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Facilitating Data-Driven Policy in the Electric Vehicle Market: Introducing the Caret® Suite

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Executive Summary

Electric vehicles (EVs) are an important solution to decarbonize light-duty transportation and a key focus of policymakers. As such, federal and state governments in the United States have already invested billions of dollars implementing a variety of different policies to spur EV diffusion, build up EV charging networks, and generally cultivate the EV ecosystem. However, policymakers face an uphill challenge in the transition to vehicle electrification, and governments lack comprehensive tools to guide and evaluate their policy decisions, especially in the long-term. We introduce an interconnected suite of software tools, Caret®, that leverages sociotechnical transitions science, decision-making analytical methods, and a modern "big data" approach to better address the complexity of EV barriers and optimize policymaking. Caret® balances the important policy goals of ensuring a smooth, timely, and equitable transition to EVs while facilitating the governmental duty to effectively allocate public funds. The transition to electric mobility can significantly reduce greenhouse gas (GHG) emissions and mitigate the impact of climate change through decarbonization, but it requires integrating data, data analysis, and software to optimize charging infrastructure, manage the impact of EV charging on the grid, and improve the EV owner experience. With the right data and software tools, stakeholders can make informed decisions, develop effective strategies, and accelerate the equitable adoption of electric mobility.

Keywords: data acquisition, electric vehicle, electric vehicle supply equipment, policy, prediction

1 Introduction to Caret®

Because the ongoing EV market transition must proceed rapidly to effectively mitigate the detrimental effects of continued reliance on internal combustion engine vehicles, policymakers do not have the luxury of following the "set it, forget it, and study it later" paradigm of the past. At the same time, the cost (in public funds) of governmental efforts to accelerate the EV market transition (e.g., through vehicle incentive policies and infrastructure subsidies) is significant (rising into billions of dollars). These efforts would be best served by a comprehensive, data-backed approach to policymaking that has been developed specifically to optimally address this process. To that end, we introduce the Caret® suite, a software platform that was developed by the Center for Sustainable Energy® (CSE) as an exemplar of this need, aiming to facilitate a practical and effective solution to the pressing need for accelerated EV adoption. Caret® weaves together three software tools that address the interconnected nexus of sociotechnical actors in the EV transition: the Caret® EV Planner, the Caret® EV Infrastructure Planner, and the Caret® EV Charging Knowledgebase. Each of these tools is described below, while Fig. 1 provides a schematic representation of how they work together.

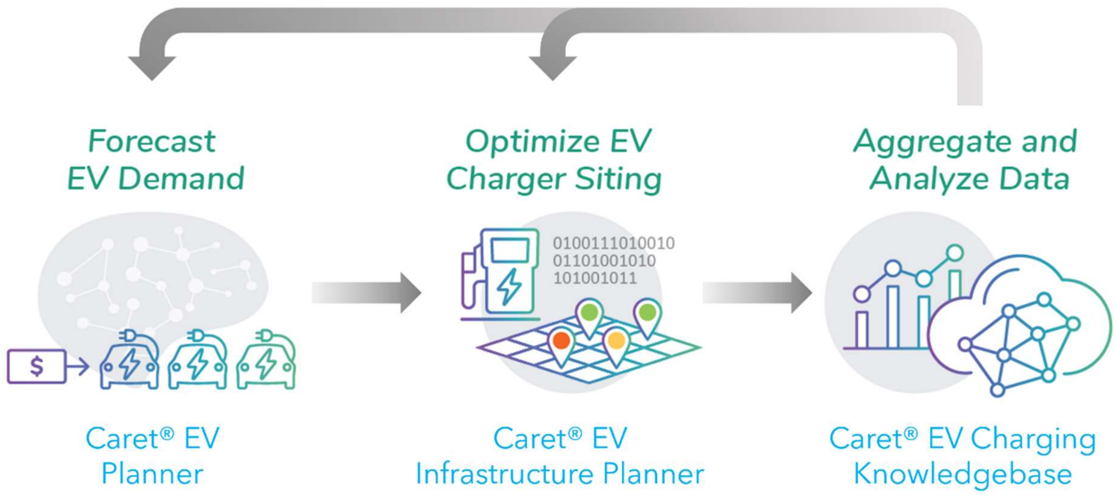

Figure 1: High-level process flow for the Caret® suite. Each tool can be used individually, but they also comprise a circular ecosystem in which EV fleet forecasts from the Caret® EV Planner inform the optimized siting of chargers by the Caret® EV Infrastructure Planner, utilization data from deployed chargers is aggregated by the Caret® EV Charging Knowledgebase, and analyses of those data feed back to the other tools to refine and improve their performance.

