Automating load shaping for EVs: optimizing for cost, grid constraints, and... carbon?

Research from Sense Labs and Singularity Energy

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New study highlights 8-14% carbon reduction potential on average and up to 43% through EV charge automation

Abstract

This study used over 100,000 sessions of in-field electric vehicle (EV) charging data and the analysis of location- and time-based fuel mix of the power grid to characterize the carbon intensity of common EV charging patterns. Combining these data sets, the study showed that optimizing EV charging for carbon intensity would yield 8-14% reductions in related carbon on average across 44 states, and an average reduction of 43% in California due to the higher proportion of renewable energy.

The study also showed that time of use (TOU) rates do not always correspond to periods of lowest carbon intensity. Instead, in all regions, carbon optimization leads to the lowest carbon impact.

The study characterizes how EV charging emissions could vary by grid balancing authorities around the country. Carbon reductions are influenced by the regional mix of energy sources, with some regions offering a potential for higher reductions, although there are significant carbon savings to be had in most regions. As more states increase the share of energy produced by renewable sources, the carbon savings potential through load shaping will increase across the country.

The study demonstrated a significant carbon reduction potential for utilities who encourage customers to automate EV charging to optimize for carbon intensity. This insight will be important as utilities and policy makers look for effective ways to meet carbon emissions goals and balance the increasing complexities on both the supply and demand sides of the power grid.

On the supply side, a greater use of variable renewable energy such as solar and wind leads to more variable generation. Knowing the location- and time-based carbon intensity offers an opportunity to encourage EV charging when low-carbon energy is cheap and plentiful. Similarly, in times of excessive cost, grid constraints, or high carbon emissions, efforts to encourage demand reductions become more valuable.

This also means that at the regional transmission level, carbon can become a dispatchable objective. Dynamic EV charging rates would require automation that responds to carbon intensity fluctuations from power sources. This approach is an option for utility programs seeking to modulate disruptive changes from the expected increase in low-carbon energy sources combined with increasing customer demand for electricity as more EVs are adopted.

While this study focused specifically on reduction of carbon emissions, as alluded to above, the same approaches should consider costs and grid constraints and jointly optimize this combination of factors. In addition, the controllable loads will expand beyond EVs and include devices in the home. The best targets for automation are major users of energy where the consumer only cares about the results – not when the energy is used.

Introduction

This study sought to answer two questions using actual in-field EV charging data and location- and time-based grid carbon intensity data: what is the carbon impact of charging an EV, and can the carbon impact be reduced by adjusting charge times based on dynamic carbon intensity?

The study relied on two sources of data: actual car charging sessions across 44 states and carbon intensity data derived from generation fuel mix data from the grid operators (i.e., ISO/RTO) and the EPA emissions data. After analyzing car charging patterns and regional carbon intensity data, the study simulated the carbon effects of adding flexibility to charging times.

The study showed that charging patterns and low carbon intensity windows varied by region and did not necessarily match with utilities' conventional on-peak/off-peak rate periods. Across all regions, the more flexibility over time, the greater the carbon reductions.

The study further analyzed the top 10 states with the most EVs in this dataset: California, Texas, Massachusetts, Washington, Florida, New York, New Jersey, Pennsylvania, Virginia and Illinois. The study also analyzed the carbon intensity trends and compared a carbon optimized charging scheme against the charging now and TOU schemes.

Data sources

Charging session data

This study examined more than 100,000 home charging sessions across 925 EVs in 44 states over a 1-year period (11/3/2019 – 11/2/2020). The anonymized data was gathered using the Sense Home Energy Monitor, a device about the size of a large smartphone that's installed in the home's electrical panel. Two sensors clamp around the service mains to monitor power usage. The monitor continuously tracks how much electricity the home is using and can detect individual devices turning on and off. It uses high-resolution waveform monitoring, measuring voltage at 1 million samples per second and current at 41 thousand samples per second, and machine learning to disaggregate the electrical signatures of individual devices in the home.

Figures 1 and 2 show the number of EVs in the study across all 30 balancing authorities and by state. The 10 states with the most EVs in this dataset were California, Texas, Massachusetts, Washington, Florida, New York, New Jersey, Pennsylvania, Georgia and Illinois.

