

# Leveraging AI / Machine Learning in Power Systems



**James Kelloway**

Energy Intelligence Manager



<https://www.linkedin.com/in/jameskelloway/>



@kellowayj1



James.Kelloway@nationalgrideso.com

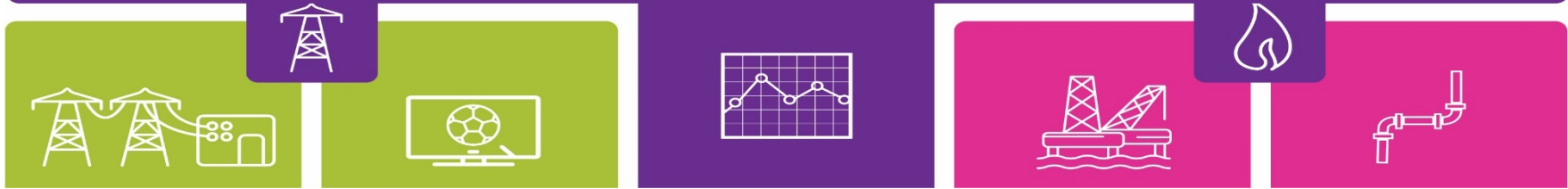
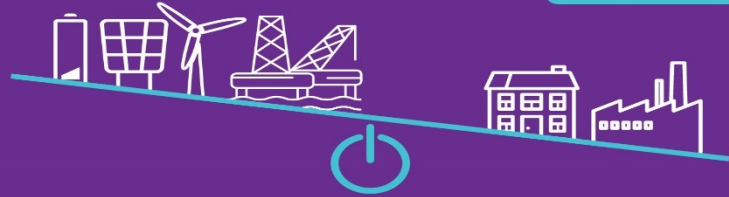
**September 2019**



# Our role as System Operator

We make sure GB's gas and electricity is transported safely and efficiently from where it's produced to where it's consumed. We ensure that supply and demand are balanced in real-time and we facilitate connection of assets to the transmission system.

A BALANCING ACT



We work with customers and stakeholders to shape the future energy market, providing analysis and insight into the changing nature of supply, demand and networks. We facilitate changes to market frameworks to accommodate new technologies and ways of working.

# Our Mission

## **Energy is the lifeblood of our society and economy**

As Great Britain's Electricity System Operator, we keep the lights on around the clock for all energy customers.

## **Climate change is the challenge of a generation**

We play a leading role in the decarbonisation of the energy system by enabling the transition to a more sustainable energy future.

## **Ambition**

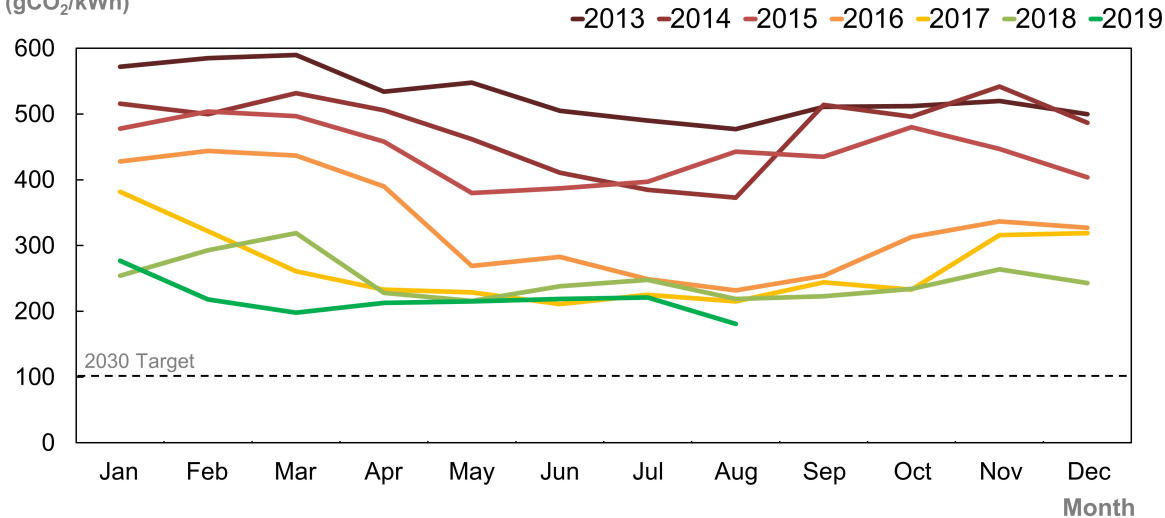
We want to be able to operate a carbon free electricity system by 2025, and we'll invest accordingly.

# What's Changing?

## The Decarbonisation of British Electricity

2018 was the 'greenest' year on record in Great Britain

Carbon Intensity  
(gCO<sub>2</sub>/kWh)



53.1% decrease  
from 2013 to 2018

2013 529 gCO<sub>2</sub>/kWh

2014 477 gCO<sub>2</sub>/kWh

2015 443 gCO<sub>2</sub>/kWh

2016 330 gCO<sub>2</sub>/kWh

2017 266 gCO<sub>2</sub>/kWh

2018 248 gCO<sub>2</sub>/kWh



# What's Changing in GB?

★ Records broken since the last Smart Grid Tech Conference in Amsterdam (March)



