CO_2 Impact Electric Vehicle Charging on a Local Microgrid: a case study in Southern California

1st Luis Fernando Enriquez-Contreras*†, Matthew Barth*†, Sadrul Ula†, Arun Raju†
*Department of Electrical and Computer Engineering
University of California, Riverside
Riverside, United States of America
lenri001@ucr.edu, jgarr023@ucr.edu, barth@ece.ucr.edu
†College of Engineering, Center for Environmental Research & Technology
University of California, Riverside
Riverside, United States of America
lenri001@ucr.edu, jgarr023@ucr.edu, barth@ece.ucr.edu, sula@cert.ucr.edu, arun@engr.ucr.edu

***Abstract*—In this paper, we evaluate a case study at the University of California, Riverside (UCR) that simulates different EV charging setups with their associated electric costs and CO_2. The CO_2 are calculated with high resolution CAISO CO_2 emissions data in order to review the different emission levels from the different setups. Electric costs are also compared in order to see the different savings the consumer will have with the different setups. It was found that Level 2 charging has a minimal impact on electric costs and CO_2 emissions, which can be offsetted with EV pricing, and by replacing trips from internal combustion engine (ICE) vehicles. Level 3 charging does cause a higher output of emissions, it can double the demand costs by itself. While the CO_2 can be offset from the prevented ICE trips, a prevention of Level 3 charging during peak times must be implemented to prevent high demand costs.**

***Index Terms*—micorgrids, demand response, CO_2 emissions, modelica, EV charging**

I. Introduction

A. Background

California is committed to reducing greenhouse gas emissions through various approaches. However, the two largest contributors to greenhouse gas emissions in California are transportation and electricity generation. In California, 18.84 % percent of 2022 vehicle sales were electric, [1] and the state plans on banning internal combustion engine vehicles by 2035 [2]. At the same time, California is increasing the number of charging stations in the state, having over 13,737 stations [3]. Electric vehicle technology has improved, and new vehicles can charge in 20-60 minutes [4]. This is due to Level 3 charging, which can be as high as 350 kilowatts (kW), as opposed to Level 2 charging, which is capped at 19 kW [4]. While this innovation has led to a higher practicality for electric vehicles, it also leads to more difficulty for the owners of these chargers since they can create a tremendous amount of loads very quickly. Most Level 2 chargers consumers use are similar in load to an air conditioner. While California tries to increase clean energy penetration, it also needs to reduce the amount of GHG emissions produced by transportation through electrification. This leads to two conundrums: how will California add enough capacity for electrified transport, and how clean is the grid to minimize the amount of emissions associated with battery electric vehicles? One proposal to mitigate the strain on the grid is to keep electricity production and EV charging local by using microgrids. A microgrid is defined as: "'a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode" As microgrids and EV chargers become ubiquitous, it is crucial to study the economic and environmental impacts EV charging, in particular fast charging, will have on microgrids.

B. Literature Review

In [5], Electric Vehicle Charging Stations (EVCS) are analyzed under different solar irradiation conditions. The study develops a demand and stochastic model, then performs a techno-economic assessment and analyzes the environmental impact of EVCS. The authors conclude that EVCS with solar's optimal configuration and investment costs are highly dependent on feed-in tariffs and the solar irradiation of the area. The CO_2 emissions were calculated on a per year basis, and do not deal with the variations of CO_2 emissions within a single day. Also, only energy charges were calculated with no demand costs calculations. 6, proposes a control algorithm is proposed that in different scenarios can minimize charging time or costs or maximize renewable energy use. The authors used a uniform distribution during peak times to model the charging loads, with only Level 2 charging at 3.3 kW and no Level 3 charging. An EV charging model is proposed in [7], that load shifts charging events from high peak times to low peak times. The authors found their current method does little to reduce peak load shaving, and solar production surplus may not be necessarily shifted to EVs due to their low availability at the time. The dataset was limited to one week], with four EVs in a system with 10 buildings. In [8], the authors run multiple scenarios with different self consumption rates, first comparing scenarios and then calculating emissions for each scenario.. The CO_2 emissions are calculated from whole life-cycle CO $_2$ emissions without a high time resolution. [9] uses the Non-dominated Sorting Genetic Algorithm- II (NSGA-II) to analyze 4 different responses with 0 % 10 % 20 % 30% EV penetration and a Monte Carlo load profile. Results were remarkable, however CO_2 calculations were not explained. and the specific impacts of Level 2 vs Level 3 charging were not shown. [10] analyzes IEEE 9 and 14 nodes that forecast the EV loads one day ahead. The author use multiple microgrids to balance out EV charging within the system. Multi-objective energy management of multiple microgrids is used to orchestrate the operation.

