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Reducing Carbon Emissions of EV Charging via User Behavior and Carbon Intensity Analysis

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ABSTRACT

The increased adoption of electric vehicles (EVs) has the potential to significantly reduce carbon emissions by decreasing reliance on fossil fuels. However, as more EVs populate our roads, there will be a heightened demand for electricity from the grid, leading to increased carbon emissions due to EV charging. Currently, most EV owners do not align their charging behavior with periods of low carbon intensity in the power grid. To reduce the carbon emissions resulting from EV charging, it is essential to alter the charging behavior of EV users. To tackle this problem, we propose a solution that leverages user charging behavior data with carbon intensity data to identify optimal charging times for EVs, resulting in reduced carbon emissions. Our simulation results using 10,000 EVs demonstrate that the proposed carbon-aware EV charging algorithm can reduce 9.3% of carbon emissions by optimizing EV charging times.

Introduction

Today, automobiles are deeply integrated into everyday life worldwide. Greenhouse gases emitted by vehicles account for 27% (around 5,981 million metric tons of CO_2) of total emissions in 2020 in the U.S. alone (U.S. Environmental Protection Agency, 2023). To reduce the impact on the environment and global warming, the transition from gas-powered to electric vehicles (EVs) will be an inevitable trend. In recent years, the number of EV cars has been growing at an increasing rate. In Texas, the total number of EVs has nearly tripled since 2020 (Granger et al., 2022). California has an estimated 1 million zero-emission vehicles (ZEVs), with a goal of 8 million ZEVs by 2030 (CARB, 2020). In 2025, an estimated 13 million vehicle sales will be fully electric or hybrid (Lutsey et al., 2018).

While EVs offer a promising solution for reducing carbon emissions in the transportation sector, the growing demand for electricity to operate EVs can also increase carbon emissions. This is particularly true when charging EVs without considering the carbon intensity of the power source. The carbon intensity of the power supply fluctuates over time due to the misalignment between high renewable energy generation and electricity demand. This mismatch results in energy waste and an upsurge in carbon emissions. Weather conditions also play a significant role in influencing renewable energy sources like solar and wind, causing their generation capacity to vary throughout the day and year. To illustrate this point, Figure 1 depicts the fluctuations in wind and solar power generation on a randomly selected day in the fall and winter seasons, highlighting substantial variances (California Independent System Operator, 2022).

