GHG Emissions Impact of a Local Microgrid: a case study in Southern California

~~Southern California microgrid emissions and price optimization under different pricing structures and control algorithms~~

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not in ECE. Did they review this paper?

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***Abstract*—As renewable energy penetration in electric grids increases with time, it becomes more important for electric utilities to update their electric ~~schedule~~ rates such that ~~optimize for low~~ they minimize GHG emissions ~~output~~. In this paper, we evaluate ~~a small~~ a case study ~~is observed where~~ of a microgrid (use) at the ~~UCR~~ (University of California, Riverside) ~~CE-CERT (College of Engineering,Center for Environmental Research and Technology) microgrid is used as model~~ to simulate different Time of Use (TOU) rate optimizations that minimize GHG emissions ~~using OpenModelica. The optimizations are~~ Using the openmodelica model, we optimize based off of ~~the~~ different electric utility rates in Southern California. ~~and are only optimized for financial benefit to the consumer~~. The different amounts of power and energy consumed by each TOU rate ~~optimization~~ is compared with CAISO emissions data in order to see the different emission levels from the different utility electric rates on a 15 minute basis. ~~This compares event utility rates impact on emissions.~~ Pricing is also compared in order to see the different savings the consumer will have with the different rates. It was found that the SCE TOU rates ~~had~~ have the most savings for the consumer and that RPU TOU flat rate had the lowest emissions.**

I don't understand this

***Index Terms*—micorgrids, demand response, TOU**

need to spell this out

I. Introduction

A. Background

California is going through a major transition in energy production, which involves a higher share of renewable energy in the electricity mix. This is to meet California's climate goals of a 48% reduction in greenhouse ~~gases~~ gas emissions by 2030 [1]. However, achieving that goal will involve utility companies, government agencies, and consumers to all play a role. Many industrial and commercial sites are adopting not only solar by installing but introducing battery energy storage systems as well. Since January 2023, California law requires new commercial buildings to have solar and battery storage systems installed [2]. This has major potential in addressing current issues associated with solar power as a large percentage of the energy mix. The infamous duck curve has only been getting steeper in recent years, leading to a huge stress onto the grid and concerns about reliability [3] [4]. Equally as important, while California has a relatively clean grid during solar peak production hours, the electrical demand does not align with these low emissions times and relies on the grid during ~~more polluting~~ times when GHG emissions are higher. Battery energy storage systems (BESS) ~~are being~~ have been proposed as one of the solutions to mitigate the duck curve ~~problems~~ problem. This paper reviews ~~flat and TOU~~ various rates (flat, TOU) of various utility companies ~~optimized for~~ coupled with a ~~UCR CE-CERT's~~ typical microgrid at UC Riverside to ~~see if~~ compare how customers ~~using~~ can use a BESS for both economic benefit ~~based on utility tariffs coincide with reducing emissions~~ and as a means of reducing GHG emissions.

check this

you need to qualify this

B. Literature Review

Previous literature has explored various topics concerning TOU (Time of Use) impacts on ~~microgrid~~ GHG emissions using a microgrid. ~~In~~ [5], a lightning search algorithm (LSA) is used to optimize a microgrid controller based on GHG emissions, energy use, and demand costs. Their model predicts a reduction of 78 to 220 tons of CO_2 from the atmosphere, does not optimize ~~on~~ using TOU rates, and calculates emissions using a flat demand. In [6], the authors investigate the deployment cost of multiple scenarios in a multi-carrier microgrid (MCMG) model that considers demand shifting, monthly peak, and emissions. They advocate for better environmental policies in the utility sector since the MCMG scenario optimized solely for GHG emissions was 39% less cost-effective than the scenario optimized for cost. In [7], simulations are run on a system ~~with~~ consisting of three microgrids while considering ~~and neglecting~~ emission charges (e.g., a carbon tax). Emissions were halved when considering emissions charges. However, the lower emission operation has a higher upfront cost and is less economically attractive

see me about SPEAKS

TOU: do you need to discuss seasonal TOU?

