Vestas

UTOPUS INSIGHTS

Infigen

Improving Accuracy of Short-Term Forecasting in the NEM

Lake Bonney Stages 2 & 3 Pilot Project

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

Lake Bonney 2 & 3 Five-minute Self-Forecast Project

Project summary

The Lake Bonney Stages 2/3 short-term forecasting project for Infigen Energy utilised four separate forecasting model approaches (implemented at different stages) to assess the incremental improvements that meteorological masts and weather models have on the accuracy of wind production forecasts when combined with high-resolution wind turbine Supervisory Control and Data Acquisition (SCADA) data, and machine learning algorithms.

The first forecast model developed was the "SCADA data only" model, which was most critical because it acted as the baseline for the other models, and was the first to be submitted into the Australian Energy Market Operator (AEMO) production environment on September 10, 2019 for both Lake Bonney 2 (LB2) and Lake Bonney 3 (LB3).

Prior to submitting forecasts to AEMO's application programming interface (API), Infigen developed its own API layer that was configured as an intermediary interface between Utopus Insights' forecasting system and that of AEMO. This layer allowed Infigen to implement additional cyber security controls on the automated submission system. A Self-Forecast Suppression system and user interface was also designed by Utopus Insights to allow Infigen's operators to supress self-forecasted values being submitted to AEMO. During these times, the Australian Wind Energy Forecasting System (AWEFS) forecast would instead be used for AEMO calculation of the dispatch target value. This tool allowed operators to minimise the times when the self-forecast was submitting unfavourable values that would negatively impact the average performance values. During the course of the project, voluntary participant suppression was used less than 0.1% of the time for LB3 and never for LB2, a reflection of the stability and reliability of the forecast models deployed.

On November 12, 2019 the self-forecast for LB3 passed AEMO's assessment followed by LB2 on December 24, 2019. It took longer to pass the assessment at LB2 due to ongoing curtailment, which prevented the self-forecast to qualify despite it performing better than AWEFS as these periods were excluded per AEMO's final assessment procedure. Based on the results of the initial assessment for the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics, LB2 and LB3 had better MAE and RMSE results than AWEFS and continued to outperform AWEFS for the duration of the project (23 weeks for LB2 and 29 weeks for LB3).

Furthermore, Utopus Insights developed, trained and deployed 3 additional models into the production environment with different priorities. The SCADA + Weather model was the second model to be deployed and was augmented by Utopus Insights' proprietary Scipher.Wx weather model. The next model deployed was the SCADA + Met Mast model, which utilised data from two met masts located at opposite ends of the site. One of these met masts was erected for the purposes of the project, and both have been streaming real-time weather data utilised by this particular forecast model. Lastly, a model was developed that combined SCADA + Weather + Met Mast. Therefore, in total, there were four core models that were submitting forecasts to AEMO's APIs. All four models performed better than AWEFS in terms of MAE and RMSE for both LB2 and LB3 for the majority of the time, especially at higher power production ranges, with only a few exceptions and for limited periods of time.

Core Forecasting Models

SCADA	SCADA real-time signals were the only source of input for this model.
SCADA + Met Mast	SCADA model augmented using real-time signals from two weather masts as additional input.
SCADA + Weather	SCADA model augmented using UI's proprietary hyperlocal weather model.
SCADA + Met Mast + Weather	Ensemble model using weather signal data from SCADA, weather masts and the hyperlocal weather model.

Table 1: Description of the four core forecasting models utilised in the project.

The model with the highest ranking when compared to AWEFS was the 'Hybrid' SCADA model for both LB2 and LB3. The Hybrid model is a combination of two SCADA models. It alternates between the two models, based on whether AEMO curtailment is occurring or not. The primary model issues the forecast when there is no curtailment, and the secondary model gets selected when curtailment is on. As the windfarm operational behaviour is noticeably different under curtailment, this approach allows for the bounds of each model to be simplified, and hence they can be optimised better.

While the SCADA-based model performed better overall compared to the other models deployed, it was demonstrated that the other modelling techniques could provide incremental benefits over the SCADA-only model as illustrated in Figure 1. As shown with the MAE performance results, the models including met mast and Scipher.Wx performed better across certain power production ranges.

