Improving electricity forecasting through better data and analytics

Chair – Cian McLeavey-Reville, National Grid ESO

Wednesday 30 October

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Improving Electricity Forecasting through better data and analytics

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Kevin Tilley

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Challenges for Accurate Electricity Forecasting

National Grid ESO fulfils a number of important functions, including:

- Operating and balancing the transmission network in real time, as safely & economically as possible (£1bn/year)
- Planning and sanctioning future transmission system outages
- Informing the wider Electricity Market – to enable efficient energy market operation (day ahead market c £30bn/year)

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Challenges for Accurate Electricity Forecasting

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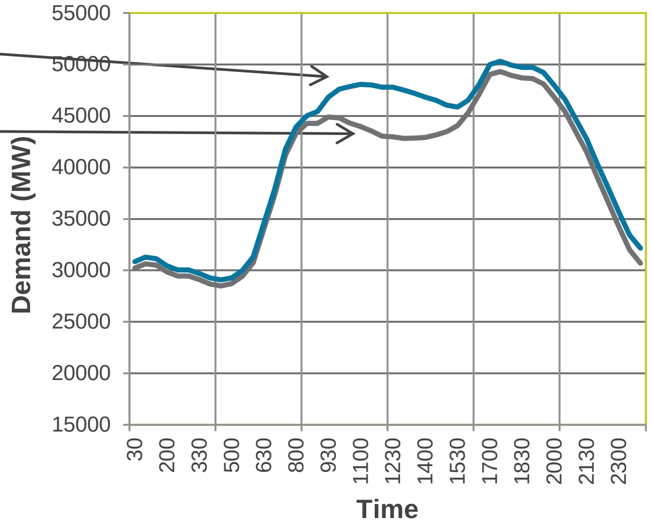
In order to fulfil these tasks, accurate national and regional short-term transmission system demand forecasts are required

UK consumption

Transmission System Demand



Transmission System Demand is lower than overall consumption because of factors such as

- distribution connected generation, for example

  - embedded wind
  - embedded solar (all solar)
  - other embedded technologies

Challenges for Accurate Electricity Forecasting

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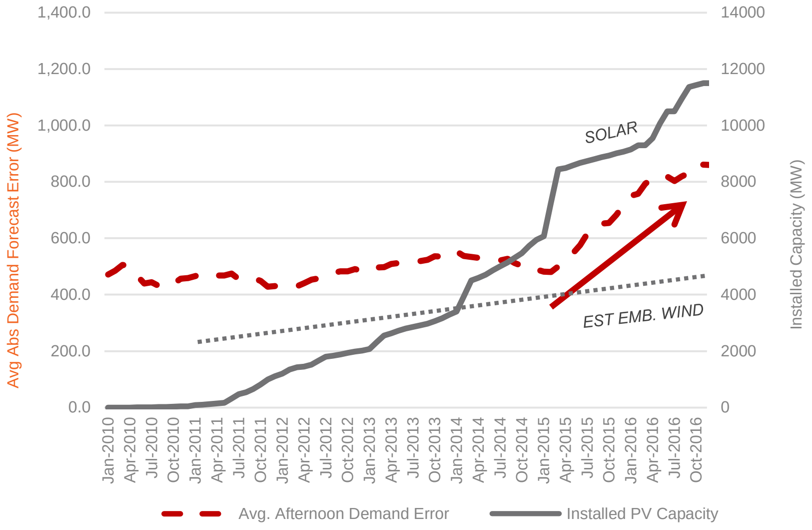
Forecasting transmission system electricity demand has become more difficult over the last decade …



… due in particular to the growth of embedded generation & for which NGESO historically has had limited data

Solar generation in particular grew hugely due to subsidies:-

1. **How to determine what solar power was being generated?**
2. **Could we improve our solar power forecasts via better power conversion models?**
3. **Could we improve our solar power forecasts via better solar radiation forecasts?**

Distribution connected wind also grew significantly … meaning demand is now extremely weather dependent …

4. Were there further enhancements to our weather forecasts that could help our demand forecasts?

Tackling the above could help manage our demand forecasts

Jamie Taylor

Sheffield Solar

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The University Of Sheffield.

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PV Monitoring Phase 3

Modelling the outturn from solar PV in near-real-time

Jamie Taylor

LCNI 2019 Glasgow

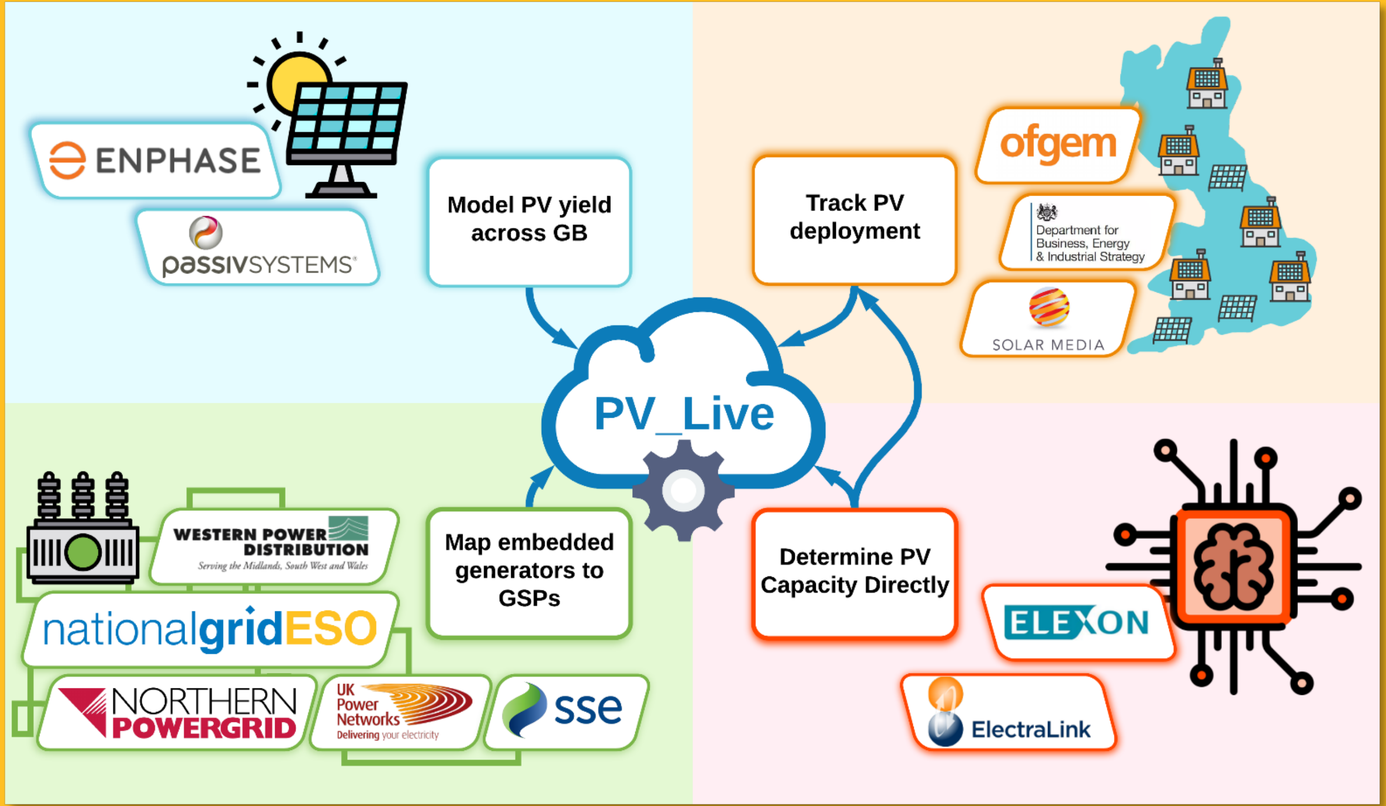
30th October 2019

Since 2015

Two-phase NIA-funded project

Modelling the nationally- and regionally-aggregated outturn from solar photovoltaics across the GB electricity network

