Model Predictive Control for Retrofit Rooftop Unit Control

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Model Predictive Control for Retrofit Rooftop Unit Control

Thesis directed by Professor Gregor P. Henze

Executive Summary

This thesis explores the viability of model predictive control strategies for a retrofit rooftop unit control solution developed by start-up technology provider Transformative Wave, called the CATALYST. This research has been conducted in conjunction with a research project funded by the Wells Fargo Innovation Incubator program, in collaboration with the National Renewable Energy Laboratory (NREL) to enhance the commercial retrofit rooftop unit control solution with optimum control development. The goal is to develop a simple, easily implementable model predictive controller to further reduce energy costs in commercial retail buildings. This thesis extends previously developed building performance simulation models and model predictive control tools to provide insight into the demands of model development and baseline optimum control results. Model development is approached by taking data provided only from the CATALYST controllers to estimate model parameters of a building and its HVAC systems sight unseen. Additional optimization tasks are evaluated to test the effectiveness of the building to improve electric grid integration and achieve carbon reductions. It was found that the MPC, within the simulation environment, was best able to reduce peak demand utility costs and to improve the building in terms of grid relationship but at the cost of increased energy consumption and carbon emissions. In terms of utility cost savings, the addition of model predictive control was able to save approximately $243 a month in utility demand charges at an increased cost of $8.42 a week resulting in total utility bill cost savings of $210 a month. This suggests an annual demand cost savings of 5% at a 2% energy cost increase.

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Acronyms and Abbreviations

MPC – Model Predictive Control

ROM- Reduced Order Model

NREL – National Renewable Energy Laboratory

VFD – Variable Frequency Drive

OA – Outdoor Air

RMSE – Root Mean Squared Error

PV – Photovoltaic Cells

RC – Resistor - Capacitor

1. Introduction

This project is to assess the feasibility of optimum, model predictive control, in retrofit applications on grocery store rooftop units. The client is Transformative Wave Technologies who produces an advanced controller for rooftop unit retrofits called the CATALYST (1). The CATALYST controller is a system designed to retrofit existing rooftop units with a variable frequency drive (VFD), economizer control, robust sensor package, web-based control and analytics and rule-based control to minimize energy consumption. The initial findings from this system have resulted in annual RTU average electrical savings of 56% (2). The key to the success of the CATALYST controller is not just the additional equipment installed inside the RTU but the application of the expert knowledge to create rule sets on how the RTU should run. This accounts for inefficiencies inherent in the HVAC design and control strategies. In a standard HVAC design strategy, the building load is calculated to meet the maximum possible demand load the building experiences, meaning the HVAC system works at its optimum design load for potentially 1% of the total operation. By leveraging staged fan speed control based on outside air temperature and economizer availability, the CATALYST system is able to stage the capacity of the RTU to levels that meet the demand load while restricting the RTU from using more energy than is necessary.

Transformative Wave was awarded this project from Wells Fargo Innovation Incubator (3) to work with NREL to develop model predictive control (MPC) for the CATALYST system to further improve energy savings. In this project, controllers from Whole Foods Market in California and Arizona were used to provide minute sampled data gathered by already installed CATALYST controllers. This thesis explores, parallel to the NREL MPC development, the process for developing a model purely from the measured CATALYST data and then tests the feasibility of MPC to save energy and utility costs. The project at NREL will develop a commercially feasible MPC controller using “off the shelf” programs and optimizers and will conclude with laboratory testing of MPC control. This thesis will use a modeling environment and MPC control developed by Corbin (4), Henze (5), Pavlak (6) and others to model and test the feasibility of MPC but the control program is not available for commercial use. This will provide the team at NREL the ability to compare their developed product with a previously developed control baseline.

Therefore, the following work steps the process of developing a model based on the provided data estimating building parameters, internal gains and an HVAC equipment with the goal of providing simplified model parameters to NREL and Transformative Wave. The modeling process uses grey box modeling procedures as outline by Braun (7) to construct a five parameter Resistance Capacitance (RC) network to simulate building interaction with environment. The procedure described by Braun includes a full building audit detailing the construction and electrical loads of the building. This project is conducted remotely from the building with the building data being sourced from NOAA weather stations, Google satellite imagery, Google Street view, and most importantly the CATALYST controller itself. This does create a challenge in accurately modeling the building as the internal gains and sensible loads are estimated with the assumption that the HVAC system measurements are accurate and the discharge air of the RTUs exactly meet the building's cooling load. From this estimated sensible load and prescribed building parameters from ASHRAE 90.1, 2007, the building model was trained and the Internal Gains were estimated through Monte Carlo simulations and Least Squares parameter estimation minimizing the Root Mean Squares Error between the model and data calculated sensible loads, fan power, cooling coil power, and overall RTU power. The MPC controller is then evaluated for effectiveness in reducing overall building energy demand, utility cost under different cost structures, building-to-grid relationship metrics and the ability to reduce carbon emissions from power generation.

2. Literature Review

Commercial Cooling Applications

Thermal comfort inside commercial buildings is rarely appreciated when building occupants are comfortable but always noticed when people are not comfortable. Accordingly, ASHRAE standard 55 defines the comfort as “that condition of mind which expresses satisfaction with the thermal environment.” Numerous studies have been conducted on this subject as discussed by Taleghani et. al. (8) as to what is considered comfortable to building occupants and in all studies the best estimate is a range of values dependent on occupant gender, level of clothing and level of activity. In the case of a retail store, the range of occupants will vary from the staff working every day and the customers. It can be expected that the staff will be consistent from day to day in gender, level of uniform and level of activity. The main changes among the staff are where and when the level of activity will occur. In the mornings and late at night one could expect that employees will be focused on the restocking of merchandise. In the kitchen sections, cooling will be important to maintain comfort around high heat generating appliances. All day, the registers will be manned with employees standing. The level of activity, while high, will at least be consistent. The customers on the other hand will change regularly. During a cold day people will be wearing more clothing and hot days wearing less. The number of customers will even change with the weather.

Because of the wide variations in thermal comfort, ASHRAE has developed the predicted mean vote (PMV) model to measure and predict thermal comfort. ASHRAE standard 55 (9) describes the process to measure parameters in which to predict occupant thermal comfort. For the purposes of this project, Figure 5.2.1.1 from Standard 55, 2004 provides the comfort zone based on operative temperature and the humidity ratio.

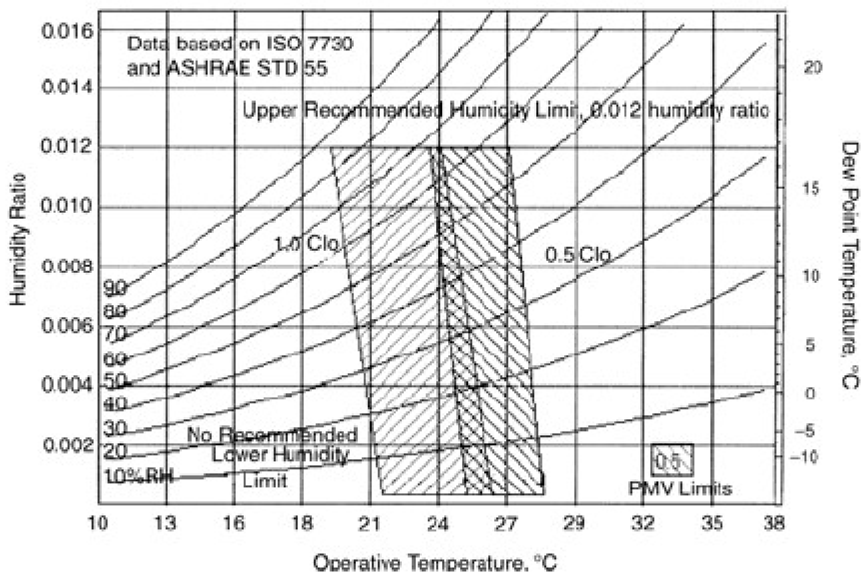


Figure 1: ASHRAE STD 55 Climate Control Comfort Zones

While these comfort bands can be further adapted, in this project the comfort zone is determine solely by the Operative Temperature for occupied and unoccupied times. While temperature set point control to maintain a comfort band is a simple task, operating within this comfort band is the key to not only maintaining customer comfort for the purposes of sales but also allowing an advanced HVAC control system to adjust the temperature set point to operate in a more efficient manner.

Importance of cooling in commercial applications and economics

For a retail store, customer comfort is important to facilitate sales. Zwebner et. al. (10) performed a study on the effects of product valuation on college students. In this study the effect of temperature was correlated to emotional warmth and then toward attitudes towards various level of consumer goods. The concept of physical warmth influences valuation of products and a consumer's willingness to pay and decrease the objective assessments of product retail prices. All of the studies showed that in a warm environment that product valuation increased. The study did not determine at what temperature product valuation increases reaches a limit. In the context of a retail store, maintaining a warm temperature inside is important to maintaining sales but there is a limit to keep the employees comfortable.

While thermal comfort is the primary purpose of commercial cooling, the economics of consumer behavior are less predictable and measurable. Hence, ASHRAE standard 55 describes how building set points are determined. The main purpose of this thesis is to measure the effects of optimum control on utility bills. The EPA Energy Star guidelines chapter 11 cites electrical energy consumption in supermarkets as 14% of total building energy consumption (11). The median energy usage for supermarkets is 191,950 Btu/ft^2. This means that the HVAC system in the Tarzana Whole Foods could potentially consume 265 MWh each year in electrical costs. At a flat rate of $.10 per kWh of energy consumption, this would be an annual cost of $26,000 just from maintaining comfort inside the building. Reducing this operating cost can help increase profit margins of a retail store which are already significantly low, ranging between 5% and 1% (12).

Another case, not evaluated in this thesis, is the interaction of the indoor environment with retail store refrigeration loads. According to the DOE study, nearly one third of the electrical energy consumption is from produce refrigeration (11). Bahman et al analyzed energy saving in supermarket refrigeration and HVAC systems (13). In this analysis, they looked at multiple studies in which to reduce energy costs of refrigeration based on the store's indoor relative humidity, finding a relationship between display case energy and relative humidity. These studies found that total energy consumption for refrigeration decreased with relative humidity of the internal air conditions. The results indicate that, for each 5% reduction of in-store relative humidity, the display case refrigeration load could be reduced 9%, thereby reducing total store energy load by 4.5%.

What makes the use of advanced controllers critical in a retail application is the result of the HVAC design process for buildings. In the case of retail buildings, maintaining an optimum climate environment is critically important for the success of sales. Because of this need, HVAC systems are designed to be oversized for the building to ensure the building is always within optimum temperature zones. Wordenchjumroen et al (14) explored how buildings were oversized in retail applications. In terms of cooling, they found that HVAC systems were oversized nearly 80% for most applications. This results in suboptimum cycling, start up, and use of RTUs leading to increased energy costs.

Use of Roof Top Units

The type of HVAC system used at this store location are Carrier Package Rooftop Units. What makes these units the HVAC system of choice is that they are easily installed on the mostly unused space of the roof and can be placed directly over the area they are responsible for climate control. This minimizes ducting inherent to a central HVAC system and increases usable space on the ground, or market level, of the store. This also makes installation and replacement relatively simple as a crane can simply lift and place the unit directly where it needs to be. There isn't much literature directly related to rooftop units due to the fact that they operate exactly like a standard package unit but with a different installation location. However, Carrier has conducted research on how to better improve their own product.

In 2002, James Pegues of Carrier conducted research into the benefits of hour-by-hour building energy analysis (15). In this study, the benefits include better estimates of energy use, higher quality system comparisons, more accurate load histories, high quality time of use energy data, and more accurate estimates of peak demand. While this seems inherent to the concept of more detailed data resulting in more detailed analysis, this becomes critical in terms of predicting building behavior in the future. As stated in the report, using a simplified, average, data style analysis misses interactions of the weather, hourly/daily variations of internal loads and the inability to predict time of day energy use and peak demands. By only analyzing the monthly energy bill in relation to the average temperature of the month, it is impossible to be able to predict when or why the peak energy cost will occur in the next month. In this thesis, the model predictive controller uses detailed hourly data to change internal temperature set points to reduce peak energy demand and usage rates.

Following this report, Carrier produced a report on the operation and application variable frequency drive (VFD) technology (16). This technology allows for the motor speed to adjust based on the demand load of the building. Since most equipment is sized for the maximum possible cooling load, the full speed of the fan is only required for about 1% of the total operation of the equipment. The result of being able to run the fan at a speed necessary for the load is that the fan does not have to start up, run at the one maximum speed, and run at the maximum power until the set point has been reached. This means that if all 8 RTUs at the store are required to run, the HVAC energy load will be at the maximum possible at that time, potentially contributing to the maximum energy demand regardless of the required cooling load. With better sensors and load calculating technology, the load can be determined based on the inlet air temperatures and the required discharge air temperature, and the fan rates can be adjusted accordingly to meet cooling demand. Additional benefits discussed in the article are lower starting current, reduced stress on motors, higher power factors, and the ability to better meet harmonic standards.

The last report that Carrier put out relevant to this topic was later in 2012 on the use of staged motor speeds (17). This report was in response to meeting ASHRAE Standard 90.1-2010 code requirements of requiring fan speed to be reduced when the space cooling load is reduced in cooling or ventilation loads. Similar to a VFD, this strategy focuses on reducing fan speed energy by allowing the RTU's fan to operate at speeds more fitting to the required load rather than trying to meet maximum, designed, cooling loads at all time. Figure 2 shows their findings in applying a two speed staged air volume system to a 20-ton standard efficiency RTU.

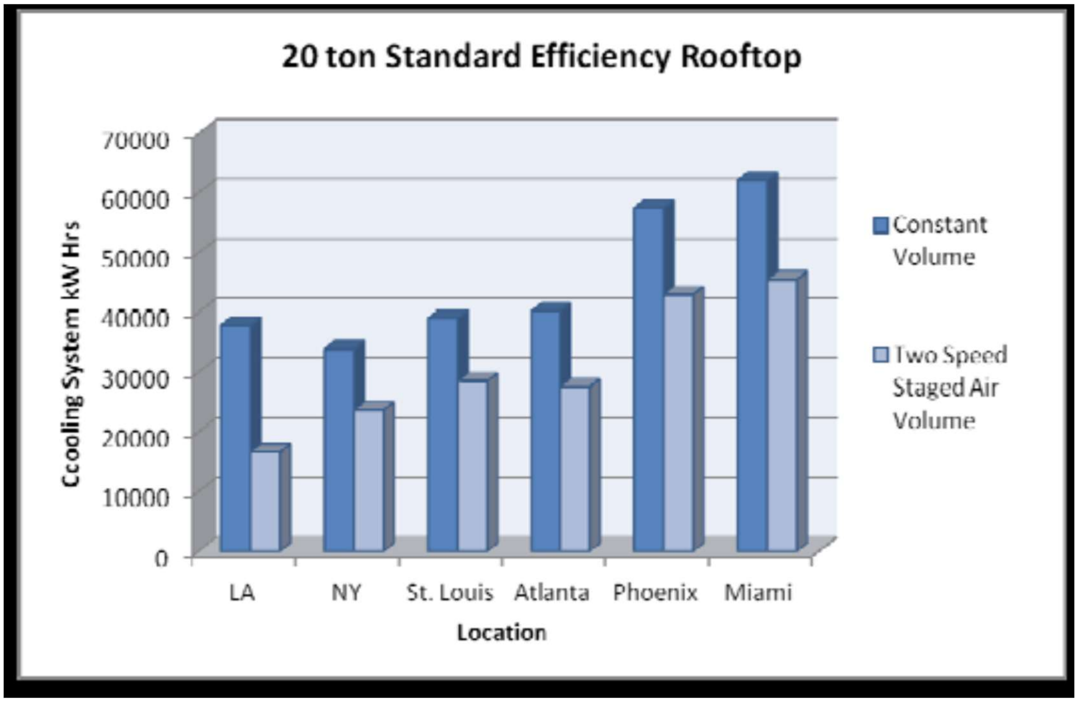


Figure 2: Power Consumption of 20-Ton Standard Efficiency Rooftop Unit (17)

These articles from Carrier are mentioned as the CATALYST product relies on, and further implements, these concepts to provide energy savings to their customers.

Energy Usage in Relation to Grid Energy

As technology becomes more complex, systems grow, and community power grids become more complex, the way buildings interact with the grid and with each other becomes not only possible but necessary. In Dr. Corbin's doctoral thesis, he analyzed the effect of large scale distributed residential HVAC control optimization on the electrical grid (18). In this, the ability of residential HVAC is analyzed to shape the power grid power profile. This is with the desire of decreasing costly peak energy loads and shape energy consumption around the availability of renewable energy consumption. Since the availability of solar and wind power changes with the weather, it seldom lines up with the grid high demand periods. By leveraging the residential power grid through signaling and MPC control, Dr. Corbin evaluates the feasibility and develops a methodology for incorporating residential building demand profiles and shaping loads to reduce peak energy power generations. To further this research, the metrics proposed are included in the cost function and applied to a retailed store. His work showed promise in reducing peak demand across the residential sector. Hence, implementing MPC throughout the entire grid to include commercial buildings could further reduce grid peak energy loads. This could be important as a commercial office building energy consumption ranges primarily between 9am to 5pm and residential energy loads are in the morning and evening while retail commercial, as seen in this study occur, afternoon and early evening. If grid loads in each sector could be moved to non-coinciding periods, total grid peak demand could be further decreased.

Transformative Wave Methodology and Application

The customer in this study is Transformative Wave working with NREL to further improve their CATALYST retrofit HVAC control solution. The CATALYST solution installs a VFD and economizer with an advanced control system. This control system sets a rule-based control strategy to maximize the use of outside air and minimize fan losses. The DOE study found that the advanced controller reduced annual RTU energy consumption between 22% and 90%, averaging 57% (2). After this study, Whole Foods adopted the CATALYST advanced controller across 1,181 roof top units equating to a 42% reduction in overall energy cost and consumption (19). Part of the retrofit solution is to add temperature sensors for outdoor air, return air and discharge air. The controller also pulls outdoor air temperature from a web-based service to help maintain accuracy since the outdoor air temperature sensor can be affected by direct solar exposure to the RTU, causing readings of outdoor air temperature greater than the actual temperature. The controller uses an expert knowledge rule set to determine fan staging and cooling staging based on the availability of cooler outdoor air. The rule set is as follows:

1. In ventilation mode, supply fan speed at 40%.

2. In economizer mode, and outside air temperature less than 58 degrees, fan speed is 75% for first stage cooling and 90% for second stage cooling.
3. If outside air temperature is greater than 58 degrees in economizer mode, supply fan speed is 90%.
4. If in first stage cooling and outdoor air temperature is greater than 70 degrees, supply fan speed is 70%, in second stage, 90%.

A CO2 sensor is also added to the return air. This provides demand control ventilation. If the measured CO2 levels are less than 1,000 ppm then the outdoor air fraction will be at the minimum if not in economizer mode. If greater than 1,000 ppm, the outdoor air fraction will adjust between the minimum and maximum outdoor air fraction.

The last bit of added technology is a web-based service to monitor the HVAC condition at a level of minute data. This minute data analysis contributes the control as cooling staging is determined by the ability, or inability, of the RTU set point after a set amount of time. The additional sensors measure the outdoor air damper position, fan power, and overall RTU power. These additional sensors are then used for fault detection reporting error messages to the building manager. All of these metrics make MPC possible and were used in this thesis to develop the building model.

Model Predictive Control

Model predictive control is not a new control concept. Richalet published one of the first papers titled “Model Predictive Heuristic Control: Applications to Industrial Processes” (20). This paper details the use of a multi-variable algorithm which uses inputs to manipulate control variables to reach desired outcome trajectories. The focus was for application in industrial processes, and, in a later review, it was identified as economically beneficial as it would balance many parameters in an uncertain, volatile, environment of the petrochemical industry in 1986 (21). Both articles cite one of the factors that make this control possible is the availability of digital controllers. Fast forward thirty years with more powerful computers, and MPC becomes much more viable for all applications. In terms of building MPC, this can be applied to HVAC controls as explored in this thesis, and to energy storage systems and grid power control as explored by Corbin. The use of MPC in this thesis focuses on the use of the building's passive thermal storage. This is directly following the work of Henze (22) in 2005 for experimenting with shifting building loads and pre-cooling the thermal mass, effectively shifting the HVAC loads to lower demand periods by using the thermal mass to cool the building as well as the incorporation of an ice storage system. These incorporated weather prediction and the optimization of a control strategy using a calibrated building model which was sent and executed in a test building environment. The successes this study was caveated by the amount of thermal energy storage available and the realism of the model.

Killian and Kozek address issues pertaining to model predicative control for buildings (23) and provide a review of MPC related studies. In this they cite that the advantages of MPC are the ability to predict disturbances in a dynamic building environment but at a cost of model development. The model development ends up being the most time-consuming part of the MPC implementation process, and there are no perfect solutions to modeling a building. Thus, the largest challenge to implementing MPC in a building is the lack of experts in the field to develop and implement MPC, making the cost of implementation much higher than conventional control strategies. They go on to mention that MPC does provide greater benefit now that more monitoring systems are being implemented in buildings, and that MPC can fit well into the incorporation of alternative energy sources.

Discussion of Tools Used for MPC

The tools used in this thesis follow the evolution of tools developed by Dr. Henze and associates. The program used is a modeling tool based on the works of Braun (7) for inverse gray-box modeling.

Braun details a method for predicting building HVAC cooling loads through the construction of a building envelope and solving the energy balance through the energy balance between internal and external sensible loads to solve for the HVAC load to maintain a constant internal temperature. The process laid out by Braun starts with the gathering of the physical data and building a resistance and capacitance network and solving the transfer functions transmitting external temperature and solar gains to the zone. The physical data required include wall materials, thickness, dimensions and orientation. Regression analysis is performed to calibrate the building model's estimate physical characteristics to measured data. This method was adopted by Corbin and used to create the tool used for many different applications of modeling to include building MPC (4), portfolio MPC (6), grid MPC (18), and for a fault detection program (24).

In the first application, Corbin explores the application of MPC based on an offline optimization inside a MATLAB environment, which feeds an optimum set point schedule vector into a online energy plus simulation to measure the effects of MPC. The findings were positive and resulted in cost savings for the two cases explored in the study. Corbin then uses this to explore the effects of MPC across the residential sector on the energy grid on the whole as mentioned above with findings that combine MPC across many buildings to improve grid dynamics (18). Pavlak also used this to explore the ability of a portfolio of buildings and suggested that MPC applied to a portfolio of separate buildings can coordinate towards the management of "communal peak demand" which in turn could influence a change in the energy market in terms of interaction between supplier and customers with many buildings. Lastly, through a slightly different application, this modeling basis was used by Henze, in cooperation with NREL, to create a fault detection program through which a building's sub metered data is compared to expected values as determined by a building model to alert building managers of potential faults inside the building (25).

Green Energy Signaling

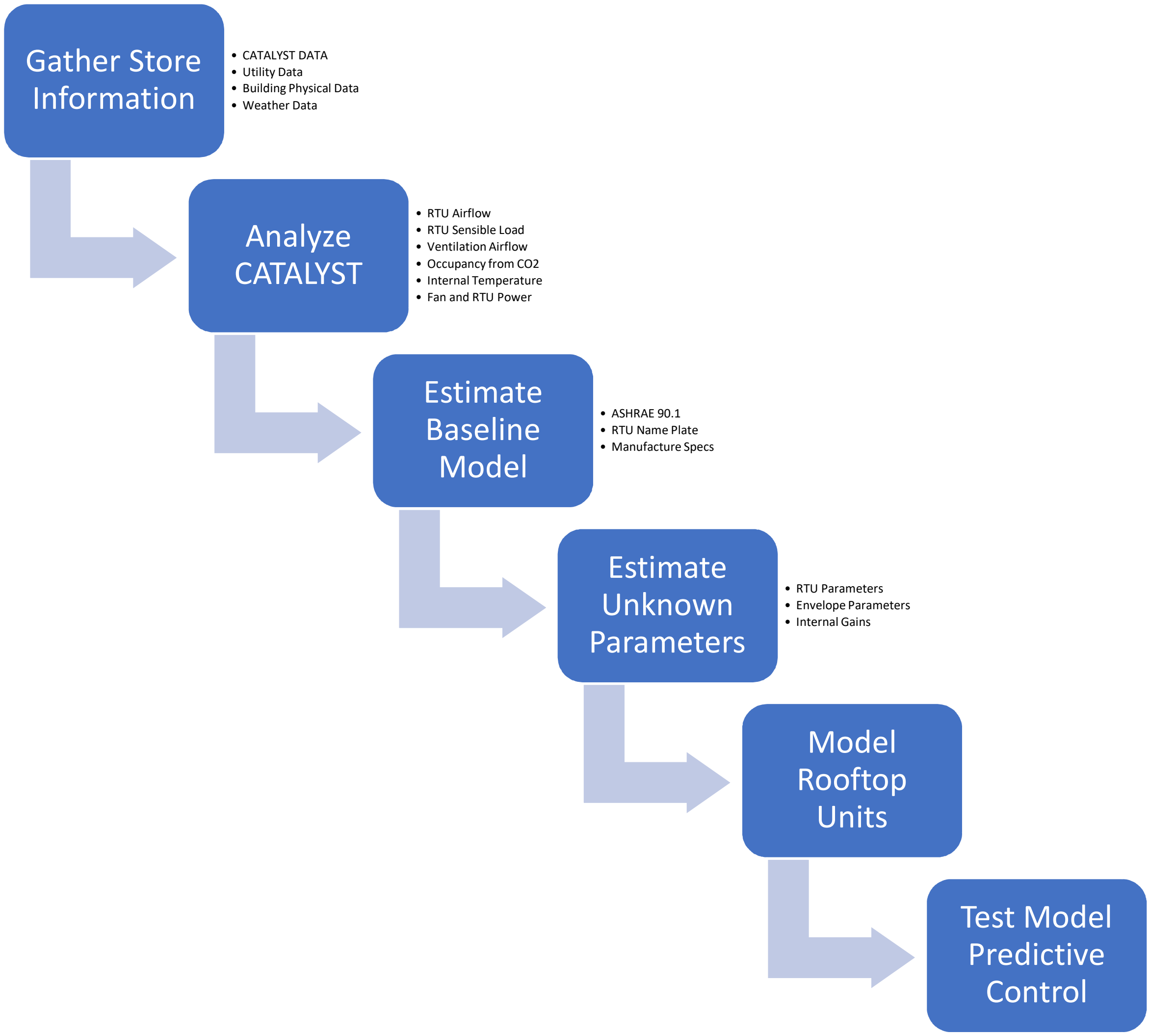
The last aspect explored is to test the ability of MPC to reduce carbon emissions by load shifting energy consumption to time periods where the source energy production is less carbon intensive. This follows the works of Greenfelder who investigated optimal control around minimizing carbon emissions (26). A non-profit company, WattTime, (27) produces a green energy signaling service consisting of the carbon composition of the regional energy generation, average carbon emissions per MWh, and marginal carbon data which represents how much carbon could be avoided by reducing energy loads at that time. This has been used with success in electric vehicle charging applications to minimize charging during carbon high production hours and maximize charging when carbon production is minimal (28). However, not much work has been accomplished in incorporating carbon signaling in building automation systems, so this thesis evaluates the ability of a building to include carbon reduction in the MPC cost function.

3. Methodology

The process to develop the model predictive controller for this project is detailed below. To develop the controller data was provided by Transformative Wave on the CATALYST controllers already installed along with basic RTU information from the installation audit at the Whole Foods Market located in Tarzana, California. The remaining data was gathered from various sources to piece together a working model for the controller. The following steps were used:

1. Gather store information as available
2. Analyze provided CATALYST data
3. Estimate building baseline models
4. Use Monte Carlo methods to estimate unknown building parameters
5. Model each roof top unit

6. Build Model Predictive Controller



The challenge associated with this project is the difference of data compared to traditional modeling procedures. Dr. Pavlak et all (5) detailed the use of a tool to predict energy consumption signaling for building operators. Required data was adopted from building audits and turned into a DOE 2-2 model to produce data predicting the HVAC system unknowns such as hourly energy consumption, internal temperature and sensible cooling loads. To generate the model for this, the same program was adopted but for use as a controller rather than an energy signaling tool. The difference in procedure is that very little audit data is available but very detailed HVAC data was available from the CATALYST controllers already installed on site. This required the estimation of physical characteristics through various means and then estimating the reduced order model parameters through previously developed least squares parameter updating procedures.

Description of the Store

The store chosen for this analysis was the Whole Foods Market located in Tarzana, California. Tarzana is a small community located outside of Los Angeles. The reason this store was chosen over other stores was the amount of data available. For example, some buildings with the CATALYST system did not have space temperature available which would have impacted the calculation of the sensible loads. No full audit data of the store was available, so the entirety of the project was conducted site unseen. This is counter to most all procedures of building modeling but was by design as CATALYST wanted procedures and a model generic enough to be applied to all buildings without a time intensive building audit. The building is then described through open source satellite imagery (Google Maps) and the data taken from the CATALYST sensors themselves.

Physical Characteristics

The building is situated on the north-western end of a small shopping complex as shown in Figure 3. The building has exterior walls on the west and a slanted north-eastern face which serves as the entrance and has the most fenestrations. The western face is connected to the rest of the shopping center while the southern face appears to be warehouse area that is not conditioned by the controlled RTUs. These two faces were not included in the ROM parameter determination as they did not have exposure to the outside elements and assumed adiabatic to a similar temperature zone. The dimensions of the building were measured, as shown in Table 1, using satellite imagery. The height of the building was estimated from standard construction as 6m.

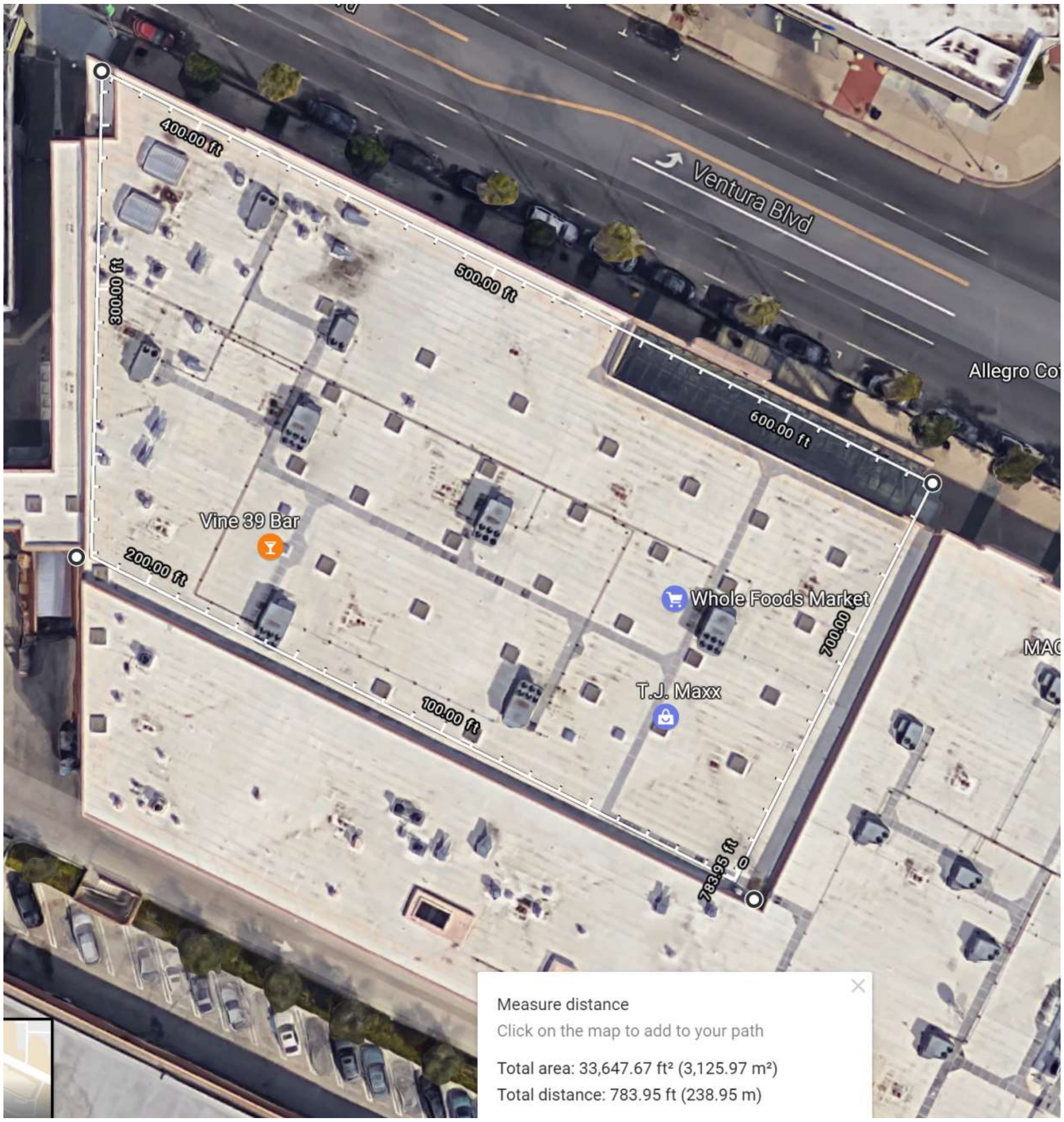


Figure 3: Google Images Satellite View of the Store

Table 1: Building Physical Dimensions

Face Dimensions	Horizontal Distance (m)	Height (m)	Area (m^2)	Glazing Ratio	Glazing Area (m^2)
North	90	6	540	0.6	324
East	43	6	258	0	0
South	68	6	408	0	0
West	48	6	288	0.05	14.4
Floor Area	3126				
Volume	18756				
Skylight Areas	62.52				

Building Orientation	27 Degrees				

The store is cooled by eight rooftop heating ventilation and cooling units (RTUs). Table 2 shows the summary of the provided audit data of each RTU. All RTUs provide both heating and cooling but only the five main sales RTUs provide two-stage heating. Three RTUs provide environmental control for the peripheral areas of the store to include the kitchen, customer seating area, warehouse and hall. The kitchen has the largest load and is served by a 10 ton and 8.5 ton, shared duty, RTU. The main floor has the largest single load and represents the largest area of the store. The main customer service area is serviced by five 25-ton RTUs.

Table 2: RTU Inventory and Properties

Unit	1	2	3	4	5	6	7	8	Total	Metric Total
Location	Kitchen	Customer Seating	Warehouse/ Hall/kitchen	North Central Sales	Central Sales	North East Sales	East Central Sales	Deli Counter		
Size (tons)	10	8.5	8.5	25	25	25	25	25		
Size (kW)	35.17	29.89	29.89	87.92	87.92	87.92	87.92	87.92	534.56	
Motor Power (HP)	3	3	3	10	10	10	10	10	59.00	
Motor Power (kW)	2.24	2.24	2.24	7.46	7.46	7.46	7.46	7.46	44.00	
Motor LFA (amps)	4.8	4.8	4.8	14	14	14	14	14		
Unit Voltage	480	480	480	480	480	480	480	480		
1st Stage Heat (Kbtu/hr)	59.8	54.3	54.3	70	70	70	70	70	518.40	
2nd Stage Heat (kbtu/hr)				96.1	96.1	96.1	96.1	96.1	480.50	
Combined Stage Heat									998.90	
1st Stage Heat (kW)	17.53	15.91	15.91	20.51	20.51	20.51	20.51	20.51	151.93	
2nd Stage Heat (kW)				28.16	28.16	28.16	28.16	28.16	140.82	
Combined Stage Heat									292.75	
1st stage cooling (kW)	17.58	14.95	14.95	43.96	43.96	43.96	43.96	43.96	267.28	
2nd stage cooling (kW)	17.58	14.95	14.95	43.96	43.96	43.96	43.96	43.96	267.28	
Economizer minimum position	15%	10%	10%	15%	20%	10%	15%	15%		
100% Fan Speed (CFM) -->(m3/s)	3500	2975	2975	8750	8750	8750	8750	8750	53200	25.00
90% Fan Speed	3150	2678	2678	7875	7875	7875	7875	7875	47881	22.50
75% Fan Speed	2625	2231	2231	6563	6563	6563	6563	6563	39902	18.75
40% Fan Speed	1400	1190	1190	3500	3500	3500	3500	3500	21280	10.00

The RTUs as installed were standard RTUs with heating coil(s), two stage cooling pushed through with a single speed supply fan. Outside air ventilation is brought in with a fixed damper. The heating coil is gas powered and the cooling coils are powered through an electric compressor. Part of the CATALYST retro fit replaced the single speed fan drive with a staged, variable speed drive, and added an outside air economizer. The main upgrade provided by the CATALYST controller is upgraded control logic. The new control logic controls when each stage of cooling comes on and the economizer cooling contribution maximized through all stages. Table 3, provided by Transformative Wave, shows the cooling sequence of operation. The cooling is divided into three buckets of cooling based on outside air temperature. In the first stage, the outside air temperature is at or below the supply air temperature, the economizer is used to provide full outside air and allow for mechanical cooling. The next bucket works with the outside air temperature greater than the supply air set point but the building loads should remain, most of cooling will be provided through the economizer and if the economizer is unable to provided enough cooling to meet set point the first stage of mechanical cooling turns on. Above 70 degrees, the economizer adjusts based on the supply air and return air temperature differential, and mechanical cooling operates as a more traditional RTU, turning on each stage of mechanical cooling if the supply air set point doesn't drop below 58 degrees F after 15 minutes of cooling.

Table 3: CATALYST Cooling Ruleset

58 Degrees F and Below	58 – 70 Degrees F	70 Degrees F and Above
1st Stage = Economizer Only @ 75% fan speed 2nd stg = Economizer @ 90% fan speed	1st Stage = Economizer @ 90% Fan Speed. 2nd Stage = 1st Stage Mechanical Cooling @ 90% Fan Speed	1st Stage = 75% fan speed 2nd Stage = 90% fan speed
No mechanical cooling	Integrated Mechanical Cooling and Economizer	1st Stage = Differential Economizer & 1st Stage Mechanical Cooling 2nd Stage = Differential Economizer & 2nd Stage Mechanical Cooling

Local Climate

Tarzana, California, is located in ASHRAE 90.1 climate zone 3. This is a coastal climate as the store is located approximately 9 miles from the coast line. The area also can be characterized by many hills creating a valley with Tarzana sitting at the northern base of the Topanga State Park and to the south-west of the Angeles national forest.

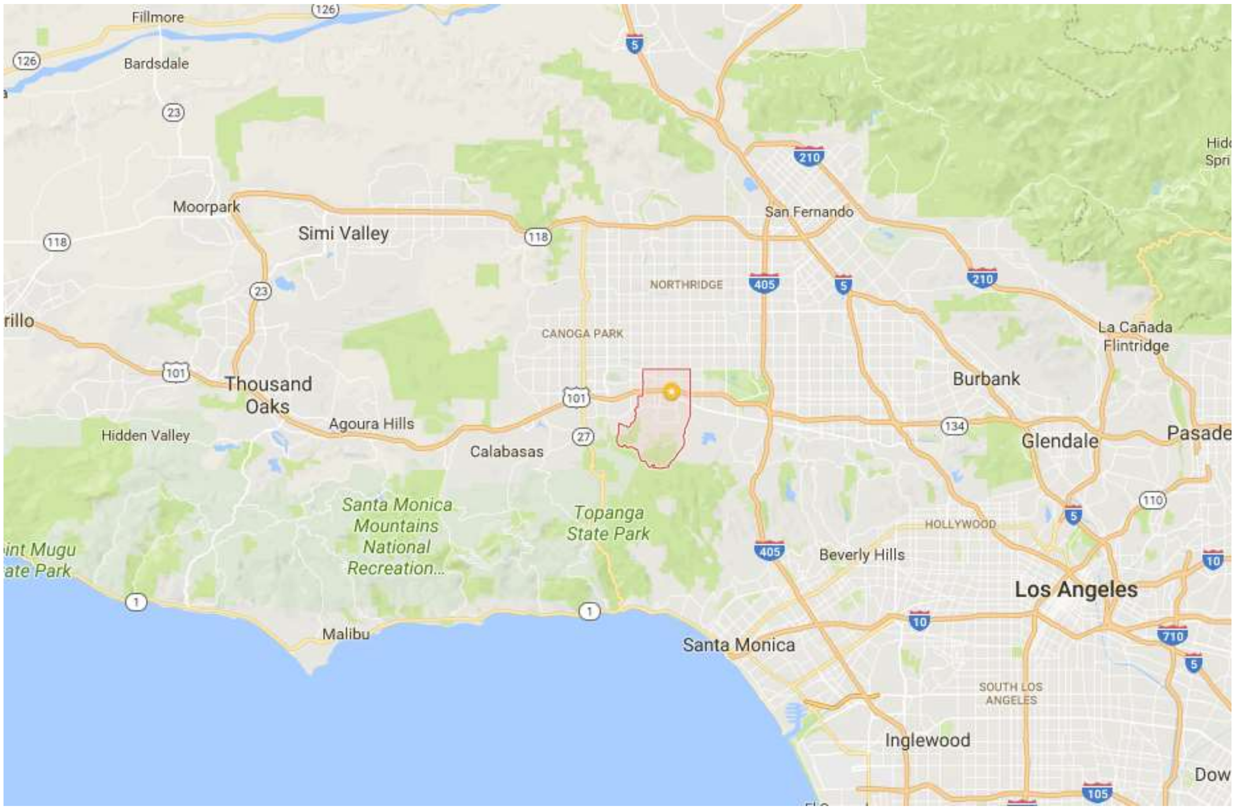


Figure 4: Tarzana Location Relating to Los Angelas

The weather is a temperate climate with moderate temperatures and an annual mean temperature around 17 degree Celsius. The summer high is less than 40 while the winter low is above 0 (see Figure 5).

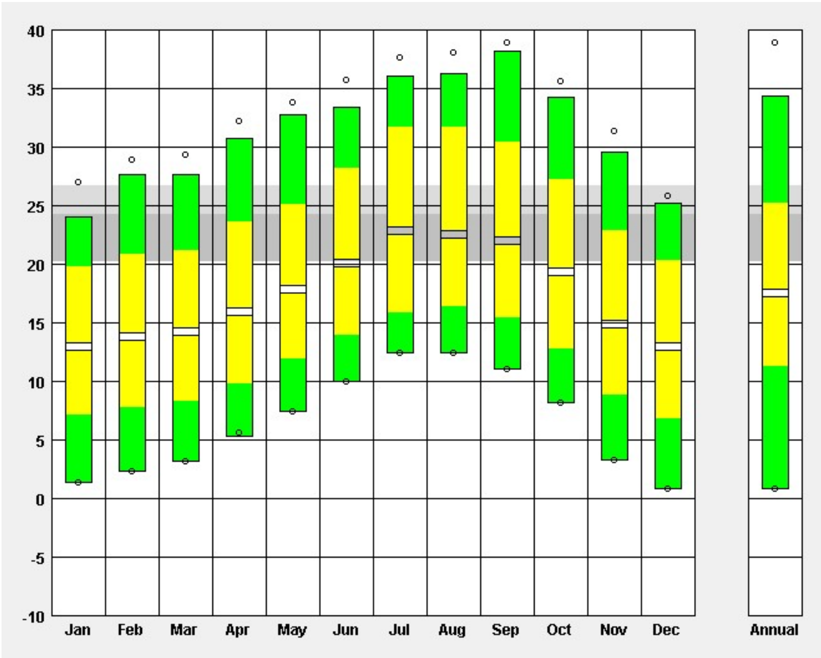


Figure 5: Monthly Temperature Rates from Climate Consultant

CATALYST Data Analysis

The CATALYST controller tracks and logs roughly 110 data points for each minute of operation. This includes the commands of the two stages of heating or cooling, fan speed, outside damper speed, unit faults, power consumption and all air temperatures. Additionally, the CATALYST unit performs a calibration test on the air damper to approximate the outdoor air (OA) ratio at 0%, 5% and 100% damper position. The air damper calibration data is generated by measuring the return air temperature, outdoor air temperature and the discharge air temperature at the called damper positions. The resultant discharge air temperature, without heating or cooling is a ratio of the return and outdoor air temperature from which the outdoor air fraction can be calculated. The CATALYST air temperature does not directly measure mixed air temperature. With the calibration data, a linear best fit line can be fitted to estimate the OA ratio at any damper position.

Using the OA ratio and the estimate flow rate based on fan speed the mixed air (MA) conditions can be calculated at each point using the equations below.

$$T_{MA} = f * T_{OA} + (1-f) * T_{RA}$$

$$T_{MA} = Mixed\ Air\ Temperature$$

$$T_{OA} = Outdoor\ Air\ Temperature$$

$$T_{RA} = Return\ Air\ Temperature$$

$$f = Outdoor\ Air\ Fraction$$

The mixed air temperature then is used to calculate the coil sensible load with equation X

$$Q_{Sens,coil} = \dot{m} * Cp_{air} * (T_{DA} - T_{MA})$$

The next state that needs to be calculated is the room sensible load met by the rooftop unit. This will be used to train the building parameters in the energy balance.

$$Q_{Sens,zone} = \dot{m} * Cp_{air} * (T_{IA} - T_{MA})$$

Lastly, the minute interval data includes a CO2 sensor which can be used to estimate the occupancy of the zone. While this isn't extremely accurate given the un predictable nature of people entering and exiting the store it does provide a starting point to estimate occupancy at any given moment at time. This become useful in defining the building schedules. The occupancy was calculated with the following equation:

$$n = \frac{\Delta CO_{2,RA} * V - \dot{m} * (f * C_{OA} + (1-f) * C_{RA} + C_{RA})}{.001667 * 1{,}000{,}000}$$

$$n = Occupants$$

$$\Delta CO_{2,RA} = Change\ of\ return\ air\ CO2\ concentration$$

$$V = Volume\ of\ the\ Building\ (m^3)$$

$$\dot{m} = Ventilation\ Flow\ Rate\ (m^3/min)$$

$$f = OA\ fraction$$

$$C_{OA} = Outdoor\ Air\ CO2\ concentration\ (400\ ppm)$$

$$C_{RA} = Return\ Air\ CO2\ Concentration\ (ppm)$$

$.001667 = Human\ CO2\ respiration\ (m^3/min)$ (29)

Baseline Model Development

To provide a starting point for the inverse model testing a baseline model must be developed to set target parameters for the Monte Carlo estimating of unknown internal gains and the least squares parameter updating.

Estimating Building Envelope

The building envelope construction is largely unknown but can be solved for with the tools provided by Dr. Pavlak. However, without any starting reference point, the tools can find many optimization points that do not reflect buildings constructed in reality. To bound the solver, a baseline construction needs to be created. To build the baseline values, ASHRAE standard 90.1, 2007 (30) prescriptive assembly maximum values in table 5.5-3 were used.

Table 4: Prescribed R values

Element		Conductivity (Btu/(h*sqft*F)	Conductivity (W/m^2*K)	Resistance (m^2*K)/W
Roof	Insulation Entirely Above Deck	0.046	0.26	3.83
Walls above Grade	Steel Framed	0.084	0.48	2.10
Floors (Slab on Grade)	Heated	0.9	5.11	0.20
Fenestration	Metal Framing (Curtainwall/Store Front U-60	0.6	3.41	0.29
	Metal Framing All Other	0.65	3.69	0.27
Skylight	Glass	1.17	6.64	0.15

These prescribed resistance values can then be used to determine the resistance of a lumped parameter RC networks as described by Braun (31). The determined RC network can then be used to run initial Monte Carlo simulations to estimate the internal loads and then refine through Least Squares updating the RC network. Lastly, the customer of this project requested as simple a model as possible, so a 5 parameter model is recommended (25).

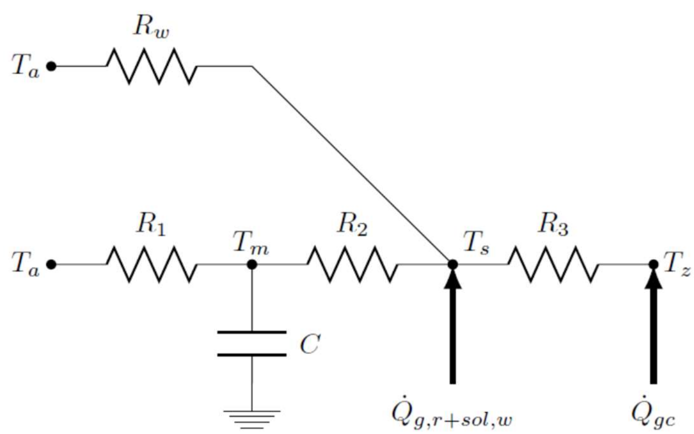


Figure 6: 5 Parameter RC model

Internal Gains Estimating

The internal gains are also largely unknown in the project. Occupancy can be estimated from the provided measured CO2 data but the exact number of people and schedule is unknown as the majority of the occupants are transient customers. The lighting internal gains is mostly uniform from the time employees arrive to the time customers arrive until closing. The appliance loads would maintain a baseline load throughout the day from refrigeration but contribute additional unknown cooking loads throughout the day.

To estimate the occupancy schedule, the building occupancy for each minute was estimated previously. The data was then compiled into on the hour data through averaging the hour. The schedule was compiled by averaging three weeks of data for each day and hour. The occupancy was then balanced so that the lowest occupancy was zero during known hours and reduced each hour by the same amount. Finally, the maximum occupancy was estimated by taking the maximum value during the schedule.

Starting with the lighting loads, the schedule was estimated based on known operating hours and the calculated occupancy schedule to see when early morning operations begin. To determine the magnitude of lighting load an informal audit was conducted at the Whole Foods in Lakewood Colorado and Superior Colorado. Lights were counted for a sample of the marketplace floor, and the load was found to be near the standard lighting load of 9.8 W/m^2.

The appliance loads were also looked at during the informal audits but, without a deeper audit of the building to count all appliances and to gather name plate information, the appliance load would be difficult to estimate. Using an Energy Star Building Manual produced by the Department of Energy (11), approximately 62% of building electric loads are from appliances with the median energy use for supermarkets of approximately 190,000 Btu/sqft. This would give a starting point based on the floor area of the building of around 117,800 Btu. The schedule was then estimated similarly through the occupancy schedule but adjusted based on known cooking times. However, this method proved to be inaccurate. To better estimate the appliance loads, the energy balance was analyzed.

$$\sum Q = Q_{Env} + Q_{infil} + Q_{Light} \ + Q_{Occ} + Q_{appliance} + Q_{sensible} = 0$$

Using the baseline construction, the environmental load can be calculated as a function of outdoor and indoor air temperatures provided by the CATALYST controllers. Infiltration was not considered due to the large variability and effects from outside conditions. The previously developed occupancy schedule was used to estimate the occupancy load. The sensible load was then calculated with the provided discharge air temperature and rated flow of each RTUs. The lighting load was based on occupied hours at a fully occupied time, shoulder hour 80% occupied time and a 10% emergency lighting only during the unoccupied hours. This leave the appliance load as the only unknown to be solved for. The resulting loads over a three-week period were then averaged to create the appliance load schedule.

Processing Weather Data

The last bit of information needed to run the model was to input weather data. The script is designed to read energy plus weather files. For model training the best data to use would be actual historical data to match the building conditions from the provided data. Temperature, dew point and wind data were adopted from NOAA using the Burbank Airport weather station (32). The last portion that was needed was the solar data. This came from another source but with data every three hours. The hourly data was then interpolated for the missing two hours in between. The data needed to be then processed into an EPW file. While an EPW file can be read and edited through Microsoft Excel or Notepad neither programs are simple or quick for removing and adding data. Big Ladder Software produces a free EPW editing program called Elements (33). Using this program, each column of data was copy and pasted replacing a data in generic EPW file created by NREL (34).

RTU Modeling

The second step in building the model is to properly model the RTUs providing cooling. In this case there are 8 RTUs that will be modeled by one simulated RTU. The components that needed to be represented were the economizer, heating coil, two stages of cooling coils and the supply fan. Using the modeling template provided by the energy signaling tool the model was developed through pre-built components. These templates were programmed using the Energy Plus Engineering Reference (35). The control logic was set to model the economizer use if the outside air was cooler than the return air. The cooling load provided through the economizer was calculated to determine if the cooling coils were needed, and then each stage used based on the need to meet load. The supply fan speed will modulate based on the sensible load requirement, required supply air temperature and the mixed air temperature. This is in place of constructing a CATALYST logic RTU since the CATALYST rules were based on minute sampled data. The full one-hour data simulated in the tool would not capture the staging control of the CATALYST.

In order to convert the program into minute sampled data and be able to better model the CATALYST rules, additional work would have to be done. Within the programming, the conversion should be relatively simple as the code is set up to be able to define the time interval. Inputs would have to be then provided at the minute interval. The CATALYST data is already provided for every minute so no conversions would have to take place. The weather data provided by NOAA and energy plus weather files all provide on the hour data which would then require the minute data to be interpolated at minute intervals between the hours. The largest effect this will have is in the computational power required to solve for a full day as the number of times steps will increase 60 times. This could result in 60 times longer to compute compared to the same computer or require a more powerful computer will increase the implementation costs. The result would be a more accurate model as the CATALYST data precision will not be reduced by characterizing 60 data points with a single data point and would better account for each disturbance which would occur through the hour.

Since this is only a moderately heating environment and no gas flow data is provided the heating coil was not calibrated. The economizer operates in a standard method so the economizer wasn't calibrated outside of the open and closed flow rates matching the maximum and minimum flow rates. The two components calibrated were the supply fan and the cooling coils. The data from the CATALYST provided the fan speed and the fan energy used. To calibrate the fan, Monte Carlo simulations will be run to evaluate the RMSE error between the simulated fan power and the model sensible loads testing fan efficiency, maximum flow rate and the fan pressure rise. The simulated fan speed will be replaced by the data-provided fan speeds. The cooling coil was similarly calibrated with the same flow rates and the actual zone temperatures. The cooling coils coefficient of performance (COP), rated cooling capacity and the sensible heat ratio were calibrated through a similar Monte Carlo testing.

For the fan, the model's part load curve was calculated through solving for the fan flow fractions and the power fractions using the CATALYST data sets. The regression line can then be used in the fan model quadratic solver. The cooling coil curves are a bit more complicated to be solved for. Transformative Wave Technologies provided empirically solved curves for a 10 ton unit for use in the model. For simplicity sake, these curves were used directly in the model for part load conditions. The effective change between the provided curves in Dr. Pavlak's model to the large, reduced order model was quite minimal. The cooling coil curves are provided in Appendix C for both stages of cooling.

PV Modeling

The last element to be modeled is the addition of a Photovoltaic (PV) electrical generation system to the building. The store currently does not have PV installed but part of the CATALYST study is to provide optimization around a PV and battery electrical storage system. To simplify this analysis, a full return of investment will not be provided. The only metrics that will be provided are the cost savings based on the utility rates provided in the analysis and the energy generated by the cells. To incorporate PV into the testing, the size of the system is estimated using PV Watts (36) capacity calculator based on estimated usable rooftop area. Based on this, there are three proposed options for PV layouts, shown in Table 5 and Figure 7.

Table 5: PV Option Sizes

Option #1	Size (m^2)	Size (kWdc)
1	547	82.0
2	480	72.0
3 (Combination)	1027	154.0

For testing, to avoid redundancy, only options one and two will be tested since option 2 is close enough to option one that there would be minimal benefit to show the difference 10 kWdc will make.

System Capacity: 82.0 kWdc (547 m2)

System Capacity: 72.0 kWdc (480 m2)

Figure 7: PVWatts Array Sizes

Using these three options, hourly PV data was estimated using the NREL System Advisor Model (SAM). The parameters provided were the constructed weather files, the system size and the panel type.

The PV Panels used were the Sunpower SPR-X19-240-BLK as specified by SAM. This company was chosen based on an online review (37) as the top manufacture. The company has been around for 30 years and has a network of local installers. This makes it a reasonable and likely source for PV panels in the area. However, this is noted to provide a reality-based panel array and is not intended as a recommendation of a company as a supplier.

The panel design assumes a low cost installation of fixed panels with a tilt of 34 degrees and a azimuth of 207 degrees to be facing south but parallel with the building orientation. Figure 8 shows the resulting power availability of the 154 kW system with respect to the hour of the week. The 82kW system will be similar but approximatly half the power generation.

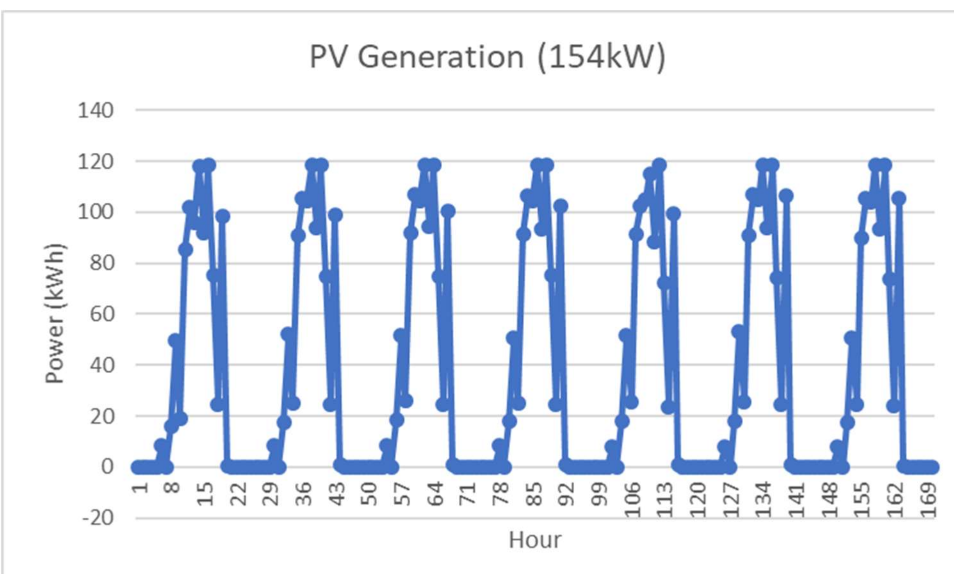


Figure 8: PV Generation Chart

Building Model Training

Once the baseline building model has been developed, the model will need to be trained to reflect the actual building response. In this case, the parameters to be trained are the building envelope RC network, the internal gains, and the lumped parameter rooftop unit.

Prescribed Calibration Procedures

Since building modeling for the use of energy savings in new construction and for retrofit measures is the primary method of justifying costs and validating effects, ASHRAE Guideline 14 (38) was published to provide a standard method for calibrating building models. The standard recommends two methods to calibrate a model: graphical and statistical. The graphical methods proposed in the guideline allow for the modeler to visually inspect and understand how the model is performing compared to the real data and a statistical range of allowable points. The statistical comparison technique uses the hourly mean bias error (MBE) and the coefficient of variation of the root mean squared error (CV(RMSE)). MBE measure the difference between the measured and simulated energy use over an hour and summed across the trial period then divided by the total measured energy use for the same time period. This works to measure the percent difference of the total simulated energy consumption and the total measured energy usage but lacks the ability to measure the total variance between each time step. The CV(RMSE) error accounts for the total variance at each time step by squaring the difference between the simulated and measured variable summing over the period and dividing by the number of time steps then taking the square root to produce the error to produce the RMSE. The coefficient of variance is then calculated by dividing the RMSE by the average measured variable and expressed in a percentage. The calibration procedures in this thesis rely on minimizing the RMSE error as this provides a better goodness of fit for the model since model predictive control is more dependent on accurately predicting, and designed to control each time step compared to daily summary statistics.

Additionally, ASHRAE Guideline 14 recommends to calibrate both a baseline model and the retrofit model to measured utility and weather data. In this case, the baseline model may be calibrated to measured data while the retrofit model modeled by modifying the baseline model with the retrofit measures. In this case, utility data is not available so the model is calibrated to measured data provided by the CATALYST sensors. Without utility data, the overall building energy consumption will be an estimate based on measured cooling loads and estimated schedules. Prior to implementation, utility data will be required to provide a more accurate baseline model.

Envelope Training Procedure

To train the model, the program developed by Dr. Greg Pavlak (38) for grey box inverse modeling was used to develop the RC network for the Tarzana Whole Foods. An iterative process is necessary to develop the best model. First, the baseline model and appliance loads will be simulated to find a baseline root mean squared error (RMSE) of the sensible loads compared to the actual data. Next, Dr. Pavlak's training program will be used to search for a minimum RMSE through Newtonian interior reflective processes. This provides a starting point to refine either the RC network parameters or the appliance loads depending on which data produces the lowest RMSE. If the least squares updating can improve the RMSE of the model, new appliance loads can be calculated using a Monte Carlo simulation. For this model the appliance maximum loads, the occupancy, appliance convective fraction and building infiltration parameters were run through Monte Carlo simulations at 200 simulations each adjusting the values +/- 100% initially comparing RMSE to the actual data. The smallest RMSE values would be used as long as the values remained within a reasonable range. The Monte Carlo simulations would be run a couple times to balance the changes in each internal load. Once reasonable and optimal results are reached the model would be retrained to see if better model parameters could be achieved. This process can take place as many times as necessary until the error curves converge at a minimum.

RTU Calibration Procedure

Once the building envelope and internal gains have been calibrated, the RTU model will also need to be calibrated. The baseline model and flows that were calculated through the provided data provide the starting point for this analysis. Since there was no existing program available to solve for the RTU parameters new scripts were created to training the model. The method was to use a similar Monte Carlo Style simulation to solve for the lowest RMSE of the fan power, RTU power, and the expansion coil power consumption. First, a test was created to run 50 simulations adjusting each parameter individually with a random number generator to find the lowest RMSE of each parameter holding all others constant. The lowest RMSE value of each parameter would then be adjusted and the whole test run again until the RMSE values converged. The fan was calibrated first based on the maximum flow rate, the nominal pressure rise across the fan and the fan efficiency. Once the fan was calibrated the two cooling coils were calibrated based on combined cooling capacity, stage balance, coefficient of performance (COP) and sensible heat ratio (SHR).

After multiple iterations of this method, an additional method was tested. This was a single set of trials in which each of the previous parameters would be adjusted based on a different set of randomly generated numbers and tested at the same time to minimize the fan power RMSE, cooling coil RMSE, RTU RMSE, and the sensible cooling RMSE. The results of both trials are presented in this paper.

Table 6: RTU Calibration Parameters

Fan Calibration Parameters	Cooling Coil Calibration Parameters
Maximum Flow Rate (m^3/s)	Total Cooling Capacity (W)
Nominal Pressure Rise (Pa)	Stage Cooling Capacity Balance (%)
Fan Efficiency	Stage 1 and 2 COP
	Stage 1 and 2 SHR

To accurately calibrate each component, data from the CATALYST unit was used as input data into the RTU. This included the calculated mixed air temperature, the actual flow rate and the sensible load of the RTU.

Monte Carlo Sampling Procedures

The building calibration follows a similar procedure as described in ASHRAE guideline 14 by using RMSE as the metric for evaluation and Monte Carlo trials as described by Harmer (39) for model calibration. First, to calibrate and estimate the internal gains simulations were run holding all but one variable constant while testing 50 combinations of that variable before repeating with all variables. This was done minimizing RMSE until the values converged at which point no new combination of variables could improve RMSE. Though this process, variables were adjusted based on their effect on the total model.

A second method was used to calibrate the RTU model. In this, each variable was randomly adjusted using a gaussian random number generator to produce a range of values and 10,000 different combinations. The RTU was then calibrated based on minimizing the error of fan power and cooling coil power with the solved values for the respective components.

Model Validation

The first model was developed based on data from April to May of 2017. However, these months could be considered much more temperate than the later months. To select the time frames, the calculated sensible load and the outdoor temperature were examined to find the test ranges in which the system will be under the most stress.

