategy used achieved up to 80–90% performance of the optimal solution, even with a small number of drones. This strategy proved to be efficient in dealing with a dynamically changing environment and uncertainty.

This study focuses on the forest firefighting scheduling problem. The aim is to assign 1 forest firefighting resource to fight 10 ignitions. In a previous study [16], an adapted GA was used to maximize the total unburned area of the ignitions and find the near-optimal sequence of actions. In this work, the solution found by the GA is then tested in a Discrete Event Simulation model developed in the FlexSim software. A simulation-based optimization approach is then developed, involving uncertainty in some parameters, to validate the solution.

This paper is organized as follows. The simulation based approach is described in Sect. 2, where a Genetic Algorithm and Simulation technique are briefly presented. The description of the problem to be solved is shown in Sect. 3. The simulation model is described in Sect. 4 and the results are shown in Sect. 5, where a statistical analysis of the results is also presented. Finally, the conclusions of this study and future work are exposed in Sect. 6.

2 Simulation-Based Optimization Approach

In this section, the theories concerning the optimization algorithm and simulation techniques adopted in this work will be briefly presented. Starting with the description of Genetic Algorithm and Simulation, the criteria that led to the selection of the computational tool and the justification for the combined application of optimization and simulation as a way of validating the solutions obtained are addressed.

2.1 Optimization Technique

A Genetic Algorithm is a metaheuristic (optimization technique) inspired by the theory of species evolution, in which the fittest individual is the survivor of a

process based on biologically inspired operators such as mutation, crossover and selection [11]. The fittest individuals are those most likely to perpetuate their genetic characteristics. GA begins with the random generation of a population of potential solutions, called chromosomes, whose qualities are evaluated by the fitness function, and the selected chromosomes then undergo the process of evolution. Several generations are obtained in a cycle that is repeated until the stopping criterion is satisfied.

2.2 Simulation Tool

Simulation is an operational research technique in which a model is created by abstracting a real-world problem into mathematical or logical terms, converted into a computational system (a spreadsheet, a programming language, or specific software) to describe the behavior of a system over time [10,20].

According to Banks [3] and Robinson [19], simulation involves imitation of the operation of a real-world process or system. Banks emphasizes that simulation is an important method for solving various real-world problems. Forbus and Berleant [8] further explain that it is a simplified model of a particular real system, generated to investigate certain aspects of that system. Its application is justified by being a technique generally faster, easier, lower cost, and with minimal risks compared to real system experiments and observations. It can be a good option for analyzing the behavior of existing systems, testing new hypotheses, or even designing new systems, allowing managers to evaluate alternatives, test various scenarios, and generate predictions with reasonable approximations.

Law and Kelton [15] described a procedure to construct a simulation model. The construction of the computational representation of the model is one of the steps in this procedure. As important as constructing the computational model is choosing the appropriate computational tool. Nowadays, there are various computational tools available on the market for building simulation models and choosing one is not trivial. It depends on factors such as the type of application, type of simulation, and expected results, among other key factors. Rashidi in [18] proposed a ranking of simulation tools generated from the application of a hybrid approach between the Analytic Hierarchy Process, Feature Analysis, and Weighted Average Sum for thirteen key factors.

This work aims to use simulation to verify the dynamic behavior of the scheduling solution obtained by the GA application. In this context, it would be necessary to use a tool with good visual aspects, considering animations, user interfaces, and dynamic graphical elements during execution. Concerning the results, the tool selected should show a good internal coding level to allow the creation of specific tasks and user functions, good experimentation resources, and efficient input and output tools. Therefore, the *FlexSim* tool [9] is chosen, taking into account the key factors defined and the results of the studies by [7,18]. It is a computational tool capable of generating discrete event simulation models that feature, in terms of logistics, the *Geographic Information System (GIS)* module, which can manage road information, which is essential for the accuracy of the results of this work.

