Forecasting Australia's electricity grid emissions to 2030

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Electricity systems worldwide are shifting their generation mix towards renewable sources to meet decarbonisation targets. Assessing Australia's progress to meet national targets requires an accurate quantification and forecasting of grid emissions. The marginal emissions factor (MEF) and average emissions factor (AEF) are commonly used metrics to assess these environmental impacts. Both factors give the change in CO2 for a unit change in demand from any electrical intervention in the grid [7]. This paper provides, to the best of our knowledge, the first long-range emissions factor forecasting for the Australian grid, using price-setter data. We forecast both factors for the National Electricity Market (NEM) and compare using multilinear regression and Random Forest (RF), a supervised machine learning algorithm.

The AEF is calculated by dividing the total emissions from the NEM by the total demand. It assumes the impact of the intervention will be distributed uniformly across all generators in the electricity system, e.g., every generator will contribute equally to an increase in demand when calculating additional emissions [5]. The MEF relies on the assumption that all changes in demand only affect the marginal generator [5]. The NEM is run by the Australian Energy Market Operator (AEMO), the body in charge of developing the grid to meet national targets [6]. Amongst many other things, AEMO runs the NEM Dispatch Engine (NEMDE) [6]. This engine receives bids in 5-minute intervals and finds the cheapest combination of generators to meet demand, considering all power and transmission constraints. This *Least-Cost Dispatch Model* has a final generator (that completes the demand requirement) known as the price setter, which has the most expensive bid. This bid decides the price for all other generators because generators receive the same amount per unit of energy [7]. In this paper, we assume the price setter is the marginal generator and only consider the price setters' emissions factor as the MEF (see *figure 1*).

Methodology

This paper's data is accessed from the online AEMO database, *NEMweb*. The analysis uses total generators, price setters, bidding, and emissions data to calculate and forecast MEF and AEF values for the NEM.

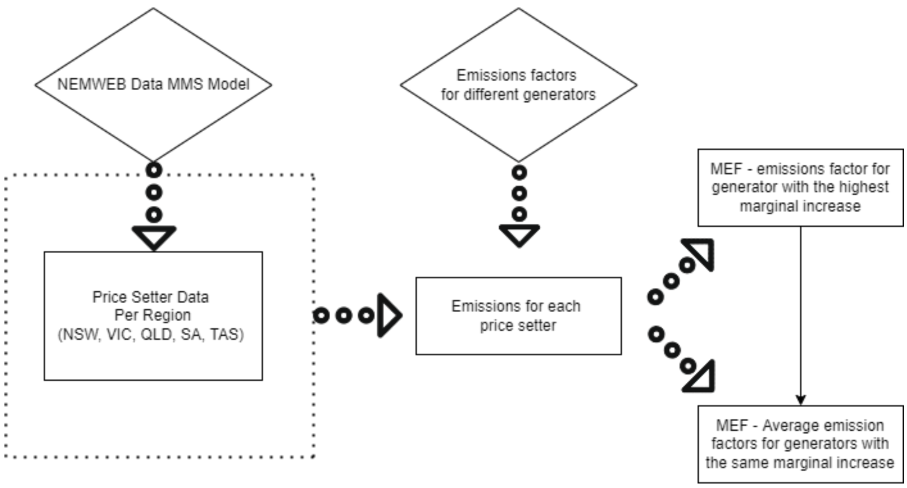

Figure 1 MEF Calculation Methodology

Finding Machine Learning Features

The features for Random Forest were found by observing MEF values from 2013 – 2021. The first step was to investigate time-varying trends. There were no observable hourly trends, monthly variations, or seasonal differences. Graphing a particular day showed no clear trends, but *figure 2* shows an averaged 24-hour period for all days in NSW, 2020. Some clear peaks and troughs are visible and smoothly connected. *Figure 3* shows a decreasing MEF from 2013 to 2021 through monthly averages. The observed reduction falls in line with the growth of renewable energy in the last ten years.