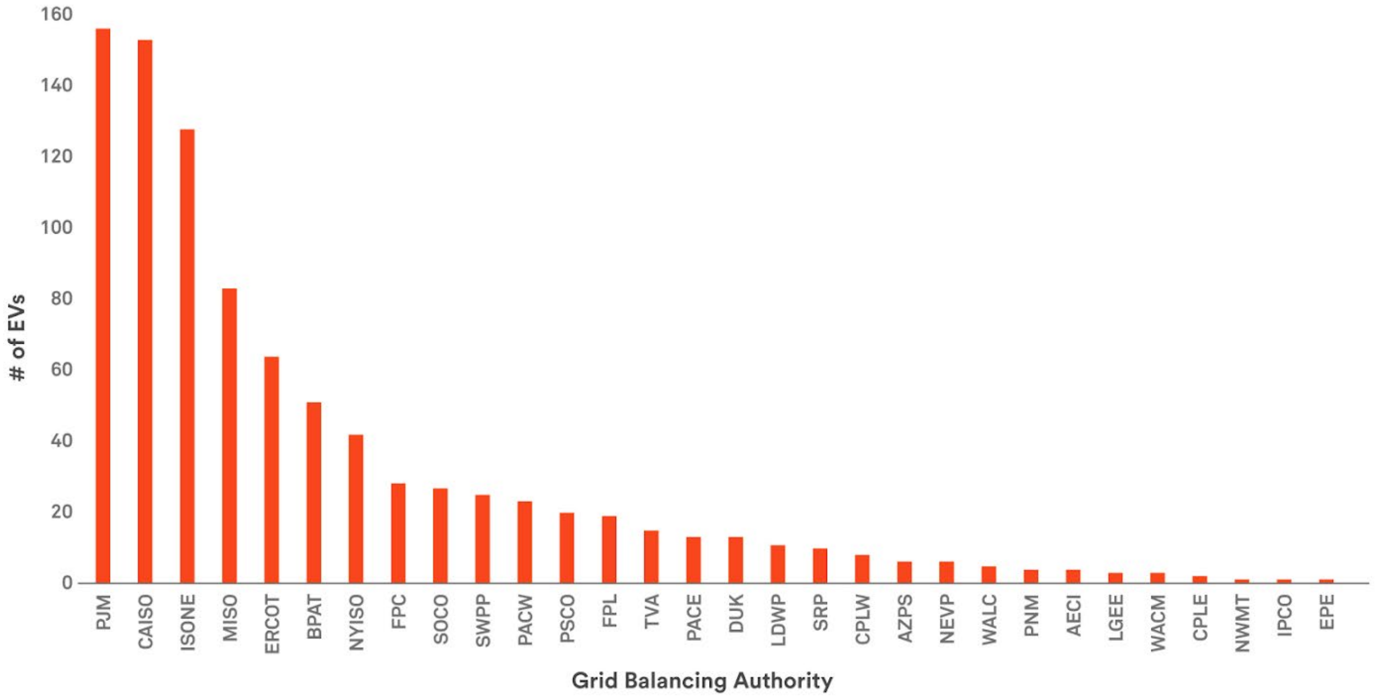

Figure 1: The number of EVs across 30 grid balancing authorities.

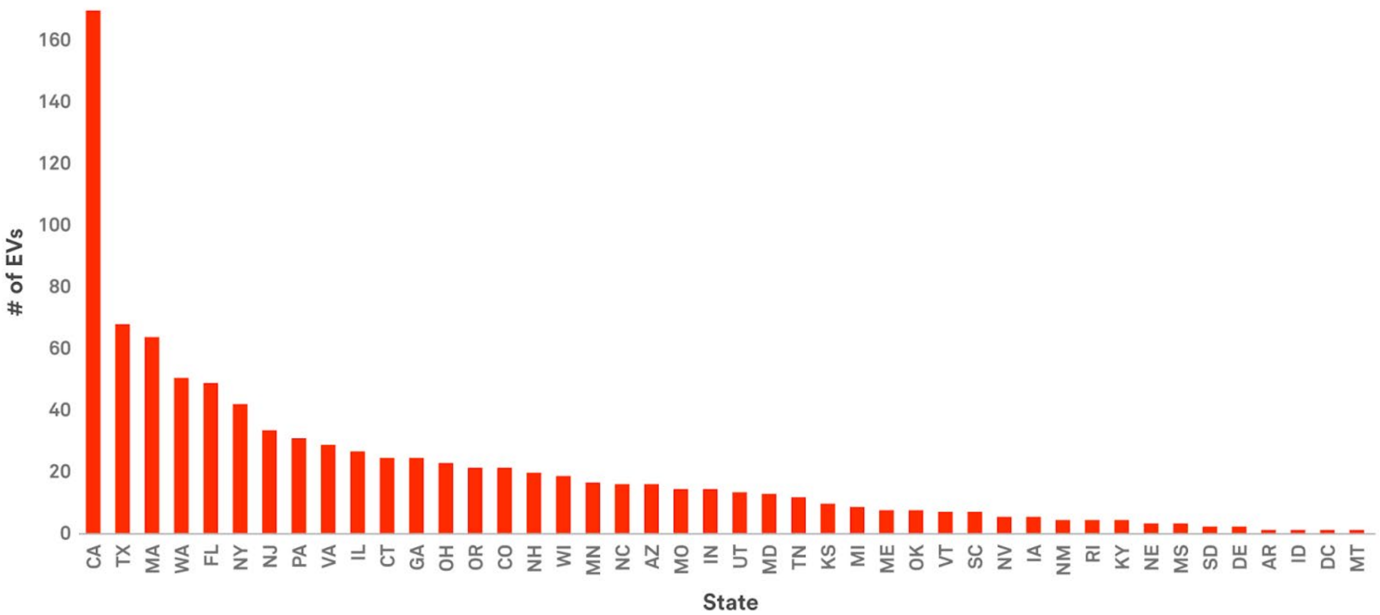

Figure 2: EV distribution by state

Carbon intensity data

About the Carbon Intensity Data Analysis

While marginal carbon intensity provides a useful signal for certain applications, average carbon intensity is used in similar contexts when large aggregate loads need to be shaped, such as in the Massachusetts Clean Peak Standard, New York City's Local Law 97, and Google's 24/7 carbon-free methodology for its data centers [3].

This analysis improves the granularity of the existing average carbon intensity data that is typically an annual average and 2-3 years old. We follow the EPA eGRID framework [4] to produce hourly average carbon intensity data using the hourly generation fuel mix data from EIA. The carbon intensity data we use in this study is based on the most granular data available today, which is on the transmission level (e.g., ISO New England's territory covers the six Northeastern states but only the aggregated generation fuel mix data is available). We would like to work with the ISO/RTO and utilities to make more granular data available to inform effective decision-making to reduce emissions.

Carbon intensity was measured in pounds per megawatt hour over the same 1-year period. The study made a region-specific analysis and characterization of the grid carbon intensity data derived based on the generation fuel mix data from the grid operators (i.e., ISO/RTO) and the EPA emissions data.

The grid fuel mix and carbon intensity data used in this study is provided by Carbonara, a grid carbon intelligence platform. Carbonara provides real-time and forecasted grid carbon data across North American electricity markets and intelligence to effectively reduce carbon. Use cases include planning, reporting, and optimization for decarbonization and electrification projects like EVs, battery storage, smart devices, and 24/7 clean power.

Simulation

Currently most EVs are charged by drivers immediately upon arrival at their charging station ("charge now") or scheduled when (TOU) rates from the utility are lower. This study identified current charging patterns and simulated automation to minimize carbon intensity. The automation performance varied according to allowable charge delay with increases up to the study maximum of 24 hours.

Overview of EV charging data

To analyze the 100,000 charging sessions, the first step was to identify prevailing household charging patterns. The study mapped all of the sessions and grouped the data into typical charging patterns over the course of 24 hours. Five types of patterns were found using the k-mean clustering algorithm:

1. **Mid-night charge type:** charging starts between 12am - 7am
2. **Mid-night + late-afternoon charge type:** charging starts between 12am - 7am or 4pm - 8pm
3. **Morning charge type:** charging starts between 8am - 12pm
4. **Late-afternoon charge type:** charging starts between 4pm - 8pm
5. **Night charge type:** charging starts between 9pm - 12am

See Appendix for time window definitions.

