Providing Charge Forecasting Analytics for EV Owners

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Providing Charge Forecasting Analytics for EV Owners

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Abstract

During the era of Global warming and Russia's war in Ukraine, there has never been more urgency in helping Ireland's electric grid migrate from fossil fuels to renewables. However, renewable power supply sometimes exceeds demand, leading to the disconnection of wind farms and the wastage of potential electricity. This paper is primarily concerned with providing forecasting tools for users to find when electricity rates are lowest due to high supply. In addition, this paper proposes an alternative expenses model for electricity providers which could results in savings for users and increased demand at peak times. This model was found to be 25% cheaper then current pricing models, using whole-sale electricity prices.

1 Introduction

1.1 Motivation

As part of the UN's Climate Report in 2022, Jim Skea, Co-Chair of IPCC Working Group III, stated that it's "Now or Never" to limit climate change to 1.5° Celsius[1]. As of 2020, electricity generation represented 22% of Ireland's total greenhouse gasses[2]. The Irish electric grid has one of the highest national percentages of potential variable renewable electricity generation, Glynn et al. (2019). Variable renewable power is power which varies in it's supply depending on the wind or the sun, inhibiting it's ability to meet demand on time. Variable power is contrasting to base-load power, such as coal or gas which is always available to meet demand. These varying levels of generated available renewable power create challenges for Ireland's grid operator, SEMO (The Single Electricity Market Operator) and Eirgrid who balance supply to meet demand.

Despite the challenges that variable power sources face, Ireland's government is attempting to phase out coal and gas power, Glynn et al. (2019). In addition [3], Ireland's electricity grid operator has forecast that energy demand will increase between 23% and 47% in the next 10 years. The phase out of fossil fuels combined with increasing demand means that current production of renewable power will need to be dramatically increased. As of June 2022, only 30% of Ireland's electricity is generated using wind power (A total of 80% of all renewable energy). Ireland's government aims to increase this share to 70%

[1]https://news.un.org/en/story/2022/04/1115452
[2]https://www.seai.ie/data-and-insights/seai-statistics/key-statistics/co2/
[3]http://www.eirgridgroup.com/site-files/library/EirGrid/EirGrid-Group-All-Island-Generation-Capacity-Statement-2019-2028.pdf

of electricity (This is an increase of two and a half times the total amount of wind power energy.)

Simply increasing wind capacity is a naive approach to meeting Irish demand. The associated problem of renewable power is that it is not always available when needed. Wind Energy Ireland[4] has raised growing concerns about the increasing amount of lost renewable power every year. 1.4 million MWh of renewable electricity was lost in 2020 when wind farms were disconnected from the grid due to excess supply. This represents enough electricity to power 70,000 houses for a year, or a total of 11.5% of all renewable power generated in Ireland [5]. Electricity providers incentivise owners by making rates lower at times where supply exceeds demand. As coal stations cannot be switched off, most often these times occur at night, but as we move to a renewable grid, they will happen during times of high wind.

One possible way to resolve the issue is with smart storage facilities in the form of pumped storage, batteries or kinetic flywheels. In this regard, Electric Vehicles (EVs) have a major role to play. On average, each EV represents a 60KwH battery, which can be charged when electricity rates are low. Helmers and Marx (2012) documented that a typical 60kWh vehicle battery requires just below 8 hours to charge completely at a 7kW charging point. Most drivers are not completing a full charge every night and are instead 'top-up' charging, to keep their cars full and ready to drive. If drivers were informed effectively about high-supply/low demand times (charge windows), Ireland's EV fleet could be using electricity that has historically been wasted. Ireland's EV owners would be incentivised by the cheaper electricity. A key role to play in this is informing EV owners of these approaching charge windows.

The purpose of this project is to investigate how effective predictive analytics is in finding optimal charge windows for EVs. To do this, historical demand, the ideal length of a charge window and the weather will be used to provide predictions. This leads us to the central question of the paper:- "**Can a real-time prediction system be used to alert EV owners to optimal charging times and thereby minimise the load on Ireland's electricity grid**"

2 Related Work

2.1 The state of renewable power in Ireland

In Western Europe, variable renewable power sources such as solar and wind are intermittent (Simons et al. (2001)). This is particularly the case if there are large low pressure weather systems without wind or sun blowing over the continent. This unreliability can result in dramatic drops in the supply of electric power across the continent.

This presents a problem as the failure of energy supply to meet demand can result in rolling blackouts and serious damage to infrastructure. Wind and solar intermittency reduces their suitability for meeting demand. Renewable base-load alternatives do exist, in the form of hydro-electric and geothermal electricity sources. Zhong et al. (2021) highlights that Sweden is leading the EU's change to renewable power, generating a higher share than any other country in the EU at 60.1%. It generates 70% of it's renewable power through constant base-load hydroelectric power, utilising its geography of lakes

[4]https://windenergyireland.com/latest-news/5364-annual-report-confirms-wind-energy-leads-fight-against-climate-change

[5]https://www.seai.ie/data-and-insights/seai-statistics/key-statistics/co2/

and mountains. However, hydroelectric power itself won't be enough to meet capacity there. This capacity can be met instead with wind power in order to make Sweden 100% renewable. It's mentioned that the fluctuation of (wind) renewable energy capacity and consumption, unless power to gas, electric vehicle and V2G technologies are mature won't allow it to meet demand. This highlights the role that battery technology will play in supporting renewables. However, both the geographical terrain, and attitude to nuclear power make Ireland's potential renewable make-up more like Germany then Sweden, having a more densely populated landscape with a lack of hydro-electricity.

Germany's energy transition policy, the "Energiewende", has been controversial, with article's like "Energy Price Increases Pose Challenge for Merkel", 2012,"Germany's Green Energy Meltdown", 2016 and "The Worlds Dumbest Energy Policy, 2019". Critics emphasise the higher electricity prices that consumers are paying, and how the shutdown of zero carbon electricity nuclear power resulted in retaining coal plants. However, their polluter-pays policy has begun to bare fruit as Rechsteiner (2021) highlights that the Energiewende has created an electricity market that incentivises users to minimise CO2 emissions through premiums and tenders for users. Originally, the system sought price guarantees for users but now "dynamic efficiency" is considered a core part of their energy policy.

Despite major progress in Ireland, Fitzgerald (2020) highlighted that a major policy shift is necessary to reduce Ireland's dependency on fossil fuels. (Crilly and Zhelev (2008)) analysed the Irish electricity market, completing projections for the future about it's Optimal Energy Resource (OER) mix, containing a balance of both renewable and fossil fuel sources optimised to meet demand while producing a minimum amount of wasted electricity. In 2005, renewable power made up 6.9% of Ireland's total grid capacity. For 2010, he predicted an optimal OER mix would include 19% renewable electric power, which it exceeded with 20.4%. Now Ireland's grid capacity contains 42.5%[6], placing it outside of the predicted OER mix. However the analytics tool used for predicting the OER mix (The CEPA Methodology), is outdated by today's standards and as part of the analysis, he strongly penalises imported electricity and doesn't account for excess wind power. Even then, it's highlighted that Ireland's renewable makeup, which consists mostly of variable wind power, places it distinctly in need of electric storage capacity. The current estimate for the OER mix stands at 50%[7]. While Ireland's SEMO system does set variable prices for electricity vendors in Ireland such as Electric Ireland or Bord Gais, the current hourly system rates employed by vendors are set monthly. This means that everyday consumers are broadly protected from large swings in electricity prices due to demand-supply fluctuations. This may need to change in order to create the same dynamic demand environment which is present in Germany. This poses the central issue of this thesis:- Can users be informed of excess power supply times and be incentivised to use them?