Max Wind

15530 MW



Max Solar

9550 MW



Max No Coal

436 Hrs



Min Gas

1556 MW



Min Carbon Intensity

57 gCO<sub>2</sub>/kWh

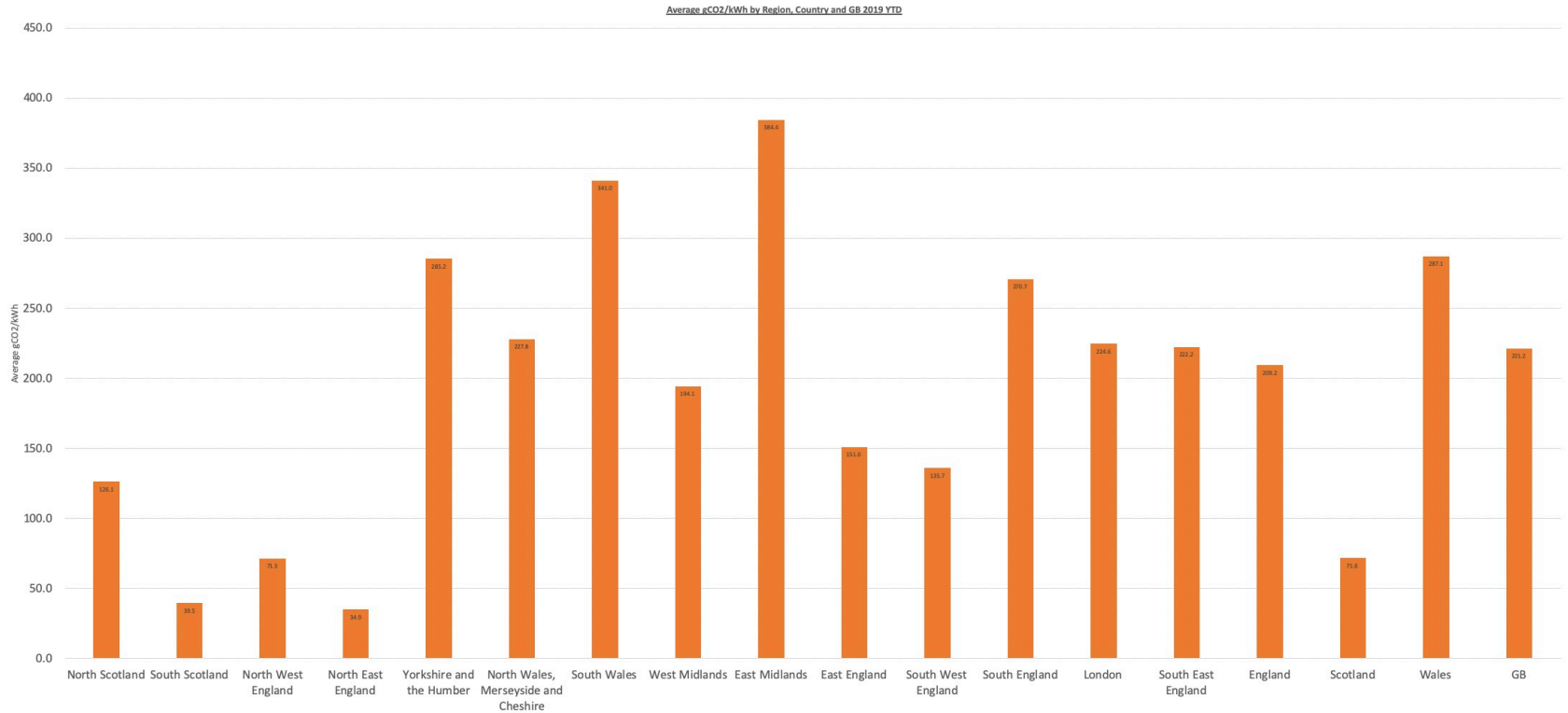


Low Carbon

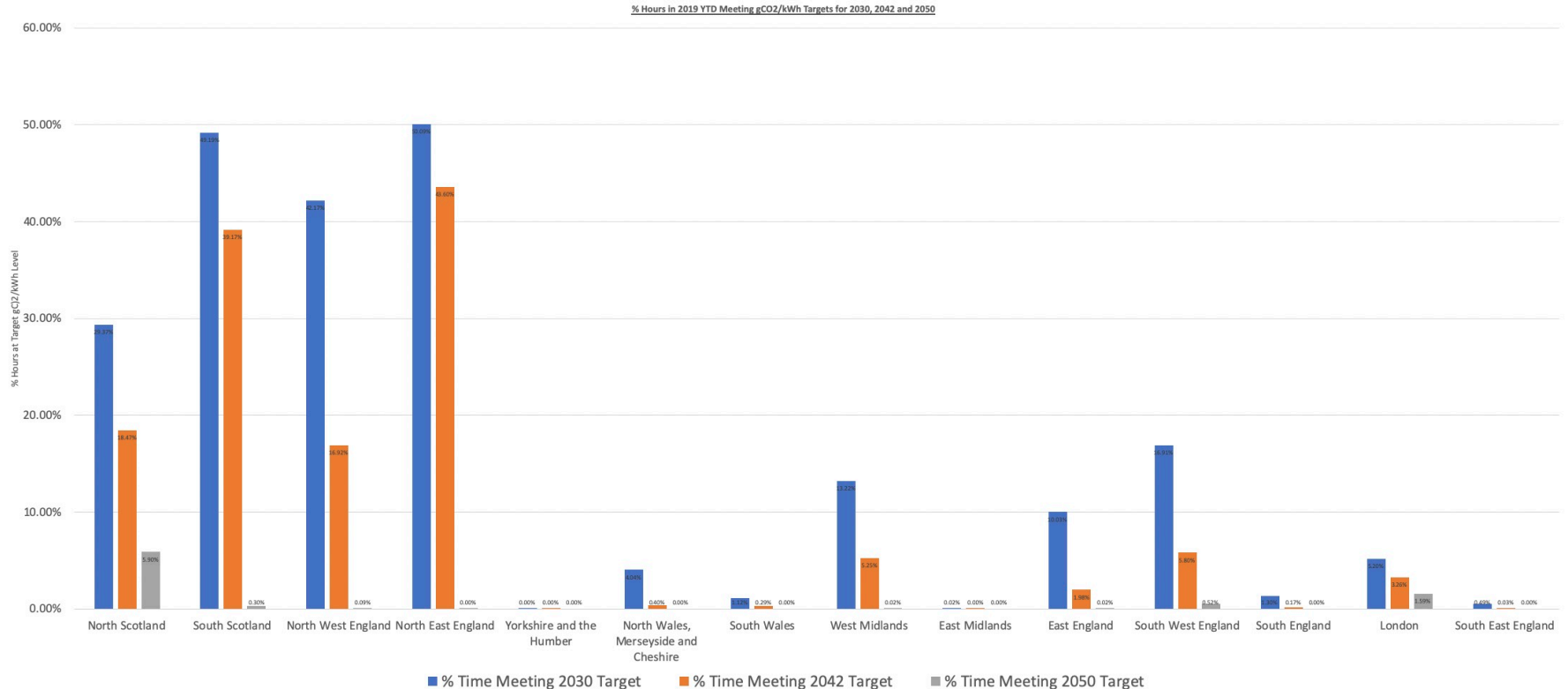
87.9%

North Scotland (Aug 14<sup>th</sup>/15<sup>th</sup>) – 30 hours straight with 0 gCO<sub>2</sub>/kWh

# What's Changing in GB? Average Carbon Intensity by Region



# What's Changing in GB? Time YTD at Future Target Levels



# What's Changing?

The 3Ds of the future!

Decarbonisation	Decentralisation	Digitisation
Paris Agreement – world wide reductions in CO2	Increasing number of small power plants this is changing	How do we connect?
Power Sector are leaders with PV, Wind and other renewables	Germany: 1000 (yr 2000) > 1.5 Million (2017)	BlockChain?
Economics of Renewables really works	GB > 1 Million PV installs	Smart Meters?
		Virtual Power Plants?

# What's Changing? Data

“The world is moving too fast for polishing!!! Data that is useful today will be redundant by the time perfect has been reached and often the people with the data are not best placed to clean it up”

