A Hierarchical Approach to Probabilistic Wind Power Forecasting

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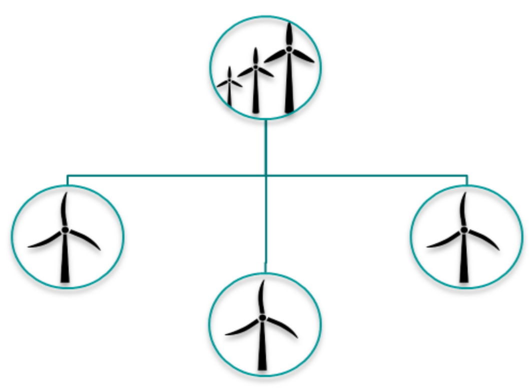
Introduction

In certain electricity networks the paradigm shift from large centralized thermal power stations to decentralised and stochastic renewable energy sources has led energy forecasting to be essential for economic and secure grid operation. Significant uncertainties in the power network are now present on the supply-side which increase the difficulty of balancing the network; to manage the influence of these renewable sources it is necessary to use predictions of future generation and, for risk minimisation, probabilistic forecasts.

Using the output of a Numerical Weather Prediction (NWP) a data-driven approach is possible for the short-term forecasting (hours to days ahead) of a single wind farm. Typically, this involves mapping concurrent NWP input features to a measured power time series at the wind farm export cable using a statistical learning technique.

Hierarchical Forecasting

Aspects of the electricity network provides a suitable framework when studying hierarchical forecasting; wind power behaviour is hierarchical by its nature, rising from the individual turbine, to farm, to regional level etc.



In the composition of this hierarchical model, the first layer is composed of out-of-sample **deterministic forecasts of each turbine** and an **aggregated deterministic farm level forecast**. These forecasts are then used as input features to **a top-level probabilistic model** which provides the desired final probabilistic forecast.

Methodology

Explanatory variables contains features derived from the NWP. Feature engineering was used to boost the predictive power of all models, this included temporal features (leading and lagging wind speed & direction forecasts, averages, ratios, and gradients) and time-of-day features.

The Gradient Boosting Trees (GBT) statistical learning techniques is used to forecast **individual turbine generation** using the above explanatory variables. This is a mean forecast determined via **square loss function.**

Penalised regression is employed to weight the individual turbine-level forecasts in the **aggregation** process to give a **deterministic wind farm level forecast**.

The **final probabilistic wind farm forecast** is then determined using the most powerfully predictive variables from the candidate pool of NWP, and lower hierarchy engineered features via the GBT algorithm with a **quantile loss** function including the 5th,10th,...,95th quantiles.