2 The Caret® EV Planner

2.1 Overview

The Caret® EV Planner (Caret®-EV) is an EV incentive policy modeling and forecasting platform for the light-duty transportation sector. It incorporates sociotechnical science [1][2][3] and the mathematics of diffusion of innovations [4][5], along with a large pool of real-world data, to predict the impact on EV adoption caused by a specified incentive policy or combination of policies. Policymakers are empowered to comprehensively and interactively evaluate the potential short-term (within a few years) and long-term (decades into the future) impacts of different policy proposals in real-time; in essence, Caret®-EV provides the capability to take EV policies for a test drive and make data-driven choices to identify an optimum configuration. It can be used to customize a mix of incentives that will accelerate EV adoption, deliver the necessary charging infrastructure, and reduce GHG emissions at the lowest cost and/or in the shortest time.

2.2 Sociotechnical Transitions

The science of sociotechnical transitions directs that each sociotechnical barrier should be addressed by a holistic and comprehensive market intervention/policy to accelerate the diffusion of a technology. The current EV market would be classified as a "sociotechnical niche"; that is, a new technology in its initial stage of transition to becoming the dominant actor in the market [6]. In order to achieve the accelerated adoption of EVs required to meet GHG emissions reduction goals, stakeholder expectations must be aligned and the interconnected nexus of sociotechnical barriers inhibiting EV diffusion must be addressed in a comprehensive manner [3][7]. While these interconnected barriers form a web, the primary barriers inhibiting EV diffusion are price, range, charging infrastructure, and consumer awareness and acceptance [3][8][9]. To ensure that the EV market achieves the accelerated growth required to meet the GHG emissions goals, it is necessary to set complementary and clear policy signals that allow the market to overcome all of the individual sociotechnical barriers. In the Caret®-EV model, the policy signals come in the form of incentives that are combined to target the barriers that must be overcome [10].

2.3 Diffusion of Innovations

The empirical concept of diffusion of innovations provides a framework for describing the characteristics of the adoption and spread of new technology [1][2][4][5][11]. The normal diffusion of a new technology is rooted in personality traits and other factors (such as level of knowledge or exposure to the new technology) that make each individual more or less likely to adopt it. It is driven by communication within social networks that acts to encourage adoption by more individuals over time. The overall distribution of these individual traits in a population is determinant of the rate of adoption in that population.

The rate at which a new technology moves up the sigmoidal (S-shaped) market share curve (i.e., the adoption rate) can be accelerated by encouraging (e.g., via incentives) the adoption of the technology among successive consumer groups (see Fig. 2). Prioritizing resource expenditures to encourage adoption early in the diffusion process (on the lower, more linear branch of the S-curve) has the largest effect on accelerating the overall adoption rate by causing the growth in market share to reach the steep (exponential) central part of the S-curve faster. The most effective incentive policy acts to accelerate the EV adoption rate as rapidly as possible and as early as possible, to reach the steep part of the S-curve as soon as possible.