Somewhere you need to describe our case study microgrid.

Paper	Flat Rate	Emissions Output	TOU	BESS	Utility Pricing Structure
[5]	X	✓	✓	✓	X
[6]	✓	✓	✓	✓	X
[7]	✓	✓	✓	✓	X
[8]	✓	✓	✓	X	X
[9]	✓	✓	✓	X	✓
[10]	✓	✓	✓	X	X
[11]	✓	✓	✓	X	✓
[12]	✓	X	✓	✓	✓
[13]	✓	X	✓	✓	✓
This Paper	✓	✓	✓	✓	✓

TABLE I: Contributions of Various Papers in the Emissions of Electric Grids

this must have a BESS

for customers. In [8], ~~5~~ five scenarios with cost and GHG emissions reduction in mind are ~~done in~~ evaluated for an isolated microgrid. The authors conclude that running the pareto control strategy is the best compromise between cost and emissions output. In [9], the authors assess different demand side management strategies utilizing the Artificial Bee Colony algorithm under different tariff structures. TOU, critical peak pricing (CPP), real-time electricity pricing (RTEP), and day-ahead pricing (DAP) seasonal pricing structures were assessed for emissions output. [10] compares microgrids considering demand response and/or electricity sharing and compares those scenarios by the amount of costs and ~~carbon~~ GHG emissions. In this paper, reducing carbon emissions also reduces costs.

what is the downfall of this paper? and this.

this doesn't make sense

This paper's main contribution is to analyze the impacts that different pricing structures have on the behavior of microgrids and the associated GHG emissions ~~outputted~~. One goal every TOU pricing schedule should have is for the economic incentives to align with GHG emission ~~output~~ reductions. This paper ~~tests~~ evaluates flat rate and TOU pricing from different electric utilities in California, for a typical university. ~~It compares the emissions from each pricing structure in place~~. This paper also uses a higher, finer resolution ~~in data~~ than most ~~papers~~ studies to date and explains ~~further~~ in further detail of a realistic simulation of a microgrid using system dynamics software.

C. Pricing (Flat vs TOU)

One of the main ~~outcomes~~ contributions of this paper is to see how a flat rate versus ~~time of use~~ TOU pricing affects user behavior? ~~and~~ the GHG emissions associated with adapting different rate schedules. A flat rate demand charge ~~for this paper~~ means the customer is charged for the maximum power consumed within a 15-minute rolling average, regardless of when this maximum occurs. A ~~time of use~~ TOU rate means the customer has a charge for the maximum amount of power used if any 15-minute rolling average within each of the predefined blocks, usually off-peak, mid-peak, on-peak, and any depending on the season super off-peak. In ~~this building's case~~ our case study, the official rate schedule is Riverside Public Utilities (RPU)'s flat demand charge; however, ~~the~~ we simulate other pricing ~~control algorithm is programmed for various~~ scenarios, for our case study microgrid including ~~whether our microgrid was on~~ the RPU's TOU rate, and an investor-owned utilities (IOU) TOU rate ~~in California~~. The Southern California Edison (SCE) and rate schedules for Southern California Edison (SCE) and Los Angeles Department of Water of Power (LADWP) are ~~also~~ analyzed in this paper as they are the other two major

You need to Note: there are demand charges and energy charges

	RPU	LADWP	SCE
Off-Peak Demand Charges ($)	1.85	0	0
Mid-Peak Demand Charges ($)	3.69	3.75	0
On-Peak Demand Charges ($)	7.38	10	18.11
Off-Peak Energy Charges ($)	0.0808	0.03522	0.03712
Mid-Peak Energy Charges ($)	0.0946	0.05595	0.06412
On-Peak Energy Charges ($)	0.1154	0.06322	0.07275
Off-Peak Hours	0 - 8, 23 - 0	0 - 10, 20 - 0	0 - 16, 21 - 0
Mid-Peak Hours	8 - 12, 18 - 23	10 - 13, 17 - 20	N/A
On-Peak Hours	12 - 18	13 - 17	16 - 21

TABLE II: TOU Schedule Rates in Southern California (as of 7/2023)

electric utilities in ~~the Los Angeles metropolitan area~~ Southern California.

