Genetic Ensemble (G-Ensemble) for Meteorological Prediction Enhancement

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Abstract— *The need for reliable predictions in environmental modelling is long known. Particularly, the predicted weather and meteorological information about the future atmospheric state is crucial and necessary for almost all other areas of environmental modelling. Additionally, right decisions to prevent damages and save lives could be taken depending on a reliable meteorological prediction process. Lack and uncertainty of input data and parameters constitute the main source of errors for most of these models. In recent years, evolutionary optimisation methods have become popular to solve the input parameter problem of environmental models. We propose a new prediction scheme that uses a Genetic Algorithm for parameter estimation in Numerical Weather Prediction Models (NWP) to enhance prediction results. The new approach is called Genetic Ensemble (G-Ensemble) and it has been tested using historical data of a well known weather catastrophe: Hurricane Katrina that occurred in 2005 in the Gulf of Mexico. Obtained results provide significant improvements in weather prediction.*

Keywords: numerical weather prediction; evolutionary computing; genetic algorithm; ensemble prediction; parameter estimation.

1. Introduction

Weather forecasting and prediction is an ongoing demand since thousands of years. Agriculture, education, entertainment, industry, astronomy, etc. usually benefit from an accurate knowledge of the weather future state. Global weather predictions are held by governments and international scientific institutions, to provide information about the present and time evolution of the atmospheric situation. However, regional predictions in certain zones are done by local organizations, governments, and scientific centers to provide predictions on basis of fine-coarse resolutions.

Weather time evolution is represented by numerical models that are commonly solved by means of computing facilities. Efforts initiated in the 1950s when the USA National Weather Service (NWS) [1] began to utilize some of the early versions of computers to make large-scale weather forecasts. Since that time, computers have become faster and more sophisticated being able to provide the scientific community (particularly to the weather forecasting community) with High Performance Computing platforms, which allow the execution of highly computing demanding weather forecast simulations. However, scientific applications continue to be more complex while research is getting more sophisticated as a result of the natural human growth of requirements. Higher accuracy, larger time scales, more complex problems and less waiting time constitute some of the new demands that should be considered from a computational point of view.

Numerical Weather Prediction (NWP) models are considered as soft-real time applications. The importance of having a degree of accuracy in the prediction in a certain time is a real challenge. Thus, ongoing investigations concentrate on methods to enhance the process of prediction, and to get results of this process faster.

As most simulation software works with well-founded and widely accepted models, the need for input parameter optimisation to improve model output is a long-known and often-tackled problem. Particularly in environments where correct and timely input parameters cannot be provided, efficient computational parameter estimation and optimisation strategies are required to minimise the deviation between the predicted scenario and the real phenomenon behaviour. With the continuously increasing availability of computing power, evolutionary optimisation methods, especially Genetic Algorithms (GA), have become more popular and practicable to solve the parameter problem of environmental models.

This work presents a new meteorological prediction scheme that uses evolutionary optimization methods that enhance the quality of weather forecast by focusing on the calibration of input parameters.

The rest of the paper is organized as follows: Section 2 gives an overview of NWP models with a brief description of the Weather Research and Forecasting Model (WRF), which constitutes the most commonly used model for weather and meteorological predictions. Section 3 focuses on the importance of accuracy in NWP models and it describes also the most widely used methods for NWP enhancement in practise. In section 4, the proposed prediction scheme (*G-Ensemble*) is presented and described. Section 5 presents

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experimental results obtained with a test case, where we compare our proposal with other enhancement methods. Finally, conclusions and future work are described in section 6

2. Numerical Weather Prediction Models and WRF

Numerical Weather Prediction is the process of guessing the future state of the atmosphere based on current weather conditions. Mathematical models are used to do the job, which treats the atmosphere as a fluid. As such, the idea of numerical weather prediction is to sample the state of the fluid at a given time and use the equations of fluid dynamics to estimate the state of the fluid at some time in the future.

Certain areas where atmosphere future conditions are to be predicted are represented by three dimensional uniform-gridded-rectangles referred as domains. The input data which corresponds to the actual state of the atmosphere is called initial conditions. Those initial conditions are assigned to all points of the grid. The horizontal distance between grid points is referred as the resolution of both the initial conditions and prediction results. Regional models (also known as limited-area models, or LAMs) allow for the use of finer grid spacing (higher resolution) than global models because the available computational resources are focused on a specific area instead of being spread over the globe. This allows regional models to resolve explicitly smaller-scale meteorological phenomena that cannot be represented on the coarser grid of a global model. Hence, a NWP model will guess the new values of the initial conditions over future time scale.

