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Evolutionary-Statistical System with Island Model for Forest Fire Spread Prediction*

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Abstract. Models are used in many areas of science to represent different systems. These models must be fed with input parameters representing some particular conditions and provide an output representing system evolution. A particular case where models are useful is forest fire spread prediction. However, in most cases, models present a series of limitations. Such restrictions are due to the need for a large number of input parameters and, usually, such parameters have some degree of uncertainty due to an inability to measure them in real time. To overcome this drawback and improve the quality of the prediction, several methods have been developed, among them S^2F^2M and ESS. This work proposes an improvement of the latter method, which incorporates the Island Model to the Parallel Evolutionary Algorithm. As a result of this development, we expect to obtain improvements in the quality of the prediction due to the increase in the diversity of cases generated because of the incorporation of the Island Model.

1 Introduction

The use of models to represent different physical systems is a common practice in various areas of science. Models must be fed with input parameters. The output of a model provides a representation of the evolution of the system over time. However, some limitations and difficulties are found when the systems that implement the models are fed with fixed values that represent dynamic parameters (i.e. parameters which vary along the time). For example, in the models used to predict the behaviour of forest fires, some input parameters (such as the wind speed) must be estimated from indirect measurements, but given its natural variability along the time not reflected in the model, produces a prediction distant from reality [1], [8]. This approach of predicting the behaviour of forest

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fire, where knowing the values of the input parameters is difficult and the resulting prediction is based on a single simulation, is known as classical prediction method. Given the uncertainty managed by such an approach at parameters level and reflected at output level, in this work we propose an improvement of the ESS method [2], [4], that increments the parallelism level by including the Island Model in the Parallel Evolutionary Algorithm (PEAs) [5], along with High Performance Computing and Statistical Analysis [7]. With this model, we expect to obtain improvements in the quality of the prediction due to the increase in the diversity of cases considered given the parallel search in multiple populations.

2 Evolutionary-Statistical System with Island Model

The Evolutionary-Statistical System with Island Model (ESS-IM) proposes an improvement of Evolutionary-Statistical System (ESS) [4]. ESS and ESS-IM belong to the Data-Driven methods with Multiple Overlapping Solution. ESS is an uncertainty reduction method based on the use of PEAs to guide the search, Statistics to calibrate the results, and Parallelism to enhance the search in time and volume terms. The PEAs of ESS are based on the scheme of Unique Population and Parallel Evaluation [5]. Instead, in ESS-IM we consider the Multiple Populations and Migration scheme (also known as Island Model).

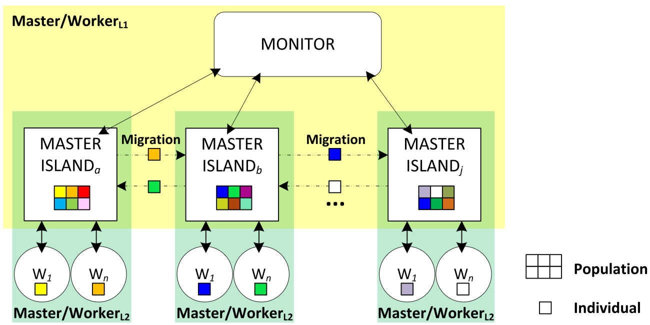

Fig. 1. ESS-IM communication model and population treatment representation.

ESS-IM, like its predecessor, is based on the Master/Worker model [6], but in this case there are two Master/Worker levels (see Fig. 1). On the one hand, at level one **(Master/WorkerL1)** the Monitor node is in charge for the prediction of forest fire behaviour. On the other hand, at level two **(Master/WorkerL2)** there are a set of islands, each one composed by a Master and some associated Workers. The Master of each island distributes the individuals to the Workers. An individual in ESS-IM represents a particular setting of the input parameter values that feeds the model. The Workers carry out the simulation and the evaluation of the fitness function of each individual in parallel, returning the results to the respective Master. Each Master is also responsible for evolving the population and performing migrations. This interaction is determined by the communication topology and the migration parameters configuration. The evolution of the islands is also carried out in parallel.

