

# Tuning G-Ensemble to Improve Forecast Skill in Numerical Weather Prediction Models

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**Abstract**—*The process of weather forecasting produced by numerical weather prediction (NWP) models is complex and not always accurate. Moreover, it is generally defined by its very nature as a process that has to deal with uncertainties. In previous works, a new weather prediction scheme, Genetic Ensemble (G-Ensemble), was presented, which uses evolutionary computing methods. Particularly, it uses Genetic Algorithms (GA) in order to find the most timely 'optimal' values of model closure parameters that appear in physical parametrization schemes, which are coupled with NWP models. The presented scheme showed significant improvement of weather prediction quality and, moreover, the waiting time for an enhanced weather prediction result was reduced by executing a parallel G-Ensemble scheme over HPC platforms. In this work, however, we test the same scheme with different GA configurations regarding its Crossover type and ratio, and by varying its initial population size in order to get better predictions. The main concern behind this work is to provide a more detailed study on how the GA used in G-Ensemble scheme could be tuned depending on the available computational resources in operational scenarios. Finally, experimental results are discussed of a weather prediction case using historical data of a well known weather catastrophe: Hurricane Katrina that occurred in 2005 in the Gulf of Mexico. Obtained results provide significant enhancement in weather prediction.*

**Keywords:** numerical weather prediction; HPC; genetic algorithm; ensemble prediction; parameter estimation.

## 1. Introduction

It is generally agreed that weather has a widespread impact on people's personal and social lives, including their jobs, their recreation, their safety, and their property. When the weather is bad, many activities become more difficult to perform. Commercial transportation slows down on the roads, on the waterways, and in the air. Businesses of all kinds are interrupted by bad weather. Power plants and energy traders rely on knowledge of the weather to

operate their equipment and to deliver power to consumers, government and business. Furthermore, accurate predicted weather variables are critically needed for other environmental modeling systems. For instance, 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.

Weather forecasting that predicts future weather state evolution is realized mainly by Numerical Weather Prediction (NWP) models that are commonly solved by means of computing facilities. That is, a 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 treat 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.

On the other hand, from a computational point of view, NWP models are considered as soft-real time large scale applications. The importance of having a certain degree of accuracy in the prediction in a certain time is a real challenge. Many factors may determine the accuracy of the predicted weather variables: the available computing power for model execution, the model itself, and the input data. Thus, ongoing research concentrates on methods to enhance the process of prediction and get results of this process faster.

However, and as most simulation software works with well-founded and widely accepted models, the need for input parameter optimization to improve model output is a well-known and often-tackled problem. Particularly, in environments where correct and timely input parameters cannot be provided, efficient computational parameter estimation and optimization strategies are required to minimize the deviation between the predicted scenario and the real phenomenon behaviour.

With the continuously increasing availability of computing power, evolutionary and parallel optimization methods, especially Genetic Algorithms (GA), have become more popular and practicable to solve the parameter problem of environmental models.

In [1], a study discussing the sensitivity of forecast skill to a set of NWP model closure parameters (input parameters)

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is provided. Furthermore, *G-Ensemble* prediction scheme is presented, which uses a GA to estimate 'optimal' values for these parameters for a certain forecast, in order to enhance forecast skill. The proposed scheme showed significant enhancement in prediction quality. In this work, more prediction results are presented and discussed regarding different configurations and scenarios of the used GA in the *G-Ensemble* prediction scheme. The aim of the presented work is to show how better predictions could be achieved by tuning the implemented GA in the *G-Ensemble* approach.

