Deep Learning Solar PV and Carbon Intensity Forecasts

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National Grid ESO, St. Catherine's Lodge, Wokingham

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Carbon Intensity Forecast

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Carbon Intensity API

National Grid, in partnership with Environmental Defense Fund Europe, University of Oxford Department of Computer Science and WWF, have developed the world's first Carbon Intensity forecast with a regional breakdown.

The Carbon Intensity API uses state-of-the-art Machine Learning and sophisticated power system modelling to forecast the carbon intensity and generation mix 96+ hours ahead for each region in Great Britain.

Our OpenAPI allows consumers and smart devices to schedule and minimise CO_2 emissions at a local level.

Current Carbon Intensity

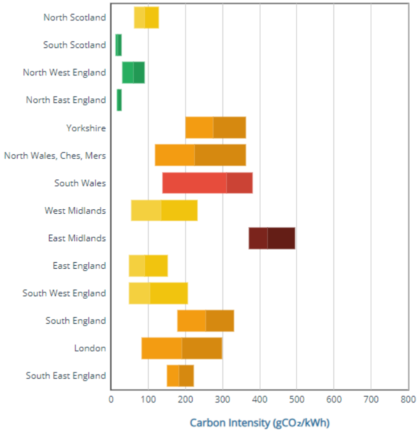
212

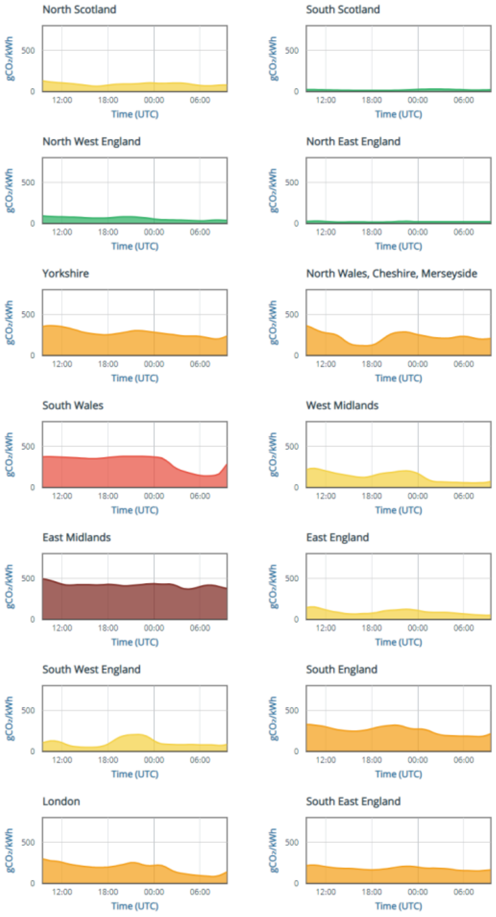
gCO_2/kWh

2-Day Carbon Intensity Forecast

+ Today	197	258	137
+ Fri	170	204	114
+ Sat	161	205	114

Values are the average, max, and min Carbon Intensity in gCO_2/kWh for each day





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Regional Carbon Intensity

- 4 day-ahead forecast for the carbon intensity of electricity and fuel types consumed for 14 regions in GB
- Breakdown of fuel types in demand mix
- Reduced GB power system 14-bus network

Carbon Intensity API Great Britain

This is the Carbon Intensity API for Great Britain developed by National Grid. Please see the official documentation. Data is available in JSON and XML.