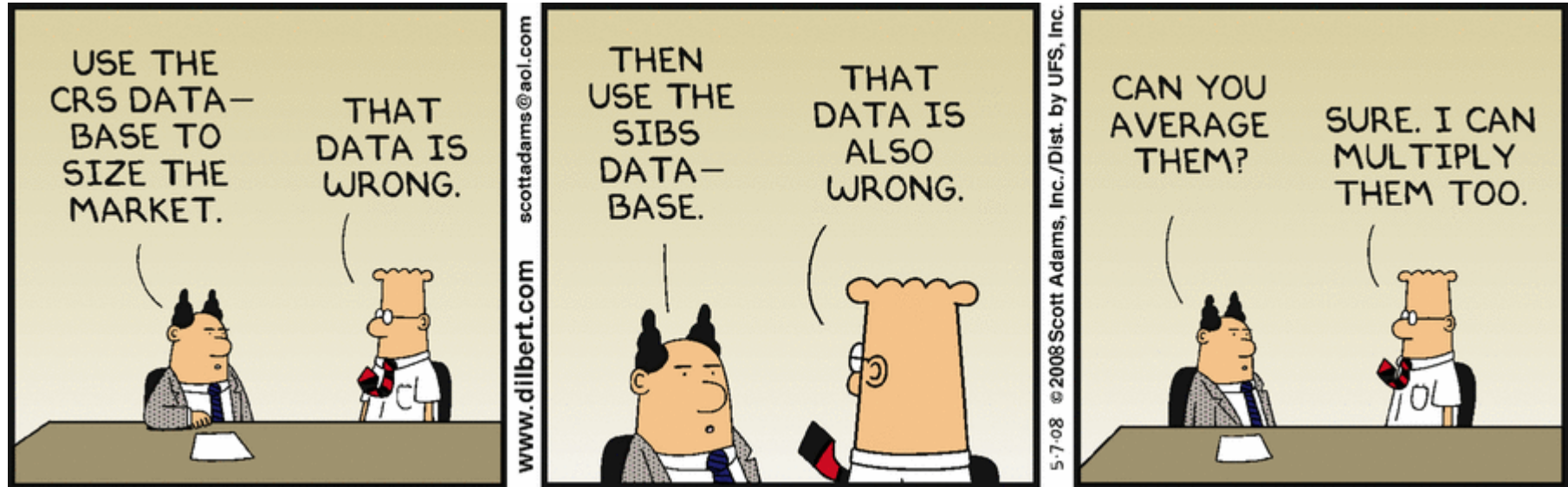


**Laura Sandys** ✓

@Laura\_Sandys

Challenging Ideas in energy & food. Chair of  
[@BEIS](#) [@ofgem](#) Energy Data Taskforce. Proud  
chair of [@food\\_foundation](#) & NED [@SGN](#)

# Why we use AI and ML?



# What is Machine Learning? Is it really AI?

**Machine Learning and Artificial Intelligence are terms that are often interchanged.**

**We are looking at Machine Learning, not Artificial Intelligence.**

## **Machine Learning**

consists of statistical techniques to give computers the ability to "learn".

The models progressively improve performance on a specific task with data, without being explicitly programmed.

## **Artificial Intelligence**

is the quest to enable a machine to mimic human behavior. Machine Learning is a core underlying part of this.



# What is Machine Learning?

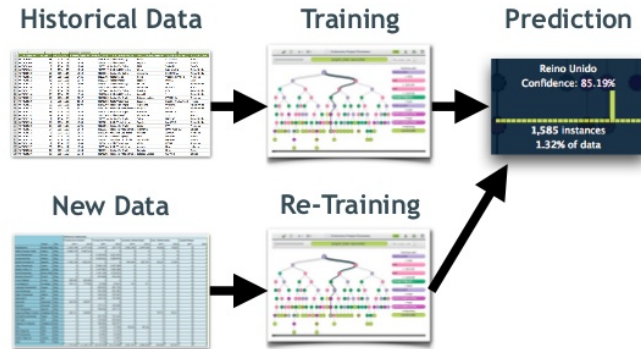
## Training and Forecasting

### Training the Ensemble

This is how the model adapts to longer term changes and trends. For PV, the optimum retrain cycle is daily.

### Forecasting / Prediction

This is how the trained model takes an input and uses it's training to predict an output.





# Solar Forecasting Case Study

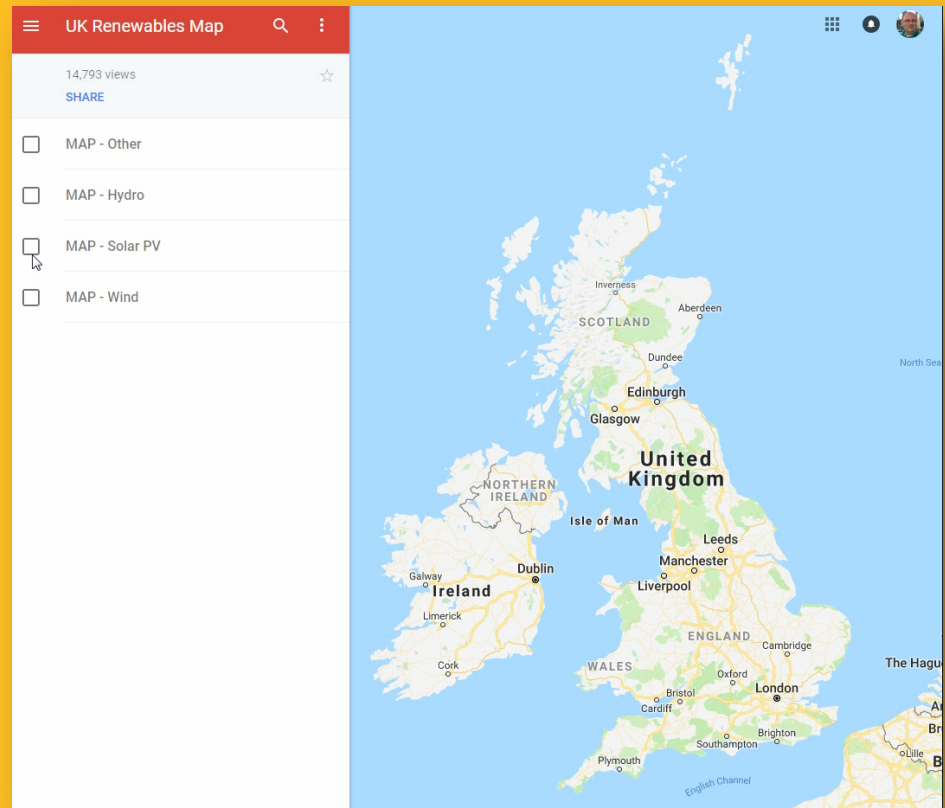
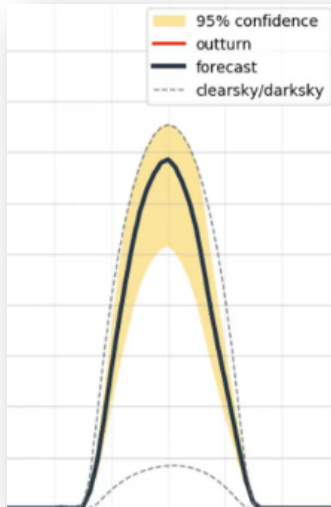
How to forecast solar net demand  
reduction with ML?



