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Energy Research and Development Division

FINAL PROJECT REPORT

DEVINE: Demonstration of Vehicle-Grid Integration in Non-Residential Environments

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PREPARED BY:

Primary Authors:
Gustavo Vianna Cezar, Siobhan Powell

SLAC National Accelerator Laboratory
2575 Sand Hill Road, Menlo Park, California, 94025
650-926-3300
https://www6.slac.stanford.edu

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PREPARED FOR:
California Energy Commission

Jeffrey Sunquist
Project Manager

Reynaldo Gonzalez
Branch Manager
Energy Systems Research Branch

Jonah Steinbuck, Ph.D.
Director
ENERGY RESEARCH AND DEVELOPMENT DIVISION

Drew Bohan
Executive Director

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PREFACE

The California Energy Commission's (CEC) Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission and distribution and transportation.

In 2012, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solutions, foster regional innovation and bring ideas from the lab to the marketplace. The CEC and the state's three largest investor-owned utilities—Pacific Gas and Electric Company, San Diego Gas & Electric Company and Southern California Edison Company—were selected to administer the EPIC funds and advance novel technologies, tools, and strategies that provide benefits to their electric ratepayers.

The CEC is committed to ensuring public participation in its research and development programs that promote greater reliability, lower costs, and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emission in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and finally with clean, conventional electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently.

DEVINE: Demonstration of Vehicle-Grid Integration in Non-Residential Environments is the final report for the DEVINE: Demonstration of Vehicle-Grid Integration in Non-Residential Environments project (EPC-17-020) conducted by SLAC National Accelerator Laboratory. The information from this project contributes to the Energy Research and Development Division's EPIC Program.

For more information about the Energy Research and Development Division, please visit the CEC's research website (www.energy.ca.gov/research/) or contact the CEC at ERDD@energy.ca.gov.

ABSTRACT

Transportation is a key contributor of greenhouse gas emissions, recognized as one of the main factors contributing to climate change. For California to reach 100 percent zero-emission new passenger cars and trucks sales by 2035, per Executive Order N-79-20, understanding the effects of increased adoption of electric vehicles on the electrical system and the infrastructure required to support them is paramount to ensuring a smooth transition from internal combustion engine vehicles to electric vehicles. This project researched, developed, and demonstrated vehicle-grid integration in non-residential facilities; quantified the effects of electric vehicle charging on the grid, including its flexibility and revenue streams; and developed strategies to manage electric vehicle load to minimize the impact on the distribution system while minimizing customer utility costs. Finally, the project developed a method to evaluate emission impacts of charging electric vehicles given the current, and future, mix of bulk generation resources.

The project focused its analysis on passenger vehicles at workplaces and on a university campus electric bus fleet. At the workplace sites selected for the project and using historical data from charging sessions, the project demonstrated that applying smart charging strategies can achieve a 25 percent cost reduction and a 76 percent reduction in peak electricity demand, as well as add 66 percent more electric vehicles to the grid without requiring infrastructure upgrades while simultaneously guaranteeing that electric vehicle energy requirements are satisfied.

The algorithm used for real-time operation, which did not have information about the future, delivered 80 percent of the theoretical total energy required by electric vehicles, with a total savings of 30 percent, and a reduction in the maximum demand of 40 percent. For the electric bus fleet, smart charging obtained up to 88 percent in cost savings, with a 57 percent peak demand reduction and 52 percent emissions reduction. Finally, a transformer thermal data-driven model was developed and resulted in a 9.8 percent root mean squared error of the mean value.

Keywords: Electric vehicles, smart charging, emissions, electric grid impacts, software, controls

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EXECUTIVE SUMMARY

Background

Concern for the environment due to climate change and its consequences to society have driven significant growth of electric vehicles in California. Emissions from the transportation sector account for approximately 41 percent of total greenhouse gas emissions in the state. The transition from internal combustion engine vehicles to electric vehicles can drastically reduce overall emissions from this sector.

This transition, however, requires electric utilities and system operators to rethink how they plan and operate the electric grid. Electric vehicles present a unique challenge since they couple the transportation and electricity sectors. This means that an electric vehicle can appear as a load at different points in the network when charging a vehicle in different locations. Moreover, a standard passenger electric vehicle consumes a considerable amount of energy, similar to what the average American home uses each day. The peak power to supply the required energy, using a standard Level 2 charger, can more than double the typical peak electricity demand of a standard single-family house in California. As a result, electric vehicles challenge the electric grid by threatening to overload the distribution network, cause accelerated aging of assets like transformers, force unplanned upgrades of grid infrastructure, and lead to system failures and outages.

Seamless integration of electric vehicles with the grid can help achieve California's SB 100 goal of 100 percent zero-carbon electricity sales by 2045 while supporting reliability and minimizing costs to ratepayers. Achieving this integration requires an understanding of the timing and location of charging sessions; the local grid infrastructure power hosting capacity; the ability to properly manage electric vehicle load using smart charging; and customer needs.

Project Purpose

The purpose of this project was to research, develop, and demonstrate vehicle-grid integration in non-residential sites to quantify the effects of electric vehicle charging on the grid, its flexibility, and revenue streams, and to develop strategies to manage electric vehicle load to minimize its effect on the distribution system while also minimizing customer utility costs.

In this project, the research team developed a suite of analysis and software tools based on real-world data to measure and demonstrate the effects of electric vehicle charging on the distribution network. In particular, this project explored the following electric vehicle impacts, individually and in combination: electricity cost under different rate structures, transformer aging, phase imbalance, harmonics, and emissions. The project further proposed and demonstrated strategies and best practices on how to mitigate these impacts through smart charging controls and fleet scheduling, while maximizing customer benefits to support widespread adoption of electric vehicles in California. Moreover, the team developed and tested software to communicate directly with different electric vehicle supply equipment, onboard charge controllers, and site operators.

Project Approach

The project team conducted the research in three phases: data collection, algorithms and analysis, and software field testing. In the data collection phase, a summary of all the data available, and their characteristics, was conducted for the three project sites: Stanford University campus, Google campus, and SLAC National Accelerator Laboratory campus. Historical data was collected and pre-processed during this phase. Moreover, characteristics of the real-time data available at each site was evaluated to inform design of the algorithms and the software to ingest, process, and store the data. Finally, during this phase additional sensors were installed to capture data of grid assets that did not exist before but were required to evaluate the effects of electric vehicle charging.

During the algorithms and analysis phase, various algorithms were developed based on the different electricity rate structures and unique characteristics of each site (i.e., employee charging for Google and SLAC) and fleet charging (Stanford University). These algorithms were developed to minimize the impact of electric vehicles on the distribution grid assets while reducing the cost of charging and evaluating revenue streams from other electricity markets such as demand response programs. Additionally, a model for the emissions was developed based on the 2019 mix and projected 2030 mix of generating resources that supply electricity to California. This model was then used to quantify the emissions impact of electric vehicle charging with and without the developed algorithms. Moreover, an analysis was performed on the impacts in transformer aging due to electric vehicle charging. Finally, in this phase, simulations of distribution systems were performed using the GridLAB-D software to evaluate the large-scale effect of electric vehicles on the system.

In the software field testing phase, the software infrastructure was developed to control and operate the charging stations in the field and demonstrate the capabilities of the proposed algorithms. However, given the COVID-19 pandemic, the three sites selected to perform the experiments were closed following local and state health authorities' guidelines. Nonetheless, a number of charging stations remained online allowing the software components such as communication and controls to be tested and validated. An experiment was also conducted at the Grid Integration Systems and Mobility Laboratory at SLAC National Accelerator Laboratory where the charging of an electric vehicle was coordinated with solar and energy storage systems to reduce power consumption from the grid.

The project involved coordination with experts from utilities, planning and operations, industry, facility managers, transportation service organizations, charging station and electric vehicle manufacturers, academics, and the project's technical advisory committee.

Project Results

The outcomes of the project were broken into four main sections: Stanford Electric Vehicle Bus Fleet, Google campus, SLAC campus, and electric vehicles at scale.

Stanford EV Bus Fleet

The team developed an optimization method that jointly scheduled the charging and assigned buses to routes while reducing the electricity cost and maximizing use of onsite solar. The project team compared the performance of the status quo (pre-COVID, no optimization), with the optimization with and without onsite solar. The daily electricity cost for the status quo was approximately $715.10. Optimizing the operation of the buses around time-of-use (TOU) rates and demand charges reduced the daily electricity cost by 54 percent, and when considering charging with onsite solar, by 87 percent. Additionally, the peak power to charge the buses when considering onsite solar was reduced by nearly 60 percent, from 350 kilowatts to 150 kilowatts. During COVID, the buses schedules were drastically reduced. Among the bus lines that were able to be controlled and were still in service, the results obtained showed that by simply scheduling charging at off-peak hours and preventing the top-off behavior to reach 100 percent state of charge, the fleet was able to reduce the weekly electricity cost by close to 47 percent. Without onsite solar, and with 2019 levels of emissions from fossil fuel generation, the controlled profile would not necessarily improve the overall emissions compared to the uncontrolled profile.

Google

The smart charging algorithms developed for Google campus included different rate structures and participation in demand response programs. The yearly cost savings obtained through smart charging including participation in demand response varied between 22 percent and 26 percent. Additionally, for such sites, an evaluation of the maximum load shed capacity was calculated to inform potential participation in other grid services. The maximum load shed capacity occurs between 9:00 a.m. and 11:00 a.m. with a maximum amount of load shed ranging from 71.92 kilowatts to 100.78 kilowatts, or 54 percent to 76 percent of the monthly uncontrolled maximum demand. From a transformer impact and aging standpoint, the project found that the transformer at the Google site could support fewer than 150 vehicles per day with uncontrolled charging, but nearly 250 vehicles with the best control schemes. Time-of-use rate schedules did not encourage any improvement. Capping the total demand at each site gave a modest improvement. The greatest number of vehicles supported, however, came from peak minimization, rates with demand charges, or the direct minimization for transformer aging. Finally, a smart charging algorithm was implemented for real-time operation using only the information provided by the charging stations at each time stamp, without knowledge of state of charge and future arrivals and departures. The results show that the algorithm could guarantee delivery a minimum of 81 percent of the total energy required by the vehicles with a 19 percent reduction in energy cost and 35 percent reduction in demand charge cost. From an emissions standpoint, there is more variation by day than by the load shapes of different smart charging strategies. This behavior is likely due to the flat median average and marginal emissions profile shapes during workplace charging hours.

SLAC

From the transformer temperature sensor installed, the team built a data-driven transformer thermal model and validated it using the site's electric vehicle charging data. The proposed model had a 9.8 percent root mean square error of the mean value and a 4.8 percent error of the maximum value, when using a test dataset. Finally, testing at the Grid Integration Systems and Mobility lab showed that by properly coordinating electric vehicle charging with solar and energy storage systems, a near net-zero power profile could be obtained to buffer the electric vehicle load from the grid.

EVs at Scale

Two analyses were performed to evaluate potential impacts of EV charging at scale focused on 1) phase imbalance and harmonics impact and 2) emissions.

The phase imbalance analysis showed that if the system was properly designed, with the neutral conductor the same size as the phase conductors, the additional current flowing in the neutral conductor due to electric vehicle charging generally would not present a problem from the system perspective. In the extreme cases, the limiting factor would be the capacity of grid assets, in particular transformers and conductors. From the harmonics perspective, an electric vehicle charging at a Level 2 station had all the current harmonics under 2 percent of the fundamental current. Even when considering the worst-case scenario where all electric vehicles would charge at the same time and phase diversity would be equal to zero, grid assets capacity would be the limiting factor.

The emissions analysis explored the electric grid generating mix of 2019 and 2030 by assuming 100 percent of personal vehicles are electric vehicles, including the additional renewable generation and the fossil generating plants that are scheduled to be decommissioned by then. The analysis investigated the questions of "How do non-residential charging options impact emissions, and how do scenarios with more or less non-residential charging compare?" and "Can emissions be included as objectives of the control to reduce the impacts?"

The project analyzed four scenarios of access to residential and non-residential charging options, with residential access ranging from low to high to universal. The key results from this analysis were the following: 1) with 2019 levels of emissions from fossil fuel generation, daytime charging would have led to higher emissions than evening charging; 2) daytime charging will be lower emission than evening charging by 2030, and non-residential infrastructure to support daytime charging should be deployed to support this type of charging; and 3) controlled charging based on emissions is challenging since there is a conflicting objective between the distribution and transmission systems. Spreading the electric vehicle charging load across the day including the late afternoon and early evening hours benefits the distribution system. Concentrating the electric vehicle charging load in the middle of the day when renewable energy, primarily from solar, is abundant and preventing charging during the critical ramp-up hours during late afternoon and early evening benefits the transmission system.

Technology/Knowledge/Market Transfer Activities

Outreach Activities, Knowledge Gained, and Feedback

The methodology developed in this project generated peer reviewed publications and presentations in conferences and workshops to academia, industry, state and federal agencies. The team received multiple rounds of feedback from technical advisory committee members, academics and industry. The main goals of the outreach activities to influence the design of the project were to:

- Get utilities involved to help understand concerns about EV loads and to explore charging strategies to protect infrastructure, reduce costs, and reduce emissions.
- Engage with other CEC project teams working in the same space and with vehicle manufacturers to implement hardware and software support for remotely managed EV charging.
- Engage with fleet operations team to understand the EV charging requirements to minimize potential impacts to routine fleet operations and improve service reliability.
- Understand user preferences to support the individual needs of EV operators.
- Engage with potential collaborators in industry and academia to integrate system level information across EVSE and distribution assets.

Intended Users

The team identified four main users that can leverage the outcomes of this work:

- **Electric utilities** can utilize the analytics, algorithms and results developed to design rate structures to better incentivize EV adoption while reducing emissions and impacts into the distribution system.
- **Industry:** EVSE companies can increase revenue by implementing smart charging to their EVSE network. Campus managers and companies such as transformer manufacturers can also use the outcomes of this project to better understand the impact of the EV load, how they can affect the overall lifetime of these systems and improve the design of new equipment.
- **Federal and state agencies** can use the results of this program to inform investments, research priorities, and policies needed to increase adoption of EVs and seamlessly integrate them with the electrical infrastructure.
- **Academia:** The results from this project can be used as foundation for new models and algorithms and innovators can generalize the application of such models and algorithms beyond what was accomplished in this project.

Continued Work and Technology Transfer

The methodology developed in this project will be incorporated into initiatives to reduce SLAC and Stanford campuses' overall emissions, in particular from transportation, and to increase resilience and reliability of power. This initiative includes exploration of integrating building controls with EVSEs, solar, and on-site generators across campuses.

Stanford's transportation team is continuing to support the analysis and development of solutions to their EV fleet including decommissioning remaining diesel buses, upgrading infrastructure, and identifying resources needed to operate the system during grid outages.

A collaboration between SLAC, Stanford and Prolec-GE on distribution transformers and how to model the impacts of EVs is underway. Specifications are being developed based on the results obtained in this project to properly test, measure, quantify and develop models that can be transferable to existing transformers.

Benefits to California

Electricity Cost Reduction

Daytime charging, in particular workplace charging, has many characteristics that make it well suited for smart charging strategies. These charging segments have high flexibility, predictable arrival and departure times, and historical data. Electric vehicle supply equipment is aggregated under one connection point to the grid and is typically from the same vendor within a site. Leveraging these particular characteristics enables implementation of different strategies to benefit the site host as well as the overall grid and ratepayers. Smart charging can be used to provide grid services such as participation in demand response programs or the ancillary services market.

Additionally, smart charging can be used to defer investments in infrastructure upgrades that would ultimately lead to an increase in electricity costs. Ensuring that grid assets are used within their capacity prevents accelerated aging, and the same infrastructure can support more electric vehicles for longer periods of time.

Moreover, users of charging infrastructure that have smart charging capabilities can generally expect lower electricity costs primarily through peak load reduction.

Finally, a lower electricity cost, driven by smart charging technologies, has the potential to enable more companies to afford the operational costs of charging infrastructure. With more charging infrastructure available to employees, a greater adoption of EVs is expected to happen which will help spur the adoption of EVs across the state.

Energy Reliability and Resiliency

Smart charging can also improve system reliability and resilience. Electric vehicle charging, in particular daytime charging, which inherently has flexibility, can be used as a flexible resource, leveraging smart charging algorithms, to ensure that over and under generation of renewable resources is properly handled to prevent outages, which can be local or, in some cases, systemwide.

When electric vehicle charging is coupled with onsite generation and energy storage systems, the reliability of the system can be greatly improved by leveraging these resources to reduce the burden on the grid through a seamless coordination. Resiliency can also be improved since these resources can operate in small microgrids. Removing load from the larger grid allows a quicker recovery.

Finally, utilities can design rate structures to leverage smart charging and shape the electric vehicle load. Given a wide adoption of smart charging, particularly daytime charging, utilities can design rates to prevent the additional demands of electric vehicles in specific hours of the day affecting the overall operation. These approaches will ultimately improve system reliability and resiliency as electric vehicle adoption grows.

Inform Policies

The results presented show the potential for charging infrastructure to improve the grid integration of EVs at deep levels of adoption. Given the current state-level goals to have higher renewable generation in the grid, timing of charging is critical. Shifting drivers from home to daytime charging improves all metrics of grid impact including ramping, use of non-fossil fuel generation, storage requirements and emissions. These results can inform policymakers in deciding which charging segments to invest to achieve the benefits of transportation electrification while minimizing grid impacts and emissions.

Moreover, to make charging controls more effective, policymakers should consider coordinating the management of grid generation and distribution impacts, and future electricity rates should better harmonize with wholesale electricity prices and could vary day by day with grid generation conditions.

CHAPTER 1: Introduction

Climate change is considered one of the biggest threats to humanity (United Nations, 2021). With the recognition that greenhouse gases (GHG) are the main cause (National Academy of Sciences, 2020), many countries around the world are trying to drastically reduce their GHG emissions to combat this change through coordinated efforts, most notably the Paris Agreement. The United States in particular is committed to cutting economy-wide emissions of GHG by 26 percent to 28 percent below 2005 levels by 2025 and to making its best efforts to reduce its emissions by 28 percent (United Nations, 2021). The main source of GHG emissions in the United States is the transportation sector (29 percent), followed closely by electricity with 25 percent (Environmental Protection Agency, 2021). Many states are pushing toward electrifying the transportation sector and relying more on cleaner electricity generation, in particular, renewable generation in both transmission and distribution systems. California is setting ambitious goals to make this transition happen.

This transition, however, requires electrical utilities and system operators to rethink how they plan and operate the grid to ensure generation meets demand. Electrical utilities were traditionally designed and operated to meet predictable demand from loads that were connected to fixed points in the network. The current scenario is drastically different. Loads are becoming smarter, with new technologies that change their behavior based on user preference, electric grid conditions, and electricity prices. Additionally, wind and solar generation, which are intrinsically intermittent, and other distributed energy resources (DER), such as energy storage systems, create new challenges for grid operators: customers are no longer only consuming electricity but also generating electricity for their own use or exporting back to the grid. Finally, the shift toward electric transportation and widespread adoption of electric vehicles (EVs), though critical to plans for achieving drastic GHG emissions reductions, creates a new set of challenges for grid operators. This new scenario is fundamentally altering the business of supplying electricity, and these changes will accelerate alongside adoption of these technologies in the coming years. This is the new energy paradigm.

Among these new energy technologies, EVs in particular present a unique challenge for grid operators since they couple the transportation and electricity sectors. This means that an EV can appear as a load in different points in the network as the driver charges at different locations. Moreover, a standard passenger EV consumes a considerable amount of energy, on average 30 kilowatt-hours (kWh) per 100 miles (DOE Fuel Economy, 2022), an amount similar to what the average American home uses each day (EIA, 2021). The demand using a standard Level 2 charger[1] is around 6.2k watts (ChargePoint, 2017), which can more than double the typical peak electricity demand of a standard single-family house in California (City of Palo Alto

[1] The Level 2 standard supports higher charging rates, but stations and cars that support it are not widely available (ChargePoint, 2017).

Utilities, 2020). As a result, EVs challenge the electric grid by threatening to overload the distribution network, cause accelerated aging of assets like transformers, force unplanned upgrades of grid infrastructure, and lead to system failures and outages (City of Palo Alto Utilities, 2020; Kevala, 2021).

However, despite these challenges, EVs bring many important benefits including reduced GHG emissions and improved local air quality and health impacts. Electrified transportation is critical to plans for deep decarbonization. Many locations around the world are setting aggressive goals to increase EV adoption, with California at the forefront. In 2012, Governor Jerry Brown issued an executive order establishing a goal of 1.5 million zero-emission vehicles in California by 2025 (California Office of Governor, 2012). In 2018, Governor Brown issued another executive order to extend this goal with a 2030 target of 5 million zero-emission vehicles (California Office of Governor, 2018). In 2020, Governor Gavin Newsom signed an executive order to ban the sale of all new gasoline-powered cars and passenger trucks by 2035 (Executive Department State of California, 2020). One of the main goals behind these efforts is to drastically reduce the emissions related to the transportation sector, which currently accounts for approximately 41 percent of California's greenhouse gas emissions (California Air Resources Board, 2021).

Better integration of EVs with the electric grid is essential for the state to reach these goals without negatively affecting the reliability and cost of power for California ratepayers. Better vehicle-grid integration will require, among many things, understanding (a) the timing of charging sessions and whether they will take place at a workplace, in public, or at a residence, (b) local grid infrastructure power hosting capacity, (c) the ability to properly manage the EV load using smart charging, and (d) customer requirements.

From a planning perspective, the timing of charging sessions (including start time, end time, and duration) dictates when to expect load to increase due to EVs. By comparing with the baseline load, without EVs, planners can understand the additional demand and allocate enough generating capacity. Moreover, knowing the timing also supports better assessment of the emissions contribution of EVs when charging from the grid. For example, if the majority of EVs charge during the day when solar generation is abundant in the grid as a whole, the average emissions per mile are considerably lower than with nighttime charging.

Knowing the charging segment where an EV will charge (workplace, public, residential) also helps planners and operators by providing information about the EV's charging flexibility and how it can be used as a resource. Flexibility is defined as the ratio between the amount of time an EV is actually charging and the amount of time the vehicle is connected to the station. On average, in the workplace segment, EVs are connected to a station between six to eight hours but their actual charging time is between three to four hours. At fast-charging public stations, meanwhile, EVs are connected for a shorter duration, less than an hour, and charge most of the time (Vianna Cezar et al., 2020). High flexibility creates opportunities to manage EV charging in ways that reduce electricity costs, defer capacity expansion, protect grid assets, and reduce overall emissions (Szinaiet al., 2020; Zhanget al., 2020; Wolinetzet al., 2018; Crozier, Morstyn, & McCulloch, 2020; Zhanget al., 2019). Additionally, knowing the charging segment where a driver plans to charge can help operators to identify potential locations in the network that will be overloaded and will require upgraded distribution grid assets such as transformers, lines, and feeders, to prevent equipment failure and outages.

Among all charging segments, workplace charging has high potential to spur the adoption of EVs as it can enable adoption for drivers without access to charging at home. It also benefits the grid by shifting charging to hours when solar is abundant. Workplace charging, in general, has the following features: 1) high flexibility, 2) large amounts of historical data, 3) relatively predictable arrival and departure times, 4) aggregation of multiple charging stations under a single point in the network, and 5) single charging station providers for each site. However, most commercial sites do not have capabilities to properly assess the impacts of EVs on their bills and equipment in-house and, given the proprietary nature of such locations, access to site measurement data and controls by other institutions can be challenging. This creates barriers to performing a real-world assessment of such impacts on the electrical infrastructure. Furthermore, it prevents the development and demonstration of new vehicle-grid integration technologies that can support California reaching its goals of transportation electrification.

In this project, a suite of analysis and software tools were developed based on real-world data to measure and demonstrate the impacts of EV charging in the distribution network. In particular, this project explored the following EV impacts, individually and in combination: electricity cost under different rate structures, transformer aging, phase imbalance, harmonics, and emissions. The project further proposed and demonstrated strategies and best practices on how to mitigate these impacts, through smart charging controls and fleet scheduling, while at the same time maximizing customer benefits to support widespread adoption of EVs in California. Moreover, software drivers to communicate directly with different electric vehicle supply equipment (EVSE) vendors, onboard charge controllers to manage charging, and a software interface for site operators were developed and tested in the field. Finally, all tools were made open-source in scientific publications (Powellet al., 2020; Moradipariet al., 2020; Tucker, Vianna Cezar, & Alizadeh, 2022; Powellet al., 2022), white papers (Levine, Powell, & Vianna Cezar, 2019), and source code.

Existing approaches to quantify the impacts of EVs in the network targeting nonresidential environments had primarily focused on using synthetic data from EVs and performing simulations using algorithms that target objectives such as minimizing electricity costs under different rate schedules (J. Quiros-Tortos, 2018; B. Ferguson, 2018; Tucker N. A., 2019), maximizing transformer lifetime (Affonso & Kezunovic, 2019; A. Sanchez, 2017), and minimizing emissions (Chenget al., 2018). Each of these objectives is usually evaluated in isolation in the literature, relying on assumptions of key parameters such as arrival/departure times and state of charge (SOC), and not considering real-time implementation constraints such as software infrastructure development and security, or communication constraints like latency.

This project aimed to fill these gaps by working with three institutions that manage workplace charging stations to run demonstrations: Google, SLAC National Accelerator Laboratory (SLAC) and Stanford University. At Google and SLAC the focus was on passenger vehicles charging at Level 2 stations; whereas, at Stanford the focus was on the electric bus fleet that operates on campus. Google offers charging to its employees at no cost and does not enforce EV removal once a vehicle is fully charged, and the majority of its stations are from ChargePoint. SLAC charges a fee for employees to charge their EVs and requires that EVs be moved once fully charged to free up spots for other drivers, and most charging stations are from PowerFlex. Stanford operates an electric bus fleet from BYD Motors LLC (BYD) that includes 38 buses and 23 chargers. From each of these demonstration sites historical data was collected, cleaned, and analyzed; temperature sensors and onboard controllers were installed when possible; software infrastructure was developed to establish communication, control vehicle charging, and provide a user interface; information about the electrical network at the site, such as electrical single line diagrams and grid assets' specifications, were obtained; and operational constraints from site operators were compiled. All of this information was used to build the models and test the capabilities of the proposed solutions to assess and mitigate EV grid impacts.

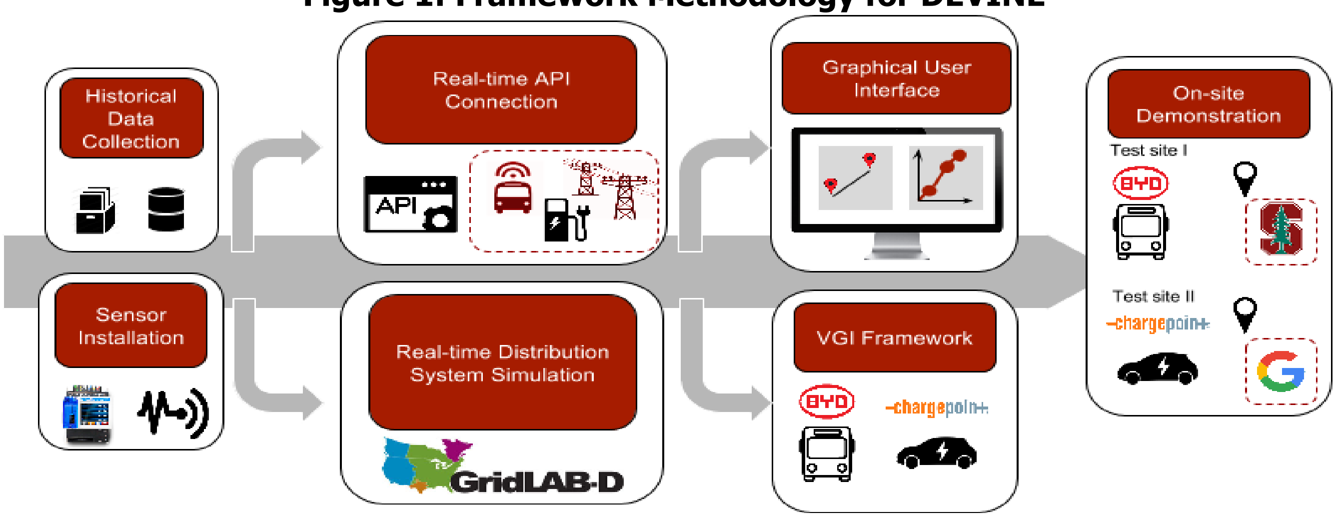
The project team has been publishing methodologies and results obtained in this project with the research community and presented at multiple conferences and meetings with academia, industry, and government agencies.

CHAPTER 2:
Project Approach

The project team was led by the Grid Integration System and Mobility Group (GISMo) within SLAC National Accelerator Laboratory and the invaluable knowledge, support, and development of SLAC partners including the team from the Smart Infrastructure Systems Lab from University of California, Santa Barbara led by Prof. Mahnoosh Alizadeh, ChargePoint through support from Paul Lipkin and Robert Calvert, and Google with support from Rolf Schreiber. The team also had support from multiple technical advisors, in particular eIQ Mobility, PowerFlex, and groups within Stanford University, including the Stanford Sustainable Systems Lab led by Prof. Ram Rajagopal and the Stanford Transportation Operations division through Brian Jackson, Matthew Brown, and Danny Finale. Each provided support and advice in different areas that made valuable contributions throughout the project with insights, direction, and guidance. Finally, the team also had support from First Transit and its dispatchers and drivers who operate the Stanford bus fleet, and Viriciti.

To achieve the project goals the team structured a framework to break the project into subcomponents that helped the organization and execution, as shown in Figure 1.

Figure 1: Framework Methodology for DEVINE



Each block corresponds to an individual task in the overall project execution and is ordered based on its dependency to the other project tasks.

Source: SLAC

This framework has a total of seven blocks grouped into three main categories: data, algorithms and analysis, and field-testing software. The project engaged with multiple sites, each with its unique characteristics. A general description of each category and key characteristics of each site follow.

Data

To understand the characteristics of each site and design the software and algorithms, the project team collected existing historical data and installed new instruments and sensors at some sites to collect additional data. The legal aspect of sharing historical data outside the institution was a common challenge faced at all sites, since in most cases the data contained either personal identifiable information, such as employees' charging sessions, or proprietary information of the site such as electrical diagrams, capacity, equipment, and cost. To avoid potential lengthy legal processes that would affect the project's execution, the team obtained an initial, small sample of pre-processed data from each site, without any personal identifiable information or proprietary site information, whenever possible, to begin developing the cleaning process and initial analytics pipeline. Another challenge was the installation of instruments and equipment, as the system being instrumented needed to be powered off and out of service for the duration of each installation. The project team worked with the operations team of each site to ensure the installation happened during times that would not affect users and clearly communicated about equipment outages in advance.

Stanford University

At Stanford University, the project worked with the Marguerite shuttle fleet, which serves the campus community. This fleet comprises 38 electric buses from BYD and has a total of 23 charging stations, each consisting of two 40-kilowatt (kW) charging connectors for a total of 80 kW per station (three-phase 480V/120A).

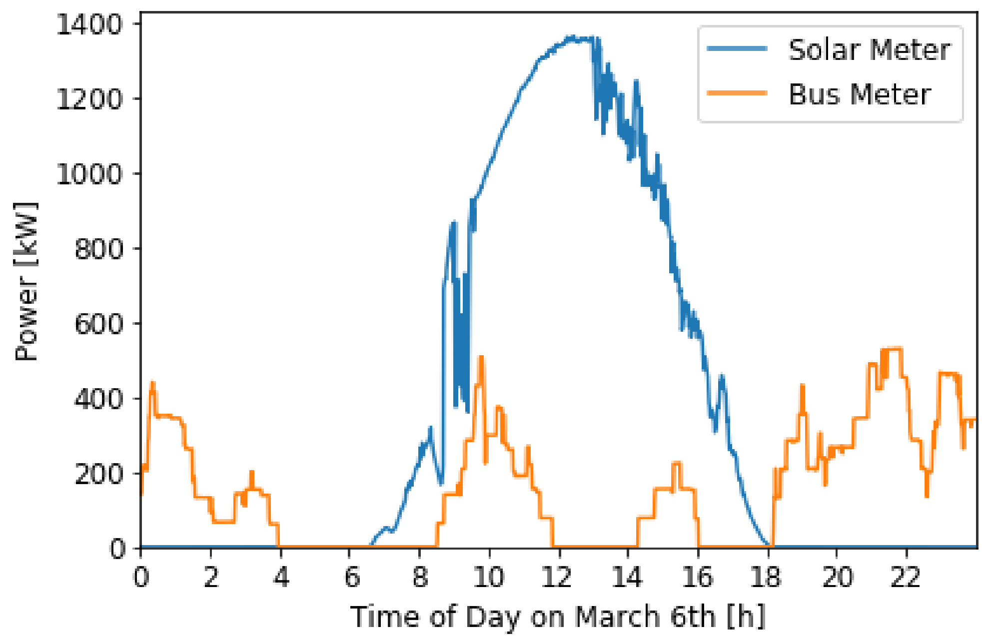
These buses use hardware and software tools from different vendors to monitor the fleet and provide real-time information to the operators and users. The telemetry data used from this site came primarily from two systems: Viriciti and ETA Transit.

Viriciti provides a platform for monitoring bus data in real-time through a hardware device installed inside the bus that connects to the controlled area network port. As part of this project, the project team installed the latest hardware from Viriciti, the Datahub (DH), which collected many of the relevant variables for operation and, in addition, had the potential to control the charging of the buses. Among the multiple data types collected, some of the most relevant include: SOC, power, energy, odometer, charging status, and global positioning system location. The sampling of the data, however, was a challenge. Some of the variables were sampled frequently such as power, at every second, and energy, every 10 seconds. However, others did not have a constant sampling frequency and the information was based on the latest sample collected by the DH, which could vary from seconds to hours. For the purpose of this project, a five-minute average was used for power, energy, and SOC.

The ETA Transit system provides the SPOT application which, similarly to Viriciti, provides real-time information about bus locations and additionally indicates which route each bus is fulfilling. This system is used by the Stanford and First Transit teams to map buses to routes based on the daily schedules and current field fleet status and to generate reports for the management team. Further, it is used by the Stanford community to get real-time information of bus locations and schedules.