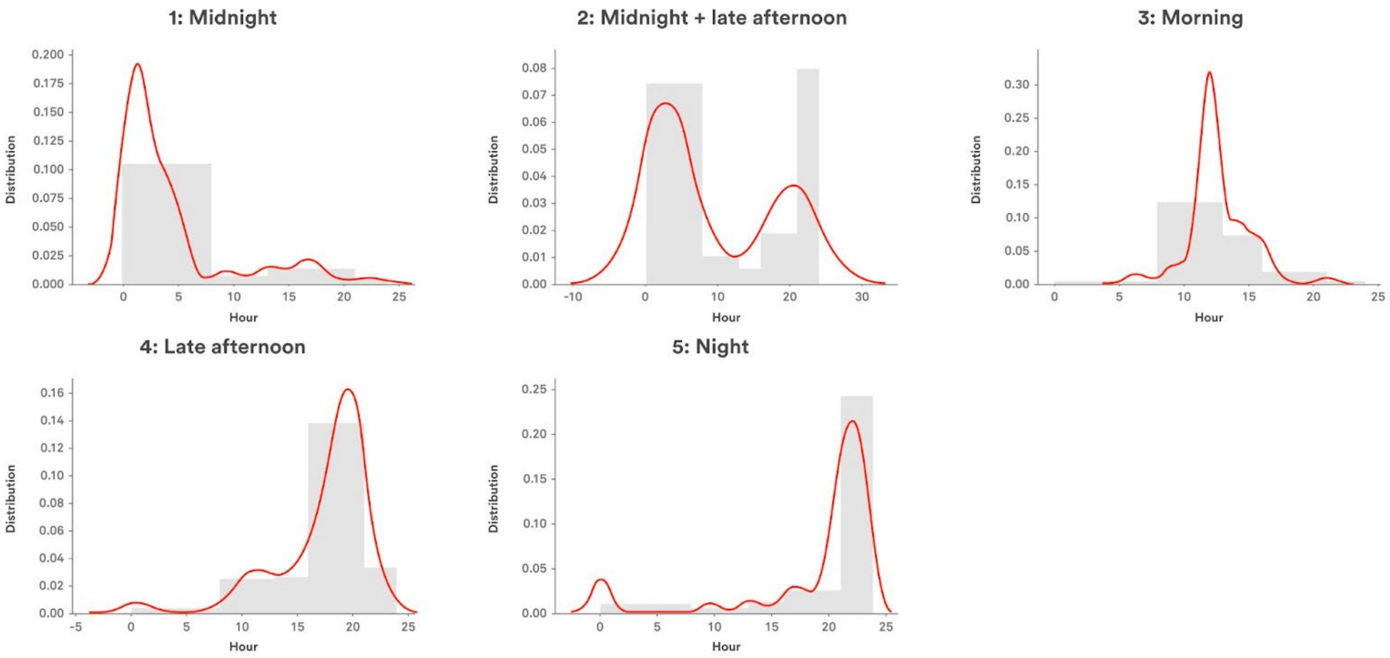

Figure 3: Charge types based on the distribution of charging start times for one household

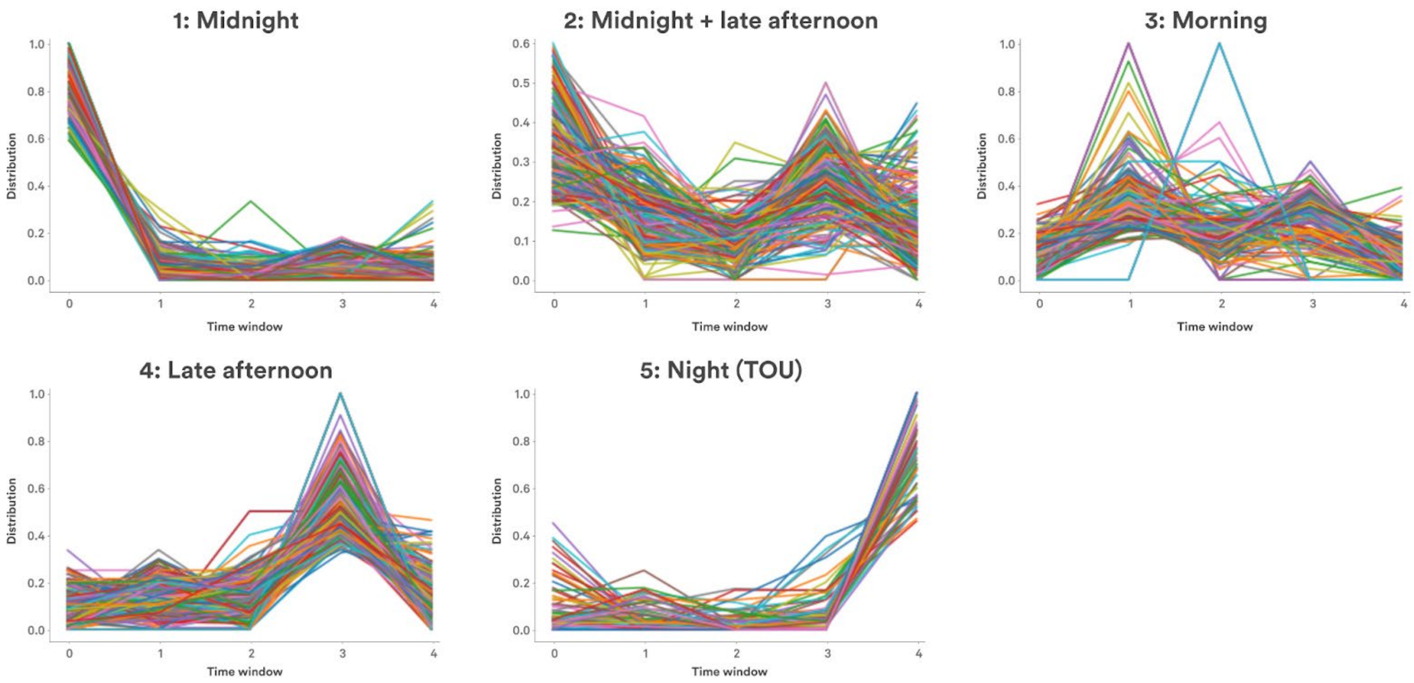

Figure 4: Charge types based on the distribution of charging start time windows for all households

Each charge type was analyzed for distribution across the households. Charge types 1 and 5 showed lower variation in distribution than other types, suggesting that EV owners were using automated features in their car or charger to schedule their charging late at night when utility rates were low.

