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Microgrid for SCU with Vehicle-to-Grid

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ABSTRACT

Santa Clara University is a large loads in Santa Clara needed two finders and a maximum of over 8MW peak demand; however, this consumption will only increase as the student body and electric vehicles on campus continue to grow. To meet this rising demand in both a sustainable and environmentally friendly manner, we proposed and simulated a complete energy management system with cost analysis of energy savings of a microgrid capable of reducing the power supplied to Santa Clara University's campus from the grid by 40% using renewable energy, vehicle-to-grid (V2G) functionality, and real SCU energy data. The project further used machine learning to match SCU's energy demand with the renewable generation for future use of optimizing the proposed system. The microgrid was simulated in MATLAB while the machine learning algorithm was developed in python. The benefits of this project provide SCU with a path to 100% clean energy, increased power reliability, and reduced operating cost for SCU. Increasing solar output on campus is the best way to achieve 100% renewable energy because the fuel cells on campus have a byproduct of carbon dioxide and are therefore not 100% renewable. Our vehicle to grid analysis showed that it is not currently a viable solution to help SCU run on 100% renewable energy; however, as electric vehicle charging capacity at SCU increases, vehicle to grid could become an important part of SCU achieving carbon neutrality.

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Our team would like to thank our Advisor, Dr. Khanbaghi, for her support and guidance throughout the project. We would also like to thank the facilities team for providing us with SCU energy data that was vital to the success of our project. Our project would not only be more difficult, but also less realistic without their cooperation.

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Chapter 1: Introduction

1.1 Background Information

A microgrid is a localized grid that has its own network of distribution and is capable of islanding from the main grid. Islanding means that the microgrid is totally disconnected from the grid [26]. When islanded, the microgrid is self-sufficient (ideally from renewable energy sources) for a certain period of time, or indefinitely, depending on the design. Islanding provides power reliability to its loads even during grid outage, which is crucial for critical loads such as hospitals and emergency response equipment. Self-sustaining, renewable energy integration, efficiency, reduced costs of electricity, and power reliability are some of the advantages microgrids provide as seen in Figure 1. Microgrids, while reducing costs through peak shaving and renewable power generation, can also provide power to the main grid if necessary.

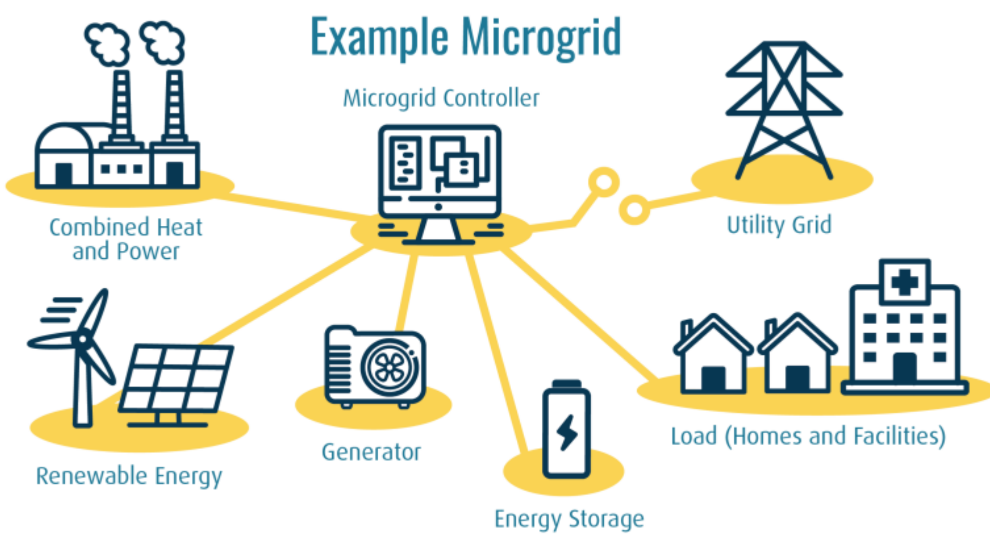

Figure 1: Microgrid Example [5]

1.2 Motivation

Microgrid deployments have become popular around the world for several reasons. Power outages are gradually increasing, which is alarming as we rely heavily on electricity to go about our daily lives and for our security. Just this past Fall quarter 2021, there have been three power outages at Cameron Refaee's home. These frequent power outages are supported by the data in

Figure 2 which shows how power outages have steadily increased from 1980 to 2012. Power demand continues to rise due to our growing population, technologies (such as electric heaters, AC, and powerful computers), and as we transition to sustainable forms of transportation.

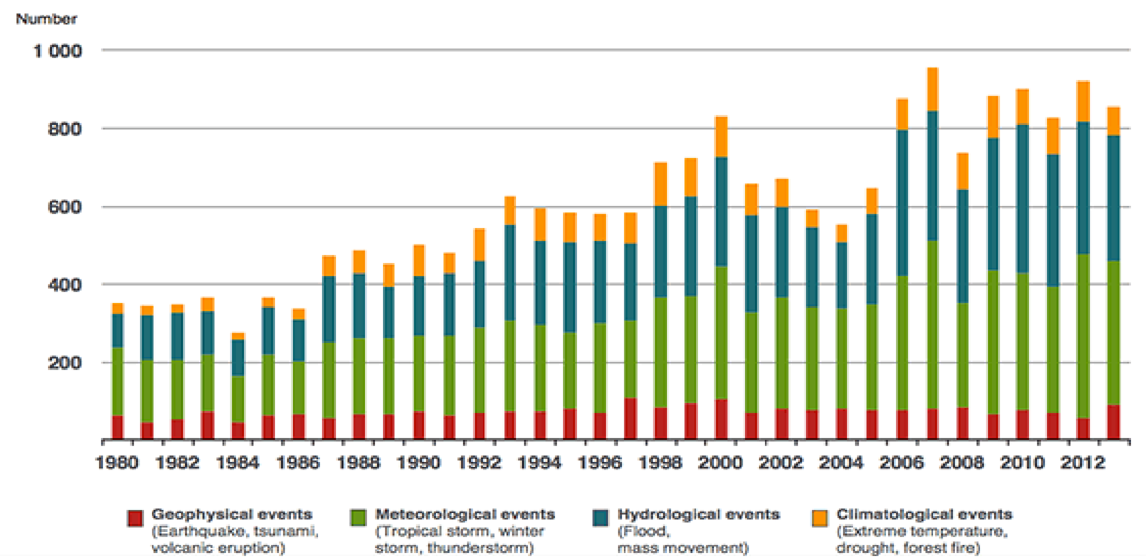

Figure 2: Number of Power Outages from 1980 to 2012 [29]

Climate change is becoming a pressing concern as global surface temperatures, according to Figure 3, have continued to rise from the early 1900’s. Since the industrial revolution, the average global temperature has risen about one degree Celsius, resulting in more extreme climate events that further reduce grid reliability. Implementing microgrids with renewable energy will not only decrease CO_2 emissions, but also improve power reliability and reduce operating costs [26].

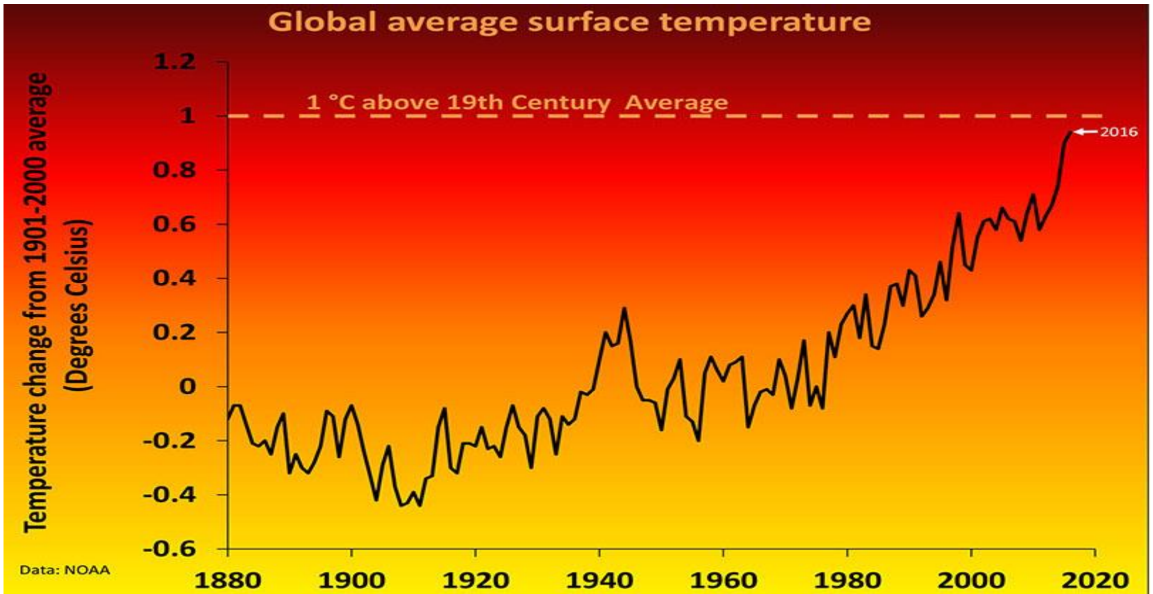

Figure 3: Average Global surface temperature

V2G is an important rising technology that can help enable the grid to support the energy requirements of charging electrical vehicles. For example, current duel motor long range Tesla Model X and S electric vehicles have a 100 kwh battery pack. According to the U.S. Energy Information Administration, the average U.S. residential utility customer used an average of 10,715 kWh per day in 2020 [3]. This means that roughly 10% of a Tesla Model X or S's battery pack could provide enough energy to fully power the average person's home. These massive batteries could power the house at night and be used in conjunction with peak shaving techniques peak needs while, for example, the owner is at work. An example of how this could work is shown in Figure 4. This figure shows the energy flowing to and from the electric vehicles and the local distribution systems of the grid to transfer power to other local sites. While a person is working, the car's battery could be used to power the grid and at the end of the workday, the owner could set a threshold to how much they want the car to be charged. This massive, decentralized battery could be used similar to how Tesla's virtual power plant that uses Tesla Powerwalls in participating owner's home to support the grid. As electrical vehicles are becoming more common, we believe that planning and implementing V2G into a SCU microgrid will help SCU achieve its sustainability goals while benefiting the community with reduced grid stress.