- Enables NGESO to improve their ***PV*** forecast
- Enables NGESO to improve their ***demand*** forecast



www.solar.sheffield.ac.uk/pvlive

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A free public service…

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Redtree Technology
Energy Sparks
DXT Commodities
martyn berry consulting
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Cyfoeth Naturiol Cymru Natural Resources Wales
MYGRIDGB
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Met Office
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SSE
UK Demand (GW) Smiths Ind. Ltd
uniper
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EDF
AURORA ENERGY RESEARCH
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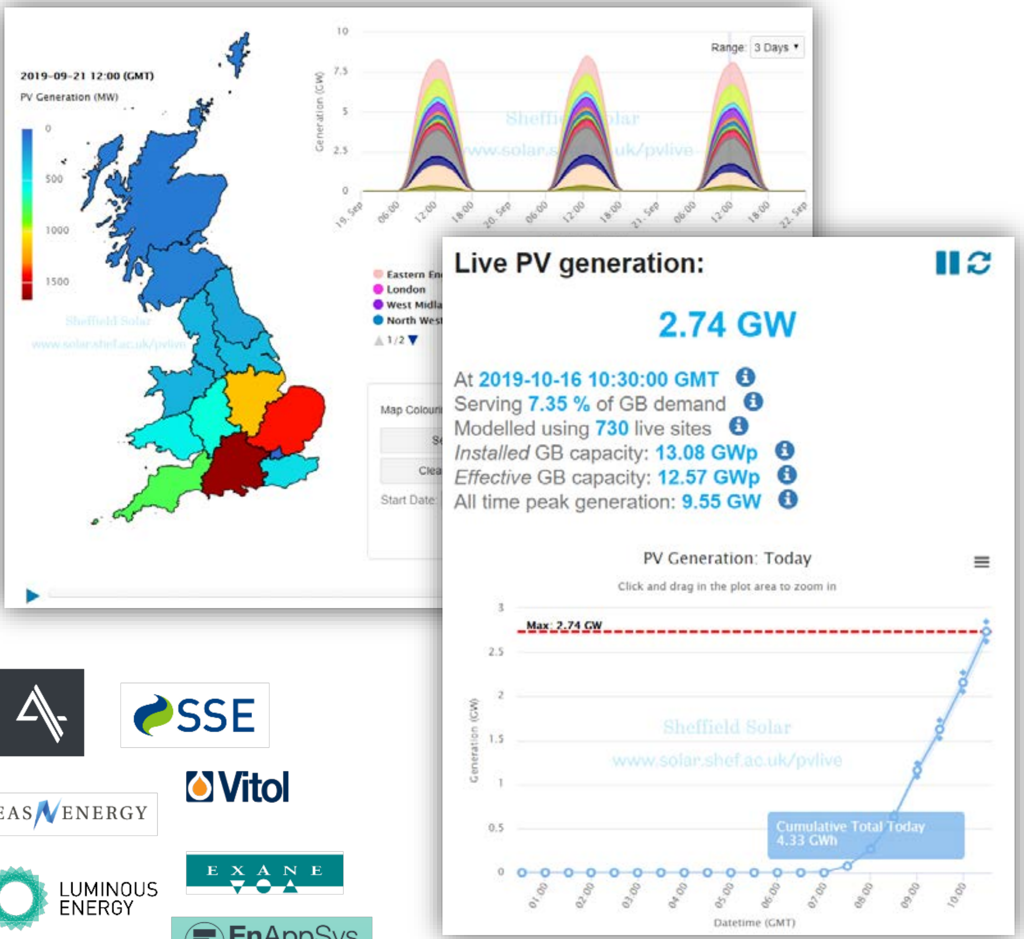
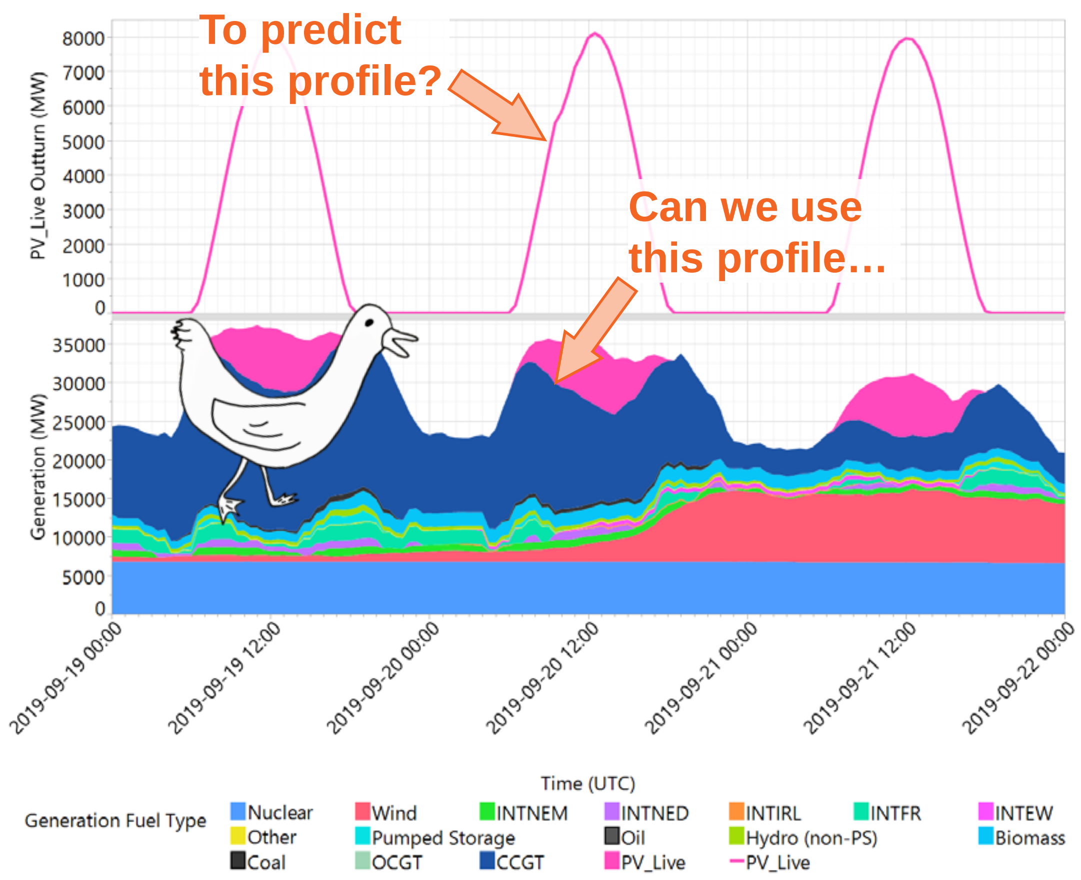


Using Machine Learning to predict deployed PV capacity



All GB PV is embedded in the distribution network…

Leading to an invisible reduction in demand on the transmission network…

Resulting in the so-called

"duck curve"

Can we extract information from the duck curve to tell us how much PV capacity has been deployed regionally?