Types 2, 3 and 4 showed higher variability, suggesting that EV owners were charging when it was convenient. Types 2 and 3 appear to be customers who are home during the day. Type 4 appears to be customers who start charging in the early evening hours after returning home from a commute.

Charging patterns nationally showed that type 5, night charging, was the least commonly chosen option.

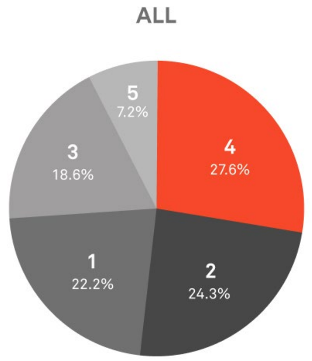

Figure 5: Breakdown of the five types across all the household data shows typical charging patterns

Grouping the types by state highlighted significant variability. For instance, in California, where TOU rates are common, type 1 charging after midnight had the highest occurrences. In Texas, Virginia, Washington and Illinois, type 4 with late afternoon charging patterns were most common. Virginia, Washington and Massachusetts had the smallest number of customers in Type 1. All of the states except California and New York had a significant percentage (roughly 25% or more) charging in the evening hours (Type 4).

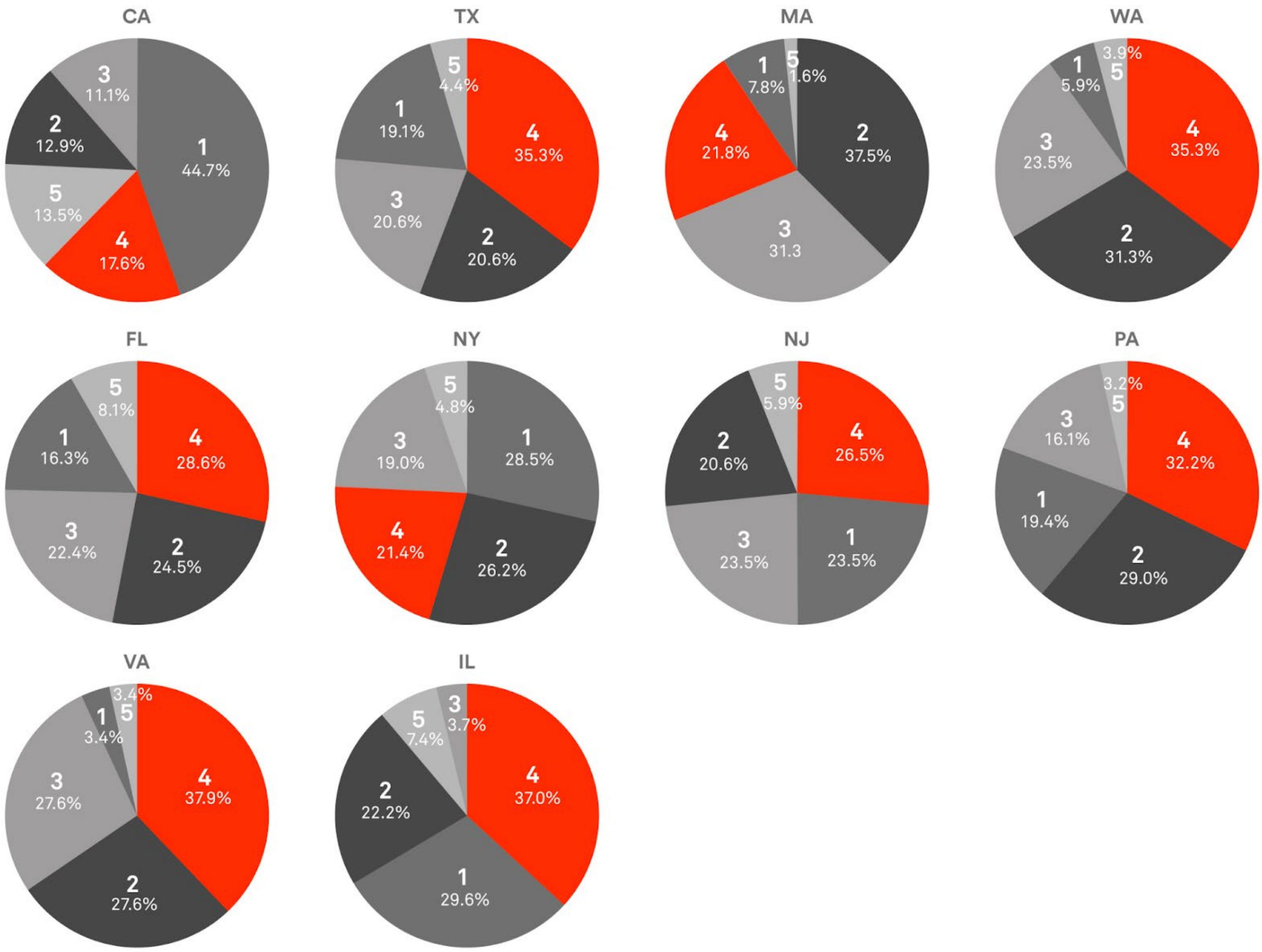

Figure 6: Charging patterns in states with the largest numbers of EVs

Overview of carbon intensity data

The study looked at the carbon intensity on the power grids in 30 grid balancing authorities. Figure 8 shows the carbon intensity of the 10 grid balancing authorities with the highest number of EV households over a one-week period. The graphs show that carbon intensity varies substantially by region.