The Weather Research and Forecasting (WRF) [2] is a widely-used numerical weather prediction model, which is considered as a next-generation mesoscale numerical weather prediction system designed to serve both operational forecasting and atmospheric research needs. WRF is composed of a variety of programs to facilitate prediction process, such as extracting global terrain data, designing domains, facilitating for real observations to be injected while model integration, and post-processing outputs.

In this work, we developed a new methodology for meteorological prediction enhancement using WRF as the Numerical Weather Prediction model. Although we have applied our methodology to WRF, the proposed strategy is a model-independent design, which could also be used with other existing NWP models such as the PSU/NCAR Mesoscale Model [3] known as (MM5).

3. Related Work

Reliable weather predictions may not prevent disasters, but at least they help in preventing their horrible effects, such as reducing the possibility of large property damages and even could help in saving lives. Furthermore, accurate predicted meteorological variables are critically needed for other environmental modelling systems. For example, wind direction and velocity variables are needed as precise as possible to predict the expansion direction and velocity of a fire propagation disaster predicted by wildfire models. It is clear that, in such cases, accurate predictions may contribute also to save human lives. Air pollution modelling and the short behaviour of natural disasters like hurricanes are other examples where reliable predictions of meteorological variables are also necessary.

The importance of reliable weather predictions motivated relevant improvements of NWP in the last 30 years. Efforts have been done in the field to enhance predictions [4], however, many sources of errors still remain. The main ones are the availability and accuracy of input data (initial conditions) on higher resolution basis, the possibility of data injection of real observations during prediction process and physical parametrization.

Physical parametrization is the representation of sub-grid-scale physical processes, that is, some meteorological processes are too small-scale to be explicitly included in NWP models. Hence, parametrization enables the representation of these processes by relating them to variables on the scales (the points of the gridded domain) that the model resolves. For example, an important meteorological process is the surface flux of energy transmitted by the terrain which helps in enhancing the prediction of other important variables like near-surface temperature, sea surface temperature and even near-surface wind velocity variables. This process normally occurs in scales less than 1 kilometre, while NWP models predicts normally on domains of grid-scales higher than 1 kilometre. Parametrization is needed in such cases to represent this process on a certain domain scale. Other examples are the typical cumulus cloud which has a scale of less than 1 kilometre, the amount of solar radiation that reaches the ground, and interactions with the surface, including the generation of drag and waves by orography. And so, all of these processes must be parametrized before they can be included in the model.

Summarizing, there is an important need to get reliable weather predictions, while it is also known that the major sources of error that reduce prediction accuracy are input data [5], availability of observed data, and the parametrization process. Thus, the efforts to enhance NWP are mainly focusing in enhancing input data, enabling injection of observed data, and estimating correctly the parameters of sub-scale parametrization process.

The two mostly used NWP enhancement methods are Three-Dimensional Variational Data Assimilation (3DVAR) and Ensemble Prediction System (EPS), which are still a center of continuous research. Actually, both methods fall within the general approach of Data Assimilation (DA) [6] for numerical prediction models. A Data Assimilation system combines all available information about atmospheric state to produce an estimate of initial conditions valid at a prescribed analysis time. It proceeds by analysis cycles. In each analysis cycle, observations of the current (and possibly, past) state of the atmosphere are combined with the results from a NWP model (the forecast) to produce an analysis, which is considered as "the best" estimate of the initial conditions of the system. DA tries to balance the uncertainty in input data and in the forecast. The model is then advanced in time and its result becomes the forecast in the next analysis cycle.

Next, we describe in more detail the two approaches that are most widely used for NWP enhancement.

3.1 Three-Dimensional Variational Data Assimilation

3DVAR [7] uses information which include observations, previous forecasts (background or first-guess), their respective errors and the laws of Physics to produce the analysis.

The basic goal of the 3DVAR system is to produce an "optimal" estimation of the true atmospheric state at analysis time, which is achieved by finding an iterative solution of a prescribed cost function, described in detail in [7]. This solution represents a minimum variance estimate of the true atmospheric state having two sources of data: background (previous forecast) and observations. This process includes the implementation of certain algorithms to estimate background, and observation errors.

