Hybrid-Parallel Uncertainty Reduction Method Applied to Forest Fire Spread Prediction

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Abstract

Fire behavior prediction can be a fundamental tool to reduce losses and damages in emergency situations. However, this process is often complex and affected by the existence of uncertainty. For this reason, from different areas of science, several methods and systems are developed and refined to reduce the effects of uncertainty In this paper we present the Hybrid Evolutionary-Statistical System with Island Model (HESS-IM). It is a hybrid uncertainty reduction method applied to forest fire spread prediction that combines the advantages of two evolutionary population metaheuristics: Evolutionary Algorithms and Differential Evolution. We evaluate the HESS-IM with three controlled fires scenarios, and we obtained favorable results compared to the previous methods in the literature.

Keywords: Hybrid Metaheuristics, Differential Evolution, Evolutionary Algorithms, Fire Prediction, Uncertainty Reduction

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1 Introduction

Forest fires are one of the most damaging natural phenomena, causing ecological, economic and human damages, among others. As an example we can mention the recent forest fire that occurred in Chile, which devastated more than 1500000 acres, destroying 1551 homes and leaving 6162 homeless, in addition to lamenting the loss of 11 fatal victims [1].

Similar situations often occur everywhere in the world. Therefore, it is important to develop methods and systems that minimize their impact. Once a forest fire has begun, predicting its behavior may be a promising tool, as this may allow for decisions to be made that minimize its effects, provided that the resulting prediction is obtained in acceptable time. However, this is not an easy task mainly due to the uncertainty affecting the prediction process.

The behavior of fire in a forest environment is determined by different variables, such as speed and wind direction, the amount and type of fuel, topography, vegetation type, among others. This information is necessary to determine the future behavior of the phenomenon. Generally, obtaining the values of these variables in real time is a complex task, although there are technologies to respond to this problem (e.g. Wireless Sensor Network, WSN [2]). It is practically unfeasible to have such measuring instruments in large forest areas with a potential risk of ignition.

Because of this, the values must be taken from indirect measurements, interpolations or approximations, which places us in the situation of *uncertainty*. Uncertainty in the input parameters directly affects the prediction quality of the method, so if we want to obtain predictions close to reality, this uncertainty must be reduced to acceptable values. Prediction systems applied to natural phenomena are highly critical due to the sensitivity of the decisions that can be made based on their predictions and the limited time available to obtain the results. Therefore, such systems are usually implemented in high-performance computing environments or HPC [3].

In this paper we present a new hybrid uncertainty reduction method applied to wildfires spread prediction, which takes advantage of the island-based parallelization scheme of the method called *Evolutionary Statistical System with Islands Model* (ESS-IM) [4], [5]. This new methodology is called *Hybrid Evolutionary-Statistical System with Island Model* (HESS-IM), allowing each island to operate with different metaheuristics in a collaborative way. HESS-IM uses Statistical Analysis [6], Parallel Computing [3], parallel evolutionary metaheuristics (Evolutionary Algorithms [7] and Differential Evolution [8]) as collaborative optimization tools under a Parallelization based on the Islands Model [7]. In [9] a preliminary work of HESS-IM was presented.

In this paper, in Section 2 the metaheuristics involved, the parallelization and hybridization strategies are described. Next, the implementation and methodology of HESS-IM are explained in Section 3. Then, in Section 4, the details of the experiments are given and the results obtained are commented. Finally, conclusions and future lines of work are discussed.

2 Metaheuristics

According to [10], metaheuristics are intelligent and general strategies that aim to improve and design heuristic procedures to solve high complexity problems. For certain problems, traditional implementations of metaheuristics often do not deliver the expected results. So it is necessary to resort to more efficient optimization strategies: *hybrid metaheuristics.*

2.1 Hybrid Metaheuristics

The efficiency of an optimization method can be increased by combining multiple metaheuristics, using different search strategies on the same solution space. This is known as Hybrid Metaheuristics (HMs), although different approaches exist to classify HMs, in [11] they have been classified into two major groups: a) HMs with collaborative combinations and b) HMs with integrative combinations. The purpose of collaborative HMs is to exchange information between different optimization techniques, whether they operate sequentially or in parallel. In this scheme, each metaheuristic operates independently, collaborating with each other only through the exchange of candidate solutions.

