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ARTICLE

Simulation analysis of the impact of ignitions, rekindles, and false alarms on forest fire suppression

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Abstract: Rekindles and false alarms are phenomena that have a significant presence in the Portuguese forest fire management system and an important impact on suppression resources in particular and fire management resources in general. In this paper, we propose a discrete-event simulation model of a forest fire suppression system designed to analyze the joint impact of ignitions, rekindles, and false alarms on the performance of the system. The model is applied to a case study of the district of Porto, Portugal, for the critical period of the forest fire season, between July and September 2010. We study the behavior of the system's point of collapse, comparing the real base scenario with a benchmark scenario built with reference values for rekindles and false alarms, and also as a function of the number of fire incidents, considering historical variations. The results of the analysis are useful for operational decision-making and provide relevant information on the trade-off between prevention and suppression efforts.

Key words: forest fire suppression, rekindles, false alarms, discrete event simulation.

Résumé : Les reprises de feu et les fausses alarmes sont des phénomènes qui occupent une place importante dans le système portugais de gestion des feux de forêt et qui ont un impact important particulièrement sur les ressources allouées à la suppression et de façon générale sur les ressources responsables de la gestion des feux. Dans cet article, nous proposons un modèle de simulation d'événements discrets d'un système de suppression des feux de forêt, conçu pour analyser l'impact conjoint des allumages, des reprises et des fausses alarmes sur la performance du système. Le modèle a été appliqué à une étude de cas dans le district de Porto, au Portugal, durant la période critique de la saison des feux de forêt, entre les mois de juillet et septembre 2010. Nous avons étudié le comportement du point de rupture du système en comparant le scénario de base réel à un scénario étalon élaboré avec des valeurs de référence pour les reprises de feu et les fausses alarmes et également en fonction du nombre de feux en tenant compte des variations historiques. Les résultats de l'analyse sont utiles pour prendre des décisions opérationnelles et fournissent des informations pertinentes au sujet des compromis entre les efforts de prévention et de suppression. [Traduit par la Rédaction]

Mots-clés : suppression des feux de forêt, reprises de feu, fausses alarmes, simulation d'événements discrets.

1. Introduction

In this paper, we propose a discrete-event simulation model of a forest fire suppression system designed to analyze the joint impact of ignitions, rekindles (re-starts), and false alarms (FAs) on the performance of the system. The application of the model is illustrated with a case study of the district of Porto, Portugal, for the critical period of the forest fire season, between July and September 2010.

Our motivation for this work comes from the perception that rekindles and FAs (malicious or good-intent calls) have unusually high values in the Portuguese forest fire management system, a quarter of all occurrences (Autoridade Florestal Nacional (AFN) 2011*a*), with potential positive feedback loops wherein suppression resources are used unnecessarily or inefficiently, leading to further degradation of system performance. Accordingly, rekindles and FAs represent an unusually high burden on the suppression resources in particular and fire management resources in general.

Because fire departments cannot presume that a call is an FA and must respond as they would to a fire (Ahrens 2003), the high values for this proportion are strenuous for initial attack (IA) crews, who get deployed to nonexistent fires, become unavailable for real fires, are deprived of time to rest and recover, or are hastily redeployed from other incidents, prematurely abandoning mop-up efforts and possibly creating conditions for fires to rekindle. In the little research available about FA performance measures (Flynn 2009), we have found values for FA calls as a proportion of all emergency calls for the US (4.4% of all calls in 2009 and 4.1% in 2010; Karter 2011), New Zealand (between 4.6% and 5.4%; Tu 2002), and the UK (5.0% in Derbyshire (Yang et al. 2003) and 6.2% in South Wales (Corcoran et al. 2007)). These numbers, when compared with the 12.3% observed in 2010 (AFN 2011*a*), suggest that there is still room for improvements regarding FAs in Portugal.

The 13.0% of rekindles registered in the same year is also an extremely high proportion, still very much above the target of 1% defined in the “Technical Proposal for a National Plan of Defense of the Forest against Fires” (Instituto Superior de Agronomia (ISA) 2005) and reveals futile suppression efforts that contribute to an overload of the suppression system. Incidentally, the 1% target may be too ambitious. Indeed, in a report on the factors that contribute to ignition, Ahrens (2010) mentions rekindles as responsible for 3% and 6% of the US local fire department responses

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to “brush, grass, and forest fires” and to “forest, woods, or wildland fires”, respectively, between 2004 and 2008.

In the remainder of this section, we review the literature, presenting an overview of the state of the art in forest fire simulation and the IA response time as a performance measure.

1.1. Forest fire simulation

Uncertain factors such as the weather, the performance of suppression resources, and fire behavior, spread, and effects are at the basis of most fire management decisions. Theoretical and computing advances in the last four decades have enabled the development of risk-based decision support systems (DSS) that provide improved active fire management through a structured assessment of the outcomes and costs associated with alternative fire management policies, budgets, and suppression resource portfolios.

In recent years, several authors have updated reviews of the state of the art in this field. Minas et al. (2012) updated the review of Martell et al. (1998) on operations research methods applied to wildfire management. Thompson and Calkin (2011) describe available decision support tools and methodologies, addressing wildfire risk assessment in face of uncertainty to facilitate cost-effective, risk-based wildfire management and planning. Mavsar et al. (2013) describe the economic efficiency analysis theory of fire management and review four fire management DSS currently applied in America and Europe. Papadopoulos and Pavlidou (2011) offer a comparative review of wildfire simulators, and Sullivan (2009) provides a comprehensive survey and review of surface fire spread simulation models. Indeed, some predefined spread model is incorporated into most wildfire simulation models to simulate the behavior of fire across a landscape (Thompson and Calkin 2011). Finally, Bettinger (2010) reviews the methods used to integrate wildfires into forest planning models using operations research techniques, starting with the seminal work of Van Wagner (1979).

A number of wildfire growth simulation models have been developed in different countries and throughout the years. Some examples are the Canadian Prometheus (Tymstra et al. 2010), in development since 1999, and, starting in the early nineties, FARSITE in the US (Finney 2004), Visual Cardin in Spain (Rodríguez y Silva and González-Cabán 2010), and the Australian SiroFire launched in 1994 — the latter has now been subsumed in the more recent and promising Phoenix RapidFire, developed by the University of Melbourne as part of a risk management model (Sullivan 2009). Finally and with a different approach, the Wildland Fire Decision Support System (WFDSS) has been in development since 2004 in the US as a support tool for risk-informed decisions on the management of escaped fires (Calkin et al. 2011; Noonan-Wright et al. 2011) using FSPro as a fire spread probability model (Finney et al. 2011*a*).