From the distribution grid perspective, the bus yard is co-located with a solar photovoltaic (PV) system of 1.9 megawatt (MW) capacity in a 480-volt (V) system. The bus yard and solar system have their own meters and are connected to an upstream three-phase transformer. The meters' data were only historical and available at 15-minute intervals. Figure 2 provides samples of the bus meter and solar meter respectively for a given day in 2019.

Figure 2: Meter Data from Stanford Bus Yard



Bus meter data and solar meter data on a sample day. Note the peaks late morning/early afternoon and late evening.

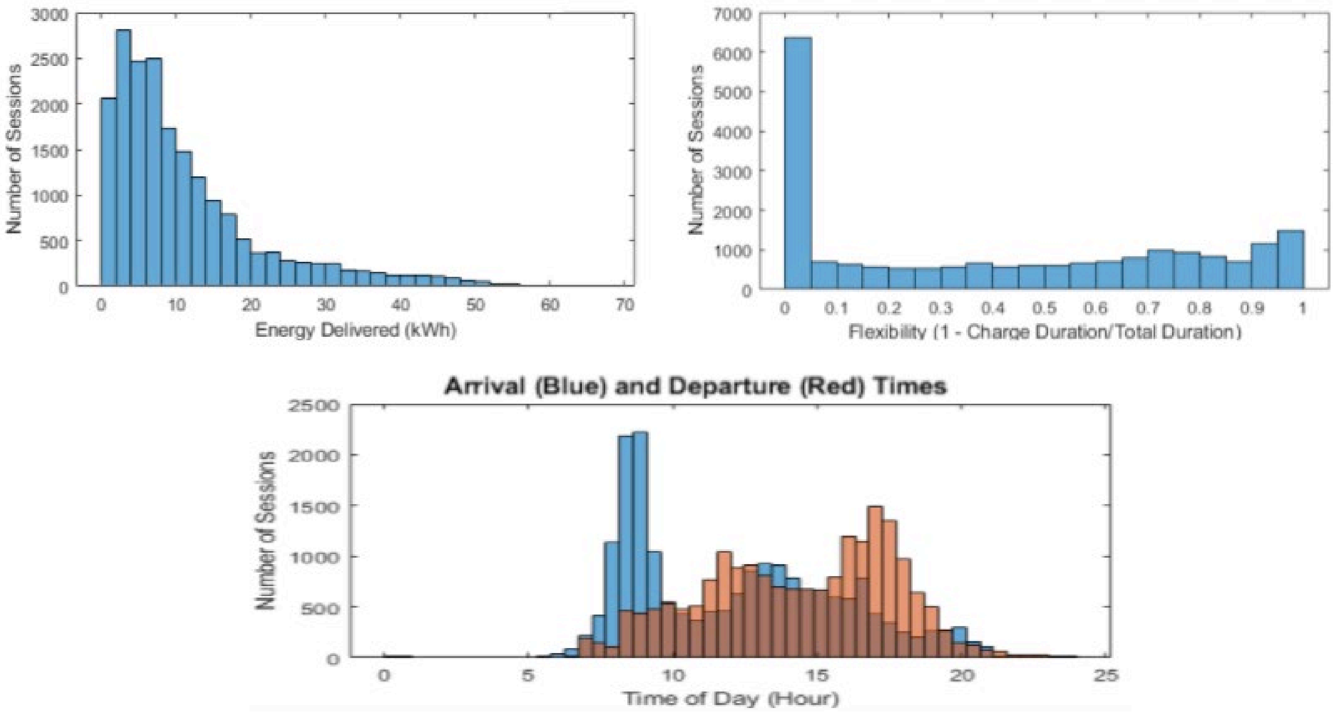
Source: SLAC

Google Campus

On the Google campus, three distinct sites were selected based on characteristics such as EVSE use rate. At all sites the EVSE information was available from ChargePoint, including both session and interval data. A session was defined as a single charging event: each session began when a vehicle connected to a station and ended when it left, i.e. plug-in and plug-out. An interval was each 15-minute block of time within a session. Data including start and end times, duration, energy, and power were provided. Additionally, historical building meter data was obtained whenever available. Appendix A provides a complete list of the data fields and each site characteristics.

For each site, analytics such as flexibility, arrival and departure times, and energy delivered were calculated. Figure 3 presents such an analysis for Site 1.

Figure 3: Analytics of Charging Sessions for Site 1



Top left: Histogram of energy delivered. Top right: Histogram of the charging flexibility. Bottom: Histogram of arrival and departure times.

Source: SLAC

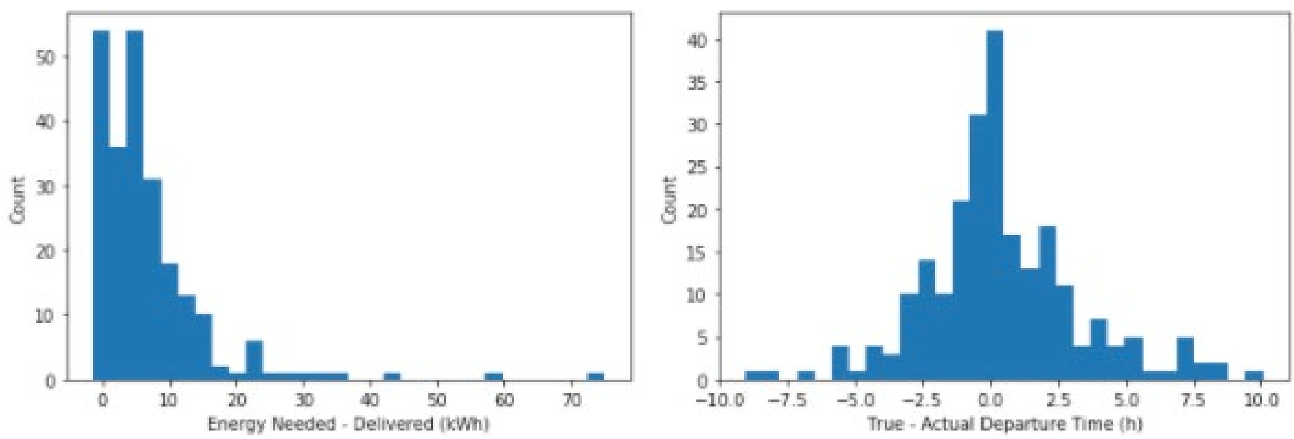
From the histograms presented in Figure 3, a few observations can be made. First, the most common energy delivered (top left graph) was between 2 kWh and 7 kWh. Since one hour of charging at a ChargePoint Level 2 station at the maximum power gave approximately 7 kWh of energy and an estimated 25 miles of driving range (ChargePoint, 2022), these sessions were charging on average 25 miles or less of range. Second, approximately 32 percent of the sessions had zero flexibility, which meant the EVs charged all the time until they were unplugged, but 46 percent of all sessions had a flexibility higher than 0.5, which meant that more than half of the time EVs at this site were not charging. Finally, this site had arrival and departure time distributions with double peaks. The largest peak in the arrival times occurred early in the morning, but a second peak occurred early in the afternoon, after lunch time. The departure time had its largest peak in the late afternoon, with a second peak late morning, before lunch. The dynamics of this site, where employees leave for lunch and then return to work, gave one explanation for this double peak.

SLAC Campus

The SLAC National Accelerator Laboratory campus has a total of 23 Level 2 EVSE from PowerFlex (PowerFlex, 2022). Similar to ChargePoint, PowerFlex collects general charging session information such as start and end times and energy delivered. However, as part of the PowerFlex ecosystem, before a session starts, users are required to input how many miles they need out of that session and what time they plan to leave. The mileage requested is further converted to energy, in kWh, by PowerFlex. This information was used by the system to optimize the charging of all stations since the EVSE did not have information about the EV SOC. Given that PowerFlex implements active controls in the stations at SLAC, the project team was not able to overwrite the commands and experiment with the approach. The team was only able to analyze the historical data collected to characterize the site. Since this system provided information about user behavior through the miles needed and departure time requested inputs, this data was used to inform the development of the real-time algorithm.

Figure 4 shows histograms of energy delivered and actual departure time. The true actual departure time was the difference between the expected departure time reported by the user and the actual departure time. This figure shows, similar to the Google sites, that most sessions delivered less than 10 kWh. Additionally, most actual departure times were within plus or minus 2.5 hours of the times reported by the users. This information was relevant to understand general user behavior and also informed the real-time optimization algorithm about statistics of departure times.

Figure 4: Analytics of Charging Sessions for SLAC Site

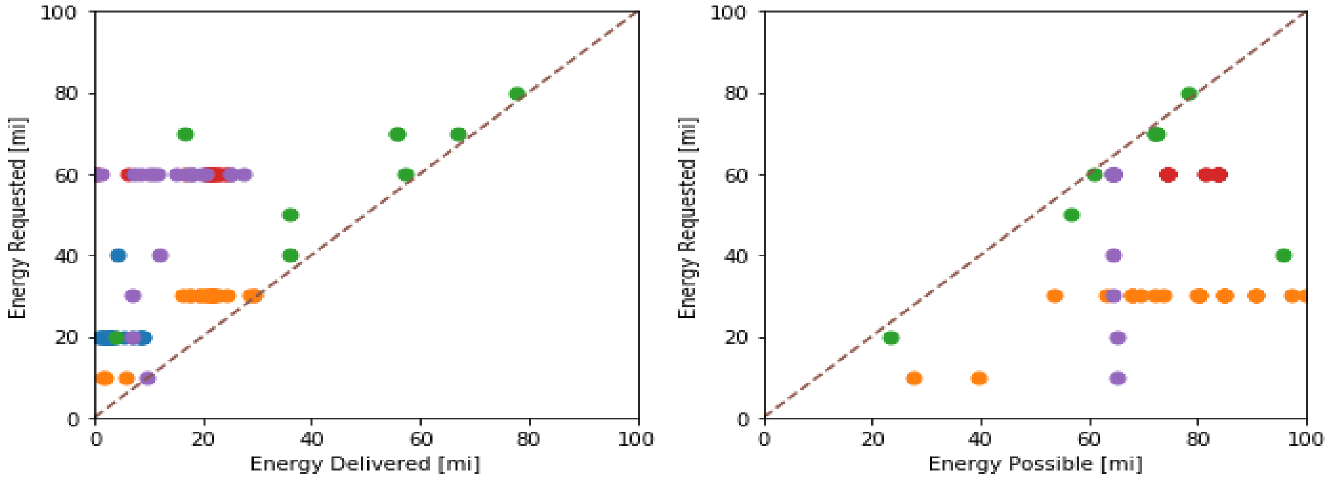


Energy delivered to EV in kWh (left) and actual departure time in hours (right). A negative number in the actual departure time means a user left earlier than expected and a positive number indicates a user left later than expected.

Source: SLAC

Figure 5 uses the top 5 drivers based on the number of sessions in the month of February 2019 and compares the energy requested with a) the actual energy delivered and b) the maximum possible energy that could have been delivered given the EV's total session time. As before, units are presented in miles based on an internal software conversion from kWh to miles. From the left graph of Figure 5, it is evident that users requested similar energy values regularly and most of the time the energy delivered was less than the requested value. The right graph helps explain the reason. The theoretical total energy that each EV could have been delivered, given the time the vehicles were parked, was mostly higher than the requested energy by the users. This showed that EVs were not running out of time to receive their requested amount of energy, and that charging stopped before either delivering the requested energy or reaching the departure time. Therefore, the main reason users often did not get the total requested energy must have been because they reached 100 percent SOC and stopped charging with less energy than requested. This ultimately meant that there was a disconnection between the information the drivers provided based on their needs and what the EVs could actually consume. As a result, this information was challenging to use in charging control algorithms since it depended on users being proactive, having a clear understanding of the purpose of reporting the information, and reporting accurate information about their energy needs.

Figure 5: Comparison Between User Input and EVSE Behavior



Each color represents a different driver, and each circle represents what happened in a charging session. Left: drivers often input similar energy requirements but mostly got less. Circles above the dashed line means the energy delivered was less than the energy requested. Right: given the duration of the sessions, most EVs had enough time to have received more energy than requested.

Source: SLAC

The EVSE stations at SLAC were connected to a dedicated three-phase 112.5 kilovolt amps (kVA), 480-208/120V transformer manufactured by Powersmiths. This transformer was floor-mounted and located inside an electrical room of a nearby building. Powersmiths also provided the capability of measuring the transformer coils temperature by adding extra sensors. The team installed three temperature sensors, one in each of the coils, and a datalogger to analyze the effect of EV charging on the transformer temperature. The data was provided at 15-minute intervals and manually queried from SLAC's server with a one-day delay. The goal was to build temperature models to assess transformer aging that could potentially be transferred and applied to other transformers without this sensing capability or for which it is impractical to perform such an installation. Figures 6a and 6b show the installation being performed and a sample of the power and temperature collected by the datalogger.

Figure 6a: Transformer Temperature Sensor Installation

Figure 6a: technician installing the temperature sensors inside transformer coils. Top right: final installation setup. Red arrow shows the sensor terminals, and the cyan arrow shows the data logger.

Source: SLAC

Figure 7b: Transformer Temperature Sensor Data Sample

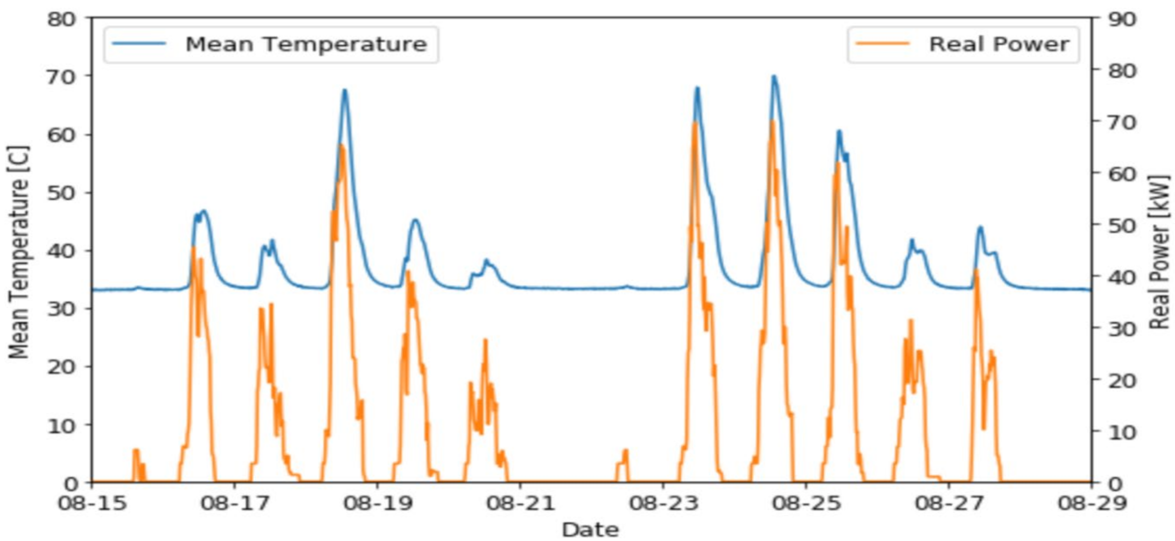


Figure 6b: Sample of the power (kW) and temperature (Celsius) data recorded over a two-week period.

Source: SLAC

Algorithms and Analysis

To assess the EV impacts in electricity cost for a hosting site, grid assets, phase imbalance, harmonics, and emissions, the team developed a suite of algorithms and analyses. These algorithms and analyses were based on the characteristics of each site, i.e. employee charging, fleet charging, and electricity rate structures, and in some cases included the overall distribution grid with residences, solar PV systems, and the transmission grid.

Smart Charging

Since passenger EVs are idle 95 percent of their lifetime, there is significant flexibility in when they can be charged (AC Propulsion, 2002). For workplace charging, many employee owned EVs sit idle most of the workday, while fleet vehicles may have a more variable pattern of idle time. Long idle periods present an opportunity for managing the EV's charging, through smart charging, to reduce electricity costs, participate in demand response programs, maximize onsite solar generation and reduce impacts on grid assets. Several smart charging algorithms were developed in this project to address the constraints of the hosting sites.

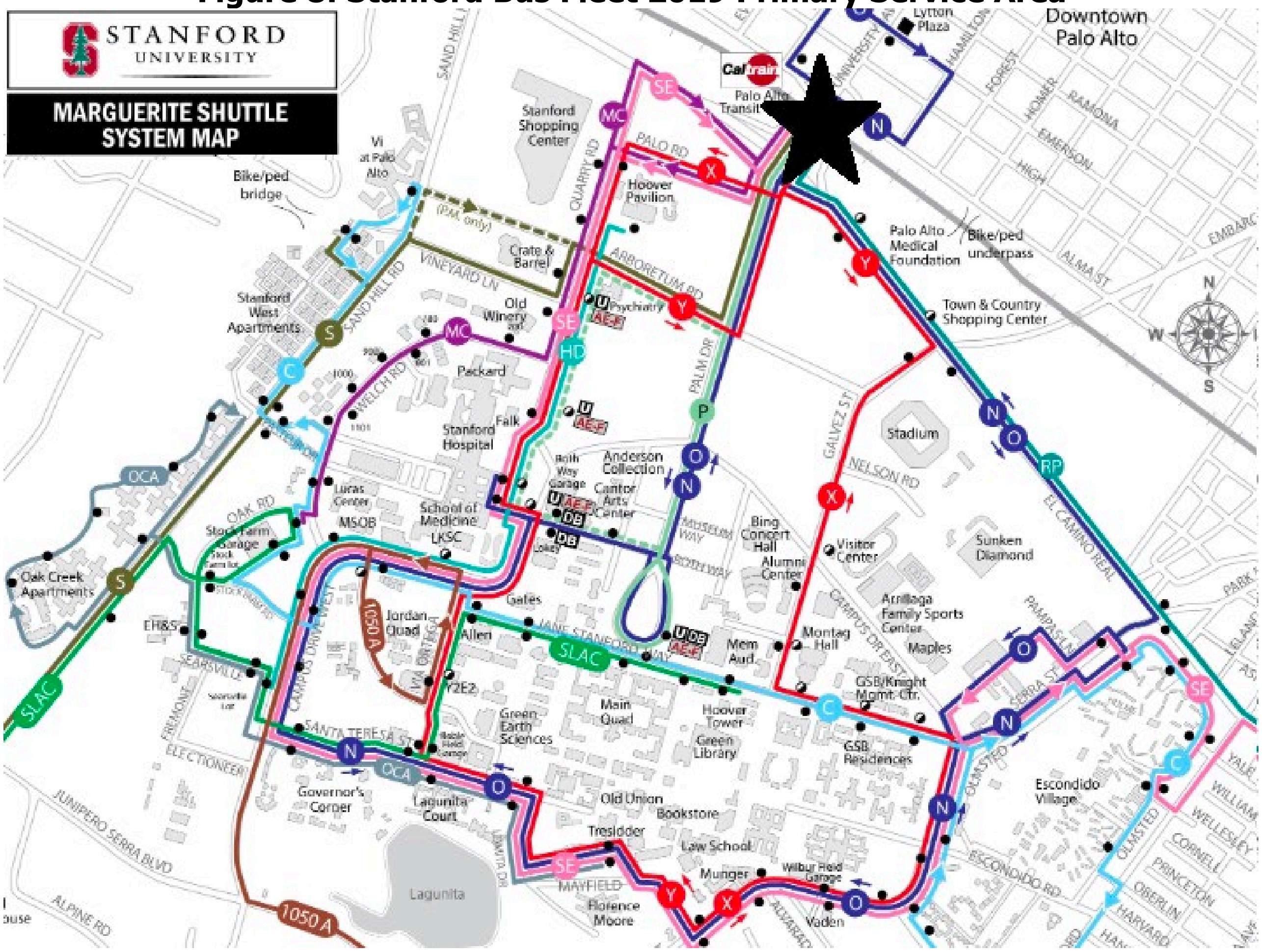
Electric Bus Fleet

At surface level, replacing traditional buses with electric buses might seem a simple task; however, many obstacles prevent a transit system from simply assigning electric buses to existing routes that were previously served by diesel buses. The two most fundamental obstacles are the restricted travel distance and lengthy recharge time of electric buses. Even with recent advances in electric transportation and battery technology, modern electric buses are commonly restricted to operate within 20 percent to 95 percent SOC to prevent stressing the batteries and reducing lifespan (Hill, 2015). Combining this SOC limitation with the high cost of large battery packs, most electric buses currently have shorter operational ranges than diesel or natural gas buses. Second, the recharging process of an electric bus takes significantly more time than the refueling process of a diesel or natural gas bus (Hill, 2015). Additionally, due to the lengthy recharge time and limited charging infrastructure, the transit system dispatcher must be mindful of how the fleet's recharging infrastructure is managed to provide adequate energy to serve routes.

The algorithm developed for the electric bus fleet at Stanford looked into the joint route assignment and charge scheduling problem. Other studies have looked into this problem (Paul & Yamada, 2014; Janovec & Kohání, 2019), however the presented approach was able to improve upon previous mobility-aware work by accounting for time-varying electricity prices, using onsite solar energy generation, and providing a minimal cost schedule for the fleet's daily operation.

Stanford bus fleet consists of 38 electric buses, 23 diesel buses, 23 electric bus chargers, and a total of 20 daily routes of which 15 are fulfilled by the electric buses. Figure 7 presents the primary service area in 2019. The time for each route trip was already defined by the dispatch team. From an electricity cost standpoint, Stanford is on direct access and buys electricity from an energy service provider (ESP). However, the university campus is exposed to time of use prices that follow Pacific Gas and Electric Company's (PG&E's) E-20 rate schedule.

Figure 8: Stanford Bus Fleet 2019 Primary Service Area



Source: Stanford University

The optimization algorithm was formulated using a mixed-integer linear programming (MILP) framework to solve for both the optimal recharging schedules and route assignments. More details on the mathematical formulation and problem constraints can be found in (Moradipari et al., 2020).

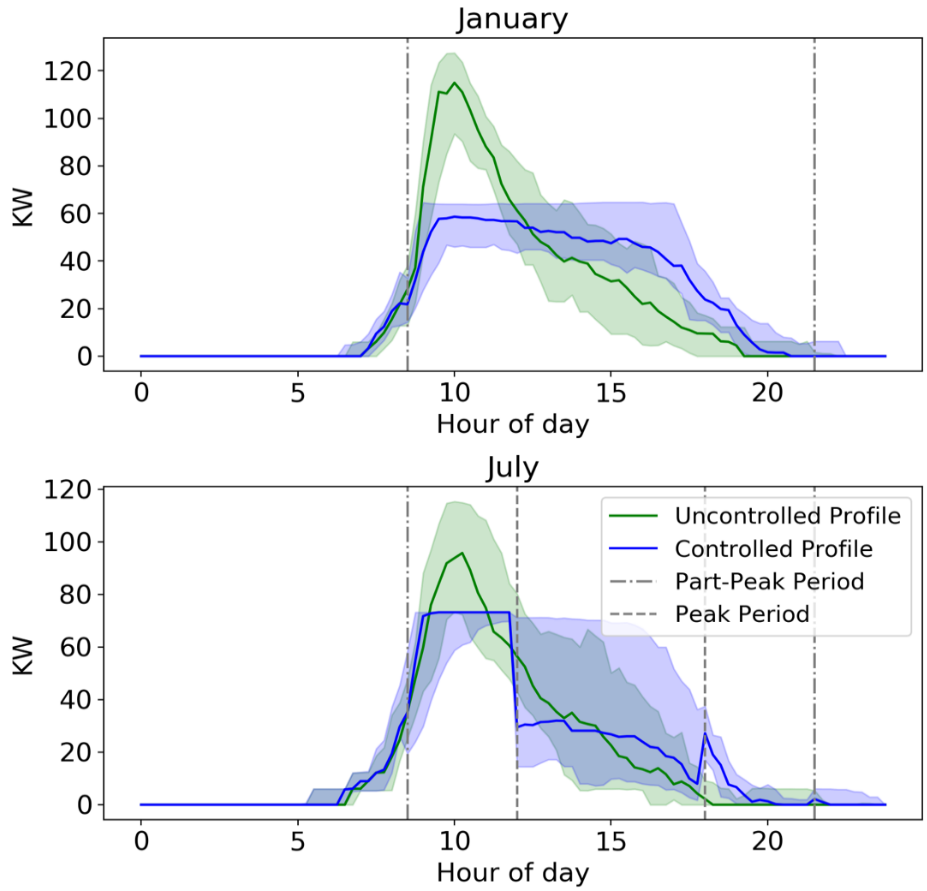
Workplace Charging

Workplace charging, as previously discussed, presents a unique opportunity for smart charging. As part of this project, smart charging algorithms were developed for different rate structures and constraints including transformer capacity. Moreover, a real-time optimization strategy was developed to be used in the field given the available information.

The general optimization formulation was based on an objective function, i.e. minimize electricity cost, given a rate structure the clusters of EVSEs were subjected to and a set of constraints. The constraints depended on the specific detail to be optimized, available data, grid assets capacity limits, such as transformers, and whether the optimization is off-line — i.e. used historical data and had information about what happened in the optimization time horizon with respect to charging— or real-time — i.e. used information as it became available.

The offline approach had information about unmanaged charging load as well as the driver's travel (arrival and departure times) and energy needs. Technical details about the mathematical formulation and problem setting can be found in (Levine, Powell, & Vianna Cezar, 2019; Powell et al., 2020). Figure 8 shows results for offline smart charging controls under different rate structures and constraints.

Figure 9: Offline Optimization with PG&E A-10 with Peak-day Pricing Events

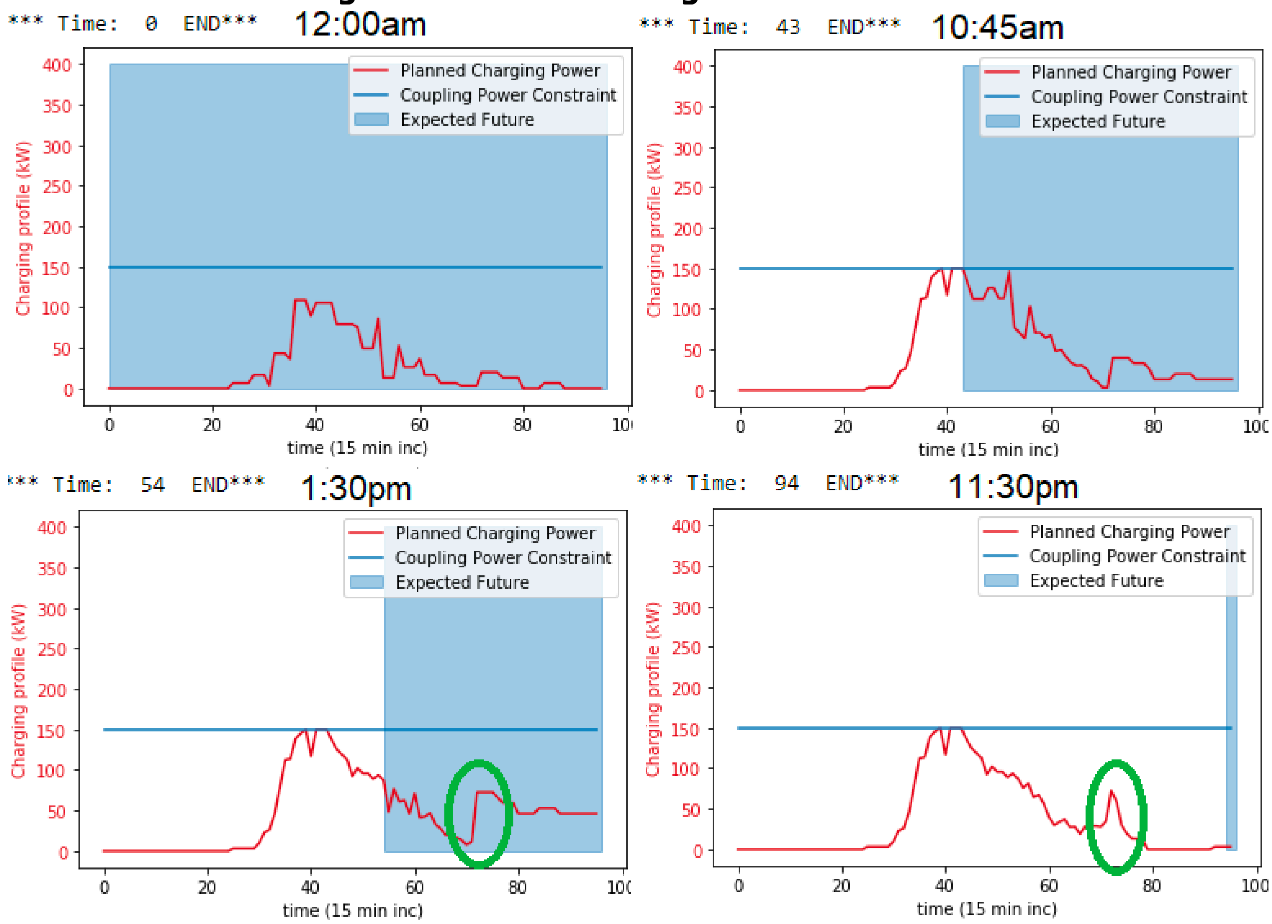


Median weekday charging profile with 10 and 90 percentile range shaded for the controlled and uncontrolled profile. The controlled July profile was based on full participation in PDP events.

Source: SLAC

The real-time optimization did not have the information the offline approach did, so it had to run either when a new event happened, i.e. vehicle arrival/departure or increase/decrease in the EV load, or run periodically to check for updates in the system conditions. The approach taken for the real-time optimization was to use a scenario generation methodology to account for each EV's unknown future departure time and certainty equivalent control to account for the unknown EV arrivals in the future. The models were built from historical data for each day of the week and the algorithm used these models as the expected future when optimizing the EV charging schedules. Since the charging control was done through the EVSE, no SOC information was available; thus the algorithm had to be SOC agnostic. Finally, the algorithm was set to ensure EVs would receive a minimum amount of energy since the optimization did not know exactly when an EV would leave. Details on the mathematical model and problem set up can be found in (Tucker, Vianna Cezar, & Alizadeh, 2022). Figure 9 shows an example of the evolution of the planned charging power.

Figure 10: Real-time Algorithm Evolution



Evolution of planned charging power. Top Left: At 12:00 a.m. the algorithm was fully using the expected future as a model for what could happen that day. Top Right: At 10:45 a.m., many EVs had arrived and the power output had started to deviate from the expected future. Bottom Left: Planned power output at 1:30 p.m. Bottom Right: At 11:30 p.m., there were no more arrivals, Red curve shows the daily power output of the 57 EVSEs. Additionally, the green circles indicate spikes in total charging power in the evening due to the algorithm waiting for cheap electricity rates to charge multiple EVs.

Source: SLAC

Transformer Aging

To understand the impact of workplace charging on a site's transformer, the team modeled failure through premature aging of the transformer's insulation, which often occurs through repeated overheating.

Models of transformer temperature can be divided into physics-based and data-driven. Physics-based modeling is supported by detailed IEEE guides and was developed through experiments measuring temperature and insulation material in a range of dry-type transformers (IEEE, 2014). New modeling techniques including computational finite element analysis have improved the resolution of physics-based models, and ongoing research using circuit- or thermodynamic-based modeling show improvements over the traditional IEEE model. Unfortunately, however, many of the parameters used in recent models are not available for the small distribution transformers used at the workplace sites in these studies. Therefore, in the first study of transformer aging, the team implemented the standard model from the IEEE guide using available parameters. The model details are available in the *IEEE Guide for Loading Dry-Type Distribution and Power Transformers*, Standard C57.96-2013 (IEEE, 2014).

Data-driven modeling took advantage of time series temperature and loading measurements to estimate model parameters directly. These have shown very good performance on larger transformer models. In this project, the team used data from newly installed temperature sensors in the transformer at SLAC to compare the two modeling approaches and publish the learned coefficients. Such data is rare for small distribution-level transformers.

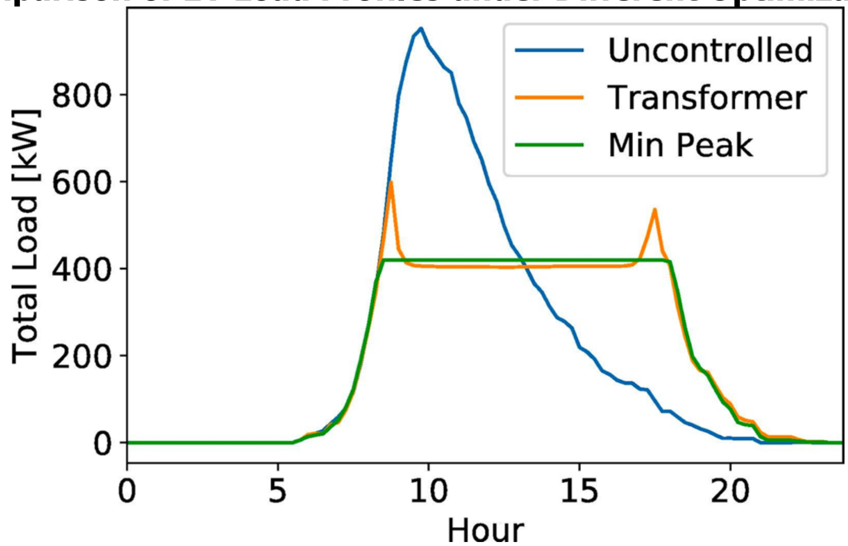
By calculating the relationship between temperature and lifetime and modeling the temperature at each time, the team could calculate the accelerated aging relative to the transformer's expected lifetime. The total loss of life over a given time period was calculated by integrating accelerated aging factor over time and used to calculate the new lifetime of the transformer (IEEE, 2014).

The project team studied transformer aging using data from the Google test sites, evaluating the aging while increasing the number of vehicles at the parking lot and changing the control scheme to minimize for different electricity rate schedules.

The team also developed a control scheme to minimize directly for the transformer's aging.

Figure 10 shows an example result of the control scheme. T studied this effect for a 225 kVA dry-type transformer at the Google site.

