Aeolius Wind Systems Wind Forecasting Demonstration Project

LESSONS LEARNT REPORT 2

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EXECUTIVE SUMMARY

The skill of four machine leaning models were evaluated using data sourced from the Macarthur windfarm. The forecast models were successful in predicting the broad trend in the incoming wind field in the 5 minutes ahead time frame, however failed to capture the turning points with the required level of accuracy. Further model development is required to improve forecast skill to permit the use of these tools in operational settings.

Similarly, a short-range (2 to 5 km) scanning Doppler lidar was trialled to evaluate its suitability for use in the power forecast applications. The lidars measurement and 5 minutes ahead forecast capability was found to be suboptimal under the environmental conditions at the test site. However, the investigation confirmed the accuracy of the wind retrievals in the far field using data from meteorological masts and provided insights into the required scanning strategies for the planned dual Doppler lidar demonstration at Macarthur windfarm in late 2020.

Lesson learnt No.1: Machine Learning Forecaster

Category: Technical

Objective: Demonstrate the five-minute ahead self-forecasts are more accurate than the AWEFS and ASEFS

This lesson describes progress with the skill of four machine learning technologies in predicting five minutes ahead power output from Macarthur windfarm in Victoria. The technologies utilise mathematical models developed by the windfarm operator (AGL) and the project team which produce their forecast by examining historical trends of wind behaviour at the Macarthur windfarm.

A potential advantage of machine learning technology is that they are relatively inexpensive once developed and installed as the required data for the forecasts is obtained using existing windfarm infrastructure (masts, SCADA, telecommunications systems).

The key insights from the first stage of the Machine Learning study include:

- There is considerable research effort internationally being directed into the use of machine learning technologies for use in wind energy forecasting. Many models have been developed and trialled internationally with varying success. There is limited evidence within the scientific and trade literature of the broadscale adoption of machine learning technologies in operational settings;

- Of the four models developed and tested at Macarthur Windfarm, all were capable of predicting the overall trend in windspeed through time, however there were inaccuracy and lags in the forecast prediction similar to (although not as severe) seen in the current Australian Wind Energy Forecasting System (AWEFS);

- Whilst many techniques provide accurate forecasts under relatively stable wind condition, all have problems identifying the so called “turning points”. These points are where there is significant change in windfield behaviour affecting power output from wind turbines. That is, the forecast models fail when most needed;

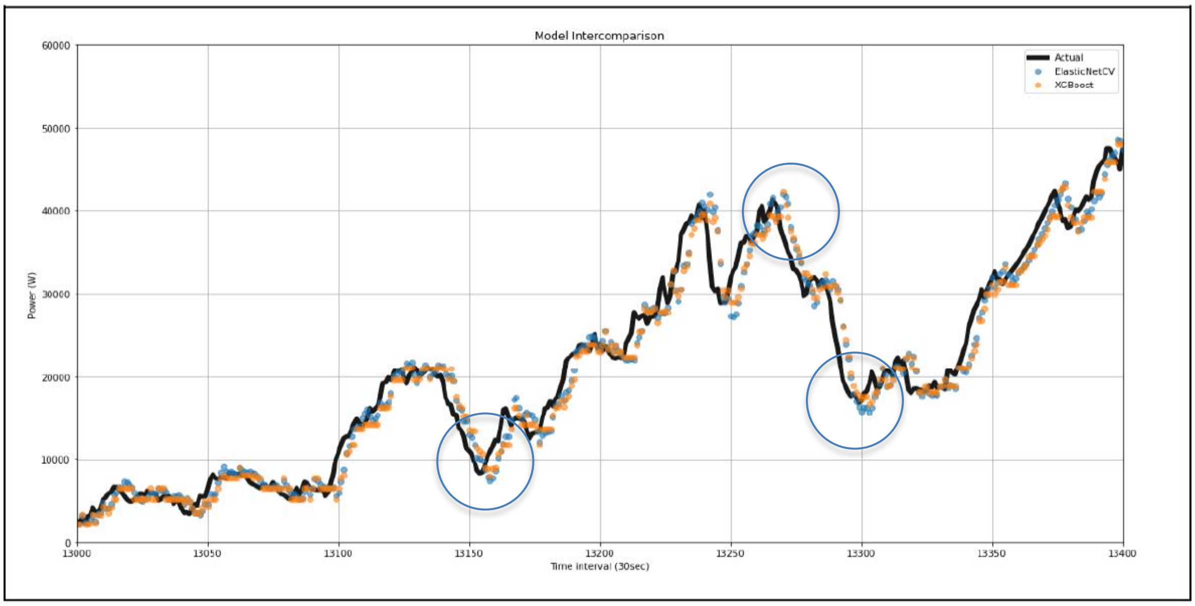

Figure 1. Example of Neural network forecaster skill demonstrating the lag between two forecasters (blue and orange trace), and actual power production (black trace) during a ramp up event. Whilst the forecasts are in reasonable agreement with actual power output for significant periods of time, they fail to capture important turning points in the overall trend with the required resolution to of use in operational forecasting (circles).

