International Conference on Computational Science, ICCS 2012

Coupling wind dynamics into a DDDAS forest fire propagation prediction system

Carlos Brun∗, Tomàs Artés∗, Tomàs Margalef∗, Ana Cortés∗

Computer Architecture and Operating Systems Department, Escola d’Enginyeria, Universitat Autònoma de Barcelona, Campus UAB, Bellaterra 08193, Spain

Abstract

Natural hazards are significant problems that every year cause important loses around the world. A good prediction of the behavior of the hazards is a crucial issue to fight against them and to minimize the damages. The models that represent these phenomena need several input parameters and in many cases, such parameters are difficult to know or even to estimate in a real scenario. So, a methodology based on the DDDAS paradigm was developed to calibrate the input parameters according to real observations of the behavior and evolution of the hazard. Such calibrated parameters are then used to provide an improved prediction for the next time interval. This methodology was tested on Forest Fire Propagation Prediction with significant results. The developed methodology takes the fire behavior and propagation during a time interval and then searches for the values of the input parameters that best reproduce the propagation of the fire during that interval. Several Artificial Intelligence (AI) methods were applied to carry out this search as fast as possible. The values of the parameters that best reproduce the behavior of the fire were then used as input parameters to predict the propagation during the next time interval. These parameters were considered constant during both time intervals and a single value for each parameter was used for the calibrating process and for the prediction stage. This methodology fits on the DDDAS paradigm since the prediction is dynamically driven by the system evolution. However, there are several parameters that are not constant through time, but they may vary dynamically. In the case of forest fires, a typical example is the wind. In some cases, when the time interval is short an average value for the wind can be a feasible value, but when the time interval is longer, in most cases, a single value cannot represent the variability of the wind. We can estimate wind behavior applying some complementary model. In this work, we are going a step further considering the dynamic behavior of such parameters. We propose an extension of the existing prediction scheme that takes into account the dynamically changing parameters by coupling a weather prediction system on a DDDAS Forest Fire Propagation Prediction system.

Keywords: fire, prediction, DDDAS, calibration, wind, simulation, fire spread, genetic algorithm

∗ Email addresses: carlos.brun@caos.uab.es (Carlos Brun), tomas.artes@caos.uab.es (Tomàs Artés), tomas.margalef@uab.es (Tomàs Margalef), ana.cortes@uab.es (Ana Cortés)
1. Introduction

Hurricanes, tsunamis, floods or forest fires, among other natural disasters still continue producing devastating effects on the world [1]. Computational Science provides tools to tackle these phenomena and thus, to minimize their impact. Researchers from different fields develop models that try to represent and predict the behavior of such hazards [2][3][4][5]. Such mathematical and physical models require some input parameters describing the conditions and environment where the hazard is happening. Each model representing a particular hazard has its own input parameters, but also different models describing the same phenomenon can consider different input parameters. In some cases, such mathematical and physical models are used to build simulators that predict the evolution and behavior of the considered phenomenon. These simulators are usually computationally intensive applications that handle a large number of input parameters in order to give a prediction of the evolution of the hazard on a certain future time. The quality of this prediction does not only depend on the model itself, but it is strongly influenced by the accuracy of the input parameters. In most real cases, it is not possible to know precisely the values of the input parameters beforehand and this drawback limits significantly the accuracy of the predictions provided by the models. It must be pointed out that parameters can be classified according to their time evolution and spatial distribution. Concerning time evolution, there are parameters that are constant along time. For example, the terrain topography and the vegetation type of a particular area are constant. Other parameters vary along time, but their variation is much slower than the evolution of the phenomenon and can be considered constant during a particular hazard, but their value must be evaluated for each particular case. This is the case of the moisture contents of vegetation. The value of this parameter depends on the temperature, precipitation, and so on, but the vegetation dries in some days or even weeks, not in minutes. Finally, there are parameters that vary very quickly, such as wind speed and direction, that can change suddenly. Even when there are no sudden changes in their values, these parameters do not have constant values for long periods of time. So, obtaining accurate data representing the state of a natural phenomenon at a particular instant is not a trivial task. In the case of forest fires, the models provide good results under stable, controlled and known conditions. Such situations imply small fires propagating for short periods of time. During such short periods of time the weather conditions can be considered static and the terrain burned can be considered uniform. However, when real scenarios are considered, fires propagate for longer time intervals and burn wide areas with variable conditions. So, in these cases the size of the studied area is much larger and irregular. Meteorological data are collected from weather stations, which are often far from the focus of the forest fire and the data acquisition frequency is not always the expected one. Therefore, it is so important finding sensitive solutions to the dynamic evolution of dynamic parameters. This point is the object of study of this work. This paper is organized as follows: Second section introduces the two-stage prediction methodology and describes the constraints encountered. Section 3 describes the inclusion of the dynamic behavior of some parameters such as wind speed and wind direction in the two-stage prediction methodology. In the following section some experimental results are presented and finally section 5 summarizes some conclusions of the work.

