CO_2 and Cost Impact Analysis of a Microgrid with Electric Vehicle Charging Infrastructure: a Case Study in Southern California

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***Abstract*—As a part of an innovative Intelligent Transportation System (ITS), this paper investigates the effectiveness of transportation-based microgrid configurations in reducing carbon dioxide (CO_2) emissions and electricity costs. A case study at the University of California, Riverside (UCR) utilizes high-resolution California Independent System Operator (CAISO) CO_2 emission data to assess the environmental impact of each microgrid configuration. Electricity costs are also compared to determine potential consumer savings. The results demonstrate that a load-following transportation microgrid strategy can significantly reduce CO_2 emissions (67%–84%) and achieve annual cost savings of approximately $24,000, even when accounting for the additional demand from daily electric vehicle (EV) charging at the building. However, battery sizing is crucial for cost-effectiveness, as load-following exhibits diminishing returns. Doubling battery capacity may yield negligible reductions in electricity costs and CO_2 emissions. This emphasizes the importance of optimizing battery capacity to achieve a balance between cost and environmental impact. The study further reveals that in general Level 2 chargers in a commercial building have minimal impact on building demand and energy charges. Conversely, a single Level 3 DC fast charger has a more significant impact, requiring increased solar and battery storage capacity for further cost reduction.**

***Index Terms*—load-following, modelica, distributed energy resources, greenhouse gas analysis, transportation electrification**

I. Introduction

A. Background

California is committed to reducing greenhouse gas emissions (GHG) through various approaches, focused on the two largest sectors: transportation and electricity generation. In California, electric vehicles (EVs) accounted for 25.4% of Q2 2023 vehicle sales [1], and the state will ban the sale of internal combustion engine vehicles by 2035 [2]. Concurrently, California is expanding the number of EV charging stations in the state, reaching over 13,844 Level 2 and 1,924 Level 3 stations [3] as of November 2023. EV technology has advanced, and new EVs can typically charge up to 80% in 20-60 minutes [4]. This is enabled by Level 3 DC fast charging, which can deliver up to 350 kilowatts (kW), compared to Level 2 charging, which is limited to 19 kW [4]. While this reduced charging time has increased the attractiveness of EVs, it also poses a challenge for the owners of these chargers, as they can quickly generate a large amount of electricity demand. As California strives to increase the share of clean energy in its electricity mix, it also needs to reduce the CO_2 emissions from transportation by promoting electrification. This leads to two conundrums: how will California provide enough capacity for electrified transportation, and how clean is the grid to minimize the emissions associated with battery electric vehicles? One method 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, and how microgrids can play an important role. EV charging differs from typical building loads, as it can rapidly ramp up to high levels at random intervals based on human behavior i.e. when they plug in. 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 GHG emissions. This paper delves into the impacts of transportation-microgrids equipped with Level 2 and Level

3 charging infrastructure on the behavior of microgrids, associated electricity costs, and CO_2 emissions within the context of Southern California. The simulations are conducted using OpenModelica [7], a dynamic modeling and simulation environment. This study distinguishes itself from previous research in many ways, including 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, need to 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 deployment 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 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. Reference [8], is developing 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. Reference [9] 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. Reference [10] 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. Reference [11] 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. Reference [12] 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. Reference [13] analyzed IEEE 9 and 14 bus systems, 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. CO_2 Emissions

Our microgrid's solar production, shown in Fig. 1, greatly overlaps with the local solar energy production within the larger grid. With a Battery Energy Storage System (BESS), we can utilize renewable energy during peak times and at night. In this scenario, the control algorithm is optimized to minimize cost for the consumer, however we want to see how low price EV charging aligns with actual CO_2 emission outputs. While the microgrid does not produce any direct CO_2 emissions, there are CO_2 emissions attributed to the microgrid when it pull power from main power grid. The simulation uses emission output calculations from California Independent System Operator (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 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. CAISO gives us an estimate of the amount of CO_2 emissions in ${}_{m}\mathrm{TON}_{CO_2}$ 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 [14]. 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 renewable solar energy.

