MERIDIAN ENERGY AUSTRALIA: Wind Forecasting Demonstration Project

LESSONS LEARNT REPORT 5

Project Details

Recipient Name	**Meridian Energy Australia**
Primary Contact Name	Chris Baldwin
Contact Email	Chris.Baldwin@meridianenergy.com.au
Reporting Period	April 2021 – September 2021

This Project received funding from ARENA as part of ARENAs Advancing Renewables Program. The views expressed herein are not necessarily the views of the Australian Government, and the Australian Government does not accept responsibility for any information or advice contained herein.

EXECUTIVE SUMMARY

This report outlines lessons that Meridian Energy Australia and the University of Melbourne have recently learnt regarding market modelling, LIDAR data analysis, and forecasting for the Mt. Millar wind farm.

KEY LEARNINGS

Lesson learnt No.1: Main effect of wind forecast accuracy is terms of mkt performance related to financial performance of generators. Worst forecast accuracy leads to greater curtailment of wind farms resulting lower revenues.
Category: Commercial
Objective: Investigate the potential system benefits of wind farms investing in short-term, self-forecasting solutions.
Details: Using the Melbourne Energy Institute's electricity market model the potential financial and environmental benefits of improved wind forecasts to an electricity system were assessed. These assessments were made with respect to the effect of wind generation penetration and forecast error on: wholesale market prices and costs; generator rates of return; system greenhouse gas emissions; certain reliability and security-related metrics.

Overall, the results of this market modelling highlight the complex interactions of renewable generation forecasts, demand forecasts and generator unit commitment and economic dispatch. We make the following observations:

- Improved forecast performance results in less operational uncertainty, and therefore enables the market operator to schedule all generators more efficiently, e.g. some coal or gas plant can be turned off more often since they are less frequently required to guarantee system security and reliability, thereby also resulting in less renewable curtailment.
- Reduced system greenhouse gas emissions is a second-order result of more efficient generator scheduling.
- Forecast uncertainty tends to increase the number of hours of unserved energy, the number of hours at market price cap, and therefore increases energy prices and overall rates of return.
- However, the larger the wind forecast error, the greater the wind curtailment and resulting lower returns to wind generators.
- With levels of wind generation > 50% by annual energy, the effects of absolute wind forecast error – mentioned above – are amplified.
- Assessment of system inertia levels shows that higher levels of VRG increase the probability of RoCoFs > 1 Hz/s due to wind forecast error.

Implications for future projects: The results from the above market modelling analysis demonstrate the need to pursue improved short-term wind generation forecasts that enable both improved financial performance to all electricity generators, as well as system security and scheduling efficiency benefits.

Lesson learnt No.2: It is possible to extract gusts from LIDAR wind speed data.
Category: Technical
Objective: Other (analysis of LIDAR wind data)
Details: Analysis of our published LIDAR data set (available here: https://melbourne.figshare.com/articles/dataset/Windcube_400S_Dynamic_Scanning_Data_Set/14526942) has revealed how to detect spatially coherent patches of elevated wind speed (known colloquially as "gusts"). The methodology to extract the gust from the wind field data is shown in Figure 1.

Implications for future projects: Projects measuring the incoming wind field should be aware that signal processing may be required to detect flow phenomena.

