Operational Demonstration of an AI-based Hyper-Local Wind and Solar Energy Forecast Enhancement

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Numerical weather predictions (NWP) are critical for addressing a wide range of weather-dependent societal needs. They are extremely valuable because of the wealth of information about the expected future atmospheric conditions that greatly impact our well-being, planned activities, decision-making, and commerce. At their core, NWP models solve the governing physical and chemical atmospheric equations over coarse time and spatial scales only afforded by the limited supercomputing resource. While great advancements have improved atmospheric forecasting, NWP models still suffer from large local biases because they are constrained over large spatial scales and across multiplex variables, creating a complex, highly non-linear system.
In this presentation, we will detail a comprehensive artificial intelligence – machine learning (AI/ML) based hyper-local optimization of NOAA operational regional NWP High-Resolution Rapid Refresh (HRRR) forecast model. Specifically, we focus on improving 80m wind speed accuracy and the related wind and solar energy forecast. We collect publicly available HRRR 80m wind speed historical forecast data and train AI/ML algorithms to correct forecast data using HRRR analysis data. We test and validate a suite of AI/ML algorithms, including 1) artificial neural networks, 2) ridge regression, 3) lasso regression, 4) support vector machines, 5) gradient boosting, 6) elastic networks, and 7) nearest neighboring clustering. Models are trained over a year of dependent data corresponding to 253 sites in Texas and validated on a year of independent testing data. We show that each model offers significant forecast improvement (+20% mean squared error) over the current official HRRR forecasts.
Additionally, an AI/ML model ensemble is created and we demonstrate that the ensemble offers significant added improvement during all seasons, times of day, sites tested, and forecast horizon times. The fully matured framework is thus simple and robust, showing that AI/ML is a natural complement to the existing NWP infrastructure. We are also to present users' routine assessments about this ensemble forecast performance enhancement which is currently receiving overwhelmingly positive

feedback.

Furthermore, leveraging our existing AI/ML database, expertise, framework, and initial compelling forecast improvement we are to discuss the likely collaboration to develop a fully functional AI/ML-NWP modeling infrastructure that can meet demanding routine operational requirements to improve urgently-needed hyper-local/temporal extreme and severe weather forecast suitable for NOAA and its global institutional partners such as KMA and most of the weather-sensitive industry.