Innovative Optimally Combined Solar Forecasts

LESSONS LEARNT REPORT #3

Project Details

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EXECUTIVE SUMMARY

This is the third public Lessons Learnt report from the ARENA funded Innovative Optimally Combined Solar Forecasts Project. As part of this project, Proa is demonstrating its solar forecasting services at three NEM solar farms in the three main climate zones of the NEM:

- Tropical: Kidston Solar Project (QLD) in partnership with owner and operator Genex Power
- Sub-tropical: Oakey 1 Solar Farm (QLD) in partnership with owner and operator Oakey 1 Asset Company.
- Temperate: Bannerton Solar Project (VIC) in partnership with owner and operator Foresight Australia.

This project will continue until January 2021. As the project progresses, we continue to learn more about self-forecasting in the NEM and techniques to increase forecast accuracy. This Knowledge Sharing report is intended to share some of the Lessons Learnt during the project, noting that this is an interim report. The Lessons Learnt presented here include:

1. Commercial: Financial optimisation of self-forecasts
2. Technical: Importance and challenges of cloud dynamics modelling
3. Logistical: A new automatic self-cleaning system for skycams.

KEY LESSONS LEARNT

Lesson learnt No. 1: Financial optimisation of self-forecasts

Category: Commercial

Causer Pays Factors is the mechanism by which AEMO recovers the cost of Regulation Frequency Control Ancillary Services (FCAS). Regulation FCAS is the service which maintains NEM frequency in a narrow band around 50 Hz during normal operations.

For this reason, when calculating the Market Participant Factors (MPFs), the procedure accounts for the sign and magnitude of deviations from the dispatch trajectory, and whether they are contributing to or reducing the need for raise or lower regulation services at each 4-second period.

The four-second performance of the Causer Pays procedure is therefore determined by both the forecasting errors and by which regulation service is in use.

The learnings from the project have shown that:

- It is possible to replicate the Causer Pays Factor procedure based on publicly available data from AEMO.
- Corrections can be made to self-forecasts based on market factors to minimise the MPF for a participant.
- The self-forecast must still outperform ASEFS in terms of MAE and RMSE to be used in dispatch.

Lesson learnt No. 2: Importance and challenges in cloud dynamics modelling

Category: Technical

The calculation of solar generation forecasts for solar farms is based on three main modelling steps:

1. the solar farm topology and operations,
2. the underlying daily cycle in the solar irradiance,
3. the impact of cloud cover on the incident irradiance of solar farms.

The models to calculate the power output of solar farms based on the incident irradiance and other parameters offer high levels of accuracy and are available from open-source libraries. The underlying daily cycle of solar irradiance is also well understood and is normally predictable, with minor uncertainty due to variations in the turbidity of the atmosphere. These turbidity variations, mainly driven by variations in the aerosol and water vapour content of the atmosphere, do not cause ramps in solar output and their impact is normally limited to approximately 10% variations in solar exposure from day to day (with the exception of extreme events arising from bushfire smoke, heavy air pollution or volcanic ash). It is therefore possible to forecast solar generation in cloudless conditions years ahead with relatively low uncertainty. Finally, the impact of clouds can reduce the power output of a site by as much as 80-90% and cause large ramps of similar magnitude in a few minutes. Clouds are the main source of uncertainty and are responsible for the greatest errors in solar generation forecasts.

Entry-level self-forecasting models can be built to account only for points 1 and 2, by using SCADA data from site and using persistence models corrected for the daily morning and evening ramps. These models have the advantage of relatively simple implementation, robustness, and predictable outcomes. However, their potential for improvement is limited as they do not address the main source of uncertainty in solar forecasts: cloud dynamics. The lessons of this project have shown the importance of modelling cloud dynamics to unlock the full potential of self-forecasts for solar farms. Accounting for cloud dynamics employs relatively complex models making use of skycam, satellite and weather models data. While these models successfully describe cloud cover, their complexity has presented additional challenges:

- First, the sensitivity of the forecasts to inaccuracies in intermediate modelling steps, requiring fine calibration and testing of the models.
- Second, more complex models require increased computing time which can negatively impact forecast accuracy, especially at short time frames such as 5 minutes ahead. Further development and optimisation of the algorithms has proven to be necessary to overcome increased computing time.
- Third, they require additional testing and monitoring to handle the increased risk of unexpected outcomes in the deployment process.