The main drawback of this method consists of the necessity of roll-back the simulation process in order to inject the new data in such a way that corrects the observed error in a progressive way as simulations go on. This way of working increases the execution time of the prediction process due to the need of re-starting the model execution from scratch.

3.2 Ensemble Prediction System (EPS)

Stochastic or "ensemble" forecasting is used to account for uncertainty. It involves multiple forecasts created with an individual forecast model by using different physical parametrizations or varying initial conditions. The ensemble forecast is usually evaluated in terms of an average of the individual forecasts concerning one forecast variable, as well as the degree of agreement between various forecasts within the ensemble system, as represented by their overall spread [8], [9]. In [10] they show how NWP models are sensitive to the choice of physical parametrization and how an ensemble could be established using these parametrizations.

A set of forecasts is then produced (each of which has a different set of initial conditions or a different physical parametrization) using a deterministic model to predict the future state of the atmosphere, and by assuming that the model is perfect without other errors, then the mean of all of the executed simulations (forecasts) is considered to be the true future state of the atmosphere.

The implementation of this method begins with the process of determining how to select the set of the various initial conditions or parametrizations as presented in [11]. As soon as this set is established, the corresponding simulations are executed to predict the relative evolution of atmospheric fields in the short future time.

EPS could be considered as a parallel method as each ensemble member is actually a stand-alone simulation, which can be executed independently of the others. Therefore, the main drawback of this scheme is the need of a huge computing power to be able to run all simulations in parallel.

4. Genetic Ensemble (G-Ensemble)

In this section, the Genetic Ensemble (*G-Ensemble*) approach for prediction enhancement is described. Although *G-Ensemble* uses the same principles of the EPS, it clearly differs in the way of how ensemble members are obtained and executed. The main idea of an EPS is to reflect possible variations in the ranges of some input parameters, thus, they simply run a variety of predictions, each of which is initiated with a different combination of those input parameters. Then, the average of all predictions results is considered as the best prediction as it actually reflects a range of variations in certain input parameters. We propose a new scheme of prediction, shown in figure (1) where we introduce a pre-prediction phase or stage, called Calibration Phase, which ends at the moment where real observations are available. Hence, the whole prediction process will be formed of two stages: Calibration and Prediction, which we describe below.

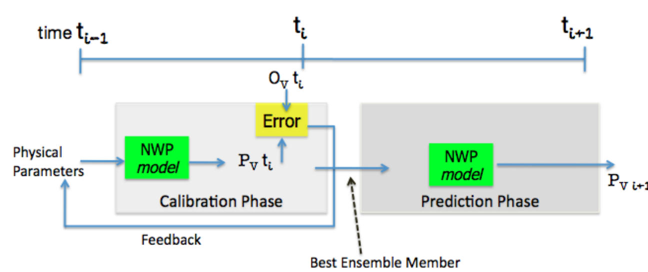

Fig. 1: Two-phase prediction scheme; t_i is time 00:00 of prediction process, t_{i-1} is a time instant previous to Prediction Phase (initial time of Calibration Phase), t_{i+1} is the future time to be predicted. "O_V" is an observed meteorological variable at time t_i, "P_V" is the predicted variable at the same time using a NWP model.

4.1 Calibration Phase

Considering that t_i is the instant time from which the meteorological variables are going to be predicted, Calibration Phase starts at a time prior to prediction time and ends at time 00:00 of prediction period, i.e. calibration is done within the period (t_{i-1}, t_i). Knowing that real observations of meteorological variables are available at time t_i, the objective of this phase is to look for the combination of the physical parameters, which produce less error compared to these observed meteorological variables at the end of the phase (at time t_i). That is, as in EPS, we initialize a set of simulations randomly, each of which has a different physical parametrization combination. This initial set, which we call *initial ensemble*, is run by the NWP model to predict meteorological variables at time t_i, then we use GA functions to obtain an improved ensemble set (which has less errors compared to observations at time t_i) and the process is repeated again many times to a certain number of iterations. At the last iteration of the GA, Calibration Phase exits with calibrated ensemble members that we refer as *G-Ensemble*, each of which has a calibrated combination of physical parameters, which produced less error than those of the *initial ensemble*. At that point, we have two alternatives for the Prediction Phase: 1) to apply the classical EPS scheme using the obtained *G-Ensemble* set, or 2) to select the ensemble member of the *G-Ensemble* with minimum error, to be the single ensemble member of the simulation that will conduct the Prediction Phase. We call this approach *Best Genetic Ensemble Member (BeGEM)*.

