ENERGY SUSTAINABILITY FOR THE COLORADO SCHOOL OF MINES: AN OPTIMAL SOLAR PLUS STORAGE SYSTEM DESIGN

by
Brian Oldfield
A thesis submitted to the Faculty and the Board of Trustees of the Colorado School of Mines in partial fulfillment of the requirements for the degree of Master of Science (Electrical Engineering).

Golden, Colorado

Date ______________________________

Signed: _____________________________________  
Brian Oldfield

Signed: _____________________________________  
Dr. P.K. Sen  
Thesis Co-Advisor

Signed: _____________________________________  
Dr. Paulo Tabares-Velasco  
Thesis Co-Advisor

Golden, Colorado

Date ______________________________

Signed: _____________________________________  
Dr. Daniel M. Knauss  
Professor and Department Head  
Department of Electrical Engineering
ABSTRACT

The latest report from the Intergovernmental Panel on Climate Change (IPCC) [1] indicates that anthropogenic emissions, including CO₂, methane, and others, have already caused approximately 1°C of global warming above pre-industrial levels. Based on their estimates, if it is possible to achieve a net zero CO₂ emissions by 2055, it is likely that global warming could be limited to 1.5°C and the worst aspects of climate change could be avoided.

The goal of this thesis is to investigate and document how the Colorado School of Mines in Golden, CO (Mines) can reduce its CO₂ emissions in a cost-effective way and contribute to solving this climate change problem. Specifically, we investigate the technical and economic feasibility of implementing rooftop photovoltaic (PV) and battery energy storage system (BESS) at Mines. The proposed analysis and design, also known as solar plus storage, enables Mines to reduce energy costs, reduce CO₂ emissions, and create a living experiment to improve educational capabilities in this field.

The analysis is a combination engineering and economic model written in R, an open-source programming language. The primary tasks are to study the Mines electrical system to develop a baseline energy model and forecast for the analysis period, and to use an optimization methodology to find the best design for a rooftop PV and BESS system under multiple scenarios. Optimization is carried out using a combination of convex optimization algorithms and parametric search. Forecasting is carried out using four test years of actual data that are scaled based on analysis of ten years of historic trends.

The results indicate a positive business case for a solar plus storage system, although the recommended designs fall short of a 100% renewable microgrid. Unless the federal investment tax credit (ITC) is included, the cost per kWh of the solar plus storage system exceeds the average electricity price Mines pays on their bills. However, a solar plus storage system still has a positive business case because it can reliably reduce the peak demand for the Mines campus, thereby reducing the demand charge paid to the utility. The proposed designs enable Mines to reduce electricity costs, reduce carbon dioxide emissions, and to create a living experiment to improve educational capabilities in this field.

The major contributions of this thesis include but not limited to the following:

1. Application of a unique and practical method for long-term electric load forecasting
2. Comparison and analysis of existing microgrid software tools for such applications
3. Design of an optimization framework that expands upon existing software tools for finding the optimal solar plus storage system
4. Multi-dimensional mapping of the search space for finding the optimal solar plus storage system, thereby establishing the convex nature of the problem
5. Application of a technique for estimating the effect of ambient temperature on electric loads, using hourly data only
6. Development of a mountain shading adjustment methodology for hourly PV output simulations
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ACKNOWLEDGEMENTS

Thanks to Sam Crispin, Mike Willey, Clifford Coghill, senior design teams at Mines, and Eryn Donnelly for the ongoing assistance, as well as their prior work and data collection related to this project. Thanks also to Dr. P.K. Sen, Dr. Paulo Tabares-Velasco, Mohammad Hassan Fathollahzadeh, Aoxia Chen, Jonathan Awerbuch, Anna McAuliffe, Andrew Nawrocki, and my family for their valuable guidance and assistance throughout this project.
CHAPTER 1: INTRODUCTION

The latest report from the Intergovernmental Panel on Climate Change (IPCC) [1] indicates that anthropogenic emissions, including CO₂, methane, and others, have already caused approximately 1°C of global warming above pre-industrial levels. Based on their estimates, the accumulated anthropogenic emissions up to the present, will persist for thousands of years in the atmosphere. However, the CO₂ currently present in the atmosphere is unlikely to cause global warming more than 1.5°C above pre-industrial levels. The climate risks associated with 1.5°C of warming are significant, but much lower than the expected damages from 2°C of warming. In other words, it’s not too late. We are not locked into a future of climate catastrophe. If people can reduce their emissions going forward, we can avoid the worst aspects of climate change. The scenarios pictured in Figure 1.1 in purple, grey, and blue assume that global CO₂ emissions reach net zero in 2055, which provides a reasonable likelihood that warming will remain below 1.5°C. If CO₂ emissions are reduced more quickly, the likelihood increases, as pictured in blue.

![Figure 1.1: Observed Global Temperature Change and Forecasted Scenarios [1]](image)

How can we reduce CO₂ emissions such that we reach net zero by 2055 and minimize our climate risk? This question deserves an entire thesis to itself, but we investigate briefly the United States energy usage, shown in Figure 1.2 [2]. Energy is given in quadrillion British thermal units (quads) (1 quad = 10¹⁵ Btu = 25.22 million tons of oil equivalent (Mtoe) = 2.93 x 10⁸ MWh), and the U.S. consumed 97.7 quads in 2017.
Figure 1.2: Estimated U.S. Energy Consumption in 2017 [2]
The biggest takeaway from this diagram is the quantity of rejected energy – over 2/3 of energy in the U.S. does not go towards the intended service. This rejected energy consists of losses such as those related to the efficiency of internal combustion engines and the thermal efficiency of electric generating units. Total rejected energy amounts to 66.7 quads and is associated mostly with burning carbon-rich fossil fuels like coal, natural gas and petroleum. The rejected energy cannot be eliminated due to physical and thermodynamic limits, but it can be reduced. Reduction in rejected energy, known as energy efficiency, is clearly the largest single way to reduce energy consumption and CO₂ emissions.

Another important aspect to investigate is energy conservation, which consists of reducing the numbers in the pink boxes on the right of Figure 1.2 – through decreased energy use for residential, commercial, industrial, and transportation services. Good examples of energy conservation are increasing one’s thermostat setpoint in the summer months to reduce air conditioning load or choosing to hold a video conference for a business meeting instead of flying for an in-person meeting. Incidentally, energy conservation reduces both rejected energy and energy services. Finally, the last way to reduce CO₂ emissions is through changing the primary energy sources, shown in the boxes on the left. To hit the IPCC target of net zero by 2055, the boxes for natural gas, coal, and petroleum must shrink to zero, be offset through carbon sequestration and storage, or some combination of the two.

Looking at Mines in particular, as seen in Figure 1.3, the university’s energy consumption is like that of other commercial sector energy consumers. This diagram is an estimate based on Mines energy bills and key efficiency assumptions of 90% for hydro, 15% for solar, 40% for wind, 33% for coal, 43% for...
natural gas, and 65% for all end-use loads. There are diesel-powered back-up generators set on campus, but this energy consumption is not included because it is only used on an emergency basis. Mines purchases all electricity and natural gas from the local utility Xcel Energy, also known as Public Service Company of Colorado. The leading sources of primary energy for Mines are natural gas, followed by coal, wind, solar, and hydro. If Mines is to reach net-zero CO$_2$ emissions, there are two real possibilities: 1) electricity generation from coal and natural gas must fall to zero and be replaced by renewable generation while natural gas loads are replaced by electric or renewable equivalents; or 2) emissions must be offset by carbon capture and storage. In reality, the solution will be a combination of the two, along with significant energy efficiency and conservation measures. In our research we focus on the electric generation component, and leave the natural gas loads, carbon offsets, energy efficiency, and energy conservation to future work.

The goal of this research is to evaluate the technical and economic feasibility of implementing rooftop photovoltaic (PV) and battery energy storage system (BESS) at the Colorado School of Mines, Golden, CO (Mines). Looking back at Figure 1.2 and Figure 1.3, this proposed system consists of a reduction in the ribbons connecting natural gas, coal, wind, and hydro to electric generation, and an increase in the ribbon connecting solar to electric generation. It does not result in a reduction in the size of the commercial energy consumption box, just a change in primary energy consumption. The proposed design enables Mines to save in electricity costs, reduce its carbon footprint, and to create a living experiment to improve educational and institutional capabilities in this field.

Photovoltaic (PV) power and battery energy storage systems (BESS) are of primary interest, as these two technologies are cost-effective at small sizes, and can provide reliable electricity that reduces the CO$_2$ footprint of the campus. Wind power is not practical on this small campus due to lack of suitable sites and unfavorable economics at small sizes. The study simulates hourly campus energy usage and on-site generation for the years 2019-2043. The optimization identifies the PV and BESS that minimizes the net present value (NPV) of electricity costs during 2019-2028 and 2019-2033, thus finding the designs that maximize economic benefit over 10 and 15-year payback periods, respectively.

1.1. Motivation

The mission statement for the Mines is “Education and research in engineering and science to solve the world’s challenges related to the earth, energy and the environment”. Our research team believes strongly in this goal, and it is the main motivation for this research. We seek to promote energy sustainability, reduced energy consumption, and a smaller carbon footprint on the Mines campus by providing an engineering-based sustainability strategy with practical solutions that also lower the overall cost of campus operations.
1.2. Scope

The limited scope of this research is to select an optimal design for an integrated photovoltaic (PV) system and battery energy storage system (BESS), also known as solar plus storage. This research does not seek to reduce or shift the timing of electric loads at Mines (load shifting), but only to find the lowest cost way to serve this load. Although addressing natural gas consumption is an important part of sustainability at Mines, we do not analyze natural gas in this research and that is left to future work. The load forecast estimates future electric demand and predicts that the load will increase as the campus grows. This forecast is a fixed quantity, and the optimization does not investigate ways to change the forecast. This study also investigates the implications on this project if Mines adopts a voluntary carbon price in its planning. The time horizon for this study is 25 years, beginning in 2019. The primary tasks are: 1) to develop a baseline energy model and forecast for the analysis period; and 2) to develop an optimal design for a solar plus storage system. This methodology is a combination engineering and economic model that seeks to select the ideal high-level engineering design.

This scope differs from other renewable optimizations in that it does not use a single test year as an input, but instead a 25-year forecast. This is important in the case of Mines, since the campus expects to see significant expansion in the future. The forecasting approach is easily extended to other cases and provides a quick-to-implement improvement over other renewable optimization software. Additionally, this scope includes the optimization of the PV tilt and azimuth angles, which is not available in other renewable optimization software.

This thesis is a detailed analysis of one aspect of a comprehensive sustainability strategy. There are many aspects of sustainability, including water, waste management, and resource efficiency, and energy is just one component. Within the energy sector, electricity is also only a fraction of the problem. The goal is not to solve the entire problem of sustainability at Mines, but to study one aspect of it, electricity, and propose a practical solution.
CHAPTER 2: LITERATURE REVIEW

In this literature review, we examine some selected similar projects at other universities and other methodologies to address similar problems.

2.1. University Campus Sustainability Projects

There are many other similar projects regarding sustainability, microgrids, and solar plus storage at other institutions, such as commercial facilities and armed forces bases. In this literature review, we focus on some selected other universities, as these types of institutions have a unique set of characteristics, such as their focus on research, education, and desire to attract funding for their programs. These traits often spur on more aggressive and more cutting-edge investments in sustainability projects than in other sectors of the economy.

2.1.1. Stanford

Stanford completed construction of its novel Stanford Energy System Innovations (SESI) facility in 2015 [3]. This $485 million project includes an electric-powered central heat pump that provides chilled and hot water for the entire campus. SESI also includes a switch from steam to hot water, and an agreement with SunPower (a developer) to build a 78.5 MW of solar PV plant, with 5.5 MW on the Stanford campus. Since chilled water and hot water are nearly always supplied at the same time, the SESI plant was equipped with a heat recovery heat exchanger between the chilled and hot water loops as an energy efficiency measure.

This project is part of a larger energy and climate plan at Stanford, which consists of planning principles, carbon dioxide emissions inventory, new construction design standards, and energy efficiency in existing buildings [4]. Although it is not currently powered entirely by renewable energy, SESI enables the possibility that all building heating and cooling loads can be served without emitting carbon dioxide. This is an expensive and experimental project that is a vision into a future in which the “electrify everything” ethos is applied more widely.

2.1.2. UC San Diego

University of California at San Diego (UCSD) implemented one of the country’s first microgrids. The system consists of a combined heat and power facility (CHP) with two 13.5 MW gas turbines and one 3 MW steam turbine, a 1.2 MW solar PV installation, and a 2.8 MW fuel cell that together provide 85% of campus electricity, and 95% of heating and cooling. The fuel cell runs on waste methane gas from nearby Point Loma Wastewater Treatment Plant, and is coupled with an absorption chiller, which uses the fuel cell waste heat to generate chilled water. A 300-kW solar thermal installation provides hot water to a portion of campus housing. There are also significant energy storage projects. Two lithium-ion batteries provide a combined 2.75 MW and 5.5 MWh in electricity storage (2-hour duration), and a chilled water thermal energy storage system provides 7 million gallons of chilled water storage.
The campus also has numerous energy storage demonstration projects, including a lithium polymer battery, a 2nd Life battery, and an ultra-capacitor bank for smoothing PV output. While it is not majority renewable, the microgrid has reduced carbon dioxide emissions and has allowed UCSD to meet its reliability and resiliency goals. In addition, monthly energy savings are estimated to be $850,000 per month. Moreover, UCSD has become a cutting-edge test-bed for microgrid technologies, which has awarded the university significant intangible benefits. [5] [6] [7]

2.1.3. Arizona State University

Arizona State University (ASU) plans to achieve carbon neutrality on all its campuses by 2025, and it is backing up this goal with action. ASU has the most PV of any university in the US, with 24.1 MW on-site and 28.8 MW off-site, including rooftop, parking lots, and ground-mounted installations. ASU also purchases renewable energy credits (RECs) to offset the remainder of its carbon dioxide emissions, and to help achieve its carbon neutrality goals. [8]

2.1.4. CU Boulder

University of Colorado at Boulder (CU Boulder) has a 31 MW gas-fired CHP plant, which is credited with avoiding 16,400 metric tons of carbon dioxide emissions per year. CU Boulder has 13 PV arrays on campus, including one car port, totaling 2.1 MW in capacity. CU Boulder has also engaged in several energy savings performance contracts (ESPCs) to improve building energy efficiency. In a partnership with NREL, CU Boulder received a DOE grant to build a 15kV microgrid on its East Campus that will have full islanding capability and renewable energy. REopt will be used to identify the most economic generation sources to support this microgrid project. [9] [10] [11] [12]

2.1.5. Colorado State University

As part of the Fort Collins Zero Energy District (FortZED) initiative and the city’s goal of 100% renewable energy by 2030, Colorado State University (CSU) has implemented a significant amount of PV and several innovative demonstration projects. The Powerhouse is platinum level LEED building completed in 2014 which hosts the Energy Institute, and exhibits many cutting-edge building technologies, including thin-film PV, 24-V DC circuits, and an evaporative cooling system. CSU has also installed 5.3 MW of PV at the Foothills Campus — enough to power one-third of the Foothills Campus annual energy, and 6.7 MW overall. There is also an 18.9 kW PV array on CSU’s Engineering Building.

CSU also constructed a biomass heating plant on the Foothills Campus that burns wood chips to produce hot water. Wood chips are sourced primarily from mountain pine beetle management and fire mitigation projects, making these a renewable source. In addition to other efficiency projects, CSU retrofitted their central heating plant on the main campus with an 800kW steam turbine to enable CHP. [13] [14] [15] [16]
2.1.6. Colorado School of Mines

Mines has taken several important steps in recent years towards sustainability. In 2011, Mines entered an Energy Savings Performance Contact (ESPC) with McKinstry, an outside consulting and construction engineering company, to improve building energy efficiency and to save on energy bills [17]. Construction was completed in March 2012, and included extensive lighting replacement and occupancy sensor installations, along with heat recovery on fume hoods and general exhaust in lab buildings Coolbaugh Hall, Alderson Hall, and Hill Hall. In 2014, Mines entered a second ESPC with McKinstry [18]. The new scope involves chiller replacement, additional lighting and occupancy sensors, and several smaller HVAC efficiency projects. Finally, there are potential plans to install a large PV array on a new parking structure.

There is a requirement for all new buildings at Mines to meet at least the LEED Gold standard, which has components related to energy efficiency and renewable energy. However, Mines doesn’t have a comprehensive plan for the foreseeable future dedicated to overall sustainability study like the other institutions discussed earlier. The Mines campus is also distinctly different from other large campuses mentioned earlier due its small size in both population and campus footprint.