API Quick Start

Base URL: api.carbonintensity.org.uk

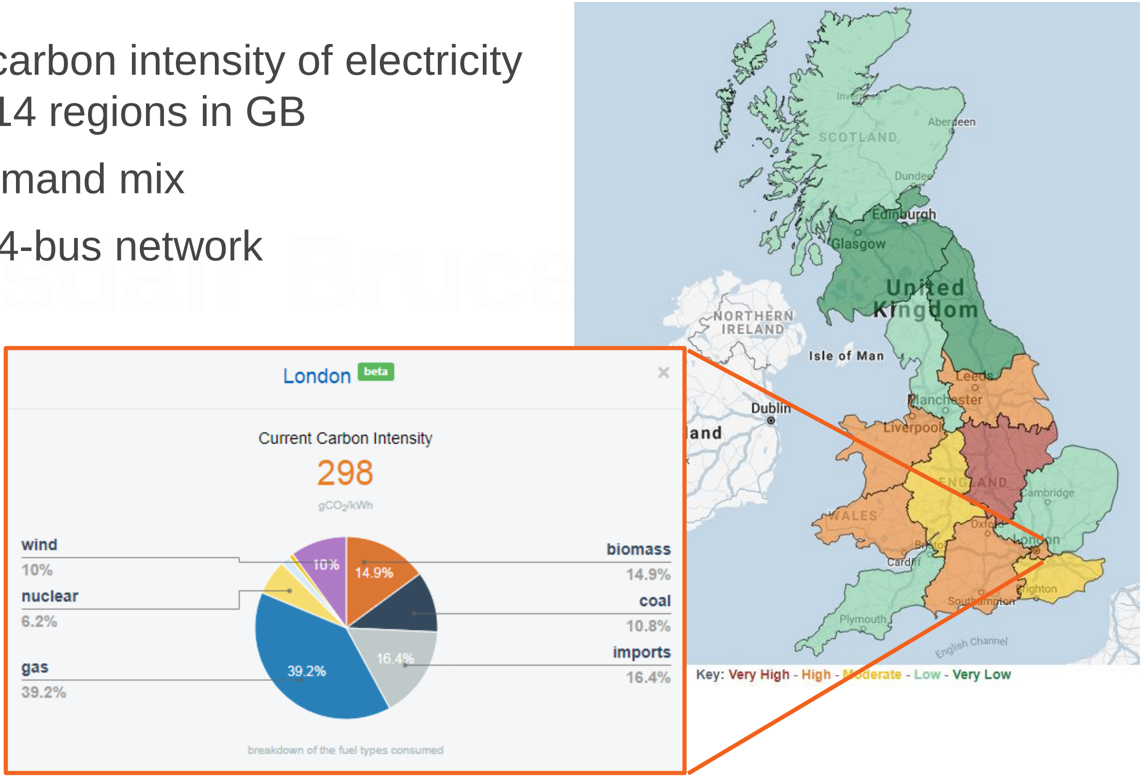
JSON

national carbon intensity

GET /intensity docs

gets current carbon intensity

api.carbonintensity.org.uk



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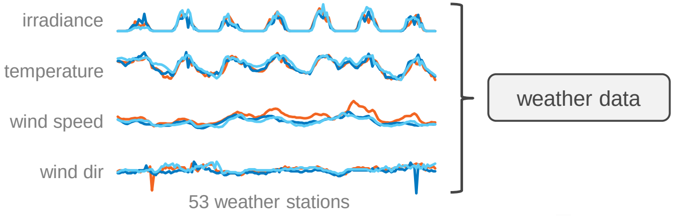
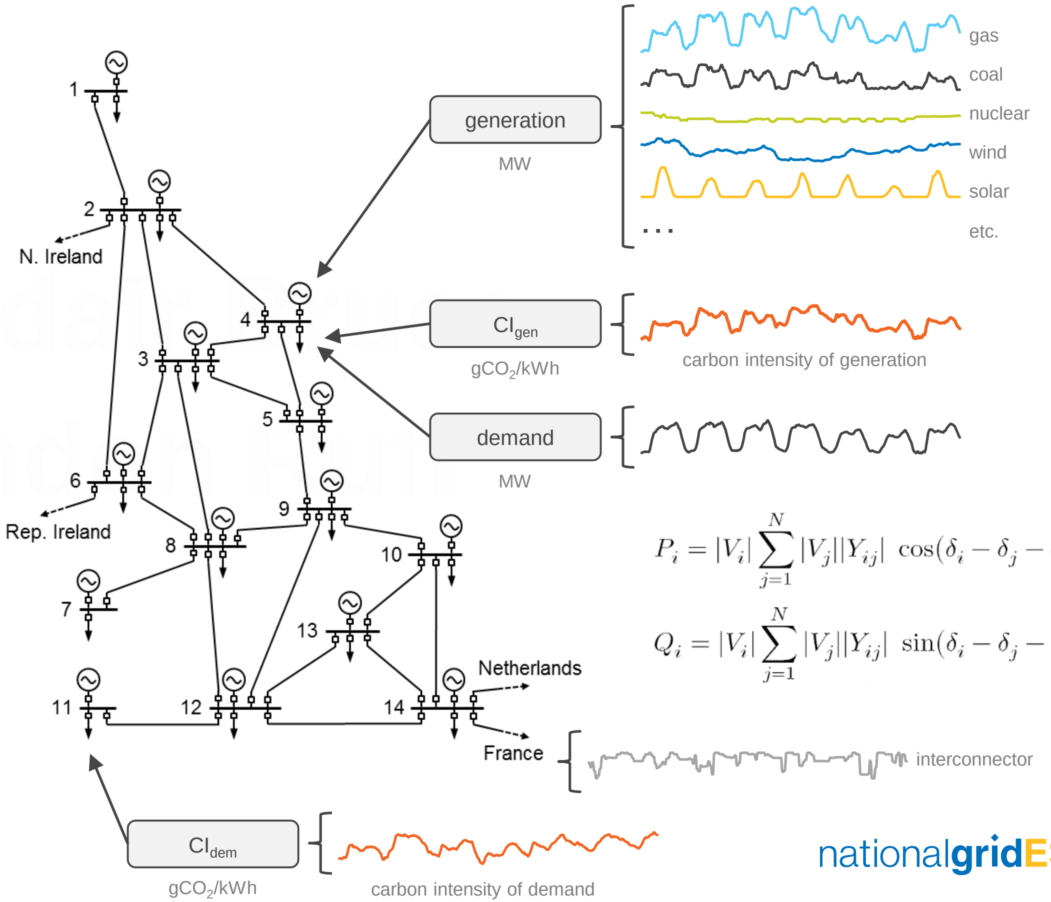
Regional Carbon Intensity