In addition to financial incentives for consumers, C.A. Goldman and Eto (2002) found that in California a public information campaign on the need to reduce electricity consumption during one hot summer in California changed consumers behaviour. It was found that consumers dramatically changed their usage habits in response to a shortage of power generation. This averted the worst of the blackouts and reflected a willingness in individuals to modify behaviour when facing short supply. While this indicated a strong support for carbon mitigation in the population from this case study, it must be kept in

[6] https://en.wikipedia.org/wiki/Renewable$_{e}nergy_{i}n_{t}he_{R}epublic_{o}f_{I}reland$

[7] https://assets.gov.ie/221399/86cb99f5-58e3-4821-bc4c-e1bb1fa706fb.pdf

mind that the population group studied were Californians, who are typically more environmentally conscious then the average population of the United States, with California dominating in green initiatives, (Lubell et al. (2009)).

Lastly, the introduction of EVs will be putting additional pressure on Ireland's electric grid, which if completely adopted by all combustion engine vehicles could double the total demand on Ireland's grid. This point however, may be decades away, as Mukherjee and Ryan (2020) highlights. (Mak et al. (2013)) mentions that policy makers should adopt more financial incentives and mandate the installation of chargers in all strategic locations. Given that EVs can be charged at specified times, this presents an opportunity to balance the intermittency of renewable power with storage ability of EVs, Helmers and Marx (2012). As seen from the section above, the renewable market in Ireland varies dramatically from having abundant supply to having none. Energy storage solutions, as explored in the next paragraph have a role to play in preventing energy wastage in the Irish market.

2.2 What can be done about wasted electricity in Ireland?

Eirgrid takes responsibility for balancing electricity supply with demand. The total supply of electricity must meet this demand in real time. Failing to meet demand would result in infrastructure damage and blackouts, as C.A. Goldman and Eto (2002) has shown. Thus, demand is generally treated as the controlling constraint in the equation, resulting in times where supply exceeds demand. When this happens, the following are possible (DeCarolis and Keith (2006)):-

- Power used for hydroelectric storage (Currently only Turlough Hill)
- Power exported to UK (Wind may create surplus power there too)
- Powering down gas and wind power (They can rarely be switched off)
- Wind farms are disconnected from the grid, causing power losses

Additional power outlets for Ireland's fluctuating supply need to be found urgently. EVs could play an important role in helping demand meet supply if they are informed about peak supply times.

2.3 The role of electric vehicles

Failure to inform EV owners about optimal charge times could create stress on Ireland's grid infrastructure. Creating a more efficient electricity grid would both lower the chance of transformer overloads, reduce our reliance on fossil fuels, voltage fluctuations and power losses which (Shibl et al. (2021)) showed. The alternative would result in greater fossil fuel reliance and increased grid stress with increased demand at sub-optimal charging times.

Lim et al. (2020) found that the wide scale adoption of EVs will have a large impact on total grid use. In their paper, they found that EVs could play a role in creating demand to meet peak supply, by using Vehicle to Grid (V2G) systems. These would utilise automated systems to feed stored electricity back to the grid. This stored electricity could play a major role in supporting renewable technology, but the volume of EV owners must reach a critical amount for it to be feasible. They found that EV owners could be making an average of 100,000 KRW ($77) per year. However their study looks at the current habits of EV owners with technology that was modern as at the release date of their paper. Furthermore, if the timing of charging EVs is coordinated, it could also improve grid resilience. (Rahimi and Davoudi (2018)) explored the possibility of car batteries being used during blackouts as emergency power supplies for homeowners. During the study, they showed that a residential customer could be served for 9 days in the summer and up to 6 days in the winter, running their home completely on the battery from the car. However, their study was carried out in a temperate part of California, and these results could be unsuitable for residents of more extreme weather varying locations like Ireland.

Ireland currently has no centralised system for smart control of power usage by distributed energy resources (DERs), i.e. smart appliances and large batteries. ESB has recently begun to roll out a program to pay those with excess electricity to contribute to the grid. From July 2022, ESB will begin paying [8]individuals for their solar power energy. The scheme is open to being used by other micro-contributors, be they wind or electric storage. While this system is a step forward, EV owners may need more information or incentives to contribute. The possibility of implementing a large scale energy distribution system in New Jersey using Machine Learning (ML) was investigated by Wang et al. (2021). They propose a fully distributed energy trading framework based on using machine learning. This framework used the electric batteries of idle cars, charging and discharging them on a regular basis to utilise EV's demand to assist wind variability. However, they are now completing numerical simulations of their project and have yet to implement it.

The use of a central smart power or distributed power to utilise the storage power of EVs to minimise grid development costs could be difficult to implement. It would require additional smart meters and boxes being installed in homes. Power being routed across the country could produce high transmission costs. Lastly, Kaviani and Hedman (2019) showed this connected Smart Grid could be open to attack. One final factor is that owners would be disincentivised by the gradual wear on their vehicles battery. Unfortunately, the scale a Smart Grid distribution project would be out of the scope for this proposal.

In their seminal review, Tao Hong et al. (2020), explores the most influential papers in the energy forecasting sphere, placing special emphasis on the last 10 years. When exploring supply forecasting using the weather, he mentions that wind power forecasting and renewable forecasting are the fastest growing fields in the literature of forecasting over the last 10 years. The methods mentioned are explored later in the "Methodology" section. However, historical research on forecasting EV usage has focused on demand forecasting, not supply forecasting. For example, Jun Bi and Guan (2018) employed regression and time series models to predict the charging times of EVs in Beijing. Their goal was to accurately predict charge times and to help drivers determine the time needed to prepare for long drives. Their study focuses on charge distribution management in sending EV owners to locations where there are empty charge stations available.

The software providing predictive analytics for EV owners has been the subject of numerous studies. Nait-Sidi-Moh et al. (2018) reviewed the need for EV drivers to be sent to usable charging stations. Cars being routed to stations with low demand charge faster than those loaded with multiple vehicles, minimising waiting times at stations and reducing load on infrastructure. Arias and Bae (2016) proposed a large demand forecasting model using Internet Of Things (IOT) and big data technologies. This involves

[8]https://www.independent.ie/news/environment/over-21000-customers-to-be-paid-by-esb-for-their-solar-power-energy-41629327.html

using weather conditions and real world traffic distributed data to forecast EV charging demand. This model would be used to increase supply to prepare for high demand hours, and so would be more use to power systems engineers then EV owners. The use of big data and IOT could be the subject of future analytics, i.e. forecasting EV power supply.

2.4 Creating suitable analytics systems

Effective easy-to-understand analytics have been shown to optimise electricity use. Friis and Haunstrup Christensen (2016) found that Smart Grid power dashboards changed homeowner behaviour to use power at non-peak times. In his study he looked at a population sample who were asked to employ energy saving techniques in line with the available power. He found that many people, especially those with young families, found it difficult to modify their established habits, such as dish-washing etc. However, the study did find that participants began to pay more attention to the weather, and would modify some of their practices to reduce electricity consumption. Consumers may not be aware of some of the relationships between electricity costs and the weather until it is outlined to them. If electricity rates change to reflect the wholesale price, i.e. charging users less when electricity is abundant, this could adversely effect those who can't change their behaviours such as young families.

The importance of presenting analytics in a user friendly way was demonstrated by Sebastian Stein et al. (2017). Their aim was to give accurate preference reports based on a users need. They highlighted that there is a need for EV-owners to be presented with uncomplicated, user-friendly interfaces. Limiting the amount of information presented to users reduced the time they spent deciding on charging times and actually improved their overall charging behaviour by an average of 70%. This was done by improving the efficiency of their charging, provided they were presented with key information. The importance of simple analytics will be realised in the real-time execution of this project.

2.5 Forecasting electricity prices on the Irish market

Tao Hong et al. (2020) found that the field of electricity forecasting "has evolved way beyond standard implementations of existing forecasting methods onto "new" problems." They give a large range of advanced artificial intelligence (AI) and ML techniques that have been applied in recent studies. These include deep learning Wang et al. (2017)),(Heng Shi and Li (2018), random forest (Mei et al. (2014)), reinforcement learning (Cong Feng and Zhang (2020)) and transfer learning (Cai et al. (2020)). Random forest and transfer learning is often used to discover hidden patterns within the algorithms. Deep learning and reinforcement learning acts as a black box to provide predictions with very little initial input.