The rest of the paper is organized as follows: Section 2 gives an overview of NWP models, a NWP general scheme, and 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 discusses the predictability sources of error in NWP models and also describes the most widely used methods for NWP enhancement in practice. In section 4, *G-Ensemble*) is described briefly. Section 5 discusses 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

Weather stems from the constant evolution of the atmosphere governed by physical laws. Using high-speed computers to solve a complex set of mathematical equations that represents the governing laws, NWP is a technique for simulating the atmospheric evolution in order to delineate the resultant weather changes. The variables involved in the equations include wind, temperature, pressure and moisture content. In principle, given the initial and boundary conditions, the atmospheric variables can be numerically solved as functions of time and form the basis of weather forecast. That is, NWP is described generally as "an initial-boundary value problem": given an estimate of the present state of the atmosphere (initial conditions), and appropriate surface and lateral boundary conditions, the model simulates (forecasts) the atmospheric evolution. The more accurate the estimate of the initial conditions, the better the quality of the forecasts.

Certain areas where atmospherical future conditions are to be predicted are represented by three-dimensional uniform-gridded-rectangles referred as domains or grids. The input data, which describe an estimation of the actual state of the atmosphere, are called initial conditions. Those initial conditions are assigned to all points of the grid. The horizontal distance between grid points is referred as the spatial 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 can not be represented on the coarser grid of a global model. Hence, a NWP model will predict the new values of the initial conditions over future time scale.

The first step of a NWP process is to extract initial conditions that are usually obtained from a global forecasting. These initial conditions are assigned to the domain grid points and, by means of the NWP model applied over a time line, at each pre-defined time period, a new 3-dimensional domain is produced having new (predicted) values of meteorological variables at all grid points.

The Weather Research and Forecasting model (WRF) [2] is a widely-used numerical weather prediction system, which is considered as a next-generation mesoscale numerical weather prediction model designed to serve both operational forecasting and atmospheric research needs.

WRF is composed of a variety of programs to facilitate the prediction process. It includes modules for global terrain data extraction, modules for real observation injection while model integration, and modules for output post-processing. It should be mentioned that 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

NWP models as well as the atmosphere itself can be viewed as nonlinear dynamical systems in which the evolution depends sensitively on the initial conditions. Moreover, weather prediction is, by its very nature, a process that has to deal with uncertainties. The initial conditions of a NWP model can be estimated only within a certain accuracy. During a forecast, some of these initial errors can amplify and result in significant forecast errors. Besides initial-condition error, weather and climate prediction models are also sensitive to errors associated with the model itself. In particular, the uncertainty due to the parameterizations of sub-grid-scale physical processes is known to play a crucial role in prediction quality (e.g., [4]). Prediction errors caused by the uncertainty in physical parameterizations is commonly referred to as model errors. Weather predictability errors are normally subject to two kinds of errors: initial condition errors and model errors.

As it has been stated before, in the case of initial conditions, input data is extracted from global forecasts. Normally, global forecasts are conducted using domains of lower grid resolutions (the distance between grid points is large). This is due to the computational power needed if the whole globe is to be predicted using finer grid spacing. As a result, interpolations are needed to extract initial conditions from lower resolution domains to assign them to local domains of

higher resolution. Unfortunately, this process is not perfect and the assigned values do not reflect the actual real state of the atmosphere. This problem is generally referred as the uncertainty of weather initial state.

On the other hand, 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 smaller than 1 kilometer, while NWP models predicts normally on domains of grid-scales higher than 1 kilometer. Parametrization is needed in such cases to represent this process on a certain domain scale.

By figuring out the main sources of error in predictability of NWP models, and over the past 20 years or so, stochastic or "ensemble" forecasting [5] became as a practical and successful way of addressing the predictability problem associated with the uncertainty in initial conditions. Moreover, several weather prediction centers have addressed this problem by developing operational ensemble prediction systems (EPS) (e.g., [6]). The main idea behind an EPS comes from the fact that the initial state of a certain variable should be seen as a probability distribution and not as a unique value, and thus, the ultimate goal of ensemble forecasting is to predict quantitatively the probability density of the state of the atmosphere at a future time. This is done by running multiple forecasts, each of which is initiated with small perturbations in the estimated initial conditions. Then, an ensemble forecast is usually evaluated in terms of an average of the individual forecasts (ensemble members) concerning one forecast variable, as well as the degree of agreement between various forecasts within the ensemble system, as represented by their overall spread [7].

