# Short-Term Forecasting Trial on the NEM

## Progress Report (April to October 2019)

January 2020

Australian Government
Australian Renewable Energy Agency

ARENA

AEMO
AUSTRALIAN ENERGY MARKET OPERATOR

## DISCLAIMER

## ABBREVIATIONS

| | |
|---|---|
| AEMO | Australian Energy Market Operator |
| API | Application Programming Interface |
| ARENA | Australian Renewable Energy Agency |
| ASEFS | Australian Solar Energy Forecasting System |
| AWEFS | Australian Wind Energy Forecasting System |
| DUID | Dispatchable Unit Identifier |
| EPC | Engineering, Procurement and Construction |
| FCAS | Frequency Control Ancillary Services |
| LIDAR | Light Detection and Ranging |
| MP5F | Market Participant Five-Minute Forecast |
| MW | Megawatt |
| NEM | National Electricity Market |
| O&M | Operations and Maintenance |
| SCADA | Supervisory Control and Data Acquisition |
| SODAR | Sonic Detection And Ranging |
| STF | Short-Term Forecasting |
| URM | User Rights Management |

## TABLE OF CONTENTS

## EXECUTIVE SUMMARY

The Australian Renewable Energy Agency (ARENA) and the Australian Energy Market Operator (AEMO) produced this report to summarise insights and progress from initial reports submitted by the 11 participants of the Short-Term Forecasting (STF) trial that is taking place between March 2019 to mid 2021.

This report focuses on insights into installing the forecasting equipment at wind and solar farms, registering as a self-forecasting provider[1] to AEMO and passing the AEMO self-forecast assessment process for the period between April to October 2019.

Early insights from the participants' reports include:

- learning by doing has been beneficial for participants to gain a better understanding of capital costs and timelines to deliver self-forecasting projects
- it is important for forecasting service providers to have a good working relationship and open communication with the wind or solar farm owner / operator and AEMO's operational forecasting team
- AEMO's troubleshooting of the self-forecasting process and the publication of procedures has assisted participants to submit and maintain their data
- ensuring forecasting technology at sites is compatible with remote operation can aid in reducing the need to conduct on site system operations and maintenance.
- wind forecasting is complex and forecasting algorithms have been revised to accommodate the complexities found in the trial
- it is important to design and maintain an effective project risk management plan to manage project risks including delays caused by contract negotiations, project partner changes, detailed design, equipment delivery, installation, commissioning, the AEMO accreditation process, and the weather.

The insights gained so far provide lessons for stakeholders across the industry including:

- owners and operators of wind and solar farms weighing up the business case for investing in both brown and greenfield renewable energy sites
- service providers including renewable energy developers, as well as engineering, procurement and construction (EPC) and operations and maintenance (O&M) organisations planning to incorporate self-forecasting equipment into the design of greenfield projects
- insights for forecasting and ancillary equipment suppliers to improve design and integration with other technologies
- academics seeking new knowledge gaps to research such as wind turbine wake impacts
- the AEMO Operational Forecasting team by highlighting the problem areas to troubleshoot.

Links to the 11 trial participants' reports are located on page 10 of this report. Individual and summary lessons learnt reports will be published by ARENA, biannually, until the end of the trial in early to mid 2021.

1 The act of creating, sending and prioritising a 5 minute ahead self-forecast to AEMO instead of the forecast determined by AEMO.

## BACKGROUND

On 18 March 2019 ARENA awarded $9.41 million to 11 participants to trial STF at large-scale wind and solar farms across Australia. The trial is being conducted in partnership with AEMO, whose operational forecasting team manages the forecast submission process and utilises the forecasts in their central dispatch engine.

Thirty five per cent of semi-scheduled wind and solar capacity registered on the National Electricity Market (NEM) form part of the trial, amounting to around three gigawatts of renewable energy[2]. The trial investigates the accuracy of the forecasting technologies used by the trial participants and the effect different weather, operational conditions and geographies has on the accuracy of forecasts across the NEM. The range of forecasting technologies includes onsite cloud cameras, wind speed radars, weather satellites, meteorological masts, infrared, and machine learning algorithms that utilise onsite and Bureau of Meteorology (BoM) weather data.