2.3 Simulation-Based Optimization Framework

Simulation and optimization are two strategies that are widely used in various engineering problems. Mathematical models have been applied combining those methodologies, thus initiating new scientific studies [5]. The problem of fire suppression has also been tackled with these strategies. Hu and Ntaimo [14] carried out a research into the simulation of forest fire propagation, the optimization of firefighting resources and the simulation of fire suppression techniques. They used a mixed integer stochastic programming model to generate firefighting resource dispatch plans and developed an agent-based discrete event simulation model to simulate fire suppression based on the generated dispatch plans. Experimental results indicated significant variations in fire suppression based on different firefighting tactics. The simulation of these tactics was important for validating dispatch plans based on optimization models. The article by Homchaudhuri et al. [12] shows the advancement of effective fireline construction strategies through resource allocation. The approach introduces a simulation and optimization technique using genetic algorithms and sophisticated forest fire propagation models. Given the uncertainties associated with weather conditions and the limited knowledge of vegetation and topographical factors, it is difficult to accurately predict forest fires. To solve this problem, Monte Carlo simulations have been used to devise robust strategies in uncertain circumstances. Through exhaustive simulations, the effectiveness of the proposed method is demonstrated in optimal allocation of resources to combat complex forest fires in dynamic and uncertain environments is demonstrated.

The strategy of applying optimization and simulation together was also adopted in this work. A code developed in *Python* for optimization using GA was connected to a simulation model developed in Discrete Event Simulation software. Figure 2 illustrates how optimization and simulation will interact to try to find the optimal result for the problem under investigation. Based on the input data, the optimizer identifies the best action scheduling for the firefighting team, using a Genetic Algorithm. The sequence obtained is then implemented in the simulator, which runs a certain number of replicas of the model, locating the best result among them. Based on this result, the input data is updated and resubmitted to the optimizer. The strategy is repeated until a stopping condition is met, identifying the sequence with the best performance at the end.

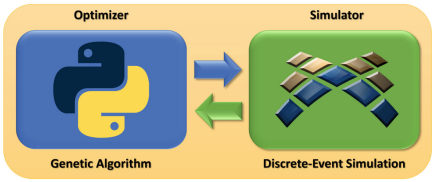

Fig. 2. Simulation-based optimization framework

3 Problem Description

This work presents a simulation-based optimization approach to determine the scheduling solution of one forest firefighting resource to combat several ignitions, under uncertainty of certain parameters. The initial data used and more details about the application of the GA to the scheduling problem can be found in [16].

The problem consists of determining the optimal schedule for a single resource (a firetruck which is based on forest firefighting land vehicle with water tank) to travel from its base to all the ignition points (which can be understood as several fronts of the same forest fire) and return to the base, in order to maximize the unburned area.

Figure 3 shows the selected study area, the fire ignitions, and routes generated from GIS that connect these locations.



Fig. 3. Fire locations on study area

At the center of the figure, in dark blue, is located the fire station, the locations of the ignitions that have requests for firefighting are marked in red square, and the numbers in the light blue circles indicate the fire ignitions. Marked in black can be seen the existing routes to attend to these locations. There are 11 interconnected locations: the fire station and the other 10 forest fire ignitions. The sum of the areas of the 10 forest fire ignitions corresponds to a total of 16124.78 ha.

4 Simulation Model

In this work, GA is implemented in the *python* (version 3.9.35) using *VScode* (Version 1.87), after being adapted from the *pymoo* framework: Single-objective Optimization in Python [4]. A permutation representation has been used to describe the scheduling solution. Under this representation, every chromosome comprises a unique sequence of integer values, each occurring only once. Consequently, each chromosome shows the sequence in which the firefighting resource will act to extinguish each ignition. Regarding the parameters used by GA, the population size was set to 20, and the GA default values for the maximum number of generations and the maximum number of function evaluations were 1000 and 100000, respectively. The GA operators used in this work were: tournament selection, order-based crossover and inverse mutation. Since GA is a stochastic algorithm, 30 independent runs were performed in order to statistically analyze its performance. The experiments were carried out on a PC 11th Gen Intel(R) Core(TM) i7-1165G7 @ 2.80 GHz, 2803 Mhz, 4 Nucleus(s), 8 Processor(s) Logic(s), 16 Gb RAM.