On the other hand, in integrative collaboration, a metaheuristic uses another metaheuristic as part of the first one in a subordinate way. In this scheme the collaboration is internal, where the operation of a metaheuristic is enhanced by the advantages of others. That is, they do not exchange solutions since both operate on the same set of solutions.

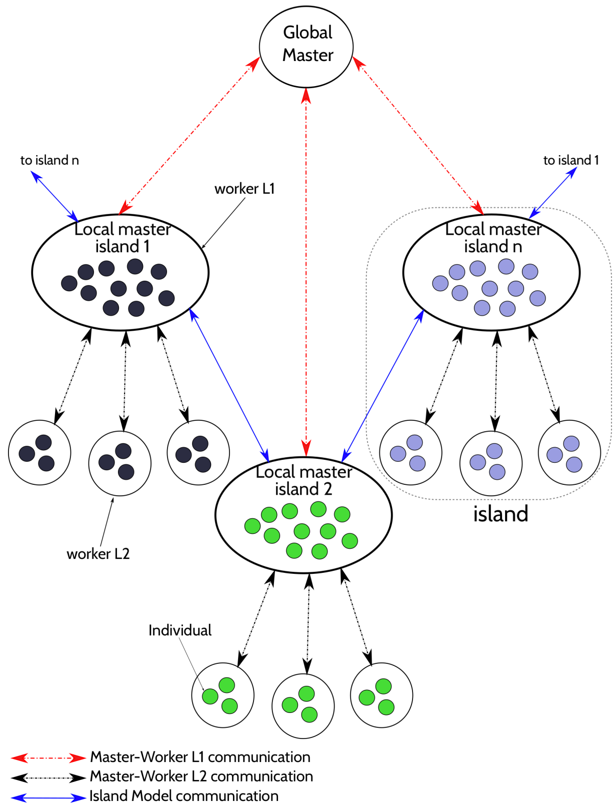

Figure 1: Island-based hierarchical parallelization scheme with double master-worker model.

2.2 Metaheuristics used in HESS-IM

HESS-IM uses a collaborative hybrid metaheuristic (HM) composed of Evolutionary Algorithms (EAs) and Differential Evolution (DE). Both are population metaheuristics, which operate by iteratively improving a set of solutions.

2.2.1 Evolutionary Algorithms

EAs constitute a search method, applied to the resolution of optimization problems, inspired by the theory of natural evolution of the species [12]. The process is based on iterations called generations, where a set of candidate solutions (called population), evolves through the application of operators that allow to imitate the principles of natural selection and survival of the fittest. Each individual has associated an aptitude value that determines the quality of the solution, this value is calculated with the mathematical function that describes the problem. The operators that allow individuals to evolve in the population are: selection, mutation, crossing and replacement. At each iteration, individuals are selected and reproduced (using the variation operators), thus creating new candidate solutions. Then a replacement process is applied to determine which individuals in the population will survive [13]. At the end, it is expected that the best individual in the population represents an acceptable solution to the problem.

2.2.2 Differential Evolution

The Differential Evolution algorithm is a population-based stochastic optimizer proposed by Price and Storn in 1995 [14]. DE begins by generating a population of individuals, which is created randomly and uniformly distributed within the range of the problem. DE uses the difference of vectors to iteratively modify the population through three vector operations: mutation, crossing and selection. It is important to note that these operators are applied to all individuals in the population. Mutation disturbs the population through the application of vector differences between members of the population, thus determining the degree and direction of new individuals generated from this process. Then, the mutant vector is subjected together with the individual from the current population to the crossover operator, generating a new vector called the test vector. Finally, the selection process to bring the next generation individuals with better features is carried out. Therefore, the fitness of each test vector is evaluated and compared to its corresponding in the current population. If the test vector has a better or equal value of the objective function, the current vector will be replaced in the next generation.

3 HESS-IM

HESS-IM is a general-purpose parallel uncertainty reduction method that can be applied to different propagation models. In this work, it has been used as a parallel uncertainty reduction method for wildfires spread prediction.