2.2. Renewable Optimization Software

Identification of the optimal size of a solar plus storage system is a well-known problem addressed in literature and by several software options. However, due to the significant load growth expected on the Mines campus, and major changes planned to the local utility’s generation portfolio, a custom-built optimization algorithm is designed in this thesis. The pros and cons of the two most commonly used software offerings are discussed below.

2.2.1. HOMER® Energy

HOMER Energy is one of the leading software offerings for modeling solar plus storage systems and selecting the optimal size of each. The software was originally developed at the National Renewable Energy Lab (NREL) and then spun off into a private company. The original software HOMER Pro is intended for planning a true microgrid, in which on-site power is used to meet all electric needs. A newer software HOMER Grid is intended for the cases like this study, where a customer receives a portion of their power from on-site generation and the rest from the grid [19].

Users start with a load profile of their home, business, or organization from a given test year, at an hourly or 15-minute interval. Users then specify which energy assets they are interested in and define the costs and design parameters. The user also defines the location of interest and the appropriate electricity rate structure. From these inputs, the output from energy assets, such as PV and wind, and the electricity bills are calculated. HOMER Grid also allows users to specify financial parameters, such as societal costs of emissions, tax credits, discount rate, utility cost escalation rate, and analysis period.
length. Once all the inputs are defined, users run the simulation, and HOMER Grid simulates each potential design, along with dispatch, and presents the user with the best designs and their economic performance.

HOMER Grid has two options for optimization algorithms. The original algorithm is a grid search that simulates all possible designs defined by the constraints and selects the most cost-effective design. To improve runtime and precision, HOMER developed a new proprietary algorithm. The battery dispatch is determined for each possible design via a mix of optimization and heuristics. While it is not a true optimization, this hybrid method has been found to provide results consistent with an optimal battery dispatch strategy. Users can optimize the tilt and azimuth angles using the sensitivity analysis feature. Overall, HOMER Grid's methods allow the software to calculate meaningful and accurate results within a runtime of several minutes.

Although HOMER Grid is an established industry standard tool, was not used for several reasons. First, it uses a single test year of historical electric load data as an input instead of a longer-term forecast. Mines expects to see significant load growth in the coming years, so optimizing based on a historical year does not reflect the future Mines will face. HOMER Grid also does not support a time-varying cost of carbon dioxide emissions. Again, this is necessary to accurately model the future. The local investor owned utility Xcel Energy plans to make dramatic changes to its generation portfolio, which will decrease the CO₂ emissions from purchased energy significantly over time. Finally, with expected future work regarding battery dispatch algorithms, the custom optimization creates a platform that can be used to test these algorithms. HOMER Grid has its own method for determining battery dispatch and does not support testing of different control strategies.

2.2.2. REopt

Renewable Optimization (REopt) is a relatively new software created at NREL. The capabilities are like those of HOMER Grid, with the addition of energy efficiency and demand response. The primary application is to optimize the size and operation of behind-the-meter energy generation, storage, and energy-consuming devices. The scope is broader than HOMER Grid, in that REopt is intended to investigate load reduction and shifting as well. REopt has been used on many college campuses across the globe, including CU Boulder, Arizona State University, and Miami University of Ohio [20]. This software has also been applied to various other clients, including US Army and Navy bases, Time Warner Cable, Alcatraz Island, New York City, and a remote Alaskan Native Village [21].

REopt formulates the problem as a mixed-integer linear program (MILP) and uses optimization to select the optimal design and dispatch strategy [21]. This is different than HOMER, which uses a mix of heuristics and optimization to determine battery dispatch. REopt includes the dispatch within the same optimization problem as overall system design. As with HOMER Grid, a key input is a single test year of hourly or 15-minute interval load data. The optimization uses this test year to simulate the entire analysis
period consisting of many years. PV simulation is done with PVWatts, another NREL software created to estimate PV output and support the PV industry. REopt is accessed in this study via the REopt Lite online version, which uses the same methods as the full REopt, but with a limited scope. The input parameters are much the same as HOMER Grid, where the user must supply cost, location, design parameters, utility rate structure, and financial parameters. REopt Lite does not offer optimization of tilt and azimuth angles, though this limitation could be overcome by using a parametric search approach, by calculating results from REopt Lite using many different tilt and azimuth angles.

![Figure 2.1: REopt Key Inputs and Outputs](image)

REopt software was not used for the same reasons as HOMER Grid: the use of a single test year and a single value for the cost of carbon dioxide emissions does not reflect the future Mines will face; and it does not create a platform for testing battery dispatch strategies and algorithms.
CHAPTER 3: CURRENT STATE

Mines is a small public university in Golden, Colorado that was founded in 1874 and sits on approximately 500 acres in a suburban setting. As of 2018, Mines had 6,268 students enrolled. The campus is growing and is assumed to eventually grow to 8,000 students. The climate in Golden, CO is quite sunny and temperate, making it a good location for PV. Wind generation was not considered due to lack of suitable sites and impracticality on the small Mines campus.

![Colorado School of Mines Campus](image)

The Mines campus currently has two main sources of energy – electricity and natural gas. Mines also consumed small amount of diesel fuel in its back-up generator sets, but this is not analyzed because it is only used for back-up power. Electricity and natural gas are purchased from Xcel Energy, a large investor-owned utility (IOU) and leader in wind generation, with 23% wind as of 2018 [23]. Steam is generated on-site at a central natural gas-fired heating plant and distributed across the campus primarily for space heating, domestic hot water, and for operating absorption chillers. Chilled water is also generated on-site at several chiller plants and distributed across the campus for space cooling. The chiller plants are a mix of electric chillers and absorption chillers, which use steam as the main energy input to generate chilled water. Electricity is used for numerous electric loads on campus, including lighting, computer loads, chilled water production, and ventilation. Natural gas is used mostly for steam generation, though it is also used for small domestic loads.
According to monthly bills collected from the internal tracking website [24], Mines spent $3.41M in 2018 on electricity and natural gas bills, with electricity making up the 76% of the cost. From an energy perspective, presented in Table 3.1 below in millions of British thermal units (MMBTU)\(^1\), natural gas made up 60% of total energy consumption in 2018. On CO\(_2\) emissions, as calculated in section 5.2.3.3 based on the EPA’s estimated societal cost of carbon, electricity made up 66% of the over 30,000 tons and $1.69M in societal costs in 2018. The cost of electricity has been relatively stable over time while the cost of gas has seen more volatility in prices.

Starting in 2018, natural gas consumption increased dramatically when construction of the new heating plant was completed. For historical context, the Mines heating plant was originally built in 1948,\(^2\)

---
\(^1\)M in MMBTU stands for \(10^3\) and not million. M in $1.69M stands for million.
and used coal-fired boilers as the primary source of steam. This plant continued operation until 1982, when a new steam line to the Coors Brewery was built. Between 1982 and 2017, Mines engaged in a utility purchase agreement of waste steam from the Coors plant; the 24/7 boiler operation on campus ceased; and the Heating Plant became a source of backup capacity for steam. The primary reason steam from the Coors plant is no longer available is that the pipeline is beyond its useful lifetime and needs replacement. In late 2017, construction of the new gas-fired boilers was completed, and Mines now has a capacity of 55,000 MBH (thousands of BTU per hour).

### Table 3.1: Energy and CO$_2$ Summary 2018

<table>
<thead>
<tr>
<th>Commodity</th>
<th>Total Cost</th>
<th>Total Cost (%)</th>
<th>MMBTU</th>
<th>MMBTU (%)</th>
<th>Cost per MMBTU</th>
<th>Tons of CO$_2$</th>
<th>CO$_2$ Cost</th>
<th>CO$_2$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity</td>
<td>$2.60M</td>
<td>76%</td>
<td>127,332</td>
<td>40%</td>
<td>$20.41</td>
<td>20,439</td>
<td>$1.12M</td>
<td>66%</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>$0.81M</td>
<td>24%</td>
<td>194,983</td>
<td>60%</td>
<td>$4.14</td>
<td>10,348</td>
<td>$0.57M</td>
<td>34%</td>
</tr>
<tr>
<td>Total</td>
<td>$3.41M</td>
<td>-</td>
<td>322,315</td>
<td>-</td>
<td>$10.57</td>
<td>30,787</td>
<td>$1.69M</td>
<td>-</td>
</tr>
</tbody>
</table>

On the electric side, the campus is served by a single 13.2kV overhead feeder, originating from Lookout Substation approximately three miles away. The substation and feeders serving the Mines campus have a total capacity of 11.7 MW [25]. The current peak electrical demand as measured by Xcel Energy is approximately 6.45 MW, so Xcel can supply an additional 5.25 MW of power from the existing substation and feeders, if necessary. The revenue meter is located at the interconnection point with Xcel. Mines is enrolled in the Primary General rate, which means it receives medium voltage service from Xcel, and steps down to service voltages using its own equipment. This arrangement offers a lower rate relative to low-voltage secondary service, since the customer must operate and maintain its own distribution network. Medium voltage is distributed in an open loop configuration around the campus, and step-down transformers provide the desired service voltage to each building.

Summer months typically have the highest electric load due to large cooling requirements, and the record peak load thus far was 6.45MW in September 2018. Mines has a total consumption over 36,000 MWh annually, and as seen in Figure 3.3, the total electricity bill each month is well over $200,000. Overall, Mines pays approximately $70/MWh (or 7.0/kWh) for electricity. Since Mines has a demand charge, cost varies over the years depending on the ratio of electricity consumption to the peak demand, known as the load factor. Winter months typically have the highest natural gas consumption due to large heating requirements. As seen in Figure 3.4 natural gas bills vary from $40,000 in the summer to over $100,000 in the winter, and consumption varies from less than 100,000 to over 240,000 therms (1 therm = BTU * $10^5 = MMBTU * $10^4$).
Figure 3.3: Electricity Monthly Costs and Consumption 2018
When natural gas and electricity are compared in the same units of energy, MMBTU, it is apparent that total energy consumption peaks in the winter due to heating loads, which are served mainly by burning natural gas in the central heating plant. As seen in Figure 3.5, energy consumption from natural gas is slightly less than energy consumption from electricity in the summer months but is much higher in the winter. As seen in Table 3.1, despite its lower overall energy consumption, electricity is the main contributor to CO$_2$ emissions.

While Xcel has a relatively clean generation fleet, it still has 44% coal-fired generation and 28% natural gas [23]. Burning one MMBTU of coal and natural gas produces 93.3 kg and 53.07 kg of CO$_2$, respectively. Additionally, the efficiency of the power plants plays a major role in the CO$_2$ emissions. On
average, the fleet of coal and natural gas power plants in the United States have overall efficiencies of 33% and 43% respectively. This means that to produce one MMBTU of electricity with natural gas in the United States, it takes over 2.3 MMBTUs of natural gas, which results in 122 kg of CO₂ emissions. For coal this number is 287 kg of CO₂ per MMBTU of electricity. [26]

Figure 3.5: Overall Energy and CO2 Consumption 2018
In this research we focus on the larger problem of CO$_2$ emissions associated with electricity consumed on the Mines campus. To reduce the CO$_2$ emissions associated with natural gas, Mines will need to investigate other ways to heat its buildings aside from burning natural gas to produce steam. This may involve using renewable fuel sources for the heating plant and keeping the steam distribution system, or by switching to electric heat pumps. Any option would be aided by significant efficiency improvements. Waste-to-energy, or burning trash, is one option for an alternative feedstock, though the scale required, expense, and emissions from such a plant make it unlikely to be adopted at Mines. A more likely option is wood or biomass, in the form of agricultural waste, or renewable natural gas, such as landfill gas. Further study on this topic is required to determine the cost, feasibility, and societal impacts of alternative fuels to natural gas.

3.1. Electric Load Profile

The source data in this section is Mines campus electric hourly load data collected from Xcel Energy, covering the years 2008 to 2016. This raw data is plotted in Figure 3.6 and Figure 3.7 below. Without any further analysis, two aspects of Mines electric load are clear just from this plot. First is the seasonal trend. Note that January 1st each year occurs above the year label in Figure 3.7. As expected for a university in a temperate climate, load is highest during late summer and fall, declines steeply during the holidays when students leave, and gradually increases throughout the spring as air conditioning requirements increase.

![Figure 3.6: Hourly Load Data for Mines Campus 2016](image-url)
The second obvious trend is the rapid load growth Mines has seen during the nine years shown in Figure 3.7. Comparing 2008 to 2016, the peak load increased from about 4.75 MW to about 6.25 MW—an increase of 1.5 MW, representing an increase of 32% over the 2008 peak load. Looking at the minimum load, there is an increase from about 2 MW to about 3 MW over the same period, which means Mines has added approximately one MW of load that is always on, known as the base load. This is an increase of 50% in its base load.

When we normalize by number of students enrolled at Mines, as seen in Figure 3.8, we see a slight downward trend in kW per student on both a peak and average basis. Note that the trend is weak, since if we remove 2008 the trend is slightly upward. Overall, we see that even though the load increases over time, it stays relatively constant when normalized by number of students. This indicates that the load growth can be estimated reasonably well given a forecast of the number of students.

There are several other trends in the data that are evident after further inspection: the typical daily load cycle; the difference between business days and weekdays/holidays; and the relationship to outdoor air temperature.
Figure 3.8: Hourly Load Data for Mines Campus 2008 – 2016 Normalized by Number of Students

Figure 3.9 and Figure 3.10 show the average daily load curves in 2016 for July and January. To produce these plots, we take the raw data, group it by month, hour, and day type (business day vs. weekend/holiday) and calculate the average load for each month/hour/day type combination. For example, take a month with 30 days total and 22 business days. To calculate the average load at 3pm on business days, we take the 22 values corresponding to business days at 3pm in that month and average them. This is done for each hour and day type combination for July 2016 and January 2016 to produce Figure 3.9 and Figure 3.10. Overall, the daily load curves follow trends typical of many commercial or institutional loads. The minimum load for each day occurs in the early morning between 3am and 5am, and the maximum load occurs sometime between noon and 3pm. There is a roughly linear morning ramp that begins at 3am and continues through the morning until approximately 11am. From 11am to 3pm the load remains relatively constant, and then follows a roughly linear decline until the minimum.

From these load profile plots, it is also easy to see the seasonal and business day vs. weekend/holiday trends. Load is significantly higher in July compared to January, due primarily to the air-conditioning load. Heating loads are significant in January, but since heat is provided by steam, heating requires relatively small electric loads associated mostly with running pumps to distribute steam around the campus. Further analysis of these load profiles could be used to estimate the magnitude of the air-
conditioning end-use load profile. Comparing business days to weekends, we see that business days have much higher loads than weekends and holidays due to less occupancy in all buildings. It is good to see that even students and faculty at Mines get to take a break on the weekend.

Figure 3.9: July Load Profile 2016

Figure 3.10: January Load Profile 2016
The average daily load curves for all months of 2016 are shown below in Figure 3.11. The overall shape of the load curve is similar from month-to-month and on business days and weekends, but the magnitude changes. July has the highest average load and December has the lowest. Load on business days can exceed weekends and holidays by a full MW.
The annual load duration curve (8,760 hours) for 2008 through 2016 is shown in Figure 3.12 below. In 2016, the maximum load was just above 6MW, and the load seldom dropped below 3MW. The median load was about 4MW, and there were about 1,000 hours in which the load exceeded 5MW. In 2008, the maximum load was well below 5MW; the minimum load was 2MW; median load was about 3MW; and there were about 1,000 hours in which the load exceeded 4MW. This plot reaffirms the conclusion that the 2008 to 2016 period was quite fast in load growth for Mines.
To delve further into this load growth, the trends in peak and mean load for 2008 – 2016 are shown in Figure 3.13 below. There is a roughly linear increase in both peak and mean load during this period, with peak load growing faster than mean load. Peak load increased from 4.71 MW in 2008 to 6.23 MW in 2016 – an increase of over 1.5 MW (about 0.2 MW per year). Meanwhile the mean load increased from 3.11 MW in 20018 to 4.13 MW in 2016 – just over 1 MW (or about 0.13 MW per year) of change. The load factor, defined as the mean load divided by the peak load, varied over the years between 0.634 and 0.667. These are typical load factors for institutional loads.

![Figure 3.13: Load Growth 2008 – 2016](image)

To delve even further, the increasing trends within each month can be seen in Figure 3.14 below. It is evident that all months exhibit this linear increase in peak and mean load, but that the summer months (June – September) have seen the largest rate of increase.

