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Towards Improving Numerical Weather Predictions by Evolutionary Computing Techniques[☆]

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Abstract

Weather forecasting 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 a previous work, a new weather prediction scheme was presented, which uses evolutionary computing methods, particularly, Genetic Algorithms in order to find the most timely 'optimal' values of model closure parameters that appear in physical parametrization schemes which are coupled with numerical weather prediction (NWP) models. Currently, these parameters are specified manually. Our hypothesis is that the NWP model forecast skill is sensitive to the specified parameter values. And thus, by finding 'optimal' values of these parameters, we aim to enhance prediction quality. In this work however, the same scheme is extended by introducing different ways of prediction evaluation during the process of searching closure parameter values. To verify our new scheme, we show prediction results of an experimental 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; evolutionary computing; ensemble prediction; parameter estimation

1. Introduction

Numerical weather prediction (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 be amplified and result in significant forecast errors.

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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., [1]). Prediction errors caused by the uncertainty in physical parameterizations is commonly referred to as model errors. Being that said, weather predictability errors are normally subject to two kinds of errors, initial condition errors and model errors.

By figuring out the main sources of error in predictability of NWP models, many efforts had been focusing on enhancing prediction quality, mainly on developing sophisticated and skillful next-generation NWP models (e.g., [2] and [3]), addressing the uncertainty of initial conditions by better estimation techniques, and also on developing physical parametrization models or schemes which are nowadays coupled with NWP models and lead to improved predictive skill.

Over the past 20 years or so, stochastic or "ensemble" forecasting [4] became a practical and successful way of addressing the predictability problem associated with the uncertainty in initial conditions. Ensemble forecasting is conducted by better estimations of the atmospheric initial state (initial conditions) which is produced by data assimilation (DA)[5] techniques, and then, initial state perturbations are computed and launched in different forecasts, each is initiated by a perturbed initial state. Early on moreover, several weather prediction centers have addressed this problem by developing operational ensemble prediction systems (EPS) (e.g., [6]). The Ensemble spread finally, is used to indicate forecast uncertainty. 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 [7, 8].

On the other hand, and in contrast to the dynamics of NWP models, which are based on fundamental physical concepts, physical parameterizations, although partly are based on fundamental concepts of physics, involve empirical functions and tunable parameters, which usually referred to as model closure parameters. Practically, all physical parametrization schemes contain closure parameters and typically, expert knowledge and manual techniques are used to define the optimal parameter values, based on observations, process studies, large eddy simulations, etc. Therefore, some parameter value combinations score better than others, but it is very demanding to manually specify the optimal combination.

In [9], it was shown how forecast skill is sensitive to a set of these closure parameters, and moreover, a prediction scheme (*G-Ensemble*) that uses Genetic Algorithm (GA), to estimate 'optimal' values for these parameters for a certain forecast, in order to enhance forecast skill was presented. The proposed scheme showed significant enhancement in prediction quality, and thus, we extend in this paper our proposal by a different implementation for forecast skill calculation when evaluating the score of a set of parameter value combinations.

The rest of the paper is organized as follows: Section 2 gives a brief description of our previous work (*G-Ensemble* scheme) for closure parameter estimation in NWP models. In section 3, the extended version of the *G-Ensemble* scheme is presented and described. Section 4 discusses experimental results obtained with a test case. Finally, conclusions and future work are described in section 5.

2. G-Ensemble

In this section, our Genetic Ensemble (*G-Ensemble*) approach [9] 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 better estimating a set of NWP model closure parameters. Our study focuses 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]) which 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 $(t_0 - t_i)$.

