DACF: Day-ahead Carbon Intensity Forecasting of Power Grids using Machine Learning

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Abstract

Electricity usage is a substantial source of carbon emissions worldwide. There has been significant interest in reducing the carbon impact of energy usage through supply-side shifts to cleaner generation sources and through demand-side optimizations to reduce carbon usage. An essential building block for these optimizations is future knowledge of the carbon intensity of the supplied electricity. In this paper, we present a Day-Ahead Carbon Forecasting system (DACF) that predicts the carbon intensity from scope 2 emissions in the power grids using machine learning. DACF first computes production forecasts for all the electricity-generating sources and then combines them with the carbon-emission rate of each source to generate a carbon intensity forecast. DACF provides a general approach that works well across a range of geographically distributed regions. DACF has a mean MAPE of 6.4% across the regions. It also achieves an average decrease of 6.4% and a maximum decrease of 8.6% in MAPE compared to the state-of-the-art. We make DACF publicly available so that it is easily accessible to researchers.

CCS Concepts

• **Social and professional topics** → **Sustainability**; • **Computing methodologies** → *Neural networks*.

Keywords

carbon intensity forecasting, electrical power grids, source production forecasts, machine learning, direct emission factor

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1 Introduction

Electricity is an integral part of modern society and is used for all aspects of our daily lives. Typically the electric grid uses a mix of renewable (e.g. solar, wind) and non-renewable (e.g. coal, natural gas) sources to generate electricity. Electricity generation is known to be one of the largest sources of greenhouse gas emissions in many countries [13, 19, 20]. These emissions depend directly on the generation sources used by the grid. Since the electricity demand varies over time and across regions, this mix of energy sources used by the grid to fulfil this demand, and hence the emissions, also vary temporally and spatially.

The need for carbon-aware systems. As the electric grid begins a transition to reduce the carbon emissions resulting from consuming electricity, techniques to shift energy demand from periods when the carbon intensity of energy is high to periods when it is low have begun to gain attention. For example, electric vehicles (EVs) can be charged aggressively during hours when the carbon intensity of electricity is low [12] (e.g., during night in regions like Texas when there is abundant wind energy). A key requirement of these carbon reduction techniques is future knowledge of the grid's carbon intensity. If carbon forecasts of the grid's energy generation are known, such techniques can exploit this knowledge to decide how much demand to shift and to what hours.

Carbon intensity forecasting. Short-term (day-ahead) forecasts of carbon intensity is an essential first step for systems and applications to become carbon aware and reduce their carbon footprint, where carbon intensity is defined as average carbon (in *grams*) per unit of energy (in kWh) produced or consumed by a system. Short-term carbon forecasting for power grids is a nascent research area. Watttime [21], and ElectricityMap [10] are commercial services that provide both real-time carbon intensity for the grid and short-term carbon intensity forecasts for many regions. However, their models are proprietary, and these services are expensive for consumer and research use. Other early research on short term forecasting of carbon intensity [3, 15] suffer from higher errors since they typically do not consider future knowledge like weather forecasts, which have a direct impact on renewable energy generation and hence the carbon intensity forecasts. These observations motivate the need for an accurate, *easily accessible* grid carbon forecasting technique that considers *both* historical data as well as future knowledge.

Our contributions. In this paper, we develop *DACF*, a day-ahead carbon forecasting system to predict the carbon intensity of the power grid of a region in the short term. We only consider scope 2 emissions [18] that account for operational emissions from the generation and consumption of electricity. In addition to historical data of the sources used for electricity generation, we consider other factors like day-ahead weather forecasts. Our key hypothesis is that using this source forecast information can significantly improve the prediction accuracy over current methods. Our specific contributions are as follows:

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1) Model accuracy and robustness. We evaluate our model in power grids of six regions across the US and Europe. DACF has Mean Absolute Percentage Error (MAPE) of 6.4% on average across all regions. Thus, our model is accurate and robust across geographically distributed regions. We claim that DACF can be used in any region with minimal changes to get good day-ahead carbon intensity forecasts. It also achieves an average MAPE decrease of 6.4% over the state-of-the-art.

2) Open-source tool. We release DACF as an open-source tool[1] that can be easily accessed by researchers and practitioners to include carbon predictions in carbon reduction optimizations.

2 Background

In this section, we provide background on power distribution grids, carbon intensity of energy, and its temporal and spatial variations.