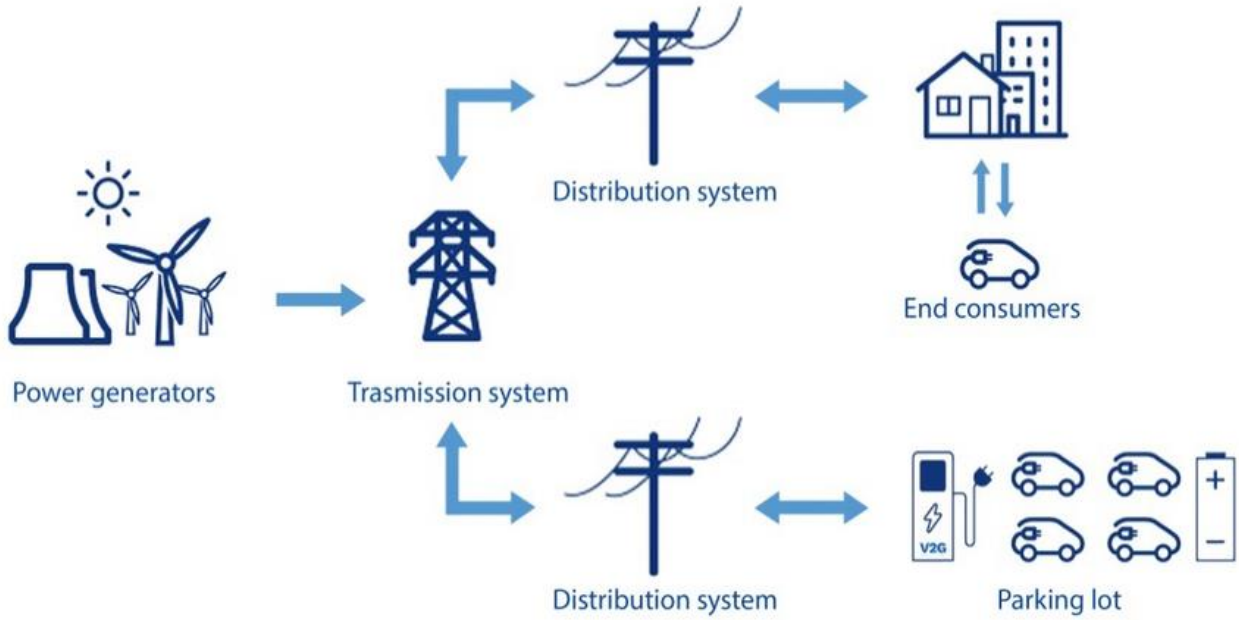

Figure 4: V2G Diagram [1]

Microgrid deployments have been deployed around the world in efforts to reduce dependency on oil and promote a cleaner environment. Tesla has installed over 120 microgrids around the world [6] that have served to promote renewable energy and decrease our carbon footprint. These successful projects, such as the one implemented on the island of Ta'u in American Samoa that consists of 6 MWh of energy storage and 1.4 MW of solar capacity that has decreased the island's diesel fuel consumption by over 100,000 gallons a year [9], show the advantages and impact that microgrids can have if adopted by SCU.

Chapter 2: Objectives

2.1 Problem Statement

Increased energy demand has put significant stress on the grid, causing power outages, while our carbon emissions have led to global warming. Microgrids have the potential to help solve both of these pressing issues while potentially saving costs as well.

2.2 Objectives

Our project's objective is to provide Santa Clara University with a path to 100% renewable energy using increased renewable output and V2G with a goal to design and simulate a complete energy management system with a microgrid capable of islanding for the entire Santa Clara University campus with vehicle-to-grid functionality using SCU energy data. We aim to successfully simulate this microgrid design using MATLAB and Simulink and verify the design in real-time using a hardware-in-the-loop simulator. If time permits, we will have one simulation using current SCU resources and another with proposed deployments (solar, fuel cell, battery, etc.) to show how SCU can reduce their operating cost, carbon footprint, increase power reliability, and plan for more EVs presence on campus. Throughout the course of the project, our objective slightly changed from using to Simulink to MATLAB. We were also unable to verify our design using the hardware-in-the-loop simulator because it did not arrive on time; however, the main objective of providing Santa Clara University with a path to 100% renewable energy remained constant.

Chapter 3: Project Plan and Implementation

3.1 Project Plan

Our project was originally planned to be entirely simulated using MATLAB and Simulink and later verified using a hardware-in-the-loop. Santa Clara University consists of multiple loads, power generators, and is connected to the grid by two feeders. Because of this complexity, we broke the project down into three design steps: lumped load, split feeder, and individualized loads. The lumped load design was a simplified model of Santa Clara University by summing the capacity of each type of source, considering only one grid feeder (adding the two together), and considering each building on campus as one large load. This allowed us to get a basic model working quickly so that we can have an elementary understanding of how the system works. After tuned the model to perform properly, we will begin to add back the complexity to the system by splitting both the feeders and modeling the load from each building individually.

Once we completed a model that is as accurate as possible to the current and planned power systems of the entire campus, we planned to move the design over to the hardware-in-the-loop simulator for real-time simulations. This is the best way to ensure that our microgrid will be both reliable and accurate to a real-life implementation of the design; however, because the hardware-in-the-loop did not arrive on time, we were unable to complete this step.

Due to the tradeoff described below in Chapter 3.2.1, our project plan had to shift when we chose to implement a purely MATLAB simulation. Instead of having the three project phases of the Simulink plan, we decided to simplify the project into two main simulations. The first simulation was a simulation of Santa Clara University’s existing renewable generation on campus with a V2G, an energy storage system, and analysis with 2019 and current load data. The second simulation was the same as the existing simulation except it had additional renewable capacity and only used the current SCU load data.

3.2 Methodology

3.2.1 Microgrid Simulation

While MATLAB is powerful tool, there are other software packages available that could have been used for our project such as python. There were two main advantages of moving to a Python implementation for our project. First, this would allow the simulation run on any machine, regardless of hardware vendor or operating system as Python is a free to use in any application and very portable. Also, this would have been an excellent learning experience for our group as we had a limited experience with Python in comparison to our experience with both MATLAB and Simulink. The disadvantage of python is fewer supporting libraries for power systems and the time it would have taken to become proficient in the language to complete the project; therefore, we ultimately decided to complete the project in MATLAB and Simulink.

While Simulink is a MATLAB product, implementing the project in Simulink versus MATLAB significantly differs. Simulink provided a visual layout of our microgrid, but each piece implemented was a black box. Simulink has a library of blocks (ex. Battery, transformer, PV, etc…) but because we didn't code the blocks ourselves, we were not sure 100% sure of the block limitations and how it functions even after looking at the MATLAB documentation.

Another path we considered taking was starting with a Simulink based implementation so that it is easier for us to visualize and understand. Then, once we have a basic Simulink model working, we would then translate it to MATLAB functions with a main script to make the simulation more robust in the long term. We would anticipate this transition from Simulink to MATLAB to be somewhat trivial for the most part given that both tools are MathWorks products.

Due to the previously stated limitations of Simulink, we debated on whether we should continue to use Simulink with the inclusion of MATLAB scripts or to just use MATLAB functions with a main script. While this might be more difficult initially, and harder to visualize, we believed that it has the potential to be more tunable and operate more reliably than a Simulink based simulation because we would have built all the function ourselves; therefore, we would know its limitations and exactly how they operate. We come across strange errors when using Simulink throughout Fall 2021 and early 2022 which we often do not find a reason for; because of this, a pure MATLAB implementation was chosen for our final simulation.

Another significant issue with using Simulink was that MathWorks has not implemented a simple method to make the simulation a multi-threaded process. This would cause our simulation to run 60 – 100 times slower in real time, depending on the step size selected. Given that the workstation we were using had 36 threads available with 128GB of memory, we explored different ways to utilize the entirety of the hardware. After consulting with MathWorks for the latter half of the Winter quarter, we concluded that there was no feasible way to utilize the hardware available to us.

3.2.2 Machine Learning

For this prediction model, we used a polynomial regression model. This is a form of regression analysis that models the relationship between the two variables as a polynomial. In our case, a 6^{th} degree polynomial yields the best result as any degree higher than this provides very little benefit in return for the additional computational power. The results were validated using a K-fold cross validation, which is a method of evaluating the performance of a model for a small data set.

