# $CO_2$ and Cost Impacts on a Transportation Microgrid with Electric Vehicle Charging Infrastructure: a case study in Southern California

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***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*—micogrids, 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, electric vehicles (EVs) accounted for 25.4 % of Q2 2023 vehicle sales [1], and the state aims to ban the sale of internal combustion engine vehicles by 2035 [2]. Concurrently, California is expanding the number of charging stations in the state, reaching over 13,737 stations [3]. EV technology has advanced, and new vehicles can charge in 20-60 minutes [4]. This is enabled by Level 3 charging, which can deliver up to 350 kilowatts (kW), compared to Level 2 charging, which is limited to 19 kW [4]. While this innovation has increased the attractiveness of EVs, it also poses a challenge for the owners of these chargers, as they can generate a large amount of load quickly. As California strives to increase the share of clean energy in its electricity mix, it also needs to reduce the GHG emissions from transportation by promoting electrification. This leads to two conundrums: how will California provide enough capacity for electrified transport, and how clean is the grid to minimize the emissions associated with battery electric vehicles? One proposal to alleviate the pressure on the grid is to localize electricity production and EV charging by using microgrids. A microgrid is defined by the Department of Energy (DOE) and the Institute of Electrical and Electronics Engineers (IEEE) 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." [5] [6]. As microgrids and EV chargers become more widespread, it is essential to study the economic and environmental impacts of EV charging, especially fast charging, on microgrids. EV charging differs from other building loads, as it can rapidly ramp up to the maximum levels at random intervals based on human behavior. An outlier event where multiple people charge at the same time can cause a significant peak in the load.

This research holds significant implications for the advancement of intelligent transportation systems, as it aims to address the economic needs of EV charging infrastructure owners and determine the optimal configuration that benefits both EV owners and the environment by minimizing greenhouse gas emissions. This paper delves into the impacts of transportation microgrids equipped with Level 2 and Level 3 charging on the behavior of microgrids, associated electricity costs, and $CO_2$ emissions within the context of southern California. The simulations are conducted using OpenModelica, a dynamic modeling and simulation environment. This study distinguishes itself from previous research by employing a higher time resolution for calculating $CO_2$ emissions, capturing data every 15 minutes.

## B. Literature Review

Transportation microgrids have gained significant traction in recent years due to the growing demand for transportation electrification. These microgrids, which combine distributed energy resources (DERs) and energy storage systems with electric vehicle (EV) charging infrastructure, offer a promising solution for integrating EVs into the power grid while minimizing environmental impact. Previous studies have investigated the economic viability of transportation microgrids, primarily focusing on energy charges associated with EV charging. However, demand charges, which reflect the peak demand imposed on the grid, should be addressed. This omission is particularly crucial for fast charging stations, which draw significant power during peak periods. A more comprehensive approach to economic analysis should consider both energy and demand charges, providing a more accurate assessment of the overall cost of operating a transportation microgrid. Research has addressed the impact of EV charging demand on transportation microgrids, often focusing on low-demand Level 2 charging. However, the increasing popularity of high-demand Level 3 charging requires a more nuanced understanding of its implications. Studies should incorporate a mix of Level 2 and Level 3 charging scenarios to accurately assess the impact of EV charging demand on microgrid operation and economics. Assessing the greenhouse gas (GHG) emissions associated with transportation microgrids is often simplified by using average $CO_2$ emissions from an area's electricity production. This approach fails to capture the variations in $CO_2$ emissions throughout the day, which can significantly affect the environmental impact of EV charging. More sophisticated GHG emission calculations should consider the time-varying nature of $CO_2$ emissions, providing a more accurate representation of the environmental impact of transportation microgrids.

Several studies have investigated the performance of electric vehicle charging stations (EVCS) under varying conditions. [7] developed a demand and stochastic model for EVCS, followed by a techno-economic assessment and an environmental impact analysis. They concluded that the optimal configuration and investment costs of EVCS with solar integration are highly dependent on feed-in tariffs and solar irradiation levels. However, their $CO_2$ emission calculations were based on annual averages and did not account for intraday variations. They only considered energy charges, omitting demand charges in their economic analysis. [8] proposed a control algorithm for EVCS that can minimize charging time, costs, or maximize renewable energy use depending on the scenario. They modeled charging loads using a uniform distribution during peak demand periods, assuming only Level 2 charging at 3.3 kW and excluding Level 3 charging. [9] proposed an EV charging model that shifts charging events from peak demand periods to off-peak times. They found that their current method had limited impact on peak load shaving and that solar production surplus may only sometimes be diverted to EVs due to their low availability at those times. Their dataset was limited to one week and involved four EVs in a system with ten buildings. [10] ran multiple scenarios with different self-consumption rates, comparing scenarios first and then calculating emissions for each. Their $CO_2$ emission calculations were based on whole-life-cycle $CO_2$ emissions without high time resolution. [11] employed the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) to analyze four different responses with EV penetration rates of 0%, 10%, 20%, and 30%, using a Monte Carlo load profile. They achieved remarkable results but did not elaborate on their $CO_2$ calculations or provide a detailed analysis of the specific impacts of Level 2 versus Level 3 charging . [12] analyzed IEEE 9 and 14 nodes, forecasting EV loads one day ahead. They utilized multiple microgrids to balance out EV charging within the system, employing a multi-objective energy management approach for optimizing microgrid operation. The forecasted EV loads did not have sudden high-demand events nor level 3 charging, which makes the forecasting model difficult to implement.