Figure 11: Comparison of EV Load Profiles under Different Optimization Strategies



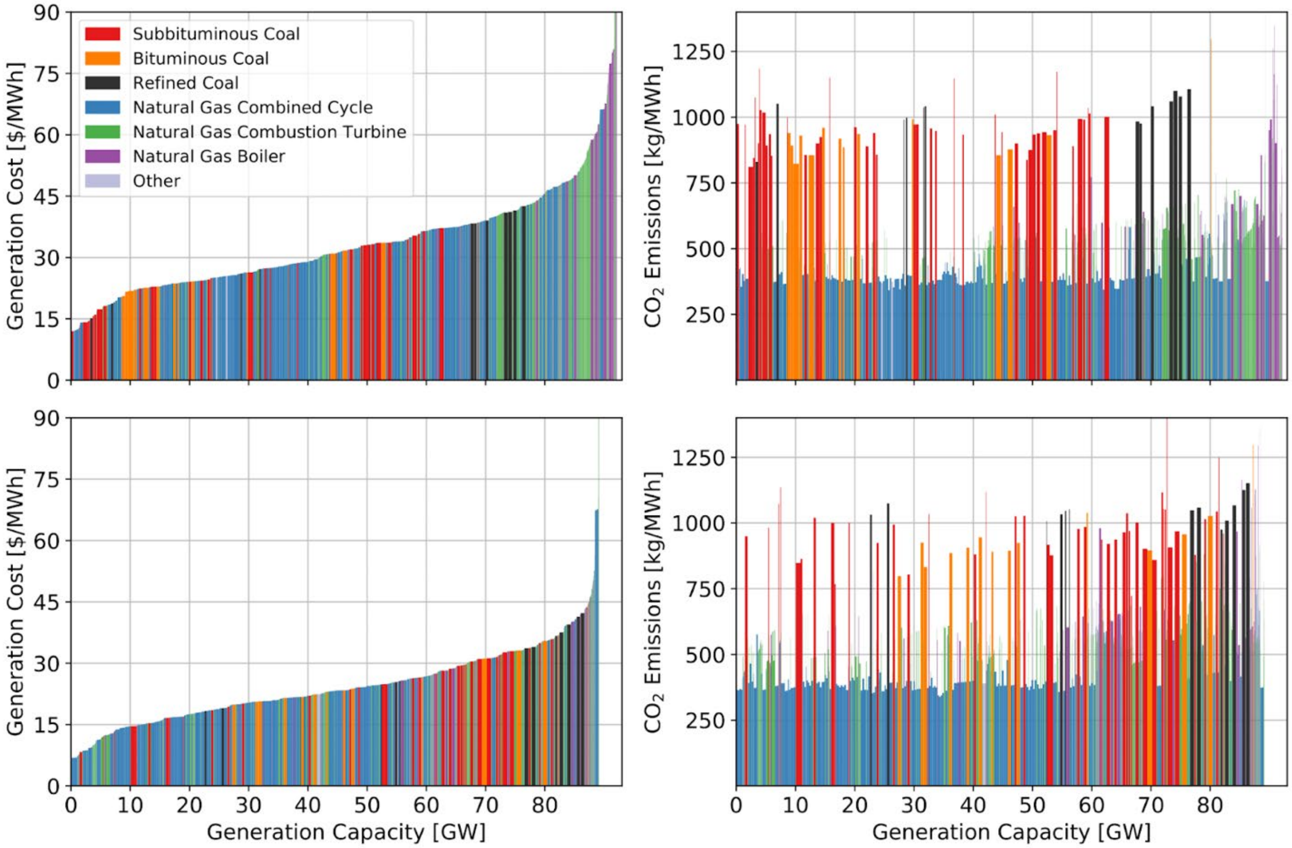
The total uncontrolled and controlled charging loads for a sample day with 355 cars in the parking lot, comparing simple peak minimization imitating a demand charge with the transformer aging minimization algorithm. The two controlled profiles were very similar, except for the small peaks allowed by the transformer aging algorithm: due to the time-delay in heat transfer in the transformer, a small spike in demand would not last long enough to cause significant heating but could be used to lower the demand during the rest of the day. Appears in the paper (Powell, Kara, Sevlian, Vianna Cezar, Kiliccote, & Rajagopal, 2020).

Source: SLAC

Emissions Model Methodology

To quantify the emissions in each charging scenario, the team modeled the United States portion of the Western Electricity Coordinating Council (WECC), extending the reduced-order dispatch model first proposed in "Reduced-order Dispatch Model for Simulating Marginal Emissions Factors for the United States Power Sector" (Deetjen & Azevedo, 2019). The dispatch model works by constructing a merit-order of generators for each week of the year based on historical cost data. For each hour of the year, the generators are dispatched to meet that hour's demand in order of lowest cost, and the emissions are calculated based on which generators were dispatched. The team updated the model published in 2017 to reflect the grid in 2019, using the latest data on renewable generation, demand, and fossil fuel generator retirements or additions. The dispatch order is illustrated in Figure 11 for two example weeks from 2019.

Figure 12: Dispatch Order for Generators in WECC Model of 2019



This figure shows the dispatch order or merit order of generators in the model for weeks 1 (top row) and 27 (bottom row) in 2019. The subplot on the left in each row shows the generation cost for each generating unit and the subplot on the right in each row shows the carbon dioxide (CO_2) emissions rate for each generator. The width of each bar represents the generator's capacity in gigawatts and the color of each bar shows the type of generator..

Source: Powell et al., 2022b.

The team also developed a model of the future grid in 2030 to evaluate the future impacts of each control scenario. To make this extension the team implemented further fossil fuel generator additions and retirements, increased the baseline electricity demand to reflect forecast electrification in other sectors, and increased renewable generation.

The model used data collected by the U.S. Environmental Protection Agency (U.S. EPA) through its continuous emissions monitoring systems for the hourly operation of each generator in WECC including fuel consumption, capacity, and emissions (U.S. Environmental Protection Agency, 2019); data collected by the U.S. EPA in its Emissions and Generation Integrated Resource database for each plant's construction date, fuel type, and location (U.S. Environmental Protection Agency, 2019); data from the U.S. Energy Information Administration (EIA) Form 923 data set for fuel purchases and prices (U.S. Environmental Protection Agency, 2019); and data from the U.S. EIA Electric System Operating Data website for nuclear, hydro, wind, and solar generation (U.S. Environmental Protection Agency, 2019).

The total emissions at each hour were calculated as the sum of emissions from each generator dispatched. Divided by the total demand served at each hour, this determined the grid's average emissions factor (AEF). The emission rate in kilograms of carbon dioxide (CO_2) per kWh of electricity produced for the last generator dispatched at each hour, the marginal generator, determined the grid's marginal emissions factor (MEF).

Smart Charging Infrastructure Planning Tool Large-Scale Emissions Optimization for Workplace Charging

In addition to the control algorithms described above, the team tested one control scheme for workplace charging at large scale with the explicit objective of minimizing emissions. This analysis was built upon in the team's recently submitted journal paper (Powell et al., 2022a; Powell et al., 2022b).

The team extracted the hourly profile of average emissions in kilograms of CO_2 per megawatt-hour from the grid dispatch model for each day and used the mean daily profile as the objective in a site-level control. The team randomly sampled from the data set of workplace charging sessions to simulate 1,000 workplace site-days with 150 vehicles in each. The constraints of each day's optimization problem included limiting the charging rate to Level 2, limiting charging for each vehicle to occur within the plugged-in time interval, and ensuring each vehicle received its full session energy. For this optimization, the team assumed all parameters were known in advance.

The team used the methodology for large-scale charging control first proposed as part of the Smart Charging Infrastructure Planning Tool project (Powell et al., 2022a; (Vianna Cezar et al., 2020) to scale these results to the WECC level for large-scale analysis. This approach informed a data-driven model of the mapping from the uncontrolled to controlled site profiles. The team normalized and divided these profiles into training, development, and testing sets and trained a Ridge Regression model with cross-validation and a grid search over the Ridge parameter. The model root mean squared error (RMSE) reported for the development set was 3.34 percent of the peak site-level load.

Phase Imbalance and Harmonics

Level 2 EVSE stations are single-phase three-wire system (or split-phase) equipment that connect to the electrical grid. Since the grid is a three-phase system, whenever a Level 2 EVSE connects to the electrical infrastructure it uses two out of the three phases. It is important to analyze the impact of split-phase units on the load balance of the distribution system. These impacts are relevant in both residential and commercial sectors since charging can happen at these locations.

In the residential sector in North America, homes use a split-phase system to connect to the distribution grid. This connection is through a single-phase distribution transformer with three-wire center-tapped split-phase secondary winding. This means that the transformer, which often connects multiple houses, has its primary side connected to a single phase out of the three-phase distribution system.

The commercial sector follows a similar approach. Within a campus/workplace, loads are connected to the system to ensure it is properly balanced. In many campuses, the Level 2 EVSE network is connected to a three-phase transformer and since each EVSE uses two out of the three phases, installers try to balance the number of EVSEs connected to each phase.

When distribution operators plan the infrastructure, they try to balance the load between the phases to prevent high neutral currents from flowing through the neutral conductor and affecting the system's efficiency and safety, causing issues such as transformer overheat and increased tap-changes to regulate voltages (Parmar, 2018; Sarwito, Semin, & Hanif, 2017). High neutral currents are not only caused by load imbalance but, even in a perfectly balanced three-phase system, they can appear due to harmonics generated by non-linear loads. Most of these higher frequency sine waves (high harmonics) cancel out similar to what is expected from the 60Hz sine waves. However, some harmonics don't cancel. In fact, they add in the neutral — in particular the third harmonic. These harmonics are called zero sequence harmonics, and they are the reason that high neutral currents exist, even though the loads may be perfectly balanced (Tyco Electronics Corportation, 2022). Harmonics can also increase losses in transformers, power cables, and malfunctioning of equipment (Woodman, Bass, & Donnelly, 2018) if not properly managed. There are standards that recommend limits in terms of harmonic content (IEEE, 1993; IEC, 2018; and 2002) but none of them specifically target EV chargers.

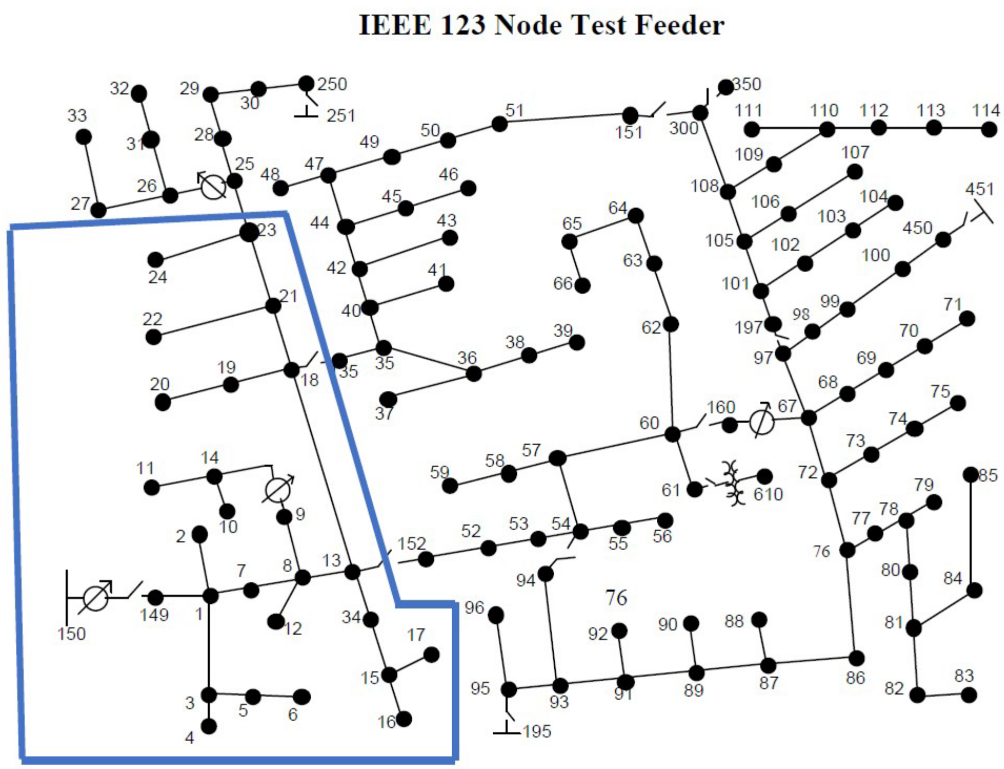
The team measured and analyzed the harmonic content of two different EVs charging in a Level 2 EVSE under different charging conditions, i.e. different fundamental current magnitude. The first observation was that the odd harmonics had a higher magnitude compared to the even harmonics. Analyzing the magnitude content of the third (180Hz) and fifth (300Hz) harmonics, the content varied between 1 percent and 10 percent of the fundamental. Additionally, the lower the fundamental the higher the percentage change in the third and fifth harmonics. From a magnitude perspective, for a fundamental of around 30A root-mean-square (rms) the third harmonic was approximately $0.3A_{rms}$ and the fifth was $0.2A_{rms}$. For a fundamental of $3A_{rms}$, the third harmonic was $0.25A_{rms}$ and the fifth harmonic was $0.08A_{rms}$ (more information on the measurements and approach can be seen in Appendix C). However, the harmonic contains not only the magnitude but also a phase component. Among the information the phase provides about the harmonic, an important one is that it can make harmonics cancel out. This is called phase diversity. Different equipment may have distinct hardware configurations that create diversity in the phase and thus, when adding (vector addition) the harmonic content of different equipment connected to the network does not necessarily increase. It is shown that in many cases the fifth harmonic has, in general, effective cancellation but is less effective in the third (Meyer, 2014). Since the third harmonic is part of the zero sequence harmonics, its content will be flowing through the neutral conductor and add to the system imbalance.

The analysis of phase imbalance was performed in the residential sector since extreme cases could be evaluated such as adding the impact of adjacent loads and PV systems. Moreover the EV load on campuses is generally small compared to the rest of the loads, i.e. buildings, and thus the overall effect is small. Finally, based on discussions with managers of the sites, this was not a concern.

To analyze the effect of load imbalance due to the penetration of EV chargers in the residences, an example was analyzed based on the standard distribution bus IEEE123 with the GridLAB-D software. Figure 12 shows the IEEE 123 network. The study involved the nodes located inside the polygon depicted in that figure. The IEEE123 distribution network has a nominal line-to-line voltage equal to 4.16kV (IEEE, 2022). Based on Pecan Street data (Pecan

Street, 2022), the power consumption of a large number of residences was used to recreate the power demand at the nodes of the distribution system and compare the case when the houses did not include EV chargers with the case when the residences did include those devices. In the standard network, the total power installed in the area defined by the polygon is S = 480kW + j 240kVAr. This load was replaced by a number of residences such that the power consumed by those houses was similar to the total power S. As such, a similar procedure to the one performed by Rivetta (Rivetta et al., 2021) was followed here to locate the houses in the network. Using the Pecan Street data, the after diversity maximum demand was calculated based on 230 residences using one-week measurements (168 hours) between July 10 and July 16, 2015. Based on that data, the peak value of the power consumed by an average residence in that period was estimated. That peak value was used to define the number of houses allocated per node, such that the total power consumed by the nodes was equal to the standard power defined in the normalized network. This procedure allowed the inclusion in the suggested area of a total of 151 houses.

Figure 13: IEEE 123 Node Test Feeder



The main three phase branches in the area are defined by the path following the nodes 150-149-1-7-13-152 and 13-18-21-23-25. Those branches are the only three phase conductors in that area of the distribution system; the rest of branches connecting the nodes to the main branches are single phase lines corresponding to phases A, B, and C.

Source: SLAC

From the standard distribution network IEEE123 data, the currents per phase flowing between nodes 149 and 1, between nodes 23 and 25, and between nodes 13 and 152 are indicated in Table 1. Those nominal values were used as reference. From this initial setup, the scenario analyzed assumed all 151 homes had a solar system and randomly assigned EVSE, including Level 1 and Level 2, to 40 percent of the homes. Further details of this scenario, including the currents in each phase and neutral are provided in Appendix C.

Table 1: IEEE123 Phase Current

	Branch 149-1	Branch 13-18	Branch 13-152
Ia [Arms]	628.42 exp(j -21.69)	228.85 exp(j -30.43)	332.01 exp(j -14.31)
Ib [Arms]	408.06 exp(j -139.63)	155.56 exp(j -155.10)	224.34 exp(j -129.30)
Ic [Arms]	501.86 exp(j 101.51)	153.35 exp(j 88.61)	265.02 exp(j 112.07)
In [Arms]	172.96 exp(j -1.59)	66.20 exp(j -25.11)	88.66 exp(j -7.16)

Source: SLAC

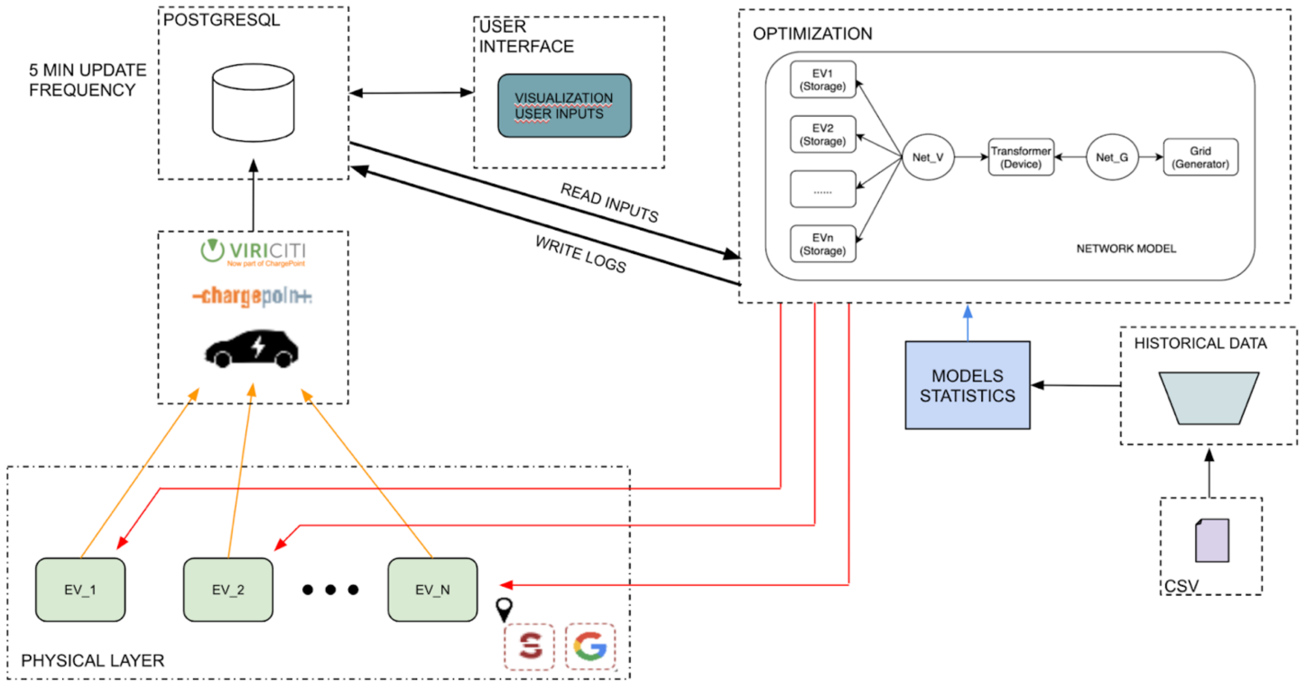
Looking at the phases and neutral currents it is evident that the system is already unbalanced. However, those values are typical in distribution systems, with neutral currents being less than 30 percent of the phase current and phases being unbalanced.

Field-testing Software

The field-testing was planned for summer 2020. However, due to the COVID-19 pandemic the project team was not able to perform the tests in the field since all site locations were closed. Even though the field deployment did not happen in the end, software infrastructure was developed that would enable the deployments, communication with the stations was established, and user interfaces were developed.

The design of the software was targeted for real-time operation. As such, for each site a data ingestion pipeline based on available, real-time, data streams was implemented. This data ingestion pipeline leveraged existing application programming interfaces (APIs) from the field devices such as EVSEs from ChargePoint and PowerFlex and bus data from Viriciti. A decision was made to run the system at a five-minute interval. The main reasons for this choice were: a) electricity rates varied at 15-minute intervals and thus a 5-minute interval captured the relevant dynamics for the optimization, and b) to prevent potential server overloading with multiple requests in a short time interval to read and write. This data ingestion pipeline was the entry point for the software system. A web application was developed using the Django web-framework (Django Software Foundation, 2022) and deployed in the Amazon Web Services cloud system (Amazon, 2022). The general architecture of the software is presented in Figure 13.

Figure 14: Software Architecture



For each site, a set of requirements was defined based on data availability, controls, type of algorithm, and importance of the user interface for site operators. Below the main characteristics of each site are presented.

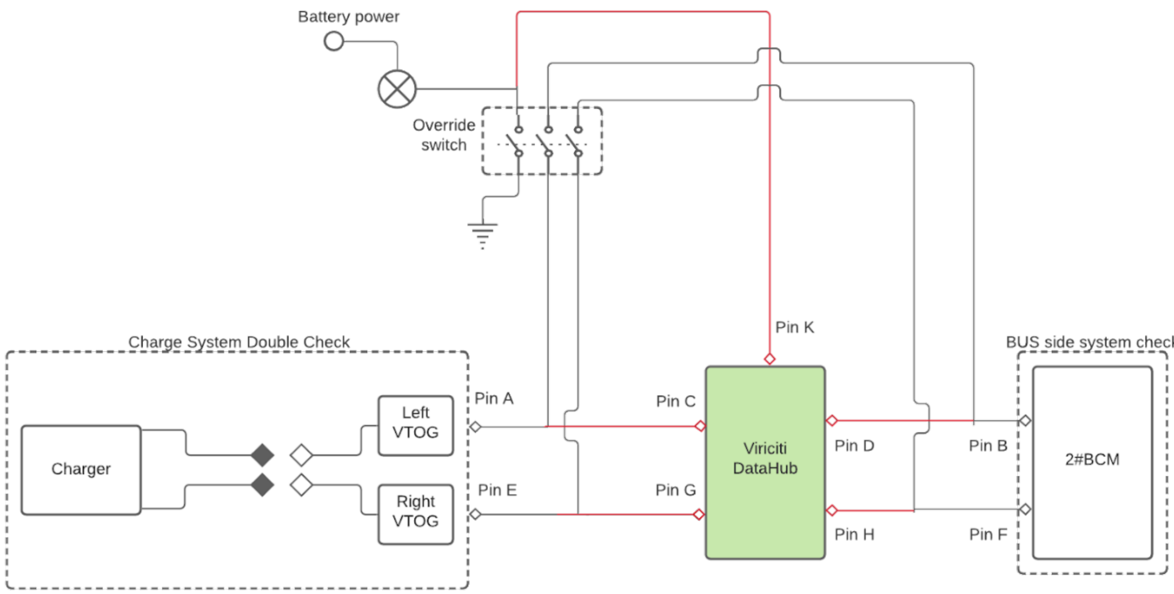
Source: Grid Integration Systems and Mobility – SLAC National Accelerator Laboratory

Stanford University

Data and Controls

The real-time data such as SOC, power, energy, location, speed, and charging status of the buses were available from the Viriciti DHs. A representational state transfer API was developed with Viriciti to allow data ingestion. The DH also had the ability to change the state of its output connections to enable the capability of start, stop, and resume charging. A new wiring diagram was obtained from BYD to enable the DH to control the charging and also provide a manual override switch in case a problem occurred with the DH. The schematic is provided in Figure 14.

Figure 15: Wiring Diagram Including Viriciti DH to Enable Remote Charging Control

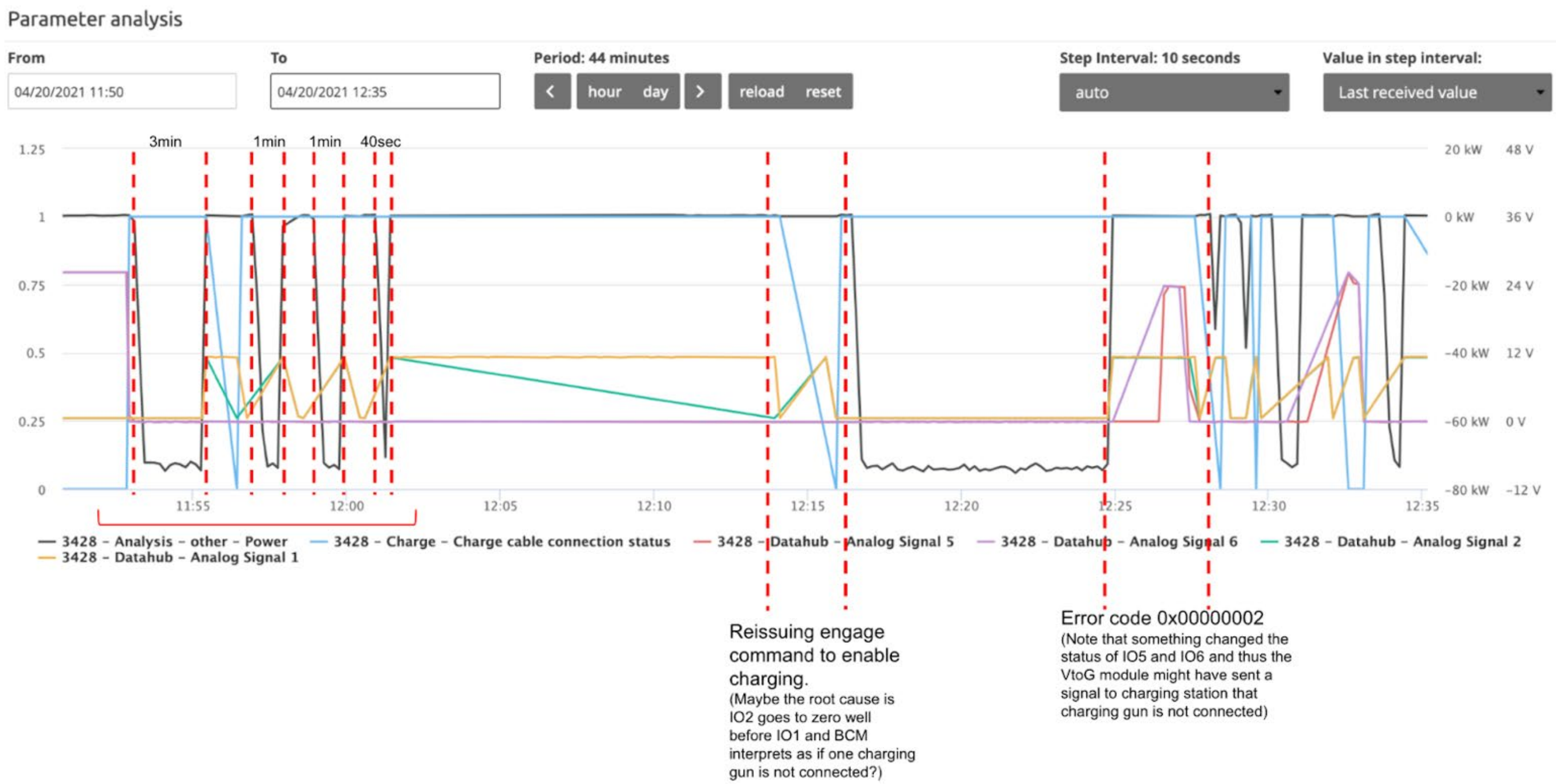


Single line diagram of bus connection showing the bus system represented by the Vehicle-To-Grid (VTOG) terminals and Body Control Module (BCM), the Viriciti DH, and override switch.

Source: SLAC

After performing the modifications, the DH was only able to stop charging but not resume or start charging. Charging would only start with manual connection or reconnection of the charging guns. After many conversations with Viriciti team in the United States and in the Netherlands and the BYD team in the United States and China, additional modifications on internal DH wiring and multiple software updates on the bus side were performed. The team then was able to successfully control the start, stop, and resume charging functionalities in the bus model K9M. However, the Stanford electric bus fleet has K7 (10 units) and K9 (10 units) models and BYD informed the team that the updated software was only available for the K9M. Therefore, only 18 buses could have remote charging control capabilities. Two buses were updated initially, and multiple tests were performed to stress the system and verify its reliability. Tests such as sending frequent stop and resume charging commands, preventing the bus from charging when charging guns are first connected and pause charging for long periods of time, and resume were tested. Figure 15 shows one of the many tests performed including the frequent start/stop commands, long standby (charging guns connected but not charging), as well as error.

Figure 16: BYD Remote Charging Control Test



Electric bus test showing system's ability to start/stop/resume with commands sent within minutes from each other, resume charging command sent after 40 minutes and stop charging command after 10 minutes. Also, this plot shows a common error when changing the charging state. The black line shows the power and the first column of the y-axis on the right shows its value with negative power indicating the bus is charging.

Source: Viriciti

Even though the team was able to successfully demonstrate the ability to remote control the charging of the K9M buses, the reliability of the system would prevent the system from operating autonomously without human supervision. The two most common errors observed were:

- 1) a start command sent to the DH would not necessarily always start the charging of the bus. In many cases the command needed to be reissued. In other words, if a start command was sent but the charging did not initiate within two minutes (it generally took 30 seconds) a stop followed by a start command was sent (middle section in Figure 15). If charging did not initiate after two attempts, the charging guns had to be removed and sometimes a power cycle in the bus and station would be required.
- 2) when the bus was on standby mode a command to engage sent from the DH to resume charging generated an error message with error code: 0x00000002 displayed at the charging station. According to BYD, this is a general error code that means charge is forbidden and the only way to reset the system was to remove the charging gun from the vehicle.

The BYD team was not able to trace the origin of such errors and, since once they happened, they required manual intervention, more tests with BYD field engineers on site would be required to reliably mitigate all the errors and deploy the system.

Algorithm

The algorithm developed to optimize the charging schedule of the bus fleet was designed based on how the fleet operates. The fleet peak hours of operation are mornings between 7:00 a.m. and 10:00 a.m. and afternoons between 3:00 p.m. and 6:00 p.m. Other hours during the day require an average usage of the fleet and evenings have low requirements. Therefore, assignments of buses to routes was performed the night before to account for any issues with the fleet during the day operations. Thus, the scheduling algorithm was not required to run in real-time.

Software User Interface

From a user interface perspective, the team conducted two surveys with dispatchers and the management team, and another with drivers to understand the important parameters from an operations standpoint: which systems were being used and what was needed. The main findings were: 1) it is important to know each buses' geographical location with respect to its current route, charging status, and SOC and to be able to generate reports and send service alert notifications to the public; 2) the main systems being used were Viriciti to obtain charging status and SOC and SPOT to obtain all other parameters (refer to the previous Data and Controls section); and 3) it was necessary to combine the relevant information from both systems into one single screen with the ability to enable/disable charging remotely. From the survey findings and the limited third-party integration capability the SPOT system had, the team concluded that the user interface for the dispatchers would provide information of the charging status, SOC, and ability to control charging remotely (see Appendix A).

Google

Data and Controls

The real-time data available at Google was primarily from the EVSE stations from ChargePoint. ChargePoint has an API using the open charge point protocol. From this API, each EVSE's port load, shed status, allowed load, and user ID were collected and the EVSE's maximum allowed load and shed status were sent back to control the EV charging.

Algorithm and Software User Interface

The algorithm developed to operate the system in real-time was designed to run at a 5-minute interval with only the information collected from the EVSE, provided above. This means that there was no information about when vehicles would arrive and leave, and no SOC information (more details are provided in the Algorithms section). From a user interface standpoint, there was no need to develop a new one since the current interface provided by ChargePoint satisfied the requirements of visualization.

SLAC

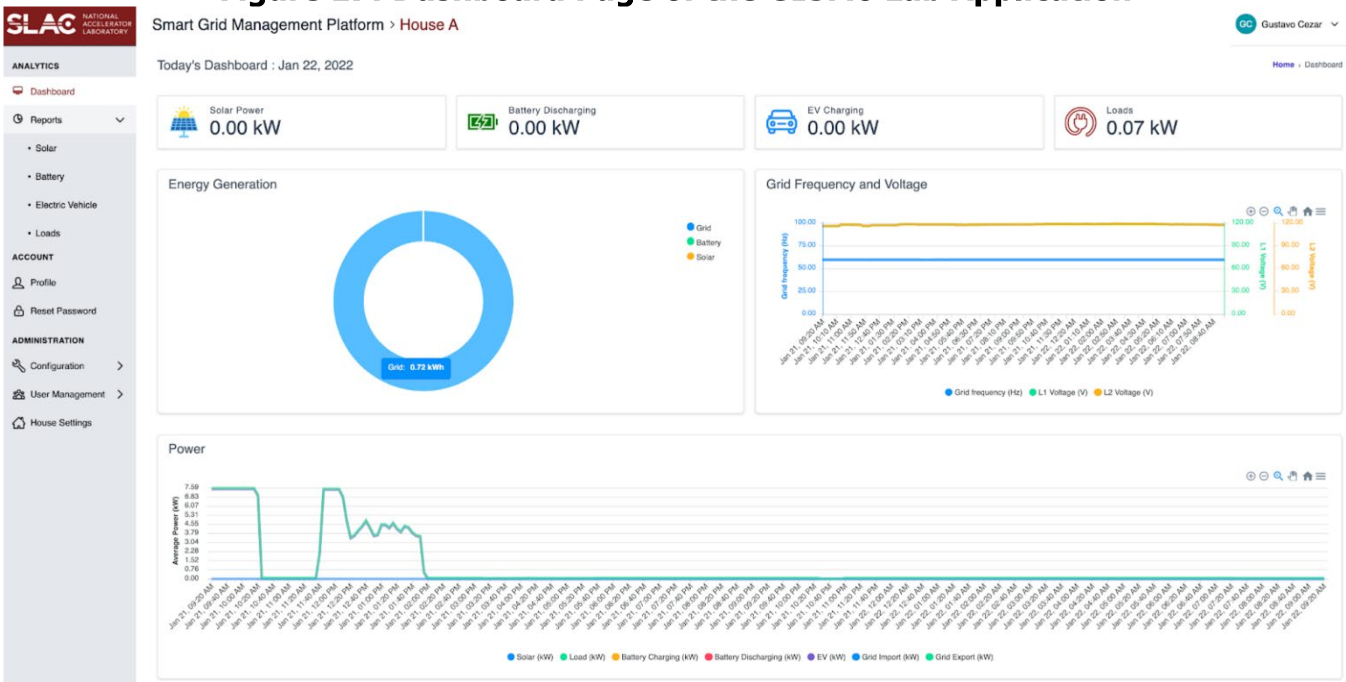
Data and Controls

Since the stations available to the employees were not available for testing, the team used the GISMo lab facility and its recently added resources to demonstrate the software capabilities and communications. The GISMo lab has two experimental sections, emulating real homes. Each experimental home contains an independent PV system, a battery energy storage system, an EVSE, multiple outlets for standard loads, and monitoring equipment. The software system, the Smart Grid Management Platform (SGMP), was developed to interface with these resources, when an API was available. The EVSEs were both from PowerFlex, and the team was granted access to the API for real-time operation. In addition to the PowerFlex API, the team developed interfaces for the monitoring equipment that was measuring each subcircuit in the main service panel and one of the battery systems. The GISMo lab also had an EV to use for experiments with the stations.