A relevant point to be considered in the Calibration Phase is the error definition being one of the core elements of this phase. In this work, we propose two different error functions to be used, what we call Single-Variable and Multi-Variable. Depending on the error function used, we have designed two *G-Ensemble* strategies: *Single-Variable G-Ensemble* and *Multi-Variable G-Ensemble*, which are described below.

4.1.1 Single-Variable G-Ensemble

The Calibration Phase is done with the goal of enhancing predictions for a single meteorological variable. The error function for the evaluation of ensemble members in our GA is the Root Mean Square Deviation $RMSD$ or Error $RMSE$, shown below in equation(1). This error function is a frequently-used measure for the evaluation of meteorological predictions [12], which measures the differences between values predicted by a model or an estimator and the values actually observed from the variable being estimated. In $RMSD$ equation, x_{obs} is an observed value of a variable x and x_{pre} is the predicted one for the same variable.

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(x_{obs,i} - x_{pre,i})^2}{n}} \tag{1}$$

Using $RMSD$ error in the Calibration Phase limits our *G-Ensemble* to be oriented to enhance predictions for one meteorological variable at a time. For example, we can use it to enhance predictions of Temperature or Precipitation, but not for both at the same time. This occurs because the error used produces a value of the variable unit that can not be compared with other variables. In order to overcome such a drawback, we proposed an alternative error function, which we refer as *Multi-Variable G-Ensemble*.

4.1.2 Multi-Variable G-Ensemble

The calibration is done with the goal of enhancing the prediction of multiple meteorological variables at the same time. To bypass the limitation imposed by $RMSD$ error, we use the Normalized $RMSD$, see equation (2).

$$NRMSD = \frac{\sqrt{\frac{\sum_{i=1}^{n}(x_{obs,i} - x_{pre,i})^2}{n}}}{x_{obs(max)} - x_{obs(min)}} \tag{2}$$

The Normalized $RMSD$ (referred as $NRMSD$) is the value of $RMSD$ divided by the range of the observed values of a certain variable. $NRMSD$ indicates the error percentage of the predicted value of a certain variable, compared to its observed values. In order to consider more than one variable at a time, we evaluate $NRMSD$ for all variables, and then, we consider the addition of all of them as the Multi-Variable error function. For example, the $NRMSD$ of a model that predicts Temperature (T) and Precipitation (P) is the percentage obtained by the summation of two Percentages: $NRMSD(T)$ and $NRMSD(P)$, as shown in equation (3).

$$Error = NRMSD(var1) + NRMSD(var2) = value\% \tag{3}$$

Therefore, the Calibration Phase and, particularly the GA, considers this error function as the objective function used to sort the intermediate individuals of the ensembles.

4.2 Prediction Phase

Once the Calibration Phase is finished, it is the turn of the Prediction Phase. At this point, either the *BeGEM* or the whole *G-Ensemble* set produced by the previous phase will be run by the NWP model. It is expected that this ensemble member will generate better predictions as it shown less error in Calibration Phase. In contrast to the classical EPS, only one simulation is executed here, while in EPS the whole ensemble set is executed.

5. Experimental Test Case

To test our approach, we used historical data of hurricane Katrina [13], see a picture in figure (2). Katrina occurred on August 28, 2005 in the Gulf of Mexico and unfortunately caused the death of more than 1,800 persons along with a total property damage that was estimated at $81 billion (2005 USD).

To Predict meteorological variables, we used WRF as the NWP model and, we used the coupled NOAH Land Surface Model (NOAH LSM) [14] for land surface physical parametrization. At runtime, NOAH LSM provides important values to WRF that correspond to subgrid-scale evolution of land surface variables (surface sensible heat flux,

Fig. 2: Satellite picture of hurricane Katrina on Aug. 29, 2005 at 12:15 p.m

surface latent heat flux, skin temperature, surface emissivity and the reflected short-wave radiation). It calculates these variables depending on a set of parameters that characterize the land surface: *Landuse* and *Soil* parameters [15]. As a result, predictions are enhanced when LSM is used as more subgrid-scale meteorological variables are injected into the model. However, these parameters fall within ranges and small changes in their values produce non-negligible differences in prediction results. The EPS comes at this point to solve the problem by generating a number of predictions, each of which has different values of *Landuse* and *Soil* parameters, hence, the final result of the prediction will be the average of the results of all predictions which are supposed to cover an "acceptable" variation in physical parametrization (land surface parametrization).