In addition to the daily, monthly, annual, and business day vs. weekend/holiday trends, there is also a strong correlation between ambient temperature and electric load. This relationship can be attributed to air conditioning load, which exhibits a roughly linear relationship with degrees above 18°C (64.4°F) — the temperature at which cooling loads will start-up. Figure 3.15 shows this relationship between load in MW on 2016 business days and ambient air temperature in degrees above 18°C.
Figure 3.14: Load Growth by Month 2008 – 2016
To establish a quantitative relationship between load and temperature, we first account for other trends in the data — namely month, hour of day, and day type (business day vs. weekend/holiday). We group the data by month, hour of day, and day type, then use linear regression to approximate the relationship between load and degrees above 18°C numerically for each month/hour/day type combination. Figure 3.16 shows one example combination, June at 12pm on business days, and the fitted line. For June business days at 12pm, the equation for the fitted line is:

$$E \approx 5.130116 + 0.047710 \times \text{(Degrees above 18°C)}$$

(3.1)

The first constant gives the average load at 18°C, and the second constant gives the slope relative to degrees above 18°C. Each month and hour combination has a unique linear fit equation. To find the typical incremental load caused by 1°C, each of the slopes were averaged. Results indicate that on average, 1°C above 18°C results in 0.0382 MW (38.2 kW) increase in load on business days and 0.0270 MW (27.0 kW) on weekends and holidays.
3.2. Campus Distribution

The campus distribution system consists of a single interconnection point with Xcel Energy, and a single underground medium voltage 13.2kV open loop circuit, rated for 600A, comprised primarily of 750 kcmil aluminum conductor [25]. The two branches of the loop are connected by a normally-open switch in the Stratton Vault. In the case of a failure in one of the two branches, this switch will close, and a portion of the load in the failed branch can be picked up by the other branch. Most buildings receive power from the loop, and others are fed directly from the Stratton Vault. Each building or set of buildings is fed by a transformer that steps the voltage down from 13.2kV to 480V and lower voltages. Mines plans to construct several new buildings to accommodate the growth in population, seen in Figure 3.17 and Figure 3.18.

In Table 3.2, Figure 3.17 and Figure 3.18, we show the transformer loading on the main campus. Most transformers are loaded less than 40%, though some are loaded higher, and are shown in red. On the left side of Figure 3.19, one can see two lines feeding other loads. This is the beginning of a second loop, that is expected to be implemented in the next few years. The future state can be seen in Figure 3.20. This second loop will be a closed loop that will serve the existing loads and several new buildings that are anticipated to be constructed soon. A new parking garage will be constructed, and this will be served by the same transformer as Green Center, fed from the Stratton Vault. In Figure 3.20, one can also see the new generator bank in the bottom right corner. This bank is connected to the main switchgear by a circuit breaker. The information here provides the current state of the campus.
distribution. No effort has been made in this thesis to make any analysis of the existing and future design philosophy adopted by the campus.

Table 3.2: Transformer Loading 2017

<table>
<thead>
<tr>
<th>Transformer Name</th>
<th>kVA</th>
<th>Buildings Served</th>
<th>2017 Peak kW</th>
<th>2017 Loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1B-1B</td>
<td>300</td>
<td>BROWN HALL/ CHILLER PLANT</td>
<td>414.72</td>
<td>14%</td>
</tr>
<tr>
<td>T1B-5A</td>
<td>2000</td>
<td>MARQUEZ HALL</td>
<td>623.37</td>
<td>31%</td>
</tr>
<tr>
<td>TSW-2</td>
<td>2000</td>
<td>HILL HALL</td>
<td>589.60</td>
<td>29%</td>
</tr>
<tr>
<td>TSW-5</td>
<td>2000</td>
<td>COORSTEK</td>
<td>623.37</td>
<td>31%</td>
</tr>
<tr>
<td>T1A-11B</td>
<td>1500</td>
<td>GENERAL RESEARCH LABORATORY</td>
<td>423.72</td>
<td>28%</td>
</tr>
<tr>
<td>T1A-13A</td>
<td>1500</td>
<td>COOLBAUGH HALL (NEW)/ COOLBAUGH HALL EMERGENCY (NEW)</td>
<td>246.40</td>
<td>16%</td>
</tr>
<tr>
<td>T1A-3A</td>
<td>1500</td>
<td>EARTH MECHANICS INSTITUTE</td>
<td>137.28</td>
<td>9%</td>
</tr>
<tr>
<td>T1B-1A</td>
<td>1500</td>
<td>BERTHOUD HALL</td>
<td>235.20</td>
<td>16%</td>
</tr>
<tr>
<td>T1B-3B</td>
<td>1500</td>
<td>ALDERSON HALL</td>
<td>467.53</td>
<td>31%</td>
</tr>
<tr>
<td>T2-2B</td>
<td>1500</td>
<td>ELM HALL</td>
<td>397.40</td>
<td>26%</td>
</tr>
<tr>
<td>T1A-10A</td>
<td>1000</td>
<td>LAKES LIBRARY/ CHILLER PLANT NO. 4</td>
<td>346.50</td>
<td>35%</td>
</tr>
<tr>
<td>T1A-13B</td>
<td>1000</td>
<td>COOLBAUGH HALL (OLD)</td>
<td>537.80</td>
<td>54%</td>
</tr>
<tr>
<td>T1A-2A</td>
<td>1000</td>
<td>STUDENT CENTER</td>
<td>174.80</td>
<td>17%</td>
</tr>
<tr>
<td>T1A-4A</td>
<td>1000</td>
<td>STADIUM</td>
<td>311.69</td>
<td>31%</td>
</tr>
<tr>
<td>T1B-2A</td>
<td>1000</td>
<td>USGS</td>
<td>214.24</td>
<td>21%</td>
</tr>
<tr>
<td>T1B-5B</td>
<td>1000</td>
<td>CHILLER PLANT NO. 5</td>
<td>311.69</td>
<td>31%</td>
</tr>
<tr>
<td>T2-7A</td>
<td>1000</td>
<td>RECREATION CENTER</td>
<td>352.20</td>
<td>35%</td>
</tr>
<tr>
<td>TSE-5</td>
<td>1000</td>
<td>GREEN CENTER/FUTURE PARKING GARAGE</td>
<td>296.64</td>
<td>30%</td>
</tr>
<tr>
<td>T1A-3B</td>
<td>750</td>
<td>GRL ANNEX</td>
<td>254.00</td>
<td>34%</td>
</tr>
<tr>
<td>T1B-4A</td>
<td>750</td>
<td>CTLM</td>
<td>233.76</td>
<td>31%</td>
</tr>
<tr>
<td>T1A-11A</td>
<td>560</td>
<td>VOLK GYM/ FIELD HOUSE</td>
<td>174.54</td>
<td>31%</td>
</tr>
<tr>
<td>T1A-5C</td>
<td>560</td>
<td>Soccer/Track CREEK SIDE DEVELOPMENT</td>
<td>174.54</td>
<td>31%</td>
</tr>
<tr>
<td>T1A-9A</td>
<td>500</td>
<td>GUGGENHEIM HALL</td>
<td>65.40</td>
<td>13%</td>
</tr>
<tr>
<td>T2-2A</td>
<td>500</td>
<td>WEAVER TOWERS</td>
<td>92.10</td>
<td>18%</td>
</tr>
<tr>
<td>T2-6A</td>
<td>500</td>
<td>MAPLE HALL</td>
<td>155.84</td>
<td>31%</td>
</tr>
<tr>
<td>TSE-4</td>
<td>500</td>
<td>STRATTON HALL</td>
<td>78.84</td>
<td>16%</td>
</tr>
<tr>
<td>T1A-5A</td>
<td>336</td>
<td>DARDEN FIELD</td>
<td>18.00</td>
<td>5%</td>
</tr>
<tr>
<td>T1A-12A</td>
<td>300</td>
<td>HEATING PLANT</td>
<td>90.72</td>
<td>30%</td>
</tr>
<tr>
<td>T1A-2C</td>
<td>300</td>
<td>BRADFORD, THOMAS, MORGAN, STUDENT DEVELOPMENT CENTER, 1404 MAPLE</td>
<td>63.68</td>
<td>21%</td>
</tr>
<tr>
<td>T1A-8B</td>
<td>300</td>
<td>SORORITIES</td>
<td>40.08</td>
<td>13%</td>
</tr>
<tr>
<td>T2-1A</td>
<td>300</td>
<td>HEALTH &amp; WELLNESS</td>
<td>93.51</td>
<td>31%</td>
</tr>
<tr>
<td>T2-3A</td>
<td>300</td>
<td>WELCOME CENTER</td>
<td>122.80</td>
<td>41%</td>
</tr>
<tr>
<td>TSE-2</td>
<td>300</td>
<td>CHAUVENET HALL</td>
<td>154.00</td>
<td>51%</td>
</tr>
<tr>
<td>TSW-4</td>
<td>300</td>
<td>ENGINEERING HALL/ MATERIALS SCIENCE</td>
<td>76.80</td>
<td>26%</td>
</tr>
<tr>
<td>T1A-7A</td>
<td>150</td>
<td>TEMPORARY MODULAR UNITS #2, #3 &amp; #4</td>
<td>84.00</td>
<td>56%</td>
</tr>
<tr>
<td>T1B-3A</td>
<td>150</td>
<td>UNIT OPS</td>
<td>223.20</td>
<td>149%</td>
</tr>
<tr>
<td>T1A-11C</td>
<td>112.5</td>
<td>PLANT FACILITIES/ TRUCK SHOP/ HAZ. MAT. STORAGE</td>
<td>135.58</td>
<td>121%</td>
</tr>
<tr>
<td>T1A-2B</td>
<td>112.5</td>
<td>RANDALL HALL</td>
<td>21.68</td>
<td>19%</td>
</tr>
<tr>
<td>T1A-1A</td>
<td>75</td>
<td>INTRAMURAL FIELDS</td>
<td>59.46</td>
<td>79%</td>
</tr>
<tr>
<td>T1A-6A</td>
<td>75</td>
<td>BUILDING GENERAL MAINTENANCE</td>
<td>23.38</td>
<td>31%</td>
</tr>
<tr>
<td>T1A-8A</td>
<td>50</td>
<td>STREET LIGHTING PANEL</td>
<td>15.58</td>
<td>31%</td>
</tr>
<tr>
<td>T1A-5B</td>
<td>15</td>
<td>&quot;M&quot; SIGN LIGHTING</td>
<td>4.68</td>
<td>31%</td>
</tr>
</tbody>
</table>
Figure 3.17: Buildings on Mines Main Campus and Transformer Loading 2017
Figure 3.18: Buildings on Mines Main Campus and Transformer Loading 2022 (Projection)
Figure 3.19: Campus One-Line 2017
3.3. Reliability

To ensure critical loads can be served during an outage, many buildings are equipped with emergency diesel generators with automatic transfer switches. Typically, these generators are sized to support emergency lighting, fire alarms, ventilation, elevators, and computers. These emergency loads are connected to a separate emergency circuit in the building. When power from Xcel is available, the building transformer serves both the emergency and regular circuits. When an outage occurs, the automatic transfer switch (ATS) disconnects the emergency load and reconnects to the generator, leaving the regular load without power. Any analysis of such design philosophy and details is again beyond the scope of this thesis.

Table 3.3: Emergency Generators by Building

<table>
<thead>
<tr>
<th>Building</th>
<th>Peak Demand (2017/2018) (kW)</th>
<th>Emergency Generator Size (kW)</th>
<th>Percent Back-Up (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marquez Hall</td>
<td>1,296</td>
<td>600</td>
<td>46%</td>
</tr>
<tr>
<td>Brown Hall</td>
<td>462</td>
<td>450</td>
<td>97%</td>
</tr>
<tr>
<td>Hill Hall</td>
<td>680</td>
<td>400</td>
<td>59%</td>
</tr>
<tr>
<td>Alderson Hall</td>
<td>548</td>
<td>350</td>
<td>64%</td>
</tr>
<tr>
<td>Coolbaugh Hall</td>
<td>760</td>
<td>300</td>
<td>39%</td>
</tr>
<tr>
<td>Maple Hall</td>
<td>164</td>
<td>200</td>
<td>122%</td>
</tr>
<tr>
<td>Berthoud Hall</td>
<td>331</td>
<td>150</td>
<td>45%</td>
</tr>
<tr>
<td>Engineering Hall</td>
<td>108</td>
<td>80</td>
<td>74%</td>
</tr>
<tr>
<td>Volk Gym</td>
<td>322</td>
<td>50</td>
<td>16%</td>
</tr>
<tr>
<td>Student Center</td>
<td>496</td>
<td>47</td>
<td>9%</td>
</tr>
<tr>
<td>Weaver Towers</td>
<td>173</td>
<td>40</td>
<td>23%</td>
</tr>
<tr>
<td>CTLM</td>
<td>559</td>
<td>32</td>
<td>6%</td>
</tr>
<tr>
<td>Recreation Center</td>
<td>398</td>
<td>30</td>
<td>8%</td>
</tr>
<tr>
<td>Green Center</td>
<td>384</td>
<td>27</td>
<td>7%</td>
</tr>
<tr>
<td>Arthur Lakes Library</td>
<td>347</td>
<td>20</td>
<td>6%</td>
</tr>
<tr>
<td>Guggenheim Hall</td>
<td>115</td>
<td>15</td>
<td>13%</td>
</tr>
<tr>
<td>Stratton Hall</td>
<td>124</td>
<td>6</td>
<td>5%</td>
</tr>
<tr>
<td>Entire Campus</td>
<td>6,395</td>
<td>7,500</td>
<td>117%</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>6,395</strong></td>
<td><strong>10,296</strong></td>
<td><strong>161%</strong></td>
</tr>
</tbody>
</table>
To further improve the reliability of electric power supply, the campus installed in 2018 a diesel generator bank consisting of three, 2.5MW generators to serve as an emergency backup for the entire campus. These generators have enough capacity and fuel supply to power the campus for 24 hours. Mines participates in Xcel’s Interruptible Service Option Credit program, which compensates customers for reducing load at short notice during system peak times. In return for this load reduction capability, Mines expects to receive over $900k per year from Xcel [27]. Mines began receiving credit for the program in May 2018. In the summer months, June through September, bills collected from the Mines internal tracking website indicate Mines received approximately $89,100 per month, and approximately $69,500 per month in the winter months. Reiterating as before, analysis of these decisions is beyond the scope of this thesis.

While these generators can serve all of Mines’ electric load under all emergency scenarios, we do not investigate using these generators for bill reduction because this does not advance Mines toward its sustainability goals. The high CO₂ emissions from burning diesel would cause an increase in emissions. To enable the generators to engage in peak shaving, building electric distribution and protection systems would need to be redesigned and rebuilt, at considerable expense. The three, 2.5MW backup generators are designed to operate in emergency island mode only, when power from Xcel is not available. While operating the diesel generator will generally be much more expensive than buying power from Xcel, there may be a business case in favor of running the generator just during peak load times to reduce the demand charge from Xcel. Again, this business case is not considered in the scope of this thesis due to the increase in CO₂ emissions such action would cause.
CHAPTER 4: POTENTIAL FOR SOLAR PLUS STORAGE

4.1. On-Site PV

On the Mines campus there is potential for four types of PV systems, presented in order from least cost to highest: 1) Fixed tilt, ground-mounted; 2) Ballasted flat rooftop; 3) Angled rooftop; and 4) Parking canopies. Fixed tilt, ground-mounted PV installations are generally sloped at the location’s latitude with respect to the ground (40° in the case of Colorado School of Mines) and pointed due South to maximize sun exposure. The ballasted flat rooftop system is designed in the same way, except the supporting structure is weighed down by ballast to keep the PV array secure. The angled rooftop system is tilted at the angle of the roof, whatever it may be. Solar parking canopies have a large support structure for a car to park under and are usually designed with only a few degrees of tilt. One and two-axis tracking systems are not analyzed for the flat rooftop design since these are uncommon and not cost-effective in this application.

![Ballasted Rooftop PV](image)

Figure 4.1: Ballasted Rooftop PV [28]

Currently, it is unknown if there is available ground space for installing ground-mounted PV. If there is, it will likely be in the Southwestern side of the campus, where it may be subject to significant afternoon shading due to the very close proximity to the mountains to the West. Since it is unknown if it is feasible to install such an array, this has been omitted from the study. Angled rooftop arrays are also not considered. It is unlikely that Mines would want to cover up the attractive Spanish tile roofs with solar panels. Additionally, there is ample flat rooftop space that can be developed at a lower cost.
To evaluate the potential for PV on the Mines campus and the trade-offs related to different design parameters, we model the PV output using NREL’s System Advisor Model (SAM) [31]. SAM allows users to create an hourly or sub-hourly simulation of a hypothetical PV system’s output. Users first define the PV system design parameters, such as the kW rating of the panels, the number of panels, the inverter type, and the tilt and azimuth angles. Users then load in a weather file, which simulates the atmospheric conditions to which the PV system would be exposed. SAM then uses a physics and engineering-based model to simulate the behavior of the hypothetical system under the atmospheric conditions defined in the weather file.
The weather input is a single year hourly dataset for Golden, CO for 2016, downloaded from the National Solar Radiation Database (NSRDB), created and maintained by NREL [33]. This weather file from NSRDB reflects actual weather observed via satellite during 2016. The key parameters in determining PV output are total solar radiation and ambient temperature. Since the data comes from satellites the solar radiation numbers do not account for shading due to surface terrain features such as mountains. To account for mountain shading, we scale down the simulated PV output from SAM using a conservative approach. See section 5.2.3.4 for more details.

