# MERIDIAN ENERGY AUSTRALIA: Wind Forecasting Demonstration Project

## LESSONS LEARNT REPORT 2

**Project Details**

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| **Reporting Period** | October 2019 – April 2020 |

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## EXECUTIVE SUMMARY

This report outlines lessons that we have recently learnt regarding our LIDAR system, the forecasting process, and the forecasting process more generally.

## KEY LEARNINGS

**Lesson learnt No.1: Forecasts should incorporate a high temperature check against the cut-out temperature for their wind turbines**

**Category: Technical**

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

**Details:** The 44 degree day on January 31st, 2020 revealed a need for us to check the temperature data from inside the turbines. That day, despite high winds, yielded low-to-moderate farm output power during the peak heat of the afternoon. After some investigation, we determined the cause of this was the internal temperature sensors of the turbines reached a temperature high enough to trigger internal shut-down. Hence our farm was experiencing high wind speeds but due to high temperature was producing nearly zero power output and so we needed to ensure our forecast incorporated this technical feature of the wind turbines installed at Mt Mercer.

**Implications for future projects:** Other participants should keep an eye on the temperature of the turbine to see if they are near the shut-down condition. We intend to add such a precaution before next summer to ensure our forecast aligns with the wind farm output.

**Lesson learnt No.2: Forecasts using LIDAR data should understand the underlying physics for the changes in wind speed due to fronts**

**Category: Technical**

**Objective:** Other (Use of LIDAR data in forecasts)

**Details:** Our first algorithm utilising LIDAR data (which is currently in pre-production) to forecast wind power performs very well for days when the wind speed changes in magnitude, but not direction. However, on days with a front passing, where both the wind direction and wind speed change, the change can occur too rapidly for our dynamic scanning technique to capture natively, which can lead to some undesirable errors in the forecast. We are currently working on a few ideas to rectify this issue.

**Implications for future projects:** Projects utilising LIDAR should be able to deal with both large changes in wind speed and large changes in wind direction that are associated with the passage of a cold front in SE Australia.

**Lesson learnt No.3: Participants should be aware that if the semi-dispatch cap and an erroneous UIGF are close to one another then NEMDE might remove the semi-dispatch cap if the erroneous UIGF is low enough to relax the binding constraint**

**Category: Technical**

**Objective:** Participants should be aware that if they are employing a persistence based forecast (or statistical forecast that relies upon the previous power value) that they should switch from the persistence model to an alternate model (without previous power values), should the farm be both constrained and operating close to the constrained cap value. This is because in constrained operation, a persistence based forecast acts as a constrained forecast rather than as a UIGF. Using constrained forecasts during constrained operation could potentially lead to NEMDE cycles of applying and then removing the semi-dispatch cap, particularly when output is heavily constrained off, potentially resulting in large power swings and increased forecast errors. We encountered a situation similar to this in our self-forecasts and think other forecasters should be aware of this.

**Implications for future projects:** The potential impact of this on self-forecasters is that they will likely have to develop two self-forecasts, one that employs previous power values, and one without, to be employed during constraint.


**Figure 1: Picture of the Leosphere Windcube 400S Scanning LIDAR system atop Mt Mercer**

**<u>Lesson learnt No.4: Forecasts using LIDAR data should note the conditions in which their LIDAR data is available</u>**

**Category: Technical**

**Objective:** Other (LIDAR data availability)

**Details:** In our previous Lessons Learnt report, we detailed the fact that the LIDAR data remains unavailable during periods of heavy rain, this is due to a combination of light scattering via rain particles and reduced availability of aerosol in the atmosphere particles during the rain. We have also observed that heavy fog can also scatter the light beam sufficiently so that LIDAR measurements are unavailable. Finally, we observed in the late 2019, nearby fires to the Mt. Mercer Wind Farm that we were able to confirm/observe that moderate-to-heavy levels of smoke do not appear to inhibit LIDAR wind speed measurements.

**Implications for future projects:** Projects utilising LIDAR should be aware the fog and rain can restrict or eliminate the viewing capability of the LIDAR. However, smoke at the levels we observed, did not appear to impede the ability for the LIDAR to measure wind speeds 10+ km away (note that this is a slight reduction from the maximum range of 14 km, for days with ideal conditions, like those shown in Figure 1).

**<u>Lesson learnt No.5: Forecasts should use current wind farm power, if possible</u>**

**Category**: **Technical**

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

**Details**: We have attempted numerous forecasting algorithms/approaches through this project, and one general rule that we have found is that forecasts that do not use the current (at the time of the forecast) wind farm power, perform worse than those that do (whether directly incorporate or indirectly via differential power prediction).