- The underlying problem appears to be the inability to deal with random fluctuations (turbulence) in the overall flow field that cannot be accurately predicted using the (historical) data set(s) which the model is trained on. Research is underway at Notre Dame University, Indiana to identify the key atmospheric processes which need to be understood to predict the frequency and intensity of turbulence. It should be noted that the randomness of events may be site specific requiring the use of customised models.

- Training on averaged total power does not work very well, particularly on log-shifted data, as features in the wind turbines are effectively ‘averaged out’. Therefore, all 140 wind turbines need to be trained collectively, only using the total power as labels. This helps account for spatial lag in the power generation, likely due to wind pressure passing through the wind farm.

- Technical problems were encountered with the available data sets that adversely affect the skill of the models. In some instances, data was unavailable due to communications outages within the windfarm. Here assumptions must be made on the power output from individual wind turbines to obtain the overall forecast. This introduces further uncertainty with model forecast skill;

The next stage of the demonstration at Macarthur is to use longer timeseries data sets (three to six months) to determine if the forecast skill of the models can be improved. The investigation will also be extended to selected windfarms in South Australia (as per the Project plan) to evaluate the effects of differing site and climatic conditions on forecast performance.

The key message from the above is that regardless of the models used, accurately predicting changes in power output under the full range of meteorological conditions using time-series data and machine learning technologies is extremely difficult and is an active area of research.

Lesson learnt No.2: Short-range scanning Doppler Lidar Forecaster

Category: Technical

Objective: Demonstrate the five-minute ahead self-forecasts are more accurate than the AWEFS and ASEFS

A forecasting trial using a relatively short-range (two to five km) scanning Doppler lidar system was undertaken at Warradarge windfarm in Western Australia. The base lidar system used in the measurement is an upgraded version of the technology deployed at Macarthur windfarm for investigating turbine wake impacts, as described in the first lessons learnt report. The new lidar incorporates an improved telescope assembly to increase measurement range and is considered by the project team to have superior performance to other products in its class.

The first step in this investigation was to evaluate instrument measurement range and accuracy using data from onsite masts under a variety of meteorological conditions. Measurement range is critical for identifying the location and behaviour of upstream features (gusts, lulls, windshear) within the mean wind flow which have potential impact on windfarm power output. The greater the measurement range, the greater the opportunity to obtain accurate forecasts using AWS's methodology.

The results from the trial suggest a range measurement improvement of 20 to 30 percent over the original technology using the new telescope

Measurement range was observed to fluctuate significantly over the 24-hr diurnal cycle at the Warradarge site, presumably as a result of changes in aerosol concentration levels.

This has implications to the deployment of this class of scanning lidar in short-range forecasting applications under the environmental conditions experienced on site. Further investigations are underway to better understand the challenge.

The initial results suggest that this technology is unsuitable for the application due to limited range, low scanning speed, and low data availability at range beyond 2.5 km across the entire 24hr cycle. It is likely that there will be significant period where forecaster will be “blind” to changes in upstream flow conditions, especially during the daytime where there are high levels of atmospheric turbulence, or under rain and fog. These challenges can be addressed using a different class of lidar together with advanced signal processing and data post processing strategies.

Notwithstanding the above, short range scanning lidar system may have application in Dual Doppler configuration, or hybrid numerical or statistical modelling forecast strategies into the future. Insights into the potential accuracy and cost effectiveness of the above will be provided through the current ARENA trial.