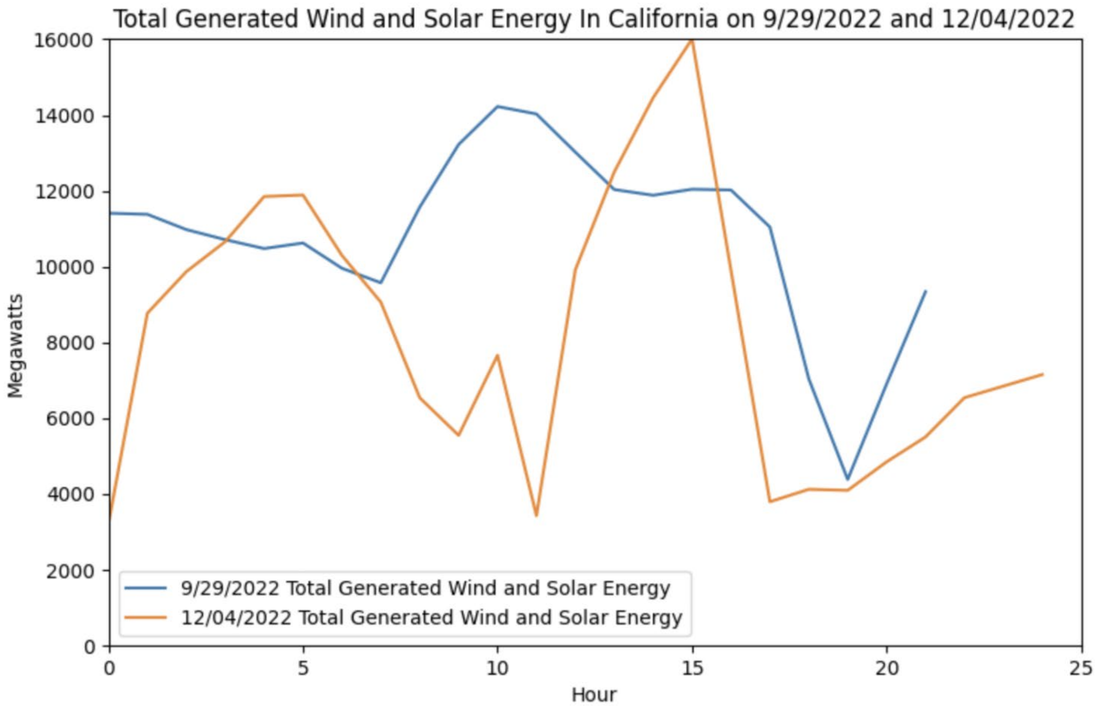

Figure 1. Renewable energy generation fluctuates over time.

Meanwhile, EV charging demands tend to be higher during certain times of the day, such as in the early evening when people return home from work and charge their EVs. The disparity between the generation of renewable energy and electrical demand can lead to both increased carbon emissions and the wastage of renewable energy, as surplus renewable power is often discarded.

The charging behavior of most EV owners tends to prioritize convenience rather than considering the amount of carbon emissions generated from the grid per unit of energy. Since EVs require noticeable power to become fully charged, the time of day they are charged can significantly impact carbon emissions. Our proposed Carbon Aware EV Charging Algorithm is a solution designed to reduce carbon emissions associated with EV charging. Our solution involves collecting and analyzing data on various aspects of EV use in both North California and Texas, including charging behavior, electric vehicle configurations, and marginal operating emission rate (MOER) data on carbon intensity. The collected data is then used to conduct various statistical analyses of carbon intensity, including finding low carbon intensity times during the day, when people usually charge their EVs during the day, and EV registrations with their respective charging rates.

To assess the effectiveness of the Carbon Aware EV Charging Algorithm, we utilize real-world carbon intensity data and simulate the charging behavior of 10,000 EVs. The simulation results demonstrate that our solution can save up to 9.3% of carbon emissions compared to charging EVs at any convenient time without considering carbon intensity. This significant reduction in carbon emissions clearly indicates the efficacy of our solution in addressing the challenge of minimizing the impact of EVs on the environment.

Related Work

The EV charging problem has been well studied in previous literature. For example, Xiong et al. (2018) proposed a two-stage distributed optimization and water-filling algorithm to minimize energy costs and accommodate demand response programs while satisfying electric vehicle energy demands. Gao et al. (2014) presented an integrated control scheme for vehicle-to-grid (V2G) operation in the distribution grid with renewable energy sources, which regulated V2G power to minimize the total operating cost while providing frequency regulation. Lee et al. (2018) proposed an adaptive charging network for large-scale, high-density EV charging using model predictive control and convex optimization. Tucker et al. (2022) proposed a smart EV charging algorithm to minimize electricity costs and demand charges by using scenario generation to account for unknown departure and arrival times. Xu et al. (2020) studied the impact of different charging strategies on greenhouse gas (GHG) emissions in Europe, finding that carbon-aware EV charging could reduce GHG emissions by 36% by simply replacing conventional cars and controlled unidirectional charging.

Regarding existing studies on user charging behavior, Hu et al. (2019) proposed a cumulative prospect theory approach to express the charging behavior of EV drivers, which identified an individual's preference toward low-risk decision-making when presented with potential gains but leaned towards taking higher risks when faced with potential losses. Harish (2021) examined the problem of overstay, where an electric vehicle remained plugged in at a charging station after completing its charging cycle. He explored the impact of meteorological factors and work or school schedules on user behavior and overstay patterns. Li et al. (2018) proposed a Bayesian-inference-based algorithm to estimate charging demand on the grid and a flexible objective function to balance the benefits of serving existing EV users and attracting more fossil-fuel vehicle drivers.

