Uncertainty Reduction Method Based on Statistics and Parallel Evolutionary Algorithms*

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Abstract. In many scientific areas, the use of models to represent physical systems has become a common strategy. These models receive some input parameters representing some particular conditions and they provide an output representing the evolution of the system. Usually, these models are integrated into simulation tools that can be executed on a computational system. A particular case where models are very useful is the prediction of Forest Fire propagation. Therefore, the use of models is very relevant to estimate fire risk and to predict fire behaviour. However, in many cases the models present a series of limitations. Such restrictions are due to the need for a large number of input parameters and, usually, such parameters present some uncertainty due to the impossibility of measuring all of them in real time. In consequence, they have to be estimated from indirect measurements. To overcome this drawback and improve the quality of the prediction, in this work we propose a method that combines Statistical Analysis and Parallel Evolutionary Algorithms.

1 Introduction

According to [5], the most important factors that affect the rate of spread and shape of a forest fire front are the fuel type (type of vegetation), humidity, wind speed and direction, forest topography (slope and natural barriers), and fuel continuity. 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 fire line in the successive simulation steps.

Our work is focused on the consideration that there is no exact set of input parameters to be applied to the propagation model because it is not possible to know the exact value of each parameter when a fire starts. Furthermore, in most cases these models cannot be analytically solved and must be solved by applying numerical methods that are only an approach to reality. These numerical solutions can be implemented as code. Thus, the precision or accuracy of the prediction is not only limited by the gap between the model and the reality, but it is also limited by the underlying processors. Such processors have

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numerical accuracy limitations: the representation of real numbers in digital machines and the ability of the processors to process these numbers [11].

Models require static parameters (topography of the land), parameters that can change very slowly (type of vegetation, also called 'fuel'), parameters that can change frequently (moisture content), and parameters that are completely dynamic (wind conditions). The precision of these parameters is the important point in prediction of the behaviour, and in many cases it is impossible to carry out some types of measurements, and still worse in some cases it is not possible to consider the parameter in a real situation.

In this context, the simple prediction of the fire line behaviour cannot be considered to be reliable for two reasons: on the one hand, the existing difficulties in accurately estimating 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. This is that we call the **classical prediction**. This classical approach is depicted in Fig. 1. In this scheme, **FS** corresponds to the underlying fire simulator, which will be seen as a black box. **RFL0** is the real fire line at time t_0 (initial fire front), whereas **RFL1** corresponds to the real fire line at t_1. If the prediction process works, after executing **FS** (which should be fed with the corresponding input parameters and **RFL0**) the predicted fire line at time t_1 (**PFL**) should coincide with the real fire line (**RFL1**).

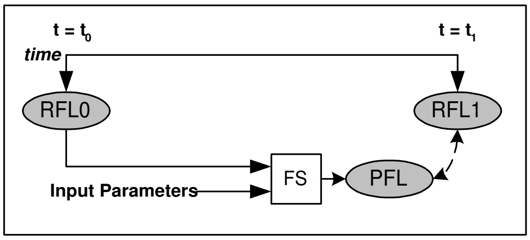

Fig. 1. Diagram of classical prediction of wildland fire propagation (FS: Fire Simulator; PFL: Predicted Fire Line; RFLX: Real Fire Line on time X)

Some examples of systems following a classical approach are [1] [2] [12] [4] [8] etc. The prediction obtained using this approach is usually different from the reality because of the difficulty of providing the model with accurate input values. Given this uncertainty, our method tries to determine the possible fire behaviour based on Statistical Analysis [10] and Parallel Evolutionary Algorithms (PEAs) [9] as optimization method.

2 Evolutionary Statistical System

The Evolutionary Statistical System (ESS), classified as Data-Driven methods with Multiple Overlapping Solution, is an improvement of the S^2F^2M

method [3]. It combines the original uncertainty reduction method implemented in S^2F^2M with the advantages that offer the PEAs, dealing with a population of scenarios relevant to the study. ESS, like its predecessor, is based on statistics, mainly on the concept of factorial experiment [10], where the combination of several factors (input parameters) defines a scenario. In this case, each scenario is represented by an individual in a population of possible solutions. For a detailed description of the method, we suggest the reader to consult [3].

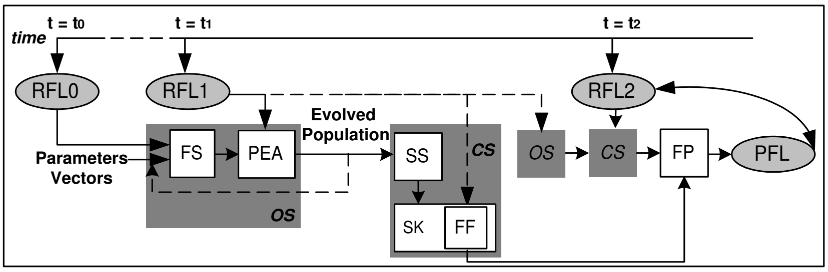

Fig. 2. Diagram of ESS (FS: Fire Simulator; PEA: Parallel Evolutionary Algorithm; OS: Optimization stage; SS: Statistical System; SK: Search K_{ign}; FF: Fitness Function; CS: Calibration stage; FP: Fire Prediction; PFL: Predicted Fire Line, RFLX: Real Fire Line on time X)

A scheme of ESS is presented in Fig. 2. As can be observed, the system is divided in two general stages: an Optimization Stage (**OS**) that implements the parallel evolutionary algorithm (**PEA** box), and the Calibration Stage (**CS**) that is in charge of the statistical method. **OS** iterates until the population reaches a certain level of quality. For each individual **FS** and the fitness are calculated in parallel. Then, every individual will be included in the Statistical System (**SS** box). The output of **SS** (a probability map) has a double purpose. On the one hand, the probability maps are used as the input of the **SK** box (Search K_{ign}) to search for the current K_{ign} (a key number used to make a prediction), which will be used at the next prediction time (t_3). In this stage, a Fitness Function (**FF**) is used to evaluate the probability map. On the other hand, the **SS** output enters a Fire Prediction box (**FP**), which will be in charge of generating the prediction map for time t_2 taking into account the K_{ign} evaluated at t_1. This process will be repeated during the execution as the system is fed with new information about the fire situation.

The architecture of the ESS is based on the Master/Worker model [6]: In each iteration the Master distributes an individual per Worker; the simulation of the model and the evaluation of fitness function are applied over each individual (tasks carried out by the Workers), returning the results to the Master. This process is repeated until every individual in the population is treated. Finally the Master evolves the population, aggregates the partial results and makes the prediction for each time step.

This system has been developed on a PC LINUX cluster using language C and MPI[7] as the message passing library.

3 Conclusions

In this work we have presented a new method to reduce the uncertainty in input parameters, in this case, applied to Forest Fire Prediction. However, the method is general enough to be used in different models (floods, avalanches, etc.). The method corresponds to a prediction improvement of a previous methodology that has been proved like a good option to solve this kind of problem. In this opportunity, we have combined the power of statistics and parallel evolutionary algorithms. As we can see in the bibliography, there are several possibilities to work with parallel evolutionary algorithms. In this first approach, we decide apply parallelism only in the evaluation of the individuals, with the goal of gradually increase the degree of parallelism to compare the results offered by each alternative. Further study should focus on the analysis and tuning of the method to obtain the best possible results and compare it with other methods.

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