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Evolutionary-Statistical System: A parallel method for improving forest fire spread prediction

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ABSTRACT

Fighting fires is a very risky job, where loss of life is a real possibility. Proper training is essential. Several firemen academies offer courses and programs whose goal is to enhance the ability of fire and emergency services to deal more effectively with fire. Among the tools that can be found in the training process are fire simulators, which are used both for training and for the prediction of forest fires. In many cases, the used simulators are based on models that present a series of limitations related to the need for a large number of input parameters. Moreover, such parameters often have some degree of uncertainty due to the impossibility of measuring all of them in real time. Therefore, they have to be estimated from indirect measurements, which negatively impacts on the output of the model. In this paper we present a method which combines Statistical Analysis with Parallel Evolutionary Algorithms to improve the quality of the model output.

1. Introduction

People have considerable fear of fire (history is replete with disastrous losses). However, fires in areas like, for instance, Western United States are natural and they benefit to the plant communities there. Periodic fires help to clear the forest floor of debris and promote the growth of sturdy, fire-resistant trees [33]. Nevertheless, expanding human populations have intruded on previously uninhabited areas, establishing their own communities in fire-prone zones. Moreover, human activities, such as fire suppression, livestock grazing, and logging, have increased the probability of hotter and more destructive fires [35].

Another example is the Mediterranean areas with dry and warm summers that favour the occurrence of fire ignition and propagation. Every year, millions of hectares are burned in Tropical, Boreal and Mediterranean forests [26], which causes a wide variety of effects, from atmospheric emissions [28], to soil erosion, biodiversity loss and drainage alterations [2]. Reduction of those negative effects of fire requires to rely on tools and methods for the assessment of the fire risk.

Tools like simulators, expose to the trainees to a convincing fire propagation model, where instructors can vary fuel types, environmental conditions, and topography. Responding to these variables, trainees may call for appropriate resources and construct firebreaks, and fundamentally, students can review the results of their decisions in the security of a computer laboratory.

Different propagation models have been developed to predict fire behaviour. They can be classified into empirical, semi-empirical, and physical models [11]. The probable fire behaviour is predicted in empirical models from average conditions and accumulated knowledge obtained from laboratory and outdoor experimental fire or from historical fires. Semi-empirical (semi-physical or laboratory models) are those models based on a global energy balance and on the assumption that the energy transferred to the unburned fuel is proportional to the energy released by the combustion of the fuel; one of the most important among these models is the pioneering work of Rothermel [31,32]. Finally, physical (theoretical or analytical) models are based on physical principles and have the potential to accurately predict the parameters of interest over a broader range of input variables than empirically based models do. Any of these models can be used to develop simulators and tools for preventing and fighting forest fires. Some old and current examples are Behave-Plus [3], FARSITE [14], FIREMAP [4], FireStation [21], WRF-Fire [22], XFire [20].

According to Fons [15] the relevant factors that affect the rate of spread and shape of a forest fire front are the fuel type (type of

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vegetation), humidity, wind speed and direction, forest topography (slope and natural barriers), and fuel continuity (vegetation thickness). Therefore, models require a set of input parameters, including vegetation type, moisture contents, wind conditions, and so on, and they provide the evolution of the fireline in the successive simulation steps. However, the result obtained after the direct application of a simulator (known as Classical Prediction and explained in Section 2) usually differs from reality because of the difficulty of providing accurate input values to the model. Given this uncertainty, we propose an alternative method, that tries to determine the possible fire behaviour based on Statistical Analysis [25] and Parallel Evolutionary Algorithms (PEAs) [24].

The method proposed, called Evolutionary-Statistical System (ESS), is based on S^2F^2M [8,10], an already validated method based on statistics and High Performance Computing (HPC). Different from classical predictions, these two methods make use of different techniques in order to calibrate the set of input parameters, and generate predictions based on a lot of possible cases (each case defined by a different set of input parameters), rather than on a single case. This is why they are classified as Data-Driven methods with Multiple Overlapping Solution. On the one hand, S^2F^2M considers the total set of cases (considering a factorial experiment based on certain ranges for each parameter) to carry out the search of the forest fire behaviour. Unlike the methods of unique solution, S^2F^2M does not make a distinction between the best and worst cases, but it determines the statistical trend of the fireline. On the other hand, the new proposed method, ESS, incorporates the PEA component to guide the search of the solution and reduce the number of cases under study in the statistical stage. In place of considering a factorial experiment (as S^2F^2M does), ESS considers just a sample of possible cases to conform a population which is evolved according to the PEA principles. The results obtained from the evolved population are then submitted to the statistical stage. In this way, it is possible to reach better results with the possibility of finding the solution even in less execution time.

