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Increase in the quality of the prediction of a computational wildfire behavior method through the improvement of the internal metaheuristic

Miguel Méndez-Garabetti [a,b,c,*], Germán Bianchini [a], Paola Caymes-Scutari [a,b], María Laura Tardivo [a,b,d]

[a] Laboratorio de Investigación en Cómputo Paralelo/Distribuido (LICPaD), Departamento de Ingeniería en Sistemas de Información, Facultad Regional Mendoza – Universidad Tecnológica Nacional, M5502AJE Mendoza, Argentina
[b] Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Argentina
[c] Instituto Tecnológico Universitario, Universidad Nacional de Cuyo, Centro Universitario, Mendoza, Argentina
[d] Departamento de Computación, Universidad Nacional de Río Cuarto, Río Cuarto, Córdoba, Argentina

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ABSTRACT

Wildfires cause great losses and harms every year, some of which are often irreparable. Among the different strategies and technologies available to mitigate the effects of fire, wildfire behavior prediction may be a promising strategy. This approach allows for the identification of areas at greatest risk of being burned, thereby permitting to make decisions which in turn will help to reduce losses and damages. In this work we present an Evolutionary-Statistical System with Island Model, a new approach of the uncertainty reduction method Evolutionary-Statistical System. The operation of ESS is based on statistical analysis, parallel computing and Parallel Evolutionary Algorithms (PEA). ESS-IM empowers and broadens the search process and space by incorporating the Island Model in the metaheuristic stage (PEA), which increases the level of parallelism and, in fact, it permits to improve the quality of predictions.
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1. Introduction

Fire has been a fundamental element in the development of civilizations. Nevertheless, it represents a threat when it spreads without control causing wildfires. Wildfires may be generated by meteorological or human factors, although independently of the cause, it always generates a great impact on biodiversity, landscape, water resources and health (i.e., they generate great losses and are harmful to the environment) [1]. For example, in 2010, the extremely high temperatures that reached a record (in the Russian summer) and the drought in the region caused a large fire that burned one million hectares of forests, killing approximately 53 people [2,3] (in addition, 806 people required medical attention). In January 2014, in General Alvear (Mendoza, Argentina), 200,000 hectares of natural forests were burned due to high temperatures, low humidity and high amount of fuel accumulated in the area [4]. Finally, during February 2015 in Cholila (Chubut, Argentina) 45,000 hectares of native forests were burned, being the worst wildfire in Argentina [5,6].

Currently, there exists a great scientific effort to develop technologies and strategies to reduce the effects caused by wildfires. However, due to the complexity of the phenomenon and its characteristics, there is still a long way to go in order to achieve such a goal. Certainly, one of the most promising tools consists in the development and improvement of the ability to predict the phenomenon behavior. More specifically, this is to determine the future behavior of a wildfire once it has started, permitting to reduce damage and losses in the environment and the population by making decisions based on the areas that are most likely to be reached by the fire. Based on this, we can say that the ability to predict wildfire behavior represents a capacity that will allow us to implement useful tools in the process of firefighting.

However, it must be remembered that the prediction of any natural phenomenon is not an easy task and it takes time, especially, if high quality prediction is desired.

Predicting wildfire spreading consists in determining which will be the direction and speed of fire propagation, the shape of

* Corresponding author at: Laboratorio de Investigación en Cómputo Paralelo/Distribuido (LICPaD), Departamento de Ingeniería en Sistemas de Información, Facultad Regional Mendoza – Universidad Tecnológica Nacional, M5502AJE Mendoza, Argentina.
E-mail addresses: mmendez@itu.uncu.edu.ar (M. Méndez-Garabetti), gbianchini@frm.utn.edu.ar (G. Bianchini), pcaymesscutari@frm.utn.edu.ar (P. Caymes-Scutari), lauratardivo@dc.exa.unrc.edu.ar (M.L. Tardivo).

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the fire front, flame intensity, etc. Once the fire has started, it is necessary to predict its progress for the near future using as much information as possible about the fire front and the environment in which this occurs (i.e., climatic conditions, terrain conditions, vegetation conditions, fuels, etc.).

It is important to emphasize that wildfire prediction, as any other natural phenomenon, is not an easy task due to the complexity of the models used, the amount of variables involved and the uncertainty that they often exhibit.

In this paper, in Section 2 the issue of uncertainty in prediction systems is described. Next, a brief explanation of the concepts and tools that are used in the development of the methods is analyzed in Section 3. The approach, implementation and methodology of Evolutionary-Statistical System with Island Model (ESS-IM) are explained in Section 4. Finally, the experimental results and comparison are shown in Section 5, and conclusions are provided in Section 6.