Forecast generation by fuel type and demand in each region

Fuel Type	gCO$_2$/kWh Carbon Intensity
Biomass†	120
Coal	937
Dutch Imports‡	474
French Imports‡	53
Gas (Combined Cycle)	394
Gas (Open Cycle)	651
Hydro	0
Irish Imports‡	458
Nuclear	0
Oil	935
Other	300
Pumped Storage	0
Solar	0
Wind	0

Staffell (2017)



$$P_i = |V_i| \sum_{j=1}^{N} |V_j||Y_{ij}| \cos(\delta_i - \delta_j - \theta_{ij})$$

$$Q_i = |V_i| \sum_{j=1}^{N} |V_j||Y_{ij}| \sin(\delta_i - \delta_j - \theta_{ij})$$

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Carbon Intensity.org.uk

Issue number: May 2018

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Regional Carbon Intensity

National Grid, in partnership with Environmental Defense Fund Europe and WWF, has developed a series of Regional Carbon Intensity forecasts for the GB electricity system, with weather data provided by the Met Office.

Introduction

National Grid's Carbon Intensity API has been extended to include forecasts for 17 geographical regions of the GB electricity system up to 48 hours ahead of real-time [1]. It provides programmatic and timely access to forecast carbon intensity. This report details the methodology behind the regional carbon intensity estimates. For more information about the Carbon Intensity API see here.

What's included in the forecast

The Regional Carbon Intensity forecasts include CO_2 emissions related to electricity generation only. The forecasts include CO_2 emissions from all large metered power stations, interconnector imports, transmission and distribution losses, and accounts for regional electricity demand, and both regional embedded wind and solar generation.

This approach considers the carbon intensity of electricity consumed in each region and uses peer-reviewed carbon intensity factors of GB fuel types [2][3]. The carbon intensity factors used in this data service are based on the output-weighted average efficiency of generation in GB and DUKES CO_2 emission factors for fuels [4]. GB regions are divided according to Distribution Network Operator (DNO) boundaries, see Figure 1.

Methodology

A reduced GB network model is used to calculate the CO_2 transfers between importing/exporting regions, which takes into account the impedance characteristics of the network, constraints, and system losses.

Estimating the carbon intensity of the electricity consumed in each region requires modelling the power flows between importing/exporting regions and the carbon intensity of those power flows. The estimated regional carbon intensity of generation uses metered data for each fuel type*.

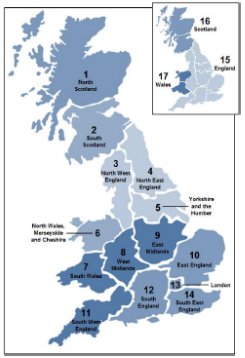

Figure 1: GB Regions and IDs for the API.

* Available from ELEXON via the Balancing Mechanism Reporting Service [5].

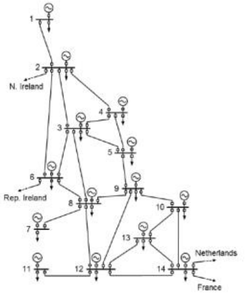

Figure 2: Electrical representation of the reduced GB network.

Step 1: Calculate the generation and CO_2 emissions at each node

The GB power system is divided into regions and represented as an N-bus network. The power generation P_i^{gen} at bus i is the sum of the generation in that region:

$$P_i^{\text{gen}} = \sum_{g=1}^{G} P_{i,g}^{\text{gen}}$$

The CO_2 emissions of each generator g is estimated to calculate the CO_2 emissions from generation in each region:

$$E_i^{\text{gen}} = \sum_{g=1}^{G} P_{i,g}^{\text{gen}} \times c_g$$

where c_g is the carbon intensity of generator's fuel type, see Table 1. Then, the carbon intensity of generation C_i^{gen} is calculated at each node:

$$C_i^{\text{gen}} = \frac{E_i^{\text{gen}}}{P_i^{\text{gen}}}$$

Step 2: Calculate power imbalance between exporting and importing regions

Calculate the power imbalance P_i at bus i by subtracting the regional power generation P_i^{gen} from the regional power demand P_i^{dem}:

$$P_i = P_i^{\text{gen}} - P_i^{\text{dem}}$$

A region is exporting power if $P_i > 0$ and importing power if $P_i < 0$.

