Axle Energy DFS Analysis

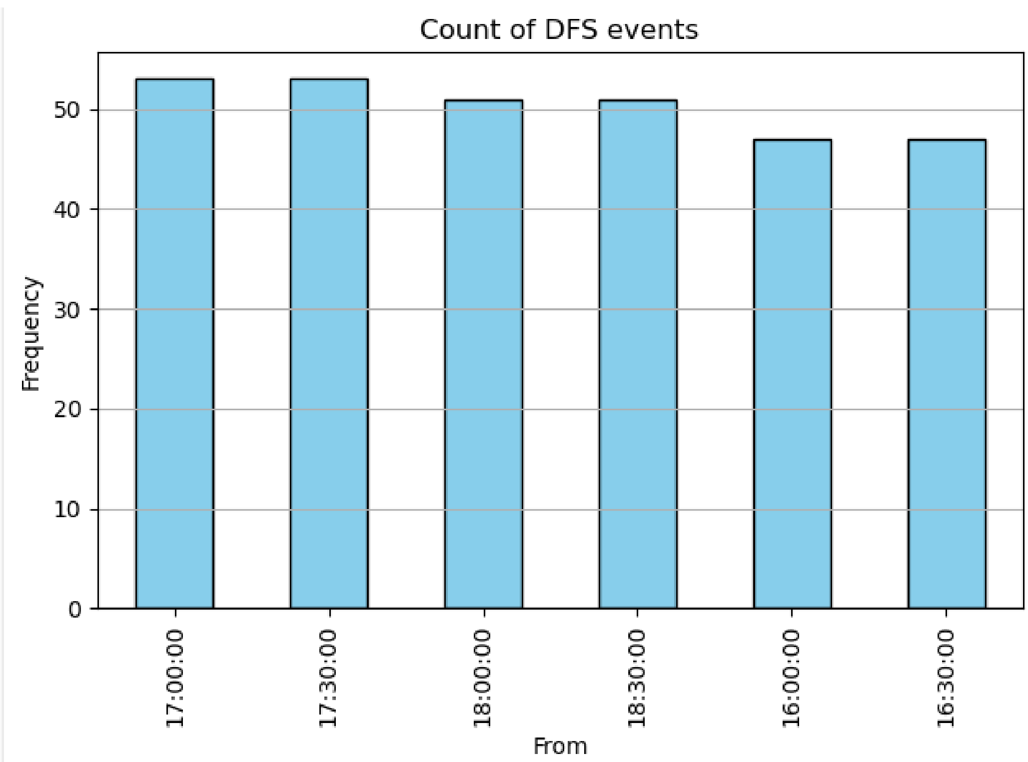
Introduction

Axle Energy participates in the Demand Flexibility Service market, which was introduced by NESO to encourage shifting electricity consumption in order to balance electricity supply and demand.

When NESO is short of positive margin, indicating there is not enough spare electricity generation, it will call on the market by publishing a DFS Service Requirement. These are typically published at 10am on the day that the Service Requirement is needed.

Between 1 December 2024 – 31 March 2025, a service requirement was called in 302 half-hours out of the total 5808 half-hours during the period, or in 5% of the half-hours.

All DFS events during the period were called for a half-hourly slot between 16:00-19:00.



3574 bids were received during the period and of these, 2051 were rejected and 1523 were accepted. Infinis Limited provided half of all accepted bids. Axle Energy provided 20.

The average bid price among the rejected bids was £494/MWh and the average bid price among the accepted bids was £370/MWh.

Analysis

This project will aim to build a model which can predict when DFS events are called, and what the accepted price will be.

The following key features will be used to make predictions:

- Loss of load probability and de-rated Margin (Elexon)
- Day-ahead aggregate generation forecast (Elexon)
- Day-ahead demand forecast (Elexon)

For the forecast to be useful, the model uses features that would be available in the morning of each day to predict DFS events that day.

The **loss of load probability and de-rated margin** values are given 1, 2, 4, 8 and 12 hours before each settlement period. For each settlement period, the model uses only the loss of load probability and de-rated margin given 12 hours earlier.

The **Day-ahead aggregate generation** forecast is published a day before delivery takes place. It takes one value per half-hour.

The **Day-ahead demand forecast** values are given for each settlement period a day in advance. It includes the National Demand Forecast and Transmission System Demand Forecast values.

All values were accessed using the Elexon API service (a nightmare for me 😅). This service limits how much data can be extracted per request, so I built a function to loop extraction requests to cover the period 1 December 2024 – 31 March 2025.