AEMO is currently responsible for forecasting how much electricity will be generated by wind and solar farms. This output varies depending on the weather and time of day. To forecast supply, AEMO uses the Australian Wind Energy Forecasting System (AWEFS) and the Australian Solar Energy Forecasting System (ASEFS). If these supply forecasts are not accurate or generators cannot meet their target, it can result in power system instability and higher operating costs. Wind and solar farms are then penalised for not meeting a required output level or can be required to curtail their generation to match their assigned forecast.

Due to this challenge the main objectives of the trial are to:

- demonstrate the ability to submit five-minute ahead self-forecasts via AEMO's web-based Market Participant Five-Minute Forecasting Application Programming Interface (MP5F API)
- demonstrate that five-minute ahead self-forecasts are more accurate than the AWEFS and ASEFS
- demonstrate the potential commercial benefits of wind and solar farms investing in short-term, self-forecasting solutions.

In line with the first two objectives, the trial provides funding for service providers on behalf of wind and solar farms to demonstrate that they can provide a more accurate self-forecast into AEMO's central dispatch system with a web based MP5F API than the currently used AWEFS and ASEFS. Improving the accuracy of forecasts will lead or should lead to increased stability for the electricity system.

The third objective aims to determine whether the commercial benefits of self-forecasts can produce a positive return on investment for the wind or solar farm. This is demonstrated by the self-forecasts sent to AEMO that can potentially assist in producing more accurate dispatch and pricing signals to the market and reduce the need for frequency regulation. This will assist in firming the value of intermittent wind and solar farms. The commercial benefit to wind and solar farms is demonstrated by the potential savings made by reducing the amount of Frequency Control Ancillary Services (FCAS) causer pays charges.

The following section provides the industry with an update on the trial participants' progress, challenges and lessons learnt to demonstrate the potential value of short-term forecasting.

2 Note: Since the announcement of the trial in March 2019, there has been a reduction from the initial 45 per cent of the NEM's registered wind and solar capacity to 35 per cent due to project site changes. The reduction represents around 0.5 gigawatts of renewable energy capacity.

## PROGRESS TOWARDS OBJECTIVES

### Objective 1: Demonstrate the ability to submit five-minute ahead self-forecasts via AEMO's web based MP5F API

#### Progress

AEMO has accredited 27 ARENA-supported semi-scheduled generating units to deliver self-forecasts for use in dispatch. Eight of these generating units have already contributed self-forecasts for use in dispatch, and the remaining 19 are aiming to have their self-forecasting capabilities ready by April 2020 for the next update. There are a total of 117 semi-scheduled generating units in the market[3].

#### Challenges

AEMO's MP5F API has been available to receive self-forecasts since 23 August 2018. Some trial participants have experienced challenges completing the stages required to have their self-forecasts registered in the MP5F API and accredited for use in dispatch. A common challenge has been that the MP5F API user account password expires every 90 days. If not renewed beforehand, AEMO's authentication service will make that user account inactive and block any further self-forecast submissions from that user. Only the operator of the wind or solar farm can reset the MP5F API User account password. This diffusion of responsibility has created delays in getting the submissions accepted again[4]. This and other issues of a new system has meant the trial participants have used some of the time contingency[5] in their project plans to avoid delays to the project completion date.

#### Lessons learnt

Although the AEMO self-forecast assessment process was a known prerequisite, a common challenge was fully understanding the MP5F API registration and self-forecast assessment process[6]. AEMO collated these lessons learnt and commonly asked questions into a Participant Forecasting FAQ[7] (published in September 2019) that includes clarification and further information on the processes.

In response to participant feedback in particular, AEMO will soon make available an API to allow self-forecast providers to directly update their password without requiring the involvement of the market participant (wind or solar farm operator). The API will provide a useful tool to manage the 90-day expiry period of passwords and avoids the diffusion of responsibility experienced initially. These lessons have improved the AEMO MP5F API process for current and future STF participants.