This paper's analyzes the impacts different Level 2 and Level 3 charging have on the behavior of microgrids and the associated electric costs and CO_2 emissions in southern California. The simulation is run in open Modelica rather than being a purely calculated model. This paper also uses a higher time resolution data than most to calculate the CO_2 emissions every 15 minutes.

C. Peak Shaving Strategy

Peak shaving is a standard method for reducing high-demand charges. Since demand charges are based on only the maximum value over the entire month, we assume the consumer wants to minimize the demand charges as much as possible. Our algorithm is based solely on cost savings for a typical microgrid. During peak-shaving, the algorithm looks at the amount of power being imported, if there is enough energy, and if the batteries can mitigate a fraction of that or the total amount.

D. CO_2 Emissions

Our microgrid's solar production greatly overlaps with the local solar energy production within the larger grid. With a BESS, we can utilize renewable energy during peak times and at night. In this scenario, the control algorithm is economically based since we want to see how EV charging aligns with actual CO_2 emission outputs. The simulation uses emission output calculations from CAISO for each time interval as a sum of all the powerplant CO_2 emissions (imports, natural gas, biogas, biomass, geothermal, coal) $\frac{\mathrm{m}TON_{\mathrm{CO_2}}}{hour}$. The CO_2 emissions output is divided by the amount of power produced (solar, wind, geothermal, biomass, biogas, small hydro, grid batteries, large hydro, imports, nuclear, coal) in MW, which gives us an emissions rate of $\frac{\frac{\mathrm{m}TON_{\mathrm{CO_2}}}{hour}}{W}$. This is multiplied with our 15-minute data kW, and a multiplier. The multiplier of $\frac{1}{4000}$ converts kW into W and to address for the four 15 minute periods in an hour multiples by four. This gives us an estimate of the amount of CO_2 emissions in $_{\mathrm{m}}\mathrm{TON}_{\mathrm{CO_2}}$ for every 15 minutes that is summed together to give us the total for the entire period. This method is similar to the one used in [11]. When the grid does not pull power from the grid or is sending power, the CO_2 emissions are assumed to be zero since we are using our solar energy.

II. Simulation in OpenModelica

OpenModelica is an open-source implementation of the Modelica programming language [12]. Modelica is a programming language that is designed for dynamic systems simulation [13]. OMEdit is the GUI interface for OpenModelica, allowing the user to draw a system for simulation [14]. The microgrid scenarios are simulated in OpenModelica using the Modelica buildings library. Lawrence Berkeley National Laboratory created the Modelica buildings library for building and district energy and control systems [15]. However, its capability for energy storage systems, bi-directional inverter, solar, and HVAC modeling make it ideal for a microgrid simulation setup. This allows us to create scenarios that do not currently exist in our microgrid, like running a month with solar with the same load, or running the BESS control algorithm for different electric rates. The power circuits are three-phase balanced circuits. The simulation of our case study microgrid is the grid-connected to the building netload. The model's net load is broken down into solar power, HVAC loads, regular building loads, electric vehicle chargers, and the BESS as shown in Figure 1.

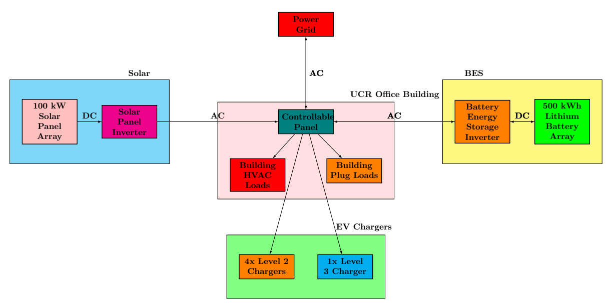

Fig. 1: Microgrid Layout

A. Validation

To ensure that our model accurately portrays our real world system, a year of real world data was used to validate the P_G output . P_G is defined as the power the microgrid sends or consumes from the grid. The actual data was compared to the simulated with a correlation coefficient of ≈ 0.965087 as shown in Figure 2.