The objective of the experiments is to predict meteorological variables evolution from time: 12:00 h. of the day 28/08/2005 to time 00:00 h. of 30/8/2005 (a period of 36 hours in which the major effects of the hurricane were produced). The evolution of meteorological variables is produced every 3 hours.

To get the evolution of meteorological variables at 12:00 h. of 28/08/2005, we used initial conditions of the atmospheric state in the zone three hours before, i.e. model started prediction from time 09:00 of 28/08/2005. For our approach (*G-Ensemble*), the Calibration Phase started from time 00:00 of 28/08/2005 to time 09:00 of the same day.

The variables predicted in our experiments were: *Latent Heat Flux LHF (W/m2)*, *Surface Skin Tempreature TSK (K)*, *2-meter Tempreature (K)*, *10-meter Wind Velocity components U10 and V10 (m/s)*, and the *Accumulated Precipitation RAINC (mm)*.

In the next two subsections, we discuss results by which we make a comparison between classical EPS and the *G-Ensemble*. Furthermore, we also analyse the computational cost incurred by both approaches.

5.1 Ensemble Vs. G-Ensemble

In this section, a comparison of prediction results is done between the classical EPS and our method (*G-Ensemble*). Figure (3) shows an experiment result of using classical EPS of 40 ensemble members (each of which has a different *Landuse* and *Soil* parameters) to predict *Latent Heat Flux LHF* variable. As shown in the figure, each line represents the predicted values of LHF every 3 hours. The dotted line represents the average of all of those predicted values of all simulations, which will be considered as the best prediction result according to the classical EPS.

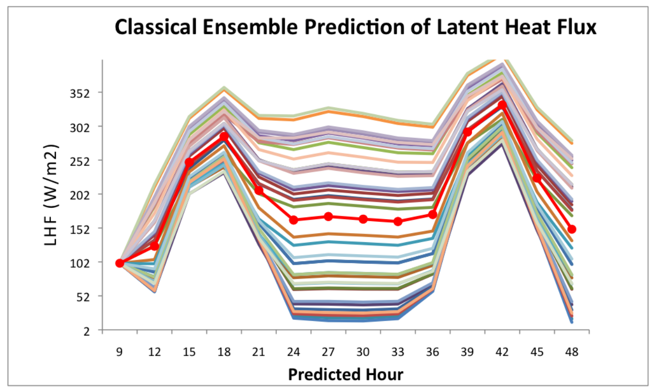

Fig. 3: Classical Ensemble of size:40 to predict Latent Heat Flux LHF.

We applied our method with *Single-Variable G-Ensemble* in two different cases: to predict LHF (results shown in figure 4) and to predict Acc. Precipitation (results shown in figure 5). In both cases, with the same initial ensemble members, we obtained a significant improvement in prediction quality. The Genetic Algorithm of the Calibration Phase was configured to iterate 20 times over an initial population size of 40 individuals (initial ensemble size). Its three main operators were configured as follows: *Selection*: (best one of two) and (roulette), *Crossover*: (probability=0.7, type: two points crossover), and *Mutation*: (probability= 0.2).

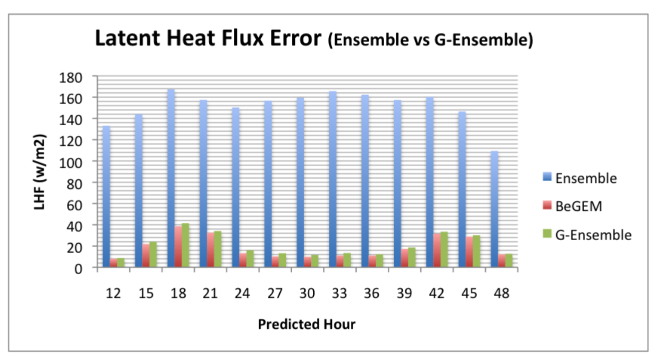

Fig. 4: Single-Variable G-Ensemble; $RMSD$ error in prediction of variable LHF.