The PV peak typically occurs at noon, and the timing of the peak load varies between noon and 3pm each day. This means that PV usually peaks before load. Ideally, PV would peak at the same time to maximize peak load reduction. Additionally, some of the PV energy production occurs in the morning before the peak energy rates begin. This is exacerbated by the prevalence of afternoon storms in Colorado, which reduces the average PV generation in the afternoon when it is most effective at reducing peak load. The PV peak can be shifted by increasing the azimuth angle above 180° (due South), thus angling the PV panels towards the Western sky and increasing efficiency in the afternoon. The drawback is that the overall energy generated by the system will be reduced.

To illustrate the trade-offs of using high and low azimuth and tilt angles, several plots are presented in Figure 4.6 below. As depicted in Figure 4.5, the tilt angle is the angle of the solar panels relative to the earth’s surface, shown as β, and the azimuth angle is the angle of the solar panels relative to North, shown as γ. Throughout the day, the azimuth angle of the sun increases and the sun moves from East to West across the sky. The elevation angle of the sun increases throughout the morning, reaches a peak at around noon, and decreases through the afternoon. In the summer months, the peak elevation angle of the sun is higher than in winter months. Overall, PV panels with a lower tilt angle will
catch more sun when the sun is higher in the sky, as occurs during summer months and towards the middle of the day. PV panels with an Eastward azimuth angle (less than 180°) will catch more sun in the morning.

Figure 4.5: PV-Sun Orientation Diagram [34]

Figure 4.6 is based on 2016 business days and PV simulation using SAM with a 180° azimuth angle and 34° tilt angle. In Figure 4.6, Figure 4.7, and Figure 4.8, values are given in per unit, where the bases are the peak load for 2016 for load and the nameplate PV kW rating for PV. Note that these are different bases, and the purpose is to compare the shape of the data and not the magnitudes. During the times inside of the dotted lines, Mines is subject to on-peak energy rates, which are 44% higher than off-peak. From Figure 4.6 it is evident that the peak of the PV output occurs before the peak load during every month, and that some of the PV generation occurs before 9am when peak energy rates come into effect.

Figure 4.7 is based on 2016 business days and PV simulation using SAM with varying azimuth angles and a 34° tilt angle. From Figure 4.7 it is evident that the peak of the PV output can be shifted to occur closer to the peak load during every month by increasing the azimuth angle.

Figure 4.8 is based on 2016 business days and PV simulation using SAM with a 180° azimuth angle and varying tilt angles. From Figure 4.8 it is evident that a lower tilt angle results in higher PV output in winter months, and a higher tilt angle is better in summer months. This makes sense due to the higher sun elevation angle in the summer. It is evident from all these plots that there are many
counterbalancing factors in designing the PV system, and that it is difficult to select these parameters using an analytical process. As such, optimization is used to find the best system design parameters.

Figure 4.6: Average Daily Per-Unit Load and PV Generation by Month
Figure 4.7: Average Daily Per-Unit Load and PV Generation by Month with Varying Azimuth Angles

Figure 4.8: Average Daily Per-Unit Load and PV Generation by Month with Varying Tilt Angles
To develop an upper bound on the total potential for PV potential on campus, Esri’s ArcMap Geographic Information System (GIS) software is used to measure the unoccupied flat rooftop and parking lot areas. The goal of this analysis is to establish an input into the optimization to prevent selection of an unrealistic value for the PV kW rating. This analysis is done visually based on satellite imagery, seen in Figure 4.9.

A typical commercial solar panel is assumed to be rated at 325W and is approximately 1m x 2m in size. This is about 1 kW/66.24 ft², assuming the panels are placed as tightly as possible. However, since the panels are tilted, they would shade each other if placed too closely. In SAM, the default value for PV spacing assumes the panels cover about 30% of the ground underneath. We take a conservative
estimate of 25% based on a tilt angle ($\beta$) of 34° and a minimum sun angle ($\alpha$) of 12.5°, the angle at which the sun drops below the mountains to the West. See Figure 4.10 for diagram and calculations, and section 5.2.3.4 for mountain shading details. On top of the prior assumptions, we assume that only 50% of the roof space that appears to be unoccupied in the satellite imagery will be suitable for PV. This accounts for setback requirements, equipment that can’t be seen on the satellite imagery, and other unknown factors that may limit PV development.

\[
\text{% Roof Coverage} = \frac{L \cdot \cos(\beta)}{L \cdot \cos(\beta) + \frac{L \cdot \sin(\beta)}{\tan(\alpha)}} = \frac{1}{1 + \frac{\tan(\beta)}{\tan(\alpha)}}
\]

Figure 4.10: Percent Roof Coverage Calculation

After dividing 1 kW/66.24 ft$^2$ by 25% to account for spacing on the roof and 50% for roof space that is not buildable, the result is an assumption of 1kW/530 ft$^2$. With these conservative numbers, the upper limit is nearly 1,200 kW for flat roof tops and over 2,150 kW for parking lots. These are not insignificant values, but even the upper bound is far less than the amount needed to supply all the power to the campus.
Table 4.1: Rooftop PV Potential by Building

<table>
<thead>
<tr>
<th>Building</th>
<th>SQFT</th>
<th>PV Max kW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green Center</td>
<td>78,181</td>
<td>148</td>
</tr>
<tr>
<td>Recreation Center</td>
<td>76,696</td>
<td>145</td>
</tr>
<tr>
<td>Stadium</td>
<td>60,216</td>
<td>114</td>
</tr>
<tr>
<td>Brown Building</td>
<td>55,039</td>
<td>104</td>
</tr>
<tr>
<td>Central Receiving</td>
<td>36,212</td>
<td>68</td>
</tr>
<tr>
<td>Alderson Hall</td>
<td>32,562</td>
<td>61</td>
</tr>
<tr>
<td>Student Center</td>
<td>30,301</td>
<td>57</td>
</tr>
<tr>
<td>Hill Hall</td>
<td>25,140</td>
<td>47</td>
</tr>
<tr>
<td>Arthur Lakes Library</td>
<td>24,549</td>
<td>46</td>
</tr>
<tr>
<td>Elm Hall</td>
<td>24,393</td>
<td>46</td>
</tr>
<tr>
<td>Maple Hall</td>
<td>23,012</td>
<td>43</td>
</tr>
<tr>
<td>Coolbaugh Hall</td>
<td>21,094</td>
<td>40</td>
</tr>
<tr>
<td>Weaver Towers</td>
<td>20,853</td>
<td>39</td>
</tr>
<tr>
<td>Marquez Hall</td>
<td>19,048</td>
<td>36</td>
</tr>
<tr>
<td>Volk Gym</td>
<td>17,663</td>
<td>33</td>
</tr>
<tr>
<td>Welcome Center</td>
<td>17,557</td>
<td>33</td>
</tr>
<tr>
<td>CTLM 2</td>
<td>17,378</td>
<td>33</td>
</tr>
<tr>
<td>Engineering Hall</td>
<td>11,457</td>
<td>22</td>
</tr>
<tr>
<td>USGS</td>
<td>8,910</td>
<td>17</td>
</tr>
<tr>
<td>Morgan Hall</td>
<td>8,327</td>
<td>16</td>
</tr>
<tr>
<td>Wellness Center</td>
<td>7,080</td>
<td>13</td>
</tr>
<tr>
<td>Bradford Hall</td>
<td>6,348</td>
<td>12</td>
</tr>
<tr>
<td>Thomas Hall</td>
<td>5,892</td>
<td>11</td>
</tr>
<tr>
<td>CTLM</td>
<td>5,467</td>
<td>10</td>
</tr>
<tr>
<td>Randall Hall</td>
<td>5,025</td>
<td>9</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>1,205</strong></td>
<td></td>
</tr>
</tbody>
</table>
Table 4.2: Parking Lot PV Potential

<table>
<thead>
<tr>
<th>Parking Lot</th>
<th>SQFT</th>
<th>PV Max kW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lot Q</td>
<td>195,781</td>
<td>369</td>
</tr>
<tr>
<td>Lot AA</td>
<td>143,047</td>
<td>270</td>
</tr>
<tr>
<td>Lot A</td>
<td>104,239</td>
<td>197</td>
</tr>
<tr>
<td>Lot F</td>
<td>96,109</td>
<td>181</td>
</tr>
<tr>
<td>Lot D</td>
<td>95,513</td>
<td>180</td>
</tr>
<tr>
<td>Lot I</td>
<td>86,226</td>
<td>163</td>
</tr>
<tr>
<td>Lot K</td>
<td>77,289</td>
<td>146</td>
</tr>
<tr>
<td>Lot CT</td>
<td>75,525</td>
<td>143</td>
</tr>
<tr>
<td>Lot FF</td>
<td>65,371</td>
<td>123</td>
</tr>
<tr>
<td>Lot E</td>
<td>61,032</td>
<td>115</td>
</tr>
<tr>
<td>Lot J</td>
<td>59,308</td>
<td>112</td>
</tr>
<tr>
<td>Lot Y</td>
<td>28,252</td>
<td>53</td>
</tr>
<tr>
<td>Lot B</td>
<td>21,403</td>
<td>40</td>
</tr>
<tr>
<td>Lot L</td>
<td>18,546</td>
<td>35</td>
</tr>
<tr>
<td>Lot C</td>
<td>15,834</td>
<td>30</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td>2,158</td>
<td></td>
</tr>
</tbody>
</table>

4.2. Battery Energy Storage System (BESS)

According to the Energy Information Agency (EIA) [35], “Over 80% of U.S. large-scale battery storage power capacity is currently provided by batteries based on lithium-ion chemistries.” For this reason, only lithium-ion batteries are considered in this analysis. Lithium-ion batteries are quite small in size, which accounts for their popularity in cell phones and electric vehicles. The volumetric energy density for Li-ion batteries ranges from 250 to 620 Wh/Liter [36]. Taking the low-end, worst-case values for volumetric energy density, a 1 MWh li-ion battery, which is larger than any optimal BESS identified in this thesis, would have a volume of 4,000 L (4m³). We can assume the actual space needed for the BESS is several times bigger than the volume of just the battery itself, to account for the cooling system and power electronics. The small size allows for a BESS to be contained within a relatively small space, perhaps within an existing building. Siting is more of an issue of electrical feasibility and fire safety. That is, where can Mines incorporate a large energy storage asset to minimize impact to the campus distribution system and comply with fire safety regulations? This is not addressed in this thesis and is left for future work.
4.3. Off-Site Renewables

While Mines does not have the physical space to support a wind energy installation, Mines could still gain credit for renewable energy and the associated reductions in carbon dioxide emissions if it supports new off-site wind and solar installations financially.

4.3.1. Renewable Energy Credits

In Colorado, the cheapest source of renewable energy is wind, so this is the obvious choice. Mines has an average electric load of about 4 MW. A typical wind turbine is 2-3 MW, with a 30-35% capacity factor. To provide entirely renewable energy to Mines, on a net basis, it only takes a few wind turbines. Customers typically support off-site renewable projects through the purchase of Renewable Energy Credits or through arrangements with their electric utility. It appears that Mines has not considered this option for offsetting its carbon dioxide emissions.

Windsource is a program offered by Xcel Energy to promote adoption of wind energy. The program is offered to both residential and commercial customers, but the costs are listed for residential customers only. The price for Mines to participate in this program would need to be negotiated with Xcel. Residential customers can buy 100 kWh of wind energy per month from Xcel for a surcharge of $1.50 per bill, up to the customer’s total usage for the month. Customers cannot purchase more wind energy than they consume. This equates to an add-on of 1.5¢/kWh, which is less than the cost of carbon dioxide emissions from Xcel Energy, calculated based on EPA’s estimate in section 5.2.3.3. Since it is cheaper than the cost of carbon dioxide emissions, the Windsource program is a good alternative to onsite generation if Mines adopts a carbon price in its planning decisions. This option must be investigated further. [37]

4.3.2. Carbon Offsets

Individuals and organizations who seek to counteract the CO₂ emissions from their activities can purchase carbon offsets. These offsets are offered by companies that can guarantee an avoided ton of carbon dioxide emissions and are certified by a third-party. Frequently these offsets are cheaper than modifying behavior to reduce carbon dioxide emissions, since the company selling the offsets can seek out the lowest cost way to avoid carbon dioxide emissions. Typically, this is done by developing renewable energy sources or by planting trees. As one example, CU Boulder has a partnership with Native Energy, which offers carbon offsets for $15.50 per metric ton, which is much cheaper than the cost to society of CO₂ emissions [38]. Individuals, labs, buildings, or departments can choose to purchase carbon offsets through a web portal provided on the CU Boulder website. If the recommended EPA price for CO₂ is adopted by Mines, this price of $15.50 per metric ton is a bargain and should be considered seriously.
CHAPTER 5: OPTIMAL SOLAR PLUS STORAGE DESIGN

The goal of the optimization in this thesis is to select the solar plus storage design that minimizes the net present value (NPV) of the electricity costs subject to a set of constraints. For the BESS, not only does the optimization choose how to size the system, but it also selects how and when the BESS is operated for each hour of the simulation. Before calculating the NPV of a proposed design, we first define the baseline energy model. This baseline model forecasts electricity consumption and costs in the future, given the information we have thus far at the writing of this thesis. This provides an economic comparison point, since any proposed design should at least be better than the baseline. The forecast also defines the electric load and consumption requirements in the future, which is an important input into the optimization.

5.1. Baseline Energy Model

In this section, we define the electrical load forecast in the base case. This forecast is used to define the electricity requirements for the future system, in terms of kWh and kW consumed during each hour of the 25-year analysis period. Note that kW and kWh are the same number when analyzed at an hourly interval. Long-term load forecasting is an art as well as a science. The purpose is not to create a forecast that is accurate for a given hour of the 25-year period, but to generate representative data that preserves the overall shape and growth trends during this period.

The forecast is based on historical data only and does not include the timing of known construction or equipment installations. For example, we know that Hill Hall has the largest electric load and its absorption chiller will be replaced with an electric chiller, which is certain to increase electric load on campus. In our forecast, this level of detail is not included, and is expected to be accounted for in our extrapolation of historical trends.

Overall, it is important to use a conservative approach and not overestimate the growth, since this will make solar plus storage unrealistically appealing. It is also important to maintain the shape of the data, including the peaks and valleys, and not to generate and overly smoothed forecast. This will change the operating principles and business case for the BESS since its purpose is to reduce peak load. An overly smoothed forecast will overestimate the load factor, hurting the business case for BESS.

We have investigated several forecasting methods in developing this thesis, but ultimately selected the method described below. In this case, the most realistic forecast is one that meets the following criteria: 1) Accurate annual growth rates for monthly peak loads, since these determine demand charges; 2) Accurate annual growth rates for overall energy consumption, since these determine energy and CO₂ charges; 3) Preservation of daily, weekly, and month-to-month trends that occur within each year, known as the “seasonality” of the data; and 4) Preservation of noise and unpredictability in the data, such that our forecast isn’t overly smoothed. For any load forecasting technique, it is important to use a historical dataset that is large enough to represent a full range of weather and loading conditions, but not
so large as to include data that is so far back in time that it does not represent the current system. Our research includes Auto-regressive Integrated Moving Average (ARIMA), linear, machine learning, and models, and we find that these methods have significant shortcomings for this application. [39]

ARIMA is a well-established, standard method for preparing long-term forecasts, and is a natural candidate for this application. It is frequently used in systems that have many independent variables and are not characterized by strong theoretical models, such as the stock market or sales forecasts. Based on our research, we cannot rule out the possibility that ARIMA could be used for this application, but we were unable to find ARIMA methods that could preserve the three levels of seasonality in the data: daily, weekly, and month-to-month. ARIMA performs very well when predicting data like monthly sales, in which there is just one type of seasonality (month-to-month). However, following the analogy of sales data, our forecast must not only predict the overall sales for each month, but also the sales within each hour of each month. We can use ARIMA to predict monthly energy consumption and peak demand, but we are unable to generate the hourly load forecast that is necessary for this analysis.