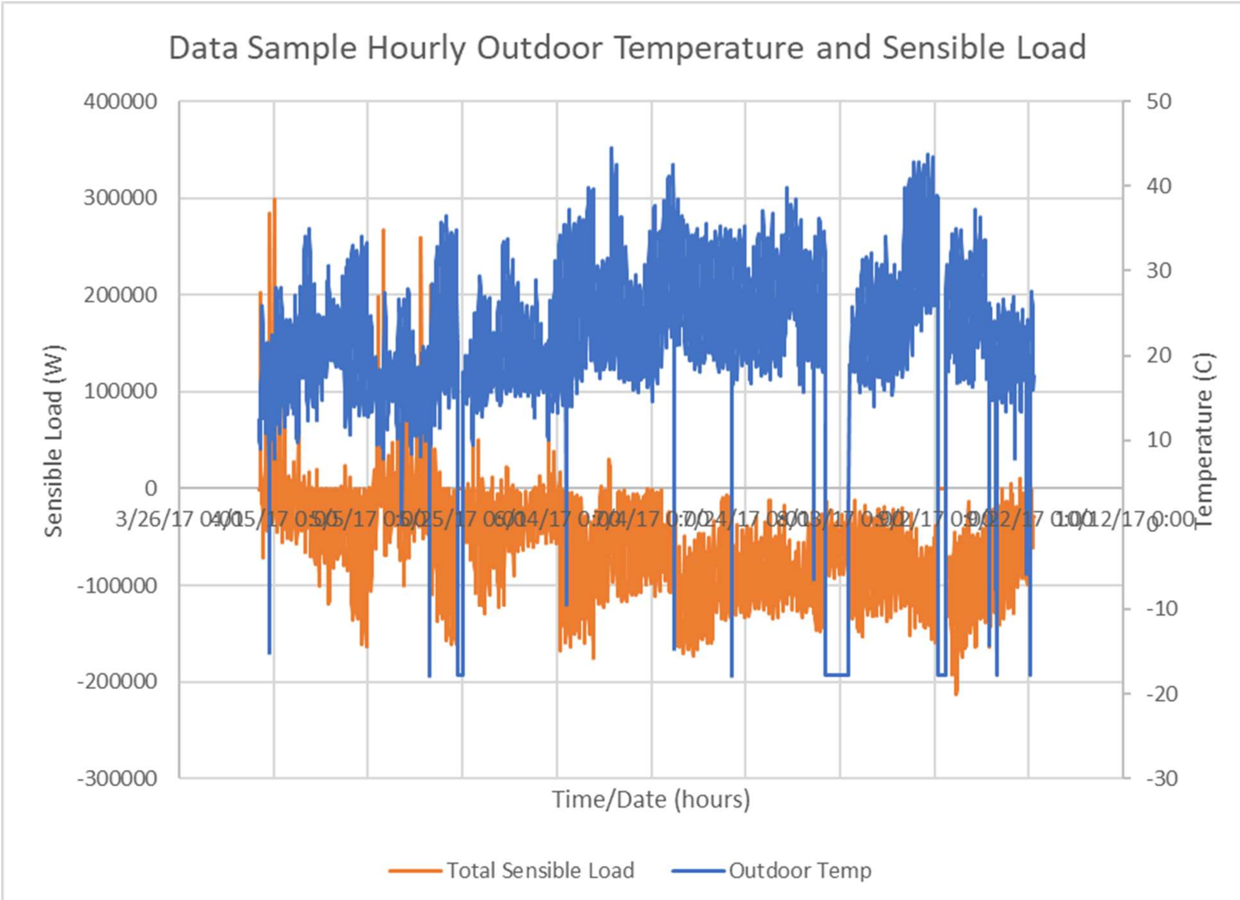


Figure 9: Hourly Temperature and Sensible Loads

Three weeks were selected: June 14th to the 21st, July 9th to the 16th and August 23rd to September 1st. The calibrated model was then evaluated based on Fan RMSE, Sensible Load RMSE, Cooling Coil RMSE and the RTU overall RMSE.

Model Predictive Control Application

The main purpose of this project is to test the application of Model Predictive Control on a commercial retail building. The program used for this application was provided by Dr. Pavlak to optimize the temperature set points of the building in order to minimize a cost function. The cost function initially supplied is a sum of the usage energy costs and a user defined demand penalty cost. In application, the primary concern is to decrease utility usage costs and decrease overall demand costs in the building providing operation cost savings throughout the year. However, using this cost function the optimizer could be set to minimize energy usage, ensure occupant comfort, and decrease a building's carbon footprint.

Testing Goals

First and foremost, the controller will be used to minimize the utility costs associated with cooling loads. However, following on Dr. Corbin's (18) research, additional metrics will be evaluated to determine the performance of the controller and the effects of the building on the grid. Although these grid metrics are less important to building owners they can be considered social responsibility metrics because increasing building performance in relation to the grid will improve overall grid performance. Below are the metrics evaluated in this thesis:

1. Energy Consumption
2. Energy Usage Cost
3. Peak Demand
    a. On Peak Demand
    b. Mid Peak Demand
4. Demand Costs
5. Peak to Valley Ratio (18)
6. Load Factor (18)
7. System Ramping (18)
8. Carbon Demand

Energy consumption is defined straight forwardly as how much energy the building will consume each day in terms of kWh. This is billed by the utility companies as time of use cost per kWh with additional generation costs based peak demand time costs.

Peak demand reduction is important to the customer as this is an additional cost based on the highest power requirements of the building each month. This is provided in terms of kW. Utility companies will also bill this based on peak and mid peak generation requirements as additional cost. Unlike the time of use costs, this is billed based on the highest demand per month.

Peak to Valley (18) ratio as suggested by Dr. Corbin is the ratio of the daily peak demand to the minimum demand. From the building perspective this means little as the utility customer is only billed based on the peak demand of the month. This metric is important to the utility company as this determines the difference between baseline utility generation and how much additional capacity is necessary for peak loads.

Load Factor (18) is a similar grid-related metric but is defined as the average demand divided by the peak demand. This provides a ratio of how much demand the building requires on a regular basis to the peak demand.

System Ramping (18) is the sum of the absolute value of the changes in building demand throughout the day. From the grid perspective this is valuable as sudden fluctuations across the grid can cause brown outs as generation capacity adjusts to meet grid energy demand.

Lastly, Carbon Demand will be characterized by the amount of carbon generated by supplying power to the building. This will be evaluated based on the marginal carbon rates supplied by WattTime. Performance by this metric will be the successful reduction of carbon intensive generation methods by shifting cooling loads to high renewable energy generation time periods.

These tests will be run for one week in July to evaluate controller performance.

The tests that are accomplished are as follows:

1. Energy Optimization Testing

2. Cost Optimization Testing
    a. Optimization under current rate structure
    b. Optimization under day ahead pricing
    c. Optimizing with current rate structure around a ramping event
3. Blended Cost Function
    a. Peak Demand Reduction
    b. System Ramping Reduction
    c. Peak to Valley ratio test
    d. Load Factor reduction
    e. Utility Carbon Dioxide production reduction

Optimizer Cost Function

The optimizer uses a cost function to evaluate the optimum results. The below function shows all the factors added into the cost function. Is penalty is calculated separately then added into the cost function.

$$Cost = TOU + energy + demand + peak\ demand + PtV + LF + Ramp + CO_2 + Event$$

$$TOU = weight * (\sum Off\ Peak\ Energy * Rate + \sum Mid\ Peak\ Energy * Rate + \sum On\ Peak\ Energy * Rate)$$

$$energy = Weight * \sum Energy\ Consumption$$

$$demand = \mathrm{Weight} * [\max(off\ peak\ demand - threshold) * cost + \max(mid\ peak\ demand - threshold) * cost + \max(on\ peak\ demand - threshold) * cost]$$

$$peak\ demand = weight * \max(demand)$$

$$PtV = weight * \left(\frac{\max(demand)}{\min(demand)}\right)$$

$$LF = weight * \left(\frac{}{\max(demand)}\right)$$

$$ramp = weight * \sum_{0}^{n=23} |demand_n - demand_{n+1}|$$

$$carbon = weight * \sum_{0}^{n=23} (energy_n * AvgCO_{2_n})$$

$$Event_n = weight * demand_n$$

For each of the tests, the weight factor is adjusted to provide a difference balance of each factor depending on either testing goals or user priorities.

Testing Comparisons

All test results will be compared only within the trials. There is no information available for the building before the catalyst upgrade to the RTUs in either the form of HVAC energy consumption or utility data. Because there is no real baseline data, and the model was calibrated through the CATALYST controller measured data, a true baseline model could not be built for comparison. The night time set point (NSU) case will be considered the baseline for each trial. The NSU and the Optimized (OPT) trials are run with the same cost function, same utility costs and the same model to provide results based on the CATALYST calibrated model. In the NSU case, the zone temperature cooling setpoint will increase outside of business hours, at 12:00am, to 26.67 Celsius (80 F) and decrease to the daytime set point, at 6:00am, of 23.89 Celsius (75 F). The NSU case models the CATALYST controller set point control as currently implemented. The OPT cases are the results by optimizing and dynamically controlling the zone temperature setpoint within the static zone temperature bounds of the NSU case.

Energy Optimization Testing

The first, almost baseline case, to be tested will be to see if the building's overall energy consumption can be decreased. This test will be set up with a flat rate energy cost per kWh and demand penalties will be not be applied. This controller will then run to minimize energy cost and therefore total energy consumption. This will evaluate if the building itself can be used as energy storage through pre-cooling in more energy efficient times such as in the morning compared to less efficient times during the heat of the day.

Energy Cost Testing

The next tests are realistic costs minimization tests. These test the ability of the controller to optimize the HVAC control to minimize real utility costs. Three cost structures will be evaluated based on the Southern California Edison Utility Rate schedules (39).

Additional Metrics

The following costs will be evaluated in addition to the utility costs. These are taken directly from Dr. Corbin's grid research and applied to this building.

1. Peak to Valley Ratio (18)
2. Load Factor (18)
3. System Ramping (18)

The goal to testing these metrics will be to decrease the overall impact the building has on the grid by decreasing the variation of the demand loads of the building.

Current Utility Cost Minimization

The current utility cost minimization incorporates the annual time of use pricing of the area in terms of dollars per kWh and demand costs. The utility structure includes seasonally variable rates as well as peak demand charges. Figure 10 shows the rate structure. Since the demand rates are calculated at the end of each month, demand will be added to the cost function as a penalty for each day but the peak demand and cost will be evaluated as the peak demand of the week.

	Delivery Service								Generation[9]	
	Trans[1]	Distrbtn[2]	NSGC[3]	NDC[4]	PPPC[5]	DWRBC[6]	PUCRF[7]	Total[8]	UG**	DWREC[10]
Option CPP										
Energy Charge - $/kWh/Meter/Month										
Summer Season On-Peak	(0.00213) (R)	0.00230	0.00866	0.00001	0.01152 (R)	0.00549	0.00043	0.02628 (R)	0.08819	0.00000
Mid-Peak	(0.00213) (R)	0.00230	0.00866	0.00001	0.01152 (R)	0.00549	0.00043	0.02628 (R)	0.05095	0.00000
Off-Peak	(0.00213) (R)	0.00230	0.00866	0.00001	0.01152 (R)	0.00549	0.00043	0.02628 (R)	0.03226	0.00000
Winter Season On-Peak										
Mid-Peak	(0.00213) (R)	0.00230	0.00866	0.00001	0.01152 (R)	0.00549	0.00043	0.02628 (R)	0.04662	0.00000
Off-Peak	(0.00213) (R)	0.00230	0.00866	0.00001	0.01152 (R)	0.00549	0.00043	0.02628 (R)	0.03712	0.00000
Customer Charge - $/Meter/Month		446.13						446.13		
Demand Charge - $/kW of Billing Demand/Meter/Month										
Facilities Related	4.64	13.17						17.81		
Time Related										
Summer Season - On-Peak		0.00						0.00	17.42	
Mid-Peak		0.00						0.00	3.43	
Winter Season - On-Peak		0.00						0.00	0.00	
Mid-Peak		0.00						0.00	0.00	

Figure 10: CPP Rate Structure

The demand thresholds will vary between the tests but the cost will remain constant based on the this utility price structure. The summary costs are shown below in Table 7.

Table 7: Summary of CPP Charges

	Demand Charges ($/kW/Month)	Time of use ($/kWh)
Maximum Demand Penalty	$17.81	
Off Peak		$0.05854
Mid Peak	$3.43	$.07723
On Peak	$17.42	$0.11447

Day Ahead Pricing

Day ahead pricing uses the energy market to determine the cost of energy a day ahead of use based on speculation of the total capacity required. The time of use prices as specified in the above test will replace with the historical day ahead prices as provided by California ISO location marginal prices for the closest node to the store (Moorpark_GN10) (40). Figure 11: Day Ahead Energy Pricing Profile shows the day ahead pricing schedule for the testing week. The peak price occurs at 8pm every day of the week.

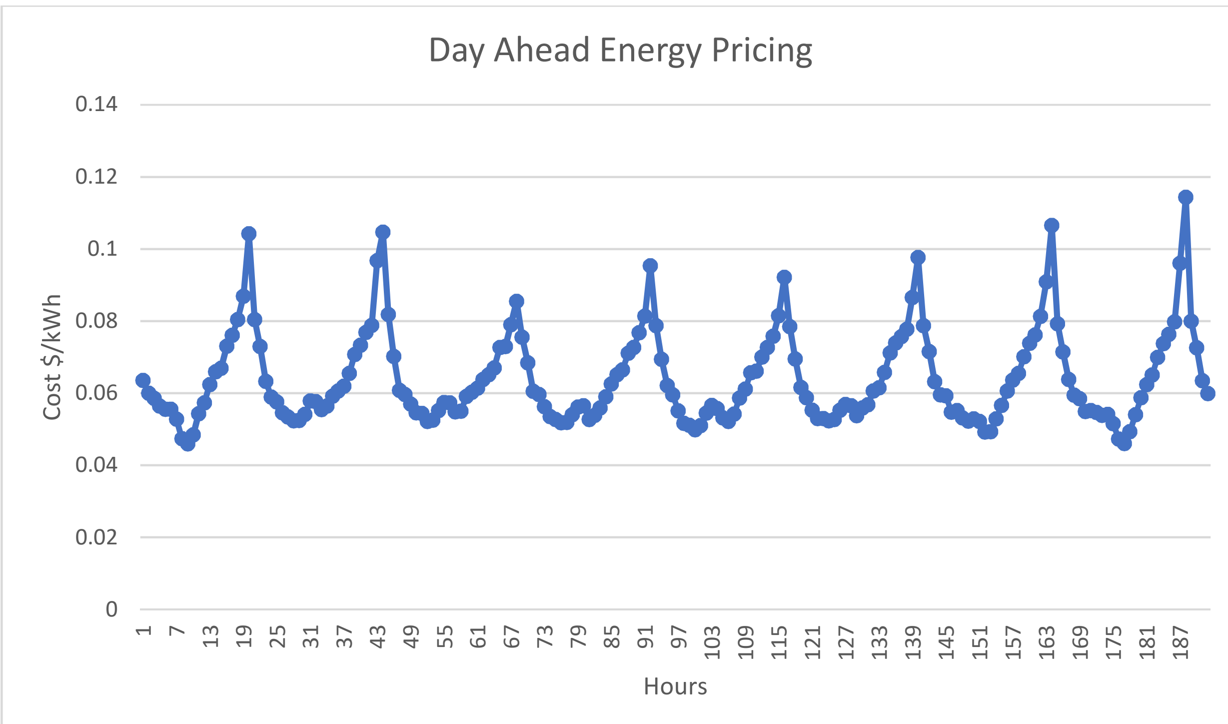


Figure 11: Day Ahead Energy Pricing Profile

Demand Response Testing

Under the utility structure currently used by Whole Foods. the store participates in a Critical Peak Pricing (CPP) program during which the customer is expected to reduce their demand load by 30 kW. To test this, an additional cost will be added to the demand penalty that will represent the opportunity cost lost by not reducing demand 30 kW below the peak demand as solved in current utility cost minimization test. In this case, there will be an additional $19.00 per kW. There is also an additional usage charge of $1.37 per kWh that will be added as per the CPP rate structure. (39) This time which this will be in effect will be simulated during the day ahead pricing peak charges for each day. The event will be tested at the peak of the day ahead pricing with the assumption that at 8pm the cost is the highest because this is also the highest demand period of the day.

Blended Cost Function Testing

The above tests can be considered traditional cost saving tests which will be immediately applicable to the building owner. The following tests have less application to building owners in terms of utility costs but can have greater grid impact. These additional tests will be incorporated into the cost function as additional penalties and testing based on weight in the cost function.

3. Blended Cost Function
    a. Peak Demand Reduction
    b. System Ramping Reduction
    c. Peak to Valley ratio test
    d. Load Factor reduction
    e. Utility Carbon Dioxide production reduction

These tests are will adjust the building's HVAC control in order to optimize the building's response to the grid. In the peak demand reduction test, a multiplier based solely on the maximum demand of the building will be added. The hope is that the controller will minimize its use during the building's peak energy consumption.

The system ramping test will evaluate the HVAC controller's ability to smooth out the building's energy demand profile. In theory, when the building's energy is expected to move quickly between highs and lows the HVAC planning horizon should account for this and either run more or less to lessen the rate of change between these. In a similar manner, the peak to valley ratio test should find the lows in building demand and run more while running less during times of high energy demand. The load factor test will then adjust according to the maximum demand to maintain a lower overall demand while maintaining a higher average demand.

Marginal Carbon Rates

Marginal carbon rates are provided by WattTime.com. These tests will test the ability of MPC to shift the HVAC load from times of low renewable generation to high renewable generation. Since power generation from solar and wind power is highly variable or limited to certain time periods of the day not all the power can be properly used and still require the use of peak power plants to support demand outside of the high green power production. This will test the load shifting ability of HVAC control to use more green energy and reduce off green power consumption.

Grid Integration

The main purpose of including these metrics is to determine the ability of the building to better integrate into the grid. Currently, each building within the grid act as “selfish consumers” and “demand” power from the grid when needed and as much as needed to satisfy requirements at the time. If a single generator was serving the building this would require the generator to be sized the building’s maximum demand but would result in inefficiencies during the minimum or sub-optimum demand range of the generator. This could be solved by adding a second generator; one to provide power at the average demand range and the second to match peak demand load as necessary. In this case, by minimizing peak demand, this would allow the second generator to be sized much smaller. If the building load were to cycle repeated with large swings in demand, this would cause the first generator to run sub-optimally like a car accelerating and decelerating in stop and go traffic and cause even greater inefficiencies in the second if the generator would have to constantly turn on and off. This would be solved by minimizing system ramping. Generators have decreased efficiencies and life when they run below their design power generation causing wet stacking. By reducing the peak to valley ratio and the load factor will maintain the generators operating efficiency and life. However, in this case this is just one building and two relatively small on-site generators. The grid on the other hand is made up of many buildings and many large generators. If one building would work to improve their relationship to the grid overall grid performance would improve but almost negligibly due to the sheer size grid demand. The advantage of integrating into the grid is not all buildings demand schedules are the same so by this diversity of loads the grid will naturally balance to an extent as office building peak demand may not be the same a retail store or the residential sector. This is the purpose od Dr. Corbin's research (18) on distributed HVAC control to improve grid operation. The goal of an optimized grid is to increase the utilization of green energy and reduce the need of peak power generation. By integrating carbon signaling into the optimizer, this could improve the amount of green energy used and shift a single building loads into high renewable production times decreasing the need for peak power generation from that single building.

Application of Photovoltaics

The next test of importance to Transformative Wave is the inclusion of onsite energy generation through PV system. The above tests will be repeated with three levels of PV generation using the criteria developed in each test to see the effects of MPC when energy can be divested from the grid. For the purposes of this test, on site energy generation will be subtracted directly from the total energy consumption of the building providing a metric not of how much energy is being used but of how much energy the building requires to draw from the grid.

4. Results

CATALYST Data Analysis

The first task was to ensure that quality data was provided. In most cases the data appeared to be complete. There were times at the beginning and the end of the provided data in which only a few of the RTUs were operating and providing data. The middle portion provided the most consistent data among all RTUs, and therefore only data between hours 2424 and 3234 were used in the testing.

Sensible Cooling Load Calculations

Starting with the sensible cooling loads, as mentioned in the methodology section, the two sensible cooling loads calculated were the coil and zone sensible cooling loads. The coil sensible load provides the amount of cooling provided by the coil into the mixture of outside air and return air. The first step to calculating the coil cooling sensible load is to determine the mixed air condition. To do this the estimated flow rates of outside air needed to be calculated. Figure 12 shows the graphs of the outdoor air ratio of each RTU. The CATALYST outdoor air calibration runs three tests with the damper at 0%, 5% and 100% damper position. However, the fan speed is not constant during the calibration leading to error. In this case, the fan speed runs at 100% at the 0% damper position resulting in a higher outdoor the air ratio than at 5% where the fan run at a reduced speed. This causes the worst error in RTU 5 with a R^2 value of .68 compared to the highest of RTU 1 at .99.

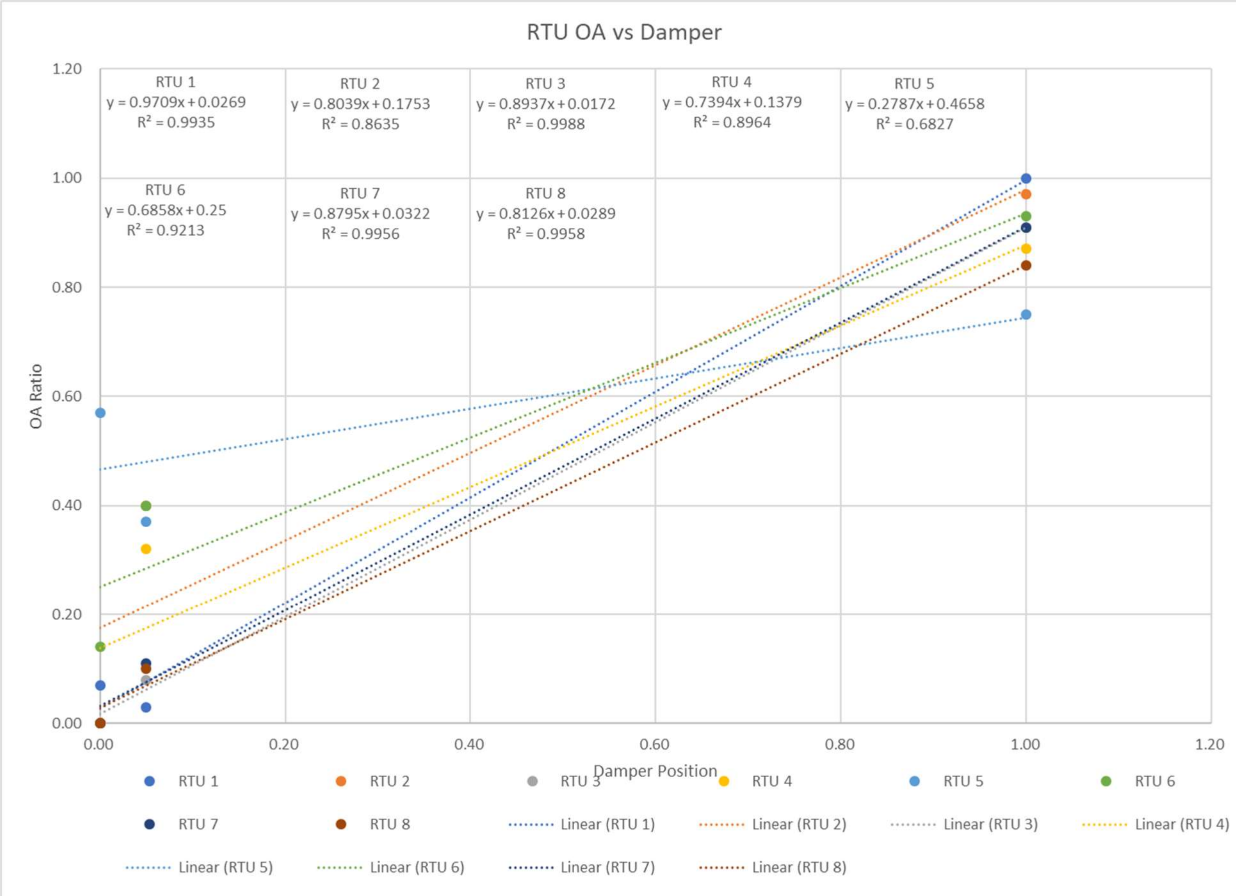


Figure 12: RTU Out Door Air Fraction vs Damper Position

The flow rate through the RTU is the next piece to be calculated. This is a simplified estimate because measured flow data is not available nor will be conducted as this would cause the cost of installation of the CATALYST controller to increase. The estimate for flow rate is therefore a simple linear estimate based on fan speed and rated fan flow. While idealized, this does provide a starting point for model development. Figure 13 shows the estimate for the three different sizes of RTUs installed at Tarzana.

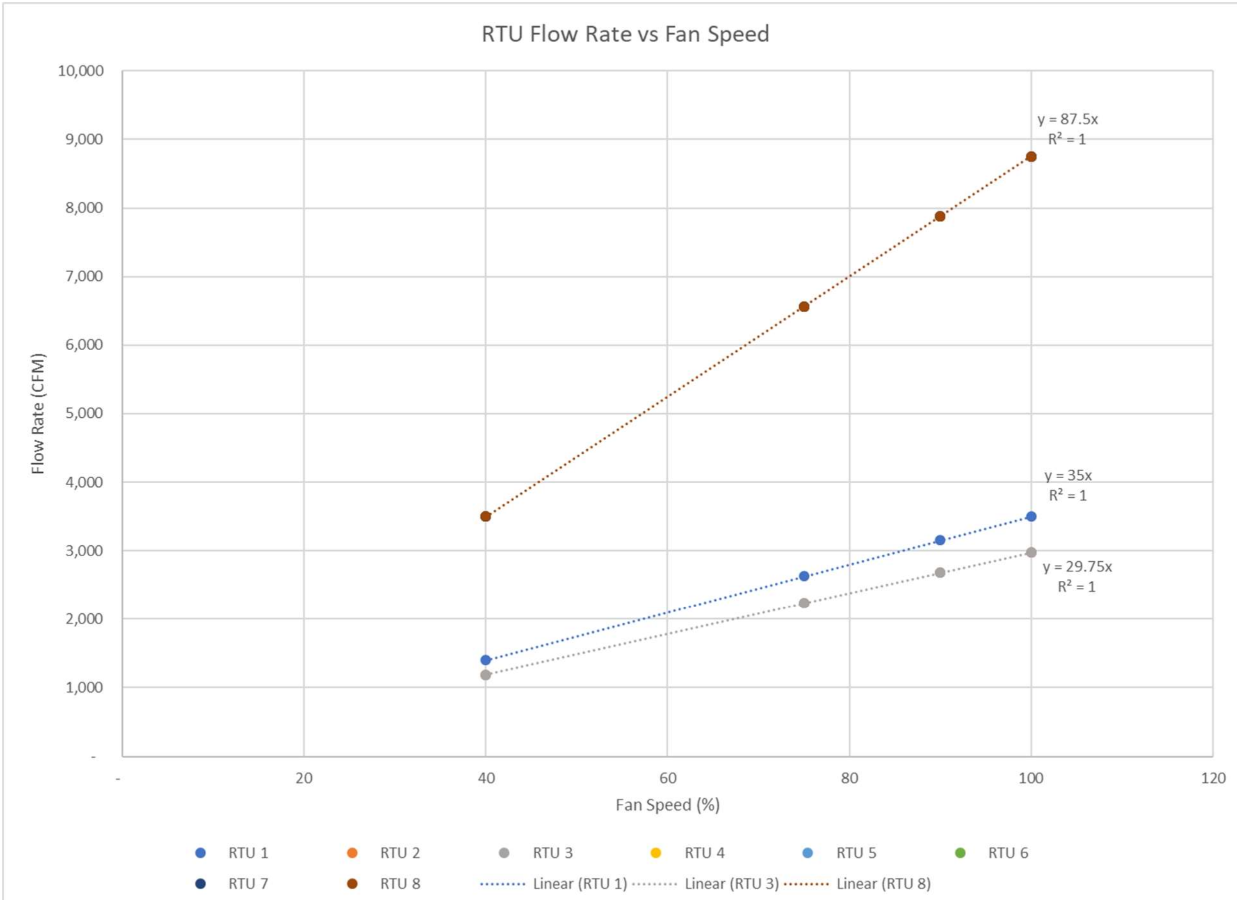


Figure 13: Fan Speed and Flow Rate Relationship

Using the calculated outdoor air ratio and the flow rate the coil sensible load can be calculated for each rooftop unit. To validate the data the sensible cooling load was plotted against the outdoor air sensor temperature and is shown in Figure 14. In Figure 14 cooling is indicated by a negative value and heating by a positive value. From this chart zone loads can be approximated based on outside air conditions as well as zone balance temperatures and maximum cooling available. In this case, Figure 14 shows that RTU 7 is only able to provide a maximum of 2,500 BTU/minute as indicated by the curve leveling off above 75 degrees. Additionally, RTU 8 appears to be in a faulted state as the unit does not contribute any significant heating or cooling loads. This could be due to the specific zone conditions never requiring additional heating or cooling from the RTU but it is also possible that the unit is not functioning properly.

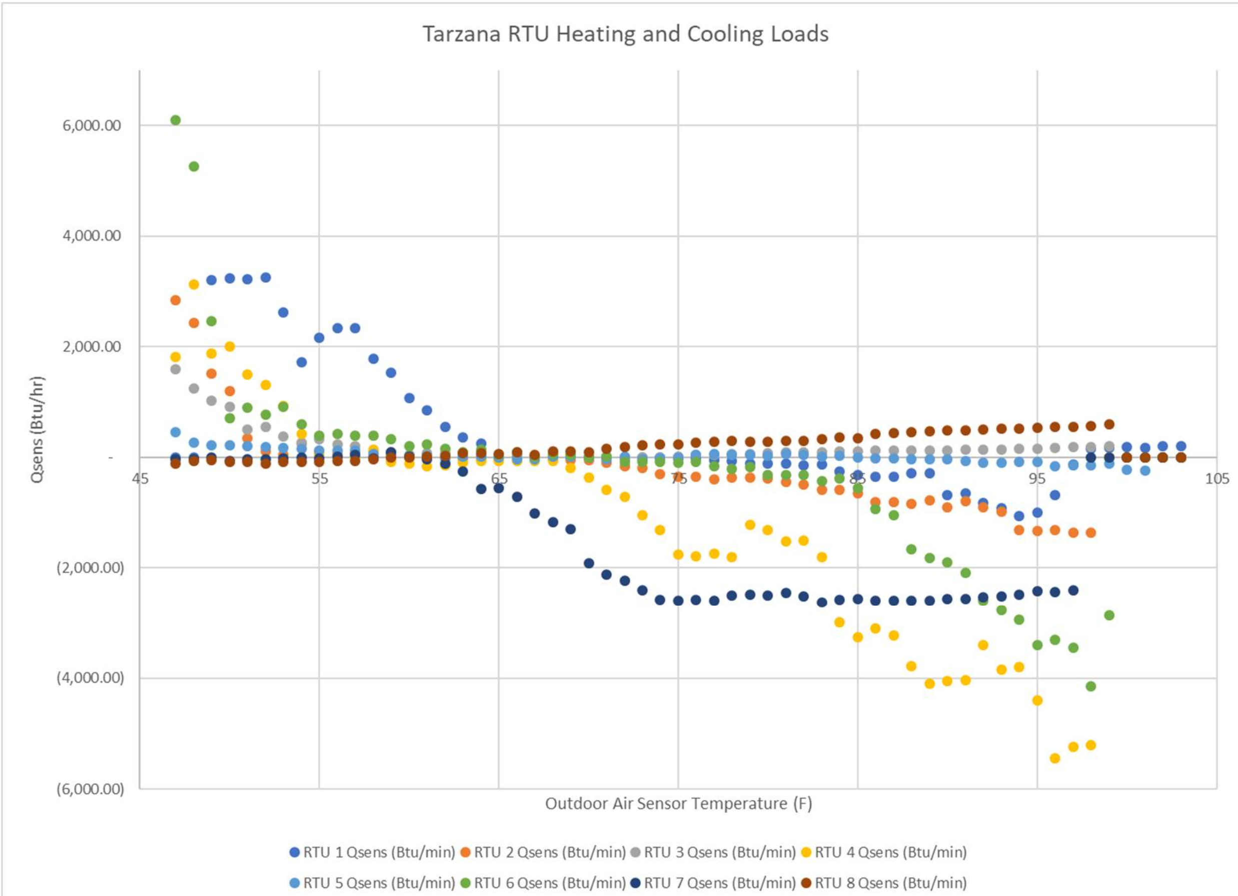


Figure 14: Temperature and RTU Sensible Load Relationship

Baseline Model

The baseline model was constructed first through estimating parameters through ASHRAE 90.1 envelope standards (30) then through common load estimation. The initial values then provided the range from which the Monte Carlo simulations were run to refine the appliance loads and least squares updating to refine the envelope parameters.

Building Envelope

Table 6 shows the baseline envelope details derived from ASHRAE 90.1, 2007, (30). These built the initial 5 parameter RC network noted in the table as well.

Table 8: Baseline Resistances

Building Estimate	Area (sqm)	Conductivity	UA	UA for R1+R2	R3	Rw
Roof	3126	0.26	816.51	816.51		
Skylight	62.52	6.64	415.36			6.64
North Wall (Wall)	216	0.48	103.03	103.03		
North Wall Fenestration	324	3.40	1103.85			3.41
East Wall	258	0.48	123.06			
East Wall Fenestration	0	0	0			
South Wall	408	0.48	194.61			
South Wall Fenestration	0	0	0			
West Wall	45.6	0.48	21.75	21.75		
West Wall Fenestration	2.4	3.69	8.86			
Ground	3126	5.11	15975.23			
			Total	941.29		10.05
			Conductivity	0.28		0.026
			Resistance	3.60	0.12	38.46

Internal Gains Estimating

Through initial model development it was discovered that the internal gains played a much more significant role in the building response than initially anticipated. The initial schedules used provided highly inaccurate results. The lighting load was determined as explained above and estimated at 9.8 W/m^2 with a schedule based on the operating hours of the building. Infiltration was assumed to follow the same schedule as the occupancy schedule with the assumption that infiltration will increase as more people enter and exit the building. The crux of this assumption is that in a super market people are transient through the building and do not spend extended time periods inside as they would inside an office building where high CO2 concentrations would build up by the same number of people staying inside the office for multiple hours at a time. Occupancy load estimation was calculated based on the

CO2 sensor data shown below. The last step was estimating the appliance load through the energy balance of all the other internal gains.

Occupancy Calculations

To gain better understanding of the internal loads schedule, specifically the occupant load, the provided CO2 sensor data was analyzed to first determine a weekly schedule and then a starting estimation of maximum occupants. Figure 15 shows the one week occupancy levels from all RTUs with the average for all zones highlighted in red. The average was used for the schedule in the ROM since this best represents the whole building best given the highs and lows of each area. This also assumes that the CO2 concentration may be higher in each zone due to a locally higher concentration of people at the time but that the CO2 levels would distribute across the open area. This open area distribution makes the RTUs better represented by the average as compared to a straight additive occupancy across the “zones.”

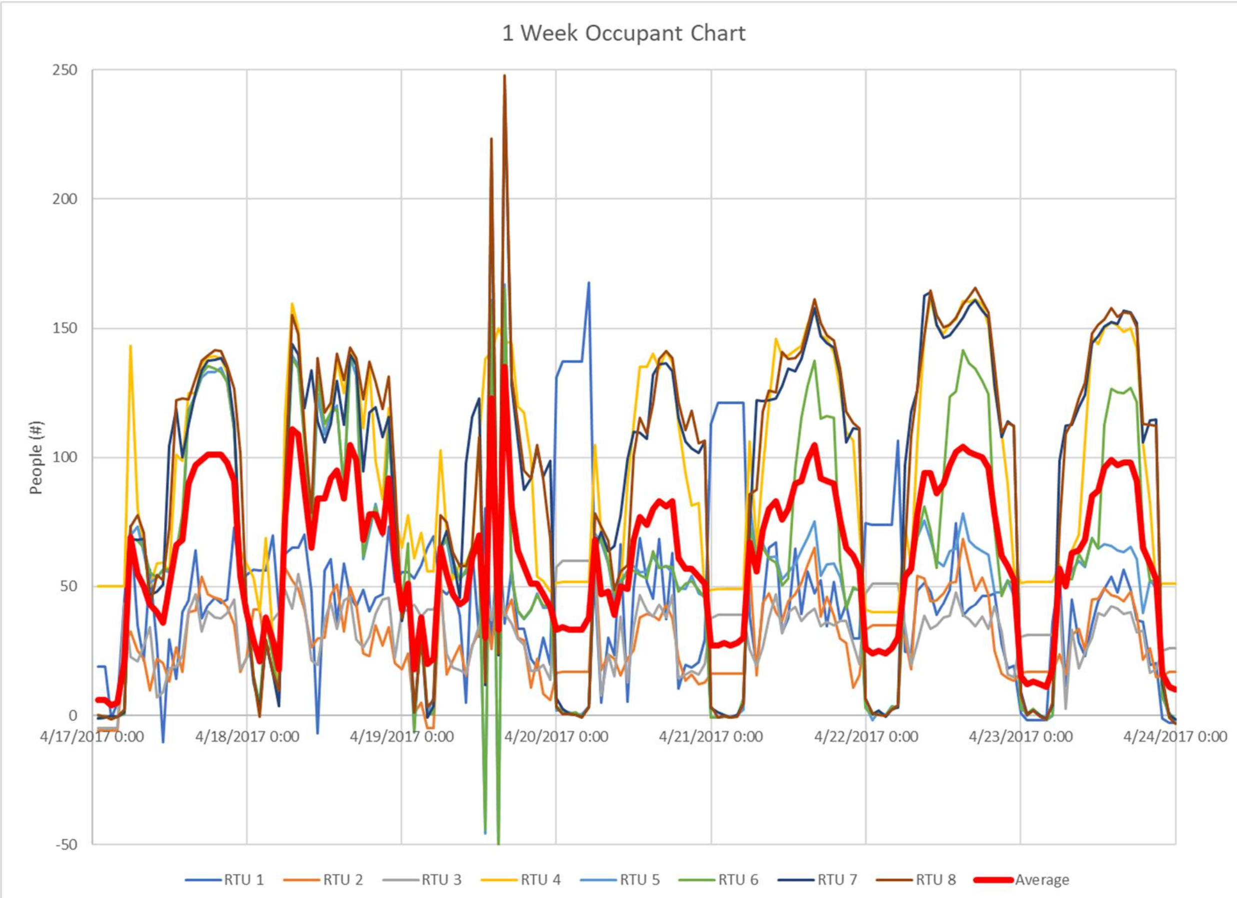


Figure 15: Building Occupancy Chart

However, as demonstrated by the graph, this is an imperfect estimate with large spikes on the third day and never reaching a full zero occupancy during the un occupied hours. This does provide the baseline starting point for schedule estimation as the magnitude of range is more important than the actual numbers. Since the model training uses the same weekly schedule occupancy levels for three weeks were averaged creating a single hourly schedule for each week. Figure 16 shows the plot of each day's occupancy schedule. The curve shows occupancy as one would expect. Occupancy starts at 0500 as workers enter for restocking and food preparation and then increases with occupants from mid to late afternoon.

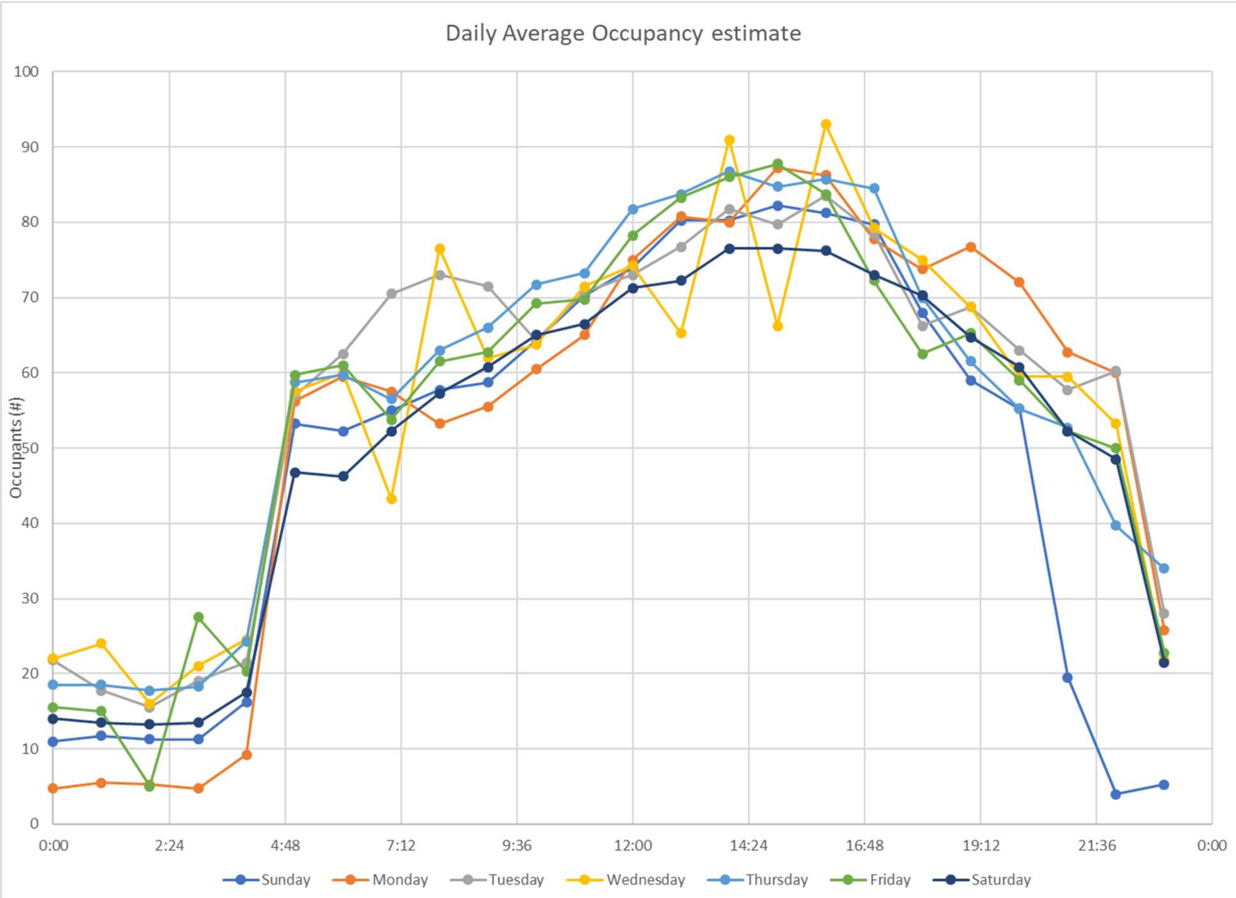


Figure 16: Daily Occupancy Schedule

Appliance Loads Estimating

After solving for the baseline building envelope, occupancy and lighting loads the appliance load schedule baseline could be solved for. Initially, a schedule was crafted based on the knowledge of the operations schedule. This proved to be moderately accurate. To be more accurate the occupancy load schedule was used for the appliance schedule but that schedule proved to be even more inaccurate. To gain a better estimate, the calculated sensible loads and the already solved schedules were used to solve for the appliance schedule through an energy balance assuming the appliance loads as the one unknown.

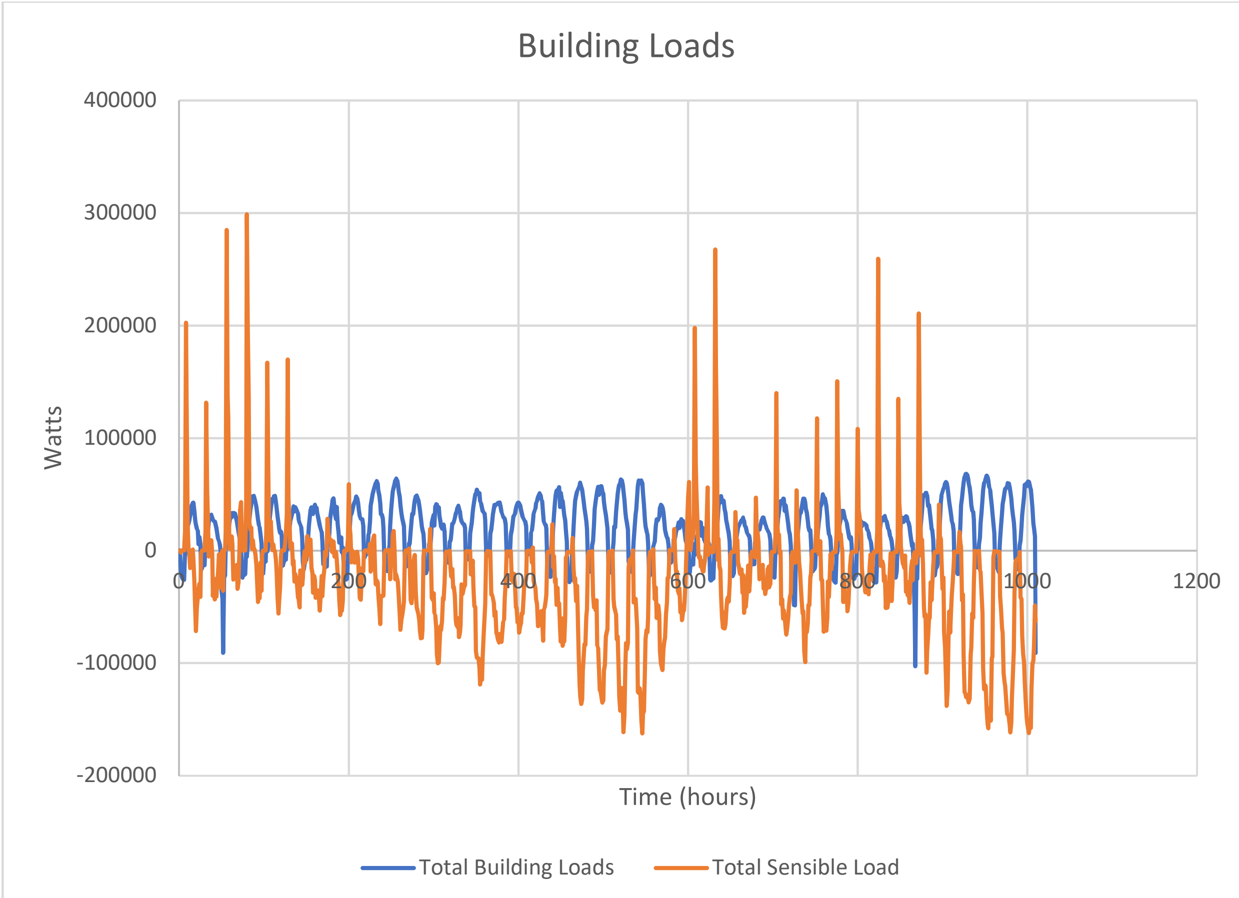


Figure 17: Building Loads vs Total Sensible Load

Figure 17 shows the building loads (lighting, occupancy and environmental loads) compared to the RTU sensible loads with cooling loads indicated by negative power. Appliance loads will be the difference between the magnitude of the building loads and the sensible cooling load. Figure 18 shows the resultant appliance schedule. This is the average of three weeks of solved appliance loads to produce one week of hourly schedule. As shown the appliance load varies constantly throughout the day and throughout the week. In general terms the appliance load does trend similarly throughout the day with the exception of Sunday which follows a lower appliance load throughout the day.

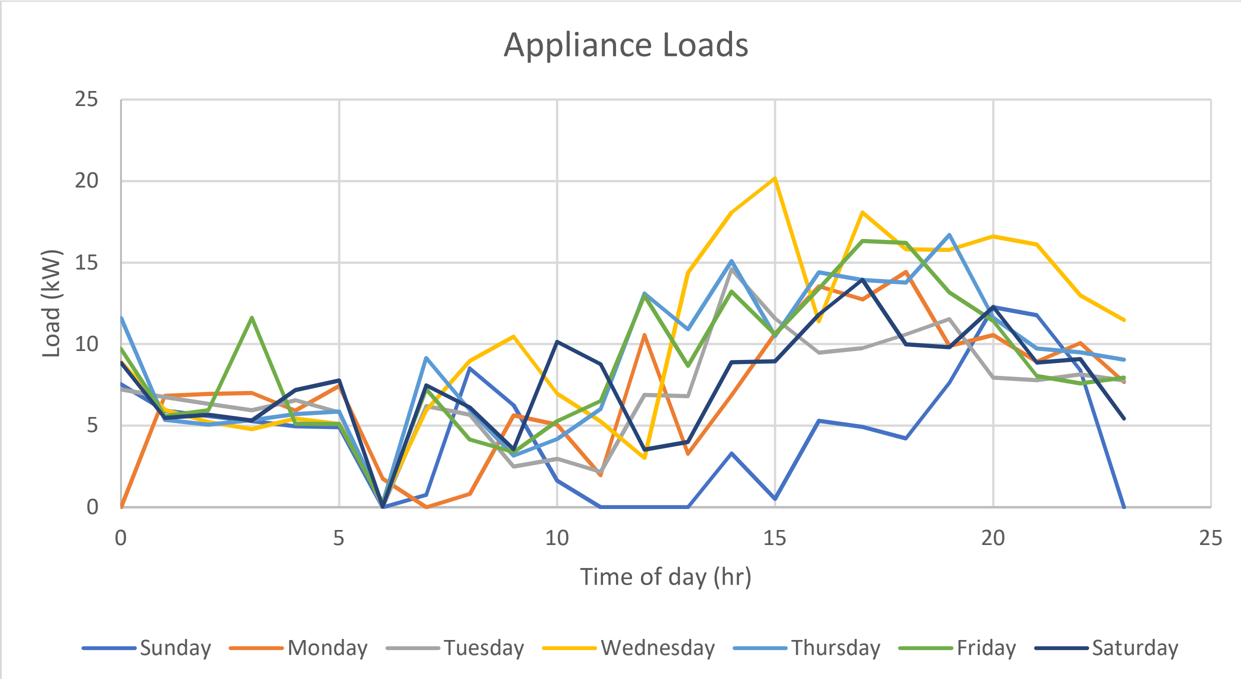


Figure 18: Daily Appliance Loads

Model Training

The model training combined both Monte Carlo testing and Least Squares parameter updating to refine the ROM into the best possible model given real world data. Table 9: Internal Loads and RC Network Training Trials shows the trials of each to develop the ROM. First, the baseline model was tested to determine a starting point. Then the model was trained using Least Squares updating to refine the RC parameters. This greatly improved the RMSE. Next the Monte Carlo testing was run twice. The first run yielded an improved appliance load but did not converge on a solution for the other internal loads. The refined appliance load fit within acceptable bounds so the new appliance load was used for a second set of Monte Carlo tests for the other internal loads. These results did converge and provided updated results. An additional test was run with the new values to see if it could be further balanced but did not produce a better result when evaluated through RMSE. The model was then run through least squares updating for a second time but the results did not improve significantly so the initial run RC network was kept.

Table 9: Internal Loads and RC Network Training Trials

	Train								Monte Carlo							
Upper Bound	4	4	2	50	10000	0.1	0.1		100		11		250		0.9	
Lower Bound	0.01	0.0004	0.01	1	500000	2	3		30		0.05		50		0.1	
	R1	R2	R3	Rw	C	Multi	Mulit	RMSE	qApp	RMSE	vInf	RMSE	people	RMSE	FcApp	RMSE
Base	1.75	1.75	0.117	38.06	106920	0.4621	0.3384	N/A	53.4	64439.85	0.05	64439.85	120	N/A	0.1	64439.85
Train 1 Results	0.788973	0.000395	0.678855	49.69147	41773.66	0.468305	1.477495	42959.43	53.4	95622.94	0.05	95622.94	120	95622.94	0.1	95622.94
MC 1	0.788973	0.000395	0.678855	49.69147	41773.66	0.468305	1.477495		31.14	44777.59	0.095294	94360.24	0.793236	88857.67	0.190588	108946.3
MC 2	0.788973	0.000395	0.678855	49.69147	41773.66	0.468305	1.477495		31.14	44777.59	0.122042	44582.82	116.5958	44777.02	0.110064	44758.84
Train 2 Results	1.137725	0.002161	0.724986	36.44384	33195.13	0.35184	1.687271	43417.46	31.14		0.12		117		0.11	

Appendix B shows the monte run graphs for each unknown parameter tested. To demonstrate how good of a fit, Figure 19 shows a the calculated sensible cooling load compared to the simulated ROM.

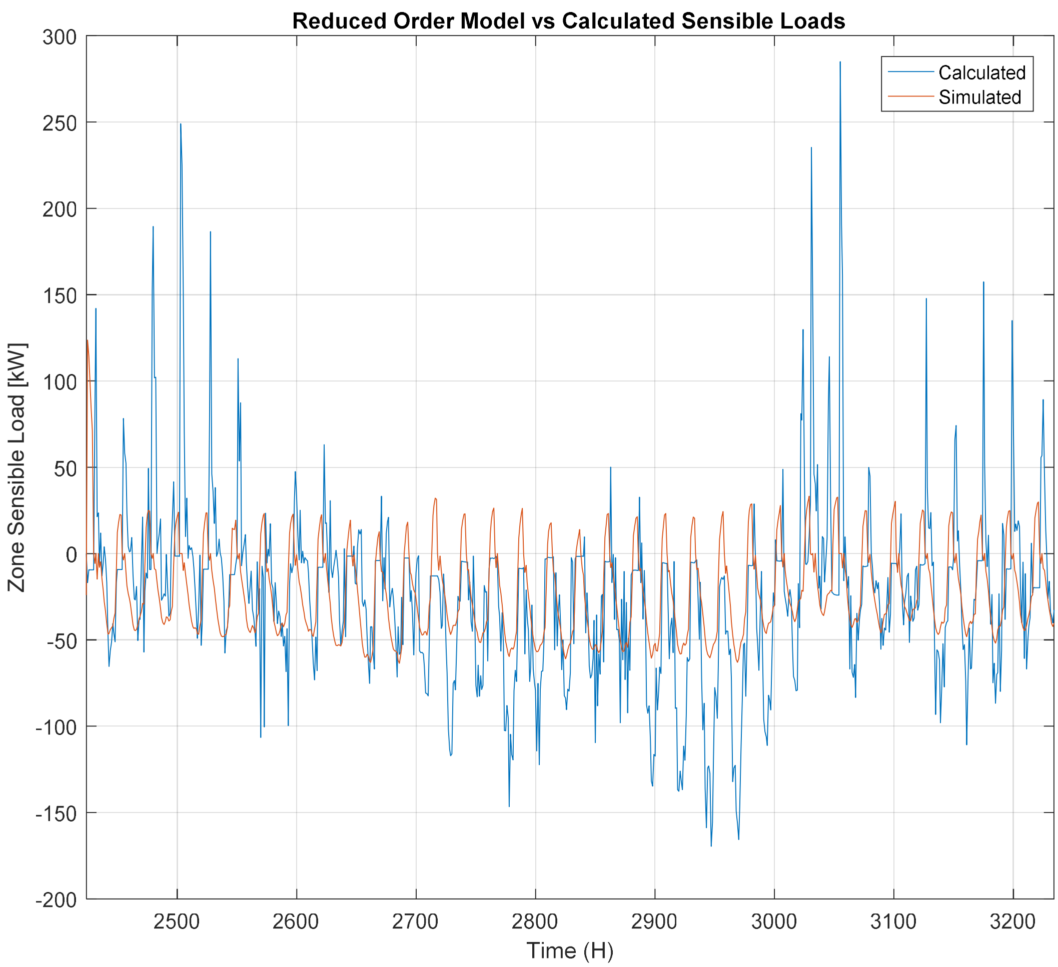


Figure 19: ROM vs Calculated Sensible Loads

The Model is able to capture the generalities of the real world data but fails to capture the peaks and extremes of the real world data. Being that the fit was marginal at best, further refining of the schedules was conducted to improve model accuracy. By solving for the independent appliance schedule treating infiltration, lighting and occupancy schedules and magnitudes as knowns a better fit was achieved. In turn, this required the model to be retrained to solve for the magnitude of each internal gain and the RC model. Table 10 shows the results of the training

Table 10: Training Results

Trials	R1	R2	R3	Rw	C	Capacitance Multiplier	Internal gains Mulitplier	qApp	vInf	people	FcApp	RMSE
Original RC	0.789	0.0001	0.679	49.69	41773	0.4621	1	21	0.12	117	0.11	41797.91
Baseline Estimating	1.8	1.8	0.117	38.4	41773	0.468	1	21	0.12	117	0.11	54469.85
Re-Trained	0.4199	0.006	0.2039	20.07	94497	3	0.6162	21	0.12	117	0.11	5322200
MC 1: Original RC	0.789	0.0001	0.679	49.69	41773	3	0.6162	10	0.5	117	0.9	43698.48
MC 2: Original RC	0.789	0.0001	0.679	49.69	41773	3	0.6162	20	0.5	225	0.9	41404.96
MC 3: Original RC	0.789	0.0001	0.679	49.69	41773	3	0.6162	40	0.5	248	0.9	38728.29
MC 4: Original RC	0.789	0.0001	0.679	49.69	41773	3	0.6162	46	1.8	248	0.9	38447.85
MC 5: Original RC	0.789	0.0001	0.679	49.69	41773	3	0.6162	49	1.8	202	0.9	38130.31
Re-Trained	0.378876	0.004097	0.258995	44.39041	82726.18	5.99906568	0.661720668	49	1.8	202	0.9	36743.61

In terms of RMSE, the model improved in performance by 7000 W over nearly five weeks of trials comparing the RMSE of the sensible loads. Appendix B shows how the Monte Carlo simulation curves better converged over the trials on these final values. To show the impact of the appliance load simulations, also in Appendix B are the comparisons between each test to show the evolution of fit.

The final fit between the calculated and simulated sensible loads are shown in Figure 20. Comparing the two figures, the new model trends better and is shifted down to not reflect heating loads during hours 2700 and 2800 that were previously modeled in the first model.

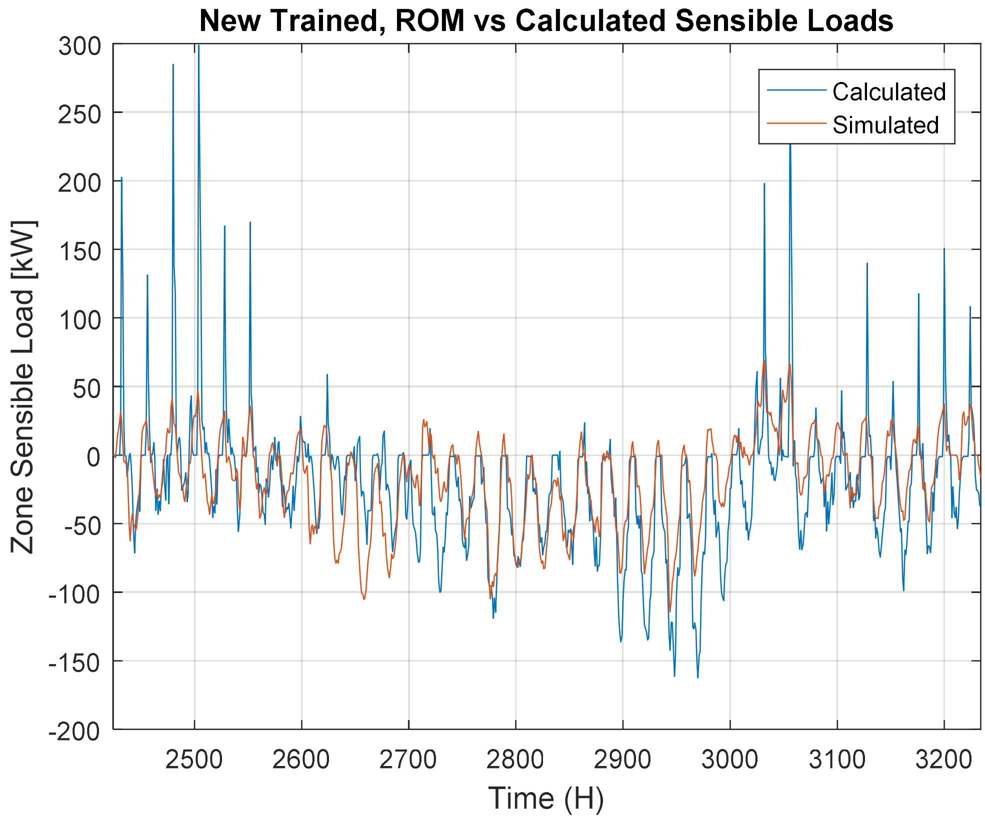


Figure 20: New Calibrated Sensible Loads

RTU Modeling

The next major component of the building to be modeled is the lumped parameter rooftop unit. As detailed in the methodology, the eight roof top units will be characterized as a single unit. This is to reduce the complexity of the model as requested by Transformative Wave. This does pose a problem as this will be modeling some components that may not exist in reality in terms of scale. The model was developed to follow the logic of a standard set point following RTU using rough order parameters from the name plate data and from previous models provided by Dr. Pavlak. The main goal in scripting was for the model to be able to logically track set points.

Figure 21 shows the resultant air flow temperatures in Celsius for a four day period. During this time the outdoor air temperature is fairly moderate allowing for economizer use during the day. At night when neither cooling or heating is required, the economizer closes to a minimum value, and the building is allowed to free float cool. This does allow for potential free/pre-cooling at night when optimizing the control logic, but for now the flow is off and the building requires no conditioning. During the day once occupancy is established, the building resumes cooling. The first stage of cooling turns on when necessary as shown between time 2510 and 2520 by the supply air temperature after the first stage of cooling (DX1Tout) dropping to around 12 degrees Celsius. The heating coil is also used to heat the building when necessary, shown at time 2550 when occupancy is established and the temperature is below the occupied heating set point. TZ does show some small jumps over the cooling set point where the building does not fully compensate until the next time shift (around 2560 and 2581) but these are minimal and do not seem to be greatly over the set point.

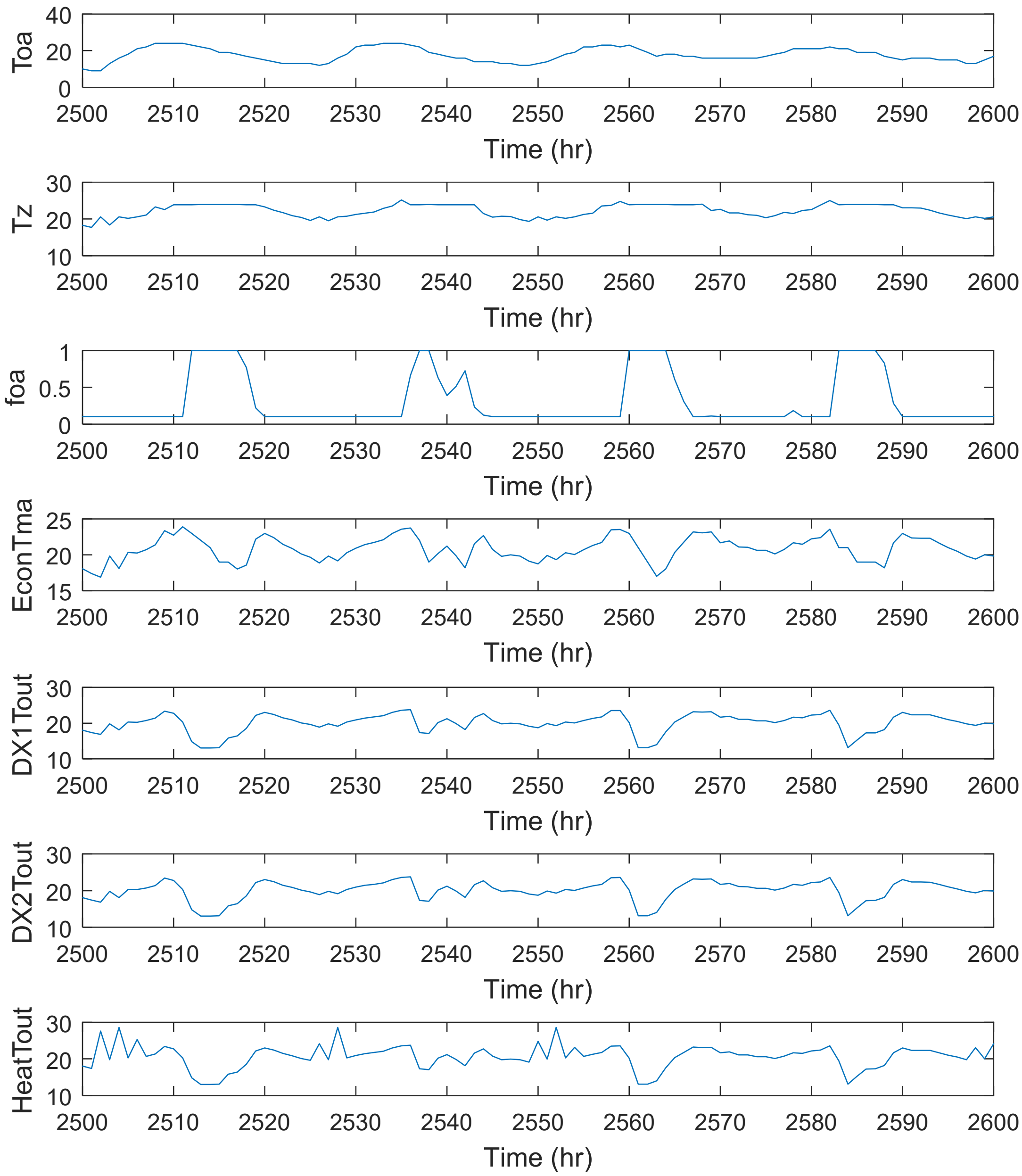


Figure 21: RTU Component Temperatures

Fan Calibration

To calibrate the fan parameters, Monte Carlo tests were set up similarly to the building parameter optimization tests. The values to be calibrated were the fan efficiency, max flow rate, and rated pressure rise based primarily on fan RMSE comparison to the provided fan power and the simulated fan power in terms of kWh. The sensible load RMSE that was use for the building model training was also considered to ensure that changes to the fan model did not have any large impacts to the building sensible loads. The data was first compiled by averaging the power and mass flow over the hour for each RTU and then summing the total power and mass flow to create the RTU hourly mass flow and power consumption.