3.1 Method Parallelization

HESS-IM uses a parallelization scheme based on the island model [7], under a double master-worker hierarchy. A general scheme can be seen in Fig. 1. As can be seen, the *global master* process coordinates the operation of all the islands. Where the *local master* of each island fulfills the worker function with respect to the global master (i.e., master-worker level 1, L1). Each island master controls a set of *workers* within their own island, who are responsible for assessing the fitness function (i.e., master-worker level 2, L2). It is important to note that each island initializes a different population, which can be evolved through different metaheuristics. The collaboration between the different metaheuristics is provided by the migration operator, which exchanges individuals between the different islands (i.e., island model communication).

3.2 Method Operation

A general scheme of the HESS-IM operation is presented in Fig. 2. As we can see, there are three types of processes: a) *monitor* process (i.e., *master global* in Fig. 2, b) *master* process (*master local* in Fig. 2) and c) *worker* process. In a HESS-IM instance where j islands are operating, and w workers per island, a total of $1+j+w*j$ processes will occur in parallel, i.e., 1 monitor process, j master processes (one for each island), and $w*j$ worker processes.

The method begins in the *monitor* process, which is responsible for sending to the *masters* of each island, the initial information of the fire (i.e., real fire map, time intervals to be considered, parameters, etc.). Each master executes the Optimization Stage (OS_{master}), initiating its previously assigned metaheuristic (i.e., EA or DE). As can be observed, the Metaheuristic stage is divided into two sub-stages: on the one hand, the Metaheuristic sub-stage of the Master process (M_M), and on the other hand, the Metaheuristic sub-stage of the Worker processes (M_W). The M_M stage is in charge of the fitness evaluation of the individuals, and the M_W stage is in charge of the rest of the operations involved in each metaheuristic. The workers of each island evaluate the individuals' fitness using a Fire Simulator (FS).

FS is based on the model defined by Rothermel [15] and implemented using the fireLib library [16]. In order to perform the fitness assessment in t_i, it is necessary to have the actual Real Fire Line (RFL) in t_{i-1} (i.e., RFL_{i-1}) and the input parameters values, which are stored in the Parameter Vectors (VP). When the individuals are evaluated, they are sent with their fitness value to the stage M_M. M_M, in addition to performing the rest of the operations of each metaheuristic (i.e., alteration of individuals, evolution of the population, etc.), is responsible for the individuals migration to the neighboring islands. The migration process consists of selecting, sending/receiving and replacing individuals between the different islands. The selection consists in choosing, from the current population, those individuals who will be sent to the rest of the islands. A semi-elitist criterion is used, where 50% of the individuals to be migrated corresponds to the best, and the other 50% is randomly selected. The selected individuals are sent every certain time (i.e., migration frequency) following a ring topology. Finally, replacement is performed, this mechanism determines those individuals of the current population that will be replaced by those arriving from other islands. When the pop-

