Vestas – Wind Forecasting for the NEM
LESSONS LEARNT REPORT 2

Project Details

Recipient Name	Vestas – Australian Wind Technology Pty Ltd (Vestas)
Primary Contact Name	Hugh McKenzie
Contact Email	hudmc@vestas.com
Reporting Period	April 2020

This Project received funding from ARENA as part of ARENA's Advancing Renewables Program - Short Term Forecasting funding round.

EXECUTIVE SUMMARY

Since the previous lessons learnt report, three new self-forecasting models have been developed by Utopus, these are the SCADA+Weather model, SCADA+Met Mast model and the SCADA+Weather+Met Mast model. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) analyses were carried out versus wind ranges and power ranges for each of the models to understand the strengths and weaknesses of each of the models. The analyses and findings have been described in detail under Lesson Learnt No 1.

Towards the end of last year, Vestas also completed the Met Mast installation project on behalf of Infigen, which included a new 'Met Mast B' with meteorological instrumentation and data logger, and the addition of a data logger on the existing 'Met Mast A'. There were some challenges in terms of data transfer to the Vestas SCADA system and to Infigen's independent met mast data service provider. These have been discussed in Lesson Learnt No 2.

Finally, in order to carry out the cost-benefit analysis of using the self-forecasting values instead of AWEFS, Infigen are developing a Causer Pays Factor (CPF) tool. Further details on the tool and its implications are described in Lesson Learnt No 3.

KEY LEARNINGS:

Lesson learnt No. 1: Model Development

Category: Technical

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

1. **SCADA model** –On the 12th of November 2019 Lake Bonney 3 passed AEMO's initial assessment by performing better than AWEFS in terms of the MAE and RMSE and by providing reliable and consistent forecasts to AEMO's production environment. Similarly, on the 24th of December 2019 Lake Bonney 2 passed AEMO's initial assessment. The forecasts are being analysed by AEMO ongoing on a short, medium and long-term basis.

   Based on the results from the 1st of November 2019 until 10th of April 2020 the MAE and RMSE for Lake Bonney 2 & 3 versus AWEFS is provided in the table below. Both Lake Bonney 2 & 3 have lower self-forecast MAE and RMSE than AWEFS indicating better performance of the self-forecasting algorithm.

2. **SCADA+Weather model** - Using its proprietary hyperlocal weather model, the inputs in the SCADA based model have been augmented using the weather forecast. The weather model forecasts several weather parameters. The objective of this model is, when combined with the real time SCADA data, to assess the benefits of additional weather features in short term forecasts. In this model, we use the hyperlocal weather forecasting, which provides a finer spatial granularity than conventional weather models

3. **SCADA+Met Mast model**: Following the installation of the met mast data loggers at each of the two sites and the connection to Utopus Insight's (UI) system, the SCADA base model was augmented using the weather mast signals as additional inputs. Met mast location and data quality play a vital role in deciding whether using input from this new source will aid the performance or not. Again, with this, the terrain also plays an important role, thus extensive analysis was conducted in order to mitigate any degradation in performance by understanding their similarity with farm-level parameters. The closer the met mast parameters are to farm-level aggregated values, the more relevant they are to the forecast model.

4. **SCADA+Weather+Met Mast model:** The two previous models' inputs were finally combined into an ensemble model using weather signal data from the live feed from the met mast and the weather forecast information from our weather model.

Input:

Accurate prediction of wind speed is critical in understanding the accuracy of the power forecast. The model which we have developed uses wind speed from different sources: met mast and UI's proprietary weather service (referred to as Wx going forward). Key insights can be drawn based on their relative performance and in order to do so, the farm-level average wind speed has been considered as baseline.

> *Farm-level average wind speed: Average of anemometer wind speed of all turbines in the farm.*
>
> *Met mast wind speed: Met mast wind speed of the respective site*

Note: This is a qualitative analysis to understand input data and the result will change depending on how the farm-level data gets aggregated.