First, the model requires a fan performance curve. This was created through plotting the power divided by the max power at 100% fan speed vs the flow fraction. Figure 22 shows the best fit curve for the part load curve of the fan. There is a lack of data between 10% fan speed and 40% fan speed where the curve appears linear through the few data points. Between 40% and 90%, the fan speed and power consumption forms a wider range of values but can be characterized by the single curve.

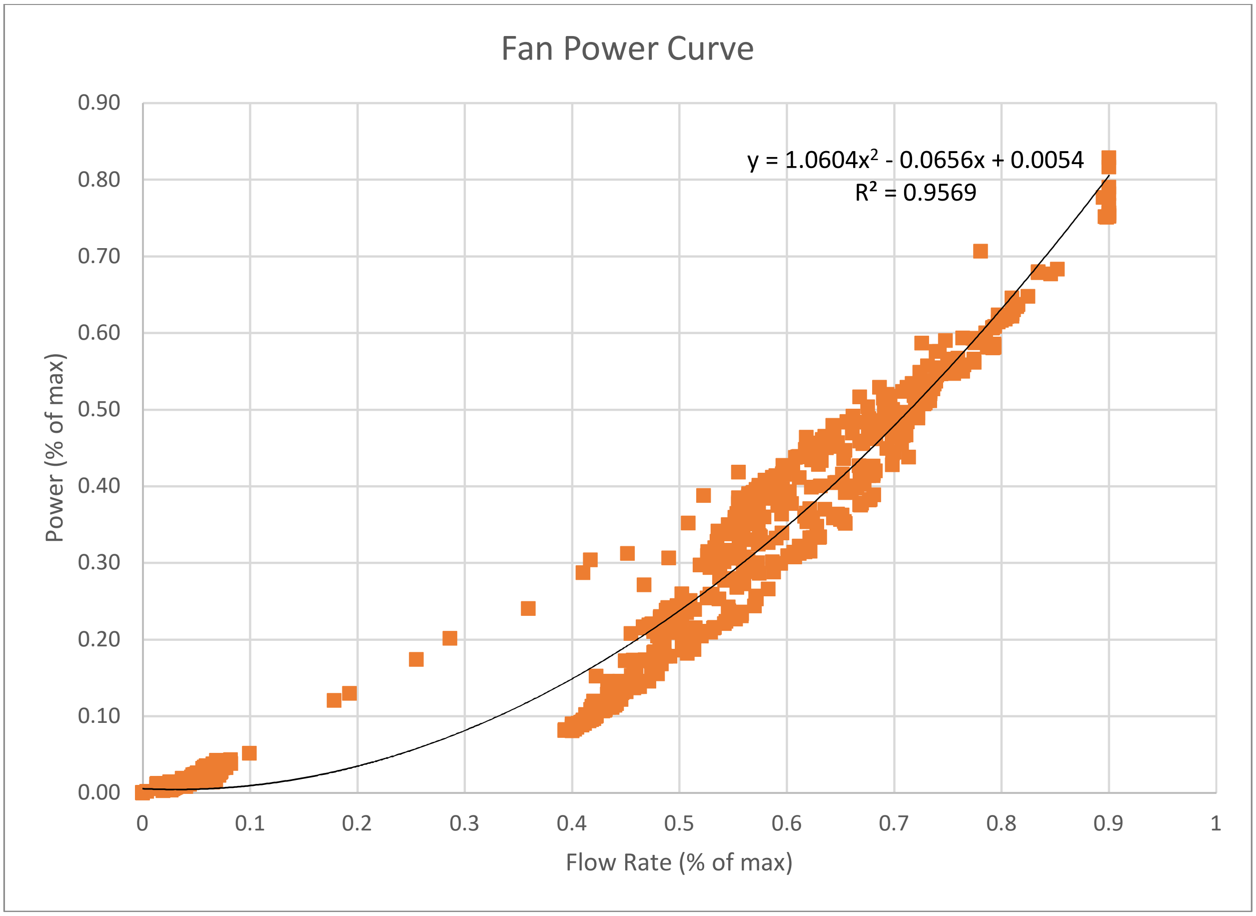


Figure 22: Fan Power Curve

After developing the curve, the RTU model script was adjusted. The resultant curve was then included in the model parameters listed above. Table 11 shows the results of the Monte Carlo trials. The main unknowns were the fan efficiency and the rated pressure rise. The max flow was assumed based on the rated flow through the RTUs but still needed validation.

Table 11: Fan Calibration Trials

Trial	Fan Effeciency	Max Flow Rate (m^3/s)	Rated Pressure Rise (Pa)	Fan RMSE	Qsens RMSE
Baseline	0.5	25	500	1.385	36774.16043
Test 1 Results	0.44	23.5	576	2.090	37053
Test 1 Modified	0.5	25	576	1.028	36915
Test 2 Results	0.52	26	565	1.209	36775
Test 2 Modified	0.5	25	565	1.022	36851
Test 3	0.5	25	565	1.022	36851
<End Test: Values Converged>					

Table 11 shows the three iterations through the Monte Carlo testing. As shown, the tests converged quickly at near the baseline values. The charts of each value are shown in Appendix C to validate the solved values. The resultant parameters reduced the RMSE kWh error from 1.3 to 1.0 but only solved from the rated pressure rise across the lumped parameter fan. This is not a major decrease but it could impact the optimization parameters of the MPC.

Cooling Coil Calibration

Following similar procedures as the building fan calibrations, the cooling coil unknown parameters were solved using Monte Carlo testing. In this case, the unknown parameters were the coefficient of performance (COP), rated sensible load, and the sensible heating ratio. The total RTU power was provided through the Catalyst data, and the fan power was subtracted out to solve for the cooling coil power.

Table 12 shows tests that were accomplished for the first stage of cooling and Appendix C provides the curves to show the convergence.

Table 12: Cooling Coil Calibration

Trial	Coeffecient of Perform	Rated Q (kW)	Rated SHR	DX RMSE	Qsens RMSE
Baseline (DX1)	3	267.2805	0.75	21.089	36851.0633
Test 1 Results	1	400	0.7	19.109	36868.49491
Test 1 Modified	1.1	250	0.75	18.190	38654.77909
Test 2 Results	1.1	250	0.75	18.190	38654.77909
<End Test: Values Converged>					

Once again, the values didn't change too much. The largest change was accomplished by adjusting the COP from 3 to 1.1. This decreases the cooling coil RMSE by 2 kW over the five-week calibration.

The second stage cooling coil was tested as well but there was no variation between the values and cooling coil RMSE. This could be due to the mild cooling conditions of the spring and may require additional calibration for the summer months. Appendix D shows the curves and how consistency of RMSE through all tested conditions.

Table 13: Second Stage Cooling Coil Calibrations

Trial	Coeffecient of Perform	Rated Q (kW)	Rated SHR	DX RMSE	Qsens RMSE
Baseline (DX2)	3	267.2805	0.75	18.190	38654.77909
Test 1 Results					
<End Test: No change in DX or Qsens RMSE>					

Model Validation

To validate the model, three test ranges were used, one week in June, July and August. The first method of testing failed to accurately model the provided data. As such, three new procedures were tested. First, the model used generalized internal gains schedules created from the April through May provided data. In the second method, the same calibration procedures were used but the generalized schedules were replaced with schedules created by calculating internal gains schedules for the entire provided data set as specified in the internal gain's schedule section. The third method further isolated the RTU model parts by replacing the model's calculated RTU input mass flow rates, sensible loads and mixed air temperatures with the provided data calculated values. For the second set of model validation, the model was calibrated to one week in July and validated on one week in June and another week in August.

Model Validation Test 1

The model calibrated in the previous steps was used and tested for the dates shown in Table 14 and evaluated based on RMSE values.

Table 14: Validation 1 Results

Test	Start Date	End Date	Start Hour	End Hour	RMSE Qsens (kW)	RMSE Fan Power (kW)	RMSE RTU Power (kW)
1	6/14/2017 0:00	6/21/2017 23:00	3937	4105	40.15	9.17	21.12
2	7/9/2017 0:00	7/16/2017 23:00	4537	4705	72.14	9.54	25.69
3	8/23/2017 0:00	9/1/2017 23:00	5689	5856	56.91	9.16	22.58

As Table 14 shows, the RMSE for fan power, RTU and sensible load increased in these new date ranges. In the case of fan power, the power increased more than nine times the calibrated model. Comparing the profiles of the sensible loads, in June (Figure 23) the building's sensible loads follow a similar profile and is the most accurate of the three test ranges. However, the model fails to follow the cooling peaks represented by the lowest negative values.

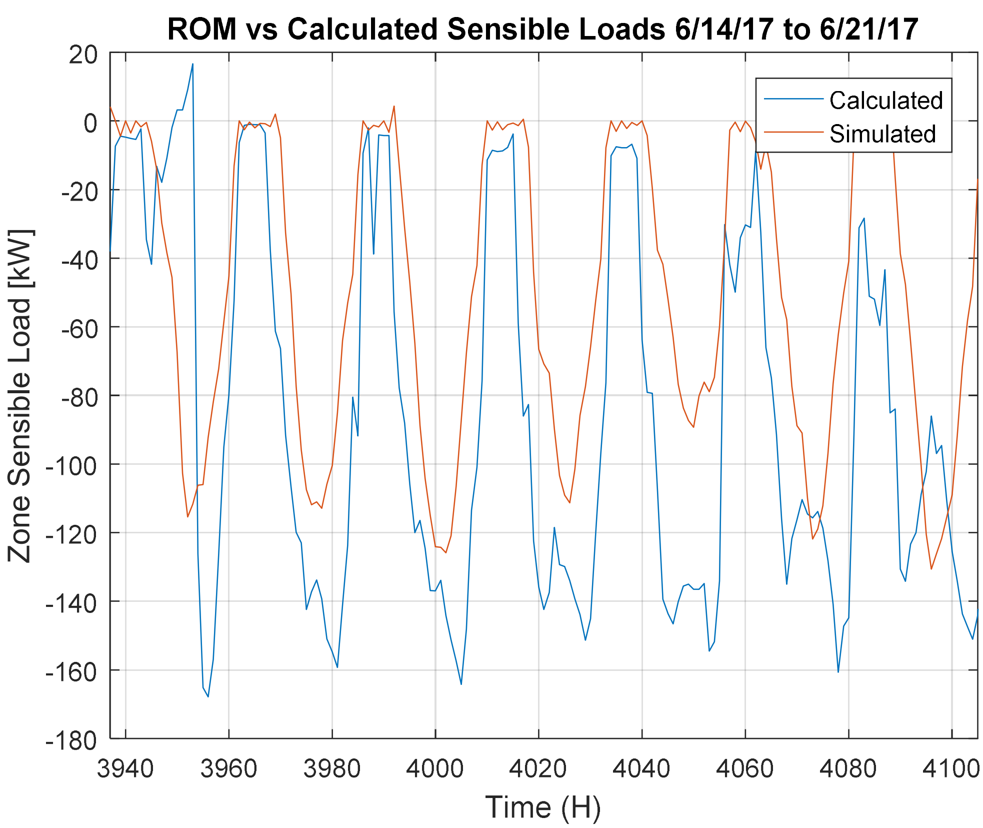


Figure 23: June Validation Sensible Loads

In July, the model fails to meet either the peaks or the lows of the sensible loads. The model follows the same trend as the calculated sensible loads but doesn't accurately capture the reality of cooling.

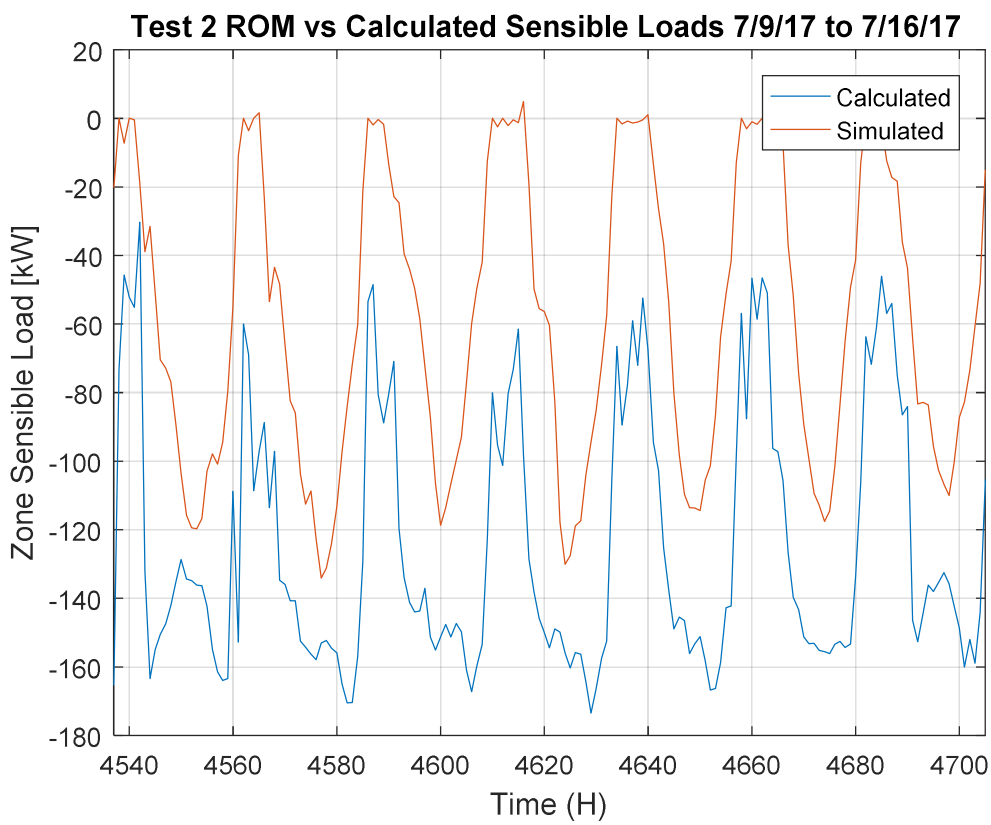


Figure 24: July Validation Sensible Loads

Lastly, in August, the model and the calculated sensible loads look very dissimilar. Neither the peaks nor the lows of the cooling load are offset, and they are dissimilar in magnitude. As such, it is hard to say that the model is able to accurately capture the reality represented by the model.

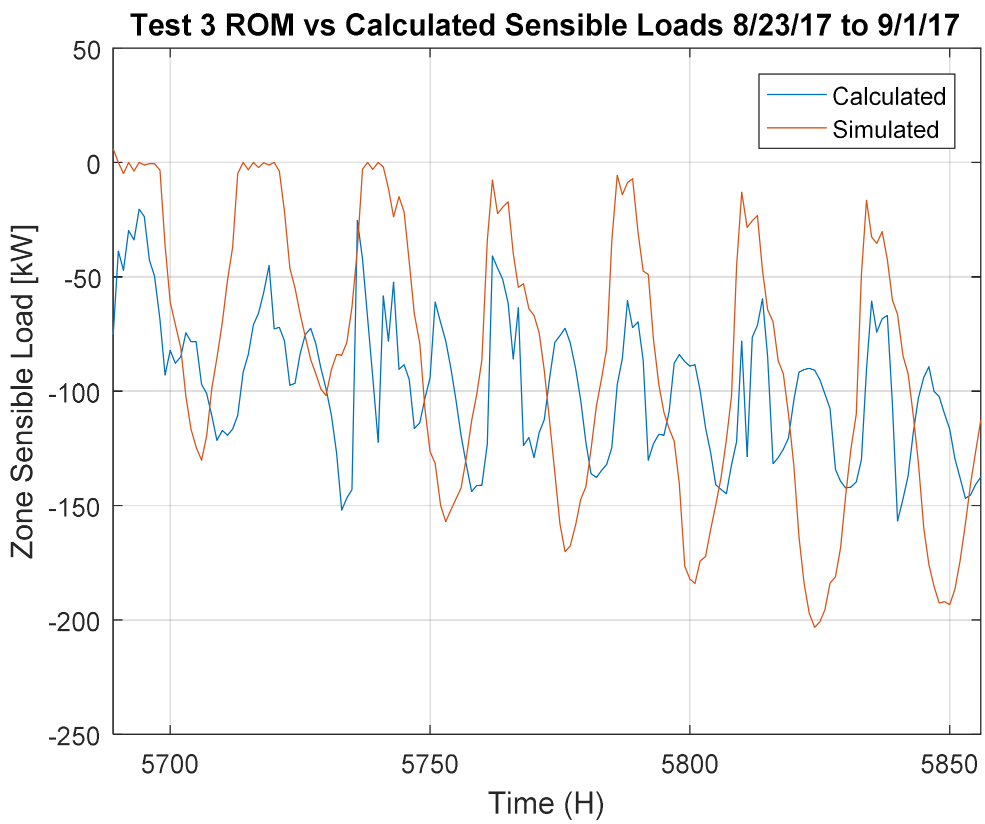


Figure 25: August Validation Results

Because of the mismatch between the calibrated model and the calculated sensible loads as well as the high error of the fan and RTU powers, the model can be considered invalid and requires re-work.

Model Validation Test 2

In the next validation test, new internal gain schedules were provided for each week, and the model was recalibrated. Table 15 shows the results of each calibration test for the fan and the RTU while appendix D shows the graphs of the RMSE used to find the minimum of each set of tests. To note, this calibration was conducted using only the model-determined internal temperatures and mass flow rate.

Table 15: Calibration 2 Fan Trials

Trial	Fan Effeciency	Max Flow Rate (m^3/s)	Rated Pressure Rise (Pa)	Fan RMSE	Qsens RMSE	RTU RMSE
Test 1 Run/initial	0.5	16	600	2.148	42,596.18	23.11
Test 1 Results/Test 2 Run	0.7	26	600	4.569	38,010.58	42.64
Test 3 Results	0.65	25	850	1.145	38,779.00	39.93
Final Results	0.65	25	850	1.145	38,779.00	39.93

After calibrating the fan, the DX coils were calibrated in a similar method.

Table 16: Calibration 2 Cooling Coil Results

Trial	Coeffecient of Perform	Rated Q (kW)	Rated SHR	DX RMSE	Qsens RMSE
Baseline (DX1)	1.1	250	0.75	34.80	28,425.75
Test 1 Results	1	400	0.7	19.11	36,868.49
Test 1 Modified	1.1	250	0.75	18.19	38,654.78
Test 2 Results	1.1	250	0.75	18.19	38,654.78
<End Test: Values Converged>					
Trial	**Coeffecient of Perform**	**Rated Q (kW)**	**Rated SHR**	**DX RMSE**	**Qsens RMSE**
Baseline (DX2)	3	267.2805	0.75	18.190	38654.77909
Test 1 Results					

Comparing the July calibration results with the April and May calibration results, the RMSE values for sensible load, fan power, and cooling coil power remain consistent. Because the DX coil didn't change after much calibration, only a couple tests were run. This was then validated against the other two weeks.

Table 17: Validation 2 Results

Test	Start Date	End Date	Start Hour	End Hour	RMSE Qsens	RMSE Fan Power (kW)	RMSE RTU Power
1	6/14/2017 0:00	6/21/2017 23:00	3937	4105	37.03	4.56	15.80
2	7/9/2017 0:00	7/16/2017 23:00	4537	4705	28.38	4.98	24.64
3	8/23/2017 0:00	9/1/2017 23:00	5689	5856	68.36	4.66	35.21

This new calibration did a much better job, according to RMSE, to model the provided data. However, the August week seems to have done worse in terms of sensible load. Comparing the charts below, the model does a better job of following the trends of the provided data. In all cases the sensible peaks and RTU peaks do not match even though the trends match better in temporal terms. Lastly, August matches better but there is a peak that the model is unable to capture at all.

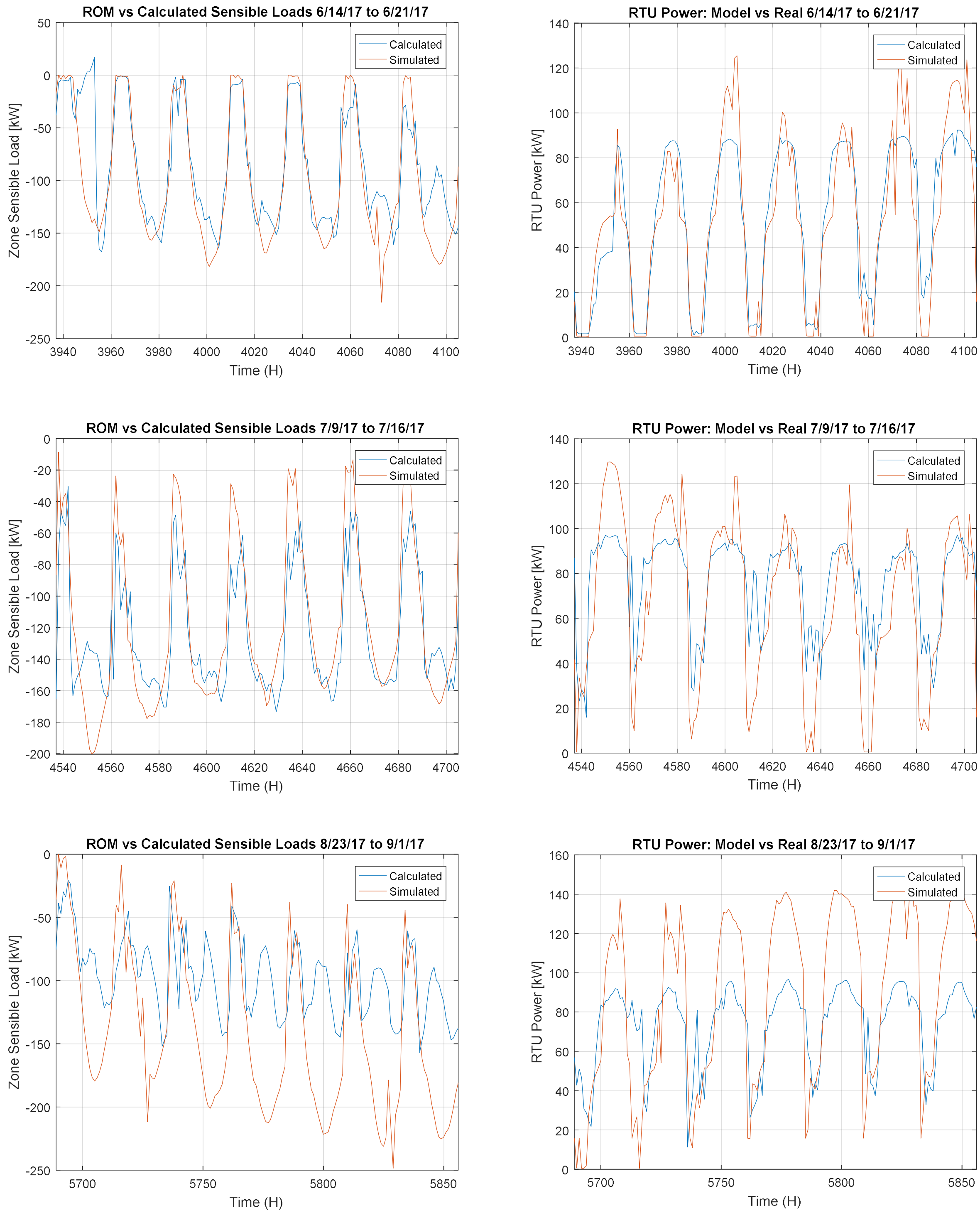


Figure 26: Validation 2 Sensible Load Charts

Model Validation Test 3

Since the second test failed to adequately to validate the model a third series of tests was created. First, the real internal temperatures were added into the model as an input as well as the provided calculated fan mass flow rate. As this is an ideal calculation, the fan maximum mass flow rate will still need to be calibrated based on the provided fan power. Additionally, calculated sensible loads were substituted in place of the model generated sensible cooling load. Lastly, the mixed air temperature was inputted into the model as well to more accurately calibrate the cooling coil model.

The procedures for testing were changed to calibrate all RTU properties at the same time. Also, rather than testing the capacity of each cooling coil, the RTU was calibrated as a total cooling capacity with a cooling coil balance term added to account for the different capacity of each cooling coil. Two methods were used. In the first method, a set of nine nested loops tested a range of values for each parameter and then manipulated each parameter independently for each value of each other value. The code is included in Appendix E. The problem with this test is that, for a reasonable range of each value, it would require approximately 50 years to compute. Instead, this test was run for approximately 12 hours before being abandoned as impractical. The next trial was completed by creating a random number generator for each parameter and run 25,000 times modifying each parameter independently for each trial. The tables below show the results as sorted by RMSE fan power, RTU power, cooling coil power, and the sensible load.

Table 18: Calibration 3 Trials

Run	Pnom	MdotMax	Feff	DX Bal	DX Tot (W)	SHR 1	COP 1	SHR 2	COP 2	RMSE Fan Power (kW)	RMSE RTU Power (kW)	RMSE DX Power (kW)	RMSE Qsens (kW)
	502.77	**21.35**	**0.62**	0.30	499,376.20	0.73	1.62	0.80	1.54	1.03	23.41	16.27	16.29
	502.77	21.35	0.62	0.30	499,376.20	0.73	1.62	0.80	1.54	1.03	23.41	16.27	16.29
	502.77	21.35	0.62	0.30	499,376.20	0.73	1.62	0.80	1.54	1.03	23.41	16.27	16.29
	502.77	21.35	0.62	0.30	499,376.20	0.73	1.62	0.80	1.54	1.03	23.41	16.27	16.29
	502.77	21.35	0.62	0.30	499,376.20	0.73	1.62	0.80	1.54	1.03	23.41	16.27	16.29
	502.77	21.35	0.62	0.30	499,376.20	0.73	1.62	0.80	1.54	1.03	23.41	16.27	16.29
	502.77	21.35	0.62	0.30	499,376.20	0.73	1.62	0.80	1.54	1.03	23.41	16.27	16.29
	665.00	21.40	0.81	0.50	400,273.00	0.84	2.34	0.79	1.06	1.03	11.19	17.87	16.19
	665.00	21.40	0.81	0.50	400,273.00	0.84	2.34	0.79	1.06	1.03	11.19	17.87	16.19
1.00	**665.00**	**21.40**	**0.81**	**0.50**	451,636.00	0.78	2.60	0.75	1.40	**1.03**	15.80	25.26	19.37

Sorted first by the fan power, the calibration is able to follow the total fan power quite accurately with all other parameters lower than in the previous tests.

Table 19: Calibration 3 Trials, by RTU Power RMSE

Run	Pnom	MdotMax	Feff	DX Bal	DX Tot	SHR 1	COP 1	SHR 2	COP 2	RMSE Fan Power (kW)	RMSE RTU Power (kW)	RMSE DX Power (kW)	RMSE Qsens (kW)
	1,152.59	22.00	0.73	0.34	366,499.57	0.83	2.54	0.71	1.88	11.25	7.76	26.51	13.96
	998.30	22.55	0.55	0.31	377,296.89	0.80	2.33	0.75	2.37	14.54	7.82	27.32	13.01
	981.64	21.97	0.63	0.42	337,796.98	0.73	2.80	0.76	1.63	10.88	8.06	25.99	14.17
	851.39	23.50	0.54	0.35	361,482.30	0.79	2.86	0.72	1.36	10.15	8.17	24.16	13.73
	724.12	22.02	0.53	0.40	316,264.10	0.75	2.81	0.70	1.20	7.96	8.27	22.39	13.42
	724.12	22.02	0.53	0.40	316,264.10	0.75	2.81	0.70	1.20	7.96	8.27	22.39	13.42
	724.12	22.02	0.53	0.40	316,264.10	0.75	2.81	0.70	1.20	7.96	8.27	22.39	13.42
	724.12	22.02	0.53	0.40	316,264.10	0.75	2.81	0.70	1.20	7.96	8.27	22.39	13.42
	724.12	22.02	0.53	0.40	316,264.10	0.75	2.81	0.70	1.20	7.96	8.27	22.39	13.42
	724.12	22.02	0.53	0.40	316,264.10	0.75	2.81	0.70	1.20	7.96	8.27	22.39	13.42

Then sorting by the RTU power the calibration is able to be twice as accurate as the prior tests and yields a lower sensible cooling load.

Table 20: Calibration 3 Trials Sorted by Coiling Coil Power RMSE

Run	Pnom	MdotMax	Feff	DX Bal	DX Tot	SHR 1	COP 1	SHR 2	COP 2	RMSE Fan Power (kW)	RMSE RTU Power (kW)	RMSE DX Power (kW)	RMSE Qsens (kW)
	1,134.97	24.15	0.46	**0.40**	**305,239.09**	**0.84**	**1.90**	**0.79**	**1.06**	21.82	31.86	10.76	13.82
	780.82	20.78	0.52	0.36	332,441.48	0.80	1.84	0.83	1.02	10.20	24.50	10.77	13.16
	780.82	20.78	0.52	0.36	332,441.48	0.80	1.84	0.83	1.02	10.20	24.50	10.77	13.16
	780.82	20.78	0.52	0.36	332,441.48	0.80	1.84	0.83	1.02	10.20	24.50	10.77	13.16
	780.82	20.78	0.52	0.36	332,441.48	0.80	1.84	0.83	1.02	10.20	24.50	10.77	13.16
	780.82	20.78	0.52	0.36	332,441.48	0.80	1.84	0.83	1.02	10.20	24.50	10.77	13.16
	780.82	20.78	0.52	0.36	332,441.48	0.80	1.84	0.83	1.02	10.20	24.50	10.77	13.16
	780.82	20.78	0.52	0.36	332,441.48	0.80	1.84	0.83	1.02	10.20	24.50	10.77	13.16
Calib	1,126.91	17.28	0.41	**0.34**	**400,272.56**	**0.82**	**2.39**	**0.84**	**1.09**	24.47	36.71	11.09	13.07
	779.06	21.63	0.57	0.32	382,266.79	0.74	2.02	0.77	1.14	8.21	20.32	11.20	12.82

Sorting again by the cooling coil power the sensible power error is also half the error as the previous calibrations. However, the RTU power is twice as large as the RTU power minimums with the fan power error being nearly 21 times larger than the fan minimum.

Table 21: Calibration 3 Trials Sorted by Sensible Load RMSE

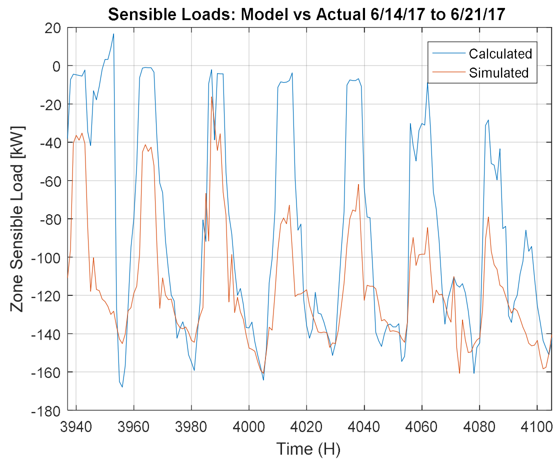
Run	Pnom	MdotMax	Feff	DX Bal	DX Tot	SHR 1	COP 1	SHR 2	COP 2	RMSE Fan Power (kW)	RMSE RTU Power (kW)	RMSE DX Power (kW)	RMSE Qsens (kW)
	897.79	16.06	0.63	0.30	307,916.73	0.72	2.97	0.71	1.37	6.23	13.57	28.19	10.67
	958.91	15.42	0.48	0.31	320,843.50	0.72	1.74	0.76	2.32	12.50	14.78	22.24	10.69
	1,157.22	21.46	0.71	0.30	305,999.59	0.71	1.71	0.81	2.41	12.21	9.72	25.49	10.86
	1,045.64	22.70	0.66	0.31	315,210.27	0.71	1.78	0.83	2.98	10.82	10.20	28.07	11.17
	961.07	20.12	0.52	0.31	327,301.14	0.70	2.83	0.82	1.58	15.37	8.84	28.31	11.17
####	689.93	17.05	0.41	0.32	330,540.66	0.72	2.33	0.71	1.71	10.57	10.92	24.18	11.19
	1,003.25	16.91	0.48	0.33	318,365.93	0.74	1.72	0.70	1.28	15.76	28.27	12.11	11.21
	679.74	17.51	0.78	0.32	301,301.38	0.73	1.22	0.82	1.41	1.46	20.57	13.72	11.24
####	672.51	20.27	0.55	0.30	312,004.73	0.74	2.36	0.76	1.69	6.16	12.38	28.40	11.26
####	967.13	15.14	0.72	0.34	311,641.56	0.72	1.03	0.72	2.78	4.65	31.37	19.59	11.27

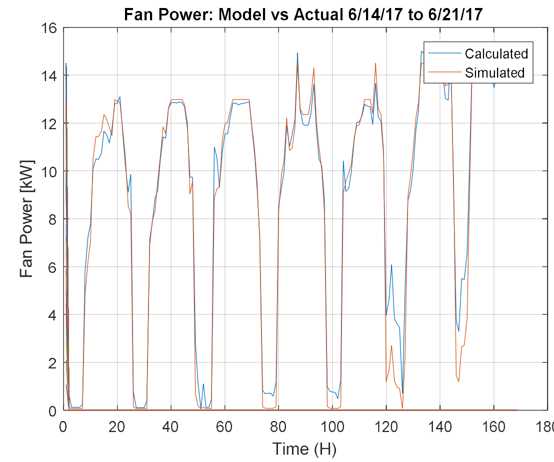
Lastly, sorted by the sensible load error, the accuracy is improved nearly three times the previous calibration attempts but with greater error in fan and cooling coil power. The results of this test seem to reflect an inability to accurately model all parameters at one time; however, each parameter can be calibrated to be very accurate. Combining the results from this test, the following validation tests were run. Table 22 shows the results of the validation tests.

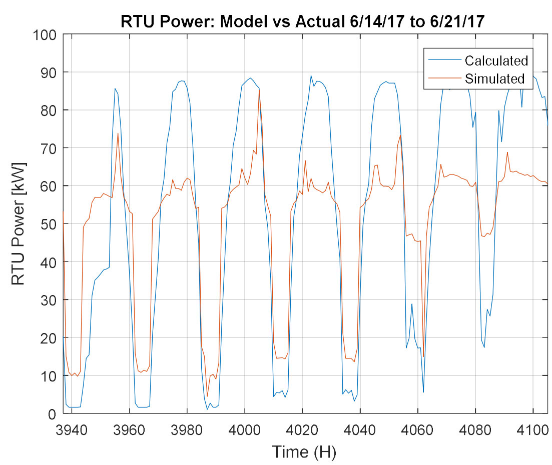
Table 22: Calibration 3 Results

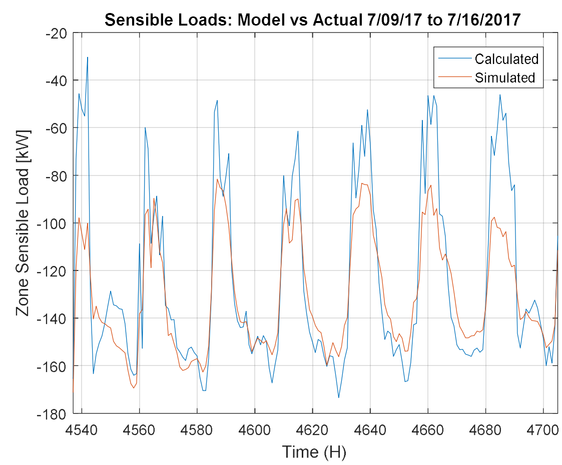
Test	Start Date	End Date	Start Hour	End Hour	RMSE Qsens (kW)	RMSE Fan Power (kW)	RMSE RTU Power (kW)	RMSE DX Power (kW)
1	6/14/2017 0:00	6/21/2017 23:00	3937	4105	46.73	0.92	19.50	26.30
2	7/9/2017 0:00	7/16/2017 23:00	4537	4705	19.37	1.03	12.53	25.26
3	8/23/2017 0:00	9/1/2017 23:00	5689	5856	42.40	1.23	16.95	29.18

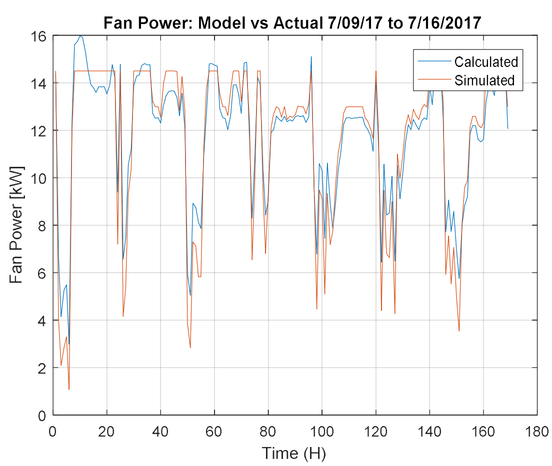
Based purely on RMSE for July, the calibration is the most accurate of the three sets of calibration tests in all values. The fan power is the lowest for all three test weeks than in the previous tests. Looking at the figures below, the model fan power accurately follows data fan power in each case with differences in the peaks where the maximum power appears caped compared to the actual. The sensible loads follow the same trend, do a better job following peak cooling loads, but don't follow the minimum cooling loads as well. RTU power is the most inaccurate of the measured variables. In this case, the RTU power fails to capture the peak RTU power.

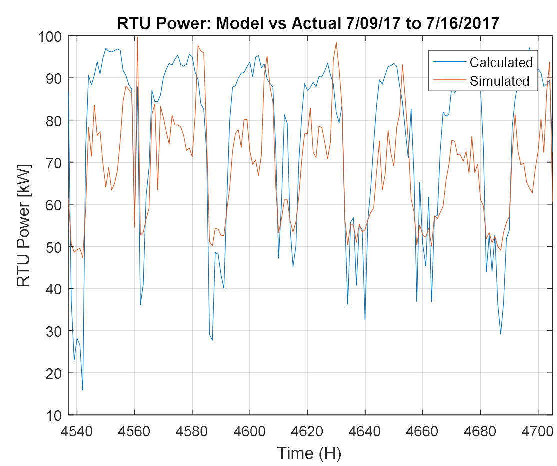












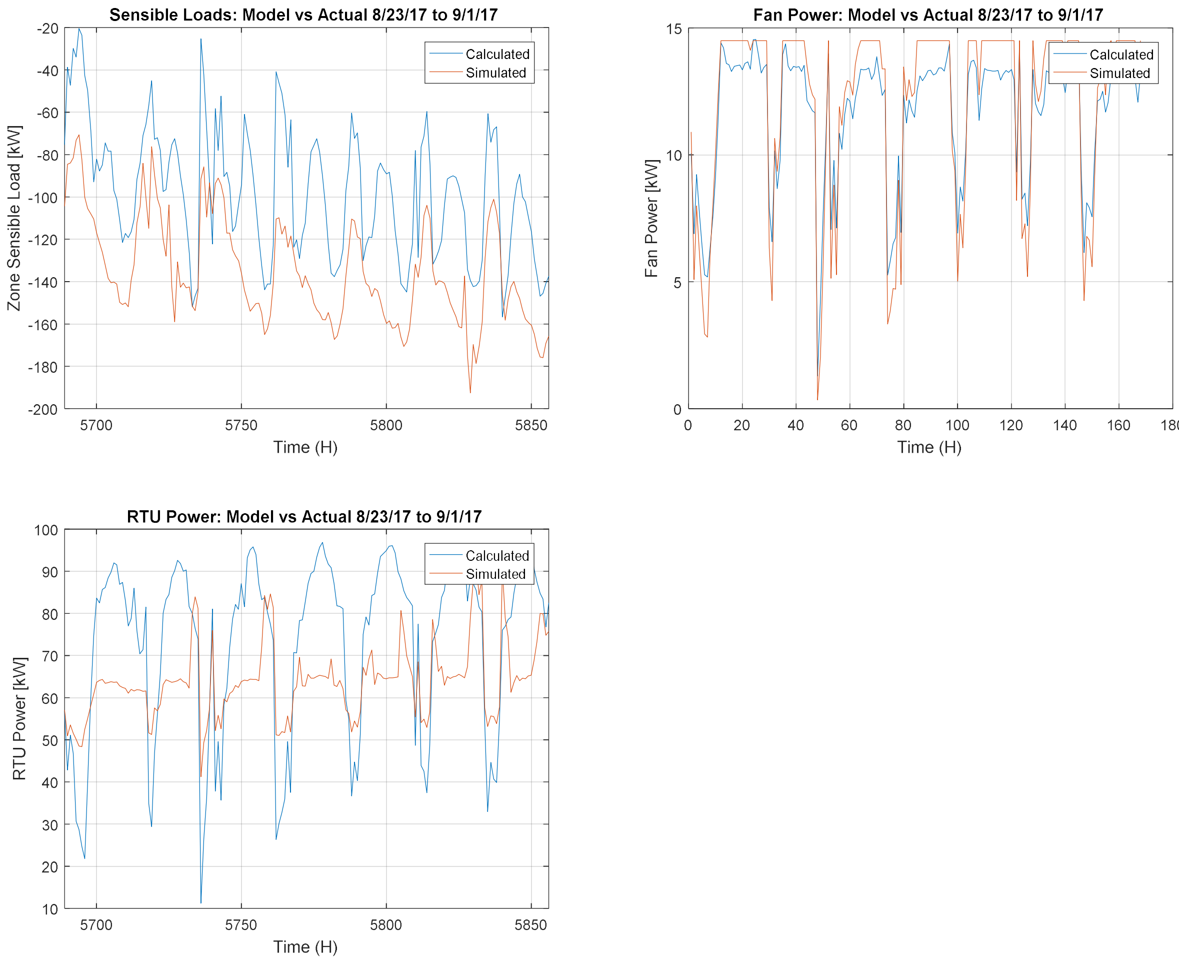


Figure 27: Calibration 3; Sensible Loads, RTU Power and Fan Power Profiles

For the purposes of MPC testing, the model does a poor job of reflecting the overall RTU power. However, this model does work for the purposes of testing control scenarios within the modeling environment.

Model Predictive Control Application Results

The model predictive control testing was accomplished at three levels of on-site PV arrays. For greater ease of demonstration, the results will be shown, after the energy optimization testing, divided between the three levels of PV. The tests that were accomplished were as follows:

1. Energy Optimization Testing
2. Cost Optimization Testing
    a. Optimization under current rate structure
    b. Optimization under day ahead pricing
    c. Optimizing with current rate structure around a ramping event
3. Blended Cost Function
    a. Peak Demand Reduction
    b. System Ramping Reduction
    c. Peak to Valley ratio test
    d. Load Factor reduction
    e. Utility Carbon Dioxide production reduction

The full results tables and figures are presented in Appendix H. The results presented in the following section are focused on certain behaviors of the controller during the testing process.

Energy Optimization Testing

The first series of tests were performed to see if the MPC controller would be able to optimize energy usage. For this, a flat rate energy price was used, and no demand penalties were added into the optimizer. Table 23 shows the results of the testing.

Table 23: Energy Optimization Results, Non-PV Case

Results	T1_NSU	T1	T1_82PV_NSU	T1_82PV	T1_154PV_NSU	T1_154PV
Test Title	Flat Rate	Flat Rate	Flat Rate	Flat Rate	Flat Rate	Flat Rate
Peak Demand (kW)	248.48	247.91	248.17	247.76	247.91	247.60
Mid-Peak Demand (kW)	203.12	202.88	177.54	177.49	165.89	165.89
On-Peak Demand (kW)	203.12	202.88	177.54	177.49	165.89	165.89
Energy Usage (kWh)	25,887.97	25,815.20	22,021.60	21,979.81	18,435.17	18,394.82
% Energy Change from NSU		-0.28%		-0.19%		-0.22%

The energy savings were the greatest from the non-PV arrayed model with diminishing returns with increasing array size. Figure 28 shows the night time set point and each optimized attempt to minimize energy use. The model internal temperature, in all cases, follows the set point with little deviation and hence is not shown.

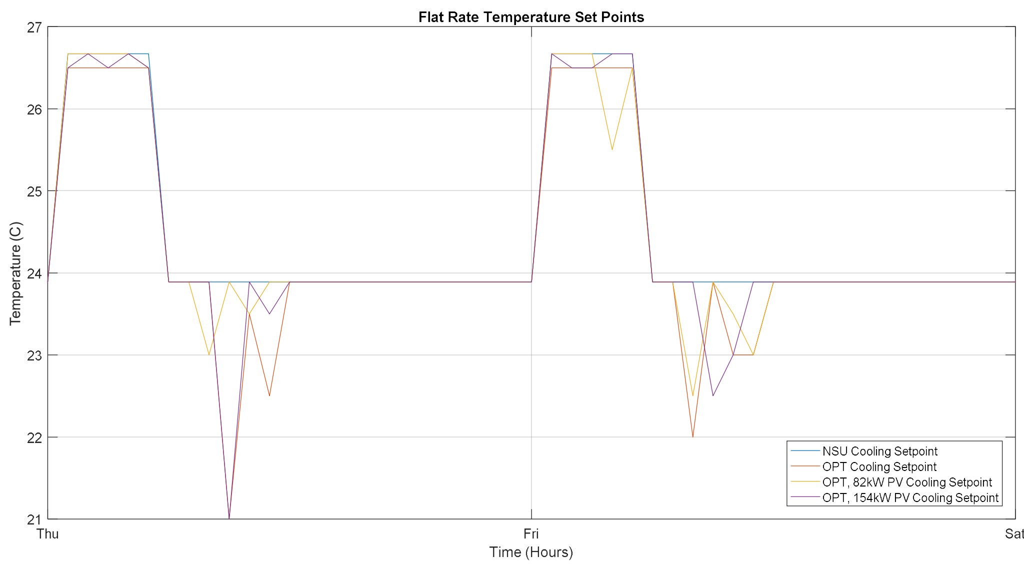


Figure 28: Cooling Set Points for Energy Optimization Case

Figure 28 demonstrates that the building does attempt to pre-cool the building before and shortly after occupancy in the building, attempting to find energy savings in the economizer time of cooler outside air temperatures. The optimizer decreases the amount of precooling based on the availability of onsite energy generation.

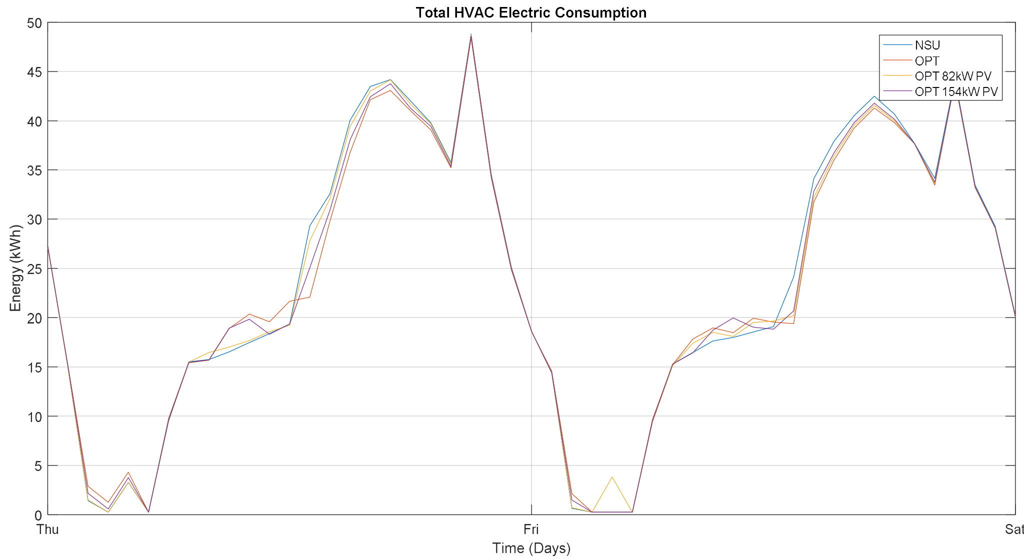


Figure 29: Energy Optimization, Non-PV, HVAC Electric Consumption

Figure 29 shows the profile of HVAC consumption. There is very little deviation between the profiles and the NSU case.

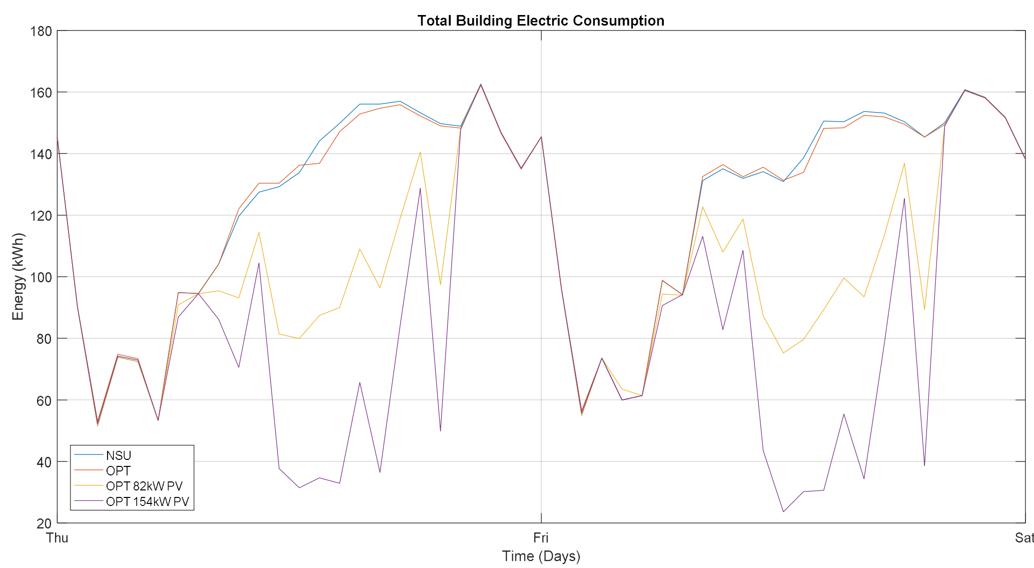


Figure 30: Energy Optimization, Non-PV, Building Electric Consumption

Figure 30 shows the total simulated building power consumption. There is a slight difference between the NSU and optimized energy levels. The greater difference can be seen between each level of PV and the no PV cases. It can be seen that the peak in power consumption decreased during the height of the day and PV generation.

Energy Cost Testing

The baseline energy reduction testing did show improvements, but not large improvements compared to the non-optimized case. The next set of tests test the controller's ability to optimize around realistic cost structure. These tests represent the economic performance of model predictive control and the ability of the controller to reduce operating costs associated with the HVAC energy usage as a part of the total building energy consumption. These costs are first, the cost savings associated with reducing utility costs under the current rate structure, followed by utility costs under prices as defined by the day ahead energy market, and then lastly under a planned demand response event. The main metrics considered are the time of use energy costs and the demand costs. Five tests were accomplished for each level of onsite power generation available, adjusting the demand penalty threshold at the following levels:

- 0 kW, all demand penalties
- Off Peak, 50kW; Mid and On Peak, 130kW
- All at 130 kW
- Average demand of each period from first test
- Maximum demand of each period from the first test

These tests were developed through trial and error to see their effects. The final two tests were developed after seeing what occurred during the first three tests. The first test, by testing with a demand threshold of 0 kW, tests the raw ability of the optimizer to suppresses demand at all hours of the day with increased cost during the peak hours. The second test focuses on reducing the maximum demand throughout the day while giving relaxed threshold during the peak hours when the penalties would be counted twice. The third test recognizes that there will be a minimum demand required by the building. By setting the threshold too low, the optimizer will penalize all demand including the minimum required by the building to operate. After seeing the results from the first three tests, the average demand penalty allows the optimizer to penalize any demand that is higher than the solved average demand for the week. The average is calculated for each threshold as the average maximum demand (threshold 1), average mid-peak demand (threshold 2), and average on-peak demand (threshold 3). Lastly, since the demand is charged from the utility company at the maximum demand reached each month, the thresholds were set at the maximum solved demand from the first, 0kW penalty threshold. Since these demand levels were already optimized at suppressing demand as much as possible, the maximum demand charge penalizes any day in which the demand goes above an optimized demand rate. Since these maximum demand levels would only occur a few times in the week, it allows the optimizer to focus on decreasing demand during those critical periods while reducing energy costs for the remaining days of the week.

Minimizing Current Utility Costs

As mentioned above, this first set of tests test the ability of the controller to reduce operating costs under the current rate structure. The rate structure comprises rates for both time and use and demand charges associated with off-peak, mid-peak and on-peak hours of the week day. The goal of the optimizer is to shift load from on-peak hours to off-peak hours where the charges are less. The demand thresholds for the fourth and fifth tests are shown in the following table.

Table 24: Utility Cost Demand Penalty Thresholds

	No PV Average (T4)	No PV Max (T5)	82kW PV Average (T4)	82kW PV Max (T5)	154kW PV Average (T4)	154kW PV Max (T5)

Threshold 1 (kW)	182	244	172	240	170	234
Threshold 2 (kW)	178	244	172	240	170	234
Threshold 3 (kW)	168	194	139	166	121	151

No PV Testing

Table 25 shows the results of the testing without onsite PV generation.

Table 25: Utility Rate Optimization, No PV, Testing Results

Results	T2a_NSU	T2a_T1	T2a_T2	T2a_T3	T2a_T4	T2a_T5
Test Title	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing
Demand Charge ($)	$ 4,425.36	$ 4,345.42	$ 4,350.27	$ 4,345.42	$ 4,333.92	$ 4,343.52
Mid Peak Charge ($)	$ 852.27	$ 836.88	$ 837.81	$ 836.88	$ 834.66	$ 836.51
On Peak Charge ($)	$ 3,538.32	$ 3,395.86	$ 3,390.42	$ 3,395.86	$ 3,412.50	$ 3,392.82
Total Demand Charge ($)	$ 8,815.95	$ 8,578.16	$ 8,578.50	$ 8,578.16	$ 8,581.09	$ 8,572.85
TOU Charge ($)	$ 7,717.69	$ 8,074.41	$ 7,990.00	$ 8,073.02	$ 7,985.47	$ 7,751.36
Total Cost ($)	$ 16,533.65	$ 16,652.58	$ 16,568.50	$ 16,651.18	$ 16,566.55	$ 16,324.20
Total Cost Savings (increase) ($)		(118.93)	(34.85)	(117.53)	(32.91)	209.44
% Energy Change from NSU		7%	5%	7%	5%	1%
Time of Use Cost Savings (Increase) ($/month)		$ (356.72)	$ (272.30)	$ (355.32)	$ (267.77)	$ (33.66)
Demand Cost Savings (increase) ($/month)		$ 237.79	$ 237.45	$ 237.79	$ 234.87	$ 243.10
% Demand Costs Savings		2.70%	2.69%	2.70%	2.66%	2.76%
% Energy Costs Savings		-18.49%	-14.11%	-18.42%	-13.88%	-1.74%
% Utility Bill Savings		-0.72%	-0.21%	-0.71%	-0.20%	1.27%

In all cases of testing, compared to the NSU run, the optimizer was able to save money through reducing demand charges. However, the resultant reduction of demand was very small and, in terms of peak demand, reduction was approximately a 2% reduction of demand. Figure 31 shows the reduction of demand for all the tests. As seen visually, the reductions are very slight for all hours but are still a noticeable reduction from the NSU value. This indicates that the optimizer is only able to do so much in reducing demand to a point. Also, this is the building demand so the optimizer must work around other sources of demand such as the appliance loads.

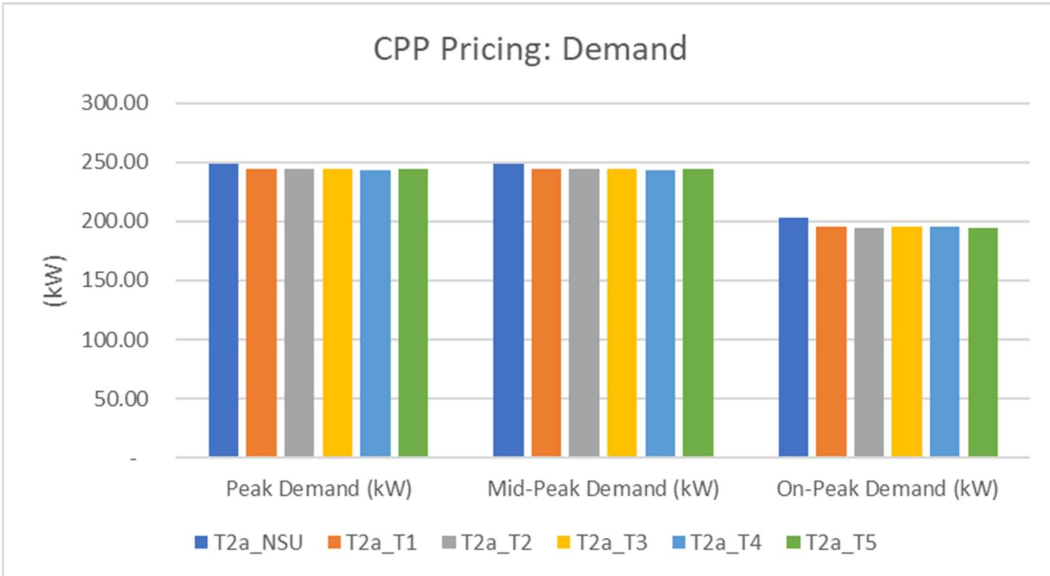


Figure 31: CPP Test Demand Results

This two percent reduction does equate to approximately $243 a month in demand charges. This cost does come at a price of increased time of use costs in all cases. Figure 32 illustrates this point. For all the tests that heavily suppress the demand charges, the time of use charges have a greater increase. The fifth case results in a lower reduction of demand charges but also has the lowest increase of time of use charges.

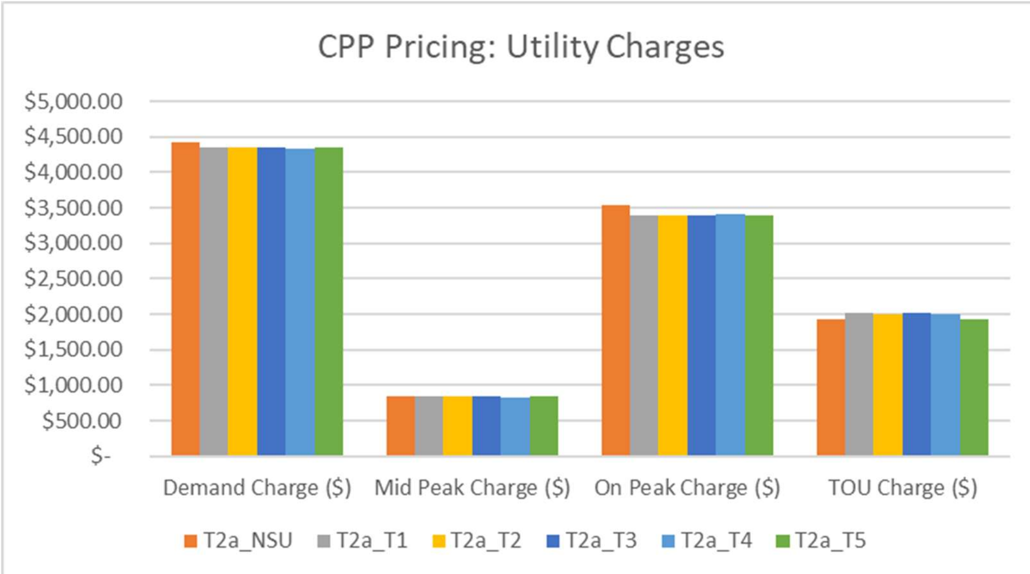


Figure 32: CPP Pricing Utility Charge Results

This resulting balance of time of use charges and demand charges makes the fifth set of thresholds the most economical. Considering that the time of use cost increase could be multiplied by the four weeks in a month, a $90.00 a week increase in time of use charges would offset the monthly demand savings of up to $270. In the fifth option, the time of use charges increase $8.42 but save $243.10 a month in demand charges, making this the only true economical option for the optimizer.

To see how the optimizer is reducing the energy cost, figure 33 shows how the set point is adjusted throughout the week to reduce demand. The HVAC unit in all cases uses precooling during the first part of the day while energy rates are low. This is what causes the increase in electric consumption to compensate for lower consumption during the peak rate hours.

Figure 33: CPP Test Cooling Set Points

Looking at the total building electrical consumption (figure 34) and the total HVAC electrical consumption (figure 35) the total building maintains a baseline minimum energy use from lighting and appliance loads throughout the day while the HVAC is able to turn on and off throughout the day as necessary. In the NSU case, when the set point increases at night, there is zero electrical consumption and minimal use during the night. The optimizer uses more night time electricity, and in the case of trial 3 Thursday morning, spikes the building energy consumption at night for pre-cooling. In most cases, the fifth trial follows the NSU schedule most closely with some night time variations to reduce peak loads.

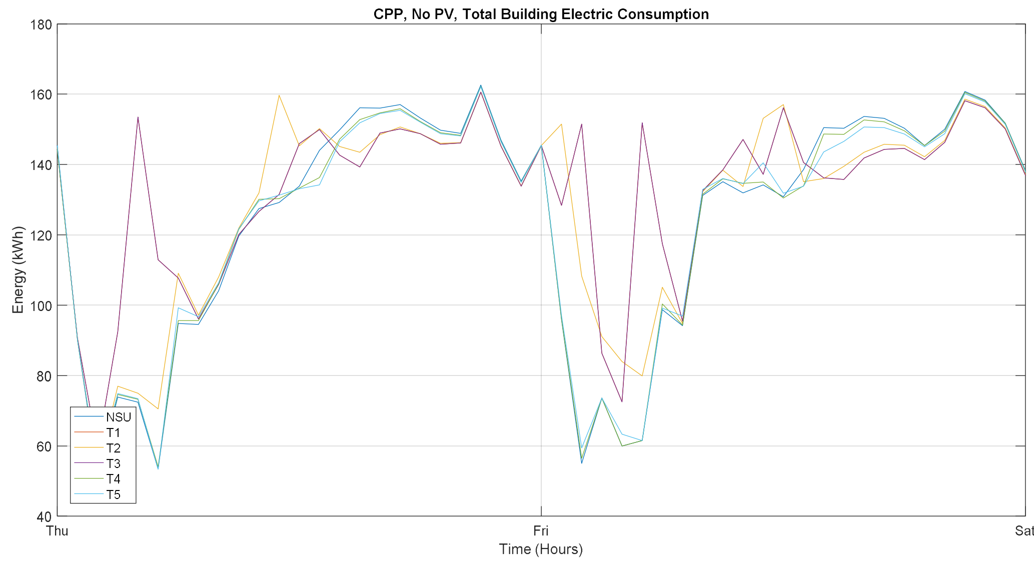


Figure 34: CPP Pricing Total Building Electric Consumption

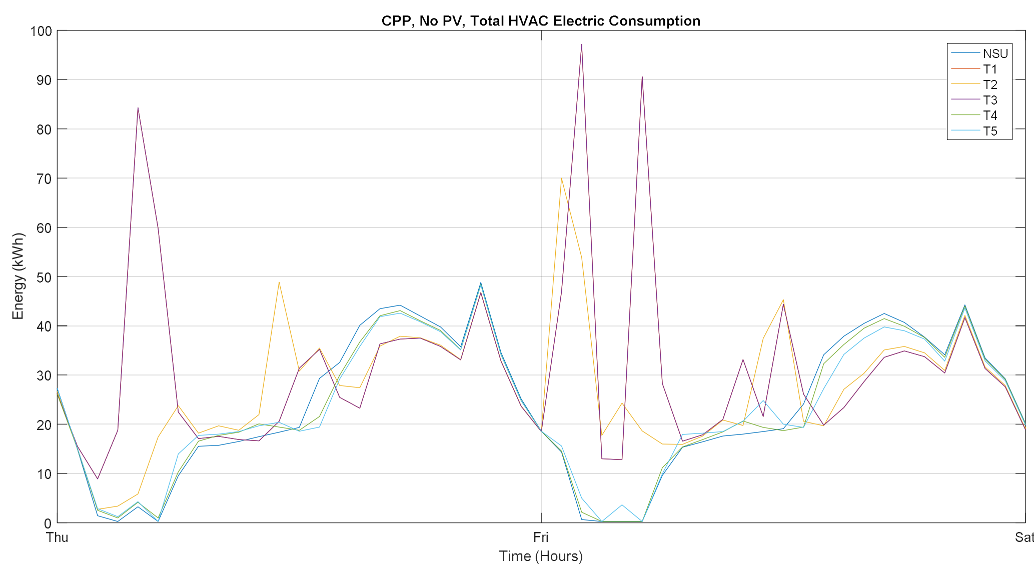


Figure 35: CPP Pricing Total HVAC Electric Consumption

This resultant profile does not improve many of the additional metrics. Table 26 shows the results in terms of the additional metrics.