Chapter 4: Implementation

4.3.1 Overview

The Microgrid for Santa Clara with V2G project consisted of five main MATLAB scrips and functions (main, V2G, Battery, and V2G/Battery state of charge check). The simulation also included two main simulations (2019 and current load and a proposed Microgrid for SCU). The machine learning algorithm developed for this project was trained and tested entirely in Python. Santa Clara University currently has a renewable generational capacity of 1 MW of solar voltaic (PV), 2 MW from Bloom Energy Fuel Cells for a combined total of 3 MW. When we started the project, SCU was looking into a Tesla battery system with a peak power of about 1 MW. SCU has since postponed these plans; however, we decided to still add the energy storage system to our simulation. Because SCU was looking at a Tesla battery of about 1MW, we used the specs of a Tesla Megapack with a power rating of 1.3 MW and energy rating of 2.6 MWh. The simulations for the 2019 data were broken down into a sunny and cloudy day to analyze how the renewable capacity from the PV changed between the two days and how much of a cost difference this could incur SCU. For the proposed system, we choose to simulate a work week (Monday – Friday) in April to better illustrate daily trends and highlight the need for increased renewable generation at SCU.

To help predict SCU's power generation and to get a better understanding of the data that we collected, we created a machine learning algorithm that can predict how much power the solar array on campus will generate at a given time.

4.3.2 Data Collection

At first, we used SCU's 2019 load data. This data only included one feeder and was in 15-minute intervals, which was the prominent reason why we decided collect irradiance data and plot our simulation in 15-minute intervals. After this simulation was completed, we used data from SCU (April, 2022) including both the feeders and the new campus building, Sobrato Campus for Discovery and Innovation (SCDI) for our current simulation.

In order to better simulate the amount of power generated from solar panels on campus, we gathered real solar irradiance data using an Arduino with two photoresistors (Figure 6) in 15-minute time intervals so it would match the interval of the load data provided to us by the SCU. It collected this data for several weeks over the Winter 2022 quarter. While the data looked as expected for most days, on very sunny days, the data looked rather strange (Figure 5).

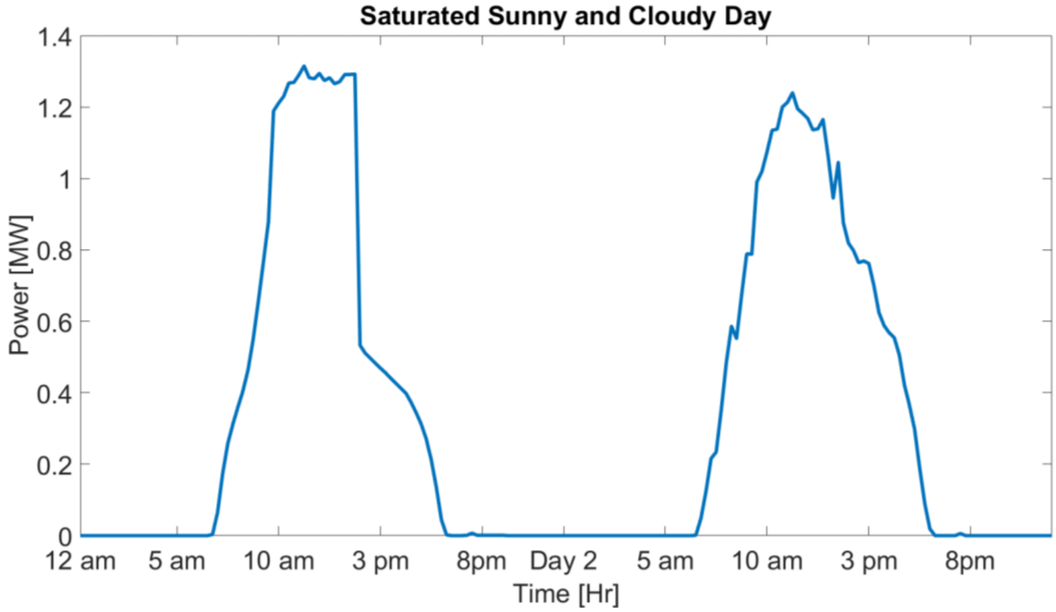

Figure 5: Irradiance of Sunny Day (Left) and Normal Day (Right)

We believe that the abundance of light on these extremely sunny days either saturated the photoresistors that we used as sensors or overheated the Arduino board itself which caused these irregular curves. Otherwise, the acceptable data was used for training a machine learning prediction algorithm which allows us to model solar power generation.

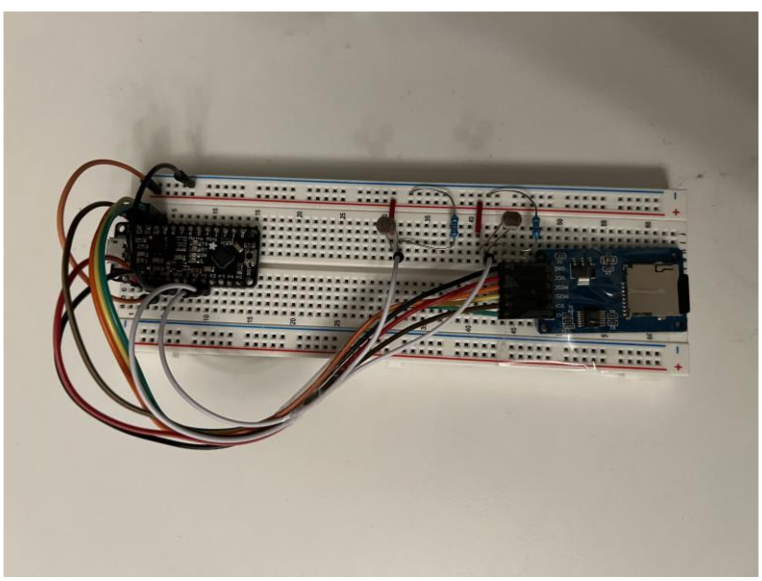

Figure 6: Arduino and Photoresistor Setup

Because the Arduino data was saturated, the next best option to achieve the most accurate PV output was to get historical irradiance data. We used historical 2021 irradiance data, GHI (Global Horizonal Irradiance which included both direct normal irradiance and diffused horizontal irradiance), from Solar Cast because it allowed us to download data specifically for Santa Clara University's campus in 15 minute intervals so it could be easily matched to the load data provided to us from SCU. The data from Solar Cast was available for free for students.

4.3.3 Main Simulation Script

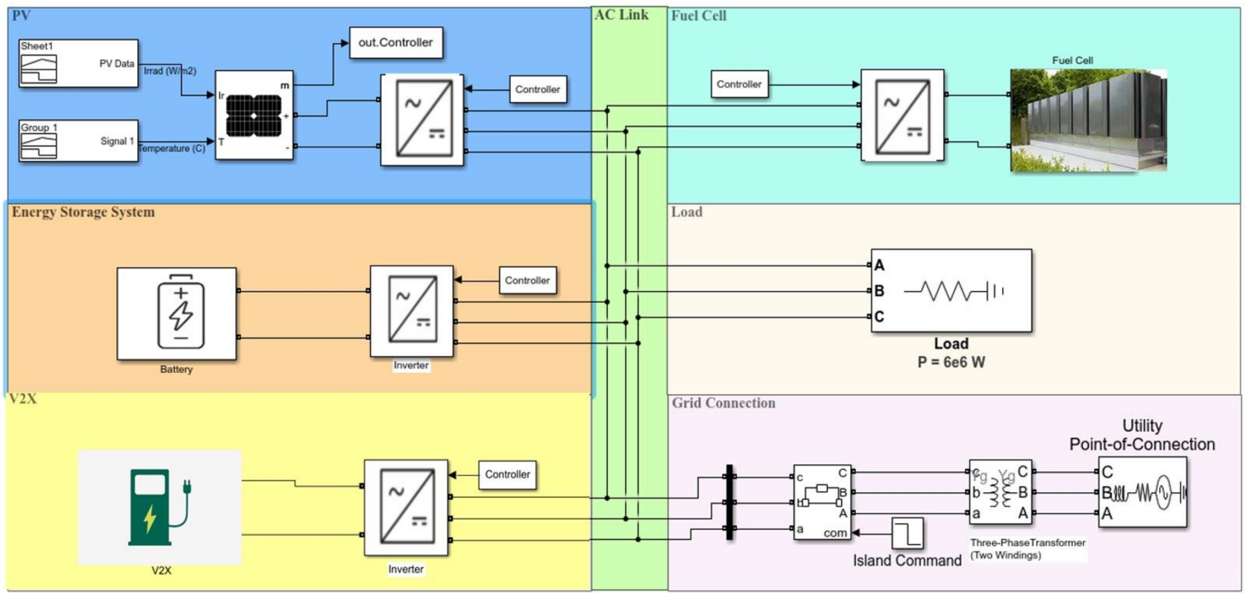

Figure 7: Block Diagram

The main MATLAB script call the V2G script, battery function, and displays all the necessary plots. The PV and fuel cell values are also calculated here. Because our data is in 15-minute intervals, we have 96 data points per day or 480 points for our weeklong simulation of our current load data. The script loops through and each iteration and calculates the PV and fuel cell power then subtracts this from the SCU load to find the grid supply. The grid supply is how much power the grid needs to supply SCU in order to meet SCU's load demand. The battery function and V2G script are then called and return their power (battery or V2G power can be positive or negative depending on if they are discharging or charging respectively). Finally, the script calculates the total amount of energy used and the cost of SCU's power bill if SCU didn't have any renewable generation and how much the power bill is with the current generation. A high-level overview over the MATLAB script is shown in Figure 7.