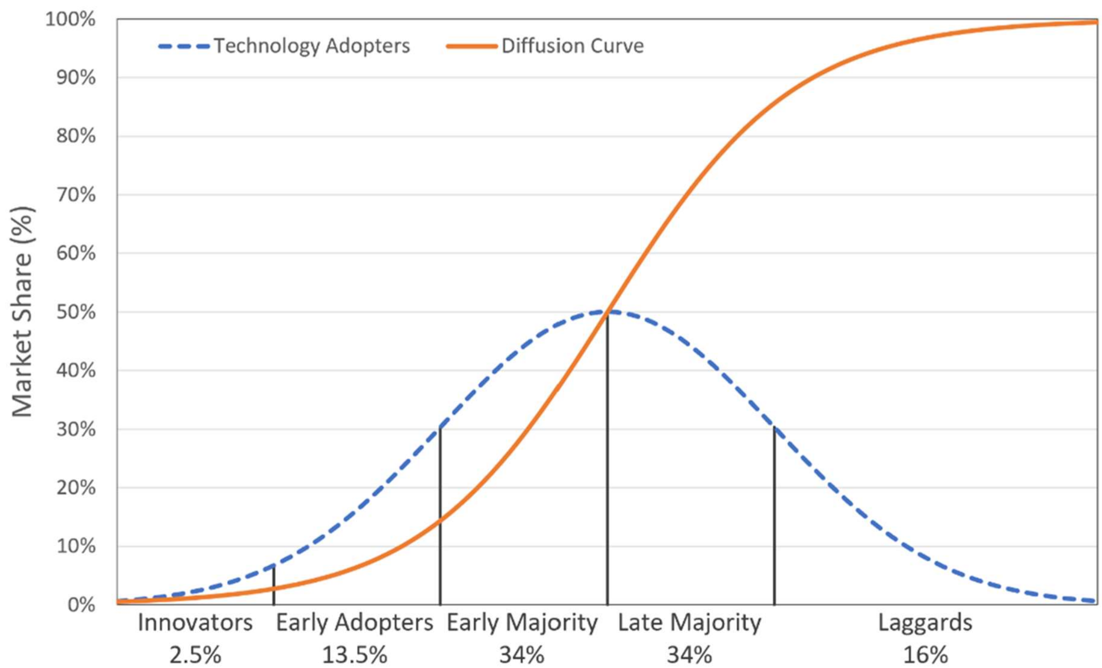

Figure 2: As successive groups of consumers adopt a new technology (dashed blue "bell-shaped" curve), its market share (solid orange "S-shaped" curve) grows and eventually reaches the saturation level. Categories of consumer groups are indicated (vertical lines) and labeled according to their willingness to adopt a new technology (high to low from left to right) and percentage of the total population represented by each group. (Figure design after [4].)

Some individuals in the final consumer group (the "laggards") might be especially reluctant to adopt the new technology on the same time scale as others; an "extra push" (e.g., legislative action such as a zero-emission vehicle mandate) might be required to convert them. The upper portion of the S-curve gradually approaches 100% but will only reach it when the last laggard has adopted – this is why setting incentive policy goals based on reaching 100% market share can be unrealistic, especially when compared to more easily achievable goals such as 90% market share.

There are two primary considerations that Caret®-EV takes into account in the relationship between policy levers and the development of the EV market.

- All barriers to EV adoption are sociotechnical in nature (see above).

- Price is the principal barrier to EV adoption, and the main policy influence that the government can address.

An accurate and reliable forecast of the optimal diffusion of EVs in the light-duty vehicle market requires a methodology that accounts for all of the sociotechnical barriers with a balanced policy that combines incentives directed at each barrier.

2.4 Modeling EV Adoption

Modeling the long-term adoption of new technologies, such as EVs, is difficult since past data are not likely to reflect future market conditions as the technology becomes better known and accepted. Common approaches rely on consumer choice models and estimates of price elasticities and cross-price elasticities of demand [12][13][14][15]. These models rely solely on historical data, assume that consumers are highly rational about vehicle adoption, and assume that adoption depends only on product attributes (e.g., cost). As such, these approaches are only useful for very near-term projections, when both the state of the technology and consumer acceptance will be similar to the recent past. To successfully model the adoption of a new technology spanning the entire market transformation (which typically lasts several decades) requires mathematical approaches that go beyond short-term consumer choice or price elasticity models [16][17]. The ideal approach to modeling EV adoption is not only grounded in data but also accounts for the sociotechnical barriers to adoption, captures the dynamic forces inherent in technology diffusion, and allows for modeling a variety of potential policy interventions directed at different stakeholders.