Table 26: CPP Pricing Grid Metric Results

Results	T2a_NSU	T2a_T1	T2a_T2	T2a_T3	T2a_T4	T2a_T5
Test Title	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing
Carbon Savings (increase) (Lbs CO2)		(1,427.75)	(1,112.29)	(1,419.87)	(986.84)	(201.83)
% Change Ramping		33%	15%	33%	18%	1%
% Change Peak to Valley Ratio		-1%	-1%	-1%	-1%	-1%
% Change Load Factor		9%	7%	8%	7%	3%
% Change Peak Demand		-2%	-2%	-2%	-2%	-2%

The result of shifting loads to off-peak hours decreases the availability of green energy such as solar so in all cases the no carbon is saved. The only other metric to not improve is the % change in ramping. The peak to valley ratio, load factor, and peak demand all improve. The peak demand reduces 2% which could account for the 1% change in the peak to valley ratio. The load factor improvement shows that the building, especially in the first test, has a more consistent average demand load. However, the cost to the grid is much higher system ramping. In the first test, by trying to suppress demand so much, the building's electrical ramping increases as much as 33%. Once again, the fifth test, in all additional metrics with exception of load factor, proves to be the best set point.

82kW PV System

The next test is the ability to reduce cost under the current cost structure with a PV system installed. Table 27 shows the raw results of the testing.

Table 27: CPP Pricing, 82kW PV, Results

Results	T2a_82PV_NSU	T2a_82PV_T1	T2a_82PV_T2	T2a_82PV_T3	T2a_82PV_T4	T2a_82PV_T5
Test Title	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing
Demand Charge ($)	$ 4,419.83	$ 4,283.71	$ 4,283.45	$ 4,283.71	$ 4,256.69	$ 4,256.92
Mid Peak Charge ($)	$ 851.21	$ 824.99	$ 824.94	$ 824.99	$ 819.79	$ 819.83
On Peak Charge ($)	$ 3,092.81	$ 2,886.18	$ 2,895.32	$ 2,886.18	$ 2,889.61	$ 2,891.33
Total Demand Charge ($)	$ 8,363.85	$ 7,994.88	$ 8,003.72	$ 7,994.88	$ 7,966.09	$ 7,968.09
TOU Charge ($)	$ 6,429.40	$ 6,964.00	$ 6,956.35	$ 6,996.56	$ 6,891.80	$ 6,496.67
Total Cost ($)	$ 14,793.25	$ 14,958.87	$ 14,960.07	$ 14,991.44	$ 14,857.89	$ 14,464.76
Total Cost Savings (increase) ($)		(165.62)	(166.82)	(198.19)	(64.64)	328.49
% Energy Change from NSU		9%	9%	10%	8%	2%
Time of Use Cost Savings (Increase) ($/month)		$ (534.60)	$ (526.96)	$ (567.17)	$ (462.41)	$ (67.27)
Demand Cost Savings (increase) ($/month)		$ 368.98	$ 360.14	$ 368.98	$ 397.76	$ 395.77
% Demand Costs Savings		4.41%	4.31%	4.41%	4.76%	4.73%
% Energy Costs Savings		-33.26%	-32.78%	-35.29%	-28.77%	-4.19%
% Utility Bill Savings		-1.12%	-1.13%	-1.34%	-0.44%	2.22%

The results are similar to the non-PV option as the total demand is reduced providing the bulk of the energy savings but at the cost of greater energy usage.

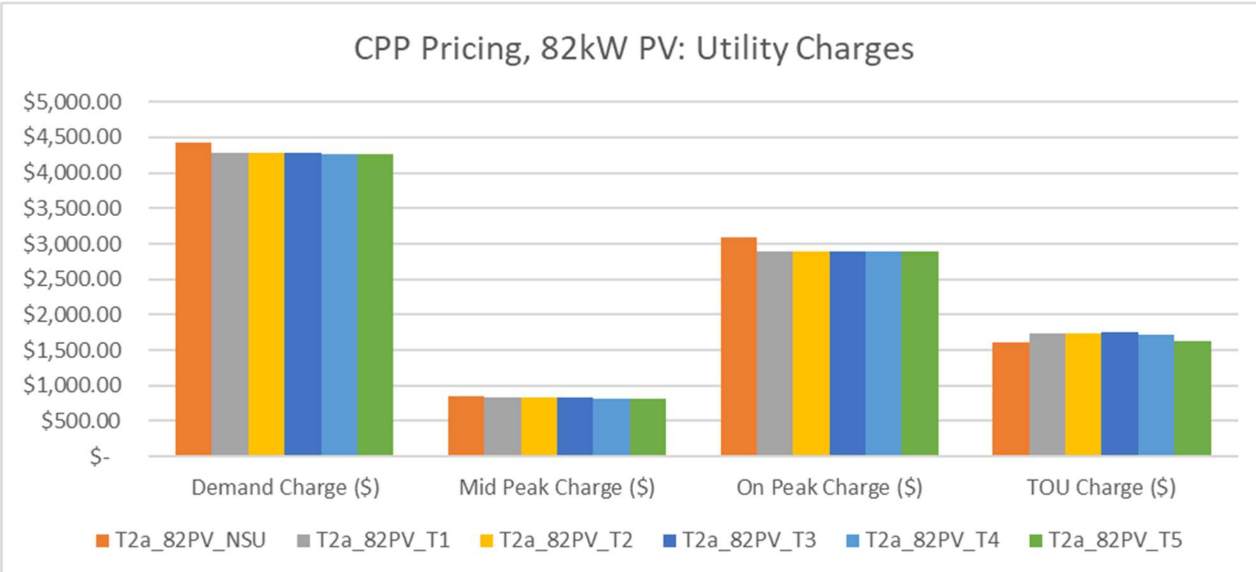


Figure 36: CPP Pricing, 82kW PV, Utility Charges

In this case, trial five has the greatest demand cost reduction by nearly $90.00 a month but with an additional time of use cost increase of $16.00 a week. The other options only save, at most in trial 4, $282 a month but with a weekly expense increase of $115 a week which would result in a $178 a month additional cost to the utility bill. Trial 5 represents the only economical setting of the controller.

Figure 37shows the cooling set points provided by the optimizer. The availability of PV during the day provides greater benefit to pre-cooling the building through the off-peak and mid-peak hours in preparation for the high-cost peak hours.

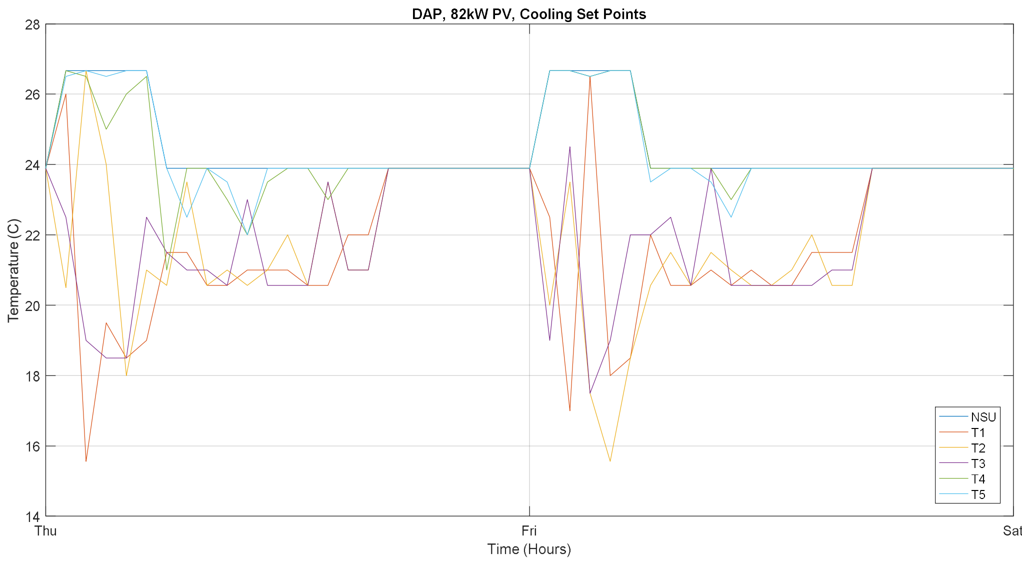


Figure 37: CPP Pricing, 82kW, Cooling Set Points

The addition of PV does result in an overall lower building energy load as shown in Figure 38 with a drop of use from the onsite power generation just before the peak energy use of the day. In all cases but the fifth trial, the optimizer takes advantage of this drop reduced building energy usage as compared to the NSU case and uses more power during that time to reduce loads during the peak hours.

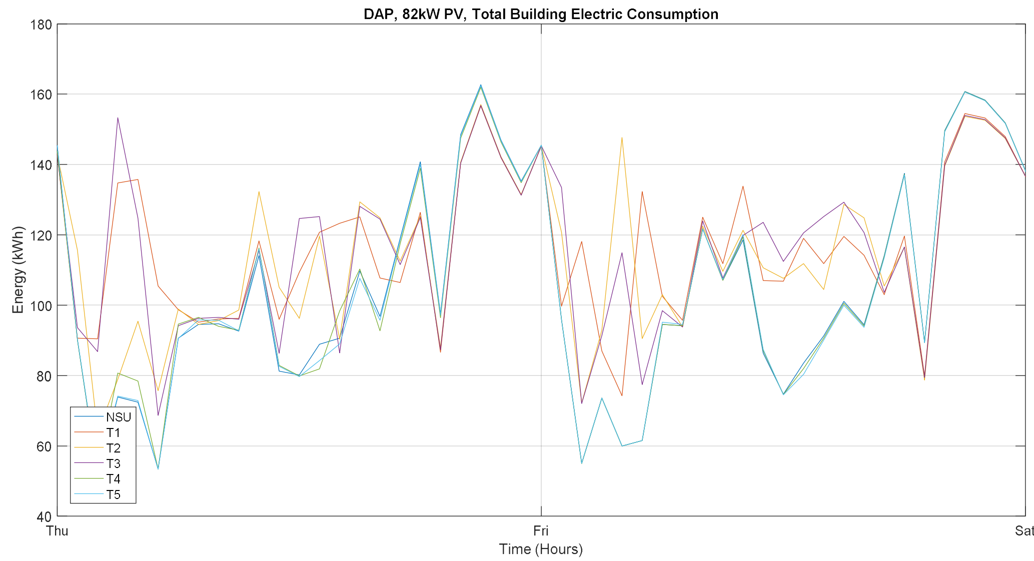


Figure 38: CPP, 82kW PV, Total Building Electric Consumption

This increased HVAC consumption is illustrated in Figure 39 with the much higher HVAC consumption throughout the day than in the non-PV case but slightly lower energy use during the peak hours.

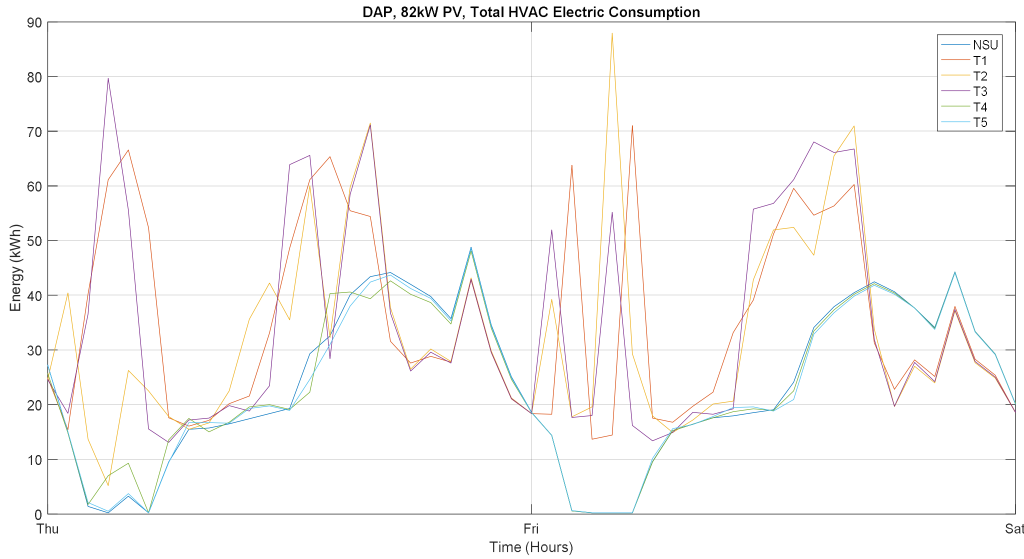


Figure 39: CPP, 82kW, Total HVAC Electric Consumption

In terms of the additional metrics, system ramping experiences only a minor increase (6%) as compared to the non-PV case which increased significantly (33%). Peak demand reduction doubles to a maximum of 4% compared to 2%. The peak to valley ratio decreases in all cases but the fifth which is indicative of a higher minimum demand and a higher average demand resulting in a more consistent, higher load factor. As with before, the higher energy usage does result in much higher carbon uses in all cases.

Table 28: CPP Princing Test, 82kW, Grid Metric Results

Results	T2a_82PV_NSU	T2a_82PV_T1	T2a_82PV_T2	T2a_82PV_T3	T2a_82PV_T4	T2a_82PV_T5
Test Title	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing
Carbon Savings (increase) (Lbs CO2)		(1,470.09)	(1,402.68)	(1,549.16)	(1,402.91)	(265.67)
% Change Ramping		-1%	6%	-2%	2%	2%
% Change Peak to Valley Ratio		-21%	-21%	-21%	-26%	1%
% Change Load Factor		13%	12%	13%	12%	5%
% Change Peak Demand		-3%	-3%	-3%	-4%	-4%

154 kW PV System

Lastly, the third level of PV is tested. Table 29 shows the results of the testing

Table 29: CPP Pricing, 154kW PV, Results

Results	T2a_154PV_NSU	T2a_154PV_T1	T2a_154PV_T2	T2a_154PV_T3	T2a_154PV_T4	T2a_154PV_T5
Test Title	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing
Demand Charge ($)	$ 4,415.04	$ 4,162.39	$ 4,162.34	$ 4,162.41	$ 4,162.35	$ 4,168.14
Mid Peak Charge ($)	$ 850.29	$ 801.63	$ 801.62	$ 801.63	$ 801.62	$ 802.74
On Peak Charge ($)	$ 2,889.83	$ 2,627.92	$ 2,662.00	$ 2,627.92	$ 2,643.66	$ 2,630.31
Total Demand Charge ($)	$ 8,155.16	$ 7,591.94	$ 7,625.95	$ 7,591.96	$ 7,607.63	$ 7,601.19
TOU Charge ($)	$ 5,232.49	$ 5,986.52	$ 5,941.39	$ 5,878.42	$ 5,771.67	$ 5,386.97
Total Cost ($)	$ 13,387.65	$ 13,578.46	$ 13,567.34	$ 13,470.38	$ 13,379.31	$ 12,988.16
Total Cost Savings (increase) ($)		(190.81)	(179.70)	(82.74)	8.34	399.49
% Energy Change from NSU		15%	14%	13%	11%	4%
Time of Use Cost Savings (Increase) ($/month)		$ (754.03)	$ (708.90)	$ (645.93)	$ (539.18)	$ (154.48)
Demand Cost Savings (increase) ($/month)		$ 563.22	$ 529.20	$ 563.19	$ 547.52	$ 553.97
% Demand Costs Savings		6.91%	6.49%	6.91%	6.71%	6.79%
% Energy Costs Savings		-57.64%	-54.19%	-49.38%	-41.22%	-11.81%
% Utility Bill Savings		-1.4%	-1.3%	-0.6%	0.1%	3.0%

In terms of costs savings, the demand reduction is double that of the non-PV case. The fifth test does not have the lowest demand reduction but does have significantly less increase in time of use charges. Once again, this makes this the most, and only, viable economic option of optimization.

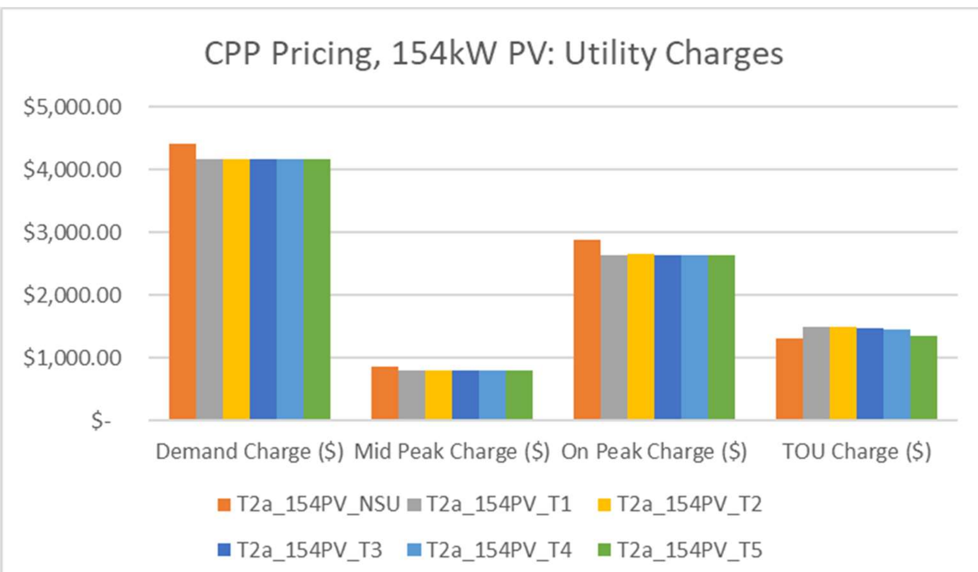


Figure 40: CPP Pricing, 154kW PV, Utility Charges

Figure 40 reinforces the point that these cost savings are minimal compared to the overall cost but would result in an eventual pay back depending on the cost of the new controller.

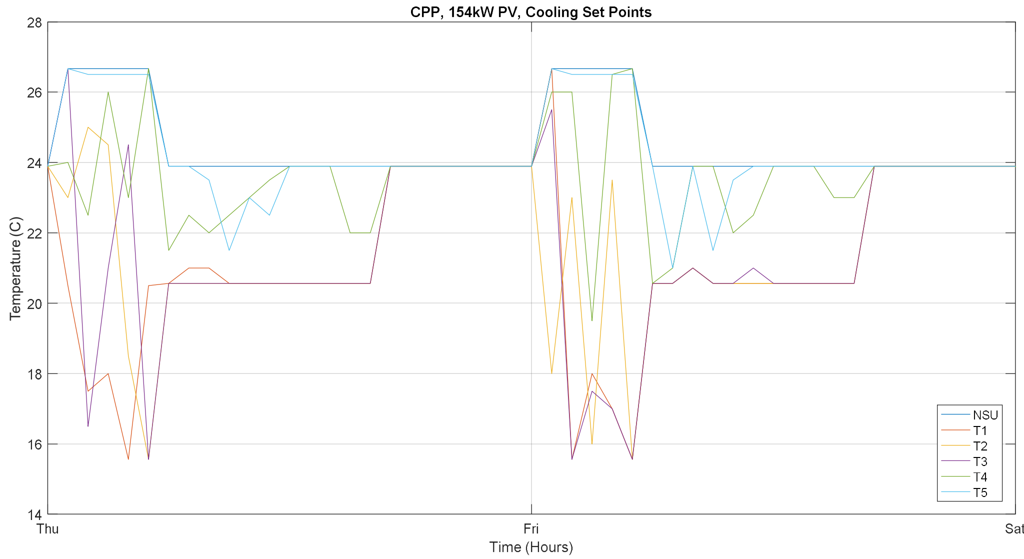


Figure 41: CPP, 154kW PV, Cooling Set Points

Error! Reference source not found. shows the cooling set point profile of determined by the optimizer. In the first three tests, the optimizer shows a profile that follows the minimum cooling set point during most of the day during high solar energy availability. The fourth and fifth tests follow a profile somewhere between the high pre-cooling set points of the first three tests and the NSU set points. Only during the high demand days of the first and last day do the profiles of the optimizer remain the most constant.

The total energy consumption of the building in **Error! Reference source not found.**shows an even higher suppressed energy consumption during the day from the higher solar generation. Especially visible is the third trial in which the optimizer fills in the valleys of the overall building consumption to reduce the peak energy consumption of the day. This is most viable between hours 130 and 150.

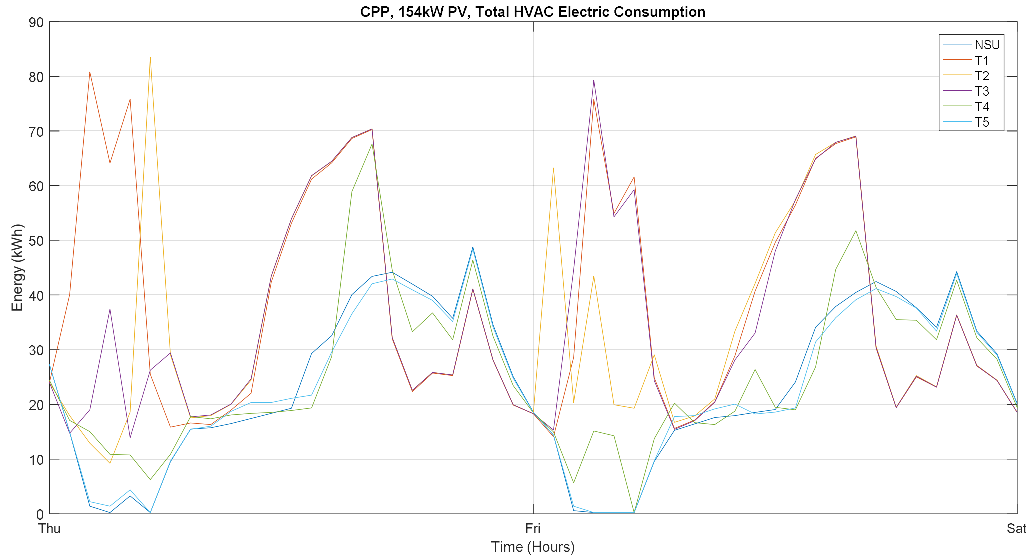


Figure 42: CPP, 154kW PV, Total Electric Consumption

The HVAC consumption shown in Figure 43 illustrates the use of HVAC to modulate the building energy consumption.

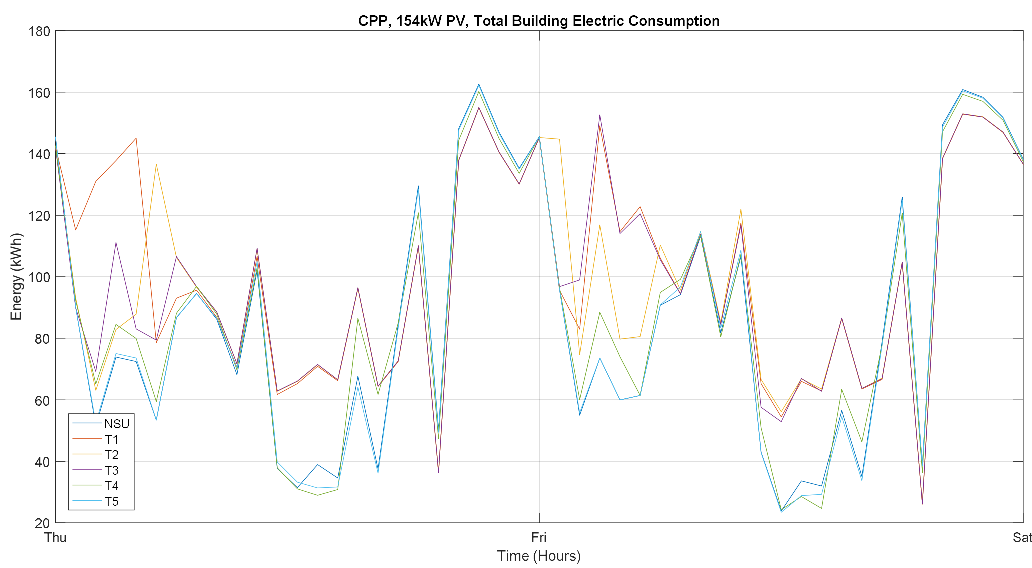


Figure 43: CPP, 154kW, Total HVAC Electric Consumption

Table 30 shows the results in terms of the additional metrics. In all cases, the load factor is improved a minimum of 10% by decreasing the peak energy load by 6% and increasing the average energy consumption. The peak to valley ratio is similarly improved with the exception of the fifth test.

Table 30: CPP Pricing, 154kW PV, Grid Metric Results

Results	T2a_154PV_T1	T2a_154PV_T2	T2a_154PV_T3	T2a_154PV_T4	T2a_154PV_T5
Test Title	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing
Carbon Savings (increase) (Lbs CO2)	(2,033.23)	(2,167.45)	(1,643.14)	(1,474.77)	(520.30)
% Change Ramping	-7%	-1%	-4%	-4%	1%
% Change Peak to Valley Ratio	-13%	-14%	-13%	-3%	2%
% Change Load Factor	22%	21%	19%	18%	10%
% Change Peak Demand	-6%	-6%	-6%	-6%	-6%

Again, carbon consumption increases in all cases in a similar manner to the total energy use increase. In terms of these additional metrics, the first test demand set points provide the optimum control in relation to grid stability.

Day Ahead Energy Pricing

The next set of the tests evaluate the ability of the controller to optimize HVAC under a new set of the time of use pricing. Under day ahead pricing, the rate structure has an overall lower cost with the exception of a much higher cost at peak energy demand. The expectation of the controller is that the controller will optimize under the peak demand constraints and a large time of use cost at peak energy demand costs. The same demand thresholds as in the previous set of tests are used.

No PV Case

Table 31 shows the results of the testing.

Table 31: Day Ahead Pricing, No PV, Results

Results	T2b_NSU	T2b_T1	T2b_T2	T2b_T3	T2b_T4	T2b_T5
Test Title	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing
Demand Charge ($)	$ 4,425.37	$ 4,352.85	$ 4,360.71	$ 4,349.91	$ 4,336.06	$ 4,342.04
Mid Peak Charge ($)	$ 852.28	$ 838.31	$ 839.82	$ 837.74	$ 835.08	$ 836.23
On Peak Charge ($)	$ 3,538.32	$ 3,401.92	$ 3,389.33	$ 3,399.05	$ 3,385.10	$ 3,373.28
Total Demand Charge ($)	$ 8,815.96	$ 8,593.07	$ 8,589.86	$ 8,586.70	$ 8,556.23	$ 8,551.55
TOU Charge ($)	$ 6,848.47	$ 7,147.36	$ 7,118.21	$ 7,108.29	$ 7,051.06	$ 6,878.99
Total Cost ($)	$ 15,664.44	$ 15,740.43	$ 15,708.07	$ 15,694.99	$ 15,607.29	$ 15,430.55
Demand Cost Savings (increase) ($/month)		$ 222.89	$ 226.10	$ 229.26	$ 259.73	$ 264.41
Time of Use Cost Savings (Increase) ($/month)		$ (298.88)	$ (269.74)	$ (259.82)	$ (202.59)	$ (30.52)
Total Cost Savings (increase) ($)		(75.99)	(43.63)	(30.55)	57.15	233.89
% Energy Change from NSU		6%	5%	5%	4%	1%
% Demand Costs Savings		2.53%	2.56%	2.60%	2.95%	3.00%
% Energy Costs Savings		-4.36%	-3.94%	-3.79%	-2.96%	-0.45%
% Utility Bill Savings		-0.49%	-0.28%	-0.20%	0.36%	1.49%

Under day ahead pricing, the time of use charge decreases approximately $200 in the NSU case from CPP pricing in the first set of tests. The cost savings in the optimized cases are comparable even with the reduced time of use energy costs. In this case, the demand thresholds for both trials 4 and 5 are adequate for an economic return although trial 5 provides the best-case savings.

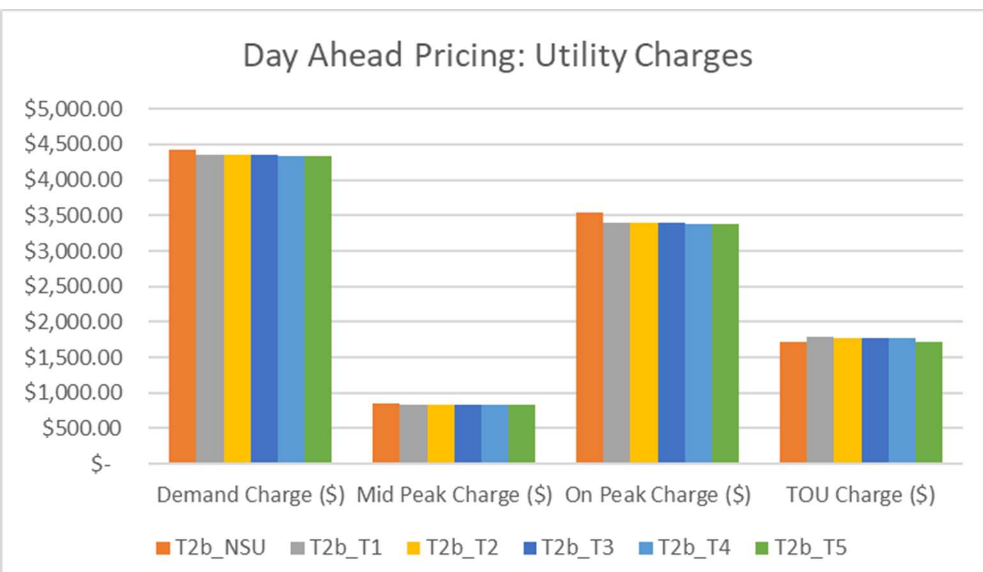


Figure 44: Day Ahead Pricing, No PV, Utility Charges

Figure 44 shows the changes in the utility charges, and the results are similar to the previous cases. Figure 45 depicts the cooling set points as solved for each case. Interestingly enough, the optimizer does employ pre-cooling as in the previous cases but does not drop the temperature set point immediately before the peak energy charges. It seems that the cumulative costs of the peak hours causes the optimizer to precool up to the peak hours.

Figure 45: Day Ahead Pricing, Cooling Setpoints

The overall building electric consumption as shown in Figure 46 shows a similar energy profile as before. During the week days, the building energy naturally decreased around the peak energy costs. This may indicate that the HVAC system can do very little to compensate for the peak energy cost.

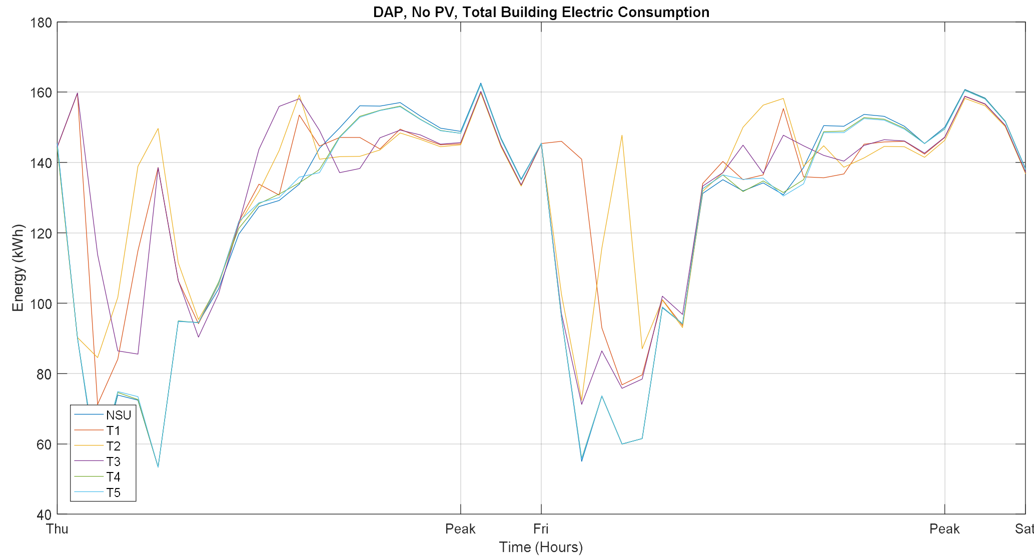


Figure 46: Day Ahead Pricing, Total Building Electric Consumption

Figure 47 shows the HVAC energy use of the building. At the peak energy price, all trials show a very similar path as the NSU case indicating the optimizer does not improve around the peak time of use energy cost even in trial 5 which, for most days, has no peak demand penalty costs.

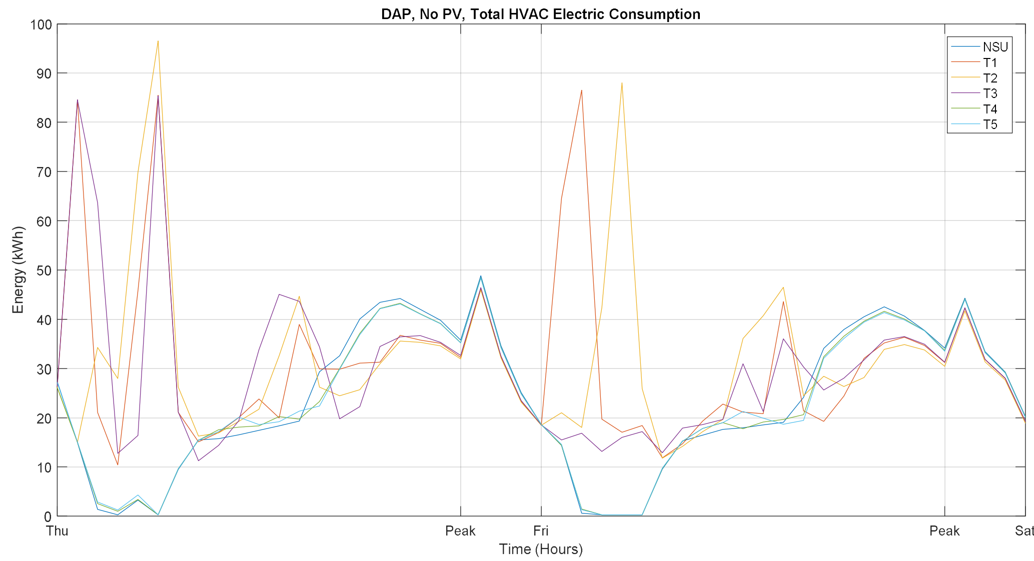


Figure 47: Day Ahead Pricing, Total HVAC Consumption

Since the total energy use is determined by estimated appliance loads based on the sensible RTU load data, this could indicate unknown events that occur at 8pm.

Table 32: Day Ahead Pricing Grid Metrics

Results	T2b_T1	T2b_T2	T2b_T3	T2b_T4	T2b_T5
Test Title	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing
Carbon Savings (increase) (Lbs CO2)	(1,227.07)	(1,153.25)	(1,102.80)	(839.29)	(172.64)
% Change Ramping	25%	22%	25%	11%	-1%
% Change Peak to Valley Ratio	-1%	-1%	-1%	-1%	-1%
% Change Load Factor	7%	7%	7%	6%	3%
% Change Peak Demand	-2%	-1%	-2%	-2%	-2%

The additional metrics are nearly identical to the CPP results although slightly diminished.

82 kW PV Case

The 82 kW PV case yielded similar results as under the CPP pricing and the non-PV case. The biggest savings compared to the non-PV option are the decrease in demand costs with a similar increase in time of use energy costs.

Table 33: Day Ahead Pricing, 82kW PV, Results

Results	T2b_82PV_NSU	T2b_82PV_T1	T2b_82PV_T2	T2b_82PV_T3	T2b_82PV_T4	T2b_82PV_T5
Test Title	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing
Demand Charge ($)	$ 4,419.83	$ 4,284.99	$ 4,277.42	$ 4,263.13	$ 4,268.85	$ 4,271.74
Mid Peak Charge ($)	$ 851.21	$ 825.24	$ 823.78	$ 821.03	$ 822.13	$ 822.69
On Peak Charge ($)	$ 3,092.81	$ 2,896.29	$ 2,923.65	$ 2,886.67	$ 2,901.41	$ 2,879.64
Total Demand Charge ($)	$ 8,363.85	$ 8,006.52	$ 8,024.84	$ 7,970.83	$ 7,992.38	$ 7,974.07
TOU Charge ($)	$ 5,813.99	$ 6,260.30	$ 6,258.98	$ 6,324.00	$ 6,149.57	$ 5,892.36
Total Cost ($)	$ 14,177.84	$ 14,266.82	$ 14,283.82	$ 14,294.84	$ 14,141.95	$ 13,866.43
Demand Cost Savings (increase) ($/month)		$ 357.33	$ 339.00	$ 393.02	$ 371.47	$ 389.78
Time of Use Cost Savings (Increase) ($/month)		$ (446.31)	$ (444.99)	$ (510.01)	$ (335.58)	$ (78.37)
Total Cost Savings (increase) ($)		(88.98)	(105.98)	(117.00)	35.89	311.40
% Energy Change from NSU		9%	10%	11%	7%	2%
% Demand Costs Savings		4.27%	4.05%	4.70%	4.44%	4.66%
% Energy Costs Savings		-7.68%	-7.65%	-8.77%	-5.77%	-1.35%
% Utility Bill Savings		-0.62%	-0.74%	-0.82%	0.25%	2.18%

There are not many changes in the cooling set points as shown in Figure 48. Again, the building does pre-cool up to about three hours prior to peak energy usage costs.

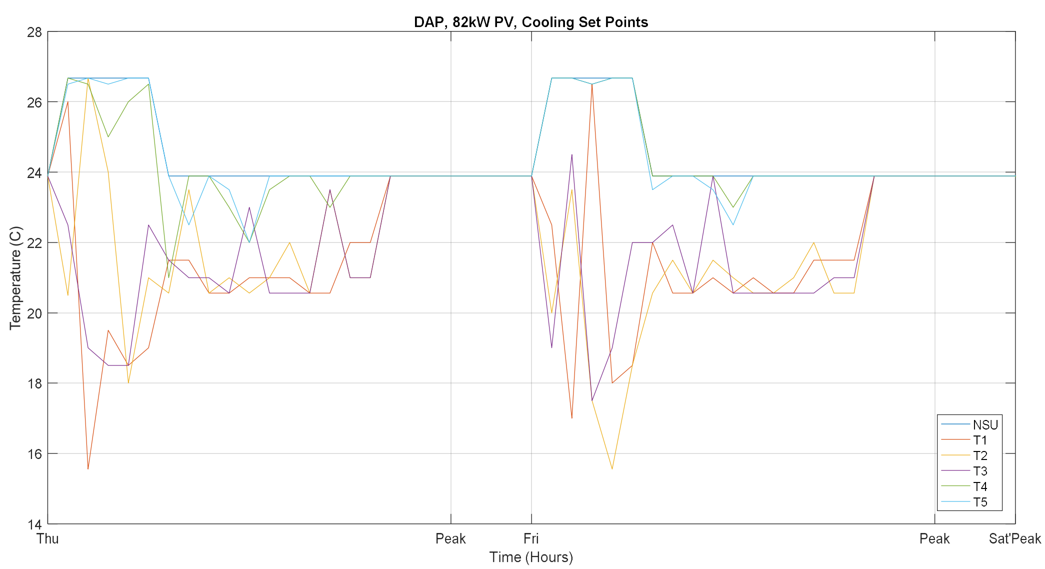


Figure 48: Day Ahead Pricing, 82kW PV Cooling Set Points

The total building energy consumption at hour 20, seen in Figure 49, is nearly identical for each of the trials indicating the optimizer is able to do very little to adjust for the increased energy costs.

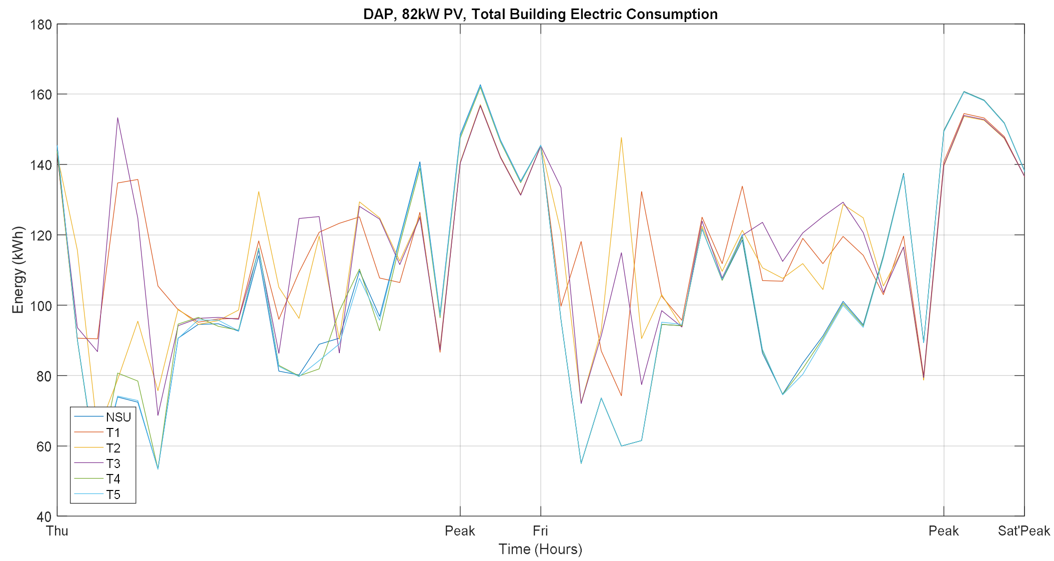


Figure 49: Day Ahead Pricing, 82kW PV, Total Building Electric Consumption

However, the total electric consumption as seen in Figure 50 does show a drop in HVAC energy below the NSU case consumption profile. This shows that the HVAC was able to adjust and help in reducing total costs but the overall effect was not significant compared to the total building energy load at the time.

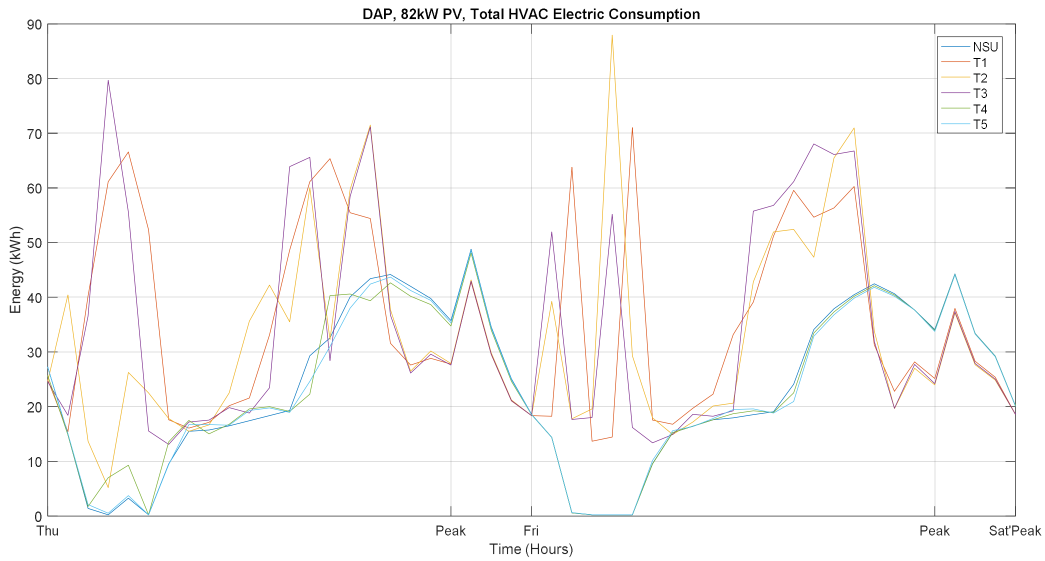


Figure 50: Day Ahead Pricing, 82kW, Total HVAC Consumption

154 kW PV Case

The 154kW PV case, like the other changes in the day ahead response tests, shows very little additional changes in energy savings. Table 34 shows the results. The time of use cost increased the most compared to all the other cases but the demand cost savings were the greatest. The total cost savings each month equate to approximately $400, which is the highest cost savings in all the testing.

Table 34: Day Ahead Pricing, 154kW, Results

Results	T2b_154PV_NSU	T2b_154PV_T1	T2b_154PV_T2	T2b_154PV_T3	T2b_154PV_T4	T2b_154PV_T5
Test Title	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing
Demand Charge ($)	$ 4,415.03	$ 4,162.38	$ 4,162.39	$ 4,162.33	$ 4,162.32	$ 4,167.53
Mid Peak Charge ($)	$ 850.28	$ 801.63	$ 801.63	$ 801.62	$ 801.61	$ 802.62
On Peak Charge ($)	$ 2,889.83	$ 2,643.46	$ 2,632.48	$ 2,642.96	$ 2,646.41	$ 2,628.14
Total Demand Charge ($)	$ 8,155.15	$ 7,607.47	$ 7,596.51	$ 7,606.90	$ 7,610.34	$ 7,598.29
TOU Charge ($)	$ 4,855.07	$ 5,436.96	$ 5,390.88	$ 5,390.37	$ 5,358.32	$ 5,015.80
Total Cost ($)	$ 13,010.22	$ 13,044.43	$ 12,987.38	$ 12,997.27	$ 12,968.66	$ 12,614.08
Demand Cost Savings (increase) ($/month)		$ 547.68	$ 558.64	$ 548.25	$ 544.81	$ 556.86
Time of Use Cost Savings (Increase) ($/month)		$ (581.89)	$ (535.80)	$ (535.30)	$ (503.25)	$ (160.72)
Total Cost Savings (increase) ($)		(34.20)	22.84	12.95	41.56	396.14
% Energy Change from NSU		15%	14%	14%	13%	4%
% Demand Costs Savings		6.72%	6.85%	6.72%	6.68%	6.83%
% Energy Costs Savings		-11.99%	-11.04%	-11.03%	-10.37%	-3.31%
% Utility Bill Savings		-0.26%	0.18%	0.10%	0.32%	3.04%

The optimizer does have the same effect with the use of PV by having a small effect on total building consumption with less HVAC consumption. This can be seen comparing Figure 51 total building electric consumption with Figure 52, total HVAC electric consumption where the HVAC energy tends to be higher than the NSU during low building usage time and lower during high building energy times.

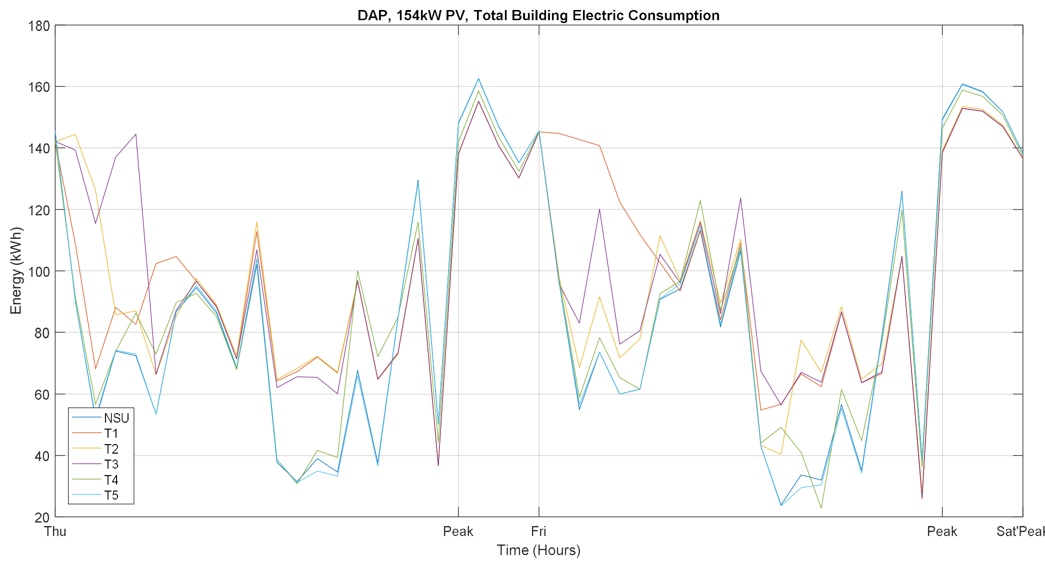


Figure 51: Day Ahead Pricing, 154kW PV, Total Building Electric Consumption

However, trial five can been seen to deviate only minimally from the NSU period with exception to the high demand periods during which it follows a similar set point to the other trials.

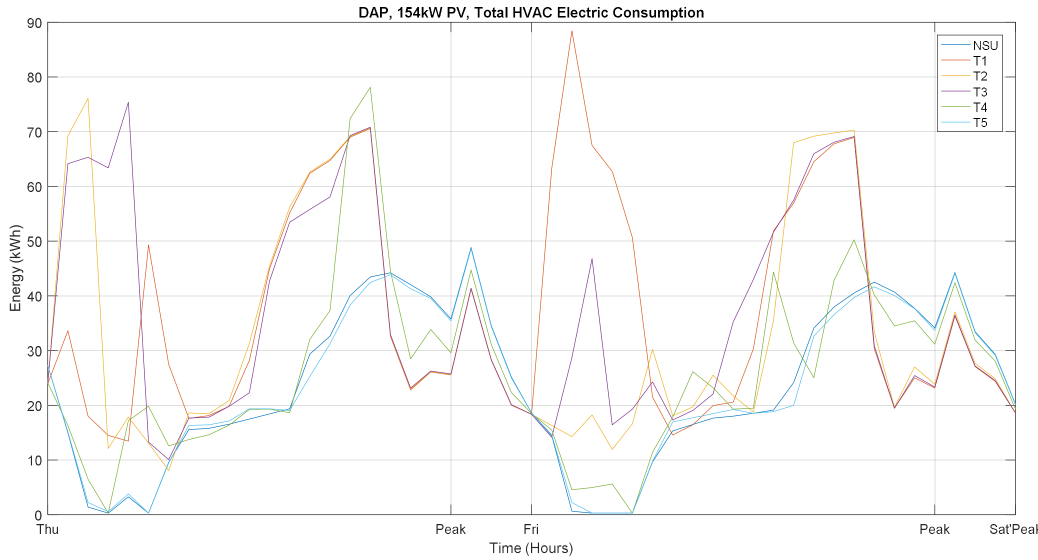


Figure 52: Day Ahead Pricing, 154kW PV, Total HVAC Electric Consumption

Evaluating the additional metrics, similar improvements were noted as before. Carbon use increased but ramping, load factor and peak demand all improved. The peak to valley ratio improved in the cases where the demand was most heavily suppressed but increased in trial 4 and 5.

Table 35: Day Ahead Pricing, 154kW PV, Grid Metrics

Results	T2b_154PV_T1	T2b_154PV_T2	T2b_154PV_T3	T2b_154PV_T4	T2b_154PV_T5
Carbon Savings (increase) (Lbs CO2)	(1,971.60)	(1,818.62)	(1,793.48)	(1,719.87)	(575.75)
% Change Ramping	-6%	-6%	-6%	-5%	-2%
% Change Peak to Valley Ratio	-13%	-18%	-15%	3%	1%
% Change Load Factor	22%	20%	20%	20%	10%
% Change Peak Demand	-6%	-6%	-6%	-6%	-6%

Demand Response Testing

The last test for more traditional utility pricing structures was to test the ability of the controller to plan around a demand response event. Under the CPP pricing, this can occur up to 12 times a year and are planned in advance. To test this, an increased price of $1.37 per kWh was added to the cost structure at 8pm every day. From a week ahead planning perspective, this is unreasonable, but this provides seven independent scenarios of testing demand response. The demand thresholds were adjusted for these tests. The first test was conducted with 130kW threshold for all demand thresholds. The remaining tests were conducted with the 2a maximum demand thresholds. An additional penalty was added to the objective function multiplying the hour 20 demand to provide a function cost. The multiplier was added for tests two through five at rates of x4, 10 and 20. The cost savings cannot be compared to the previous cases as the costs are slightly contrived to force the controller to respond. Any additional cost incurred above the 2a case during the demand response event represents more of an opportunity cost associated by not lowering demand during this time. The results were similar in effect to the day ahead price schedule in that the optimizer was able to reduce HVAC and total energy consumption during the event but not enough to meet the 30 kw goal of the rate structure. The costs do not account for any credits that would be added for a successful decrease in demand during the event period.

Event Demand Reduction: Hour 20

The testing of demand reduction at the same hour has the Day Ahead Price peak price resulted in similar results with similar cooling profiles. The below tables show the results numerically. In all cases the total building demand during that time was reduced but not enough to compensate for the whole required demand reduction and at the cost of greater energy consumption.

Table 36: Demand Reduction Event

Results	T2a_NSU2	T2c_T1	T2c_T2	T2c_T3	T2c_T4	T2c_T5
Event Demand (max)	248.48	243.77	243.94	240.53	239.40	238.41
Event Demand Reduction		4.70	4.54	7.95	9.07	10.06
% Energy Change from NSU		6%	1%	5%	8%	11%

Results	T2a_82PV_NSU3	T2c_82PV_T1	T2c_82PV_T2	T2c_82PV_T3	T2c_82PV_T4	T2c_82PV_T5
Event Demand (max)	248.17	240.34	238.29	234.92	234.46	233.98
Event Demand Reduction		7.83	9.88	13.25	13.71	14.19
% Energy Change from NSU		10%	2%	8%	13%	16%

Results	T2a_154PV_NSU4	T2c_154PV_T1	T2c_154PV_T2	T2c_154PV_T3	T2c_154PV_T4	T2c_154PV_T5
Event Demand (max)	247.900	233.71	233.93	233.84	233.71	233.71
Event Demand Reduction		14.19	13.97	14.05	14.19	14.19
% Energy Change from NSU		14%	5%	12%	19%	19%

Event Demand Reduction: Shifted hour

Lastly, to test if the lack of results was due to the building demand already nearing a low, an additional hour was tested for each level of PV to see if greater reductions could be made.

Table 37: Event Demand Reduction, Shifted Hour Results

Results	T2c_NSU_E2	T2c_E2	T2c_82PV_NSU_E2	T2c_82PV_E2	T2c_154PV_NSU_E2	T2c_154PV_E2
Event Demand (max)	194.44	189.82	154.91	148.14	119.13	112.66
Event Demand Reduction		4.62		6.78		6.48
% Energy Change from NSU		11%		16%		18%

In this case, a higher percentage reduction was made but, overall, the reduction remained about the same in magnitude. To see if any of the set points adjusted accordingly, the following figures show that the set point does adjust from a lower temperature set point just before the event time and increases to a higher temperature at the event in the two PV cases.

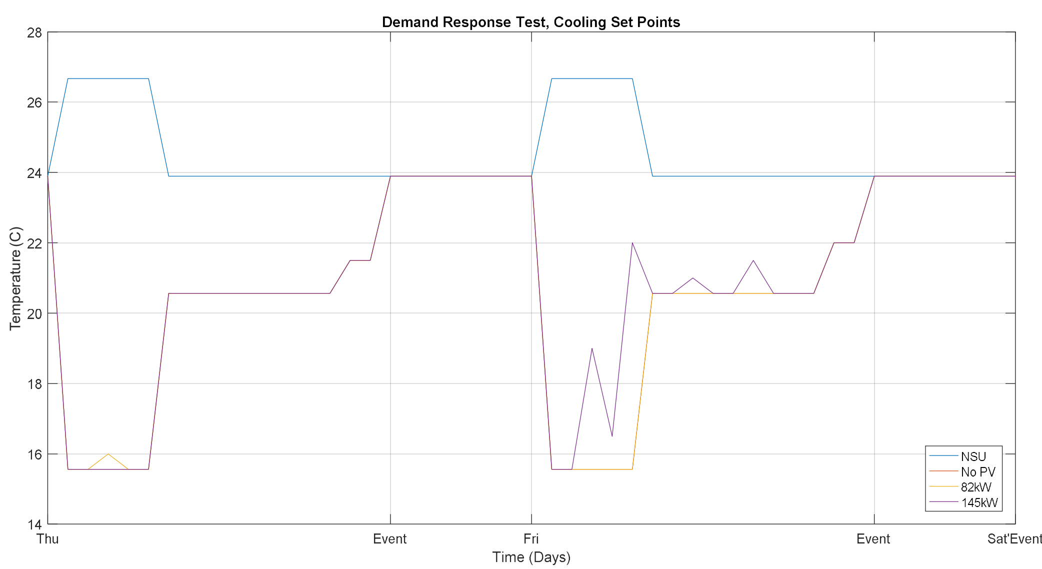


Figure 53: Demand Response, Shifted Hour, Cooling Set Points

Comparing the building HVAC energy consumption for each level of PV to their NSU cases, in all cases the energy consumption is below the NSU HVAC energy consumption. However, it isn't as significantly low as expected for a demand reduction event.

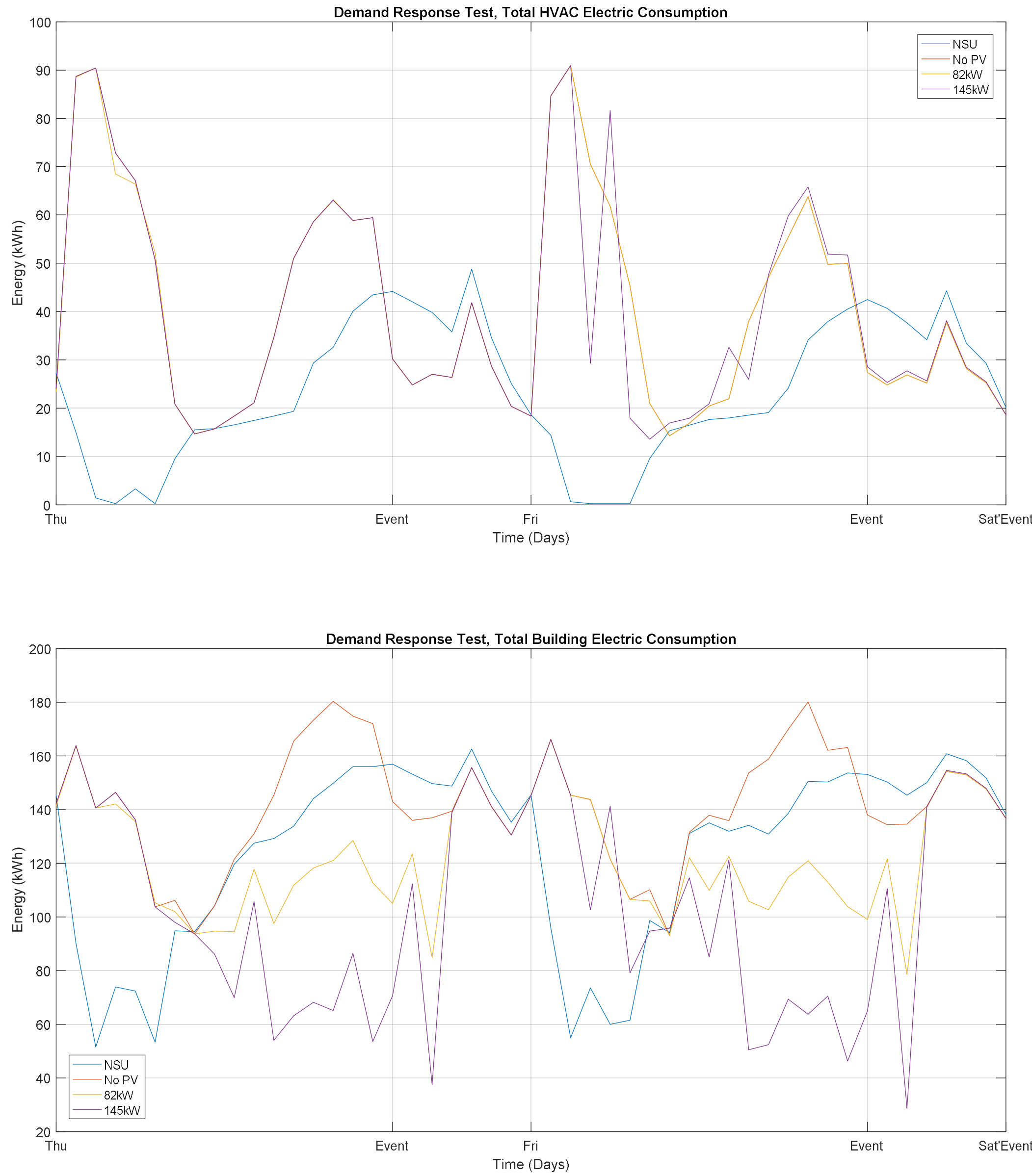


Figure 54: Demand Response Test, Total Electric Consumption

The lack of response could mean that the optimizer may need more expert knowledge in the code, meaning, that if a demand response event is known in advance, a demand constraint will be added which the optimizer must obey.

Event Hour Demand Reduction Results

To look deeper at the reductions of the demand response test, table 43 shows the change for each day. The average demand response for the week ranges between 2 to 9kW based on how hard the penalty is applied.

Table 38: Demand Reduction Daily Results

Test: Event Hour 20	9	10	11	12	13	14	15	16	Average	Avg Change	% Delta
T2c_NSU	179.92	161.42	162.78	146.07	148.83	150.04	159.05	248.48	169.57	-	0%
T2c_T1	177.59	160.28	160.74	142.69	145.56	146.17	156.49	243.77	166.66	2.91	2%
T2c_T2	177.46	161.07	161.81	144.98	147.84	147.68	154.76	243.94	167.44	2.13	1%
T2c_T3	177.87	154.99	154.79	135.74	139.03	139.91	151.24	240.53	161.76	7.81	5%
T2c_T4	177.38	151.94	154.12	135.24	138.81	140.06	150.45	239.40	160.93	8.65	5%
T2c_T5	177.12	152.14	152.43	134.84	138.46	138.98	149.14	238.41	160.19	9.38	6%

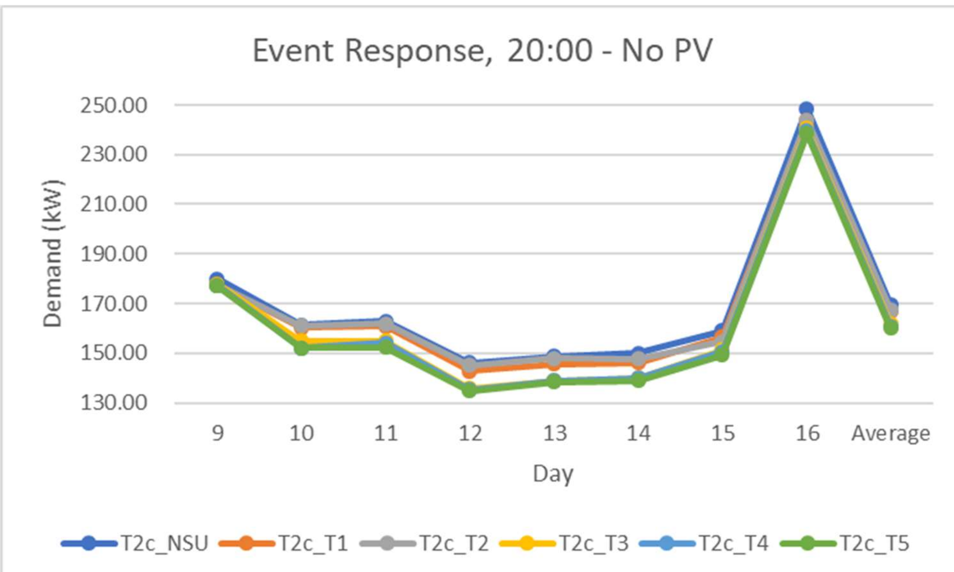


Figure 55: Event Response Daily Response

The first PV case achieves higher demand reduction. This illustrates the added flexibility of having onsite energy generation to manage the building's energy loads. Table 39 shows that this case was able to achieve higher change with less penalty charge, though this change levels off much quicker as well.

