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Machine Learning for Applied Weather Prediction

Sue Ellen Haupt, Jim Cowie, Seth Linden, Tyler McCandless, Branko Kosovic, Stefano Alessandrini

Research Applications Laboratory
National Center for Atmopsheric Research

Boulder, CO 80301 USA

haupt@ucar.edu

***Abstract*—The National Center for Atmospheric Research (NCAR) has a long history of applying machine learning to weather forecasting challenges. The Dynamic Integrated foreCasting (DICast®) System was one of the first automated weather forecasting engines. It is now in use in quite a few companies with many applications. Some applications being accomplished at NCAR that include DICast and other artificial intelligence technologies include renewable energy, surface transportation, and wildland fire forecasting.**

Keywords—artificial intelligence, machine learning, renewable energy, surface transportation, weather forecasting

I. Introduction

Weather forecasting has progressed from being a very human-intensive effort to now being highly enabled by computation. The first big advance was in terms of numerical weather prediction (NWP), i.e., integrating the equations of motion forward in time with good initial conditions. But the more recent improvements have come from applying artificial intelligence (AI) techniques to improve forecasting and to enable large quantities of machine-based forecasts.

One of the early successes of the use of AI in weather forecasting was the Dynamical Integrated foreCast (DICast®) System. DICast builds on several concepts that mimic the human forecasting decision process [1}. It leverages the NWP model output as well as historical observations at the site for the forecast. It begins by correcting the output of each NWP model according to past performance. DICast then optimizes blending of the various model outputs, again building on the past performance record. DICast has been applied to predict the major variables of interest (such as temperature, dew point, wind speed, irradiance, and probability of precipitation) at sites throughout the world. Fig. 1 illustrates the improvement provided by DICast over the individual NWP models that it is based on. It is typical for DICast to outperform the best individual model by 10-15%, which is considered a large improvement in weather forecasting. One advantage of DICast is that it can be trained on a relatively limited dataset (as little as 30 to 90 days) and updates dynamically to include the most recent forecast information. The gridded version of this system, the Graphical Atmospheric Forecast System (GRAFS) can interpolate forecasts to data-sparse regions.

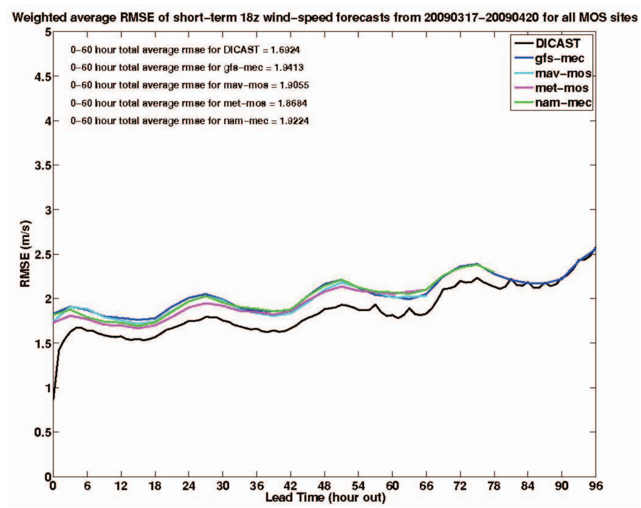

Figure 1. Performance of DICast® (root mean squared error) relative to input models for wind speed averaged over a 35-day period. DICast results in black.

II. Applications of Machine Learning

DICast and other machine-learning methods have been applied by the National Center for Atmospheric Research (NCAR) to various needs for targeted weather forecasts. Such applications include hydrometeorological forecasting for agricultural decision support [2], forecasting road weather to enhance the safety of surface transportation [3-5], forecasting movement of wildland fires, and predicting wind [6] and solar power [7] for utilities and grid operators to facilitate grid integration.

An example of using multiple AI methods for targeted forecasts is predicting solar power production. Fig. 2 illustrates the various technologies that were brought together to provide timely, reliable forecasts to enable grid integration of solar power, with the AI methods outlined in red. AI methods are used in both Nowcasting (forecasting the first 6 hrs) and in forecasting for Day-Ahead grid integration. DICast is one of the methods that blends input from multiple forecast engines. For the very short ranges, NCAR developed a regime-based solar irradiance forecasting system. This system uses k-means clustering to identify cloud regimes, then applies a neural

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network to each regime separately. This system was shown to out-predict neural networks that did not utilize regime separation [8]. The Nowcasting and DICast systems are merged via smart blending, then irradiance is converted to power output using a model regression tree. The utilities prefer probabilistic information; thus, an analog ensemble (AnEn) method is applied to estimate probability bands. The AnEn method uses compares the current forecast to similar, or analogous, past forecasts. Those most similar are identified and matched to their corresponding historical observations. That collection of historical observations becomes the analog ensemble. The mean corrects the forecast and the spread is used to estimate the probability distribution of the forecast. This method was shown to work well for solar power [9], as well as for many other variables. This system is an example of a Big Data solution in meteorology [7] that blends a variety of large volumes of disparate, complex observational data, NWP model output, and AI model forecasts at a velocity that is useful for decision support. It is critical to include data quality control and engineer for graceful degradation in the event that not all data arrive on time to assure veracity. It was estimated that if all utilities were to utilize these forecasts, that $455 M potential discounted savings over the 26 years of the analysis in the U.S. alone [10].

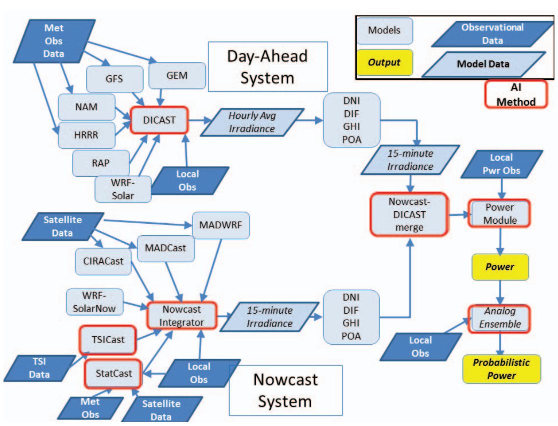

Figure 2. NCAR's Sun4Cast® solar power prediction system. AI methods are outlined in red.

SUMMARY

The example discussed here is just one of many emerging applications of applied weather forecasting that blends the best of our knowledge of physics, numerics, and artificial intelligence using smart Big Data and leveraging the Internet of Things. Applications such as these is the future of improved weather forecasting.

ACKNOWLEDGMENT

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