2. Two-stage prediction methodology

The classic way of predicting forest fire behavior relies on the evolution results provided by a certain forest fire spread simulator. Typically, the input parameters needed by the underlying fire simulator such as the initial state of the fire front (RF = real fire), terrain characteristics, vegetation types, meteorological information and so on are obtained/estimated at a certain time $t_i$, fed into the simulator in order to provide a fire front evolution at a later time $t_{i+1}$. Comparing the simulation result (Simulated Fire = SF) from time $t_{i+1}$ with the advanced real fire (RF) at the same instant, the forecasted fire front tends to differ to a greater or lesser extent from the real fire line. One reason for this mismatch is that the classic prediction of the fire is based on a single set of constant and uniform input parameters. To overcome this drawback, a simulator independent data-driven prediction scheme was proposed to optimize dynamic model input parameters [6]. Introducing a previous calibration step as shown in Figure 1, the set of input parameters is calibrated before every prediction step. The solution proposed come from reversing the problem: how to find a parameter configuration such that, given this configuration as input, the fire simulator would produce predictions that match the actual fire behavior. This process is defined as a parameter calibration process. Once, the input parameter set that best describes the current behavior of the fire has been determined, this set of parameters could also be used to describe best the immediate future, assuming that meteorological conditions remain constant during
the next prediction interval. Then, the prediction becomes the result of applying to the model a set of adjusted input parameters. This two-stage fire prediction methodology reduces the negative impact of input parameters uncertainty. In the Calibration stage we use a Genetic Algorithm (GA) where the evolution operations applied in the GA are driven according to the observed real fire behavior. Population is formed by a set of scenarios, and each scenario - an individual - represents a configuration of input parameters. Each parameter is considered a gene of an individual for the GA. For every scenario, a simulation is executed to reproduce the behavior of the fire during the time interval \( t_i - t_{i+1} \). The population of scenarios is evolved by applying the data driven GA a certain number of iterations. The individual that provides the best adjustment among the simulated and real propagation after this number of iterations is introduced in the simulator with the real fire front at time \( t_{i+1} \) to provide a prediction at time \( t_{i+2} \) (SF \( t_{i+2} \)). This methodology follows the DDDAS paradigm [7] since it takes the actual evolution of the system to determine the values of the parameters that control the system.

![Figure 1: Two-stage prediction methodology](image)

As we have just mentioned, this two stage prediction strategy provides good results when the working hypothesis is accomplished, that means, that environmental conditions keep quite similar through the whole process (Calibration and Prediction stages). These conditions are feasible in the case of prescribed burnings where the conditions of the terrain, vegetation, and weather are easily controlled. In these cases, the terrain is bounded to some thousands of square meters, with fairly stable weather conditions, uniform vegetation type and short spread times (few hours or less). Figure 2.a shows one of this burnings. However, when this methodology is transferred to large forest fires, there is a substantial change in fire conditions. In these cases, the terrain may reach hundreds of hectares, so the topography could be very irregular, vegetation will probably be heterogeneous, there could be changing weather conditions both in terms of place and time, and, furthermore, the fire can last several days (see Figure 2.b). The dynamic behavior of parameters such as wind speed and wind direction cannot be represented by a single value during the calibration time interval and the same value for the prediction time interval. In a previous work, a first approach to overcome this drawback was proposed [8]. In that work, a mechanism to detect sudden changes in wind conditions was introduced so that when a sudden change is detected on the wind conditions, the calibrated value for the wind parameters were not used in the prediction stage, but the measured value of the wind parameters at the beginning of the prediction stage was injected as input parameter in the prediction simulation. However, the main limitation of that methodology is to evaluate the continuity of the new value of the wind parameters along the whole prediction time interval. If the sudden change is just a peak in the wind conditions and, it is not representatives for the whole prediction interval, the inclusion of such value in the prediction stage is unrealistic. So, new methods and strategies must be introduced in the DDDAS Forest Fire Propagation Prediction System to be able to tackle the conditions of real big fires.