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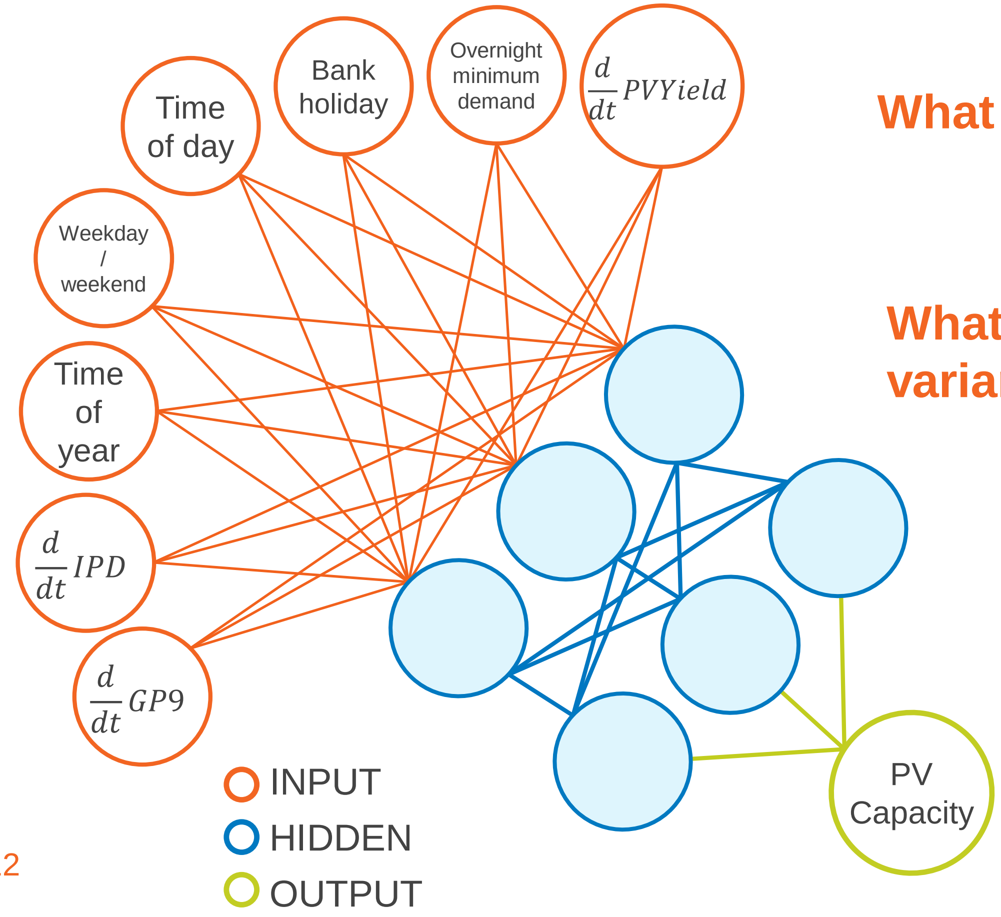
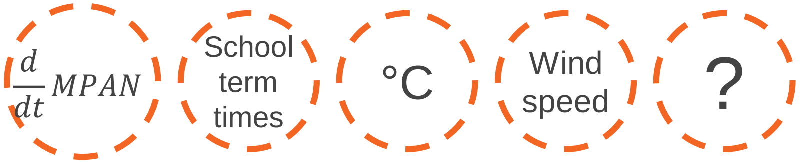
Parameterisation of the ANN



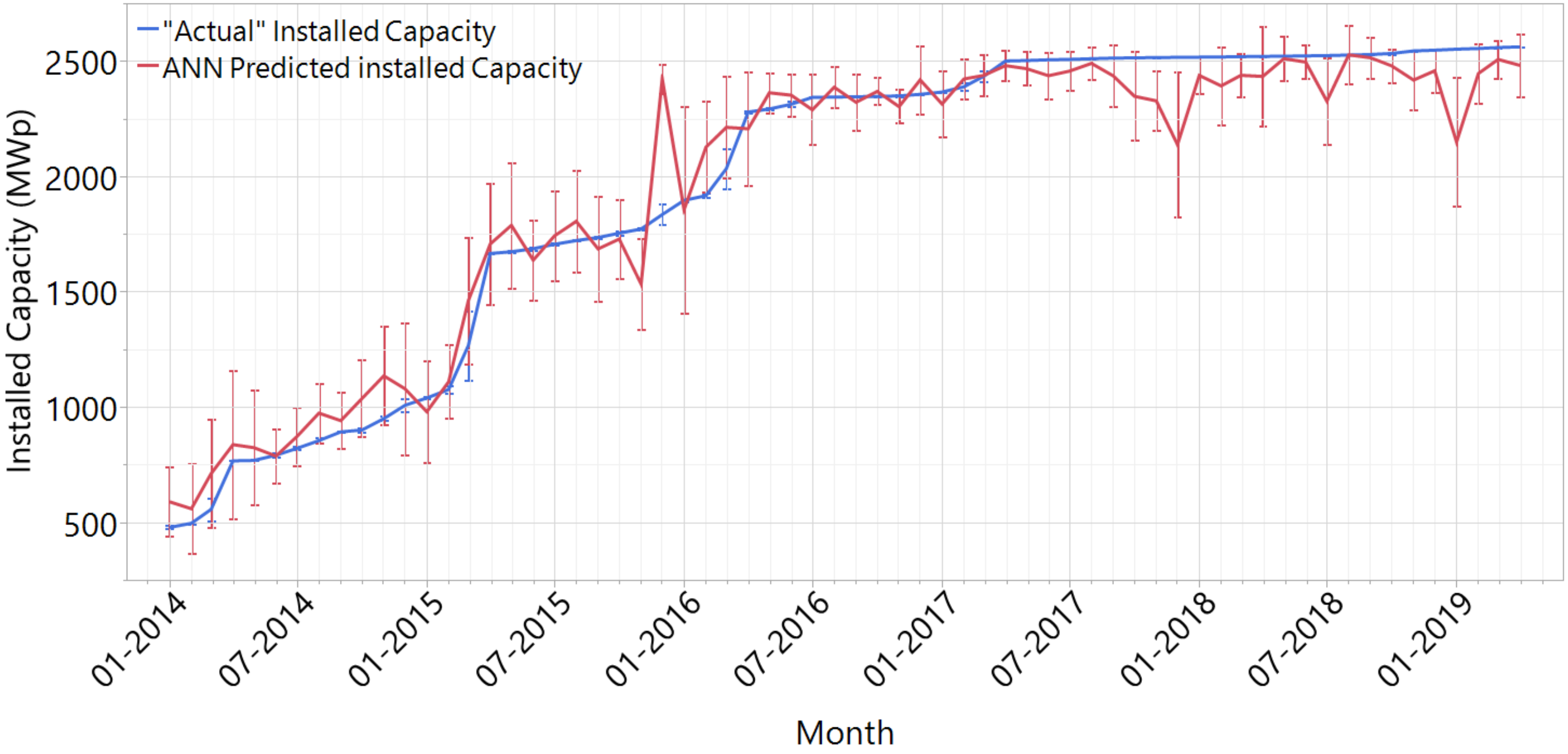
What drives regional electricity demand?

Or, more precisely…

What parameters can be used to explain variance in observed demand that is not caused by PV?



