Optimization for an Uncertainty Reduction Method Applied to Forest Fires Spread Prediction

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Abstract. Forest fires prediction represents a great computational and mathematical challenge. The complexity lies both in the definition of mathematical models for describing the physical phenomenon and in the impossibility of measuring in real time all the parameters that determine the fire behaviour. ESSIM (Evolutionary Statistical System with Island Model) is an uncertainty reduction method that uses Statistic, High Performance Computing and Evolutionary Strategies in order to guide the search towards better solutions. ESSIM has been implemented with two different search strategies: the method ESSIM-EA uses Evolutionary Algorithms as optimization engine, whilst ESSIM-DE uses the Differential Evolution algorithm. ESSIM-EA has shown to obtain good quality of predictions, while ESSIM-DE obtains better response times. This article presents an alternative to improve the quality of solutions reached by ESSIM-DE, based on the analysis of the relationship between the evolutionary strategy convergence speed and the population distribution at the beginning of each prediction step.

Keywords: Forest fires · Prediction · Island model
Evolutionary Algorithms · Differential Evolution · Parallelism

1 Introduction

The prediction of natural phenomena, such as forest fires, is considered a very important task that implies a high degree of complexity and precision. Generally, simulation tools implement models that attempt to explain and predict the spread of fire on the ground. These models usually require certain input parameters to represent the various dynamic factors that determine the behaviour of the fire. However, it is not possible to have accurate values for all these factors before the fire ignition or during the fire spread. This lack of precision, also

A. E. De Giusti (Ed.): CACIC 2017, CCIS 790, pp. 13–23, 2018.
https://doi.org/10.1007/978-3-319-75214-3_2

called uncertainty, negatively affects the quality of the prediction. Therefore, the challenge lies in the development of computational methods that can improve the knowledge of the input parameters values, so as to reduce the uncertainty, and hence, to obtain more realistic predictions.

The Evolutionary Statistical System with Islands Model, ESSIM, [6] is an uncertainty reduction method that has been applied to forest fires prediction and is classified within the Data Driven Methods with Multiple Overlapping Solutions (DDM-MOS) [1]. ESSIM uses Evolutionary Strategies to guide the search process towards good quality solutions, a Statistical component to analyse the fire trend, and a parallel evaluation to obtain short term solutions. Its first computational design included Evolutionary Algorithms as search strategy, and the method was renamed ESSIM-EA. Subsequently, the Differential Evolution metaheuristic was used, determining the ESSIM-DE method. ESSIM-EA has proven to obtain good quality of predictions, meanwhile ESSIM-DE significantly reduces response times.

Both methods have been studied in recent years with the aim of improving their performance. Two static tuning studies were carried out for the evolutionary parameters of ESSIM-EA in [2,3]. Also, the parameters related to islands model of ESSIM-DE and the evolutionary parameters of ESSIM-DE, have been statically calibrated in [4] and [5], respectively. In these two last studies, some improvements were found for certain prediction steps, but they have been non significant. This paper presents a proposal to improve the quality obtained by ESSIM-DE based on the analysis of the population distribution at the beginning of each prediction step. The objective is to determine the relationship between the convergence speed of the metaheuristic that guides the search process, with respect to the predictions quality obtained in the different time steps of the fire's progress. This study represents the starting point for obtaining a general behaviour pattern that allows us to determine the distribution the population must have at the beginning of each prediction step.

The work is organized as follows. Section 2 describes the ESSIM method and the search metaheuristics used by ESSIM-EA and ESSIM-DE. Section 3 presents the proposal to improve the quality of predictions obtained by ESSIM-DE, called ESSIM-DE(r). Section 4 presents the experimentation carried out to validate the proposal. Finally, Sect. 5 presents the conclusion and future work.

