# Forecasting Marginal Emissions Factors in PJM

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## Abstract

Many climate change applications rely on accurate forecasts of power grid emissions, but many forecasting methods can be expensive, sensitive to input errors, or lacking in domain knowledge. Motivated by initial experiments using deep learning and power system modeling techniques, we propose a method that combines the strengths of both of these approaches to forecast hourly day-ahead MEFs for the PJM region of the United States.

## 1 Introduction

From demand response to electric vehicle charging, many decarbonization strategies rely on an understanding of how clean the electricity from the power grid is at any given time. In particular, the emissions intensity of the power grid varies from moment to moment depending on which generators are producing power, which in turn depends on factors such as the amount of electricity demand and the amount of renewable energy available. There has therefore been a great deal of interest in characterizing both the *average* and *marginal* emissions intensities of the power grid, which capture the emissions associated with different sets of generators producing power at any given time [1–3].

In this proposal, we consider the challenge of forecasting *marginal emissions factors* (MEFs), which describe the emissions associated with marginal generators (i.e., generators that would respond to small changes in demand at a given time). MEFs are important for a variety of climate-relevant applications, such as optimizing industrial or residential equipment, smart electric vehicle charging, or the design of emissions-cognizant electricity prices [4]. Prior work has aimed to develop real-time estimates and forecasts of MEFs using dispatch models [5, 6], flow tracing [7], and machine learning [8]. However, full power system models can be expensive to run, cheaper "reduced form" power models can be extremely sensitive to errors in their inputs, and purely machine learning-based methods can suffer from failures related to a lack of domain knowledge.

In this work, we propose to forecast marginal emissions factors in a way that leverages the strengths of both machine learning and (reduced-form) power system models. This is motivated by our initial explorations, which found that naively forecasting MEFs using a neural network or a simple dispatch model suffered from several limitations. We describe this initial exploration as well as our proposed method, which involves incorporating differentiable power system models within neural networks.

## 2 Problem Statement

We seek to develop day-ahead hourly forecasts of $CO_2$ MEFs in the Mid-Atlantic region power pool (PJM), which is the largest competitive wholesale market in the United States. To do so, we plan to employ a combination of weather data from the National Oceanic and Atmospheric Administration,[1] market data from PJM,[2] and dispatch models that simulate power system operations (e.g., [9]).

[1] See `https://www.ncei.noaa.gov/data/global-hourly`.
[2] See `http://dataminer2.pjm.com`.

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| **Forecast Method** | **RMSE** |
|---|---|
| Persistence baseline | 190.84 |
| Neural network baseline | 212.25 |
| Dispatch with forecasted inputs baseline | 213.69 |

Table 1: Results of our initial investigation (reported on test data from September-December 2017). We find that neither baseline we consider performs better than a (prescient) persistence baseline that predicts the average MEF over the time period considered.

We plan to assess the quality of our forecasts based on their accuracy with respect to the ground truth. However, we first acknowledge two important limitations of this metric. One limitation is that there is a lack of ground truth data on MEFs, which has led to a fair amount of work characterizing historical marginal emissions factors via methods such as regression [3, 10–13]; in our initial approach, we plan to compare accuracy with respect to a proxy "ground truth" simulated using a reduced-order dispatch model (e.g., [9]), while acknowledging that these labels may be flawed. Another limitation is that accuracy is not fully reflective of the goals of our method, as we would ideally instead measure the extent to which our factors actually help reduce emissions (see, e.g, [14]); however, as these factors may be used for many different purposes, we felt that accuracy was the best "generic" metric to use.

### 2.1 Initial Investigation

In our initial investigation, we constructed MEF forecasts using two methods: an end-to-end neural network forecasting method, and a method forecasting inputs to a reduced-order dispatch model. Both models were trained on data from January 2016 to August 2017, and tested on data from September to December 2017. We now describe these aspects in more detail.

**Ground truth.** Due to a lack of actual ground-truth data, we generate "ground truth" MEFs by running the reduced-order dispatch model [9] on historical data. This model is open-source and can produce point estimates of MEFs on an hourly basis (whereas historical regression analysis techniques can only compute factors for clusters of hours). We had also considered calculating MEFs directly from historical data from the EPA[3] by dividing the change in emissions by the change in fossil demand; however, this method led to a large number of outliers due to the outsized impact of small changes in hourly generation or emissions, leading us to rely on simulated factors instead.

**Neural network baseline.** Using this "ground truth" data, we trained a neural network via supervised learning to generate MEF forecasts. Our features included factors impacting power plant heat rates and fossil fuel power demand in PJM, which are major factors influencing MEFs. Specifically, we inputted the next day's electricity load forecast, the last week's nuclear generation, the next day's weather forecasts (air temperature, dew point temperature, sky ceiling height, wind speed, sea level pressure),[4] and yearly sinusoidal features. As shown in Table 1 and Figure 1, this method fails to capture fluctuations in MEFs throughout the day, instead predicting an MEF closer to the mean.