II. Simulation in OpenModelica

OpenModelica is an open-source implementation of the Modelica programming language [15]. Modelica is a programming language that is designed for dynamic systems simulation [7]. 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]. Further, its capability for energy storage systems, bidirectional 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, shown in Fig. 1, for example 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 Fig.1.

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.

B. Solar Generation and Building Loads

The solar power in our model is based on the historical solar data from a 100 kW photovoltaic (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 (Fig. 5), and Level 3 EV chargers. While other building loads follow a typical daily and yearly pattern, EV loads are different since they stochastically switch on and off, depending on when people plug in. Our case study microgrid has four Level 2 chargers, so it can have four "steps" of 5 kW each, while there is only one "step" of 50 kW with the Level 3 chargers. To generate EV loads in our model, SCADA data is used for the Level 2 charger. For the Level 3 charger, a Poisson random distribution is used to generate the number of charge sessions in a day, the arrival times, and charging durations based on real world data recorded over a year.

Data from the Level-2 charger SCADA system was utilized to determine the parameters for the probability density function (PDF) depicted in Fig. 3. Additionally, the power output of the Level 2 chargers is illustrated in Fig. 4. Analysis of the historical data revealed three distinct peak charging periods occurring at 7:00, 9:00 and 13:00 respectively, with average number vehicle arrivals 6, 2, and 1 during each peak respectively. The Level 2 SCADA data is used in the simulation for the Level 2 charger load. The random arrivals for Level 3 charging are modeled with three peak times at 7:00, 9:00, and 13:00, an average number of vehicle arrivals of 2, 1, and 1 respectively. Level 3 charging has a mean charging time of 30 minutes. Leveraging these parameters, the EV random arrivals function generates random arrival times and durations. The function employs the NumPy library [18] [**?**] 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.

D. BESS and Load-Following

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 load-following algorithm utilizing BESS SOC and the grid meter output. The algorithm charges the battery when excess solar power is exported to the grid, and when the battery needs to be charged. Our algorithm reads the net load from the grid model and determines the amount of CO_2 being produced during that interval. Algorithm 1 shows the load following-algorithm sufficient for 0 kW operation.

Algorithm 1: Load-Following

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

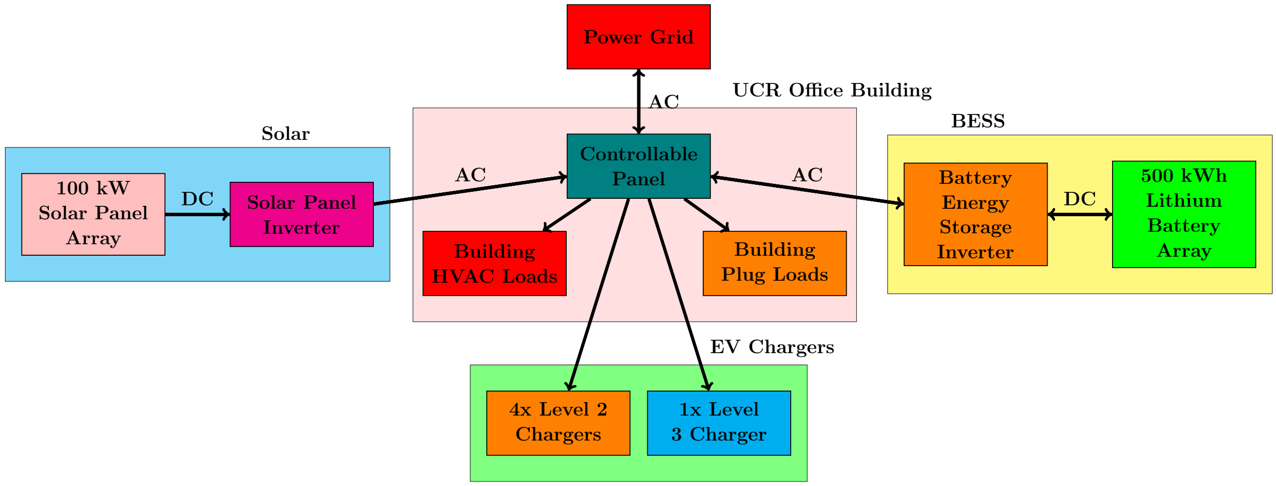

Fig. 1: Microgrid Architecture of our Case Study Example BESS: Battery Energy Storage System