# State of PV in GB

**13.05 GW PV**  
(Capacity Nov 2018)

**Max Yield 9.38 GW or 72%**  
(26/05/17)



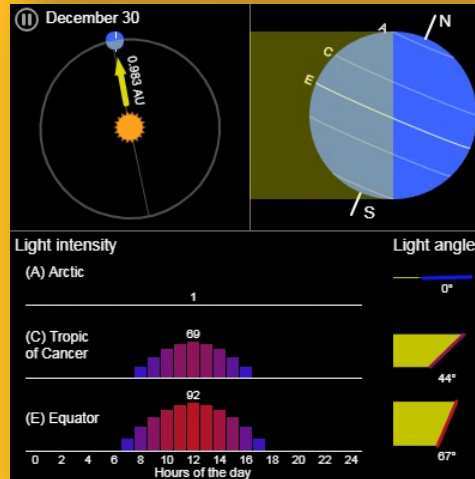
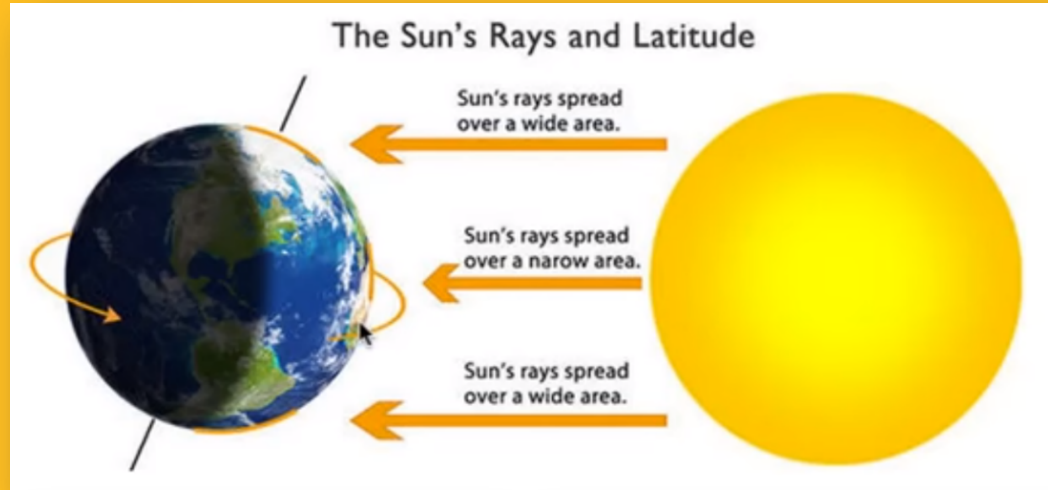
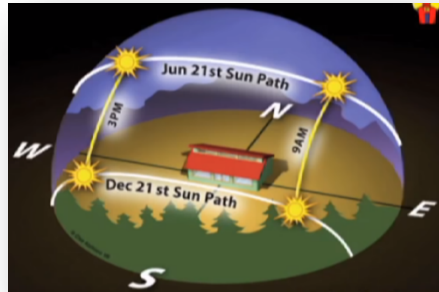
Source: DBEIS Renewable energy planning database monthly extract – Solar Sites > 1 MW

Excludes c. 1 Million Domestic PV Installations (Source MyGridGB)

# State of PV in GB

## Latitude & Seasonal Impacts

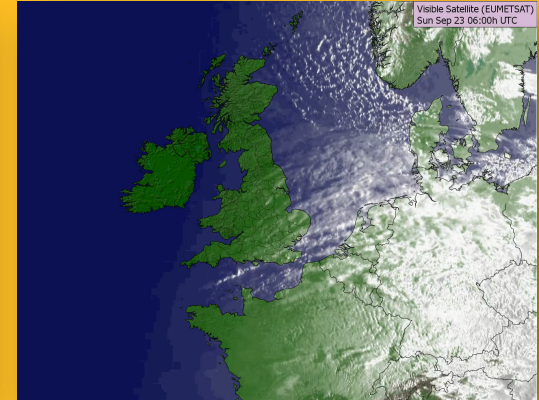
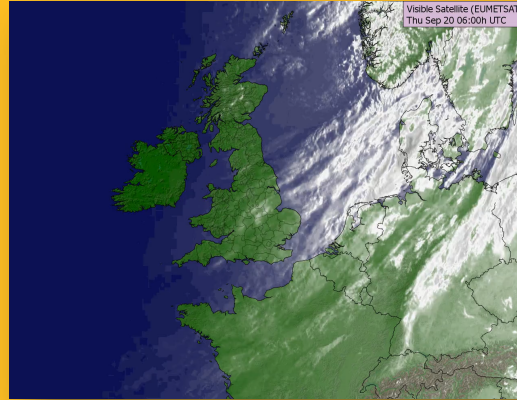
Seasons not related to the proximity of the sun



# State of PV in GB

## Weather

Extremes observed and impact of climate change



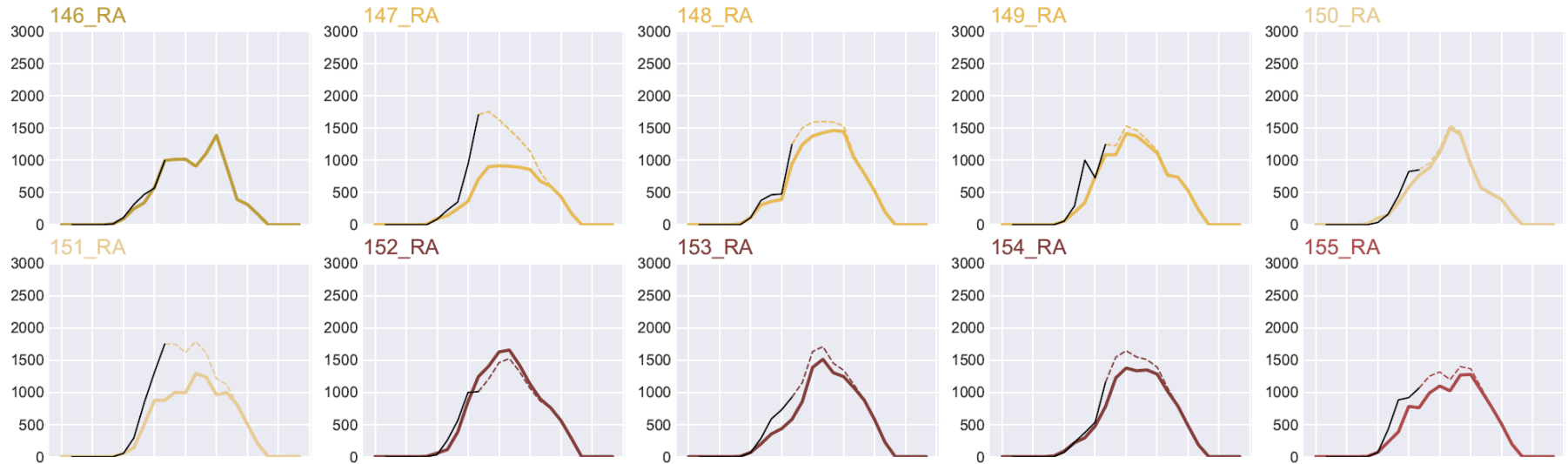
**Weather** has the single biggest impact on PV Generation



# Nowcasting - Solar Irradiance

$\text{kJ/m}^2$

10 sample weather stations



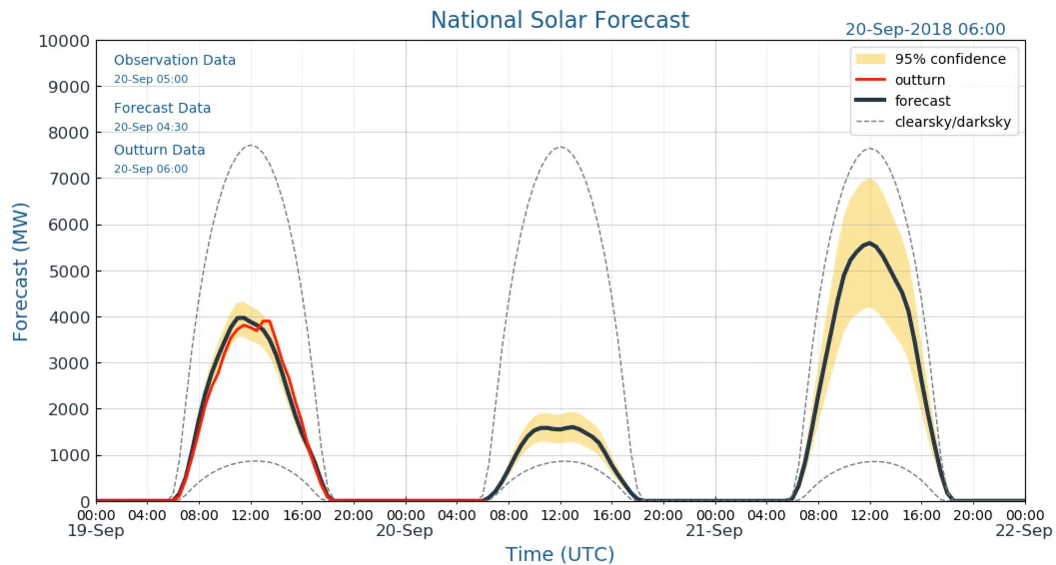
Solid coloured line = forecast (6h), Solid black line = observation (1h), Dashed coloured line = Nowcast (1h)