To model the EV market transformation, Caret®-EV implements a logistic growth function of adoption over time, as observed in a variety of other technologies [4][11], parameterized by a Bass diffusion model customized to the EV market. At its foundation, the model is calibrated using 5 years of data from 16 EV incentive programs in the United States and other countries around the world, relating incentive dollars to the corresponding increase in EV sales. By using EV market data and regression techniques to model sales over time, this approach gives a more complete picture of the relationship between incentive levels, time, and EV adoption than could be provided using price elasticity or choice models over the same long timeframe. Finally, Caret®-EV incorporates a learning algorithm, in which model predictions are replaced by data as they become available, which allows the projections to stay on track with reality and fine-tunes the model predictions over time.

Primary outputs of Caret®-EV include:

- The annual total costs of the EV incentive policy, as well as totals by policy component (e.g., new EV incentives, used EV incentives, income-qualified add-on incentives, etc).
- Annual EV market share and number of EVs purchased (both incentivized and not incentivized; for example, see Fig. 3).
- Annual reduction in light-duty transportation sector GHG emissions.

Because of the data-rich nature of the modeling process, numerous additional outputs can be obtained, such as annual fleet composition and age distributions, co-benefits and return-on-investment, electricity and gasoline consumption, and so on.

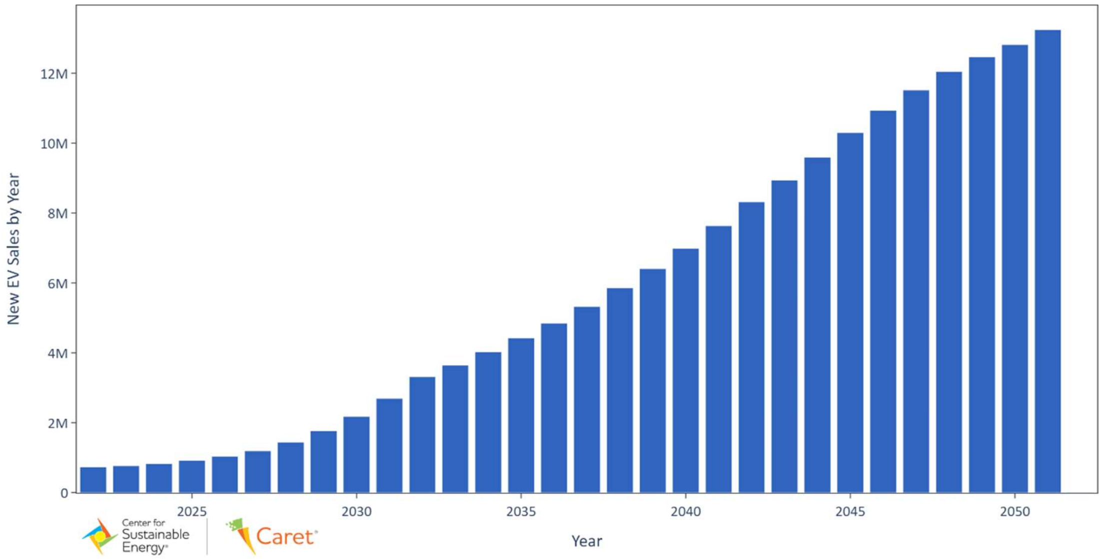

Figure 3: Sample new EV sales projections from the Caret® EV Planner for the U.S. under the influence of the Inflation Reduction Act of 2022 (IRA) rebates. Annual sales continue to increase rapidly even after the IRA rebates end at the start of 2033 because the early investment in the EV market transformation shifted the market onto a more accelerated diffusion pathway.

3 The Caret® EV Infrastructure Planner

3.1 Overview

The lack of public charging infrastructure is among the main barriers to EV adoption and can be addressed through government and private investments. Application of these funds will have to fulfill the needs of current and expected EV drivers as well as encourage others to adopt EVs. To accomplish both of these goals efficiently requires data-driven planning and objective analysis that is network- and vendor-neutral. The Caret® EV Infrastructure Planner (Caret®-EVI) uses geospatial mapping and multi-criteria decision analysis (specifically, the Technique for Order of Preference by Similarity to Ideal Solution, or TOPSIS, algorithm – see below) to create an EV charger installation plan that reflects prioritized goals based on a holistic view of multiple simultaneous data layers.