2. Uncertainty in wildfire prediction

In wildfire behavior prediction there are different sources of uncertainty that affect the precision of the method. These sources are related to the limitations of the model used, parameters with unknown values, dynamic changes produced by the model, discretization of values, the difficulty to quantify the parameter values in real time, etc. In this section the sources of uncertainty and the existence of uncertainty in classical prediction are briefly discussed.

2.1. Uncertainty sources

The uncertainty concept itself has different meanings and levels that can refer to the lack of knowledge, the lack of certainty, among others. In this context, we refer to the lack of knowledge of the parameters that determine the behavior of the model. Mainly, this kind of uncertainty is usually observed in those variables that present a dynamic behavior. Some examples of this kind of variables are wind speed, wind direction, humidity content in vegetation, etc. These variables strongly affect wildfire behavior and should be measured in real time. To do this, devices such as wireless sensor networks (WSNs) could be of great help [7]. By using this type of sensors in areas affected by fires, we can obtain temperature measurements, wind speed and direction, etc. An example of this is [8] where WSNs are used as a tool for early detection and wildfire monitoring.

While the use of WSN can be a promising tool to reduce uncertainty in the input parameters, this technology can only be used in protected areas where the installation of a sensor network is possible. However, it is not feasible to install an extensive network of WSN in forests worldwide. Therefore, it is necessary to develop and improve methods and tools to address the problem of uncertainty into input parameters.

In our work, we consider that there is no exact set of input parameters to feed the propagation model because it is not possible to know the exact value of each parameter at the beginning of the fire and through the time. Furthermore, in most cases these models cannot be analytically solved and must be solved by applying numerical methods that are only an approximation to reality. Therefore, to make a wildfire behavior prediction with estimated values cannot be considered as reliable.

2.2. Classical prediction

In general terms, the Classical Prediction method consists in evaluating the position of the fire after a certain initial period of time, using any existing fire simulator behavior. A general scheme of this kind of methodology can be observed in Fig. 1. As can be seen, the simulator (**FS**) is fed by two sets of data: the real fire line of the wildfire at time t_n (RFL_n), generally represented by a map that shows the burned area where the fire started, and the information that describes the environment on which the fire spreads, such as weather data, vegetation, and terrain description (all these data are called input parameters). Each input parameter has a value assigned, and this set of values, along with RFL_n, is used by **FS** to make the prediction of the fire line (**PFL**) for the next time instant (t_{n+1}) through a single simulation. Furthermore, it is necessary to say that in any prediction method it is expected the estimated prediction carried out by the simulator to match reality in the best possible way. However, due to the model complexity, the uncertainty in the input parameters, and since the prediction is based on a single simulation, this prediction methodology provides generally predictions that are far from reality. Examples of classical prediction in wildfires are [9–15]. Due to the limitations of Classical Prediction, the development of methods that allow for reducing the uncertainty in order to improve the prediction quality has been necessary.

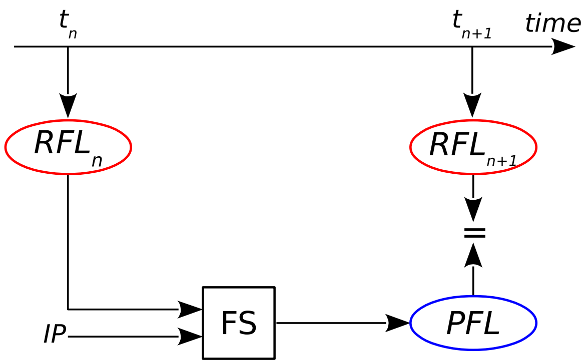

Fig. 1. Classical Prediction: diagram of wildfire propagation (**FS**: Fire Simulator; **PFL**: Predicted Fire Line; **IP**: Input Parameters; **RFL**$_n$: Real Fire Line on time n).

2.3. Uncertainty reduction

As we mentioned before, one of the factors that obstruct the classical prediction methods to obtain similar predictions to reality is lack of precision, i.e., the uncertainty in the parameters that feed the model. When this imprecision is present, the prediction capacity of the method is considerably affected, since this is equivalent to feeding the simulator with incorrect values, which usually will produce wrong predictions.

Due to the imprecision of the input parameters and the difficulty to measure them in real time, it is necessary to turn to some technique which will be able to reduce uncertainty, such as the Data Driven Methods (DDM). The DDM consider a large number of values for each parameter, instead of a single value for each parameter. Subsequently, these methods perform a search (i.e., by means of Genetic Algorithm, Taboo Search, Simulated Annealing) to find a set of parameters which describes, in the best possible way, the previous fire behavior that will be used to predict the near future behavior, based on some kind of time and space locality.

In other words, the DDM perform a calibration to obtain these “optimal” values of input parameters. Nevertheless, these methods obtain a single set of values, and for those dynamic parameters, the value found is not generally useful to correctly describe the model behavior. This category of methods is called Data Driven Methods of Unique Solution [16–18].

There is another classification of DDM that works with overlapping cases and combinations of parameters to make

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