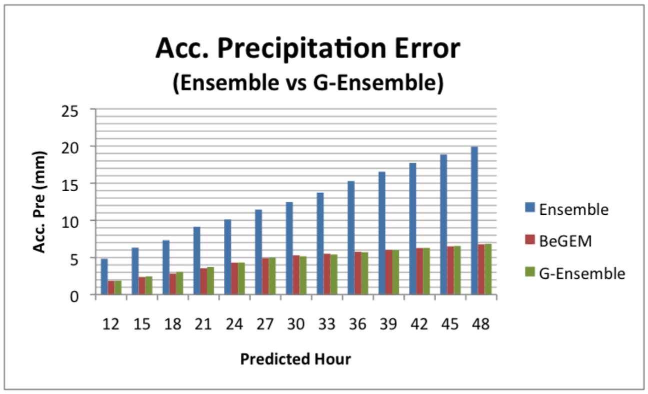

Fig. 5: Single-Variable G-Ensemble; $RMSD$ error in prediction of variable Acc. Precipitation.

The results of the Calibration Phase are the enhanced 40 individuals (*G-Ensemble* members). As shown in figures 4 and 5, the average error of *G-Ensemble* predictions is always less than the average error of the classical EPS referred as Ensemble in the figures. Furthermore, if we just run a single prediction with *BeGEM* of the Calibration Phase, errors are even reduced more.

We also used our approach to enhance predictions of a set of meteorological variables at the same time, by applying the *Multi-Variable G-Ensemble* and using the error $NRMSD$ (shown in equations 2 and 3) in Calibration Phase as the fitness function of the GA. In this case, we were also able to obtain significant improvements in the prediction of a set of meteorological variables at the same time.

Figure 6 shows the results obtained in this case. Again, significant reduction of the $NRMSD$ were obtained in the prediction of a set of meteorological variables together.

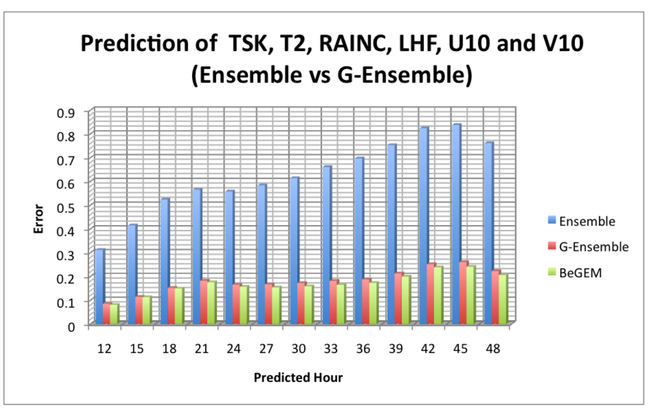

Fig. 6: Multi-Variable G-Ensemble; $NRMSD$ in prediction of variables: Latent Heat Flux LHF, Surface Skin Tempreature TSK, 2-meter Tempreature, 10-meter Wind Velocity components U10 and V10, and the Accumulated Precipitation RAINC.

Additionally, we observed that a reduction of the $NRMSD$ of a set of variables also provides an enhancement in the prediction of each meteorological variable alone. In other words, all six variables were better predicted when *G-Ensemble* oriented to reduce the $NRMSD$ of those variables together. To illustrate these results, we show in figure (7) how the corresponding prediction error of *Latent Heat Flux LHF* was reduced by the *G-Ensemble* oriented to reduce the $NRMSD$ of the six variables (the same effect was observed in the other five variables).

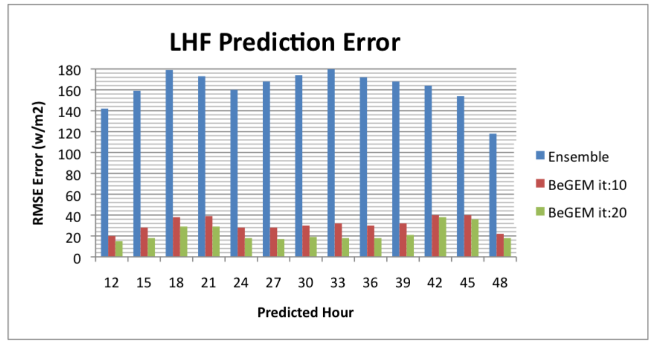

Fig. 7: $RMSD$ prediction error of Latent Heat Flux LHF(W/m2) in prediction using BeGEM produced in iterations 10 and 20 of the Calibration Phase of the Multi-Variable G-Ensemble.