Linear models start with a list of independent variables that are known to be good predictors of the dependent variable. The user then defines a formula to represent the relationship between the independent variables and the dependent variables. The formula has constants, which are determined through a curve-fitting algorithm. Using historical data, a curve-fitting algorithm is used to define the constants, and a formula, known as a linear model, is created. It is tricky to fit a linear model since the user must guess at the type of formula, and it usually requires an iterative approach of adding variables and changing the formula to get a good fit. This technique is very good when a theoretical model is available, but we do not have one for electricity consumption at Mines. Additionally, the technique requires a forecast of the independent variables to generate a forecast of the dependent variable.

In our case, a linear model would likely include weather conditions (e.g. temperature, solar irradiance), calendar information (e.g. time, day of week, month, holidays), and number of students enrolled at Mines as independent variables. Calendar information is easy to find, and the number of students can be predicted to reasonable accuracy, but as most of us know, predicting the weather is difficult. In place of weather predictions, energy modelers often use typical meteorological year (TMY) data. The TMY datasets are combinations of sections of historical datasets from many different years to create one 365-day year that simulates a typical weather year in the location of interest. It is possible to generate a 25-year forecast of load using a linear model based on a TMY weather dataset, however it is very repetitive and doesn't capture the variability in the data. The weather forecast would be the same every year, which doesn't capture unlikely weather and loading events that can affect the bills.
Machine learning models, when applied to this forecasting application, are like linear models in that they rely upon a relationship between a set of independent variables to predict the dependent variable. The method of establishing the relationship is what differs between linear and machine learning models. With machine learning, the user does not need to define the formula, and instead it is defined by the machine learning algorithm. All the user needs to provide is the set of predictive independent variables, and the algorithm will find the right formula. It is a powerful technique, but also requires significant iteration, as the algorithms have several parameters that affect the model performance. The shortcoming is the same as the linear model – it requires a TMY dataset to define the weather, and the result is a forecast that is very repetitive and lacks enough variability to make it realistic.

Our concept is to use several years of actual data as the starting point, and to use scaling factors to account for annual growth. The use of actual data as the starting point ensures that the noise, variability, and the three seasonal trends are all maintained. Linear regression is used to establish the growth factors in both peak load and energy consumption. The growth factors in the historical dataset are quite high, and the load on the small Mines campus would rise to an unrealistic level if these growth rates were maintained in the future. As such, we decrease the linear growth rates exponentially over time to ensure reasonable final values of peak load and energy consumption. The methodology is described in detail below.

We start with the most recent four complete years of actual load data (2013 – 2016) and repeat these to represent 2019 – 2043. For example, 2015 data is used to forecast 2019, 2023, 2027, 2031, and so on until 2043. Similarly, 2014 is used to forecast 2022, 2026, 2030, 2034, and so on until 2042. This actual data is scaled by peak load and energy consumption to account for expected load growth. The load growth scaling factors are determined via linear regression of the historic data from 2008 to 2016. First, with the data grouped by year, month, and day type (business day vs. weekend/holiday), the average and peak loads are calculated. For each month and day type combination, linear regression is used to fit two lines – one for peak load and another for mean load – both of the form \( y = mx + b \). The slope \( m \) describes the average linear rate of change over the period 2008 to 2016 and can be used to extrapolate peak and mean load in the future.

The data is then aggregated by season, in which June to September is considered “summer” and all other months are “winter”, and the linear growth rates were averaged over each combination of season and day type. The results are shown below. The biggest finding is that summer peak load on business days grew faster than all other quantities. In winter, the load growth is the same for business days, weekends, and holidays.
<table>
<thead>
<tr>
<th>Season</th>
<th>Month</th>
<th>Day Type</th>
<th>Mean Load Growth (MW/Year)</th>
<th>Peak Load Growth (MW/Year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter</td>
<td>January</td>
<td>Business Day</td>
<td>0.111</td>
<td>0.122</td>
</tr>
<tr>
<td>Winter</td>
<td>January</td>
<td>Weekend/Holiday</td>
<td>0.110</td>
<td>0.077</td>
</tr>
<tr>
<td>Winter</td>
<td>February</td>
<td>Business Day</td>
<td>0.123</td>
<td>0.133</td>
</tr>
<tr>
<td>Winter</td>
<td>February</td>
<td>Weekend/Holiday</td>
<td>0.120</td>
<td>0.139</td>
</tr>
<tr>
<td>Winter</td>
<td>March</td>
<td>Business Day</td>
<td>0.127</td>
<td>0.152</td>
</tr>
<tr>
<td>Winter</td>
<td>March</td>
<td>Weekend/Holiday</td>
<td>0.130</td>
<td>0.157</td>
</tr>
<tr>
<td>Winter</td>
<td>April</td>
<td>Business Day</td>
<td>0.126</td>
<td>0.132</td>
</tr>
<tr>
<td>Winter</td>
<td>April</td>
<td>Weekend/Holiday</td>
<td>0.123</td>
<td>0.134</td>
</tr>
<tr>
<td>Winter</td>
<td>May</td>
<td>Business Day</td>
<td>0.121</td>
<td>0.142</td>
</tr>
<tr>
<td>Winter</td>
<td>May</td>
<td>Weekend/Holiday</td>
<td>0.124</td>
<td>0.161</td>
</tr>
<tr>
<td>Summer</td>
<td>June</td>
<td>Business Day</td>
<td>0.162</td>
<td>0.203</td>
</tr>
<tr>
<td>Summer</td>
<td>June</td>
<td>Weekend/Holiday</td>
<td>0.152</td>
<td>0.181</td>
</tr>
<tr>
<td>Summer</td>
<td>July</td>
<td>Business Day</td>
<td>0.156</td>
<td>0.205</td>
</tr>
<tr>
<td>Summer</td>
<td>July</td>
<td>Weekend/Holiday</td>
<td>0.164</td>
<td>0.170</td>
</tr>
<tr>
<td>Summer</td>
<td>August</td>
<td>Business Day</td>
<td>0.149</td>
<td>0.185</td>
</tr>
<tr>
<td>Summer</td>
<td>August</td>
<td>Weekend/Holiday</td>
<td>0.141</td>
<td>0.161</td>
</tr>
<tr>
<td>Summer</td>
<td>September</td>
<td>Business Day</td>
<td>0.165</td>
<td>0.203</td>
</tr>
<tr>
<td>Summer</td>
<td>September</td>
<td>Weekend/Holiday</td>
<td>0.146</td>
<td>0.127</td>
</tr>
<tr>
<td>Winter</td>
<td>October</td>
<td>Business Day</td>
<td>0.139</td>
<td>0.179</td>
</tr>
<tr>
<td>Winter</td>
<td>October</td>
<td>Weekend/Holiday</td>
<td>0.142</td>
<td>0.208</td>
</tr>
<tr>
<td>Winter</td>
<td>November</td>
<td>Business Day</td>
<td>0.137</td>
<td>0.143</td>
</tr>
<tr>
<td>Winter</td>
<td>November</td>
<td>Weekend/Holiday</td>
<td>0.130</td>
<td>0.133</td>
</tr>
<tr>
<td>Winter</td>
<td>December</td>
<td>Business Day</td>
<td>0.122</td>
<td>0.142</td>
</tr>
<tr>
<td>Winter</td>
<td>December</td>
<td>Weekend/Holiday</td>
<td>0.127</td>
<td>0.135</td>
</tr>
</tbody>
</table>

Table 5.2: Load Growth Rates by Season and Day Type

<table>
<thead>
<tr>
<th>Season</th>
<th>Day Type</th>
<th>Mean Load Growth (MW/Year)</th>
<th>Peak Load Growth (MW/Year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Summer</td>
<td>Business Day</td>
<td>0.158</td>
<td>0.199</td>
</tr>
<tr>
<td>Summer</td>
<td>Weekend/Holiday</td>
<td>0.151</td>
<td>0.160</td>
</tr>
<tr>
<td>Winter</td>
<td>Business Day</td>
<td>0.126</td>
<td>0.143</td>
</tr>
<tr>
<td>Winter</td>
<td>Weekend/Holiday</td>
<td>0.126</td>
<td>0.143</td>
</tr>
</tbody>
</table>
If the above linear growth rates are applied to the historic data and extrapolated to 2043, the result is unrealistic. Peak load would reach nearly 12MW in 2043, and average load would exceed 8MW. Mines has limited land area available and does not expect to add enough students to justify those levels of loading. To make the forecast more realistic, the growth rates are decreased exponentially over time, which keeps current trends, but leads to a smooth leveling out and stabilization of the campus load over time. The formulas for the growth rates and loads are show below.

\[ \text{Mean Load Growth Rate} \ (t) = \text{Mean Load Growth Rate} \ (0) \times e^{\frac{-t}{\tau}} \quad (5.1) \]

\[ \text{Peak Load Growth Rate} \ (t) = \text{Peak Load Growth Rate} \ (0) \times e^{\frac{-t}{\tau}} \quad (5.2) \]

\[ \text{Mean Load} \ (t) = \text{Mean Load} \ (0) + \text{Mean Load Growth Rate} \ (0) \times \left( \tau - \tau \times e^{\frac{-t}{\tau}} \right) \quad (5.3) \]

\[ \text{Peak Load} \ (t) = \text{Peak Load} \ (0) + \text{Peak Load Growth Rate} \ (0) \times \left( \tau - \tau \times e^{\frac{-t}{\tau}} \right) \quad (5.4) \]

The time constant \( \tau \) affects both the final value of the peak/average loads and the rate of decline of the growth rates. As \( t \) approaches infinity, \( \left( \tau - \tau \times e^{\frac{-t}{\tau}} \right) \) approaches \( \tau \), which means the final peak load is \( \text{Peak Load} \ (0) + \text{Peak Load Growth Rate} \ (0) \times \tau \). We select \( \tau \) based on our best guess for what this final value will be.

The best information we have about the future of the Mines campus is the total number of students. We use linear regression to establish a correlation between the peak and mean load and the number of students enrolled at Mines for the years 2008 to 2016, seen in Figure 5.1. The relationship was found to be approximately 1.016 kW in peak load and 0.670 kW in average load per additional student enrolled at Mines.

\[ \text{Peak Load [MW]} \approx 0.353543 + 0.001016 \times (\text{Number of Students}) \quad (5.5) \]

\[ \text{Average Load [MW]} \approx 0.220728 + 0.000667 \times (\text{Number of Students}) \quad (5.6) \]

In Figure 5.1, 2008, 2010, and 2012 are the furthest data points from the trendline for peak load, and in Figure 5.2, 2008 and 2010 are the furthest from the trendline for average load. Analysis of historical weather data shows that 2012 was quite a hot year, with an average temperature of 8.26°C, which is 1.45°C above the average temperature across the 2008 – 2016. This explains the high peak load in 2012, which was necessary to keep up with space cooling requirements in the uncommonly hot weather. 2008 had a higher than average number of hours above 32°C (27 compared to an average of 15.33 across 2008 – 2016) but was otherwise an ordinary year in terms of temperature. 2010 seems to be entirely unremarkable in terms of temperature. Since 2008 and 2010 are not explained sufficiently by
the weather data, we expect the difference is caused by another factor, perhaps the opening of a new building in 2011 that would have increased load substantially.

Figure 5.1: Correlation between Number of Students and Peak Load

$\text{Peak Load [MW]} = 0.353543 + 0.001016 \times \text{(Number of Students)}$

$R^2 = 0.929$

Figure 5.2: Correlation between Number of Students and Average Load

$\text{Average Load [MW]} = 0.220728 + 0.000667 \times \text{(Number of Students)}$

$R^2 = 0.954$
We expect the campus population to reach a maximum value of 8,000 students, which is supported by the facilities management department at Mines. Extrapolation of the relationship between peak load and number of students gives a peak load of 8.5MW for 8,000 students. We select a $\tau$ of 11.4, which gives a final peak load of 8.5MW as $t$ approaches infinity using \[ \text{Peak Load} = \text{Peak Load} (0) + \text{Peak Load Growth Rate} (0) \times \tau. \] We create the forecast by taking this value of $\tau$ and applying the adjusted growth rate factors to the four test years, repeating the test years as discussed earlier. The result is seen in Figure 5.3 below. This forecast is the basis for the optimization, which seeks the lowest cost way to serve this future load.
5.2. Optimization

The overall optimization problem is how to minimize the NPV of electricity cost using a solar plus storage system. In all optimization problems, there is an objective function and a set of constraints. The objective function provides the value of the dependent variable to be optimized using one or more independent variables as inputs. The constraints provide limits on the independent and dependent variables. In our case, the formula representing the NPV of electricity costs is the objective function. Since we seek to minimize the value of the objective function, the problem is considered a minimization problem. The value of the objective function depends on the independent variables described below.

There are five independent variables that represent the system design: 1) PV nameplate kW rating; 2) PV azimuth angle, the angle panels face relative to true North; 3) PV tilt angle, the angle panels face relative to the earth’s surface; 4) Battery nameplate energy (kWh) rating; and 5) Battery nameplate power (kW) rating. There are other aspects in the design of such a system, but these are the most important from a cost perspective. In addition to the system design variables, there are also two vectors of independent variables of length 219,150 each (365.25 days per year * 24 hours per day * 25 years = 219,150 hours), corresponding to the charging and discharging of the BESS at each hour of the analysis period. The need to optimize for the BESS operation adds significant complexity to the problem. In future work, analytical methods for determining BESS operation can be used in place of optimization, which will speed up runtime and provide a platform for evaluation of different operating schemes and principles.

The problem is split into two loops to solve, with one nested inside of the other. The outer loop is the selection of the five system design parameters that minimize the NPV of electricity costs over the analysis period. The inner loop is the optimal charging and discharging of the BESS at each hour. The system design parameters are solved via parametric search, and the BESS charging and discharging is solved with a convex optimization algorithm. To reduce the amount of data stored in memory at a given time, the BESS charging and discharging optimization is solved for each month individually.

The workflow is as follows, and can be seen in Figure 5.4: 1) Select a potential design within the constraints; 2) Solve for the economically-optimal battery operation for each hour of the first month of the analysis period using the convex optimization algorithm; 3) Repeat battery operation optimization until the last month of the analysis period; and 4) Calculate the net present cost of electricity across the entire analysis period. This process is repeated for all potential designs within the constraints, and the design with the lowest net present cost of electricity is selected as the best design.

The precision of the optimization is set to +/- 2.5 kW for PV and BESS power ratings, +/- 2.5 kWh for BESS energy ratings, and +/- 1° for the PV tilt and azimuth angle. Further work could improve upon this workflow to reduce runtime. While the grid search does eventually find the optimal design, and the convex optimization does provide an optimal BESS dispatch strategy, the whole process requires about 17 hours to run – much longer than is reasonable for a commercial software.
Figure 5.4: Optimization Methodology Overview

Table of Designs

<table>
<thead>
<tr>
<th>Design #</th>
<th>PV kW</th>
<th>PV Azimuth Angle</th>
<th>PV Tilt Angle</th>
<th>BESS kW</th>
<th>BESS kWh</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

System Design Optimization

Design = 1

Simulate PV Output

Solar PV Generation = [Simulated generation per kW] * [Installed kW]

Month = 1

BESS Optimization

BESS Operation: One Month ECOS Optimization

Add to Full BESS Operation

Month + 1 Until Month = 12 * 25

Calculate NPV

Add to Full NPV Table

Sort Designs 1:n by NPV

Optimal Design

Optimal Design

Optimal Design

Optimal Design

Design = 1

Design + 1 Until Design = n

Full NPV Table

Design # | NPV w/ CO₂ | NPV w/o CO₂
---------|------------|-------------
1        |            |             
...      |            |             

NPV Table

<table>
<thead>
<tr>
<th>Design #</th>
<th>PV kW</th>
<th>PV Azimuth Angle</th>
<th>PV Tilt Angle</th>
<th>BESS kW</th>
<th>BESS kWh</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>...</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
All the code is written in R, an open source programming language. The CVXR package was used for optimizing battery operation. The CVXR package is written in C by A. Fu, B. Narasimhan, and S. Boyd of Stanford University [40], and is intended for solving convex optimization problems. Other versions, CVX and CVXPY are available for use in MATLAB and Python as well. The CVXR package allows users to write in object-oriented language, which is not typical for R, and offers several algorithms which vary in performance for different problems. The best optimization algorithm for our problem, due to its quick runtime and accurate solution, is ECOS (embedded conic solver), an open-source numerical software package also written in C [41].

To illustrate the trade-offs in system design parameters, several plots are shown below. These are two dimensional slices of the six-dimensional space that is made up by the five system design parameters and the dependent variable – the net present value. Each plot shows the impact on the dependent variable of changing one of five independent system design parameters. The plots together draw a picture of this six-dimensional space, and it is dome-shaped. For each of the five variables, the optimal point lies somewhere in the middle of the search space. The slope is steepest at the edges, and steadily decreases approaching the optimal point, where the slope is zero. This dome shape makes the problem easy to solve and provides high confidence that the local optimal points represent the global optimum. Each plot shows variance from the 15-year NPV optimal design, calculate with CO\textsubscript{2} costs but without the investment tax credit.

