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

1st Luis Fernando Enriquez-Contreras[*†], Jacqueline Garrido[*†], 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

2nd A S M Jahid Hasan
Department of Electrical and Computer Engineering
North South University
Dhaka, Bangladesh
jahid.hasan12@northsouth.edu

3rd Jubair Yusuf
Department of Electrical and Computer Engineering
University of California, Riverside
Riverside, United States of America
jyusu001@ucr.edu

***Abstract*—As renewable energy penetration in electric grids increases with time, it becomes more important for electric utilities to update their electric rates such that they minimize CO_2 emissions. In this paper, we evaluate a case study at the University of California, Riverside (UCR) to simulate different Time of Use (TOU) rate optimizations that minimizes electric costs while analyzing CO_2 output, by using the openmodelica model, we based on different electric utility rates in Southern California. The different amounts of power and energy consumed by each rate is compared with CAISO CO_2 emissions data in order to review the different emission levels from the different utility electric rates on a 15 minute basis. Electric costs are also compared in order to see the different savings the consumer will have with the different rates. It was found that Southern California Edison (SCE) TOU rate had the most savings for the consumer and that Riverside (RPU) TOU flat rate had the lowest CO_2 emissions.**

***Index Terms*—micorgrids, demand response, TOU, CO_2 emissions, modelica**

I. Introduction

A. Background

B. Literature Review

This paper's main contribution is to analyze the impacts different pricing structures have on the behavior of microgrids and the associated CO_2 emissions. One goal every TOU pricing schedule should have is for the economic incentives to align with CO_2 emission reductions. This paper evaluates flat rate and TOU pricing from different electric utilities in California. This paper also uses a higher time resolution than most to date and explains in further detail of a realistic simulation of a microgrid using system dynamics software.

C. Pricing (Flat vs TOU)

D. 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, in this simple algorithm, we assume the consumer wants to minimize the demand charges as much as possible. The algorithm is based solely on cost savings for a typical microgrid. During flat-rate 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. With TOU, peak shaving is prioritized more during on-peak times, and shifts demand to mid-peak and off-peak hours.

E. CO_2 Emissions

Our microgrid's solar production greatly overlaps with the local solar energy production within the larger grid. This leads to the problem within our microgrid that while it is zero CO_2 emissions during solar peak hours we still rely on the 30 main electrical grid during off peak hours, which is when there are higher CO_2 emissions. However, with a BESS, we can utilize renewable energy during peak times and at night. In this scenario, the control algorithm is economic-based since we want to see how the TOU rates align with actual CO_2 emissions output. 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) ${}_{\mathrm{m}}\mathrm{TON}_{CO_2}$ / 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 (TON_{CO_2} / hour) / W. This is multiplied with our 15-minute data kW, and a multiplier of 1/4000 to convert kW into W and to address for the 4 15 minute periods in an hour. This gives us an estimate of the amount of CO_2 emissions in $_{m}TON_{CO_2}$ 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 [1]. 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 [2]. Modelica is a programming language that is designed for dynamic systems simulation [3]. OMEdit is the GUI interface for open Modelica, allowing the user to draw a system for simulation [4]. The microgrid scenarios are simulated in open Modelica using the Modelica buildings library. Lawrence Berkeley National Laboratory created the Modelica buildings library for building and district energy and control systems [5]. 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 .

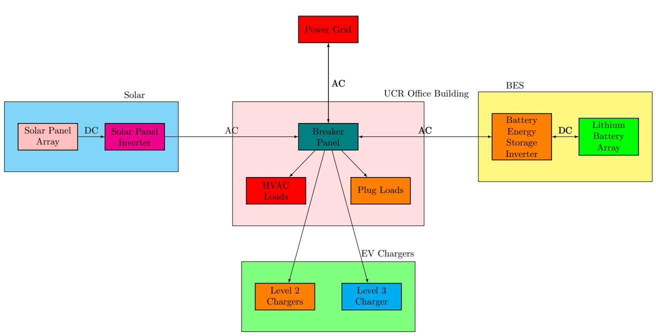

Fig. 1: Microgrid Layout

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 consume from the grid. The actual data was compared to the simulated with a correlation coefficient of ≈ 0.965087 as shown in Figure 2.

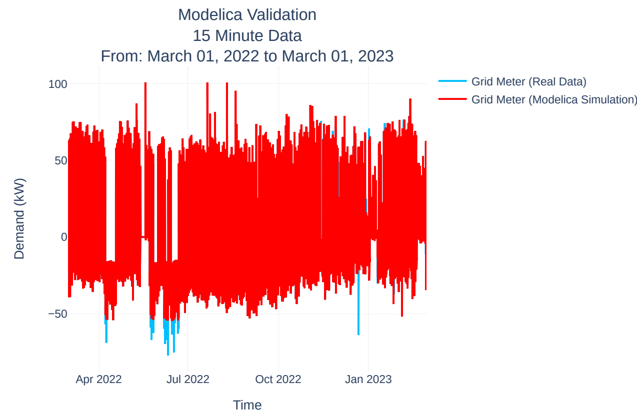

Fig. 2: Whole Year Validation

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 a 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.