Power distribution grids. The electric grid in any region consists of a complex network of power plants, generator stations, transmission lines and distribution centers. In general, there are system operators who are in charge of managing the power grid and supplying electricity to match the current demand. Typically, the mix of sources generating electricity in a region's power grid at any instant is governed by several factors — current electricity demand, availability of a source in that region at that time, cost of generating electricity using a specific source, etc. Consequently, the source mix and the carbon intensity vary from region to region and across time.

Average carbon intensity. Each energy source generating electricity emits a certain amount of carbon per unit of electricity generated, which we refer to as that source's direct carbon-emission rate (in g/kWh). Since we account only for scope 2 emissions, we follow the median carbon-emission rate due to direct emissions that only include operational emissions when a source is converted to electricity. The rate for each source is specified in [7, 8]. In some cases, the generation source is unknown; we assume such sources (labelled as "other") are non-renewable by default. Table 1 shows the direct carbon-emission rate of the sources (in g/kWh) generating electricity in various regions. Renewable sources include solar, wind, hydro, geothermal and biomass.

Coal	Oil	Natural gas	Renewables + Nuclear	Other
760	406	370	0	575

Table 1: Carbon-emission rate (g/kWh) for different sources

Mathematically, we determine the average carbon intensity (in g/kWh) of a region at a particular time using the equation below:

$$C_{avg} = \frac{\sum (E_i * CR_i)}{\sum E_i} \tag{1}$$

where E_i is the electricity generated (MW) by a Source i & CR_i is the carbon-emission rate (g/kWh) for that source.

2.1 Carbon intensity variability

In this paper, we consider six geographically distributed regions across the US and Europe, as follows:

- **US:** California (CA), Pennsylvania-Jersey-Maryland (PJM), Texas (TX), New England (NE).
- **Europe:** Sweden (SE), Germany (DE).

Region	Fossil fuel (%)	Renewables (%)	Avg. Carbon Intensity (g/kWh)
CA	53.6	34.6	200.62
PJM	60.4	5.2	295.98
TX	63.7	25.2	301.86
NE	60.4	11.9	231.95
SE	6.9	63.2	39.79
DE	38.3	49.1	241.54

Table 2: Avg. yearly carbon intensity across regions (2020)

Spatial variability. We compute Table 2 from the datasets we have used and from Table 1. Table 2 shows the correlation between the percentage of electricity generated by non-renewables and the annual average carbon intensity in a region. We see that carbon intensity varies spatially across countries and regions. In general, regions with a higher dependence on fossil fuels have a higher average carbon intensity than those with a high percentage of renewables.

Temporal variability. Even within a region, the fraction of each energy source contributing to electricity generation varies over time. For example, solar energy may be abundant during the day but will not be present during the night. So, carbon intensity will be less during the day when more solar energy is available than during the night for a given electricity demand. Consequently, the average carbon intensity also varies temporally.

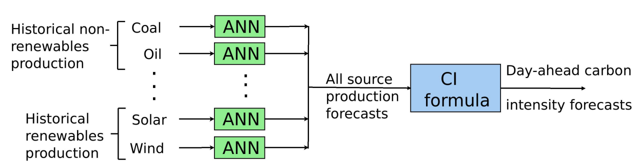

Figure 1: DACF architecture. "Historical" denotes past 24 hours. "Day-ahead" denotes the next 24 hours. CI formula is the formula to get avg. carbon intensity (refer Eq. 1)

3 DACF system architecture

In this section, we describe DACF, our system for forecasting the average hourly carbon intensity of the power grid of a region for the next 24 hours, given the carbon-emission rate of each source generating electricity, hourly electricity source mix for the last 24 hours, and the day-ahead weather forecast. Fig. 1 shows the system architecture. For simplicity, we introduce the following terms that we will use throughout the paper:

- **Historical source production:** Hourly electricity generated (in MW) by a source in the past 24 hours.
- **Source production forecast:** Hourly predicted day-ahead electricity generation by a source (in MW).

[1] https://github.com/UMass-LIDS/DACF

DACF is based on three key insights. First, it does not rely only on historical data for making predictions. Instead, it incorporates *future knowledge* like weather forecasts to obtain individual source production forecasts and uses those to derive the carbon intensity forecasts. Second, when using historical data, DACF considers both long-term (e.g., seasonal) and short-term (e.g., hourly) patterns when making source production forecasts. Finally, DACF incorporates deep learning techniques for forecasting.