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 ~~only since the expectation is that the consumer uses the algorithm to achieve the maximum savings~~. During flat-rate peak shaving, the algorithm looks at the ~~amount of power being imported~~ power demand, ~~if there is enough energy~~ the available renewable energy, and if ~~the batteries~~ energy storage (BESS) can mitigate a fraction of that or the total amount. With the TOU scenario, peak shaving is prioritized more during on-peak times, and shifts demand to mid-peak and off-peak hours.

E. GHG Emissions

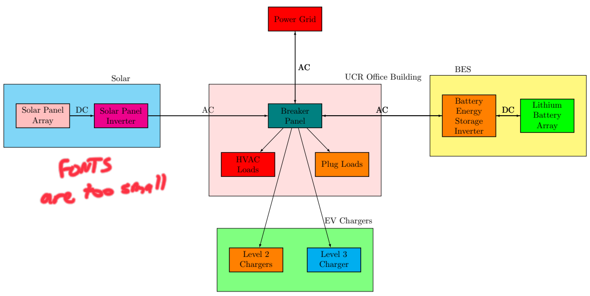
~~The~~ Our microgrid's solar production greatly overlaps with the local solar energy production within the larger grid. This leads to the problem within our microgrid that while it is zero emissions during solar peak hours, we still rely on the ~~30~~ main electrical grid during off peak hours which is when ~~the grids are even more polluting~~ there are higher GHG emissions. However, with a BESS, we can utilize ~~solar power~~ renewable energy during peak times and at night. In this ~~experiment~~ scenario, the control algorithm is economic-based since, ~~we want to see~~ evaluating how the TOU rates align with actual GHG emissions output. The simulation uses GHG emission output calculations from CAISO for each time interval, and the amount of power pulled from the grid is multiplied by this average. This method is similar to the one used in [11]. This gives us an estimate of the amount of CO_2 emissions from the microgrid when it consumes power from the grid. When the grid does not pull power from the grid or is sending power, the emissions are assumed to be zero, since we are using our solar renewable energy.

when does our solar differ from CAISO?

II. SIMULATION IN OPENMODELICA

The microgrid scenarios are simulated [ref] in open Modelica using the Modelica buildings library. 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.

you need to describe OpenModelica



FONTS are too small

Fig. 1

A. Validation

To ensure that our model accurately portrays our realworld system, a ~~One~~ year of realworld 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.