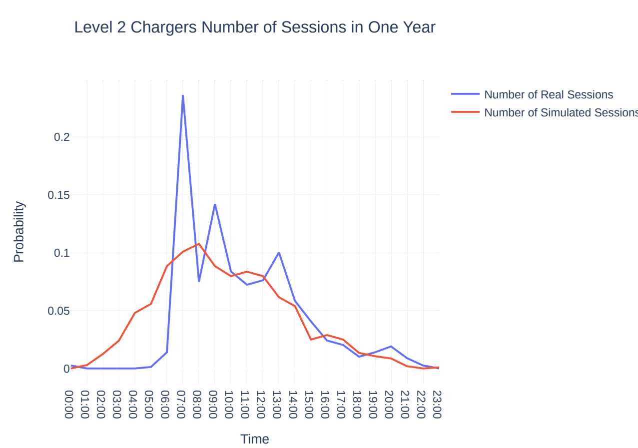

Fig. 3: Probability Density Function of the Level 2 EV Charger Validation

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.

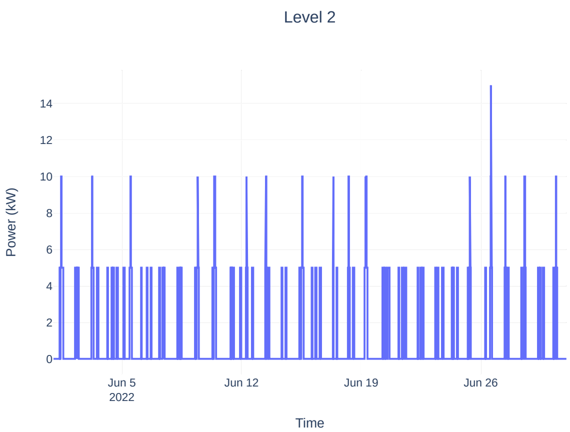

Fig. 4: Level 2 Chargers Simulated Power Output

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 microgrid is modified in open Modelica for layout and scenarios. The scenarios are described in Table I. Scenarios 1 and 2 are modified in open Modelica directly by shutting down both the solar system and the BESS in scenario 1 and shutting off the BESS in scenario 2. Scenarios 3 -6 by modifying the Python control algorithm open Modelica calls for the BESS. Scenario 3 represents the microgrid's current flat rate pricing structure, while scenarios 4-6 represent different optimizations if our microgrid were under different TOU rates. Each scenario is run independently of one another, and the power outputs of the different components in the simulation are shown in Figure 5. Each scenario's power pulled from the grid is juxtaposed in Figure 6, and the daily CO_2 emissions average from each scenario is shown in Figure 7. The emissions and electric price amount of each scenario is shown in II. The CO_2 emissions savings has scenario 1 as a reference since there is no locally-produced renewable energy in this scenario.

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

Scenario	
1	Level 2 Charging with no BESS
2	Level 3 Charging with no BESS
3	Level 2 and Level 3 Charging with no BESS
4	Level 2 Charging with BESS
5	Level 3 Charging with BESS
6	Level 2 and Level 3 Charging with no BESS

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

Scenario	Demand Charges ($)	Energy Charges ($)	Total ($)	Emissions ($mTCO_2$)	$ Emissions Savings
1	17090	32212	49302	47	0
2	14460	7059	21519	30	36
3	12907	8768	21675	26	44
4	15297	6584	21881	34	27
5	14394	2308	16702	34	27
6	7127	0	7127	35	25