Some preliminary results



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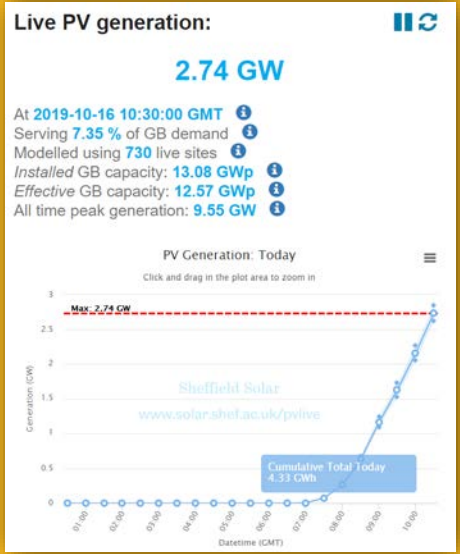
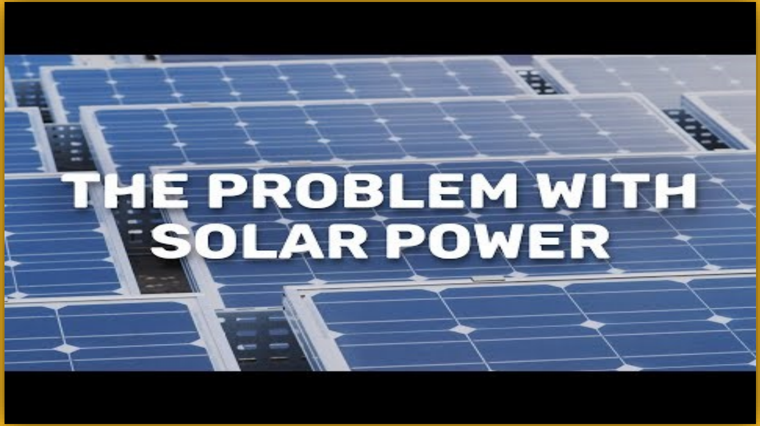
www.solar.shef.ac.uk/pvlive





www.shef.ac.uk/research/features/solar

www.smarternetworks.org/project/nia_ngso0008

Find out more…

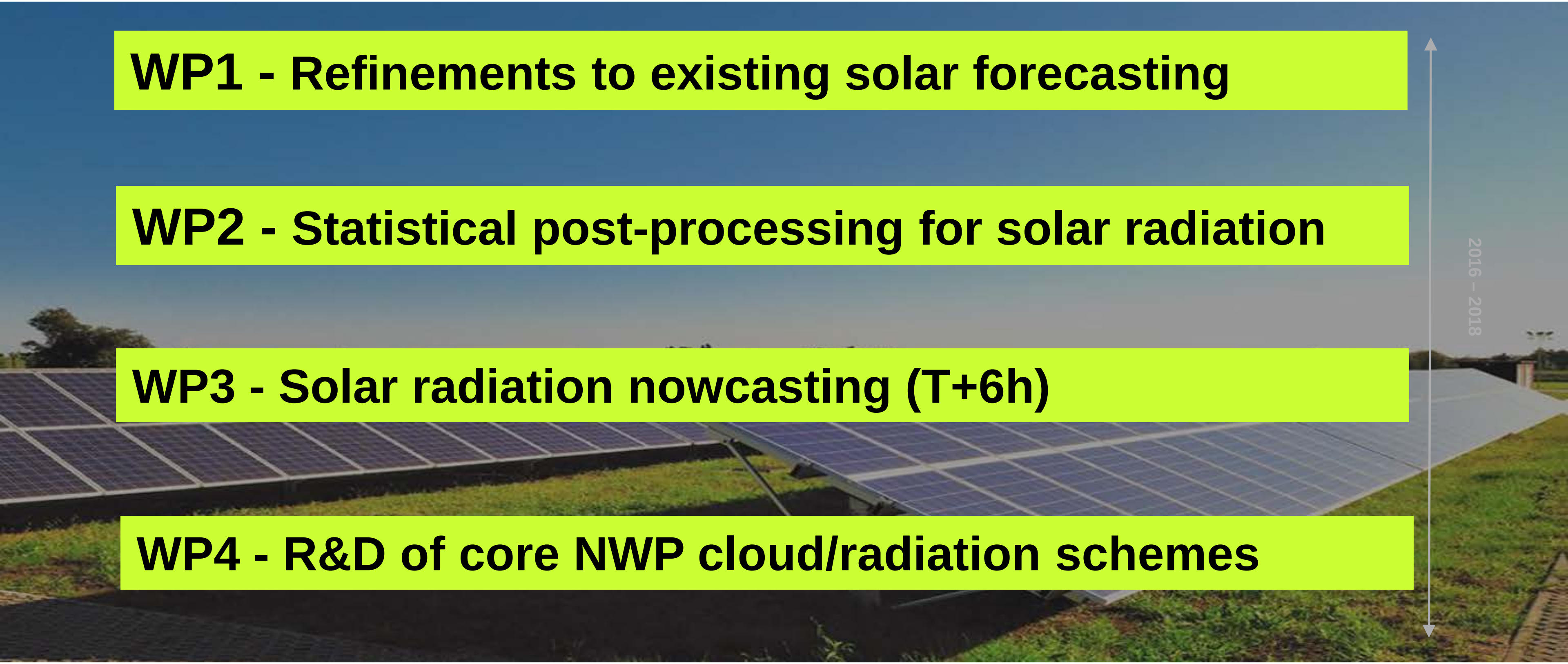
Ian Pearman

Met Office

Improved Solar Radiation Forecasting

Ian Pearman, Met Office

Improved Solar Radiation Forecasting



WP1 - Refinements to existing solar forecasting

WP2 - Statistical post-processing for solar radiation

WP3 - Solar radiation nowcasting (T+6h)

WP4 - R&D of core NWP cloud/radiation schemes

2016 – 2018

www.metoffice.gov.uk

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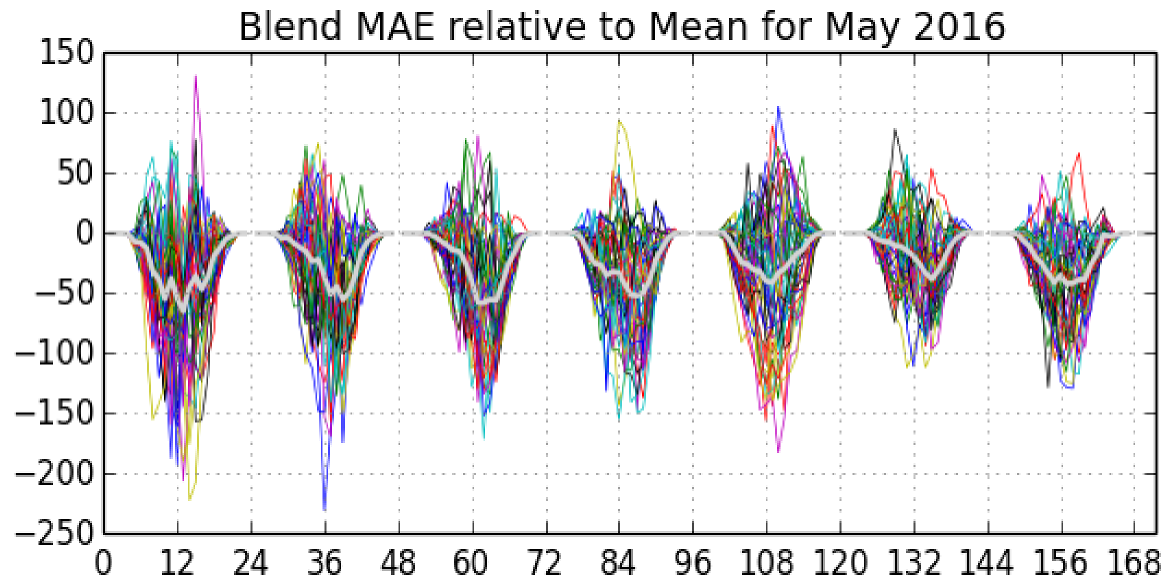
Improved Solar Radiation Forecasting

WP1 - Refinements to existing solar forecasting

Replace ensemble mean with multi-model optimally weighted blend.