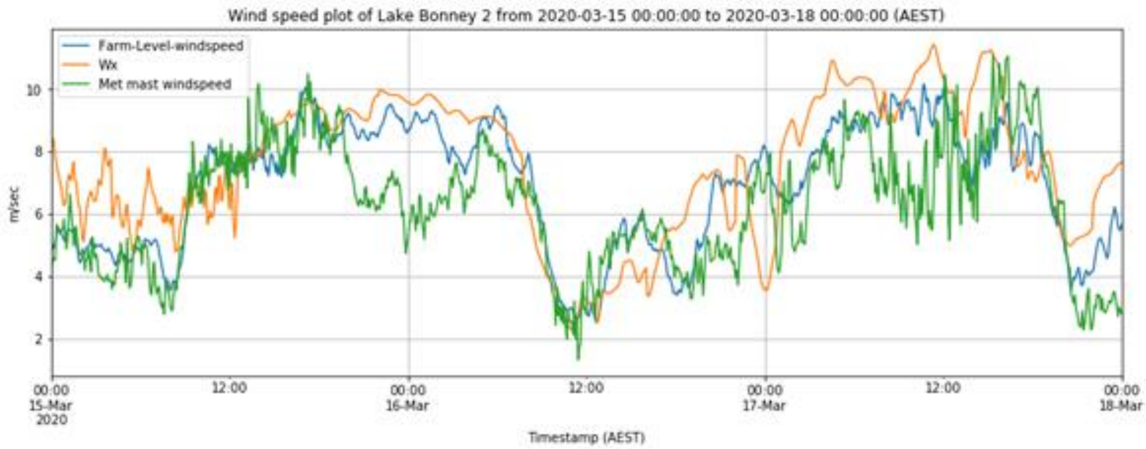


Figure 1:Plot showing wind speed comparison across different sources

The above plot gives the following insights:

- Both met mast and Wx under and over forecast wind speed at times.
- The wind speed measurement from the met mast is more volatile as compared to Wx.
- Although there is certain amount of bias in both met mast and Wx, both still follow the trend of the farm-level average wind speed.
-

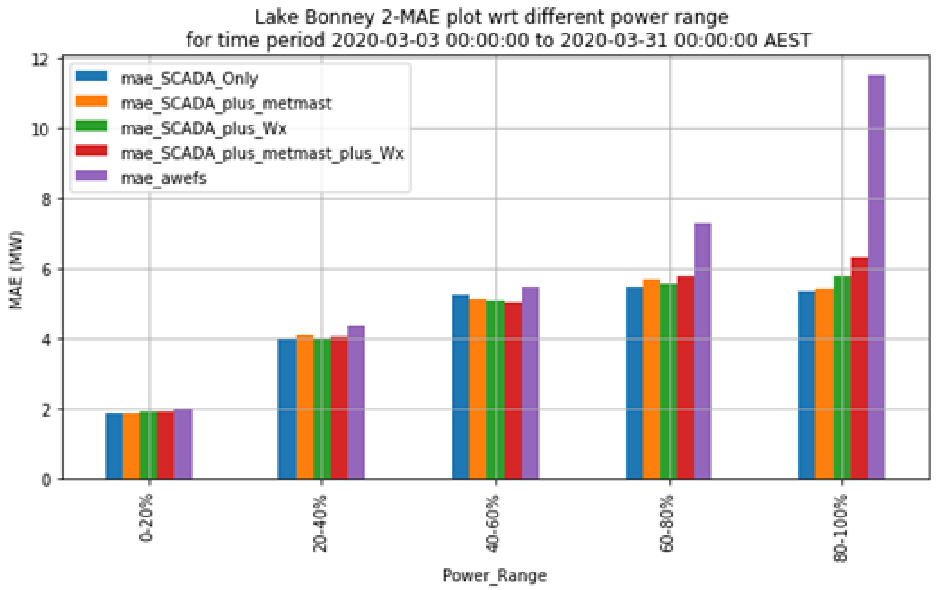
<u>Power range wise MAE & RMSE of Forecast:</u>

