# Dynamic Model Performance-Driven Weighting System for Nowcasting

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## Abstract

*This paper describes a dynamic model performance-driven weighting system for real-time, short term weather forecasting. The selected data sources include three numerical weather prediction models and observations. The performance of each NWP model for the past 6 hours or a specified period is statistically analyzed and continuously evaluated. Based on the performance of the three models, a weight is derived and assigned to each model. A new integrated forecast model is then generated by blending forecasts from the three models with corresponding dynamic weights plus a bias correction. Five major forecast parameters from 22 American and Canadian airports are selected as case studies for development and application of the system. Dynamic model verification is also carried out. The integrated model shows enhanced nowcasting accuracy. The resulting components for this system can be widely used for processing data from different models, different locations, and different weather parameters in real time.*

**Keywords: Numerical weather prediction models, nowcasting, model performance-driven weighting system, model verification**

## 1. Introduction

Nowcasting is short-period weather forecasting and usually refers to the weather at the current time and the weather changes over the next 6 hours. Currently, nowcasting techniques are primarily based on extrapolation of radar echoes, satellite imagery of clouds and/or lightning location data and various modeling approaches. Different numerical weather prediction (NWP) models, such as the Canadian GEM (Global Environmental Multiscale) regional and LAM (Limited Area Modeling) models, the American RUC (Rapid Update Cycle) model, are being used to do nowcasting. However, there are a number of challenges in using them in real time. Major challenges include: the uncertain performance of each model to produce quality forecasts under various weather conditions, how to select the best model for the forecast, and the lack of evaluation / verification of the forecast accuracy.

The present research is developing a system that can: 1) automatically compare observations and forecasts from different NWP models, 2) evaluate each model's performance, 3) continuously calculate weights for each model, 4) generate a new integrated model, and 5) select an optimal model for nowcasting. Simultaneously, the system performs model verification and tests whether the integrated model improves forecast accuracy.

## 2. Data processing

The system is comprised of 5 major components: i) data pre-processing, ii) data transformation, iii) data interpretation and evaluation, iv) forecast decision making, and v) forecast presentation.

In this study, data from three NWP models along with observational data are collected and analyzed. The real-time data from RUC, GEM regional and LAM models, and surface observations are transmitted from different data source locations into the data server. The components residing on the application server perform a range of functions, such as: interpolation, extrapolation, calculation of derived quantities, model performance evaluation, error and accuracy analysis of model prediction, regression analysis, and derivation and analysis of the performance-driving weights. Data from 22 American and Canadian airports (Toronto International plus its alternates) are used to develop and test the system. The selected parameters include: temperature, relative humidity, wind speed, wind direction, and cross wind.

## 3. Results and analysis

There are five major features of the system:

1) *Checking model performance in real time.* The user can select different models to check model performance for the past specified period. Statistics such as correlation coefficient, minimum, maximum, bias, and total root square error for each parameter are calculated.

2) *Continuously generating a new integrated model.* The weight of each NWP model is calculated based on model performance. Generally, the better the model performance, the higher the weight assigned to the model. If one model generated a very high percentage of error and the correlation coefficient was very small, all weights for the NWP models will be adjusted. When the forecasts from all 3 NWP models have similar bias (much higher or less than observation), bias corrections are made. A new integrated model is then generated by blending forecasts from the NWP models with their corresponding weights and bias correction.

3) Dynamically selecting an optimal model from several different models. It is assumed that the near-future model performance will be similar to its performance during the past few hours. With continuous comparison of each of the 4 model performance (3 NWP & Integrated), the model with the best performance for a specified parameter for the past six hours is deemed the "Optimal" model for the nowcasting period.

4) Performing dynamic model verification. Methods for model verification include calculation of mean error, bias, mean absolute error, root mean square error, mean square error, correlation coefficient, confidence interval and optimal model hits.

5) Disseminating model outputs in an easy to understand way. The system can generate a highly optimized, integrated forecasting presentation on the fly. The outputs from models and observations can be presented in various formats such as time series graphs, error bars, scatter plots of the error, box plots, and tabulated of statistics. Figure 1 shows an example of a graphical output.

Figure 1 is a time series graph (from Hamilton airport) with three parts: a period from the past 12 to 6 hours, the past 6 hours to now (at 18:54 p.m, June 9, 2009), and now to the next 3 hours. The graph can be used to explain how the system combines the model outputs and observations to generate integrated forecasts. For the first part – left of the green vertical line, the graph plots forecasts from three NWP models and observations. An integrated forecast was generated based on three model performances in the past six hours plus bias correction and plotted in a cyan color with solid square symbols on the second part, where observations and forecasts from three NWP models are also plotted. Comparing these two parts, the graph reveals how the three model forecasts performed in the past and how the integrated forecasts are generated and performed in the next forecast period of 6 hours. All NWP model forecasts plus integrated forecasts for the future 3 hours are plotted on the third part (right of red vertical line).

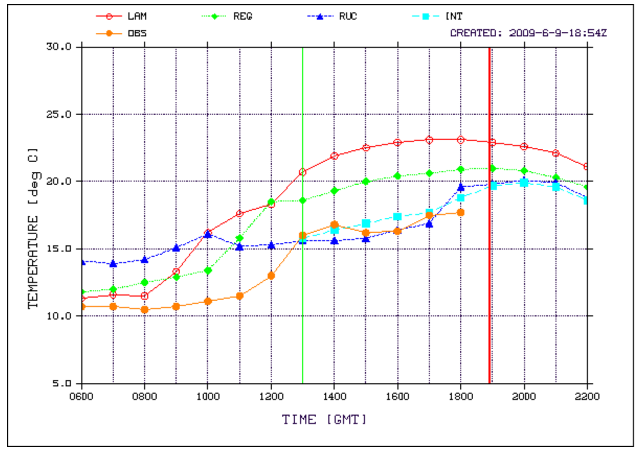


**Fig. 1. Time series graph with 3 periods of comparison**

Table 1 gives the percentage of the integrated model as an optimal model for a test period of more than 1000 hours. It is found that the integrated model has the highest frequency of being selected as the optimal model for all forecast parameters. The selected percentage is almost 80% for some forecast parameters at certain airports, for example, wind speed for airport CYXU (London).

**Table 1 Percentage of INT model as optimal model**

| Site | Temp. | Relative humidity | Wind speed | Wind direction | Cross wind |
|---|---|---|---|---|---|
| CYYZ | 45 | 60 | 63 | 64 | 64 |
| CYOW | 43 | 51 | 63 | 62 | 65 |
| CYUL | 36 | 51 | 67 | 64 | 72 |
| CYXU | 45 | 61 | 80 | 68 | 78 |
| CYTR | 46 | 43 | 65 | 72 | 78 |
| CYYB | 33 | 60 | 78 | 62 | 70 |

## 4. Conclusion

This paper presents a dynamic model performance-driven weighting system for assisting real-time nowcasting. The integrated model shows enhanced nowcasting accuracy for 5 major forecast parameters at 22 North American airports. The components developed for this system can be easily reused in processing different data sources, different weather forecast parameters and different locations.


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