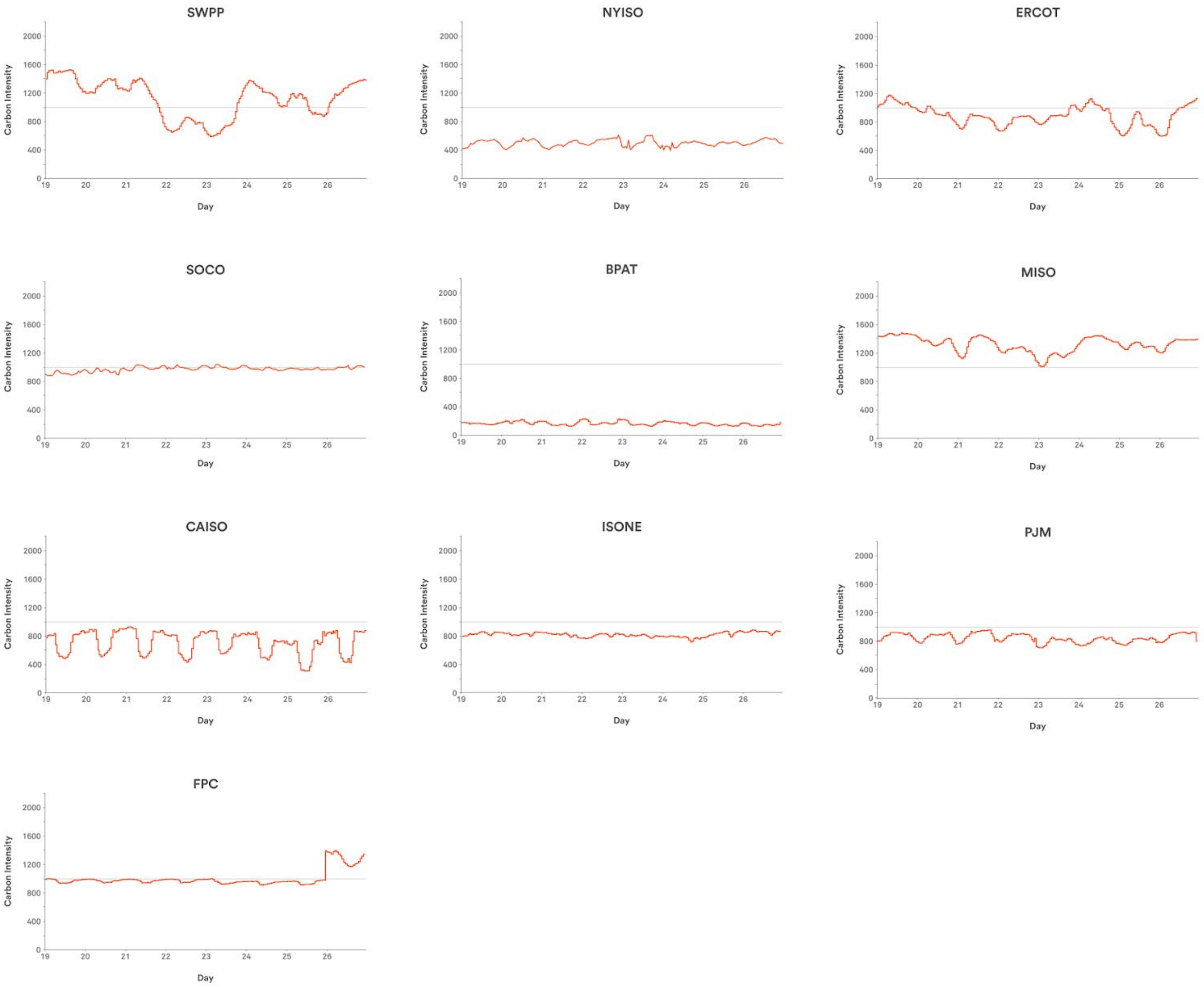

Figure 8: Carbon intensity (lbs/MWh) over a 7-day period with the gray line indicating the national annual average

Table 1: Variations in Carbon Intensity for 10 Grid Balancing Authorities

Grid Authority	Max value/min value
CAISO California Independent System Operator	307%
SWPP Southwest Power Pool	259%
ERCOT Electric Reliability Council of Texas	197%
BPAT Bonneville Power Authority Transmission	181%
NYISO New York Independent System Operator	154%
FPC Duke Energy Florida, Inc.	153%
MISO Mid-con nent Independent System Operator	145%
PJM Pennsylvania Jersey Maryland	135%
ISONE Independent System Operator New England	123%
SOCO Southern Company Services, Inc.	117%

When carbon intensity was analyzed in real time, it was evident that carbon intensity varies widely from region to region and over time. As more renewable energy sources come onto the grid in various regions, carbon intensity will become more dynamic.

Table 1 shows the magnitude of variation across grid regions. For instance, BPAT has smaller absolute values but the magnitude of the variation is higher than MISO, which has high average carbon intensity but smaller variation.

Simulation setup

We next assessed whether flexibility to charge within a certain time window would have an impact on carbon emissions when compared to the baseline scenario. We assumed the consumer had flexibility to charge within a certain time window ranging from 6 to 24 hours.

It's possible to have a 24-hour or an even longer time window for residential EV drivers because they may not use their EV every day.

- Same start time
- New end time = end time + h (6 hours – 24 hours)

We compared the baseline CO_2 (as seen in the data) versus optimized CO_2 (charging during the lowest carbon intensity times to reach the same kWh). A percent reduction is characterized as the total baseline CO_2 minus the total optimized CO_2 divided by the total baseline CO_2.

Across all the regions and households, analyzing baseline CO_2 versus optimized CO_2 showed an 8-14% reduction in carbon on average when households charged to reduce carbon.

The highest carbon reduction of 43% was found in California.

The data indicated that optimizaton gets better with time flexibility. If you can shift charging within a 24 hour window, you can achieve 14% carbon reductions on average; if you can only shift by 6 hours, the carbon reduction is 8% on average.