Images courtesy of (L to R): Fulcrum 3D and Vestas

3 As of 21/1/2020
4 Proa Analytics, Lessons Learnt Report 1 (October 2019), p. 6
5 DNV GL, Lessons Learnt Report 1 (October 2019), p.2
6 Ibid.
7 AEMO, "Participant Forecasting FAQ" (September 2019), Available: Participant Forecasting FAQ September 2019

## Objective 2: Demonstrate the five-minute ahead self-forecasts are more accurate than the AWEFS and ASEFS

### Background

For a self-forecast to be assessed as more accurate than AWEFS or ASEFS forecast, the self-forecaster must first submit their self-forecast to AEMO within a controlled assessment period. On average, the self-forecast must on average be more accurate than the AWEFS or ASEFS forecasts over a minimum eight-week initial assessment period during which the unit cannot be not constrained-off[8] for more than 20 per cent of the time[9]. This is the minimum requirement before AEMO can assess the self-forecast and accredit its use in dispatch.

### Progress

On average, the eight ARENA supported accredited self-forecasts are more accurate than forecasts produced by AWEFS and ASEFS, as noted in the AEMO assessment period explained above. The trial participants have confidence that onsite, high-dimensional weather forecasting models can significantly outperform AWEFS and ASEFS.

Results of self-forecasts being used in the market dispatch can be found via the AEMO's NEMWEB portal[10] where the intermittent generation dispatch forecasts for the intervals of the previous day are published the next day. This data includes all AWEFS / ASEFS forecasts and all self-forecasts submitted for each wind and solar farm classified by their Dispatchable Unit Identifier (DUID) code.

### Challenges

There have been a number of external challenges to demonstrate self-forecasts are more accurate than AWEFS and ASEFS. AEMO's self-forecast assessment procedure[11] and trial participants lessons learnt reports[12] list what external challenges can be expected when developing self-forecasts to a level of accuracy that is higher than AWEFS or ASEFS including:

- seasonal weather challenges
- commissioning of generation assets
- network constraints
- negative spot prices triggering a halt or curtailment to generation.

### Lessons learnt

Early lessons learnt for wind forecasting found that there was a need to revise existing algorithms and machine learning designs to better forecast the effect of; site terrain[13], wind turbine wakes[14], extreme wind speeds[15] and turbulence[16]. Both wind and solar forecasters also learnt that rainfall has a non-trivial impact on the accuracy of their forecasts[17]. There were also lessons learnt on how ancillary technology on site, like control systems and site data parameters, influenced the forecasters ability to develop accurate forecasting models. These lessons are detailed on pages 5–7.

8 Constrained-off means the unit's energy target is less than its dispatch forecast
9 Unless they also provide unit possible power to AEMO in real-time via Supervisory Control and Data Acquisition (SCADA)
10 AEMO, Intermittent Generation Dispatch Forecasts - Public.
11 AEMO, Semi-Scheduled Generation Dispatch Self-Forecast – Assessment Procedure.
12 Vestas, Lessons Learnt Report 1 (October 2019), p. 1. Proa Analytics, Lessons Learnt Report 1 (October 2019), p. 4. Fulcrum 3D (Wind), Lessons Learnt Report 1 (October 2019), p. 2. Advisian, Lessons Learnt Report 1, (October 2019), p. 2.
13 Meridian, Lessons Learnt Report 1 (October 2019), p. 2.
14 Aeolius Wind Systems, Lessons Learnt Report 1 (October 2019), p. 2.
15 Fulcrum 3D (Wind), Lessons Learnt Report 1 (October 2019), p. 2.
16 Windlab, Lessons Learnt Report 1, (October 2019), p. 2.
17 Fulcrum 3D (Solar), Lessons Learnt Report 1 (October 2019), p. 2. & Meridian, Lessons Learnt Report 1 (October 2019), p. 3.