Ideal behavior framework centered around carbon intensity closely follows a pattern that usually combines user behavior and EV emission data. Will et. al (2022) explained how informing users of lesser-known attributes of carbon intensity from EVs could create an effective framework for carbon-neutral charging services. Set in France and Germany, Ensslen and colleagues (2017) showed how specific smart charging services could serve as a strategy to reduce vehicle-specific emissions. Colmenar-Santos et al. (2019) proposed a distributed control system to manage charge and discharge strategies that address the mismatch between load and renewable generation with V2G technology. Chen et al. (2019) investigated both day and night charging scenarios combined with system load demand to propose an emission-oriented charging scheme that reflects emissions reduction that has not yet been incorporated in the current market of electricity transactions.

The most similar study was conducted by Cheng et al. (2022), which examined the impact of EV charging on power grids with real-time electric grid carbon intensity in California. They proposed a carbon-aware charging scheme that minimizes the carbon emissions contributed by EV charging events while satisfying constraints such as EV users' charging schedules, charging station transformer limits, and physical battery constraints. Our work is unique from theirs because we analyzed a wider range of carbon intensity data from both California and Texas. In addition, they did not simulate the charging behaviors of popular EV brands when the carbon intensity is low to determine how changing EV charging behavior might reduce overall emissions. These differences highlight the unique contributions of our paper to the EV charging field.

Carbon Intensity Data Analysis

Carbon intensity refers to the amount of carbon emitted per unit of energy, which is measured in pounds of emissions per megawatt-hour (e.g., CO2 lbs/MWh). The Marginal Operating Emissions Rate (MOER) is a widely used metric to quantify the amount of carbon emissions associated with the production of a unit of energy at a specific point in time. Wattime provides access to real-time, forecast, and historical MOER admissions from local electric grids in both California and Texas, representing the emissions rate of the electricity generators responding to changes in load on the local grid every five minutes (Wattime, 2023).

To reveal the year-over-year carbon intensity changing patterns, we apply the statistical least squares regression model on four years of California and Texas MOER data obtained from Wattime and determine patterns of carbon intensity. A least squares regression model is used to analyze the line that best matches the sum of the squared distances between the observed and predicted values of the dependent variable (Drapper & Smith, 1998). Our analysis model takes MOER data from 2018 to 2022 and outputs the data points representing the average MOER at every hour of the day. This allows us to analyze the relationship between time and MOER, uncovering trends and patterns within the dataset.

Read data from file containing 2018-2022 MOER into a DataFrame
$df_C I \leftarrow pd.read_c sv('CIModel.csv')$
Filter the DataFrame to desired the 'year' columns
$df_C I \leftarrow df_C I.query('year >= 2021'\&\&'year <= 2022')$
Extract dependent variable and independent variables into separate variables
$y \leftarrow df_C I['MOER']$
$x \leftarrow df_C I[['hour'_1,'hour'_2,'hour'_3,'hour'_4,'hour'_5,'hour'_6,'hour'_7,'hour'_8,'hour'_9,'hour_1 0','hour_1 1','hour_1 2','hour_1 3','hour_1 4','hour_1 5','hour_1 6','hour_1 7','hour_1 8','hour_1 9','hour_2 0','hour_2 1','hour_2 2','hour_2 3']]$
Add a constant term to the independent variables
$x \leftarrow sm.add_c onstant(x)$
Fit the Ordinary Least Squares model using the dependent variable and independent variables
$model \leftarrow sm.OLS(y, x).fit()$

Figure 2. Least squares regression model for MOER data analysis.

We analyzed the periods of the day when the MOER was low to identify common daily patterns in the hourly carbon intensity. By utilizing a least squares regression model with data from California's MOER between 2018 and 2022, we observed a distinct hourly pattern. Figure 3 illustrates that the MOER (represented on the y-axis in lbs/MWh) tends to decrease after 2 p.m. and remains low until midnight in California. However, the regression model also indicates that the MOER data generally exhibits high and stable values, making it less favorable for carbon-conscious EV charging in Texas. This might result from California already having more restrictions on carbon emissions and providing more incentives on renewable energy, which has a significant impact on the power grid (U.S. Energy Information Administration, 2023). Since there is a low carbon time period usually after 2 p.m. in the California data, we use California’s carbon intensity data in our simulation to illustrate prominent carbon savings using our proposed Carbon Aware EV Charging Algorithm.