TABLE I: Simulated Scenarios of the example UCR Microgrid under Different Battery Sizes and EV Charging Demands

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

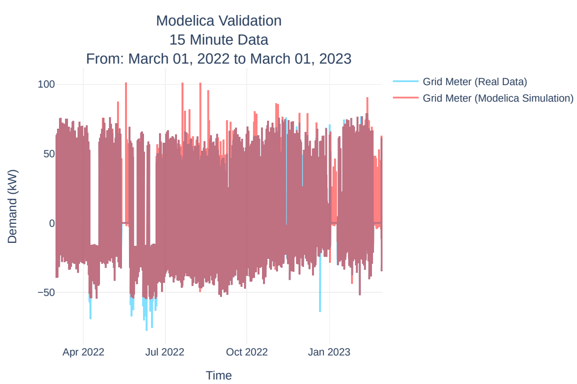

Fig. 2: Whole Year Validation of the Microgrid Architecture in OpenModelica. The bright blue and red is the real data and simulated data respectively. The dark red is the overlap between real and simulated data.

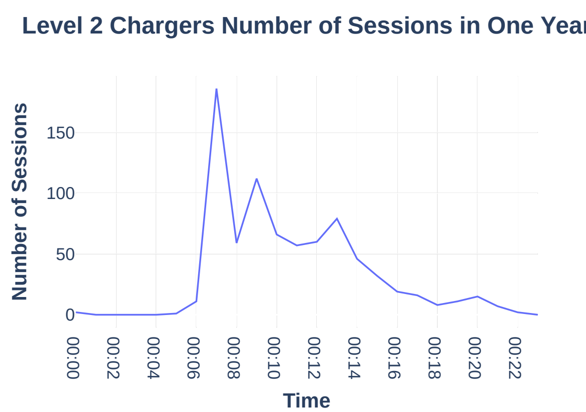

Fig. 3: Level 2 EV Charger Probability Density Function Created by Using Actual Charging Data Obtained from a SCADA System

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.

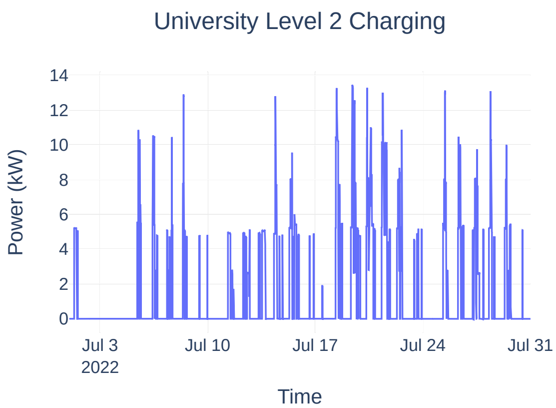

Fig. 4: Example Level 2 Chargers Power Draw from SCADA system

Fig. 5: Level 2 Charging Setup

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. 6. 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% or import power from the grid when it is under 20%.

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 9. 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 6, 7, and 8 show box plots of the power output. Fig. 6 is for the entire year, while Figures 7 and 8 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. 6 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.

Figures 9 and 10 demonstrate the challenges that arise when utilizing Level 3 charging compared to Level 2 charging. In Fig. 9, the microgrid mostly maintains zero power consumption from the grid, occasionally exporting power to the grid with minimal imports. In Fig. 10, the microgrid still maintains a mostly zero power consumption, but experiences higher power imports from the grid due to battery depletion. While the demand peaks vary significantly between Level 2 and Level 3 charging, the overall energy consumption of the microgrid compared to local solar production remains similar, as shown in Table III.