2 ESSIM General Description

ESSIM is a method for uncertainty reduction designed with parallel evaluation through a double-hierarchy *master/worker* communication mechanism. Figure 1 presents the general scheme of ESSIM. The higher hierarchy level includes a process called *monitor*, which is in charge of sending initialization information, collecting the processed data in the final stage of the simulation and determining the output values. In the lower hierarchy level, the ESSIM processes are organized on islands. Each island is composed by a *master* process responsible for initializing a population of individuals, which represent different values combinations for the environmental conditions under which the fire occurs.

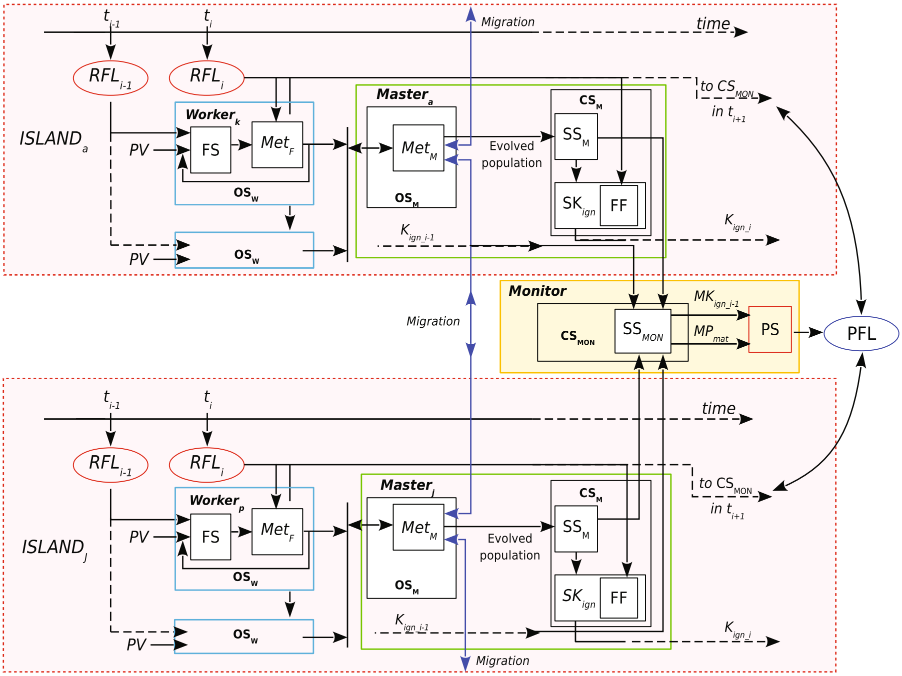

Fig. 1. General ESSIM diagram. **FS**: Fire Simulator, **Met**$_M$: Metaheuristic in *Master*; **Met**$_F$: Metaheuristic (fitness evaluation); **OS**$_W$: Optimization Stage in *Worker*; **OS**$_M$: Optimization Stage in *Master*; **SS**$_{MON}$: Statistical Stage in *Monitor*; **SS**$_M$: Statistical Stage in *Master*; **SK**$_{ign}$: Search for K$_{ign}$; **K**$_{ign\ t}$: key ignition value for instant t; **FF**: Fitness Function; **CS**$_M$: Calibration Stage in *Master*; **CS**$_MON$: Calibration Stage in *Monitor*; **PS**: Prediction Stage; **PFL**: Predicted Fire Line; **RFLx**: Real Fire Line on instant x; **PV**: Parameter Vector (population individual); **MK**$_{ign}$: Monitor K$_{ign}$ value; **MP**$_{mat}$: Monitor Probability Matrix.

The *master* process distributes each individual among certain *worker* processes, which are assigned the task of performing the fire behaviour simulation for each received individual, task carried out in the Optimization Stage (**OS**$_W$). Also, the *workers* must evaluate the quality of the simulation, by means of a fitness function. To that end, the **OS**$_W$ stage has two internal sub-stages called Fire Simulation (**FS**) and the fitness function evaluation associated with the metaheuristic used by ESSIM as search engine (**Met**$_F$). **FS** must be fed with the real fire line at the time instant t_{i-1} (RFL_{i-1}) together with the individual depicting an input parameters vector (**VP**). In order to represent the different fire lines, the terrain is divided in cells and a neighbourhood relationship defines whether each cell will be burned, and also what time the fire will reach those cells. The output of **FS** consists of a map of the terrain in which each cell is labelled with its ignition time.