Figure 2 24-hour MEF averaged for 2020 in NSW

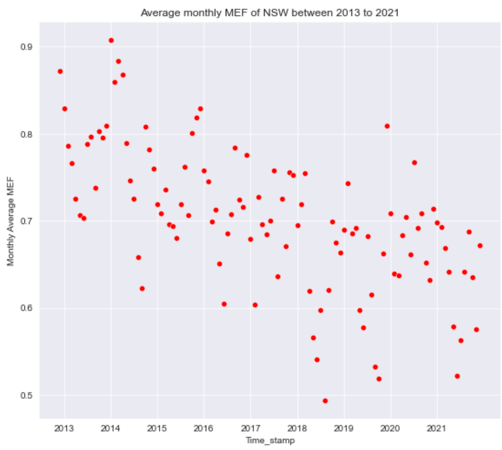

Figure 3 Averaged Monthly NSW MEF from 2013-2021

Figure 4 shows the average daily MEF for 2018. There appears to be a slight drop in the middle months between June and September. *Figure 5* shows the daily average spot price – the price given to all generators and set by the price setter every 5 minutes. There appears to be a slight increase in the spot price between June and September. Upon further investigation, the spot price and MEF have a correlation of -0.68, which validates the observation of an anticorrelated relationship between the two variables, previously observed [1][3][4].

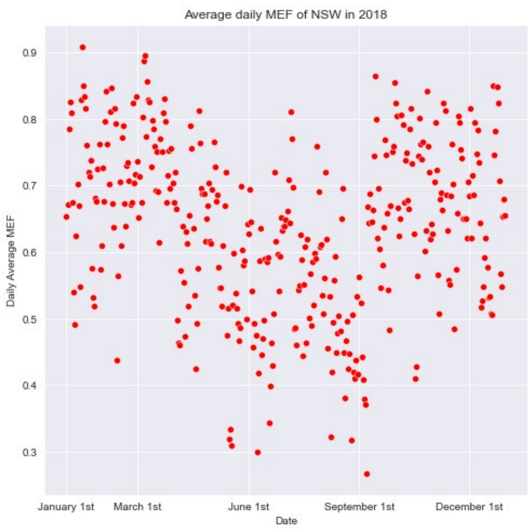

Figure 4 Average daily MEF for 2018 in NSW

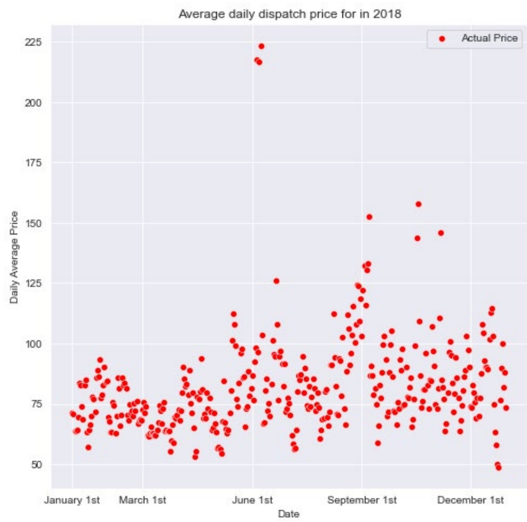

Figure 5 Average daily spot price for 2018 in NSW

Forecasting the Generation Mix

The generation mix outlines the proportions of different energy types and their contributions to the grid. Generation mix is the single factor for calculating the AEF (*equation 1*). Generation mix will also be used for the MEF forecast, as it lists the generators that could be on the margin.

$$AEF = \sum_{energy\ type\ e} proportion(e) * emissions\ factor(e) \tag{1}$$

The generation mix for 2030 was estimated using the generation mix from 2021 and an AEMO forecast on generation capacity by technology type from their Integrated System Plan 2022 [2]. The following methodology and assumptions were made:

(1) The change in the contribution of each fuel type (to the demand) is proportional to the change in the capacity of each fuel type between 2021 and 2030. For example, the coal capacity drops by 66.76%, so its average contribution to the demand will also drop by 66.76%

(2) The reference day (May 4th, 2030) will have the same average generation mix as the yearly average of 2030. The generation mix fluctuations are hard to predict over a year, but the variance is not high

(3) The behaviour of a fuel type on a day in 2030 is identical to the behaviour of a fuel type on a day in 2021. The ratio between fuel and average fuel proportions is the same for every point (*see figure 6).*