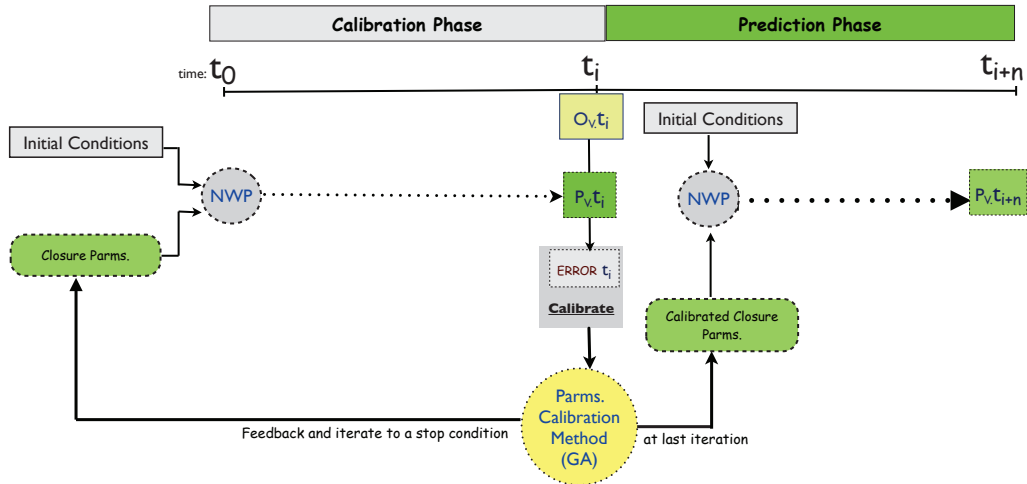


Figure 1: Two-phase prediction scheme; NWP is the a numerical weather prediction model. t_i is time 00:00 of prediction process, t_0 is a time instant previous to Prediction Phase (initial time of Calibration Phase), t_{i+n} is the future time to be predicted. "O_V" is an observed meteorological variable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

The process of closure parameter estimation in Calibration Phase proceeds as follows:

- (i) 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);
- (ii) the generated parameter values are inserted to the ensemble prediction model;
- (iii) 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;
- (iv) evaluation of a fitness function for each ensemble member is done at time t_i ;
- (v) 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 ; and
- (vi) the process is repeated iteratively until an acceptable error value, or a predefined number of iterations is achieved.

The used fitness function depends on the number of meteorological variables to be better predicted, as such, if the *G-Ensemble* is used to enhance prediction for one single meteorological variable, we use the root mean square error (*RMSE*) as the the fitness function for the GA to be minimized. This approach is referred to as *Single-Variable G-Ensemble*. In contrast, as it is necessary to enhance prediction for a set of meteorological variables, the normalized root mean square error (*NRMSE*) is used as the fitness function to be minimized during Calibration Phase, (see equation (1)). This approach is called *Multi-Variable G-Ensemble*.

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

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, the *NRMSE* is evaluated for all variables, and then, the addition of all of them is considered as the Multi-Variable fitness function.

For example, the *NRMSE* of an ensemble member that predicts Temperature (*T*) and Precipitation (*P*) is the percentage obtained by the summation of two percentages: *NRMSE(T)* and *NRMSE(P)*, as shown in equation (2).

$$Error = NRMSE(var1) + NRMSE(var2) = value\% \tag{2}$$

In spite of the fact that the objective in our scheme is to minimize the *RMSE* or *NRMSE* in Calibration Phase, as the fitness function used for the evaluation of ensemble members, other fitness functions are applicable to be used 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 was that, for short-range weather forecasts, if the forecast skill is improved in the Calibrations 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.

3. Extended G-Ensemble

In this section, an extended version of the *G-Ensemble* approach is presented. Precisely, the main change is done in the Calibration Phase, as such, it is supposed that evaluating ensemble members during Calibration Phase according to one single observation for each meteorological variable is not that fair, basically, due to the stochastic nature of NWP ensembles, some ensemble members may change their performance over time. Hence, to help the used GA to take better decisions when selecting the set of ensemble members that will reproduce a consecutive generation of ensemble members in each iteration, *G-Ensemble* scheme is extended such that it becomes capable to evaluate ensemble members according to a window of observations rather than ‘one-point’ observation.

Back to Fig.(1), ensemble members are evaluated according to real observations available at t_i . In contrast, the extended version of our *G-Ensemble* (shown in Fig. (2)), ensemble members are evaluated according to observations available in more than one point during Calibration Phase.