Lesson learnt No. 3: Automatic Self-cleaning Stations for skycams

Category: Logistical

As described in the Lessons Learnt Report[1] #2, soiling of skycams (e.g. from dust) impairs their forecasting ability. While periodic cleaning by O&M staff at the site helps, this does not completely solve the problem. Ideally skycams would be cleaned on daily or weekly basis, but due to personnel availability, cost, and sometimes difficult access to the instruments (e.g. skycams installed at significant heights), this is not feasible.

Proa has designed and installed an innovative automatic self-cleaning system able to clean the lenses of skycams with pressurised water on a periodic basis. The project has demonstrated very good results of the self-cleaning system to remove dust or other atmospheric contaminants, but traces or droppings from birds still required manual intervention. For this reason, the functionality of the automatic self-cleaning has been extended to actively deter wildlife from approaching the instruments.

An example of the positive effects of the ACS is shown in Figure 1 below.

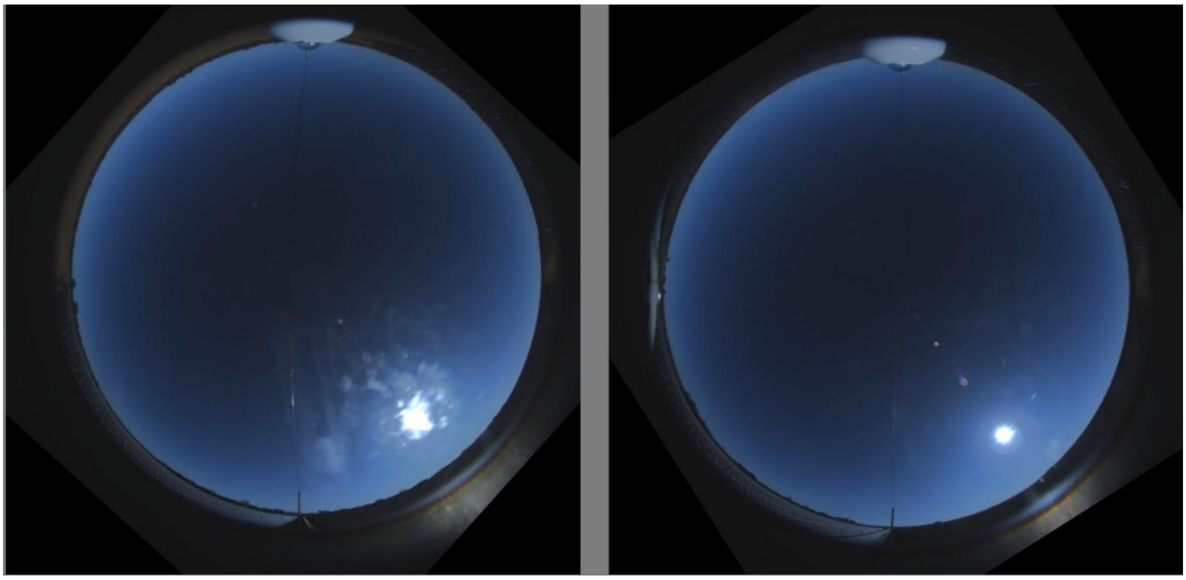

Figure 1: Comparison between two skycams on same site, after 4 weeks of operation with (right) and without the automatic self-cleaning system.

[1] https://arena.gov.au/knowledge-bank/proa-analytics-solar-farm-short-term-forecasting-project-lessons-learnt-2/