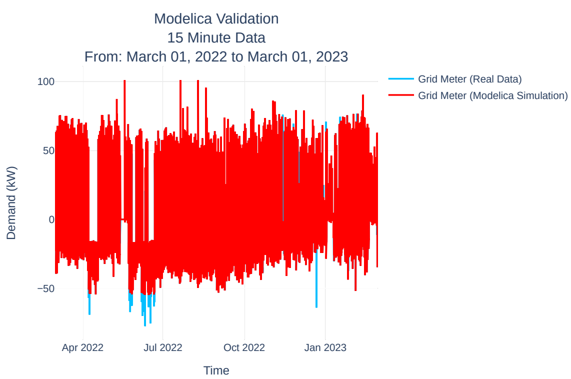


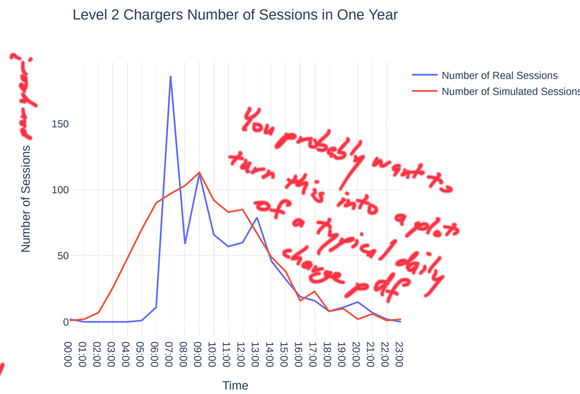
Fig. 2

B. Solar Generation and Building Loads

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

C. EV Charger Loads

Our model also considers transportation loads, in the form of EV chargers. The EV chargers are represented ~~in~~ as two models~~:~~ the Level 2 EV chargers, and ~~the~~ Level 3 EV chargers. While ~~the rest of the~~ other loads follow a typical daily and yearly pattern, ~~and the load is somewhat continuous;~~ EV loads are different since they switch on and off~~, so the load is 0 -28.8 kW. The~~ Our case study microgrid has ~~4~~ four Level 2 chargers, so it can have 4 "steps" of 7.2 kW each, while there is only one "step" of 50 kW with the Level 3 chargers. ~~Both~~ 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 realworld data.



per year?

You probably want to turn this into a plots of a typical daily charge pdf

Fig. 3: Number of Real and Simulated Sessions

Historical data was collected from the Level~~-~~2 charger to determine the parameters for the ~~triple~~ Poisson random generator following a typical daily charge pdf shown in Fig 3. The 3 "peaks" are assumed to be 3 Poisson distributions of different heights. The height are adjusted by the number of arrivals in a day. The higher the peak the higher the number of arrivals will be. The peak times are implemented by inputting the 3 peak hours into the random generator. The parameters for this simulation are as follows: number of arrivals = [0.3, 0.18, 0.12], peak times = [7, 9, 13]. The modelica model calls Python within the simulation to generate the EV load output. The numpy random library is used as the backbone for the EV charging model, and a seed of 10 is used to give the same random output for the different scenarios.

Given this daily charge pdf, we utilize a uniform random generator to simulate charging events.

consider showing this for a typical month, and just show charge events

Fig. 4: Level 2 Power Output

reference this in the text

D. BESS and Peak Shaving

The BESS is ~~represented as~~ modeled as a battery connected to a bidirectional inverter. ~~Unlike the other components,~~ 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, ~~that decision is based on the output of the~~ using BESS SOC and the grid ~~meter~~ demand as inputs. The algorithm charges the battery when excess solar power is ~~exported to the grid~~ being generated, and the battery needs to be charged ~~and discharged to the microgrids when the microgrid imports more than 0 kW of power and the SOC of the battery is above the minimum threshold~~. A Python module reads the net load from the grid and determines the amount of CO_2 ~~the microgrid~~ being produced during that interval. Figure 5 ~~is a rudimentary~~ shows the peak shaving algorithm sufficient for flat rate demand response. However, for a TOU pricing structure, both energy and demand charges are assumed to be be TOU rates with no additional flat rate demands. The TOU peak shaving algorithm is presented in Equation 1 and further described in [14] , [12] .

this doesn't make sense

$$\min f\left(\boldsymbol{P}^G\right) = \Delta t \boldsymbol{\alpha}^{\boldsymbol{T}} \boldsymbol{P}^G + \max\left(\boldsymbol{\beta}^{\text{on}} \boldsymbol{P}^G\right) + \max\left(\boldsymbol{\beta}^{\text{Mid}} \boldsymbol{P}^G\right) + \max\left(\boldsymbol{\beta}^{\text{off}} \boldsymbol{P}^G\right) \quad (1)$$