However, and although it has been realized that there is a stochastic nature of physical parameterizations in ensemble prediction (predictability is sensitive to variations in physical parameters), it has not been straightforward to develop theoretically sound, and also practical, formulations for how to insert parameterization uncertainty into ensemble development [8], [9].

#### 4. G-Ensemble

In this section, Genetic Ensemble (*G-Ensemble*) approach [1] for prediction enhancement is briefly described, as well as the set of the model closure parameters targeted for better estimation. The main objective of the presented scheme is to enhance prediction quality by improving the estimation

of a set of NWP model closure parameters. The study is focussed on finding 'optimal' values of *Landuse* and *Soil* closure parameter (the land surface parameters and the impact they have are described in [10]). The optimization of these parameters will serve as a prove of concept of our method, which could be applied to other parameters. These parameters are found in land surface physical schemes (LSM) (e.g., [11], [12]) that are coupled to most NWP models. The proposed scheme consists of two phases: Calibration Phase and Prediction Phase (depicted in Fig.(1)).

Considering that  $t_i$  is the instant time from which the meteorological variables are going to be predicted, i.e. prediction is done within the period  $(t_i-t_{i+n})$ , Calibration Phase starts at a time prior to prediction time and ends at time 00:00 ( $t_i$ ) of prediction period, i.e. calibration is done within the period  $(t_0-t_i)$ . The process of closure parameter estimation in Calibration Phase proceeds as follows:

- 1) at the beginning of Calibration Phase (time  $t_0$  in Fig. (1): a sample of the targeted parameter values from ensemble proposal distribution is generated (perturbations in closure parameter values);
- 2) the generated parameter values are inserted to the ensemble prediction model;
- 3) an ensemble of forecasts (the prediction model is different for each ensemble member regarding the targeted parameter values) is conducted to predict meteorological variables at time  $t_i$ , where real observations are available;
- 4) evaluation of a fitness function for each ensemble member is done at time  $t_i$ ;
- 5) genetic algorithm functions (selection, crossover and mutation) are used to generate a new ensemble distribution from the set of combinations of closure parameters which score better predicting at time  $t_i$ ;
- 6) the process is repeated iteratively until a predefined number of iterations, or an acceptable error value is achieved.

The used fitness function depends on the number of meteorological variables to be better predicted. That is, if the *G-Ensemble* is used to enhance prediction for one single meteorological variable, the root mean square error (*RMSE*) as shown as shown in equation (1), is used to be the fitness function for the GA. We refer to this approach as *Single-Variable G-Ensemble*. Referring to equation (1),  $x_{obs}$  is an observed value of a variable  $x$  and  $x_{pre}$  is the predicted one for the same variable.

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

In contrast, as it is necessary to enhance prediction for a set of meteorological variables, the normalized root mean square error (*NRMSE*), is implemented as the fitness function to be minimized during Calibration Phase (equation (2)).