### Site terrain and optimised measurement locations

A significant advantage for wind forecasting was learnt by Meridian in the detailed design phase, which showed that it is useful to have access to terrain and topographical maps with 50cm contour lines to ensure the optimal placement of the Light Detection and Ranging (LIDAR) and meteorological masts[18]. Additionally, designing LIDAR equipment that can be easily moved across the site is beneficial to optimise the correlation between upstream measurements and measured wind speed (or generation) at any turbine location[19].

The importance of this is stressed by Windlab, as the placement of LIDAR measurement locations gives a pattern of influence that is quite variable across a geographic area, even a small wind farm. As such, careful choice of measurement locations is key to cover all turbines[20].

Equipment wise, Aeolius Wind Systems found that the short-range scanning Doppler LIDAR provided capacity to map wind fields in high spatial resolution (100m) at Macarthur wind farm with a consistent range of 3 km, sometimes longer when atmospheric aerosol loadings are heavier. The maximum distance where data of sufficient quality and quantity could be obtained to derive vector wind fields was approximately 2.5 km. Within that range only six turbines could be accurately forecast[21].

The implications for future projects using these insights may assist in the detailed design phase to ensure the equipment procured is compatible with being positioned and easily re-positioned on the site terrain and ensure that the equipment has the capacity to produce the required forecasting resolution for the wind farm.

Images courtesy of (L to R): Vestas and Proa Analytics

### Wind turbine wakes

Aeolius Wind Systems emphasised that it is critical to understand wake behaviour in large wind farms with multiple turbines in order for physical based LIDAR forecasting strategies to succeed. This includes quantifying the impacts of 'upstream' turbines on leeward (facing away from the wind) turbines to evaluate the impacts on electricity production and in turn STF accuracy[22]. High frequency sensors and additional information on turbine wake behaviour is needed to help fill this knowledge gap. Aeolius Wind Systems plans to address this knowledge gap in parallel to their ARENA STF trial project.

18 Meridian, Lessons Learnt Report 1 (October 2019), p. 2.
19 Windlab, Lessons Learnt Report 1, (October 2019), p. 2
20 Ibid, p. 4-5.
21 Aeolius Wind Systems, Lessons Learnt Report 1 (October 2019), p. 2.
22 Ibid.

### Extreme wind speeds and turbulence

Windlab found that forecasting wind speed and turbulence requires a forecast algorithm that can accommodate this daily changing variance in wind [23]. This turbulence or randomness of wind is strongest during the daytime when the sun's heating provides buoyancy for the creation of turbulent eddies. This is seen very consistently in the daily changing variance in both the horizontal and vertical wind speeds and is expected to continue and become stronger in the summer heat[24]. The forecasting data for summer 2019/2020 will provide further insights into wind forecasting.

### Forecasting in and after rain

Another lesson learnt for both wind and solar farms, is how rainfall affects the accuracy of forecasts. For solar forecasting, rainfall generally correlates with clouds, which helps lower panel temperatures and reduces soiling[25]. These benefits are captured by the detailed power model which uses real time SCADA data. For wind forecasting, SODARs perform better than LIDARs in rain, fog, smog and other low visibility scenarios[26]. There are some environments where both SODARs and LIDARs have performance limitations (e.g. arid areas with clean air), a short mast may be a better solution in these situations. To manage the effect of rainfall on forecast accuracy it is suggested that adequate hardware redundancy is installed on site to counter the impact on weather forecasting equipment.


Images courtesy of (L to R): Vestas and Fulcrum 3D

### Control system interfaces

Control system interfaces and accurate DC current sensors are needed to be able to build detailed power models, which are an essential component for accurate forecasting[27]. Currently, there is no "standard" for control system interfaces on solar farms[28]. Instead, proponents had to build workarounds for power plant controller and inverter controller algorithms to overcome the currently obscure systems. The need for improved, standardised documentation on this equipment (DC current sensors, control system interfaces and inverters) is a lesson learnt for suppliers[29], which could be an implication for future projects to list as a requirement in their procurement process.