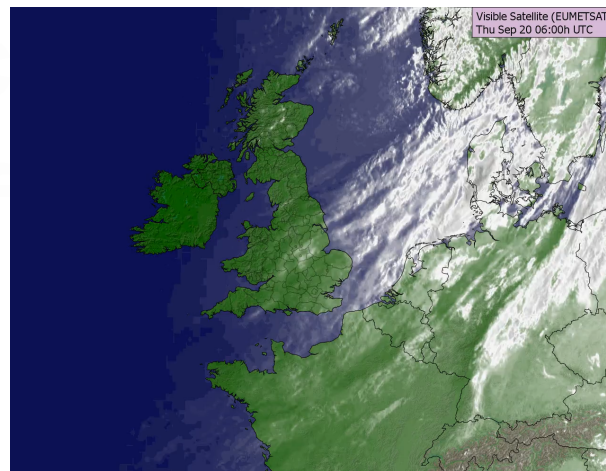
# Aftermath of Storm Ali

Heavy cloud cover across GB results in very low solar PV output

Forecast dynamically adjusts to changing conditions



MetDesk:

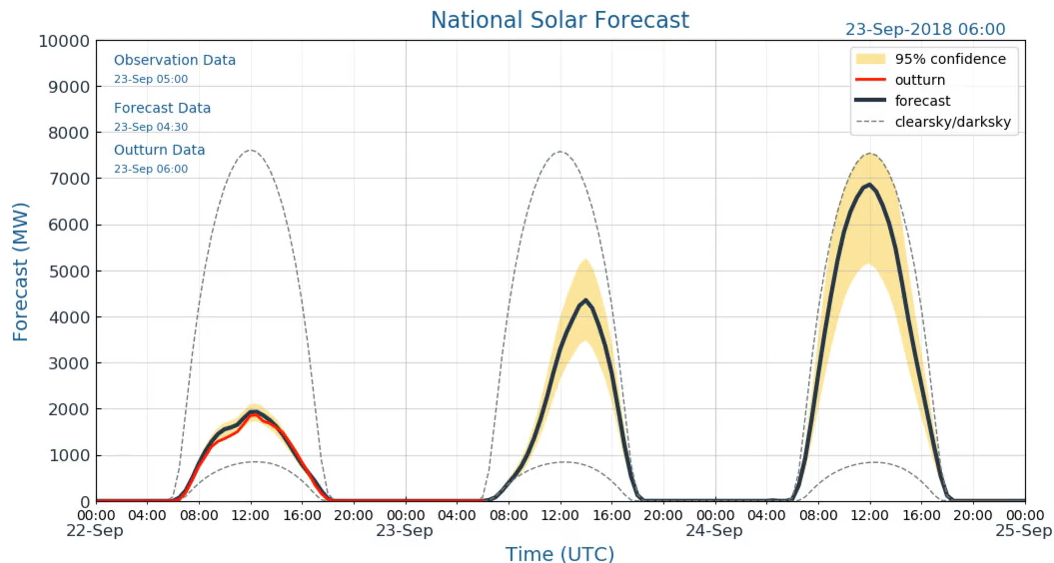


Interactive

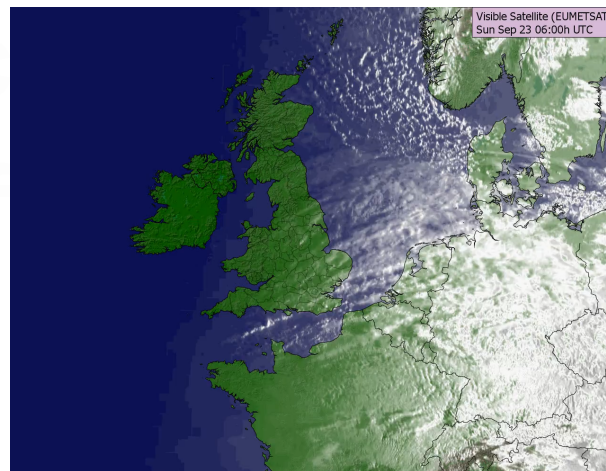
# Nowcasting

Complex cloud formations are hard to predict

Forecast updates using observation data from Met Office, correcting for poor irradiance forecasts