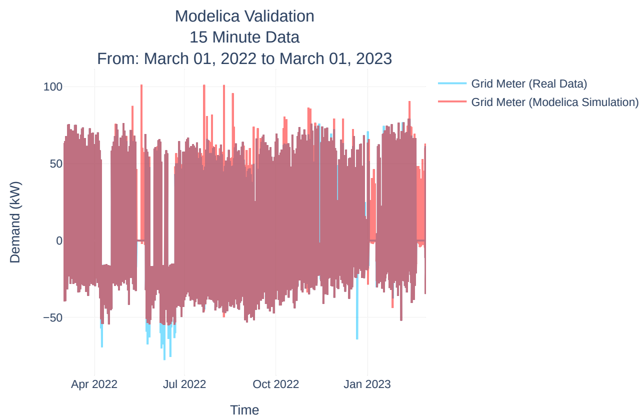

Fig. 2: Whole Year Validation

B. Solar Generation and Building Loads

The solar power in our model is based on the historical solar data from our PV array. The HVAC loads and the regular building loads are represented separately in this model but utilize the same method; they both use historical real world power data to represent their load in the system.

C. EV Charger Loads

Our model also considers transportation loads in the form of EV chargers. The EV chargers are represented as two models: Level 2 EV chargers, and Level 3 EV chargers. While other loads follow a typical daily and yearly pattern, EV loads are different since they switch on and off. Our case study microgrid has four Level 2 chargers, so it can have four "steps" of 7.2 kW each, while there is only one "step" of 50 kW with the Level 3 chargers. To generate EV loads, we use a Poisson random generator to generate the number of charge sessions in a day, the arrival times, and charging durations based on real world data.

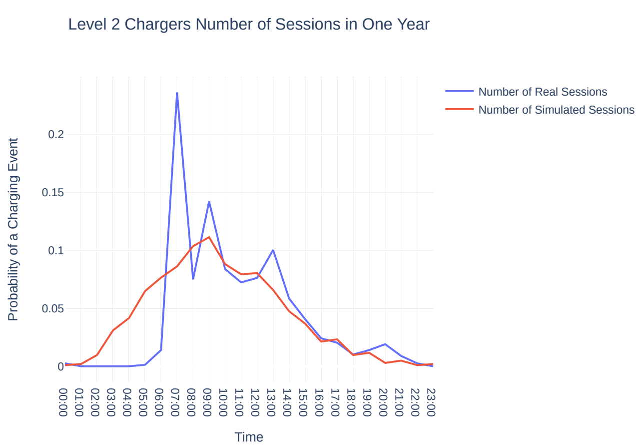

Fig. 3: Probability Density Function of the Level 2 EV Charger Validation

Historical data was collected from the Level-2 charger to determine the parameters for the Poisson random generator, following a typical daily charge pdf shown in Figure 3, and the power output of the Level 2 chargers in Figure 4.