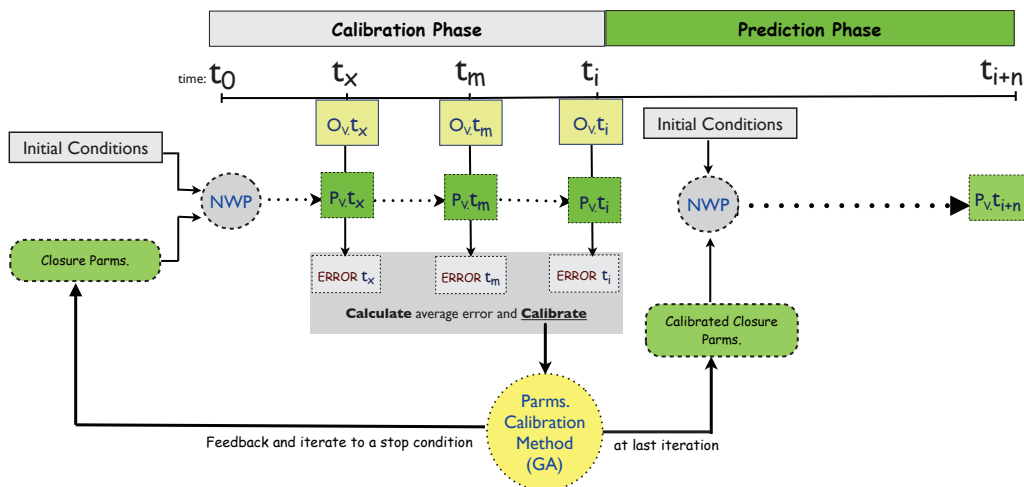


Figure 2: Extended Two-phase prediction scheme; NWP is the a numerical weather prediction model. t_i is time 00:00 of prediction process, t_0 is a time instant previous to Prediction Phase (initial time of Calibration Phase), t_{i+n} is the future time to be predicted, t_x and t_m are time instants within the Calibration phase where real observations are available as in t_i . "O_v" is an observed meteorological variable and "P_v" is the predicted variable.

If prediction is needed to take place from time t_i to $t_i + n$, Calibration Phase is to be conducted in the interval $(t_0 - t_i)$, however, observations could be available at times t_x, t_m (any model time steps that fall within Calibration Phase), as well as at time t_i . Being these observations available, the GA fitness function considers the average error of the three error values calculated at times t_x, t_m and t_i , for each ensemble member according to the three observations available at the same time instants.

The same process is done for Calibration and Prediction as described in the pervious section, however, the *BeGEM* in the Calibration Phase of the extended version of the *G-Ensemble* is produced by evaluating its forecast skill according to a window of observations rather than a 'one-point' observation.

In the next section, experimental results are discussed to verify prediction enhancement gained by the proposed extended *G-Ensemble* scheme.

4. Experimental Evaluation

To test our approach, we used historical data of hurricane Katrina[13], 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 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 model is configured to predict the evolution of meteorological variables each one hour and the spatial resolution of the domain was 12km. The used NWP model in our experiments was the Weather Research and Forecasting (WRF) [2] 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 variables predicted in our experiments were: *Latent Heat Flux LHF (W/m²)*, *2-meter Temperature (°C)*, and the *Accumulated Precipitation RAINC (mm)*.

In the subsequent experiments, prediction errors (*RMS E* and *NRMS E*) produced during Prediction Phase of three ways of prediction are compared;

- (a) *G-Ensemble* approach, where Calibration considers 'one-point' observation, at time 09:00 of 28/08/2005 (*BeGEM(1 - point)*)
- (b) *G-Ensemble* extended approach, where Calibration considers a window of observations, at time 7:00, 8:00 and 09:00 of 28/08/2005 (*BeGEM(window)*).
- (c) The EPS, 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).

It should be mentioned, however, that all the subsequent results represent the average of a set of executions. This is done to assure that the obtained results are reliable by avoiding the randomness which could be produced in GA operations in some cases. Firstly, we show experimental results for two different cases: to predict Accumulated Precipitation (results shown in Fig.5(a)) and to predict Latent Heat Flux (results shown in Fig.5(b)).

The Genetic Algorithm of the Calibration Phase was configured to iterate 15 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).

In both cases, with the same initial ensemble members used in the EPS case, a significant improvement in prediction quality obtained by the *G-Ensemble* approach over the EPS. Additionally, it could be also observed that better enhancements in predictions were obtained by the extended *G-Ensemble* approach.

The extended *G-Ensemble* approach is also used to enhance predictions of a set of meteorological variables at the same time, by applying the *Multi-Variable G-Ensemble* and using the error *NRMS E* in Calibration Phase as the fitness function of the GA. In this case, significant improvements in the prediction of a set of meteorological variables at the same time were also obtained. Fig.(4) shows the results obtained in this case. Again, significant reduction of the *NRMS E* was obtained in the prediction of a set of meteorological variables together and, the extended version of *G-Ensemble* shows a better forecast skill.