5-10% improvements in solar irradiance Mean Absolute Error.



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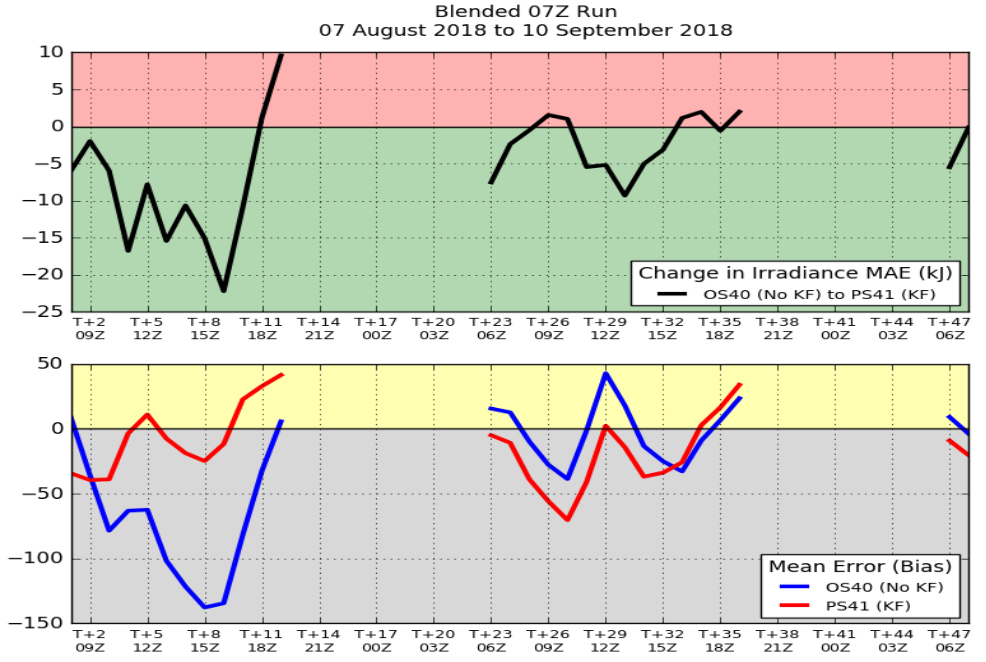
Improved Solar Radiation Forecasting

WP2 - Statistical post-processing for solar radiation

Reviewed a number of statistical techniques.

Implemented a Kalman Filter bias correction.

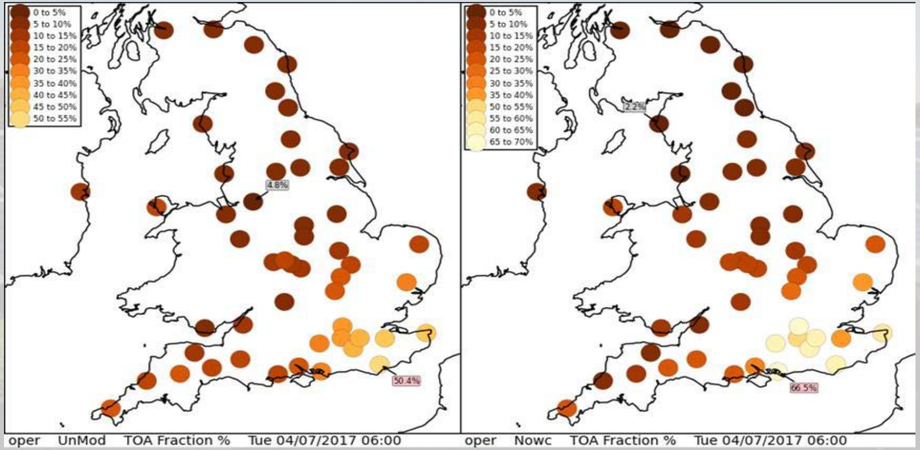
Day 1 forecast improvement giving a further reduction in blend MAE of 1-2%

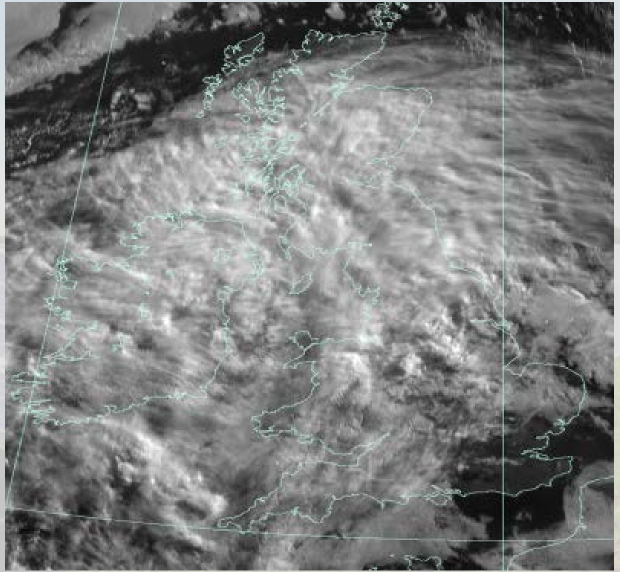


Improved Solar Radiation Forecasting

WP3 - Solar radiation nowcasting (T+6h)

Use satellite cloud to refine model cloud forecast.





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Improved Solar Radiation Forecasting

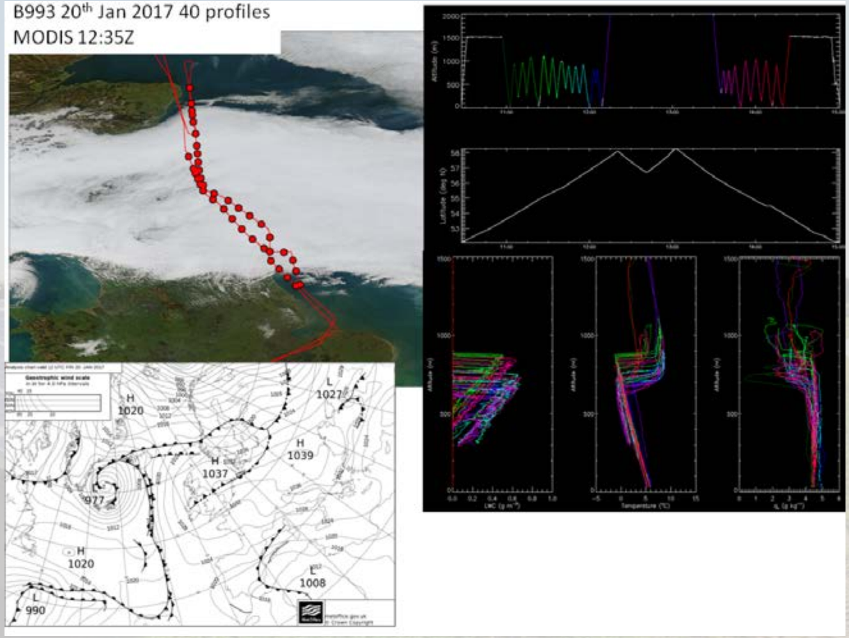
WP4 - R&D of core NWP cloud/radiation schemes

Detailed investigation into cloud biases

Exploit observational campaigns

Focus upon low, shallow cloud sheets

Enhancements to NWP cloud schemes scheduled for future operational releases



Benefits propagate beyond National Grid and the Energy Sector into any cloud-sensitive industry application.