With limited financial funds, equipment, and human resources, forest managers must decide how to build a portfolio of alternative fire management options such as community prevention (e.g., education, public campaigns), fuel treatment (e.g., prescribed burning, thinning, mechanical fuel removal), presuppression (e.g., firefighter recruitment and training, maintenance of fuel breaks and water sources), suppression, and restoration (Mavsar et al. 2010). This requires an evaluation of how wildfires spread, with and without suppression, and their impact in terms of the monetary value of destroyed or damaged assets (Mendes 2010). Since FEES, the Fire Economics Evaluation System (González-Cabán et al. 1986; Mills and Bratten 1982), and even though sometimes not considering adequately the effects of nonmarket resources (e.g., recreation, flora and fauna, soil, air and water quality, or cultural heritage) (Brillinger et al. 2009), computer simulation, geographic information systems, and the economic evaluation of losses and wildfire fighting costs have been successfully combined in some integrated systems that “provide sufficient data to enable the efficient economic choice of the best combination of fire combat resources per fire type, the integration of cost–benefit analysis, modeling incidence probability as well as the spread of fires lines with and without intervention, per intervention and fire type” (Mendes 2010).

Examples of these systems currently in use include the Canadian LEOPARDS (Level of Protection Analysis System; McAlpine and Hirsch 1999), the Chilean KITRAL (“fire” in the indigenous Mapuche language; Mavsar et al. 2013), the US FPA (Fire Program Analysis; http://www.forestsandrangelands.gov/FPA/index.shtml), which includes the large-fire simulation system FSim to estimate average burn probabilities and fire size distributions (Finney et al. 2011*b*), and the Spanish SINAMI (Sistema Nacional para el Manejo de Incendios Florestales; Rodríguez y Silva and González-Cabán 2010). The latter is a more advanced and updated version of the US California Fire Economics Simulation Model (FPPS/CFES), operating under the same principles (Mavsar et al. 2013).

As the previous review highlights, the existing fire spread simulators and wildfire DSS based on economic models are very detailed and powerful. In contrast, our system is a screening model that, with less fidelity, explicitly considers rekindles and FAs, phenomena that have not been captured in previous simulation work. Our modeling efforts aim at evaluating their impact on the performance of fire management operations in a season and deriving additional implications for strategic fire management planning.

Analytical solutions using standard mathematical methods are always a preferred approach, but when their application is not possible, as is almost always the case when working with complex systems (White and Ingalls 2009), simulation is arguably the most robust method applied to model real-life stochastic systems that evolve probabilistically over time (Minas et al. 2012). Discrete event simulation (DES), system dynamics, and agent-based modeling are three of the most used systems modeling approaches in the simulation field. DES mimics the dynamics of a real system as a chronological sequence of events and was the approach that we chose for our analysis.

1.2. Response time as a performance measure

Fire occurrence rates vary over both time and space (Martell 2001), and an increased response time is considered intrinsically linked to a decreased probability of containment of new fires (Quince 2009) and a larger intensity-weighted area burned (Mercer et al. 2008). That is the reason why, in forest fire management organizations, fire managers must minimize IA response times (Martell 2001). Indeed, it is reasonable to assume that the longer that it takes to attack a fire, the larger the fire size will be at attack (Islam 1998) because the fire grows as it waits (Islam et al. 2009; Martell 2001). Accordingly, the larger the fire is at the beginning of the IA, the more likely it is that the fire will escape (Islam 1998). In addition, IA resources will be there for a longer period of time, so the next occurring fire may have to wait even longer and therefore that delayed response can ripple over time and affect the ability of the suppression system to respond to fires occurring even several days later (Martell 2001).

Hence, it is reasonable to use response time as a performance measure to evaluate an IA and for operational decision-making, as it is well understood by fire managers (Islam 1998). Minimizing fire crew response time is crucial to minimizing the number of fires that escape IA (Islam et al. 2009). Therefore, the use of response time as a proxy of suppression effort is meaningful because it is related to available suppression resources (Butry 2007) and most strategic fire management planning models use this simple performance measure of effectiveness to reflect suppression cost effectiveness (Martell 2007; Quince 2009).

For any fixed quantity of mobile suppression resources such as IA crews, as the occurrence rate increases, so do response times, and thus, daily IA effectiveness will saturate at some rate, beyond which the proportion of fire escapes will increase (Cumming

2005). The limit at which the system starts to fail is what we call "point of collapse", the performance measure that we chose to evaluate the joint impact of ignitions, rekindles, and FAs on forest fire suppression.

The remainder of the paper is structured as follows: in section 2, we describe the study site, the data and methods used in this study, the conceptual model, and its implementation as a DES model; in section 3, we present the parameterization of the model and the results for the base case and for the sensitivity analyses; in section 4, we discuss the results; and in section 5, we offer some conclusions and suggestions for future work.

2. Materials and methods

In this paper, we present an exploratory case study. The impact of rekindles and FAs on the performance of suppression systems has been given scarce attention by research in forest fire management. At such a preliminary research phase, we chose to focus our work on describing a revelatory case and developing initial insights about that impact, based on a combination of observation, data analysis, and simulation modeling and analysis.

In this section, we start by providing an overview of the study site, the sources of information, and the analysis methods that we have used. We then describe our conceptual model of the operation of a suppression system and its implementation as a discrete-event simulation model.

2.1. Study site

In 2010, according to data provided by Autoridade Florestal Nacional (National Forest Authority) (AFN 2011*a*), the Portuguese suppression system handled 32 357 incidents, of which 12.3% were FAs and 13.0% were rekindles. At the district level, the proportion of rekindles and FAs varied from 0% to 41% and from 5% to 26%, respectively. There are four key motives for the choice of the district of Porto in the critical period between July and September 2010 as a case study: the district is particularly interesting as it has a high number of fire occurrences and available data about deployed resources; the proportion of rekindles and FAs is slightly below but still in line with national figures; 84% of the ignitions, corresponding to 96% of the burnt area, occur in the 3-month period considered; and 2010 is a year with appropriate data on FAs (see subsection 2.4.3 below).

The district of Porto is located in northwestern Portugal and is home to 1.82 million people in an area of 2331 km^2 (Supplementary Table S1).[1] The population density is 781 people·km^{-2}, ranging from 1587·km^{-2} near the coastline to 366·km^{-2} in the interior and extremes in the 18 municipalities of 119 and 5786·km^{-2}, the maximum corresponding to the district capital, Porto (the second-largest city in Portugal after Lisbon, the capital). This kind of variation is typical in the European Mediterranean region (San-Miguel-Ayanz et al. 2013).

Forest accounts for 48% of the land use in the district, with a total area of 111 347 ha, divided between 60 081 ha of stands, 40 089 ha of shrubs, and 11 177 ha of burnt areas in recent years. Seventy-five percent of the forest area is located in the rural interior, distant from the sea (Supplementary Table S2). In 2010, the district had 3785 registered firefighting volunteers, with a density of about 30 ha of forest per volunteer, ranging from 14 in the seaside to almost 47 in the interior, where, in fact, they are also most needed.

The district has a historical trend of a very high number of forest fires, which remained through 2010, with a very high proportion of forest fires with a burnt area less than 1 ha (90.6% of the approximately 6000 incidents) (Supplementary Table S3).

This trend is consistent with the wildfire ignition risk map for Portugal (Catry et al. 2009), which relates the high number of fires in the district to human presence and activity, in particular, population density, human accessibility, land cover, and elevation. In fact, the district of Porto, besides the referred high population density with an extended wildland–urban interface (WUI) between the coastline and the interior, features a high road density, agriculture-related burning practices, and shepherding-related burning practices.