Table 39: Daily Event Response, 82kW PV

Test: Event Hour 20	9	10	11	12	13	14	15	16	Average	Avg Change	% Delta
T2c_82PV_NSU	179.59	161.08	162.43	145.72	148.48	149.70	158.75	248.17	169.24	-	0%
T2c_82PV_T1	174.38	154.34	156.10	137.86	139.71	139.62	149.33	240.34	161.46	7.78	5%
T2c_82PV_T2	173.91	157.59	160.89	145.15	147.93	148.00	150.57	238.29	165.29	3.95	2%
T2c_82PV_T3	173.95	151.60	153.68	136.03	138.96	139.19	148.90	234.92	159.65	9.59	6%
T2c_82PV_T4	173.90	150.95	152.72	134.46	137.87	138.87	147.72	234.46	158.87	10.37	6%
T2c_82PV_T5	173.51	150.95	151.74	134.45	137.69	138.61	147.63	233.98	158.57	10.67	6%

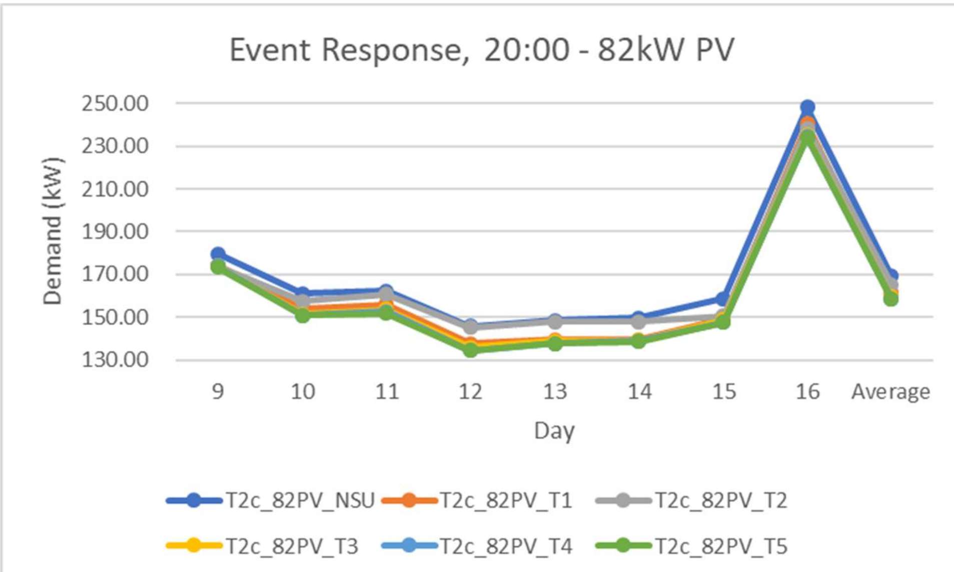


Figure 56: Event Response, 82kW PV, Chart

Following a similar trend from the 82kW PV case, with less event demand the penalty reaches higher reduction but doesn't improve as much with the added penalties.

Table 40: Daily Event Reduction Results, 154kW PV

Test: Event Hour 20	9	10	11	12	13	14	15	16	Average	Avg Change	% Delta
T2c_154PV_NSU	179.29	160.77	162.13	145.42	148.18	149.39	158.48	247.90	168.94	-	0%
T2c_154PV_T1	171.83	151.60	151.78	135.65	137.84	138.88	148.02	233.71	158.67	10.57	6%
T2c_154PV_T2	172.05	156.70	161.62	144.41	146.73	142.03	150.58	233.93	163.51	5.73	3%
T2c_154PV_T3	171.99	151.47	153.21	136.14	139.60	138.83	148.20	233.84	159.16	10.08	6%
T2c_154PV_T4	171.75	150.65	151.32	134.14	137.40	138.34	147.48	233.71	158.10	11.14	7%
T2c_154PV_T5	171.75	150.65	151.32	134.14	137.40	138.34	147.48	233.71	158.10	11.14	7%

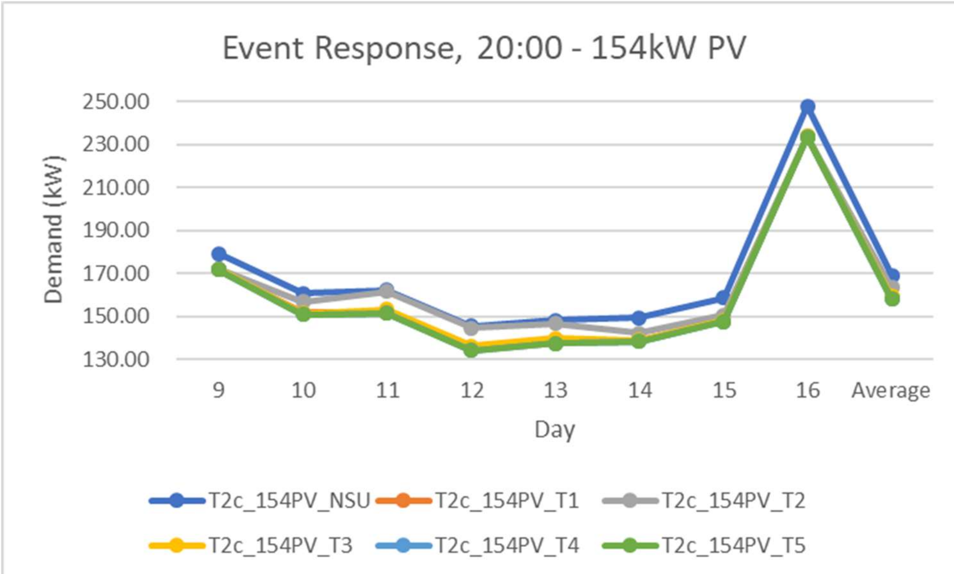


Figure 57: Event Response Chart, 154kW

Shifting the event three hours earlier in the day, the reductions are improved from the previous cases as shown in table 46 but are still not at the level required by the demand event reduction.

Table 41: Event Response Daily Results, 154kW PV

Test: Event Hour 17	9	10	11	12	13	14	15	16	Average	Avg Change	% Delta
T2c_NSU	194.44	173.81	156.23	179.65	156.99	153.13	175.68	178.39	171.04	-	0%
T2c	189.82	163.03	143.54	166.46	143.01	138.07	165.58	169.33	159.86	11.18	7%
T2c_82PV_NSU	154.91	134.56	116.84	140.24	119.00	114.11	136.93	139.45	132.01	-	0%
T2c_82PV	148.14	122.53	102.49	128.53	105.04	99.06	123.40	126.67	119.48	12.52	9%
T2c_154PV_NSU	119.13	99.04	81.19	104.57	84.62	78.80	101.84	104.20	96.68	-	0%
T2c_154PV	112.66	88.02	67.39	91.39	70.65	64.91	89.17	95.29	84.93	11.74	12%

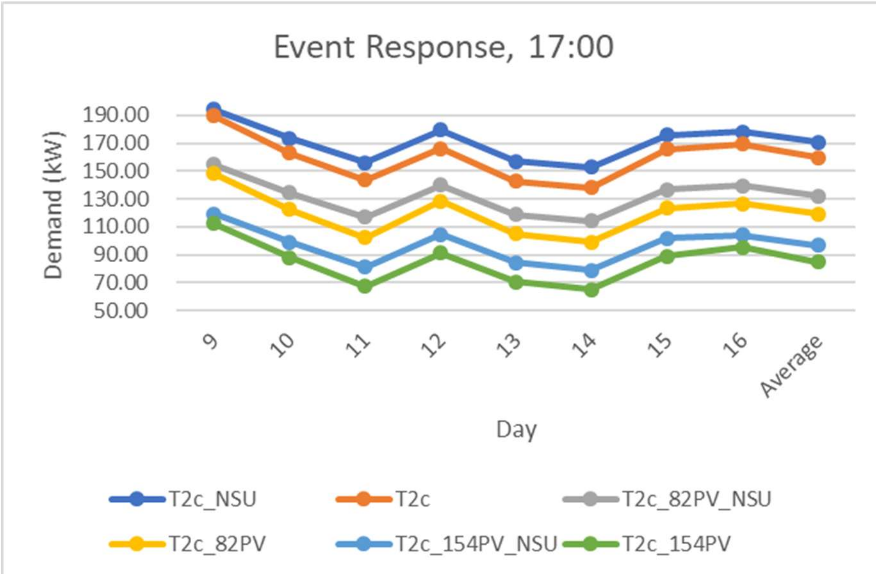


Figure 58: Event Response Daily Results, 154kW PV

Blended Cost Function Testing

The last set of tests were to test the ability of the controller to minimize the building's impact on the grid. While the purpose of these tests are not to determine the cost effectiveness of these measures, the time of use rate structure of test 2a, CPP schedule, was used to provide an additional cost in the function to optimize around. Three levels of penalties were assessed. The levels were chosen at a low, medium and high penalty level. At the low multiplier level, the penalty will be nearly equal to that of the time of use penalties. The medium level penalty will be applied as a greater weight of the cost function. The high level penalty is intended to be more than double the time of use and demand penalties so as to dominate the cost function. The other cost function penalties will be applied as the same in test 2a, with the maximum, mid-peak and on-peak demand penalty threshold at the maximum measured reduced demand from previous tests. While in this test it is possible to have just adjusted the slope of the building demand penalty by adding a new multiplier, it allowed for an additional modifier than could be independently controlled.

Peak Demand Reduction

The low, medium and high multiplier for peak demand were the peak demand times 1, 3 and 6. This multiplier is applied directly to the peak demand for each day and then added into the cost function. In the cost function, on the average day, the other demand penalties applied are around 90 and time of use at approximately 200. At the penalty level of 1, the average demand of 150kW applies an additional penalty of 150 to the cost function. This then accounts for less than half of the total cost function penalty. By multiplying by 3, the peak demand penalty applied equates to 450 of a total cost function value of 740, making this more than half of the function while the multiplier of 6 causes the demand penalty to account for around 80% of the cost function. Table 42 shows the results of these tests.

Table 42: Peak Demand Reduction Results

Results	T3a_PD1	T3a_PD2	T3a_PD3
Test Title	Peak Demand Test	Peak Demand Test	Peak Demand Test
Energy Savings from NSU (increase) (kWh)	(194.42)	(738.95)	(795.03)
Total Cost Savings (increase) ($)	245.48	292.57	296.93
% Energy Change from NSU	1%	3%	3%
Time of Use Cost Savings (Increase) ($/week)	$ (5.20)	$ (37.07)	$ (43.43)
Demand Cost Savings (increase) ($/month)	$ 250.68	$ 329.64	$ 340.36
Carbon Savings (increase) (Lbs CO2)	(183.69)	(640.16)	(619.23)
% Change Ramping	-1%	5%	11%
% Change Peak to Valley Ratio	-1%	-2%	-2%
% Change Load Factor	3%	6%	7%
% Change Peak Demand	-2%	-3%	-4%

The results are that the building peak demand is able to be reduced up to 4% in the cost function, but this comes at the cost of increased system ramping, carbon and energy consumption. This could, however, be beneficial in terms of cost savings by reducing peak costs. The three tests could save $230, $181 and $167 a month. What this test shows is that there are further peak demand reductions that could be made but that this metric cannot be applied as a blanket multiplier as demonstrated in this test. This penalty drives greater time of use costs during days that are below the peak demand and will unnecessarily adjust to reduce demand by using more energy but achieve no demand costs savings. This suggests that the optimum demand threshold may not be the lowest maximum demand from the previous tests but set to the second highest demand predicted, or historically known, for the month. This will allow the optimizer to work around time of use charges to save costs during most days and then on the critically high demand days work to suppress demand to save the monthly demand charge.

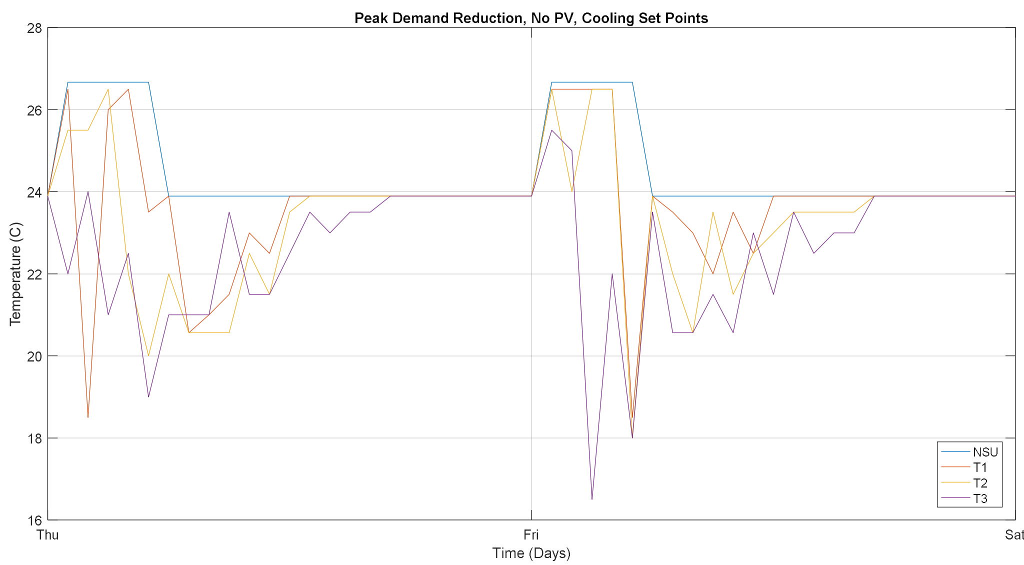


Figure 59: Peak Demand Reduction Cooling Set Points

Looking at the set point control in Figure 59: Peak Demand Reduction Cooling Set Points, it can be seen that the optimum demand reducing set points use pre-cooling before the high demand times to reduce peak demand. The results can be seen in Figure 60 of the total building electric consumption.

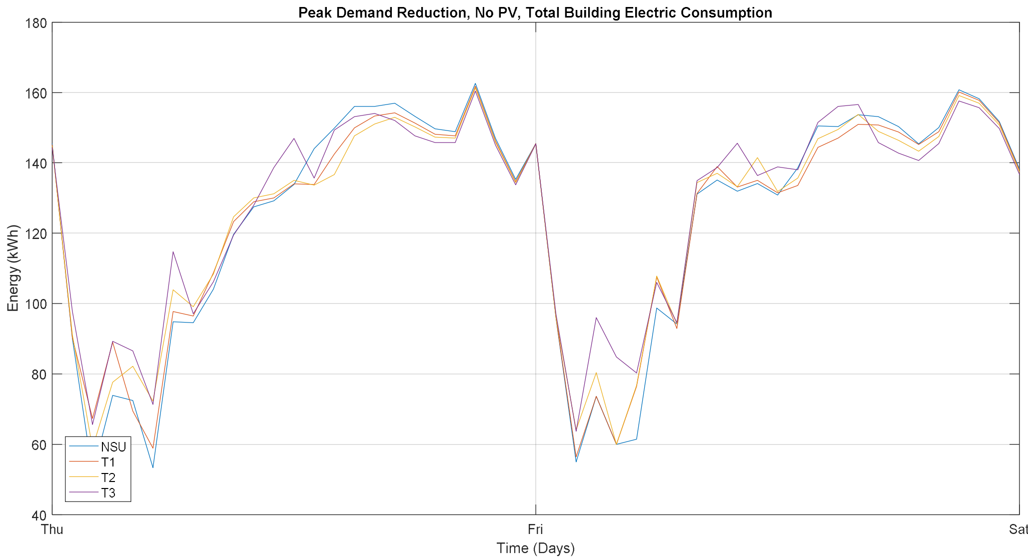


Figure 60: Peak Demand Reduction, Total Building Electric Consumption

In most cases, it can be seen that the optimized HVAC profile is always under the peak demand of the NSU case. The oddity can be seen in the last day in which there is an extremely large spike in energy usage following another large demand period during which all optimized cases have larger usage than the NSU case in preparation for the large spike.

Then looking at the first level of PV options, the results of Table 43are similar but show a larger peak demand reduction.

Table 43: Peak Demand Reduction, 82kW PV, Results

Results	T3a_82PV_PD1	T3a_82PV_PD2	T3a_82PV_PD3
Test Title	Peak Demand Test	Peak Demand Test	Peak Demand Test
Energy Savings from NSU (increase) (kWh)	(460.98)	(911.51)	(1,161.54)
Total Cost Savings (increase) ($)	370.79	397.65	396.92
% Energy Change from NSU	2%	4%	5%
Time of Use Cost Savings (Increase) ($/week)	$ (24.39)	$ (64.10)	$ (84.95)
Demand Cost Savings (increase) ($/month)	$ 395.19	$ 461.74	$ 481.87
Carbon Savings (increase) (Lbs CO2)	(376.67)	(634.17)	(796.88)
% Change Ramping	6%	2%	-3%
% Change Peak to Valley Ratio	-1%	-25%	-22%
% Change Load Factor	6%	10%	12%
% Change Peak Demand	-4%	-5%	-6%

Figure 61 shows that the optimizer is able to accomplish these greater reductions with a much greater use of building pre-cooling especially during the daytime hours when onsite power generation is much more available.

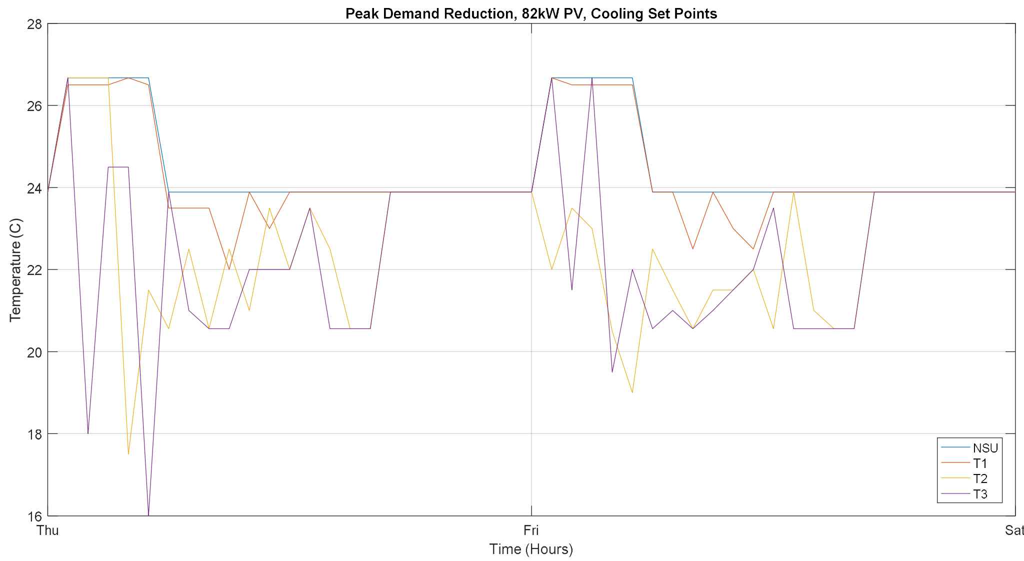


Figure 61: Peak Demand Reduction, 82kW PV, Cooling Set Points

Looking at the building electric consumption in Figure 62, it is hard to see how this affected the peak energy demand of each day. On the first and last days of the week, it can be seen that the NSU case electric consumption has higher peak demand than the optimized cases but less so during the week days. However, the optimizer did reduce the maximum peak energy load which is the main period that will be counted during the billing month.

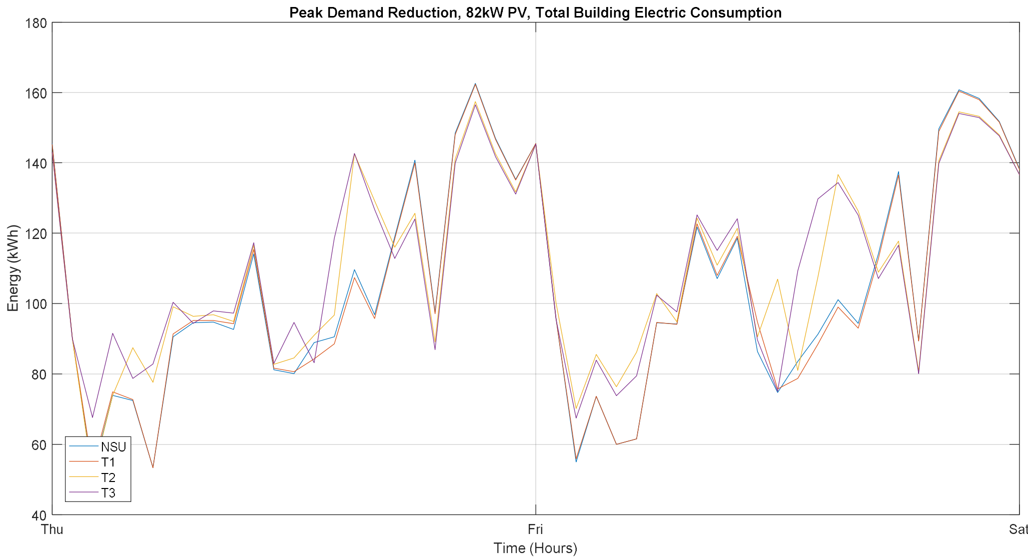


Figure 62: Peak Demand Reduction, 82kW PV, Building Electric Consumption

Lastly, looking at the maximum PV case, the peak demand was reduced by 6% for each case with minimal demand cost savings occurring with each increase in demand penalty. The cost of decreasing the maximum demand by a small amount came at an increase energy savings resulting in $90 a week to save $4 a month.

Table 44: Peak Demand Reduction

Results	T3a_154PV_PD1	T3a_154PV_PD2	T3a_154PV_PD3
Test Title	Peak Demand Test	Peak Demand Test	Peak Demand Test
Energy Savings from NSU (increase) (kWh)	(699.38)	(1,170.20)	(1,649.65)
Total Cost Savings (increase) ($)	518.78	476.36	430.16
% Energy Change from NSU	4%	6%	9%
Time of Use Cost Savings (Increase) ($/week)	$ (36.95)	$ (80.04)	$ (121.83)
Demand Cost Savings (increase) ($/month)	$ 555.72	$ 556.40	$ 551.99
Carbon Savings (increase) (Lbs CO2)	(526.87)	(828.59)	(1,111.57)
% Change Ramping	-2%	-1%	-5%
% Change Peak to Valley Ratio	0%	-7%	-18%
% Change Load Factor	10%	13%	15%
% Change Peak Demand	-6%	-6%	-6%

This result shows that the optimizer has already reached a maximum demand reduction and that there is nothing more it can do to save demand. Figure 63 shows again heavy pre-cooling before the peak demand periods to reduce HVAC loads during those periods.

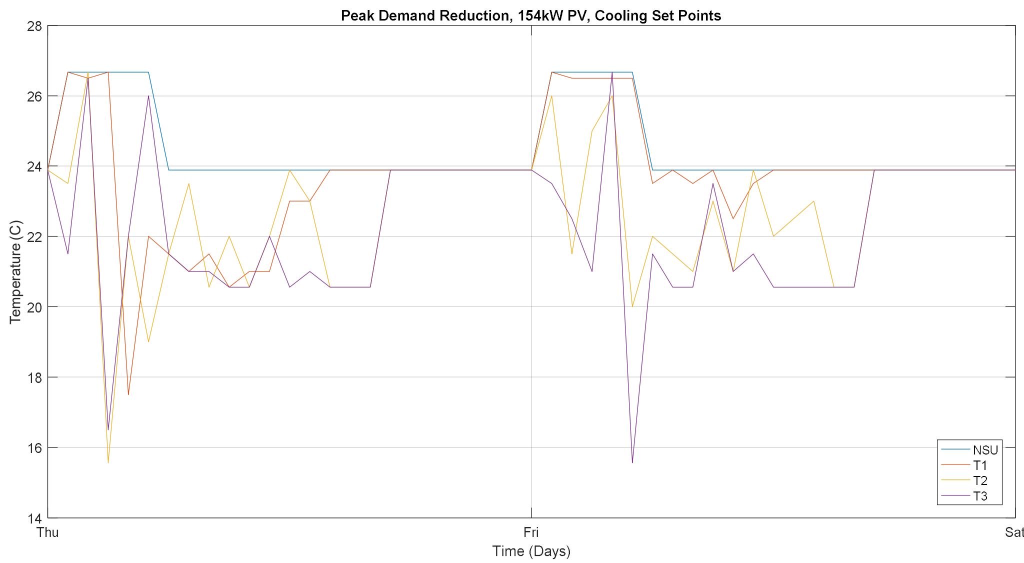


Figure 63: Peak Demand Reduction, 154kW PV, Cooling Set Points

Figure 64 shows the building electric consumption; it looks similar to the previous PV case with the exception of a lower building electric profile throughout the middle of the day from the increase in PV use power generated.

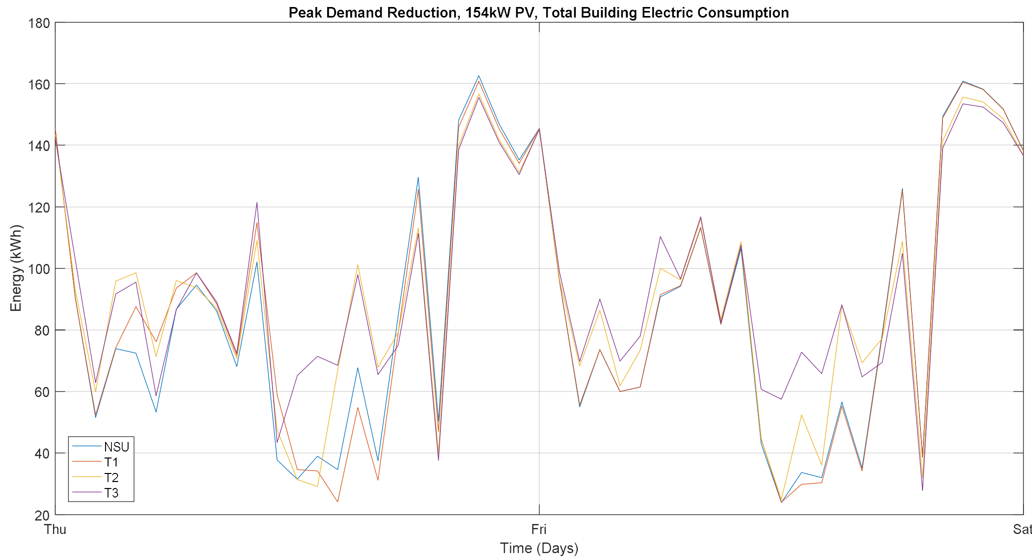


Figure 64: Peak Demand Reduction, 154kW PV, Total Building Electric Consumption

The results of the peak reduction test provided less than hoped for peak demand reductions. This can be a function of the building loads already being high or that the controller can only do so much within the temperature bounds in place. Also, considering that overall peak reduction only needs to occur to reduce the peak energy loads for one hour during the month to provide cost savings to the customer, this approach of peak energy suppression is not a viable option to overall cost reduction.

System Ramping Reduction

The next metric to be evaluated is the building's system ramping. This is an absolute summation of all changes in system demand. The theory of applying this to the HVAC system is that, by adjusting the temperature set point and increasing the amount of energy consumed by the HVAC, the overall building load can be "smoothed" to decrease grid fluctuations and grid ramping. Like peak demand reductions, this multiplier was applied by multiplying the calculated system ramping by 1/3/6 and applying this penalty directly to the cost function.

Table 45 shows the results of the no PV case of system ramping. The penalty reduced system ramping by up to 18%. However, given that the third trial decreased ramping less than the second trial, this method of reducing system ramping is again imperfect. Just adding this penalty decreased ramping by 15% compared to the optimizer, under similar demand rules, which increased ramping by 1%. This metric also reduced peak demand, improved load factor and the peak to valley ratio as well. This did come at the cost of increased energy consumption.

Table 45: System Ramping Test Results

Results	T3a_SR1	T3a_SR2	T3a_SR3
Test Title	System Ramping Test	System Ramping Test	System Ramping Test
Energy Savings from NSU (increase) (kWh)	(598.40)	(755.03)	(395.70)
Total Cost Savings (increase) ($)	242.89	184.81	130.12
% Energy Change from NSU	2%	3%	2%
Time of Use Cost Savings (Increase) ($/week)	$ (32.63)	$ (43.74)	$ (21.32)
Demand Cost Savings (increase) ($/month)	$ 275.52	$ 228.55	$ 151.44
Carbon Savings (increase) (Lbs CO2)	(495.67)	(633.50)	(338.37)
% Change Ramping	-15%	-18%	-17%
% Change Peak to Valley Ratio	-1%	-1%	-1%
% Change Load Factor	5%	5%	3%
% Change Peak Demand	-2%	-2%	-1%

The set point control in Figure 65shows greater set point modulation than in the previous non PV scenarios.

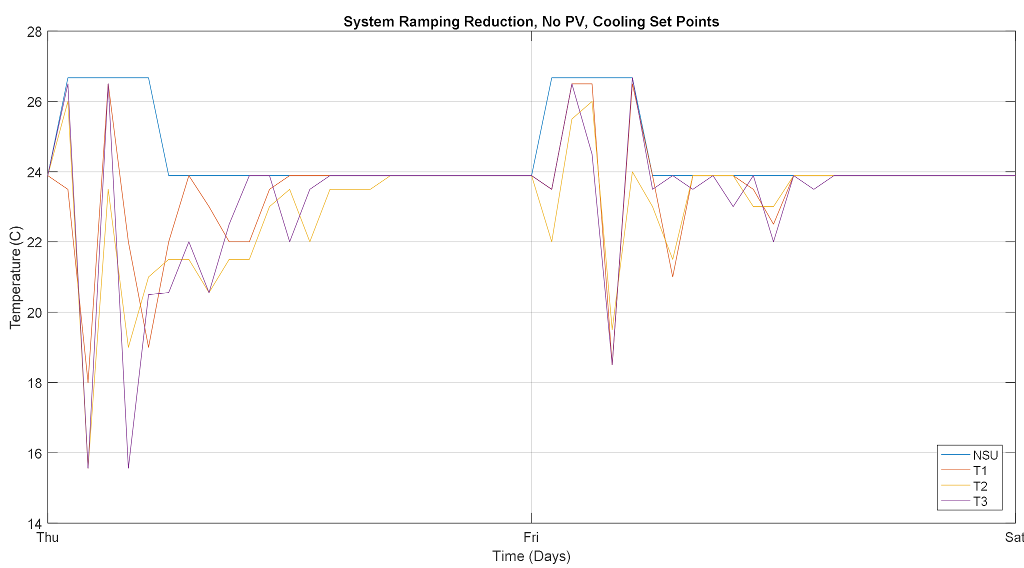


Figure 65: System Ramping Cooling Set Points

The result of set point modulation can be seen in the total building energy consumption. For all days in which the valleys of the energy profile are raised in the optimized cases, minor adjustments to the peak profile are made.

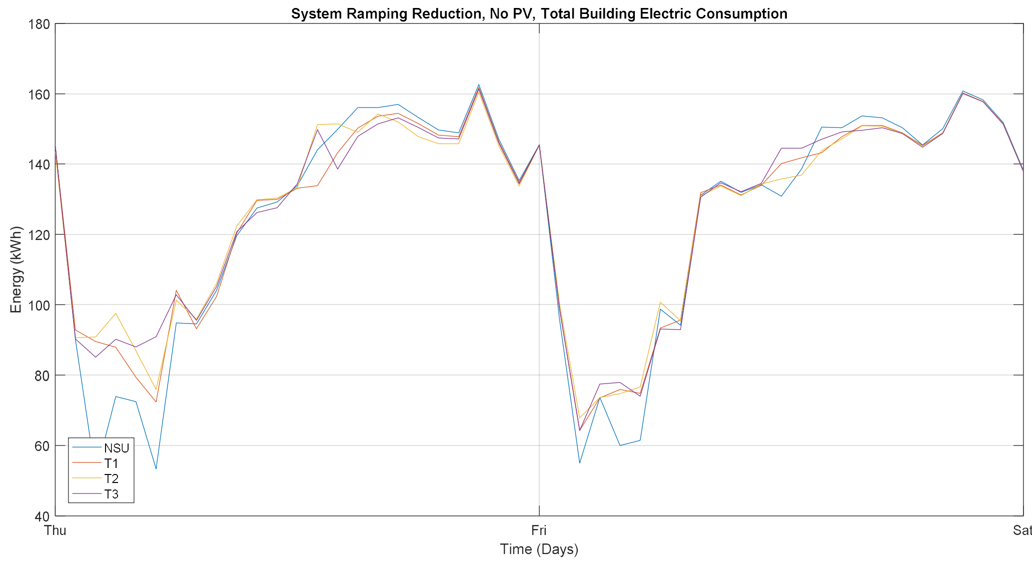


Figure 66: System Ramping Test Total Electric Consumption

Considering the same metric with PV added, the optimizer reduces the system ramping by 21%. However, this comes with a much greater energy consumption cost. This again improved peak demand, load factor, and the peak to valley ratio as well.

Table 46: System Ramping Test, 82kW PV, Results

Results	T3a_82PV_SR1	T3a_82PV_SR2	T3a_82PV_SR3
Test Title	System Ramping Test	System Ramping Test	System Ramping Test
Energy Savings from NSU (increase) (kWh)	(1,719.12)	(1,890.82)	(2,410.28)
Total Cost Savings (increase) ($)	273.09	286.42	241.79
% Energy Change from NSU	8%	9%	11%
Time of Use Cost Savings (Increase) ($/week)	$ (117.04)	$ (129.35)	$ (159.49)
Demand Cost Savings (increase) ($/month)	$ 390.13	$ 415.77	$ 401.27
Carbon Savings (increase) (Lbs CO2)	(1,269.11)	(1,392.16)	(1,812.87)
% Change Ramping	-21%	-21%	-22%
% Change Peak to Valley Ratio	-25%	-35%	-27%
% Change Load Factor	13%	13%	16%
% Change Peak Demand	-5%	-4%	-5%

The cooling set points in Figure 67 again are modulated to increase HVAC consumption or decrease as necessary.

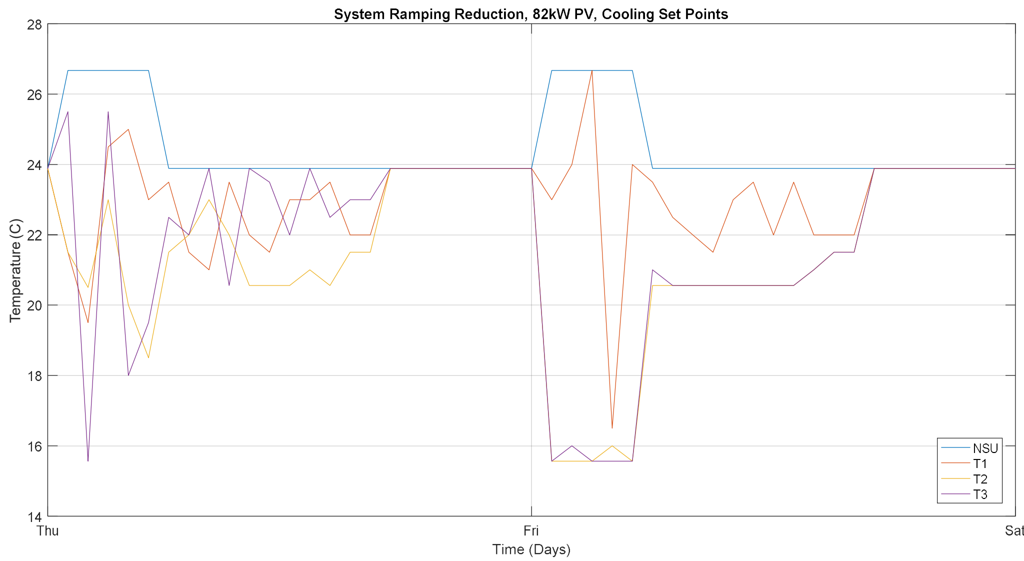


Figure 67: System Ramping, 82kW PV, Cooling Set Points

The resultant building electric consumption is noticeably smoother between the peaks and the valleys.

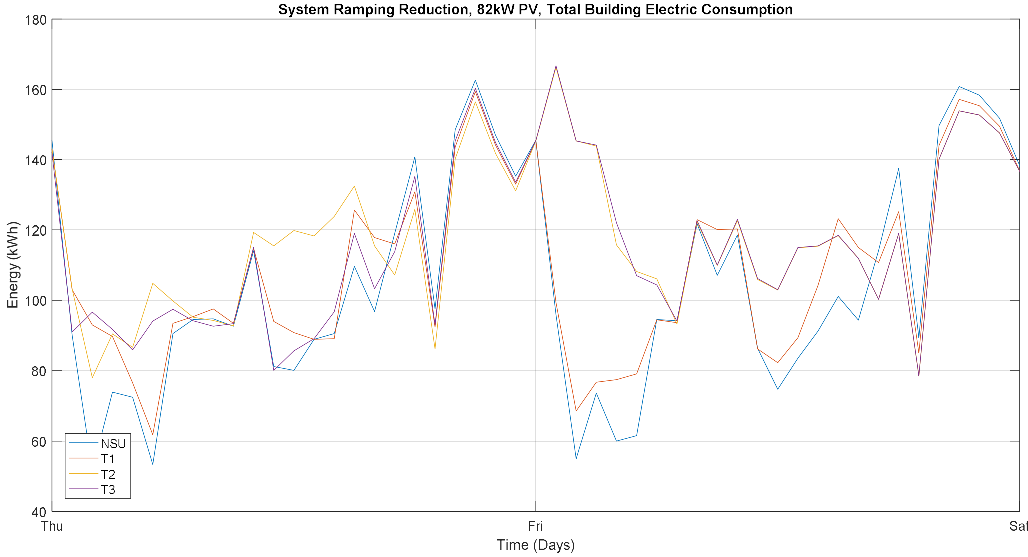


Figure 68: System Ramping Test, 82kW PV, Total Building Electric Consumption

In the highest PV case, there was less change in ramping than in the middle PV case despite improving load factor, peak to valley ratio, and peak demand at the cost of greater energy consumption as seen in Table 47.

Table 47: System Ramping Test, 154kW PV, Results

Results	T3a_154PV_SR1	T3a_154PV_SR2	T3a_154PV_SR3
Test Title	System Ramping Test	System Ramping Test	System Ramping Test
Energy Savings from NSU (increase) (kWh)	(2,445.98)	(2,251.57)	(1,943.20)
Total Cost Savings (increase) ($)	344.97	267.82	337.68
% Energy Change from NSU	13%	12%	11%
Time of Use Cost Savings (Increase) ($/week)	$ (165.18)	$ (153.65)	$ (133.45)
Demand Cost Savings (increase) ($/month)	$ 510.15	$ 421.47	$ 471.12
Carbon Savings (increase) (Lbs CO2)	(1,763.84)	(1,628.69)	(1,384.20)
% Change Ramping	-20%	-19%	-20%
% Change Peak to Valley Ratio	-14%	-6%	-24%
% Change Load Factor	20%	18%	17%
% Change Peak Demand	-6%	-4%	-5%

The HVAC system, again, modulates set point to smooth out the building electric consumption.

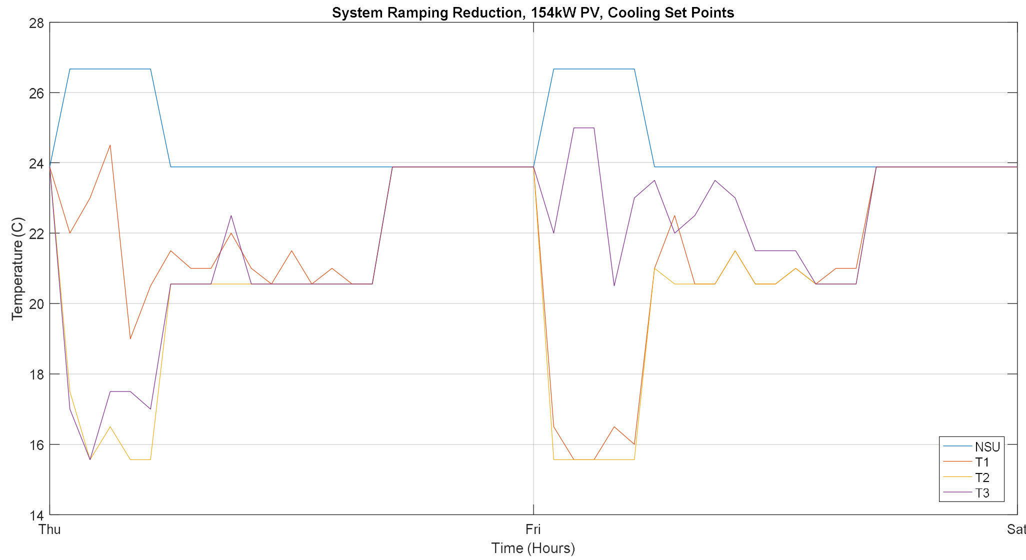


Figure 69: System Ramping Reduction, 154kW PV, Cooling Set Points

Figure 70 shows the building electric consumption profile. The difficulty posed by this higher PV case is that the greater PV generation naturally creates a lower valley on the grid than in the non-PV case.

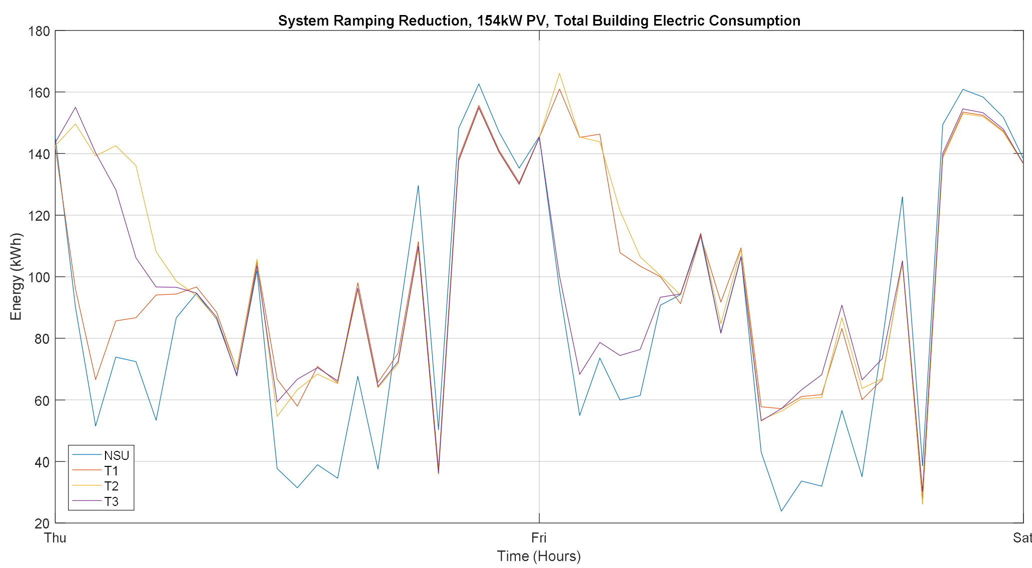


Figure 70: System Ramping Reduction, 154kW PV, Total Building Electric Consumption

The final results of this test show that this metric is a viable penalty to improve multiple metrics. The determination that needs to be made is the cost benefit of improving grid metrics at the expense of usage costs.

Peak to Valley Reduction

Similar to the system ramping, the peak to valley ratio focuses on reducing the amount of system changes except this time by minimizing the peak demand and increasing the minimum demand. The multiplier is applied to the calculated peak to valley ratio at creating a penalty 50/150/300 times more than the peak to valley ratio.

Table 48 shows the results of the non-PV test. In this case the peak to valley ratio is improved minimally with exception of the second test. Otherwise there was little improvement to the other metrics or the peak to valley ratio. The biggest change was the improvement of the load factor.

Table 48: Peak to Valley Test Results

Results	T3a_PV1	T3a_PV2	T3a_PV3
Test Title	Peak to Valley Test	Peak to Valley Test	Peak to Valley Test
Energy Savings from NSU (increase) (kWh)	(1,424.76)	(1,936.70)	(2,045.57)
Total Cost Savings (increase) ($)	182.10	889.41	220.88
% Energy Change from NSU	6%	7%	8%
Time of Use Cost Savings (Increase) ($/week)	$ (78.43)	$ (105.91)	$ (115.67)
Demand Cost Savings (increase) ($/month)	$ 260.52	$ 995.32	$ 336.55
Carbon Savings (increase) (Lbs CO2)	(1,229.00)	(2,001.84)	(1,680.65)
% Change Ramping	6%	-7%	0%
% Change Peak to Valley Ratio	-1%	-14%	-2%
% Change Load Factor	7%	31%	12%
% Change Peak Demand	-2%	-18%	-3%

Figure 71 shows the set point modulation to achieve these improvements. Again, there are more aggressive pre-cooling set points compared to the previous cases.

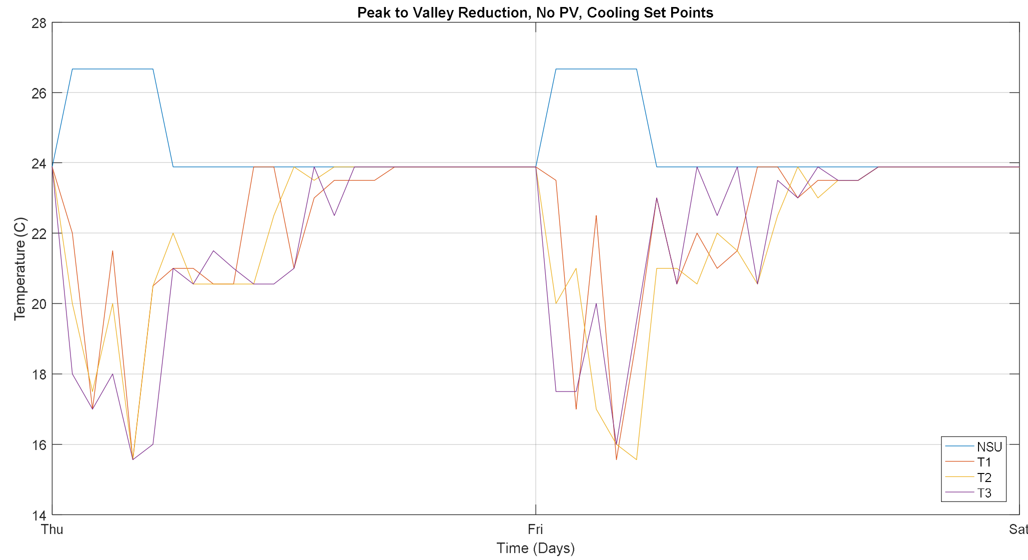


Figure 71: Peak to Valley Test Cooling Set Points

Figure 72 shows a small reduction of energy consumption peaks but a much greater increase in the valley. This increase in the valley can be seen again in table 53 with the high increase of energy usage.

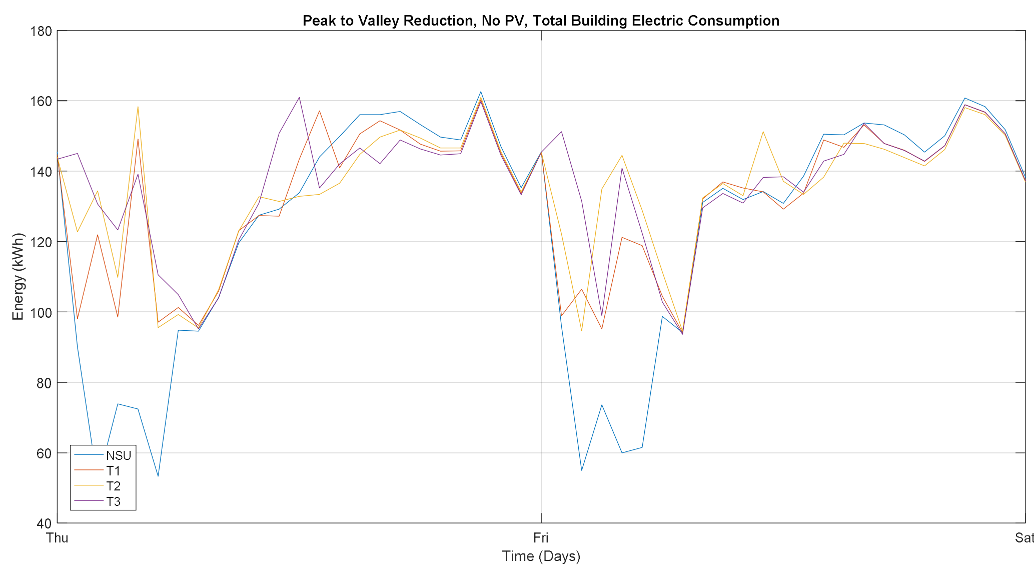


Figure 72: Peak to Valley Test Total Building Electric Consumption

Table 49 shows the medium PV case results. In this case, the peak to valley ratio was greatly improved. The lack of peak demand change shows that this must have been accomplished by increasing the valley demand at the 8% increase of energy consumption.

Table 49: Peak to Valley, 82kW PV, Test Results

Results	T3a_82PV_PV1	T3a_82PV_PV2	T3a_82PV_PV3
Test Title	Peak to Valley Test	Peak to Valley Test	Peak to Valley Test
Energy Savings from NSU (increase) (kWh)	(1,682.16)	(1,863.79)	(1,764.98)
Total Cost Savings (increase) ($)	279.48	89.03	109.99
% Energy Change from NSU	8%	8%	8%
Time of Use Cost Savings (Increase) ($/week)	$ (99.48)	$ (117.48)	$ (108.63)
Demand Cost Savings (increase) ($/month)	$ 378.96	$ 206.51	$ 218.62
Carbon Savings (increase) (Lbs CO2)	(1,324.77)	(1,460.03)	(1,402.57)
% Change Ramping	-3%	5%	0%
% Change Peak to Valley Ratio	-34%	-39%	-36%
% Change Load Factor	11%	8%	8%
% Change Peak Demand	-3%	0%	0%

Figure 73shows the cooling set points are aggressively changing all days except the last day.

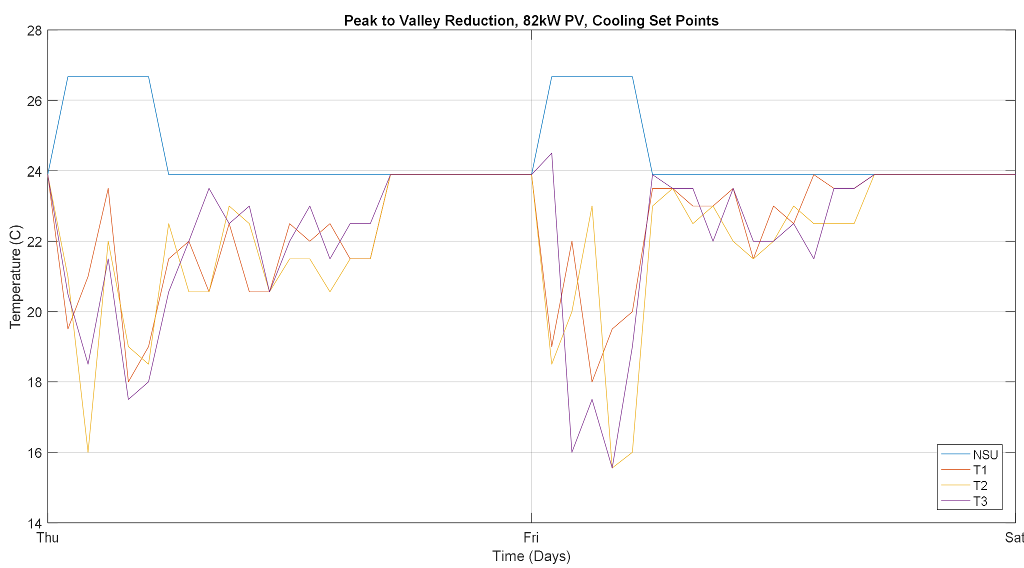


Figure 73: Peak to Valley, 82kW PV, Cooling Set Points

Figure 74 shows higher energy consumption during the valleys but with no change in the peak energy consumption compared to the NSU case.

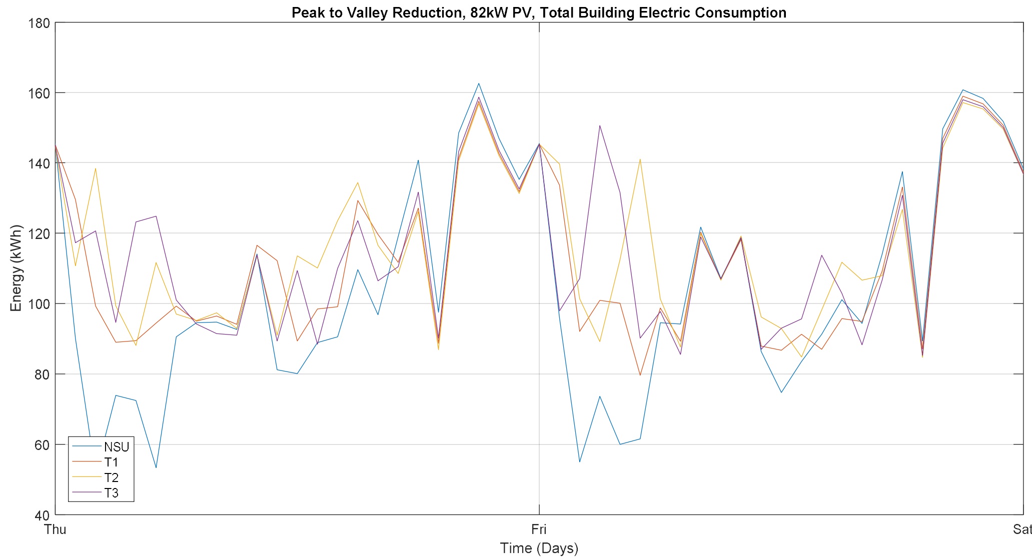


Figure 74: Peak to Valley, 82kW PV, Total Building Electric Consumption

The high PV scenario showed similar results as the medium PV scenario but with less energy use considering the greater level of PV available. This also reduced the peak demand while improving load factor and system ramping.

Table 50: Peak to Valley, 154kW PV, Test Results

Results	T3a_154PV_PV1	T3a_154PV_PV2	T3a_154PV_PV3
Test Title	Peak to Valley Test	Peak to Valley Test	Peak to Valley Test
Energy Savings from NSU (increase) (kWh)	(1,107.58)	(1,152.44)	(1,122.09)
Total Cost Savings (increase) ($)	482.99	473.55	460.98
% Energy Change from NSU	6%	6%	6%
Time of Use Cost Savings (Increase) ($/week)	$ (72.95)	$ (76.70)	$ (74.10)
Demand Cost Savings (increase) ($/month)	$ 555.94	$ 550.25	$ 535.09
Carbon Savings (increase) (Lbs CO2)	(815.30)	(838.41)	(824.15)
% Change Ramping	-1%	-5%	-2%
% Change Peak to Valley Ratio	-35%	-34%	-34%
% Change Load Factor	12%	13%	12%
% Change Peak Demand	-6%	-6%	-6%

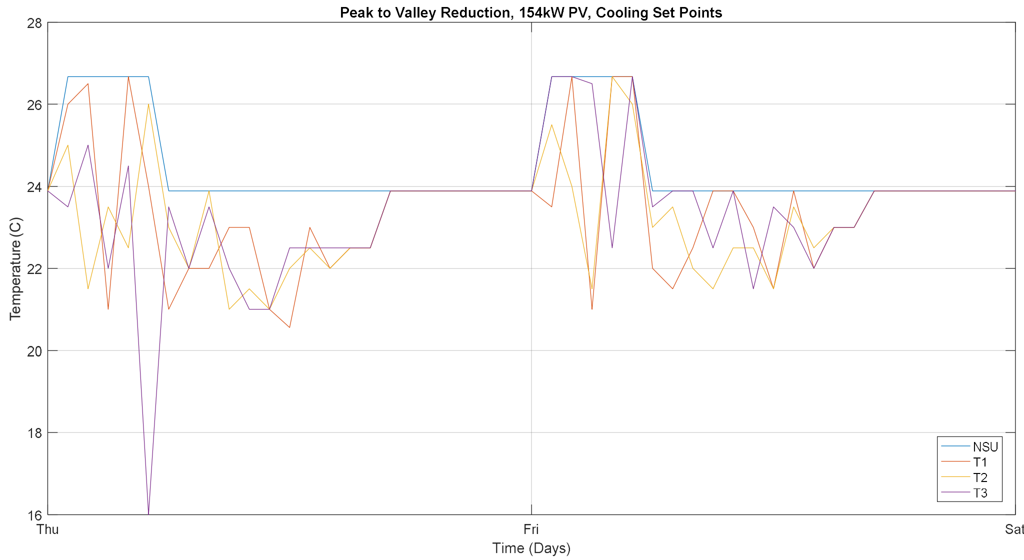


Figure 75: Peak to Valley, 154kW PV, Cooling Set Points

Figure 75 shows the modulation of set points showing similar profiles as the previous cases. In Figure 76, the building energy consumption doesn't appear to be different than the NSU case, which is interesting as this doesn't appear to reflect a 30% change in the peak to valley ratio.

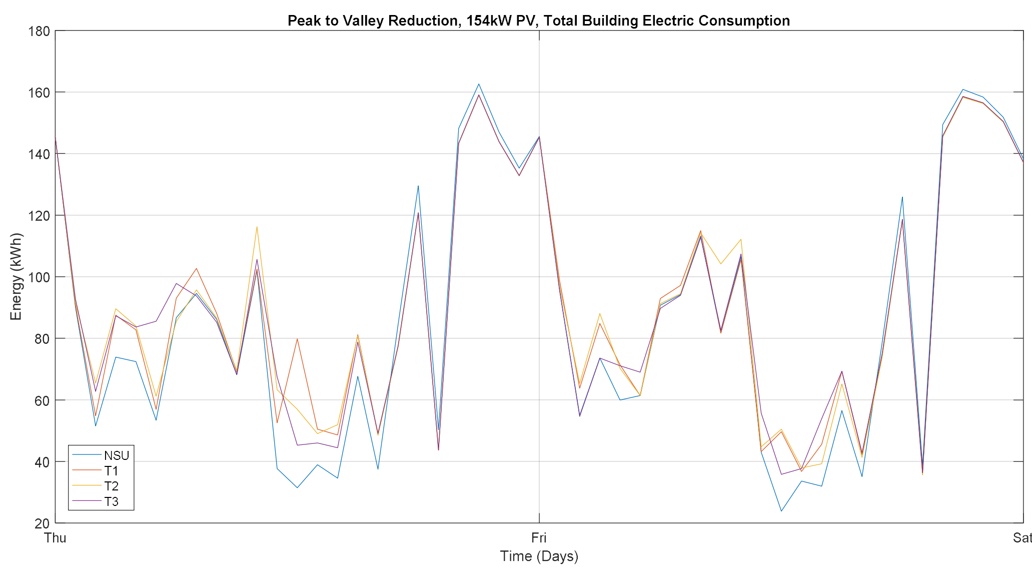


Figure 76: Peak to Valley, 154kW PV, Total Building Electric Consumption

Load Factor Improvement

The last of Dr. Corbin's system metrics to be evaluated are improving the building's load factor. In this case, since this is the one value that needs to be increased to be improved, the penalty was calculated by subtracting the calculated load factor from 1 and multiplying by a scaling factor of 300/600 and 900.

Evaluating the three levels of PV at the same time, the load factor was improved similarly almost regardless of the multiplier but with the level of PV increasing the load factor results. In each case, these improvements came again at the cost of much greater energy consumption but were not dependent on the scaling factor used.

Table 51: Load Factor Test Results

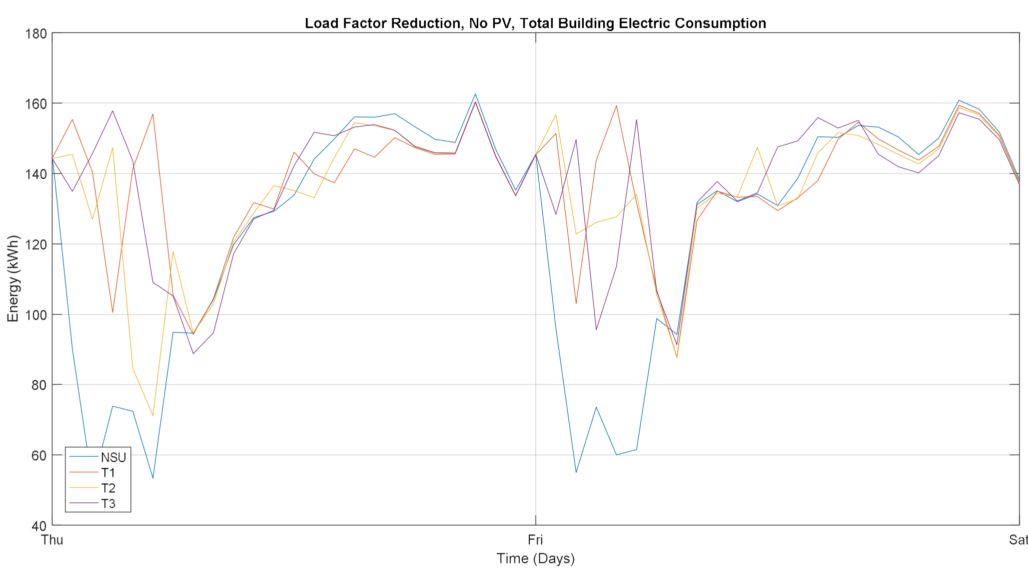
Results	T3a_LF1	T3a_LF2	T3a_LF3
Test Title	Load Factor Test	Load Factor Test	Load Factor Test
Energy Savings from NSU (increase) (kWh)	(2,102.74)	(2,099.64)	(2,331.55)
Total Cost Savings (increase) ($)	246.11	236.12	239.99
% Energy Change from NSU	8%	8%	9%
Time of Use Cost Savings (Increase) ($/week)	$ (114.68)	$ (116.79)	$ (132.34)
Demand Cost Savings (increase) ($/month)	$ 360.79	$ 352.91	$ 372.33
Carbon Savings (increase) (Lbs CO2)	(1,703.80)	(1,674.80)	(1,874.95)
% Change Ramping	26%	15%	18%
% Change Peak to Valley Ratio	-2%	-2%	-2%
% Change Load Factor	12%	12%	13%
% Change Peak Demand	-4%	-4%	-4%

Results	T3a_82PV_LF1	T3a_82PV_LF2	T3a_82PV_LF3
Test Title	Load Factor Test	Load Factor Test	Load Factor Test
Energy Savings from NSU (increase) (kWh)	(2,688.35)	(3,075.80)	(3,135.80)
Total Cost Savings (increase) ($)	320.16	296.79	293.54
% Energy Change from NSU	12%	14%	14%
Time of Use Cost Savings (Increase) ($/week)	$ (169.94)	$ (201.91)	$ (203.90)
Demand Cost Savings (increase) ($/month)	$ 490.10	$ 498.70	$ 497.43
Carbon Savings (increase) (Lbs CO2)	(2,037.20)	(2,298.52)	(2,368.72)
% Change Ramping	9%	-6%	-7%
% Change Peak to Valley Ratio	-22%	-27%	-36%
% Change Load Factor	19%	21%	21%
% Change Peak Demand	-5%	-6%	-6%

Results	T3a_154PV_LF1	T3a_154PV_LF2	T3a_154PV_LF3
Test Title	Load Factor Test	Load Factor Test	Load Factor Test
Energy Savings from NSU (increase) (kWh)	(3,020.99)	(3,322.60)	(3,308.68)
Total Cost Savings (increase) ($)	371.10	351.58	342.41
% Energy Change from NSU	16%	18%	18%
Time of Use Cost Savings (Increase) ($/week)	$ (189.65)	$ (212.99)	$ (212.38)
Demand Cost Savings (increase) ($/month)	$ 560.75	$ 564.57	$ 554.79
Carbon Savings (increase) (Lbs CO2)	(2,280.40)	(2,518.21)	(2,477.20)
% Change Ramping	-6%	-12%	-12%
% Change Peak to Valley Ratio	-23%	-18%	-12%
% Change Load Factor	23%	25%	25%
% Change Peak Demand	-6%	-6%	-6%

By improving the load factor, the peak demand was decreased comparably between the levels of PV. Ramping increased significantly in the non PV case but decreased in the high PV scenario. The peak to valley ratio was also improved. This is to be expected as the methods to improve load factor would be to either decrease peak demand or increase the average demand.

Evaluating the cooling set points, in all cases, the set points modulate similarly to the all of the previous cases using more energy throughout the day. The result is decreased peak consumption well as a higher average energy consumption as depicted in the following figures.