This is a Simulink block diagram of our design. We have our photovoltaic system, or PV for short, in blue and includes all the solar panels on campus, along with the electronics that invert the DC power generated to AC for distribution. The fuel cell model is in teal. We have a 2MW fuel cell on campus, provided by Bloom Energy, and this acts like a constant source in our system. Battery storage is the orange box, and this component captures excess energy generated from the renewable resources for later use. The battery was implemented as a Tesla 1.3MW 2.6 MWh Megapck. The load is modeled in the white box and in our simulation, we used real load data provided by SCU. Our simulated components respond to the load dynamically as it increases and decreases. The grid connection to our system is in the bottom right. The school has two separate grid connections, or feeders. Our simulation combines these two feeders for simplicity. Finally, the V2G system is the yellow box. We modeling 40 electric vehicles, each with an 82KWh battery (this is the battery from a Tesla Model 3 Long Range). SCU has about a charging capacity on campus of about 40 electric vehicles which is why we chose our V2G system to have 40 cars in it.

4.3.4 Battery

The Battery function calculates the SOC (state of charge) of the battery and ensures that it does not charge above the maximum SOC or below the minimum SOC using another function (SOC Check) that checks the new SOC and returns the adjusted power and energy levels ensuring the SOC of the battery is kept within the boundaries set, as seen in the flow chart in Figure 7. The inputs to the function are the current SOC and energy of the battery, grid supply, and the maximum power the battery is allowed to output. The function returns the new SOC, energy, and battery power. According to the Tesla website, their power packs have a 100% debt of discharge. While charging a battery to 100% and draining it completely is detrimental to its long term lifespan, we assumed that the batteries provided by Tesla are larger than the energy rating, but software limited; therefore, we set the 1.3 MW, 2.6 MWh Tesla Powerpack to have a minimum SOC of 0% and a maximum SOC of 100%.

The battery only charged when there was excess renewable generation. When the renewable generation is greater than SCU’s load, the battery would charge from this excess energy generation, and discharge whenever the load was greater than the renewable generation. For the battery, the load is considered the sum of the SCU and V2G loads. The battery was not charged overnight, unless where the generation was greater than the load, because SCU is not on TOU (Time of Use) or demand response. Time of Use is where the utility provider chargers its customer a different amount per kWh while demand response is the utility provider can charger a higher amount per kWh during an event such as a heat wave to reduce stress on the grid.

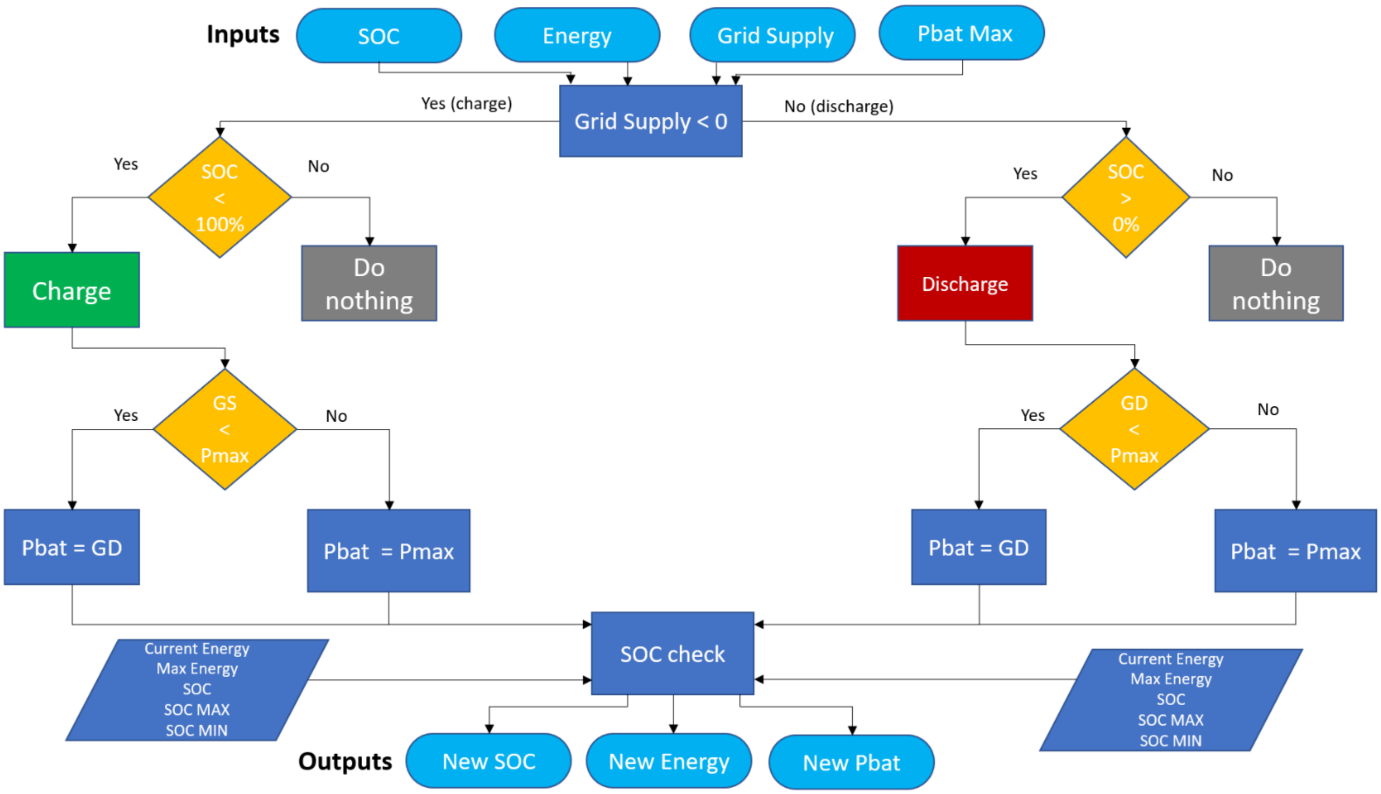

Figure 8 8: Battery Code Flow Chart

4.3.5 Vehicle-to-Grid

Santa Clara University currently has a charging capacity of about 40 cars which is why we chose to simulate a V2G fleet of 40 cars. Each car has an 82 kWh battery pack, a maximum SOC of 90% and a minimum SOC of 60%, and could charge / discharge at a maximum rate of 11 kW which was based on V2G stations currently available today. An 82 kWh battery for each car was chosen because it was based on a very popular electric vehicle (EV) currently on the market, the long range Tesla Model 3.

For predictability, the algorithm we chose to implement was time dependent, This assumed that all the cars arrived at campus at the same time with 60 kWh, and that their owners would leave after 5PM and want a fully (90% SOC) charged car when they leave. The charging and discharging times are seen below in Table 1 and are based on peak power usage times and when we thought people would arrive and or leave campus. Assuming that students and faculty arrived on campus in the morning, the cars were charged after they arrived from 8 AM – 1 PM, then discharged from 1 - 4 PM if SCU's load was greater than the renewable generation. Finally, the cars would be changed back up to 90% from 4 – 5 PM. To ensure the cars did not charge or discharge above or below their maximum / minimum SOC set points, a separate V2G SOC check function was implemented. This function was similar to the one used for battery function.

Table 1: V2G Charging / Discharging Schedule

Charging	Discharging	Charging
8 AM – 1 PM	1 PM – 4 PM	4 PM – 5PM

4.3.6 PV and Fuel Cell

SCU has a 1 MW PV system and 2 MW fuel cell system from Bloom Energy. calculate the power output from the PV, we used the formula $P = A * Irradiance$. Because the PV system has a maximum output of 1 MW and that the maximum irradiance the panels can receive is 1000 W/m^2, the area of the PV panels can be solved for which was $1000m^2$. To scale up the PV to 4 MW for the proposed simulation, we simply multiplied the power of the PV by a scaling factor until the maxim value of the PV system was 4 MW.

The Bloom Energy Fuel Cells on campus output a constant 2 MW. Because the fuel cell output can essential be viewed as a constant source and since we are not chemical engineering majors, the fuel cell was simply modeled as $P = 2e6\ W$.

4.3.7 Machine Learning

From the K-fold cross validation, we can see the mean-squared error plotted in Figure 8, where it is much more favorable with degrees higher than five. Figure 7 shows the irradiance data gathered from the Arduino over a 24-hour period (this is several days of data in a single 24-hour frame). The red curve superimposed on the irradiance data is the polynomial regression model produced from our algorithm. These plots were generated using the matplotlib package in Python.