Alexi Reynolds

Smith Institute

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Smith institute
for Industrial Mathematics and System Engineering

Optimisation of Weather Data to Improve Energy Forecasting

Dr Alexi Reynolds, Business Development Manager

LCNI October 2019, Glasgow

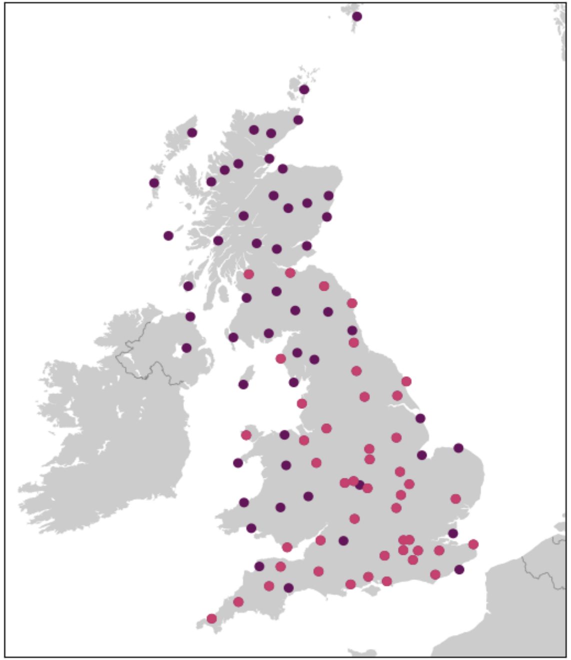
Smith institute

NIA report authored by **Dr Thomas Hawes** and **Dr Jakob Blaavand**

Background

- **Motivation:** can the accuracy of demand forecasts be improved through changes to the weather feeds?
- **Data:** Provided with 2 weather datasets A and B.

	Dataset A	Dataset B
No. of weather stations	53	104
Forecast horizon	14 days	6 hours (or 10 days if the forecast is generated at 7am or 7pm)
Temporal resolution	1 hour	1 hour (or 1 hour, up to 4.7 days ahead; 6 hours, 4.7-10 days ahead)



Pink stations in both datasets, purple stations only in dataset B.

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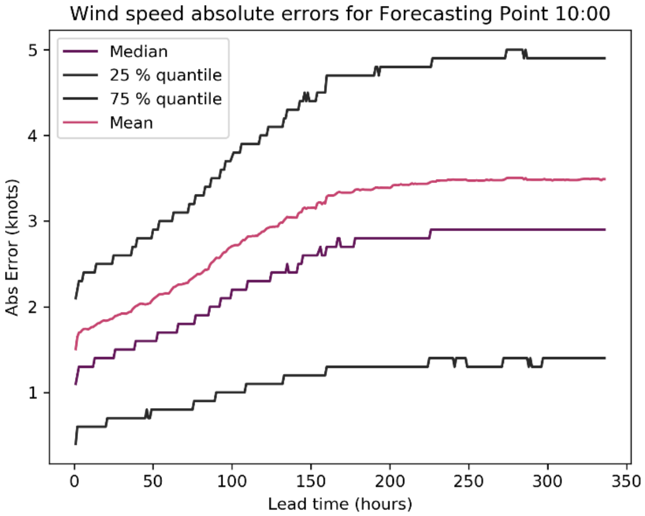
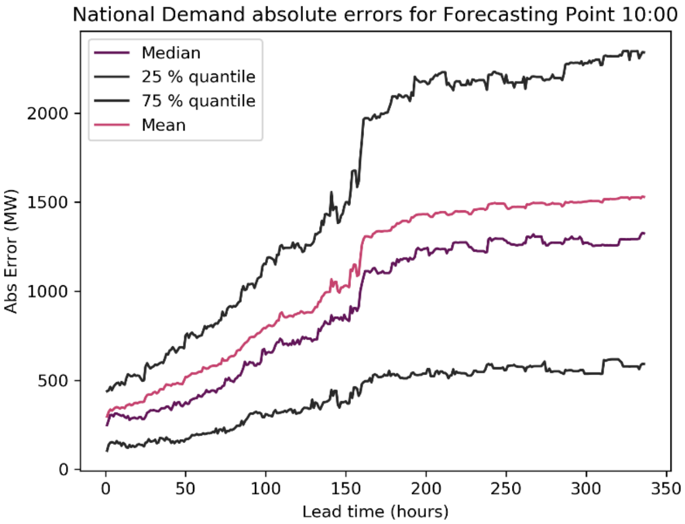
Temporal Analysis

Question: How often should we get new weather forecasts?





National Demand Weather = Weather regression model – PV – Embedded Wind

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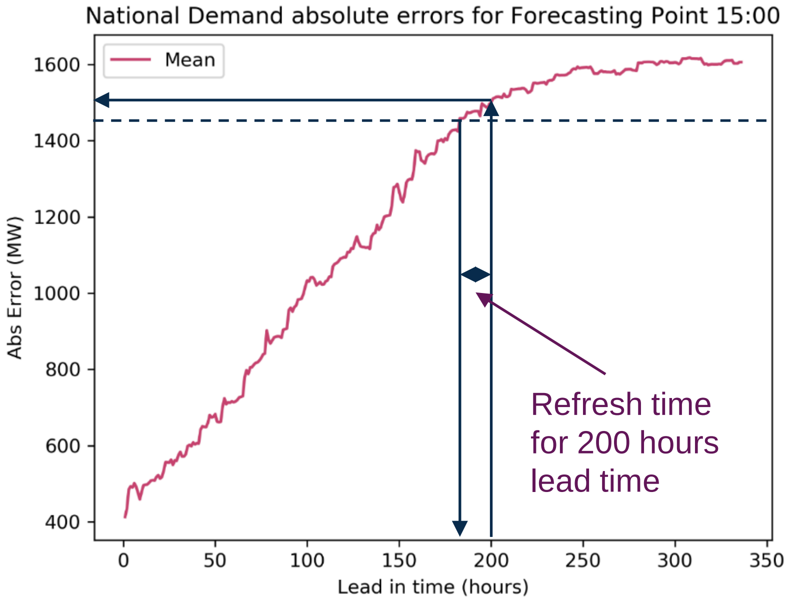
Temporal Analysis

- Guided by NGESO we consider refreshing a forecast worthwhile when a forecast has improved by 10MW or more.



Planning window (h)	PV	Met Wind	ND	Freq	Recommendation
1-4		3	1	1	1
5-12	4	3	2	2	1
12-24	6.5	3	5	3	3
24-48	4.5	4	3.5	3.5	3
48-168	4	3	3	3	3
168-336	45.5	19	10	10	12

Recommendations

- Increase the frequency of delivery of weather forecasts.