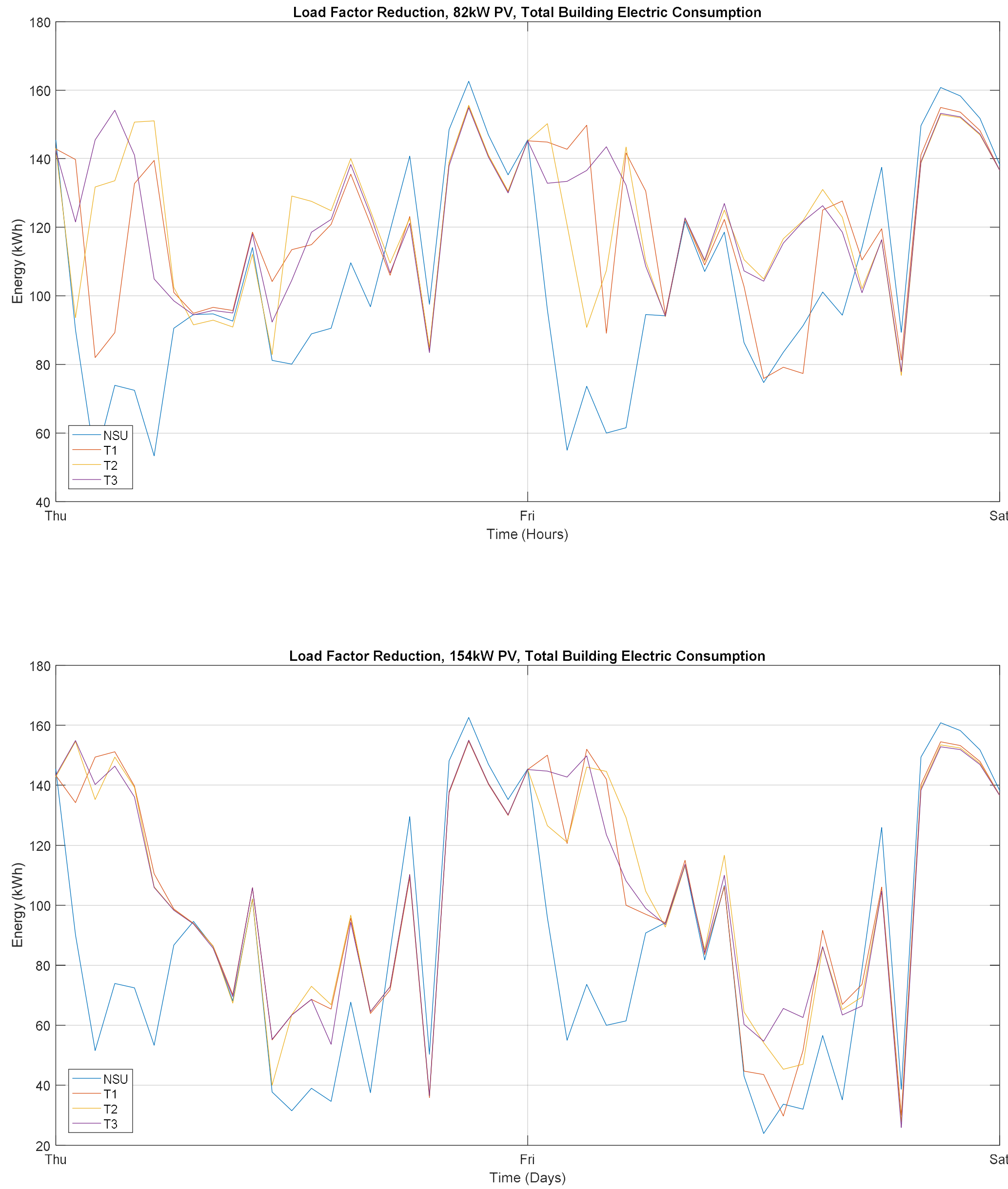


Figure 77: Load Factor Reduction, Total Building Electric Consumption

The resultant improved load factor shows that a minimal penalty can improve the building load factor profile. Since this could result in increased system ramping, this suggests that if the load factor penalty is applied, a system ramping penalty should be applied as well to maintain a smoother energy demand profile. Between the two, peak demand and the peak to valley ratio can be improved as well.

Carbon Reduction Test

The last set of tests were to test the ability of the controller to reduce carbon emissions. The penalty was applied to the cost function by multiplying the resultant carbon emissions by a multiplier and adding it to the penalties. The first multiplier was determined from the California Cap and Trade program's website price of carbon in terms of dollars per tonne of CO2 emissions. As of November 2nd, the cost of carbon was $15.40 per tone of CO2 (41). The peak cost was in July 24, 2012 at $19.54 per tonne CO2. For rounding purposes, the peak cost was used as the first multiplier as an economic comparison based on the cap and trade costs. Additionally, to find other carbon costs for comparison, the UK carbon tax of nearly $25 per tonne of emissions (42) was considered as an addition but the difference in costs was too minimal to justify another test. The final multipliers used were .01, .10, .5 and 1 per pound of CO2 generated from building consumption. Demand and time of use cost penalties were applied in the same manner as the previous tests by using the penalty structure of test 2a.

The following tables show the result of the carbon testing. In all cases, carbon was not reduced but all other metrics showed similar savings to test 2a. This means that this carbon penalty had little to no effect on the optimizer.

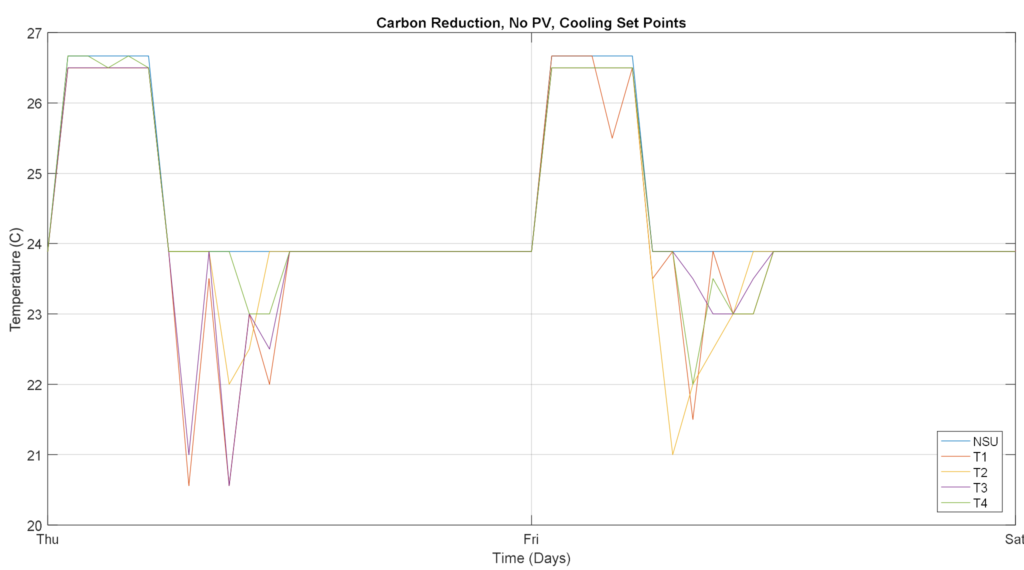
Table 52: Carbon Reduction Tests Results

Results	T3a_CO1	T3a_CO2	T3a_CO3	T3a_CO4
Test Title	Load Factor Test	Load Factor Test	Load Factor Test	Load Factor Test
Energy Savings from NSU (increase) (kWh)	(155.77)	(136.90)	(123.61)	(82.77)
Total Cost Savings (increase) ($)	248.35	243.52	231.45	215.98
% Energy Change from NSU	1%	1%	0%	0%
Time of Use Cost Savings (Increase) ($/week)	$ (4.58)	$ (4.90)	$ (4.33)	$ (2.48)
Demand Cost Savings (increase) ($/month)	$ 252.93	$ 248.42	$ 235.79	$ 218.46
Carbon Savings (increase) (Lbs CO2)	(139.66)	(134.21)	(106.56)	(77.87)
% Change Ramping	2%	3%	0%	-1%
% Change Peak to Valley Ratio	-1%	-1%	-1%	-1%
% Change Load Factor	3%	3%	2%	2%
% Change Peak Demand	-2%	-2%	-2%	-2%

Results	T3a_82PV_CO1	T3a_82PV_CO2	T3a_82PV_CO3	T3a_82PV_CO4
Test Title	Load Factor Test	Load Factor Test	Load Factor Test	Load Factor Test
Energy Savings from NSU (increase) (kWh)	(328.89)	(327.20)	(177.72)	(155.79)
Total Cost Savings (increase) ($)	354.32	370.19	310.53	327.34
% Energy Change from NSU	1%	1%	1%	1%
Time of Use Cost Savings (Increase) ($/week)	$ (16.34)	$ (16.72)	$ (9.01)	$ (7.97)
Demand Cost Savings (increase) ($/month)	$ 370.66	$ 386.91	$ 319.54	$ 335.31
Carbon Savings (increase) (Lbs CO2)	(280.82)	(245.76)	(113.53)	(102.06)
% Change Ramping	3%	-3%	0%	0%
% Change Peak to Valley Ratio	-3%	-1%	0%	-1%
% Change Load Factor	5%	5%	5%	4%
% Change Peak Demand	-3%	-4%	-4%	-3%

Results	T3a_154PV_CO1	T3a_154PV_CO2	T3a_154PV_CO3	T3a_154PV_CO4
Test Title	Load Factor Test	Load Factor Test	Load Factor Test	Load Factor Test
Energy Savings from NSU (increase) (kWh)	(768.90)	(695.21)	(358.10)	(185.16)
Total Cost Savings (increase) ($)	512.82	514.89	475.13	384.43
% Energy Change from NSU	4%	4%	2%	1%
Time of Use Cost Savings (Increase) ($/week)	$ (43.13)	$ (38.99)	$ (19.67)	$ (9.23)
Demand Cost Savings (increase) ($/month)	$ 555.95	$ 553.88	$ 494.80	$ 393.66
Carbon Savings (increase) (Lbs CO2)	(595.45)	(513.98)	(238.16)	(120.41)
% Change Ramping	-1%	-1%	-4%	-3%
% Change Peak to Valley Ratio	-2%	0%	0%	1%
% Change Load Factor	10%	10%	7%	6%
% Change Peak Demand	-6%	-6%	-5%	-5%

The following figures do show that the optimizer is attempting to pre-cool the building but this could be in preparation for the peak energy costs.



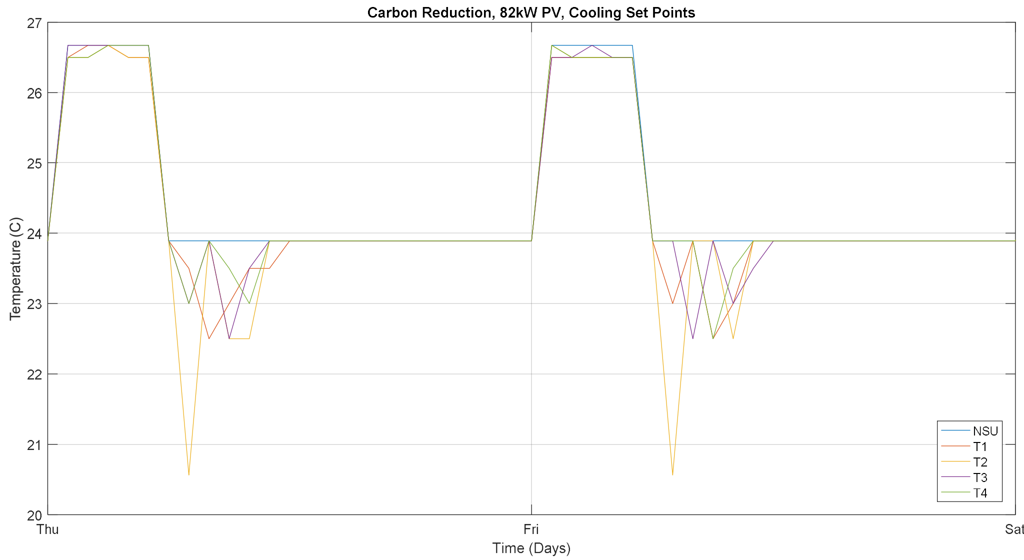
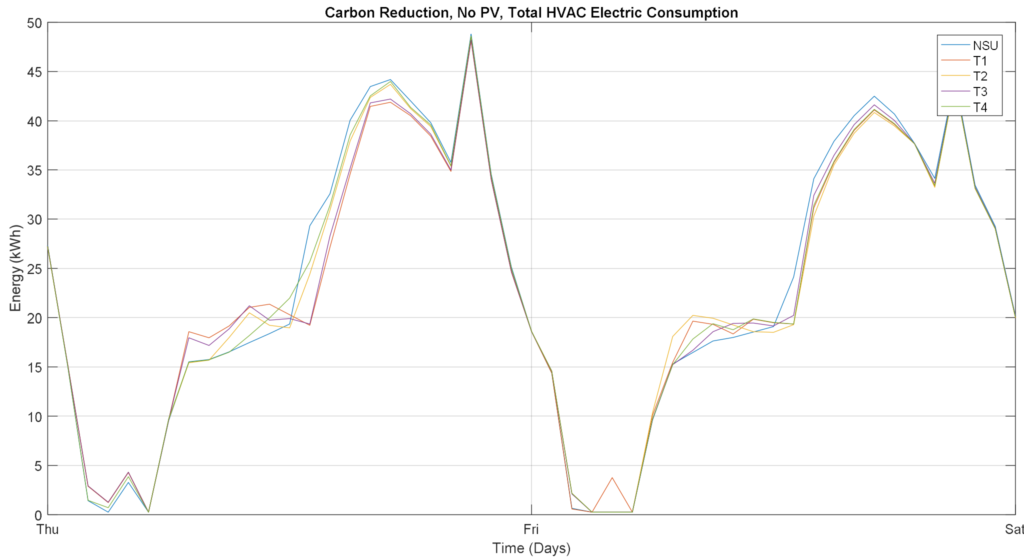
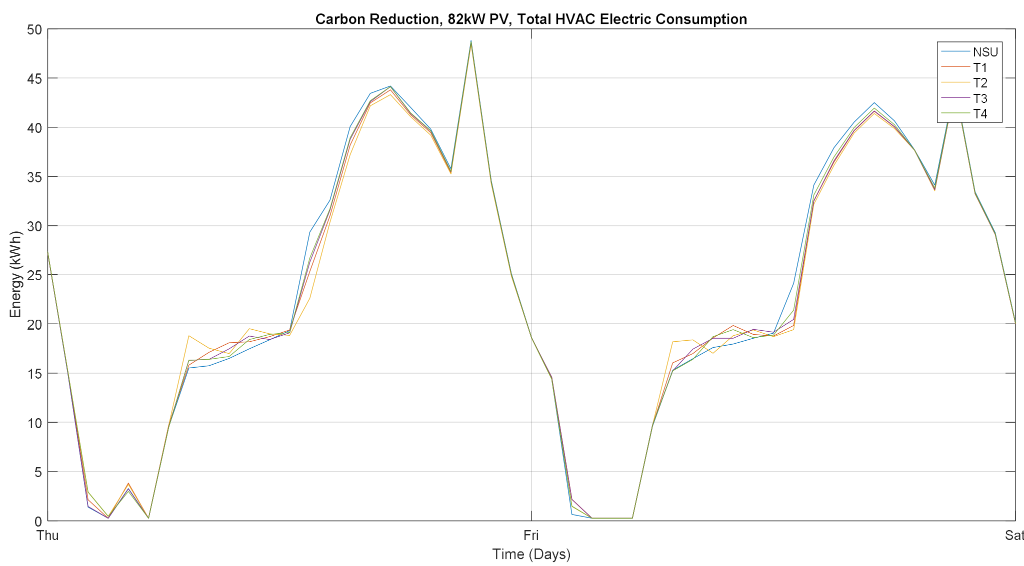


Figure 78: Carbon Reduction Set Points

However, the HVAC energy consumption profile shown in the following figures indicates that there was very little deviation due to the carbon penalty from the NSU case. The big adjustments were made in set point on the first and last day to reflect the attempt of the optimizer to minimize demand as these were the two highest energy demand days.


Carbon Reduction, No PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Days)
Thu
Fri
Sat
NSU
T1
T2
T3
T4


Carbon Reduction, 82kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Days)
Thu
Fri
Sat
NSU
T1
T2
T3
T4

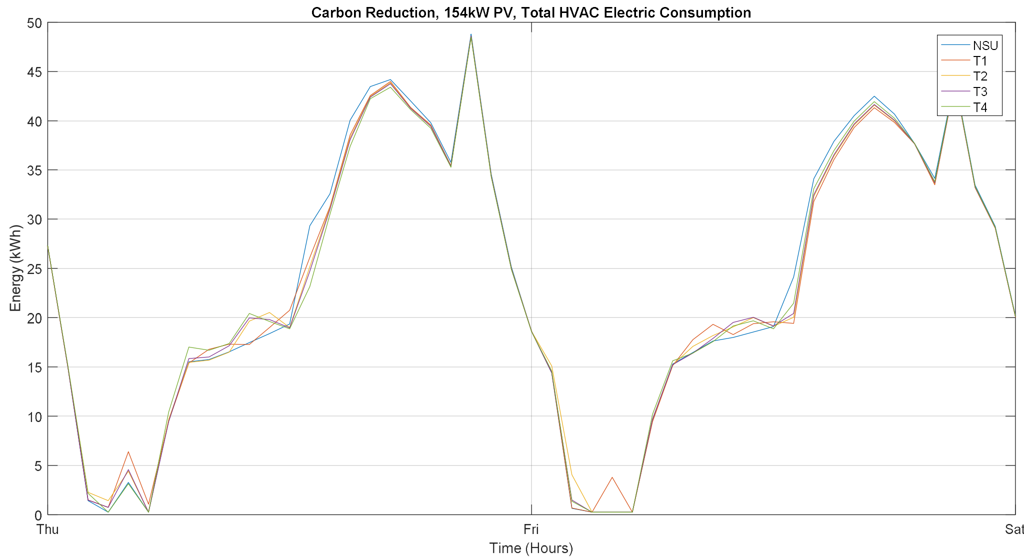
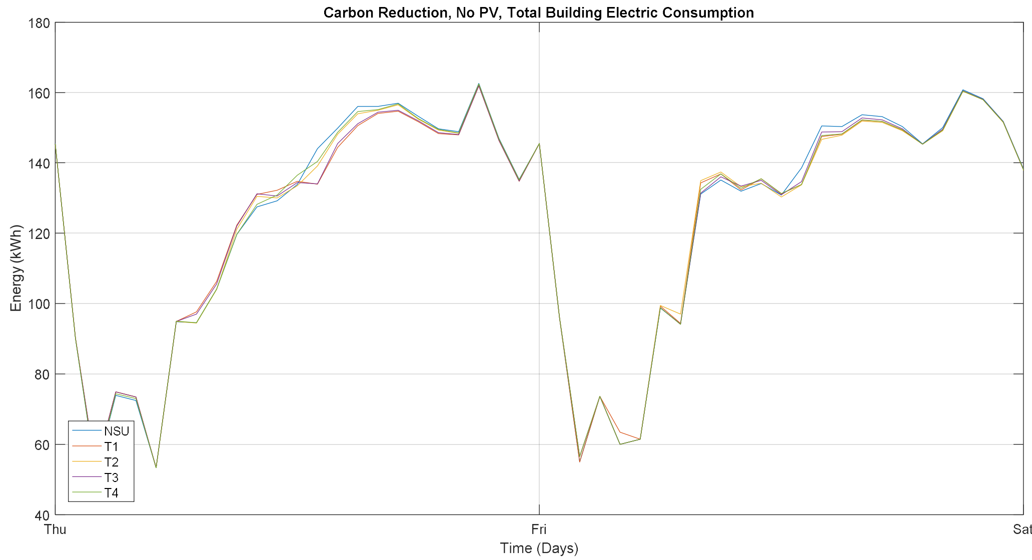
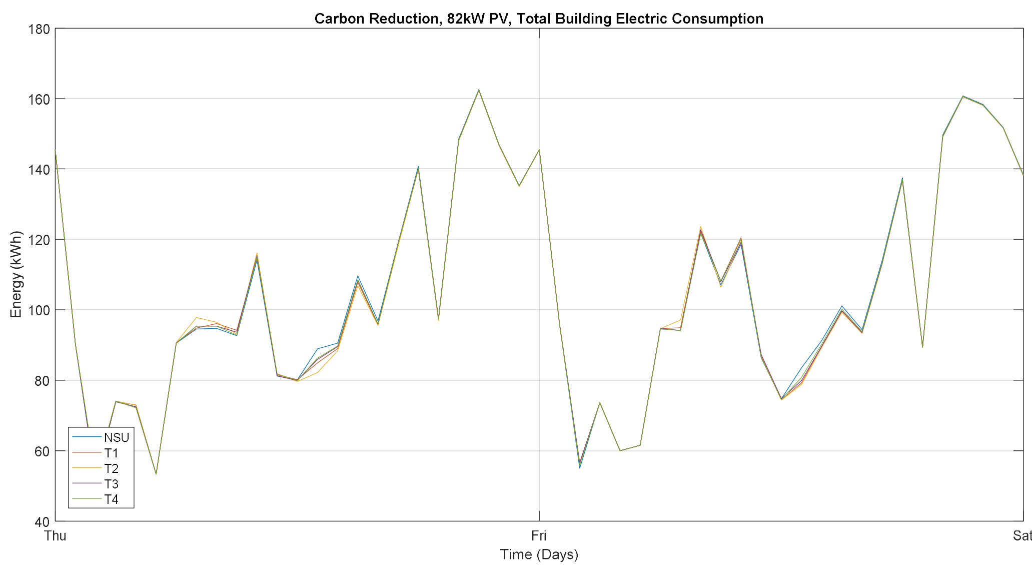


Figure 79: Carbon Reduction, Total HVAC Electric Consumption

Since carbon production is a result of the total building electrical consumption, the below figures shows the total building electric consumption for all levels of PV. As can be seen, there is very little deviation between the profiles of all the trials with exception of the times when the peak energy load is being suppressed.


Carbon Reduction, No PV, Total Building Electric Consumption
Energy (kWh)
180
160
140
120
100
80
60
40
Thu
Fri
Sat
Time (Days)
NSU
T1
T2
T3
T4


Carbon Reduction, 82kW PV, Total Building Electric Consumption
Energy (kWh)
180
160
140
120
100
80
60
40
Thu
Fri
Sat
Time (Days)
NSU
T1
T2
T3
T4

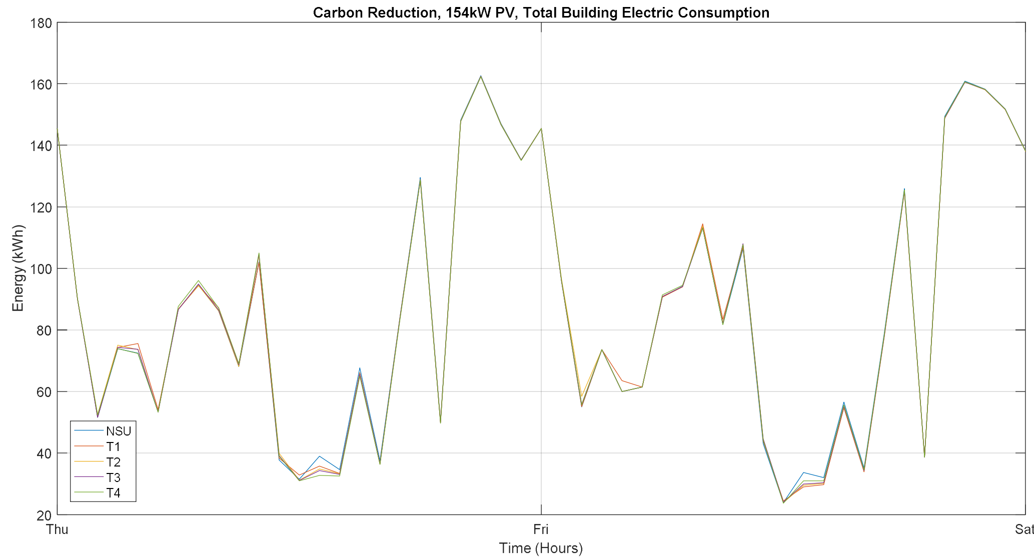


Figure 80: Carbon Reduction Total Building Electric Consumption

To try to determine why carbon production was not improved, the following figure shows the average carbon production rate from the grid as provided from the WattTime API (27).

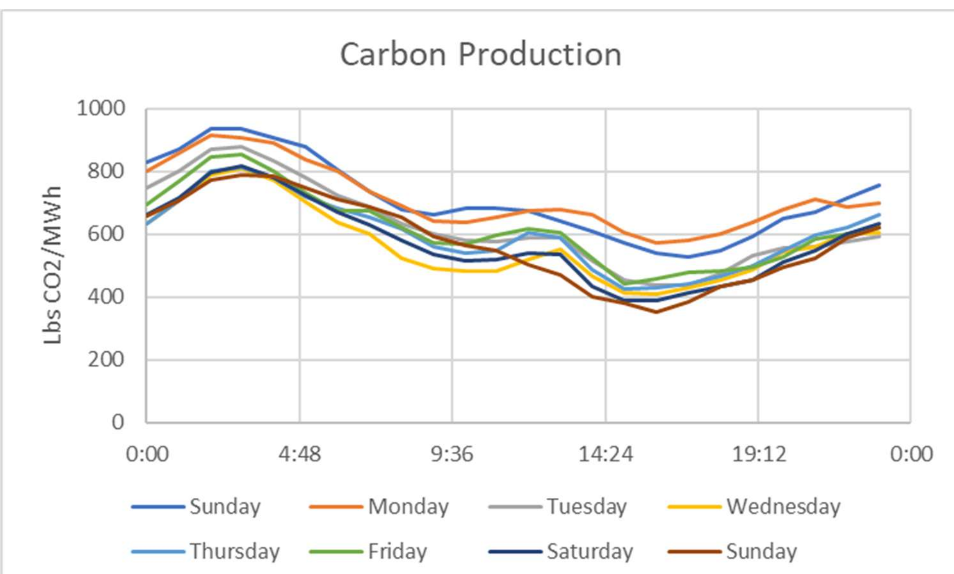


Figure 81: Average Carbon Source Production

Carbon production is shown to peak during the early hours of the morning assuming there is minimal wind and no solar production available. The average carbon production gradually decreases to half of the peak mid afternoon with the availability of solar power prior to increasing in the evening. The expected result would be that the optimizer, especially in the PV cases, would drive the HVAC set points lower mid afternoon to minimize the cost function. This indicates that the problem could be in how the penalty is applied to the cost function. Table 58 shows the applied penalties from carbon. In all cases, the penalty does not change significantly, meaning that the optimizer cannot see enough of a difference between the levels of carbon at each step.

Table 53: Carbon Cost Function Penalty

Day	9	10	11	12	13	14	15	16
NSU Penalty	22.95	24.30	19.96	18.02	16.98	17.75	17.22	16.86
CO_1 Penalty	24.15	24.16	19.99	18.05	16.94	17.75	17.20	17.22
% Penalty Change	5.20%	-0.58%	0.13%	0.16%	-0.24%	-0.03%	-0.11%	2.09%
NSU Penalty	229.53	243.02	199.61	180.24	169.76	177.54	172.18	168.62
CO_2 Penalty	241.27	241.39	199.68	180.14	169.69	177.41	171.74	172.61
% Penalty Change	5.12%	-0.67%	0.04%	-0.06%	-0.04%	-0.08%	-0.25%	2.36%
NSU Penalty	1,147.63	1,215.12	998.04	901.21	848.79	887.71	860.90	843.10
CO_3 Penalty	1,197.12	1,207.75	996.81	900.57	846.57	886.61	859.08	861.26
% Penalty Change	4.31%	-0.61%	-0.12%	-0.07%	-0.26%	-0.12%	-0.21%	2.15%
NSU Penalty	2,295.25	2,430.24	1,996.08	1,802.41	1,697.59	1,775.42	1,721.80	1,686.20
CO_4 Penalty	2,373.89	2,416.57	1,995.59	1,800.28	1,696.81	1,772.32	1,717.49	1,709.93
% Penalty Change	3.43%	-0.56%	-0.02%	-0.12%	-0.05%	-0.17%	-0.25%	1.41%

A potential fix to this issue could be to change the multiplier to penalize the carbon emissions from a set threshold value, such as the minimum produced carbon from the week, subtract that value from the produced carbon, and then apply the penalty multiplier.

5. Conclusion and Future Work

In this thesis, building modeling and model predictive control testing was conducted of a Whole Foods Market in Tarzana, California, to support studies by NREL and efforts by Transformative Wave Technologies to develop a better control strategy. If a better optimum control is found feasible through this study, this will be implemented on the CATALYST retrofit control system already in use at multiple retail stores. To support this, the building was modeled from data being monitored by the CATALYST system. From this data, indoor temperature, HVAC temperatures, and building sensible loads were determined. Further estimating building parameters, appliance loads, infiltration, and other internal gains were estimated. The building envelope was first baselined from ASHRAE 90.1 prescribed building envelope construction. These were used to estimate the parameters of a five parameter resistance and capacitance model as proposed by Braun (7) in his work. A grey box building model was trained from the previously calculated sensible loads and internal temperatures using inverse modeling procedures and program developed by Pavlak et al. (5). This refined the parameters based on the data to provide a more accurate model. Root Mean Squared error was used to evaluate the accuracy of the model. The model was trained initially from the data provided during a five-week period in April and May, 2017.

A RTU was modeled from the data as well during the April and May time period based on the operational rules of the CATALYST controller and evaluated by RMSE. The RTU modeling based on the CATALYST ruleset was inaccurate. The difficulty was translating the logic of the CATALYST controller, which operates in a real time, minute sampling environment, to the hourly sampling model environment. The more complex logic was abandoned in favor of a more generic RTU model. This model was able to achieve more accurate results. The whole building model, calibrated for April and May, was then validated for three weeks, one each in June, July and August. The model did not translate, resulting in double or more error as evaluated by RMSE. New schedules were calculated based on the CATALYST data for all hours of the provided data. The internal gains were also calibrated to the real data through Monte Carlo testing to estimate the appliance, infiltration, appliance convective fraction, and occupancy. The model was then recalibrated for the week in July to within 15% of the provided data. Validating the new model to the June and August weeks, the model accuracy, as determined by RMSE, increased to 20% or 40%.

The results of the RTU modeling suggest that a more adaptive approach needs to be taken. Since this model was created, calibrated and validated from real world data at certain periods of time, the model does not adapt well from all the immeasurable changes that occur on a regular basis. Swapping from a generalized, averaged, weekly schedule for schedules based on the data, and calibrated through Monte Carlo testing immediately yielded lower error results. Changes to the building envelope provided only minimal changes in error indicating that the building envelope does not have large impact. Even changing the parameters of the RTU model had less effect. This leads to the conclusion that the internal gains required a more adaptive model to predict how the building will respond. Even with a more accurate internal gains model, the dynamic nature of a retail store will make modeling the biggest challenge in implementing model predictive control.

Since the model was proven as accurate for the one week in July, testing of model predictive control commenced for the one week in July. Control was tested for three levels of PV (no PV, medium, and high) because one of the goals of the NREL study is to test MPC with the use of onsite PV power generation. The controller was then tested to optimize energy consumption, utility costs savings under the existing rate structure, cost savings under day ahead pricing, a demand event, and lastly to optimize around additional parameters.

In the case of testing the ability of the controller to reduce only energy usage based on a flat rate energy cost, the controller was able to save minimal energy compared to the night time set point profile. It was able to do so with a few small adjustments of pre-cooling during the earlier hours of the day. This result is disappointing as the hope is that the controller would be able to use cooler weather to pre-cool the building through economizer mode reducing energy use throughout the day. The cause could be an imperfect model, a low capacitance building or high internal gains that heat the building at a faster rate than the capacitance can hold energy over the hour. If the last case is true, then the current CATALYST rules provide nearly the same level of energy savings by meeting the cooling load through advanced economizer logic.

Next the controller was tested around the current utility rate structure. This testing has the most immediate implications for Whole Foods and Transformative Wave. The controller was tested to balance time of use and demand energy costs. Reducing the building's energy demand cost came at the expense of greater energy use. In all cases tested, this resulted in a higher time of use energy cost but a reduced demand energy charge. By optimizing the controller around decreasing only the maximum demand charges during the week, the controller was able to decrease the maximum demand charge when necessary and also optimize energy consumption around the time of use rate structure. The resultant cost savings were approximately $250 a month without PV on site.

The next set of tests were to evaluate the controller under a day ahead pricing structure. This should be optimal for the controller to optimize around the couple of hours of high peak time of use costs. The results were on par with the CPP results, and the controller showed some set point control prior to the peak energy costs but not as much as would be expected.

The last rate structure based test was the demand reduction event. The ability of the optimizer was tested with different penalty multipliers applied to the event demand and added to the cost function. The optimized control was able to reduce the event demand by up to 10 kW, but didn't reach the overall goal of 30kW reduction. This could be for multiple reasons. First, the HVAC energy costs do not represent the largest energy loads of the building. Second, the optimizer solves through running many profiles and choosing the profile which has the lowest cost function value. An added constraint could be added in the solver to force the energy reduction. Lastly this could be a constraint of the model, and the cooling loads cannot decrease to maintain comfort conditions.

Grid metrics proposed by Dr. Corbin were evaluated. In all cases, the building's system ramping, peak demand, load factor and peak to valley ratio could be improved. This does come at a much larger energy consumption. Additionally, by applying the penalties to the cost function in the manner conducted in these tests, suboptimum results may have been created. The results suggest that a more optimal method would be to apply thresholds similarly to peak demand based on the maximum and minimum demand values. Also, to improve these metrics, an energy storage system can be applied and set to charge during the valleys, improving the minimum demand and average demand thereby reducing the magnitude of the evaluated metrics.

The proposed carbon optimization measure did not have significant carbon savings and resulted in increased carbon emissions. This could be from a poor application of the carbon penalty in the cost function. A revised penalty could be applied based on the amount of change from a baseline or minimum carbon level. Otherwise, despite a large carbon penalty, the low percentage change in carbon levels did not provide enough impetus for the cost function to find a meaningful minimum around carbon production.

The use of PV and the optimizer does provide greater benefit than without PV. While it could be expected that PV will reduce the energy bill simply by reducing the energy purchased by the utility company, combining PV with a model predicted control profile can achieve further energy savings. In all cases, the use of PV allowed the optimizer to have a greater percentage of reductions in the target metric of demand, time of use cost or any of the additional metrics. This suggests that, as more energy saving systems are added to buildings, advanced optimum control will maximize the energy savings achieved by maximizing the effect of each measure.

The addition of the additional grid relation improving metrics are promising ways to improve overall grid effectiveness and efficiency. However, these would require incentive for building owners to implement these grid improvement measures, as in each case the time of use energy cost increased making optimum control not cost effective by adding to electrical energy consumption.

The biggest block to the implementation of model predictive control is the reliability and development of the model. The time to create the model based on available data and maintain calibration must be fast and reliable to maintain low costs. Based on the best case savings solved in tests of approximately $250 in July, a best guess would be a total savings of $1000 a year assuming less electrical saving will occur outside of the summer months. To maintain a five-year simple payback, the controller must cost less than $5000 to implement including labor and equipment. This makes the further development and testing being conducted at NREL important to validate the application of model predictive control.

The bottom line savings of model predictive control to the building customer is cost savings by reducing the monthly peak demand bill at an increased cost of time of use energy costs. First, the addition of PV, using a night time set back schedule with the model tested is shown in the below table

Table 54: Effects of on-site energy generation

Night Time Setback	No PV	82kW PV	154kW PV
Monthly TOU Energy Charge	$ 8,815.95	$ 8,363.85	$ 8,155.16
Monthly Demand Changes	$ 7,717.69	$ 6,429.40	$ 5,232.49
Monthly Utility Bill	$ 16,533.65	$ 14,793.25	$ 13,387.65
Savings with PV	N/A	$ 1,740.40	$ 3,146.00
% Savings	N/A	10.5%	19%

The savings are associated with the month of July, the cost savings will vary depending on the time of the year as overall building electric demand will be less during the winter months with a lower cooling requirement than in the summer.

The below tables summarizes the cost savings compared to the night time set back control at each level of on site generation.

Table 55: MPC cost results summary

MPC addition	No PV	82kW PV	154kW PV
Monthly TOU Energy Charge	$ 8,572.85	$ 7,968.09	$ 7,601.19
Monthly Demand Changes	$ 7,751.36	$ 6,496.67	$ 5,386.97
Monthly Utility Bill	$ 16,324.20	$ 14,464.76	$ 12,988.16
Savings to NSU Case	$ 209.45	$ 3 28.49	$ 399.49
% Savings to NSU Case	1.3%	2.2%	3.0%

Since the actual utility costs were unavailable, this study suggests that the addition of model predictive control could save Whole Foods 1.3% a year in utility costs based on this model. This assumes that the controller will save the same each month. This will also required the inclusion of gas energy costs for the winter. In terms of applicability across different stores, MPC should be able to provide better control in environments with greater variation in temperatures between night and day. MPC, however, will be limited in extreme such as in Arizona with night time lows greater than the indoor set point limiting the use of economizer and free cooling. The only way to improve MPC under those extremes would require greater energy capacitance.

Future Works

Further improvements need to be made to the building and RTU models. These include the prediction of internal gains and HVAC unit response. Prior to any implementation of a new retrofit control to the building, the total building energy needs to be calibrated to the utility data. The method proposed estimates total building energy load but without comparison to the real utility data. The availability of sub metered data of lighting loads, appliances, and other heat generating devices will allow for accurate internal gains calculations as well as building energy consumption schedules the MPC controller can adjust HVAC schedules around to further minimize utility costs.

While the addition of model predictive control did result in cost savings, the overall savings are less than 1% of the entire modeled building energy costs. This can be accounted for by the fact that the average piece of the electric bill represented by climate control cooling is only 14% of the total bill (11). Refrigeration remains the highest electric consumer inside the building. However, the processes and theories associated with HVAC temperature control can be applied to refrigeration. Costs could be saved by employing optimum set point control by using the thermal mass inside the refrigerators and adjusting within a set temperature bounds. While this would be a much smaller range for refrigerators, freezers could easily adjust within temperature levels below freezing with negligible impact to the food inside.

The addition of energy storage systems to the building model could only further increase the ability of the controller to save energy costs and peak demand functions. Based on these studies and the limitations of battery storage systems, the battery would be required to store energy during the low energy use/cost times to discharge during critical time periods. The main time periods the tested model in this project would benefit from battery storage would be peak, mid-peak and on-peak periods.

Another level of control that needs to be tested is the application of RTU unit coordination. In this thesis, the RTUs were characterized by a single RTU. Added levels of demand reduction could be applied by coordinating when and how many RTUs turn on at any given time. The complexity of this would require a minimal computational fluid dynamics (CFD) model as proposed by Kim et al (43). Another simplified model that could be considered would be in relation to the surface node of the five parameter model as illustrated in figure 89. This solution would not be as elegant, neglects the interzonal heat transfers, and represents the interaction of each zone with the surface node of the five parameter model.

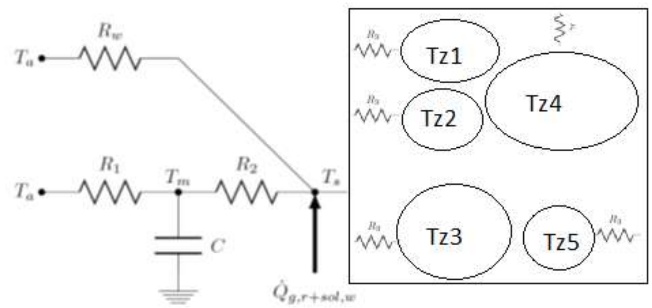


Figure 82: Proposed simplified multizone model

This model has not been tested or validated. The additional steps would have to include estimating each zone's internal gains and the correlation of each zone to the outside conditions.

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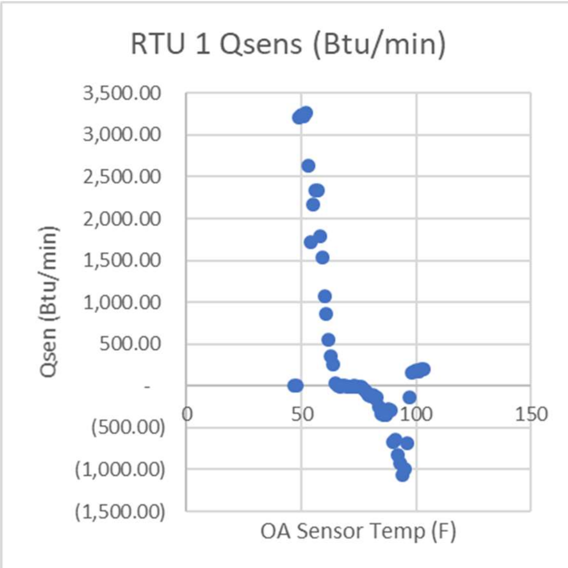
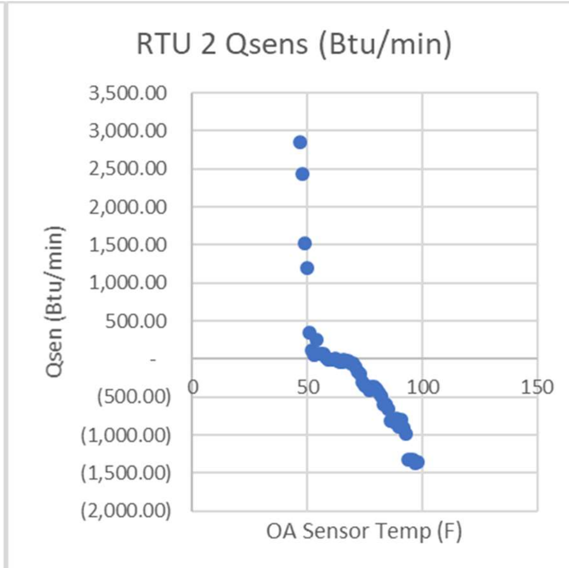
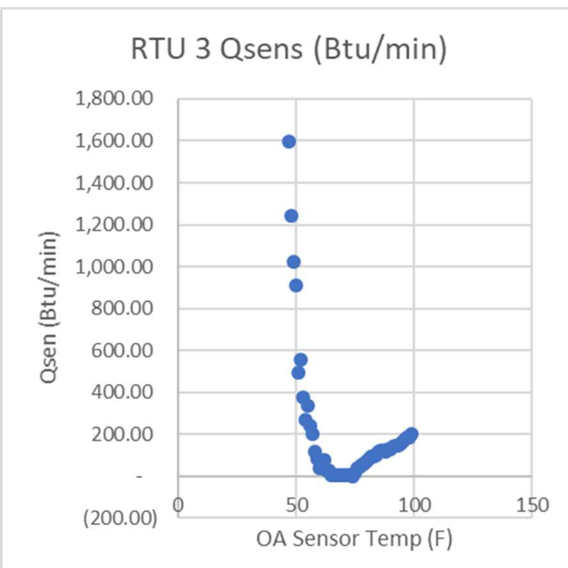
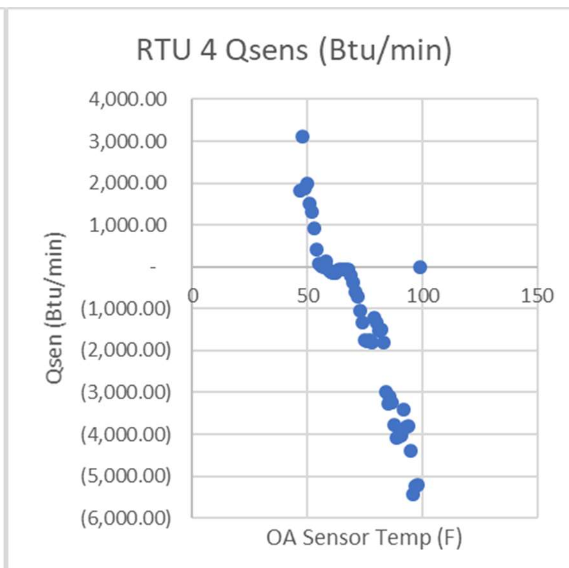
Appendices

Appendix A: Individual RTU Occupied Coil Sensible Loads

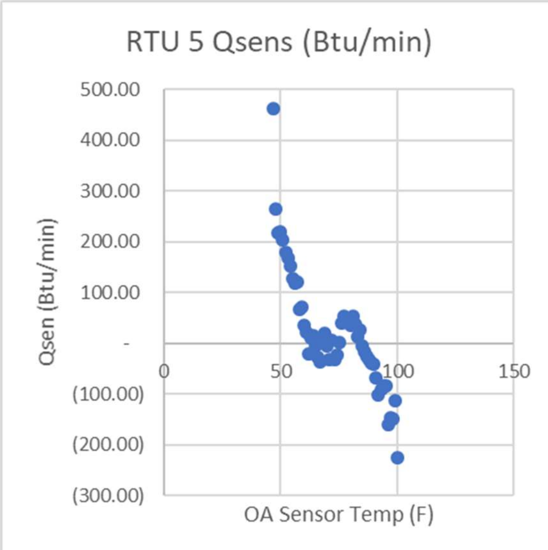


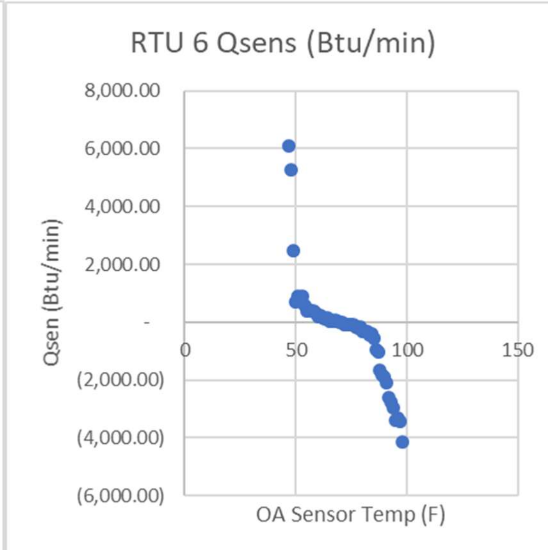


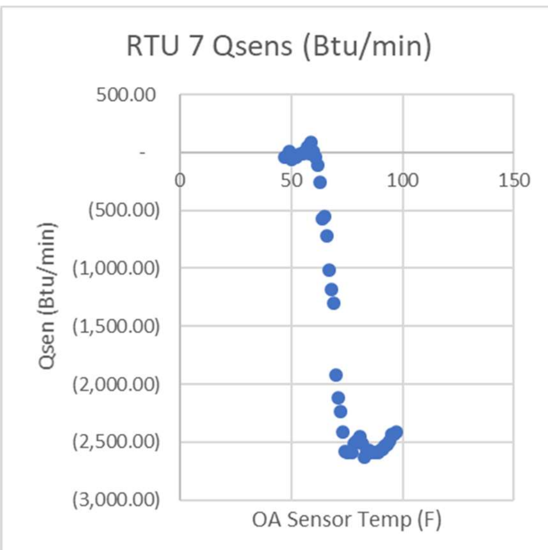


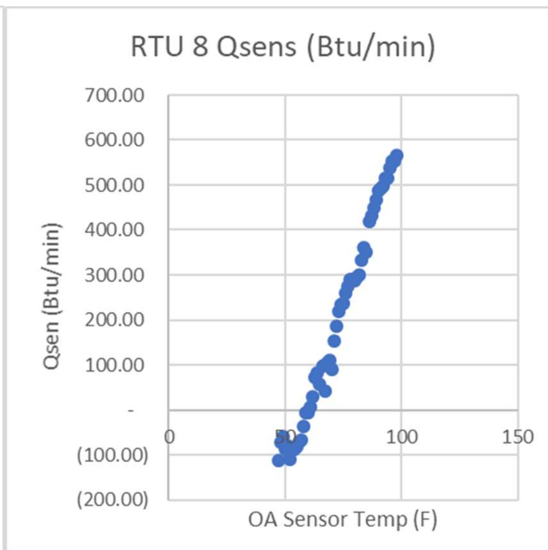


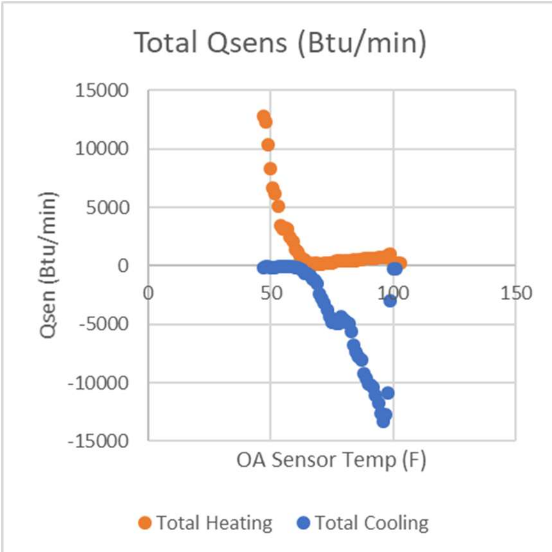
3


RTU 5 Qsens (Btu/min)
500.00
400.00
300.00
200.00
100.00
-
(100.00)
(200.00)
(300.00)
0
50
100
150
Qsen (Btu/min)
OA Sensor Temp (F)


RTU 6 Qsens (Btu/min)
8,000.00
6,000.00
4,000.00
2,000.00
-
(2,000.00)
(4,000.00)
(6,000.00)
0
50
100
150
Qsen (Btu/min)
OA Sensor Temp (F)


RTU 7 Qsens (Btu/min)
500.00
-
(500.00)
(1,000.00)
(1,500.00)
(2,000.00)
(2,500.00)
(3,000.00)
0
50
100
150
Qsen (Btu/min)
OA Sensor Temp (F)

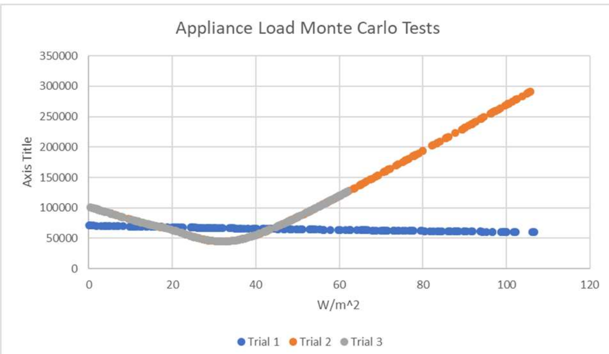

RTU 8 Qsens (Btu/min)
700.00
600.00
500.00
400.00
300.00
200.00
100.00
-
(100.00)
(200.00)
0
50
100
150
Qsen (Btu/min)
OA Sensor Temp (F)

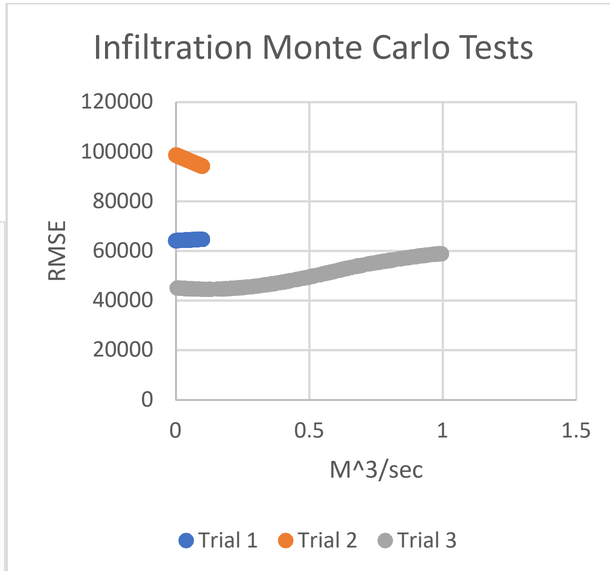


As the figures show, the properly working cooling coils increase cooling as outdoor temperature increases. This holds true for all RTUs except RTU 3, 5 and 8 where cooling shows no significant increase in cooling output, or in the case of RTU 8, provides a heating load from the fan and outside air moving through the unit. This was noted to Whole Foods and later discovered that RTU 8 had a bad compressor.

Appendix B: Monte Carlo Testing

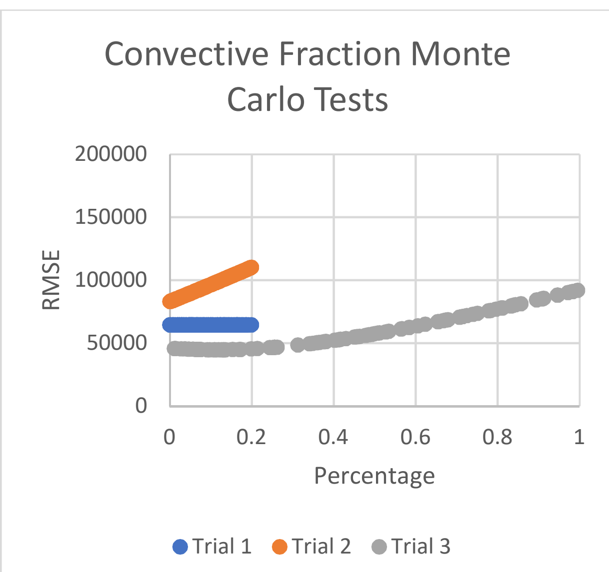
April Model calibration

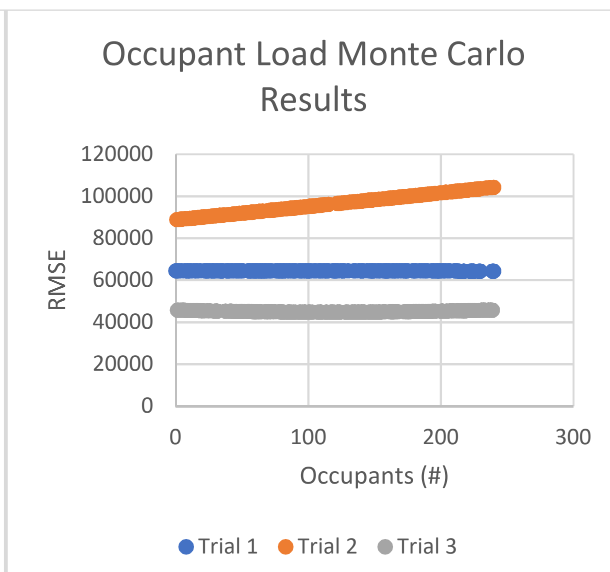




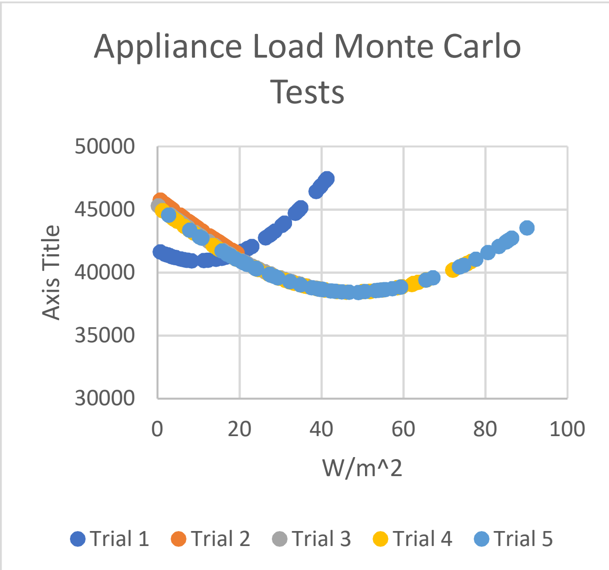
The infiltration tests were originally not converging so the bounds were increased to encompass 0 to 1.

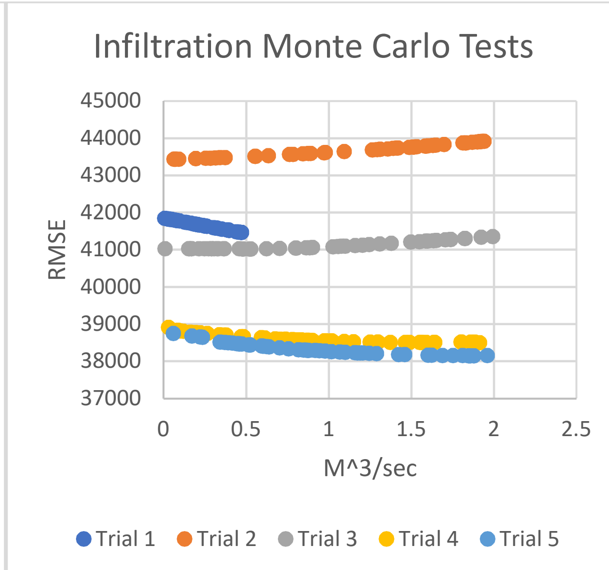
In trial three the curve is able to reach a minimum.

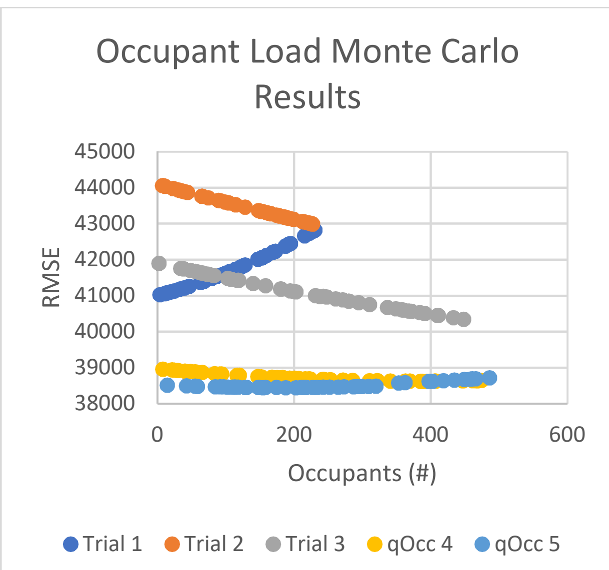


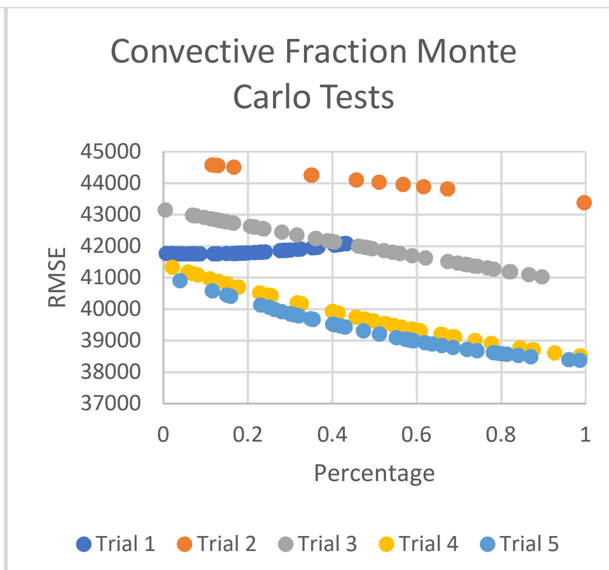


Below are the second trials of appliance load training. The charts show a much better convergence of values than the previous tests.

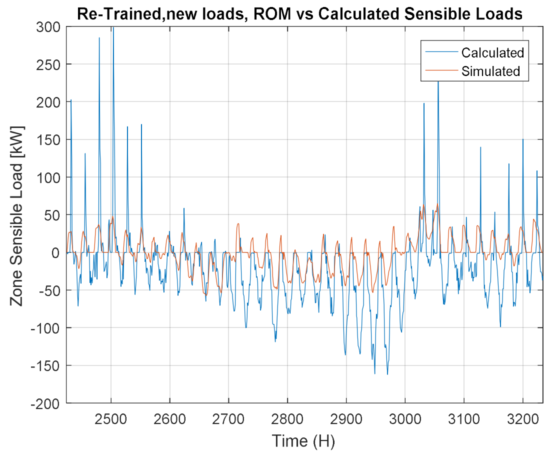


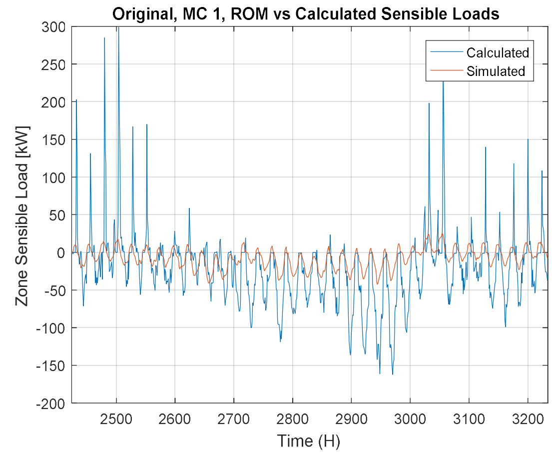


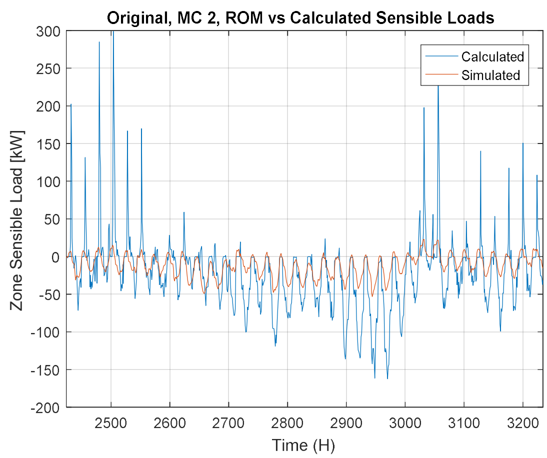


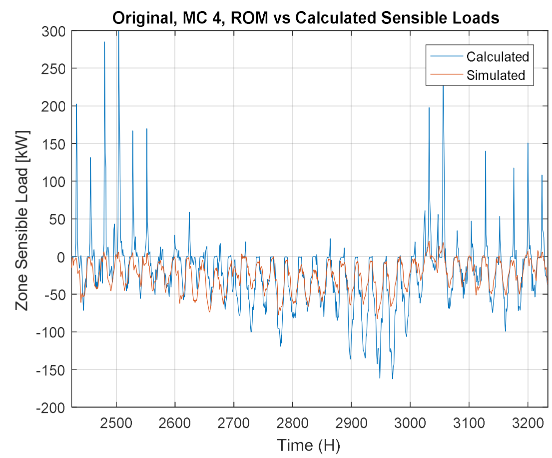


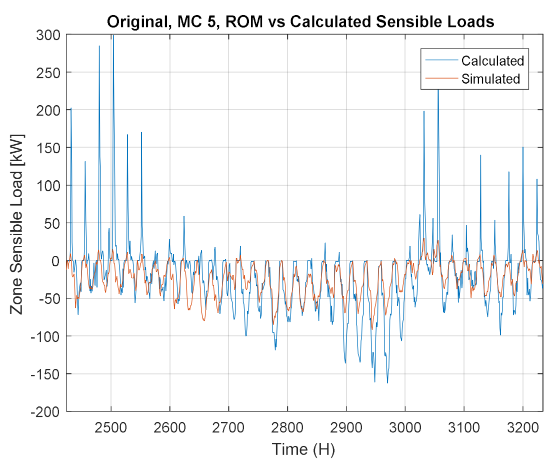
As illustrated by the above charts, after three trials the values begin to converge to a point of minimal difference between trial 4 and trial 5. Unlike the previous tests, where the testing stopped as soon as the RMSE began to increase, these tests provided greater confidence that the values are accurate. Additionally, the slop in the final trials shows how much greater the impact each load has on the overall error. For example, infiltration possibly has the most negligible effect as the difference between the highest error and the lowest error is approximately 1000 W. In comparison, the appliance load ranges quickly between 45000 W and 38000 W indicating much greater effect on the overall load.