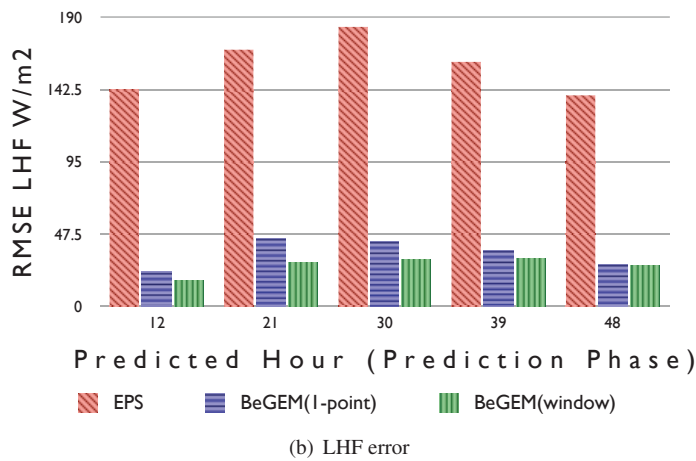
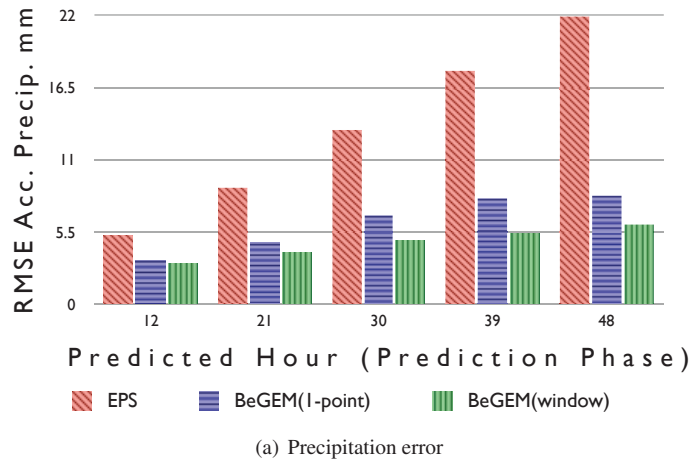


Figure 3: Single-Variable G-Ensemble ; (a): RMSE error in prediction of variable Acc. Precipitation and (b): variable LHF. Results are of classical EPS, BeGEM(1-point) and BeGEM(window) for both variables.

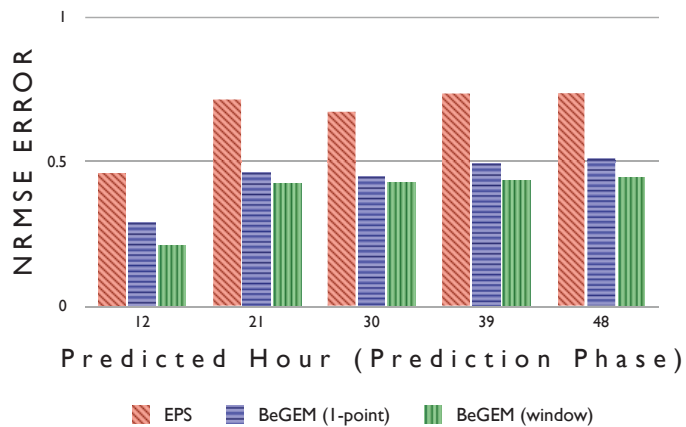


Figure 4: Multi-Variable G-Ensemble; NRMSE in prediction of variables: Latent Heat Flux LHF, 2-meter Temperature, and the Accumulated Precipitation RAINC.

Additionally, it is observed that the reduction in the *NRMS E* of the three variables together, also provides an enhancement in the prediction of each meteorological variable alone. In other words, all variables were better predicted when *G-Ensemble* oriented to reduce the *NRMS E* of those variables together. To illustrate these results, Fig.(5) shows how the corresponding prediction error of each variable was reduced when *G-Ensemble* was oriented to reduce the *NRMS E* of the three variables together.