A detailed scheme of ESS-IM is presented in Fig. 2. As can be observed, the system has two Optimization Stages **(OS-Worker and OS-Master)**, two Calibration Stages (**CS-Master** and **CS-Monitor**) and finally a stage of Fire Prediction **(FP)**. In the following, we briefly explain all these activities that are carried out in each prediction step. **OS-Worker** implements a portion of Parallel Evolutionary Algorithm (**PEA**$_F$ box). In this stage, each individual is applied to the model and also is evaluated by the fitness function. Moreover, **OS-Master** (one per island), is responsible for controlling the genetic evolution of the island population, iterating until the population reaches a certain level of quality. **OS-Master** also makes the selection of those individuals who will be migrated.

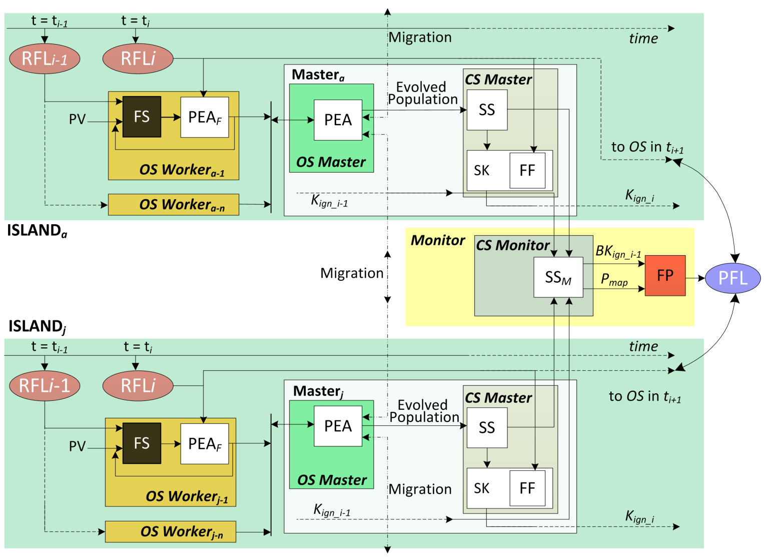

Fig. 2. Diagram of ESS-IM. **FS**: Fire Simulator; **PEA**: Parallel Evolutionary Algorithm; **PEA**$_F$: Parallel Evolutionary Algorithm (fitness evaluation); **OS**: Optimization stage; **SS**: Statistical System; **SK**: Search K_{ign}; **FF**: Fitness Function; **CS**: Calibration stage; **FP**: Fire Prediction; **PFL**: Predicted Fire Line; **RFLX**: Real Fire Line on time X; **SS**$_M$: Statistical stage (monitor); **PV**: Parameters Vectors; **BK**$_{ign}$: Best K$_{ign}$; P$_{map}$: Probability Map).

CS-Master is in charge of the statistical phase [3]. As in ESS, the **SS** box output (a probability map) has a dual purpose. On the one hand, the probability maps are used as the input of the **SK** box (Search K_{ign}: Key Ignition values, a key number used to make a prediction) to search the current K_{ign} value, which will be used at the next prediction time. In this stage, a Fitness Function (**FF**) is used to evaluate the probability map. On the other hand, the output of **SS** box enters to **CS-Monitor**. Therefore, **CS-Monitor** is fed with the probability maps and K_{ign} calculated by the different islands. There are different criteria to design the **CS-Monitor**. One option is to choose the best K_{ign} of all islands (island synchronization is needed). Another option is to calculate just one K_{ign} based on statistical map that aggregates the statistical maps of each population. Finally, the K_{ign} that is firstly found could be considered. Due to the existence of the different mentioned alternatives, we will conduct a detailed comparison of these options to determine which provides more quality in the prediction.

3 Conclusions

We have presented a method for uncertainty reduction, which increases the features to take advantage of parallel environments. The parallelism degree is increased in the evolutionary algorithm moving from a scheme of Unique Population and Parallel Evaluation to a Multiple Populations and Migration scheme. In this proposal, complexity increases over previous versions because we are working with multiple related populations. Owing to this, there are many issues to be considered: the different ways to implement the statistical method, the different alternatives for implementing the Fire Prediction stage, the influence of different migration strategies, the possibilities of communication topologies, among others. Further study should focus on the analysis and tuning of the method to obtain the best possible results and compare it with other existing methods.

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