The average daily CO_2 emissions from each scenario are shown in Fig. 11. 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. This case study shows that the integration of a BESS coupled with peak morning charging significantly alters the characteristic emissions profile of the microgrid, deviating from the conventional duck curve paradigm. Unlike the typical afternoon peak observed in traditional duck curve scenarios, the microgrid under examination exhibits a peak demand period during the early morning. This phenomenon is attributed to the near depletion of the battery reserve, diminished solar power generation, and heightened electric vehicle (EV) demand during this timeframe. Table II shows each scenario's emissions and electric price amounts.

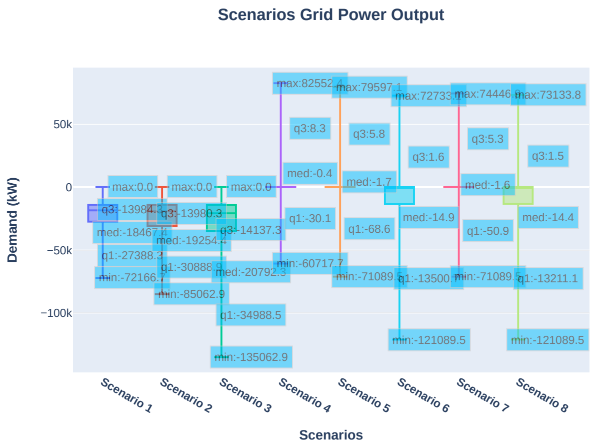

Fig. 6: Power measured from the meter for the entire year

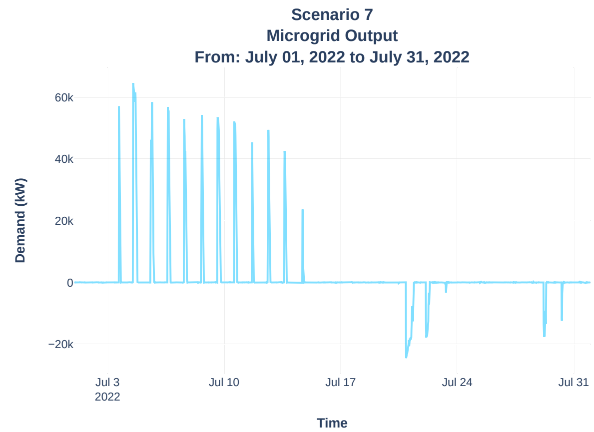

Fig. 9: Load Following Failures after Battery Depletion (Level 2 Charging, 1 MWh BESS)

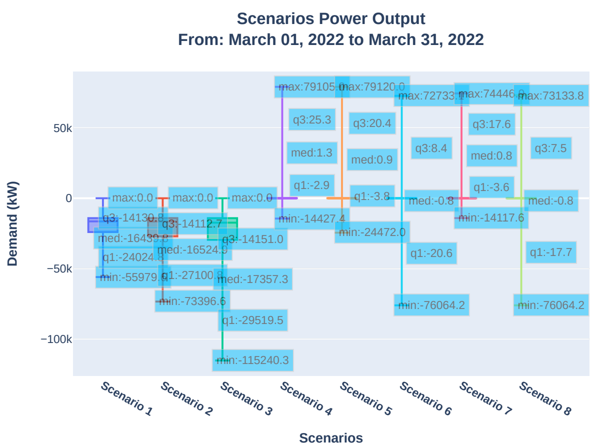

Fig. 7: Power measured from the meter for the month of March

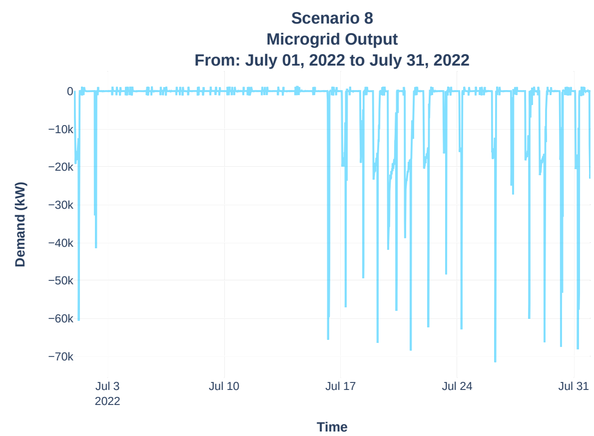

Fig. 10: Load Following Failures after Battery Depletion (Level 2 and Level 3 Charging, 1 MWh BESS)