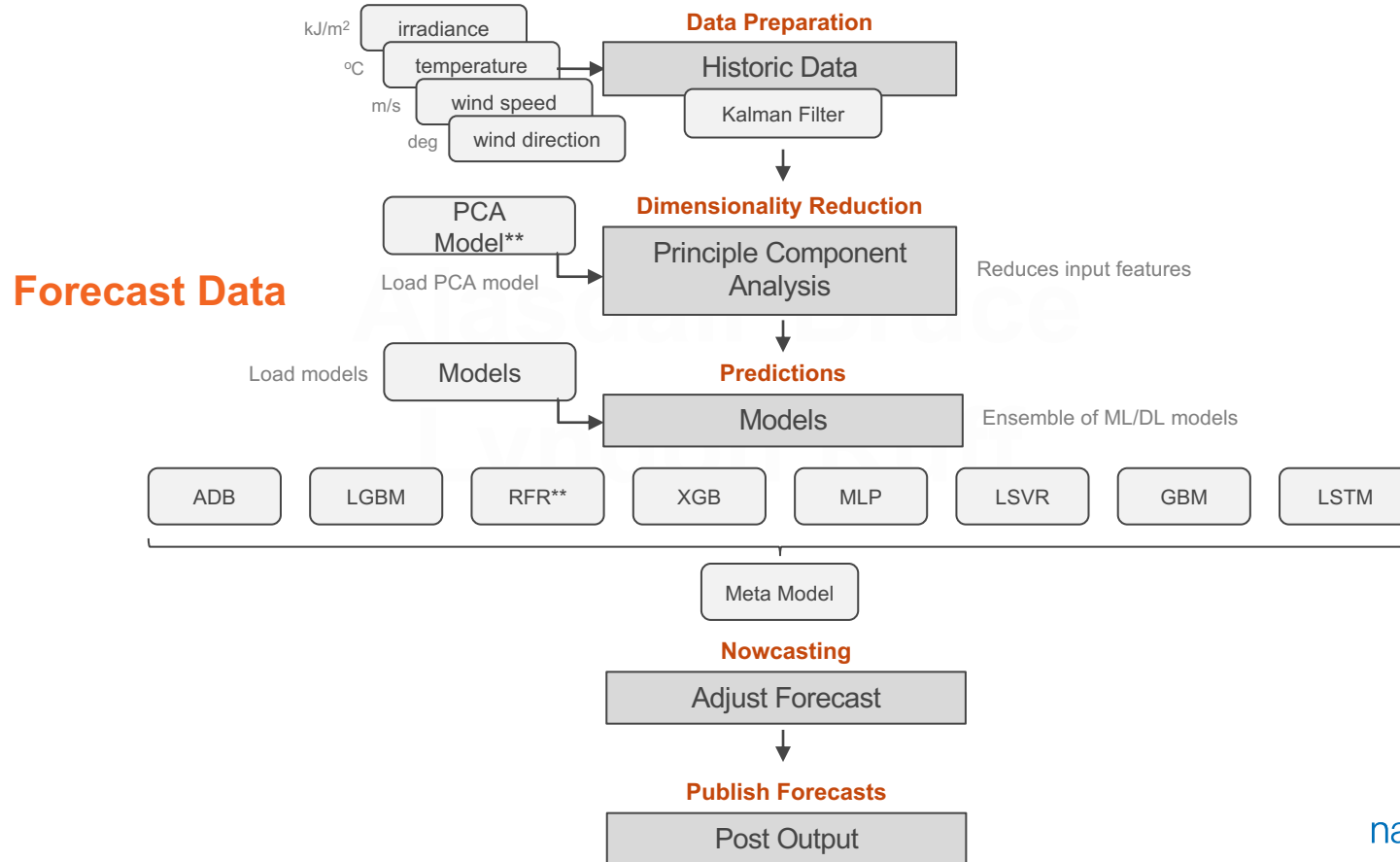


MetDesk:



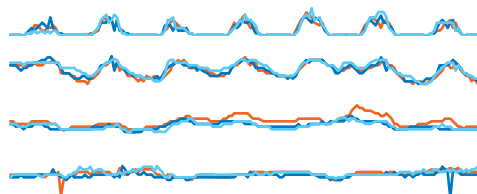
Interactive

# National Solar Models





## Input weather data



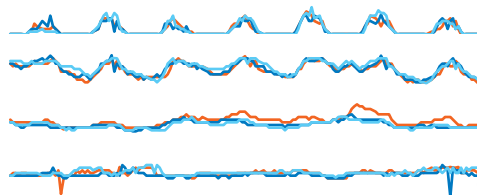
LGBM

```
'num_boost_round': 2000,  
'reg_alpha': 0.4,  
'num_leaves': 31  
...
```

## Forecasts from base models



**MAE = 240 MW**

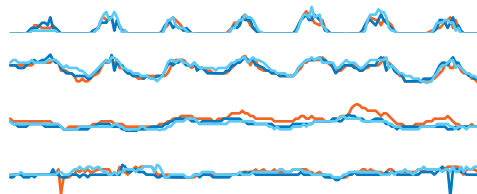


RFR

```
'n_estimators': 500,  
'min_samples_split': 2,  
'max_features': None  
...
```



**MAE = 280 MW**

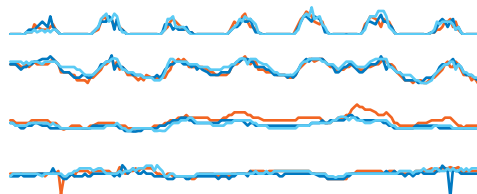


XGB

```
'n_estimators': 2000,  
'learning_rate': 0.01,  
'max_depth': 10  
...
```



**MAE = 260 MW**



LSTM

⋮



**MAE = 250 MW**

⋮

More models

## Deep Neural Net

META

```
'hidden_layer_sizes': (128, 64, 32),  
'activation': 'relu',  
'solver': 'adam',  
'alpha': 0.0001  
...
```

## Forecast from meta model

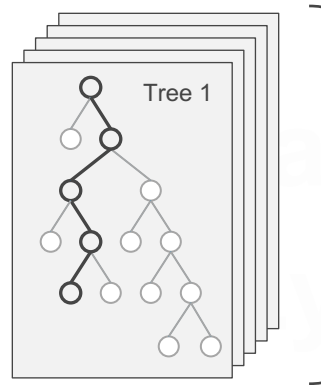


**MAE = 220 MW**

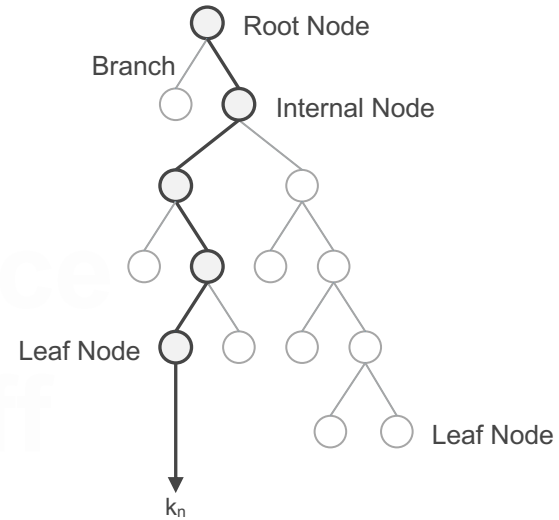
5-10% improvement on  
MAE compared to best  
base model

# RFR - Random Forest Regression

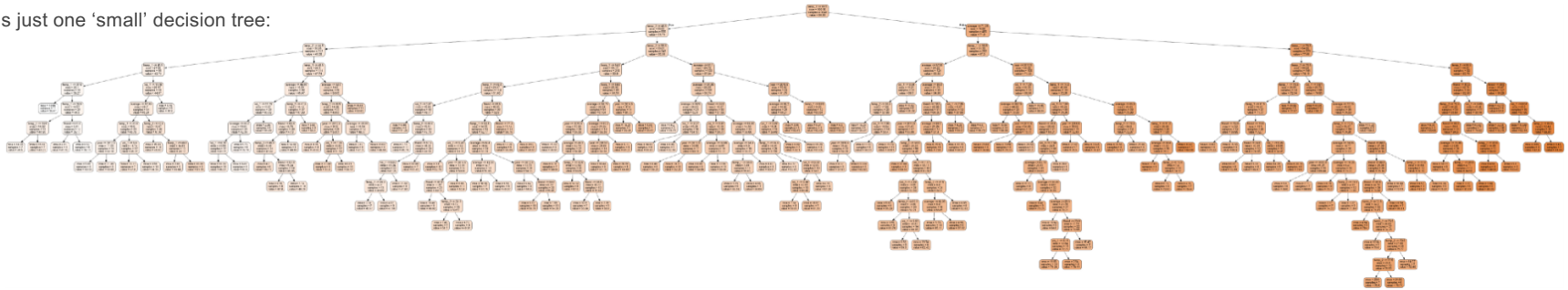
Random Forest Regression models will typically use up to 1000 decision trees in each ensemble