From the previous discussion it can be stated that including wind dynamic behavior in the two-stage prediction process must improve fire spread prediction quality when dealing with large scale forest fires. Such wind dynamic behavior must be considered in both stages, calibration and prediction. In the calibration stage, the data concerning the time interval \( t_i - t_{i+1} \) is available. So, in this stage, the simulations executed to reproduce the behavior during the interval \( t_i - t_{i+1} \), can be fed with the real measured values of the wind parameters during that interval. It implies that the simulation of the forest fire propagation does not consider constant values for the wind parameters, but the measured value for each time subinterval is injected in the simulator. So, these wind parameters are not introduced in the individuals of the GA and are not calibrated. The other parameters concerning moisture contents and vegetation features are calibrated in the calibration stage. This methodology is represented in Figure 3.

An additional advantage of the introduction of the wind parameters in the calibration stage instead of calibrating them as another gene is that the search space for the GA is significantly reduced and, therefore, the other parameters considered in the GA can reach better values and this fact allows reaching smaller calibration errors in shorter time. In the prediction stage, it is not possible to introduce the exact dynamic values of the wind parameters beforehand. To overcome this limitation a numerical weather prediction (NWP) model [9] can be used to predict the wind dynamic behavior coupling the above described forest fire spread prediction system and a NWP (see Figure 4). In this case, the quality of the forest fire propagation prediction significantly depends on the quality of the wind parameters prediction obtained from the NWP. A similar idea has been recently proposed in [10][11][12]. These works show the benefits of considering the influence of the heat flux generated by the fire itself into the surface wind of the meteorological model.
However, those approaches are focused on interfacing intra-models for executing a unique fire simulation evolution. In our work, as it has been stated, we do not rely on a unique simulation, but on the execution of thousands of them. The way we propose to couple both models are in a pipeline way were the values obtained at each NWP step is fed in the corresponding fire simulation step as is shown in Figure 4.

Figure 4: Calibration stage with dynamic observed parameters injection

4. Experimental results

In this section we describe the experimental study carried out to demonstrate the prediction quality improvements when coupling forest fire spread model with weather forecast systems. FARSITE simulator [13], based on Rothermel fire propagation model[14], has been used as forest fire spread simulator and, as it was previously mentioned, we rely on Genetic Algorithm (GA) as a Calibration strategy. We used a population size of 50 individuals and the number of iterations has been set to 10. In order to avoid random effects, each experiment has been repeated ten times and the results shown below are the mean value of the corresponding ten results. As a experiment’s fire to test our proposal, we have used a synthetic fire. This experiment’s fire is generated using a synthetic irregular topography where the size of the terrain is about several thousand square kilometers. The map has 459 rows and 550 columns and, every cell has a resolution of 30 meters. This synthetic terrain is divided in 4 regions (see figure 5). The first region is a flat terrain followed by an upslope of 26 degrees corresponding to the second region. The third region is a downslope equivalent to the second region and finally, there is another flat terrain that ends the map. Vegetation is the same in the whole terrain and it is based on model 7 from Albini classification [15], based on a chaparral and shrub fields vegetation. Experiment’s fire wind varies from 3 to 15 mph in both experiment’s fires used as benchmark. The ignition point has been placed in the first region and, due to wind conditions, fire propagates towards second region.