DACF uses individual forecasting models to predict electricity generated by each renewable (e.g., solar and wind) and non-renewable (e.g., coal and natural gas) sources. While DACF currently uses machine learning models for these individual forecasts, its "plug and play" architecture allows any individual forecasting model to be replaced with a different type of forecasting model. If any such forecasts are already available publicly (for example, solar and wind forecasts are available in [5] for California), our architecture enables such predictions to be used as an alternative to using our models. Indeed, as such forecasts improve with the design of better models (e.g., a better wind forecasting model), DACF can progressively better its own overall carbon forecast.

Specifically, we consider the historical source production for each source as input, and output the source production forecast for each source individually. Then, we apply Eq. 1 on those source production forecasts to get the carbon intensity forecast.

3.1 Obtaining source production forecasts

We employ Artificial Neural Network (ANN) models to get the source production forecasts for all sources. Fig. 2 shows our ANN architecture.

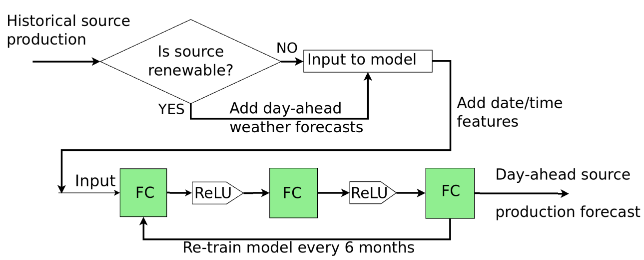

Figure 2: ANN model design and architecture

We consider the following sources of electricity:

- **Non-renewable:** Coal, natural gas, oil, nuclear, other.
- **Renewable:** Solar, wind, hydro, geothermal, biomass.

Each region uses a subset of the above sources for generating electricity. We take one source at a time from the relevant subset and consider the following factors as input to the ANN models:

1) Historical source production. We already have the hourly historical electricity generation by various sources for each region.

2) Date and time features. For all sources, we also add date and time-related features to the ANN model to capture any daily and seasonal trends in the data. Date and time-related features include hour of the day, hour of the year, and whether the current day is a weekday or a weekend.

3) Day-ahead weather forecasts. Weather conditions affect renewable generation and hence the day-ahead carbon intensity. For example, more wind speed correlates with more electricity generation from wind. Consequently, we use day-ahead weather forecasts as features to predict source production forecasts for renewable sources (solar, wind, and hydro). We use wind speed (in m/s), temperature (in K), dewpoint temperature (in K), downward short-wave radiation flux (in W/m^2, also known as solar irradiance), and total precipitation (in kg/m^2) as the weather variables.

3.2 Applicability across regions

We now discuss the generality of our approach. DACF's plug and play architecture and a generalized approach of individually predicting forecast for each source provide sufficient flexibility to be used in power grids of regions worldwide, despite notable differences in source mix across such power grids. While DACF needs to be retrained with the training data for a particular region, our evaluation shows that DACF works well across geographically distributed regions *without changing the model hyperparameters*.

3.3 Open-source implementation

DACF is implemented in Python. We use Keras [6] and Tensorflow [1] for implementing the ANN models. Our datasets and code are publicly available at ***https://github.com/UMass-LIDS/DACF***. We hope researchers and practitioners can easily use it to incorporate carbon intensity predictions into carbon optimization problems.

4 Empirical evaluation

We now evaluate the forecast performance of DACF. We show how DACF performs across power grids of several geographically distributed regions. We also compare our approach with other methods and show that DACF is more accurate than the current state-of-the-art.

4.1 Experimental methodology

Datasets. Table 3 lists the data sources for the six regions we have considered in this paper. We obtain any source production forecasts not available publicly using our ANN models.

Region	Historical source production	Solar/Wind forecasts	Weather forecasts
CA	EIA [2]	OASIS [5]	NCEP GFS ds084.1 [17]
PJM, TX, NE		N/A	
SE	ENTSOE [11]	ENTSOE [11]	
DE			

Table 3: Data sources

Weather data aggregation. The bounding box for any region is publicly available at [9]. We follow the weighted average method suggested in [16] to aggregate the weather data across a region, where the weights are the earth area covered by each latitude-longitude grid.

Model training and testing. We consider a three-year period (2019 – 2021) for training DACF and predicting average grid carbon intensity. The data is in hourly granularity. If any value is missing, we assume that the conditions are the same as the previous hour and copy over the value from the previous row in the dataset. For each source, we re-train the ANN models every six months. We use the predictions of the last six months of 2021 for testing.