(4) The extra energy over the demand is stored in grid level storage to meet the net demand, and any extra energy that can't be stored is curtailed. Grid always stores or discharges according to the difference between supply and demand (*see figure 8*)

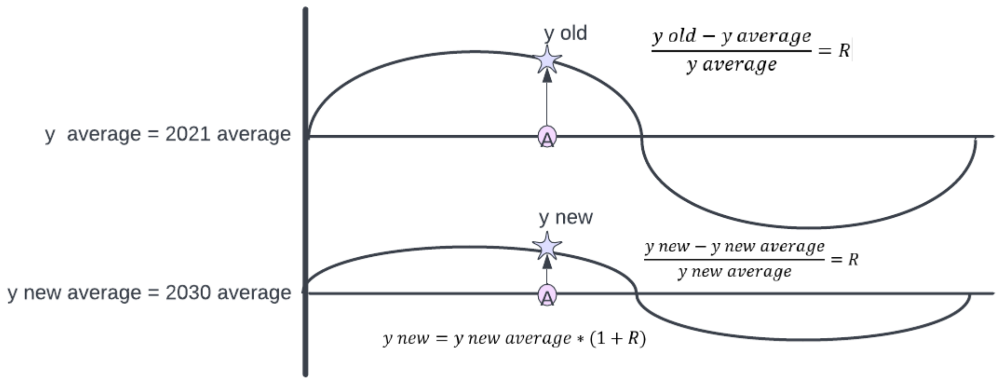

Figure 6 Rescaling generation mix over a day in 2030 with reference to 2021

The predicted generation mix was used to calculate the forecasted AEF using *equation 1*. Based on all the findings above, the following features were used in forecasting MEF (*see Table 1*). The two algorithms were accessed through the python libraries Scikit-Learn and Statsmodel.

Results

Table 1 Random Forest MEF Prediction Models

Model	Features/Inputs				Accuracy
5-minute MEF RF Model	Generation Mix	Price	Demand	Time of day (minutes)	87.68%
Hourly Average MEF RF Model	Generation Mix	Price	Demand	Time of day (per hour)	71.62%
Daily Average MEF RF Model	Generation Mix	Price	Demand	Day of year	91.40%
Multilinear Regression MEF Model	Generation Mix	Price	Demand	5-minutes as an index	78.91%

While the *daily average RF* model has higher accuracy, the *5-minute RF* model was preferred for its granular predicting capability. The chosen reference day was May 4th, 2021, compared to May 4th, 2030 (see *Figure 7* and *Figure 8).* This generation mix is calculated from the AEMO forecast, which is an optimistic prediction of the nation meeting net-zero targets [2]. There is significantly less coal, and a lot of the demand is met by Solar during sunlight hours. During these solar hours, all the excess solar charges grid scale storage for peak hours.