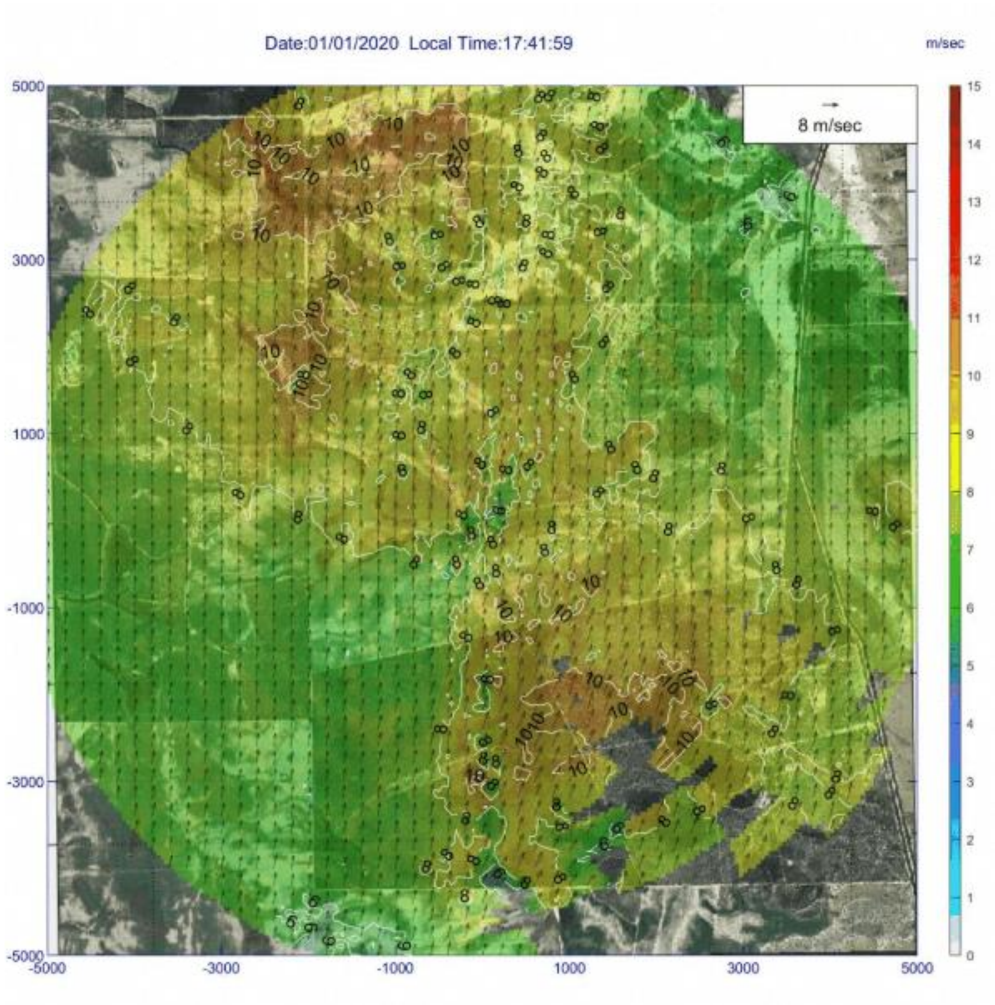

Figure 2. Example of 10-minute average wind speed terrane following windfield at 40 M agl. The structure and complexity of the windfield over the 78.5 km_2 area is clearly illustrated in the plot. An understanding of atmospheric dynamics and the effect of topography on flow behaviour upstream of the windfarm is crucial for securing accurate power forecasts.

The next stage of the investigation is to evaluate the forecast skill during periods where the instrument measurement range exceeds 5 km. Several measurement strategies will be trialled to address the limitations with the low powered short range lidar scanning lidar system. The learnings from this work will be used in the planning for the dual Doppler demonstration using the high powered lidar technology which is scheduled for delivery in late 2020. This investigation will be undertaken at several locations including the Macarthur windfarm.

The instrument may also be deployed to evaluate the skill of dual Doppler retrieval software developed for the Macarthur trial. Here the data from both the low and high powered lidars will be utilised to construct the windfield in the first 5 km measurement range and to generate 5 minutes ahead forecasts when environmental conditions permit.

Implications for future projects:

- There is a significant knowledge gap in identifying the causal factors driving random fluctuations in atmospheric flow field behaviour which undermines the performance of neural network forecasters. Further research is required to identify the main atmospheric variables (or combination of variables) such as atmospheric stability, turbulence intensity, surface roughness, wind shear, direction, velocity etc. that need to be incorporated into the models to improve predictive skill. A collaborative research effort between local and overseas who are already working on this challenge would provide a cost-effective pathway;

- Development of custom metrics for weighting points in neural network forecaster data sets is required. A challenge with fitting any model to the time series data is that there are many points following local trends. However, the turning points, which occur much less frequently, are more important to model correctly to render the technology useful in operational application;

- Comparing all models precisely is difficult as there are areas where some models perform better than others. In addition, on such a short time frame of data, it is hard to evaluate which will give the greater performance long term. What is clear from all models is there is significant lag i.e. over- and undershooting the turning points.