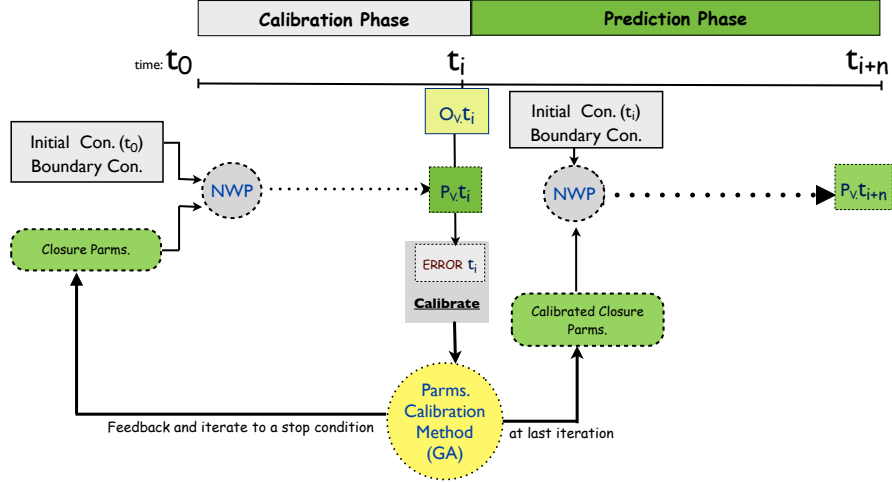


Fig. 1: Two-phase prediction scheme; NWP is the a numerical weather prediction model.  $t_i$  is time 00:00 of prediction process,  $t_0$  is a time instant previous to Prediction Phase (initial time of Calibration Phase),  $t_{i+n}$  is the future time to be predicted. "O<sub>V</sub>" is an observed meteorological variable at time  $t_i$ , "P<sub>V</sub>" is the predicted variable at the same time using a NWP model.

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

This approach is called *Multi-Variable G-Ensemble*. In *NRMSE* equation,  $x_{obs}$  is an observed value of a variable  $x$  and  $x_{pre}$  is the predicted value for the same variable. The Normalized *RMSE* (*NRMSE*) is the value of *RMSE* divided by the range of the observed values of a certain variable. *NRMSE* indicates the error percentage of the predicted value of a certain variable, compared to the range of its observed values. In order to consider more than one variable at a time, we evaluate *NRMSE* for all variables, and then, we consider the addition of all of them as the Multi-Variable fitness function.

Despite the fact that the objective in the presented approach is to minimize the *RMSE* or *NRMSE* in Calibration Phase, as the fitness function used for the evaluation of ensemble members, other fitness functions can be applied in the presented scheme. The GA could be oriented to minimize any other targeted fitness functions.

At the last iteration in the Calibration Phase, the values of closure parameters, which produced the least value of *RMSE* or *NRMSE*, i.e. the ensemble member with the best forecast skill score at time  $t_i$ , is selected to be used in Prediction Phase. This ensemble member is called: Best Genetic Ensemble Member (*BeGEM*). Our hypothesis is that, for short-range weather forecasts, if the forecast skill is improved in the Calibration Phase by a set of a calibrated closure parameters then the same closure parameter values will also improve forecast skill during Prediction Phase.

By now, in Prediction Phase, a deterministic forecast is used in our experiments. In other words, the *BeGEM*, which is the ensemble member having the calibrated closure

parameter values is the single forecast to be conducted in Prediction Phase. However, the produced *BeGEM* could be integrated in any type of EPS considering perturbations in initial conditions during Prediction Phase.

*G-Ensemble* scheme was extended in [13] to evaluate ensemble members according to a window of observations rather than 'one-point' observation. Time windowing to the optimization procedure was introduced and the performance (prediction quality) of *G-Ensemble* was enhanced as the used GA was better guided when more observation intervals were considered in the evaluation of ensemble members. Moreover, *Parallel Multi-Level G-Ensemble* was presented in [14], where a multi-chromosome GA was implemented in *G-Ensemble* scheme to optimize various sets of input parameters and the whole scheme was paralleled using Master/Worker paradigm and was tested on a HPC platform.

The obtained results showed significant improvements in prediction quality and less execution times over classical prediction scenarios. It should be mentioned, however, that the implemented GA in *G-Ensemble* scheme was tested in [1], [13], [14] using the same type of GA Crossover and fixed Crossover and Mutation probability ratios. In the next section, more experiments are conducted and discussed regarding different execution scenarios, were different GA configurations are introduced to *G-Ensemble*, in order to evaluate the gained prediction quality in accordance to each different configuration.

## 5. Experimental Evaluation

To test our approach, we used historical data of hurricane Katrina [15], which 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). The objective of the experiments is to predict the evolution of a meteorological variable 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 model is configured to predict the evolution of meteorological variables every three hours; and the spatial resolution of the domain was 12km. The used NWP model in our experiments was WRF and all Physics schemes were the same for all experiments.