Due to Ireland being a small market, these studies on predicting price variability have only been carried out a handful of times. The first most relevant study was carried out by Crilly and Zhelev (2008), who investigated the optimal fuel mix to minimise the cost of electricity while meeting Ireland's Kyoto guidelines. As part of this study, accurate forecasts of Ireland's share of renewable power was created. Furthermore, Francesco Arci et al. (2018) investigated forecasting the short-term wholesale prices on the Irish single market. The forecasting algorithm was built with artificial neural networks (ANNs) using weather data and historical demand. The created model was 80% accurate to the total price for up to 24-hours ahead of the predicted time. This is a useful benchmark for electricity prices, but for our model to be useful to drivers, we would hope to increase this predicted time period to one week. Lastly, Christian O'Leary et al. (2021) studied K-Nearest-Neighbour (KNN) algorithms and found that they out-performed ANNs. These KNNs can have a high dependency on input variables, and a failure to match historical results may be due to missing information.

2.6 Literature review Conclusion

In conclusion, the variable renewable power supply in Ireland has led to moments in time where there is excess electricity in the market, resulting in wind farms being disconnected form the grid. Research has shown that there is a growing need for electric storage, either as hydroelectric storage or electric batteries. EVs will be increasing the total electricity demand in Ireland, and unfortunately, information on abundant electricity supply times is not being conveyed to owners. A suitable analytics system for forecasting these abundant supply times will improve demand at critical times and reduce electricity wastage.

3 Methodology

3.1 Data Selection and Pre-processing

In Wholesale electricity prediction Publicly available weather datasets and the electricity generation are the two most important and easily attainable sources of data, (Tao Hong et al. (2020)). Both are used for this study. The Knowledge Discovery in Datasets (KDD) methodology was chosen due to it's historical use in predictive trends, identifying correlations and use in forecast prediction,Plotnikova V (2020). The use of the Cross-Industry Standard Process for Data Mining(Crisp-DM) methodology was considered, but as this report was focused on exploring theoretical models ahead of investigating business understanding KDD was chosen. Secondly, the waterfall order of tasks carried out suited the simple implementation of the project, as other stakeholders were not involved.

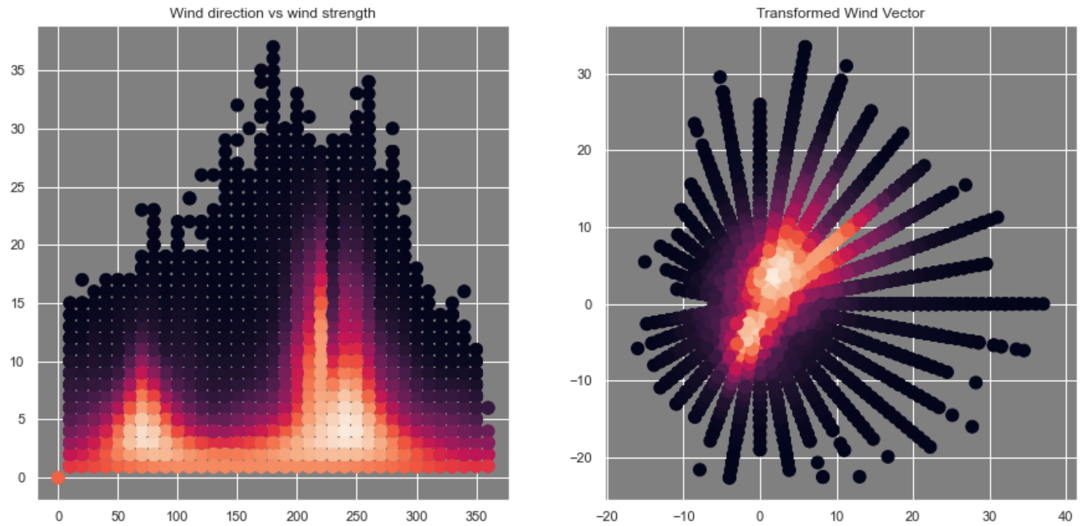
In order to create predictions of low demand periods in the grid, two datasets are necessary. One on the historical weather (The predictor variables) and one on the historical energy generation and demand (Target Variables). Forecasts of the available wind power are generated using the weather forecast. A third dataset was chosen from the wholesale electricity price in Ireland to investigate correlations between supply/demand and the wholesale price of electricity prices. The three datasets for the project are taken from Met Éireann, The Sustainable Energy Authority of Ireland (SEAI) and The Single Electric Market Operator (SEMO) respectively. All are publicly owned companies and publish their data publicly, and so the data was published under a Creative Commons Attribution 4.0 International (CC BY 4.0). The first pertaining to historical weather, the second to electricity usage and the last to wholesale electricity prices.

Pre-processing of the data involved the investigation of outliers and backfilling missing data. When backfilling, it's important that reasonable values are used to fill gaps (ie if a weather station stops recording above a specific temperature). The data is transformed to be numerical and continuous so that it's suitable for feeding to ML algorithms. The data is then mined, both by exploratory analysis and ML algorithms to produce an alternative model to predict a numerically continuous variable.

Missing data is backfilled using seasonal adjustment and interpolation. This is because of it's historical popularity when dealing with data Missing Completely at Random(MCAR). These null values are filled when creating the join between the two datasets using pythons seasonal interpolation function. Seasonal interpolation was chosen because of it's historical popularity when dealing with data Missing Completely at Random(MCAR),(Velasco-Gallego and Lazakis (2020)).

As part of the transformation, three time-series variables were extracted, the time of year, day of week and hour of day. Both electricity generation and demand have been found to vary due to seasonality of heating houses, traditional dinner cooking times and varying work week habits. All of these variables are cyclical, however when training a numerical model, the number 24 and 0 despite meaning the same time of day, would create completely different inputs. Thus a sin and cos of each period was created to allow improved modeling of time-series data. Next the wind-power and wind-direction variables were transformed into a single x-y wind vector, which gives the wind strength in each x-y axis at a given point in time, as shown in figure 1.

Figure 1: Wind Direction Transformation



As part of their overview of ML models, Tao Hong et al. (2020) highlighted the importance of having an understanding of the relationships of the variables when creating ML models for electricity forecasting. Heng Shi and Li (2018) found in their case it improved the accuracy of their ANN results. An Independence test is carried out on the variables to explore relationships and find eigenvalues. This is done to have the possibility to create an initialized first layer of the ML algorithms which reflects the dynamics of the system.

3.2 Machine Learning Techniques

The methods chosen in the creation of real-time forecasting depend highly on the granularity of the demands which are being met. As the exploration is intended to provide a week-ahead forecast based on the weather, the granularity level expected is low, at approximately one hour to a half hour. The techniques in theory could be scaled up for industrial use, but this would require increased granularity in the provided data. If the simple model proves effective, the predictions could be integrated into IOT technology, automatically charging EVs or Distributed Energy Resources (DERs) when excess capacity is expected in the Irish Grid. In this project, simple ML techniques are explored in their predictive power.

Suitable ML techniques explored as part of this project include multivariate Autoregressive Integrated Moving Averages (ARIMA) modelling (Heng Shi and Li (2018)), deep learning (Wang et al. (2017)), Random forest (Mei et al. (2014)) and K-nearest-Neighbours (KNN) (Cong Feng and Zhang (2020)). The ARIMA model generates a timeseries forecast based on historical trends having some impact on future values. The multivariate type of ARIMA model takes into account other variables in it's predictions. It's broadly expected that electricity prices will reflect historic patterns so the ARIMA model will provide a baseline model to compare results. Despite the model being far simpler then other deep learning algorithms studied, the results of the model may provide insight into seasonal trends in the data.