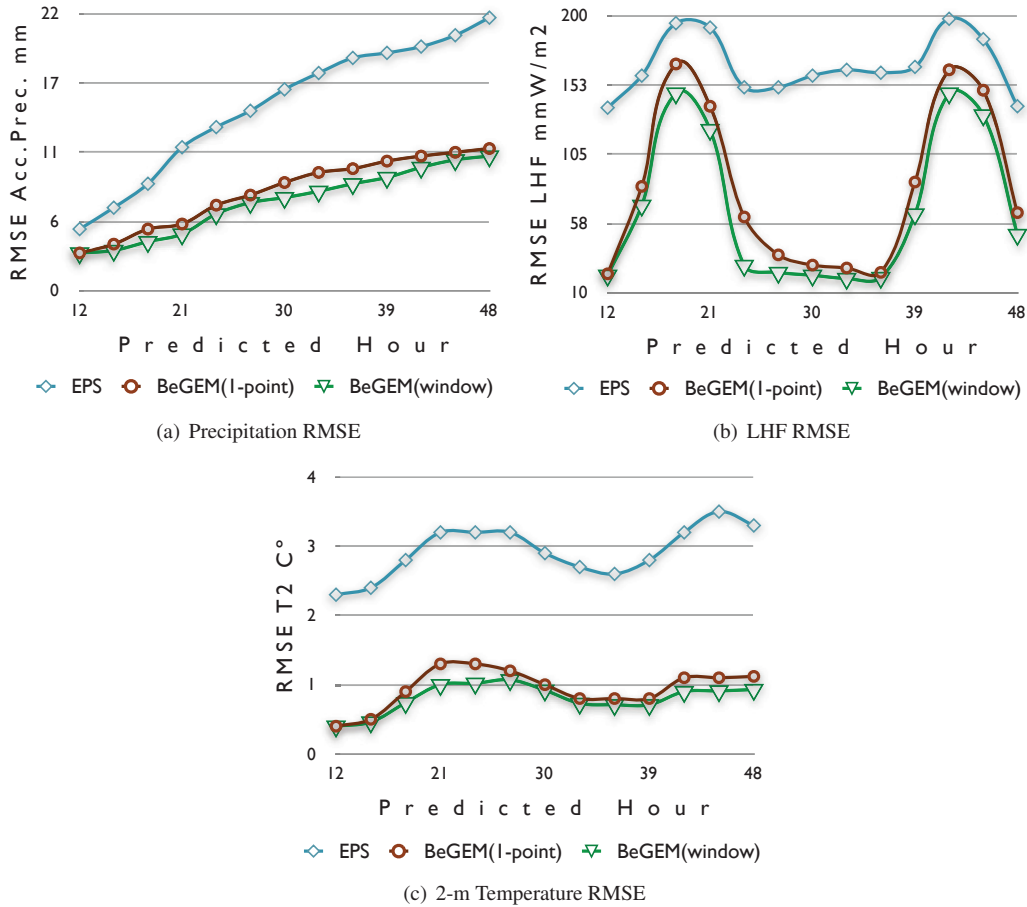


Figure 5: RMSE prediction error of: (a) Accumulated Precipitation RAINC, (b) Latent Heat Flux LHF), and (c) 2-meter Temperature. Prediction using BeGEM (1-point) and BeGEM (window) produced after 15 iterations of the Calibration Phase of the Multi-Variable G-Ensemble.

The results obtained in our experiments approve 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 when it considers a window of observations rather than one single point observation. Actually, we believe that the reason behind this is that, the used GA in the Calibration Phase is better guided by more fairly error value when this error reflects an interval of time rather than one single point, to evaluate the performance of each ensemble member which determines its probability to be selected for subsequent iterations by the GA.

Finally, it was shown in [9] that the proposed *G-Ensemble* approach is cost effective computationally compared to the classical EPS over a parallel computing environment, many execution scenarios were tested over a cluster of 30 computing nodes, and the prediction quality was significantly enhanced, whereas, execution time was reduced in comparison with a classical EPS run in Prediction Phase. Besides, in the extended *G-Ensemble*, no new computations are introduced; fitness evaluation over more than one point is not computing intensive; that is, it involves simple mathematical operations to calculate the average error regarding various observations.

5. Conclusions and future work

This work describes our ongoing investigation mainly focused on enhancing short-range weather forecasting by estimating optimal NWP model closure parameter values, using an evolutionary computing method; genetic algorithm. In [9], it is shown how forecast skill is sensitive to model closure parameter values, moreover, *G-Ensemble* prediction scheme is presented, which aggregates a Calibration Phase to the prediction process, where these parameter values are optimized to improve forecast skill. The *G-Ensemble* prediction scheme showed a significant improvement in prediction quality.

In this paper, *G-Ensemble* is extended in a way in order to consider more than observation point in the evaluation of forecasts during Calibration Phase. This addition enables the genetic algorithm which is used during Calibration Phase, to make better decisions when selecting between forecasts through its iterations. By introducing this capability to our scheme, it was shown by experiments, that forecast skill is improved while no computational cost is added.

Both the *G-Ensemble* and the presented extension, could be integrated in any operational EPS, that is, the produced *BeGEM* with the calibrated closure parameters could be considered as a well-tuned model regarding its closure parameters. Hence, for a certain forecast to be conducted using an EPS (considering perturbations in initial conditions), *BeGEM* provides a ‘physics’ well-tuned model to maximize EPS prediction quality.

These results encourage us to continue our research efforts by testing our scheme over larger sets of model closure parameters, as well, we are 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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