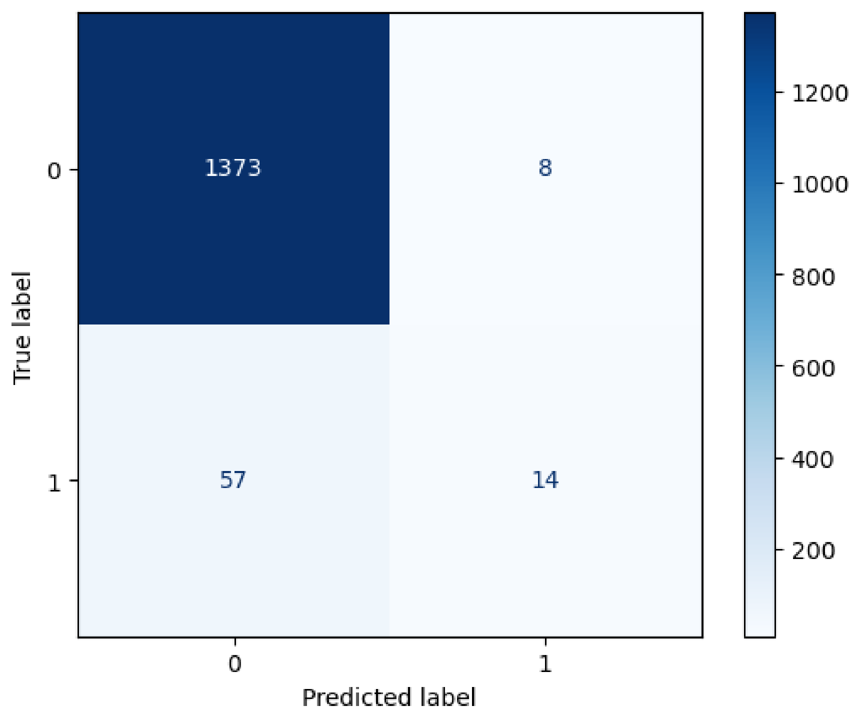
The analysis was done in a Jupyter notebook. The notebook is attached but is not very organized!

The first part of the notebook fetches data for all the features in the period between 1 December 2024 – 31 March 2025, and merges them into one dataframe, along with data for accepted bids and average accepted bid price from NESO (calculated as DFS Provider Bids Accepted Total Cost / 0.5*DFS Procured MW).

The second part builds two models. The first model is a classification model which predicts during what half-hours DFS event will be called. The second model is a regression model which predicts what the average accepted bid price will be.

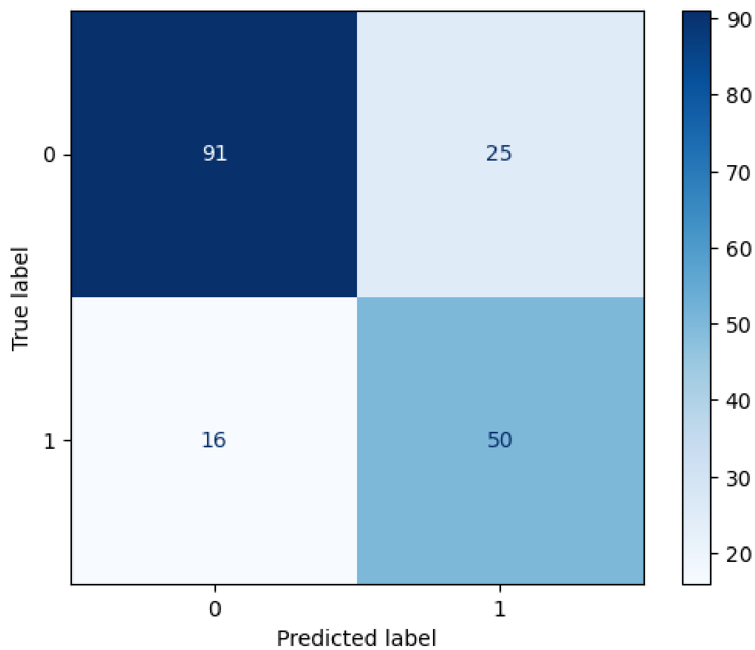
Results

Both the classification and regression models are random forest models. Initially, I ran the classification model on the entire dataset. This resulted in high accuracy 95%, but this was mostly because the model guessed almost every half-hour would be a non-event. In the confusion matrix below, 0 represents no DFS event during the half-hour, and 1 represents a DFS event. Only 14 of 71 events in the test set were correctly predicted.