In the critical period of 2010, approximately 9% of the incidents in the district of Porto were FAs, and 10% were rekindles (Fig. 1).

Every year, the national authorities define the number of contracted firefighting crews (formed by two teams of men working 12 h daily each) for each district. In 2010, the number was 76 for the district of Porto. These contracted crews are supplemented with crews of volunteers and, when necessary, crews from neighboring districts (in an unspecified number). In 2010, each contracted crewmember received a wage of 41 euros per 24 h of work, paid by the central government. The fuel spent in the operations was paid at the end of the season. A helicopter was rented for this part of the year.

2.2. Data and analysis methods

Our work involved the development of a conceptual model, its implementation as a discrete-event simulation model, the parameterization of the model, a base-case simulation analysis, and simulation sensitivity analyses. The conceptual and discrete-event simulation models were developed through an iterative process of literature review, field trips, informal meetings, formal recorded interviews, and statistical analysis of a database of fire suppression interventions.

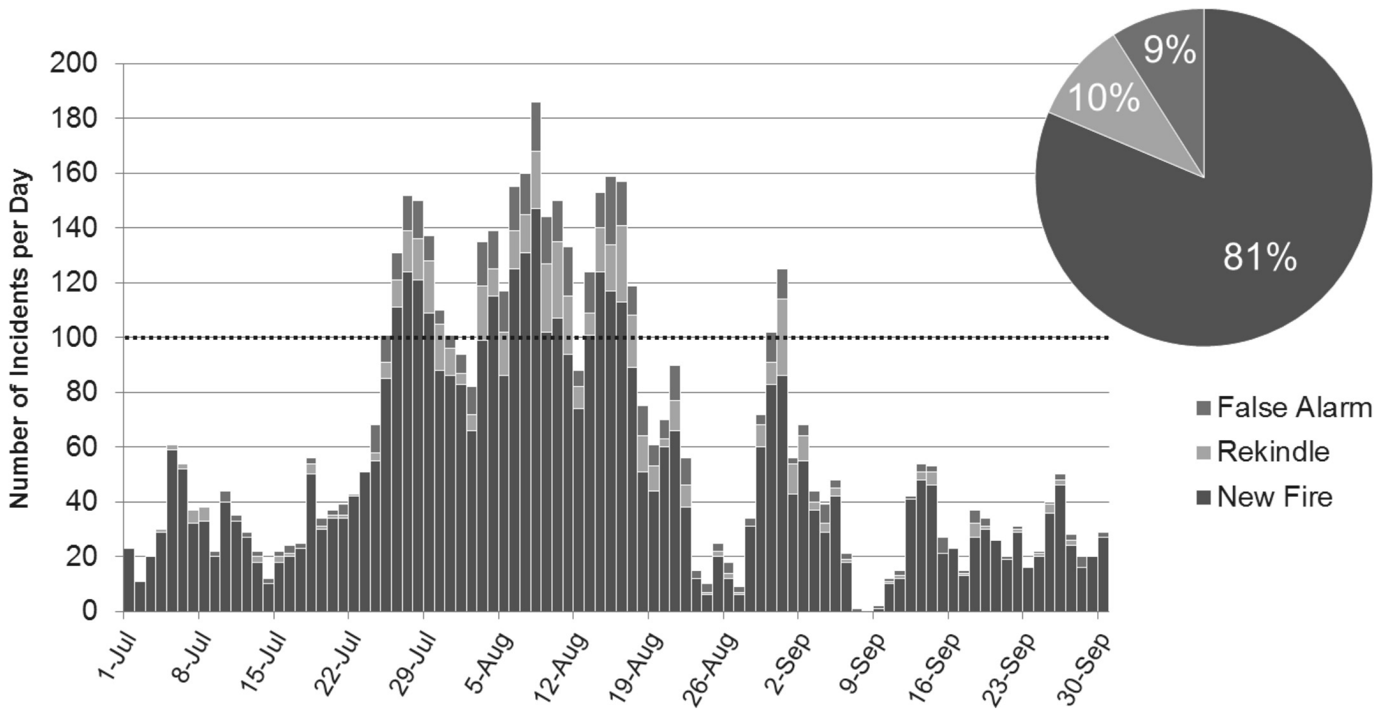
The meetings and interviews were held with public and private stakeholders. In the public sector, they were held with the district office of rescue operations (Centro Distrital de Operações de Socorro, CDOS) of two different districts (Lisbon and Porto), where the dispatch centers at the district level are located, with the forest fire first intervention special police force (Grupo de Intervenção de Proteção e Socorro, GIPS), and with the Portuguese forest authority (Autoridade Florestal Nacional, AFN). For the private sector, contacts were made with the Portuguese farmers' confederation (Confederação dos Agricultores de Portugal, CAP), with a private firefighting force (AFOCELCA), and with a Portuguese pulp company (grupo Portucel Soporcel). These meetings and interviews were useful for understanding the suppression system and the data recorded in the official databases and for comparing the operational standards with the field reality and to have a first-hand impression of the system operation under pressure.

For the case study of the district of Porto in the critical period, between July and September 2010, we combined and jointly analyzed two databases: one from AFN, with the dimension, duration, causes, and locations of forest fires (Tedim et al. 2013); and the other from the Porto CDOS, with the type and number of resources used in firefighting operations. The joint database was used to parameterize and validate the model. Multiple descriptive statistics analyses and statistical tests were used to derive the parameters of the simulation model, as described later in Results subsection 3.1.

Whenever our data did not comply with some of the parametric tests assumptions, we performed nonparametric tests such as the Kruskal–Wallis H test and the Mann–Whitney U test (Wilcoxon rank-sum test) (Fagerland and Sandvik 2009), with the homogeneity of variance assumption validated in both cases through a nonparametric Levene's test (Nordstokke and Zumbo 2010) at the 5% level of significance. These nonparametric tests and other

[1]Supplementary materials are available with the article through the journal Web site at http://nrcresearchpress.com/doi/suppl/10.1139/cjfr-2013-0257.

Fig. 1. Ignitions, rekindles, and false alarms in the district of Porto between July and September 2010.



analyses such as 2 × 2 contingency tables and pairwise comparisons of means were performed in IBM SPSS software.

Finally, the simulation model was implemented in Arena (Rockwell Automation, Inc., Wexford, Pennsylvania). In its parameterization, goodness-of-fit tests (Kolmogorov–Smirnov, Anderson-Darling, and chi-square) were used in EasyFit (MathWave Technologies, http://www.mathwave.com) to guide the choice among the classic probability distributions available in Arena, and base-case simulation analysis was used to validate the model.

The model was subsequently used with sensitivity analyses to understand the impact of ignitions, rekindles, and FAs on the performance of the suppression system, particularly on the "point of collapse". For this indicator, we chose an average waiting time of 10 min. The value emerged from our interviews as the limit beyond which the system starts to fail for lack of capacity to respond to all simultaneous occurrences.