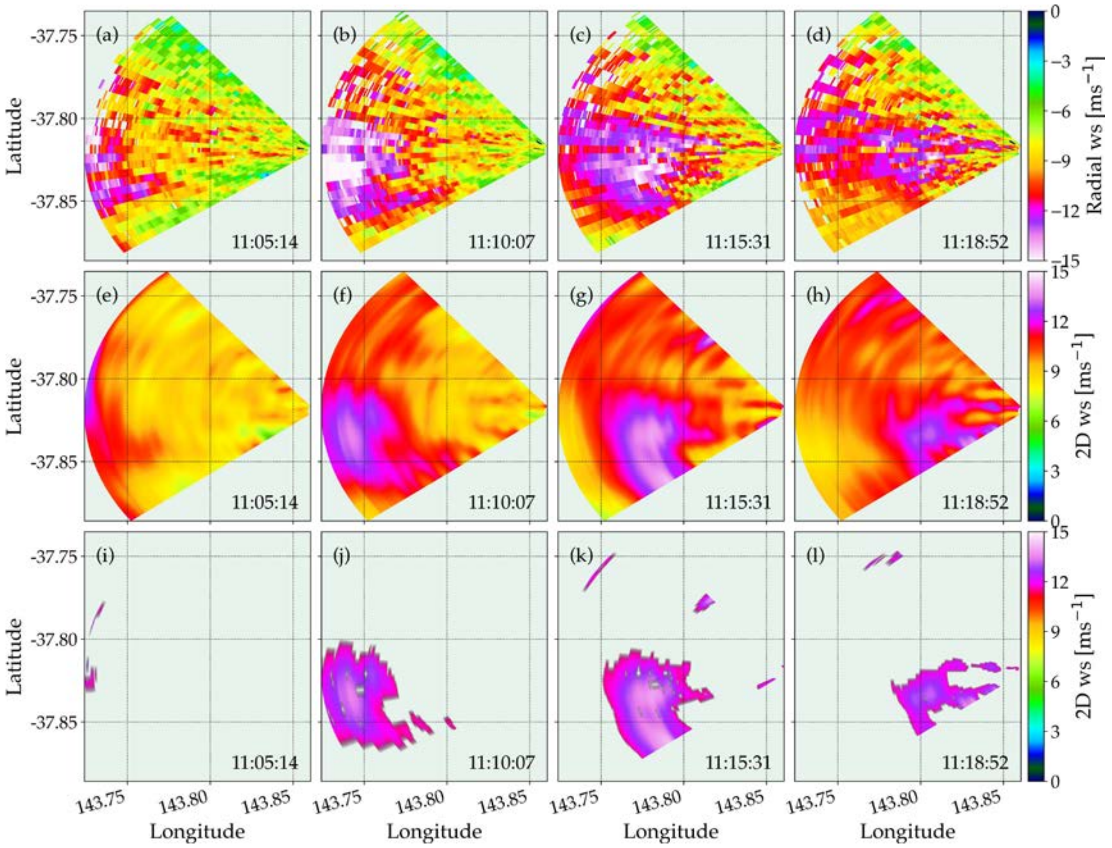

Figure 1: (a-d) Instantaneous snapshots of velocity field data. (e-h) shows a background correction applied to velocities in the images above. (i-l) show the extracted gust from the wind field data.

Lesson learnt No.3: Different sized gusts propagate at different velocities relative to the mean wind speed

Category: Technical

Objective: Other (analysis of LIDAR wind data)

Details: Analysis of our published LIDAR data set (available here: https://melbourne.figshare.com/articles/dataset/Windcube_400S_Dynamic_Scanning_Data_Set/14526942) has revealed that spatially coherent patches of elevated wind speed (known colloquially as "gusts") tend to advect at different velocities depending on their size. This is shown in Figure 2. For gusts that are smaller than 1 km, the gusts tend to move at the mean wind speed for the velocity field. For gusts larger than 1 km, the gusts tend to move faster than the mean wind speed for the velocity field. It is believed that this is due to these larger structures stretching vertically where they are influenced by the faster wind speeds from higher in the atmosphere.

Implications for future projects: Projects measuring the incoming wind field should be aware that gusts move at different speeds relative to the background wind field, depending on their size.

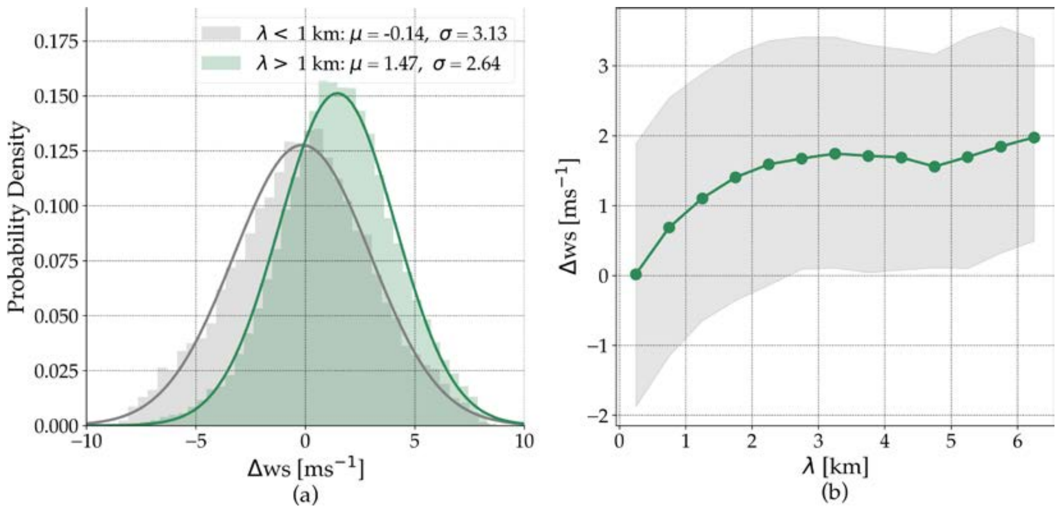

Figure 2: (a) histogram of the difference between gust propagation speed and background wind speed. Small gusts are shown in grey and larger gusts are shown in green. The solid line denotes a Gaussian distribution for each histogram with the mean and standard deviation given in the legend. (b) difference between the background wind speed and gust speed versus size of the gust. The grey area shows the 25th and 75th percentile range.

Lesson learnt No.4: Optimal forecast class can depend on state/regional constraints as much as input data.

Category: Technical

Objective: Demonstrate the ability to submit five-minute ahead self-forecasts via AEMO's web based MP5F API.

Details: Previously, when developing a forecast for the Mt. Millar wind farm, we found that much like the Mt. Mercer wind farm, a statistical forecasting approach was the best way to go in terms of power-forecasting accuracy. However, now that we are in the process getting ready to deploy said Mt. Millar forecast, it has become apparent a machine learning based approach will be needed. This is because the extremely frequent limiting of generation due to local distribution line thermal constraints and volatile generation pricing. Hence, despite the fact its technically less accurate, a machine-learning based approach will have to be used to correctly deal with generation with those constant and sometimes related limitations on generation.

Implications for future projects: Future projects should be aware that each forecast will have to be bespoke for the wind/solar farm and its regional generation limitations.