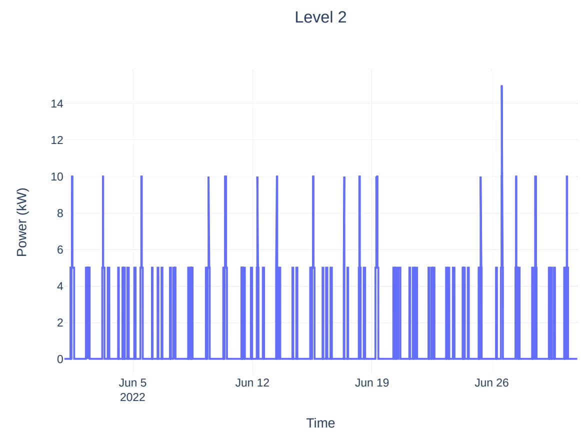

Fig. 4: Level 2 Chargers Simulated Power Output

D. BESS and Peak Shaving

The BESS is modeled as a battery connected to a bidirectional inverter. The BESS output is controlled by generated data from the control algorithm. The BESS output is computed in real-time by using a peak shaving algorithm utilizing BESS SOC and the grid meter output. The algorithm charges the battery when excess solar power is exported to the grid, and the battery needs to be charged. Python code reads the net load from the grid model and determines the amount of CO_2 being produced during that interval. Algorithm 1 shows the peak shaving algorithm sufficient for flat rate demand response.

Algorithm 1: Peak Shaving

net_load, SOC ← Modelica Data Output **if** *if condition* **then**
    net_load <= -15 kW and SOC > 20 % and net_load >= -100 kW BESS_inverter = -net_load - 15 kW
else if *net_load <= -100 kW and SOC > 20 %* **then**
    BESS_inverter = -100 kW
else if *net_load >= 0 kW and SOC < 90 % and net_load <= 100 kW* **then**
    BESS_inverter = -net_load
else if *net_load >= 0 kW and SOC < 90 %* **then**
    BESS_inverter = 100 kW
else
    BESS_inverter = 0

III. Results

The charging setup in OpenModelica is modified for different layouts and scenarios, as described in Table I.

Scenario 1 represents the baseline case where only the building loads, such as air conditioners, appliances, and lights, are connected to the grid. Scenario 2 represents the case where a building installs four Level 2 EV chargers. Scenario 3 adds one Level 3 charger to the building in addition to the Level 2 chargers. Scenario 4 is the first case that utilizes a microgrid, which includes 100 kW of solar power and 500 kWh of battery storage. This scenario demonstrates the peak-shaving capabilities of a microgrid without EV chargers, creating high demand. This can be thought of as the baseline case for the BESS microgrid. Scenarios 5, 6, 7, and 8 represent a transportation-microgrid with EV chargers; the BESS capacity is varied to different sizes that include or exclude Level 3 charging to show which BESS size offers the lowest cost and the lowest CO_2 emissions, as well as the impact Level 3 charging has on the transportation-based microgrid.

Each scenario is run independently of the others, and the power outputs of the different components in the simulation are shown in Fig. 5. Scenarios 1, 2, and 3 are constantly negative, meaning they pull power from the grid. Scenarios 3-8, on the other hand, mostly stay at zero, meaning they either export power to the grid when the BESS SOC is over 90

While the load-following algorithm should limit the amount of power consumed at any time to near zero kW, there are still times when the BESS cannot supply the building with power. This happens when the BESS is too depleted, and there is little to no solar power to replenish it, as shown in Figure **??**. The two main reasons for these events are multiple cloudy days and electrical faults. The larger the battery capacity, the less frequently the battery is depleted, and the microgrid can better weather events of low solar output. Most of the low solar power events occur during the winter months.

Figures 5, **??**, and **??** show box plots of the power output. Fig. 5 is for the entire year, while Figures **??** and **??** show selected months. The box plots show that all three figures' mean and 75th percentile are almost identical at 0 kW. This implies that load following is functioning correctly most of the time. However, the outliers show when the BESS fails to keep the power pulled from the grid at 0 kW. Fig. 5 shows that Scenarios 4 - 8 have almost identical values. However, this is because the figure is maximum for the entire year. Only a few of the billing months have a solar outage long enough to cause BESS depletion that causes a demand peak almost as large as the no BESS scenario (Scenario 2).

Just one outlier will change the demand charge for the entire billing month. In some months, the maximum demand peak of Scenario 2 and 3 is similar since they have the same load, but for most of the months, it is reduced significantly, reflected in the reduced demand charges of the building.

The average daily CO_2 emissions from each scenario are shown in Fig. 10. Scenario 2, with its increased charging events, shows about a 26% increase in CO_2 emissions compared to Scenario 1. The CO_2 emissions from the transportation-microgrids are lower than a conventional building, even with the additional load from the EV chargers. While adding 17% to 45% more CO_2 emissions compared to a microgrid without EV charging infrastructure (Scenario 3), those CO_2 emissions are easily offset by charging an average of 12 EVs per day. Table II shows each scenario's emissions and electric price amounts.