Table 1: Carbon intensity factors for each fuel type and interconnector import [2][3].

Fuel Type	gCO_2/kWh Carbon Intensity
Biomass†	120
Coal	937
Dutch Imports‡	474
French Imports‡	53
Gas (Combined Cycle)	394
Gas (Open Cycle)	651
Hydro	0
Irish Imports‡	458
Nuclear	0
Oil	935
Other	300
Pumped Storage	0
Solar	0
Wind	0

Step 3: Forecasting Ahead

The regional demand P_i^{dem}, generation P_i^{gen}, and carbon intensity of generation C_i^{gen} is forecast two days ahead using a state-of-the-art Machine Learning (ML) algorithm. This requires forecasting the regional generation mix at 30-min temporal resolution.

Step 4: Three-Phase Newton Raphson AC Power Flow

A network of N buses and L lines is described by an $L \times N$ incidence matrix $\mathbf{A}$, such that $A_{l,i} = 1$ if line l starts at bus i, $A_{l,j} = -1$ if line l ends at bus j, and $A_{l,k} = 0$ if $k \neq i \neq j$. The power equations for the AC power flow in polar form are:

$$P_i = |V_i| \sum_{j=1}^{N} |V_j||Y_{ij}| \cos(\delta_i - \delta_j - \theta_{ij})$$

$$Q_i = |V_i| \sum_{j=1}^{N} |V_j||Y_{ij}| \sin(\delta_i - \delta_j - \theta_{ij})$$

where $|Y_{ij}|$ is the admittance, $|V_i|$ and $|V_j|$ are the bus voltages, δ_i and δ_j are the phase angles at buses i and j, respectively. A three-phase Newton Raphson iteration is performed to calculate the active and reactive power flows between buses i and j.

† Using 'consumption-based' accounting, the carbon intensity attributable to biomass electricity is reported to be 120 ± 120 gCO_2/kWh [2]. The large uncertainty relates to the complex nature of biomass supply chains and the difficulty in quantifying non-biogenic emissions.
‡ The carbon intensity of interconnector imports is calculated using monthly ENTSO-E data and annual EuroStat data [2].

Step 5: Carbon Intensity of Active and Reactive Power Flows

The carbon intensity of power flows on lines L between N buses is represented as an $L+N \times 1$ matrix $\boldsymbol{C}$, where the carbon intensity of power flowing out of a bus is equal to the weighted average of the carbon intensity of power flowing into that bus.

We also define $\boldsymbol{D}$ as an $L+N \times L+N$ matrix and $\boldsymbol{y}$ as a $L+N \times 1$ matrix:

$$\boldsymbol{y} = \boldsymbol{D}.\boldsymbol{C}$$

Lines

For a given line l, we find each bus i where power flows into this line, such that $A_{l,i}.P_l > 0$. Then we find all other lines m from which power flows to this bus, such that $A_{m,i}.P_m < 0$.

$$D_{l,m} = -A_{m,i}.P_m$$

If $P_i > 0$ then:

$$D_{l,L+i} = P_i$$

$$D_{l,l} = \sum_m A_{m,i}.P_m - P_i$$

otherwise:

$$D_{l,l} = \sum_m A_{m,i}.P_m$$

Buses

For a given bus i we find each line l where power flows into this bus, such that $A_{l,i}.P_l < 0$.

$$D_{L+i,l} = -A_{l,i}.P_l$$

$$D_{L+i,L+i} = \sum_l A_{l,i}.P_l$$

If $P_i > 0$ then:

$$D_{L+i,L+i} = 1$$

$$y_{L+i} = C_i^{\text{gen}}$$

Then the carbon intensity of power flows on all lines and at all buses is:

$$\boldsymbol{C} = \boldsymbol{D}^{-1}.\boldsymbol{y}$$

Step 6: Calculate the carbon intensity of power consumed in each region

The carbon intensity of the power consumed in each region is therefore:

$$C_i^{\text{dem}} = \begin{cases} C_i^{\text{gen}} & \text{if } P_i > 0 \\ \dfrac{P_i^{\text{gen}} \times C_i^{\text{gen}} - P_i \times C_{L+i}}{P_i^{\text{dem}}} & \text{otherwise} \end{cases}$$

"National Grid are now projecting regional carbon intensities for the GB electricity system"

Limitations

This work does not consider the CO_2 emissions of embedded generators that National Grid does not have visibility of or have access to operational metered data. Future work will look at estimating the contributions of these embedded generators to regional and national carbon intensity.