Random forest produces probabilistic forecasts which provide useful information regarding the probabilities of different outcomes for power generation. A low probability, but high wind-generation forecast would provide less security for EV-owners, than if the following day may have a more secure, but lower probability of producing results. Moreover the impact of each variable on the results can be separated to find how strong it's impact on producing forecasts is. This model is completed first, to ensure only variables which have a strong impact on results are chosen for future models. In literature by Mei et al. (2014), the random forest model had been shown to give high f1-accuracy when predicting electricity prices.

The KNN model provides useful benchmarks which are used to compare to historical results in Ireland. Christian O'Leary et al. (2021) showed KNN algorithms are useful for forecasting electricity in Ireland. In contrast to this Al-Qahtani and Crone (2013) found that feature engineering for KNN can be a daunting task. Initial analysis plays a critical role in generating eigenvalues and features.

ANNs can permit the modelling of nonlinear and complex relationships through straight forward "plug and chug" modelling by users. Despite this, highly accurate ANNs often have an input layer which reflects the dependence of different variables, as explored by Tao Hong et al. (2020). Thus the generation of our ANN input layer is informed by our initial analysis, and by the results from the random forest models. However, Wang et al. (2017) highlights that the input layers don't always need to reflect the functional relationship between load and weather variables, suggesting a weak dependence.

A useful benchmark for the results of the models is provided by SEAI which generates a forecasted wind variable, which is compared to the results of the outputs of each model.

Lastly, the analytics were generated in a simple and effective way to communicate optimal charging times to EV owners. Following the principals in Sebastian Stein et al. (2017), suitable visualisation were created using outputs from a trained ML model using the weather forecast for that week. In this context, a dashboard is a reporting mechanism that displays key metrics so they can be examined easily by users. The dashboard is tailored for EV owners, highlighting periods which represent the most appropriate charging time during the week.

4 Design Specification

4.1 Data Analysis

The merged weather-electricity use dataset has over 27000 rows and 144 columns. The weather data was stored in zipped historical data files for all the various weather stations in Ireland. The data was scraped using a bash script to pull and unzip the data from 8 weather stations. Data is published on a monthly basis.

The electricity usage data is pulled on a monthly basis from the SEAI website. Each yearly csv pull is separated, as too many api calls to the SEAI website caused it to crash, thus each bash file was split between two yearly files, with 12 csv's being pulled on 4 different variable sets. If execution of each bash file is split over a 5 minute interval, the website doesn't crash.

Electricity prices are published on a weekly basis, and aren't stored publicly on the SEMO website , and so need to be scraped and stored on a regular basis. A [9]crontab was created with bash file using curl and awk to create a query to generate a csv. The three csv's are then joined together using python on the date-time column. Both the SEAI and SEMO datasets are half-hourly, whereas the Met Éireann dataset is hourly so the half hourly tick data is lost during processing, however, abundant training data over the three years is left over.

Pre-processing involved filling rows in the data which were MCAR. The datasets were then joined together. Only columns which can be forecasted by Met Éireann's forecasting API were used. Transformation firstly involved using min-max scaling to standardize the weather columns. Then periodic variable such as the time and the wind direction were converted into cos-sin variables. Additional input variables were created which could reflect dynamics of weather systems in Ireland.

4.2 Machine Learning

The machine learning algorithms were taken from literature on electricity price forecasting and included random forest models, ARIMA models, Artificial neural networks and convolutional neural networks spanning multiple hours of the day.

The simpler model ARIMA model was used as a baseline to complete cost/benefit trade-off against the more complex algorithms involving the weather as an input. The seasonal adjusted arima model was applied to the generated wind electricity.

For the random forest model, different variations of input variables were selected for training, as the model itself can over-fit training data, growing multiple unpruned branches. Scikit-Learn's Randomized-Search-CV method was used to select hyperparamaters for both random forest and the ANN model. A grid of hyperparameter ranges was defined from which random samples were chosen. K-Fold cross validation was performed with each combination of values. Hyperparamaters which were tuned for the ANN models included the number of layers, the nodes in each layer, the learning rate and the batch number.

[9]https://www.tutorialspoint.com/unix$_{c}ommands/crontab.htm$

4.3 Data Pipeline Architecture

Several central principles of pipeline design listed by Helu et al. (2020) were followed. Firstly, the pipelines were built to be re-playable to ensure data availability in the case of a server-failure. However, some of the files which were being downloaded vary week on week, such as the electricity price dataset or the weekly weather forecast.

The data pipelines were also built to be reliable, scalable and secure. If other weather stations are added to training data, their co-ordinates can be used to generate additional forecasts. The data is stored on a secure remote server and the code base is backed up to a private git-hub in the case of an outage.

4.4 Website Design

Following the principals laid out by Beaird et al. (2020), the web site is designed to be simple, providing a minimalist layout. The site's logical layout follows the inverted pyramid; The most essential data has been placed in a central spot on the dashboard. Following this, the remaining data is displayed in a logical order.

As Sebastian Stein et al. (2016) has highlighted, the ease of use of the chosen UI is essential in changing customer behaviour. To keep the dashboard simple, no emphasis was placed on making the dashboard interactive.

5 Implementation

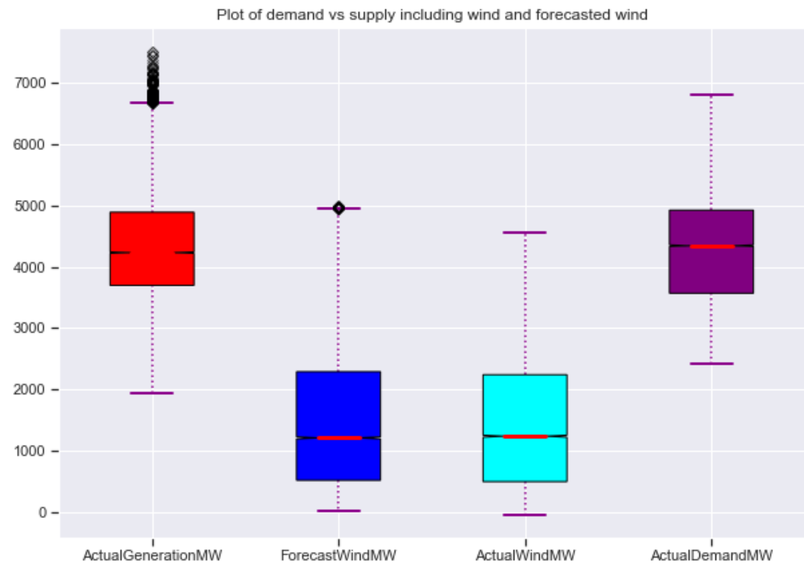
5.1 Data Analysis

A brief analysis was completed on the cleaned weather dataset, and overall both data sources from Met Éireann and from SEAI were excellent bar some missing rows. However, wholesale price data on electricity was collected on a weekly basis, which meant that only four weeks worth of training data was available, so it was left out of machine modelling, but included in co-linearity analysis and used to test minima price forecasting. From the Eirgrid dataset there are 28 missing rows and 59 entries from the SEAI dataset, which were backfilled using seasonal adjustment and interpolation. Training data from eight weather stations in Ireland was initially pulled, with this number narrowed down to four to improve the efficiency the ML algorithms. Columns such as the dew point, the wet bulb temperature and the cloud cover are not available as weekly forecasted variable from met Eireann.

Outlier analysis was carried out on each set of variables, as shown below in figure 2. The average actual wind generated at 1241 MW is far below the the average demand of 4231 MW. The highest outliers on the graph are in Actual Generation, when the generated electricity can exceed demand. Looking at the actual demand, we can see that at all times there is demand in the Irish grid, however the actual wind generation at times goes to zero, and some negative values were found in the dataset. This is due to cyclical aerodynamic loads on blades, which are caused by highly turbulent, variable conditions which adversely effect turbine performance.