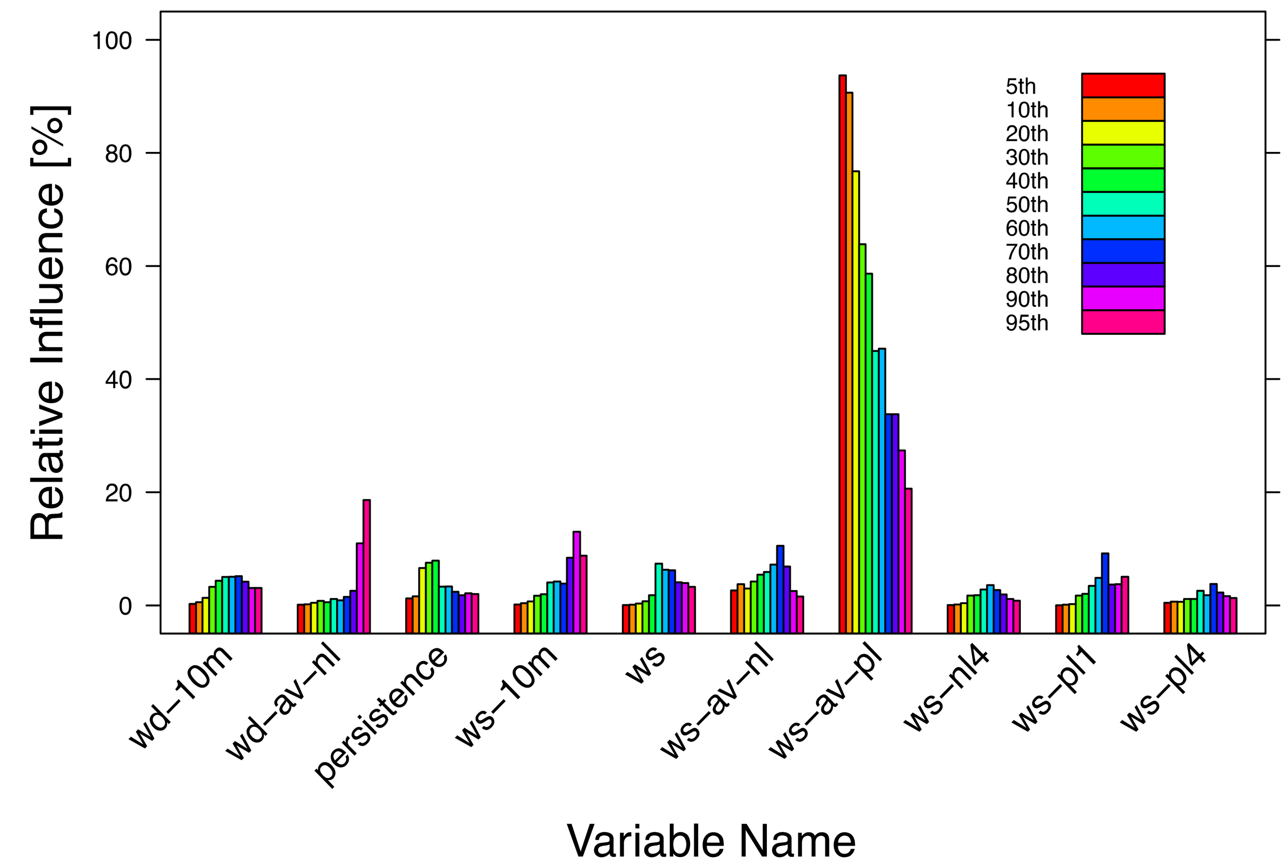
In total **two probabilistic benchmark models** are used. These robust and very competitive benchmarks are based on the conventional approach to forecasting, using solely the smoother wind farm level power data and are used to determine **any improved skill of the layered approach.** One consists of power forecasts at the farm level produced using GBTs and the quantile loss function The other is based on the Analog Ensemble technique (AnEns).

Case Study

The methodologies are tested at **Gordonbush** wind farm operated by SSE in the UK. This is a large utility scale park with 35 2MW turbines spread across an area of approximately 15km^2.