3.2 Multi-Criteria Decision-Making

The TOPSIS algorithm, introduced in 1981, aids in the selection of the best alternative from a set of available options based on multiple criteria [18][19][20]. It operates by calculating the relative closeness of each alternative to an ideal solution, which is determined by the most desirable values for all criteria. TOPSIS then ranks the alternatives based on their Euclidean distances from both the ideal and negative-ideal solutions (i.e., the solution with the least desirable values for all criteria), and selects the alternative with the shortest distance to the ideal solution and the longest distance to the negative-ideal solution as the best choice.

As applied in Caret®-EVI, the ideal solution is defined for a specified geographic area (a map grid cell) based on a customized weighting system that describes the relative importance of the presence (or absence) of specific data features in and/or around (at specified radii) that map grid cell. For example, a weighting system might include data features such as the median income of residents, presence of convenience stores and shopping centers, absence of existing public charging infrastructure, and proximity to major roads or intersections, with each feature given a numeric weighting of relative importance in the ideal solution. Numeric features (such as population, income, or proximity to a geographic feature) are additionally assigned a desired direction toward or away from the ideal solution; for example, higher or lower median income in a map grid cell could each be considered more ideal in different weighting systems. Caret®-EVI then identifies the map grid cell closest to the ideal solution, and ranks all other grid cells by distance away from the ideal solution. Fig. 4 shows an example of a Caret®-EVI map.

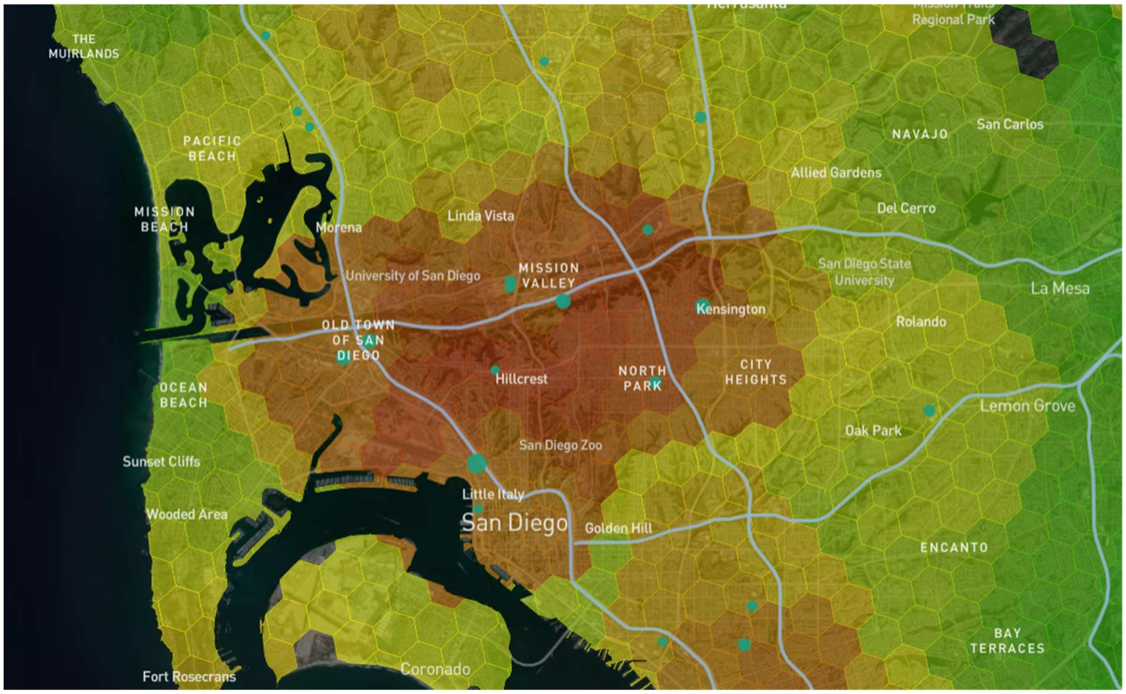

Figure 4: Sample Caret® EVI Planner map for the area around San Diego, California, showing the most suitable (green) to least suitable (red) grid cells for optimum siting of new direct current fast chargers (DCFC) based on a simple weighting system. The map also shows the location of the designated Alternative Fuel Corridor (AFC) highways (light blue lines) and the location of existing DCFC (green circles). The size of the charger markers is proportional to the number of chargers at a given site. The simple weighting system illustrated here was designed to avoid placing new chargers close to concentrations of existing chargers; hence, the least suitable (red) grid cells correspond to the areas with the largest numbers of currently existing chargers.