Note:

- We have only considered forecasts outside periods of curtailment for this analysis.
- Certain timestamps for a given model will get ignored if it contains missing forecast. Missing forecast can be seen due to the following reasons:
    - Data latency
    - Planned or unplanned site outage
    - VPN connectivity issue
    - Communication loss.
- In wind speed range-based analysis we have ignored wind speeds greater than 16m/sec, thus there were only 4 categorical values along X-axis, but we have not taken this approach for power analysis. Still it is suggested that any conclusion drawn from the 80-100% power range might be inconclusive due to a smaller number of data points.

- The result shown below is calculated using the forecast generated and stored at Utopus Insights' end. Since a few forecasts might get rejected due to submission time constraints, the values might change if we replicate the same analysis using the data captured at AEMO's end. However, we believe the difference would be marginal.

Lake Bonney 2



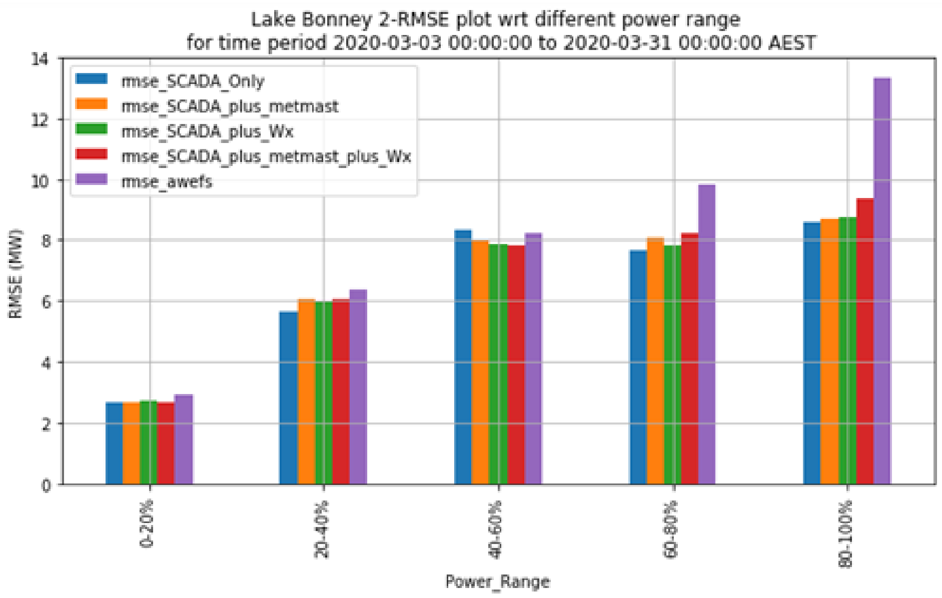
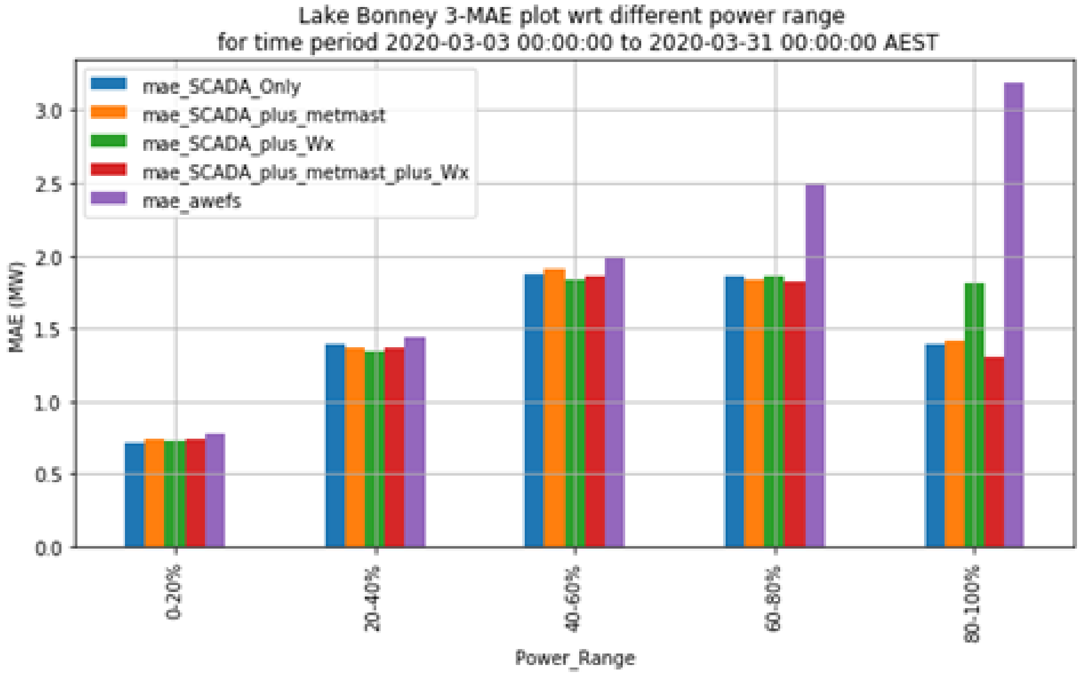