When **FS** ends the simulation, each obtained map is introduced in the $\mathbf{Met}_F$ stage, in order to compare the simulated map with the t_i instant real map (RFL_i) and thus to determine the fitness value for each individual. In ESSIM, the fitness function is given by the expression (1), where 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 simulated map without the subset of burned cells before starting the simulation.

$$fitness = \frac{|A \cap B|}{|A \cup B|} \tag{1}$$

Subsequently, the fitness values together with the simulated map for each individual are sent to the *master* process, which is also in charge of performing the migration of certain selected individuals to another island. The amount of individuals selected is a parameter of ESSIM and they replace the worst members of the target island.

Once the population evolves through different generations or reaches a certain aptitude, it is introduced in the Calibration Stage ($\mathbf{CS}_M$). In this stage the evolved population feeds a sub-stage called Statistical Stage ($\mathbf{SS}_M$). The output of $\mathbf{SS}_M$ is a probability matrix that considers the contribution of all the individuals and is used for a dual purpose. On the one hand, it is used to search the Key Ignition Value in the sub-stage SK_{ign} (Search K_{ign}). The K_{ign} value represents the wildfire behaviour pattern in a specified time interval, and it is used to make the prediction in the next time instant (t_{i+1}). The evaluation of the probability matrix is carried out in the Fitness Function stage (**FF**). On the other hand, the j outputs of the $\mathbf{SS}_M$ together with the j K_{ign} values calculated by the j islands are sent to $\mathbf{CS}_{MON}$. In this stage the *monitor* process selects the best K_{ign} value from all the islands (MK_{ign}). This value together with the probability matrix from the corresponding island (MP_{mat}) is used to make the prediction for the next instant of time (t_{i+1}) in the Prediction Stage (**PS**). For further details on other prediction methods types, on the searching K_{ign} value process and on ESSIM, see [5] or [7].

As previously mentioned in Sect. 1, it is possible to instantiate ESSIM with different search strategies in the evolutionary stages. The main characteristics of two strategies used with ESSIM are summarized below.

ESSIM-EA: Evolutionary Algorithms: Evolutionary Algorithms (EAs) are considered efficient search methods to solve optimization problems, inspired by the process of natural selection [8]. The search space is organized as a set of individuals that make up a population, each one representing a possible solution. The population evolves iteratively, through generations, imitating the principles of biological evolution and the survival of the fittest. To achieve this purpose, the process consists in selecting from the population a sample of parents, which are subjected to different operators to generate a set of offspring. Subsequently, they are introduced to the population replacing individuals with the worst features.

ESSIM-DE: Differential Evolution: The Differential Evolution algorithm (DE) is a population-based stochastic optimizer that uses vector differences to modify each individual in the population. In contrast to EA, the mutation, crossover and selection operators are applied in each generation to each individuals from the population. The mutation operator applies vector differences between each *current individual* and certain randomly selected individuals. Subsequently, each mutated individual is submitted together with the current individual to the crossing operator, generating a new vector, called *trial vector*. Finally, in the selection stage, the best candidate is determined between the *current individual* and the *trial vector*. The one with the best fitness function value will survive for the next generation.