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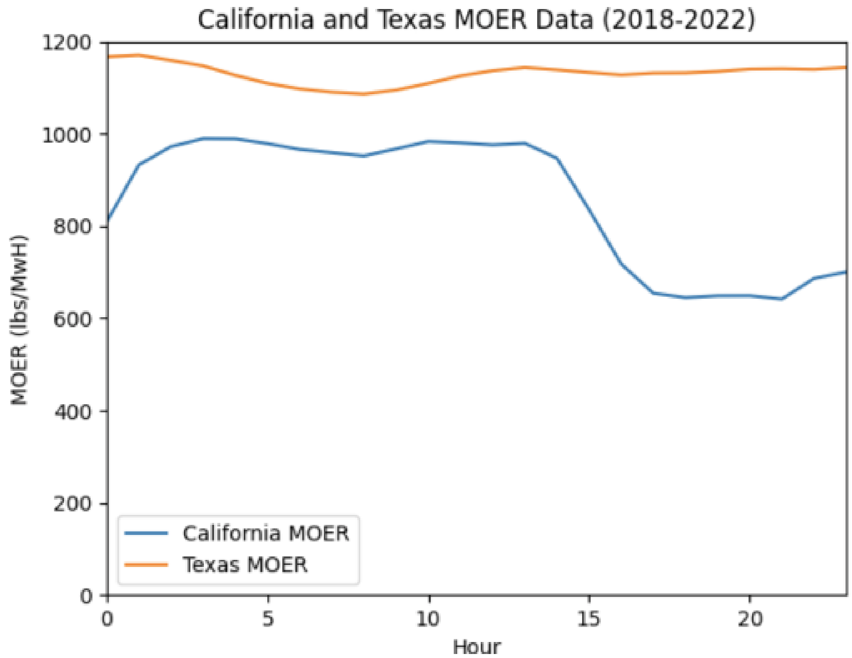

Figure 3. Comparison between California's and Texas's respective MOER data.

User Charging Behavior Analysis

Understanding both user charging habits and carbon intensity patterns is crucial for effectively reducing carbon emissions from electric vehicle charging. To gain insights, we analyzed data from multiple sources. We compared California's and Texas' MOER data with user charging behavior data obtained from ElaadNL (2020, April).

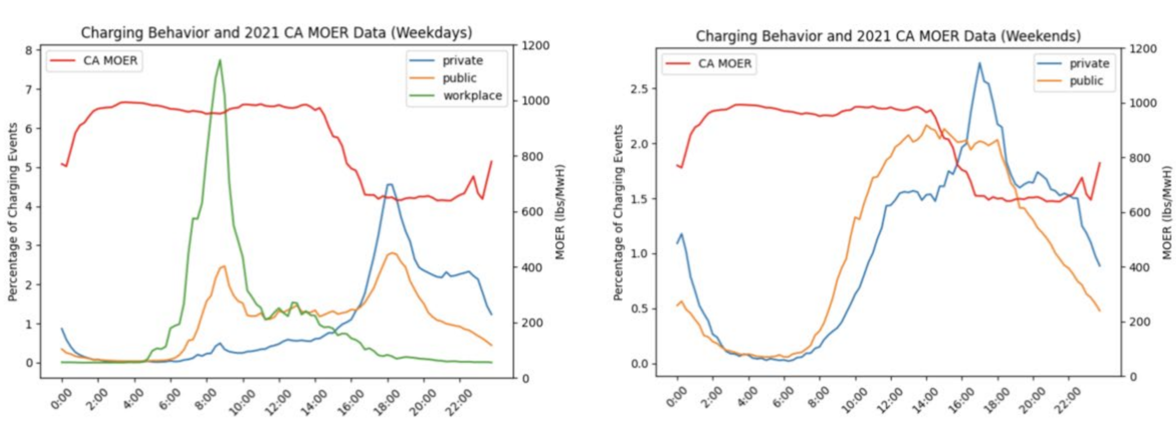

Figure 4. Charging behavior of EVs on weekdays and weekends.