We use Root Mean Square Error (RMSE) as the loss function to minimize during training. We implement early-stopping and model-checkpointing mechanisms to avoid overfitting and get the best-trained model. We use Mean Absolute Percentage Error (MAPE) for evaluating DACF performance.

4.2 DACF performance across regions

We evaluate the prediction errors across the six geographically distributed regions in terms of MAPE. Fig. 3 shows a 3-day time series for the actual and predicted carbon intensities of the power grid in California. We see that DACF follows the actual pattern and is able to match the unpredictability in the time series.

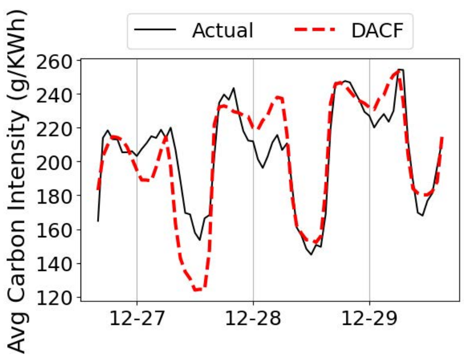

Figure 3: DACF predictions closely match actual values for California, following the diurnal pattern of lower carbon intensities during the day when solar production is high

Region	Mean	Median	90th percentile	95th percentile
CA	7.41	6.30	12.21	14.04
PJM	3.30	2.71	5.80	6.89
TX	8.05	6.40	14.55	20.76
NE	4.44	3.51	8.35	9.75
SE	6.47	5.14	11.39	14.32
DE	9.08	6.44	19.84	24.86

Table 4: DACF performance across regions (MAPE)

Table 4 list the mean and percentile MAPE values over the whole test period for all the regions. DACF performs well across all the regions, with the mean MAPE of 9.08% in the worst case. On average, DACF has a MAPE of 6.4% across the regions.

4.3 Comparing DACF with state-of-the-art

We now compare DACF with the model proposed by Leerbeck et al. [14] (labelled as *SOTA*), which is a non-proprietary state-of-the-art method. They use historical source production, weather forecasts and solar/wind production forecasts to predict day-ahead carbon intensities. They also use a combination of linear regression and splines for forecasting, and ARIMA for residual correction. Since the code is not publicly available, we develop our own implementation that incorporates the main elements of their approach that is based on linear regression but without non-renewable source production forecasts. Additionally, Leerbeck et al. [14] use lifecycle (operational and infrastructural) emission rates for their carbon intensities. However, we use the representative implementation to forecast carbon intensities using direct (only operational) emission rates to perform a fair comparison with our approach.

Other efforts on forecasting short-term carbon intensities [3, 15] consider only historical source production data and have higher prediction errors than *SOTA* [14], and hence are excluded for brevity.

Region	SOTA	DACF
CA	7.94	7.41
PJM	3.59	3.30
TX	8.19	8.05
NE	4.86	4.44
SE	6.80	6.47
DE	9.91	9.08

Table 5: DACF outperforms the state-of-the-art (SOTA)

Table 5 compares DACF with *SOTA* in terms of average MAPE across all the regions. We see that DACF outperforms *SOTA* and achieves an average decrease of 6.4% and a maximum reduction of 8.6% in MAPE in comparison with the state-of-the-art.

5 Related Work

National Grid ESO [4] provides free APIs for short-term carbon intensity forecasts (using direct emissions) in the UK, but neither their model nor the data are publicly available and hence cannot be used in another region. Tomorrow's *ElectricityMap* [10], and Watttime [21] provide short-term carbon intensity forecasts for many regions. However, their forecast data is proprietary and is expensive for consumer and research use. Leerbeck et al. [14] use *ElectricityMap's* [10] proprietary data and consider lifecycle (operational and infrastructural) emission factors for predicting carbon intensity, which is not applicable if we only account for scope 2 emissions [18]. They also do not consider non-renewable source production forecasts as features. Lowry [15] and Bokde et al. [3] use statistical methods to get carbon intensity forecasts. However, both these works only consider historical data to get the predictions, whereas we include future knowledge also.

6 Conclusions

In this paper, we presented DACF, an open-source system for day-ahead predictions of the grid's carbon intensity. DACF obtains source production forecasts for each source generating electricity in the power grid of a region and computes the carbon intensity forecast using Eq. 1. DACF has a mean MAPE of 6.4% across the regions. It also achieves an average decrease of 6.4% and a maximum decrease of 8.6% in MAPE over the state-of-the-art. Further, its plug-and-play framework and a general approach enable it to work well across a range of geographically distributed regions. As future work, we plan to extend DACF to incorporate the impact of energy exchange between regions, provide forecasts based on both lifecycle and direct emission rates, and provide multi-day forecasts.