3 ESSIM-DE(r): Optimization for ESSIM-DE

ESSIM-DE has shown to obtain a decreasing tendency in terms of average fitness values. In [7] it was observed that ESSIM-DE begins with a good performance, but as the fire progress, the fitness averages values show a downward trend for the successive steps. In such experiments the population is initialized with random values following a uniform distribution. This process is done only once, at the beginning of the execution. Then, the population evolves by means of the Differential Evolution operators: in DE all individuals participate in the mutation and crossover processes, so in each generation each population member is mutated and crossed with other individuals from the current generation. This approach differs from the way in which the Evolutionary Algorithms apply the operators, metaheuristic used by ESSIM-EA, in which the number of individuals participating in the evolutionary process is determined by a parameter defined by the user. In our experimentation, the usage of a value lower than 50% the total individuals is a configuration for which ESSIM-EA has obtained a good performance, regarding the predictions quality. This characteristic constitutes a marked difference between both metaheuristics. Therefore, this difference would possibly produce a negative impact on the results quality obtained by ESSIM-DE.

Taking into account the way in which each metaheuristic applies the evolutionary operators, it was proposed to analyse the distribution of the population fitness in the different prediction steps. The associated hypothesis is that ESSIM-DE can have a premature convergence: the whole population evolves in an accelerated way during the first time steps, thus it converges to a limited solution space which prevents from obtaining better individuals in the successive steps of the fire evolution. Therefore, it would be possible to alter this distribution by restarting the population at the beginning of each prediction step. In this way, Differential Evolution could explore a new solutions space, independent from the previous ones. Consequently, ESSIM-DE(r) was designed with a population diversification operator applied at the beginning of each prediction step, which **re-initializes the population** with random values within the range of each variable, following a uniform distribution.

Table 1. Real fire cases description: dimensions, slope, initial time, end time and time step for each case.

Case	Width (m)	Length(m)	Slope (degr.)	Ini. T. (min)	Incr. (min)	End T. (min)
A	95	123	21	2	2	12
B	60	90	6	2	2	10
C	75	126	19	3	1	9

With the aim of verifying the hypothesis, it was proposed to compare the distribution of the fitness reached by both ESSIM-DE and ESSIM-EA. To do this, both methods were subjected to experimentation using different cases of controlled burns carried out in Serra de Louçã, (Gestosa, Portugal) [9]. The size of each map was defined according to the available area, the characteristics of the land and the requirements of the project. For each case, discrete time intervals have been defined representing the spread of the fire front. Table 1 describes the characteristics of the three cases used in this work. It is important to note that ESSIM-EA and ESSIM-DE use a calibration step. Then, in order to feed the prediction chain, both methods cannot make predictions in the first instant of time.

The fitness of each population member was registered, with a population size of 200 individuals, and its distribution is analysed by means of boxplots. In order to facilitate the understanding of results, we selected the outputs obtained in an execution of case study C, consisting of six simulation steps, and the finalization condition was established to reach 15 evolutionary generations in each step.

Figure 2 shows three graphs corresponding to the second, fourth and sixth simulation step obtained with ESSIM-EA. To simplify the analysis, each chart includes three boxplots that represent the distribution of the population every five iterations.

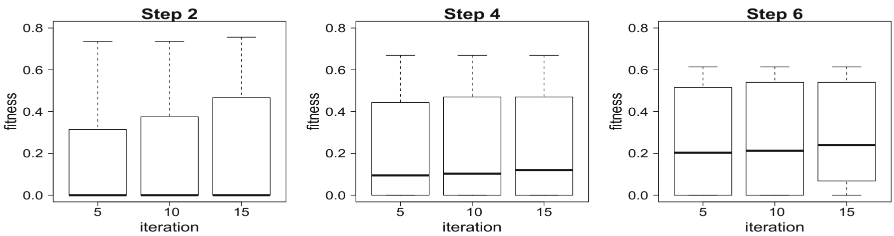

Fig. 2. Population fitness distribution obtained by ESSIM-EA for case C.

As can be seen from Fig. 2, in the second step the population starts with fitness values closer to zero (the median is close to zero). As the population evolves through different generations, the distribution changes slightly towards higher values. It can be seen that in iteration 15 of the sixth simulation step the median reaches a value close to 0.2 and the distribution boxplot reaches a maximum value of 0.6 (higher whisker).