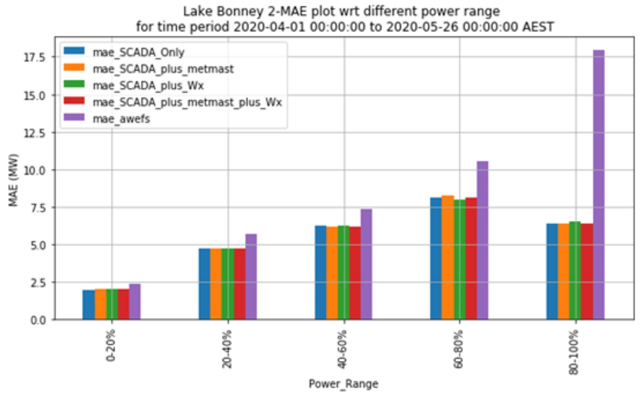

Figure 1: LB2 forecast model performance across different power ranges.

Additional run time of these forecast models will help identify how the additional inputs could further improve the forecast accuracy, providing the foundation for an ensemble model that would make the best use of the available information. Experiencing different operating conditions would be necessary to clearly identify the full range of opportunities presented by these alternative models.

Overview of forecast model performance

Since being unsuppressed by AEMO, the self-forecasts have been used in dispatch (meaning the AEMO reading of the farm availability equals the self-forecasted value if not constrained) around 96% of the time, with voluntary participant suppression occurring less than 0.1% of the time for LB3 and never for LB2.

Over a period of 23 weeks for LB2 and 29 weeks for LB3 (see Figure 2), the self-forecast's MAE outperformed AWEFS' MAE by an average of 17.4% and 13.0% respectively.

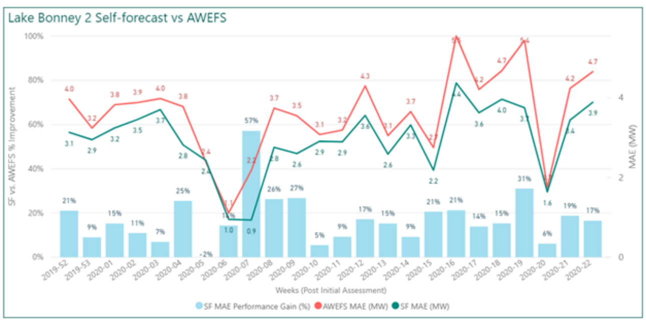

Figure 2: LB2 Week on Week MAE performance of self-forecast vs AWEFS from 24/12/2019 – 01/06/2020 during non-curtailment periods

Over the same evaluation period the self-forecast outperformed AWEFS RMSE by an average 16.8% for LB2, and 12.3% for LB3.

While the self-forecast stayed within 50% of the error band compared to the actual production less often than AWEFS at both parks, the self-forecast was within 0.5%-20% error bands more often than AWEFS, and therefore still achieved higher overall accuracy. Although the self-forecast is more accurate than AEMO's default AWEFS in terms of traditional error metrics (MAE and RMSE), which was the objective of the self-forecast development process and AEMO's subsequent assessment procedure, when evaluated for non-absolute variance it is shown that the self-forecast is skewed to underestimate generation. Conversely, it is observed that AWEFS has a tendency to overestimate at LB2 and LB3 using 5-minute data. From analysing all semi-scheduled generators two years of data, there was a very slight overall bias to under-supply within the NEM, though it is almost negligible.

The main point of Infigen's observations was that the overestimation bias from AWEFS at the Lake Bonney wind farms is causing large raise not enabled factors, and, due to a very slight market bias towards raise regulation, Infigen was able to achieve financial gains by the self forecast not only being more accurate, but also underestimating on average.

During times of high wind, both forecasts become less accurate, but the self-forecast is less affected than AWEFS. While we see an increase in error during high output, the error for the self-forecast remains much lower than AWEFS, indicating that the self-forecast performs better at high wind conditions when comparing to AWEFS.

Accuracy was assessed following the project methodology and is in line with AWEFS measurements. It is yet to be concluded whether the self-forecast is turbine-agnostic as it relies upon certain SCADA signals that may not be available on all wind turbines. While we anticipate the same performance results to be possible for other turbines, operational validation would be required as signal quality also plays a great role in achieving high accuracy results.

Impact of forecast on causer pays factor

By accurately forecasting the future possible generation, the park can meet its dispatch target more closely, which should in theory result in a better Causer Pays Factor (CPF), in turn reducing market charges. By employing a 5-minute ahead self-forecast for both parks, the combined CPF for LB2 and LB3 is reduced by an estimated 26% when compared with AWEFS, which translates to an estimated 26% reduction in causer pays charges.