Software User Interface

The software was developed to establish communication with the resources and show the control capabilities. Since there was only one EV and two EVSE, the demonstration of the algorithm capabilities was very limited. The focus of the development was then on visualization, analytics, and customization of the data ingestion. The analytics component, in particular for the EVSE, included power and cumulative energy at five-minute intervals, number of charging events, and average duration of charging sessions. The customization component of the data ingestion allowed researchers to change or add to the way data was being collected in real time, for example, by implementing mathematical operations of multiple data streams, adding new measurements, and changing the sampling rate. Figure 16 and Figure 17 show the user interface developed for the GISMo lab.

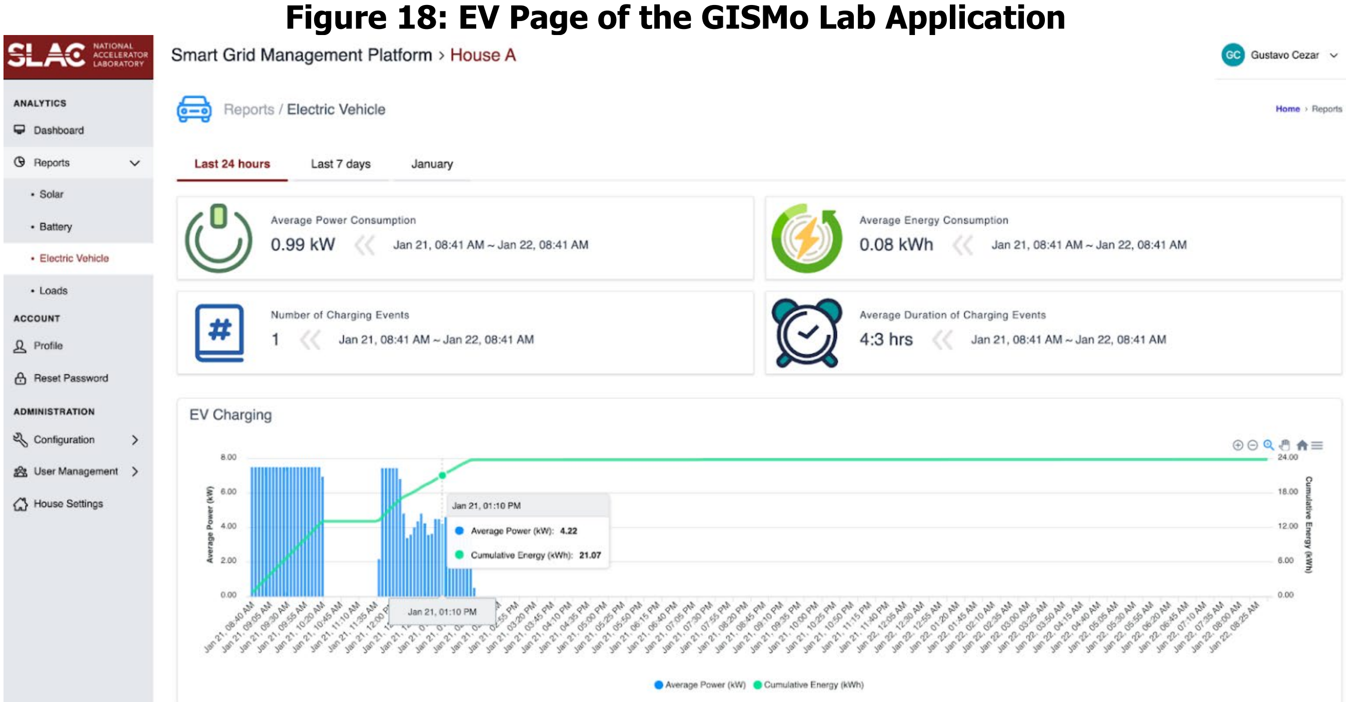
Figure 17: Dashboard Page of the GISMo Lab Application



This image shows the main page of the software developed for the GISMo lab showing the available resources data and metrics. The tab on the left let the user navigate to other pages within the application to look into deep details of each resource and change configurations without needing to go to the source code.

Source: SLAC

Figure 18: EV Page of the GISMo Lab Application



This image shows the EV detailed page with key event metrics and the time series graph.

Source: SLAC

CHAPTER 3: Project Results

This chapter provides an analysis of the results obtained in this project to meet the project goals of 1) quantifying the impacts of EVs on the grid, in particular transformer impacts, phase imbalance, harmonics, and emissions and 2) evaluating the potential of smart charging as a value stream for workplace charging under different rate structures while minimizing the infrastructure impact and satisfying user needs. The project aimed to test the algorithms developed in the field in at least two test sites during spring and fall of 2020. However, given the COVID-19 pandemic, the demonstration sites were closed and multiple stations within the sites were decommissioned. Nonetheless, many insights were obtained and lessons learned that can inform future projects and increase their likelihood of success.

This chapter organizes the results by site. First, the chapter analyzes the Stanford electric bus fleet, presenting the results of the joint route assignment and charge scheduling problem with electricity cost minimization, then discussing the site emissions. Then the chapter further discusses the field tests and challenges with the hardware, bus software, and reliability. Following the Stanford fleet discussion, the analysis and results for the smart charging algorithms and emissions model at Google are presented with discussion of some of the challenges encountered with communication with the stations. Lastly, the analysis and results from the SLAC site are presented with the transformer analysis with the real data, the emissions model, and a discussion about the GISMo lab software. The last section of this chapter discusses the impacts of EV charging at a larger scale with regard to emissions and phase imbalance.

Stanford EV Bus Fleet

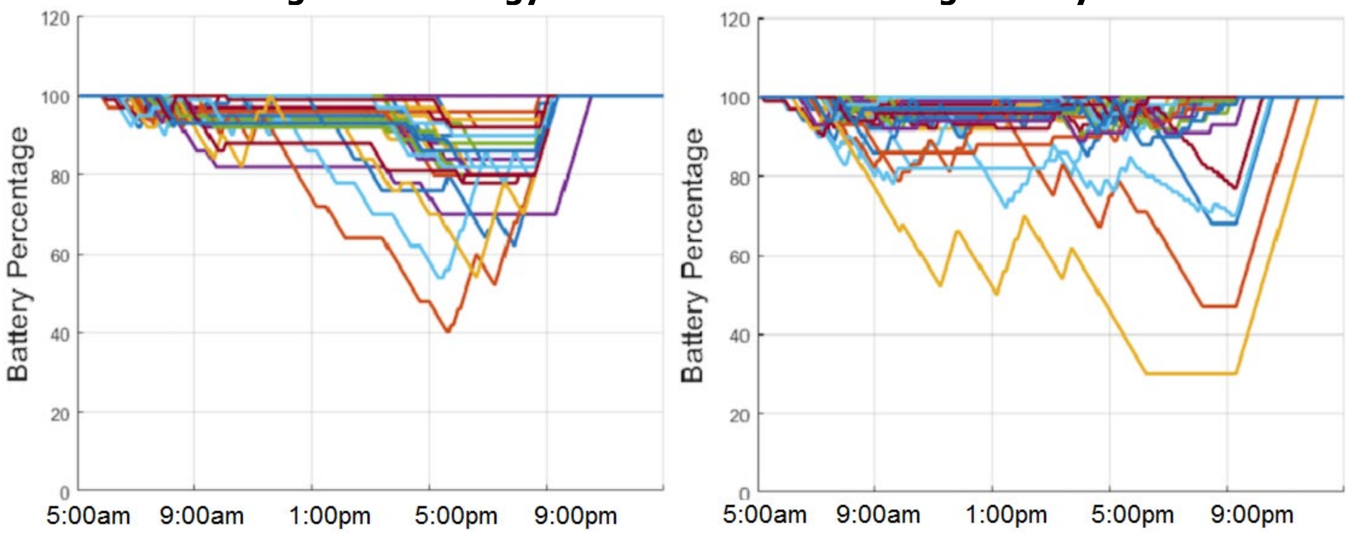
Smart Charging Analysis

As presented in Chapter 2, the goal of optimization is to jointly schedule the charging and assign buses to routes while reducing the electricity cost and maximizing the onsite solar use. Further, the electric bus fleet system serves as many as 20 unique routes, 15 of which are fulfilled by the electric fleet, with predefined schedules, for a total of 352 trips per day during the week. Finally, the minimum SOC was constrained to 20 percent based on the survey conducted with drivers, who identified this as the minimum level with which they were comfortable driving back to the bus yard to charge. Detailed information about the mathematical model and formulation can be found in (Moradipari et al., 2020).

This analysis reports on the charging schedule, route assignments, and cost savings when comparing the proposed mixed-integer linear programming (MILP) solution with onsite solar generation, without onsite solar generation, and the status quo (the status quo is the actual operations of the Stanford Marguerite Fleet from October 7, 2019), which did not exploit free onsite solar generation.

Figure 18 presents the energy levels of each bus in the fleet during the day when the dispatch was generated through the project's proposed MILP. Time on the x-axis began at 5:00 a.m., as this was the start of the earliest route that must be fulfilled. The left plot shows the energy levels of the buses when the MILP was not using onsite solar generation. The right plot shows the battery levels of the buses when the MILP accounted for onsite solar generation. It will become clearer when examining Figure 18 that the buses charge more during midday in the right plot than the left, to make use of the free onsite solar.

Figure 19: Energy Used for Each Bus During the Day

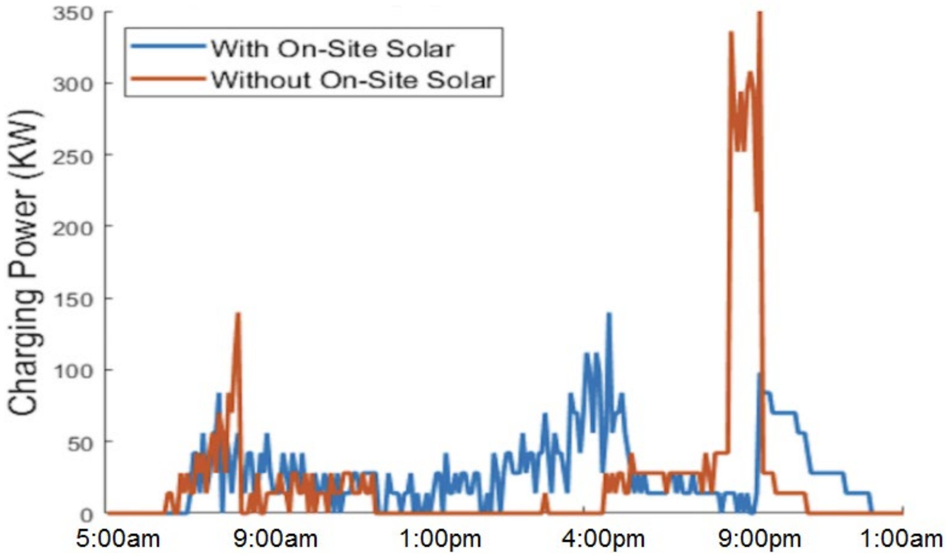


Left: Battery levels for each electric bus when considering a fleet without available onsite solar. Right: Battery levels for each electric bus when optimizing with available onsite solar generation.

Source: SLAC

Figure 19 presents the total charging power of the fleet across the entire day. The red curve presents the total charging power for the MILP solution that does not exploit onsite solar generation. Conversely, the blue plot shows the fleet's total charging power from the MILP solution that does account for onsite solar generation. It is clear from this plot that the solution that accounted for onsite solar (blue) was able to charge in the middle of the day when solar is abundant; however, the solution that did not exploit solar (red) did not charge during the midday as the electricity prices are highest at this time. Instead, the fleet had a spike in charging power in the evening when electricity rates decrease. This large transient in the evening could be detrimental to grid stability, increase in harmonics, accelerate aging of grid assets (i.e. transformers), and potentially lead to demand charges for the fleet dispatcher due to high power consumption. As such, the solution making use of onsite solar generation with a forecasting method is preferable.

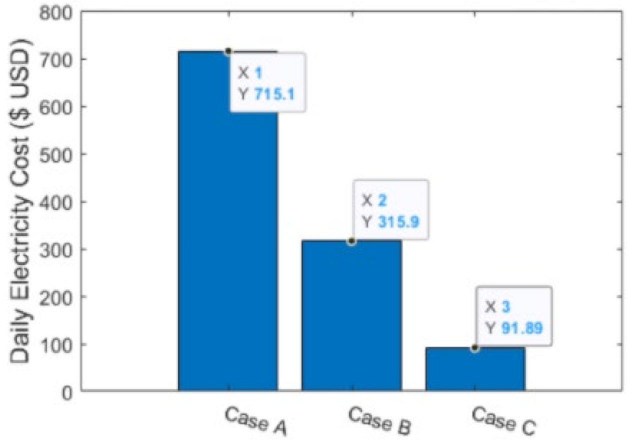
Figure 20: Comparison of Total Charging Power with/without Onsite Solar



Source: SLAC

Last, Figure 20 presents the daily electricity costs for the three different test cases. In Case A: Status Quo, the project team had access to the data from the operations of the Stanford Marguerite fleet on October 7, 2019, and calculated the cost of charging the fleet under the E-20 rate structure. As such, under normal operation, the daily operational cost was $715.10. Case B corresponded to the solution of the proposed MILP with the same routes, buses, and chargers as Case A; however, the mobility-aware solution reassigned buses to new trips and rescheduled the charging of each bus. In Case B, the MILP solution did not account for onsite solar and the daily cost was $315.90. Case C was identical to Case B; however, the MILP accounted for the onsite solar generation and had access to the daily solar forecast. As such, the daily cost was reduced to $91.89. From these results, it is evident that the fleet dispatcher benefitted from the MILP formulation for routing and charging (55 percent decrease in cost in Case B).

Figure 21: Comparison of Daily Electricity Cost



Price Comparison for three different regimes: Case A: Status Quo, electric bus charging data obtained from real-implementation (Stanford Marguerite Shuttle) on Oct 7, 2019. Case B: Mobility-Aware MILP solution for same routes and buses as Case A, without onsite solar generation. Case C: Mobility- Aware MILP solution for same routes and buses as Case A, with onsite solar generation.

Source: SLAC

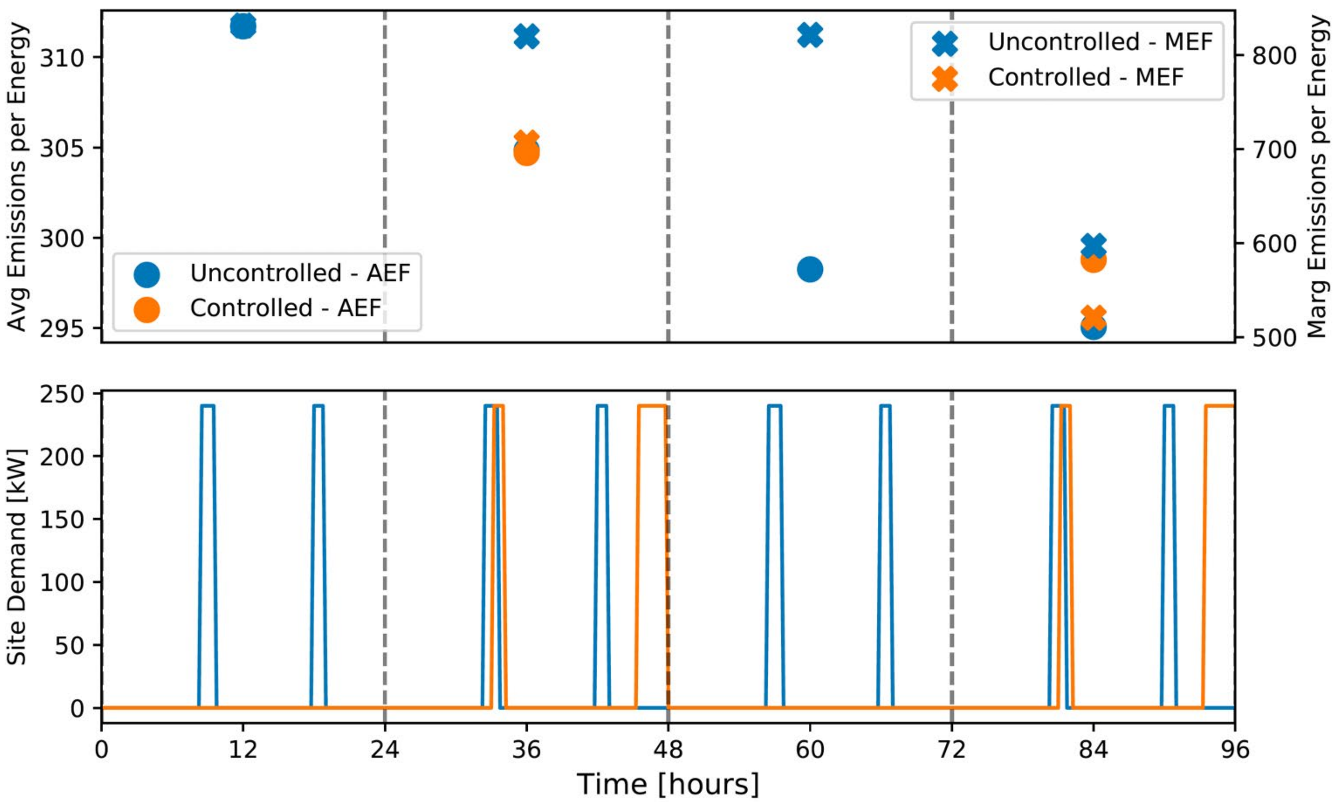
Since the only bus model that had the capability of remote charging was the K9M, although not reliably as explained in Chapter 2, another analysis was performed, with the reduced bus schedule given the COVID-19 restrictions. This schedule had the K9M buses fulfilling primarily two routes, HD and MC lines. HD line used four buses to fulfill four trips in the morning and four trips in the evening. MC line used three buses to fulfill three morning trips and three evening trips. Historical data for buses performing these routes were analyzed to define a baseline for energy used and to compare the performance of the smart charging approach given the new proposed charging schedule. Given the historical data analysis, it was determined that in the worst case a bus would use 81 kWh of energy to complete a single trip in the MC line route and 65 kWh for HD line. The status quo load, i.e. uncontrolled charging, and the charging load based on the proposed schedule using the smart charging algorithm is shown in the bottom graph of Figure 21 for HD line and in the bottom of Figure 22 for MC line. The buses serving HD line need to charge twice a week during the 10:00 a.m. to 2:00 p.m. time period. During this period, they had to charge on average for one hour. Thus their midday flexibility index was 0.75 for 10:00 a.m. to 2:00 p.m.. Additionally, they also had to charge three times a week during the off-peak hours from 9:30 p.m. to 4:30 a.m. During this seven-hour window, the buses had to charge on average for 3.25 hours. Thus, their nighttime flexibility index was 0.54. For the MC Line, buses only charged during the off-peak hours and on average only needed 2.7 hours of charging. Additionally, the minimum SOC for the buses doing HD line was 40 percent and MC line was 50 percent. From a cost savings perspective, the schedule using the smart charging was able to save 37 percent for the HD line and 56 percent for the MC line. These savings came primarily from charging mostly during off-peak hours and preventing the top-off behavior of always connecting the buses to the stations if they were not in use irrespective of time of the day and SOC. This leaves enough energy on the buses to make drivers comfortable adopting such schedules. Appendix B shows the schedules provided to the dispatch team.

Emissions Model

From the uncontrolled and controlled profiles, based on the proposed schedule for HD and MC lines, the emissions model proposed in Chapter 2 was applied. The team calculated the emissions profile of each, during four days in September 2021.

The team used a model of the 2019 grid and assumed the emissions profiles would be similar on those days in 2019 and 2021. The results of the analysis, presented in Figure 21, for HD line, and Figure 22, for MC line, show that the effect of controls was inconsistent day-to-day: emissions per mile increased some days and decreased others.

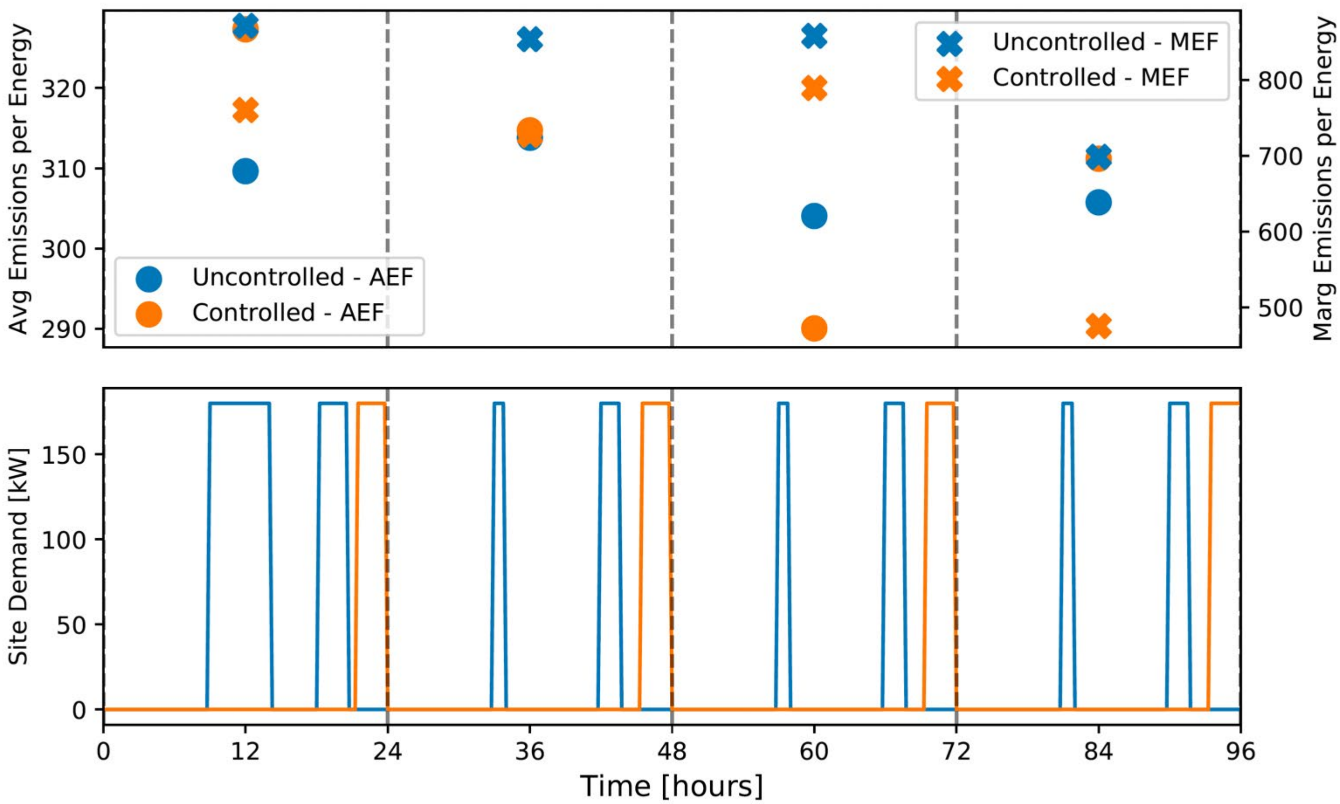
Figure 22: Comparison of the Emission's Profile for HD Line



This figure shows the Marginal and Average Emissions Factors (MEFs and AEFs) [top] and load profile [bottom] for the HD line during September 14 – 17. The control scheme did not charge on the first and third day, so there are no emissions rates shown for those days. The emissions are shown per energy in grams (g) CO_2/kWh. Calculating the added emissions using the average and marginal emissions factor methods are shown on the left and right axes of the upper plot.

Source: SLAC

Figure 23: Comparison of the Emission's Profile for MC Line



This figure shows the emissions (AEFs and MEFs) [top] and load profile [bottom] for MC line for September 14 – 17. The emissions are shown per energy in g CO_2/kWh. Calculating the added emissions using the average and marginal emissions factor methods are shown on the left and right axes of the upper plot.

Source: SLAC

Google

Smart Charging Analysis

Demand Response

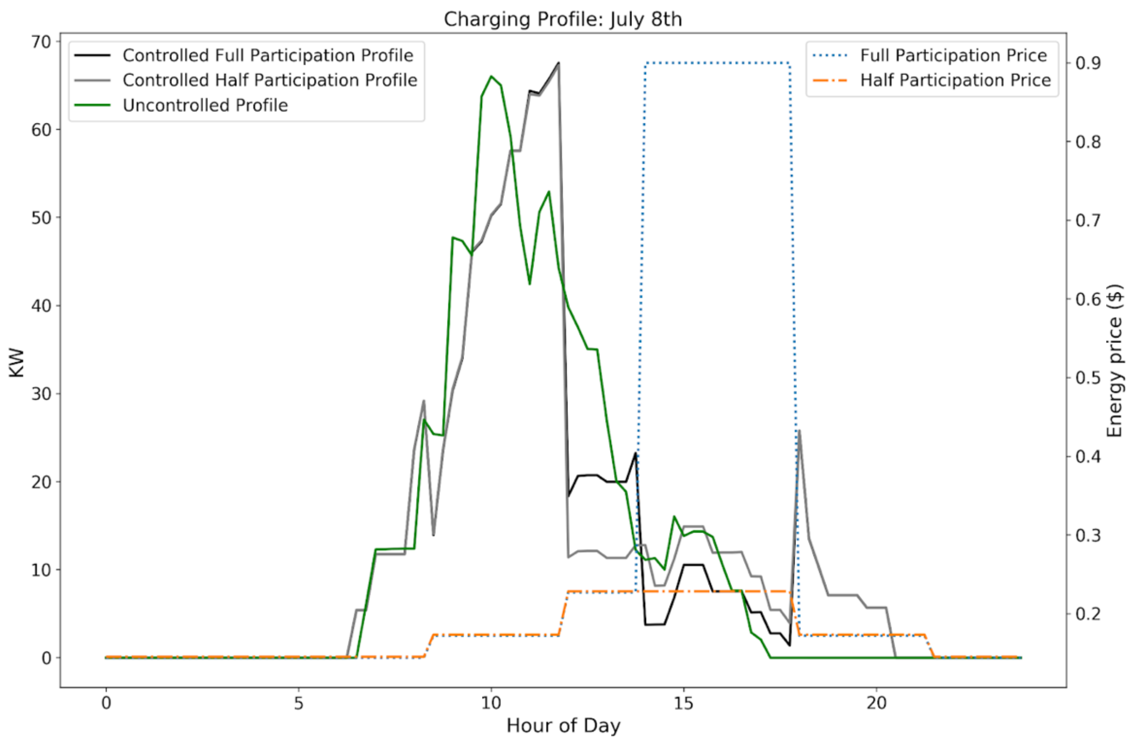
The demand response potential of workplace electric vehicle charging using the Google demonstration site was quantified. While EVs have the potential to participate in multiple demand response markets and programs, the focus of this analysis was on participation in time of use and peak day pricing (PDP) tariffs. Particularly during a PDP pricing event, customers faced a high energy charge from 2:00 p.m. to 6:00 p.m. Key vehicle charging parameters were extracted from the ChargePoint data at the Google site from 2017 and used to implement optimal control algorithms to minimize cost of charging on PG&E's A-10 and E-19 Tariffs.

One of the main differences between these two rate structures was that for E-19, in the summer, participants in PDP incurred time varying energy charges, a max demand charge, peak and part-peak demand charges, PDP energy charges, and PDP demand credits. Additionally, the peak and part-peak demand charges were determined based on a capacity reservation level (CRL). Customers were billed based on this level of usage even if their actual usage was below this level. During a PDP event, participants were charged for energy usage above the CRL at a higher rate. To compensate for incurring high PDP energy charges, customers were credited for their peak usage above the CRL during the peak and part-peak period.

Figure 23 shows the uncontrolled charging profile and controlled charging profiles for the A-10 tariff on July 8 — when a PDP event was implemented for the full participation optimization, but the event was not implemented for half participation. There was a noticeable response to the high energy charges in the full participation profile compared to half participation. More charging occurred during the peak period before the PDP event started in the full participation profile and less charging occurred during the PDP event compared to the half participation profile.

Most of the savings for the A-10 tariff were achieved by reducing the demand charge. There was limited ability for charging to be shifted into off-peak periods and load was shifted from the early part-peak period into the peak period to avoid the hefty demand charge, causing energy charges to decrease minimally or increase slightly. If the charging session time frames were more flexible, greater energy charge savings would be achieved by pushing load into off-peak periods and further reducing the peak load. Since most workplace charging sessions occurred during the part-peak and peak periods, off-peak charging potential was minimal.

Figure 24: Comparison of EV Charging Profiles for A-10 Tariff with PDP

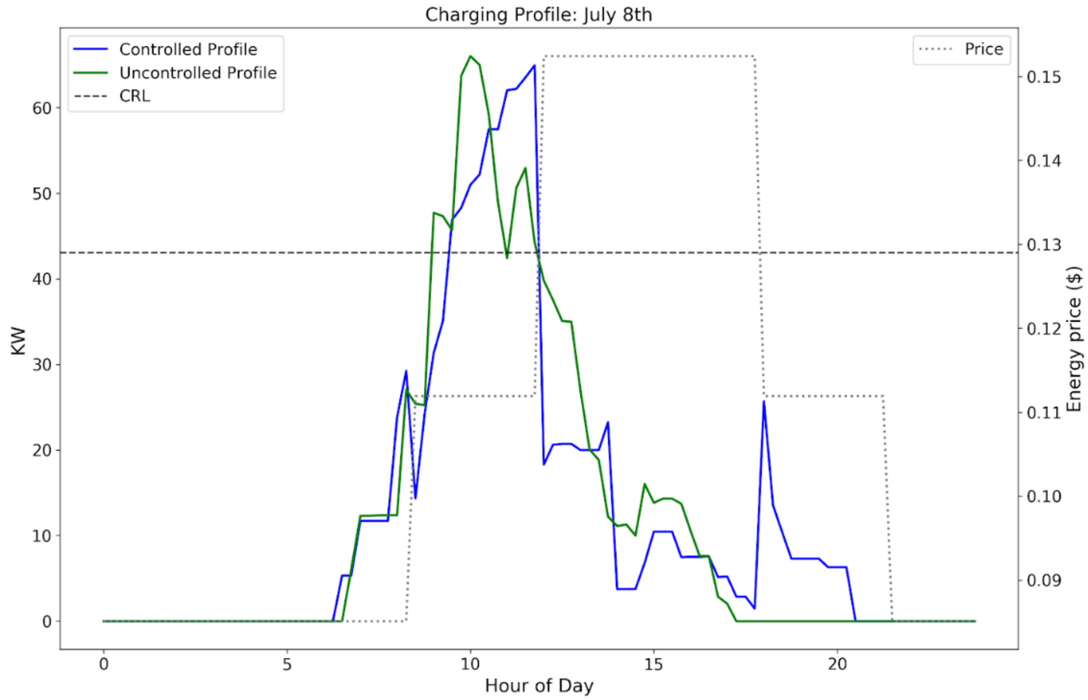


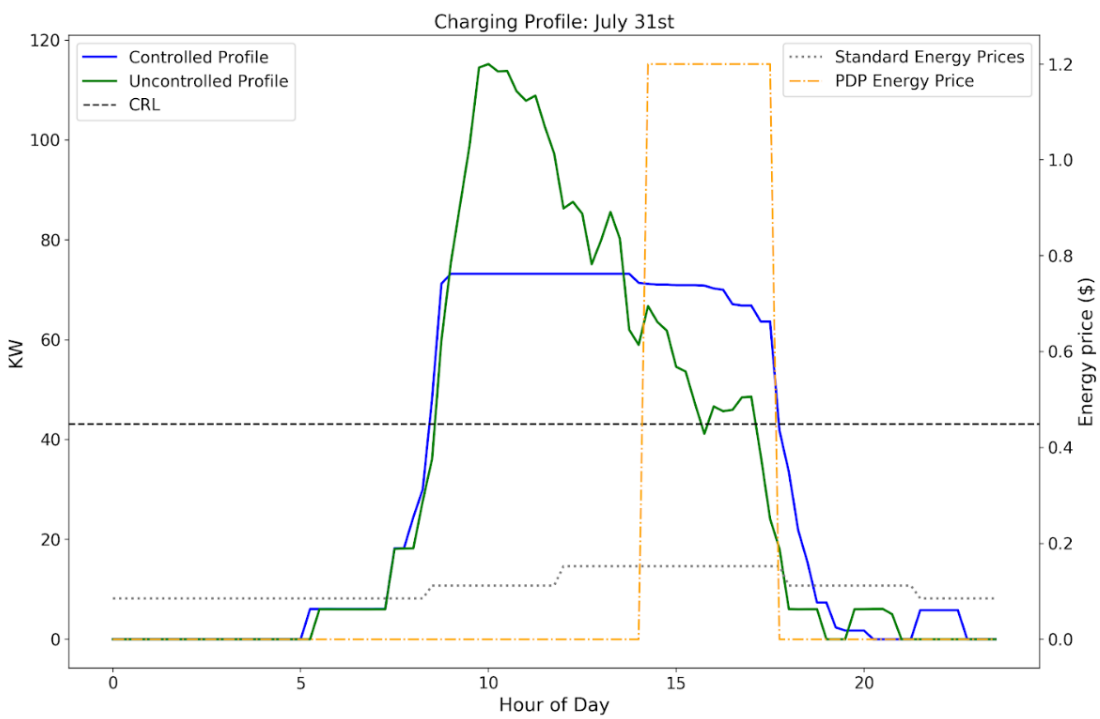
Charging profile on July 8 where the full participation profile was optimized for the high peak day pricing charges and the half participation profile was optimized based on the standard charges.

Source: SLAC

Figure 24 shows the uncontrolled charging profile and controlled charging profiles for the E-19 tariff. During most PDP events, usage did not exceed the CRL when it was set to 43.08 kW (50 percent of average maximum peak period demand of the summer months). During these events no PDP energy charges were incurred. There was one event each in June, July, and August in which the usage exceeded the CRL. During those events, the maximum usage was only slightly less than the maximum demand for the month, indicating significant charging demand with limited flexibility during these times. As seen in the profile for the July 31 event, the daily uncontrolled peak was flattened in the controlled charging scenario, pushing charging load into the event to avoid incurring a higher maximum demand charge.