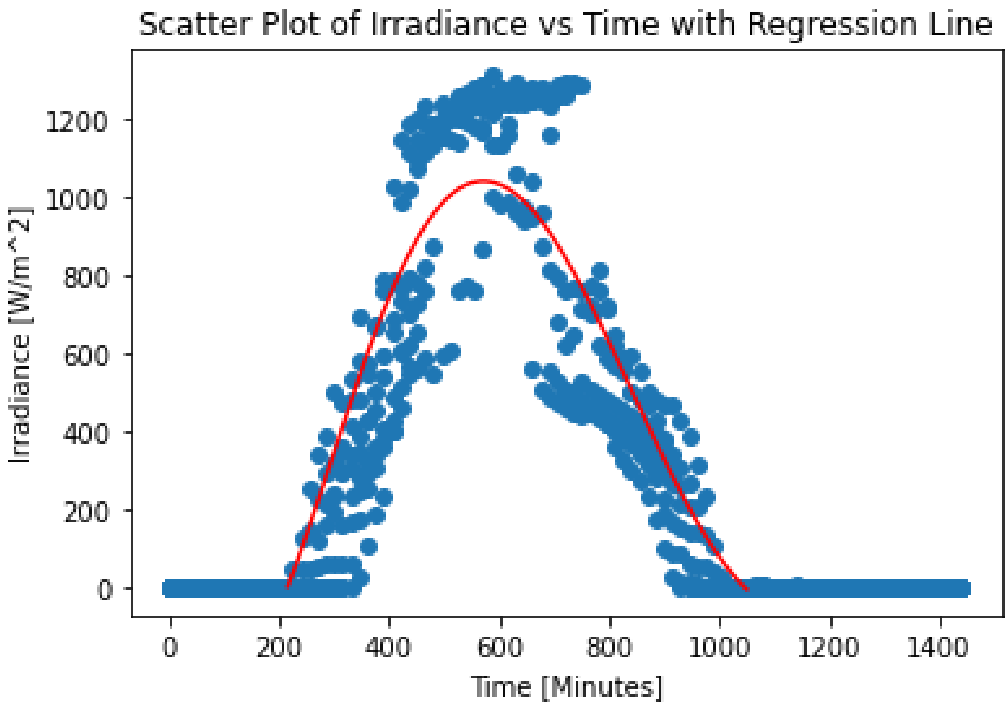

Figure 99: Regression Model (Red) Over Irradiance Data

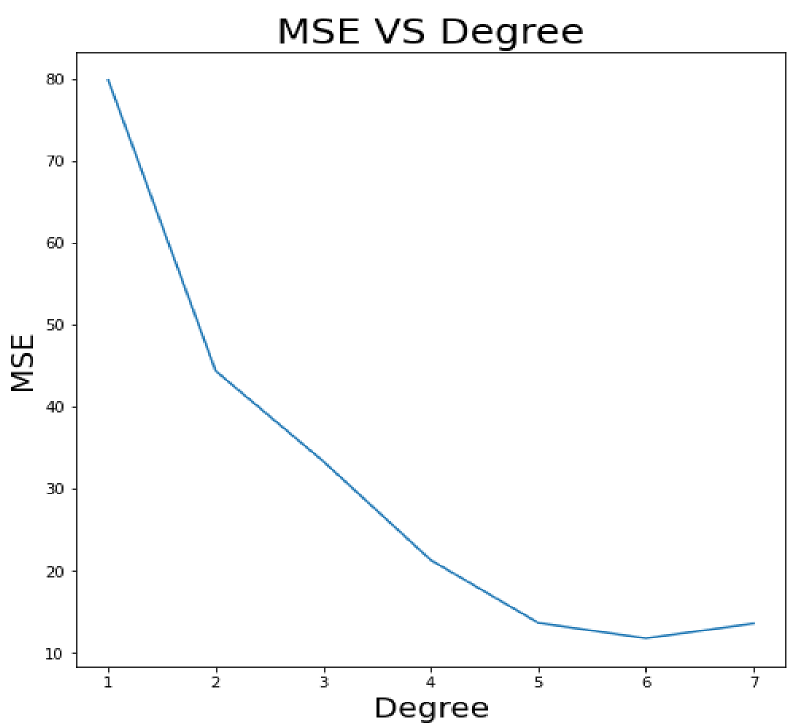

Figure 10: Mean-Squared Error of the Model by Degree

Chapter 5: Results

5.1 SCU Current Simulation

5.1.1 Sunny Day vs Cloudy Day

While the 2019 data only contained load data for one of the feeders, it provided an insight into how an energy storage system, such as a battery, could help SCU achieve 100% renewable energy. In Figure 9, the top left plot is the SCU generation plot. The PV (in green), peaks at 1 MW and has a uniform shape with a potential small cloud passing over the panels in the morning. This is expected as the data was taken from June when the PV system will have its peak performance and because it was taken from a sunny day. The fuel cell (in yellow) is a constant 2 MW, and the battery (in orange) is charging or discharging based on the load conditions.

The SCU load plot in Figure 9, the load is in purple and peaks at about 3.1 MW and is steadily increasing as people arrive on campus from about 5am to 3PM. In the Battery Power plot (below the SCU Load plot), the battery power is negative when it is charging and positive when it is discharging or delivering power to the SCU load. As previously described in Chapter 3.2.3, the battery only charges when the SCU generation is greater than its load. In the plot, we can see that this mainly occurs during the middle of the night when the SCU load is at its lowest and before people start to arrive on campus. This can be seen from the Battery SOC plot in Figure 9 as the battery SOC is steadily increasing till about 8 AM where the SCU load becomes larger than the renewable generation on campus.

The bottom right two plots of Figure 9 are the V2G Power and SOC plots. Because the V2G algorithm is time dependent, the vehicles start charging at 8AM as seen by the negative power in the V2G Power plot as the cars are absorbing power and their SOC is increasing. The algorithm charges the cars from 8 AM to 1 PM; however, the cars reach their maximum SOC of 90% at approximately 9:30 AM and stop charging and remain idle until they are ready to be discharged from 1 – 4 PM. When the cars are discharging, their power is positive as they are delivering power to the SCU load, and their SOC is decreasing. Finally, the cars are charged back up at the end of the day from 4 – 5 PM.

The Load with V2G plot in Figure 9 displays SCU load (in purple) and SCU load with V2G (in grey). The spikes in the grey line are due to the cars charging but if we look at when SCU has its peak demand (1 – 4 PM), the grey line is below the purple line. This is because the cars are peak shaving as they are reducing SCU's peak demand during when electricity rates can be high; thus, saving SCU money.

In the top right graph of Figure 9, the SCU load with V2G is again plotted in grey, SCU renewable generation in orange, and the grid supply is plotted in red. The grid supply is how much power is being supplied to SCU from the grid. Ideally, we want this red line to always be zero so SCU will run on 100% renewable energy and be grid independent. The grid supply to SCU is zero until a little before 5PM. This is because the battery runs out of energy and SCU's load is greater than the renewable generation on campus. With more renewable generation on campus, this red line can remain zero for longer and eventually be perpetually zero.