The combination of sensitivity analysis with simulation analysis allowed us to directly address the two main research questions in this work.

- How do rekindles and FAs influence the average waiting time of an incident (ignition, rekindle, or FA) until suppression resources are available to be dispatched?
- How does the total number of incidents influence the point of collapse of the suppression system?

2.3. A conceptual model of the operation of a suppression system

Figure 2 displays the conceptual model that was created. The suppression operation starts with the communication of the incident to the dispatch center. The incident may or may not be an FA, but the operator has no way of distinguishing, so an IA crew will always be dispatched to the site:

- In the case of an ignition or a rekindle, the fire may be suppressed with the IA or escape and require an extended attack (EA) operation. In both cases, a rekindle may occur after a delay (represented in Fig. 2 as "//").
- In the case of an FA, the operation consists of the discovery and confirmation that there is no ignition. This operation, even with shorter duration than IAs in the case of a confirmed ignition, takes time, which needs to be considered.

Since 2006, Portugal has adopted a "muscled attack" dispatch policy. According to the operational standards, for an IA, a CDOS should dispatch a team with two engine crews (two vehicles with a water tank and three to five firefighters each), a third large vehicle with extra water supply (which has a driver and an assistant), and a helicopter, if available. If the fire is not contained after 90 min, an EA should start, with the dispatch of more resources.

2.4. A discrete-event simulation model

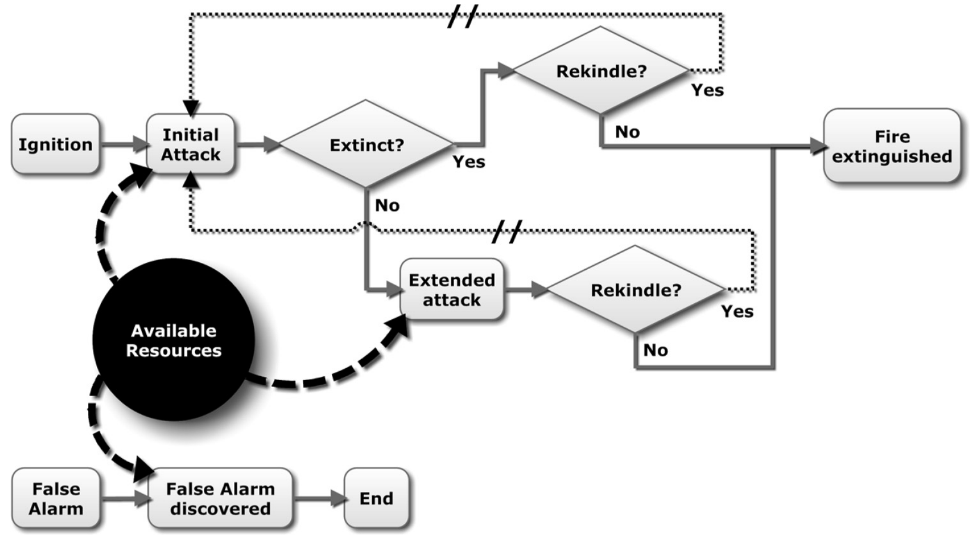
The discrete-event simulation model has five main components: (1) incident occurrence and communication ("arrival", using queuing theory terminology), generating ignitions, rekindles, and FAs; (2) ignition and rekindle attack, simulating IA, fire escape, EA, and resource allocation; (3) FAs, simulating the verification operation, and the corresponding resource allocation; (4) statistics collection; and (5) simulation control logic. Definitions of the Arena modules used are provided in Supplementary Table S4, and the implementation of the simulation model is presented in Supplementary Figs. S1 to S5.

2.4.1. Incident arrival

The correlation between the number of forest fires (and burnt area) and the weather (concerning the ignition and propagation conditions) is well established (Finney 2005; Wotton 2009). Different levels of daily severity rating (DSR) thus present different operational challenges for the suppression system. Accordingly, in the construction of the model, we differentiate days in two classes of daily incident frequency (DIF).

We modeled the arrivals of ignitions, rekindles, and FAs as nonstationary Poisson processes (Bookbinder and Martell 1979). As the numbers of incidents can change significantly during the day, we implemented a nonstationary process for the arrivals in our model, considering rates of arrival that change hourly

Fig. 2. Conceptual model of the operation of a forest fire suppression system.



throughout the day. In Arena, this was accomplished by using the piecewise-constant method that divides the time frame of the simulation into subintervals of 1 h over which a flat arrival rate is assumed. Specifically, the incidents (entities) are created in a "create" module with the time between arrivals controlled by a "schedule" module containing the means for each of the 24 hourly intervals. These 24 parameters are configurable in the model and can easily be changed later after obtaining the expected number of arrivals per hour through data analysis of the incidents of interest.

In this component (Supplementary Fig. S1), the numbers of occurrences in each day are differentiated in classes of DIF, "class A" and "class B". We used two "create" modules, one for each of the two classes of DIF considered. A "decide" module filters the arrivals according to the DIF class of the current day in the simulation. This process is similar, and replicated, for ignitions, rekindles, and FAs.

2.4.2. Ignition and rekindle attack

This component (Supplementary Fig. S2) includes the definition of the fire duration, the assignment of resources for IA, the transition to EA, and the assignment of resources for EA. The logic is similar for ignitions and rekindles. Because the available resources (ground crews and helicopters) have an associated cost, at the end of the simulation, Arena is able to compute suppression costs.

Setting the duration of a fire incident, according to a probability distribution, is the first step in this module. The following step is a "process" module, which will seize (reserve) the parameterized ground crews and, if available, an aircraft. For all of the modules of our model, the queue discipline is "first in first out" (FIFO), and the resources have the same allocation priority. The resources are seized for the minimum time between the fire duration and the maximum duration for an IA, i.e., the resources sent to the fire are the resources required for an IA.

A "decide" module will consider the fire extinguished if the duration is less than the maximum duration for an IA, and the resources will subsequently be released. Otherwise, the EA phase starts and additional resources are required. If the required resources are available, the fire goes into EA immediately, seizing all of the resources (the ones initially seized for the IA, as well as the additional ones later seized for the EA) for its remaining duration.

In very extreme situations, the required additional resources may not be available, and to avoid leading the simulation into a deadlock, the resources that were allocated to the fire's IA are released, and the fire waits for enough resources to become available, growing freely.

2.4.3. False alarms

When the resources of the forest fire suppression system are deployed to an incident that is found not to be a forest fire but still a fire (e.g., a garbage can burning) or not to be a fire at all, the incident is classified as a "false alarm" in the database; indeed, with the exception of 2010, it is not possible to distinguish between FAs and no forest fires. For the sake of detail, in the false alarm component, we separately modeled non-forest fires (also called "false" false alarms, FFA) and FA (truly nonexistent fires). With FA (Supplementary Fig. S3, top), similarly to an IA, the parameterized ground crews and, if available, an aircraft will be dispatched. The resources are seized for the duration of the operation of checking that there is no fire, according to its probability distribution.