Figure 25: Comparison of EV charging profiles for E-19 with PDP and CRL





Top: no PDP event day charging profile with CRL. Bottom: PDP event day charging profiles with CRL.

Source: SLAC

The monthly savings resulting from implementing the smart charging controls under the two tariffs are shown in Table 2.. The savings were calculated based on what the bill would be given the charging profile reconstructed from ChargePoint data (uncontrolled charging).

Table 2: Percentage Savings Achieved through Smart-Charging Control

	A-10	E-19
Month	Savings	Savings
January	23.77%	33.69%
February	21.95%	30.78%
March	21.26%	30.82%
April	23.30%	33.08%
May	21.69%	16.79%
June	23.62%	19.44%
July	19.81%	16.82%
August	24.30%	22.08%
September	23.58%	20.78%
October	22.55%	19.81%
November	22.74%	32.43%
December	24.98%	34.15%
Total	22.76%	25.39%

Source: SLAC

Another analysis was performed to investigate the load shed capacity of EV charging at each hour. The load shed capacity was determined by optimizing charging with a demand penalty applied at the given hour. For all months, the maximum load shed capacity occurred between 9:00 a.m. and 11:00 a.m. This timing was expected as there was significant demand in the uncontrolled profiles as employees arrived at work and charging could be delayed significantly at this hour as it is at the beginning of most charging sessions (see Appendix B for further details). The maximum sheddable load at these hours ranged from 71.92 kW to 100.78 kW, or 54 percent to 76 percent of the monthly uncontrolled maximum demand.

Transformer Analysis

The results of the transformer aging analysis shown in Figure 25 reveal a large difference between uncontrolled and controlled charging. For this analysis, simpler control schemes were modeled based on rate schedule designs, and the number of vehicles in the parking lot was increased to see how many could be supported without aging the transformer in each case (Powell et al., 2020).

Figure 26: Comparison of the Effects of Different Smart-Charging Schemes in the Transformer Lifetime

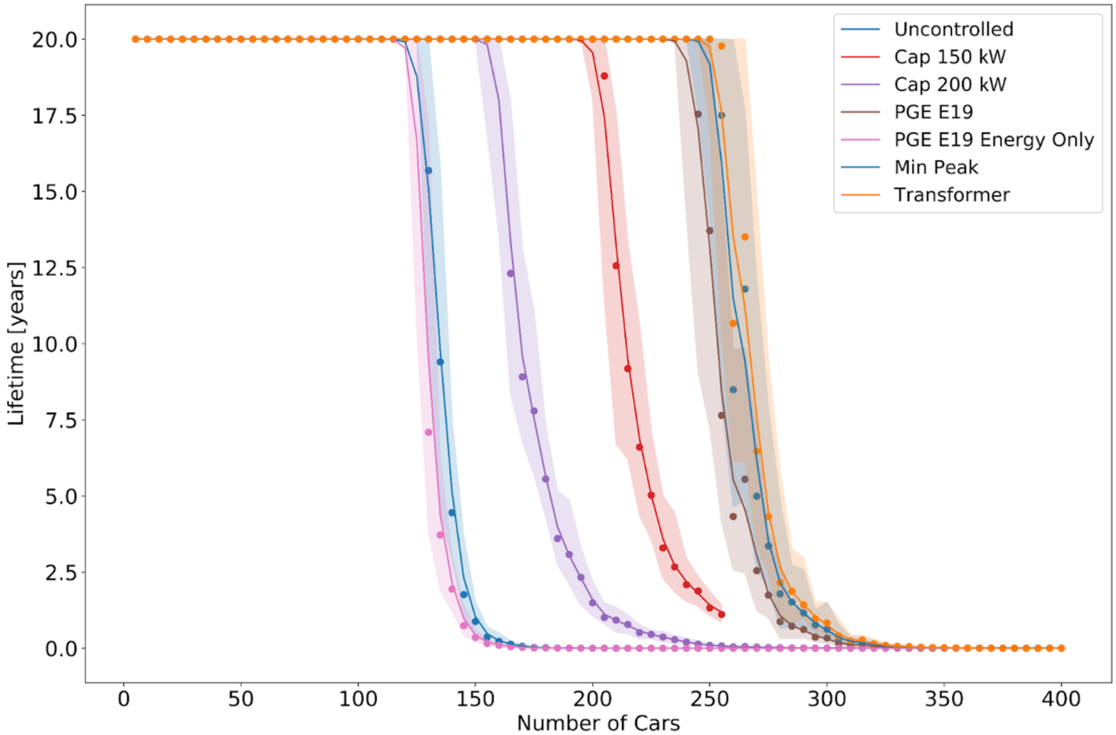


Figure 25 shows the transformer lifetime (capped at 20 years) as the number of vehicles in the parking lot was increased (Powell et al., 2020). The Cap control schemes did not have objectives but placed limits of 150 and 200 kW on the total demand. The Min Peak control scheme minimized the maximum demand as its objective. The PGE E19 control schemes were designed for PG&E's E-19 rate schedule.

Source: SLAC

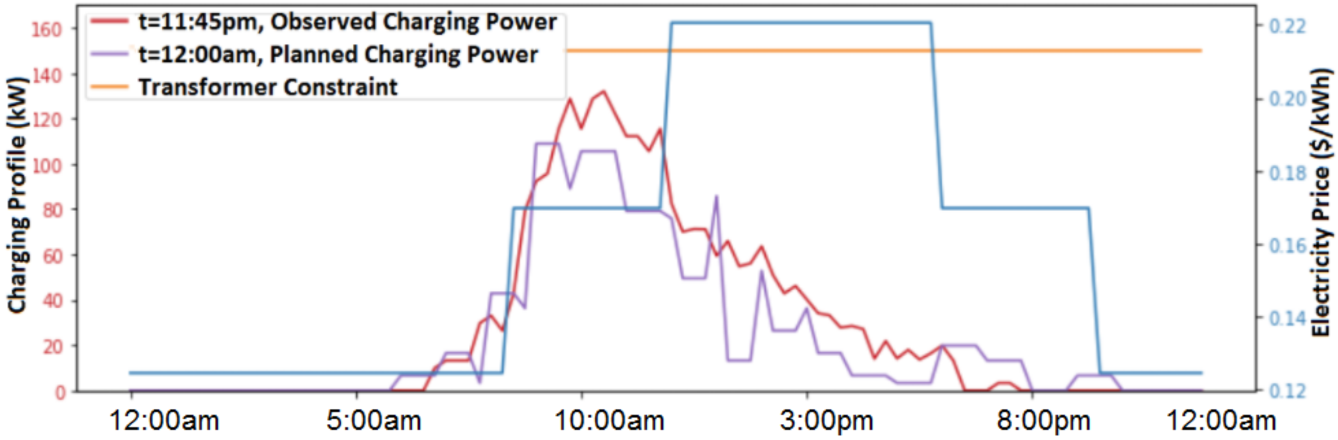
The project team found that the transformer at the Google site could support fewer than 150 vehicles per day with uncontrolled charging, but nearly 250 vehicles with the best control schemes. Time-of-use rate schedules did not encourage any improvement, as shown by the Energy-Only implementation of the PG&E E-19 rate. Capping the total demand at each site gave a modest improvement. The best case, however, came from peak minimization, rates with demand charges, or the direct minimization for transformer aging.

This result is encouraging: at sites with high use, demand charges and peak minimization can be used to encourage controls that protect distribution transformers by reducing peak demand.

Real-Time Charging

The real-time charging algorithm using the scenario generation and certainty equivalent control performance was evaluated (Tucker, Vianna Cezar, & Alizadeh, 2022). Figure 26 presents a comparison of a weekday's predicted daily charging schedule and the actual daily charging power that occurred that day. As seen in Figure 26, the daily model did a good job predicting the future load for this location. Furthermore, note that most of the power was scheduled for delivery during the partial-peak electricity rates during the mid-morning (8:30 a.m. – 12:00 p.m.) and the charging power decreased rapidly during the peak electricity rates midday (12:00 p.m. – 6:00 p.m.).

Figure 27: Real-time Predicted Daily Charging Schedule vs Actual Daily Charging Power



In this figure, the red curve shows the EV charging load that happened on that day using the real-time algorithm. The purple curve shows what the algorithm predicted the model to be at the start of the day. The orange curve shows the transformer nominal capacity. Blue curve shows the electricity price.

Source: SLAC

Table 3 presents several test cases. In these tests, w_1 and w_2 were varied in the objective function between (2,1) and (10,1) to show how the algorithm swapped priority from minimizing electricity cost to maximizing user utility for receiving energy. Additionally, the transformer constraint that couples all the EVs together between 250 kW and 100k W was varied. Table 3 also shows the total energy delivered over the two-week period and the total cost of purchasing that energy from the grid from energy rates as well as the total cost due to demand charges (displayed as percentages compared to the status quo values). The last two columns in Table 3 show whether or not the test case included a constraint that forced the EVSEs to charge at a certain rate for the first hour that a new EV was plugged in. The idea behind this was to ensure that EVs would receive some minimum amount of energy, even if they were only plugged in for a short duration, or if they arrived during peak electricity rates. The project team experimented with forcing the EVs to charge for the first hour of a new session at their maximum rate, half their maximum rate, a quarter of their maximum rate, and without this constraint altogether. The second-to-last column indicates whether or not this constraint was included, and the last column indicates the charge rate that was used for this first hour (p_{max} = 6.6kW). The first row of this table shows the total energy delivered and the total energy cost for the status quo (i.e., no algorithm in place, just the energy consumed and cost for June 17 to June 29, 2019). The (w_1, w_2) = (10,1) results in Tests 07–13 indicate that the smart charging algorithm was able to reduce energy costs and demand charges while delivering adequate energy (greater than 80 percent of the status quo energy) to the EVs.

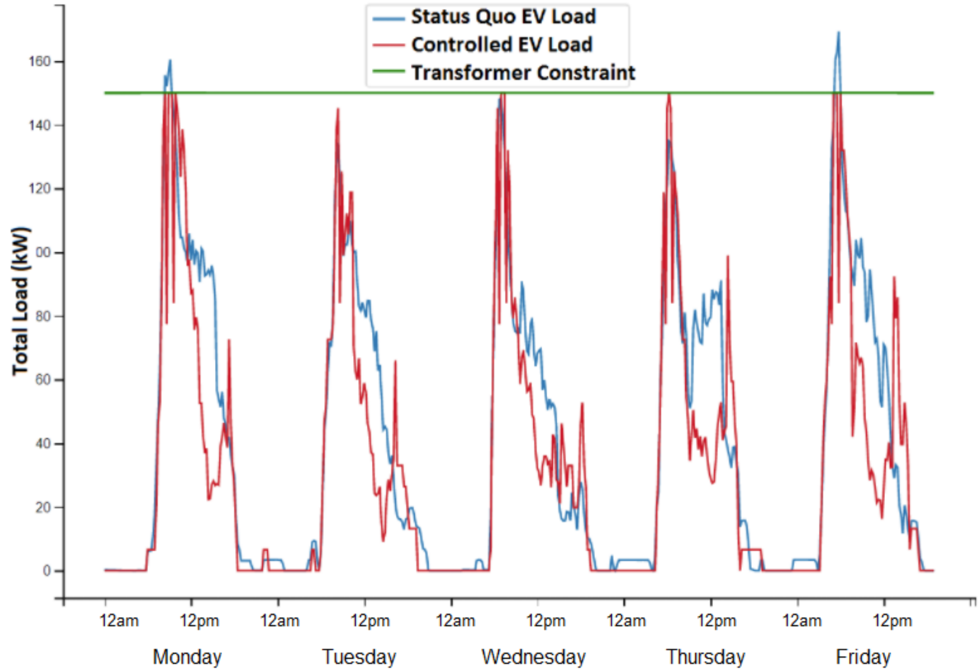
Table 3: Results for 13 Test Cases

Test #	w_1	w_2	Coupling Constraint (kW)	Energy Delivered	Electricity Purchase Cost	Demand Charge Cost	Forced Initial Charge	Initial Charge Rate
Status Quo	n/a	n/a	n/a	100%	100%	100%	n/a	n/a
01	2	1	250	50.13%	45.78%	64.50%	Yes	$\frac{1}{2}p_{max}$
02	2	1	150	50.01%	45.83%	88.76%	Yes	$\frac{1}{2}p_{max}$
03	2	1	125	50.68%	46.33%	73.96%	Yes	$\frac{1}{2}p_{max}$
04	2	1	110	50.44%	45.94%	65.09%	Yes	$\frac{1}{2}p_{max}$
05	2	1	110	44.20%	36.40%	65.09%	No	n/a
06	2	1	100	45.05%	37.45%	59.17%	No	n/a
07	10	1	100	81.93%	81.36%	59.17%	No	n/a
08	10	1	150	83.85%	81.03%	88.76%	No	n/a
09	10	1	250	84.21%	80.98%	89.94%	No	n/a
10	10	1	100	Infeasible	Infeasible	Infeasible	Yes	$\frac{1}{2}p_{max}$
11	10	1	110	81.76%	81.09%	65.09%	Yes	$\frac{1}{2}p_{max}$
12	10	1	150	83.49%	81.80%	88.76%	Yes	$\frac{1}{2}p_{max}$
13	10	1	150	Infeasible	Infeasible	Infeasible	Yes	p_{max}
13	10	1	250	87.25%	84.81%	97.63%	Yes	p_{max}

Source: SLAC

Table 3 also shows the transformer capacity constraint that coupled the charging power of all the EVs was varied. In the status quo, there was no coupling constraint and the total load peaked at 169 kW. However, with the real-time smart-charging algorithm in place, the team could constrain the total load. This allowed for the location to use a smaller transformer capacity, increase the number of charging ports for EVs, or increase their other non-EVs loads (e.g., the nearby offices could safely use more power without worrying about exceeding the transformer capacity due to the EVSEs). Figure 27 shows a five-day comparison of the Test 08 load (see Table 3) compared to the status quo load. As seen in this plot, the smart-charging algorithm was able to enforce a transformer capacity limit at 150 kW without sacrificing much energy delivered. Furthermore, the smart-charging profile purposely dropped below the status quo during the middle of each day to avoid the peak electricity rates from 12:00 p.m. to 6:00 p.m.

Figure 28: Comparison of Monday-Friday Load Profile of Real-time Algorithm and Status Quo



Comparison of the weekday load for the status quo (i.e., no algorithm in place) vs. the smart-charging algorithm with parameters as listed in Test 08 of Table 3. The status quo load (blue) delivered more power during the middle of each weekday during peak electricity rates but the controlled load dipped down during this period to avoid peak prices and then increased when electricity rates lowered in the evening. Additionally, the smart-charging algorithm enforced the transformer constraint (green line).

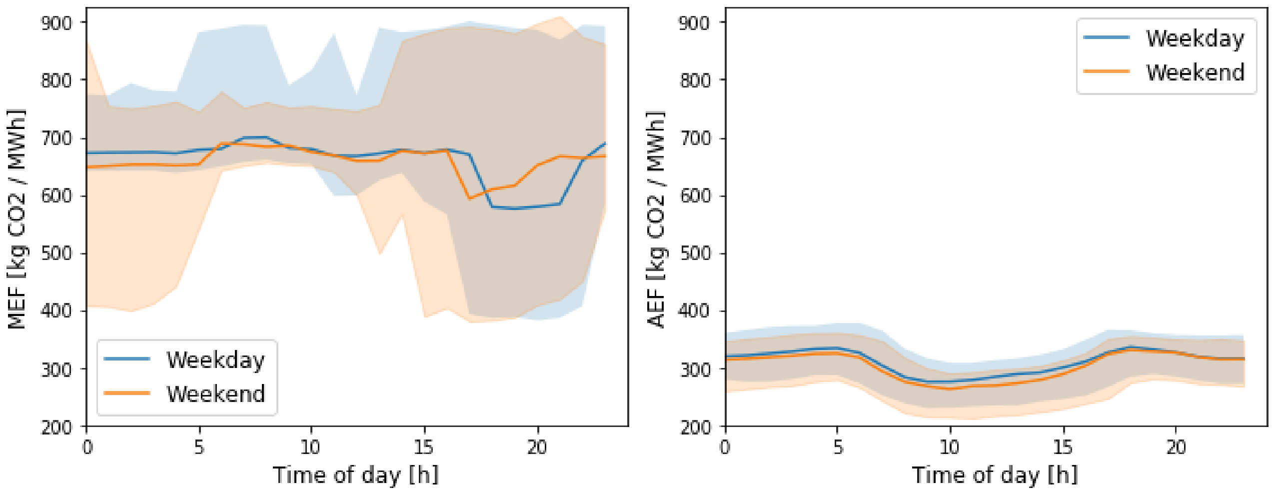
Source: SLAC

Emissions Results

The team analyzed the emissions impacts of several control strategies for the Google sites to evaluate whether these controls would increase or decrease emissions relative to uncontrolled charging. The different test cases for each site follow the parameters selection from Table 3..

The marginal and average emissions profiles modeled for 2019, explained in the Emissions Model Methodology section in Chapter 2, are shown in Figure 28. Average emissions were more consistent, consistently lower during the middle of the day in times of high solar, and consistently higher in the late afternoon, evening, and just before sunrise. Marginal emissions, by contrast, were highly variable, and there was a less clear shape throughout the day of periods of high and low marginal emissions.

Figure 29: Weekday and Weekend Marginal and Average Emissions Factors

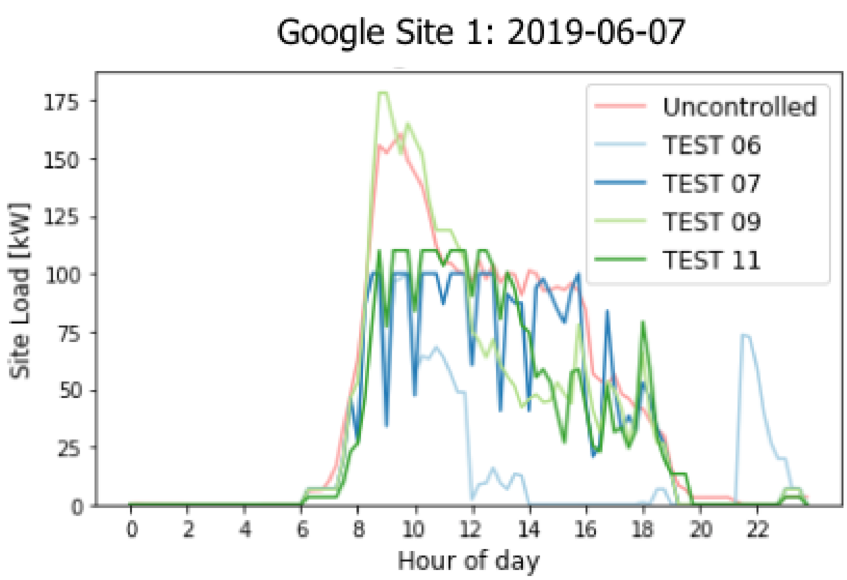


Weekday and weekend marginal and average emissions factors (MEFs and AEFs) for the model of 2019 in WECC. The lines show the median value over all weekdays or weekends at each hour and the colored bands show the 25th–75th percentile.

Source: SLAC

This variation was reflected in the results for each site. Each site shows variation in emissions, calculated both with average and marginal emissions and per unit energy, but in general there was more variation by day than by load shapes due to different control schemes. This was likely due to the flat median average and marginal emissions profile shapes during workplace charging hours. The results for this analysis are shown in Figure 29, Figure 30, and Figure 31 for site 1. The analysis for the other sites can be seen in Appendix B.

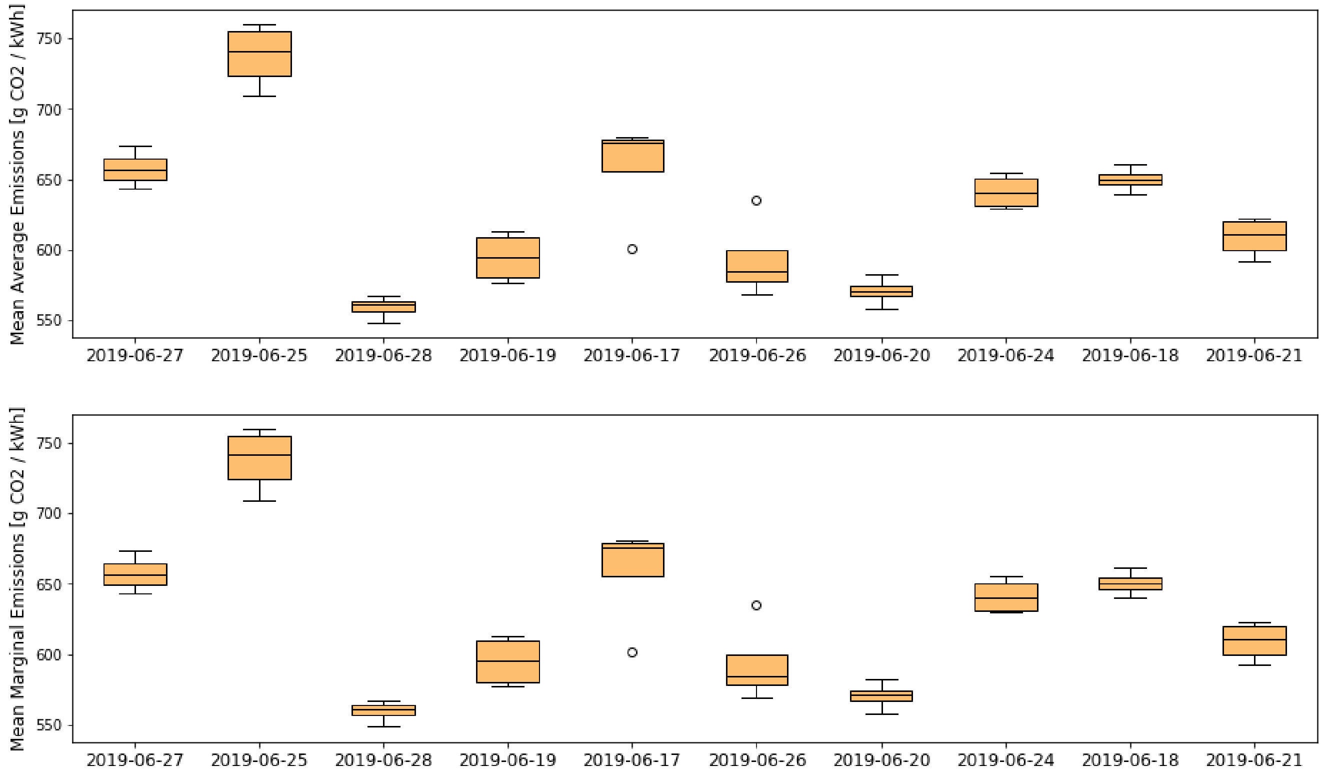
Figure 30: Comparison of the Managed Load Profiles and Status Quo for Site 1



Sample loads on one weekday from Site 1 site showing the different control scheme results: tests 6, 7, 9, and 11.

Source: SLAC

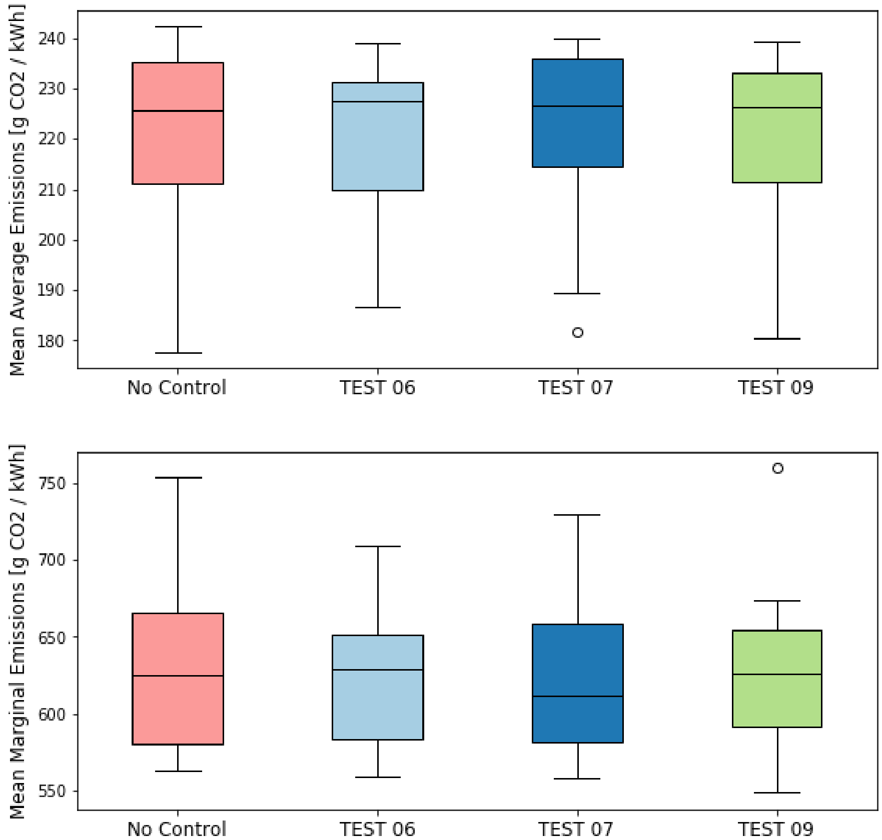
Figure 31: Weekday Distribution of AEF and MEF for Site 1



Each box shows the distribution across different control schemes of average or marginal emissions (per energy) on different weekdays tested at Site 1.

Source: SLAC

Figure 32: Test Cases Distribution of AEF and MEF for Site 1



Each box shows the distribution across different weekdays of the average and marginal emissions for each control scheme tested at Site 1. As a percentage, the median changed very little relative to uncontrolled charging in each case.

Source: SLAC

SLAC

Lastly, the analysis and results from the SLAC site discuss the transformer analysis with the real data and the emissions model and ends with a discussion about the GISMo lab software. The last section of this chapter discusses the impacts of EV charging at a larger scale in regard to emissions and phase imbalance.

Transformer Analysis

Using measurements from the temperature sensors installed in the transformer at the SLAC site, the team was able to train a data-driven model of the temperature.

To train the model, the team used data from August 10 to 23 and tested several models. Many data-driven transformer temperature models use the previous time step temperature to predict the current time step, an auto-regressive form, but the team decided not to include temperature as an input because it may have been unavailable at many sites. The team developed an equation denoting the temperature inside the transformer windings, the ambient temperature, and the loading factor, then calculated by dividing the load by the transformer nameplate capacity.

Ordinary least squares (OLS) regression was used to fit the equation as a linear model. At the SLAC site, the transformer was indoors in a temperature-controlled building, so the team modeled the ambient temperature as constant. These results were calculated using the statsmodels package in Python. Table 4 shows the model statistics and Table 5 shows the model coefficients.

Table 4: Regression Statistics for SLAC Transformer Data-driven model

Dep. Variable:	Temperature	**R-squared:**	0.774
Model:	OLS	**Adj. R-squared:**	0.774
Method:	Least Squares	**F-statistic:**	4182.
No. Observations:	1223	**Prob (F-statistic):**	0.00
Df Residuals:	1221	**Log-Likelihood:**	-2758.0
Df Model:	1	**AIC:**	5520.
Covariance Type:	nonrobust	**BIC:**	5530.

The high R-squared suggested a strong model fit: 77 percent of the variation in the temperature measurement was explained by these input variables.

Source: SLAC

Table 5: Regression Model Coefficients

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0769	0.000	479.677	0.000	0.077	0.077
Ambient Temperature	1.6149	0.003	479.677	0.000	1.608	1.621
K^2	102.1785	1.580	64.669	0.000	99.079	105.278

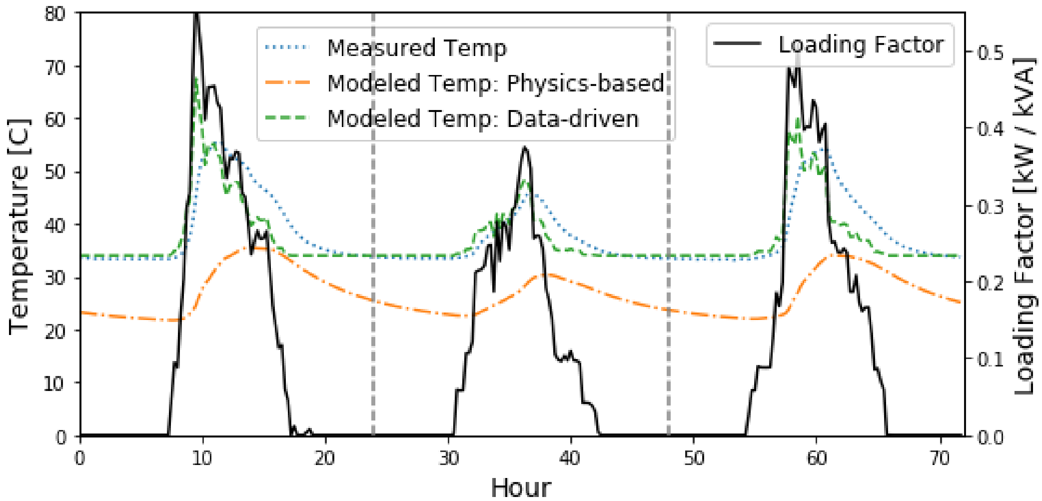
Coefficients for SLAC transformer data-driven model. All were highly significant (p<0.001)

Source: SLAC

When applied to a test set of August 24 to September 30, the model root mean squared error was just 9.8 percent of the mean value during that time and 4.8 percent of the max value.

For comparison, the team calculated the coefficients to model the same transformer using the IEEE Guide’s physics-based model, making the same assumptions to use nameplate reported values as in the study of the Google transformer. This model performed worse, reporting root mean squared error values of 33 percent of the mean and 16 percent of the max temperature when applied to the same test period. The difference between the two models is illustrated in Figure 32.

Figure 33: Comparison of Transformer Temperature Model



Results for the transformer temperature modeling at SLAC, shown for September 1–3, 2021. The three-temperature series use the left y-axis: the measured mean coil temperature, the temperature predicted by the IEEE physics-based transformer model, and the temperature predicted by the data-driven transformer model trained on data from the previous month. The black solid series using the right y-axis shows the transformer loading: overnight the transformer was not in use; during the day, it reached peaks of near 50 percent nameplate capacity.

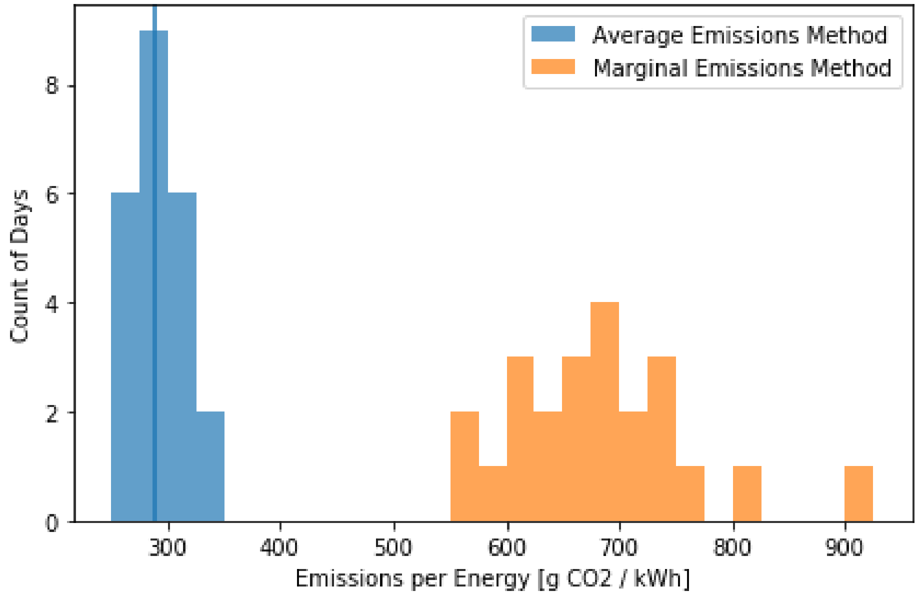
Source: SLAC

The physics-based model seemed to overestimate how much the transformer cooled, particularly overnight when the measurements suggested a plateau value more than 86°F (30°C). The physics-based model also had a significant time delay, while the data-driven model and the temperature measurement tracked the rapid changes in loading more quickly. This difference may have been due to the application: EV demand at a workplace increases very steeply in the morning, and the physics-based model may have been designed for loads that change more slowly. This difference may also have related to the type and generation of transformer: the transformer at the SLAC site was newer and more efficient than older models. Finally, this difference may have been due to the calibration of the model: if more detailed information had been available to calculate the physics-based coefficients, the physics-based model may have performed better.

Emissions Analysis

The team evaluated the emissions from the SLAC EV charging demand using both the average and marginal emissions methods for a range of days in August and September 2021. The team used the model developed for the 2019 grid, based on the most recent complete plant data available, and assumed the emissions factors would be of similar shape. The results shown below in Figure 33 highlight the range in emissions seen day-to-day.

Figure 34: SLAC EV Load AEF and MEF Comparison



Histogram of average and marginal emission factors per energy calculated using EV charging demand from the SLAC site on weekdays between August 12 and September 27.

Source: SLAC

The median value highlighted was 288.8, meaning that the electricity used to serve EV demand in 2019 had an approximate carbon intensity of 288.8 grams (g) CO_2 per kWh. This was much lower than the marginal emissions results thanks to the alignment of workplace charging with hours of high solar generation.

Smart Grid Management Platform

As presented in Chapter 2, the SGMP developed at the GISMo lab targeted not only controlling the EVSE, but also other DERs such as battery energy storage systems and even solar by curtailing solar production to test different algorithms and dispatching strategies.