**Dispatch with forecasted inputs baseline.** Our second method involved using a neural network to forecast inputs to the reduced-order dispatch model, and then running the dispatch model to generate MEF estimates. In particular, this model takes (forecasts of) total fossil fuel power generation as input. To estimate fossil generation, we trained a neural network using weather data to predict the hourly sum of solar, wind, and hydro generation over the next day. We then subtracted this forecast as well as the previous week's average nuclear generation from PJM's load forecasts. As shown in Table 1 and Figure 1, while this approach captures the fluctuations in the MEF, there is a large variation in the accuracy of the forecasts at different hours of the day. Due to the nature of the dispatch model, a small error in the fossil demand forecast can lead to a different power plant that is "on the margin" at that hour, resulting in large errors in the predicted MEF value.

### 2.2 Proposed Direction

Our investigation underscores the importance of more deeply combining traditional machine learning approaches with power system modeling approaches when developing MEF forecasts. In particular,

[3]Available at `https://ampd.epa.gov/ampd/`.

[4]As we did not have access to historical weather forecasts, we instead simulated weather forecasts by adding random noise to actual weather data (assuming that weather forecasting errors are normally distributed error.

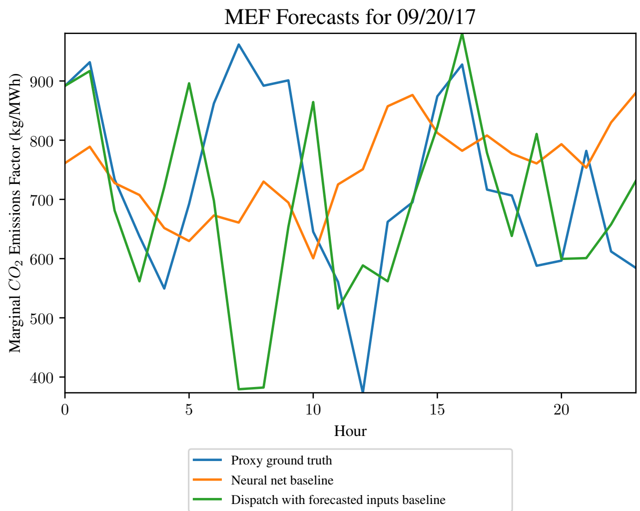


Figure 1: Representative results for our initial investigation.

we believe that it is important to develop methods that mitigate the input sensitivity associated with reduced-form dispatch models, but continue to incorporate domain knowledge that can help capture information such as the wide fluctuations of MEFs.

Our proposal is thus as follows: We propose to forecast fossil fuel generation using a neural network and pass this forecast through a reduced-order dispatch model (as in the dispatch-based approach above). However, instead of training the neural network to optimize for the accuracy of its fossil generation forecasts, we will instead train the neural network to optimize for the accuracy of its MEF forecasts (as in the neural network-based approach above). Formally, let $N_\theta : \mathcal{X} \to \mathbb{R}^{24}$ be a neural network parameterized by $\theta$ that maps from features to hourly day-ahead fossil fuel generation forecasts, and $d : \mathbb{R}^{24} \to \mathbb{R}^{24}$ be a reduced-order dispatch model that maps from fossil generation to hourly marginal emissions factors. For training inputs $x \in \mathcal{X}$, ground truth labels $y \in \mathbb{R}^{24}$, and some loss function $\ell$, we then propose to train our neural network to optimize

$$\underset{\theta}{\text{minimize}}\, \ell(d(N_\theta(x)), y). \tag{1}$$

MEF predictions for future hours (i.e., on the test set) would then be given by $\hat{y} = d(N_\theta(x))$. The potential advantage of this framework is that it incorporates knowledge from reduced-order dispatch models (potentially enabling it to capture MEF fluctuations) while employing direct supervision on the MEF outputs (which ideally will mitigate input sensitivity issues by incentivizing the neural network to avoid mistakes that induce large errors in the output of the dispatch model).

While in concept simple, optimizing this model via gradient descent requires differentiating through all components of the loss, including the dispatch model $d$. Luckily, we can leverage recent advances in differentiable optimization layers (see, e.g., [15, 16]) for this purpose. In particular, we plan to employ a dispatch model that is amenable to implicit differentiation techniques, such as the differentiable economic dispatch or optimal power flow models described in previous work [14, 17].

## 3 Conclusion

We propose a method for estimating day-ahead $CO_2$ MEFs in the PJM region, in order to inform power system interventions such as demand response, electric vehicle charging, or market design. There are currently websites that publish historical MEF assessments from regression- and simulation-based models, which have been used by various entities for applications such as power system optimization and the procurement of renewable energy.[5] Once developed, we hope our MEF forecasts can be posted publicly alongside these historical assessments to aid decision-makers as they design interventions that reduce greenhouse gas emissions.

[5]For instance, see `https://cedm.shinyapps.io/MarginalFactors/`.

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