We then compared three different charging behaviors of the Types 2-4 households (charge now types) to assess the carbon impact of TOU charging:

- Charge now: as seen in the data
- TOU: delay charging until 12am (although different utilities may have different TOU programs, midnight belongs to off-peak hours across the board and actual charging data also shows that drivers scheduled EV charging to start late at night as seen in Figure 4)
- Carbon optimized: charge when the grid carbon intensity is lowest

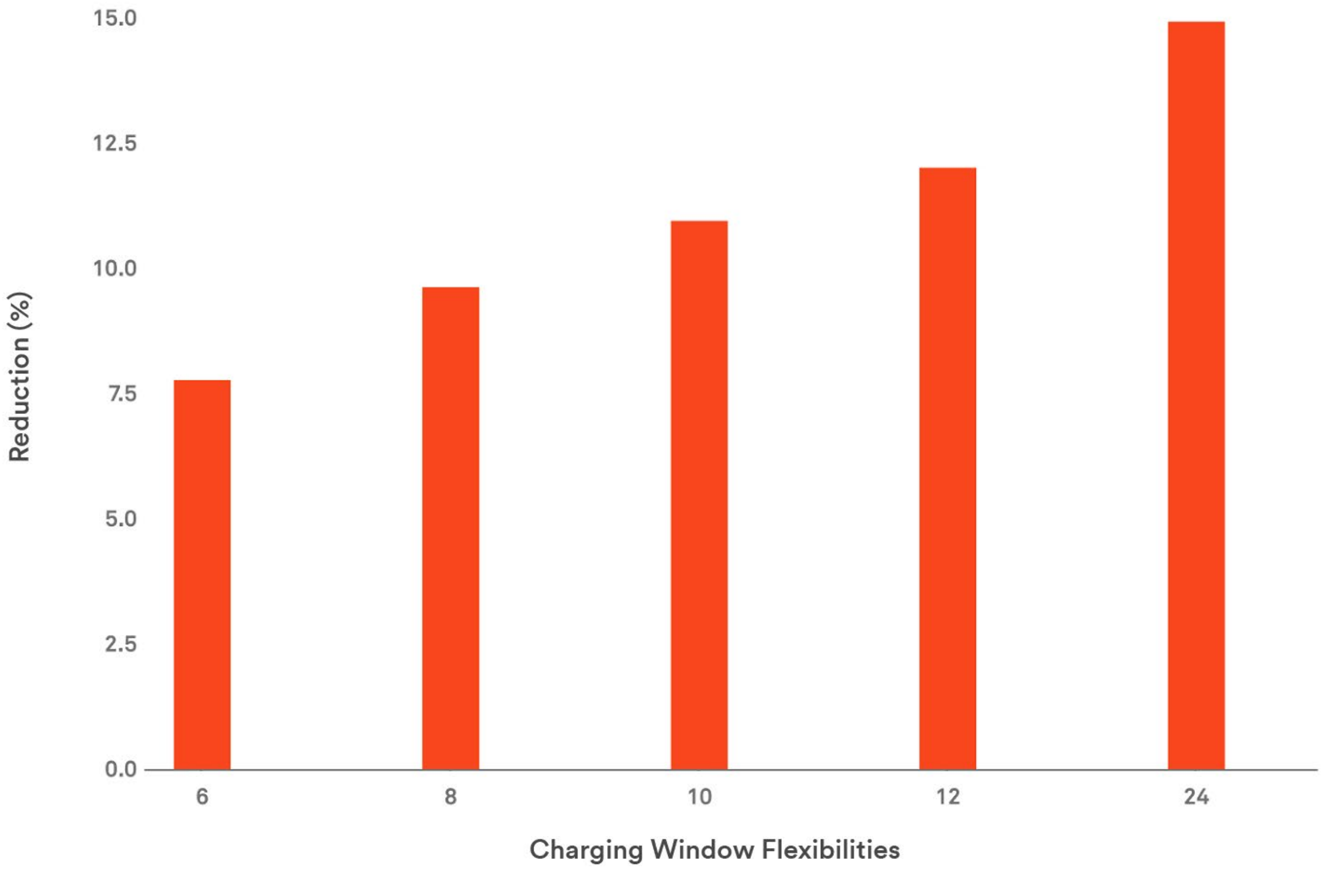

Figure 9: Carbon reduction percent with different charging window flexibilities

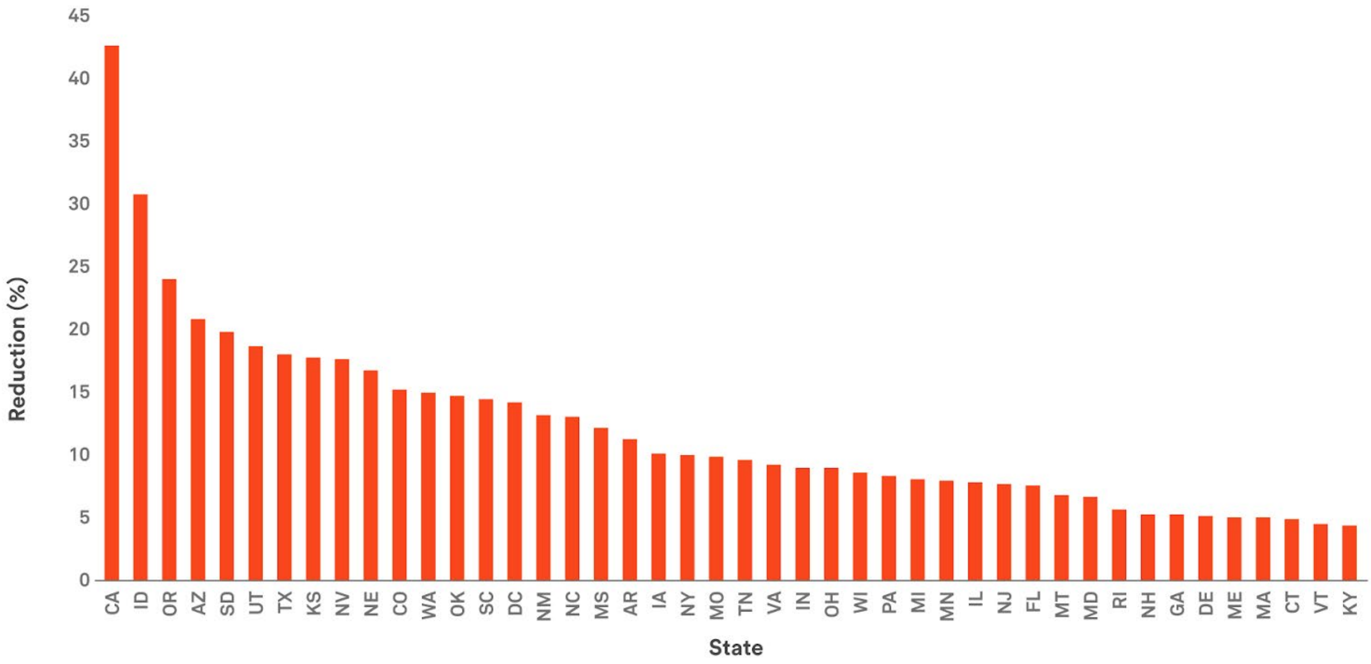

Figure 10: Carbon reduction percent by state (24 hours flexibility)