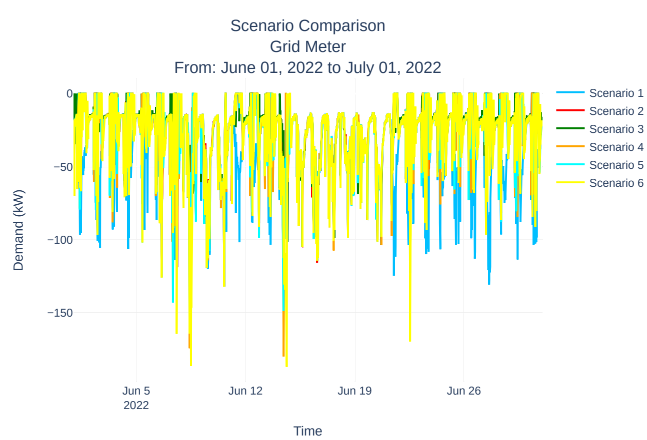

Fig. 6: Summer Net Load Scenario Comparison

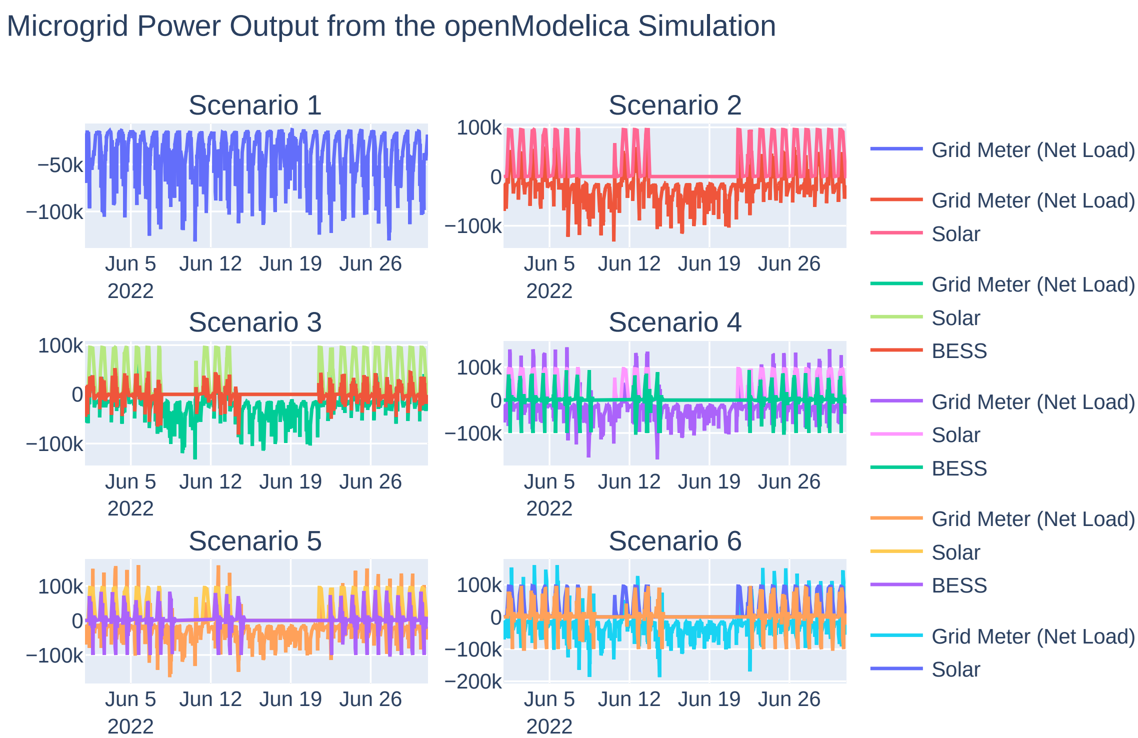

Fig. 5: openModelica Power Simulations

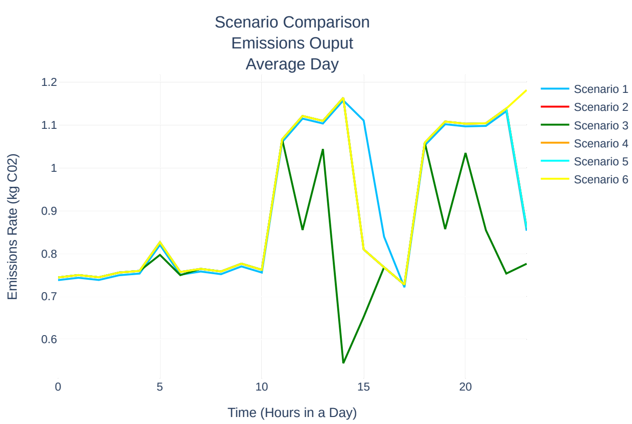

Fig. 7: Microgrid CO_2 Emissions Outputs Averages During Times of Day

IV. Conclusion

The lowest pricing structure for the microgrid customer is SCE's TOU pricing structure, while the lowest emitting setup is standard TOU peak shaving with RPU's flat rate demand cost pricing structure. While adding reliability to any microgrid, a BESS does not always guarantee reduced CO_2 emissions. The opposite is even possible, depending on the pricing structure of the utility. As seen in this paper, all the utility companies have Off-Peak hours during the nighttime, and any price-optimized control algorithm would prioritize charging during that period, so higher net-load peaks occur with a TOU-controlled BESS microgrid. A higher peak during off-peak hours is economically favorable and lower overall demand cost. While current TOU pricing is a great method to mitigate the stress on the grid during on-peak hours, there is major CO_2 production to pricing structure when it comes to microgrids. A balance needs to be met between grid resiliency, lower CO_2 emissions, and profitability. As BESS become more ubiquotus there will a need to make TOU rates with loads that incorporate BESS, as we do right with solar rates. Cheap nighttime off-peak hours incentivize nighttime charging for BESS when the grid in California is most reliant on natural gas for power. A stronger emphasis is also needed on clean nighttime energy, such as wind, geothermal, hydroelectric, and nuclear power, to be further integrated into California's electric grid.

V. Future Works

Future papers will investigate different microgrid setups and optimizations for a more in-depth analysis. The effects NEM 3.0 will have on pricing and CO_2 emissions compared to NEM 2.0 is of great interest. Also control algorithms and electric utility TOU rates that can optimize pricing and CO_2 emissions will also be assessed.

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