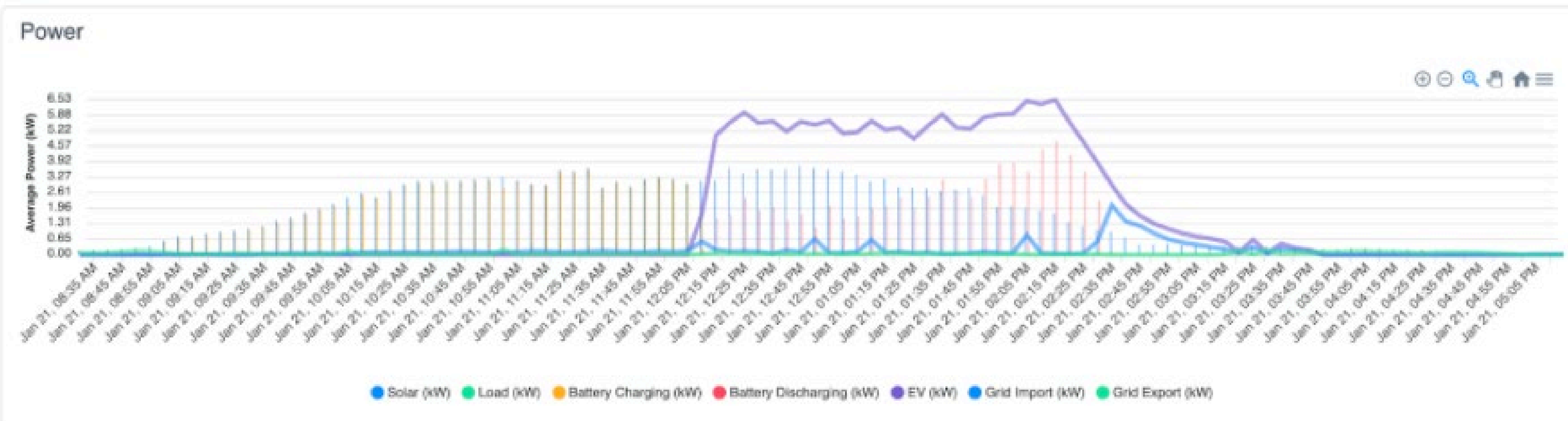
Recall that the GISMo lab emulated two homes, House A and House B. Both homes had similar DERs where, based on manufacturers, some provided ways to directly interface and control while others did not. Figure 34 shows the ability of SGMP to control the EV charging at House A from the maximum charging power to zero and values in between. Figure 35 shows a more interesting case in House B: how the integration and coordination of EV, solar, and energy storage could help minimize the consumption from the grid. During the early morning, the battery system charged from solar (battery charging is indicated by the yellow bars and solar production by the blue bars). Once an EV started charging (solid purple line), the battery started to discharge (red bars) to provide the remaining power, after the solar. The consumption from the grid (solid blue line) kept at, or very close to, zero watts for most of the charging time, indicating that the EV charging was close to net-power zero from the grid.

Figure 35: Control of EV Charging from SGMP

Demonstration of ability to control EVSE from the maximum charging power to zero and values in between.

Source: SLAC

Figure 36: Integration of Solar, Storage, and EV



Integration and coordination of solar, storage, and EV charging to minimize grid consumption when charging an EV.

Source: SLAC

EV Impacts at Scale

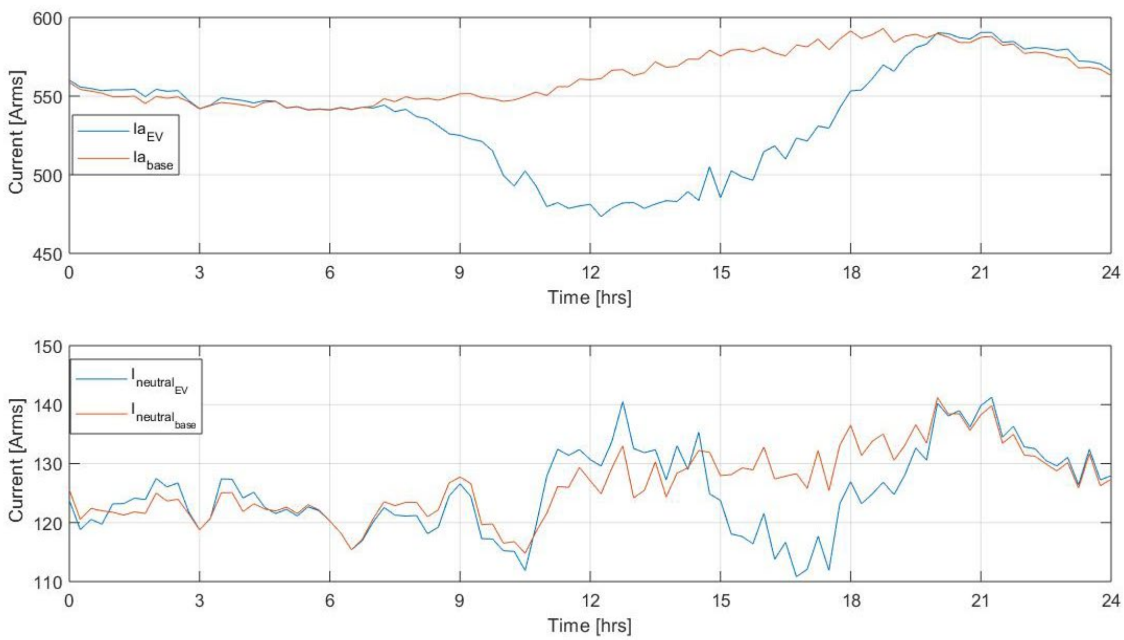
Two analyses were conducted to evaluate the impacts of EV at scale: the potential issues of phase imbalance and the emission's impact.

Phase Imbalance and Harmonics

The distribution network analyzed in this section is presented in Figure 16, Chapter 2. A comparison was performed between the base case and the scenario of all 151 homes including solar and 40 percent including EVs (65 EVs in total).

Figure 36 shows that the impact of PVs in the currents was very strong between 8:00 a.m. and 7:00 p.m., and the impact of the EV charging load in the current was minimal. In this figure, the phase A current flowing between nodes 149 – 1 is depicted in the top plot, comparing the baseline current with the total current when EV chargers and PVs were added to the residences. The bottom plot compares the currents flowing in the neutral conductor. The figure shows the slight increment of the current per phase and in the neutral conductor due to the EV chargers added to the area; however, due to the diversity of charging times all sessions did not necessarily overlap. Noticeably, the system already had a large neutral current without the addition of EVs and PVs. This neutral current came from the natural imbalance of loads between phases in the distribution network.

Figure 37: Comparison of Current Impact between Base Case and PV/EV Scenario

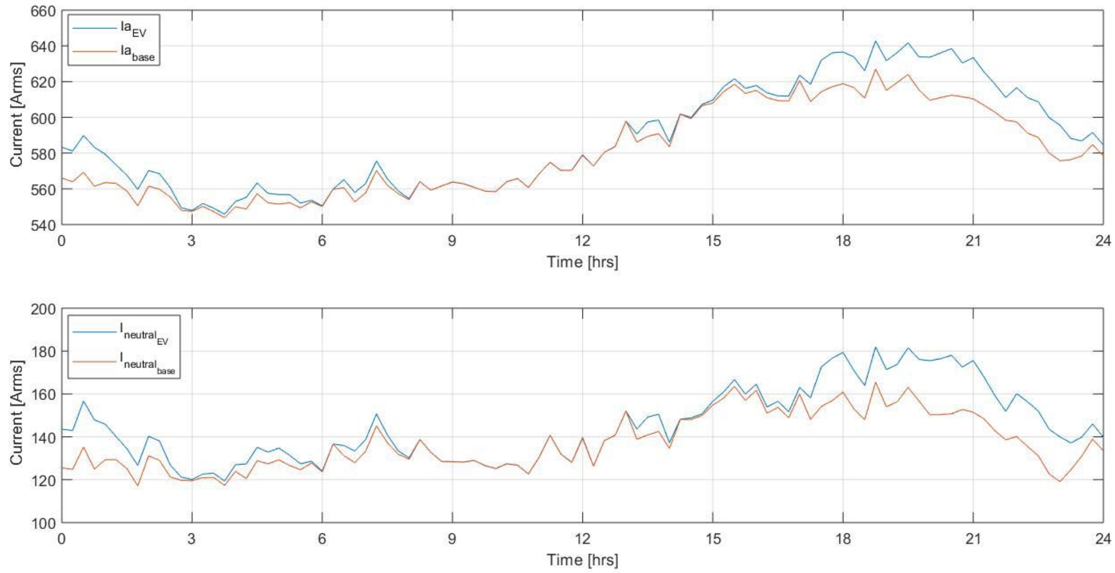


Detail current flowing in phase A [top] and neutral [bottom] between nodes 149 – 1. There was minimum impact of the EVs in the system neutral current indicating that in this scenario EVs did not affect the system significantly.

Source: SLAC

An extreme case was analyzed assuming none of the residences had PVs and all the EV chargers were added to houses connected to phase A. Figure 37 shows the phase A and neutral current with and without the EVs added.

Figure 38: Comparison of Phase and Neutral Current with and without EVs

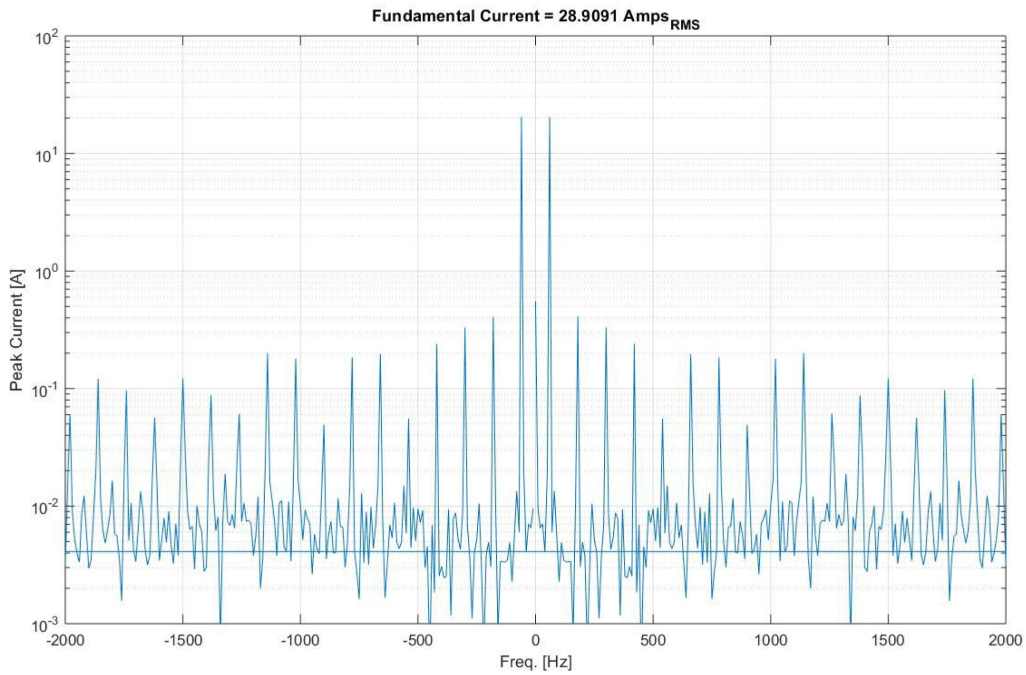


The system imbalance observed in the distribution grid due to the EV chargers added to the residences was minimal given that the system was already unbalanced for the normalized network; but it is possible to extrapolate some conclusions. If the original system was designed to be perfectly balanced, the conductors size should be the same, i.e. neutral conductor should match the phase conductors for the maximum load. Therefore, the steady state returning current over the neutral conductor could theoretically be equal, or even higher, than the phases' maximum current. Therefore, this analysis suggests that the impact of the EV chargers in the balance and stability of the distribution grid was not critical if the neutral conductor for the original design of the network took into account some degree of current unbalance among phases.

Source: SLAC

The current waveform of a Nissan Leaf charging in a Level 2 EVSE was measured in the GISMo lab and its harmonic content evaluated. Figure 38 shows the spectrum analysis of an EV charger operating with an input current equal to 28.9A_{rms}. It is possible to observe that all the current harmonics are less than 2 percent of the fundamental current.

Figure 39: Harmonic Content of a Nissan Leaf Charging in an L2 Station



The fundamental component can be seen as the largest peak. The other peaks correspond to the odd harmonics since the even harmonics were very small.

Source: SLAC

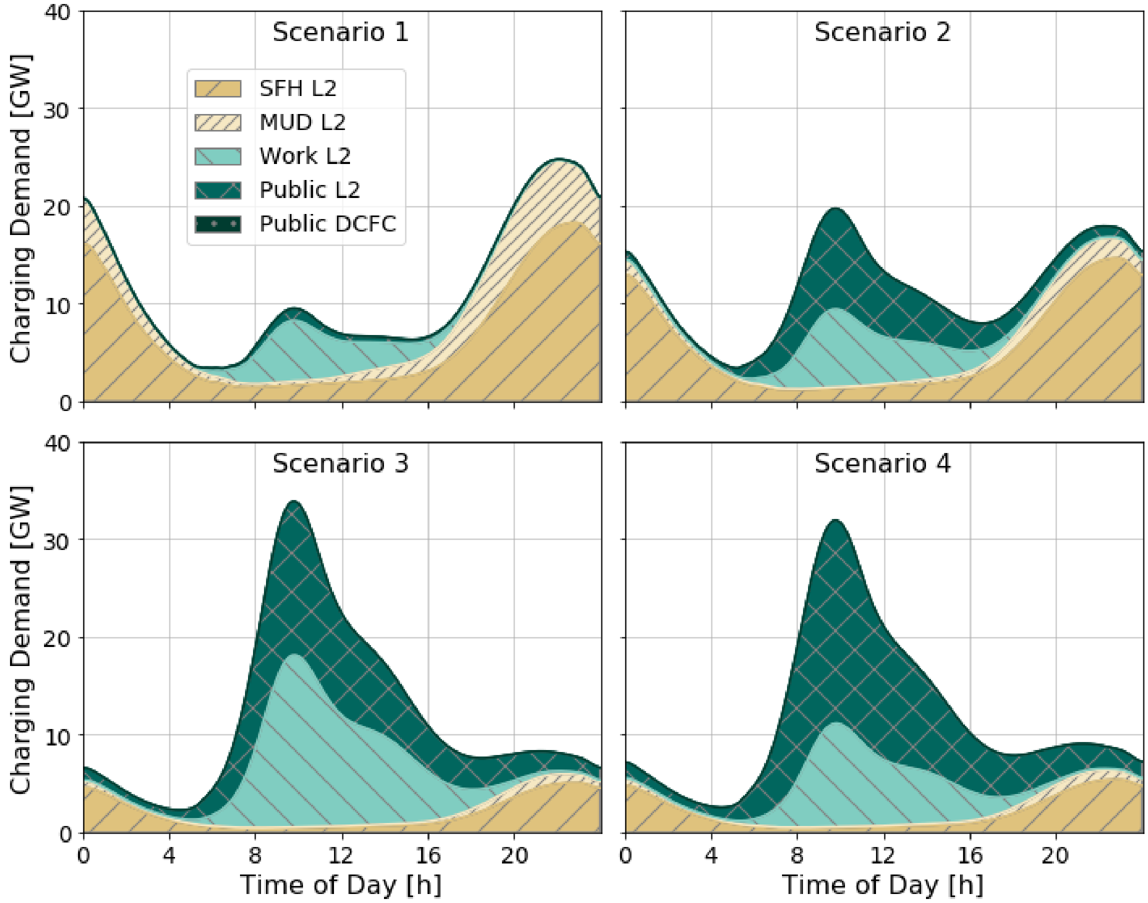
Since the third harmonic content of the EVs measured was relatively low, it was concluded that for such analysis, even considering the worst-case scenario where all EVs would charge at the same time and phase diversity was zero, the amount of current flowing through the neutral conductor would not significantly impact the overall system balance. At this point the capacity would be the limiting factor.

Emissions Impact

The project team used the grid model and charging data to investigate the emissions of charging at a larger scale. The first key research question addressed was: "How do non-residential charging options impact emissions, and how do scenarios with more or less non-residential charging compare?"

The team developed four scenarios of access to residential and non-residential charging options, with residential access ranging from low to high to universal and rescaled behaviors found in the charging data to estimate the daily charging demand in each scenario for all drivers in the Western interconnection grid (WECC). Figure 39 shows the load profiles.

Figure 40: Charging Demand Scenarios for 100 Percent Electrification in WECC



In Scenario 1, access to residential charging either at a single-family home (SFH) or a multi-unit dwelling (MUD) was universal. In Scenario 2, access to residential charging was high. In Scenarios 3 and 4, access to residential charging was low: in Scenario 3, workplace charging access was relatively high and carried more of the demand; in Scenario 4, public charging carried most of the demand (Powell et al., 2022b).

Source: SLAC

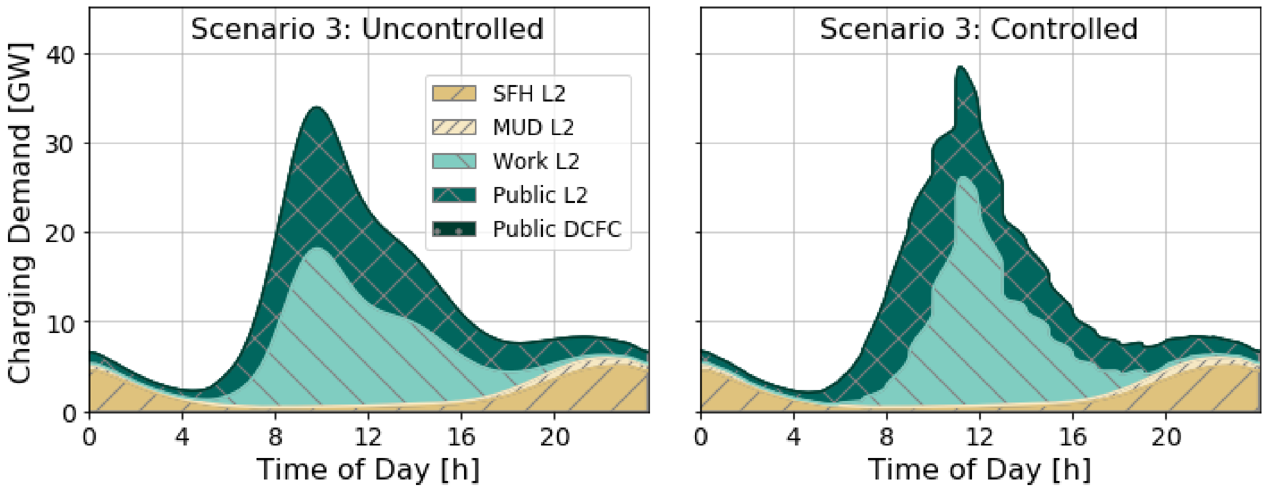
If 100 percent of personal vehicles had been electric in 2019 and charged according to these four scenarios, the two scenarios with highest non-residential charging would have resulted in higher grid emissions. Modeling the 2030 grid, however, with higher renewables and storage and the retirement of many coal generators, the two scenarios with highest non-residential charging would result in the *lowest* grid emissions.

Figure 41 shows the added grid emissions per mile of EV charging for each of the four scenarios, if 100 percent of vehicles in WECC had been electrified in 2019 vs 2030. The 2030 grid model assumes 2.5 times the 2019 levels of both wind and solar, as well as increased baseline demand, storage, and fossil fuel generator retirements. Those results assume uncontrolled workplace charging.

The next research question to address was: "Can emissions be included as objectives of the control to reduce the impacts?" Upon implementing the large-scale emissions optimization control scheme in the workplace charging segment, as described in Chapter 2, the workplace demand was concentrated into times of low average emissions, with a peak just before noon.

Using Scenario 3 with low residential charging and high workplace charging access as an example, Figure 40 shows the uncontrolled and controlled workplace charging profiles when the average-emissions-minimizing control was applied. Studying the emissions shows that this actually increased emissions in both the 2019 and 2030 grids relative to uncontrolled charging.

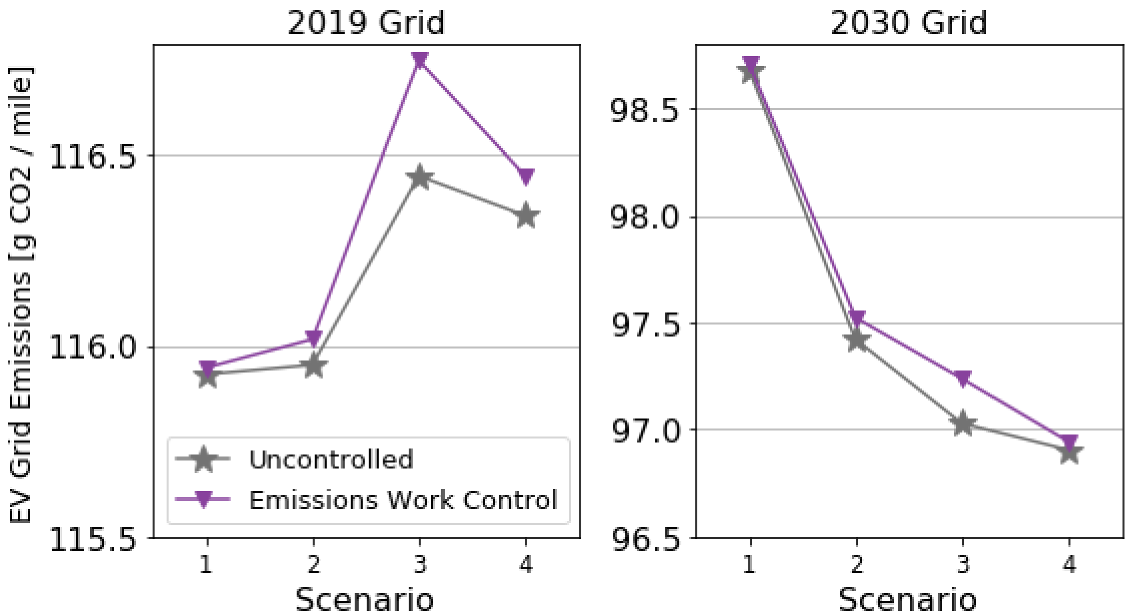
Figure 41: Load Shape with Average-Emissions-Minimization Control



Source: SLAC

Studying the impact of applying workplace charging control aimed at minimizing average emissions, finds the emissions per mile traveled actually increased relative to uncontrolled workplace charging with the proposed control scheme, as shown in Figure 41 (Powell et al., 2022b). This highlights the challenge in using average emissions factors to guide charging. The average carbon intensity of electricity generated during the day, before adding EV charging, is low thanks to the presence of high levels of solar generation. However, when EV charging demand is added at those hours, unless there is solar being curtailed, renewables cannot instantly be added to meet that new demand and it is instead met by increasing fossil fuel generation. The marginal emissions factors of generators at that hour better explain the increase in emissions, and higher emitting plants are often on the margin midday. In the long term, however, adding consistent demand midday through charging will increase demand for solar and support additional solar deployments.

Figure 42: Impact of Charging Control on EV Grid Emissions per Mile



Source: SLAC

In summary, the key results from this analysis are:

- Daytime charging would have led to higher emission in 2019.
- Daytime charging will have lower emissions than evening charging by 2030, and non-residential infrastructure to support daytime charging should be deployed to support this type of charging.
- Controlled charging based on emissions is challenging and needs further research attention.

These results and scenarios are extended and further explored in the team's recently submitted paper (Powell et al., 2022b).

CHAPTER 4: Technology/Knowledge/Market Transfer Activities

Outreach Activities, Knowledge Gained, and Feedback

The methodology developed in this project generated, to date, three peer-reviewed publications[2,3,4] in relevant power system, transportation, and energy conferences. Additionally, it generated one report to a project site partner quantifying in detail the potential in cost savings obtained through implementing smart charging at that location. The team also presented the work in conferences and workshops to academia, industry, and state and federal agencies, such as IEEE Power and Energy Society General Meeting in 2020 and 2022, RT Spotlight in 2019, Center for Community Energy V2G (Vehicle to Grid) Virtual Conference in 2021, California Public Utilities Commission Electric Program Investment Charge Policy + Innovation Forum in February and October of 2021, and California Energy Commission (CEC) Energy Innovation Tour in 2022, to understand the directions each is taking, exchange ideas, and inform the team's research goals on how to help solve the problem of increasing adoption of EVs and reducing emissions.

The team received multiple rounds of feedback from technical advisory committee members, academics, and industry. The most relevant feedback that heavily influenced the design of the project were:

a) Get utilities involved to help understand the pain points from their angle.
b) Engage with other CEC project teams working in the same space.
c) Engage with fleet operations team.
d) Understand user preferences.
e) Think about new ways to integrate system-level information.

Get Utilities Involved to Understand Pain Points from Their Angle

To address this recommendation the team met with different utilities in and out of state including PG&E, City of Palo Alto, National Grid, and Holy Cross Energy. Most were concerned

[2] Powell, Siobhan; Emre Can Kara, Raffi Sevlian, Gustavo Vianna Cezar, Sila Kiliccote, and Ram Rajagopal. 2020. "Controlled workplace charging of electric vehicles: The impact of rate schedules on transformer aging." Applied Energy (Elsevier) 115352.

[3] Powell, Siobhan; Gustavo Vianna Cezar, Elpiniki Apostolaki-Iosifidou, and Ram Rajagopal. 2022. "Large-Scale Scenarios of Electric Vehicle Charging with a Data-Driven Model of Control." Elsevier Energy (Energy).

[4] Moradipari, A.; N. Tucker, T. Zhang, G. Vianna Cezar, and M. Alizadeh. 2020. "Mobility-Aware Smart Charging of Electric Bus Fleets." IEEE Power & Energy Society General Meeting. IEEE. 1-5.

about the additional overall load EVs would be adding to the system and the timing. The team explored this concern by developing multiple charging strategies looking into protecting infrastructure, reducing cost based on electricity tariff, and reducing emissions to shape the load to support a higher number of EVs while reducing grid impacts and meeting customer needs. Another common concern was the residential infrastructure requirement to support residential charging and impacts on assets such as transformers. The team instrumented one of the transformers it had access to and developed multiple analysis and a data-driven temperature model to assess transformer aging.

Engage with Other CEC Project Teams Working in the Same Space

To address this recommendation, the team reached out to the project manager and connected with other teams working on similar topics, such as electrifying and managing charge of fleets, in particular buses, since this is still an area that requires development and industry engagement. A common issue reported by all teams was the challenge in controlling the charging of the buses. Even within the same vehicle/charger manufacturer the same methodology worked differently among projects. To address this common issue among projects, the project team worked extensively with the partners and vehicle manufacturers to understand the small differences, such as software and firmware versions, and new wiring and procedures, which often were not properly documented and performed extensive testing to show the ability to manage charging remotely.

Engage with Fleet Operations Team

For this recommendation, the project team met frequently not only with the management and planning teams, but also with the dispatch team and drivers to provide a clear understanding of what the goals were and understand how they operate to minimize the impact in their routine and operations.

Understand User Preferences

To address this recommendation the project team conducted surveys with fleet managers, operators, and drivers to understand preferences and capture information that could drive behavior. The team also analyzed data from drivers using workplace charging at SLAC.

Think about New Ways to Integrate System-Level Information

Finally, for this recommendation the team engaged in discussions of new potential collaborations with other research teams from industry and academia to include building controls and enable real-time monitoring and communication capabilities with distribution system assets, in particular transformers, that can be integrated with EV charging controls.

Intended Users

The team identified four main users that can leverage the outcomes of this work:

- **Electric utilities.** Electric utilities can use the analytics, algorithms, and results developed to design rate structures to better incentivize EV adoption while reducing emissions from and impact to the distribution system. Additionally, they can use the results obtained to incentivize EVSE and third-party companies to continue developing and providing smart charging solutions to minimize EV load impact on the infrastructure. Moreover, utilities can use the analysis and results obtained from the transformer analysis to better quantify whether their distribution level transformers are experiencing accelerated aging given the additional EV loads, and other loads, to prevent failures and catastrophic events. Finally, even though this project targeted non-residential environments, the technology developed can be translated to other sectors. For example, the transformer analysis would also apply to the residential sector. Another example would be incentivizing smart technologies and manage charging in the residential sector to spur adoption of EVs, in particular, in disadvantaged communities. These locations often cannot install Level 2 chargers because they will require an upgrade of the main service panel, which can be costly. If managed charging is adopted, building codes could be updated and allow homes to install Level 2 managed EVSE.

- **Industry.** Similar to electric utilities, different sectors of the industry can use the outcomes and knowledge created by this project. EVSE companies can increase revenue by implementing smart charging to their EVSE network. This project demonstrated a diverse set of control strategies applied in different cases to show the benefits of such an approach. Very few companies are actively, and successfully, doing this. Among all workplace campus managers with which the project team interacted, common feedback was the lack of smart charging capabilities in the charging stations they had on site. Another revenue stream that EVSE companies, campus managers, and third-party aggregators can leverage is the market participation of EVs as a flexible resource. Finally, campus managers and companies such as transformer manufacturers can also use the outcomes of this project to better understand the impact of the EV load and how that understanding can affect the overall lifetime of these systems and improve the design of new equipment.
- **Federal and state agencies.** These agencies can use the results of this program to inform the next line of investments and research needed to increase adoption of EVs and seamlessly integrate them with the electrical infrastructure, in a practical way. In addition, agencies can use the outcomes to create new policies and mandates, or modify current ones, to better align with the most current findings from research, technology development, and implementation.
- **Academia.** The results from this project can be used as foundation for new academic research. Models and algorithms developed are open source and accessible to researchers to use and potentially create new frameworks and generalize the application of such models and algorithms beyond what was accomplished in this project.

Continued Work and Technology Transfer

The methodology developed in this project is already generating interest from different segments. With the knowledge obtained working with SLAC and Stanford and knowing the close collaboration between these institutions in multiple fields, an initiative called Living Lab is forming. The goal of this initiative is to leverage the capabilities and resources of each campus and work together to design, implement, and demonstrate solutions that look into sustainability and reducing overall campus emissions, from transportation in particular, and increase resilience and reliability of power. Under this initiative, exploring the integration of building controls with cross-campus EVSE, solar, and onsite generators is one of the main topics. Similarly, to the Living Lab, the Bits and Watts initiative at Stanford with its EV50 program is already leveraging the algorithms, communication, and software capabilities developed in this project and applying them to their specific goals.

Stanford transportation team, which manages the electric bus fleet, is very keen to continue to support the analysis and development of solutions to its fleet. One current issue is the unequal use of the fleet, with some buses being used more than others. Smart charging is a mechanism to ensure uniform use of the fleet by leaving underused buses fully charged while leaving overused buses in need of charging. Another interest area for further collaborating is in helping to plan how to decommission the current diesel buses and replace them with electric buses. Key questions to address include 1) will the size of their infrastructure need upgrading? and 2) what resources are needed to operate the system for 4, 8, and 24 hours without power?

A collaboration is underway between SLAC, Stanford, and Prolec-GE on distribution transformers and how to model the impacts of EVs. Prolec-GE is one of the largest transformer manufacturers, and their expertise and active involvement of their research engineering team will add additional information and operational considerations to the analysis. Further, a Smart Transformer white paper is being defined and specifications are being developed based on the results obtained in this project to properly test, measure, quantify, and develop models that can be transferable to other transformers that cannot be instrumented.

Finally, SLAC is part of a team led by PostRoad Foundation, which will deploy and demonstrate the benefits of transactive energy systems in residences in New Hampshire as part of a project funded by the Building Technologies Office within the U.S. Department of Energy. The framework developed in this project provides the basis for underlying software architecture and hardware to communicate and control the EVSE.

CHAPTER 5: Conclusions/Recommendations

SLAC, UCSB, and ChargePoint teams have demonstrated the many benefits of the capabilities of vehicle-grid integration. Additionally, they addressed multiple challenges with respect to communication with devices and hardware, as well as real-time software implementations. Unfortunately, the COVID-19 pandemic, severely affected the demonstration component of the project since the selected demonstration sites were closed and, to this date, have very limited use of the EVSE infrastructure in place. Nonetheless, the teams worked hard to improve the knowledge gap about the effects of EVs in the distribution system, ways to mitigate those effects, and the hardware and software used to manage the charging.

Project Outcomes

For the Stanford electric bus fleet, a 55 percent daily electricity cost savings could be achieved by optimizing the charging schedule and electric bus assignment to routes, and up to 88 percent savings could be achieved if leveraging onsite solar generation. These savings were based on using the entire electric fleet with the pre-COVID 2019 schedule. Using the limited schedule during COVID and including only the electric buses that were able to have charging controlled remotely (K9M bus model), the new proposed solution was able to save approximately 47 percent in electricity costs. These savings come primarily from charging mostly during off-peak hours and preventing top-off behavior when charging. From an emissions standpoint, using the analysis during COVID, the proposed schedule reduced the emissions by approximately 25 percent compared to the status quo. Finally, the team was also able to demonstrate the capabilities of remotely controlling the charging of BYD's K9M models through Viriciti's DH hardware. However, there are still reliability issues related to internal bus/station firmware and software that prevent this system from being deployed as a production-ready software package.

For the Google site, different smart charging mechanisms were implemented targeting several rate structures, demand response, reducing transformer impacts, real-time operations, and emissions. For sites under PG&E's A-10 and E-19 electricity tariffs participating in demand response programs, for example, the annual cost savings were approximately 23 percent and 25 percent, respectively. Additionally, based on the flexibility of EV charging, it was found that the maximum sheddable load capacity occurred between 9:00 a.m. and 11:00 a.m., and the capacity ranged from 71.92kW to 100.78kW, or 54 percent to 76 percent of the monthly uncontrolled maximum demand. From the transformer impact analysis, the project team found that some sites could support fewer than 150 vehicles per day with uncontrolled charging, but nearly 250 vehicles with the best control schemes. Time-of-use rate schedules did not encourage any improvement in the number of EVs supported. Capping the total demand at each site gave a modest improvement. The best case, however, came from peak minimization, rates with demand charges, or the direct minimization for transformer aging. For the algorithm designed to operate in the field in real-time conditions with only data available from the EVSE, different scenarios were evaluated by including transformer constraint, minimum amount of charge and different weights for the objective functions (electricity cost and EV energy). In general, the algorithm was able to deliver more than 80 percent of the requested energy while reducing the energy cost by 20 percent and demand chargers by 40 percent. Finally, from an emissions perspective, a comparison between different controlled and uncontrolled profiles was performed for the real-time algorithm. No significant variation between the different controlled and uncontrolled profiles among the three sites was found. This is likely due to the flat median average and marginal emissions profile shapes during workplace charging hours.

At the SLAC site, a data-driven model of the temperature of the transformer feeding the EV stations was developed based on sensors installed in the transformer coils. The model reported a root mean square error of just 9.8 percent of the mean value during that time and 4.8 percent of the maximum value. Finally, at SLAC, the team developed and deployed a software platform, the SGMP, to manage and control the lab resources that included EV charging stations, solar, battery energy storage systems, and loads. The project team demonstrated how solar, battery, and EVSE can be coordinated to reduce the dependency on grid power when charging an EV.