The user charging behavior data was collected and modeled in 15-minute intervals, capturing the distribution of arrival times for charging events at private, public, and workplace locations on weekdays, as well as private and public locations on weekends. For example, in Figure 4A, the data reveals that 3% of EVs utilizing workplace chargers initiate charging at 7:00.

By analyzing the ElaadNL data set, we identified specific charging patterns. On weekdays, there is a notable charging spike around 8:30 when individuals arrive at their workplaces and another around 18:30 when they return home, as illustrated in Figure 4A. Interestingly, these spikes in the workplace and public charging frequencies occur during periods of high MOER, indicating particularly suboptimal charging times. On weekend days, both public and private chargers experience an increase in charging frequencies starting at 8:00. Public charger frequencies level off around 12:00 and decline after 18:00, while private charger frequencies peak at 17:30 and decrease shortly after.

EV data set

To accurately calculate the carbon emissions of different EVs, we collected data of popular EV brands from EV Compare (2021) and the Dallas-Fort Worth Clean Cities Coalition (2021, September), which includes 25 distinct EV models, each with its own configuration (e.g., Tesla Model 3 Performance, Tesla Model 3 Long Range AWD), totaling 104 total configurations. Table 1 represents a small portion of our EV data set.

Table 1. Simplified sample of 7 EV models from our data set, including market share, battery capacity, and charging power.

EV Model	Market Share (%)	Battery Capacity (kWh)	Max DC Charging Power (kW)
Tesla Model 3	28.5	75	210
Tesla Model X	9.65	100	250
Nissan Leaf	2.85	62	100
Chevrolet Bolt EV	1.92	65	55
Porsche Taycan	0.93	79	225
Audi e-Tron	0.87	71	120
BMW i3	0.72	33	50

In order to simulate the relative frequency of each car model, our EV data set included each model's market share, brand, battery capacity, and charging rate. Some models of EVs include the Tesla Model 3 and Model X, as well as non-Tesla brands such as the Chevrolet Bolt EV and the Porsche Taycan. Based on the market share of each EV model, certain models will be generated in our simulation more often than others. For example, on average, 10 Tesla Model 3s will be generated for every 1 Nissan Leaf because the Model 3 accounts for roughly 28% of registered EVs in Texas, while the Leaf accounts for only 2.8% of EVs in Texas.

Carbon Aware EV Charging Algorithm

Algorithm

The algorithm takes in several parameters: the EV data, MOER data, public, private, and workplace charging data for the weekdays (Figure 4A), and public and private charging data for the weekends (Figure 4B). For our simulation, we assume the MOER does not deviate from altering EV charging times.

```
Simulation of Charging EVs
Read in Car data, MOER data, Weekday Charging Data (public, private, workplace), Weekend Charging Data (public, private)

for each weekday do
    for each 15-minute interval do
        SIM(Day, Time, Weekday Charging Data)
    end for
end for
for each weekend day do
    for each 15-minute interval do
        SIM(Day, Time, Weekned Charging Data)
    end for
end for
Calculate total CE for the week

function SIM(Day of Week, Time of Day, Charging Data)
    calculate the number of cars to be charged based on Charging Data
    for each Car to be charged do
        if Weekday and Car charges between 2:00 - 14:00 then
            delay charging until 14:15
        end if
        if Weekend and Car charges between 10:00 - 14:00 then
            delay charging until 14:15
        end if
        calculate Required Charging Time
        calculate Carbon Emission (CE) of Car based on MOER and Charging Time
    end for
end function
```

Figure 5. Carbon Aware EV Charging Algorithm.