Firstly, a simulation model was created to observe the dynamic behavior of the proposed scheduling. The model considers the time spent between the necessary movements between each site, configured using the GIS module available in the FlexSim software. In order for the model to find the best route to follow, given the planned sequence of actions, each location was connected to the other 10 locations in the model. As a result, an origin-destination matrix is obtained, in which it is observed that certain paths have differences between outbound and inbound trips, some of them significant in terms of distance (km) and/or time (h). Table 1 presents the times, in hours, spent on travel between the 11 designated locations for investigation, where the number zero refers to the fire station.

Table 1. Travel time to each location

	0	1	2	3	4	5	6	7	8	9	10
0	0.00	0.99	0.78	0.28	0.21	1.69	0.19	0.28	0.33	0.63	0.39
1	0.99	0.00	0.42	1.04	0.95	1.29	1.13	1.22	1.28	1.48	1.33
2	0.78	0.42	0.00	0.91	0.82	1.52	0.97	1.06	1.07	1.27	1.17
3	0.28	1.04	0.91	0.00	0.10	1.71	0.35	0.43	0.56	0.85	0.54
4	0.21	0.95	0.82	0.11	0.00	1.62	0.32	0.41	0.49	0.78	0.52
5	1.69	1.29	1.51	1.71	1.62	0.00	1.80	1.89	1.97	2.26	2.00
6	0.20	1.12	0.96	0.35	0.31	1.79	0.00	0.20	0.41	0.71	0.32
7	0.29	1.21	1.05	0.43	0.40	1.88	0.21	0.00	0.53	0.82	0.19
8	0.33	1.28	1.08	0.56	0.49	1.97	0.41	0.53	0.00	0.54	0.53
9	0.61	1.47	1.27	0.85	0.78	2.26	0.71	0.80	0.55	0.00	0.85
10	0.40	1.32	1.16	0.54	0.51	1.99	0.32	0.19	0.53	0.85	0.00

Based on the results of the optimization procedure described in [16], a model was generated to adhere to the optimal planning: $FS \rightarrow F_5 \rightarrow F_9 \rightarrow F_1 \rightarrow F_{10} \rightarrow F_2 \rightarrow F_7 \rightarrow F_8 \rightarrow F_3 \rightarrow F_6 \rightarrow F_4$, where FS is the fire station and F_i is ignitions ($i = 1, ..., 10$). In other words, the vehicle departs towards the first defined location (Ignition 5, F_5). Upon arrival, the action time is timed according to Table 2. Then, the vehicle departs from this point towards the second location (Ignition 9, F_9), where the action time is also timed. And so on, until returning to the fire station, completing the scheduling.

Table 2. Defined firefighting times

	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}
hours	0.2	1.8	1.4	1.0	1.4	0.2	0.1	0.6	0.8	1.2
seconds	720	6480	5040	3600	5040	720	360	2160	2880	4320

4.1 Model Verification and Validation

As mentioned earlier, simulation involves the construction of a computational model that mimics a process or system. When building this model, adaptations are necessary to reduce the complexity of the problem, increase its understanding, and expedite the obtaining of a solution, which should represent a reasonable approximation of reality. The process of verification and validation of a simulation model aims to identify the level of accuracy of the model. While verification is the process of ensuring that the computational model created exhibits sufficient accuracy, validation is the process of ensuring that the model is sufficiently accurate for the purpose for which it was constructed [19]. Sargent [22] described several techniques for the verification and validation of simulation models. Thus, comparison with other validated models is considered in this study, comparing the results obtained in the simulation model with empirical results from analytical models, for example.

In this context, Matos et al. [16] developed an optimization model that uses the GA to maximize the unburned area by generating a near-optimal scheduling of ignitions. Taking into account the comparison criterion presented by Sargent, based on the input data and results available in [16], a discrete event simulation model was generated to evaluate the described scenario, and the results were compared, as shown in Table 3. This table shows a divergence in the values for the burned area column. This is due to an error identified in the calculation of this area in the original work, which was corrected so as not to influence subsequent analyses. As observed, the results indicate a small error, as expected, in terms of total time, given the precision with which *FlexSim-GIS* handles geographical distances between the points of operation. Therefore, it was considered that the results of the simulated model were compatible with the analytical model, validating the simulation model. Therefore, based on a validated simulation model, experiments can be executed, as the results can be considered reliable.