Figure 5.5: 15-Year Net Present Value vs. PV Rating
Figure 5.6: 15-Year Net Present Value vs. PV Azimuth Angle

Figure 5.7: 15-Year Net Present Value vs. PV Tilt Angle
Figure 5.8: 15-Year Net Present Value vs. Battery Energy Rating

Figure 5.9: 15-Year Net Present Value vs. Battery Power Rating
5.2.1. Objective Function

The formulation of the objective function can be seen in the equations below, where $y$ is the numeric year from 1 to $n$ (number of years in analysis period), $m$ is numeric month from 1 to 12, $h$ is numeric hour from 1 to 24, and $d$ is a logical variable indicating business day or weekend/holiday. Several equations below refer to the investment tax credit, or ITC, which is a federal tax credit intended to increase investment in renewable energy. The ITC is discussed further in sections 5.2.3.4 and 5.2.3.5.

Note that $n$ has a large effect on the size of the proposed system. The payback period is defined as the year in which the net present costs of the optimal design fall below the net present costs in the base case. At this point, the project has “broken even”, since the capital investment has been recovered, and the project saves money going forward. If $n$ is set to the maximum of 25 years, the optimization will seek to minimize the net present costs at the end of 25 years. It is possible that this solution will not break even until late in the analysis period. If $n$ is set to 10 years, the optimization will prioritize the net present value at the end of 10 years, resulting in a smaller system that can recover capital costs more quickly.

5.2.1.1. Electricity Bill

\[
Electrical Cost NPV = \sum_{y=1}^{n} (Annual\ Electricity\ Bill \times (1 + Discount\ rate)^{-y}) \tag{5.7}
\]

Annual Electricity Bill

\[
= \sum_{m=1}^{12} Monthly\ Energy\ Charge + Monthly\ Demand\ Charge \tag{5.8}
\]

+ Monthly Fixed Charge

Monthly Energy Charge = \[
\sum_{All\ Hours\ in\ Month} Energy\ Rate \times Hourly\ Xcel\ kWh \tag{5.9}
\]

Energy Rate = \[
\frac{0.04265}{kWh} \text{ for } 9 \leq h \leq 20 \text{ and } d = \text{business day}, \tag{5.10}
\]

\[
\text{and } \frac{0.02963}{kWh} \times (1 + \text{Rate escalation})^y \text{ for all other } h \text{ and } d
\]

Monthly Demand Charge = Demand Rate \times \max(Hourly\ Xcel\ kW) \tag{5.11}

Demand Rate = \[
\frac{20.52}{kW} \times (1 + \text{Rate escalation})^y \text{ for } 6 \leq m \leq 9, \tag{5.12}
\]

\[
\text{and } \frac{15.81}{kW} \times (1 + \text{Rate escalation})^y \text{ for all other } m
\]
\[ Monthly \ Fixed \ Charge = $322 \times (1 + Rate \ escalation)^y \]  
(5.13)

5.2.1.2. Carbon Dioxide Cost

\[
CO_2 \ Cost \ NPV = \sum_{y=1}^{n} \sum_{All \ Hours \ in \ Year} \text{Cost of } CO_2 \text{ emissions per kWh} \times \text{Hourly Xcel kWh} \]  
(5.14)

5.2.1.3. PV Cost

\[ PV \ Cost \ NPV = PV \ Capital \ Cost \ NPV + PV \ O&M \ Cost \ NPV - PV \ ITC \ NPV - Salvage \ Value \ NPV \]  
(5.15)

\[ PV \ Capital \ Cost \ NPV \]

\[ = \sum_{PV \ Types} PV \ Size \ (kW) \times PV \ Capital \ Cost \left( \frac{\$}{kW} \right) \times (1 + Discount \ rate)^{-year \ installed} \]  
(5.16)

\[ PV \ O&M \ Cost \ NPV \]

\[ = \sum_{PV \ Types} \sum_{y=1}^{n} PV \ Size \ (kW) \times PV \ O&M \ Cost \left( \frac{\$}{kW \times Year} \right) \times (1 + Discount \ rate)^{-y} \]  
(5.17)

\[ PV \ ITC \ NPV \]

\[ = \sum_{PV \ Types} PV \ Size \ (kW) \times PV \ Capital \ Cost \left( \frac{\$}{kW} \right) \times (1 + Discount \ rate)^{-year \ installed+1} \times ITC \% \]  
(5.18)

\[ PV \ Salvage \ Value \ NPV \]

\[ = \frac{\text{Modulus}(\frac{n}{PV \ lifetime})}{PV \ lifetime} \times PV \ Size \ (kW) \times PV \ Capital \ Cost \left( \frac{\$}{kW} \right) \times (1 + Discount \ rate)^{-n} \]  
(5.19)

5.2.1.4. BESS Cost

\[ BESS \ Cost \ NPV = BESS \ Capital \ Cost \ NPV + BESS \ Replacement \ Cost \ NPV + BESS \ O&M \ Cost \ NPV - BESS \ ITC \ NPV - BESS \ Salvage \ Value \ NPV \]  
(5.20)
BESS Capital Cost NPV

\[
\begin{align*}
&= \left( \text{BESS Size (kW)} \times \text{BESS kW Cost } \left( \frac{\$}{kW} \right) + \text{BESS Size (kWh)} \right) \\
&\times \text{BESS kWh Cost } \left( \frac{\$}{kWh} \right) \times (1 + \text{Discount rate})^{-\text{year installed}} \tag{5.21}
\end{align*}
\]

BESS Replacement Cost NPV

\[
\begin{align*}
&= \left( \text{BESS Size (kW)} \times \text{BESS kW Cost } \left( \frac{\$}{kW} \right) + \text{BESS Size (kWh)} \right) \\
&\times \text{BESS kWh Cost } \left( \frac{\$}{kWh} \right) \times (1 + \text{Discount rate})^{-\text{(year installed+BEES lifetime)}} \\
&\times \left( \text{BESS Size (kW)} \times \text{BESS kW Cost } \left( \frac{\$}{kW} \right) + \text{BESS Size (kWh)} \right) \\
&\times \text{BESS kWh Cost } \left( \frac{\$}{kWh} \right) \times (1 + \text{Discount rate})^{-\text{(year installed+2+BEES lifetime)}} \tag{5.22}
\end{align*}
\]

BESS O&M Cost NPV

\[
\begin{align*}
&= \sum_{y=1}^{25} \left( \text{BESS Size (kW)} \times \text{BESS kW O&M Cost } \left( \frac{\$}{kW \times \text{Year}} \right) \\
&+ \text{BESS Size (kWh)} \times \text{BESS kWh O&M Cost } \left( \frac{\$}{kWh \times \text{Year}} \right) \right) \\
&\times (1 + \text{Discount rate})^{-y} \tag{5.23}
\end{align*}
\]

BESS ITC NPV

\[
\begin{align*}
&= \left( \text{BESS Size (kW)} \times \text{BESS kW Cost } \left( \frac{\$}{kW} \right) + \text{BESS Size (kWh)} \times \text{BESS kWh Cost } \left( \frac{\$}{kWh} \right) \right) \\
&\times (1 + \text{Discount rate})^{-\text{year installed+1} \times \text{ITC (\%)}} \tag{5.24}
\end{align*}
\]

BESS Salvage Value NPV

\[
\begin{align*}
&= \frac{\text{Remainder (BESS lifetime)}}{\text{BESS lifetime}} \\
&\times \left( \text{BESS Size (kW)} \times \text{BESS kW Cost } \left( \frac{\$}{kW} \right) + \text{BESS Size (kWh)} \right) \\
&\times \text{BESS kWh Cost } \left( \frac{\$}{kWh} \right) \times (1 + \text{Discount rate})^{-n} \tag{5.25}
\end{align*}
\]
5.2.1.5. Overall Cost

The overall cost, which is the objective function in this analysis, is given by the formula below.

\[
\text{Overall Cost NPV} = \text{Electricity Cost NPV} + \text{CO}_2 \text{ Cost NPV} + \text{PV Cost NPV} + \text{BESS Cost NPV}
\]  

(5.26)

5.2.2. Constraints

The constraints put bounds on the optimization, which cuts down the search space, improves runtime, and ensures the results are reasonable and realistic.

5.2.2.1. Load Balance

For each hour analyzed, the electric load must be met by some combination of Xcel, PV, and BESS, where input is battery charging (load) and output is battery discharging (supply).

\[
\text{Load}_h = \text{Xcel}_h + \text{PV}_h + \text{BESS Output}_h - \text{BESS Input}_h
\]  

(5.27)

5.2.2.2. BESS Energy Balance

The state of charge (SOC) of the BESS must equal the state of charge (SOC) from the last hour plus the battery output, adjusted for battery losses.

\[
\text{BESS SOC}_h = \text{BESS SOC}_{h-1} - \frac{\text{BESS Output}_h}{\text{Discharging Efficiency}} + \text{BESS Input}_h * \text{Charging Efficiency}
\]  

(5.28)

5.2.2.3. BESS Charging Limits

To ensure a full lifetime for the battery, it is important to keep the battery within charging limits. The battery charging and discharging may not exceed its rated power. In the case when the ITC is applied, the battery must be charged only by the PV system.

\[
\text{SOC Lower Limit} \leq \text{BESS SOC}_h \leq \text{SOC Upper Limit}
\]  

(5.29)

\[
0 \leq \text{BESS Output}_h \leq \text{BESS Size (kW)}
\]  

(5.30)

\[
0 \leq \text{BESS Input}_h \leq \text{BESS Size (kW)}
\]  

(5.31)

\[
0 \leq \text{BESS Input}_h \leq \text{PV}_h \text{ in ITC case only}
\]  

(5.32)
5.2.2.4. PV Size Limit

The sum of all PV kW ratings must not exceed the PV upper limit, defined in section 4.1.

\[
0 \leq \sum PV \text{ Size (kW)} \leq PV \text{ Upper Limit}
\] (5.33)

5.2.2.5. PV Output

The PV system output is equal to the modeled output per kW multiplied by the PV system size.

\[
P_{\text{PV}} = PV \text{ Size (kW rated)} \times \text{Modeled PV Output} \left(\frac{kW}{kW \text{ rated}}\right)
\] (5.34)

5.2.3. Assumptions

Below are descriptions of the methodologies for some of the key assumptions in this thesis.

5.2.3.1. Electricity Rates and Escalation

<table>
<thead>
<tr>
<th>Component</th>
<th>Description</th>
<th>Calculation</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed Cost</strong></td>
<td>Fixed Monthly Fee</td>
<td>Service and Facility Charge ($322)</td>
<td>$322/month</td>
</tr>
<tr>
<td><strong>Summer Demand Charge</strong></td>
<td>Charge per kW for highest 15-minute demand during the billing month, for June 1 to September 30</td>
<td>Demand Charge ($3.86) + Generation and transmission demand – summer season ($14.26) + DSMCA ($0.38) + PCCA ($1.37) + TCA ($0.32)</td>
<td>$20.52/kW</td>
</tr>
<tr>
<td><strong>Winter Demand Charge</strong></td>
<td>Charge per kW for highest 15-minute demand during the billing month, for October 1 to May 31</td>
<td>Demand Charge ($3.86) + Generation and transmission demand – winter season ($9.55) + DSMCA ($0.38) + PCCA ($1.37) + TCA ($0.32)</td>
<td>$15.81/kW</td>
</tr>
<tr>
<td><strong>On-Peak Energy Charge</strong></td>
<td>Charge per kWh for all energy consumed between 9am and 9pm on weekdays</td>
<td>Energy Charge ($0.00458) + Mandatory Time-of-Use On-Peak ($0.03807)</td>
<td>$0.04265/kWh</td>
</tr>
<tr>
<td><strong>Off-Peak Energy Charge</strong></td>
<td>Charge per kWh for all energy consumed outside of peak hours</td>
<td>Energy Charge ($0.00458) + Mandatory Time-of-Use Off-Peak ($0.02505)</td>
<td>$0.02963/kWh</td>
</tr>
</tbody>
</table>
Mines is enrolled in the Primary General rate structure, described below in Figure 5.10. Note that the production meter charge is not required unless the customer exports power to Xcel, which does not occur in any scenario. Using the structure and adjustments in Figure 5.10, the rates are summarized in Table 5.3. Note also that this thesis used hourly data but that the demand charge is determined by 15-minute demand. As such, our work tends to underestimate the demand charge, since the maximum demand over a 15-minute period will exceed the maximum demand over an hourly period.
According to the U.S. Energy Information Administration (EIA) [26], commercial electricity prices for the Mountain region are expected to increase by 1.97% per year in nominal dollars between 2018 and 2034 (Figure 5.11 and Table 5.4). For this analysis, we maintain the current rate structure, but escalate it by the average growth rate over the full period. As an observation, this is less than the discount rate of 3%, which means that electricity rates are expected to decrease in real dollars over the study period.

**Energy Prices: Nominal: Commercial**

![EIA Price Forecast 2018-2034](image)

**Table 5.4: EIA Price Forecast 2018-2034 [26]**

<table>
<thead>
<tr>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity</td>
<td>nom $/MMBtu</td>
<td>29.63</td>
<td>28.28</td>
<td>28.51</td>
<td>29.36</td>
<td>30.10</td>
<td>30.86</td>
<td>31.63</td>
<td>32.51</td>
<td>33.34</td>
<td>34.24</td>
<td>35.08</td>
<td>36.08</td>
<td>36.95</td>
<td>37.95</td>
<td>38.87</td>
<td>39.71</td>
<td>40.50</td>
<td>1.97%</td>
</tr>
</tbody>
</table>

5.2.3.2. Discount Rate

The discount rate is a sensitive lever in any economic model. If the discount rate is too high, future savings are discounted much more than upfront capital cost, making the project economics look worse than actuality. The opposite is true of a discount rate that is too low. The power of compound
interest results in very large changes in the business case with only small changes in the discount rate. Selecting the right discount rate is complex because it must encompass several factors, including the expected inflation during the analysis period, risk and uncertainty around the investment, and the rate of return of other investments. In this analysis we use the National Institute of Standards and Technology (NIST) discount rate used in energy savings projects, which is 3% [42].

5.2.3.3. Cost of Carbon Dioxide Emissions

The cost of carbon dioxide emissions is calculated based on EPA’s published social value of carbon dioxide emissions [43], Xcel’s current and forecast non-renewable generation mix in Colorado [23] [44] [45] [46], EIA’s assumptions on emissions per unit energy for coal and natural gas power plants, and EIA data regarding average heat rates for coal and natural gas power plants [26]. Note that this forecast assumes that CO₂ per kWh is the same at all hours of the day and year. This is not the case, since the generation mix at a given hour will be different than the average generation mix for the year, however this is our assumption. It is a conservative assumption, since the solar plus storage system will offset electricity consumption during high load periods for the Colorado electric grid overall, when fossil fuels will make up a larger percentage of the generation mix.

\[
Cost \ of \ Carbon = \sum_{Fuel \ Types} \frac{\$}{Ton \ CO_2} \cdot \frac{Ton \ CO_2}{BTU} \cdot \frac{3,412 \ BTU}{kWh} \cdot \frac{1}{Efficiency} \cdot \text{Fraction of Generation Mix}
\]  

(5.35)

In the EPA document [43], the societal cost of carbon dioxide emissions is given in the table below, in 2007 dollars and $/metric ton. Using a discount rate of 3%, each price should be scaled by \((1.03)^{(2018 - 2007)} = 1.384\) to convert to 2018 dollars. Prices are given at 5-year intervals, and we use linear interpolation to determine the cost of carbon dioxide emissions in years omitted from the table.

Table 5.5: EPA Societal Cost of Carbon Dioxide Emissions 2010 - 2050

<table>
<thead>
<tr>
<th>Year</th>
<th>5% Average</th>
<th>3% Average</th>
<th>2.5% Average</th>
<th>High Impact (95th Pctl at 3%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>10</td>
<td>31</td>
<td>50</td>
<td>86</td>
</tr>
<tr>
<td>2015</td>
<td>11</td>
<td>36</td>
<td>56</td>
<td>105</td>
</tr>
<tr>
<td>2020</td>
<td>12</td>
<td>42</td>
<td>62</td>
<td>123</td>
</tr>
<tr>
<td>2025</td>
<td>14</td>
<td>46</td>
<td>68</td>
<td>138</td>
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<tr>
<td>2030</td>
<td>16</td>
<td>50</td>
<td>73</td>
<td>152</td>
</tr>
<tr>
<td>2035</td>
<td>18</td>
<td>55</td>
<td>78</td>
<td>168</td>
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<tr>
<td>2040</td>
<td>21</td>
<td>60</td>
<td>84</td>
<td>183</td>
</tr>
<tr>
<td>2045</td>
<td>23</td>
<td>64</td>
<td>89</td>
<td>197</td>
</tr>
<tr>
<td>2050</td>
<td>26</td>
<td>69</td>
<td>95</td>
<td>212</td>
</tr>
</tbody>
</table>

The carbon price in each year can be multiplied by the average tons (1,000kg) of CO₂ emissions per kWh to determine the incremental price per kWh due to CO₂ emissions. The Xcel generation mix in 2018 is available from their website [23], and is 44% coal, 28% natural gas, 23% wind, 3% solar, and 2%
other renewables. In fall 2018, Xcel released a public statement announcing a Colorado Energy Plan [45], which includes a 2026 goal of 24% coal, 23% natural gas, 39% wind, 13% solar, and <1% hydroelectric. In December 2018, Xcel announced plans to “deliver 100 percent carbon-free electricity to customers by 2050” [46]. These projections were used in our analysis, and the portfolio mix during in-between years was estimated by linear interpolation.