OLD: 4 x 14 days ahead

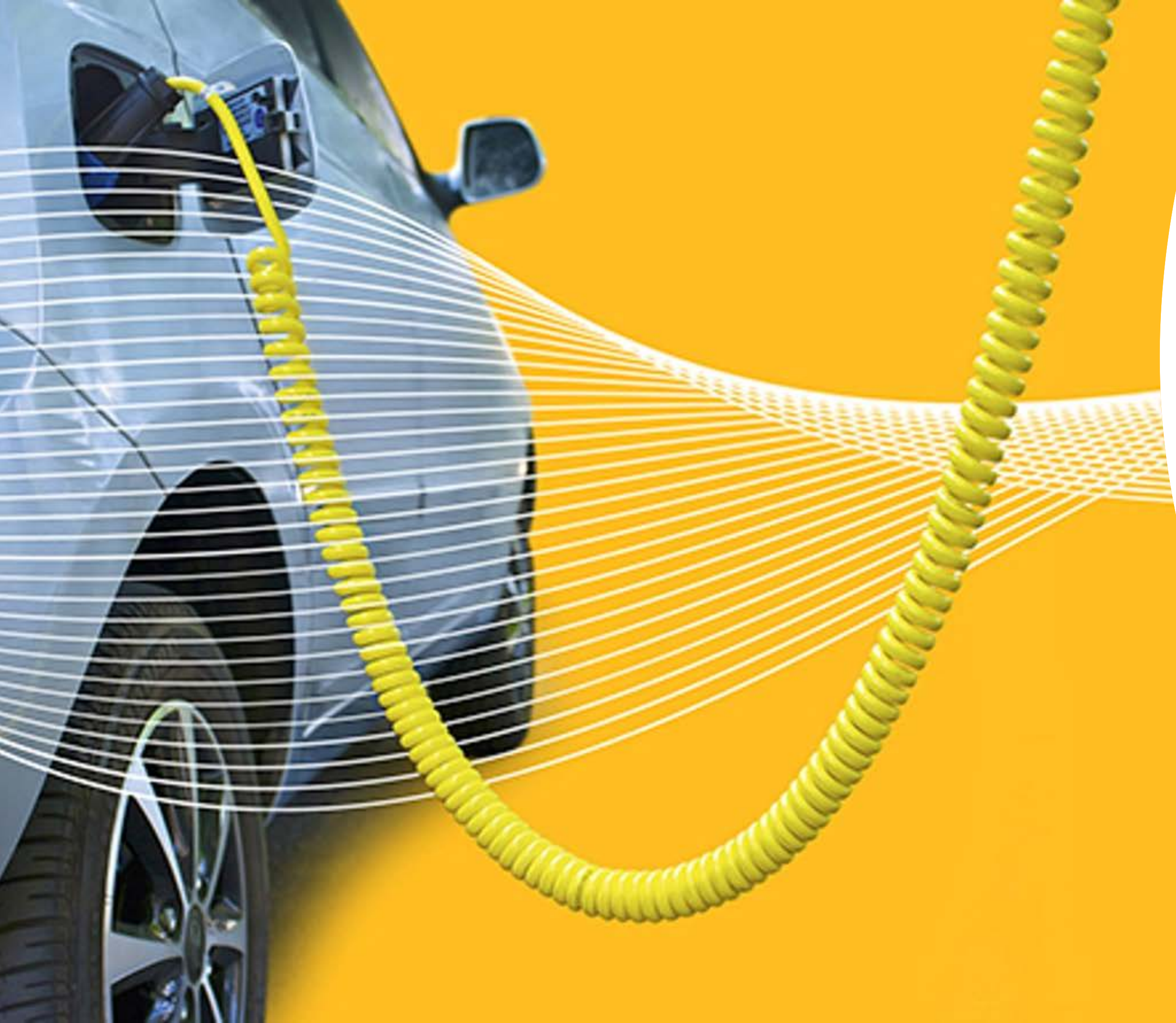
NEW: 24 x 12 hours ahead
8 x 7 days ahead
2 x 14 days ahead

- Distance between weather stations and highest capacity generation should be minimised

- Focus should be given to weather variables which impact power forecast accuracy most

- Recommendations are mostly ‘common sense’, the key contribution of this project was to quantify the likely benefits and provide practical steps to achieving them

- Recommendations were also made for modelling improvements based on a literature review



Kevin Tilley

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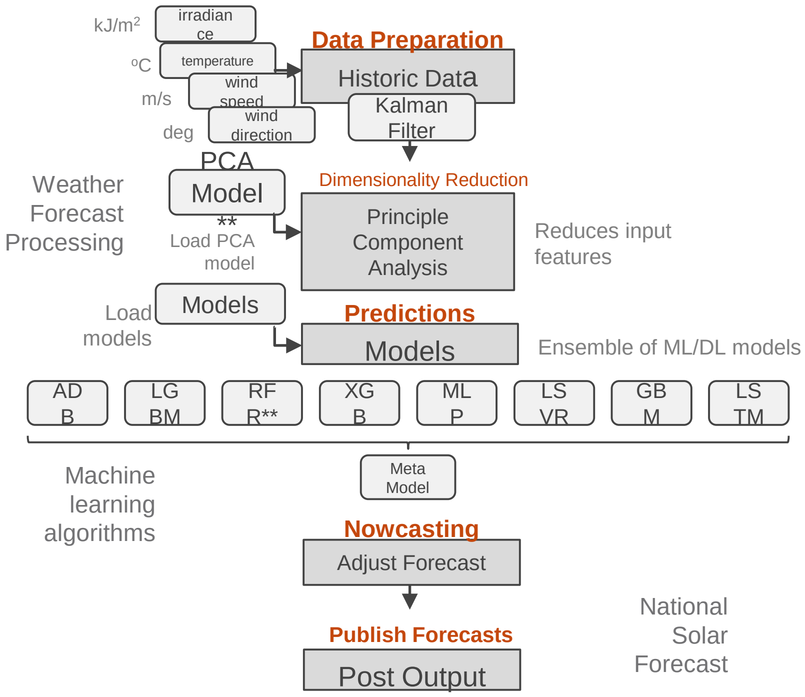
Machine Learning based Solar Generation Forecasts

- In 2017 we embarked on a 3month NIA project with the Alan Turing Institute for Data Science (NIA_NGS0001)

- Investigated advanced statistical & machine learning techniques to the forecasts of solar power & developed prototype algorithm based on random forest regression

- In the first half of 2018, NGESO explored a number of additional techniques:-
  - Correction of weather data according to recent observations
  - Addition of further machine learning approaches
  - Use of a 'meta-model' to select best combination of constituent machine learning forecasts