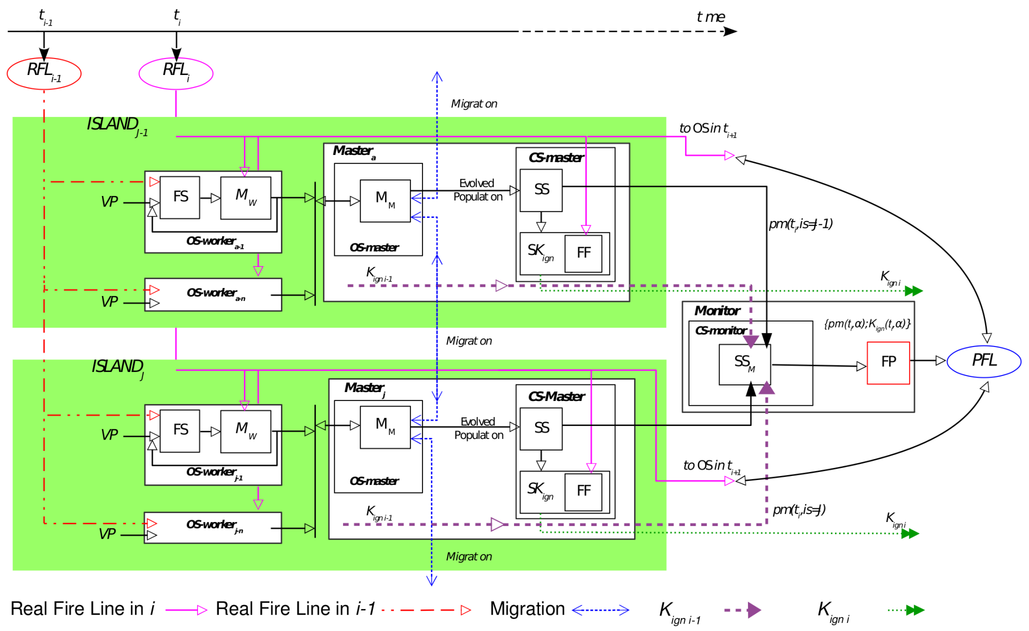

Figure 2: Hybrid Evolutionary-Statistical System with Island Model: **FS**: Fire Simulator; **PEA**: Parallel Evolutionary Algorithm; $\mathbf{M}_M$: Metaheuristic sub-stage in master; $\mathbf{M}_W$: Metaheuristic sub-stage in worker; **OS**: Optimization Stage; **SS**: Statistical Stage; **SK**: Search K_{ign}; $\mathbf{K}_{ign}$: key value used to make the prediction model; **FF**: Fitness Function; **CS**: Calibration Stage; $\mathbf{SS}_M$: monitor Statistical Stage; $\mathbf{MK}_{ign}$: monitor $K_{ign}value$; **FP**: Fire Prediction; **PFL**: Predicted Fire Line; $\mathbf{RFL}_x$: Real Fire Line on time x; **PV**: Parameters Vectors; **pm**: probability map.

ulations of the different islands have evolved, they are sent to the master process Calibration Stage (CS_{master}). In CS_{master} the Key Ignition Value (K_{ign}) is calculated, which is generated from a calculated probability map based on all individuals. The K_{ign} value represents the behavior pattern of the fire and is obtained in the Search K_{ign} stage (SK_{ign}).

At every instant of time i, on each island j, a key ignition value is generated $K_{ign}(t_i, is)$ and a probability map $pm(t_i, j)$, which are sent to the Calibration Stage of the *monitor* process $CS_{monitor}$. The Statistical Stage of the monitor process (SS_M) generates in t_i a pair of values composed of a probability map and a key ignition value according to the Eq (1).

$$\{pm(t_i, \alpha); K_{ign}(t_i, \alpha)\} \tag{1}$$

Where α indicates the number of island that has obtained the best fitness value. Finally these values are entered in the Fire Prediction stage (FP). FP calculates the Predicted Fire Line for the next time instant $i + 1$, i.e., PFL_{i+1}.

4 Experimentation and Results

For the experimentation, three controlled real burning were used (Serra de Louçã, Gestosa, Portugal)[17]. In order to verify whether the metaheuristics hybridization offers improvements in prediction quality, the results of the HESS-IM were compared with those produced by ESS-IM, ESS [18] and Classical Prediction (i.e., without using any uncertainty reduction method, for more information see [5]). ESS is a previous version of ESS and it is based on a Unique Population and Parallel Evaluation scheme.

For each experiment, the quality of prediction and the improvement degree has been evaluated at certain time instants. These instants are called prediction steps and correspond to discretizations to represent the advance of the fire front. In Table 1, the initial and final time values of each prediction step and its increment value can be observed.

Table 1: Duration of the experiments.

Exp.	Initial time (min)	Increment (min)	Final time (min)
A	2	2	12
B	3	1	9
C	2	2	10

4.1 Quality of Prediction

The prediction quality is calculated using the fitness function based on the Jaccard-Index [19] described in Eq (2).

$$Fitness = \frac{|A \cap B|}{|A \cup B|} \quad (2)$$

In which A represents the set of cells in the real map without the subset of burned cells before starting the simulations, and B represents the set of cells in the simulation map without the subset of burned cells before starting the simulation. It is important to remember that a fitness value equal to 1 indicates a perfect prediction and a value close to 0 indicates a very poor prediction.