## C. Peak Shaving Strategy

Peak shaving is a widely adopted strategy for mitigating high-demand charges. As demand charges are solely determined by the maximum power consumption over an entire billing period, it is assumed that consumers seek to minimize these charges to the greatest extent feasible. Energy charges, on the other hand, represent the cost associated with the total energy consumed during the billing period and are calculated as a summation rather than a maximum value. The proposed algorithm is designed to optimize cost savings for a typical microgrid. During peak-shaving periods, the algorithm assesses the imported power, evaluates the availability of sufficient energy, and determines whether batteries can mitigate a portion or the entirety of the imported power demand.

## 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. While the micorgrid does not produce any direct $CO_2$ emissions, but rather the indirect 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 ${}_{\mathrm{m}}\mathrm{TON}_{CO_2}$ 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 [13]. 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 [14]. Modelica is a programming language that is designed for dynamic systems simulation [15]. OMEdit is the GUI interface for OpenModelica, allowing the user to draw a system for simulation [16]. 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 [17]. 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.

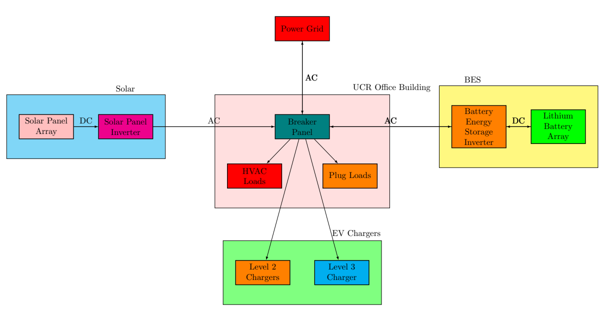


Fig. 1: Microgrid Layout

### 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.

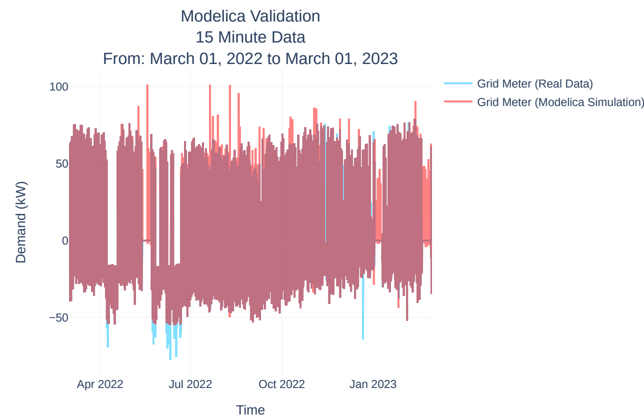


Fig. 2: Whole Year Validation

### 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.

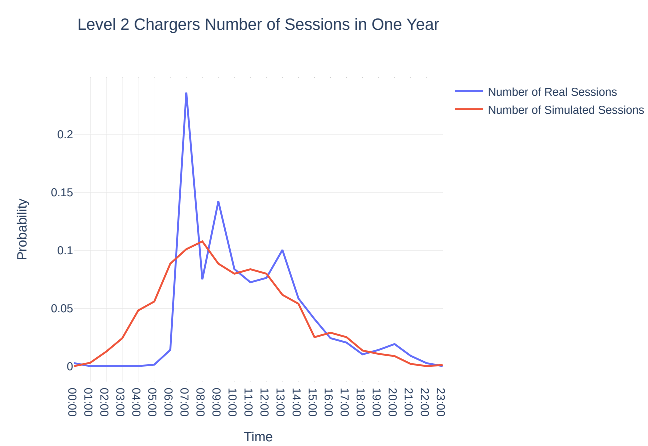


Fig. 3: Probability Density Function of the Level 2 EV Charger Validation

Historical data from the Level-2 charger was utilized to determine the parameters for the Poisson random generator, consistent with the typical daily charge probability density function (PDF) depicted in Figure 3. Additionally, the power output of the Level-2 chargers is illustrated in Figure 4. Analysis of the historical data revealed three distinct peak charging periods occurring at [7, 9, 13] hours, with average vehicle arrivals during each peak of [6, 2, 1], respectively. A mean charging time of 90 minutes was assumed. Leveraging these parameters, the EV random arrivals function generates random arrival times and durations. The function employs the NumPy library in Python to create a Poisson random distribution with means centered around the peak times. To ensure consistency across different scenarios and prevent any outlier event from the EV charging load disproportionately influencing higher demand events, a random data seed value of 10 was employed to ensure every charging event is the same. The random arrivals for Level 3 charging are modeled with three peak times at [7, 9, 13] hours, an average vehicle arrival count of [2, 1, 1], and a mean charging time of 30 minutes.