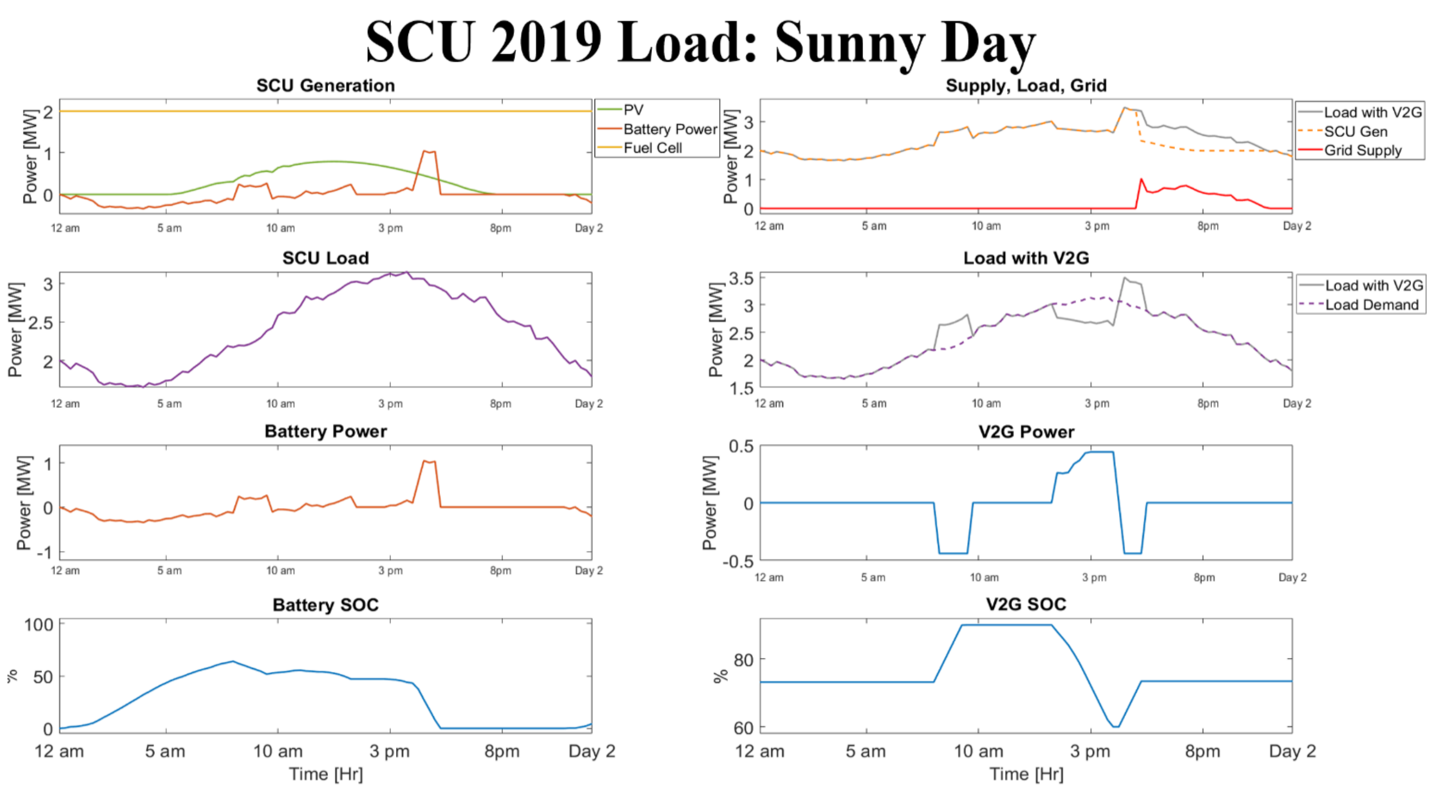

Figure 1110: SCU 2019 Load: Sunny day

Figure 12 11: SCU 2019 Load: Cloudy Day

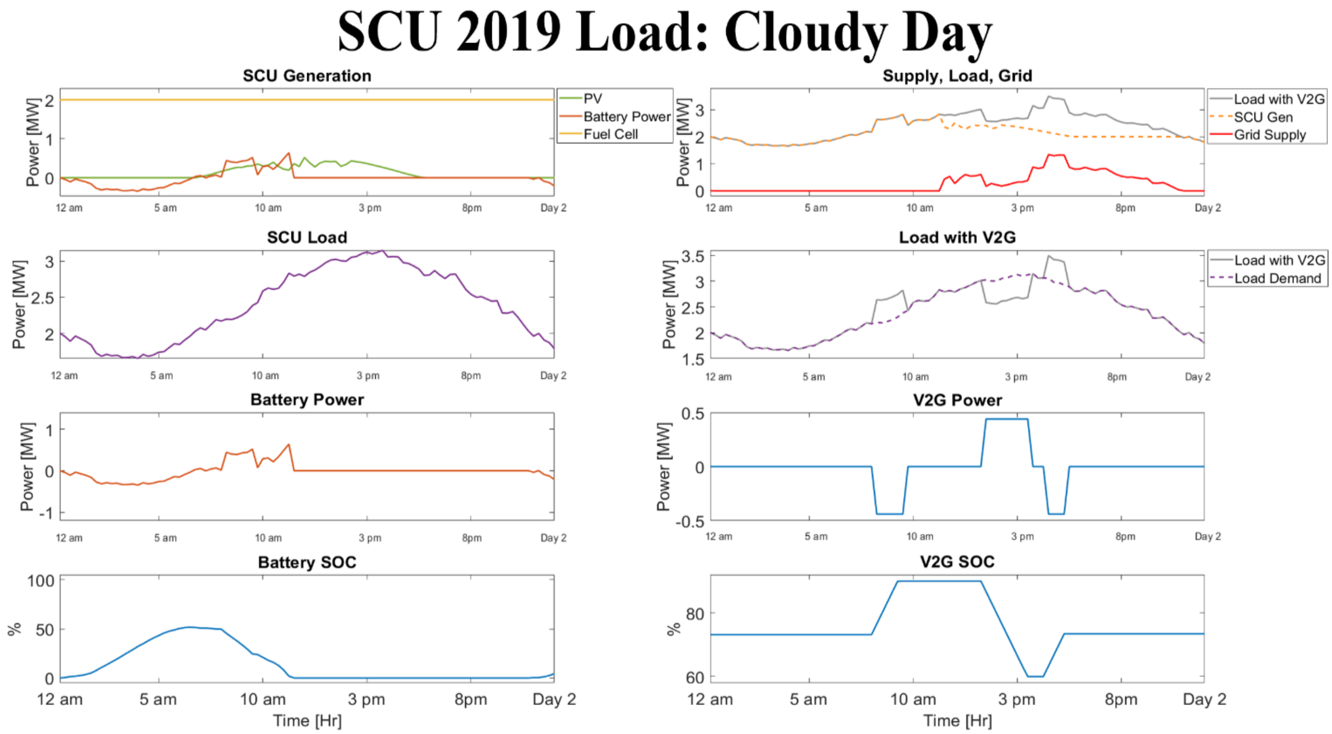

Figure 10 displays the same 2019 load; however, the PV system outputs much less power because the day is cloudy as seen by the PV not peaking at 1 MW and has a much less uniform shape. This is expected as the data was taken from a day in October and on a non-sunny day. Because of the reduction in PV output, the battery SOC in Figure 10 does not charge as much compared to the maximum battery SOC in Figure 9, on the sunny day. In Figure 10, the V2G plots remained the same as those of Figure 9, but the grid supply in the top right plot of Figure 10 remained non-zero for much longer because of the reduce PV generation was not able to charge the battery as much. As a result, the battery was discharged earlier in the day than on the sunny day. This means that the grid is supplying SCU with more energy and SCU is more reliant on the grid, not using 100% renewable energy.

This demonstrates the importance of an energy storage system and the need for over generation on ideal days so the battery can be fully charged at the start of a non-ideal day (such as a cloudy or rainy day) so the battery can be deployed longer throughout the day, reducing the gird supply. With a large enough combination of renewable generation and energy storage unit, SCU could become fully islanded from the grid (grid supply would be zero) for extended periods of time, running on 100% renewable energy and independent from grid outages.

5.1.2 Sunny vs Cloudy Day Energy and Cost Analysis

There was a large energy difference in the energy supplied from the grid between the sunny and cloudy day. This energy difference is broken down in Table 2 below and the same load data was used for each day. If we analyze how much energy then grid would need to supply SCU if SCU had no renewables, it would be 54.21 MWh; however, with renewables, it is only about 2.96 MWh on a sunny day and 6.57 MWh on a cloudy day. This shows how the renewables on campus are significantly reducing the grid supply to SCU, but still more generation is needed to become fully independent from the gird and to run on 100% renewable energy. We are not allowed to disclose exact numbers relating to the SCU energy bill; however, difference between the total cost of energy supplied from the grid on the sunny vs the cloudy day is over $500. This cost difference on non-ideal days can be diminished through an energy storage system and overgeneration from sunny days to have the storage system be fully charged at the start of the non-ideal day.

Table 2: Sunny Day vs Cloudy Day Grid Supply

Energy Supplied from the gird	Sunny Day	Cloudy Day
With Renewables	2.96 MWh	6.57 MWh
Without Renewables	54.21 MWh	50.6 MWh

5.1.3 Current Load Analysis

The 2019 load data from one feeder provided a good insight into how an energy storage system could help provide SCU with a path to 100% renewable energy and grid independence but the load data was only about half of the current load. We acquired new data in Spring of 2022 that included both feeders and the new building that is shown below in Figure 11. In this figure, the SCU Generation plot has the same PV, fuel cell, and battery, but it is for five days now. The Load plot (in purple) in the left column of Figure 11 is the current, 2022, SCU load data taken from a week in April. Most noticeable aspect of this plot is that the load peaks at almost 8 MW and has a minimum of a little over 4 MW.

This is significant because the load is always greater than SCU's renewable generation. Because the battery only charges when the renewable generation is greater than the load, the battery is never able to charge. This is seen by the battery power remaining zero in the SCU Generation plot and Battery Power Plot, and is confirmed by the Battery SOC staying zero in the Battery SOC plot. The V2G plots remained the same with the cars charging and discharging at their scheduled times. The most important line in Figure 11 is the grid supply (in red) from the Supply, Load, Grid plot in the top right of this figure.

The grid supply line is never zero, signifying that SCU constantly needs to be supplied with power from the gird. There is still a large difference between grey line (SCU load with V2G) and red line (grid supply), indicating how the renewable generation on campus is significantly reducing the energy supplied from the grid to SCU, but it also shows how SCU needs increased renewable generation on campus to minimize the grid supply to zero and run on 100% renewable energy. This will also lead to increased cost savings as discussed in Chapter 4.3.

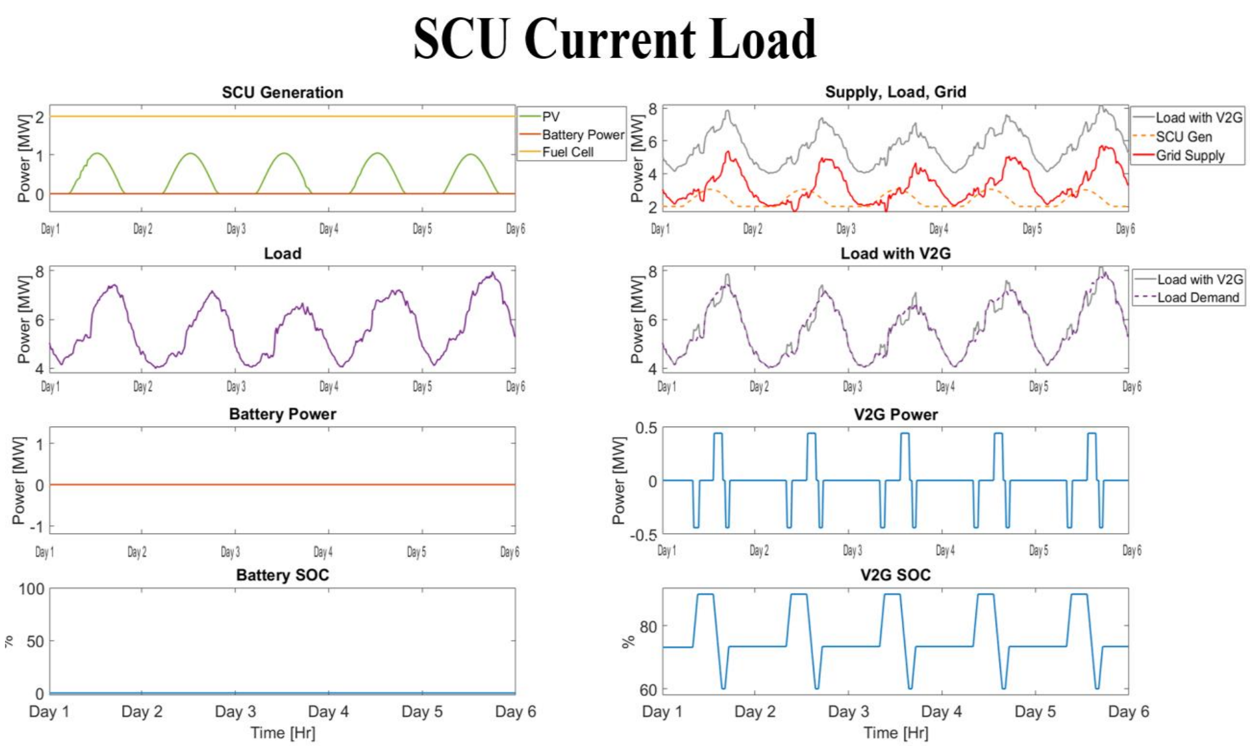

Figure 1312: SCU Current Load

5.1.4 Current Load Cost Analysis

The current load with both feeders is much larger than the 2019 data with only one feeder. Without renewables, the grid supply to SCU would be a massive 136.67 MWh; however, with renewables, this is reduced to 80.05 MWh for savings of up to over $8,000/day on a sunny day. While these daily savings are immense, these still be significantly increased with additional renewable capacity added to Santa Clara University's campus.