With FFA (Supplementary Fig. S3, bottom), the parameterized ground crews will be seized for a time interval following the respective probability distribution. With considerably less information about these incidents, we decided to implement only one class of DIF.

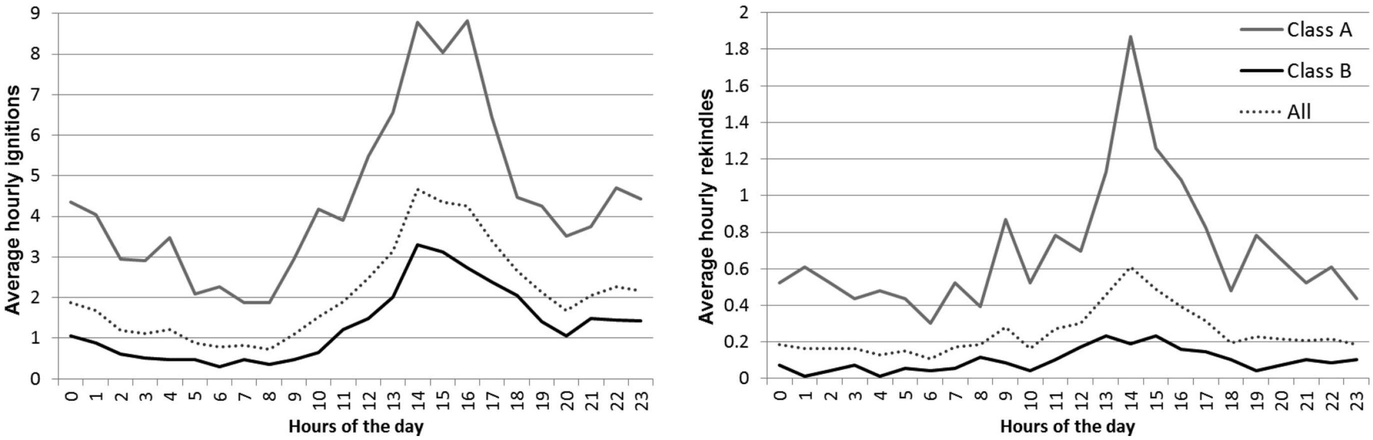
2.4.4. Statistics collection and simulation control logic

At a final processing stage, a statistics collection component (Supplementary Fig. S4) computes the total numbers of incidents, and the duration of the fire (the sum of waiting and service times) is also available.

The multiple effects that influence the burnt area (e.g., weather conditions, fuel type and level of accumulation, wind speed and direction, or whether the fire spreads downhill or uphill) are not all reflected in its duration. However, if we were able to find statistically significant relationships (by analyzing historical data) between the fire duration in each of the DIF classes and the burnt area in stands and burnt area in forest (stands plus shrublands), the model is prepared to be parameterized with such (four) relationships and compute the burnt area for each fire. With the burnt area for each fire, the model can also calculate the associated value losses by multiplying the burnt areas by parameterized constants with the monetary lost value for each burnt hectare.

Finally, CO_2 emissions are computed using the official guidelines of AFN (AFN 2011*b*), which follow Narayan et al. (2007), distinguishing between stand and shrubland burnt areas, each with a specific emission factor. As the model computes, for each fire, forest burnt area and stand burnt area, the shrubland area is

Fig. 3. Average hourly ignitions (left) and rekindles (right) in Porto between July and September 2010.



computed by subtracting burnt stand area from burnt forest area. However, because this part of the model is not needed for the analysis presented in this paper, we will not describe its parameterization in subsection 3.1.

The simulation control logic component (Supplementary Fig. S5) controls the change of day, the DIF class, and the end of the process of creation of new incidents. "Days" are created at a constant daily rate and assigned to an appropriate DIF class. After the last day of the simulation, the ignitions are stopped. Nevertheless, all of the fires that are ongoing in the last day of the simulation are allowed to end.

All modules of the model were implemented with parameters that are defined externally, enabling much simpler debugging, reconfiguration, or extended analysis processes. For a comprehensive list of all configurable variables and expressions, see Supplementary Table S5.

3. Results

In this section, we present two sets of results: (*i*) in subsection 3.1, the results from the statistical analysis of the combined AFN and Porto CDOS databases, used to parameterize the simulation; and (*ii*) in subsection 3.2, the results of the combined simulation and sensitivity analyses.

3.1. Model parameterization

Throughout this subsection, we illustrate the parameterization of our simulation model using analysis of historical data for the study site.

3.1.1. DIF classes

Through observation of the histogram of the daily number of incidents, there seems to be a division at around 100 incidents. Our interviews with the district dispatch center confirmed this threshold — for a lower number of incidents, the response capability is easily sufficient. Accordingly, we decided to consider a DIF class A as above 100 incidents/day and a DIF class B as below that threshold (horizontal line in Fig. 1).

We further tested the differences between these classes, as well as the rest of the year, concerning fire duration. The Kruskal–Wallis H test revealed that fire durations (in minutes) are significantly affected by the DIF class of the day, with $H(2) = 248.34$, $p < 0.001$, and mean ranks of 3421.25 (median = 121.00), 2848.72 (median = 100.00), and 2518.20 (median = 89.00) for classes A, B, and the rest of the year, respectively. Pairwise comparisons using Mann–Whitney tests, with adjusted p values, revealed significant differences between the fire durations for all classes ($p < 0.001$).

In our analysis, we consider several stochastic elements such as the number of fires and the duration of each fire. However, the daily weather conditions that drive the simulation are deterministic (Podur and Martell 2007) and follow the 2010 historical sequence of daily class of DIF.

3.1.2. Ignitions, rekindles, and false alarms

The evolution of both the rates of ignitions and the rates of rekindles (Fig. 3) during the day follows an expected pattern (Bookbinder and Martell 1979), with a peak in mid-afternoon.

The evolutions of FA and FFA are presented in Supplementary Fig. S6. FFAs have behavior similar to that of ignitions and rekindles. With the exception of a peak at the beginning of the night, FAs also follow a pattern described in the literature (Tu 2002), with a valley during the night.

3.1.3. Duration of interventions

The histogram with the duration of interventions, jointly considering ignitions, rekindles, and FAs, is presented in Fig. 4, and individual histograms for each type of intervention are included in Supplementary Figs. S7 and S8. The shapes for new fires and rekindles are very similar, with fewer fires extinct in the first hour than in the second but decreasing in number after that, with a long tail; on the contrary, the bar height for FA is always descending. The durations of the interventions associated with each type were modeled with individual probability distributions for each of the DIF classes.

In all analyses — ignitions, rekindles, and FAs (DIF classes A and B) and FFAs — we used an empirical distribution when the distribution with highest fit in EasyFit, and significant at 0.01, was not available in Arena; in the other cases, the lognormal distribution was always the selected distribution.

3.1.4. Initial attack and extended attack

To differentiate between fires that were suppressed in the IA and those that escaped and required EA, we sought to identify the threshold in the duration of the fire at which this transition occurs.