The fire propagates during 8 hours and wind direction and wind speed is changed every 30 minutes. Calibration stage will consider the time interval from hour 0 to 4 and Prediction stage will predict the fire behavior from hour 4 to 8. In particular, we are interested in showing the benefits of predicting very dynamic parameters such as wind speed and wind direction when the working hypothesis for the two-stages prediction method is not accomplished. For this purpose, we organize this section in two parts:

- Homogeneous conditions scenarios: in this set of scenarios we will introduce a slight variability in wind parameters from Calibration stage to Prediction stage in such a way that the working hypothesis is accomplished;
- Heterogeneous conditions scenarios: in this set of scenarios sudden changes are introduced both in wind speed and wind direction during the Prediction stage and, therefore, the working hypothesis is broken.
In both cases, we carry out three different kinds of experiments. The first kind of experiment is the basic two-stage experiment (Experiment 1). In these experiments, the wind conditions, moisture values and fuel conditions are introduced as genes in the individuals of the GA population. So, the wind speed and wind direction are calibrated by the genetic algorithm as the other parameters. During the time interval $t_i - t_{i+1}$, the values of the parameters are considered constant. The calibrated values provided by the genetic algorithm for all the parameters are then used as input parameters for the prediction stage during the time interval $t_i - t_{i+1}$.

In the second kind of experiments (Real data assimilation Experiment 2), the wind conditions are not calibrated, but their measured values are assimilated dynamically on each subinterval (1 hour) in the simulations of the calibration stage. We consider that wind speed and direction are measured every 60 minutes instead of the 30 minutes real wind evolution. In real wildfire cases, the wind data frequency depends on meteorological data sources of the studied zone. These measured values are not the same as the ones which are used to generate experiment’s fire but these values have some measurement error. So the parameters that are calibrated by the GA are the moisture parameters and fuel conditions. In the prediction stage, the calibrated moisture and fuel parameters and the last measure of the wind parameters are used. So, the prediction is based on a single measured value for the wind conditions.

The third kind of experiment is the model coupling experiment (Experiment 3). In these experiments, the calibration stage behaves like in experiment 2. The wind conditions are assimilated dynamically and the moisture and fuel parameters are calibrated. However, for the prediction stage the wind conditions are provided by a NWP model, such as WRF. The experiment’s synthetic fire considers that the wind conditions changes every 30 minutes. For testing our approach, we assume that the NWP model provides values that have a small deviation from the ones of the fire used as benchmark. So, we are not injecting the real value of the wind conditions, but we are injecting certain perturbation on these values. The range of the perturbation is generated considering the statistical behavior of weather predictions. Table 1 summarizes how each one of the three kind of experiments manages the most sensitive input parameters such as wind speed and wind direction and the four moisture components: moisture content of dead fuel at 1 hour (M1), moisture content of dead fuel at 10 hours (M10), moisture content of dead fuel at 100 hours (M100) and moisture content of live fuel (Mherb).

Table 1: Settings of wind, moisture and fuel characteristics input parameters for each experiment.

<table>
<thead>
<tr>
<th>Prediction scheme</th>
<th>Input. Parameters</th>
<th>Calibration Stage</th>
<th>Prediction Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment 1: Basic two-stage prediction</td>
<td>Wind</td>
<td>Random Values</td>
<td>Calibrated values</td>
</tr>
<tr>
<td></td>
<td>Fuel Moisture</td>
<td>Random Values</td>
<td>Calibrated Values</td>
</tr>
<tr>
<td>Experiment 2: Real Data Assimilation</td>
<td>Wind</td>
<td>Real Data Sampling</td>
<td>Real Unique Value</td>
</tr>
<tr>
<td></td>
<td>Fuel Moisture</td>
<td>Random Values</td>
<td>Calibrated Values</td>
</tr>
<tr>
<td>Experiment 3: Models Coupling</td>
<td>Wind</td>
<td>Real Data Sampling</td>
<td>Forecasted Values</td>
</tr>
<tr>
<td></td>
<td>Fuel Moisture</td>
<td>Random Values</td>
<td>Calibrated Values</td>
</tr>
</tbody>
</table>

Figure 5: Elevation map of synthetic terrain used in the experiments
experiment’s synthetic fire, and in the 3 experiments for the homogeneous scenarios. Figure 7 shows the time evolution of wind speed and wind direction considered in the experiments for the heterogeneous scenarios. It is important to note what is an homogeneous and an heterogeneous scenario in this work. In homogeneous scenarios, the average of the values in calibration stage is similar to the average in prediction stage. Although the values of wind components of experiment’s fire in Figure 6 are very irregular the average of these values in every stage is almost the same. In heterogeneous scenarios (see figure 7), the difference of the average of these values between stages is greater than in homogeneous conditions.