Figure 5: Four Self Forecast Model analysis versus AWEFS in terms of MAE and RMSE for each power range at Lake Bonney 2

Lake Bonney 3



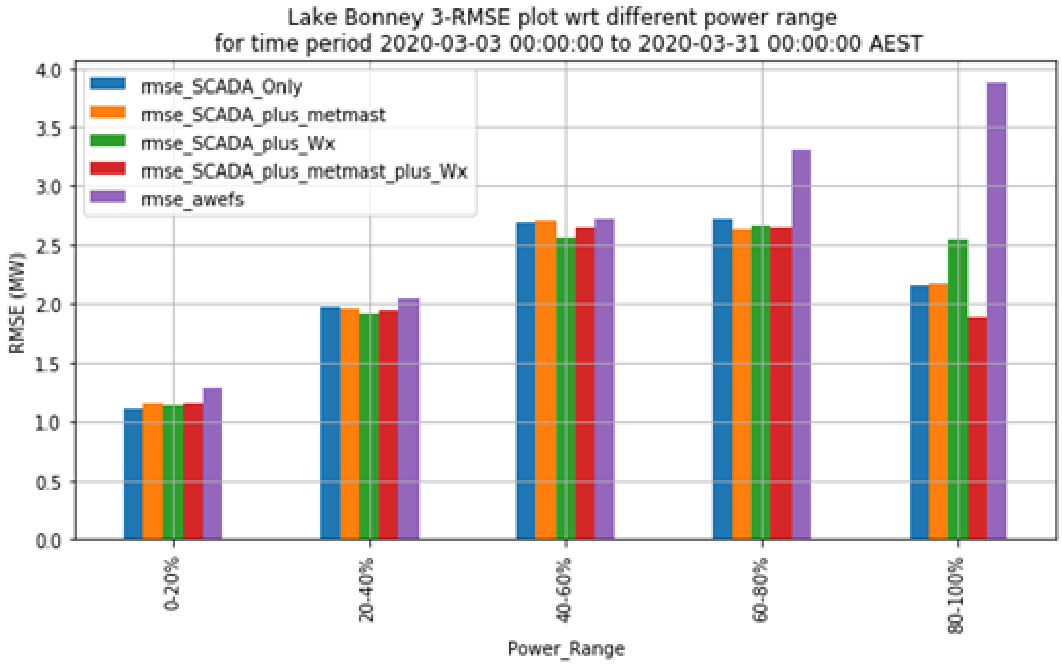


Figure 6: Four Self Forecast Model analysis versus AWEFS in terms of MAE and RMSE for each power range at Lake Bonney 3

Across all power ranges, all the four models seem to outperform AWEFS forecast most of the time. The SCADA Only model has ran for a longer period of time and its performance was improved over time but the additional models deployed have still shown accuracy gain under certain operating conditions as shown in the previous charts.