The main function of the Carbon Aware EV Charging Algorithm covers the 7 days of the week. For the 5 weekdays of the week, we use the public, private, and workplace charging data specific to weekdays; for the 2 weekend days, we use the respective public and private weekend charging data. Each day of the week is broken into 96 15-minute intervals, which total up to 24 hours. For each of the 96 intervals per day, the algorithm simulates the charging of a certain number of EVs. The number of EV charging varies depending on the day of the week and the time of day, and the EV models charging depends on the market share of EVs (see Table 1). Each EV's charging time is first calculated by dividing its battery capacity (kWh) by its charging rate (kW). The carbon emissions are then calculated by multiplying the charging time of the car by the MOER data for the corresponding time interval. The resulting carbon emissions are added to the total carbon emissions for the week.

To calculate how much carbon emissions could be saved with a more optimized charging behavior, we implemented some changes to each car's charging behavior. On weekdays, if a user decides to charge their EV between 2:00 and 14:00, we delay that charging until 14:15, as this is when the MOER starts to decrease. For weekends, if an EV begins charging from 10:00 to 14:00, we delay charging until after 14:00. By delaying charging until the MOER decreases, we can reduce overall carbon emissions. On weekdays, workplace chargers are most impacted by this delay, as the majority of workplace charging occurs at nonoptimal times. The second most impacted by the delay are public chargers, of which a large proportion are used at 8:00 (as seen in Figure 4A). Weekend charging is generally less affected by this delay in charging, as the weekend charging data and MOER data are roughly inverses of each other.

Results

From our initial simulations without carbon aware EV charging, we calculated that 10,000 EVs would emit 75,000 pounds of carbon within a week. This number dropped to 68,000 pounds after optimizing the user behavior of EV charging, which is a 9.3% reduction in emissions. Based on our study, we found that we could significantly reduce carbon emissions from EV charging by simply adjusting the charging behavior of users and taking into account both the vehicles and charging stations used. While this was only one simulation to reduce carbon emissions, we believe more urban optimizations and changing how people charge their EVs could further reduce emissions.

References

California Air Resources Board. (2020, October 31). *Assessment report and development of resources: Local government zero-emission vehicle multi-modal ecosystem.* Assessment Report and Development of Resources: Local Government Zero-Emission Vehicle Multi-Modal Ecosystem. https://ww2.arb.ca.gov/our-work/programs/sustainable-communities-program/research-solicitations/local-gov-ZEVs

California Independent System Operator. (2022, September 29). Today's Outlook. https://www.caiso.com/TodaysOutlook/Pages/index.html

Chen, X., Tan, C.-W., Kiliccote, S., & Rajagopal, R. (2019). Electric vehicle charging during the day or at night? A perspective on carbon emissions. *2019 IEEE Power & Energy Society General Meeting (PESGM)*. https://doi.org/10.1109/pesgm40551.2019.8973578

Cheng, K.-W., Bian, Y., Shi, Y., & Chen, Y. (2022). Carbon-Aware EV Charging. *System and Controls*. https://doi.org/10.48550/arXiv.2209.12373

Colmenar-Santos, A., Muñoz-Gómez, A.-M., Rosales-Asensio, E., & López-Rey, Á. (2019). Electric vehicle charging strategy to support renewable energy sources in Europe 2050 low-carbon scenario. *Energy*, *183*, 61–74. https://doi.org/10.1016/j.energy.2019.06.118

Dallas-Fort Worth Clean Cities Coalition. (2021, September). Texas Electric Vehicle (EV) Registration Tool. https://app.powerbi.com/view?r=eyJrIjoiNjc4OGYyYjQtYWM2ZC00YjllLWJlYmEtYzdkNTQ1MTc1NjM2IiwidCI6IjQwZDZmOWI4LWVjYTctNDZhMi05MmQ0LWVhNGU5YzAxNzBlMSIsImMiOjR9

Draper, N.R., & Smith, H. (1998). *Applied Regression Analysis* (3rd Edition). Wiley Series in Probability and Statistics.