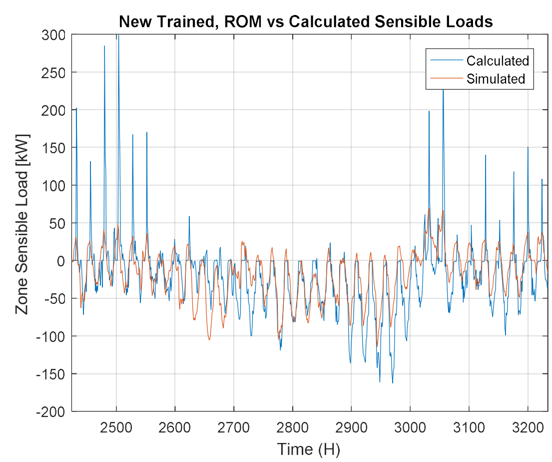








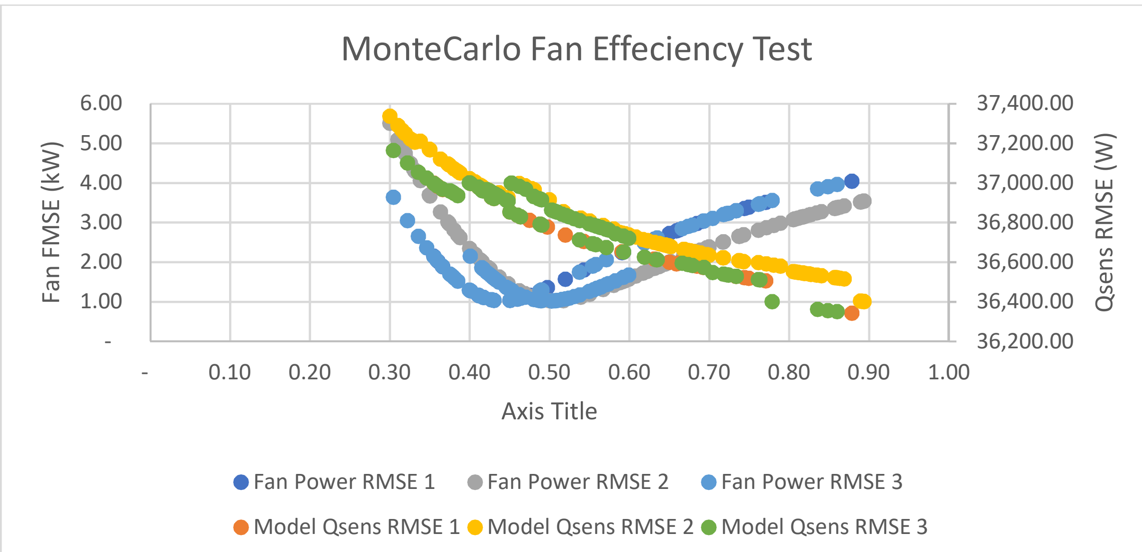




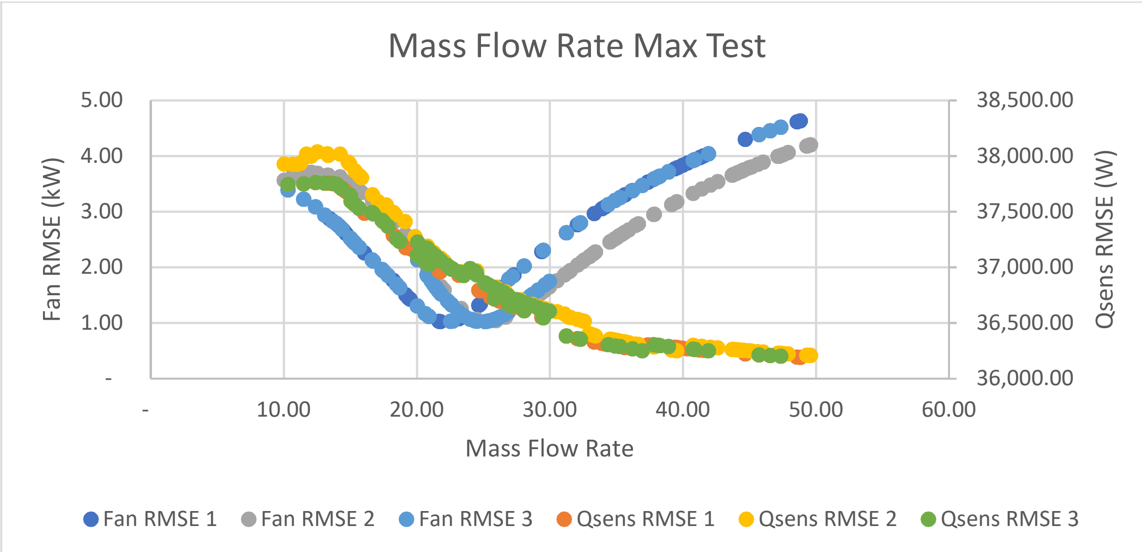
The above charts show the evolution of fit between the trials. Originally, the model is able to capture the trend, but not magnitude, of the sensible loads. But by merely increasing certain loads such as the appliance and occupancy loads but decreasing the infiltration, there is a shift of the curve downward and an increase of magnitude. These models then fail to capture the heating effects and negate more of the environmental effects. By trial 5, the magnitude of the loads seems to better track the sensible load profile in both magnitude and schedule, at which point the model is re-trained and new parameters are established. Overall, the resistance values are decreased and show a greater impact of the outside environment on the model. This is indicated by the model better matching peak loads, though not perfectly, than before in both heating and cooling periods.

Appendix C: RTU Calibration Curves

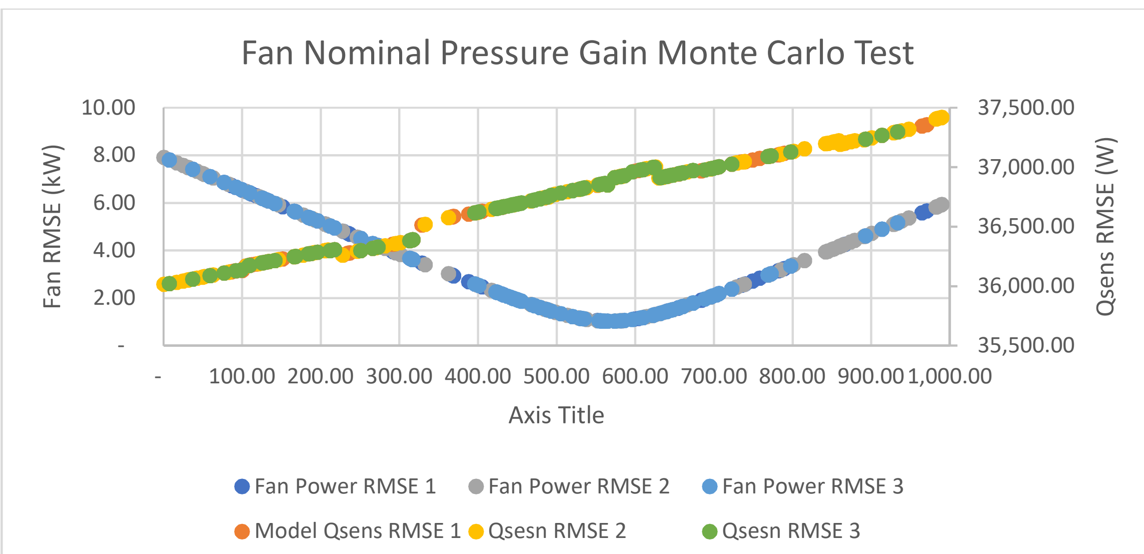
The first calibration was to test the fan parameters. In this the fan efficiency didn't change much. The value of .5 was initially used as a middle value to start the testing. However, this was the final value through the testing as the fan RMSE increased significantly below or above 50%. The sensible load RMSE decreased as efficiency improved. This is assuming that high efficiency has less heat addition to the RTU supply air.



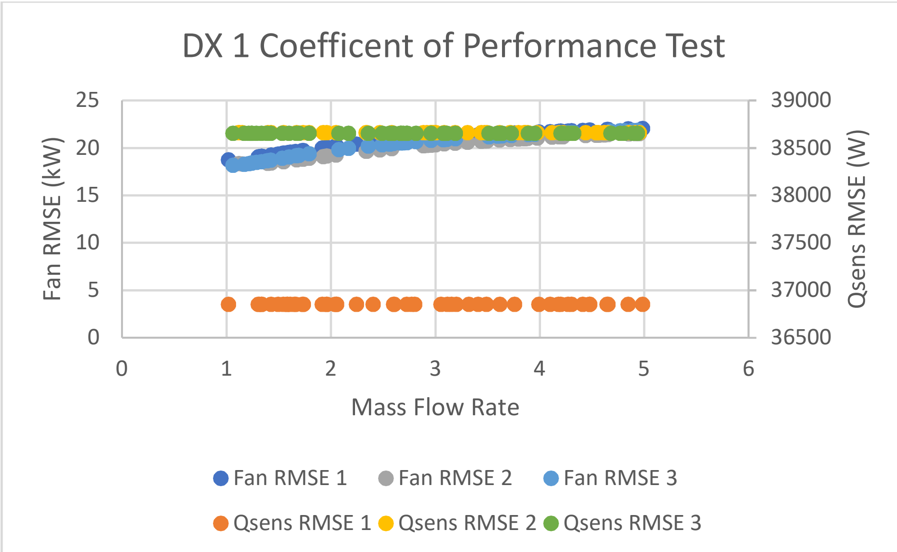
The mass flow rate had a very apparent minimum value between the tests. In fact, the same minimum error was reached showing that the rule is followed as expected. However, the value settled at the starting test value affirming that the assumed flow rate does hold accurately through the modeling process. However, the overall sensible load does decrease with higher flow, which could indicate that more heat is being added to the supply air.

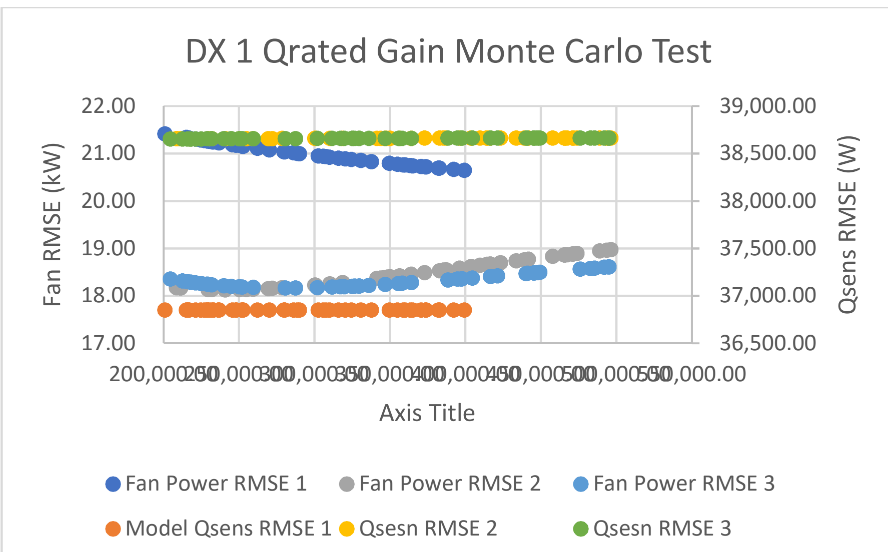


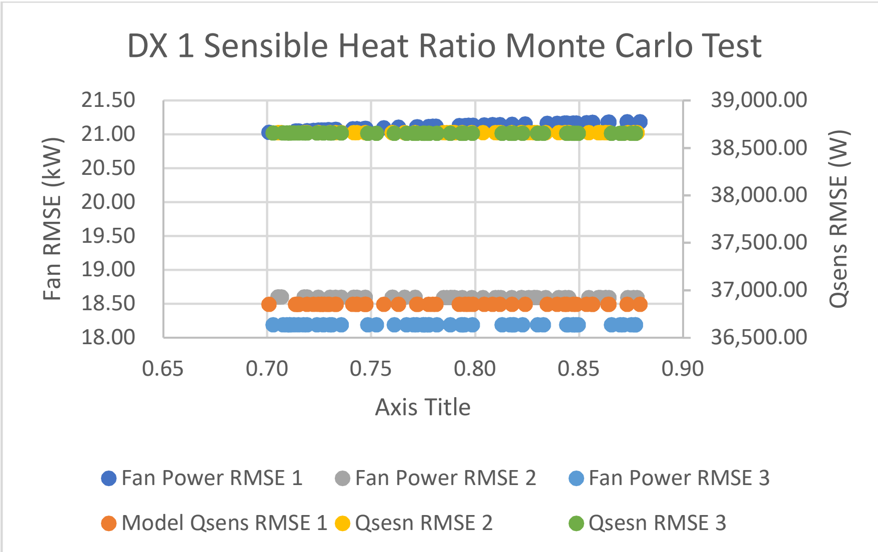
In testing the fan nominal pressure gain, the RMSE did not change for either the sensible load or the fan power. The minimum was consistent and apparent as illustrated below.

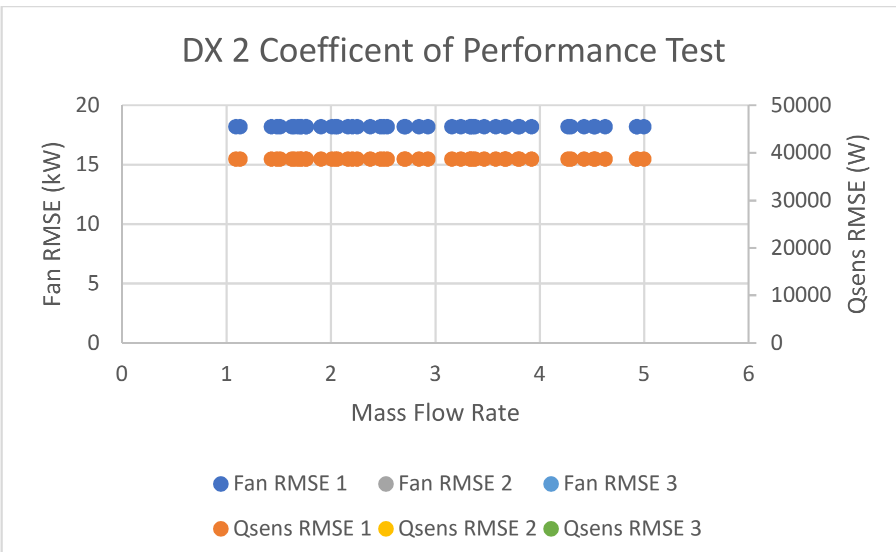


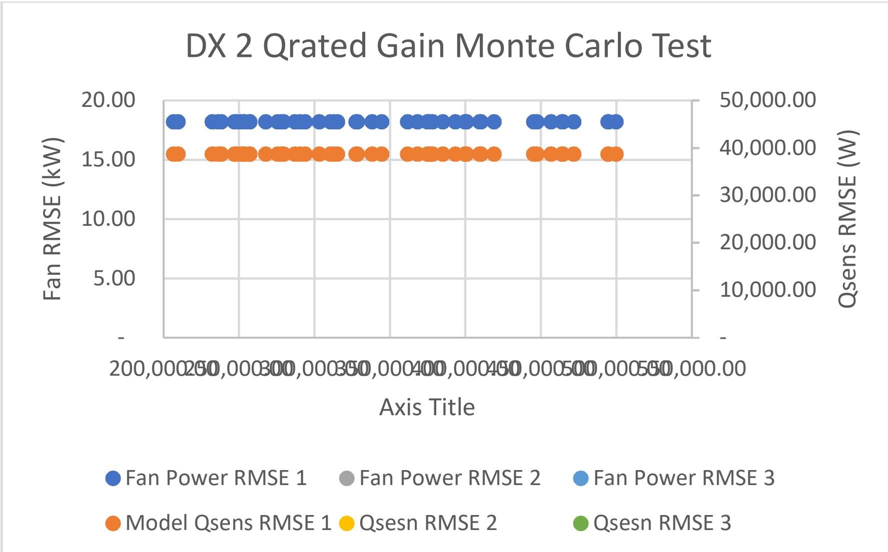
Similar curves are shown below for calibration of the two stages of cooling coils.

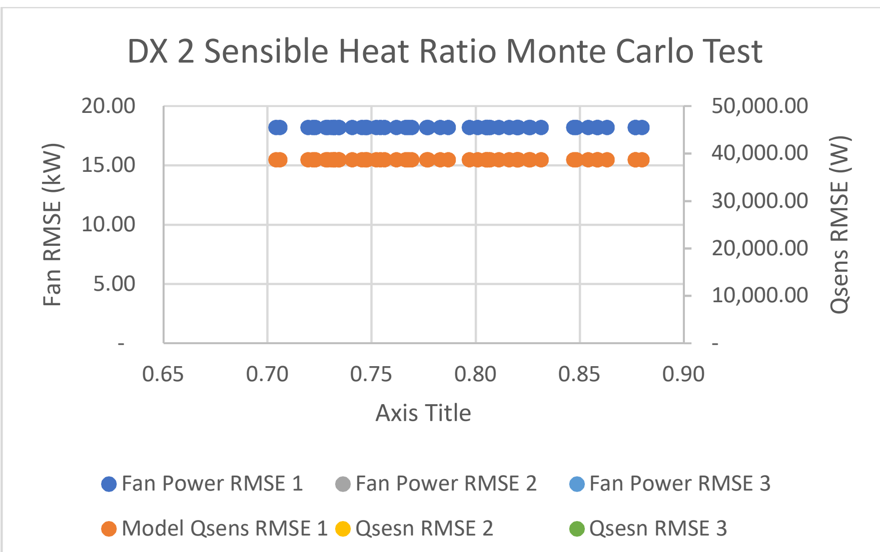

DX 1 Coefficent of Performance Test
Fan RMSE (kW)
Qsens RMSE (W)
Mass Flow Rate
25
20
15
10
5
0
39000
38500
38000
37500
37000
36500
0
1
2
3
4
5
6
Fan RMSE 1
Fan RMSE 2
Fan RMSE 3
Qsens RMSE 1
Qsens RMSE 2
Qsens RMSE 3


DX 1 Qrated Gain Monte Carlo Test
Fan RMSE (kW)
Qsens RMSE (W)
22.00
21.00
20.00
19.00
18.00
17.00
39,000.00
38,500.00
38,000.00
37,500.00
37,000.00
36,500.00
Axis Title
Fan Power RMSE 1
Fan Power RMSE 2
Fan Power RMSE 3
Model Qsens RMSE 1
Qsesn RMSE 2
Qsesn RMSE 3

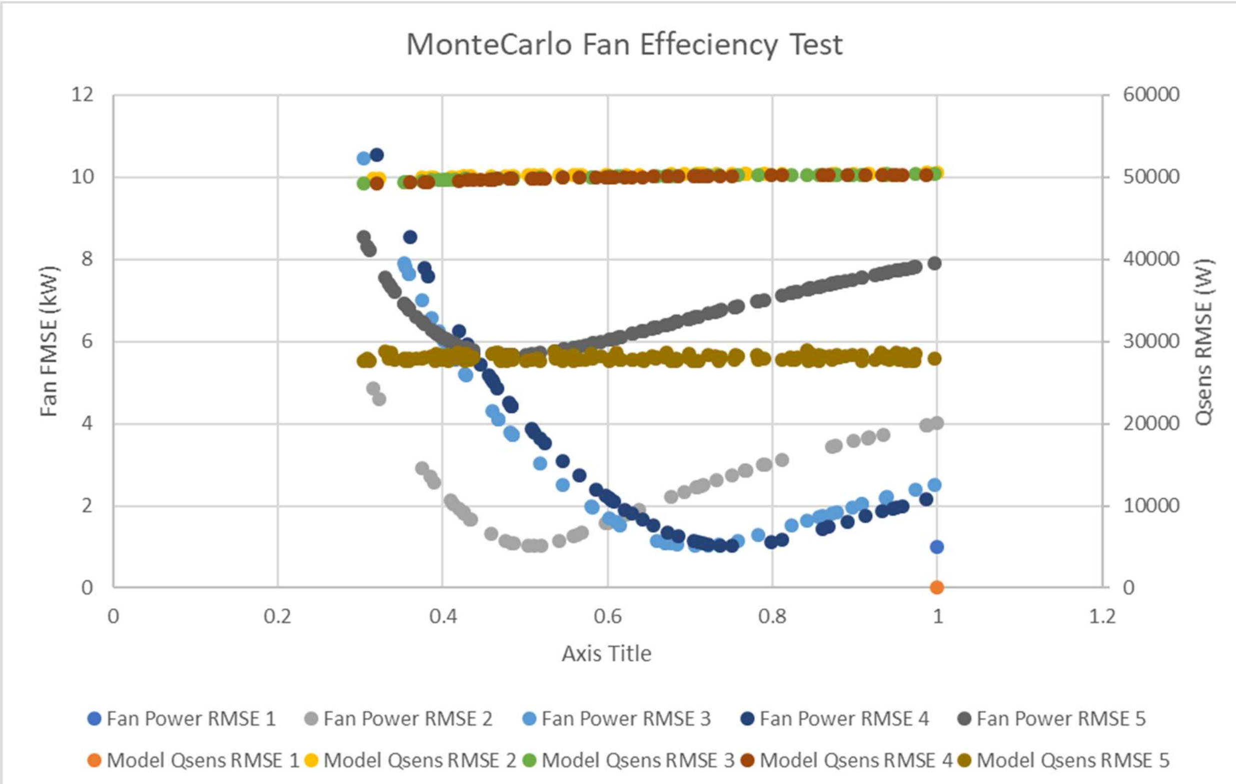

DX 1 Sensible Heat Ratio Monte Carlo Test
Fan RMSE (kW)
21.50
21.00
20.50
20.00
19.50
19.00
18.50
18.00
39,000.00
38,500.00
38,000.00
37,500.00
37,000.00
36,500.00
Qsens RMSE (W)
0.65
0.70
0.75
0.80
0.85
0.90
Axis Title
Fan Power RMSE 1
Fan Power RMSE 2
Fan Power RMSE 3
Model Qsens RMSE 1
Qsesn RMSE 2
Qsesn RMSE 3

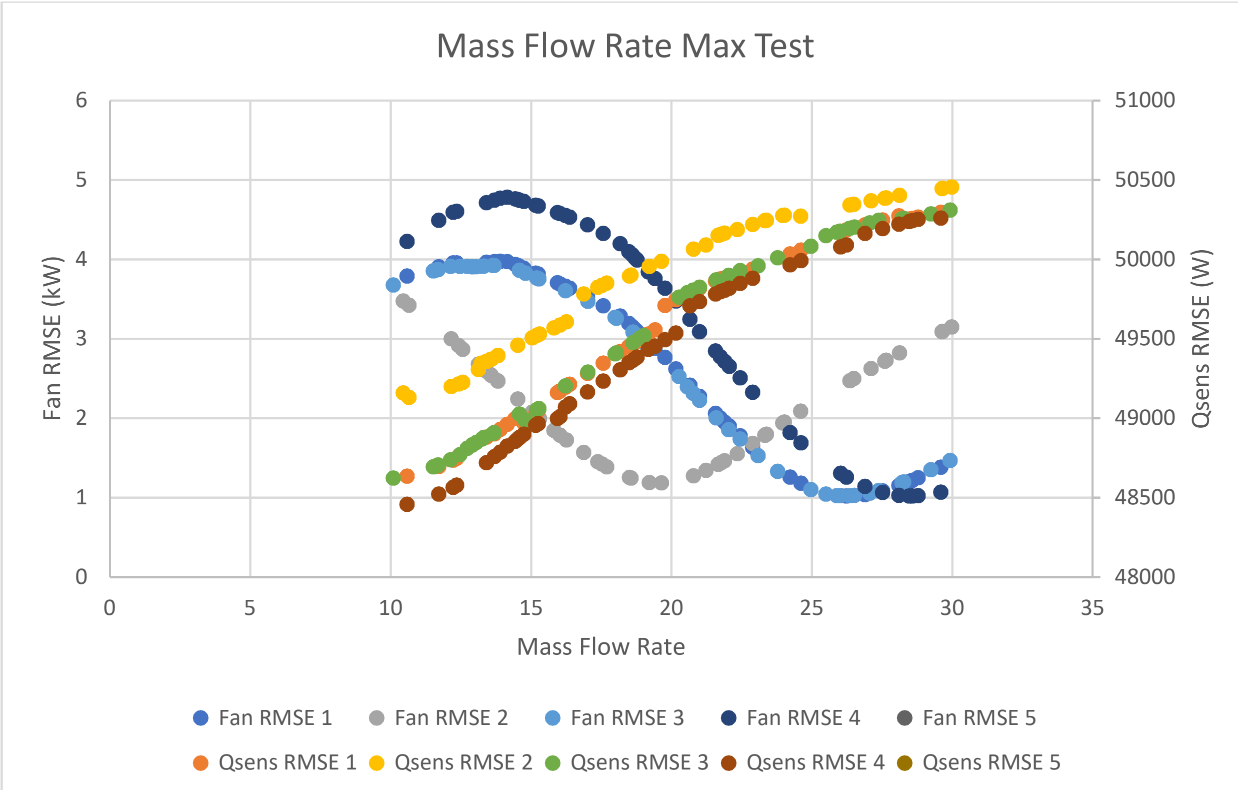

DX 2 Coefficent of Performance Test
Fan RMSE (kW)
20
15
10
5
0
50000
40000
30000
20000
10000
0
Qsens RMSE (W)
0
1
2
3
4
5
6
Mass Flow Rate
Fan RMSE 1
Fan RMSE 2
Fan RMSE 3
Qsens RMSE 1
Qsens RMSE 2
Qsens RMSE 3

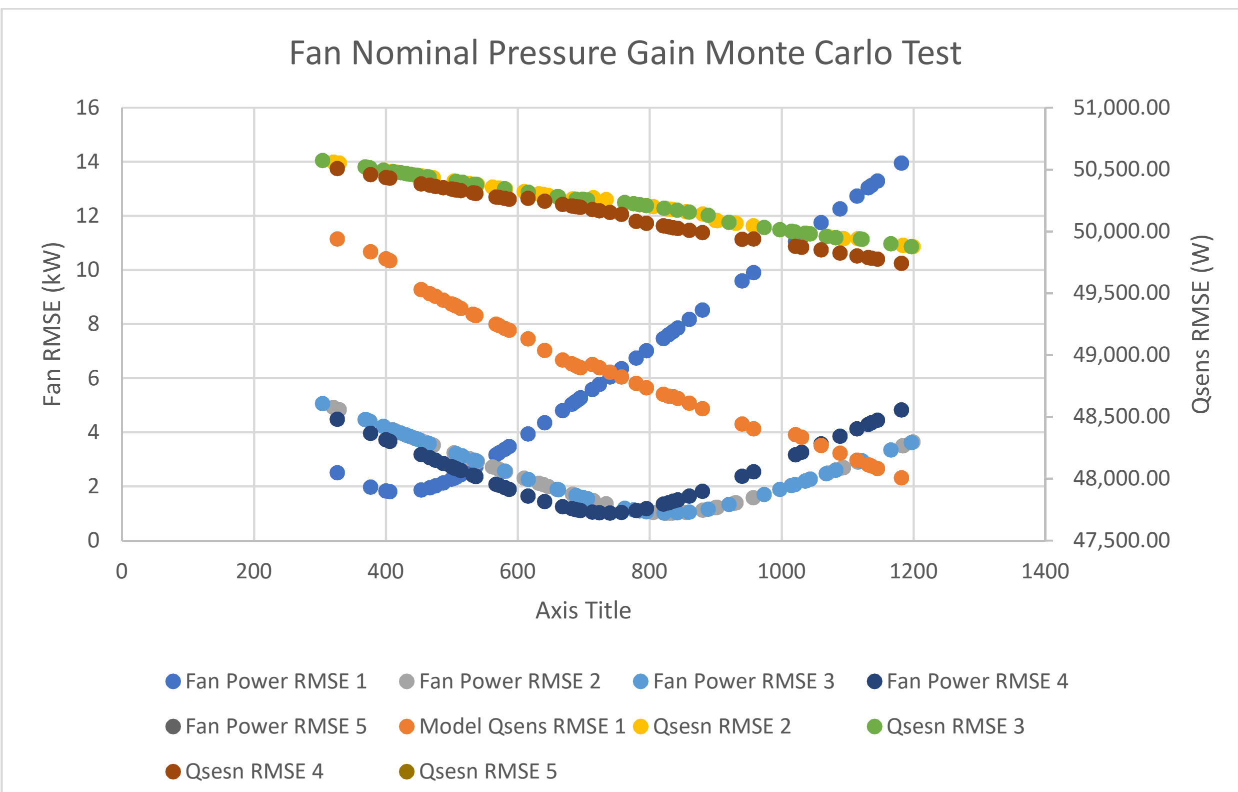

DX 2 Qrated Gain Monte Carlo Test
Fan RMSE (kW)
Qsens RMSE (W)
20.00
15.00
10.00
5.00
-
50,000.00
40,000.00
30,000.00
20,000.00
10,000.00
-
200,000.00
250,000.00
300,000.00
350,000.00
400,000.00
450,000.00
500,000.00
550,000.00
Axis Title
Fan Power RMSE 1
Fan Power RMSE 2
Fan Power RMSE 3
Model Qsens RMSE 1
Qsesn RMSE 2
Qsesn RMSE 3

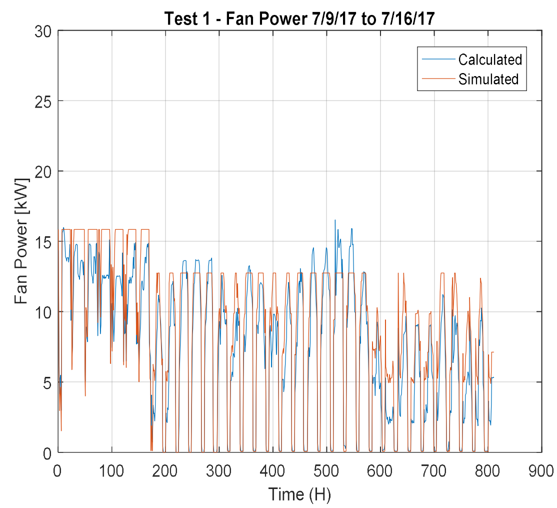

DX 2 Sensible Heat Ratio Monte Carlo Test
Fan RMSE (kW)
Qsens RMSE (W)
20.00
15.00
10.00
5.00
-
50,000.00
40,000.00
30,000.00
20,000.00
10,000.00
-
0.65
0.70
0.75
0.80
0.85
0.90
Axis Title
Fan Power RMSE 1
Fan Power RMSE 2
Fan Power RMSE 3
Model Qsens RMSE 1
Qsesn RMSE 2
Qsesn RMSE 3

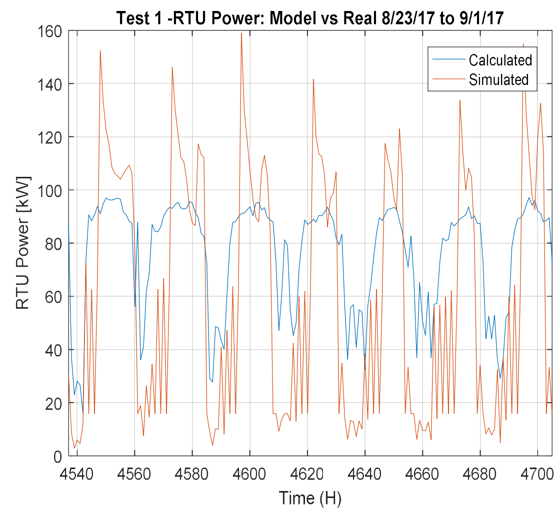
Appendix D: July Model Calibration Simulation Charts

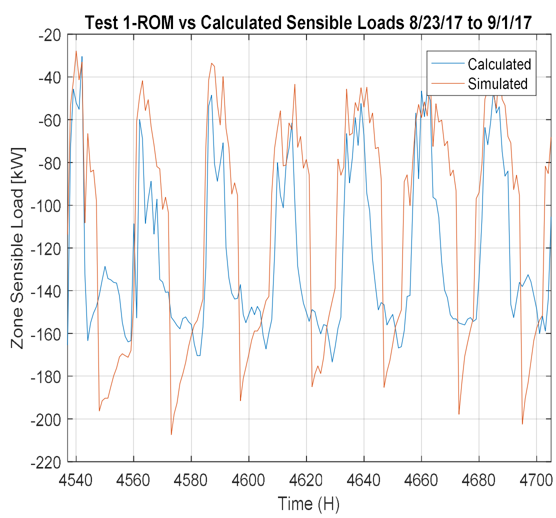


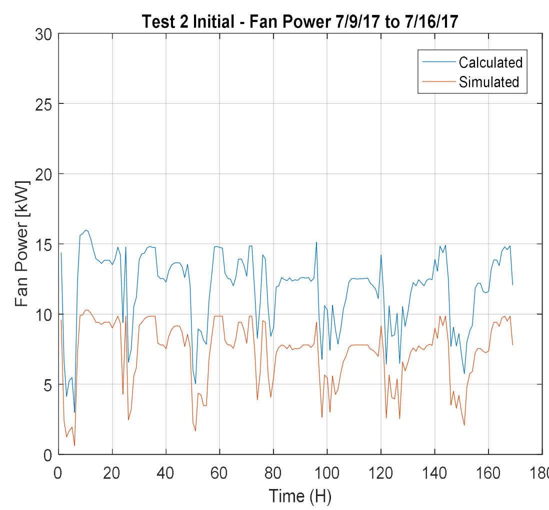

Mass Flow Rate Max Test
Fan RMSE (kW)
Qsens RMSE (W)
Mass Flow Rate
0 1 2 3 4 5 6
48000 48500 49000 49500 50000 50500 51000
0 5 10 15 20 25 30 35
Fan RMSE 1
Fan RMSE 2
Fan RMSE 3
Fan RMSE 4
Fan RMSE 5
Qsens RMSE 1
Qsens RMSE 2
Qsens RMSE 3
Qsens RMSE 4
Qsens RMSE 5

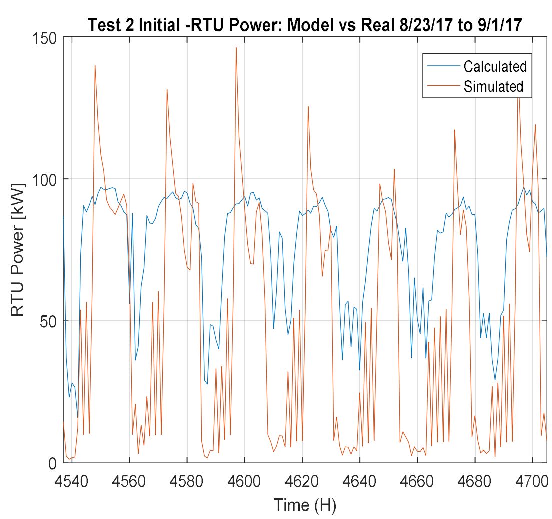

Fan Nominal Pressure Gain Monte Carlo Test
Fan RMSE (kW)
Qsens RMSE (W)
Axis Title
0 2 4 6 8 10 12 14 16
47,500.00 48,000.00 48,500.00 49,000.00 49,500.00 50,000.00 50,500.00 51,000.00
0 200 400 600 800 1000 1200 1400
Fan Power RMSE 1
Fan Power RMSE 2
Fan Power RMSE 3
Fan Power RMSE 4
Fan Power RMSE 5
Model Qsens RMSE 1
Qsesn RMSE 2
Qsesn RMSE 3
Qsesn RMSE 4
Qsesn RMSE 5

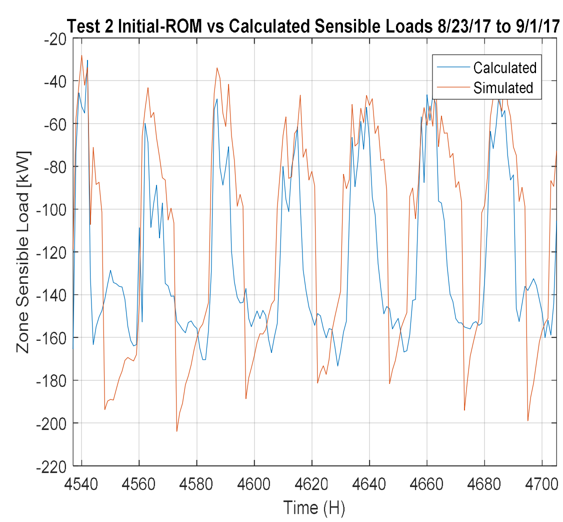

Test 1 - Fan Power 7/9/17 to 7/16/17
Calculated
Simulated
Fan Power [kW]
Time (H)

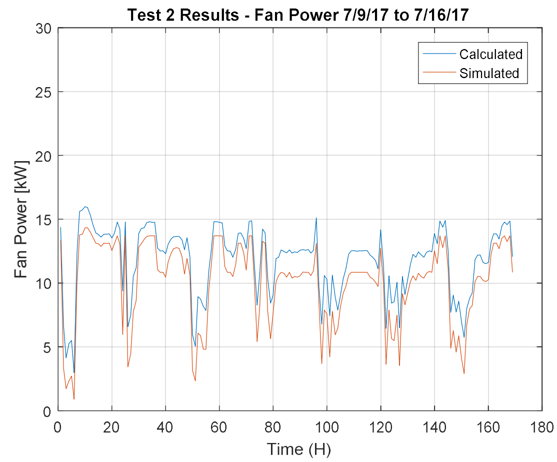

Test 1 -RTU Power: Model vs Real 8/23/17 to 9/1/17
Calculated
Simulated
RTU Power [kW]
Time (H)

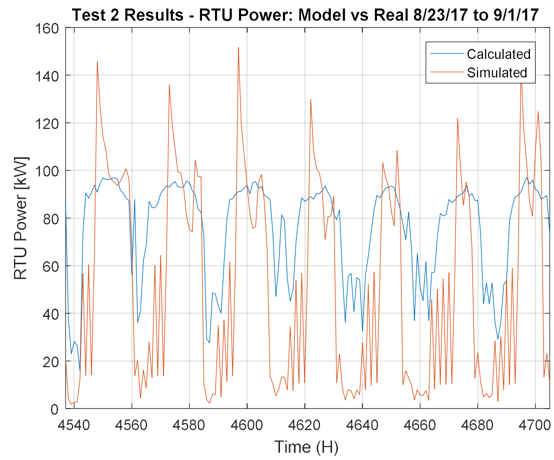

Test 1-ROM vs Calculated Sensible Loads 8/23/17 to 9/1/17
Calculated
Simulated
Zone Sensible Load [kW]
Time (H)

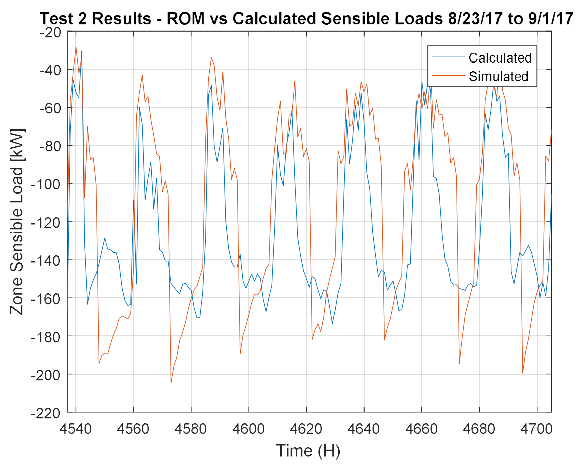

Test 2 Initial - Fan Power 7/9/17 to 7/16/17
Calculated
Simulated
Fan Power [kW]
Time (H)

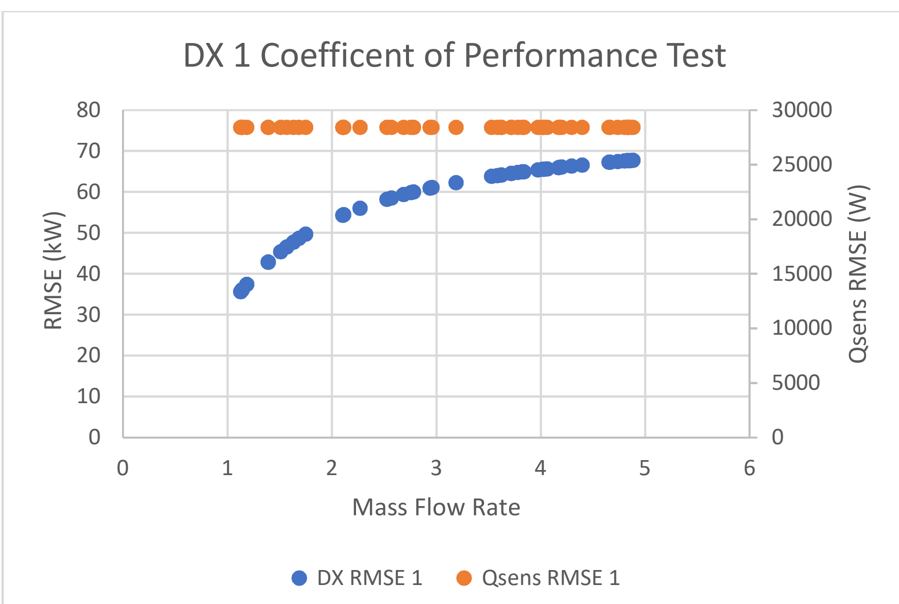

Test 2 Initial -RTU Power: Model vs Real 8/23/17 to 9/1/17
Calculated
Simulated
RTU Power [kW]
Time (H)

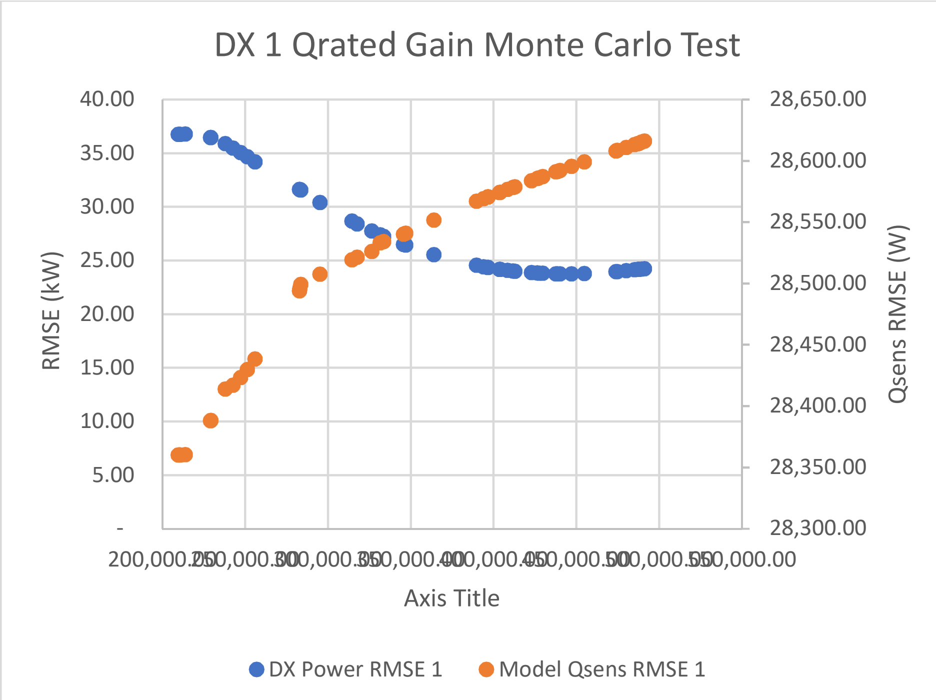

Test 2 Initial-ROM vs Calculated Sensible Loads 8/23/17 to 9/1/17
Calculated
Simulated
Zone Sensible Load [kW]
Time (H)

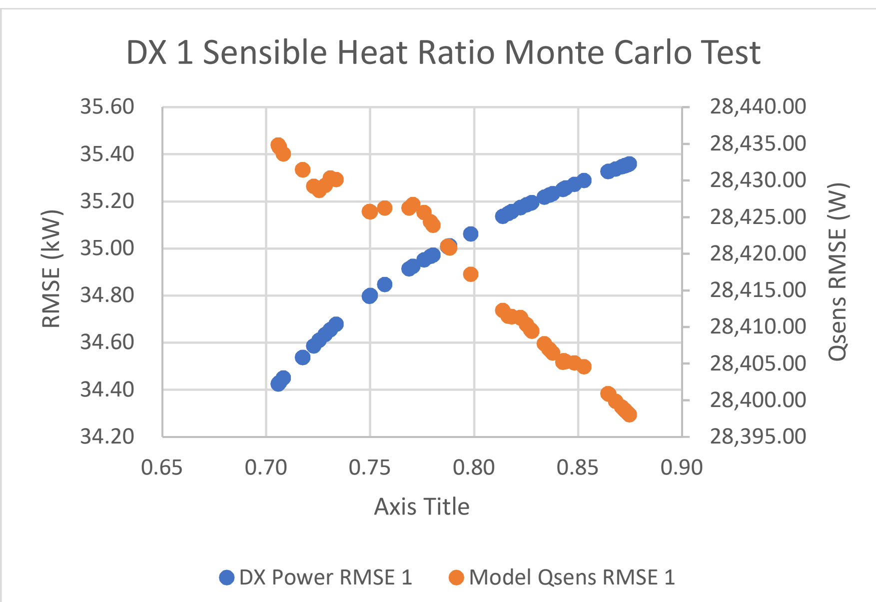

Test 2 Results - Fan Power 7/9/17 to 7/16/17
Calculated
Simulated
Fan Power [kW]
Time (H)

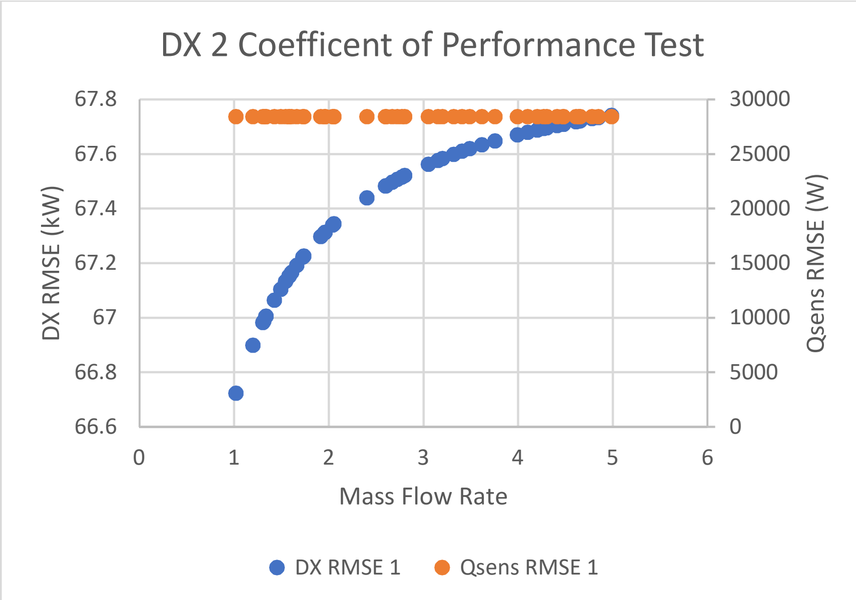

Test 2 Results - RTU Power: Model vs Real 8/23/17 to 9/1/17
Calculated
Simulated
RTU Power [kW]
Time (H)

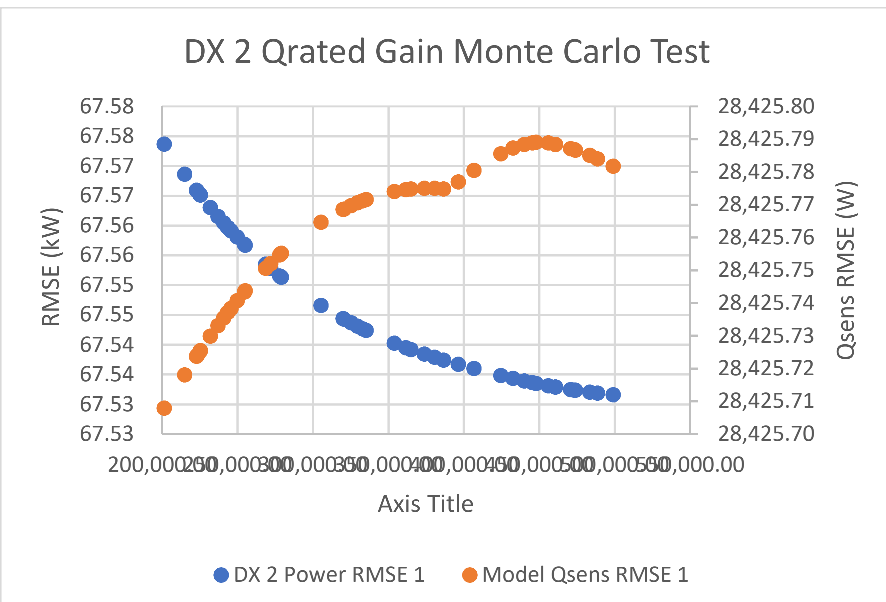

Test 2 Results - ROM vs Calculated Sensible Loads 8/23/17 to 9/1/17
Calculated
Simulated
Zone Sensible Load [kW]
Time (H)

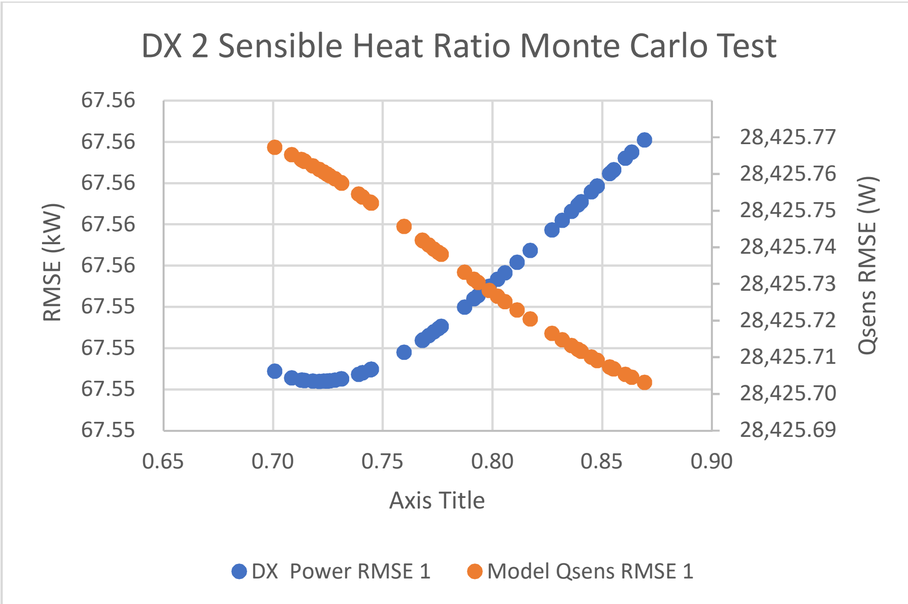

DX 1 Coefficent of Performance Test
RMSE (kW)
Qsens RMSE (W)
Mass Flow Rate
DX RMSE 1
Qsens RMSE 1


DX 1 Qrated Gain Monte Carlo Test
40.00
35.00
30.00
25.00
20.00
15.00
10.00
5.00
-
RMSE (kW)
28,650.00
28,600.00
28,550.00
28,500.00
28,450.00
28,400.00
28,350.00
28,300.00
Qsens RMSE (W)
200,000.00
250,000.00
300,000.00
350,000.00
400,000.00
450,000.00
500,000.00
550,000.00
Axis Title
DX Power RMSE 1
Model Qsens RMSE 1


DX 1 Sensible Heat Ratio Monte Carlo Test
35.60
35.40
35.20
35.00
34.80
34.60
34.40
34.20
RMSE (kW)
28,440.00
28,435.00
28,430.00
28,425.00
28,420.00
28,415.00
28,410.00
28,405.00
28,400.00
28,395.00
Qsens RMSE (W)
0.65
0.70
0.75
0.80
0.85
0.90
Axis Title
DX Power RMSE 1
Model Qsens RMSE 1


DX 2 Coefficent of Performance Test
67.8
67.6
67.4
67.2
67
66.8
66.6
30000
25000
20000
15000
10000
5000
0
0
1
2
3
4
5
6
DX RMSE (kW)
Qsens RMSE (W)
Mass Flow Rate
DX RMSE 1
Qsens RMSE 1


DX 2 Qrated Gain Monte Carlo Test
67.58
67.58
67.57
67.57
67.56
67.56
67.55
67.55
67.54
67.54
67.53
67.53
28,425.80
28,425.79
28,425.78
28,425.77
28,425.76
28,425.75
28,425.74
28,425.73
28,425.72
28,425.71
28,425.70
RMSE (kW)
Qsens RMSE (W)
Axis Title
DX 2 Power RMSE 1
Model Qsens RMSE 1


DX 2 Sensible Heat Ratio Monte Carlo Test
RMSE (kW)
67.56
67.56
67.56
67.56
67.56
67.55
67.55
67.55
67.55
Qsens RMSE (W)
28,425.77
28,425.76
28,425.75
28,425.74
28,425.73
28,425.72
28,425.71
28,425.70
28,425.69
0.65
0.70
0.75
0.80
0.85
0.90
Axis Title
DX Power RMSE 1
Model Qsens RMSE 1

Appendix E: 50 Year Run Time MC Code

```
% Load ROM params and update weather file
dirpath = './Buildings/5p_Validation';
param = loadDataStruct([dirpath, '/romIDF']);
param.sim.weather = [dirpath, '/weatherTemplate.epw'];
train = csvread([dirpath, '/train.csv']);
fan_pwr=csvread([dirpath, '/fan_pwr_summer.csv']);
RTU_pwr=csvread([dirpath, '/RTU_pwr_summer.csv']);
fan_MF=csvread([dirpath, '/MF_summer.csv']);
MA_temp=csvread([dirpath, '/MA_Temp.csv']);
DX_pwr=RTU_pwr-fan_pwr; %Solve for just the DX power assuming all other power
consumption is negligible


runs=10;
MC=rand(runs,1);
starthour = 4537; endhour = 4705;

t=1;

%% Set Bounds
%Flow Pressure Gain test
Pnom_org=param.bldg.hvac.SF.Pnom;
Pnom_low=300;
Pnom_high=1200;
Pnom_test=(Pnom_low+Pnom_high)/2; %[pa]
Pnom_range=(Pnom_high-Pnom_low);

%Max Flow test
MdotMax_org=param.bldg.hvac.SF.MdotMax;
MdotMax_low=10;
MdotMax_high=30;
MdotMax_test=(MdotMax_low+MdotMax_high)/2; %[pa]
MdotMax_range=(MdotMax_high-MdotMax_low);

%Fan Effeciency test
Feff_org=param.bldg.hvac.SF.Feff;
Feff_low=.3;
Feff_high=1;
Feff_test=(Feff_low+Feff_high)/2; %[pa]
Feff_range=Feff_high-Feff_low;

%Total Cooling Capacity Test
DX1_org=param.bldg.hvac.DX1.Qrated;
DX2_org=param.bldg.hvac.DX2.Qrated;
DX_tot_org=DX1_org+DX2_org;
    %Current Total:534561, DX1=Total*.34, DX2=Total*.66
DX_tot_low=  300000;
DX_tot_high= 500000; %above 500k seems to crash.
DX_tot_range=(DX_tot_high-DX_tot_low);
DX_tot_test=(DX_tot_low+DX_tot_high)/2;

%Total Cooling Capacity Balance Test
```

```
DX1_org=param.bldg.hvac.DX1.Qrated;
DX2_org=param.bldg.hvac.DX2.Qrated;
DX_bal_org=.5; %Percentage to DX1
DX_tot_org=DX1_org+DX2_org;
    %Current Total:534561, DX1=Total*.34, DX2=Total*.66
DX_bal_low=.25;
DX_bal_high=.75;
DX_bal_range=(DX_bal_high-DX_bal_low);
DX_bal_test=(DX_bal_low+DX_bal_high)/2;

%DX 1 Sensible Heat Ratio test
SHRrated_org=param.bldg.hvac.DX1.SHRrated;
SHRrated_low=.7; %Below .6 the sim won't run
SHRrated_high=.87;
SHRrated_test=(SHRrated_low+SHRrated_high)/2;
SHRrated_range=(SHRrated_high-SHRrated_low);

%DX 1 Coeffecient of Performance test
COPrated_org=param.bldg.hvac.DX1.COPrated;
COPrated_low=1;
COPrated_high=5;
COPrated_test=(COPrated_low+COPrated_high)/2;
COPrated_range=(COPrated_high-COPrated_low);

%DX 2 Sensible Heat Ratio test
SHRrated_org=param.bldg.hvac.DX2.SHRrated;
SHRrated_low=.7; %Below .6 the sim won't run
SHRrated_high=.87;
SHRrated_test=(SHRrated_low+SHRrated_high)/2;
SHRrated_range=(SHRrated_high-SHRrated_low);

%DX 2 Coeffecient of Performance test
COPrated_org=param.bldg.hvac.DX2.COPrated;
COPrated_low=1;
COPrated_high=5;
COPrated_test=(COPrated_low+COPrated_high)/2;
COPrated_range=(COPrated_high-COPrated_low);



%% Monte Carlo Test
count=1;
for a=1:runs %Fan Nomial Pressure Gain

    if a>1
        param.bldg.hvac.SF.Pnom=Pnom_test+Pnom_range*(MC(a,1)-.5);
    end
    run_Pnom=param.bldg.hvac.SF.Pnom;


   for b=1:runs %Fan Max Flow
       if b>1
           param.bldg.hvac.SF.MdotMax=MdotMax_test+MdotMax_range*(MC(i,1)-
.5);
       end
```

```
        run_MdotMax=param.bldg.hvac.SF.MdotMax;

        for c=1:runs  %Fan Effeciency
            if c>1
                param.bldg.hvac.SF.Feff=Feff_test+Feff_range*(MC(i,1)-.5);
            end
            run_Feff=param.bldg.hvac.SF.Feff;

            for d=1:runs  %Total DX Balance
                if d>1
                    DX_bal=DX_bal_test+DX_bal_range*(MC(i,1)-.5)
                    param.bldg.hvac.DX1.Qrated=DX1_org*DX_bal;
                    param.bldg.hvac.DX2.Qrated=DX2_org*(1-DX_bal);
                else
                    DX_bal=DX_bal_org;
                end


                for e=1:runs %DX Balance total capacity
                    if e>1

param.bldg.hvac.DX1.Qrated=(DX_tot_test+DX_tot_range*(MC(i,1)-.5))*DX_bal;

param.bldg.hvac.DX2.Qrated=(DX_tot_test+DX_tot_range*(MC(i,1)-.5))*DX_bal;
                    end


run_DX_tot=param.bldg.hvac.DX1.Qrated+param.bldg.hvac.DX2.Qrated;


                    for f=1:runs %DX 1 SHR
                        if f>1

param.bldg.hvac.DX1.SHRrated=SHRrated_test+SHRrated_range*(MC(i,1)-.5);
                        end

                        run_SHR1rated=param.bldg.hvac.DX1.SHRrated;

                        for g=1:runs %DX 1 COP
                            if g>1

param.bldg.hvac.DX1.COPrated=COPrated_test+COPrated_range*(MC(i,1)-.5);
                            end
                            run_COP1rated=param.bldg.hvac.DX1.COPrated;

                            for h=1:runs % DX 2 SHR
                                if h>1

param.bldg.hvac.DX2.SHRrated=SHRrated_test+SHRrated_range*(MC(i,1)-.5);
                                end
                                run_SHR2rated=param.bldg.hvac.DX2.SHRrated;


                                for i=1:runs %DX 2 COP
```

```
                                    if i>1
param.bldg.hvac.DX2.COPrated=COPrated_test+COPrated_range*(MC(i,1)-.5);
                                    end
run_COP2rated=param.bldg.hvac.DX2.COPrated;

                                    try
                                        simROM_MC
                                    catch
                                        RMSE_FanPwr=0;
                                        RMSE_RTUPWR=0;
                                        RMSE_DXpwr=0;
                                        RMSE_Qsens=0;
                                    end




                                    %run values
                                    results(count,1) = run_Pnom;
                                    results(count,2) = run_MdotMax;
                                    results(count,3) = run_Feff;
                                    results(count,4) = DX_bal;
                                    results(count,5) = run_DX_tot;
                                    results(count,6) = run_SHR1rated;
                                    results(count,7) = run_COP1rated;
                                    results(count,8) = run_SHR2rated;
                                    results(count,9) = run_COP2rated;

                                    %Error Values
                                    results(count,10)= RMSE_FanPwr;
                                    results(count,11)= RMSE_RTUPWR;
                                    results(count,12)= RMSE_DXpwr;
                                    results(count,13)= RMSE_Qsens;

                                    count=count+1
                                    total=runs^9
                                end
                            end
                        end
                    end
                end
            end
        end
    end
end


save 'DX_MC_Big_1'
```

Appendix F: RTU Calibration Code

```
% Load ROM params and update weather file
dirpath = './Buildings/5p_Validation';
param = loadDataStruct([dirpath, '/romIDF']);
param.sim.weather = [dirpath, '/weatherTemplate.epw'];
train = csvread([dirpath, '/train.csv']);
fan_pwr=csvread([dirpath, '/fan_pwr_summer.csv']);
RTU_pwr=csvread([dirpath, '/RTU_pwr_summer.csv']);
fan_MF=csvread([dirpath, '/MF_summer.csv']);
MA_temp=csvread([dirpath, '/MA_Temp.csv']);
DX_pwr=RTU_pwr-fan_pwr; %Solve for just the DX power assuming all other power
consumption is negligible

Trial_time=8; %s/run
Est_run_time=12*60;%Min
runs=round(Est_run_time*60/Trial_time); %Set Est_run_time for the amount of
testing time desired

starthour = 4537; endhour = 4705;

t=1;

%% Set Bounds
%Flow Pressure Gain test
Pnom_org=param.bldg.hvac.SF.Pnom;
Pnom_low=500;
Pnom_high=700;
Pnom_test=(Pnom_low+Pnom_high)/2; %[pa]
Pnom_range=(Pnom_high-Pnom_low);
MC_1=rand(runs,1);

%Max Flow test
MdotMax_org=param.bldg.hvac.SF.MdotMax;
MdotMax_low=20;
MdotMax_high=25;
MdotMax_test=(MdotMax_low+MdotMax_high)/2; %[pa]
MdotMax_range=(MdotMax_high-MdotMax_low);
MC_2=rand(runs,1);

%Fan Effeciency test
Feff_org=param.bldg.hvac.SF.Feff;
Feff_low=.5;
Feff_high=.85;
Feff_test=(Feff_low+Feff_high)/2; %[pa]
Feff_range=Feff_high-Feff_low;
MC_3=rand(runs,1);

%Total Cooling Capacity Test
DX1_org=param.bldg.hvac.DX1.Qrated;
DX2_org=param.bldg.hvac.DX2.Qrated;
DX_tot_org=DX1_org+DX2_org;
    %Current Total:534561, DX1=Total*.34, DX2=Total*.66
DX_tot_low=  300000;
```

```
DX_tot_high= 450000; %above 500k seems to crash.
DX_tot_range=(DX_tot_high-DX_tot_low);
DX_tot_test=(DX_tot_low+DX_tot_high)/2;
MC_4=rand(runs,1);

%Total Cooling Capacity Balance Test
DX1_org=param.bldg.hvac.DX1.Qrated;
DX2_org=param.bldg.hvac.DX2.Qrated;
DX_bal_org=.5; %Percentage to DX1
DX_tot_org=DX1_org+DX2_org;
    %Current Total:534561, DX1=Total*.34, DX2=Total*.66
DX_bal_low=.3;
DX_bal_high=.45;
DX_bal_range=(DX_bal_high-DX_bal_low);
DX_bal_test=(DX_bal_low+DX_bal_high)/2;
MC_5=rand(runs,1);

%DX 1 Sensible Heat Ratio test
SHRrated_org=param.bldg.hvac.DX1.SHRrated;
SHRrated_low=.7; %Below .6 the sim won't run
SHRrated_high=.87;
SHRrated_test=(SHRrated_low+SHRrated_high)/2;
SHRrated_range=(SHRrated_high-SHRrated_low);
MC_6=rand(runs,1);

%DX 1 Coeffecient of Performance test
COPrated_org=param.bldg.hvac.DX1.COPrated;
COPrated_low=1;
COPrated_high=3;
COPrated_test=(COPrated_low+COPrated_high)/2;
COPrated_range=(COPrated_high-COPrated_low);
MC_7=rand(runs,1);

%DX 2 Sensible Heat Ratio test
SHRrated_org=param.bldg.hvac.DX2.SHRrated;
SHRrated_low=.7; %Below .6 the sim won't run
SHRrated_high=.87;
SHRrated_test=(SHRrated_low+SHRrated_high)/2;
SHRrated_range=(SHRrated_high-SHRrated_low);
MC_8=rand(runs,1);

%DX 2 Coeffecient of Performance test
COPrated_org=param.bldg.hvac.DX2.COPrated;
COPrated_low=1;
COPrated_high=3;
COPrated_test=(COPrated_low+COPrated_high)/2;
COPrated_range=(COPrated_high-COPrated_low);
MC_9=rand(runs,1);

results=zeros(runs,13);

for i=1:runs
    i
    runs
```

```
    if i>1
        param.bldg.hvac.SF.Pnom=Pnom_test+Pnom_range*(MC_1(i,1)-.5);
    end
    run_Pnom=param.bldg.hvac.SF.Pnom;

    if i>1
        param.bldg.hvac.SF.MdotMax=MdotMax_test+MdotMax_range*(MC_2(i,1)-.5);
    end
    run_MdotMax=param.bldg.hvac.SF.MdotMax;

    if i>1
        param.bldg.hvac.SF.Feff=Feff_test+Feff_range*(MC_3(i,1)-.5);
    end
    run_Feff=param.bldg.hvac.SF.Feff;

    if i>1
        DX_bal=DX_bal_test+DX_bal_range*(MC_4(i,1)-.5);
        param.bldg.hvac.DX1.Qrated=(DX_tot_test+DX_tot_range*(MC_5(i,1)-
.5))*DX_bal;
        param.bldg.hvac.DX2.Qrated=(DX_tot_test+DX_tot_range*(MC_5(i,1)-
.5))*(1-DX_bal);
    else
    DX_bal=DX_bal_org;
    end
    run_DX_tot=param.bldg.hvac.DX1.Qrated+param.bldg.hvac.DX2.Qrated;



    if i>1
        param.bldg.hvac.DX1.SHRrated=SHRrated_test+SHRrated_range*(MC_6(i,1)-
.5);
    end
    run_SHR1rated=param.bldg.hvac.DX1.SHRrated;

    if i>1
        param.bldg.hvac.DX1.COPrated=COPrated_test+COPrated_range*(MC_7(i,1)-
.5);
    end
    run_COP1rated=param.bldg.hvac.DX1.COPrated;

    if i>1
        param.bldg.hvac.DX2.SHRrated=SHRrated_test+SHRrated_range*(MC_8(i,1)-
.5);
    end
    run_SHR2rated=param.bldg.hvac.DX2.SHRrated;

    if i>1
        param.bldg.hvac.DX2.COPrated=COPrated_test+COPrated_range*(MC_9(i,1)-
.5);
    end
    run_COP2rated=param.bldg.hvac.DX2.COPrated;

    try
        simROM_MC
    catch
        RMSE_FanPwr=0;
```

```
        RMSE_RTUPWR=0;
        RMSE_DXpwr=0;
        RMSE_Qsens=0;
    end

    %run values
    results(i,1) = run_Pnom;
    results(i,2) = run_MdotMax;
    results(i,3) = run_Feff;
    results(i,4) = DX_bal;
    results(i,5) = run_DX_tot;
    results(i,6) = run_SHR1rated;
    results(i,7) = run_COP1rated;
    results(i,8) = run_SHR2rated;
    results(i,9) = run_COP2rated;
    %Error Values
    results(i,10)= RMSE_FanPwr;
    results(i,11)= RMSE_RTUPWR;
    results(i,12)= RMSE_DXpwr;
    results(i,13)= RMSE_Qsens;

end

save 'DX_MC_1_loop_1'
```

Appendix G: Process Steps

1) Initial Data Analysis
    a. Estimate OA ratio from damper position for each RTU
    b. Estimate flow rate from fan speed for each RTU
    c. Calculate mixed air conditions from outdoor air ratio, return air temperature and outdoor air temperature
        i. Use average of web temperature (when available and OA temperature)
        ii. Disregard outdoor air temperature when greater than 5 degrees F higher than web temperature
        iii. Outdoor air temperature will be most accurate when there is no solar effects. Otherwise, this represents a sol-air temperature.
    d. Calculate each RTU Zone Sensible loads (Qsens=m*cp*(Tda-Tzone)
    e. Build weather data
        i. https://www.ncdc.noaa.gov/cdo-web/datasets#LCD
        ii. Commercially available Reliable source for solar data
2. Building Modeling
    a. Build zone sensible load training input files (train.csv)
        i. Sum each zone sensible load over the hour
        ii. Need to match input data with their respective hour in the year totally 8760 hours in the year
    b. Build zone temperature training input file
        i. Average each RTU sensor zone
        ii. Need to match input data with their respective hour in the year totally 8760 hours in the year
    c. Build weather data
        i. Use NOAA website above for most weather data from a nearby weather station
        ii. Need to find a source of solar data to fill in the missing data from NOAA
        iii. Compile data into a .EPW file using elements software
            1. Can use a default EPW as a template and to fill in missing data with previous year's data
            2. Previous years data may not be technically accurate but it's better than nothing
    d. Estimate building physical properties
        i. Building physical properties would best be determined through a building audit however if this is not available or feasible alternatives are suggested
        ii. Estimate wall lengths from building drawings, satellite imagery (Google maps) or other sources.
        iii. Estimate building floor area
        iv. Estimate glazing area. If measurements are unavailable it is possible to use Google street view
        v. Estimate building orientation
        vi. Estimate initial RC network parameters
            1. Use ASHRAE 90.1 minimum construction specifications as reference for resistance values
        vii. Estimate building schedules

1. Lighting schedule from occupied hours and from customer questionnaire
2. Estimate occupancy from RTU CO2 sensor
3. Estimate appliances from user-provided information
4. Estimate infiltration from hours of operations
    a. Building occupancy schedule may work as well since as occupancy increases so does the use of doors

viii. Estimate building loads
1. Use baseline of 9.8 W/sqm for lighting loads
2. Determine peak occupancy through CO2 sensor
3. Determine appliances through audit or median of 190,000 Btu/sqft from (11)
4. Estimate infiltration

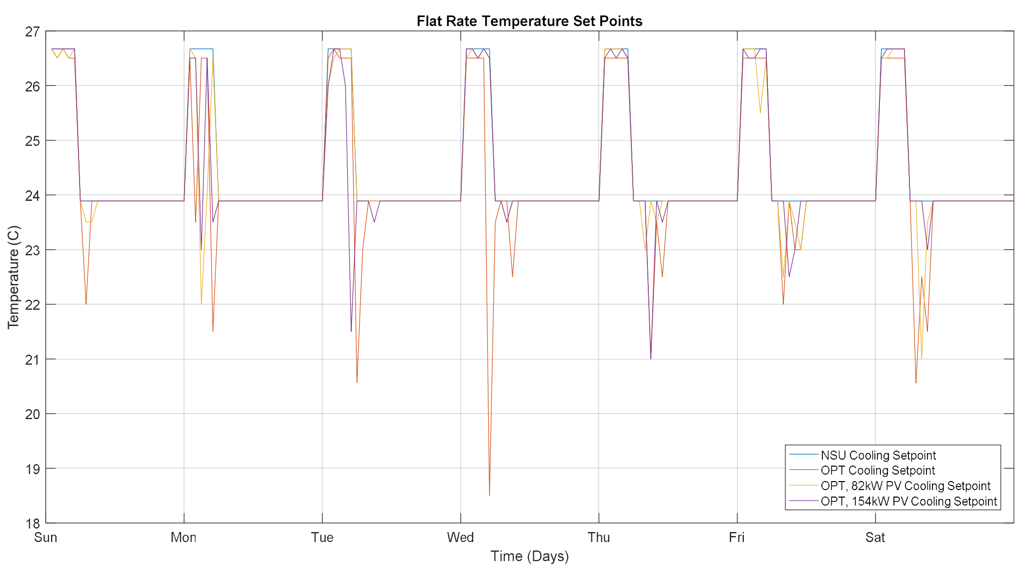
ix. Train reduced order model
1. Test RC network based on estimated values to establish starting RMSE
2. Train model parameters for new RC network parameters
3. Solve/update building internal loads based on minimizing RMSE
    a. Appliance load peak
    b. Occupancy peak
    c. Appliance convective fraction
    d. Infiltration
4. Train RC parameters again based on best internal gains
5. Repeat steps 3 and 4 until lowest possible RMSE is obtained

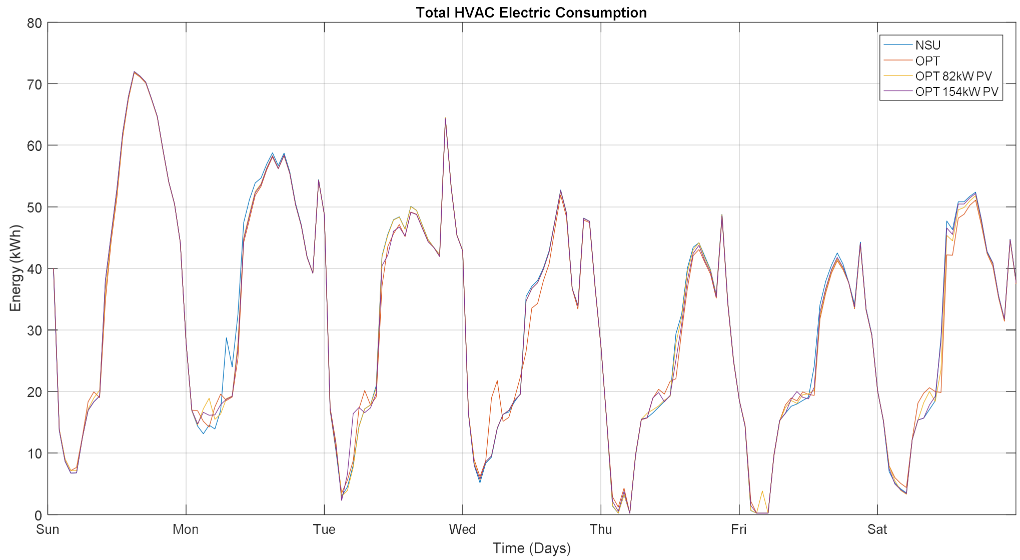
3. Model RTU Zones
    a. Use the RC network that was trained in step 2
    b. Compile individual zone sensible loads into hourly input data for the year (train.csv)
    c. Use Monte Carlo simulations to solve for R3 and the zone area
    d. Update zone internal gains as necessary for each zone using Monte Carlo simulations
4. Implementing MPC Controller
    a. Use the model or utility to determine the peak demand load for the month and simulate potential reduction
    b. Use the determined peak demand loads to set threshold of peak demand either at simulated MPC reduced peak demand load or at the utility charged peak demand less the percentage reduced in the simulation
    c. Monitor model to ensure the calibration remains accurate.