this needs an explanation

subject to

$$E^B_{t+1} = E^B_t + P^B_t \cdot \Delta t, \forall t \in \boldsymbol{T}^{\mathbf{tot}}$$
$$E^{Bmin} \leq E^B_t \leq E^{Bmax}, \forall t \in \boldsymbol{T}^{\mathbf{tot}}$$
$$P^B_t = P^{B+}_t - P^{B-}_t, \forall t \in \boldsymbol{T}^{\text{tot}}$$
$$0 \leq P^{B+}_t \leq \delta_t P^{B+\max}, \forall t \in \boldsymbol{T}^{\mathbf{tot}}$$
$$0 \leq P^{B-}_t \leq (1-\delta_t) P^{B-\max}, \forall t \in \boldsymbol{T}^{\mathbf{tot}}$$
$$0 \leq \delta_t \leq 1, \forall t \in \boldsymbol{T}^{\mathbf{tot}}$$
$$P^{B+}_t = \eta^+ P^{SB}_t, \forall t \in \boldsymbol{T}^{\mathbf{tot}}$$
$$P^S_t = P^{SB}_t + P^{SL}_t, \forall t \in \boldsymbol{T}^{tot}$$
$$P^L_t = P^{SL}_t + P^{BL}_t + P^G_t, \forall t \in \boldsymbol{T}^{\text{tot}}$$
$$P^{BL}_t = \eta^- P^{B-}_t, \forall t \in \boldsymbol{T}^{tot}$$
$$P^{SL}_t \geq 0, \forall t \in \boldsymbol{T}^{tot}$$

All of these variables need to be defined

III. Experiment

A. Scenarios

You need to write a paragraph here that discusses the different scenarios; you can't just give a table

Scenario	
1	Building with no solar power nor BESS
2	Building with solar power but no BESS
3	Building with solar power and a BESS that utilizes flat rate peak-shaving
4	Building with solar power and a BESS that utilizes RPU TOU rate peak-shaving
5	Building with solar power and a BESS that utilizes LADWP TOU rate peak-shaving
6	Building with solar power and a BESS that utilizes SCE TOU rate peak-shaving

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

FONTS need to be enlarged

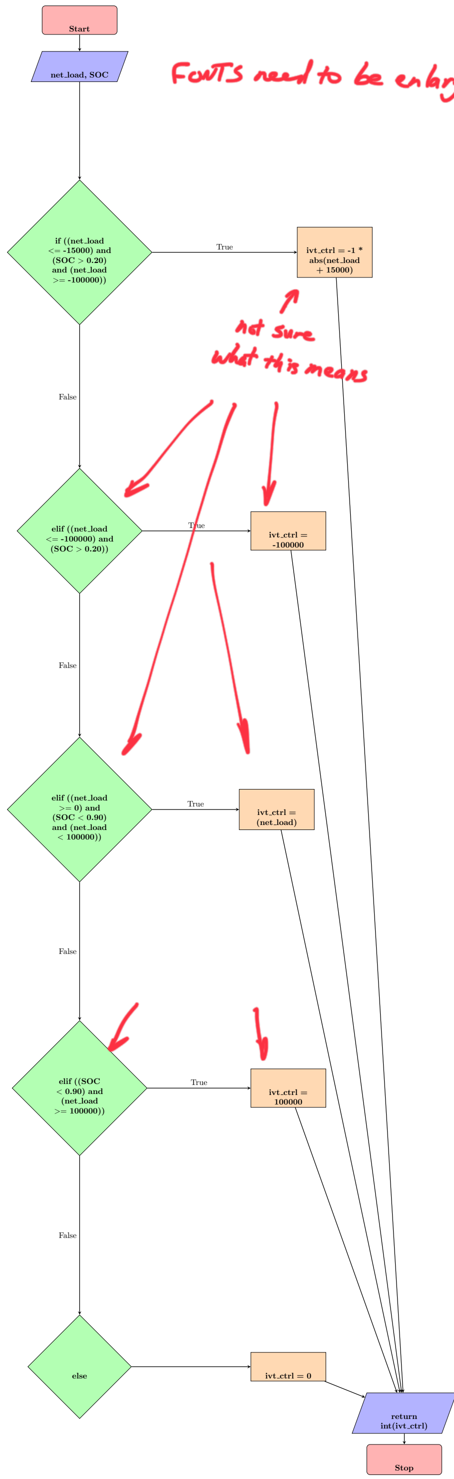
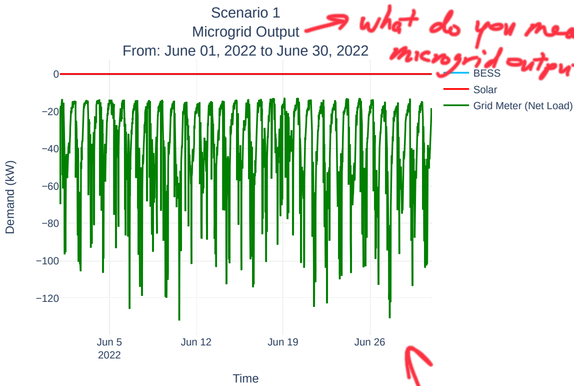