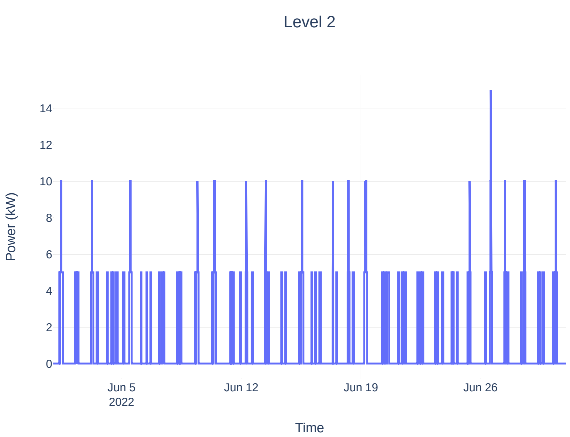


Fig. 4: Level 2 Chargers Simulated Power Output

### *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 is modified in OpenModelica for different layouts and scenarios. The scenarios are described in Table I. Scenario 1 is the baseline case where only the building loads such as the air conditioners, appliances, and lights are connected to the grid. Scenario 2 is the case where a building installs four Level 2 and one Level 3 charger. Scenario 3 represents a transportation microgrid that has solar power and a BESS for peak shaving. Each scenario is run independently of each other, and the power outputs of the different components in the simulation are shown in Figure 5. Scenario 1 and 2 are both constantly negative meaning they are constantly pulling power from the grid. Scenario 3 on the other hand is mostly positive or limited to -15, meaning it's either exporting power to the grid or it's consuming only 15 kilowatts. The reason for the 15 kilowatt floor is because with the utility companies electric rate a minimum of 15 kilowatts is charged for the demand, meaning that a zero demand microgrid will not make a financial difference for the user. While the peak shaving algorithm should limit the amount of power consumed at any time to be limited to 15 kilowatts, there are still some 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 9. The two main reasons for these events that happen are multiple cloudy days and electrical faults. During the winter months, most of the low solar power events occur since that is when most of the rain falls in southern California. Figures 5, 6, and 7 show box plots of the power output. Figure 5 is for the entire year while Figures 6 and 7 show selected months. The box plots show that all three figures mean and 75th percentile are almost identical at 15 kW. This implies that peak shaving is functioning correctly most of the time. However, the outliers show when the BESS fails to keep the power pulled from the grid at 15 kW. 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 are similar since they have the same load, but for most of the months, it is reduced significantly which is reflected on the reduced demand charges of the building. Each scenario's power pulled from the grid is juxtaposed in Figure 8.The average of daily $CO_2$ emissions from each scenario is shown in Figure 11. Scenario 2 with its increased charging events shows about a 26 % increase of $CO_2$ emissions compared to Scenario 1. The $CO_2$ emissions from the transportation microgrid are lower than a conventional building even with the additional load coming from the EV chargers. The emissions and electric price amounts of each scenario are shown in Table II.