From EIA data [26], the emissions from burning coal and natural gas are assumed to be 93.3 and 53.07 kg CO$_2$ per Million BTUs, respectively. Heat rates for Xcel generating facilities could not be found, so we use an EIA estimate of 10,493 and 7,870 BTUs per kWh for coal and natural gas, respectively. We assume the heat rates will remain constant over time, though in reality they may rise or fall as the age and types of generating facilities change. One can calculate the thermal efficiency of a power plant by dividing 3,412 BTU/kWh (the direct energy conversion between BTUs and kWh) and the heat rate (the actual number of BTUs required to produce one kWh). This gives an assumed efficiency of 33% for coal and 43% for natural gas for the United States generation fleet overall. After converting units and applying the formula above, we get the following result for additional cost per kWh due to CO$_2$ emissions, in 2018 cents per kWh.

![Figure 5.12: Cost of Carbon Dioxide Emissions per kWh from Xcel Energy 2018 – 2044](image-url)
The cost of carbon starts high, at 3 cents per kWh. For comparison, this is approximately the same as the off-peak energy charge that Mines pays to Xcel. Due to dramatic changes in the generation portfolio for Xcel, the cost of carbon declines steadily to 0.7¢ in 2044. EPA presents the bolded value 3% discount rate as their middle-of-the-road scenario, and this was adopted in our analysis.

5.2.3.4. PV Design, Cost, and Output

The installed cost of PV and batteries have both decreased dramatically in recent years, so it is important to include the cost decline in any economic analysis. Using a bottom-up, bill-of-materials approach, a group at NREL [47] estimated the cost of PV at $2.13/Wac (Watts alternating current) for a ballasted commercial rooftop. This type of system corresponds to the type of design that would be implemented on the flat rooftops at Mines. Estimates for the cost of solar carparks vary, but they are known to be more expensive than the residential cost, which NREL estimates to be $3.22/Wac. A conservative estimate of $3.67/Wac is used in this thesis. Quick analysis shows that the $3.67/Wac price is not economic, and solar carparks were not investigated further. We adopt the above cost estimates as the base year costs in our model. Since the PV system can be expected to last 25 years, it will not need to be replaced during the analysis period, and therefore we do not forecast future costs.

In the investment tax credit (ITC) case we assume Mines is eligible to collect the federal solar ITC. We assume construction begins in 2019, and therefore Mines is eligible for the full ITC of 30% [48]. This 30% is applied to the total cost of installing the PV system, and is collected in the following year, 2020, as a reduction in its federal income taxes. Further work is required to determine Mines eligibility to receive this tax credit, since it may not pay federal income taxes. If this is the case, Mines may still be able to claim some of the ITC if it pursues a third-party ownership model and the third-party owner pays federal income taxes. This possible arrangement is also left to future work.

The PV output is modeled using NREL’s System Advisor Model (SAM) [31]. Rooftop PV systems can vary in both azimuth angle and tilt angle. We model 1,066 different rooftops system designs, corresponding to 2-degree azimuth angle increments from 160 to 240 degrees, and 2-degree tilt angle increments from 20 to 70 degrees. Common practice dictates an azimuth angle of 40 degrees,
corresponding to the latitude, and an azimuth angle of 180 degrees (due South) to get the most out of solar panels. With further inspection, it is evident that the problem is more complex, described below.

Of the systems modeled, the PV design that produces the most energy over its lifetime is a 160-degree azimuth angle and a 36-degree tilt angle. However, the peak load for Mines occurs in the afternoon, which suggests that a higher azimuth angle and higher tilt angle should be used to maximize output in the afternoon and reduce demand charges. On the other hand, the weather is usually clearer and cooler in the morning, and Mines has prominent mountains to the West, implying an Eastward direction might be better. Furthermore, peak loads and demand charges are higher in the summer, implying a lower tilt angle would be best to maximize output for high summer sun elevation angles. There are many counterbalancing factors involved in selecting the azimuth and tilt angles, which is why an optimization is used to choose these angles.

The weather input is single year hourly datasets for Golden, CO in the years 2013 – 2016, downloaded from the National Solar Radiation Database (NSRDB). It is important to note that these weather files from NSRDB are determined from a combination of satellite models and land-based empirical data, and so the data may or may not account for shading due to terrain features. The data reflects actual weather observed. However, given the proximity to the Rocky Mountains, this dataset could cause SAM to overestimate PV output in the late afternoon. To verify this, simulated PV output is plotted alongside the sun elevation angle, collected from Sun Earth Tools [49]. Given the similar shape of
the data at low elevations angles, seen in Figure 5.13, it is apparent that it does not account for mountain shading.

To account for the mountain shading, we scale down the simulated data using a conservative approach. We assume the mountains to the West all have the same elevation angle as the most prominent mountain in the Western sky when viewed from the Western edge of the Mines main campus, Mt. Zion. Using a topographic map, we estimate the elevation angle of Mt. Zion at approximately 12.5 degrees when viewed in front of the furthest West building that has potential for PV. Then we zero out all PV production occurring when the sun dropped below 12.5 degrees in elevation.

5.2.3.5. BESS Design, Cost, and Operation

Base year BESS costs are estimated at $350/kWh + $400/kW. For a 1kW, 2-hour duration battery, this corresponds to $1,100, which is consistent with the EIA data [50]. According to Navigant Research [51], battery costs are expected to decline by 6% until 2022, and then a modest 1.2% going forward. In the investment tax credit (ITC) case we assume Mines is eligible to collect the federal solar ITC for its energy storage asset. We assume construction begins in 2019 and that the battery is charged entirely by the PV system, and therefore Mines is eligible for the full ITC of 30% [52]. This 30% is applied to the total cost of installing the BESS system, and is collected in the following year, 2020, as a reduction in its federal income taxes. As described earlier, further work is required to determine Mines eligibility for this tax credit, and potential arrangements for collecting a portion of the tax credit.

Charging limits were set at 20% and 90% to strike a balance between battery performance and longevity [36]. Operation of the battery is calculated with the ECOS optimization algorithm, which seeks to minimize the energy, demand, and carbon dioxide charges in each month. This control strategy assumes complete knowledge of the future and perfect control, which therefore represents the best-case scenario. When installed, the battery will have an imperfect control strategy, and will not achieve the same level of savings. Future work should investigate the best control strategy for the battery using observations of the optimal battery dispatch as input. The figures in this section display optimal battery operation under various scenarios. We model the operation of the battery with the ITC, when the battery must charge only from the PV system, and without the ITC, when the battery may charge from the grid as well.

Figure 5.14 shows the projected peak load day for the forecast year 2019, which is expected to occur in early September on a weekday, and the battery operation in the non-ITC case. On a peak load day for the month, the main goal for the BESS is to minimize the peak load to reduce the demand charge. In this scenario, the PV rating is 545 kW, and the battery is rated for 415 kWh and 195 kW. The weather for the day is likely hot with a mix of clouds and sun, based on the high peak load and the PV output of less than half of the rating. After the fast morning ramp, the load climbs steadily from 8am to 2pm, and the PV system climbs to its high value for the day of 200 kW. Just as the load reaches its peak at 2pm, the PV output drops nearly 150 kW. Without the battery, the 545 kW PV system would have only achieved
about 50 kW in peak savings. Fortunately, the battery was able to pick up the slack of the PV system, and achieve a peak load savings of over 200 kW. Demand charges in the summer are approximately $20/kW, so this system saves over $4,000 in demand charges on just this one day.

![Figure 5.14: Forecast Peak Load Day 2019](image)

A similar pattern can be seen in the projected peak load day for 2022, shown in Figure 5.15. This also shows the non-ITC case, when the battery may charge from the grid. On this day, also in early September, the morning is much sunnier, and the PV output is much higher, reaching almost 450 kW in the middle of the day. However, the PV output drops by 400 kW over the course of two hours while load is at its peak. At 3pm the BESS turns on at its full power, keeping the peak savings to about 250 kW. The
BESS plays an important role in firming up the PV output. Due to the rate structure, reducing peak demand is what really saves money on the electric bill. Without the BESS, Mines would see a much smaller peak demand reduction, and the business case for PV would be much worse.

While it is a secondary money-saver, another important task of the BESS is to minimize energy charges on non-peak days. The day pictured above is a non-peak load day from early September 2019 in the non-ITC case. The battery does not back-up the PV system when it drops from 1pm to 3pm since load is not near its peak for the month. Instead, the battery seeks to minimize on-peak energy charges, which are 44% higher from 9am to 9pm. This behavior is seen in the relatively constant discharging of the
battery from 9am to 9pm. On weekends and holidays, energy is on off-peak rates, and the battery does not discharge.

Figure 5.16: Forecast Non-Peak Load Weekday, September 2019
Figure 5.17 shows an example week of the optimized results from February 2019. This figure demonstrates all typical battery operating patterns in the non-ITC case. On Saturday and Sunday, the battery does not operate since there are off-peak rates all day. On Wednesday, the load is at its peak for the month, so the battery discharges to reduce the peak as much as possible. On the other business days, the battery discharges consistently throughout the day to reduce energy charges. Charging occurs during off-peak hours of business days.

Figure 5.18 shows the same week and solar plus storage system size as Figure 5.17, except the battery is only allowed to charge from the PV system, as is required to receive the full ITC. On Wednesday, the battery operates the same way – it discharges as much possible to flatten out the peak. On other weekdays, there is much less of an on-peak energy reduction since the battery may not be fully charged during the day. On-peak rates are from 9am to 9pm, so there is only a brief window in the morning for the battery to charge from the PV system. The other time the battery may charge is during day time hours over the weekend when the PV system is producing electricity.
As mentioned above, future work should investigate analytical methods to determine the best BESS control strategy. However, we can see from the optimization method that it works as intended and provides insight into how the control strategy should work.

To simplify the optimization problem, we do not model the degradation of the battery over time, and we assume the BESS must be replaced entirely after ten years. As lithium-ion batteries age, their capacity decreases, meaning the quantity of energy that can be stored in the battery declines. Once the capacity drops below a certain threshold, determined by the user, the battery is replaced to maintain the BESS performance. The rate of capacity decline is related to the number of cycles the battery experiences and the depth of the cycles. If the battery is charged and discharged more frequently, or more deeply, it will lose capacity faster. To counteract the capacity decline, BESS can be oversized, and limits on state of charge can be used to minimize wear and extend the lifetime of the system. We assume the battery state of charge is kept between 20% and 90% to extend the lifetime, but we do not investigate oversizing. We assume the energy rating remains the same over the lifetime of the system.
Estimates of lithium-ion battery lifetime are given in number of cycles, and they vary in magnitude depending on the source and assumed depth of discharge. Our research indicates that a lithium-ion battery kept at 20-90% charging limits can be expected to last a few thousand cycles in its lifetime. The optimization algorithm indicates that the battery will have one cycle per day on business days, and none on the weekend. Assuming 250 business days per year, the battery will experience 2,500 cycles over ten years. As such, we believe the ten-year lifetime is reasonable simplifying assumption. [53] [54]

5.2.3.6. Salvage Value

It is important to note that the net present value includes the PV and BESS salvage values, assessed at the end of the analysis period. The salvage value represents the residual value left in the PV or BESS system for at the end of the analysis period. The BESS is expected to last 10 years before it must be replaced, and the PV system is expected to last 25 years. As such, at the end of the 10-year analysis period, the BESS has zero value, and it has completely deteriorated. At the end of the 15-year analysis period, the BESS has been replaced once, and the second BESS is halfway through its lifetime. For both 10 and 15-year analysis periods, the PV system still has some salvage value at the end. The salvage value is assumed to decline linearly over the lifetime of the equipment.
CHAPTER 6: OPTIMIZATION RESULTS & DISCUSSION

The results below show the optimal designs under eight different scenarios. The bottom line NPV values give the total value of the solar plus storage system over the 10 or 15-year analysis period. The positive values indicate an overall benefit of these investments. The overall $/MWh values provide the total costs incurred by the solar plus storage system divided by the net generation from the system over the analysis period, including the reduction for battery losses.

Table 6.1: Custom Optimization Results Without ITC

<table>
<thead>
<tr>
<th></th>
<th>$N = 10 Years, Without CO₂</th>
<th>$N = 10 Years, With CO₂</th>
<th>$N = 15 Years, Without CO₂</th>
<th>$N = 15 Years, With CO₂</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PV Design</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>kW Rating</td>
<td>50</td>
<td>335</td>
<td>100</td>
<td>545</td>
</tr>
<tr>
<td>Azimuth Angle</td>
<td>200°</td>
<td>184°</td>
<td>200°</td>
<td>180°</td>
</tr>
<tr>
<td>Tilt Angle</td>
<td>34°</td>
<td>34°</td>
<td>34°</td>
<td>34°</td>
</tr>
<tr>
<td>Capital Cost</td>
<td>$103,398</td>
<td>$692,767</td>
<td>$206,796</td>
<td>$1,127,039</td>
</tr>
<tr>
<td>Salvage Value</td>
<td>$46,163</td>
<td>$309,290</td>
<td>$53,094</td>
<td>$289,361</td>
</tr>
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<td>O&amp;M Cost</td>
<td>$8,820</td>
<td>$59,094</td>
<td>$24,687</td>
<td>$134,545</td>
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<td><strong>BESS Design</strong></td>
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<tr>
<td>kWh Rating</td>
<td>205</td>
<td>305</td>
<td>220</td>
<td>415</td>
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<tr>
<td>kW Rating</td>
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<td>145</td>
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<td>$108,495</td>
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<td>$0</td>
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<td><strong>Savings &amp; NPV</strong></td>
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<tr>
<td>Energy Charge Savings</td>
<td>$29,724</td>
<td>$187,853</td>
<td>$82,608</td>
<td>$446,739</td>
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<td>Demand Charge Savings</td>
<td>$194,840</td>
<td>$410,565</td>
<td>$347,123</td>
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<tr>
<td>CO₂ Savings ($)</td>
<td>-</td>
<td>$124,469</td>
<td>-</td>
<td>$279,890</td>
</tr>
<tr>
<td>CO₂ Savings (% of Emissions from Electricity)</td>
<td>0.2%</td>
<td>1.2%</td>
<td>0.3%</td>
<td>1.9%</td>
</tr>
<tr>
<td>Overall $/MWh NPV</td>
<td>$188.13</td>
<td>$89.19</td>
<td>$129.75</td>
<td>$83.71</td>
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<td>NPV</td>
<td>$40,759</td>
<td>$106,720</td>
<td>$81,145</td>
<td>$219,288</td>
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Table 6.2: Custom Optimization Results With ITC

<table>
<thead>
<tr>
<th>N = 10 Years, Without CO₂</th>
<th>N = 10 Years, With CO₂</th>
<th>N = 15 Years, Without CO₂</th>
<th>N = 15 Years, With CO₂</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PV Design</strong></td>
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<td></td>
</tr>
<tr>
<td>kW Rating</td>
<td>1,080</td>
<td>1,205</td>
<td>645</td>
</tr>
<tr>
<td>Azimuth Angle</td>
<td>180°</td>
<td>176°</td>
<td>184°</td>
</tr>
<tr>
<td>Tilt Angle</td>
<td>32°</td>
<td>34°</td>
<td>32°</td>
</tr>
<tr>
<td>Capital Cost</td>
<td>$2,233,398</td>
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<td>$1,333,835</td>
</tr>
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<td>Salvage Value</td>
<td>$997,115</td>
<td>$1,112,522</td>
<td>$342,455</td>
</tr>
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<td>O&amp;M Cost</td>
<td>$190,513</td>
<td>$212,564</td>
<td>$159,232</td>
</tr>
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<td><strong>BESS Design</strong></td>
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</tr>
<tr>
<td>kWh Rating</td>
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<td>605</td>
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<tr>
<td>kW Rating</td>
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<td>$0</td>
<td>$0</td>
<td>$69,265</td>
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<tr>
<td>O&amp;M Cost</td>
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<td>$38,410</td>
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<td><strong>Savings &amp; NPV</strong></td>
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</tr>
<tr>
<td>Energy Charge Savings</td>
<td>$600,240</td>
<td>$672,512</td>
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</tr>
<tr>
<td>Demand Charge Savings</td>
<td>$787,868</td>
<td>$819,669</td>
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<tr>
<td>CO₂ Savings ($)</td>
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<td>$455,216</td>
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<tr>
<td>CO₂ Savings (% of Emissions from Electricity)</td>
<td>4.0%</td>
<td>4.4%</td>
<td>2.3%</td>
</tr>
<tr>
<td>Overall $/MWh</td>
<td>$62.90</td>
<td>$61.71</td>
<td>$69.39</td>
</tr>
<tr>
<td>NPV</td>
<td>$300,500</td>
<td>$752,330</td>
<td>$337,332</td>
</tr>
</tbody>
</table>

As expected, a longer analysis period results in a larger system overall, since there is a longer time for savings to accrue and offset the higher upfront capital cost. The one exception to this rule is when the ITC is included but CO₂ is not. In this case, the 10-year analysis period results in a larger system because the battery must be replaced in year 11, and this is not included in the objective function. The ITC only applies to upfront capital, and not money spent maintaining an existing system. As such, this replacement battery is purchased at full price, without the ITC discount. While the larger battery can support a larger PV system and earn more savings, it is not enough to offset the cost of replacement. In the 15-year scenario, the system is much smaller since it includes the full price battery replacement. We do not see the same effect when both the ITC and CO₂ are included. We believe this is because the business case is very strong in these scenarios, and the battery replacement cost makes up a relatively small percentage of the overall project.
Also as expected, the ITC results in a larger system overall, and a much larger PV system. When the societal cost of carbon dioxide emissions is included, the recommendation is 1,205 kW of PV, which would take up all available flat rooftop space. This result indicates that solar carparks are not economical at our assumed price. With the ITC, the cost of energy from the solar plus storage system is much lower, making it competitive with Xcel for on-peak energy, and allowing for a large system to be economical.

