Development of a Machine Learning-Based, Dynamic, Granular Grid Outage Forecasting Algorithm

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Background/Objectives. As the long-term trend in global warming continues, both the frequency and severity of hazardous weather events are expected to increase posing significant threats to the electric power infrastructure with cascading effects on integrated infrastructure and human populations. While efforts at hardening the grid infrastructure can decrease vulnerability, damage to the utility assets such as cables and distributed energy resources is unavoidable. A necessary component of a complete grid resiliency plan is a highly dynamic, granular outage forecasting capability to tell where, when, and what outages occur, inform service restoration preparation up to several days prior to the storm, and direct restoration activities during and after the storm.

Approach/Activities. To address this need we have developed and evaluated multiple machine learning-based, dynamic, granular grid-outage forecasting algorithms based on historical detailed component outage information from a single New York State utility and output from operational and customized weather forecast models. In the first implementation, we carefully selected a set of weather variables in the output from two publicly available, operational weather forecast models, the North American Mesoscale Forecast System (NAM) and the Global Forecast System (GFS) as input to an innovative two-layered, stacked dynamic neural network using a sliding time window that makes the best use of the time series weather forecast data available. To facilitate the training of the forecasting model, data standardization is performed by converting weather forecast data to data of comparable magnitudes, zero mean, and unit variance for individual input variables. In the second implementation, a customized version of the Weather Research and Forecasting Model (WRF) and additional information on vegetation (tree height) and road length (as a proxy for overhead wire length) are used as input to an Extreme Gradient Boosting algorithm, a methodology often used to build outage prediction models. These approaches are applied to a number of case studies to demonstrate the performance of the different frameworks.

Results/Lessons Learned. Using a subset of storm cases not included in the training datasets, the outage predictions are evaluated over different time and spatial scales. Preliminary results indicate outage predictability that is comparable to previous data-driven outage prediction studies to multiple day forecast lead times. Next steps include consideration of uncertainties in outage reporting times and development of storm-type specific outage prediction algorithms. These newly developed algorithms, with forecast lead times out to 120 hours, will be combined with nowcasting models previously developed by our group as a storm response planning and deployment tool aimed towards improving efficiency of restoration activities and improved grid resiliency. The ultimate goal will be the implementation of the frameworks into an operational tool that can be adopted by utilities to greatly enhance the situational awareness and facilitate the service restoration.