The quality of each approach is measured by an error function. The error function considered is the symmetric difference among the real burned area and the predicted burned area. In the optimal case, the real and the predicted burned area coincide and the symmetric difference is 0. The following subsections show the experimental results for the homogeneous and heterogeneous conditions scenarios.

4.1. Homogeneous conditions

The experiments settings used in this experimental block correspond to a wind speed and wind direction samplings with low variability between calibration and prediction stage. The average of wind speed values in calibration stage is 8 mph and 9.25 in prediction stage. In wind direction case, the average is 258.3 degrees in calibration stage and 255.6 in prediction stage. As we can observe, the conditions are almost the same on average. Under this favorable conditions, the basic two-stages prediction method best works. Figure 8 represents the mean errors obtained in the three described experiments for the calibration and prediction stages.

It can be observed in Figure 8 that the calibration and prediction errors are quite similar in the three experiments. This was the expected behavior since the wind conditions are quite stable during the whole calibration and prediction stages and then a single value can represent the wind behavior quite successfully. However, even in the favorable case, the results show a tendency to reduce the error when the weather prediction model is introduced and the wind values for the prediction stage are considered.
4.2. Heterogeneous conditions

In this case, wind conditions (speed and direction) are not constant, but they present a higher degree of variability between stages. The average of wind speed values in calibration stage is 6.1mph and 11.5 in prediction stage. This average, in wind direction case, is 225.4 degrees in calibration stage and 305 degrees in prediction stage. It means that the wind conditions are significantly different in the calibration and prediction intervals. Figure 9 presents the mean error values for the 3 considered experiments in the calibration and prediction stages.

It can be observed that the calibration error is quite similar in the three experiments, because the wind conditions are more or less stable during that interval. However, since there is a sudden change in the wind conditions during the prediction interval, the prediction error is significantly different. Experiment 3, where the wind conditions during the prediction stage are injected from the predictions of a NWP model reduces the error significantly. Experiment 2, that considers the wind conditions at time $t_{i+1}$ for the whole interval $t_i - t_{i+1}$, produces the worst prediction results since the wind conditions considered are not representative for the time prediction interval.
5. Conclusions

Natural hazard evolution prediction is a key issue to minimize the damage. There are physical and mathematical models that try to represent the behavior of such hazards. These models require certain input parameters that in some cases are difficult to know or even estimate during a real emergency. This input parameter uncertainty is a serious drawback and provoke that in most cases the evolution predictions are not enough accurate. A two stage methodology was developed. In this methodology a calibration stage based on observation of real evolution was introduced to determine the values of the parameters that best represent the evolution of the hazard. However, there are certain parameters that present a dynamic behavior and vary during the evolution of the emergency. For these dynamic parameters the calibration process is not feasible when the condition changes from the calibration interval to the prediction interval. In this case it is necessary to introduce some complementary model that can predict the evolution of the dynamic parameters to inject the predicted values for these parameters in the prediction stage. In this work, the forest fire propagation has been considered. The wind speed and direction are parameters that affect the fire propagation, but they have a dynamic behavior and in most real cases they are not constant during the calibration and prediction stages. This is particularly true when the fire takes several hours or even days and burns hundreds of hectares. So, the coupling of a Numerical Weather Prediction model has been considered with the DDDAS forest fire propagation system has been considered. The results show that when the wind conditions are quite stable the estimation of a constant value for the wind is a good approach. However, when the dynamic behavior is more significant and the wind conditions vary from the calibration to the prediction stage the wind parameters cannot be calibrated but they must be predicted by a weather prediction model. The preliminary results are very significant and the prediction error is reduced.

Acknowledgements

This research has been supported by MICINN-Spain TIN2007-64974 and TIN2011-28689-C02-01.

References