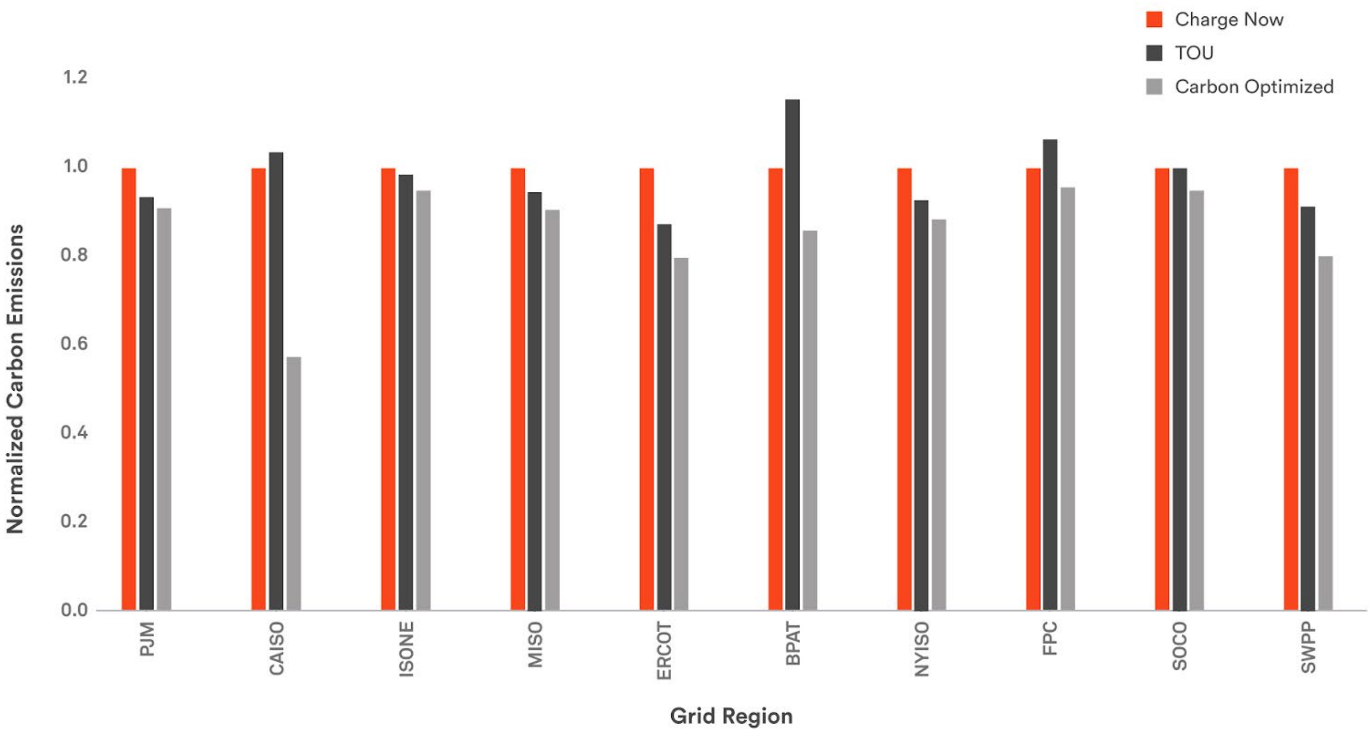

Figure 11: Normalized carbon impact comparison in top 10 grid regions

Results

The significant variability in carbon intensity patterns across various regions means that TOU rates do not always correspond to periods of lowest carbon intensity. Instead, in all regions, carbon optimization leads to the greatest carbon reduction impact (Figure 11). For instance, in California (CAISO), where carbon intensity varies by 307%, choosing carbon optimization reduced carbon an average of 43%. In Texas (ERCOT), where carbon intensity varies by 197%, carbon optimization could reduce carbon by 18%. As increasing numbers of EVs are adopted, this magnitude of reduction could have a measurable impact on reaching state climate change goals.

Charging according to TOU could actually increase carbon impact in some cases. The TOU strategy led to higher carbon impact in three regions (CAISO, BPAT, and FPC), suggesting that TOU rate periods at utilities in those regions are not aligned with the carbon intensity of energy sources from the grid. In other regions, the TOU strategy led to lower or similar carbon impacts compared with charge now.

Across all regions, optimizing EV charging for carbon intensity would yield 8-14% reductions in related carbon on average. The more time flexibility in the charging window, the greater the carbon reductions. This suggests that a strategy that automates charging on the consumer's behalf by offering options to charge within 8, 12 or 24 hours, for instance, will most successfully optimize for the dynamic changes in carbon intensity on the grid.

The analysis of carbon intensity demonstrated that peak hours are not necessarily dirty hours. Just as we need weather data to plan our daily activities, we also need carbon intensity data and forecasts to plan our electricity usage to reduce peak emissions, not just peak demand. Some regions, such as CAISO, have a clear daily pattern and so could benefit from better design of TOU rates that take carbon intensity into account. Some have smaller variations (ISONE, SOCO), and today have limited opportunities for carbon reduction by shaping loads. Others (SWPP, ERCOT) have large variations in carbon intensity but without clear daily patterns; these are the regions which will benefit the most from full real-time automation of key loads in residences.

While some regions show wider variations in their carbon intensity over the course of a day, all regions had enough variability to offer significant opportunities for carbon savings by taking advantage of dynamic variations as they occur, as shown in Figure 8. As more renewables come onto the grid, carbon intensity will become even more dynamic in the future. As a result, simple mechanisms like time of use will become less successful and will need to be replaced by dynamic, automated approaches.