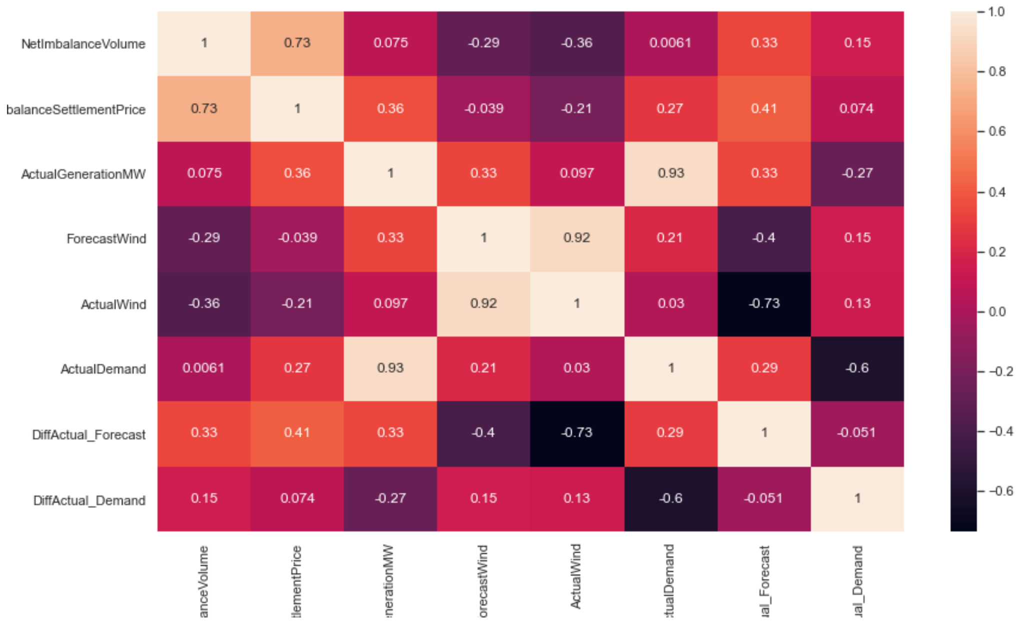
Below in figure 2, a correlation map is shown for the combined dataset of SEAI generation and wholesale price of electricity, taken from SEMO. The imbalance settlement price is a key feature, which according to Ireland's grid operator "gives a key indication of the performance of the market". Sensibly, the actual demand is more highly correlated

Figure 2: Outlier analysis of Generation and demand



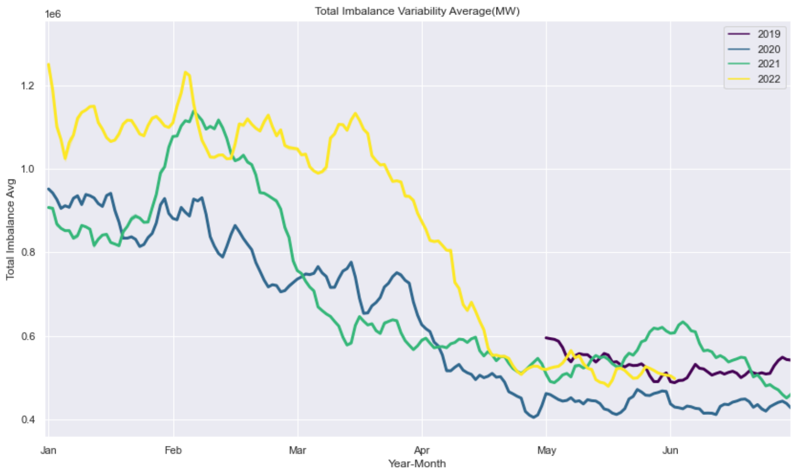
with this variable than the supply. However, the difference between these two isn't as correlated with the price of electricity as the difference between the forecast electricity and the actual generated wind power. In preparation for peek times in Ireland, gas and coal power stations are switched on, however, if incorrectly predicted, this results in the importation of electricity from abroad and stress being applied to the Irish market.

Figure 3: Correlation Heat Map for prices and



A brief investigation into the rolling supply - demand variation (That is the averaged rate of change of the difference between supply and demand) is shown to have been highest in 2022, this is possibly due to the integration of more renewable sources into the grid, which can create a more varying supply-demand difference. The war in Ukraine, which began around the 24th of February has gradually increased the price of electricity for consumers due to increased fossil fuel prices. However, this change was found to have minimal impact on either supply or demand, as both are in line with average for the last 3 years. The integration of variable renewable power sources has had a larger impact then the war on supply-demand variations.

Figure 4: Average Rolling Supply-Demand Differential



5.2 Data Pipeline Architecture And Processing

The importance of transforming variables to be continuous and sensible is mentioned in the literature so the following transforms were carried out. Firstly a mapping of the wind direction and velocity to a singly x-y wind vector as shown below. This maps the 0-360 variable to a smooth cos-sin input and ensures that the wind direction has no effect on the model if the wind is absent. This mapping is shown in figure 1.

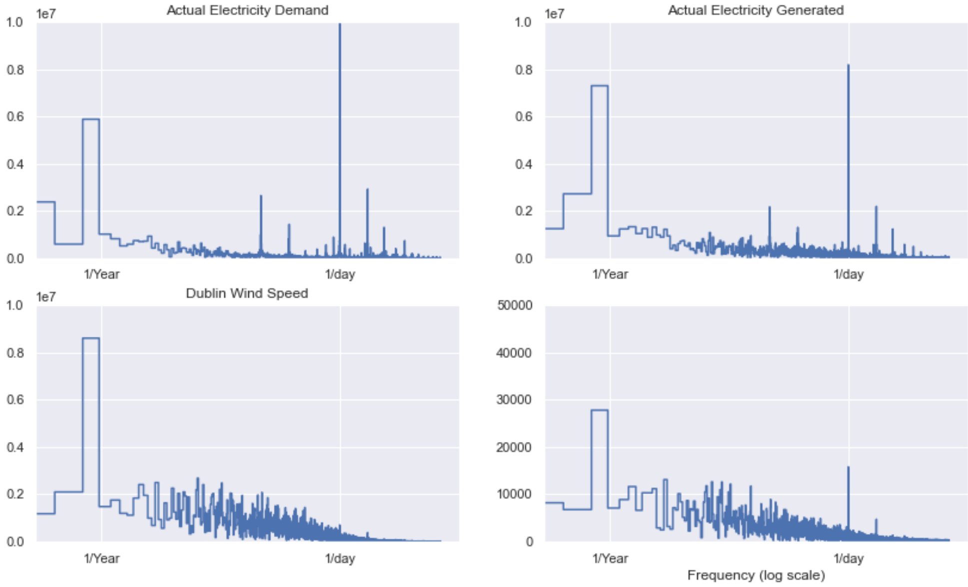
The next transform involved looking at the periodicity of thee predicted variables in order to transform the time variable to the appropriate period. Electricity demand is shown to have both a daily and a yearly component. This variation is accounts for the increased demand for home heating in the winter, and the collective daily habits of individual electricity use. The daily periodicity however is missing from the the daily wind speed graph, reflecting the lack of wind during summer months.

From these graphs two distinct time periodicities were decided on and created that reflected the sin and cos of the yearly and daily periodicity.