However, this percent decrease contains uncertainty due to estimation methodology. Even though it was hypothesised that improved accuracy would directly relate to an improved

CPF, on further analysis, it was observed that most of the improvements to CPF are because the self-forecast tends to underestimate generation, while AWEFS overestimates generation. In the case of LB2 and LB3, the CPF improvement of 26% can be explained by the observation that over the period considered, the market consistently required more Regulation Raise Frequency Control Ancillary Services (FCAS) than Regulation Lower FCAS to be utilised. Hence underestimating generation is helpful to frequency as it effectively delivers more generation into the market than expected during dispatch. This also indicates that an improvement in CPF may be possible even if a self-forecast does not have a better MAE or RMSE than AWEFS.

The reason the market requires more raise than lower regulation has not been confirmed, with one of the possible drivers being that there is an overestimation of many semi-scheduled generators. If this were to change and most generators provided a forecast with a bias to under-forecast, then it is possible that this may result in AEMO requiring more Regulation Lower FCAS. This means that even though semi-scheduled generators may be able to improve their CPF in the short term and positively contribute to grid frequency, it may not mean that the dispatch process is made significantly more accurate.

Reduced Causer Pays Factor

An estimated reduction of 26% in Causer Pays Factor observed at Lake Bonney 2 and 3 over the pilot period was attributed to the performance of the Self Forecast.

Benefits to grid, market and consumers

Accurate self-forecasting values from windfarms will provide AEMO with a more accurate representation of what the future possible power may be. With the increased accuracy, we would expect a decrease in unexpected power output movements compared to the dispatch assumption made by AEMO, and a decrease in frequency variations in the system. A decrease in frequency variations thanks to more accurate forecasting should decrease the minimum amount of Regulation FCAS that must be procured in dispatch as a reserve. It would also reduce the amount that the Regulation FCAS providers will utilise.

In addition to a lower CPF, the broader benefits of a more accurate forecast are mostly captured in the form of increased grid stability. The more detailed and granular forecasting using information that is potentially unavailable to AWEFS gives the market a more transparent representation of actual output. Forecasting of system constraints as well as price become more accurate with a better forecast, helping to improve grid strength.

Figure 3 helps to visualise how the MW error (between forecast output and actual output) correlates to the FCAS factor – being lower not-enabled factor or raise not-enabled factor (LNEF and RNEF).

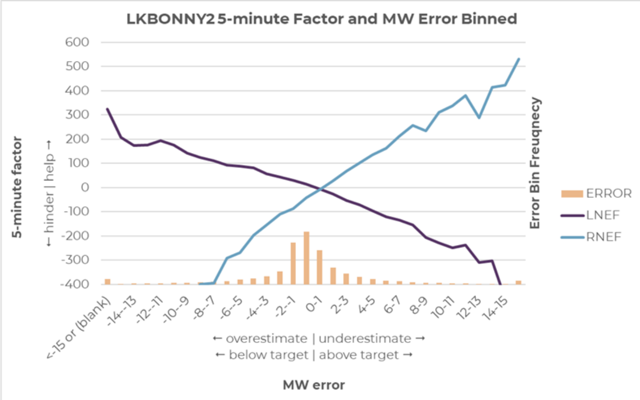

Figure 3: 5-minute average factors for each 1 MW error bin at LB2.

Figure 3 demonstrates that for negative MW errors (indicating an over-estimation, or generation below the target) increases the Lower Not Enabled Factor (LNEF), as it is decreasing the need for lower regulation (that helps to bring frequency down when there is an over-supply). It also leads to a more negative (worse) Raise Not Enabled Factor (RNEF), as it is negatively contributing to the requirement for raise regulation (to bring frequency up when there is an under-supply).

Conversely, the positive MW errors (indication of under-estimation, or generation above the forecast) leads to a better RNEF and a worse LNEF.

The correlation coefficients for LNEF are −0.45 and −0.49 and for RNEF 0.57 and 0.59 for LB2 and LB3 respectively. There is quite a lot of noise in the data, which is expected since the wind farms are certainly not large enough relative to the whole NEM to drive this relationship. These numbers are reasonably suggestive of linear relationships (a value of ±1 is total positive/negative linear correlation).

While self-forecasting may be prevailing as an option for semi-scheduled participants to undertake, there are larger changes being made to the management of system frequency, such as the enforcement of Primary Frequency Control across most generators, that need to be assessed in conjunction, to understand how the requirements from frequency control markets may change over time.