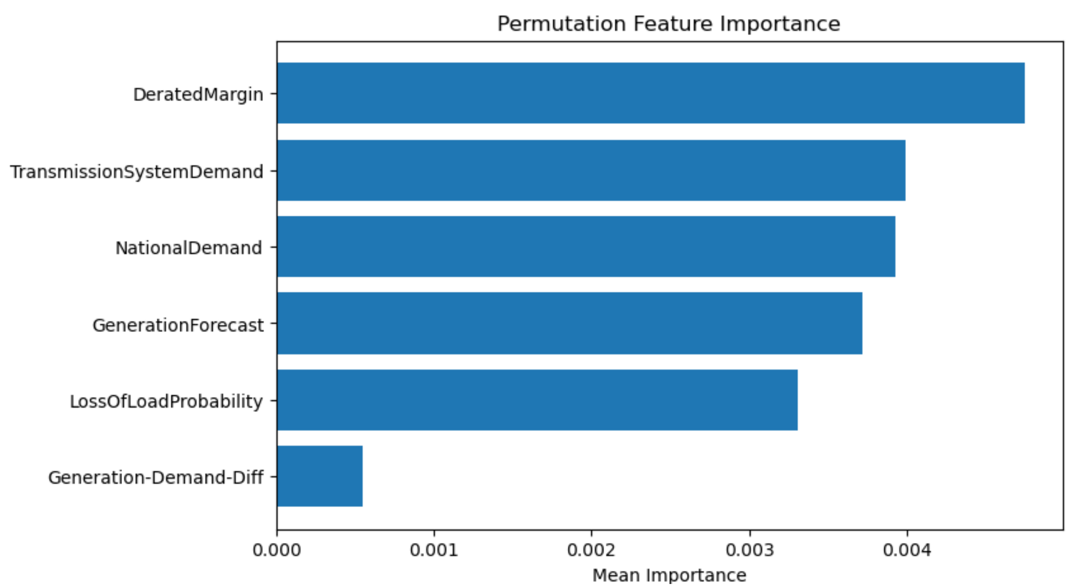
The issue is that the dataset is highly imbalanced. There are far more non-events than events, so the model learns to predict 0 almost all the time.

To fix this, given that all DFS events occurred during 16:00-19:00, I restricted the dataset to only include these hours. This results in a far more balanced dataset where 40% of all half-hours have a DFS event. Below is the confusion matrix obtained from running the random forest on this model.

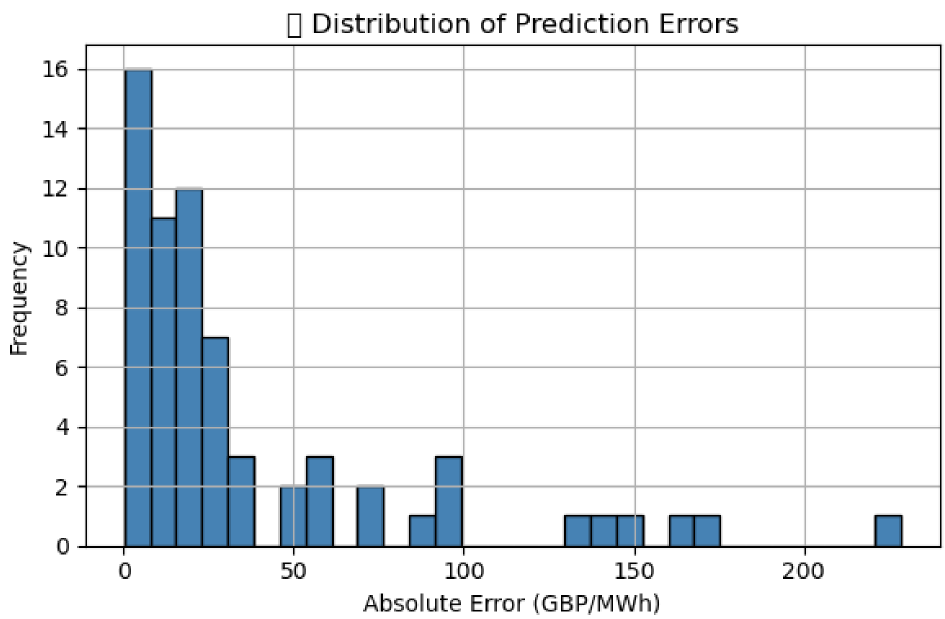


50 out of 66 DFS events in the test set were correctly predicted. 91 out of 116 non-events were correctly predicted, resulting in an ROC AUC Score of 0.87.

Feature importance analysis shows all features were moderately important for predictions. I did not do any feature engineering except adding a Generation-Demand diff column, but this did not help much, as shown below.



The second model is another Random Forest model which tries to estimate the average accepted bid in GBP per MWh. Here the dataset is restricted to the rows where a bid has been accepted. Then the same procedure as before, Random forest, separate train and test, no fancy stuff. This results in an R^2 of 0.72 and mean absolute error of £37/MWh. The graph below shows the distribution of prediction errors.



Discussion

The results show that relatively simple models with only a few features can produce reasonably accurate predictions for when DFS events are likely to be called, and what bids are likely to be accepted.

More accurate predictions could likely be made by incorporating more relevant data, feature engineering and testing more sophisticated models such as neural networks.