4.2 Improvement Degree

As an additional measure we calculate the improvement that each method performs in each prediction step and it is described in Eq. (3). This indicates how much the negative impact of the lack of precision in the input parameters is reducing.

$$i_s(\%) = \frac{(F(method)_s - F(cp)_s)100}{E(cp)_s} \quad (3)$$

where i_s represents the improvement of each prediction step s, and $F(method)_s$ corresponds to the prediction quality value obtained by each method in each step, $F(cp)_s$ corresponds to the fitness value obtained by classical prediction, and $E(cp)_s$ represents the classical prediction error in each prediction step (i.e., *1-*$F(cp)_s$).

4.3 Analysis of Results

It is important to note that, except for the Classical Prediction, the methods evaluated here (i.e., HESS-IM, ESS-IM and ESS) have a non-deterministic behavior. Therefore, each experiment was executed 30 times for each method. Hence, the values obtained are the average of the results for each experiment. Another important consideration is that both HESS-IM, ESS-IM and ESS cannot perform predictions at the first instant of time due to the need of perform the Calibration Stage (see Figs. 3, 4 and 5).

4.4 Experiment A

This experiment had a total duration of 10 minutes and was performed on a field with an area of 125,776ft^2 and with a slope of 21°. Fig. 3 represents the quality of prediction obtained for each method. As can be seen, HESS-IM obtains better prediction quality in most of the prediction steps, except for minute 10 where it is slightly surpassed by ESS-IM. This can also be seen in terms of the improvement degree, where HESS-IM achieves an improvement over 70% in steps 1, 2 and 4 (minutes 6, 8 and 12), see Fig. 6. Finally, HESS-IM reaches the best prediction value at minute 8, with an average equal to 0.81025.

4.5 Experiment B

The simulation of this experiment has a total duration of 6 minutes, the terrain is somewhat smaller than that of experiment A, with an area of 101,718ft^2 and a slope of 19°. As can be seen in Fig. 4, HESS-IM obtains better prediction quality in three prediction steps (minutes 5, 6 and 9). In the rest of steps, ESS-IM is the method that obtains the best quality of prediction; moreover, it is the method that obtains the highest average equal to 0.749407 at minute 8. In terms of the improvement degree (Fig. 7) we can observe that there is no method that reaches 60%, in any prediction step. This is because the Classical Prediction obtains much higher values to those of experiment A. Finally, it is important to note that HESS-IM obtains the highest improvement value, reaching 56.7% at minute 6.

4.6 Experiment C

This experiment corresponds to a flatter terrain, with a slope of 6 degrees and a total surface of 58,125ft^2. The simulation starts at minute 2 and goes until minute 12. The quality of prediction average obtained by each method is similar (see Fig. 5), although HESS-IM obtains better values in the last two steps (minutes 8 and 10). From the point of view of the improvement degree, we can observe in Fig. 8 a similar behavior to experiment A, where HESS-IM stands out as the method that offers the best results.

The obtained results demonstrate that the hybridization technique used and the selected metaheuristics, improve the search mechanism of the method; allowing for more accurate and reliable predictions.

The experiments were carried out on a cluster Linux with 32 processing units (Intel-Q9550 processors), 4 GB of RAM, Gigabit Ethernet network and under a message passing environment MPI [20].

5 Conclusions

A new hybrid-parallel uncertainty reduction method called HESS-IM: *Hybrid Evolutionary-Statistical System with Island Model* has been introduced. HESS-IM uses a hybrid-parallel metaheuristic based on a collaborative scheme using

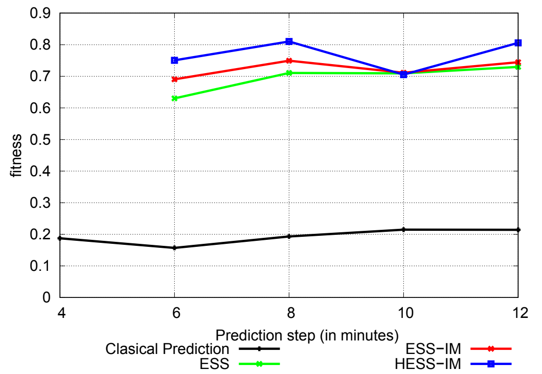

Figure 3: Experiment A: fitness comparison obtained for each method.