Results

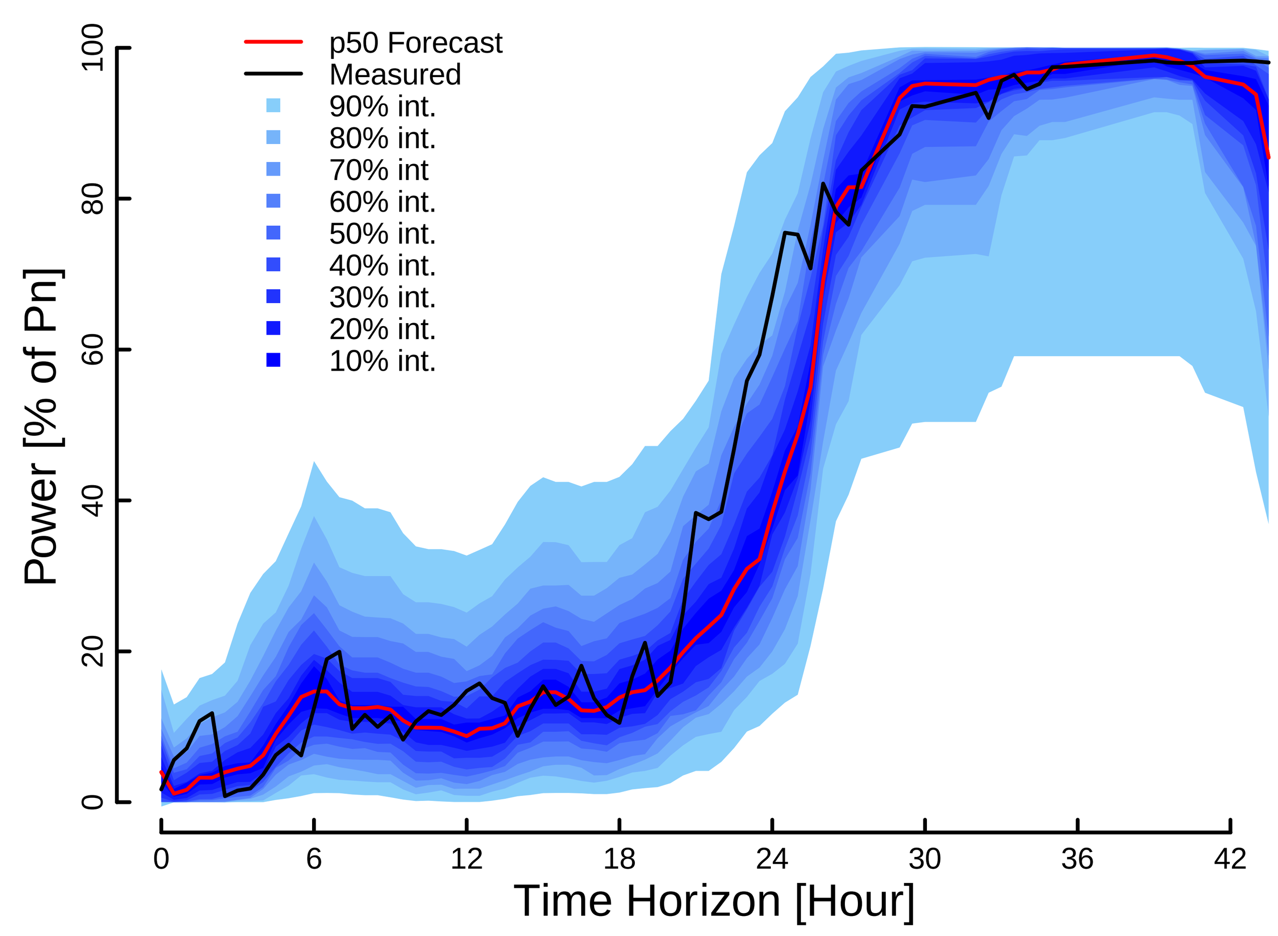
For ensemble decision trees, it is important to evaluate variable importance via the measure "relative influence" which allows the user to look under the hood and gauge the most powerfully predictive variables in the model. The figure below illustrates the importance of selected variables across key quantiles in the probabilistic GBT benchmark



The high importance of the engineered temporal features across all quantiles indicates the importance of what is essentially smoothing of the deterministic meteorological forecast by using average (av) features and leading (pl) & lagging (nl) inputs of wind speed (ws) and direction (wd).

The Continuously Ranked Probability Score (CRPS) is a measure of probabilistic forecast skill which compares each predictive forecast distribution against the empirical distribution of the observation. **Average improvements** across the forecast horizon in CRPS of **0.6% and 1.6% are obtainable from the hierarchical approach** on a blind-testing dataset when compared to the two benchmark models based on GBT regression and the AnEns technique respectively.

It should be emphasised that the benchmark method used are state-of-the-art and based on the top two methods from the GEFCom2014 wind power forecasting competition. In the context of simply better utilisation of existing data, with no necessary large investments in new equipment, this modest improvement could have an accumulated large impact across a portfolio with no necessary cost overheads. The figure below gives an example of the resulting density forecast from the layered model approach.



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