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 predicted variable in the following experiments is the *Latent Heat Flux (LHF W/m<sup>2</sup>)* using the *Single-Variable G-Ensemble* approach. However, it must be pointed out that any other meteorological variable could have been used and similar conclusions would be obtained. Examples of such variables can be find in [1], [13], [14], where both approaches of the *G-Ensemble (Single-Variable G-Ensemble and Multi-Variable G-Ensemble)* are tested to enhance prediction for a set of meteorological variables. The presented results explore the sensitivity of *G-Ensemble* forecast skill to some variations in its GA operations. In particular, we study the sensitivity to the GA Crossover type (one-point and two-points), to the probability to the initial GA population size (initial ensemble members size) and, finally, to the number of GA generation iterations in the Calibration phase.

The goal behind these tests is to provide a more completed insight of the scenarios and possibilities of how to configure an operational *G-Ensemble* according to the time allowed for prediction process and to the number of computing resources available. In the subsequent experiments, prediction errors *RMSE* produced during Prediction Phase of two ways of prediction are compared:

- 1) *Single Variable G-Ensemble* approach, with different initial ensemble sizes, Crossover type and ratio, and different number of iterations in Calibration Phase.
- 2) The *EPS* approach, which is used to refer to the average error of an ensemble forecast conducted by the initial ensemble members used in the first iteration of Calibration Phase (an ensemble forecast such that the prediction model is different for each ensemble member regarding the targeted parameter values, these variables are not calibrated).

Firstly, Fig. (2) shows an experimental result for a classical *EPS* prediction of 40 ensemble members (each of which has a different combination of the targeted closure parameters) to predict (every 3 hours) the evolution of *Latent Heat Flux LHF*. The evolution of the values of *LHF* variable was notably under-estimated in this case. Thus, it could

be easily concluded that there is a significant margin of enhancement in prediction which could be achieved.

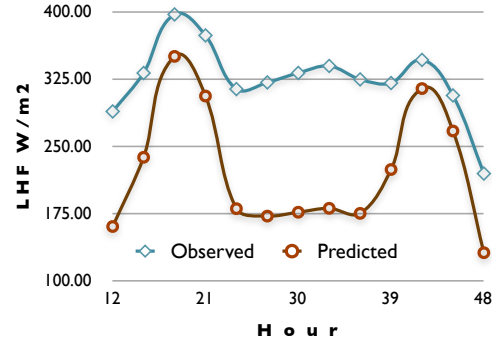


Fig. 2: Classical *EPS* prediction results compared to observed values.

In Fig.(3(a)), prediction error is shown by using the *G-Ensemble* approach with different initial ensemble sizes to predict *LHF* variable compared to the classical *EPS* of the same ensemble sizes. The prediction error of the *G-Ensemble* approach is also depicted alone for the sake of clarity in Fig.(3(b)).

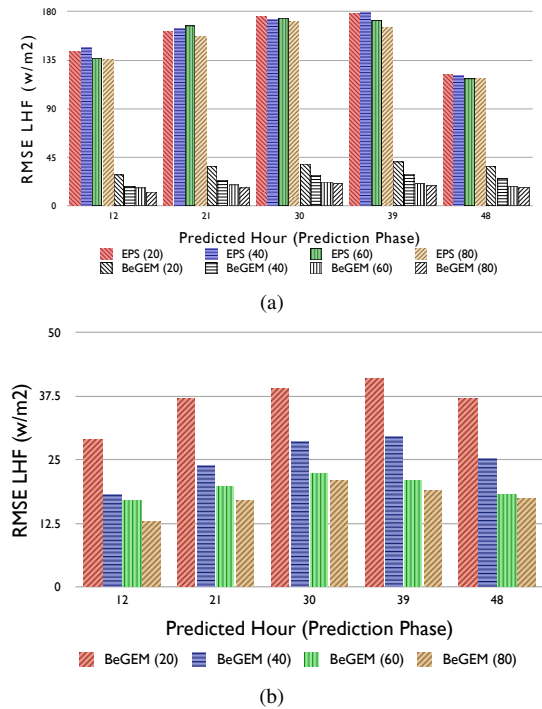


Fig. 3: *RMSE* of *LHF* prediction. (a): *Single-Variable G-Ensemble* prediction error Vs. *Classical EPS* prediction error. Results are of *classical EPS(x)* and the *BeGEM(x)*, where *x* refers to the initial ensemble size. (b): A snapshot of (a) to demonstrate *RMSE* of the different *BeGEM(x)*.