5.3 Machine Learning

The cleaned dataset was loaded into an ML notebook, where it was split into training and validation datasets. Normally, a scikit-learn split will split the data after a set cut-off point, which could be 80 % of the dataset. However, with increased renewable penetration the dataset and it's dependencies are always changing. Secondly, the split dataset was

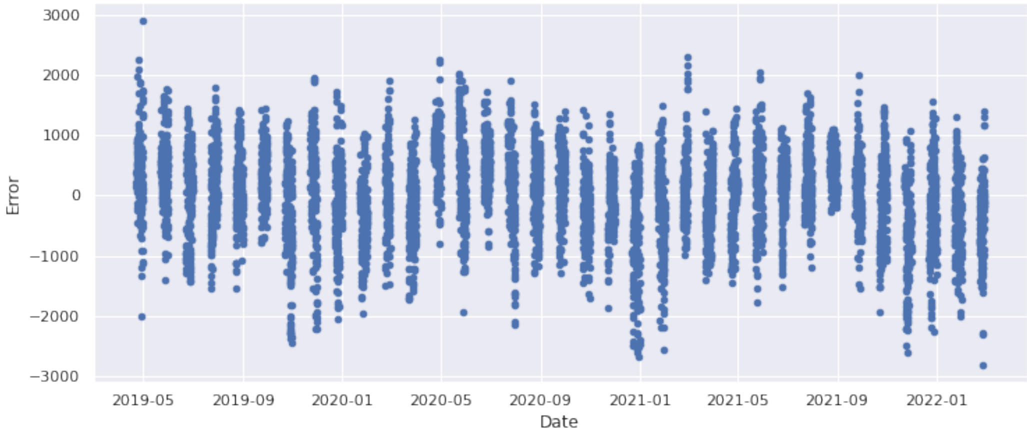
Figure 5: Fourier Transforms vs time



not randomized. Adjacent values can be used to improve predictions for a given hour. If a sustained period of high winds, gas powered stations are deactivated, which can increase the likelihood of higher renewable power penetration into the market. Demolli et al. (2019). Thus a train-test split was chosen to split each month in the dataset into a train and validation dataset. The 23rd of each month was taken. An example of a similar split can be found here

The second model chosen was random forest. This model was an ideal early candidate for model production as it highlights the feature importances of it's constituent columns. In the case of highly technical models, the default random forest can become large and over-fitted. Despite this, the random forest model trained in under 10 minutes and proved to have very accurate results. Tao Hong et al. (2020) highlighted other studies completing power prediction work have used random forest as it couples with non-linear relationships quite well. This usually lead to low bias vs variance. The use of randomized dataset can lead to data leakage, as neighbouring hours have similar wind generation, or actual generations, which was avoided in the historical weather dataset by using a train-test split dividing each month. For the latest testing, which completed on the 5th of August, an r2 value of 81.2 % .

Figure 6: Random Forest Outlier Plot



From the outliers, we can see that there is no single month that has outsized number of outliers, except that there tends to be more outliers during winter months. Outlier plots like the one above help to highlight periods where forecasted data is outside of an expected range. The plot shows that there could be some seasonal variation of the errors in prediction.

Figure 7: Random Forest Column Importances

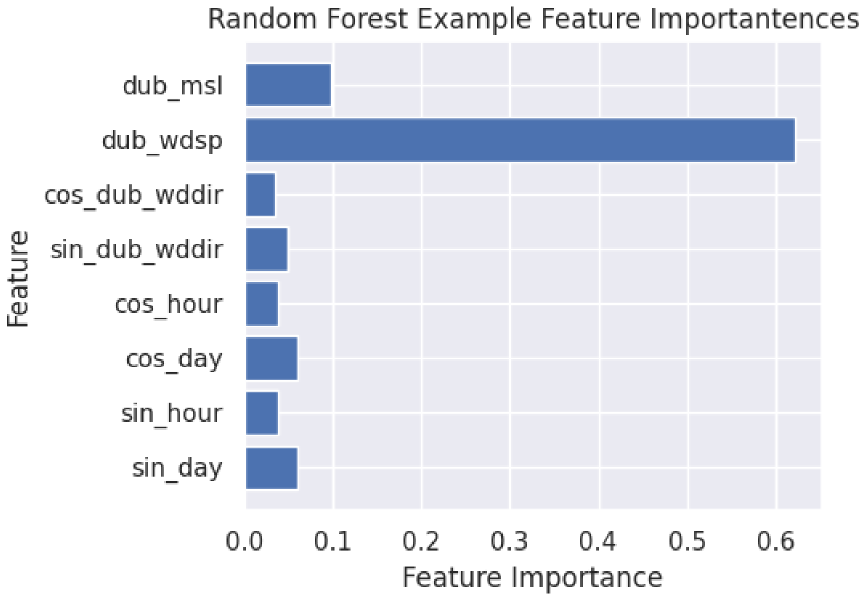


Figure 7 displays the feature importances of a random forest model created with a selection of columns. Due to the co-linearity between the wind speeds at the different stations, these columns are not eigenvalues and so may have hidden dependencies. However they give an idea of the importance of each feature to other models. Surprisingly, the wind speed in Dublin is one of the most important stations for determining Ireland's generated electricity. This could be down to gusts occurring along coastal stations which are not associated with higher wind speeds in wind farms. A future model could investigate the use of more inland stations and their impact on power generation using random forest.

ANN's are often used to model complex systems while digesting large volume's of data. Nielson et al. (2020) Showed that ANN's have had a proven track record when forecasting both electricity generation and demand. The ANN's used in this study were taken from Google's KERAS library. A worked through example of forecasting day ahead weather is found here. Different versions of the ANN were trained, with parameters varying the layers between 3 and 5, with the neurons varied between 50 and 200 neurons for the middle layers.

For this model, three activation layers were used, each with 110 units and each using the "relu" activation layers. In early models, attempts were made to engineer the first activation layer. One possible dependency explored was that a difference between wind directions or the average wind speeds in coastal stations could effect wind generation, say if a low pressure anticyclone was passing over Ireland. However, when tested, these columns were found to have no correlation to the wind power. There was no difference between the engineered layer and non engineered input layer. Thus the model depended on the sheer volume of data being used to train the model. Future work could examine engineered columns in the dataset.

Two variations of ANN's were used, one in which an hourly window of forecasted weather data was taken of the data to predict, and another in which 24 hours worth of data points were used to predict the generated wind power of the hour at the end of the window. This means for a given output, the model was being passed 240 input variables if all columns are used. The general theory of this is that the hours leading up to the time of prediction could have some impact, say if gas powered electric generators get deactivated due to high wind penetration, this could improve total renewable penetration. However, this model failed to produce more accurate results. This could possibly be due to the over-fitting of the fitting data. For future work, a smaller window could be used, with a selection of the most significant columns being used.

In figure 8 shown above, we see an example prediction window being used. Eirgrid's model, shown in blue, frequently overshoots the actual wind generation at higher wind generations (from the 26th-27th), but outperforms the ANN and Random Forest model at lower powers.

5.4 Website Design

The website was designed to be simple and user friendly. This meant showing only a handful of metrics, such as the most optimal time to charge, the forecast for the week ahead. A mock up of the site design, which can be found the code base is shown below in figure 9.

On the bottom of the page a charging forecast is generated using the forecasted weather for the week ahead. To keep the model simple, it highlights in a binary way, where the greyed out windows on the graph shown are the optimal charging windows.