Table 3: Current Load Energy and Cost Analysis

Energy Supplied from the gird	Sunny Day	1 Day Cost Savings
With Renewables	80.05 MWh	$8k+/day
Without Renewables	136.67 MWh	$0/day

5.2 V2G Findings

After analyzing the impact of V2G on SCU's load and the energy supplied to SCU from the grid, we found that V2G had a negligible impact on the overall load. The V2G simulation did not show a large reduction in the grid supply with V2G. This could be because the cars were charged up at the end of the day, resulting in their net energy supplied to SCU's load to be insignificant. SCU also does not currently have an incentive to implement V2G for peak shaving because SCU is not on TOU (Time of Use) or demand response. Time of Use is when the utility company charges their customer a different $/kWh at different times of the day while demand response is when during a time of peak demand (ex: during a hot summer day when everyone is running their AC units), the utility company will have a demand charge where people will be charged a higher amount $/kWh to incentivize customers to shift their energy usage to a different time to avoid the higher energy prices. Because SCU is charged the same $/kWh no matter what time of the day it is, there is no financial incentive for SCU to reduce their peak demand or load shift, thus no incentive to implement peak shaving with V2G; however, as V2G technology matures, EVs become more prevalent, and SCU increases the charging capacity on campus, we think V2G could become a vital part in helping SCU achieve 100% renewable energy and grid independence.

We also must explore other options than V2G to provide a path for SCU to run on 100% renewable energy. Scaling up solar capacity is one way to increase renewable generation on campus, but we also must education the students and faculty on their actions (such as turning on the AC) can increase our peak demand and what steps that can take to reduce our peak demand through load shifting. Machine Learning can also be used to help predict our future renewable generation and match it to our predicted load. This could tell us ahead of time if action is needed to reduce SCU's power consumption so SCU could always run on 100% renewable energy. Finally, we do think that a more complex V2G algorithm could show promising results and help provide a path for SCU to by 100% renewable.

5.3 Proposed System

5.3.1 Overview

For the proposed system, we wanted to reduce SCU's grid supply by about 40%. SCU can add around an additional 3 MW (not including SCDI) of solar if the parking lots, structures, and building rooftops are used. For this proposed system, we added and additional 3 MW of PV for a total of 4 MW PV capacity on campus. The same 1.3 MW, 2.6 MWh battery that was used in the SCU current simulation was implemented. We chose not to increase the capacity of the fuel cell because the Bloom Energy Fuel Cells have a byproduct of $C0_2$, making them not a 100% renewable energy resource.

5.3.2 Energy and Cost Analysis

With the extra renewable capacity from the three additional megawatts of PV and with the same load of 136.67 MWh without renewables, the grid supply to SCU with renewables is now only 55.29 MWh. This is an energy difference of 81.38 MWh, an increase of about 25 MWh when compared to our current renewable capacity on campus. The additional renewable generation lead to a 50% increase in daily savings when compared to our current system from about \$8,000+/day to \$12,000+/day. The savings can continue to increase as the renewable generation on campus continues to increase until SCU is running on 100% renewable energy for maximum energy savings.

Table 4: Proposed System Energy and Cost Analysis

Energy Supplied from the gird	Sunny Day	1 Day Cost Savings
With Renewables	55.29 MWh	$12k+/day
Without Renewables	136.67 MWh	$0/day

5.3.3 Simulation Result

In Figure 12, Proposed SCU Microgrid, the top left plot, SCU Generation, displays the increased PV capacity. The PV (in green) peaks at 4 MW while the fuel cell (in yellow), was kept at a constant 2 MW, and the battery power (orange) charges and discharges based on if the renewable generation is greater than the load. In thr current system, the battery was never able to charge because the load was always greater than the renewable generation; however, with the increased capacity of PV, the battery is now able to charge. This is seen by the battery SOC increasing in the Battery SOC plot in Figure 12.

The V2G algorithm was kept the same and is still time dependent as seen by the V2G Power and V2G SOC plots in light blue in the bottom right of Figure 12. Due to the increased PV capacity, SCU is now able to run on 100% renewable energy (for short periods of time) as seen by the red grid supply line equaling zero in the Supply, Load, Grid plot. When the grid supply is zero, SCU is running on 100% renewable energy and is grid independent. There is also a larger difference between the Load with V2G (grey line) and the grid supply, showing how the increased PV is reducing the energy supplied from the grid to SCU. While reducing SCU’s grid supply by about 40% is a great step for SCU to become 100% renewable, SCU will still need to add more renewable generation on campus to achieve 100% renewable energy and grid independence.

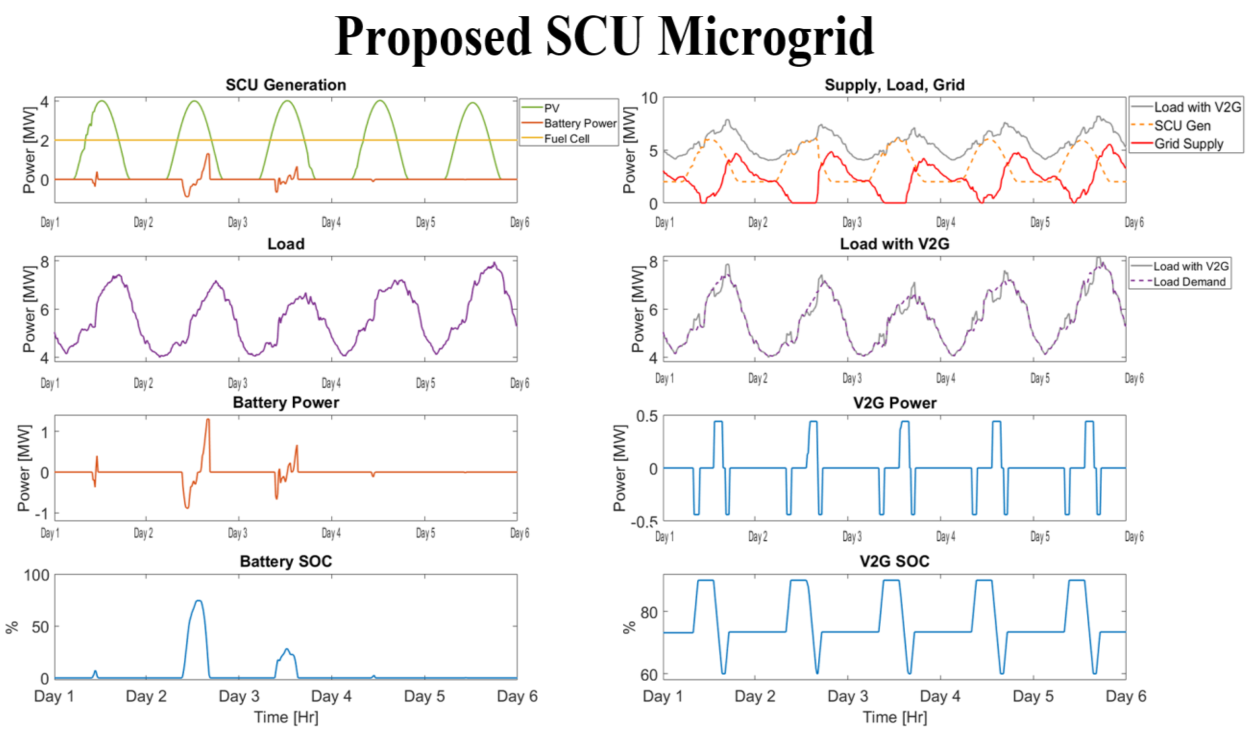

Figure 14 13: Proposed SCU Microgrid

5.4 Machine Learning

The machine learning model yielded a model with approximately 97% prediction accuracy. This will allow better control of our microgrid system, such as when we need to ready resources before the load will increase. Anticipating load increases will not only benefit the grid as the grid operator will know what to expect from our load but will also allow us to predict how many cars we will potentially need on campus to be able to store the solar power generated in case the load is not large enough to absorb all the renewable generation power.

Given the success of the generation of this algorithm, we figured that creating more models for our other sets of data would prove to be fruitful. As of now, we are working on creating two more machine learning prediction models for the load of our campus. We believe that we have a warranted use case for more machine learning in this project as predicting power usage and generation would greatly optimize our system in real life. This requires two different models as the load on the weekdays is much greater than that of the weekends due to the scheduled nature of the campus. Figures 15 & 16 are plots of 2019 load data over a 24-hour period, recorded every fifteen minutes for weekends and weekdays respectively. These are plotted similarly to the irradiance data shown previously.