Contact:

If you have any suggestions, comments or queries please contact: Alasdair.Bruce@nationalgrid.com or Lyndon.Ruff@nationalgrid.com.

References

[1] Carbon Intensity API (2017). "Carbon Intensity API". Available online at: www.carbonintensity.org.uk

[2] GridCarbon (2017). "GridCarbon: A smartphone app to calculate the carbon intensity of the UK electricity grid". Available online at: www.gridcarbon.uk/

[3] Staffell, Iain (2017). "Measuring the progress and impacts of decarbonising British electricity". In: Energy Policy 102, pp. 463–475, DOI: 10.1016/j.enpol.2016.12.037

[4] DUKES (2017). "Digest of UK Energy Statistics (DUKES)". Available online at: www.gov.uk/government/collections/digest-of-uk-energy-statistics-dukes

[5] BM Reports (2017). "Generation". Available online at: https://www.bmreports.com/bmrs/?q=generation/

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BM Reports (2017). “Generation”. Available online at: https://www.bmreports.com/bmrs/?q=generation/

National DL Solar Forecast new

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We would like to acknowledge the Alan Turing Institute for their initial involvement with Solar PV Forecasting

The Alan Turing Institute

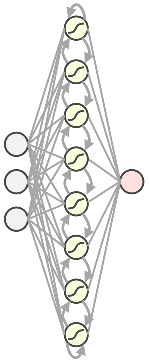
Hardware

- Windows 2012 Server R2
- x8 NVIDIA® Tesla® V100 Tensor Core GPUs
- x2 Intel® Xeon® Platinum 8167M 2.00 GHz (52 cores, 104 threads)
- 3 TB Fast Storage

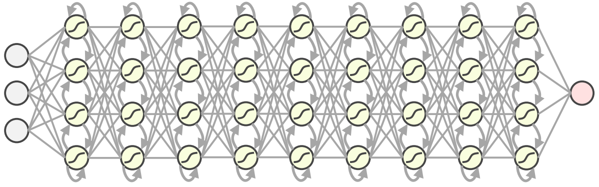
Software

- Python 3.6 64-bit
- Anaconda 5.2 64-bit
- RStudio
- CUDA Toolkit v9.0
- NVIDIA cuDNN 7.0

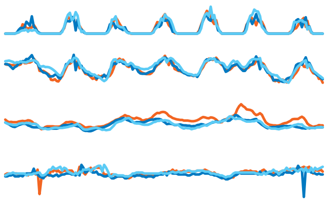
Shallow NN



Deep NN



National DL Solar Forecast new



kJ/m² irradiance
°C temperature
m/s wind speed
deg wind direction

Forecast Data

Data Preparation

Historic Data — 53 weather stations

Kalman Filter

Dimensionality Reduction

PCA Model

Load PCA model

Principle Component Analysis — Reduces input features

Predictions

Load models

Models

Models — Ensemble of ML/DL models

ADB | LGBM | RFR | XGB | MLP | LSVR | GBM | LSTM

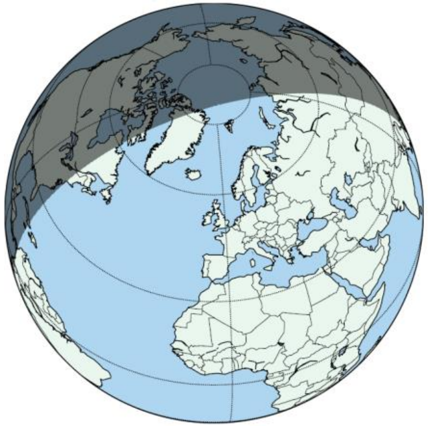
Meta Model

Nowcasting

Adjust Forecast — Update forecast every 1 hour

Publish Forecasts

Post to EFS — EFS Tables, MongoDB, AWS…



PVLIB Python physics library

Predictions made every 1 hour

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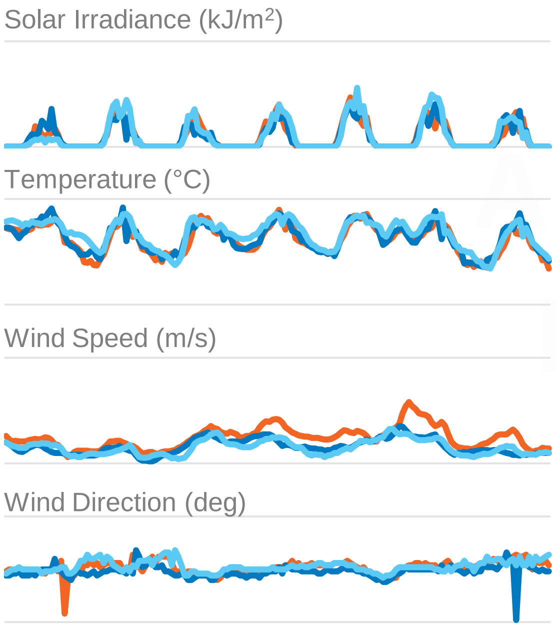
Model Training

Use historic weather data to train ML model to predict historic outturn



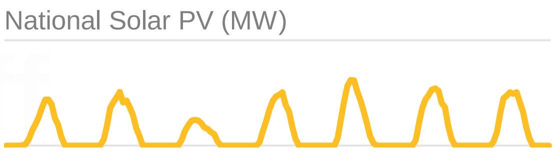
Synthetic Features

...