Initial prototypes of the model involved highlighting the rolling peak times every 12 hours. However, during a time of low supply, a relative peak may be too small to have a large impact in the total amount of wind power being generated. Initial versions of this model were highlighting windows which have a slightly above average charging cost. And so it was decided that the model would only highlight if the total generation was

Figure 8: ANN vs Random forest vs SEAI forecasted wind electricity

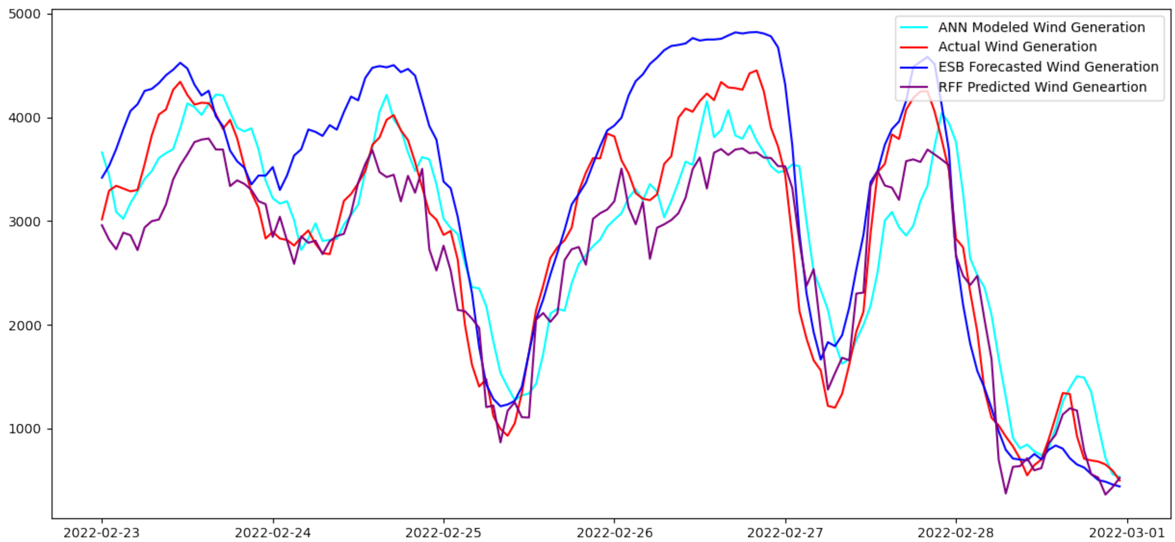
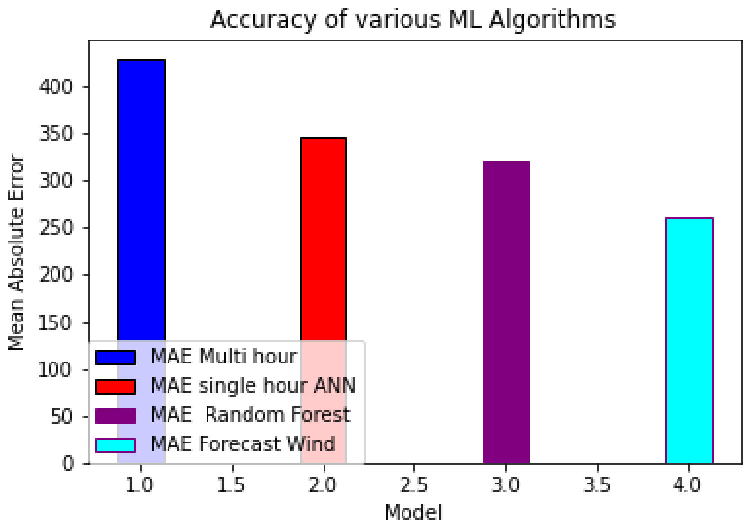


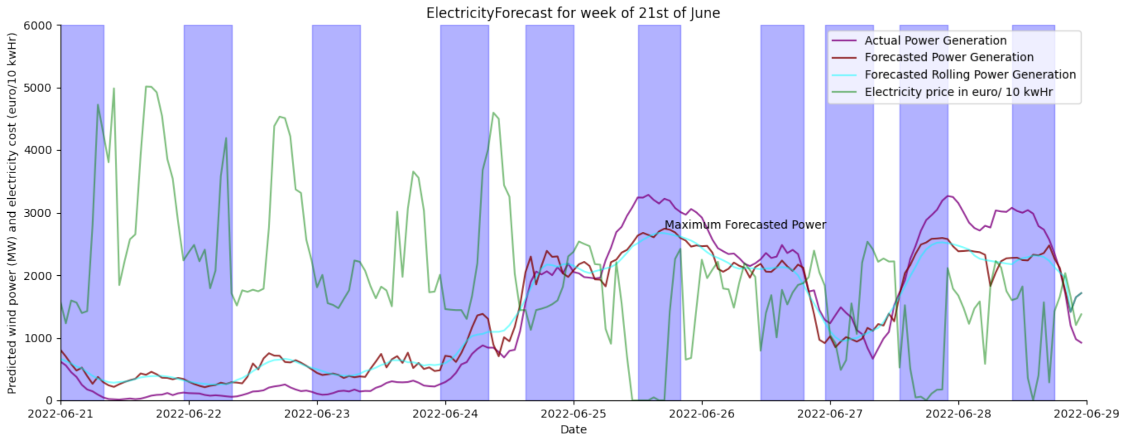
Figure 9: ANN vs Random forest vs SEAI forecasted wind electricity



above the average for the previous year (in this case it was approximately 1500 MW). Highlighting only these windows means that it could be a week before users would have a time highlighted to them. Therefore, an ensemble model was created, where if the total predicted generation was below average, then the nightly rate would be highlighted.

If the generation was expected to be above average, then the peak would highlighted, with neighbouring windows in the direction of the nightly rate would then be highlighted. The difference between the new nightly rate and the average is double the difference between the regular nightly rate. Additionally, 10% more hours were being highlighted in the future as possible cheaper charge windows for consumers. Applying the Chi-sqaure test with 95% significance and we fail to reject the null hypothesis, that this

Figure 10: ANN vs Random forest vs SEAI forecasted wind electricity



model predicts cheaper electricity rates for 8 hour windows then the current electricity rates.

6 Evaluation

6.1 Machine Learning Model Accuracy

The ESB provides a useful benchmark for the machine learning models created in this paper used in forecasting wind power. As part of their historical database on electricity, SEAI provides both the actual generated power and their own forecasted electricity generation. We can measure the difference between their forecasted power and the actual power generated, in the same way we measure the error in each ML model. In figure 11 the R-Squared(R2) scores of the three machine learning models are compared with ESB's own electricity penetration:- The highest R2 score is achieved by ESB with an R2 of 90 %. The ANN and Random forest model both achieve an R squared of 81 %. This is surprising, as it could be expected that an ANN model would pick up on hidden complexities in the model, which the random forest model would not. However, as the model is highly dependent on the wind speed in Phoenix park for predictions, it could be the over-fitting play's a roll in the case of the ANN.

The outliers in the random forest plot shown above had some seasonal variation. When investigated more thoroughly, it was found that some of the deviation from the expected values was occurring due to hetero-scadacity in the results. This was particularly apparent with the ESB's weekly forecast. At higher expected windspeeds, their model would repeatedly over estimate the total wind generation possible. This was most likely due to the limit on the total renewable penetration, as coal power stations can't be switched off easily, instead wind farms are disconnected from the grid. This is also evidenced in figure 10 above where the ESB's forecast overshoots at higher expected wind generations.

In an ideal homoscadatic model, the blue line highlighted in the error plot shown in figure 12 would be horizontal.