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

| Scenario | |
|---|---|
| 1 | Standard Building with no EV Chargers |
| 2 | Standard Building with Level 2 and Level 3 Charging |
| 3 | Microgrid Building with 500 kW Solar, 500 kWh BESS, No EV Charging |
| 4 | Microgrid Building with 500 kW Solar, 100 kWh BESS, Level 2, and Level 3 Charging |
| 5 | Microgrid Building with 500 kW Solar, 250 kWh BESS, Level 2, and Level 3 Charging |
| 6 | Microgrid Building with 500 kW Solar, 500 kWh BESS, Level 2, and Level 3 Charging |
| 7 | Microgrid Building with 500 kW Solar, 1 MWh BESS, Level 2, and Level 3 Charging |
| 8 | Microgrid Building with 500 kW Solar, 1 MWh BESS, Level 2, and Level 3 Charging |

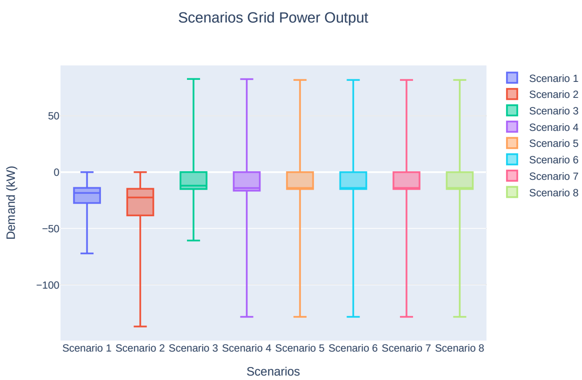


Fig. 5: Power measured from the meter

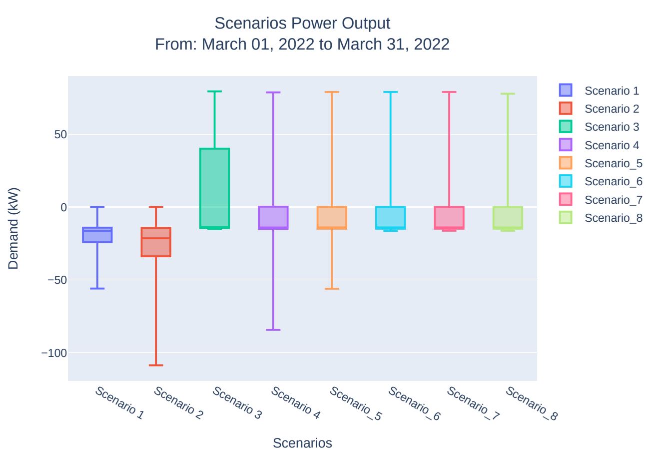


Fig. 6

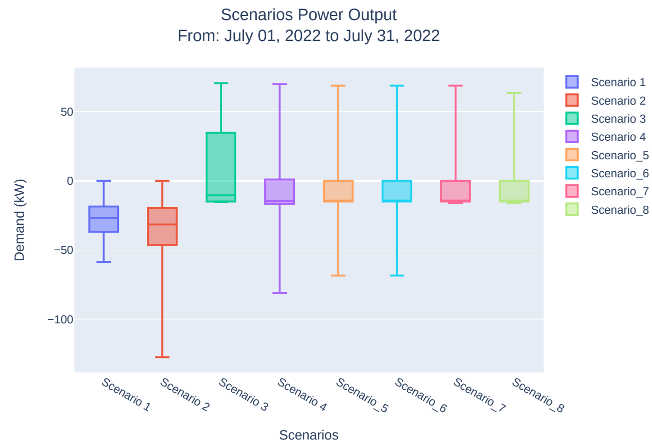


Fig. 7

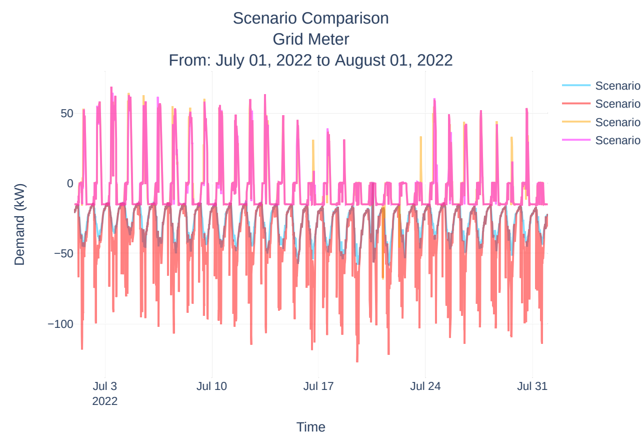


Fig. 8: Summer Net Load Scenario Comparison

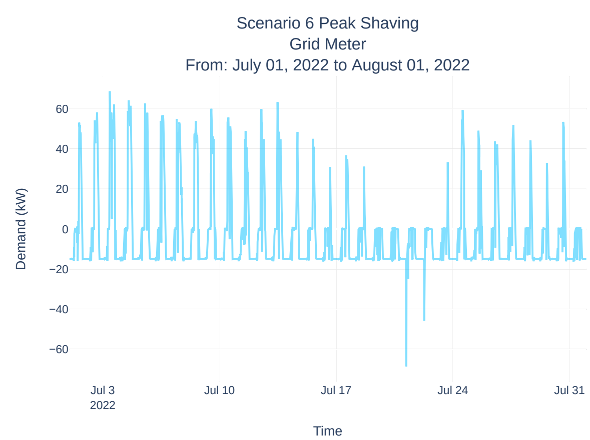


Fig. 9

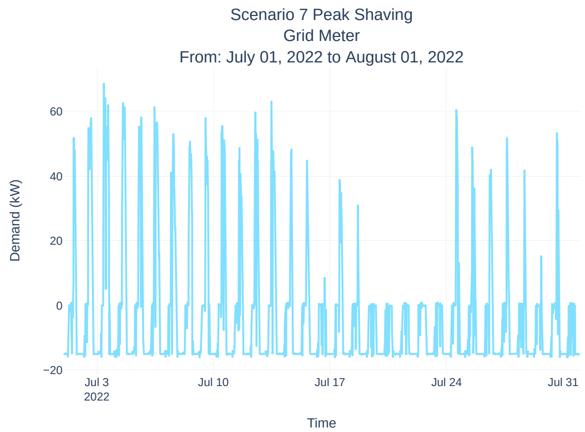


Fig. 10

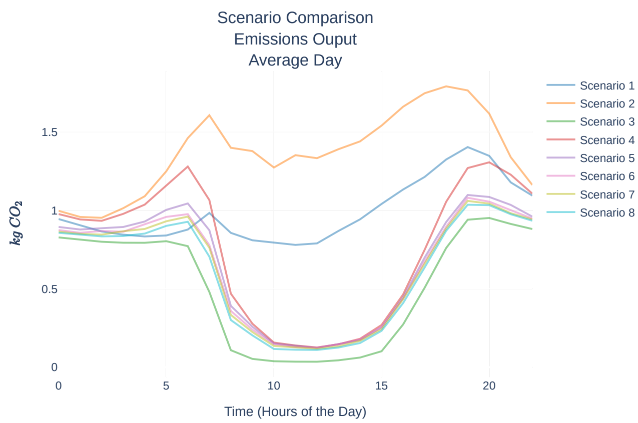


Fig. 11: Microgrid $CO_2$ Emissions Outputs Averages During Times of Day

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

| Scenario | Demand Charges ($) | Energy Charges ($) | Total Cost ($) | $CO_2$ Emissions (mTons ) |
|---|---|---|---|---|
| 1 | 7695 | 22736 | 30431 | 34 |
| 2 | 17343 | 32289 | 49632 | 47 |
| 3 | 3904 | 0 | 3904 | 18 |
| 4 | 14341 | 8209 | 22550 | 26 |
| 5 | 13193 | 8937 | 22130 | 23 |
| 6 | 12909 | 9239 | 22148 | 22 |
| 7 | 10835 | 9418 | 20253 | 22 |
| 8 | 9811 | 9577 | 19388 | 21 |