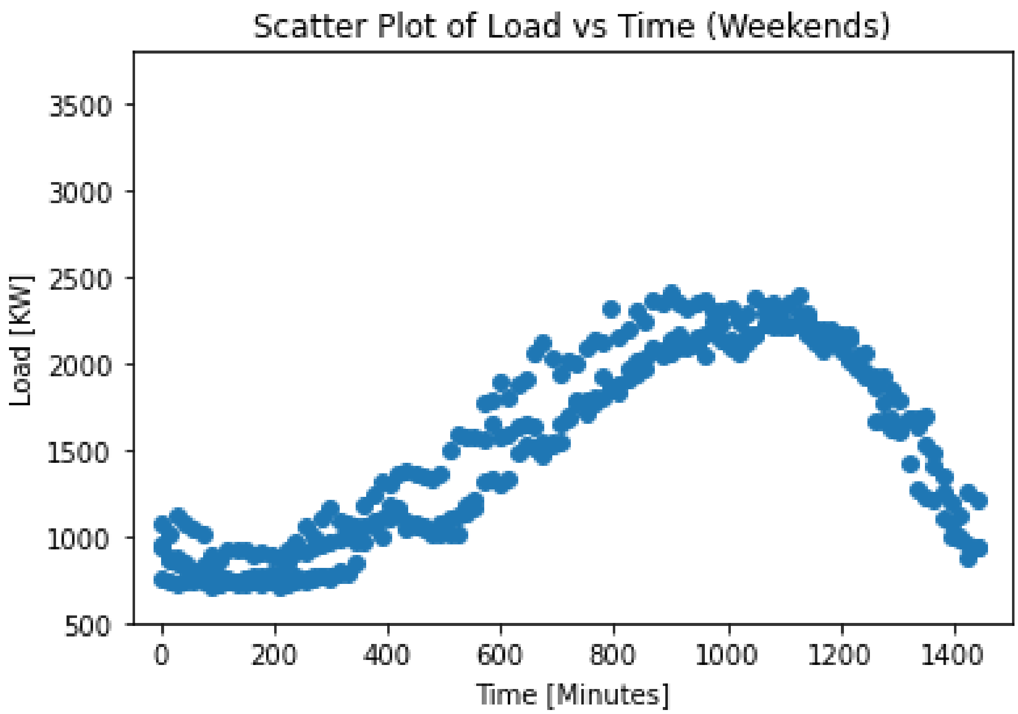

Figure 15 14: 24 Hour Load on the Weekend

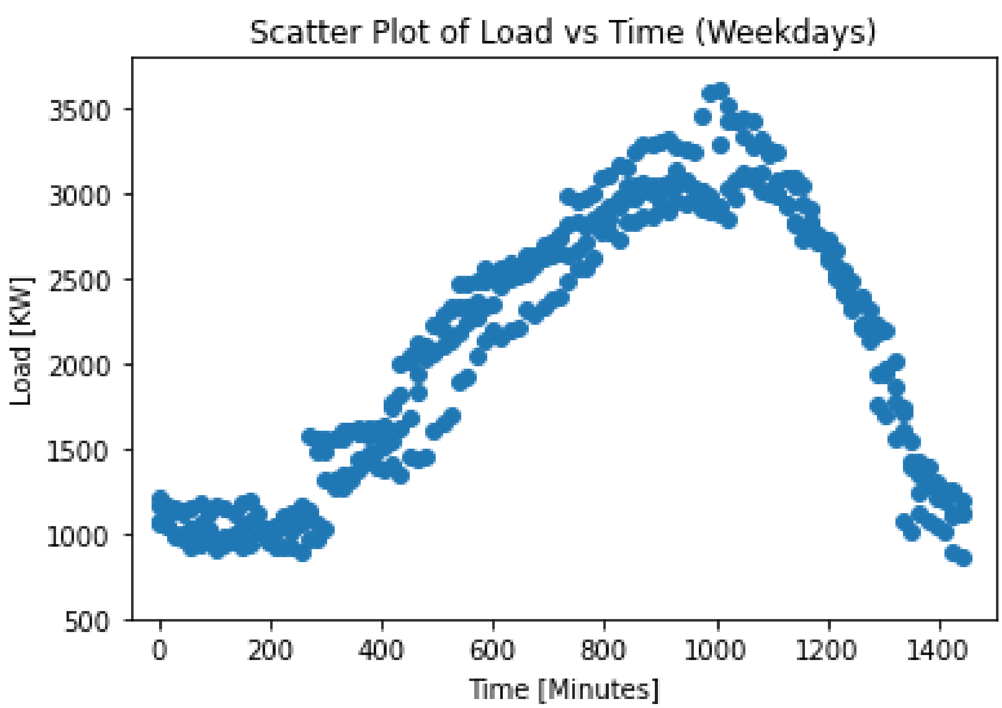

Figure 16 15: 24 Hour Load on a Weekday

We can see that for each respective day, there is a clear curve that each load follows. Since everything that happens on campus follows a schedule, the load is inherently predictable, unlike other facilities that are randomized in usage. A machine learning algorithm for this would make it even more predictable. Again, having algorithms like these would provide us with valuable knowledge that will help anticipate how much power we will need to generate for a given usage and time, which will allow for further optimizations in both our simulation and a real-life system.

5.5 Project Success

Overall, we have been able to create a versatile framework for modelling the power generation and usage behaviors of the campus. Given its portability in MATLAB, the system is quite modular, which would allow for the addition of either new subsystems or scaling the currently simulated systems to a greater capacity. Also, since the simulation has been written in MATLAB, it has the potential to be ported over to a hardware-in-the-loop system in the future. This will allow for more complexity in each component, while maintaining the run time of the system to real-time.

As for the machine learning aspect of the project, this has given us a new perspective into our power generation and usage. Through these algorithms, we can create accurate predictions of how much power we will generate, how much power we will absorb, and how much battery storage (or V2G capacity) we would need as a result of these two predictions. So, in a real-life implementation of our proposed system, these predictions can be invaluable. Since the algorithms have been written in Python, they can easily be used with other data sets in the future; given our somewhat limited data sets, the algorithms should be retrained when larger sets are available to improve and guarantee both the accuracy and the performance of each model.

Chapter 6: Professional Issues, Constraints, and Modern Standards

6.1 Testing Environment and Limitation

While our project was purely simulation based, and not ever implemented in real life, testing our work was only on our workstation computer. However, this proved to be vital to the direction of our project due to the long simulation times; therefore, we progressed to using MATLAB instead of Simulink.

With our original Simulink simulation, test runs quickly proved to be infeasible as running just a few minutes of our simulation would take at least a full day of run time. This limitation in our testing method forced us to transition over to a MATLAB script-based simulation, where the run time was much faster than real-time.

As far as testing our machine learning algorithm, a K-fold cross validation is a proven, reliable way to test the performance of an algorithm. Given how low the mean-squared error of the model became, we can confidently label this as a valid prediction model.

Modern standards that were implemented into our project to insure its validity and professionalism. The standards that our project used were American National Standards (ANSI) and the Institute of Electrical and Electronics Engineers (IEEE).

6.2 Ordering Issues

Our original plan for the project included the eventual transition of moving our Simulink/MATLAB based simulation to a hardware-in-the-loop real-time simulator from OPAL-RT. This would have allowed us to simulate our system very precisely with excellent accuracy and control over most parameters. This system was expected to arrive on campus by the end of January 2022; however, it is now scheduled to arrive June 2022. Even though we were unable to acquire the hardware-in-the-loop in time for our conference, we were still able to make an accurate and detailed simulation in MATLAB running on the host workstation.

6.3 Ethical Considerations

Given that our project is simulation based, there are no immediate ethical concerns or considerations to be had. However, if the system were to be implemented, there would be a positive impact on climate change, grid stability both on and off campus, and an overall reduction in carbon footprint. This is all due to the extensive use of renewable energy sources to generate power on campus which makes the on-campus grid power more stable while reducing the load on the city's grid.

A negative impact that our current system has on campus is the fuel cells use natural gas to generate power. While this is “greener” that using another fossil fuel, like diesel, it still produces CO_2. Our design considers this and attempts to offset the impact with the implementation of more solar panels, larger battery storage units, and more electric vehicles on campus to approach carbon neutrality.

Chapter 7: Future Work and Conclusion

7.1 Future Work

We believe that the hardware-in-the-loop simulator, which was expected to arrive earlier this year, is set to be delivered to our lab this summer. This would be a natural next step in our project as it was a system that we had originally planned to learn and use for our simulation. Given that our simulation is now based in MATLAB, it should be relatively straightforward to transfer it over to the hardware-in-the-loop. Running our simulation on this system would give us greater control over more parameters in the system, and would allow for real-time simulations, which introduces more realism into our project.

With the success of our machine learning prediction model for solar power generation, we would like to pursue implementing more machine learning algorithms to create more predictions based on our other data sets, like the campus load previously mentioned.

7.2 Summary and Conclusion

Overall, we have successfully designed and simulated a working model of our school’s current and potential on campus power grid. We did this by first considering the entirety of the system to be a simple microgrid. In an effort to increase its potential, we added battery storage to our model along with more photovoltaic panels. The hallmark addition to the system was the vehicle-to-grid component as it allowed us to learn several key concepts: how a vehicle-to-grid system works, how we can implement it in our microgrid, and what would be required of the design to make this a useful addition. Our results concluded that V2G is not currently a viable solution for SCU due to the current charging capacity on campus and how SCU is not on TOU; however, in the future, V2G could play a vital role in providing SCU with a path to 100% renewable energy.

We found that these improvements in renewable energy usage greatly increase financial savings for the university as well, since the campus would not have to absorb as much power from the grid, or at all in some cases. Even greater than the financial impact of this project is the environmental impact that it carries as the increased usage of renewable energy on campus alleviates stress on the grid, which mainly uses fossil fuels to generate its power; thus, significantly decreasing Santa Clara University's carbon footprint.

Last, we successfully implemented machine learning into our project to create a prediction model of our solar power generation for a given time of day. This will allow for further optimizations in the simulation, and will also pave a path for future datasets, especially larger datasets, so that the algorithm can be trained more accurate.

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