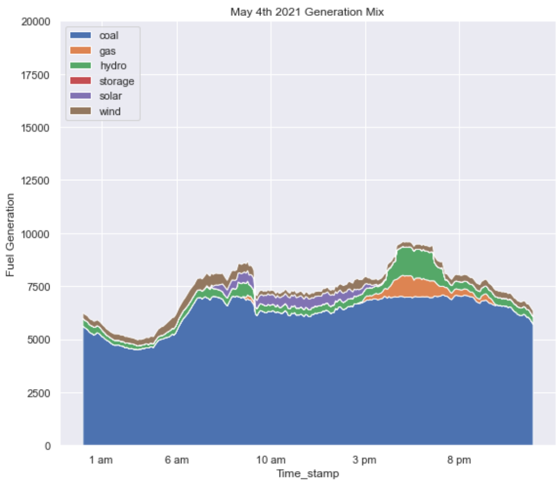

Figure 7 NSW Generation Mix for May 4th, 2021

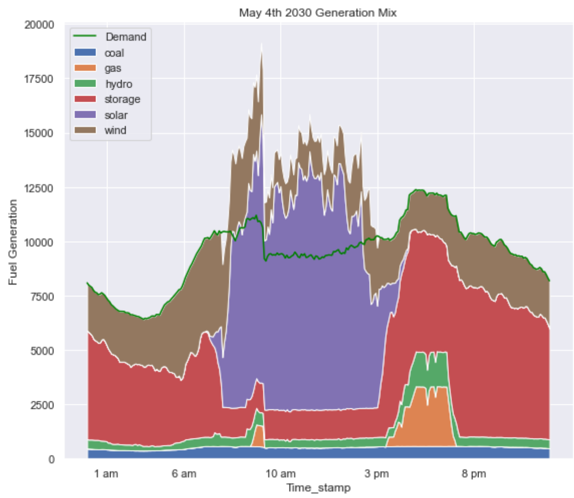

Figure 8 NSW Generation Mix for May 4th, 2030

Figure 9 shows the MEF fluctuating significantly due to various generators being on the margin, and an almost constant AEF. *Figure 10* shows the forecasted AEF and MEF, using the *5-minute RF* model. The MEF is much higher than the AEF because a coal generator could often still be on the margin despite the massive reduction in coal. The fluctuating nature of MEF is lost in the forecasting process, and a more averaged MEF value is left.

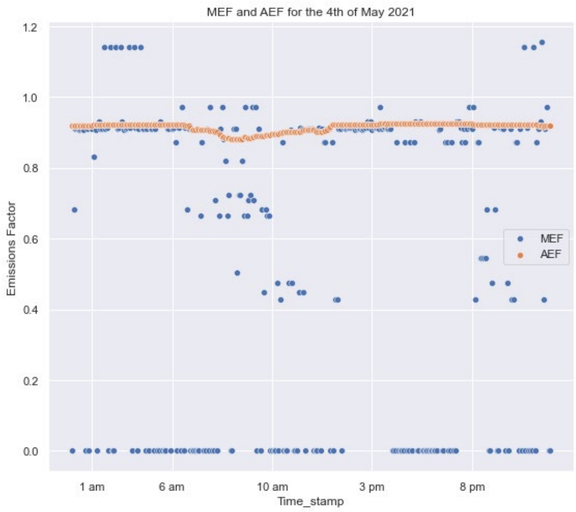

Figure 9 AEF and MEF for May 4th, 2021

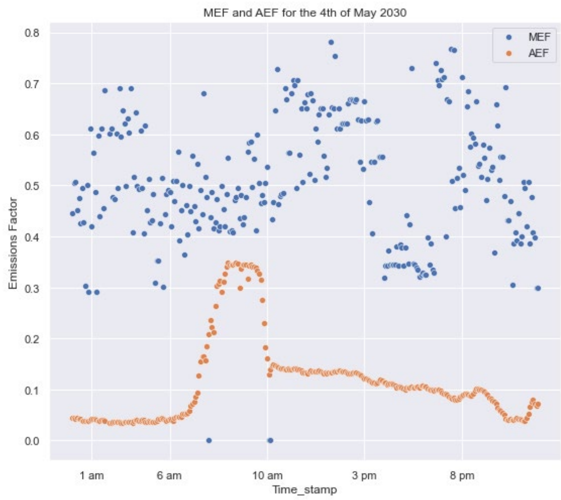

Figure 10 Forecasted AEF and MEF for May 4th, 203

Conclusion

The rescaled generation mix (using AEMO forecasts) has lots of grid scale storage. It should be an aspiring 2030 target to meet national climate goals. The *5-minute RF* model has the same granular capability as the *multilinear regression model*, but with an 8.77% higher accuracy. The *daily averaged RF* model has the best accuracy (91.4%, see *table 1*) if 24-hour averaged values are sufficient. Based on the *5-minute RF* model, the MEF in 2030 decreases by 32% on average, while the AEF in 2030 decreases by 82.6% on average. This large AEF reduction implies a big drop in net emissions.

References

[1] T. Nelson, T. Nolan, and J. Gilmore, "What's next for the Renewable Energy Target – resolving Australia's integration of energy and climate change policy?*," *Australian Journal of Agricultural and Resource Economics*, vol. 66, no. 1, pp. 136–163

[2] AEMO, "2022 Integrated System Plan For the National Electricity Market Important notice"

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