3.3 Operational Workflow

The general process of using Caret®-EVI is as follows:

1. **Stakeholders collaboratively determine a weighting system** to determine site suitability for charger installation based on data features important to meeting goals.
2. **Visualize the region of interest** with satellite imagery and relevant data layer(s), such as traffic density, health and environmental risk factors, existing chargers, etc.
3. **Apply geographic filters** as desired to isolate data-defined regions of interest within a broader locale (e.g., only include regions that are located in a disadvantaged community or within 1-mile driving distance of an Alternative Fuel Corridor).
4. **Examine the site suitability rankings** and adjust the weighting scheme as needed to refine the achievement of goals. This yields the first output product: a rank-ordered list of optimum charger installation sites in a grid of hexagonal cells overlaid on the selected region.
5. **Simulate the installation of a selected type and number of chargers.** The number of "installed" chargers can be based on a budget for EV infrastructure or on a customized EV fleet size forecast made by Caret®-EV. The simulation is accomplished by adding a charger at the highest ranked site, recalculating the suitability score of all grid cells to account for the impact of the new charger, then adding a charger at the new highest ranked site (which might still be the same site as in the previous iteration), recalculating the suitability score of all grid cells, and so on. This iterative feedback process continues until all chargers are installed. This yields the second output product: an optimized order-of-installation list including the recommended number of chargers at each site.

4 The Caret® EV Charging Knowledgebase

4.1 Overview

As the rate of EV adoption in the United States accelerates, there will be a need for more than 2 million public and workplace Level-2 and DCFC EV charging ports by 2030 [21][22]. If only 50% of these are deployed as networked "smart" chargers, then they could generate more than 40 terabytes per day of raw utilization data describing the evolving real-world behavior of EV drivers and ongoing diffusion of EVs. The Caret® EV Charging Knowledgebase (Caret®-KB) was designed to store, aggregate, process, and analyze that wealth of data.

4.2 Description and Usage

The Caret®-KB back-end securely aggregates anonymized charger utilization data in a hierarchy of vendor- and program-specific silos in a scalable cloud-based data lake securely hosted on Amazon Web Services. Its front-end dashboard provides search and filtering functionality, as well as automatic and customizable calculation of summary statistics, key performance indicators, and other data-backed insights to better understand how, when, and where EV charging happens (see Fig. 5). Data-driven decisions can then prioritize future charging investments as consumer behavior and technology change over time. Insights derived from these data feed back to the other Caret® tools to refine their performance; for example, by better linking the numbers and types of chargers required to service an EV fleet in different locales under a variety of driving conditions in Caret®-EV, and by providing additional data features to factor into determinations of the optimum siting of new chargers in Caret®-EVI.

Caret®-KB can help government agencies at all levels from municipal to national, power utilities, EV service providers, and business enterprises fine-tune their charger deployment and charging support strategies. It provides objective answers to questions like:

- What is the load profile for different charger location types, such as convenience stores, parking facilities, workplaces, and multi-unit dwellings?
- How much energy does EV charging consume per month in a specified locale?
- How reliable are Level-2 and DCFC charging stations?
- How does weather impact charger usage?
- What GHG emissions reduction is being achieved?