As a maximum of two engine crews and one aircraft are allocated to the IA (according to operational standards), we obtained an initial lower bound for this threshold as the average duration of the fires with a number of allocated resources within that interval. Then we used a multiplicative factor to perform a sensitivity analysis with the simulation and obtain a threshold consistent with our field data.

As suggested by Fig. 5, rekindles present higher adversity — in all conditions, IA and EA have higher average durations than for fires directly resulting from ignitions. Furthermore, these values are evidence that the operational rule that places this threshold at 90 min is not being strictly followed, a fact that in some of our interviews was attributed to insufficiencies in resource capacity during the critical period. To check if these differences are signif-

Fig. 4. Histogram of the duration of interventions (all incidents) in Porto between July and September 2010.

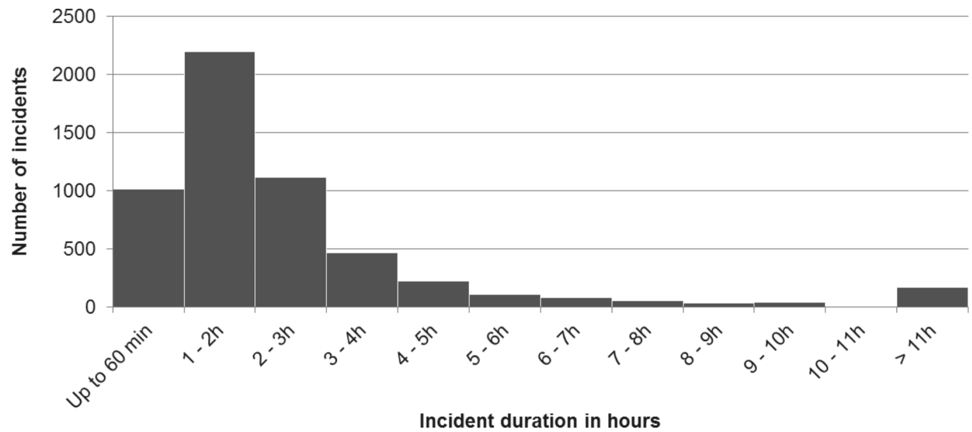
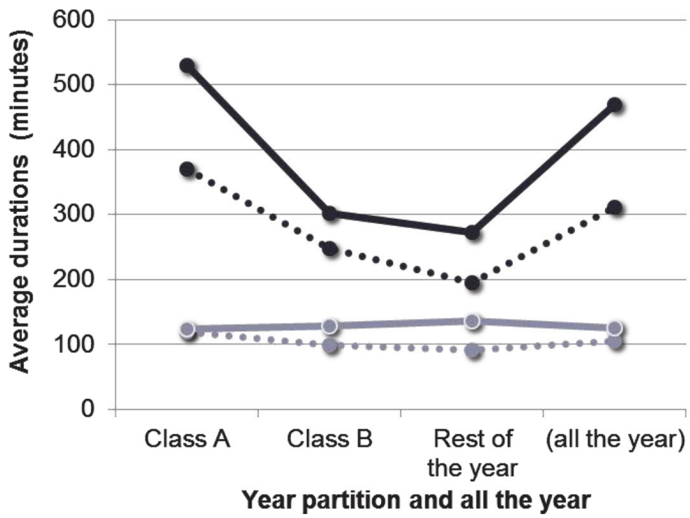


Fig. 5. Average durations of initial and extended attacks for new fires and rekindles in Porto for 2010.



	Class A	Class B	Rest of the year	(all the year)
New Fire Initial Attack	118	99	91	105
New Fire Extended Attack	370	248	195	311
Rekindle Initial Attack	123	128	136	125
Rekindle Extended Attack	529	302	271	470

icant, we tested the differences between fire durations belonging to different classes of incidents and DIFs with a series of Mann–Whitney U tests.

In days of class A, the duration of new fires (median = 99.00 min) does not differ significantly from that of rekindles (median = 102.00 min) if the fire is contained during the IA, with U = 201 026.50, z = –1.49, and $p > 0.05$. However, if they escape, the duration of new fires (median = 212.00 min) is significantly less than that of rekindles (median = 334.00 min), with U = 29 950.50, z = –4.44, and $p < 0.001$.

In days of class B, the opposite happens, with the duration of new fires (median = 86.50 min) being significantly less than that of rekindles (median = 109.00 min) if the fire is contained during the IA, with U = 87 675.00, z = –3.65, and $p < 0.001$. For fires that escape, the duration of new fires (median = 171.50 min) does not differ significantly from that of rekindles (median = 203.00 min), with U = 6111.50, z = –1.40, and $p > 0.05$.

Nevertheless, it should be noted that the differences for both new fires in days of class A and rekindles in days of class B become statistically significant at 0.10.

Furthermore, we tested this difference for the rest of the year, which has fewer ignitions per day than the critical period. We found that the duration of new fires (median = 82.00 min) does not differ significantly from that of rekindles (median = 97.50 min) for fires contained during the IA, with U = 6077.00, z = –0.95, and $p > 0.05$; and if they escape, the duration of new fires (median = 178.00 min) also does not differ significantly from that of rekindles (median = 219.00 min), with U = 26.50, z = –1.04, and $p > 0.05$.

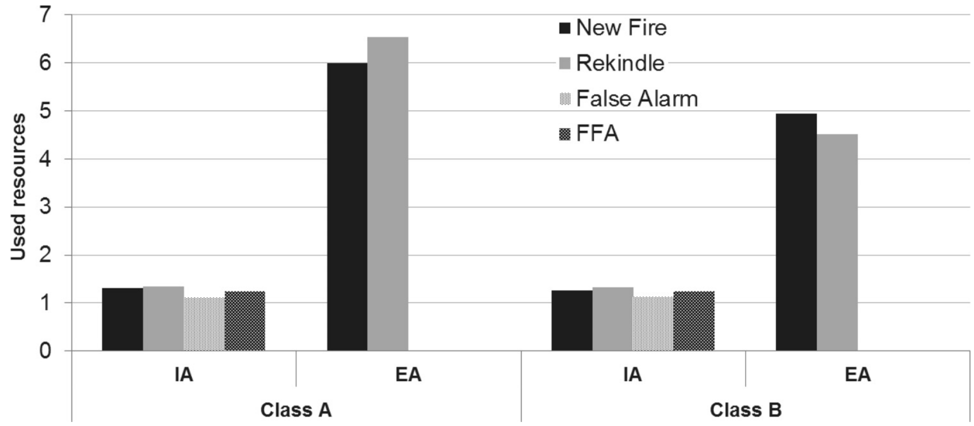
These results seem to point to the duration of rekindles in days with higher number of incidents being greater than the duration of new fires. In fact, overall, the duration of new fires (median = 120.00 min) is significantly lower than that of rekindles (median = 125.00 min) in days of class A (U = 488 391.50, z = 2.20, $p < 0.05$), as well as in days of class B (new fires, median = 99.00 min; rekindles, median = 120.05 min; U = 198 865.00, z = 3.38, $p < 0.001$) and in the rest of the year (new fires, median = 89.00 min; rekindles, median = 111.00 min; U = 13 185.50, z = 1.76, $p < 0.05$).