When looking at the larger electrical system, the team analyzed the impact of phase imbalance and harmonics. From the analysis performed, the phase imbalance in the system at scale, generally, will not create problems for the system. The main problem continues to be capacity and grid asset limits. However, extreme cases such as all EVs charging at the same time and in the same phases can present a challenge, in particular overloading the neutral conductor due to unbalanced loads and harmonics, in particular the third harmonic, due to non-linear loads. However, due to diversity and possibility of harmonic cancellation, these cases are unlikely to happen in practice.

Finally when comparing scenarios with more or less non-residential charging in the system, given the grid conditions and generating resources of 2019 and 2030, and considering 100 percent of passenger vehicles electrified, the team found that a) daytime charging would have led to higher emission in 2019, b) daytime charging would be lower emission than evening charging by 2030, and non-residential infrastructure to support daytime charging should be deployed to support this type of charging, and c) controlled charging based on emissions is challenging and needs further research attention.

Lessons Learned

The team faced many challenges during this project and learned lessons on how to overcome and prevent those challenges moving forward. These lessons can be useful for other researchers, teams, and projects. Some of the most important lessons include:

- Legal: If the project requires access to proprietary information or data containing personal identifiable information, getting the legal approvals can be lengthy. Working very early with the partners, defining what is needed from a data standpoint, and connecting the legal teams of the institutions involved is critical. Additionally, if the data requirements are still being defined, it is advised to overestimate what will be needed rather than adding on to the existing agreement at a later date.
- Delay from vendors/manufacturers: Working with equipment from a variety of manufacturers and vendors that are not part of the project team can be challenging. In

many cases, support is not immediately available and changes in equipment hardware and software can be time consuming and costly. Requesting, testing, and debugging new equipment features can be a big challenge. Therefore, it is critical to know what will be needed from an equipment standpoint and whether such capabilities already exist or are being developed if the manufacturer is not part of the project team. Additionally, building a relationship with the product manufacturer and having a responsive contact person who is interested in the project outcomes is important to get prompt support.

- Input from different stakeholders: In large-scale projects, having a clear understanding of the different stakeholders and their perspectives is key. Management/planning stakeholders have a different view of the problem compared to operations stakeholders. Sometimes they might even have conflicting information or a difficult relationship. Being able to address everyone's concerns and needs and building a good relationship with all stakeholders are key to success.
- Software Application Programming Interface (API): Software and APIs are becoming increasingly important when it comes to accessing and controlling devices. A well-documented API with clear instructions is key to accelerate the development of the software and algorithms. Even with good documentation, evaluation of the performance in the field under real-world conditions will require performance of many tests. Moreover, there are no standards adopted by EV and EVSE manufacturers; thus integration with different equipment will require writing a different set of software drivers.

Future Research

This project will take multiple directions for future research to continue advancing a seamless integration of electric vehicles with the grid.

The first direction is targeting distribution transformers. The data-driven model developed using the transformer temperature was able to capture and predict the variation in temperature with given EV loads. The new direction will investigate the transferability of such models to other transformers that cannot be instrumented, either because it is expensive, impractical, or impossible. The team is in discussions with transformer manufacturers to pursue collaborations that will help in this direction by understanding what information can be transferred and what needs to be specific.

The second direction will look into exploring ways to add more functionalities to a transformer regarding information exchange and controls. The concept of the smart transformer and its capabilities will be defined. These capabilities will include, but not be limited to:

- Communication leveraging the Industrial Internet of Things.
- Controls to enable the transformer to perform tap changes and change voltage based on higher level information, and to communicate directly with local resources such as EVSEs, EVs, solar and energy systems, and building and smart home controls.
- Sensing capabilities such as temperature, harmonics, and phase.

The third direction is exploring global coordination among networked EVSE and answering how global coordination of EVSE will perform compared to individual sites optimizing their own operation. The project team found that there is a conflicting objective between the distribution system, which tries to protect its infrastructure while maximizing use of its stations and in many cases can shift loads to late afternoon and early evening, and the transmission system, which looks into pushing more of the EV load to daytime to reduce the ramping requirements in the late afternoon and early evening.

The fourth direction is looking into integration of multiple distributed energy resources such as EVSE/EV and solar and storage systems, with loads to minimize the impacts of such resources in the grid through coordination. Each individual resource has great potential on its own but can achieve greater benefits if coordinated with other resources. Further, within this scope, vehicle to grid capabilities will be explored given that this has greater potential for additional benefits when properly coordinated.

Lastly, the team will continue to work on the intersection of electrification of transportation and grid impacts. From the multiple discussions the team had throughout this project with different stakeholders, it is clear that there are many unanswered questions as to whether the current grid can support the current goals of EVs and, if not, what modifications are required to support those goals. To ensure the goals set by the state can be achieved without compromising the entire grid and thus affecting ratepayers, in particular those living in disadvantaged communities, a stronger interdisciplinary effort among industry, academia and research institutions, policy makers, and electric utilities, among others, must be in place. Within these institutions, it is of utmost importance to have experts in planning and operations discussing solutions since on many occasions conflicting objectives exist.

CHAPTER 6: Benefits to Ratepayers

Smart Charging as a Tool to Reduce Electricity Costs

Daytime charging, in particular workplace charging, has many characteristics that make it well suited for smart charging strategies. These charging segments have high flexibility, predictable arrival and departure times, and historical data, and the EVSEs are aggregated under one connection point to the grid and are typically from the same vendor. Leveraging these particular characteristics, different strategies can be implemented to benefit the site host as well as the overall grid and ratepayers. Smart charging can be used to provide grid services such as participating in demand response programs or the ancillary services market. This would prevent electric utilities from dispatching more expensive and polluting generation resources to meet the load demands which ultimately increase the electricity costs and generate more emissions that can impact the population's health.

Additionally, smart charging can be used to defer investments in infrastructure upgrades that would ultimately lead to an increase in electricity costs. Ensuring that grid assets are used within their capacity prevents accelerated aging, and more EVs can leverage the same infrastructure for longer periods of time.

Finally, users of charging infrastructure that have smart charging capabilities can generally expect lower electricity costs since the site host, overall, will pay less compared to not having smart charging capabilities.

Smart Charging as a Way to Improve Grid Resilience and Reliability

Smart charging can also improve system reliability and resilience. With the increasing adoption of renewable generation and its intrinsic intermittent characteristic, a load that requires reliable power to operate cannot fully count on such generation being available. This means that there might be moments where generation is more or less than what is needed. EV charging, in particular daytime charging, which inherently has flexibility, can be used as a flexible resource, leveraging smart charging algorithms, to ensure that over and under generation of renewable resources is properly handled to prevent outages, which can be local or, in some cases, systemwide.

Coupling EV charging with onsite generation and energy storage systems can greatly improve the reliability of the system by leveraging these resources to reduce the burden on the grid through a seamless coordination. Resiliency can also be improved since these resources can operate in small microgrids and, by removing load from the larger grid, allow a quicker recovery.

Finally, utilities can leverage smart charging to inform the design of rate structures to shape the EV load. Given a wide adoption of smart charging, particularly daytime charging, utilities can design rates to prevent the additional demands of EVs in specific hours of the day impacting the overall operation. These approaches will ultimately improve system reliability and resiliency as the EV adoption grows.

Summary of Results

Table 6 and Table 7 present a summary of the major results obtained from analyses performed in each site, i.e. university campus with an electric bus fleet and workplace campus with passenger EVs. The Charging Strategy column is related to what the optimization was capable of doing. If the charging was only able to change in time but no control over power delivery was possible, it is identified as Shift. If power delivery was able to be controlled, it is identified as Shed+Shift. Finally, if solar is available and used within the optimization, the charging strategy is identified as OnSite Solar+Shed+Shift. The results presented in these tables are the best case among all the results presented in Chapter 3.

Table 6 presents two test cases, one with all the 38 electric buses (pre-COVID) and another with only 7 buses (during COVID). The Savings column is with respect to the uncontrolled charging, i.e. the status-quo. The values of Max Demand Reduction and Emissions Reduction for the test case, including all the buses, compare the values between the two charging strategies, thus the Shed+Shift is the reference case. The test case with seven buses uses as a reference the status-quo for that case. Since in this case there is a small number of buses demand reduction was not considered.

Table 6: Electric Bus Fleet Summary Results

Site	Test Cases	Charging Strategy	Savings	Max Demand Reduction	Emissions Reduction	Guaranteed Energy Delivered
University campus electric bus fleet	38 BYD Buses (K7, K9, K9M)	Shed+Shift	55%	REFERENCE	REFERENCE	100%
		On-Site Solar+Shed+Shift	88%	57%	52%	100%
	7 BYD Buses (K9M)	Shift	47%	0	25%	100%

Table 7presents the summary of two test cases, Offline and Real-Time. The Offline case reflects the analysis performed using the full knowledge of the charging events; whereas, the Real-Time has no knowledge of future information.

Table 7: Workplace Passenger EV Summary Results

Site	Test Cases	Charging Strategy	Savings	Max Demand Reduction	Additional EVs w/out Infrastructure Upgrade	Guaranteed Energy Delivered
Workplace - passenger vehicles	Offline	Shed+Shift	25%	76%	66%	100%
	Real-Time	Shed+Shift	30%	40%	NA	80%

Source: SLAC

LIST OF ACRONYMS

Term	Definition
AEF	average emissions factor
API	application programming interface
A_{rms}	ampere root-mean-square
CO_2	carbon dioxide
CRL	capacity reservation level
DEVINE	Demonstration of Vehicle Grid Integration in Non-residential Environments
DER	distributed energy resources
DH	Datahub
ESP	energy service provider
EV	electric vehicle
EVSE	electric vehicle supply equipment
g	Gram
GHG	greenhouse gas
IEEE	Institute of Electrical and Electronics Engineers
kVa	kilovolt-amperes
kW	Kilowatt
kWh	kilowatt-hour
MEF	marginal emissions factor
MILP	mixed integer linear programming
PDP	Peak Day Pricing
PG&E	Pacific Gas and Electric Company
PV	Photovoltaic
RMSE	root mean squared error
SGMP	smart grid management platform
SOC	state of charge
TOU	time of use
U.S. EIA	United States Energy Information Administraton
U.S. EPA	United States Environmental Protection Agency
UI	user interface
V	Volt
VGI	vehicle grid integration
W	Watt
WECC	Western Electricity Coordinating Council
Wh	watt-hour

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APPENDIX A: Data Availability

Each site had a different set of characteristics and data availability that informed the design of the different components of the project. This appendix provides further information on each site.

Stanford University

The Stanford University fleet comprises 38 electric buses from BYD and has a total of 23 charging stations, each consisting of two 40 kW charging connectors for a total of 80kW per station (3-phase 480V/120A). Figure A-1 shows Stanford's bus yard and charging stations.

Figure A-1: Stanford bus yard with buses connected to the charging stations

Caption: The telemetry data used from this site came primarily from two systems, Viriciti and ETA Transit.

In addition to the information provided in Chapter 2, the Viriciti telemetry also provided variations of the main data used, described in Chapter 2, such as SOC and energy "used in service" and "not in service", among others. However, when performing analysis of these variations to understand their potential it was found that they were not accurate on what they were reporting. The two main causes of such discrepancies were: 1) the dependency on drivers to accurately report when in service and 2) understanding the underlying formula to calculate these variables since they were reported as data points in the controlled area network port that the DH collected. Therefore we decided not to use these variations. Table 1 shows all the data Viriciti system collected through the DH.

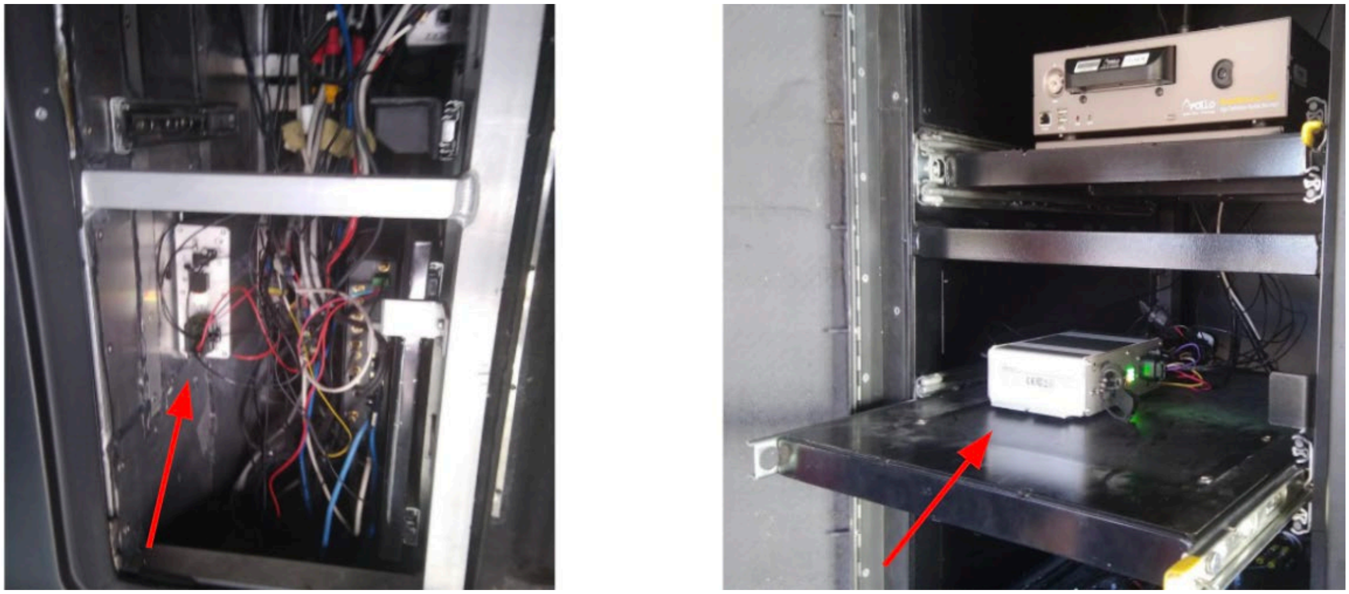
Table A-1 shows the Information provided by the Viriciti API.

ENERGY_IDLED_PER_DAY	ODO_PER_DAY	ENERGY_DRIVEN_PER_DAY	TIME_CONSUMED_PER_DAY	SOC_USED	ODOMETER	COOLANT_TEMP_RIGHT
EFFICIENCY_CUR_KM	acceleration	energy_idled	time_driven	speed_from_rpm	contacter_status	trip_distance
ENERGY_RECOVERED	power	energy_recovered_per_day	time_driven_per_day	charge_cable_con_status	precharge_contact	kneeling
ESTIMATED_RANGE_INSERVICE	energy	soc_filtered	time_idled	battery.soc	parking_brake	wheelchair_ramp
ENERGY_INSERVICE_PER_DAY	energy_used	efficiency_cur_km_driving	time_idled_per_day	battery.voltage	front_door	cont_driving_range
ENERGY_NOT_INSERVICE_PER_DAY	energy_used_per_day	efficiency_cur_km_inservice	time_charged	gps_position	rear_door	rpm
SOC_USED_INSERVICE_PER_DAY	energy_consumed	time_used	time_charged_per_day	gps_speed	door_status	engine.temp_status_left
SOC_USED_NOT_INSERVICE_PER_DAY	energy_consumed_per_day	time_used_per_day	time_ignition_on	charging_status	brake_switch	engine.temp_status_right
TIME_STOPPED	energy_charged	time_recovered	time_ignition_on_per_day	battery.current	gear_position	battery.lowest_bat_cell_temp
ENERGETIC_STATE	energy_charged_per_day	time_recovered_per_day	soc_charged	coolant_temp_left	speed	battery.highest_bat_cell_temp
ODO_REFERENCE	energy_driven	time_consumed	soc_charged_per_day			

Table A-1: Viriciti parameters exposed through API

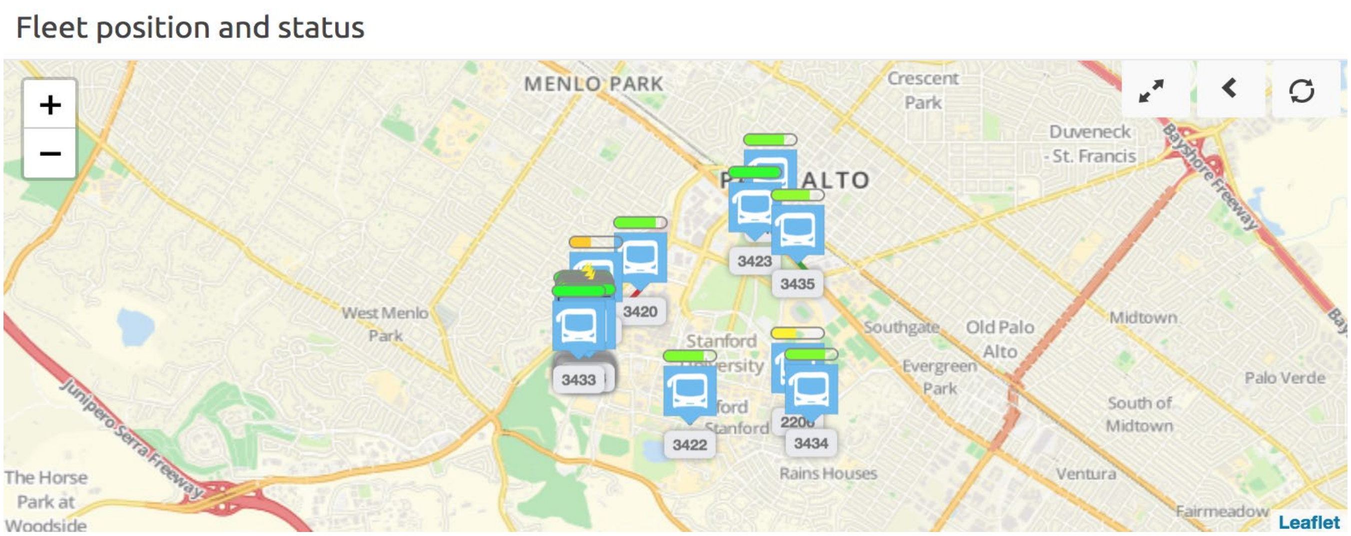
Figure A-2 shows two pictures of Viriciti's Datahub installed in each bus and Figure A-3 shows a screenshot of the Viriciti web portal.

Figure A-2: Viriciti Datahub installed in Stanford's BYD buses.



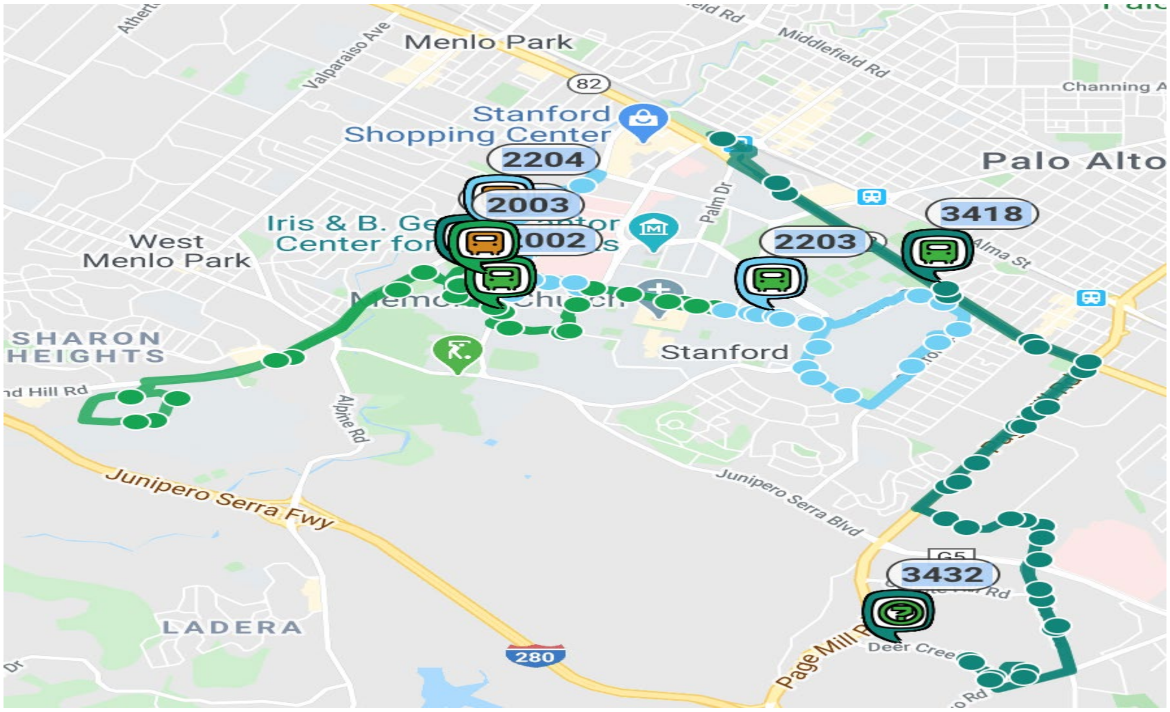
Caption: Installation location is dependent on bus model and year. Left image is from a BYD K9 model and the right image is from a BYD K9M model.

Figure A-3: Viriciti web portal with real-time buses information



Caption: The SPOT telemetry system, as discussed in Chapter 2, provides real-time bus location and routes. It also provides reporting that is used by the operators. Figure A-4 shows the information one can view and download from the system. Figure A-5 shows one of the reports the SPOT app can generate for the Stanford bus fleet.

Figure A-4: SPOT dashboard



Caption: SPOT web portal showing 3 routes, out of 20, and which buses are fulfilling them.

Figure A-5: SPOT reporting system

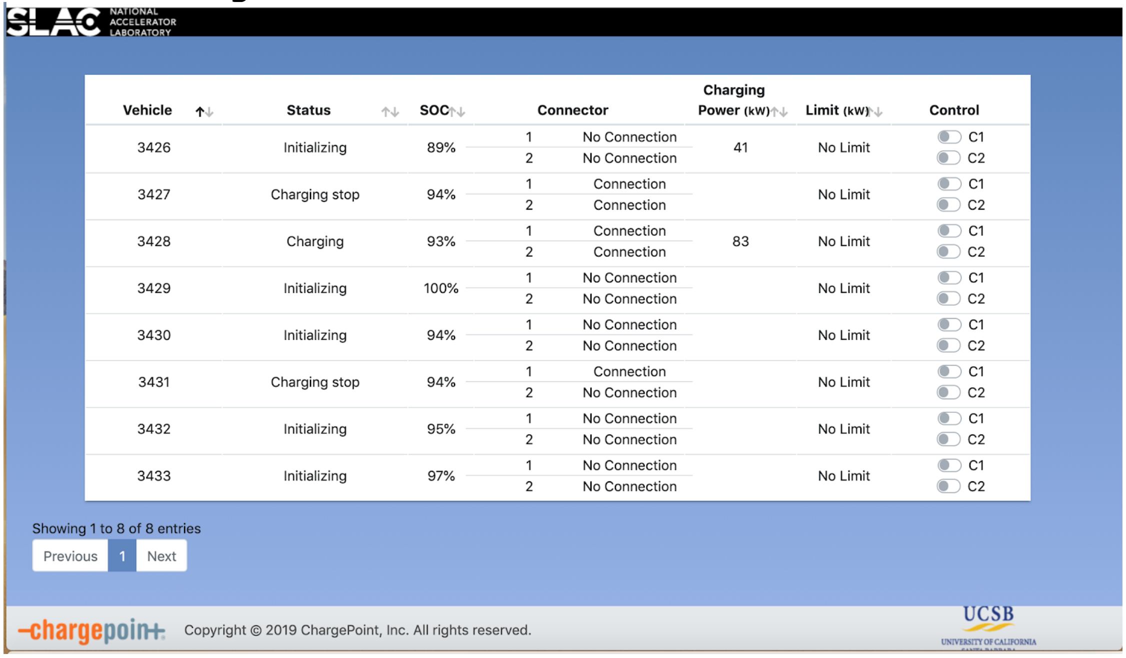
Vehicle Statistics by Trip -All

09/10/2019 to 09/12/2019

Date	Route	VehicleID	Number	Start	End	StartLocation
2019-09-10	Research Park	3428	06:59-39	06:46:58	07:22:48	37.4377,-122.178 (http://maps.google.com/maps?z=12&q=37.4377,-122.178)
2019-09-10	Research Park	3428	07:57-39	07:52:59	08:24:58	37.444,-122.167 (http://maps.google.com/maps?z=12&q=37.444,-122.167)
2019-09-10	Research Park	3428	08:57-39	08:54:27	09:26:31	37.4438,-122.166 (http://maps.google.com/maps?z=12&q=37.4438,-122.166)
2019-09-10	Research Park	3428	15:49-37	15:07:13	16:14:20	37.4063,-122.156 (http://maps.google.com/maps?z=12&q=37.4063,-122.156)
2019-09-10	Research Park	3428	17:03-37	16:59:03	17:34:55	37.3954,-122.15 (http://maps.google.com/maps?z=12&q=37.3954,-122.15)
2019-09-10	Research Park	3428	18:23-37	18:18:53	18:49:20	37.3953,-122.15 (http://maps.google.com/maps?z=12&q=37.3953,-122.15)
2019-09-10	Research Park	3430	06:32-39	06:16:38	06:53:37	37.4338,-122.18 (http://maps.google.com/maps?z=12&q=37.4338,-122.18)
2019-09-10	Research Park	3432	06:59-39	07:06:58	07:21:08	37.4326,-122.18 (http://maps.google.com/maps?z=12&q=37.4326,-122.18)

Caption: Report providing information about trip statistics by route and bus

Figure A-6: Stanford bus fleet user-interface



Caption: The user interface developed to remotely control the charging of the buses is shown in Figure A-6.

Google Campus

At Google, the characteristics of each of the three sites are as follows:

Site 1:

Number of Level 2 EVSE: 57

Number of sessions: 19,322 over one year

Electricity tariff: E19S

Transformer capacity: 300kVA for 30 EVSE and 150kVA for 18 EVSE

Site 2:

Number of Level 2 EVSE: 57

Number of sessions: 19,799 over one year

Electricity tariff: B10S in Q2 2020

Transformer capacity: 500kVA

Site 3:

Number of Level 2 EVSE: 62

Number of sessions: 8764 over six months

Electricity tariff: A10SX

Transformer capacity: 500kVA

These sites had ChargePoint stations which provided many data fields. Table A-2 presents the fields available from the ChargePoint historical data.

Table A-2: Data fields obtained from ChargePoint historical data

1	Unique identifier for each charging session
Session Start Time	Timestamp of when the session started
Session End Time	Timestamp of when the session ended
Session Energy	Total energy in kWh consumed in a session
Interval ID	Unique identifier of each charging interval within a session
Interval Start Time	Timestamp of when an interval started within a session
Interval End Time	Timestamp of when an interval ended within a session
Interval Energy	Total energy in kWh consumed in an interval
Interval Avg Power	Average power in kW utilized in an interval
Charging Station Ports	Number of ports in a charging station
Charging Station ID	unique, anonymous identifier of a charging station
Charging Port ID	anonymous identifier of a charging port
Driver ID	unique, anonymous identifier of a driver who initiated the session
Queue	Driver position in a queue for charging
SOC	State of charge

APPENDIX B:
Algorithms Analysis

Bus Schedules

Figures B-1 and B-2 show the bus schedules provided to the dispatch team to operate the fleet.

Figure B-1: HD-Line Schedule

HD-LINE - 4 buses

Assuming max kWh used is 65kWh for morning/afternoon HD trip:

	Mon	Tues	Wed	Thurs	Fri	
HD AM1	324kWh>260kWh	194kWh>130kWh	324kWh>260kWh	194kWh>130kWh	324kWh>260kWh	Bus 6
HD AM2	324kWh>260kWh	194kWh>130kWh	324kWh>260kWh	194kWh>130kWh	324kWh>260kWh	Bus 7
HD AM3	324kWh>260kWh	194kWh>130kWh	324kWh>260kWh	194kWh>130kWh	324kWh>260kWh	Bus 8
HD AM4	324kWh>260kWh	194kWh>130kWh	324kWh>260kWh	194kWh>130kWh	324kWh>260kWh	Bus 9
		Charge all buses to 60%		Charge all buses to 60%		
HD PM1	260kWh>194kWh	194kWh>130kWh	260kWh>194kWh	194kWh>130kWh	260kWh>194kWh	Bus 6
HD PM2	260kWh>194kWh	194kWh>130kWh	260kWh>194kWh	194kWh>130kWh	260kWh>194kWh	Bus 7
HD PM3	260kWh>194kWh	194kWh>130kWh	260kWh>194kWh	194kWh>130kWh	260kWh>194kWh	Bus 8
HD PM4	260kWh>194kWh	194kWh>130kWh	260kWh>194kWh	194kWh>130kWh	260kWh>194kWh	Bus 9
		Charge all buses to full after 9:30pm (9:30pm is start of 'off-peak' hours in e-20 rate structure)		Charge all buses to full after 9:30pm (9:30pm is start of 'off-peak' hours in e-20 rate structure)	Charge all buses to full after 9:30pm (9:30pm is start of 'off-peak' hours in e-20 rate structure)	

Lowest reached energy: 130kWh = 40% SoC

Figure B-2: MC-Line Schedule

MC-LINE - 3 buses

Assuming max kWh used is 81kWh for morning/afternoon MC trip:

	Mon	Tues	Wed	Thurs	Fri	
MC AM1	324kWh>243kWh	324kWh>243kWh	324kWh>243kWh	324kWh>243kWh	324kWh>243kWh	**Bus 3**
MC AM2	324kWh>243kWh	324kWh>243kWh	324kWh>243kWh	324kWh>243kWh	324kWh>243kWh	**Bus 4**
MC AM3	324kWh>243kWh	324kWh>243kWh	324kWh>243kWh	324kWh>243kWh	324kWh>243kWh	**Bus 5**
MC PM1	243kWh>162kWh	243kWh>162kWh	243kWh>162kWh	243kWh>162kWh	243kWh>162kWh	**Bus 3**
MC PM2	243kWh>162kWh	243kWh>162kWh	243kWh>162kWh	243kWh>162kWh	243kWh>162kWh	**Bus 4**
MC PM3	243kWh>162kWh	243kWh>162kWh	243kWh>162kWh	243kWh>162kWh	243kWh>162kWh	Bus 5
	Charge all buses to full after 9:30pm (9:30pm is start of 'off-peak' hours in e-20 rate structure)	Charge all buses to full after 9:30pm (9:30pm is start of 'off-peak' hours in e-20 rate structure)	Charge all buses to full after 9:30pm (9:30pm is start of 'off-peak' hours in e-20 rate structure)	Charge all buses to full after 9:30pm (9:30pm is start of 'off-peak' hours in e-20 rate structure)	Charge all buses to full after 9:30pm (9:30pm is start of 'off-peak' hours in e-20 rate structure)	

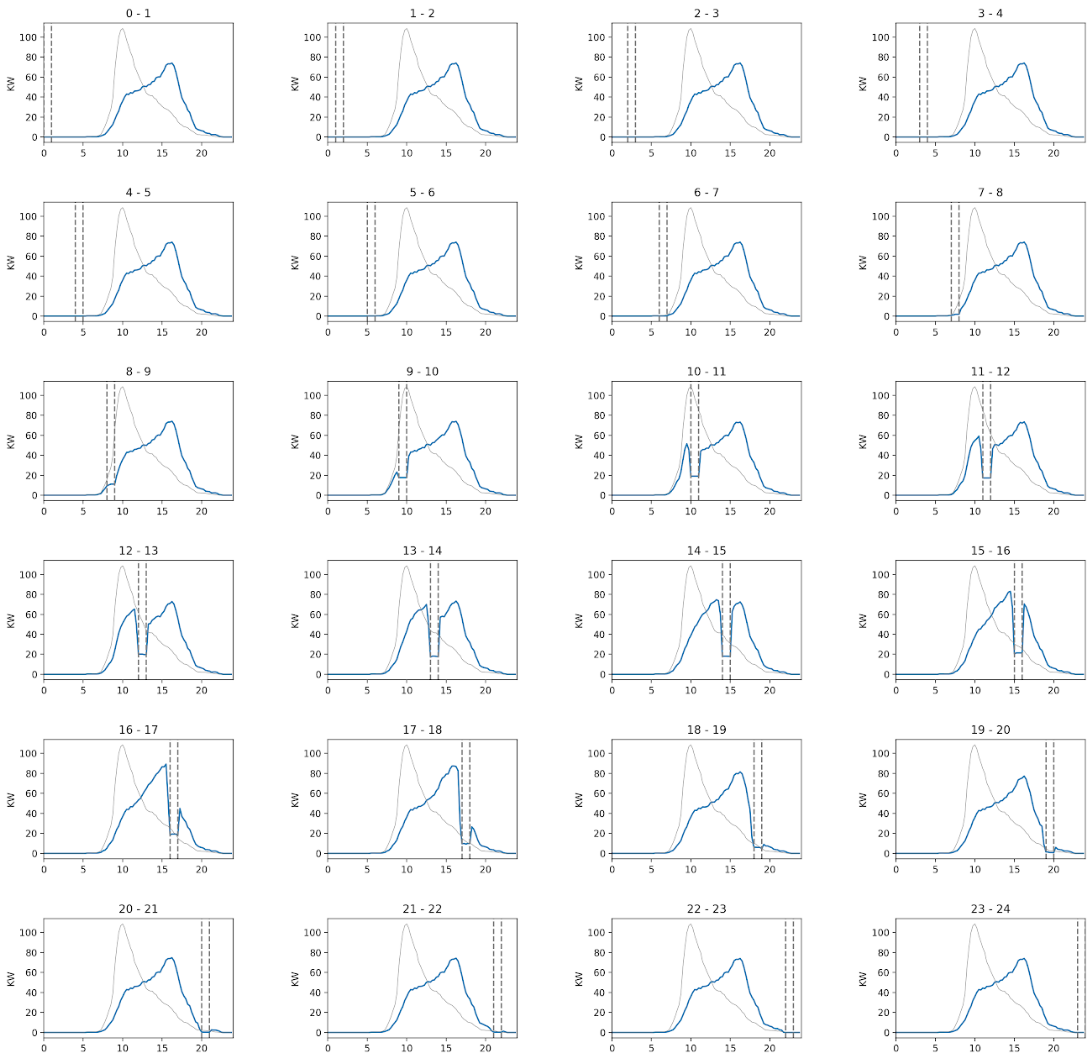
Lowest reached energy: 162kWh = 50% SoC

Google

Hourly load shed capacity of EV charging

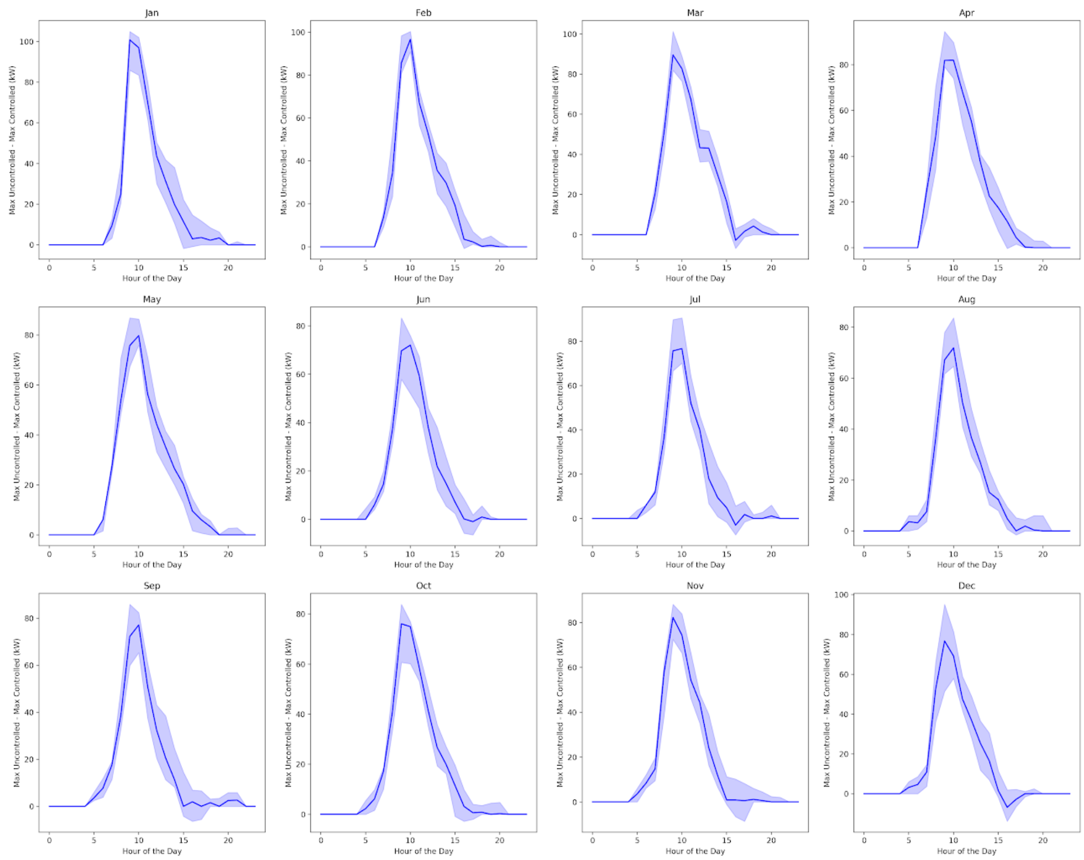
The hourly load shed capacity was determined by optimizing charging with a demand penalty applied at the given hour. The results of the average weekday profile with the hourly demand penalty for January is shown in Figure B-3. The controlled charging profile shows depressed load in the hour in which the demand charge is applied.