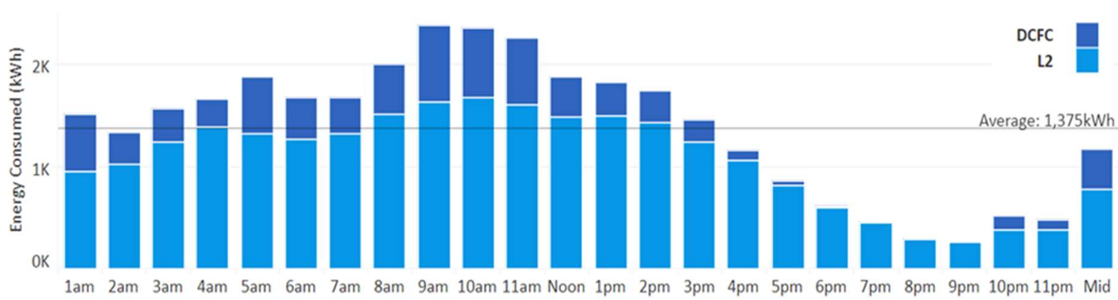

Figure 5: Example of a Caret® EV Charging Knowledgebase dashboard metric showing variable energy consumption throughout the day for selected public EV chargers in California. Hourly energy consumption values for DCFC and Level-2 (L2) chargers are correlated during the day, with consumption for both types of chargers increasing and decreasing approximately in tandem. Total consumption (DCFC plus L2) peaks between 9am and 11am. A continual decline in energy consumption is observed after 11am until 9pm, with consumption for only L2 chargers observable between 6pm and 9pm. The overall daily average consumption level is 1,375 kWh, with consistent consumption patterns above average between 3am and 3pm, and (mostly) below average at other times. Throughout the day, L2 chargers manifest about 80% or more of the total hourly energy consumption. Data-backed metrics like this can be used to infer real-world EV driver usage patterns and inform factors such as optimum charger placement and time-variable electricity grid demand needs.

5 Conclusions

The March 2023 report from the United Nations Intergovernmental Panel on Climate Change [23] presents this dire warning:

> *"Climate change is a threat to human well-being and planetary health (very high confidence). There is a rapidly closing window of opportunity to secure a liveable and sustainable future for all (very high confidence)… The choices and actions implemented in this decade will have impacts now and for thousands of years (high confidence)."*

The accumulation of carbon dioxide (CO_2) in Earth's atmosphere is the primary driver contributing to climate change [24]. Although global CO_2 emissions from human sources did not immediately rebound to their pre-pandemic levels following 2020, they had already returned to their historic growth trend by the end of 2021, with the largest growth from the transportation sector [25][26]. In 2021, the transportation sector in the United States contributed 38% of the nation's annual CO_2 emissions, the largest single source. Of that, 58% of the CO_2 emissions originated from light-duty personal vehicles (with another 25% coming from commercial trucks and buses) [27]. Globally, "on road" transportation accounted for almost 80% of CO_2 emissions [25].

The transformation of the transportation sector towards electric mobility presents a significant opportunity to reduce GHG emissions and mitigate the impact of climate change through decarbonization. However, realizing this potential will require the integration of data, data analysis, and software. While the EV market is poised for rapid growth in the coming years, it is crucial that we take advantage of the wealth of data that are (and will be) available, and develop and utilize data-backed software tools to further facilitate this transformation. With the right data and software in hand, we can optimize charging infrastructure, more effectively manage the impact of EV charging on the electric grid, and improve the user experience for EV owners. These tools will allow stakeholders in the EV market to make informed decisions, develop effective strategies, and accelerate the equitable adoption of electric mobility. The Caret® software suite developed by CSE represents one such solution contributing towards a sustainable future.

Acknowledgments

Center for Sustainable Energy® is a national nonprofit that accelerates adoption of clean transportation and distributed energy through effective and equitable program design and administration. Governments, utilities and the private sector trust CSE for its data-driven and software-enabled approach, deep domain expertise, and customer-focused team. CSE's fee-for-service business model frees it from the influence of shareholders, members, and donors, and ensures its independence.

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Presenter Biography

Donald W. Hoard is the Director of Data Science, Analytics, and Quantitative Research at the Center for Sustainable Energy®. He has a Ph.D. in astronomy from the University of Washington and worked as a NASA technical support scientist, science educator, and researcher in observational astrophysics for 20 years before transitioning into applied data science, where he focused on analyzing and understanding user interactions with software and technology. He currently manages the overall Caret® project as well as directly contributing to its development.