Forest of decision trees

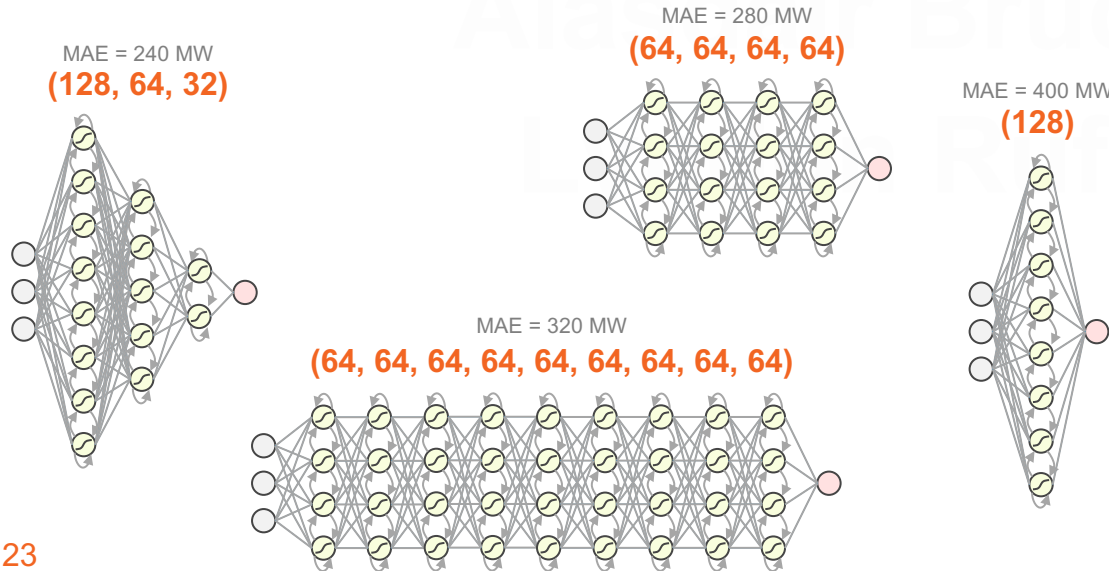


This is just one 'small' decision tree:



# Meta - Neural Net Architecture Search

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

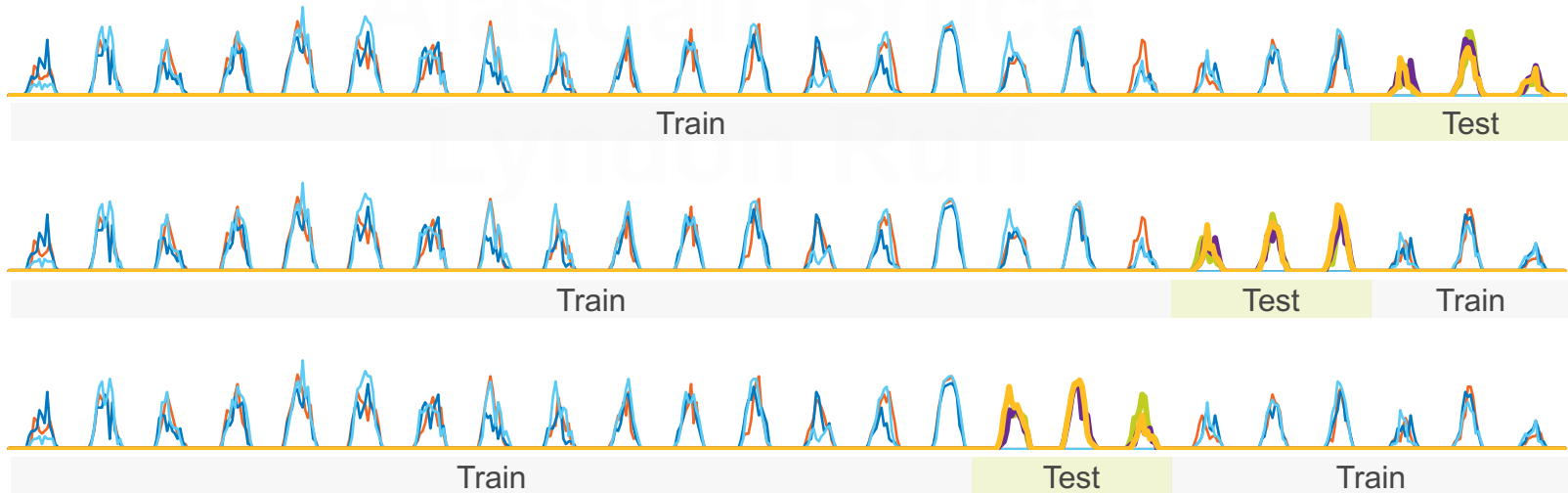


```
param_grid = {'hidden_layers': [1, 2, 3],
              'neurons_i': [64, 96, 128],
              'L1_i': [0, 0.0001],
              'L2_i': [0, 0.0001],
              'batch_normalization_i': [0, 1],
              'activation_i': [Activation('tanh'), LeakyReLU()],
              'dropout_i': [0, 0.05, 0.1, 0.15, 0.2],
              'neurons_1': [64, 96, 128],
              'L1_1': [0, 0.0001],
              'L2_1': [0, 0.0001],
              'batch_normalization_1': [0, 1],
              'activation_1': [Activation('tanh'), LeakyReLU()],
              'dropout_1': [0, 0.05, 0.1, 0.15, 0.2],
              'neurons_2': [64, 96, 128],
              'L1_2': [0, 0.0001],
              'L2_2': [0, 0.0001],
              'batch_normalization_2': [0, 1],
              'activation_2': [Activation('tanh'), LeakyReLU()],
              'dropout_2': [0, 0.05, 0.1, 0.15, 0.2],
              'neurons_o': [64, 96, 128],
              'L1_o': [0, 0.0001],
              'L2_o': [0, 0.0001],
              'batch_normalization_o': [0, 1],
              'activation_o': [Activation('tanh'), LeakyReLU()],
              'dropout_o': [0, 0.05, 0.1, 0.15, 0.2],
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              'batch_size': [train_X.shape[0]]
}
```



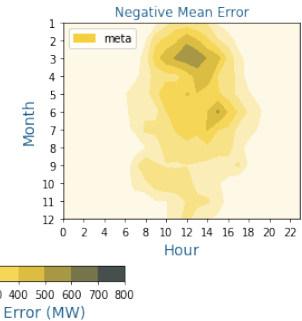
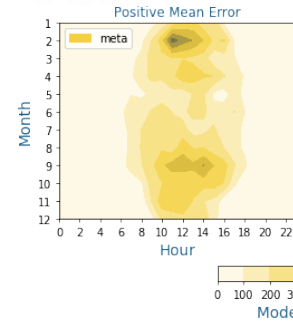
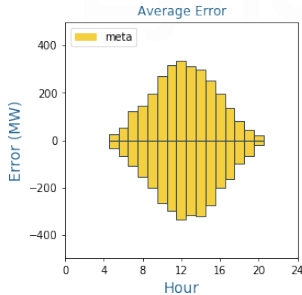
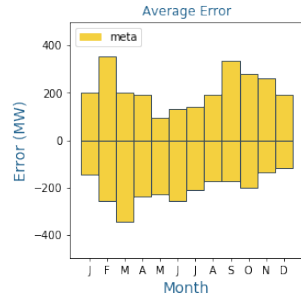
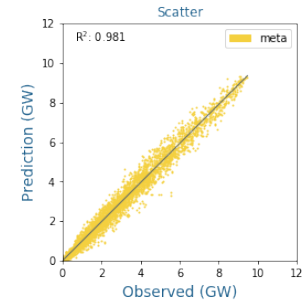
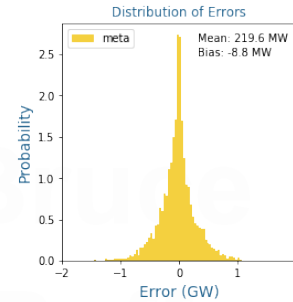
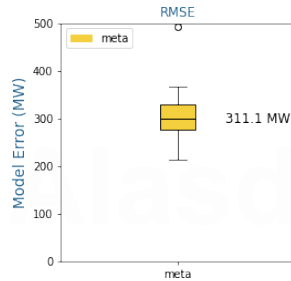
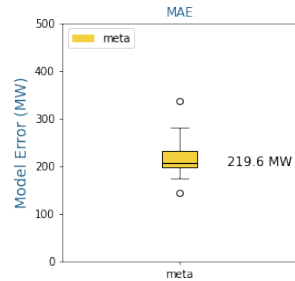
# Evaluate Model Performance