Figure B-3: January average weekday profile with a demand penalty applied at each hour



Caption: The hourly load shed capacity from this optimization was calculated as the difference between maximum demand in the uncontrolled profile and the controlled profile for the hour in which the demand penalty was applied. The median hourly load shed ability for each month is shown in Figure B-4.

Figure B-4: EV charging load shed capacity



Caption: Median hourly weekday load shed capacity and 25-75 percentile shaded for each month

Real Time Optimization Results

In the following section we present the results running the algorithms for the 3 sites.

Site 1

Figure B-5 and Table B-1 provide the load profiles and the results summary of the top 4 test cases.

Figure B-5: Top four profiles out of the 13 Test Cases for Site 1

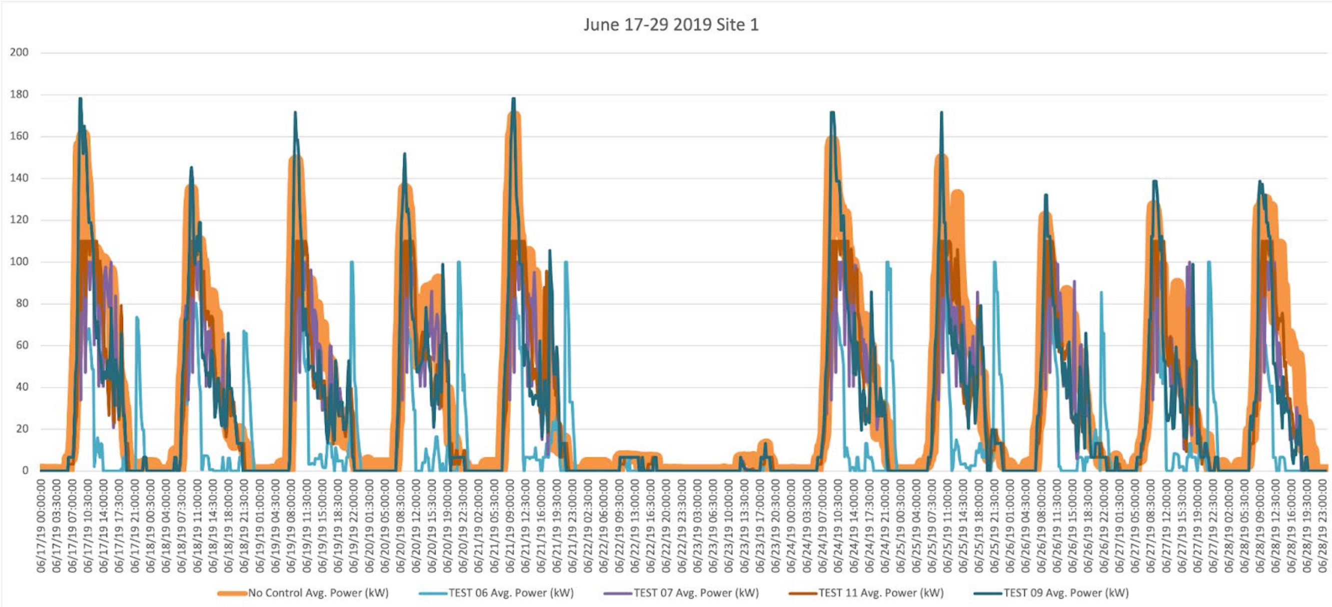


Table B-1: Top four results out of the 13 Test Cases for Site 1

June 17-29 2019 Site 1								
Test #	**w1**	**w2**	**Coupling Constraint (kW)**	**Energy Delivered**	**Electricity Purchase Cost**	**Demand Charge Cost**	**Forced Initial Charge**	**Initial Charge Rate**
Status Quo	n/a	n/a	n/a	100%	100%	100%	No	n/a
6	2	1	100	44%	36%	59%	No	n/a
7	10	1	100	82%	81%	59%	No	n/a
11	10	1	110	82%	81%	65%	Yes	1/2 Pmax
9	10	1	250	85%	82%	105%	No	n/a

Site 2

Figure B-6: Top four profiles out of the 13 Test Cases for Site 2

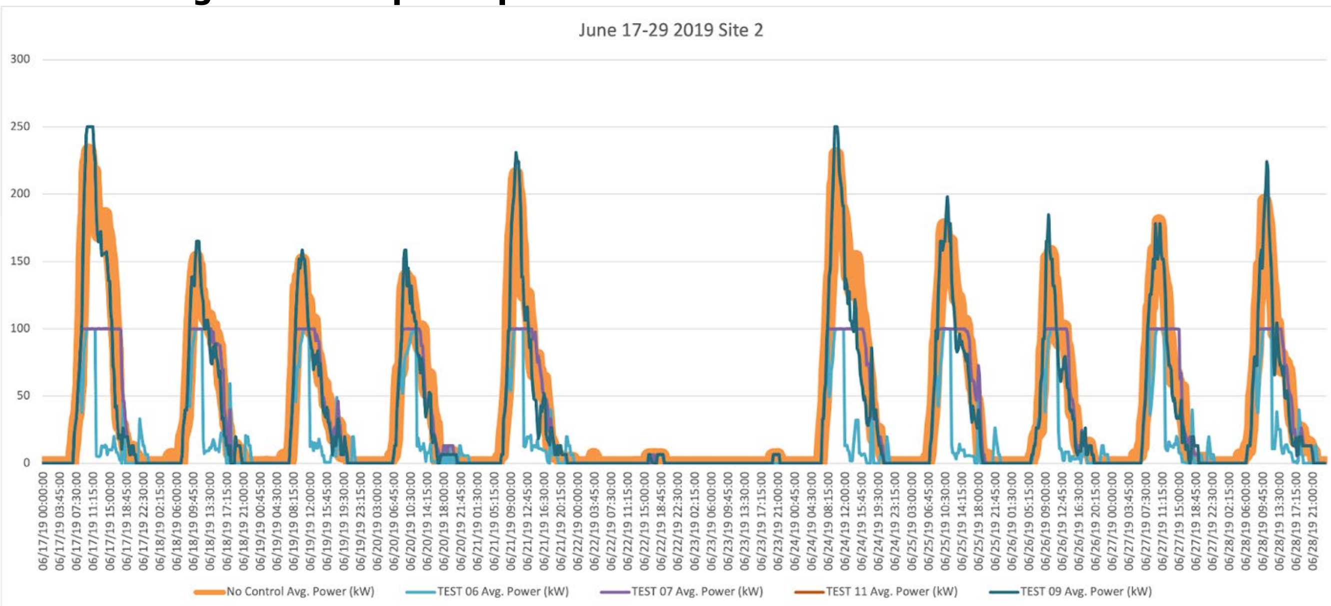


Table B-2: Top four results out of the 13 Test Cases for Site 2

June 17-29 2019 Site 2								
Test #	**w1**	**w2**	**Coupling Constraint (kW)**	**Energy Delivered**	**Electricity Purchase Cost**	**Demand Charge Cost**	**Forced Initial Charge**	**Initial Charge Rate**
Status Quo	n/a	n/a	n/a	100%	100%	100%	No	n/a
6	2	1	100	42%	37%	43%	No	n/a
7	10	1	100	82%	83%	43%	No	n/a
11	10	1	110	Infeasible	Infeasible	Infeasible	Yes	1/2 Pmax
9	10	1	250	94%	92%	107%	No	n/a

Caption: Figure B-6 and Table B-2 provide the load profiles and the results summary of the top 4 test cases.

Site 3

Figure B-7: Top four profiles out of the 13 Test Cases for Site 3

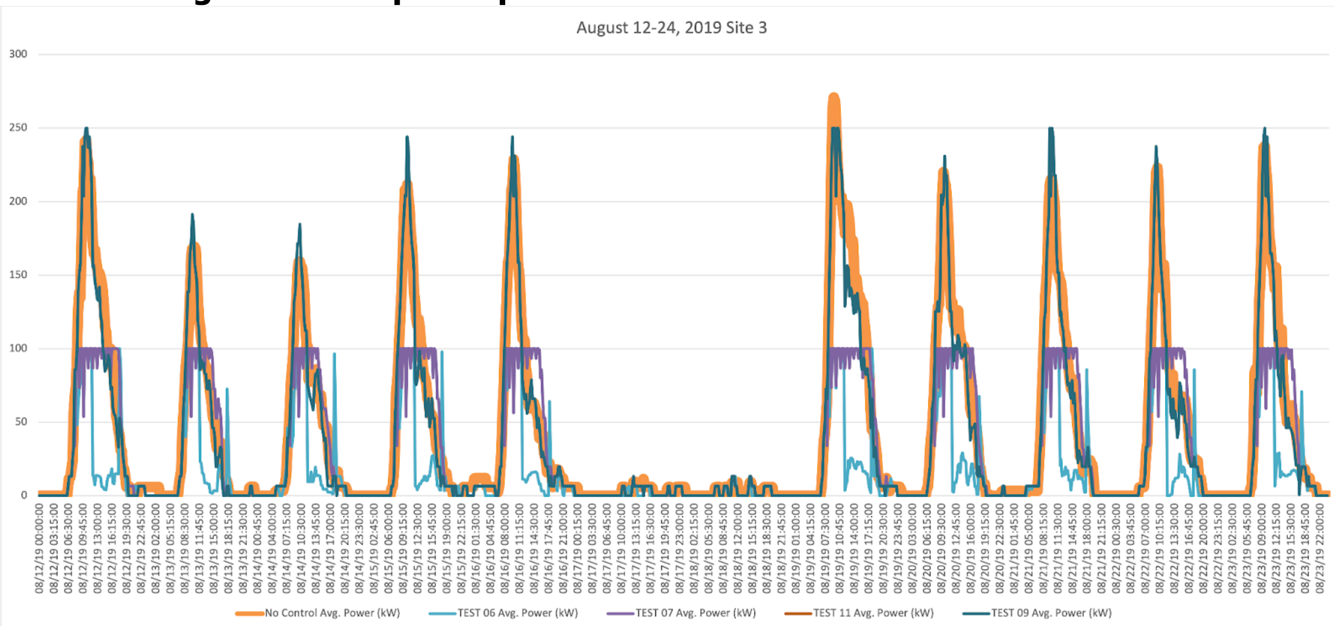


Table B-3: Top four results out of the 13 Test Cases for Site 3

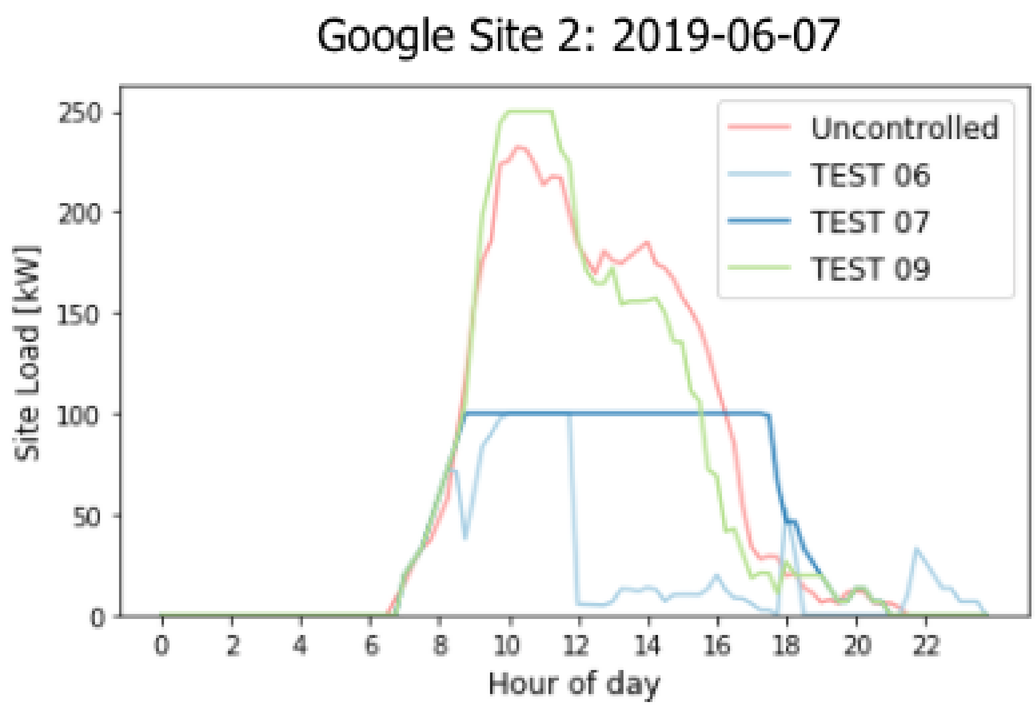
August 12-24 2019 Site 3								
Test #	**w1**	**w2**	**Coupling Constraint (kW)**	**Energy Delivered**	**Electricity Purchase Cost**	**Demand Charge Cost**	**Forced Initial Charge**	**Initial Charge Rate**
Status Quo	n/a	n/a	n/a	100%	100%	100%	No	n/a
6	2	1	100	43%	39%	37%	No	n/a
7	10	1	100	79%	82%	37%	No	n/a
11	10	1	110	Infeasible	Infeasible	Infeasible	Yes	1/2 Pmax
9	10	1	250	95%	93%	92%	No	n/a

Caption: Figure B-7 and Table B-3 provide the load profiles and the results summary of the top 4 test cases.

Emissions Results for Google Sites

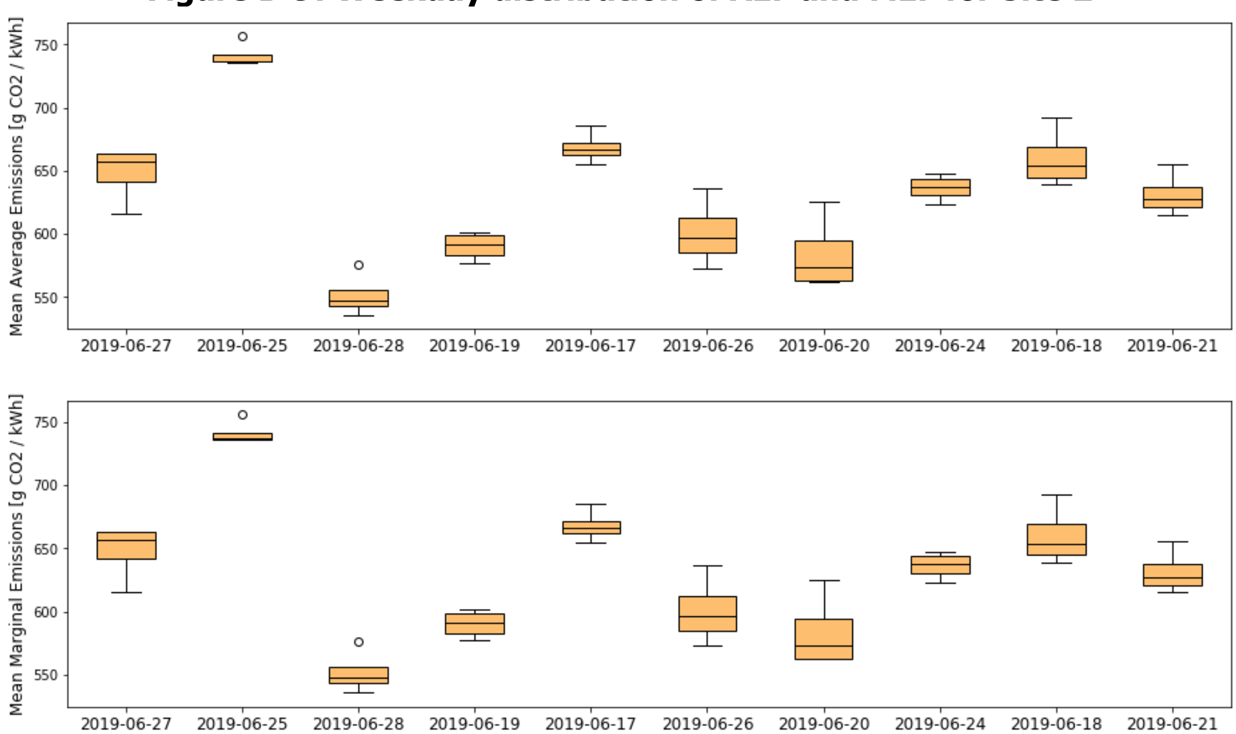
This section reports the additional emissions results from Chapter 3, section Emissions Results, for the other sites at Google. Figures B-8 through B-13 show the load shapes under different control schemes, and the average and marginal emissions profile applied in different days and across different control schemes. As noted in Chapter 3, there is more variation by day than by EV load shapes.

Figure B-8: Comparison of the managed load profiles and status quo for Site 2



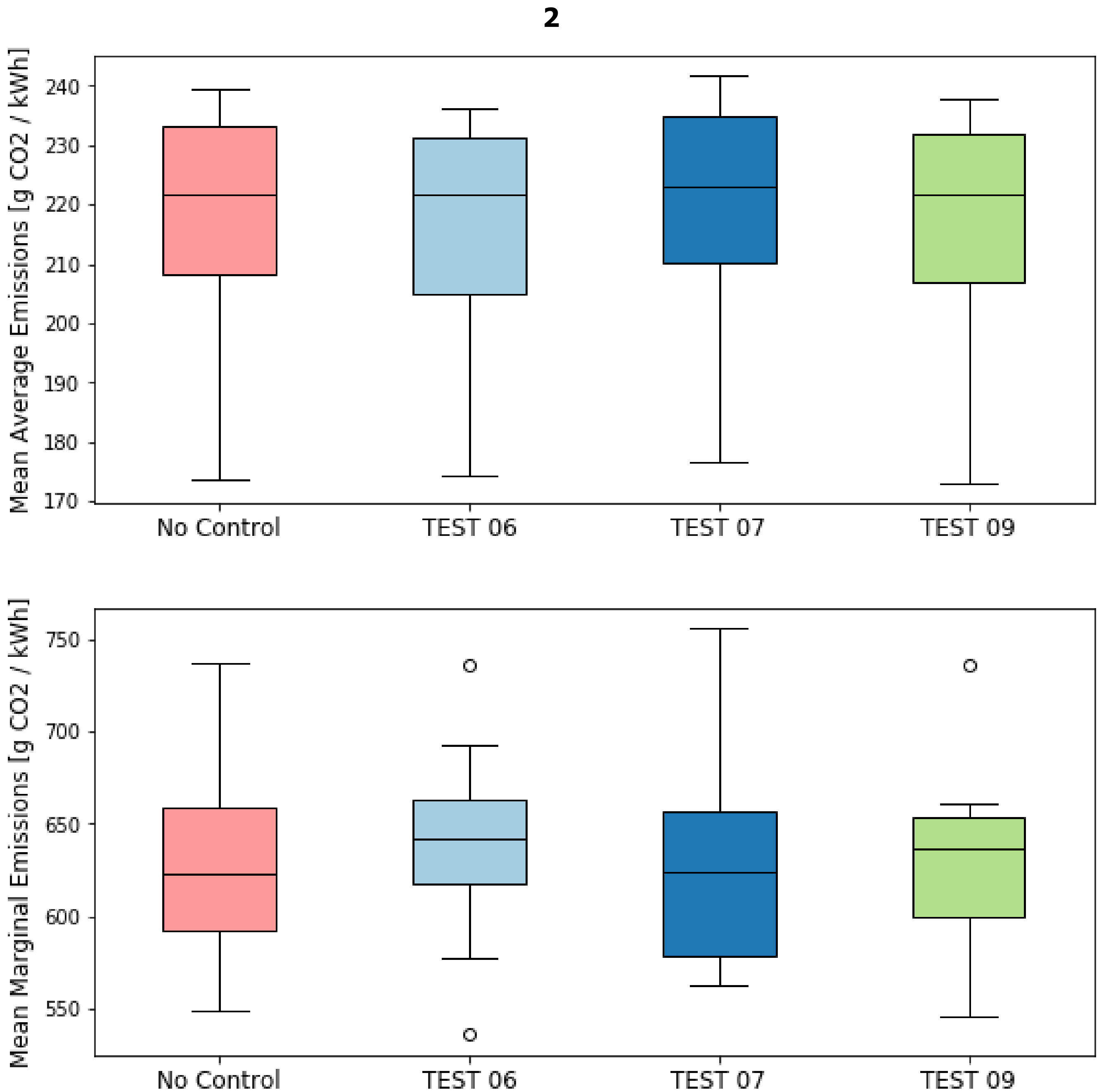
Caption: Sample loads on one weekday from Site 2 showing the different control scheme results: tests 6, 7, and 9.

Figure B-9: Weekday distribution of AEF and MEF for Site 2



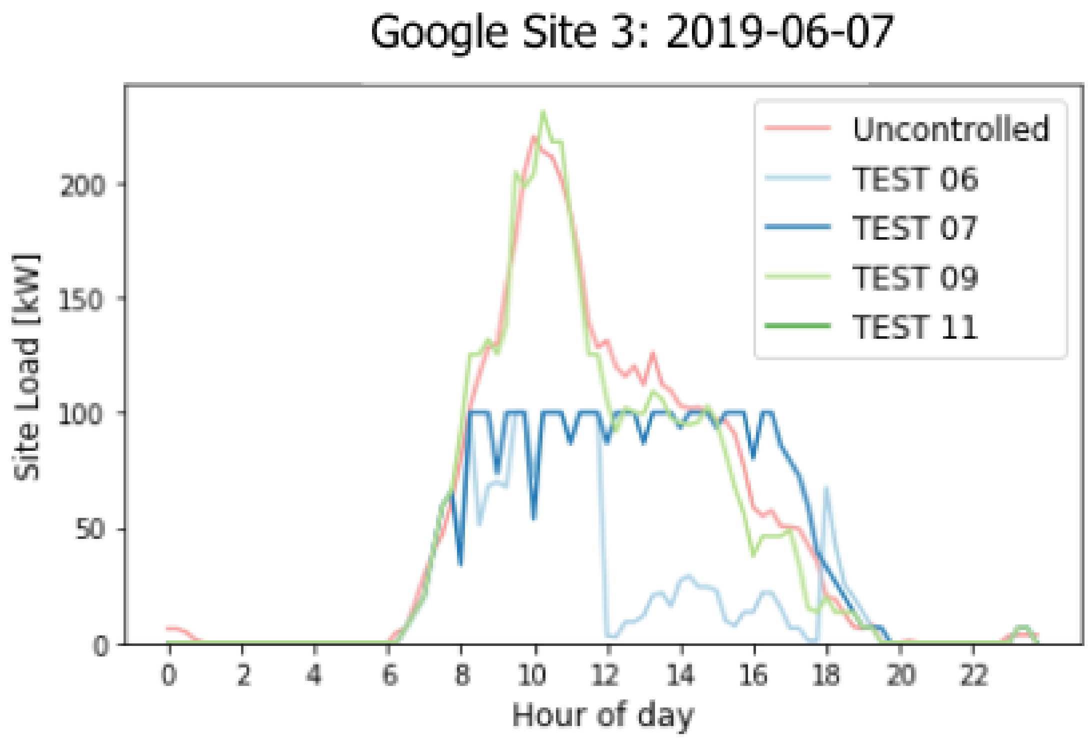
Caption: Each box shows the distribution across different control schemes of average or marginal emissions (per energy) on different weekdays tested at Site 2.

Figure B-10: Comparison of the effects of different smart charging schemes for Site



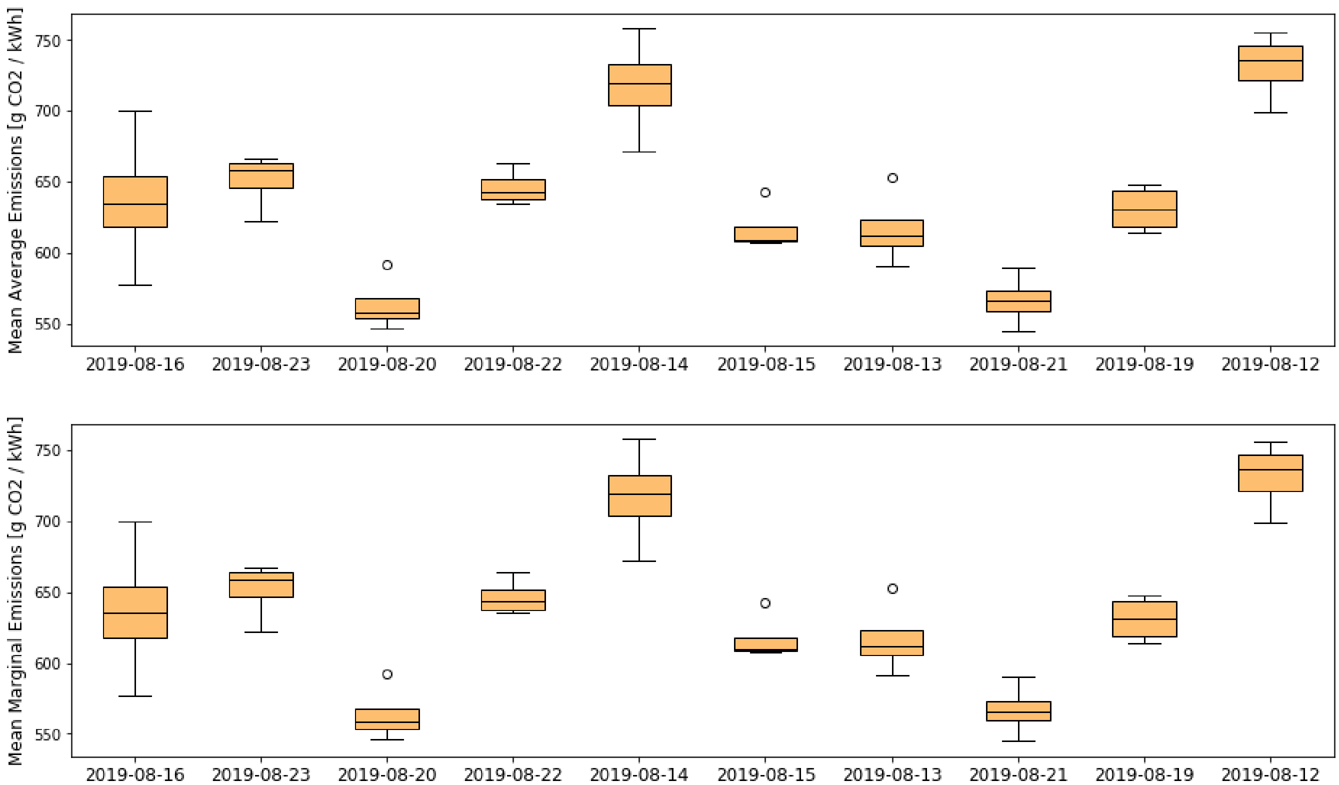
Caption: Each box shows the distribution across different weekdays of the average and marginal emissions for each control scheme tested at Site 2. As a percentage, the median changes very little relative to uncontrolled charging in each case.

Figure B-11: Comparison of the managed load profiles and status quo for Site 3



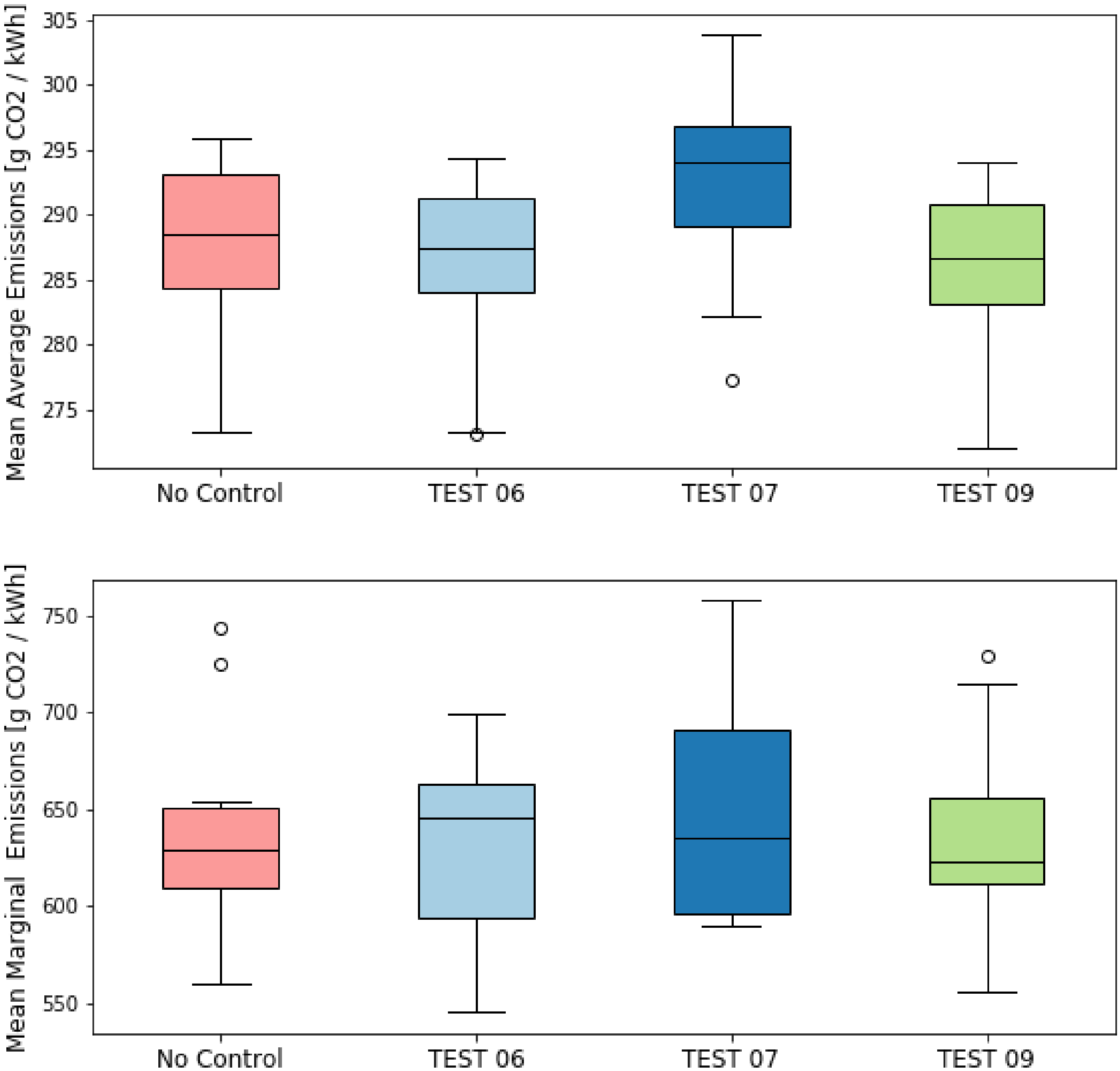
Sample loads on one weekday from the Site 3 showing the different control scheme results: tests 6, 7, 9, and 11.

Figure B-12: Weekday distribution of AEF and MEF for Site 3



Caption: Each box shows the distribution across different control schemes of average or marginal emissions (per energy) on different weekdays tested at Site 3.

Figure B-13: Comparison of the effects of different smart charging schemes for Site 3



Caption: Each box shows the distribution across different weekdays of the average and marginal emissions for each control scheme tested at Site 3. As a percentage, the median changes very little relative to uncontrolled charging in each case.