Figure 3 shows the fitness of the population corresponding to the second, fourth and sixth simulation steps for ESSIM-DE. Unlike the previous case, it can be clearly seen that at the end of the second simulation step the population reaches fitness values closer to 0.8. It is also observed in the second simulation step that after five iterations the population has low distribution, which causes the method to reach its maximum exploration capacity, therefore in the successive steps Differential Evolution can not provide improvements. In this example, as well as in the rest of the considered cases, it is observed that ESSIM-DE converges faster than ESSIM-EA. This behaviour causes an accelerated tendency of the solutions towards local optima in the initial time instants of the fire spread. Therefore, in the last steps the metaheuristics can not bring improvements, which leads to a fitness declining tendency.

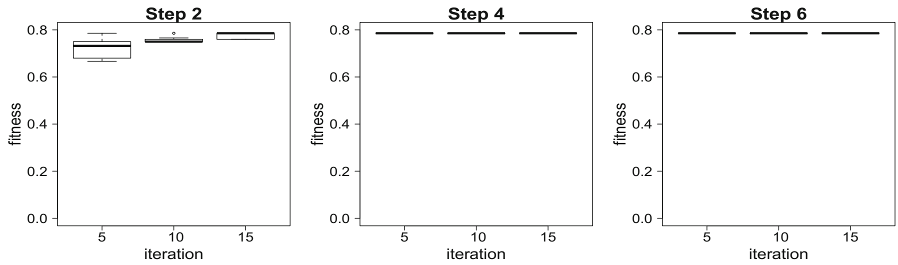

Fig. 3. Population fitness distribution obtained by ESSIM-DE for case C.

Ideally, it is intended that the developed methods obtain both short-term and reliable solutions, but the response speed and the high probability of convergence are often contradictory objectives [10]. This is the case of ESSIM-DE, since it obtains short-term solutions, with good quality in the first prediction steps, but with a decreasing trend. With the aim of improving the quality of the prediction, the population diversification operator of ESSIM-DE(r) allows the incorporation of a new solution space at the beginning of each prediction step. In this way, the original processing scheme of Differential Evolution is not altered and the optimization of the individuals is carried out according to the prediction step being considered. This variant of the method was named ESSIM-DE(r), to distinguish the version that includes the operator of diversification with restarting of the populations, with respect to the original version.

4 Experimentation and Obtained Results

To validate the proposal, different experiments were carried out with ESSIM-EA, ESSIM-DE and the new approach ESSIM-DE(r), using the three controlled burns cases of Table 1. In each experiment, the results obtained with 30 different seeds were averaged. The island model was configured with 5 islands, 7 *workers* per island in all methods. The migration process involves 20% of the population

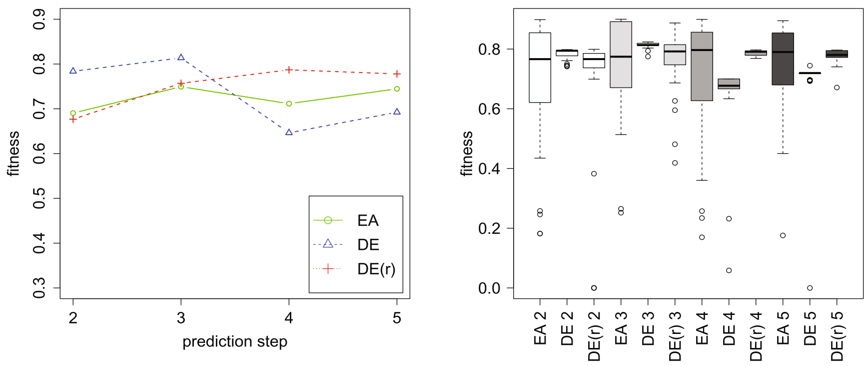

Fig. 4. Experiment I. *Left*: Average fitness values. *Right*: Distribution of the fitness prediction values.

individuals, and is carried out in each iteration. The finalization condition in the evolutionary process, per step, consists in reaching a fitness threshold of 0.7 for the best member of the population. This threshold was established taking into account a fitness value that represents an acceptable prediction quality. The size of each population was defined as 200 individuals. For ESSIM-DE and ESSIM-DE(r) the same configuration of evolutionary parameters was used: crossover probability 0.3, mutation factor 0.9, binomial crossover.