- Split/fold data into k folds using **k-Fold Cross Validation**
- Train models on train set (k-1), evaluate performance on test set (k), repeat k times on different folds
- k-fold cross validation allows models to be tested on **unseen historical data**
- Prevents Neural Nets and other complex ML models from overfitting, ensuring the model will perform well with future unseen data



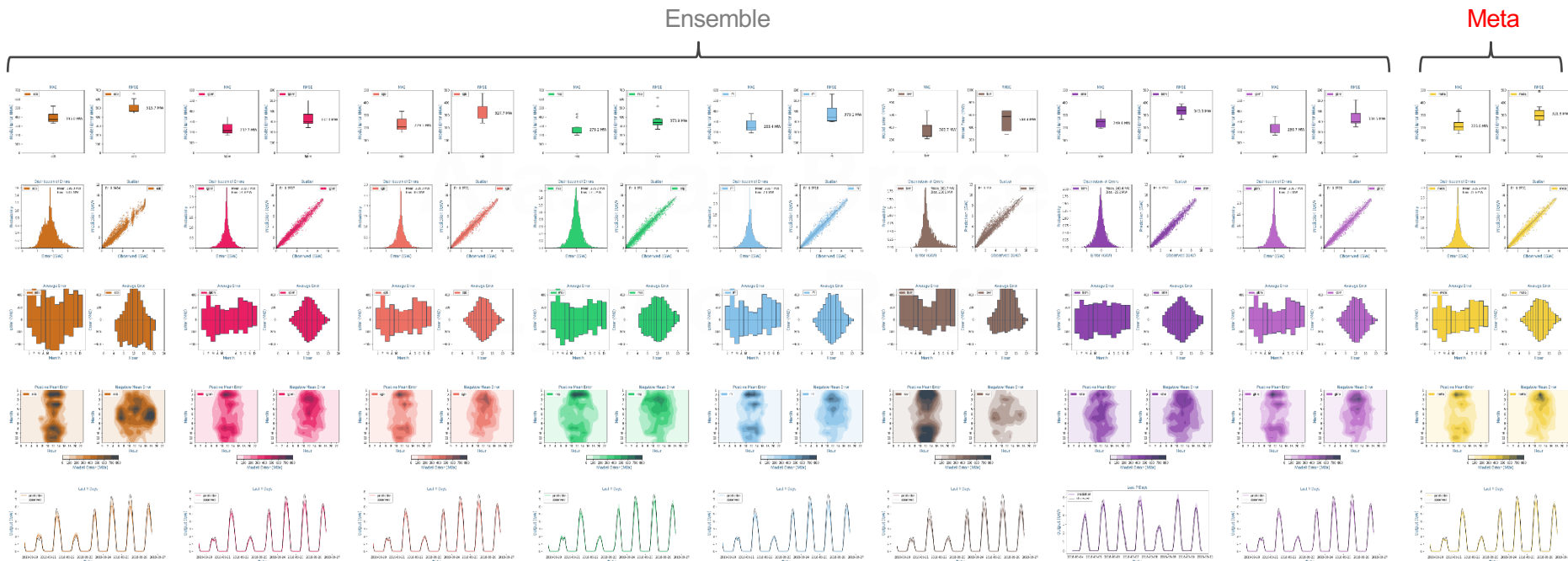
# Evaluate Model Performance

Evaluate the performance of models using k-Fold Cross Validation



# Ensemble

- Charts are generated showing the evaluation metrics during training




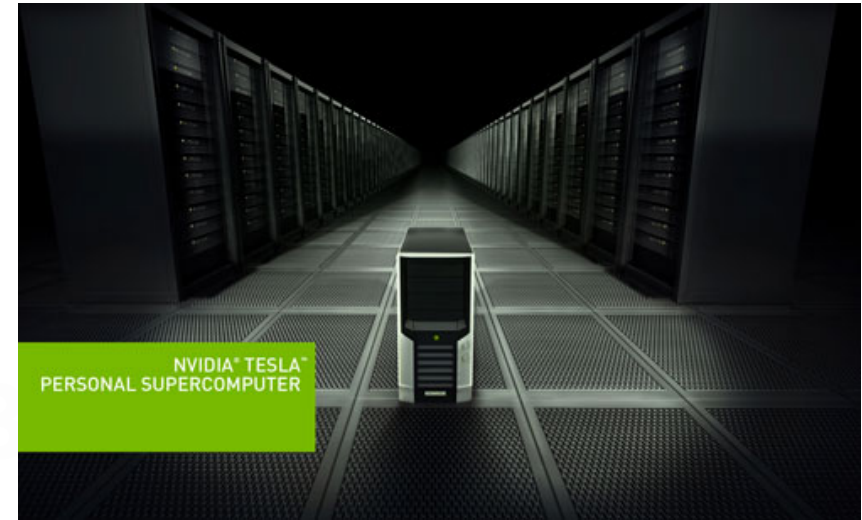
# Super Computer

## Hardware



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

## Core Software

- Python 3.6 64-bit  python™
- Anaconda 5.2 64-bit  ANACONDA.
- RStudio  R Studio
- CUDA Toolkit v9.0  NVIDIA CUDA
- NVIDIA cuDNN 7.0  cuDNN



TESLA V100 PRODUCT SPECIFICATIONS

	 NVIDIA Tesla V100 for PCIe-Based Servers	 NVIDIA Tesla V100 for NVLink-Optimized Servers
Double-Precision Performance	up to 7 TFLOPS	up to 7.8 TFLOPS
Single-Precision Performance	up to 14 TFLOPS	up to 15.7 TFLOPS
Deep Learning	up to 112 TFLOPS	up to 125 TFLOPS
NVIDIA NVLink™ Interconnect Bandwidth	-	300 GB/s
PCIe x 16 Interconnect Bandwidth	32 GB/s	32 GB/s
CoWoS HBM2 Stacked Memory Capacity	32 GB / 16 GB	32 GB / 16 GB
CoWoS HBM2 Stacked Memory Bandwidth	900 GB/s	900 GB/s

## Solar Case Study

40% MAE

Improvement with ML



Our most accurate forecasting months have been the last two months



# National Grid ESO

## Ambition

We want to be able to operate a carbon free electricity system by 2025, and we'll invest accordingly.

UK has committed in law to be net zero before 2050.

Machine Learning is a critical part of achieving this.

# National Grid ESO

## Where we are now

The rate of change in our industry will never again be as slow, the volumes of data so small, or the combinations of assets so simple as they are today.

Lyndon Ruff

# Questions?



**James Kelloway**

Energy Intelligence Manager



<https://www.linkedin.com/in/jameskelloway/>



@kellowayj1



James.Kelloway@nationalgrideso.com