Comparing figures 2 and 10, we can see that certain states with high EV ownership as well as higher carbon reductions offer more potential for emissions reductions. For instance, California and Texas are the top states for EV drivers as well as carbon potential. Other states such as Oregon and Arizona have high potential carbon savings but relatively fewer EV drivers.

In developing carbon reduction models, utilities can use the location- and time-based carbon intensity data to incentivize customers to shape their consumption to reduce peak emissions in a way similar to today's demand response program aiming to reduce peak demand. The data can also be used by utilities and their customers to track their emissions in a more accurate and timely manner in order to evaluate their decarbonization progress and inform more effective planning to meet their goals.

Conclusion

The study demonstrated the feasibility of using home energy monitoring to automate EV charging to reduce carbon emissions at the household level. It showed that carbon reductions of 8-14% could be achieved across most regions in the U.S. and a higher reduction of 43% in California. These findings indicate the potential for higher carbon reductions as regions use more renewable energy.

The utility industry is facing pressures to meet CO_2 reduction goals while keeping pace with more intermittent sources of power and anticipating new energy loads from EVs. The ability to jointly optimize for CO_2, cost, and grid constraints can provide the best performance at a system level. Dynamic signals from the power grid combined with EV charging automation could be used to shape consumer behavior, modulate peak demand as EV adoption grows, inform utilities' incentive programs and reduce carbon.

At the same time, utilities and grid operators will be reliant on consumer acceptance of smart home technologies. Active consumer participation is necessary for demand and load to become more adaptable and responsive. Programs could be designed with realtime messaging that emphasizes the satisfaction EV owners will have from knowing they can charge during periods when energy is cleaner, cheaper and plentiful.

While this study analyzed the potential for carbon reduction only, a more comprehensive approach would also take into account energy costs and constraints on the grid. Optimizing for these factors jointly would identify the best times to use energy from both the consumer's and grid operator's perspective. Previous studies [5] have shown that this multi-objective optimization approach can achieve close to the optimal results.

Acknowledgement

The authors wish to acknowledge and thank Mike Philips, Carol McGarry, and Chelsea Officer at Sense, as well as Jeff Burka at Singularity and Greg Miller at UC Davis for their contributions to this research paper.

Appendix

The analysis of EV charging patterns used the following charging start time windows:

- mid-night: 0-7am
- morning: 8am-12pm
- early afternoon: 1pm-3pm
- late afternoon: 4pm-8pm
- night: 9pm-12am

Figure 12 shows carbon intensity patterns for all 10 grid balancing authorities (shown separately in Figure 8):

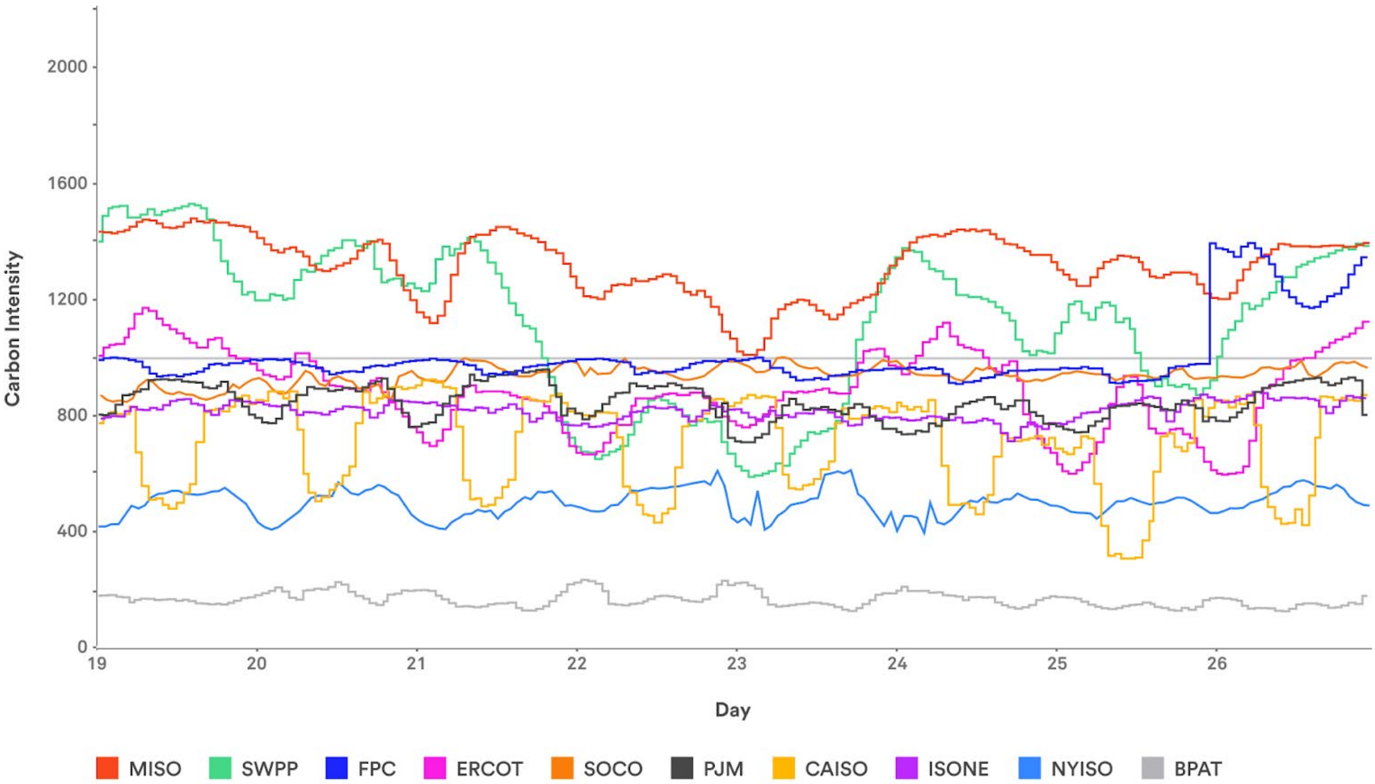

Figure 12: Comparison of Carbon Intensity (lbs/MWh) by Grid Balancing Authorities

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