Table 3. Validation by comparing models

	Unburned area (ha)	Burned area (ha)	Travel time (h)	Process time (h)	Total time (h)	Saved area
Matos et al.(2022) [16]	16029.38	95.4	11.88	8.70	20.58	0.9941
Matos et al.(2022) adj	15913.60	211.18	11.88	8.70	20.58	0.9869
Simulation Model	15937.29	187.49	10.79	8.70	19.49	0.9884
Error	0.57%	–	9.18%	–	5.30%	0.57%

4.2 Adding Uncertainty

From a validated simulation model, different scenarios can be tested, and experiments can be conducted. Thus, initially, uncertainty related to the time required to combat fire ignition points was incorporated into the model by replacing deterministic data with probability distributions. This procedure was named Experiment 1 (Exp. 1). Next, the travel time (journeys made between one ignition point and another) was also converted into probability distributions, as a way of increasing the robustness of the simulation model. This procedure was named Experiment 2 (Exp. 2). However, it is important to note that, for travel time, only travel delays were considered, as it is understood that there is no possibility of making journeys faster than defined in Table 1. Delays, in turn, characterize problems related to traffic (congestion or detours) or resource breakdowns.

Due to the lack of historical data, normal distributions of the combat and travel time were used, as shown in Table 4.

Table 4. Probability distribution for process and travel time

Location		F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}
Process time (h)	Mean	0.20	1.80	1.40	1.00	1.40	0.20	0.10	0.60	0.80	1.20
	S.Dev.	0.02	0.18	0.14	0.1	0.14	0.02	0.01	0.06	0.08	0.13
Travel time (h)	Mean	1.51	1.16	0.56	0.31	1.69	0.35	1.06	0.53	2.26	1.36
	S.Dev.	0.15	0.12	0.06	0.03	0.17	0.04	0.11	0.05	0.23	0.14

The combat and travel time are modelled by a probability distributions. An experimental design with 30 replications was executed, and the results were recorded. For each replication, the total time and the total unburned area were calculated. The total unburned area was calculated as described in [16].

Figure 4 displays the combat time variation for each ignition point in each experiment replication. Figure 5 presents a comparison between the total time and the area not burned, showing that there is no correlation between these two variables.