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References

[1] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. 2015. TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems. http://tensorflow.org/ Software available from tensorflow.org.

[2] US Energy Information Administration. 2018. Real-time Operating Grid. Retrieved February 6, 2022 from https://www.eia.gov/electricity/gridmonitor/dashboard/electric_overview/US48/US48

[3] Neeraj Dhanraj Bokde, Bo Tranberg, and Gorm Bruun Andresen. 2021. Short-term CO2 emissions forecasting based on decomposition approaches and its impact on electricity market scheduling. *Applied Energy* 281 (2021), 116061.

[4] A Bruce, Lyndon Ruff, James Kelloway, Fraser MacMillan, and Alex Rogers. 2021. Carbon intensity forecast methodology. *National Grid ESO: Warwick, UK. Available online: https://github. com/carbon-intensity/methodology/raw/master/Carbon% 20Intensity% 20Forecast* 20 (2021).

[5] California ISO. 2005-2022. Open Access Same-time Information System (OASIS). Retrieved February 8, 2022 from http://oasis.caiso.com/mrioasis/logon.do

[6] François Chollet et al. 2015. Keras. https://keras.io.

[7] Climate Change. 2014. Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp. Retrieved February 8, 2022 from https://archive.ipcc.ch/pdf/assessment-report/ar5/wg3/ipcc_wg3_ar5_annex-iii.pdf#page=7

[8] Department of Business, Energy and Industrial Startegy. 2021. 2021 Government Greenhouse Gas Conversion Factors for Company Reporting. Retrieved April 26, 2022 from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1049346/2021-ghg-conversion-factors-methodology.pdf

[9] ElectricityMap. 2020. Zone bounding boxes. Retrieved February 8, 2022 from https://github.com/electricityMap/electricitymap-contrib/blob/master/config/zones.json

[10] ElectricityMap. 2022. ElectricityMap. Retrieved February 8, 2022 from https://electricitymap.org/

[11] European association for the cooperation of transmission system operators. 2008. ENTSOE transparency platform. Retrieved February 8, 2022 from https://transparency.entsoe.eu/

[12] Julian Huber, Kai Lohmann, Marc Schmidt, and Christof Weinhardt. 2021. Carbon efficient smart charging using forecasts of marginal emission factors. *Journal of Cleaner Production* 284 (2021), 124766.

[13] International Energy Agency. 2019. Global Energy & CO2 Status Report 2019: Emissions. Retrieved February 8, 2022 from https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data

[14] Kenneth Leerbeck, Peder Bacher, Rune Grønborg Junker, Goran Goranović, Olivier Corradi, Razgar Ebrahimy, Anna Tveit, and Henrik Madsen. 2020. Short-term forecasting of CO2 emission intensity in power grids by machine learning. *Applied Energy* 277 (2020), 115527.

[15] Gordon Lowry. 2018. Day-ahead forecasting of grid carbon intensity in support of heating, ventilation and air-conditioning plant demand response decision-making to reduce carbon emissions. *Building Services Engineering Research and Technology* 39, 6 (2018), 749–760.

[16] Luke George. 2021. The Correct Way to Average the Globe. Retrieved February 8, 2022 from https://towardsdatascience.com/the-correct-way-to-average-the-globe-92ceecd172b7

[17] National Centers for Environmental Prediction, National Weather Service, NOAA, U.S. Department of Commerce. 2015. NCEP GFS 0.25 Degree Global Forecast Grids Historical Archive. Retrieved February 8, 2022 from https://doi.org/10.5065/D65D8PWK

[18] United Satets Environmental Protection Agency. 2021. Greenhouse Gas Protocol: Scope 2 Guidance. Retrieved April 26, 2022 from https://ghgprotocol.org/sites/default/files/standards/Scope%202%20Guidance_Final_Sept26.pdf

[19] US Environmental Protection Agency. 2021. Global Greenhouse Gas Emissions Data. Retrieved February 8, 2022 from https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data

[20] US Environmental Protection Agency. 2021. Sources of Greenhouse Gas Emissions. Retrieved February 8, 2022 from https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions#:~:text=Larger%20image%20to%20save%20or%20print%20The%20Electricity%20sector%20involves,2O)%20are%20also%20emitted.

[21] Watttime. 2022. Watttime. Retrieved February 8, 2022 from https://www.watttime.org/