$f: X \to y$

Model

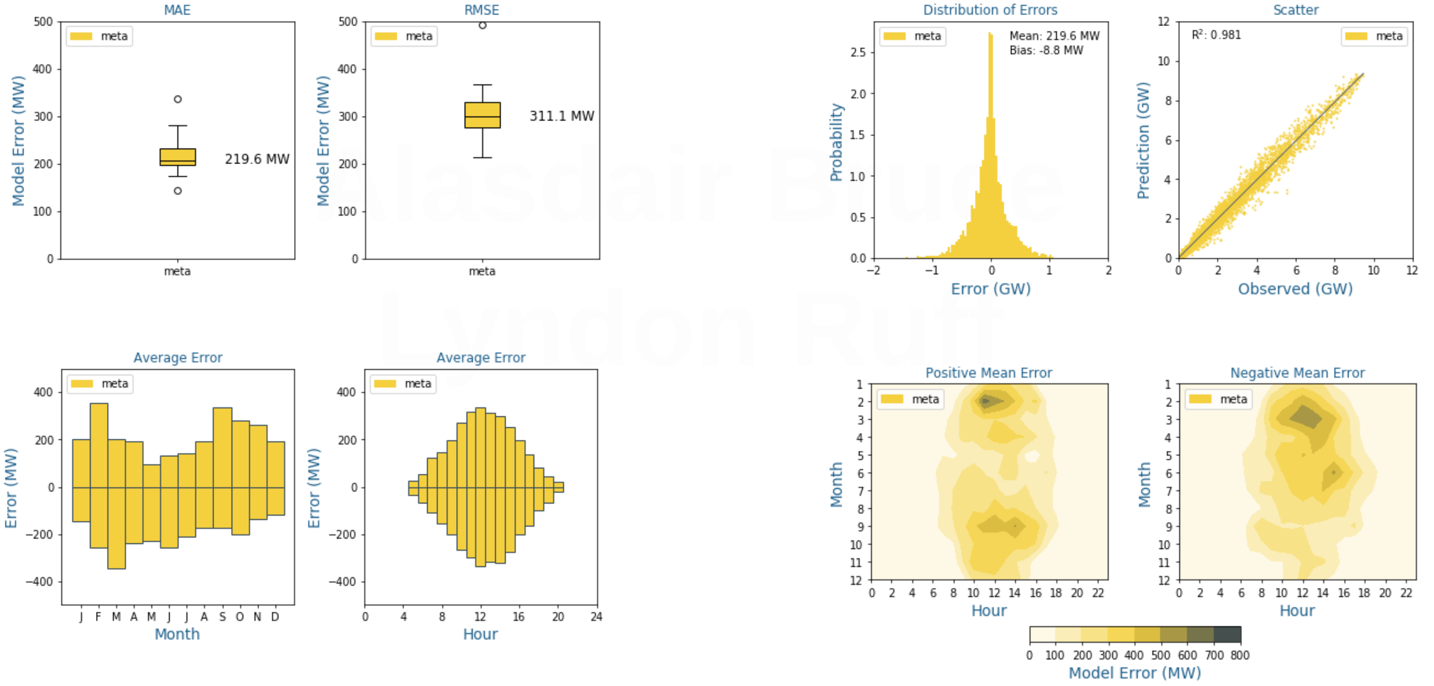
ML model maps patterns between historic weather and historic solar PV