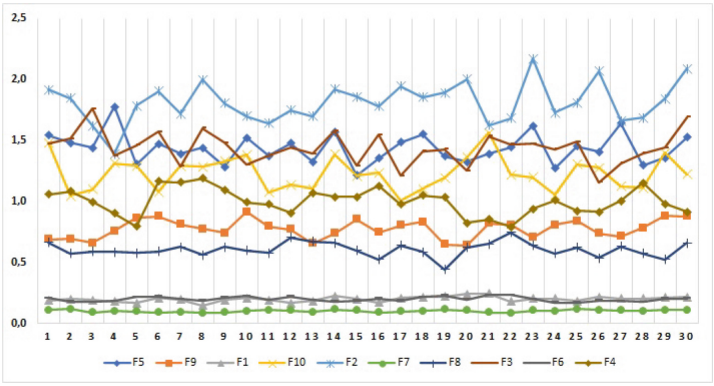

Fig. 4. Random process variation

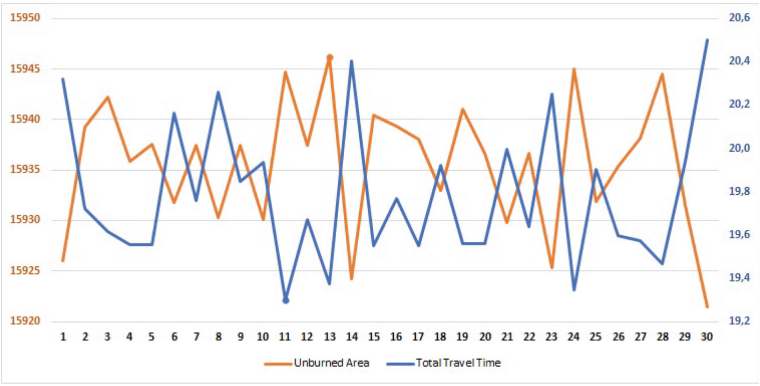

Fig. 5. Total time and unburned area results

5 Discussion of Results

Based on the experimental procedure described in Sect. 4, six simulation cycles (runs) were performed, to validate the solution presented by GA or find a new solution that maximizes the unburned area. It should be noted that the computational time required by GA was negligible for effective decision-making.

The first run was executed considering the schedule obtained by GA in [16], $FS \rightarrow F_5 \rightarrow F_9 \rightarrow F_1 \rightarrow F_{10} \rightarrow F_2 \rightarrow F_7 \rightarrow F_8 \rightarrow F_3 \rightarrow F_6 \rightarrow F_4$, in two stages. In the first stage, only the combat time was converted into probability distributions (Exp.1), based on the deterministic provided in [16]. In the second stage, in addition to combat time, travel time was also converted into probability distributions (Exp.2), taking into account the times described in the origin-destination matrix available in Table 1. At each stage, the simulation was run completely in all 30 runs, and the results were recorded for later analysis. Table 5 shows the average result, based on the unburned area of the 30 replicates in this

first simulation run, and the best result, which showed the largest unburned area among them.

Table 5. Results from experiments 1 and 2

		Unburned area (ha)	Burned area (ha)	Travel time (h)	Process time (h)	Total time (h)	Saved area (%)
Simulation Model		15937.29	187.49	10.79	8.70	19.49	98.84
Exp.1	Mean	15935.62	189.16	11.00	8.79	19.79	98.83
	Best	15946.20	178.58	11.00	8.38	19.38	98.89
Exp.2	Mean	15929.33	195.45	11.23	8.62	19.85	98.79
	Best	15947.32	177.46	10.96	8.00	18.96	98.90

Hypothesis tests were carried out for each result obtained. Considering the total travel time of Exp.1, there was a significant statistical difference, which suggests that there was an increase in performance when uncertainty was added to combat times. In terms of area burned, there was a decrease of 11.2% compared to the theoretical results. With Exp.2, there was a statistical difference between the averages, indicating a decrease of 7.5% in the burned area, based on the average result, and 16% based on the best result. The best result obtained in Exp.2 was adopted to continue the simulation-based optimization procedure.

In the following five runs, only Exp.2 (randomized combat and travel time) was considered, and analyses were carried out based only on the best result (maximum unburned area).

For a better understanding of the procedure used, Fig. 6 shows the flow of the simulation-based optimization process for the six planned experimental runs.

Once all six experimental runs had been carried out, the scheduling and respective results were recorded, as shown in Table 6. In this table, "Ref" identifies the result obtained from the model that disregards uncertainty in both combat time and travel time. It is important to note that in some runs the optimizer was unable to generate a different schedule to the previous one. This behavior may have occurred due to the random nature of the combat and travel processes that vary times for better or worse, generating a new OD matrix that is not significant in terms of optimization.

The results shown in Table 6 indicate statistical differences between each of the runs in relation to the result of the deterministic model. These differences represent the sensitivity of the simulation model to the presence of uncertainty in the variables of interest. However, the results confirm the scheduling initially determined by GA as the best possible result for the problem under investigation.