23 Windlab, Lessons Learnt Report 1, (October 2019), p. 2
24 Ibid.
25 Fulcrum 3D (Solar), Lessons Learnt Report 1 (October 2019), p. 2.
26 Fulcrum 3D (Wind), Lessons Learnt Report 1 (October 2019) & Meridian, Lessons Learnt Report 1 (October 2019), p. 3.
27 Fulcrum 3D (Solar), Lessons Learnt Report 1 (October 2019), p. 2.
28 IMC, Lessons Learnt Report 1, (October 2019), p. 2.
29 Fulcrum 3D (Solar), Lessons Learnt Report 1 (October 2019), p. 3.

### Data parameters

In setting up the LIDAR scanning parameters, there was a trade-off between spatial resolution and sampling frequency. Meridian found higher sampling frequency was preferable for the purposes of short-term forecasting[30]. Meridian also found through their work that there are skill caps (maximum level of forecasting ability for a given approach) on all forecasting techniques. Meridian's examination of simple machine learning approaches has shown that the approaches perform no better than statistical methods when given on-site farm data. Deep learning/off-farm data is likely to be essential to greatly increase the skill cap of forecasting[31].

Advisian noted that constraint periods for future projects (where the output of the wind and solar farms are artificially reduced due to maintenance outages or AEMO restrictions) needed to be removed from the training data set[32]. Excluded data was more than had been originally expected, which reduced the amount of data available for model training. With this in mind, Advisian expects periodic retraining the self-forecasting model following production to achieve incremental improvements in model accuracy[33].

Image courtesy of Fulcrum 3D

30 Meridian, Lessons Learnt Report 1 (October 2019), p. 3.
31 Ibid, p. 4.
32 Advisian, Lessons Learnt Report 1, (October 2019), p. 2.
33 Ibid.

## Objective 3: Demonstrate the potential commercial benefits of wind and solar farms investing in short-term, self-forecasting solutions

### Progress

As the trial is still in the early stages, demonstration of commercial benefits (linked to the objective of using self-forecasts in central dispatch to produce more accurate dispatch and pricing signals to the market and in turn reduce the need for frequency regulation) yet to be confirmed.

### Challenges

Being the first trial of its kind, the ability for a wind or solar farm to self-forecast is currently not able to be subcontracted to a third-party owned, turnkey solution. This is due to the need for Semi-Scheduled Generator asset owners/operators to be actively engaged with their third-party forecasting technology providers to send self-forecasts to the AEMO MP5F API. Market participant will also always be responsible for ensuring to the accuracy of their self-forecast to the market regardless of the technology service provider.

Challenges can also be found in the form of knowledge gaps. IMC noted that an economic model that relates the Frequency Control Ancillary Services (FCAS) causer pays penalty to the quality of solar forecasts in the NEM does not currently exist[34]. Some trial participants are currently working on filling this gap by developing economic models and the insights and findings will be shared in a future report.

### Lessons learnt

#### Project delays

There were a range of delays to projects that were (in part) connected to the complex contracting structures, and terms and conditions between multiple parties[35]. It is recommended for future projects that self-forecast service providers build in additional contingency for the contract negotiation period[36] to ensure that the project risk management plan has adequate mitigation strategies to deal with site and project partner changes[37]. When sourcing equipment, self-forecast service providers should identify suppliers with lead times that align with project timeline requirements. These lessons are useful when considering scaling or replicating STF solutions in the future[38].

#### Computationally expensive models

Advisian identified that there are high degrees of seasonality in the underlying wind farm data that requires more complex modelling approaches. The data used to train the models is also large. Together, these factors have considerable impact on the computation power needed to train models within a reasonable time frame. Advisian have used cloud-hosted computing resources, which allow their computing platform to scale as needed to support model iterations[39].