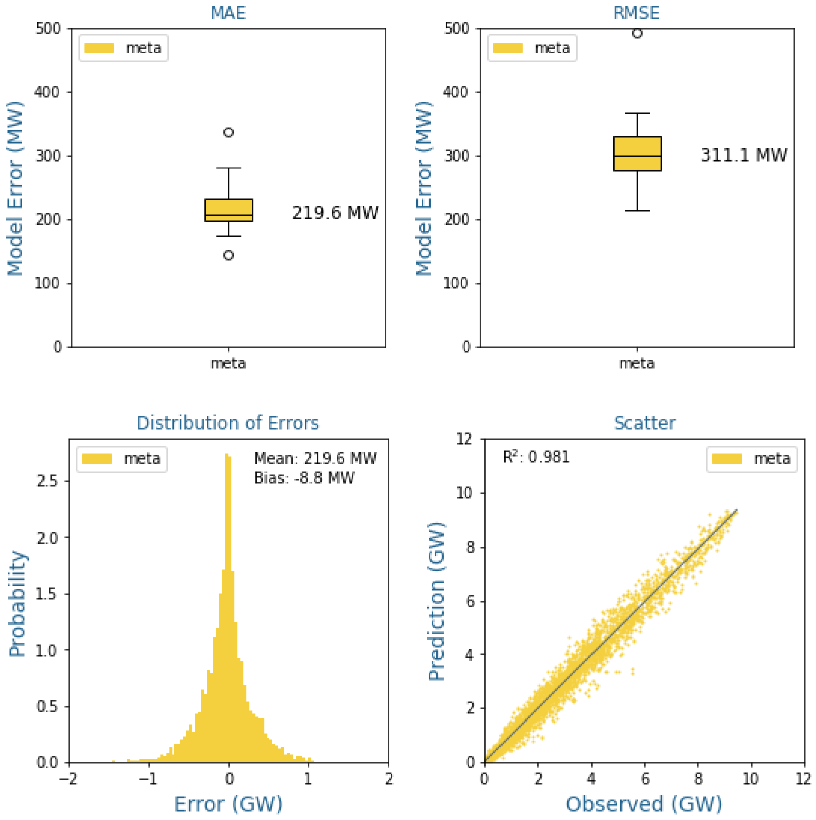


Machine Learning based Solar Generation Forecasts

- During testing, the ML forecasts were assessed to be around 33% (c. 150MW) more accurate (MAE) compared to the existing system (using SS outturns as the reference)

- New ML based solar power forecasts were incorporated directly into the operational process for calculating demand in Sept18

- Further information can be obtained at the NGESO stand (Thurs 31st), or from the following:-
  - https://www.nationalgrideso.com/news/eso-and-alan-turing-institute-use-machine-learning-help-balance-gb-electricity-grid
  - https://www.turing.ac.uk/research/impact-stories/towards-greener-grid



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Implementation of these Projects

Solar outturn estimates:-

- April16 SS national solar outturns used by NGESO to build better national solar forecasts

Improved Solar Power Conversion models:-

- Sept18 NGESO ML national solar power forecast based on Turing NIA is operational

Improved Solar Radiation forecasts:-

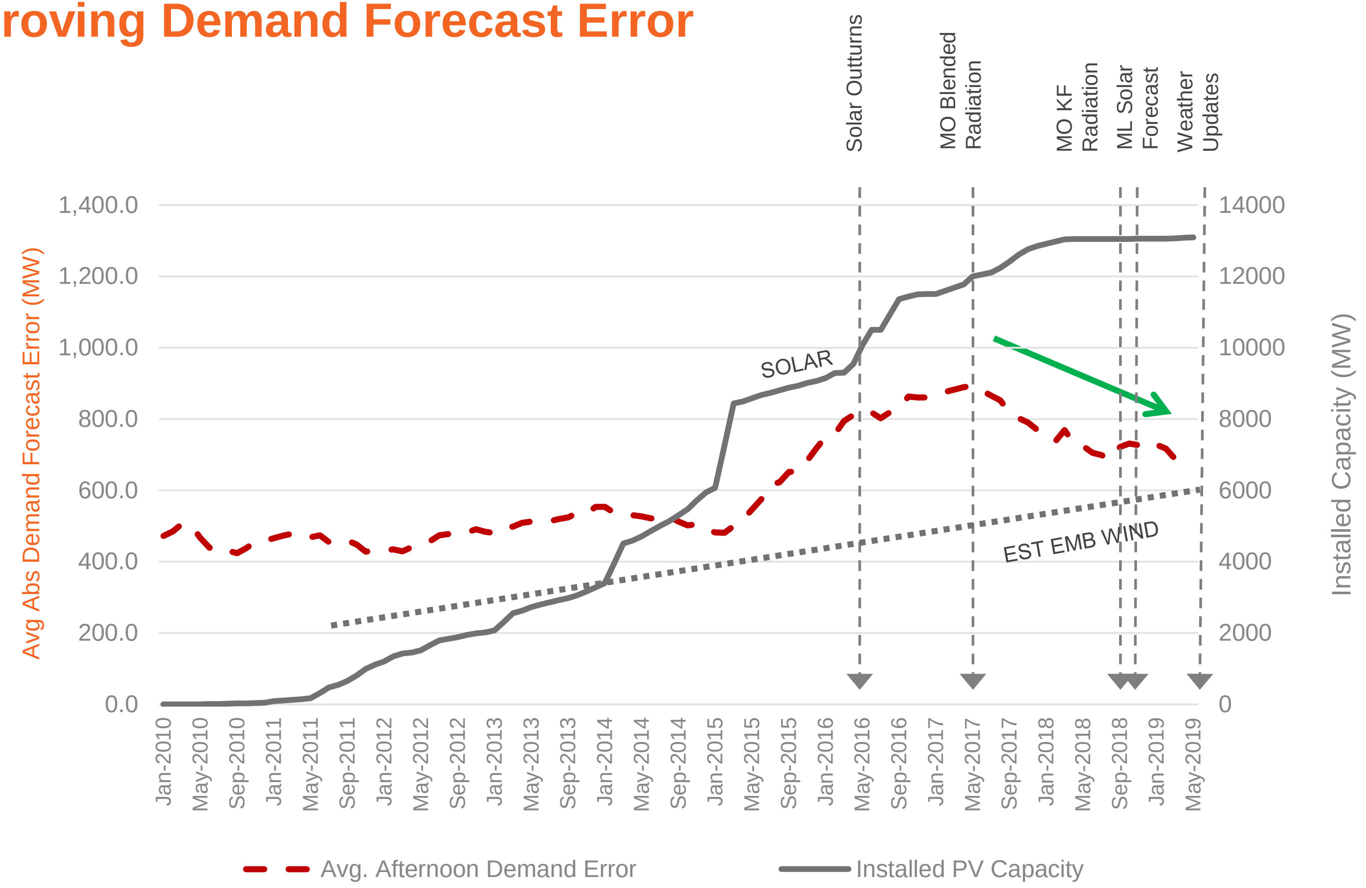
- May17 MO blended solar radiation forecasts brought into weather forecasts
- Sept18 MO Kalman-Filtered solar radiation forecasts brought into weather forecasts

Improved Optimisation of Weather Services:-

- Summer19 Smith: 12 x MO forecasts per day (up from 4), System speed improvements

… other improvements (wind generation / GSP improvements) also !

The Improving Demand Forecast Error



Future Electricity Forecasting Challenges

Whilst many issues related to solar generation have been addressed & we are now implementing improved weather services, the future will still present challenges …

Maintaining & improving existing embedded models …

Solar, embedded wind

FES19 indicates potential increases of solar & emb. wind capacities from ~ 13 & 6GW today to up to 20GW & 7GW (CR Scenario) in 2025, yet visibility decreasing due to loss of subsidy registration for example

Tackling other high impact types of embedded generation …

Growth of other embedded technologies, and new technologies / operating regimes from batteries, EV, Heat-pumps etc

FES19 indicates potential increases of other embedded tech from ~ 14GW today to 22GW (CR Scenario) in 2025 – including batteries/head-pumps etc. Similar visibility issues.

The Energy Forecasting team at NGESO also forecasts weather-dependent generation which participates in the Balancing Mechanism ...

From Dec19, wider access to the BM will introduce many new aggregators/generators above 1MW, and some FES19 scenarios indicate up to 33GW Tx wind maybe connected by 2025

FES19 indicates potential increases of transmission system connected wind from ~ 13GW today to 33GW (Two Degrees Scenario) in 2025

Initiatives being discussed at eg BEIS Energy Data Task Force ie mandatory Asset Registration & others

Metered data – since 2018 NGESO obtained access to metering from ElectraLink. Holds great potential after further data processing

New analytics/models needed for accurate demand and generation forecasting

Q&A