Finally, we checked if the proportion of escaped fires is different between new fires and rekindles in the three cases (class A, class B, and rest of the year). For each case, a 2 × 2 contingency table analysis was conducted to evaluate whether "fire escaping (no, yes)" was associated with "rekindle (no, yes)". The analysis yielded Pearson χ^2 values of (1, N = 2777) = 0.58, (1, N = 2280) = 0.001, and (1, N = 1047) = 1.57, respectively, which are less than the critical value of 3.84 at the 5% level of significance in all cases. Thus, despite the differences observed in our sample, the proportions of escaped fires are not significantly different ($p > 0.05$).

3.1.5. Allocated resources and costs

Using the same logic of analysis, we were able to estimate the resources allocated to IA and EA, again considering the two DIF classes (Fig. 6). In this case, the data also provided evidence that

Fig. 6. Average number of crews dispatched to initial and extended attacks in Porto between July and September 2010.



the operational standards IA dispatch rule is not being strictly applied in practice.

The data do not discriminate between contracted and volunteer crews or between district and out-of-district crews; they simply include the number of engines present in each incident. Thus, we parameterized the model only with the average number of engine crews, without loss of generality, because there should be one vehicle with extra water supply for each two engine crews according to operational standards. Regarding costs, in the model, we assign to each engine crew a fixed contract cost of €10 per hour (rounded up from €8.54) and do not consider other costs (e.g., firefighter training, food, fuel spent, engine maintenance, and others). The rented helicopter is assigned a variable cost of €788 per hour of usage.

Throughout the process of model construction and parameterization, we made sure that the results of the model were consistent with the real data, paying particular attention to the evolution of the number of ignitions and crews involved in suppression operations, as well as the number of aircraft missions.

3.2. Sensitivity analysis

After parameterizing the model using data from the study site, the district of Porto, we present in this subsection the actual simulation results.

3.2.1. Benchmark levels for rekindles and false alarms

We ran the simulation for different levels of daily occurrences and also compared benchmark conditions with the base scenario (the current conditions), varying the number of available crews. With eight scenarios (40%, 60%, 80%, 120%, 140%, and 160% of the current level of daily occurrences, as well as the benchmark and base scenarios), each analyzed with 30 different levels for the number of suppression crews available, we ran 240 fires–crews scenarios, with 2000 replications each. In the literature, we found studies using 500 replications (e.g., Podur and Martell (2007) or Podur and Wotton (2010)); however, after a sensitivity analysis, we concluded that with our simulation, we should use at least 1000 replications, and in fact, we chose to use twice that number.

We started by assessing the average waiting time for different levels of crew capacity, under the base scenario and under a benchmark scenario in which the number of rekindles is reduced from 10% to 1%, the target in the "Technical Proposal for a National Plan of Defense of the Forest against Fires" (ISA 2005), and the number of false alarms is reduced from 9% to 4.5%, in line with international levels (Corcoran et al. 2007; Karter 2011; Killalea 1998; Tu 2002; Yang et al. 2003). The results of this analysis are presented in Fig. 7.

3.2.2. Point of collapse and the number of incidents

Between 2001 and 2009, the average number of daily incidents in the critical period ranged from 39.2% to 162.6% of the value of 2010. We analyzed seven points in this range — 40%, 60%, 80%, 100%, 120%, 140%, and 160% — using the same experimental design as in subsection 3.2.1. For each level, Fig. 8 illustrates the point of collapse, which was determined as the minimum level of crews that keeps the average waiting time below 10 min. The points of collapse were determined using exponential regressions adjusted to the relationships between mean waiting time and crew capacity, considering all positive values for the mean waiting times.

4. Discussion

Our data analysis of forest fire incidents in the district of Porto, between July and September 2010, highlights the importance of addressing the phenomena of rekindles and false alarms. Jointly, rekindles and false alarms represent almost 20% of the incidents, with daily peaks that are exactly coincident with the peaks of requests of suppression resources for real new forest fires. Although, on average, FAs use resources for a time interval less than that of an IA, there is a very high opportunity cost to that time. In the case of rekindles, this is worsened by the fact that rekindle suppression operations are much harder, as made clear from the fact that both IA and EA durations are higher for rekindles.

The extra pressure that these additional classes of incidents put on the suppression system raises difficult challenges to its management. We believe that the deviations from operational standards that we found in our data analysis (e.g., that the IA often extends beyond 90 min and that the average number of engine crews dispatched to IAs is approximately 1, instead of the recommended 2) are evidence of this pressure. In a fire-prone country with an extensive WUI, where the average number of fires in the last decade corresponds to over 50% of the whole EU Mediterranean region (San-Miguel-Ayanz et al. 2013), increasing suppression effectiveness is particularly important to avoid small fires becoming mega-fires in days of critical fire danger (Tedim et al. 2013).

Using our simulation analysis to study the impact of rekindles and false alarms on the performance of the suppression system, we found that bringing them down to benchmark levels, with a joint reduction of approximately 13.5% in the number of incidents (9.0% from rekindles and 4.5% from false alarms), would lead to a reduction in the number of crews required to keep the average waiting time under 10 min from 112 to 101; in short, bringing them down to benchmark levels would lead to a reduction in the point of collapse of approximately 9.8%. This reduction in the number of engine crews translates to a reduction of €236 500 in suppression costs per year (€283 800 when adding the proportional number of water supply vehicles).

Fig. 7. Average waiting times as a function of crew capacity for base and benchmark scenarios.

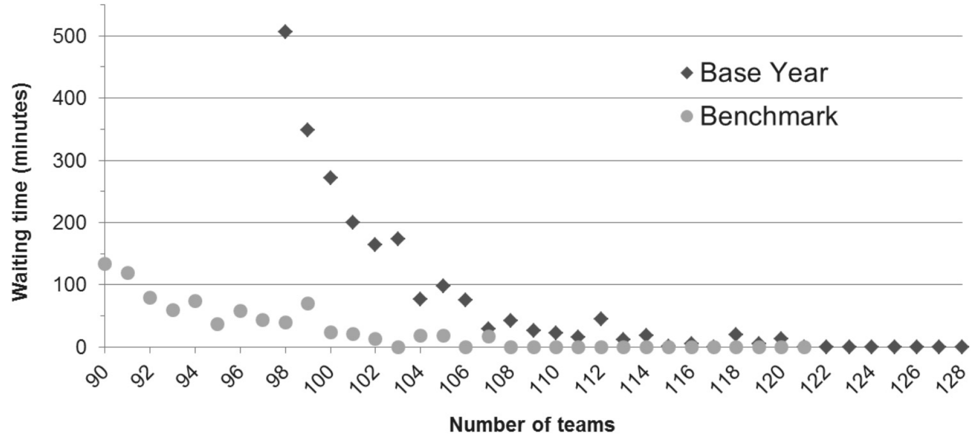
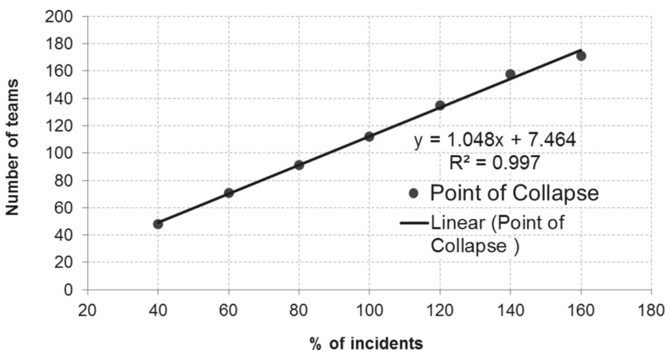


Fig. 8. Point of collapse as a function of the average number of daily incidents (with 2010 value as base).