5.2 Accuracy versus Cost

The problem of the uncertainty in NWP initial conditions produces what is called ”imperfectness” in prediction accuracy. The previous mentioned methods, among others [16]–[18], are implemented to reduce the margin of the ”imperfectness” in prediction accuracy. However, the trade-off between cost (execution time) and prediction accuracy is an important factor that should be considered to select the most suitable enhancement method.

In scenarios with a limited number of computational resources, EPS is not an eligible method as it needs lots of resources to execute a set of predictions. Using our approach, we obtained a significant reduction of computational time when we executed an experiment comparing classical ensemble with *G-Ensemble*. Predictions were executed in parallel over a cluster of 80 computing nodes. Figure (8) shows the prediction error of an experiment to enhance prediction of 6 meteorological variables, using classical EPS and the *Multi-Variable G-Ensemble* in 5 different scenarios, which correspond to different GA settings. The execution time of all scenarios and their settings are listed in (table 1).

In four scenarios of *G-Ensemble* (scenarios 2, 3, 4, and 6), we observed a significant reduction in execution time along with its corresponding reduction of prediction error. A classical EPS of 40 ensemble members *Ensemble(40)* could be replaced by any scenario of *BeGEM(40)* calibrated by (5, 10, or 15) iterations of the GA. Similarly, *BeGEM(20)* with 20 initial ensemble members iterated 20 times at

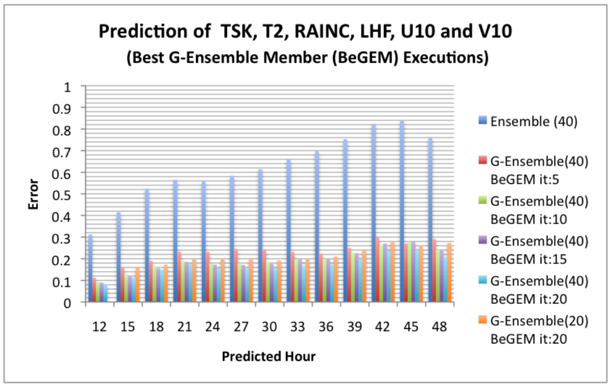

Fig. 8: Multi-Variable G-Ensemble; $NRMSD$ of prediction of variables: Latent Heat Flux LHF, Surface Skin Tempreature TSK, 2-meter Tempreature, 10-meter Wind Velocity components U10 and V10, and the Accumulated Precipitation RAINC.

Table 1: Execution time Vs Scenario

Number	Scenario	G-Ensemble	# of Iterations	Ex.Time
1	*Ensemble(40)*	No	-	1120 m.
2	*BeGEM(40)*	Yes	5	369 m.
3	*BeGEM(40)*	Yes	10	709 m.
4	*BeGEM(40)*	Yes	15	1024 m.
5	*BeGEM(40)*	Yes	20	1549 m.
6	*BeGEM(20)*	Yes	20	709 m.

Calibration Phase constitutes another scenario that reduces both prediction error and execution time. Only in one case (scenario 5), our method incurred in an execution time larger than classical ensemble. This is due to the number of iterations used in the Calibration Phase by the GA, which was 20 iterations. Fortunately, significant improvement in prediction quality (almost similar) is gained by calibrating with less number of iterations (as in scenarios 2, 3, and 4), or by reducing the size of initial ensemble members (as in scenario 6). This means that this case could be prevented by either calibrating with less number of iterations or by reducing the size of initial ensemble members.

In summary, *G-Ensemble* method provides the possibility to select between various scenarios considering a balance between prediction quality and prediction cost.

6. Conclusions and future work

In this work, we have briefly described Numerical Weather Prediction models, along with a description of WRF as one of the most widely used models in the field. We highlighted the importance of the accuracy in NWP models, discussing also the basic two methods used for prediction enhancement. We analysed the penalties incurred by these methods in terms of time execution costs and prediction accuracy.

We have introduced *G-Ensemble*, as a new scheme that enhances weather predictions. It uses an evolutionary algorithm to estimate best possible physical parameters that will provide more reliable predictions.

The *G-Ensemble* prediction scheme showed a significant improvement in prediction quality. Thanks to the enhancement in prediction accuracy, more sophisticated schemes might be developed in the near future by injecting observed meteorological variables at run-time. These results encourage us to continue our research efforts by adding methods that handle real observations and deciding their injection intervals at run-time in order to get more reliable meteorological predictions.

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