Overview of financial benefits and costs

The net annual benefit based on the estimated cost saving from causer pays charges for both LB2 and LB3 was $198,000 based on the calculated median 28-day cost reductions. There has however been a large historical variance in both the CPF and Regulation FCAS charges over different 28-day evaluation periods at both windfarms, which makes it hard to narrow the estimated savings. Based on the observed period, the corresponding annual bounds from extrapolating individual 28-day periods becomes $35,600 to $2,306,400 in savings.

The $2.3 million upper bound saving was calculated using the maximum observed 28-day FCAS charge as well as the maximum observed CPF improvement, then extrapolated for an entire year. The 28-day FCAS charge used was taken from February this year, where SA was islanded for several weeks following a storm that caused destruction of network transmission towers.

It is unlikely that the highest CPF improvement and the high FCAS charges from February would occur simultaneously, and particularly rare for these to occur over the entire year. The high upper bound savings value instead demonstrates the variability in CPF payments. Even though a short testing time (November 2019 – May 2020), the variability in these payments was very large. Extrapolating monthly 28-day CPF values could result in grossly varied annual saving and needs to be understood when discussing a monthly “average” CPF value or savings. This variability is a result of many external factors within the energy market, including grid events, FCAS requirements, bidder behaviour, seasonal or annual changes, changing energy mix etc.

Grid events, such as separation of regions (particularly for South Australia, Tasmania and Queensland), are likely to produce adverse FCAS charges due to a more stringent requirement to source FCAS services locally (greater local demand, increasing costs). While these events are not uncommon, they are not expected to occur in each 28-day period within a year.

The quantum of regulation FCAS requirements vary as a result of AEMO assessed grid requirements at the time, which influences price (where higher FCAS requirement is more likely to increase the cost at which FCAS regulation is sourced). This minimum requirement increased substantially in the first half of 2019, where Raise and Lower Regulation requirement increased from 130 / 120 MW to 220 / 210 MW respectively.

In addition to the markets changing procurement requirements, FCAS costs are also heavily influenced by participant bidding behaviour. Regulation markets are orders of magnitude smaller than the energy spot market with fewer participants which means that adjustments in bidding by market participants can have large impacts on price, further contributing to the volatility. Recently there has been a change in market dynamics in the regulation markets causing prices to be notably lower than before, impacting FCAS costs. In the short time, this reduces the overall benefit of self-forecasting, but it is again uncertain if this trend will continue. There is a small seasonality component with regulation prices since they tend to be weakly linked with energy prices, but the vast majority of volatility comes from extreme and unpredictable events.

Additionally, causer pay factors and improvements are expected to be volatile and hard to predict due to NEM wide winds and frequency deviations. Wind gusts also have significant influence over the CPF, as higher wind gusts lead to hard to forecast conditions, and it is less likely that the output from the parks will follow the expected trajectory.

Frequency deviations in the NEM will also cause CPF to vary dramatically at the parks, as the frequency deviations are heavily influenced by external factors – though are what drive the calculation of the CPF.

Figure 4 shows a histogram of all possible annual savings when applying the observed 28-day CPF improvements for the duration of the project to the past 2 years of 28-day FCAS charges for LB2 and LB3. Note the frequency increases very slightly for a saving of $1,000,000+, this is because of the extreme FCAS costs that occurred as a result of extreme events and market volatility.

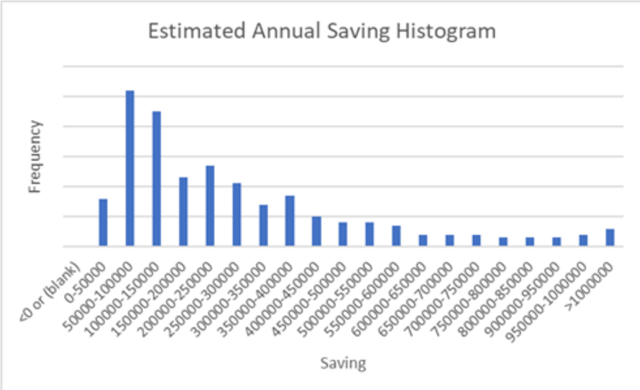

Figure 4: Frequency of estimated annual savings (in dollars) scenarios when applying the observed 28-day CPF improvements for the duration of the project to the past 2 years of 28-day FCAS charges for LB2 and LB3.

Following the close of the project, Infigen engaged in a commercial agreement with Utopus Insights for the latter to continue to provide forecast services.