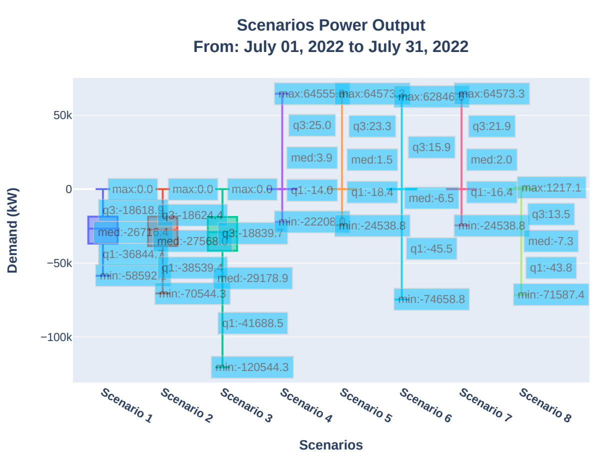

Fig. 8: Power measured from the meter for the month of July

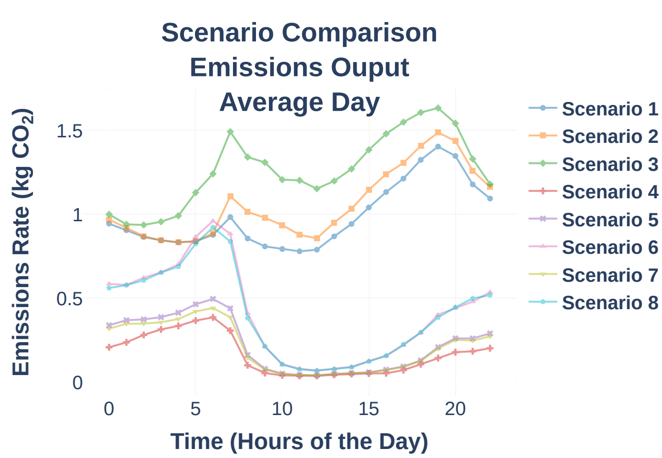

Fig. 11: CO_2 Emissions Outputs Averages During Times of Day, using a microgrid setup

TABLE II: Microgrid Utility Prices and CO_2 Emissions Output under Different Battery Sizes and EV Charging Demands

Scenario	Demand Charges ($)	Energy Charges ($)	Total Cost ($)	CO_2 Emissions ($_m$Tons)
1	6616	22736	29352	34
2	8196	24607	32803	37
3	14235	29693	43928	43
4	3887	2387	6274	5
5	5133	3853	8986	7
6	11329	8238	19567	14
7	5022	3814	8836	7
8	11400	8133	19533	14

TABLE III: Microgrid Building Power Generation & Consumption
(This table determines if the renewable energy produced is sufficient to meet demand)

Billing Month	Energy Produced (MWh)	Capacity Factor %	No EV Charging (MWh)	Level 2 Charging (MWh)	Level 2 & 3 Charging (MWh)
Entire Interval	202	23	-183	-198	-239
Mar_01_2022 to Mar_31_2022	22	29	-14	-15	-19
Apr_01_2022 to Apr_30_2022	15	21	-15	-16	-19
May_01_2022 to May_31_2022	12	16	-10	-11	-14
Jun_01_2022 to Jun_30_2022	16	23	-21	-22	-26
Jul_01_2022 to Jul_31_2022	26	36	-21	-21	-25
Aug_01_2022 to Aug_31_2022	23	31	-22	-24	-27
Sep_01_2022 to Sep_30_2022	20	28	-21	-23	-26
Oct_01_2022 to Oct_31_2022	18	24	-16	-17	-21
Nov_01_2022 to Nov_30_2022	15	21	-12	-13	-16
Dec_01_2022 to Dec_31_2022	11	15	-11	-12	-15
Jan_01_2023 to Jan_31_2023	10	13	-8	-10	-13
Feb_01_2023 to Feb_28_2023	9	14	-7	-8	-11