TABLE I: Simulated Scenarios of the UCR Microgrid using Different Layouts and Electric Pricing Structures

Scenario	
1	No EV Charging with no BESS
2	Level 2 Charging with no BESS
3	Level 3 Charging with no BESS
4	Level 2 and Level 3 Charging with no BESS
5	No EV Charging with BESS
6	Level 2 Charging with BESS
7	Level 3 Charging with BESS
8	Level 2 and Level 3 Charging with no BESS

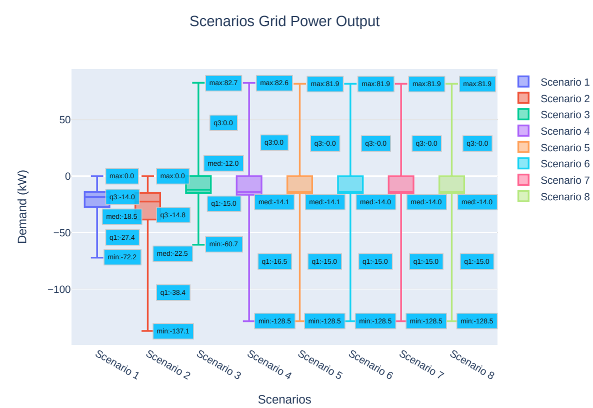

Fig. 5: Power measured from the meter

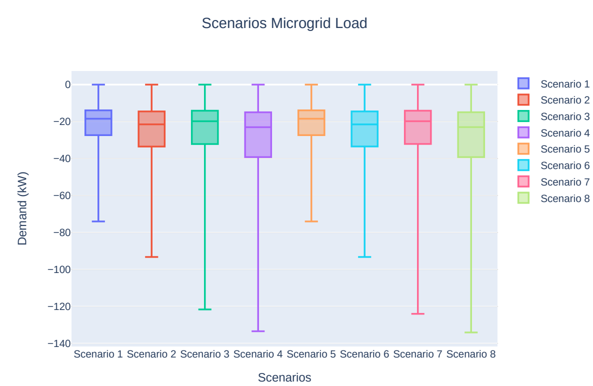

Fig. 6: Load of all the microgrid components

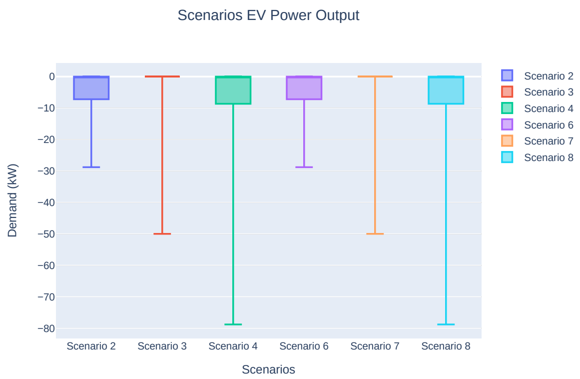

Fig. 7: Loads from the EV chargers

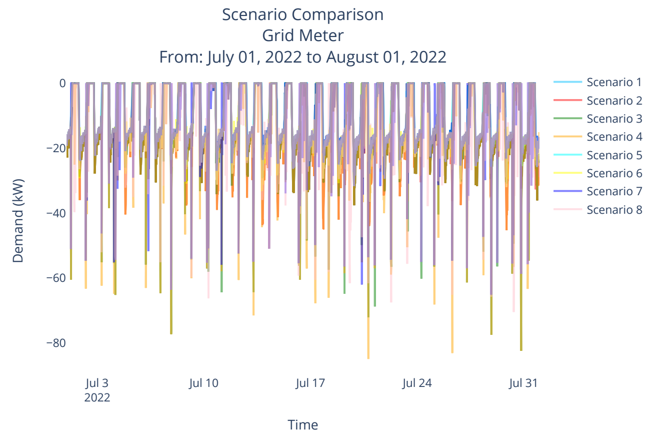

Fig. 9: Summer Net Load Scenario Comparison

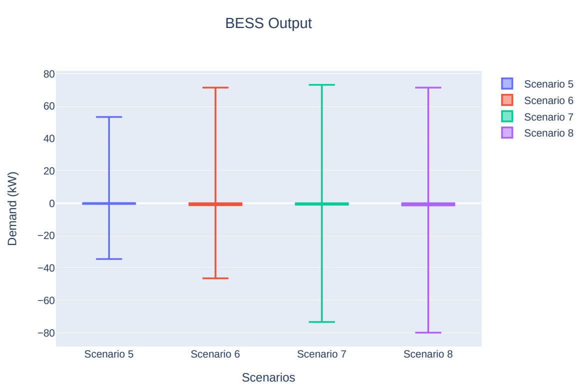

Fig. 8: Power produced or consumed from the BESS

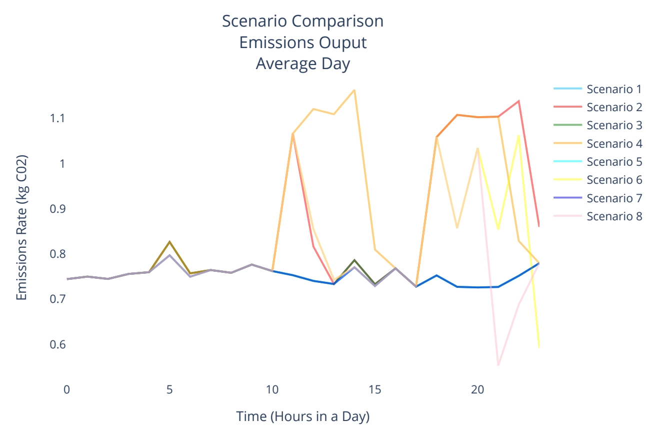

Fig. 10: Microgrid CO_2 Emissions Outputs Averages During Times of Day

TABLE II: Microgrid Utility Prices and CO_2 Emissions Output under Different Pricing Scenarios and Pricing Structures

Scenario	Demand Charges	Energy Charges	Emissions
1	6171	0	21
2	7963	2147	25
3	12816	2749	26
4	14438	7274	30
5	4992	0	19
6	6755	2925	22
7	12053	4149	23
8	13109	8822	26

IV. Conclusion

Electric vehicle charging will have a significant impact on the electric costs and emission levels of a microgrid. Level 2 charging had a relatively minimal effect on costs, with a 60 to 90% increase in electricity costs, which is not much considering that four Level 2 chargers were used. However, just one Level 3 EV charger can cause double to quadruple electric costs. Level 2 chargers have a very small impact on demand charges even when all four chargers are running since the 7.2 kilowatts of each EV charger is much less, and each has