Fig. 5: Flat Rate Peak Shaving Algorithm Flowchart



what do you mean by microgrid output?

Fig. 6: Scenario 1

This needs to be described in words

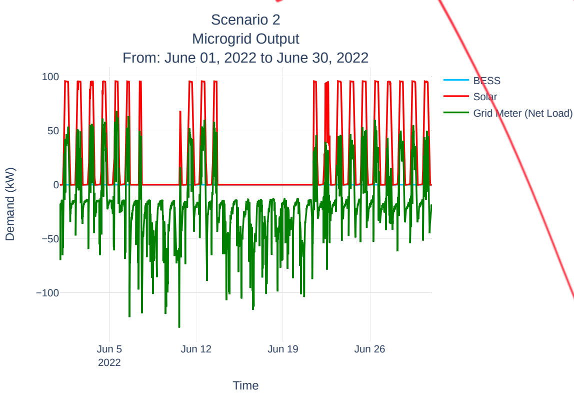


Fig. 7: Scenario 2

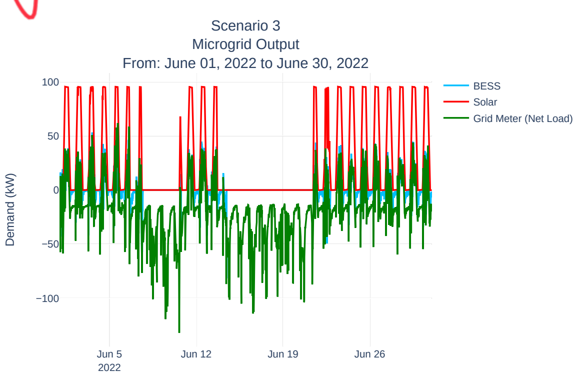


Fig. 8: Scenario 3

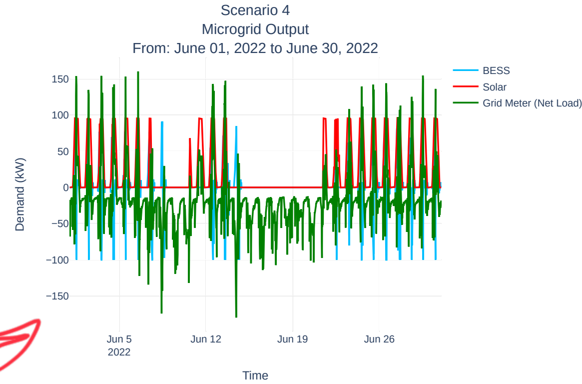


Fig. 9: Scenario 4

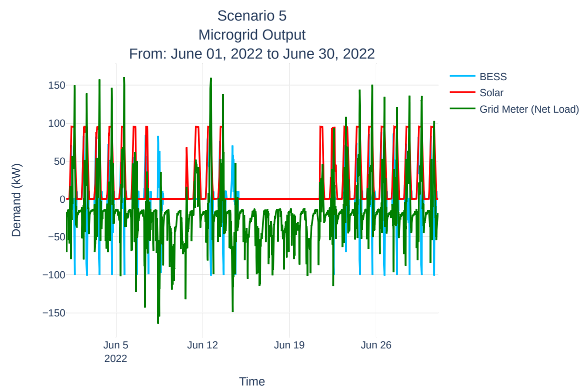


Fig. 10: Scenario 5

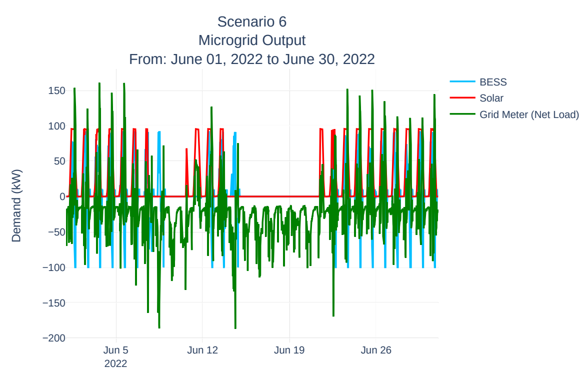


Fig. 11: Scenario 6

I'm not sure what these graphs are showing compared to what?

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

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

These results need to be carefully explained in the text

IV. Results and Conclusion

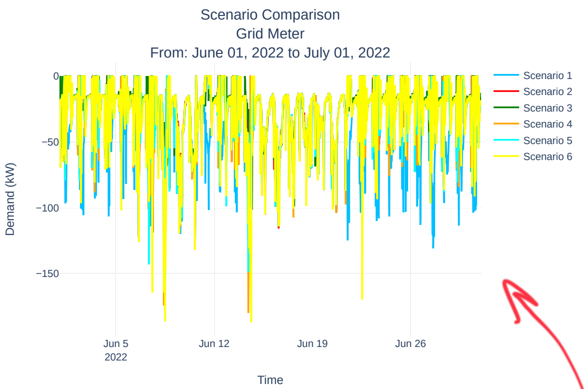


Fig. 12: Summer Net Load Scenario Comparison

Not sure what this is without a text explanation

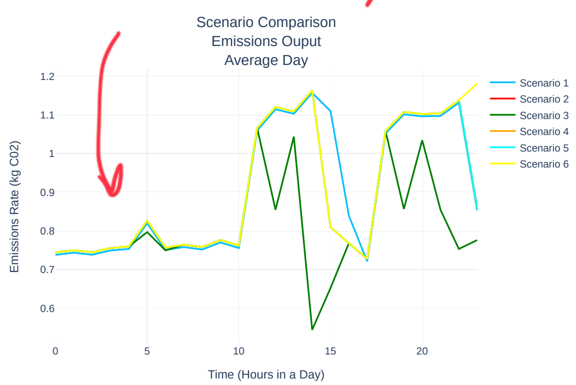


Fig. 13: Microgrid Emissions Outputs Averages During Times of Day

based on what criteria?

The best 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. Surprisingly, adding a BESS to a microgrid will add reliability to any microgrid, but it does not always guarantee reduced 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 ~~despite it~~. While current TOU pricing is a great method to mitigate the stress on the grid during on-peak hours, there is ~~a~~ major ~~environmental problem~~ CO2 production to pricing structure when it comes to microgrids. Cheap nighttime off-peak hours incentivize nighttime charging for BESS when the grid in California is most reliant on natural gas for power. 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 emissions compared to NEM 2.0 is of great interest. Also control algorithms and electric utility TOU rates that can optimize pricing and emissions will also be assessed. 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.

where?

a microgrid has a BESS by definition! You need to rephrase this

These results and conclusions section is pretty weak. You need to explain in more detail.

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