#### Speed of deployment & remote access

Aeolius Wind Systems found that it is possible to deploy and implement a LIDAR based monitoring strategy at an Australian wind farm at relatively short notice (several weeks) if the proponent has access to hardware with range measurement capability beyond 6 km, advanced data post processing software, and analytical skills[40]. They also found it is important for a site to have access to reliable, high-speed telecommunication capability, for the LIDAR wind forecaster to succeed. Whilst suitable infrastructure may be in place at the wind farm control centre, remote connection may not be available at the site where the forecaster is installed. This challenge needs to be addressed in the early stages of planning a monitoring demonstration[41]. Fulcrum 3D have implemented telecoms in their projects where remote communications are working well (via a dedicated NBN connection) which enables Fulcrum 3D to perform system maintenance remotely.

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34 IMC, Lessons Learnt Report 1, (October 2019), p. 2.
35 Ibid. & Solcast, Lessons Learnt Report 1, (October 2019), p. 1.
36 Advisian, Lessons Learnt Report 1, (October 2019), p. 2.
37 Solcast, Lessons Learnt Report 1, (October 2019), p. 1.
38 Advisian, Lessons Learnt Report 1, (October 2019), p. 2.
39 Ibid, p. 1.
40 Aeolius Wind Systems, Lessons Learnt Report 1 (October 2019), p. 2.
41 Ibid, p. 2.

## CONCLUSION AND NEXT STEPS

It is clear that the STF trail is beginning to demonstrate that proposed technologies have the potential to provide self-forecasts to AEMO that are more accurate than AWEFS and ASEFS systems within a five-minute ahead period.

The insights gained to date provide lessons for stakeholders across the industry including:

- owners and operators of wind and solar farms weighing up the business case for investing for both brown and greenfield renewable energy sites
- service providers including renewable energy developers, as well as engineering, procurement and construction (EPC) and operations and maintenance (O&M) organisations planning how to incorporate self-forecasting equipment into the design of greenfield projects
- insights for forecasting and ancillary equipment suppliers to improve design and integration with other technologies
- academics seeking new knowledge gaps to research
- the AEMO Operational Forecasting team by highlighting the problem areas to can troubleshoot.

ARENA and AEMO will share more insights of the trial through a variety of events and publications in 2020.

## LIST OF THE ARENA SHORT-TERM FORECASTING TRIAL PARTICIPANTS

| ARENA project page | Renewable energy forecasted | Primary forecasting hardware | Location | ARENA funding (Total project cost) | Lesson Learnt Report #1 |
|---|---|---|---|---|---|
| Advisian Pty Ltd | Wind & Solar | Sky cameras | QLD & SA | $499k ($999k) | Link |
| Aeolius Wind Systems Pty Ltd | Wind | LIDAR | VIC | $1.89m ($3.93m) | Link |
| DNV GL Pty Ltd | Wind | N/A (real-time site data provided) | VIC | $270k ($541k) | Link |
| Fulcrum 3D (Solar Project) | Solar | Fulcrum3D CloudCAMs | QLD | $490k ($991k) | Link |
| Fulcrum 3D Pty Ltd (Wind Project) | Wind | Loggers & SODAR | NSW, VIC & SA | $493k ($953k) | Link |
| Industrial Monitoring & Control Pty Ltd | Solar | Cloudcam & satellite | NSW, VIC & QLD | $1.24m ($2.12m) | Link |
| Meridian Energy Australia Pty Ltd | Wind | LIDAR & Anemometers | VIC & SA | $2.18m ($5.52m) | Link |
| Proa Analytics Pty Ltd | Solar | Skycam & satellite | VIC & QLD | $728k ($1.39m) | Link |
| Solar and Storage Modelling Pty Ltd (Solcast) | Solar | Skycam & satellite | NSW, VIC, QLD | $781k ($2.57m) | Link |
| Vestas Australian Wind Technology Pty Ltd | Wind | Meteorological masts | SA | $405k ($1.1m) | Link |
| Windlab Limited | Wind | LIDAR | VIC & QLD | $393k ($813k) | Link |

Further information is available at
**arena.gov.au**

**Australian Renewable Energy Agency**

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