Historic outturn

Model Training

Evaluate the performance of models using k-Fold Cross Validation



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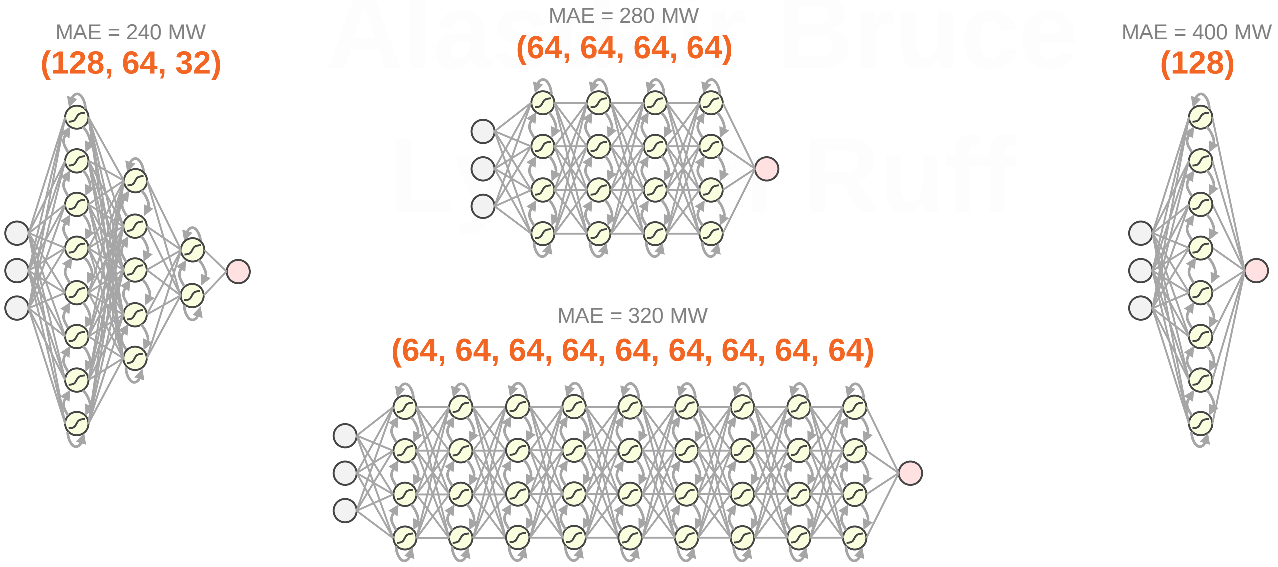
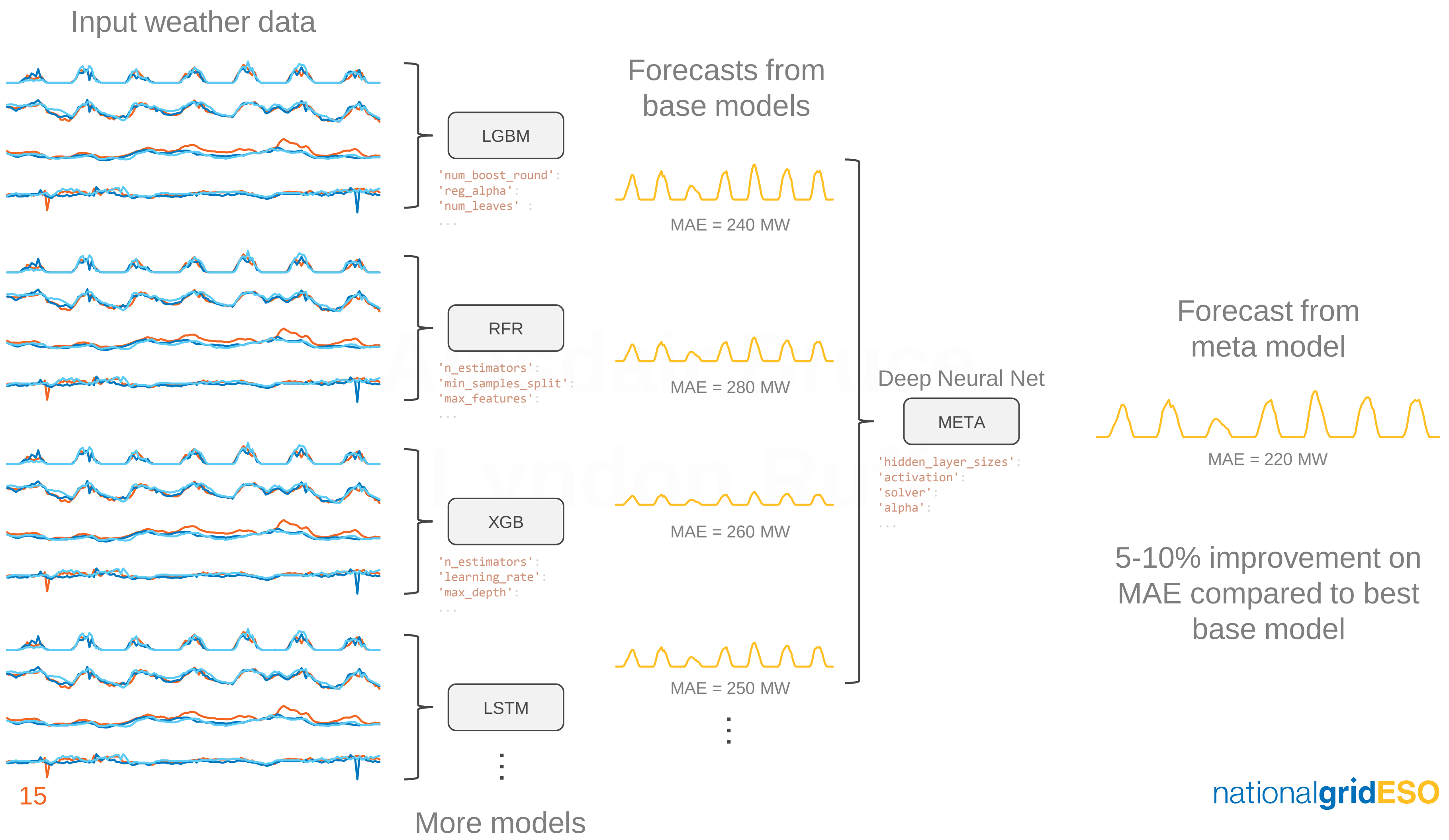
Neural Net Architecture Search