## IV. Conclusion

Transportation microgrids are an innovative solution for reducing the electric costs and emission levels of an EV charging setup. A comparative analysis of different scenarios shows that a transportation microgrid can offer significant savings and $CO_2$ over a conventional system. For a 100 kW 500 kWh transportation microgrid system, the annual savings are estimated to be $8,000 a year or $80,000 over a 10-year battery lifetime, even with additional demand from EV chargers. Compared to a building that installs EV chargers without a microgrid, the annual savings are even more substantial, reaching $27,000 a year or $270,000 over a 10-year battery lifetime. This implies that the transportation microgrid can triple the savings from switching from a conventional building. Moreover, the transportation microgrid can reduce the $CO_2$ emissions by more than 50% compared to the conventional building and by about 67% compared to the scenario where the microgrid does not supply the building with clean energy. Therefore, the user has a strong economic and environmental incentive to adopt a transportation microgrid. However, increasing the battery capacity does not necessarily improve the performance of the microgrid. As shown in the month of July in Figures 9 and 10, doubling the battery capacity can eliminate some peaks from a couple of cloudy days, but the additional savings of $2,000 per year do not justify the cost of the extra capacity. Lastly, a 15 kW demand price floor has a negative impact on $CO_2$ emissions, as it discourages the user from maintaining the net load at zero in a peak shaving setup.

## V. Future Works

Future research will explore different, more advanced control strategies to optimize the electric costs and $CO_2$ emissions of the transportation microgrid. These strategies will include preventing users from charging during high peak times, maximizing the use of the clean energy produced by the solar panels, and minimizing the power drawn from the grid during high $CO_2$ times. The effect of the new net energy metering policy in California on the value of the BESS system will also be assessed.

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