Figures 4, 5 and 6 show the obtained results. The left graphs of each figure correspond to the averages fitness values obtained for each prediction step and method. In each graph, the x axis represents the different prediction steps, and the y axis represents the average fitness values obtained from evaluating the predicted map with respect to the real map of the fire's progress. To simplify the notation, ESSIM-EA is symbolized by "EA", ESSIM-DE by "DE", and the ESSIM-DE(r) is symbolized "DE(r)". The left graphs of each figure represent the distribution of the 30 results obtained with different seed, grouped by colors (gray scale) according to the prediction step. The cases A, B and C of Table 1 were used in the experiments I, II and III, respectively.

Experiment I: It can be seen from the left graph of Fig. 4, that ESSIM-DE obtains the best fitness values for the first two prediction steps. However, the fitness values decline as the fire progresses. For its part, ESSIM-DE(r) obtains better results than ESSIM-EA in prediction steps 3, 4 and 5 with average fitness values close to 0.8. A low distribution of the fitness results obtained by ESSIM-DE(r) is also observed from the right graph of Fig. 4. This property is desirable for methods that operate with metaheuristics, since it is an indicator of the robustness of the method in effectively solving different instances of the problem [8]. According to both characteristics, we can conclude in this experiment that ESSIM-DE(r) is the method with the best performance.

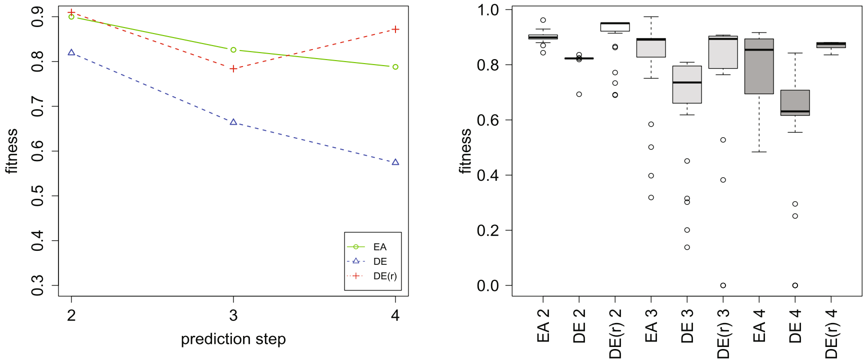

Fig. 5. Experiment II. *Left*: Average fitness values. *Right*: Distribution of the fitness prediction values.

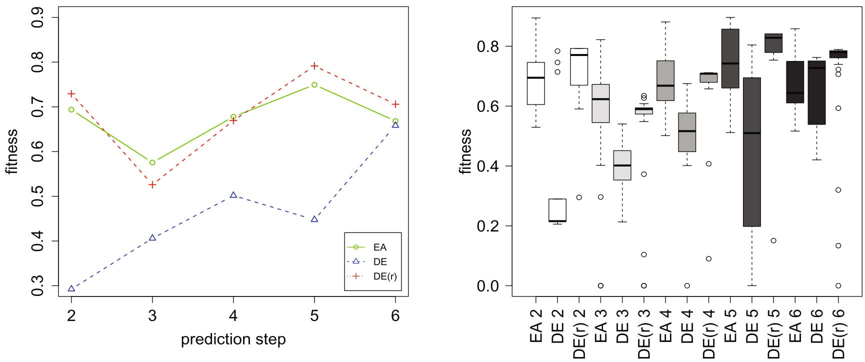

Fig. 6. Experiment III. *Left*: Average fitness values. *Right*: Distribution of the fitness prediction values.