TABLE IV: Riverside Public Utility Commercial Demand Rate [19]

		Per Meter, Per Month Effective January 1,				
		2024	2025	2026	2027	2028
Customer Charge	Flat Charge	$22.10	$22.10	$22.10	$22.10	$22.10
Reliability Charge	Flat Charge	$90.00	$90.00	$90.00	$90.00	$90.00
Network Access Charge	$ Per kW	$1.75	$1.75	$1.75	$1.75	$1.75
Demand Charge	First 15 kW or less of billing demand, flat charge	$160.95	$160.95	$160.95	$160.95	$160.95
Demand Charge	All excess kW of billing demand, per kW	$10.73	$10.73	$10.73	$10.73	$10.73

IV. Conclusions

Transportation-microgrids have emerged as a compelling solution for mitigating the electrical costs and emission levels associated with EV charging infrastructure. A comprehensive analysis of various scenarios reveals significant economic and environmental benefits of transportation-microgrids compared to conventional systems, as depicted in Table II. For transportation-microgrid systems using a load-following algorithm, the estimated annual savings range is similar at around $23,000 to $24,000 for our case study, even with the additional demand from EV chargers. This implies that load-following transportation-microgrids provide the same amount of savings even with varying demand and a sufficiently large BESS. The cost of demand and the cost of energy saved follow the same trend of the total cost, with the overall amount of savings being similar, $3,000 and $21,000 respectively which is calculated from the commercial utility rate shown in Tables IV, V. Furthermore, load-following transportation-microgrids can reduce CO_2 emissions by 67% to 85%, which is approximately 30 tons of CO_2 in our case. It is important to note that while the scenarios show similar reductions in electricity prices and

TABLE V: Riverside Public Utility Commercial Energy Rate [19]
Note: The net energy metering rate to sell electricity to the grid is at $0.076 per kWh [20]

Per kWh Effective January 1,						
		2024	2025	2026	2027	2028
Tier 1	0 – 30,000kWh	$0.1242	$0.1242	$0.1242	$0.1242	$0.1242
Tier 2	Over 30,000 kWh, per kWh	$0.1360	$0.1360	$0.1360	$0.1360	$0.1360

CO_2 emissions, users are strongly incentivized to acquire additional clean energy sources (solar and wind), especially when adding a Level 3 fast charger, while a couple of Level 2 chargers do not heavily strain an office building. The new net energy metering policies make low CO_2 emission load-following more economically viable compared to just peak-shaving [20]. The BESS is being used to reduce the amount of energy pulled from the grid rather than saving up energy to possibly address a couple of peak cases in a month.

It is important to note that increasing the battery capacity does not necessarily guarantee improved microgrid performance. Addressing the most challenging solar power outages requires a significant increase in battery capacity, while providing only marginal CO_2 and cost savings in return. Also, extra capacity is not very useful for CO_2 emissions reductions without adding extra solar power to be able to completely charge the battery during daylight hours. Lastly, any sensible microgrid planning requires addressing three key parameters that are: clean energy generation, energy storage, and load management. Doing only two of the three creates situations where the microgrid alone will not be able to power the building.

In conclusion, transportation-microgrids represent a promising solution for reducing the environmental and economic impact of EV charging infrastructure. However, careful consideration of battery capacity, generation capacity, and electricity pricing structures is crucial to optimizing the microgrid's performance and cost-effectiveness.

V. Future Work

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 electric vehicle load allocation 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 effects of the new net energy metering policy in California on the value of the BESS system will also be further assessed. Additionally, the impact of different time-of-use (TOU) rates in California on electric costs and CO_2 emissions will be analyzed.

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