**Implications for future projects**: Forecasts not employing the current wind farm power would likely be improved if they add the current wind farm power (at the time of forecast) as an input for their forecasting algorithm.

**Lesson learnt No.6: Forecasters should be aware of what drives the large changes in power for their wind farm**

**Category:Technical**

**Objective:** Other (Meteorological drivers of power ramps)

**Details:** A PhD student on this project has performed an analysis of the drivers of wind power ramps for our Mt. Mercer Wind Farm. Their study examined 2.5 years of archival wind power data and determined the drivers of our strongest wind-power ramps. They determined that cold fronts (and a period of time shortly following the front) were the physical phenomenon responsible for most of the ramps in wind power. High turbulence intensity (associated with a destabilised atmospheric boundary layer) was the phenomenon that was responsible for the second largest number of ramps in the timeframe. One figure from this journal article is reproduced in Figure 2, highlighting the frequency of occurrence of these ramp drivers versus the cause. We hope to publish this work soon to detail how other wind farm operators can analyse their power data to determine what drivers are responsible for their power ramps.

**Implications for future projects:** Learning the meteorological drivers of wind power ramps is an important first step in determining the conditions under which you are most likely to observe a future ramp in wind power. Participants should perform similar analyses if they have not already done so.

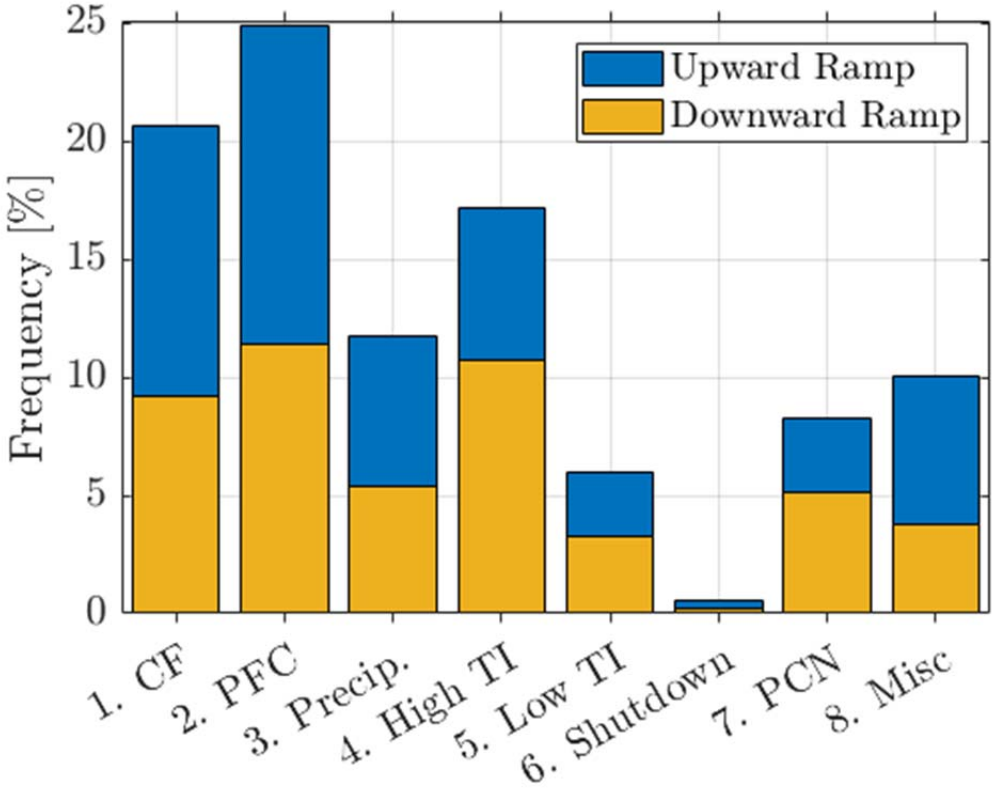


**Figure 2: Ramp occurrence frequency versus underlying cause. The categories for causes are: 1. Cold front, 2. Post-cold-frontal conditions, 3. Precipitation (not associated with the passage of a cold-front), 4. High turbulence intensity, 5. Low turbulence intensity (associated with stable atmospheric boundary layer phenomenon), 6. Wind farm shutdown, 7. Power-curve nonlinearity (i.e. large wind speed variations in the cubic region of the power curve), and 8. Miscellaneous causes (farm wake, yaw misalignment, etc.).**