Experiment II: The case used in experiment II consists of four simulation steps. It can be observed from the analysis of the left graph from Fig. 5, that ESSIM-DE and ESSIM-EA have fitness averages values decreasing tendency. However, this behaviour is not reflected in step 4 for ESSIM-DE(r), which obtains an average value close to 0.9 (remember that a fitness value of 1 is equivalent to a perfect prediction). Moreover, ESSIM-DE(r) obtains a very low distribution of the results in the fourth step (see right graph of Fig. 5), which indicates an excellent performance.

Experiment III: It can be observed from the left graph of Fig. 6, that ESSIM-DE(r) significantly improves the averages of fitness obtained with respect to ESSIM-DE, and obtains average values higher than those obtained by ESSIM-EA for prediction steps 2, 5 and 6. It is also possible to see from the boxplots in the right graph of Fig. 6, that ESSIM-DE(r) obtains a lower distribution of the results for these steps. Therefore, it is again corroborated that the proposal is effective, improving the performance of the original version of ESSIM-DE and surpassing the results obtained with ESSIM-EA for three prediction steps.

Table 2 shows the average execution times obtained for each experiment. In the experiments A and B, the proposal implemented with ESSIM-DE(r) to restart the population in each step causes the convergence to be slower, which leads to obtaining average execution times greater than ESSIM-DE. However, either of the two versions ESSIM-DE or ESSIM-DE(r) obtains better response time than ESSIM-EA, with a reduction of up to 80%.

Table 2. Average execution times

Experiment	ESSIM-EA	ESSIM-DE	ESSIM-DE(r)
I	01:01:15	**00:49:05**	00:54:20
II	00:50:10	**00:27:49**	00:32:48
III	02:11:38	00:41:20	**00:25:53**

From the analysis carried out, we can verify that there is a direct relationship between the convergence speed of the metaheuristics used as a search engine and the quality of the predictions obtained. The proposal to improve the quality of predictions has proven to be effective for the test cases considered: ESSIM-DE(r) has improved the quality of the solutions found, compared to the results obtained by both ESSIM-EA and the original version of ESSIM-DE, with low distribution of results. The execution times for ESSIM-DE(r) are similar and even lower than the original version of ESSIM-DE. All this indicates that the improvement proposal has been effective for the considered experiments.

5 Conclusions

This paper presents an alternative to improve the quality of the solutions obtained by the ESSIM-DE method, based on the analysis of the fitness population distribution at the beginning of each prediction step. It was corroborated that ESSIM-DE has a high convergence speed at the initial instants of the fire evolution. Therefore, in the last prediction steps DE can not provide improvements, which leads to a decreasing trend in the obtained fitness values. A variant was proposed to mitigate this effect without modifying the DE metaheuristic processing scheme. To achieve that purpose, it was decided to generate an initial population with uniform distribution at the beginning of each prediction step. This variant of the method was called ESSIM-DE(r), and it has been shown to improve the quality of the predictions, obtaining low distribution of the results for the cases considered.

This proposal considers the generation of a new search space at the beginning of each prediction step. However, in some cases it may be convenient that certain individuals from the population persist throughout the simulation, with the objective of maintaining some of the environmental conditions along the different prediction steps. In this sense, the proposal presented in this article does not allow to conserve such characteristics, since the entire population is regenerated in each step. For this reason, as future works we plan to analyse other alternatives to get out of stagnation without regenerating a completely different search space. The objective is to study and define a mathematical model that allows us to stablish the distribution that the population should follow at the beginning of each prediction step.

Acknowledgements. This work has been supported by UTN under the projects EIUTIME0003939TC and EIUTNME0003952, and by MEC-Spain under the project TIN2014-53234-C2-1-R. The first author would like to thank CONICET for the PhD Grant provided.

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