Figure 11: R2 scores of ML Algorithms

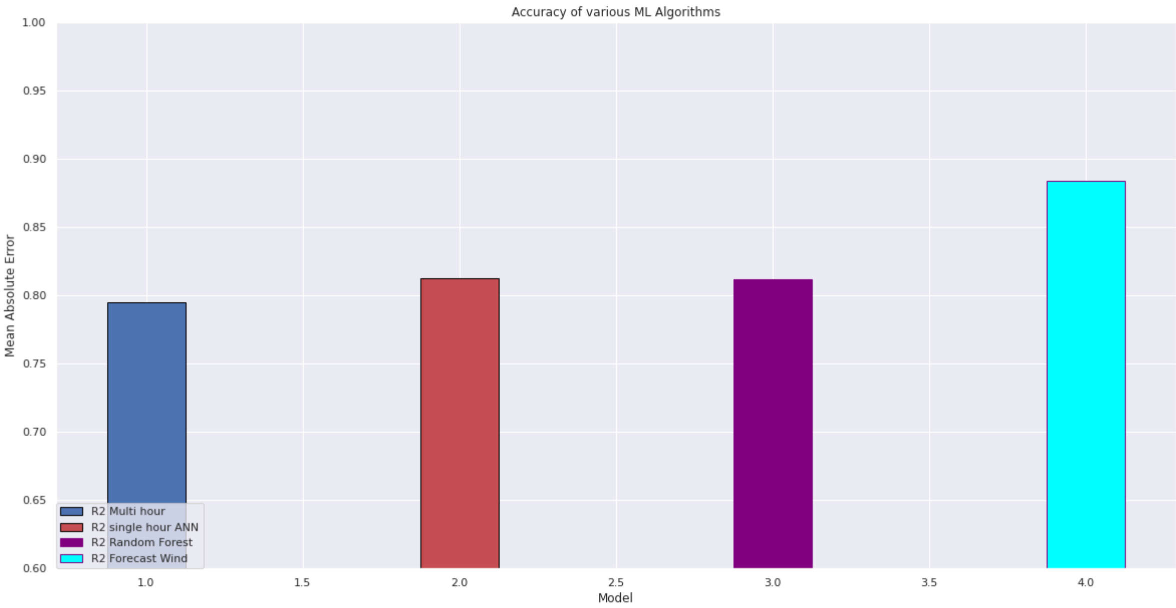
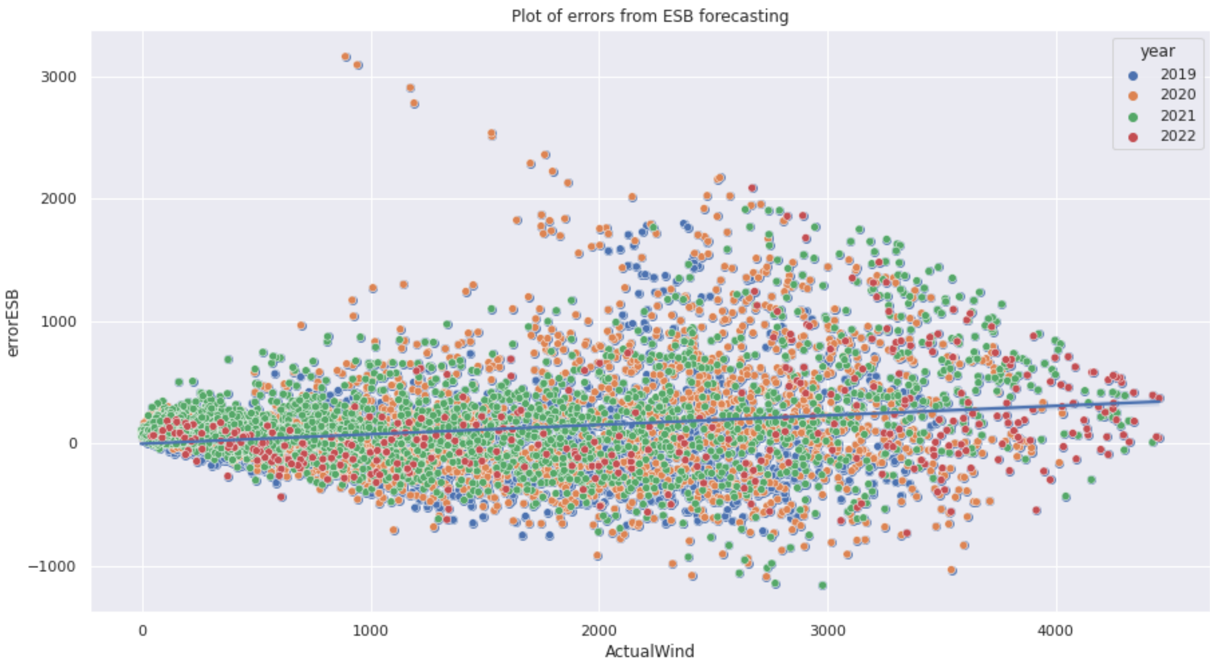


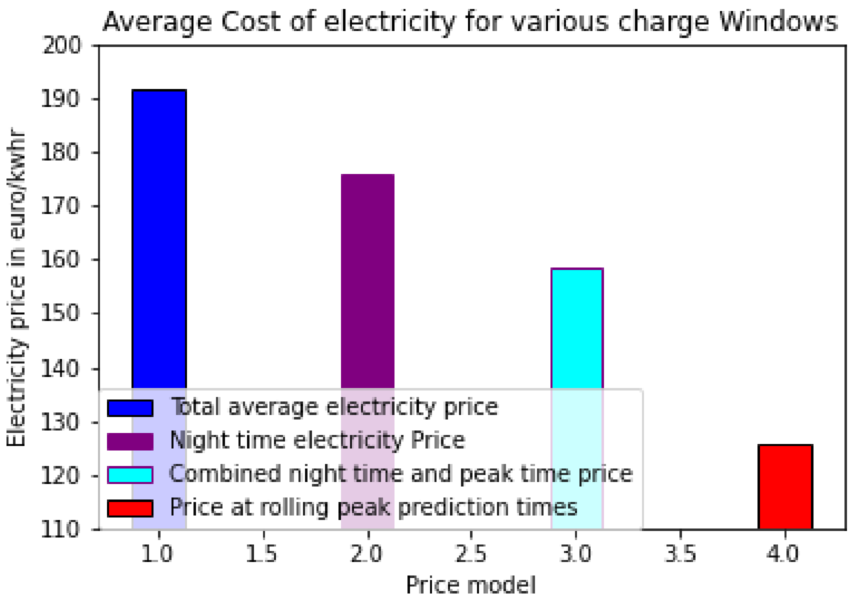
Figure 12: Error spread for the ESB forecasted results



6.2 Evaluation of optimal charge time Forecasting

To evaluate the forecasting model, the highlighted charge time windows were used to select prices from the historical price times dataset. As this dataset only consisted of approximately one months worth of data, it was only used for testing the trained wind production model. The mean cost of electricity over the test period was 191 euro per kWhr. The price at rolling peak production times, was found to be 138 euro per kWhr, but these points only represnt 10 % of the dataset. The average price of nightly electricity (Between 12:00 pm and 8 am) is 175 euro per kWhr. This is below average by 16 euro, and highlights one third of the dataset.

Figure 13: Average Price of electricity per window



The Final column in figure 13 is the combined night time and peak time electricity price, which uses a combination of peak time prediction and nightly prediction to calculate a mean price of 171 euro per kWhr. This is 25% increase in the difference of the price between the mean price, compared to the nightly rates model. In addition, the model highlights 40% of the times in the dataset. The transition from nightly rate prediction to peak time prediction can be seen in the model in figure 10.

7 Conclusion and Future Work

The goal of this thesis was to forecast cheaper times for electricity users to charge electric vehicles or use other distributed energy resources. The difference between the cost of charging a vehicle during these periods is up to twice the difference as the traditionally used nightly rates. The model pulls on a weather forecast for a handful of locations in Ireland to generate a future time series of the electrical wind power. These times are turned into charge windows, which for a given 24 hours, highlight the cheapest charging times for EV owners based on wholesale electricity prices.

Future improvements could be made both on the machine learning algorithms, to match the R2 values of the Eirgrids own wind electricity power predictions. This could involve more complex combinations ANN window'ing models, or the combination of random forest and an ANN to produce an Ensemble model. Secondly, if the wholesale cost of electricity was collected for a long period, it could be used as training data, instead of the total wind power produced.

Wholesale electricity prices are currently not used by major electricity providers to set rates for individual consumers. In order for this model to be viable wholesale electricity providers did switch to this type of model, it could incentivize EV owners to use electricity at times where there is abundant power in the market. The dynamic pricing model is currently in use in Germany which has dramatically changed it's electricity market. While there has been no announcement of plans to change pricing models, in light of recent developments regarding shortages in Ireland,[10], this may be a step the government will be taking to avoid blackouts.

A definite element of the reason why electricity providers are not using these pricing models is because consumers look for simple pricing models, as consumers are often bound by household tasks and have little scope to adjust their consumption to fit demand. Therefore future work should look at investigating methods of integrating a smart charge prediction system as part of a smart home. This would remove the need for individual consumers to plug in or plug out electric vehicles.

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