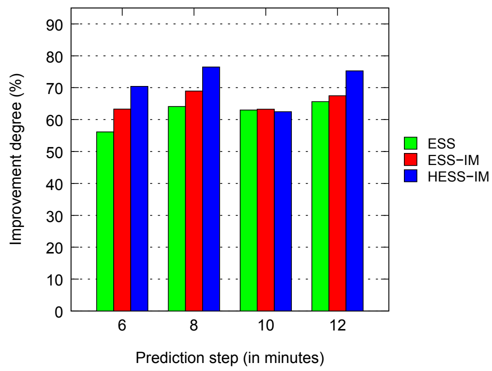

Figure 6: Experiment A: improvement comparison obtained for each method.

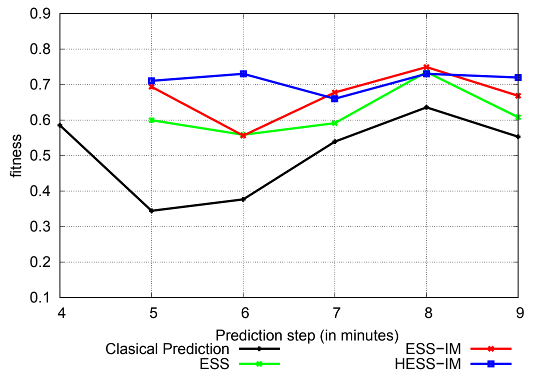

Figure 4: Experiment B: fitness comparison obtained for each method.

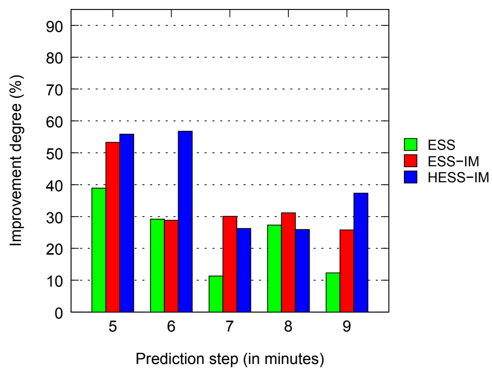

Figure 7: Experiment B: improvement comparison obtained for each method.

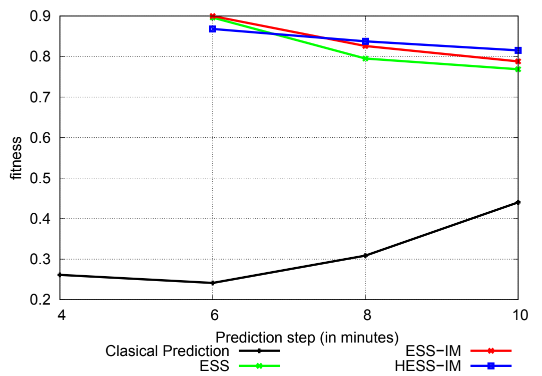

Figure 5: Experiment C: fitness comparison obtained for each method.

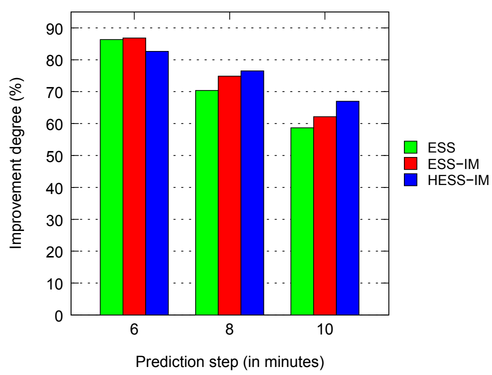

Figure 8: Experiment C: improvement comparison obtained for each method.

Evolutionary Algorithms and Differential Evolution, under a parallel strategy based on islands with double master-worker hierarchy. The evaluation of the method was carried out by its application to three real controlled fires where the quality of prediction and the improvement degree of the method were evaluated. The results obtained were compared with the Classical Prediction and two previously developed methodologies: ESS and ESS-IM. In addition, these results prove that the hybridization technique used and the selected metaheuristics improve the search mechanism of the method, allowing for more accurate and reliable predictions. Finally, as future work, we plan to develop a framework that allows HESS-IM to operate with multiple metaheuristics. Additionally, we plan to use GPUs to improve the performance of the method.

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