Implications for future projects:
While additional forecasting run time across all 4 models will be necessary to fully assess their relative accuracy performance, they all performed well and are worth considering when seeking 5min forecast improvements. It would likely be beneficial to run all models for a longer period of time and conduct additional experiments to further identify and isolate performance gains from each forecast models so a wider range of operating condition can be analysed.

Lesson learnt No. 2: Met Mast Data Transfer

Category: Technical

Objective:
Obtain and stream uninterrupted weather measurement data at either end of the site to be incorporated into the forecast models.

Vestas completed the Met Mast installation project on behalf of Infigen, which included a new ‘Met Mast B’ with meteorological instrumentation and data logger, and the addition of a data logger on the existing ‘Met Mast A’. The data from the two met masts were used for the development of Forecasting Models B (Turbine SCADA data + Met Mast) and D (Turbine SCADA data + Met Mast + Weather Model).

The new data logger (Vestas VMET panel) installed at Met Mast A, required to stream data for the forecasting models, was unable to continue to stream data via the existing 4G network and instead the SCADA network was the only point of connection. The 4G connection was previously used by Infigen to transfer data from Met Mast A to an independent service provider to collect raw data from the met mast independently.

This led to temporary communication loss between Met Mast A and the independent service provider as Met Mast A data was being fed to the Vestas Online Business (VOB) server and therefore was not considered to be truly raw data. To address this, Vestas configured direct access to the VMET panel via the SCADA network, without any interference from the VOB server and Infigen developed a new system for data transfer via FTP connection to its independent met mast data service provider.

Implications for future projects:
The FTP data transfer methodology is now being implemented at all the new met masts that are being installed across Infigen’s new wind farms where the new logger is being used.

For future installations of VMET panels by Vestas, a more thorough investigation of data streaming requirements will be undertaken during the planning process and scoped accordingly.

Lesson learnt No. 3: Causer Pays Factor (CPF) Calculation Tool

Category: Technical

Objective:

Demonstrate the potential commercial benefits of wind and solar farms investing in short-term, self-forecasting solutions.

Causer pays charges depend on the 'causer pays factor' which is a measurement tracking the impact of generator output on the grid frequency on a 4 second basis. These factors are computed only once every 4 weeks and used for an upcoming 4-week period. This means that since the self-forecasts have become unsuppressed (Lake Bonney 3 (LB3) on the 12th of November and Lake Bonney 2 (LB2) on the 24th of December), only the most recent 3 CPF calculated include self-forecasting. Because of this limited data and the high variability in the historical CPFs, any inferences regarding substantial changes due to self-forecasting are highly speculative and unreliable. The results so far are inconclusive; it cannot yet be said that there is a definite improvement or change in CPF due to self-forecasting.

As a result, a more detailed analysis that will use 4 second SCADA data to directly compare theoretical CPFs under AWEFS and self-forecasting is in development for the final report.

The use of 4 second data to calculate the CPF has been quite challenging due to the following reasons:

1. Since CPF is calculated on a monthly basis, the 4 second dataset for one month is quite huge. Moreover, the dataset is a in a format which is not easily accessible.
2. Furthermore, the procedure to calculate CPF is not very straightforward and it is hard to replicate and match AEMO's published data.

As such, if ARENA/AEMO could provide a workshop that runs through the calculation procedure it would be very helpful for Infigen to determine the economic benefit, accurately.

Implications for future projects:

Once developed the CPF calculation tool will help Infigen continuously monitor the impact of the self-forecasts on the causer pays factor and assess the overall cost benefit of using self-forecasts instead of AWEFS and hence determine one of the financial value drivers of the project. If Infigen decide to implement the self-forecasting algorithm at the other windfarms, the same CPF calculation tool can be used to evaluate the financial benefits at those windfarms as well.