Including carbon dioxide costs and the ITC have an interesting effect on the PV design, which is to change the azimuth angle to be further East. Based solely on the Xcel rate structure, not including CO\textsubscript{2} or the ITC, there is not much benefit to saving energy – demand savings in the afternoon are what really count. On-peak energy is only 44% higher than off-peak, and both values are quite low. When CO\textsubscript{2} costs are added in, the value of energy savings increase significantly, and the azimuth angle decreases accordingly to catch more sun and produce more energy overall. When the ITC is included, the azimuth angle decreases further.

The PV simulations from SAM indicate that, of the designs modeled, a PV system with an azimuth angle of 160° and a tilt angle of 36° would produce the most energy. This means that a residence in Golden, CO should orient its solar panels at an azimuth angle of 160° and a tilt of 36° since the residential rate is constant over time and does not have a demand charge. However, due to the demand charge, this is not the best design for Mines because the PV system would produce less electricity during the peak loading periods. The lower tilt angles recommended by the optimization are likely caused by the higher demand charge in the summer months. To get the most demand charge savings, the system should be tilted further backward to produce more energy when the sun is high.

Our results support the general rule-of-thumb that a 2-hour duration battery is best for peak-shaving, since all BESS have approximately a 2:1 ratio of energy to power. Overall, the cost per MWh of electricity purchased from Xcel in the base case is about $70/MWh (see Chapter 3), which is less than the cost per MWh from the solar plus storage system when the ITC is excluded, but greater when the ITC is included. This means that solar plus storage is cost-effective for peak shaving only in the non-ITC case, but for both peak shaving and energy reduction in the ITC case.

The following example illustrates how the demand charge affects the business case for solar plus storage in the non-ITC case. Recall that the demand charge in the summer months is approximately $20/kW, and the energy charge is approximately 4.5¢/kWh during on-peak times. Assume it is the last day of the month, and so far in the month the peak load is 6,300 kW, but now the load is 6,400 kW during a 15-minute period. The energy consumed during that 15 minutes is 6,400 kW \div 4 = 1,600 kWh, and the cost incurred is $20 * (6,400 – 6,300) + $0.045 * 1,600 kWh = $2,072. Dividing the cost by the kWh, we get $2,072 / 1,600 kWh = $1.30 / kWh or $1,300 per MWh. This is the marginal cost of electricity from Xcel during the peak load, and it is an easy price to beat. The marginal price at peak load exceeds vastly the price of energy produced from the solar plus storage system, which is $62 per MWh in the best case.
and $188 per MWh in the worst case. Unless PV and battery prices skyrocket, there will always be a business case for solar plus storage due to the electricity rate structure.

![Figure 6.1: Monthly Load Profiles Year 2020 Business Days, 545 kW PV, 195 kW / 415 kWh BESS](image)

As seen in Figure 6.1, the PV system causes a reduction in the peak load on an average basis, though the reduction is skewed towards the first part of the peak. The battery charging and discharging is
difficult to see in these load profile because the timing varies day-to-day. The load profile also illustrates the limits of the business case for the solar plus storage system, and why the recommended systems are relatively small compared to the load when the ITC is excluded. As stated previously, the solar plus storage system cannot compete with Xcel on energy production from a cost perspective when the ITC is excluded, and the main way the solar plus storage system can save money is through demand charge reduction. When the ITC is included, a much larger PV system is economical, and the balance between energy savings and demand savings is more equal.

The peak load for Mines typically occurs in the mid-afternoon, while the PV system is producing electricity, and continues to stay high through to the early evening when the PV system stops being able to produce electricity. This is illustrated in Figure 6.2, which shows the effect of increasing the PV and BESS size. The system can only reduce the evening peak load by discharging the battery. Unless the duration of the battery is very long, which results indicate is not cost-effective, the evening peak can only be reduced a small amount and can only be shifted out until the time when PV system is no longer able to produce energy. This is a limit of the solar plus storage system – it cannot achieve significant peak load outside of daylight hours without a very large battery.

Figure 6.2: September 2020 Business Day Load Profiles, Increasing System Sizes
Figure 6.3: Cash Flow Diagram 10-Year Solution Excluding CO₂ Cost, Excluding ITC
Figure 6.4: Cash Flow Diagram 10-Year Solution Including CO₂ Cost, Excluding ITC
Figure 6.5: Cash Flow Diagram 15-Year Solution Excluding CO₂ Cost, Excluding ITC
Figure 6.6: Cash Flow Diagram 15-Year Solution Including CO₂ Cost, Excluding ITC
Figure 6.7: Cash Flow Diagram 10-Year Solution Excluding CO₂ Cost, Including ITC
Figure 6.8: Cash Flow Diagram 10-Year Solution Including CO₂ Cost, Including ITC
Figure 6.9: Cash Flow Diagram 15-Year Solution Excluding CO₂ Cost, Including ITC
Figure 6.10: Cash Flow Diagram 15-Year Solution Including CO₂ Cost, Including ITC
6.1. HOMER Results

For comparison, we calculate results using HOMER Grid. As much as possible, we try to replicate the assumptions used in our study, and we reuse the azimuth and tilt angles identified by our custom optimization. Note that this is not a one-to-one, direct comparison, and that comparison should be done carefully before conclusions are made. Since only one test year can be used, we use the first year’s load forecast, which is 2019. Since only one value for CO₂ emissions can be used, we use the average value over the analysis period. Overall, the results are consistent with our custom optimization. The PV BESS sizes in the HOMER results are smaller than in our results. Aside from the simplifications made, this may also be due to the dispatch strategy, which may not take advantage of all money saving opportunities, or the way salvage value is calculated.

<table>
<thead>
<tr>
<th>PV Design</th>
<th>kW Rating</th>
<th>Azimuth Angle</th>
<th>Tilt Angle</th>
<th>kWh Rating</th>
<th>kW Rating</th>
<th>Net Present Value (NPV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N = 10 Years, Without CO₂</td>
<td>160</td>
<td>180°</td>
<td>32°</td>
<td>233</td>
<td>120</td>
<td>$54,487</td>
</tr>
<tr>
<td>N = 10 Years, With CO₂</td>
<td>643</td>
<td>176°</td>
<td>34°</td>
<td>233</td>
<td>107</td>
<td>$196,845</td>
</tr>
<tr>
<td>N = 15 Years, Without CO₂</td>
<td>583</td>
<td>184°</td>
<td>32°</td>
<td>317</td>
<td>133</td>
<td>$276,529</td>
</tr>
<tr>
<td>N = 15 Years, With CO₂</td>
<td>1,205</td>
<td>176°</td>
<td>34°</td>
<td>467</td>
<td>217</td>
<td>$937,821</td>
</tr>
</tbody>
</table>

6.2. REopt Results

For comparison, we also calculate results using the REopt Lite online tool. As with HOMER Grid, we try to replicate the assumptions used in our study as much as possible, and we reuse the azimuth and
tilt angles identified by our custom optimization. The results, seen below, are consistent with those from our custom optimization, though the recommended size of the battery is smaller. We provide some reasons for the differences below.

Table 6.5: REopt Results Without ITC

<table>
<thead>
<tr>
<th>PV Design</th>
<th>kW Rating</th>
<th>N = 10 Years, Without CO₂</th>
<th>N = 10 Years, With CO₂</th>
<th>N = 15 Years, Without CO₂</th>
<th>N = 15 Years, With CO₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>Azimuth Angle</td>
<td>200°</td>
<td>184°</td>
<td>200°</td>
<td>180°</td>
<td></td>
</tr>
<tr>
<td>Tilt Angle</td>
<td>34°</td>
<td>34°</td>
<td>34°</td>
<td>34°</td>
<td></td>
</tr>
</tbody>
</table>

| BESS Design | kWh Rating | 90 | 163 | 208 | 280 |
| kW Rating | 62 | 69 | 108 | 143 |
| Net Present Value (NPV) | $22,340 | $51,216 | $63,844 | $138,504 |

Table 6.6: REopt Optimization Results With ITC

<table>
<thead>
<tr>
<th>PV Design</th>
<th>kW Rating</th>
<th>N = 10 Years, Without CO₂</th>
<th>N = 10 Years, With CO₂</th>
<th>N = 15 Years, Without CO₂</th>
<th>N = 15 Years, With CO₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>Azimuth Angle</td>
<td>180°</td>
<td>176°</td>
<td>184°</td>
<td>176°</td>
<td></td>
</tr>
<tr>
<td>Tilt Angle</td>
<td>32°</td>
<td>34°</td>
<td>32°</td>
<td>34°</td>
<td></td>
</tr>
</tbody>
</table>

| BESS Design | kWh Rating | 380 | 455 | 415 | 583 |
| kW Rating | 225 | 246 | 253 | 299 |
| Net Present Value (NPV) | $274,134 | $683,165 | $296,267 | $850,053 |

REopt offers an option for the Public Service of Colorado Primary General Rate, but it does not include the time-of-use component to the energy charges. Instead we use the custom rate option, which allows the user to specify a demand and energy charge, but not an on and off-peak energy charge. For demand we use a weighted average of the demand charge, and for energy we use the on-peak energy rate since the solar plus storage system will be offsetting on-peak energy primarily. The use of one energy charge hurts the business case for the battery since it cannot take advantage of the difference between on and off-peak energy rates as an arbitrage opportunity. As such, the battery only discharges to reduce the monthly peak load. This may explain why the recommended sizes of the BESS are smaller. From REopt Lite’s outputs, it appears that its algorithm works well to reduce the monthly peak loads as much as possible.
The cost of carbon dioxide emissions was included by increasing the energy charge. REopt Lite does not include salvage value by default, making it very difficult to have a positive business case when the analysis period is ten years. It is simply not enough time for the savings to accrue. To include the salvage value, we incorporate the depreciated value of the system at the end of the analysis period into the upfront capital cost. The ITC is adjusted upward to account for this reduction in capital cost and to maintain a 30% value based on the upfront capital cost before the reduction. Overall, we find that these results affirm our model. Other key differences between REopt and our model are the lack of load growth, the use of one test year, and the averaging of several important quantities like the demand charge and CO₂ price.
CHAPTER 7: FUTURE WORK

This thesis performs a detailed analysis of only one aspect of a comprehensive sustainability strategy. To accomplish the broader goal of sustainability at Mines, further work is required. In addition, there are several areas for improvement and development of the framework created as discussed below.

7.1. Comprehensive Energy Sustainability

The broader energy strategy is summarized in the Figure 7.1 below. If Mines is to pursue a goal of complete energy sustainability or a net-zero energy philosophy, as a minimum, these are the following steps that must be taken. Electricity generation must be made entirely renewable. Steam generation must either be converted to use waste, biomass, renewable gas, or electricity as an energy input, or replaced by electric heat pumps. Chilled water generation needs to be fully electrified. Any natural gas loads must be converted to electric equivalents. In short, the strategy is to electrify everything, and to find a renewable way to generate steam or hot water for space heating.

![Figure 7.1: Net-Zero Microgrid Transition Strategy](image)

7.2. Deferrable Loads and Energy Efficiency

A key finding of this research is that peak demand reduction, or improving the load factor, is the best and perhaps easiest way to reduce the electricity bill from Xcel. In this study, this reduction was
achieved through a solar plus storage system. It is very likely that there are alternate ways for Mines to reduce its peak demand. Future work should investigate equipment replacement and changes to equipment operation to reduce peak demand.

As with deferrable loads, it is very likely that there are lower cost ways to reduce energy consumption than with solar plus storage. Mines has taken significant steps in efficiency already, primarily in lighting retrofits and in HVAC efficiency. Further analysis should identify further energy efficiency opportunities like adopting conservation voltage reduction (CVR). Future work should compare these demand reduction and energy efficiency opportunities alongside solar plus storage in the optimization to select the most cost-effective set of projects.

7.3. Stochastic Optimization

The methods used in this thesis rely upon a certain forecast of future weather, campus growth, and electrical load. Future work should include optimization under uncertainty in these variables, known as stochastic optimization. It is not clear how this method will compare with the method presented in this thesis for practical application.

7.4. Investment Timing Optimization

From this research, it is clear that solar plus storage is an economically-viable investment for Mines. However, when investing in technologies that have steep price declines, such as li-ion batteries, it can be more economical to wait for prices to decline before investing. If the value of electricity bill savings over the waiting period is less than the price decline during the same period, it is better to wait, even if the project has a positive business case without waiting. This is a common problem faced by companies and individuals who want to use adopt technologies but are afraid of investing too early. Future work will expand the optimization to include variations in investment timing, to determine when Mines should invest, given several different price forecasts for PV and BESS.

7.5. BESS Operating Algorithms

This research assumes a perfect dispatch of the BESS. That is, the battery is used to minimize the demand charge as much as possible, given the size of the battery. It never discharges too quickly, leaving it unable to shift the end of the daily peak load. It never discharges too slowly, failing to reduce the demand charge as much as it could have. The optimization models how the battery would be operated given a completely certain forecast of electric load. To model the battery operation more accurately in the optimization, one must use the operating algorithm that will be employed by the battery and the control system when installed. Future work should also include a study of BESS operating algorithms to design and select the best one for this application.
7.6. Financial and Ownership Models

Future work should investigate the effect of different financing and ownership models. The current model assumes complete ownership and financing by Mines. The cost of borrowing is not modeled. It is assumed that capital expenditures come from cash on hand, and that O&M expenditures come out of Mines existing operating budget. It is common for renewables projects to be financed and owned by a separate entity, which sells the electricity to the customer at a fixed or negotiated price. This arrangement shifts the risk and the capital burden onto this entity, making the project easier to implement for Mines, but also reducing project savings for Mines. Mines has engaged in a similar arrangement for energy savings projects in the past, so it is likely that Mines will seek this arrangement for the proposed project. Even if Mines were to own the project entirely, the typical fund-raising method is to sell bonds to cover incremental costs of the project. The debt service in this arrangement is not modeled, and this will also reduce the project savings. The methodology presented here could easily be changed to accommodate any of the arrangements described above.

7.7. Electrical Feasibility and Impacts

The largest system from the optimization is a 1,205 kW PV system combined with an 815 kWh and 385 kW BESS. While this would only provide a portion of the electricity for the Mines campus, it could have a significant impact on the electrical distribution on campus. It is likely that transformers and circuit breakers will see higher current with the new system, and that currents will change direction as the PV and BESS system changes between producing and consuming power. Further study will need to utilize power flow models to identify any equipment overloading or fault current issues. A protection coordination study should also be conducted to make sure the new system is adequately protected and to address any protection issues caused by the new system.
REFERENCES CITED