The ongoing costs of maintaining the associated infrastructure within Infigen’s systems are considered negligible once the integration with AEMO and Utopus Insights is completed. It is estimated that on average 2 hours per week will be used by either the Infigen IT team or Operations Control Centre to monitor and troubleshoot the system. For the sake of the cost-benefit analysis, this has been assumed to be $200 per week.

To setup the IT system that submits and monitors the self-forecast within Infigen's systems, a one-off cost of $25,700 was incurred by Infigen to build the IT application and infrastructure to submit and monitor self-forecasts received from Utopus and sent to AEMO.

If Infigen were to configure another self-forecast for a different asset they would be using the already configured IT application and infrastructure where extra costs would be incurred (in the order of $1000 - $1500/ year) as annual running costs to ensure that the new asset is operational.
The ongoing costs of maintaining the met mast constructed as part of this project are estimated to be $5,000 per year. Since the data from the met mast is used as an input for the self-forecasting algorithm, reliability of the data is important. The $5000 refers to the maintenance and reporting costs for the met mast which requires a specialist team to carry out on-site inspections and appropriate remedial works for the met mast components such as sensors, data loggers, cabling etc. The height of the met mast built at Lake Bonney is 80 meters, however it is unclear if the height of the met mast would influence the maintenance costs.

Technology and product development

In addition to the self-forecast product (available to the market via Vestas/Utopus Insights), an intermediate API layer and CPF calculation tool were created by Infigen. The API enabled greater control over which forecast is dispatched to AEMO, while the CPF tool gives the ability to calculate the value of the reduction in CPF attributable to the more accurate self-forecast. These additional features could potentially be utilised across Infigen's other assets should they decide to implement self-forecasting.

Areas for future improvement / Key lessons learnt from the project

The CPF calculation tool requires large volumes of high-resolution 4-second data, e.g. one year of 4-second data is several hundred gigabytes. The use of 4-second data to calculate the CPF has been quite challenging due to the following reasons:

- The dataset for CPF calculation for a 28-day period using 4-second data is ~30 GB, with a total of 8.064 csv files and 870 million rows of data. Moreover, the dataset is in a format which is not well-suited for large volumes of data, and is also not easily accessible.

- Furthermore, the procedure to calculate CPF is not very straightforward as the exact process is poorly documented, complex and resource-intensive, making it hard to replicate and match AEMO's published data. A full calculation of CPFs requires 5-minute factors to be calculated for all metered units, interconnectors and regions. AEMO does publish this information, but again, it is not in an accessible format.

While we believe that there would be benefit in pointing participants towards the Causer Pay Factor data and making this more accessible and available, the biggest hurdles with data for completing the analysis was the way in which the data is formatted. Improvements in data formatting and usability would be useful to trial participants, with the "variables" and "elements" .csv files being difficult to work with, a recommendation is to put variables and elements within a single file and publish the data in a format that's easier to digest into a database. The list of excluded intervals and the 28-day aggregate factors are in a .pdf format which makes them difficult to extract data from in automated processes. It should also be noted that there is missing data on the AEMO website, with a gap between the historical and 2-month rolling window.

Due to complexities around CPF determination, particularly regarding the interconnectors and non-metered generation and loads, a worked example would also be beneficial for trial participants in completing the analysis which would include details on the Causer Pays methodology AEMO use to calculate the CPF.

Infigen was assisted by AEMO during the project, readily answering questions that were raised and clarifying the proposed approach. This type of clarification and walk-through may be beneficial to other industry participants.

Partnership

Following the success of the Pilot Project, Infigen and Utopus Insights (a Vestas company) have continued their partnership, with the Self Forecast continuing to be supplied as a subscription. The Self Forecast will continue to be submitted to AEMO in the dispatch process.

Conclusion

This project has demonstrated that self-forecasting in the NEM provides semi-scheduled generators with the opportunity to more accurately predict their electricity production and more closely meet their dispatch target. By doing so, they can reduce their exposure to FCAS Causer Pays costs and contribute to stabilising the grid.

Accurate short-term power forecasting improves the value capture of renewable energy asset investments while contributing to a more secure power system. When the supply of electricity more accurately meets the demand, in other words, when the forecasted production meets actual production, there is less reliance on high cost FCAS generation. With less FCAS required and a greater proportion of low-cost renewables in the energy mix, the wholesale cost of energy is expected to reduce, benefitting the Australian consumer.

Following the success of this project, Vestas and Utopus Insights have made their scalable 5-minute self-forecasting solution commercially available and are excited to partner with owners and operators of semi-scheduled generators in the NEM to improve their business cases while enabling renewables to contribute to a more stable grid.