The Genetic Algorithm was configured to iterate 20 times over an initial population size of 40 individuals. Its

three main operators were configured as follows: *Selection*: (elitism: best one of two), *Crossover*: (probability=0.7, type: two points Crossover), and *Mutation*: (probability= 0.2). As shown in Fig.(3), in all cases with different initial ensemble sizes, *G-Ensemble* provides less error values in prediction compared to EPS predictions with the same initial ensemble members. A significant improvement in prediction quality is always gained.

Additionally, it can be observed that increasing the size of an EPS does not produce better results. Actually this happens because EPS results represent an average of the predictions of all ensemble members and, knowing that these members are varied regarding their closure parameters in a random way, using more members does not assure less average error. In contrast, increasing initial ensemble size, which will be calibrated iteratively by the *G-Ensemble* provides better prediction results as observed in the same figure. That is, by increasing the initial ensemble size in *G-Ensemble*, the probability for finding better solutions through GA iterations, also increases.

On the other hand, Fig.(4) shows the GA convergence in the Calibration phase of *G-Ensemble* approach. As such, the error of the best ensemble member through GA iterations is depicted in the figure, using different initial ensemble sizes. As it could be observed, the *BeGEM* produced after 10 iterations when *G-Ensemble* was conducted using an initial ensemble size of 80 members, was equal or slightly better than the same *BeGEM*, produced after 20 iterations when *G-Ensemble* was conducted by 20 initial ensemble members.

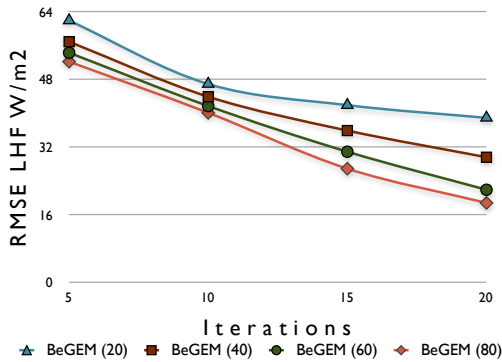


Fig. 4: Calibration phase: *BeGEM* performance through the Calibration phase iterations for different initial ensemble sizes.

Then, according to the availability of computing resources, their number and the interval of availability, a certain scenario of the combinations between initial ensemble size and number of iterations, could be selected. Execution times and *G-Ensemble* scalability on HPC systems for different combinations regarding the number of iterations during Calibration Phase could be found in [14].

We also tested the *G-Ensemble* approach to predict the same meteorological variable (LHF) by changing the type

of the GA Crossover during Calibration phase (Fig. 5(a)), and by changing the GA Crossover probability (Fig. 5(b)).

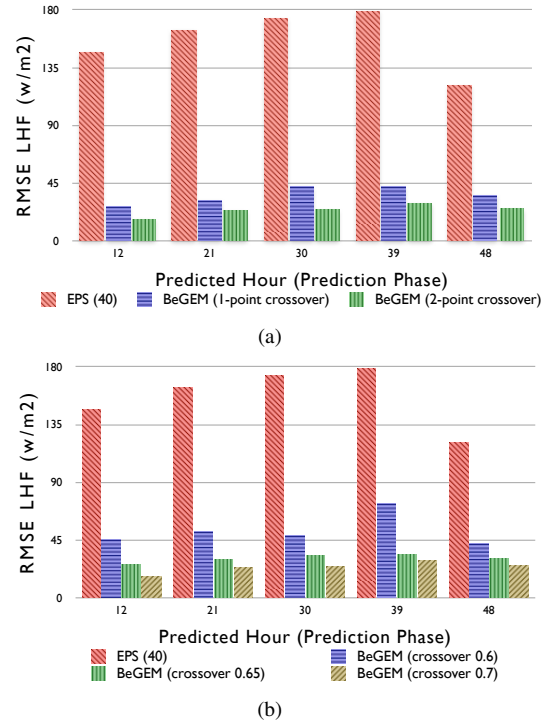


Fig. 5: *BeGEM* RMSE in prediction of LHF produced in (a): using 1-point and 2-point GA Crossover in the Calibration phase, and (b): using 2-point GA Crossover but with different Crossover probability ratios.