ElaadNL. (2020, April). Open Datasets for Electric Mobility Research. https://platform.elaad.io/analyses/ElaadNL_opendata.php

Ensslen, A., Schücking, M., Jochem, P., Steffens, H., Fichtner, W., Wollersheim, O., & Stella, K. (2017). Empirical carbon dioxide emissions of electric vehicles in a French-german commuter fleet test. *Journal of Cleaner Production*, *142*, 263–278. https://doi.org/10.1016/j.jclepro.2016.06.087

EV Compare. (2021). *EV compare - electric car comparison, marketplace and Community*. EV Compare.io. https://evcompare.io/

Gao, S., Chau, K. T., Liu, C., Wu, D., & Chan, C. C. (2014). Integrated Energy Management of plug-in electric vehicles in power grid with renewables. *IEEE Transactions on Vehicular Technology*, *63*(7), 3019–3027. https://doi.org/10.1109/tvt.2014.2316153

Granger, R., Howard, S., Melgoza, H., & Chamberlain, M. (2022, March 24). Texas EV Infrastructure Deployment Plan. Austin; Texas Department of Transportation.

Harish, A. (2021). *Overstay at Electric Vehicle Charging Stations at the University of California San Diego*.

Hu, L., Dong, J., & Lin, Z. (2019). Modeling charging behavior of battery electric vehicle drivers: A cumulative prospect theory based approach. *Transportation Research Part C: Emerging Technologies*, *102*, 474–489. https://doi.org/10.1016/j.trc.2019.03.027

Lee, Z. J., Chang, D., Jin, C., Lee, G. S., Lee, R., Lee, T., & Low, S. H. (2018). Large-scale adaptive electric vehicle charging. *2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*. https://doi.org/10.1109/smartgridcomm.2018.8587550

Li, J., Sun, X., Liu, Q., Zheng, W., Liu, H., & Stankovic, J. A. (2018). Planning Electric Vehicle Charging stations based on user charging behavior. *2018 IEEE/ACM Third International Conference on Internet-of-Things Design and Implementation (IoTDI)*. https://doi.org/10.1109/iotdi.2018.00030

Lutsey, N., Grant, M., Wappelhorst, S., & Zhou, H. (2018, May 15). *New study shows where the auto industry is primed for the transition to electric vehicles*. International Council on Clean Transportation. https://theicct.org/new-study-shows-where-the-auto-industry-is-primed-for-the-transition-to-electric-vehicles/

Tucker, N., Cezar, G., & Alizadeh, M. (2022). Real-time electric vehicle smart charging at workplaces: A real-world case study. *2022 IEEE Power & Energy Society General Meeting (PESGM)*. https://doi.org/10.1109/pesgm48719.2022.9917194

U.S. Energy Information Administration. (2023). *California State Profile Analysis*. EIA. https://www.eia.gov/state/analysis.php?sid=CA#:~:text=In%202022%2C%20nonhydroelectric%20renewable%20resources,from%20one%20industrial%20cogeneration%20plant.

U.S. Environmental Protection Agency. (2023). *Sources of Greenhouse Gas Emissions and Removal*. Greenhouse Gas Emissions. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

WattTime. (2023). *Get The Data*. WattTime Data. https://www.watttime.org/get-the-data/

Will, C., Lehmann, N., Baumgartner, N., Feurer, S., Jochem, P., & Fichtner, W. (2022). Consumer understanding and evaluation of carbon-neutral electric vehicle charging services. *Applied Energy*, *313*, 118799. https://doi.org/10.1016/j.apenergy.2022.118799

Xiong, Y., Wang, B., Chu, C., & Gadh, R. (2018). Vehicle Grid integration for demand response with mixture user model and decentralized optimization. *Applied Energy*, *231*, 481–493. https://doi.org/10.1016/j.apenergy.2018.09.139

Xu, L., Yilmaz, H. Ü., Wang, Z., Poganietz, W.-R., & Jochem, P. (2020). Greenhouse gas emissions of electric vehicles in Europe considering different charging strategies. *Transportation Research Part D: Transport and Environment*, *87*, 102534. https://doi.org/10.1016/j.trd.2020.102534