The simulation of the spread of forest fires is a challenge from the computational point of view, given the complexity of the models involved, the need for efficient numerical methods and resource management. In this context, the method presented in this paper is an important tool for the prevention and prediction of forest fires, given that it provides a better prediction of the forest fire behaviour. This is a general method which could be applied on different propagation models (e.g. floods, snow avalanches, landslides, etc.), but in this article we present its application to forest fire spread prediction.

In this paper, we describe the direct use of a simulator (known as classical prediction) in Section 2. Section 3 describes the proposed methodology, implemented in a system called Evolutionary-Statistical System (ESS) [7]. In Section 4 we use a set of real cases of forest fires for evaluating ESS in contrast to S^2F^2M; we also comment on the obtained results related to the execution time and the speedup obtained when we work on a cluster computer. Finally, we present the main conclusions.

2. Classical prediction

Classical prediction approach is depicted in Fig. 1. In this scheme, **FS** corresponds to the underlying fire simulator, which is considered as a black box. **RFL0** is the real fireline at time t_0 (initial fire front), whereas **RFL1** corresponds to the real fireline at t_1. If the prediction process works properly, after executing **FS** (which should be fed with the corresponding input parameters and **RFL0**) the predicted fireline at time t_1 (**PFL**) should coincide with the real fireline (**RFL1**).

As we previously mentioned, models require static parameters (e.g. information about topography), parameters that can change very slowly (type of vegetation), parameters that can change frequently (moisture content), and parameters that are completely dynamic (like wind conditions). The precision of these parameters is a very important point in prediction of the behaviour. However, in many cases it is impossible to carry out any type of measurement, particularly in real fire situations, which is a critical situation to feed the simulation model.

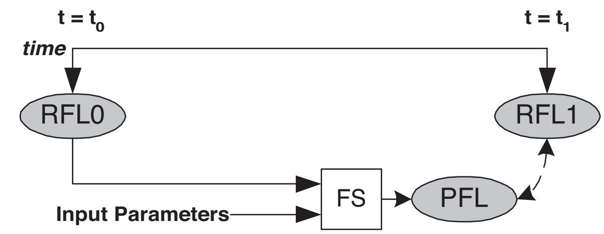

Fig. 1. Diagram of classical prediction of forest fire propagation (FS, Fire Simulator; PFL, Predicted Fireline; RFLX, Real Fireline on time X).

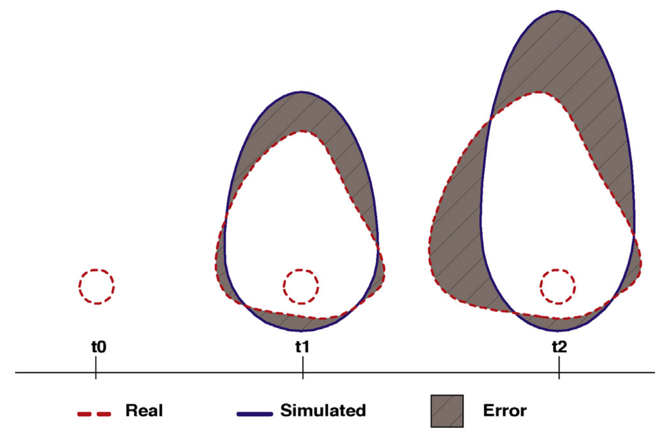

Fig. 2. Error using classical prediction.

Generally, the obtained prediction using this classical approach does not match the reality [5,29]. A simple example can be seen in Fig. 2, where it can be appreciated the error between the real fireline and the predicted fireline. One reason for the discrepancy between real and simulated propagation stems from the difficulty of feeding the model with accurate input values. Uncertainties in the input variables can have a substantial impact on the result errors and should be considered.

In this context, the classical prediction of the fireline behaviour cannot be considered to be reliable for two reasons: on the one hand, the difficulties in making an accurate estimation of the parameters and, on the other hand, the resulting prediction is based on a single simulation, which does not constitute a reasonable basis for making a decision given the uncertainty of the parameters.

3. Evolutionary-Statistical System

In the uncertainty reduction field, we propose a new method which we called Evolutionary-Statistical System (ESS) [7]. Such a method combines the strength of three components: Evolutionary Algorithms (EAs), Statistics and Parallelism. The method generates predictions based on the statistical analysis of a population of cases, in contrast to the single case considered by the classical prediction. The population is constituted by a set of individuals which are also referred as scenarios. Each individual or scenario constitutes a different setting of the input parameters under study (i.e. each individual arises as a combination of the possible values of