The obtained results show that when *G-Ensemble* used 2-points Crossover in its GA during Calibration phase, prediction results were slightly better, and the same happened when Crossover probability was higher.

That is, when configuring the GA implemented in the *G-Ensemble* scheme on a relatively small size of initial ensemble members, better prediction quality could be obtained by 2-points Crossover and higher Crossover probability. Actually, this is due to the size of the initial ensemble size (initial population size): by using 2-point Crossover and a higher probability of Crossover operations, more variations in ensemble members could be obtained during each iteration of the Calibration Phase. This enhances the ability of the GA to look for better solutions over small initial populations, which is normally the case of NWP executions, where ensemble sizes are normally up to 50 ensemble members.

The results obtained in our experiments confirm our hypothesis that, on one hand, better estimation of model closure parameter values enhances weather prediction quality and, on the other hand, the proposed Calibration Phase leads to better estimation of closure parameter values by tuning the used GA. Additionally, different scenarios could

be applied in an operational *G-Ensemble* according to the available computing resources by varying initial ensemble sizes and the number of GA generation iterations.

We can conclude that *G-Ensemble* is a better choice compared to classical EPS. As shown here, *G-Ensemble* outperforms EPS in terms of parameter estimation but it has been also shown in [1], [13], [14] that the proposed *G-Ensemble* approach is cost effective computationally compared to the classical EPS over a parallel computing environment. In those works many execution scenarios were tested over a HPC environment, and the prediction quality was significantly enhanced, whereas, execution times were reduced in comparison with executions of classical EPS in Prediction Phase.

## 6. Conclusions and future work

This work describes our ongoing research focused on enhancing short-range weather forecasting by estimating 'optimal' NWP model closure parameter values, using an evolutionary computing method.

In [1], it was shown how forecast skill is sensitive to model closure parameter values. Moreover, *G-Ensemble* prediction scheme was presented, which aggregated a Calibration Phase to the prediction process, where these parameter values were optimized to improve forecast skill. The *G-Ensemble* prediction scheme showed a significant improvement in prediction quality. *Parallel Multi-Level G-Ensemble* was presented in [14], where a multi-chromosome GA was implemented in *G-Ensemble* scheme to optimize various sets of input parameters. Additionally, the whole scheme was paralleled using Master/Worker paradigm and was tested executing it over a HPC platforms. The obtained results showed significant improvements in prediction quality and less execution times over classical prediction scenarios.

In this paper, a complementary work is introduced by conducting and discussing more experiments regarding different *G-Ensemble* execution scenarios, where different GA configurations are introduced to *G-Ensemble* in order to evaluate the gained prediction quality in accordance to each configuration. As a result, it could be concluded that in scenarios of limited number of the available computing resources, where only small ensemble sizes could be applicable, *G-Ensemble* scheme provides better weather predictions by using 2-point Crossover in its GA, and also by using higher Crossover probability ratio. On the other hand, in scenarios where more computing resources are available, and thus, larger ensemble sizes could be used, our results showed that classical EPS does not enhance prediction

results by increasing initial ensemble sizes, whereas *G-Ensemble* does. That is, forecast skill in weather predictions could be enhanced almost linearly by *G-Ensemble* scheme as the initial ensemble size increases.

These results encourage us to continue our research efforts by testing our scheme over larger sets of model closure parameters. And we are also planning to design methods that handle real observations during prediction process deciding their injection intervals at run-time in order to get more reliable meteorological predictions.

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