- Find optimal NN architecture and hyperparameters by searching through large number of permutations (~20,000)
- Assess number of hidden layers, activation functions, optimizers, epochs, batch size, regularization, batch normalization etc.




Input weather data
LGBM
'num_boost_round':
'reg_alpha':
'num_leaves' :
...
RFR
'n_estimators':
'min_samples_split':
'max_features':
...
XGB
'n_estimators':
'learning_rate':
'max_depth':
...
LSTM
More models
Forecasts from base models
MAE = 240 MW
MAE = 280 MW
MAE = 260 MW
MAE = 250 MW
Deep Neural Net
META
'hidden_layer_sizes':
'activation':
'solver':
'alpha':
...
Forecast from meta model
MAE = 220 MW
5-10% improvement on MAE compared to best base model
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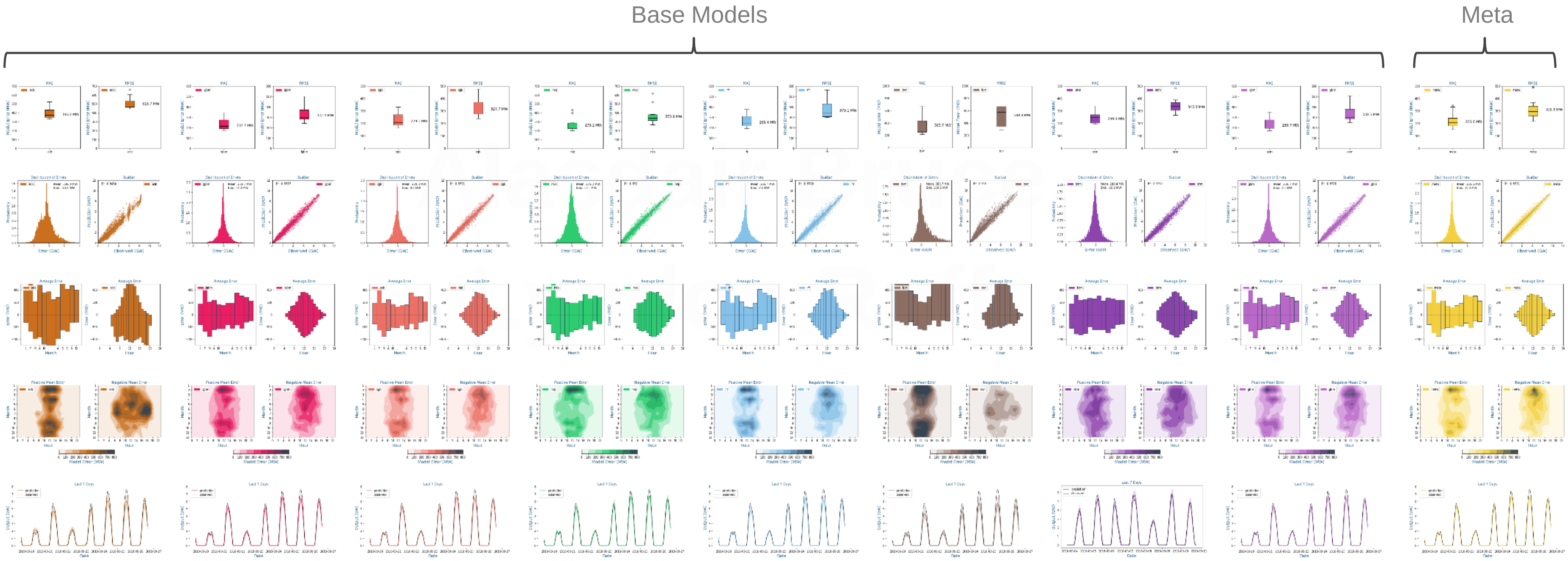
Ensemble

- Charts are generated showing the evaluation metrics during training



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