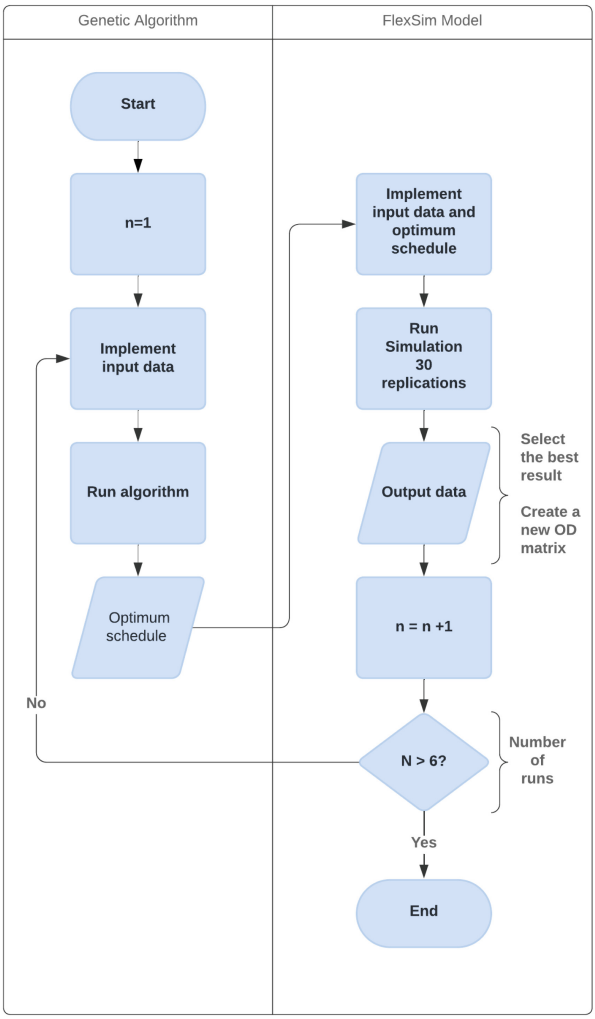

Fig. 6. Simulation-based optimization process flow

Table 6. Results of the experimental design

Runs	Scheduling	Unburned area (ha)	Travel time (h)	Process time (h)	Total time (h)	Saved area (%)
Ref	[5 9 1 10 2 7 8 3 6 4]	15937.29	10.79	8.70	19.49	98.84
1	[5 9 1 10 2 7 8 3 6 4]	15947.32	10.96	8.00	18.96	98.90
2	[5 9 2 10 1 3 8 4 7 6]	15925.71	10.87	8.26	19.13	98.77
3	[5 9 2 10 3 1 8 4 7 6]	15923.26	10.89	8.29	19.18	98.75
4	[5 9 2 10 3 1 8 4 7 6]	15921.37	11.10	8.24	19.34	98.74
5	[5 9 2 10 3 1 8 4 7 6]	15925.86	10.94	8.22	19.16	98.77
6	[5 3 2 10 9 1 8 4 7 6]	15939.69	10.32	8.25	18.57	98.85

6 Conclusions and Future Work

This work has highlighted the application of engineering in the search for solutions to problems that directly affect the quality of life of people and their environment and ecosystem. The occurrence of forest fires has increased in recent years and is essentially due to natural or human factors. Therefore, it is necessary to look for solutions that can manage fire suppression, such as optimizing firefighting actions.

In order to find a solution that would mitigate the impacts caused by this phenomenon, minimizing the total unburned area, a simulation-based optimization approach was used to properly plan the actions of one available resource to combat 10 ignitions. The solution was obtained by applying a Genetic Algorithm to the available data on the time and distance between the points of fire ignition and the combat time arbitrated for each. A simulation model was then built in FlexSim software, which was duly verified and validated. The model was prepared to take into account uncertainty in travel and combat time, and to interact with the optimizer, always trying to find a better solution to the problem. Once this model was in place, six experimental runs were carried out, which generated four different schedules. The results for the unburned area for the six runs were: 1) 98.90%; 2) 98.77%; 3) 98.75%; 4) 98.74%; 5) 98.77%; 6) 98.85%. As can be seen, the results did not deviate significantly from those presented by the model initially generated by GA (98.84%). Considering the uncertainty in travel time and process time, the original scheduling (run number 1) showed the most significant result, maximizing the unburned area.

For future work, we suggest investigating: a) The search for and insertion of real data, obtained from official websites; b) The inclusion of a greater number of resources; c) The inclusion of work shifts for the teams involved; d) Control of the volume of water used, with possible refilling at predetermined locations.

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