This means that managing false alarms, for instance, will lead to a lower number of incidents in the system, which reduces pressure and releases resources that become available for real fires and to invest more time in mop-up operations, thus reducing the number of rekindles, contributing again to reduce the number of incidents, and so on, in a positive feedback loop (Pacheco 2011).

Effective management of false alarms requires proper recording of these incidents to understand the phenomenon and take appropriate measures (Corcoran et al. 2011; Flynn 2009; Pacheco 2011). Studies evidence that the motivations behind malicious false alarms may differ from place to place (Corcoran et al. 2007, 2011). Identifying the calling number (Killalea 1998), clustering high-risk zones by phone prefix (Yang et al. 2003), returning a call when it sounds suspicious (e.g., school sound behind), and asking to talk with an adult if a child's voice is heard are some of the actions that can be taken. The last two measures were implemented by Porto CDOS and were pointed out in our interviews as part of the reason why the district has fewer false alarms. As for the good-intent false alarms, the public can be informed about what should be reported, and overall, publicizing the real costs of false alarms is also an option that may be considered (Killalea 1998).

To reduce rekindles, some authors suggest improvements in post-fire management by enhancing suppression effectiveness (e.g., properly training firefighters in mop-up operations) and active surveillance, as firefighters often leave a fire prematurely to respond to new IA demands (Pacheco et al. 2012). Increasing crew capacity and adjusting dispatch rules are also options that could be considered. For instance, if an active crew is dispatched to a new fire (to minimize waiting time), another crew (the first available) should later return to the fire site just vacated to ensure sufficient mop-up and prevent rekindles. Overall, contracted crews could always be out of the headquarters, either fighting a fire or engaged in active surveillance and prevention.

Another very important challenge for the suppression system is the huge interannual variability in the number of ignitions. We sought to characterize the impact of overall ignitions on the point of collapse, and for the range of values observed between 2001 and 2010, we found a linear relationship between the number of ignitions and the point of collapse, with a decrease of 1.00% in the daily rates of ignitions leading to between 0.85% and 0.96% reduction in the number of required suppression teams in the range that we studied. Because 98% of ignitions are of human origin (arson, negligence, or accidental), this indicator provides a relevant threshold for the investment in prevention: a reduction of 1% in ignitions allows for a reduction of the point of collapse of one firefighting team, inverting the vicious circle of more fire, more teams.

Our results support the relevance of the point of collapse as a useful indicator in capacity decisions for a suppression system. Arriving early increases the probability of containing the fire in its initial stage, and additionally, if the resources are insufficient, the pressure to attack starting fires increases the premature abandonment of mop-up operations of already controlled fires, leading later to more rekindles and thus even more fires (Collins 2012; Pacheco et al. 2012).

There are several limitations in our model that do not challenge the essence of our analysis but limit its applicability to study other important aspects of the operation and the management of a suppression system.

- The sequence of daily classes of DIF is not stochastic.
- We did not analyze and model weekly patterns for occurrences, but they were mentioned in our fieldwork and identified in the literature. As an example, in New Zealand, false alarms grow approximately 50% on weekends (Tu 2002).
- The queue disciplines are always FIFO and do not differentiate in terms of priority, for instance, between IA and EA.
- The fire durations depend on the daily class of DIF and depend on the resources allocated only indirectly (the scarcity of resources increases the waiting time, thus the fire duration).
- Very large forest fires do not have a differentiated treatment.
- The loss of productivity that results from the overload in consecutive high DIF days, or from relocating crews to less familiar sites, has not been modeled (Podur and Martell 2007; Wallace 1978).
- The study was confined to a single district and a single year.

We believe that these limitations do not have a qualitative impact on the results of the analysis that we conducted in this paper.

However, overcoming the first two can add more precision to the model; addressing the third can be useful to analyzing alternative dispatch policies; and the last three may become more significant if the model evolves to a simulation of the suppression system over a larger region (a set of districts). Regarding the fourth, having a direct dependence also on the number of deployed suppression crews will perhaps increase the accuracy of the computation of the burnt area.

Our model is prepared to compute value losses and CO_2 emissions, relating the impact of a fire with the variables present in the model, namely the burnt area, which in turn may be computed from the duration of the fire through regression analysis of historical data (see subsection 2.4.4). Value losses and CO_2 emissions depend directly on burnt area, and burnt area depends directly on the probability distribution of the duration of the interventions (related with ignitions and rekindles) and indirectly on the number of crews. Thus, the consistence of such results depends on the reliability of the regression, which will increase with more independent variables. If parameterized with that information, the model is currently prepared to evaluate the impact in terms of value losses and CO_2 emissions of different levels of crew capacity, false alarms, and rekindles.

Moreover, because we have suppression cost data available to compute value losses, we can use OptQuest, the simulation optimization module of Arena, to determine the number of crews that minimizes the sum of suppression costs and value losses (the system total cost), or we can plot the evolution of costs and losses with the number of engine crews available.

5. Conclusion

In this paper, we describe a discrete-event simulation model of a forest fire suppression system, which we use to analyze the joint impact of ignitions, rekindles, and false alarms on system performance. The model has been created and applied with a screening logic, i.e., it has lower fidelity than previously proposed models, but it considers additional factors not captured in prior work such as rekindles and false alarms, and it enables a wider exploration of the suppression system's design space.

The results of an analysis based on the case of the district of Porto in Portugal for the critical period between July and September 2010 show how a joint reduction of rekindles and false alarms to benchmark levels leads to a significant improvement of the system's point of collapse and provide useful information on the trade-off between prevention and suppression efforts.

The model can be applied to other regions, and because the model considers dispatch decisions and the performance of the IA response system (which represents approximately 90% of suppression activity), it can be used by managers to improve the effectiveness of the suppression system and, at the same time, reduce its costs.

With the perspective of more severe fire seasons in the future and because we cannot change the weather, one of the remaining options is to reduce the human impact (Flannigan et al. 2013). Our results point to the importance of managing false alarms and diminishing rekindles, which can be achieved through changes to current policies, namely through education programs, law enforcement, and the use of more effective suppression techniques.

Ongoing work, largely stimulated by this analysis, aims at exploring the relationship between IA efforts and fire escape probabilities and at optimizing the timing, sizing, and location of different types of prevention and suppression resources and activities from intra- and inter-annual perspectives.

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