a max peak relative to the system. However, the 50 kW peaks created by the Level 3 charger nearly eclipse the demand for the HVAC units, and both used in unison can double the maximum peak and the demand costs. This happens mostly at noon when HVACs and EVs run simultaneously. Energy chargesboth with and without the BESS are similar, albeit slightly higher with BESS. This was expected since BESS does not reduce energy costs, only demand charges with the flat rate used by the university's utility company. The costs of Level 2 charging is significantly easier to recover compared to Level 3 charging. The difficulty is that just one charging event that aligns with the other loads can easily double the price of that month's electrical bill. Implementing a Level 3 charging control system must prohibit users from utilizing fast charging at peak hours when charging one vehicle can cause major costs to the provider. Aside from the major cost differences, locally produced solar power combined with EV charging has a huge potential to reduce CO_2 emissions from transportation. Even when utilizing both Level 2 and3 chargers and no BESS, there's only a 42% increase of carbon dioxide emissions compared to no EV charging at all, increasing volume from 21 tons of CO_2 to 30 tons of CO_2. The X amount of vehicle trips mitigates this slight increase in CO_2 if combustion engine vehicles were used instead.

V. Future Works

Future papers will investigate different more advanced control strategies to further decrease electric costs and CO_2 by preventing users from charging during high peak times, utilize the clean energy produced by the solar panels, and only pull power from the grid during low CO_2 times.

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