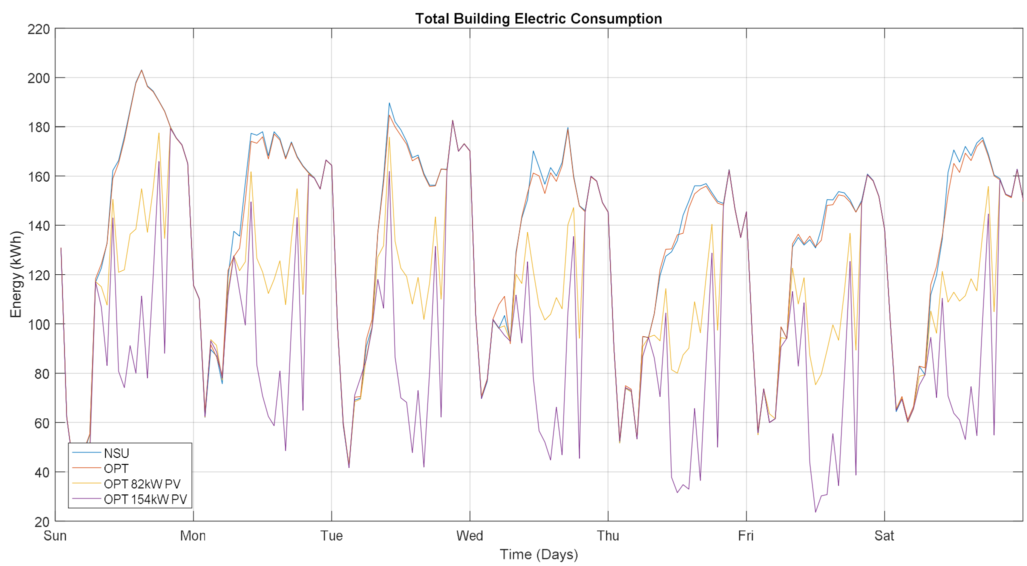
Appendix H: Trial Weekly Charts

Energy Optimization Testing

	T1_NSU	T1	T1_82PV_NSU	T1_82PV	T1_154PV_NSU	T1_154PV
Test Title	Flat Rate	Flat Rate	Flat Rate	Flat Rate	Flat Rate	Flat Rate
Demand Charge ($)	$ 4,425.40	$ 4,415.27	$ 4,419.99	$ 4,412.67	$ 4,415.22	$ 4,409.80
Mid Peak Charge ($)	$ 696.69	$ 695.89	$ 608.98	$ 608.77	$ 569.01	$ 569.01
On Peak Charge ($)	$ 3,538.32	$ 3,534.24	$ 3,092.81	$ 3,091.79	$ 2,889.83	$ 2,889.83
Total Demand Charge ($)	$ 8,660.41	$ 8,645.40	$ 8,121.78	$ 8,113.23	$ 7,874.06	$ 7,868.64
TOU Charge ($)	$ 1,887.23	$ 1,881.93	$ 1,605.37	$ 1,602.33	$ 1,343.92	$ 1,340.98
Total Cost ($)	$ 10,547.64	$ 10,527.33	$ 9,727.16	$ 9,715.56	$ 9,217.99	$ 9,209.62
Peak Demand (kW)	248.48	247.91	248.17	247.76	247.91	247.60
Mid-Peak Demand (kW)	203.12	202.88	177.54	177.49	165.89	165.89
On-Peak Demand (kW)	203.12	202.88	177.54	177.49	165.89	165.89
Energy Usage (kWh)	25,887.97	25,815.20	22,021.60	21,979.81	18,435.17	18,394.82
Ramping (kW)	2,523.74	2,473.60	3,716.73	3,698.51	5,536.13	5,506.78
Peak to Valley Ratio	5.33	5.33	4.33	4.32	6.73	6.79
Load Factor	0.54	0.54	0.46	0.46	0.39	0.39
Carbon (Lbs CO2)	15,408.02	15,380.55	13,318.60	13,299.33	11,382.28	11,363.83
Energy Savings from NSU (kWh)		72.77		41.79		40.35
Cost Savings ($)		20.31		11.60		8.36
% Energy Saving from NSU		0%		0%		0%



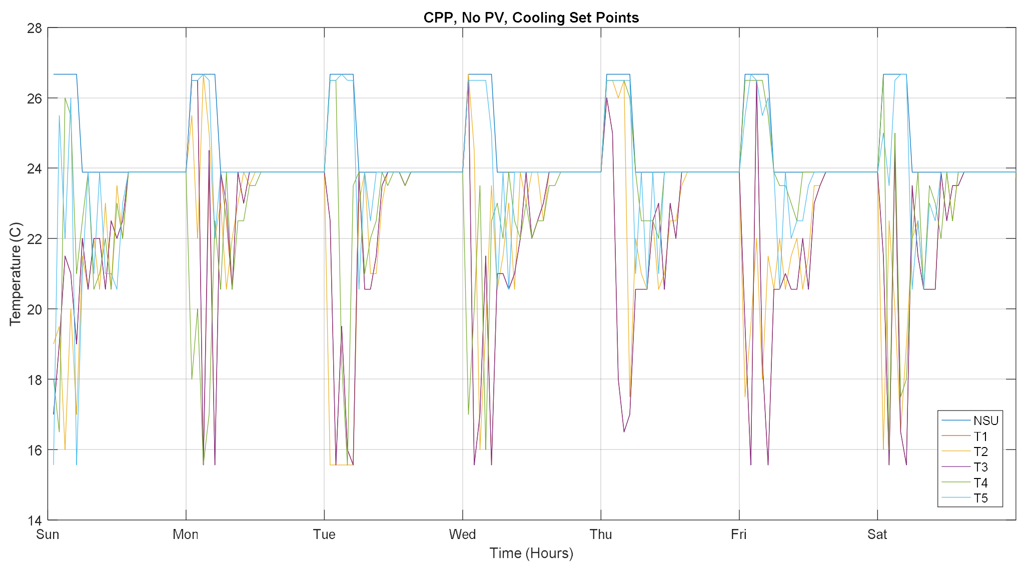

Total HVAC Electric Consumption
NSU
OPT
OPT 82kW PV
OPT 154kW PV
Energy (kWh)
0
10
20
30
40
50
60
70
80
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Days)

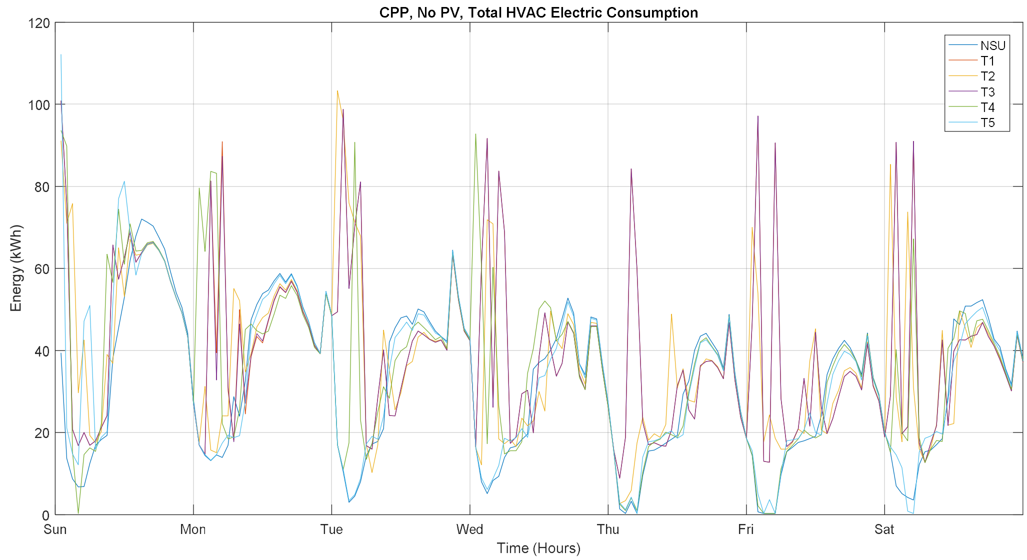

Total Building Electric Consumption
NSU
OPT
OPT 82kW PV
OPT 154kW PV
Energy (kWh)
20
40
60
80
100
120
140
160
180
200
220
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Days)

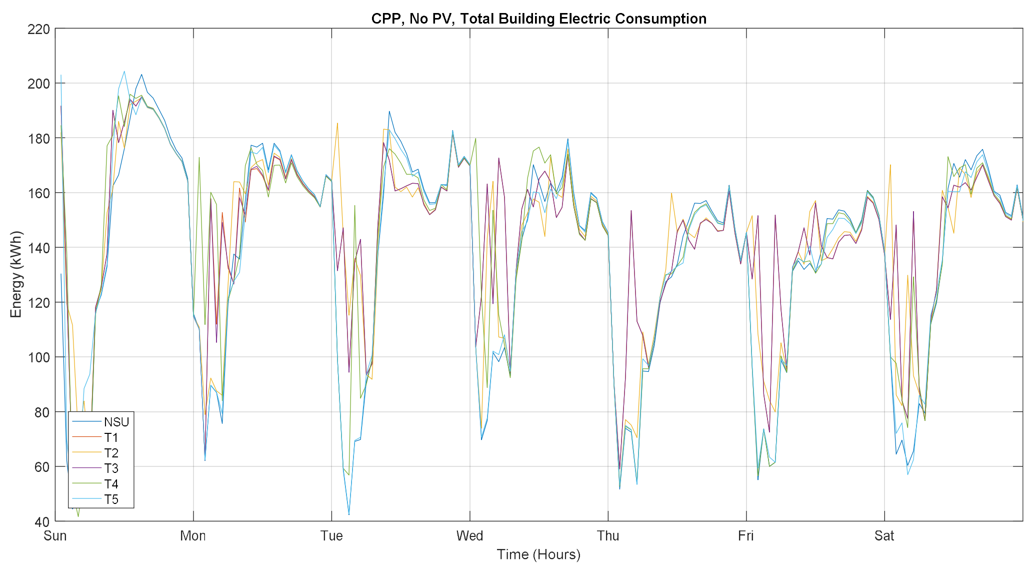
Energy Cost Testing

No PV

Results	T2a_NSU	T2a_T1	T2a_T2	T2a_T3	T2a_T4	T2a_T5
Test Title	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing
Demand Charge ($)	$ 4,425.36	$ 4,345.42	$ 4,350.27	$ 4,345.42	$ 4,333.92	$ 4,343.52
Mid Peak Charge ($)	$ 852.27	$ 836.88	$ 837.81	$ 836.88	$ 834.66	$ 836.51
On Peak Charge ($)	$ 3,538.32	$ 3,395.86	$ 3,390.42	$ 3,395.86	$ 3,412.50	$ 3,392.82
Total Demand Charge ($)	$ 8,815.95	$ 8,578.16	$ 8,578.50	$ 8,578.16	$ 8,581.09	$ 8,572.85
TOU Charge ($)	$ 1,929.42	$ 2,018.60	$ 1,997.50	$ 2,018.25	$ 1,996.37	$ 1,937.84
Total Cost ($)	$ 10,745.38	$ 10,596.77	$ 10,576.00	$ 10,596.42	$ 10,577.45	$ 10,510.69
Peak Demand (kW)	248.48	243.99	244.26	243.99	243.34	243.88
Mid-Peak Demand (kW)	248.48	243.99	244.26	243.99	243.34	243.88
On-Peak Demand (kW)	203.12	194.94	194.63	194.94	195.90	194.77
Energy Usage (kWh)	25,883.81	27,581.90	27,191.32	27,573.84	27,098.29	26,097.92
Ramping (kW)	2,525.21	3,361.07	2,914.58	3,357.16	2,970.04	2,558.76
Peak to Valley Ratio	5.33	5.28	5.29	5.28	5.27	5.28
Load Factor	0.54	0.59	0.58	0.59	0.58	0.56
Carbon (Lbs CO2)	15,405.00	16,832.75	16,517.29	16,824.87	16,391.83	15,606.83
Energy Savings from NSU (increase) (kWh)		(1,698.09)	(1,307.51)	(1,690.03)	(1,214.48)	(214.11)
Total Cost Savings (increase) ($)		148.61	169.38	148.96	167.92	234.69
% Energy Change from NSU		7%	5%	7%	5%	1%
Time of Use Cost Savings (Increase) ($/week)		$ (89.18)	$ (68.08)	$ (88.83)	$ (66.94)	$ (8.42)
Demand Cost Savings (increase) ($/month)		$ 237.79	$ 237.45	$ 237.79	$ 234.87	$ 243.10
Carbon Savings (increase) (Lbs CO2)		(1,427.75)	(1,112.29)	(1,419.87)	(986.84)	(201.83)
% Change Ramping		33%	15%	33%	18%	1%
% Change Peak to Valley Ratio		-1%	-1%	-1%	-1%	-1%
% Change Load Factor		9%	7%	8%	7%	3%
% Change Peak Demand		-2%	-2%	-2%	-2%	-2%

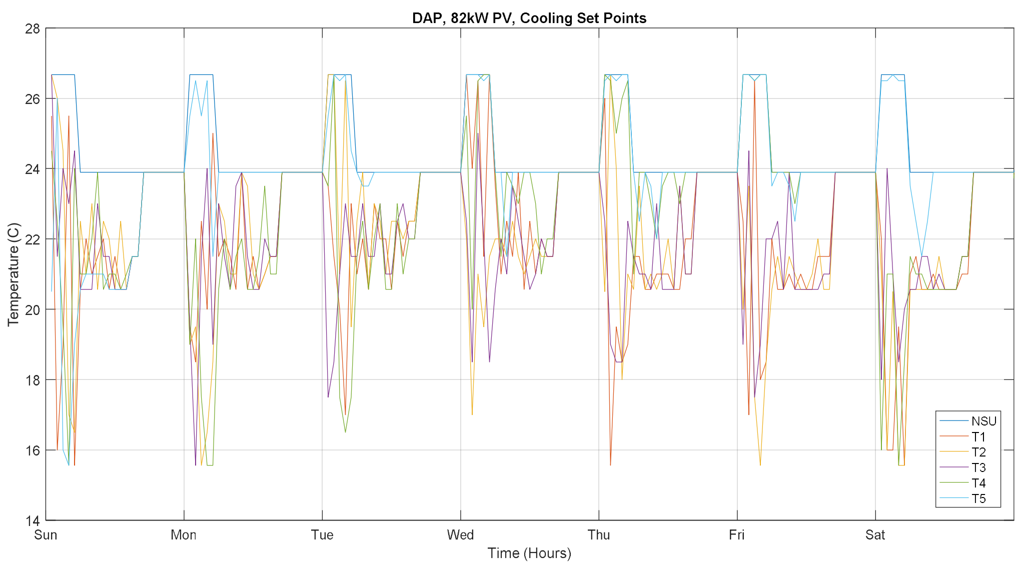


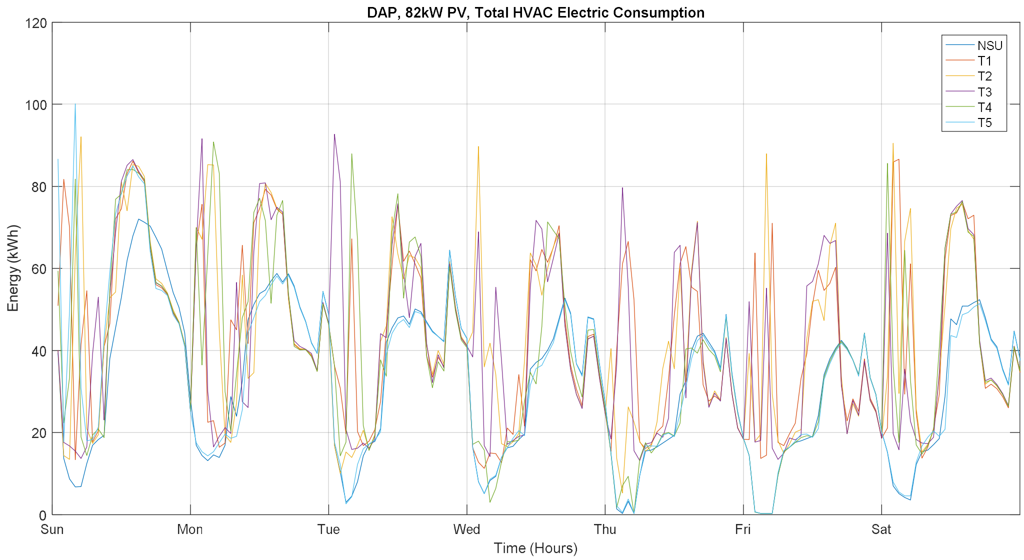

CPP, No PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Hours)
0
20
40
60
80
100
120
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3
T4
T5

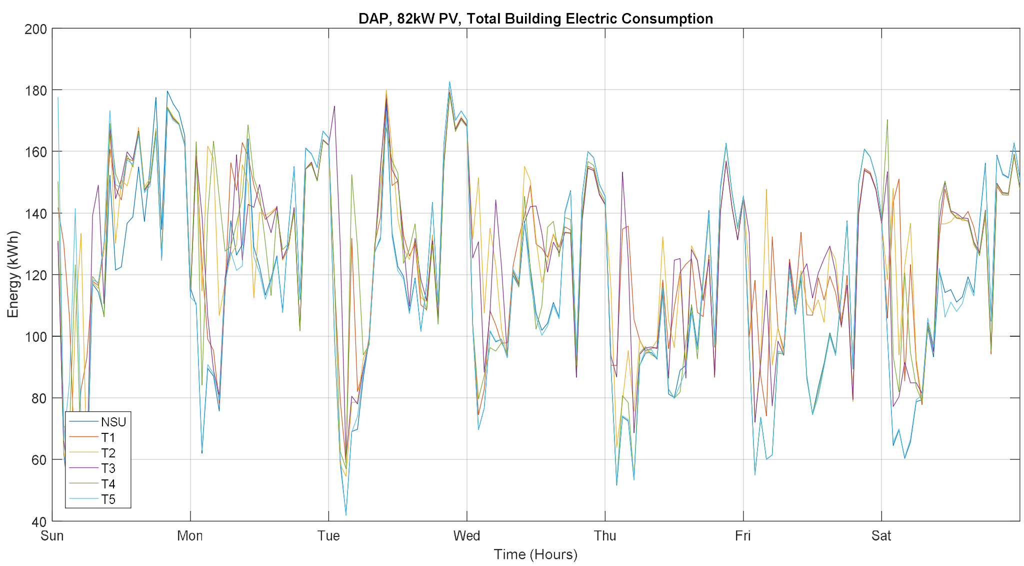

CPP, No PV, Total Building Electric Consumption
Energy (kWh)
Time (Hours)
40
60
80
100
120
140
160
180
200
220
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3
T4
T5

82kW PV System

Results	T2a_82PV_NSU	T2a_82PV_T1	T2a_82PV_T2	T2a_82PV_T3	T2a_82PV_T4	T2a_82PV_T5
Test Title	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing
Demand Charge ($)	$ 4,419.83	$ 4,283.71	$ 4,283.45	$ 4,283.71	$ 4,256.69	$ 4,256.92
Mid Peak Charge ($)	$ 851.21	$ 824.99	$ 824.94	$ 824.99	$ 819.79	$ 819.83
On Peak Charge ($)	$ 3,092.81	$ 2,886.18	$ 2,895.32	$ 2,886.18	$ 2,889.61	$ 2,891.33
Total Demand Charge ($)	$ 8,363.85	$ 7,994.88	$ 8,003.72	$ 7,994.88	$ 7,966.09	$ 7,968.09
TOU Charge ($)	$ 1,607.35	$ 1,741.00	$ 1,739.09	$ 1,749.14	$ 1,722.95	$ 1,624.17
Total Cost ($)	$ 9,971.20	$ 9,735.88	$ 9,742.80	$ 9,744.02	$ 9,689.04	$ 9,592.26
Peak Demand (kW)	248.17	240.52	240.51	240.52	239.01	239.02
Mid-Peak Demand (kW)	248.17	240.52	240.51	240.52	239.01	239.02
On-Peak Demand (kW)	177.54	165.68	166.21	165.68	165.88	165.98
Energy Usage (kWh)	22,007.07	24,009.59	23,931.97	24,115.62	23,842.89	22,347.31
Ramping (kW)	3,721.48	3,682.92	3,927.31	3,636.39	3,812.56	3,804.55
Peak to Valley Ratio	4.38	3.48	3.45	3.48	3.25	4.44
Load Factor	0.46	0.52	0.52	0.52	0.52	0.49
Carbon (Lbs CO2)	13,307.97	14,778.06	14,710.65	14,857.12	14,710.87	13,573.63
Energy Savings from NSU (increase) (kWh)		(2,002.52)	(1,924.90)	(2,108.55)	(1,835.83)	(340.24)
Total Cost Savings (increase) ($)		235.33	228.40	227.19	282.16	378.95
% Energy Change from NSU		9%	9%	10%	8%	2%
Time of Use Cost Savings (Increase) ($/week)		$ (133.65)	$ (131.74)	$ (141.79)	$ (115.60)	$ (16.82)
Additional Metrics						
Demand Cost Savings (increase) ($/month)		$ 368.98	$ 360.14	$ 368.98	$ 397.76	$ 395.77

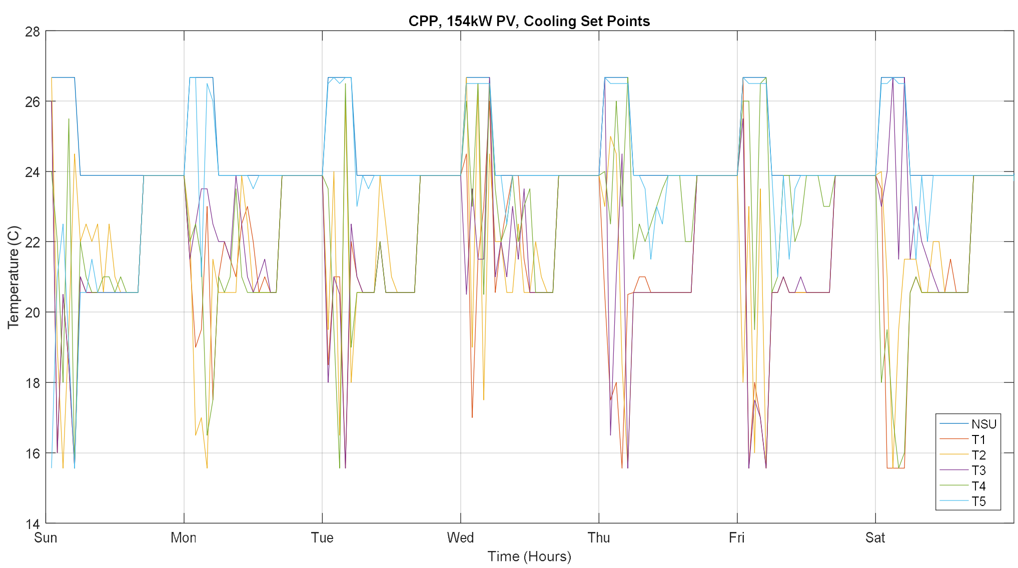


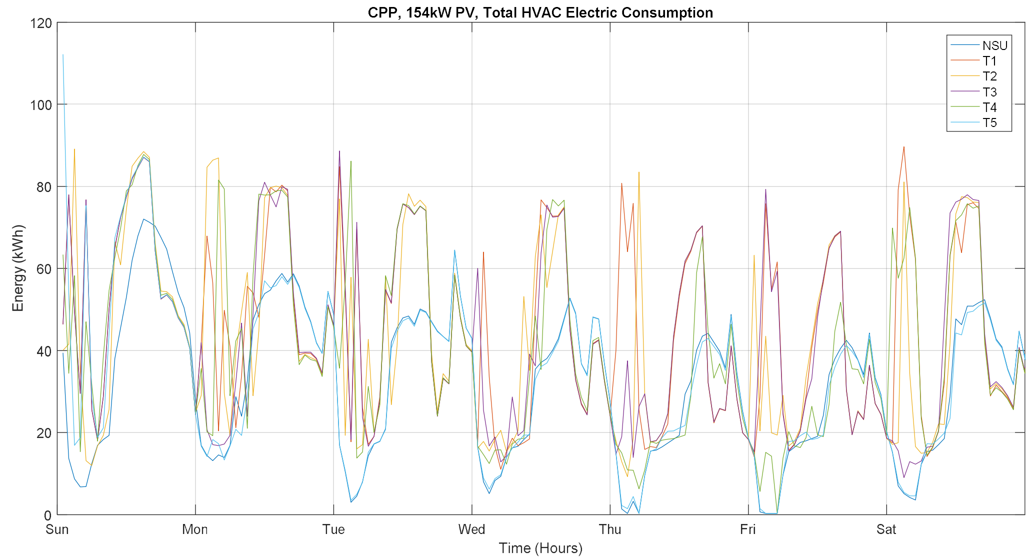

DAP, 82kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
0
20
40
60
80
100
120
NSU
T1
T2
T3
T4
T5

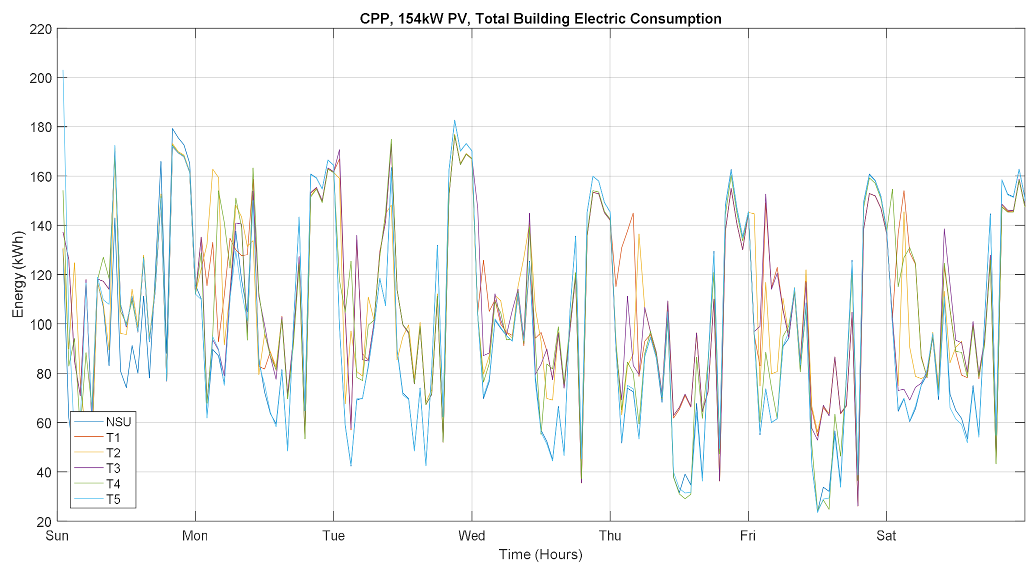

DAP, 82kW PV, Total Building Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
40
60
80
100
120
140
160
180
200
NSU
T1
T2
T3
T4
T5

154kW PV System

Results	T2a_154PV_NSU	T2a_154PV_T1	T2a_154PV_T2	T2a_154PV_T3	T2a_154PV_T4	T2a_154PV_T5
Test Title	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing	CPP Pricing
Demand Charge ($)	$ 4,415.04	$ 4,162.39	$ 4,162.34	$ 4,162.41	$ 4,162.35	$ 4,168.14
Mid Peak Charge ($)	$ 850.29	$ 801.63	$ 801.62	$ 801.63	$ 801.62	$ 802.74
On Peak Charge ($)	$ 2,889.83	$ 2,627.92	$ 2,662.00	$ 2,627.92	$ 2,643.66	$ 2,630.31
Total Demand Charge ($)	$ 8,155.16	$ 7,591.94	$ 7,625.95	$ 7,591.96	$ 7,607.63	$ 7,601.19
TOU Charge ($)	$ 1,308.12	$ 1,496.63	$ 1,485.35	$ 1,469.61	$ 1,442.92	$ 1,346.74
Total Cost ($)	$ 9,463.28	$ 9,088.57	$ 9,111.30	$ 9,061.57	$ 9,050.55	$ 8,947.93
Peak Demand (kW)	247.90	233.71	233.71	233.71	233.71	234.03
Mid-Peak Demand (kW)	247.90	233.71	233.71	233.71	233.71	234.03
On-Peak Demand (kW)	165.89	150.86	152.81	150.86	151.76	150.99
Energy Usage (kWh)	18,416.88	21,198.50	21,019.17	20,737.69	20,450.06	19,113.15
Ramping (kW)	5,541.32	5,164.38	5,475.20	5,316.75	5,327.52	5,589.81
Peak to Valley Ratio	6.73	5.87	5.82	5.84	6.55	6.84
Load Factor	0.39	0.47	0.47	0.46	0.46	0.43
Carbon (Lbs CO2)	11,368.94	13,402.16	13,536.39	13,012.07	12,843.70	11,889.23
Energy Savings from NSU (increase) (kWh)		(2,781.63)	(2,602.30)	(2,320.81)	(2,033.18)	(696.28)
Total Cost Savings (increase) ($)		374.71	351.98	401.71	412.73	515.35
% Energy Change from NSU		15%	14%	13%	11%	4%
Time of Use Cost Savings (Increase) ($/week)		$ (188.51)	$ (177.23)	$ (161.48)	$ (134.80)	$ (38.62)
Additional Metrics						
Demand Cost Savings (increase) ($/month)		$ 563.22	$ 529.20	$ 563.19	$ 547.52	$ 553.97
Carbon Savings (increase) (Lbs CO2)		(2,033.23)	(2,167.45)	(1,643.14)	(1,474.77)	(520.30)
% Change Ramping		-7%	-1%	-4%	-4%	1%
% Change Peak to Valley Ratio		-13%	-14%	-13%	-3%	2%
% Change Load Factor		22%	21%	19%	18%	10%
% Change Peak Demand		-6%	-6%	-6%	-6%	-6%



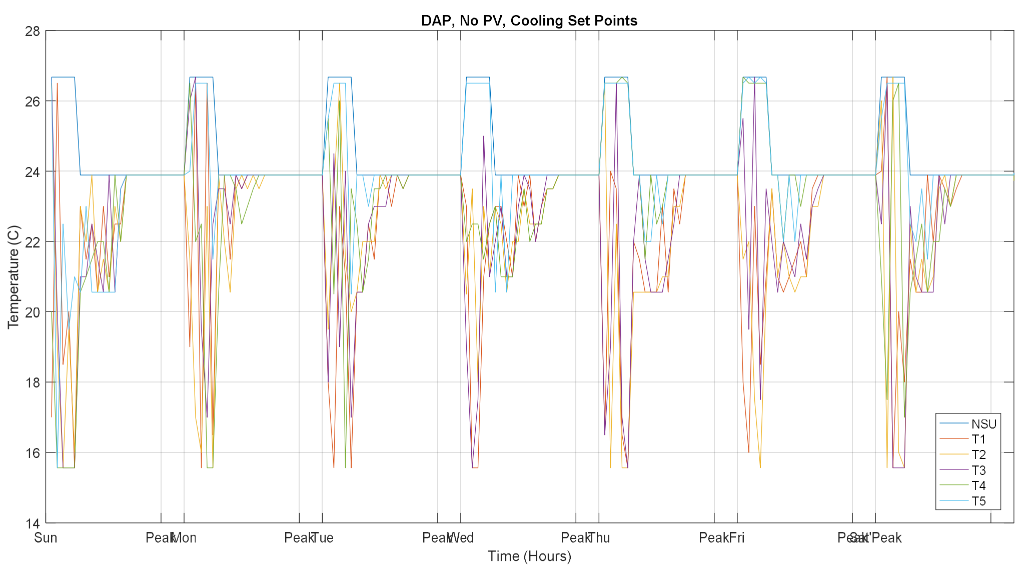

CPP, 154kW PV, Total HVAC Electric Consumption
Energy (kWh)
0
20
40
60
80
100
120
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Hours)
NSU
T1
T2
T3
T4
T5

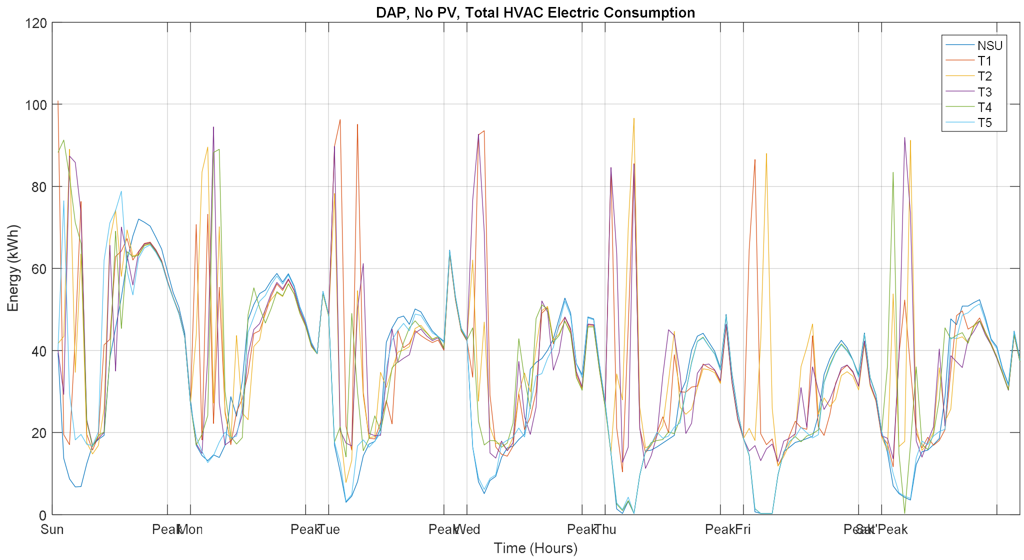

CPP, 154kW PV, Total Building Electric Consumption
Energy (kWh)
20
40
60
80
100
120
140
160
180
200
220
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Hours)
NSU
T1
T2
T3
T4
T5

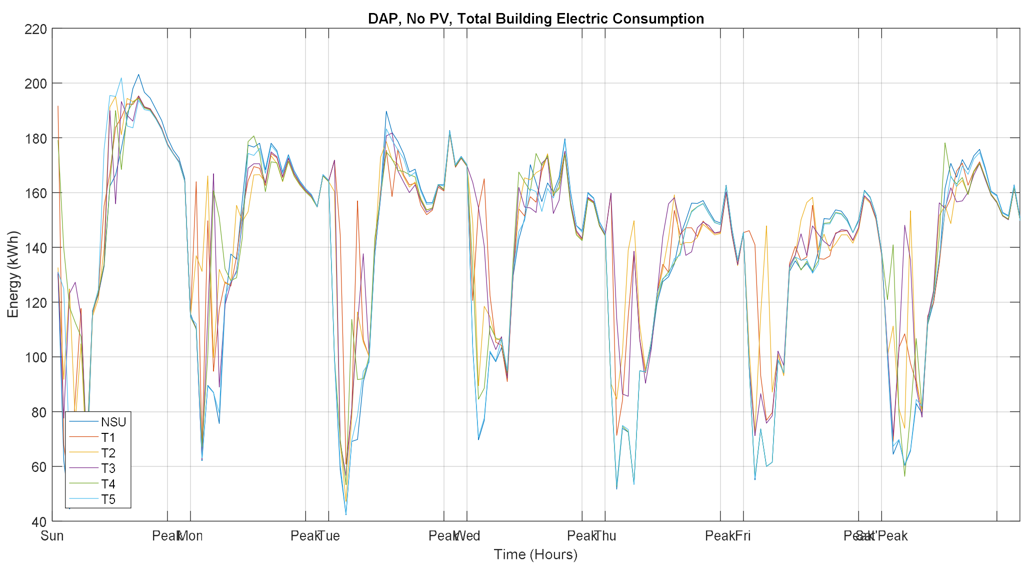
Day Ahead Energy Pricing

No PV Case

Results	T2b_NSU	T2b_T1	T2b_T2	T2b_T3	T2b_T4	T2b_T5
Test Title	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing
Demand Charge ($)	$ 4,425.37	$ 4,352.85	$ 4,360.71	$ 4,349.91	$ 4,336.06	$ 4,342.04
Mid Peak Charge ($)	$ 852.28	$ 838.31	$ 839.82	$ 837.74	$ 835.08	$ 836.23
On Peak Charge ($)	$ 3,538.32	$ 3,401.92	$ 3,389.33	$ 3,399.05	$ 3,385.10	$ 3,373.28
Total Demand Charge ($)	$ 8,815.96	$ 8,593.07	$ 8,589.86	$ 8,586.70	$ 8,556.23	$ 8,551.55
TOU Charge ($)	$ 1,712.12	$ 1,786.84	$ 1,779.55	$ 1,777.07	$ 1,762.76	$ 1,719.75
Total Cost ($)	$ 10,528.08	$ 10,379.91	$ 10,369.41	$ 10,363.77	$ 10,319.00	$ 10,271.30
Peak Demand (kW)	248.48	244.40	244.85	244.24	243.46	243.80
Mid-Peak Demand (kW)	248.48	244.40	244.85	244.24	243.46	243.80
On-Peak Demand (kW)	203.12	195.29	194.57	195.12	194.32	193.64
Energy Usage (kWh)	25,884.25	27,361.55	27,251.73	27,198.32	26,875.04	26,069.82
Ramping (kW)	2,525.17	3,156.20	3,068.61	3,148.81	2,791.38	2,489.28
Peak to Valley Ratio	5.33	5.29	5.29	5.29	5.28	5.28
Load Factor	0.54	0.58	0.58	0.58	0.57	0.56
Carbon (Lbs CO2)	15,405.32	16,632.39	16,558.58	16,508.12	16,244.61	15,577.96
Energy Savings from NSU (increase) (kWh)		(1,477.29)	(1,367.47)	(1,314.06)	(990.79)	(185.56)
Total Cost Savings (increase) ($)		148.17	158.67	164.31	209.09	256.78
% Energy Change from NSU		6%	5%	5%	4%	1%
Time of Use Cost Savings (Increase) ($/week)		$ (74.72)	$ (67.43)	$ (64.95)	$ (50.65)	$ (7.63)
Additional Metrics						
Demand Cost Savings (increase) ($/month)		$ 222.89	$ 226.10	$ 229.26	$ 259.73	$ 264.41

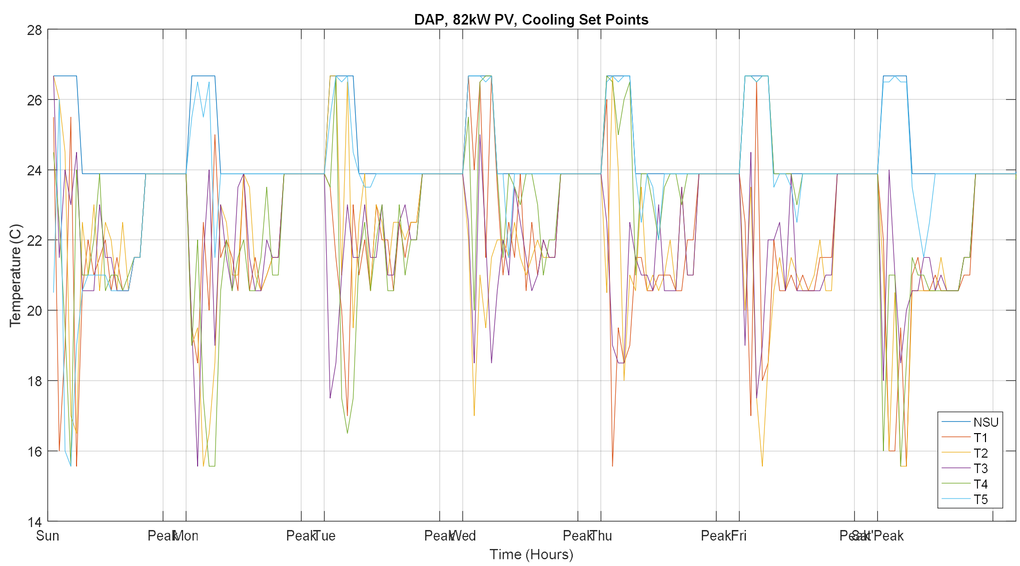


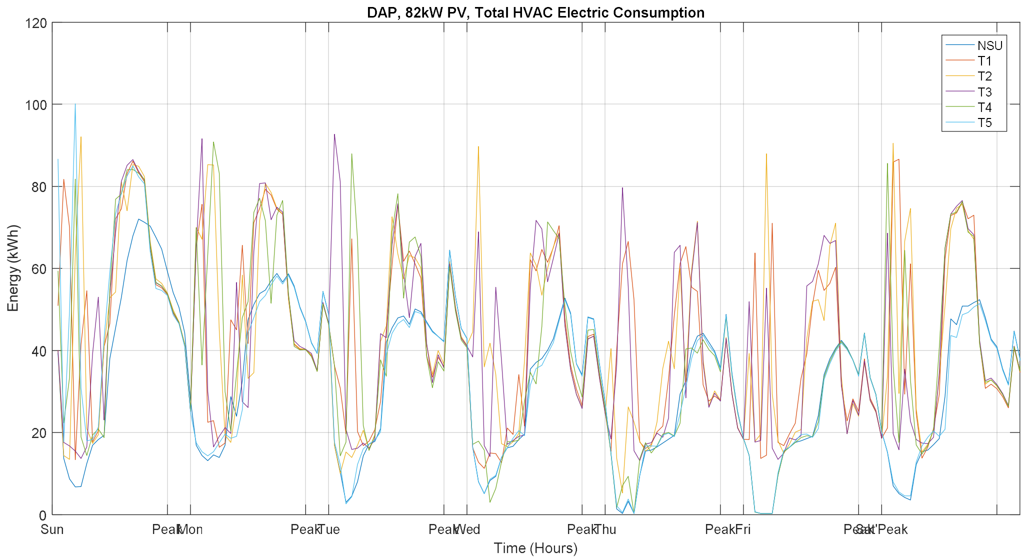

DAP, No PV, Total HVAC Electric Consumption
NSU
T1
T2
T3
T4
T5
Energy (kWh)
0
20
40
60
80
100
120
Sun
Peak
Mon
Peak
Tue
Peak
Wed
Peak
Thu
Peak
Fri
Peak
Sat
Peak
Time (Hours)

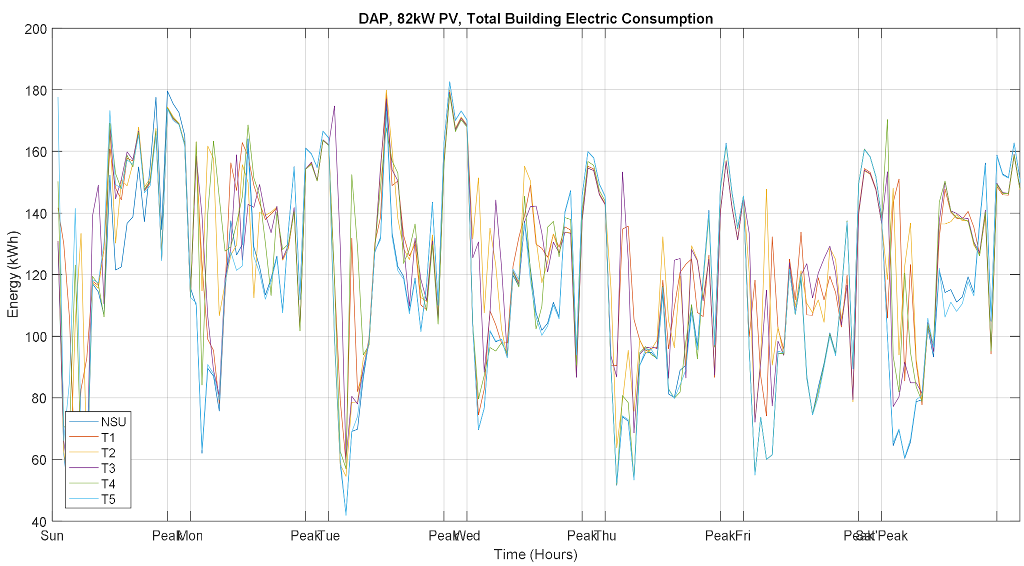

DAP, No PV, Total Building Electric Consumption
NSU
T1
T2
T3
T4
T5
Energy (kWh)
40
60
80
100
120
140
160
180
200
220
Sun
Peak
Mon
Peak
Tue
Peak
Wed
Peak
Thu
Peak
Fri
Peak
Sat
Peak
Time (Hours)

82kW Case

Results	T2b_82PV_NSU	T2b_82PV_T1	T2b_82PV_T2	T2b_82PV_T3	T2b_82PV_T4	T2b_82PV_T5
Test Title	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing
Demand Charge ($)	$ 4,419.83	$ 4,284.99	$ 4,277.42	$ 4,263.13	$ 4,268.85	$ 4,271.74
Mid Peak Charge ($)	$ 851.21	$ 825.24	$ 823.78	$ 821.03	$ 822.13	$ 822.69
On Peak Charge ($)	$ 3,092.81	$ 2,896.29	$ 2,923.65	$ 2,886.67	$ 2,901.41	$ 2,879.64
Total Demand Charge ($)	$ 8,363.85	$ 8,006.52	$ 8,024.84	$ 7,970.83	$ 7,992.38	$ 7,974.07
TOU Charge ($)	$ 1,453.50	$ 1,565.08	$ 1,564.74	$ 1,581.00	$ 1,537.39	$ 1,473.09
Total Cost ($)	$ 9,817.34	$ 9,571.59	$ 9,589.59	$ 9,551.83	$ 9,529.77	$ 9,447.16
Peak Demand (kW)	248.17	240.59	240.17	239.37	239.69	239.85
Mid-Peak Demand (kW)	248.17	240.59	240.17	239.37	239.69	239.85
On-Peak Demand (kW)	177.54	166.26	167.83	165.71	166.56	165.31
Energy Usage (kWh)	22,007.07	24,094.78	24,105.56	24,396.57	23,572.92	22,384.23
Ramping (kW)	3,721.30	3,590.13	3,949.06	4,118.32	3,940.07	3,837.65
Peak to Valley Ratio	4.39	3.18	3.54	2.98	3.31	4.36
Load Factor	0.46	0.52	0.52	0.53	0.51	0.49
Carbon (Lbs CO2)	13,307.96	14,826.17	14,842.25	15,081.54	14,480.37	13,619.93
Energy Savings from NSU (increase) (kWh)		(2,087.71)	(2,098.49)	(2,389.50)	(1,565.85)	(377.17)
Total Cost Savings (increase) ($)		245.75	227.76	265.51	287.57	370.18
% Energy Change from NSU		9%	10%	11%	7%	2%
Time of Use Cost Savings (Increase) ($/week)		$ (111.58)	$ (111.25)	$ (127.50)	$ (83.89)	$ (19.59)
Demand Cost Savings (increase) ($/month)		$ 357.33	$ 339.00	$ 393.02	$ 371.47	$ 389.78

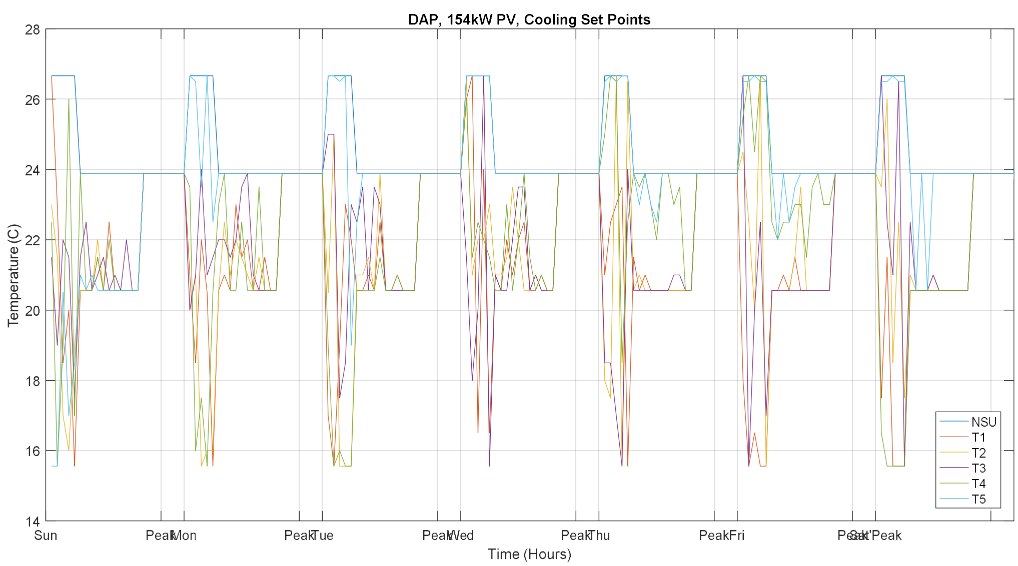


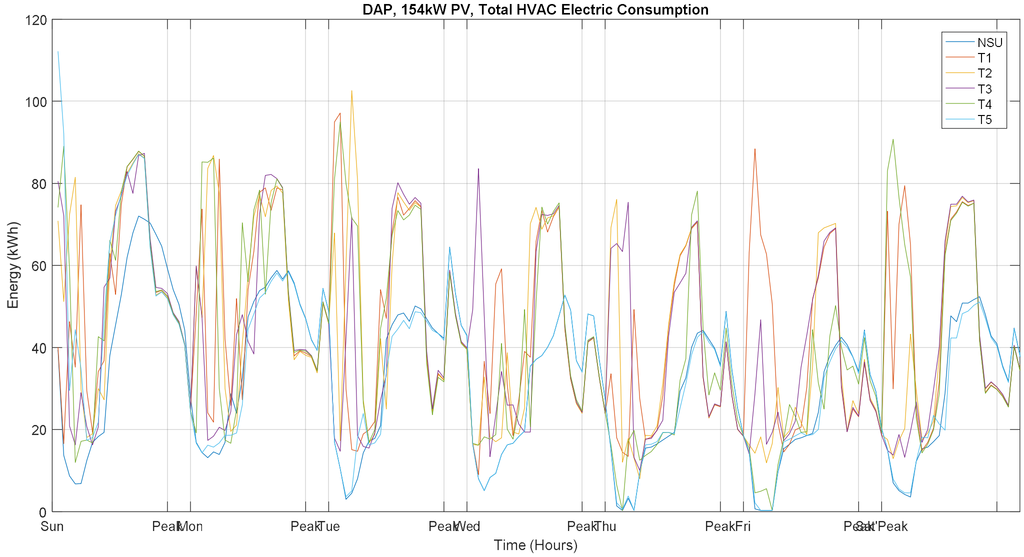

DAP, 82kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Peak
Mon
Peak
Tue
Peak
Wed
Peak
Thu
Peak
Fri
Peak
Sat
Peak
NSU
T1
T2
T3
T4
T5

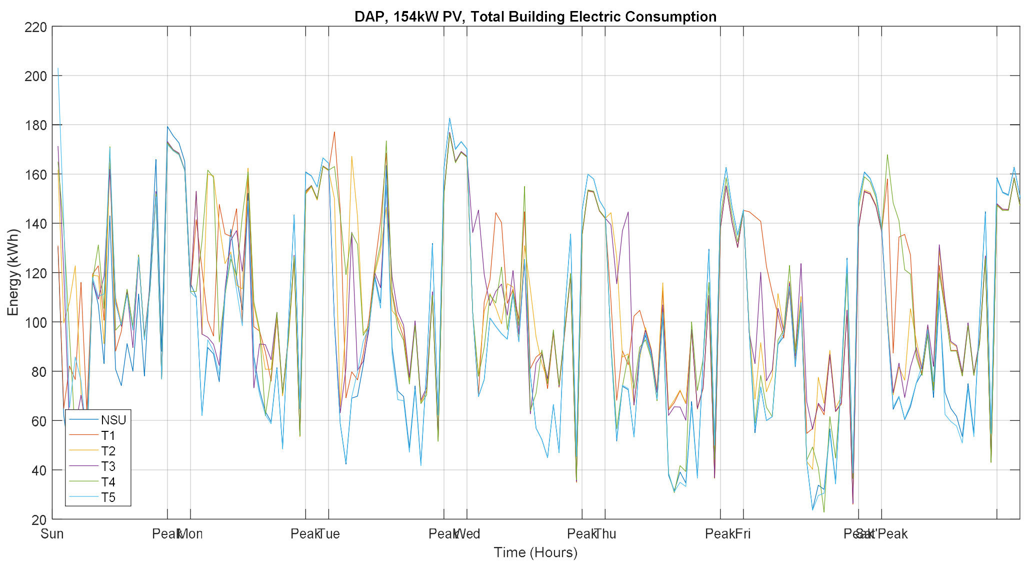

DAP, 82kW PV, Total Building Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Peak
Mon
Peak
Tue
Peak
Wed
Peak
Thu
Peak
Fri
Peak
Sat
Peak
NSU
T1
T2
T3
T4
T5

145kW Case

Results	T2b_154PV_NSU	T2b_154PV_T1	T2b_154PV_T2	T2b_154PV_T3	T2b_154PV_T4	T2b_154PV_T5
Test Title	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing	DA Pricing
Demand Charge ($)	$ 4,415.03	$ 4,162.38	$ 4,162.39	$ 4,162.33	$ 4,162.32	$ 4,167.53
Mid Peak Charge ($)	$ 850.28	$ 801.63	$ 801.63	$ 801.62	$ 801.61	$ 802.62
On Peak Charge ($)	$ 2,889.83	$ 2,643.46	$ 2,632.48	$ 2,642.96	$ 2,646.41	$ 2,628.14
Total Demand Charge ($)	$ 8,155.15	$ 7,607.47	$ 7,596.51	$ 7,606.90	$ 7,610.34	$ 7,598.29
TOU Charge ($)	$ 1,213.77	$ 1,359.24	$ 1,347.72	$ 1,347.59	$ 1,339.58	$ 1,253.95
Total Cost ($)	$ 9,368.92	$ 8,966.71	$ 8,944.23	$ 8,954.50	$ 8,949.92	$ 8,852.24
Peak Demand (kW)	247.90	233.71	233.71	233.71	233.71	234.00
Mid-Peak Demand (kW)	247.90	233.71	233.71	233.71	233.71	234.00
On-Peak Demand (kW)	165.89	151.75	151.12	151.72	151.92	150.87
Energy Usage (kWh)	18,416.72	21,136.58	20,913.47	20,921.21	20,755.77	19,169.53
Ramping (kW)	5,541.55	5,213.32	5,221.95	5,205.97	5,254.93	5,445.86
Peak to Valley Ratio	6.73	5.88	5.49	5.73	6.95	6.80
Load Factor	0.39	0.47	0.47	0.47	0.46	0.43
Carbon (Lbs CO2)	11,368.83	13,340.43	13,187.45	13,162.30	13,088.70	11,944.58
Energy Savings from NSU (increase) (kWh)		(2,719.85)	(2,496.75)	(2,504.49)	(2,339.05)	(752.80)
Total Cost Savings (increase) ($)		402.21	424.69	414.42	419.00	516.68
% Energy Change from NSU		15%	14%	14%	13%	4%
Time of Use Cost Savings (Increase) ($/week)		$ (145.47)	$ (133.95)	$ (133.82)	$ (125.81)	$ (40.18)
Demand Cost Savings (increase) ($/month)		$ 547.68	$ 558.64	$ 548.25	$ 544.81	$ 556.86

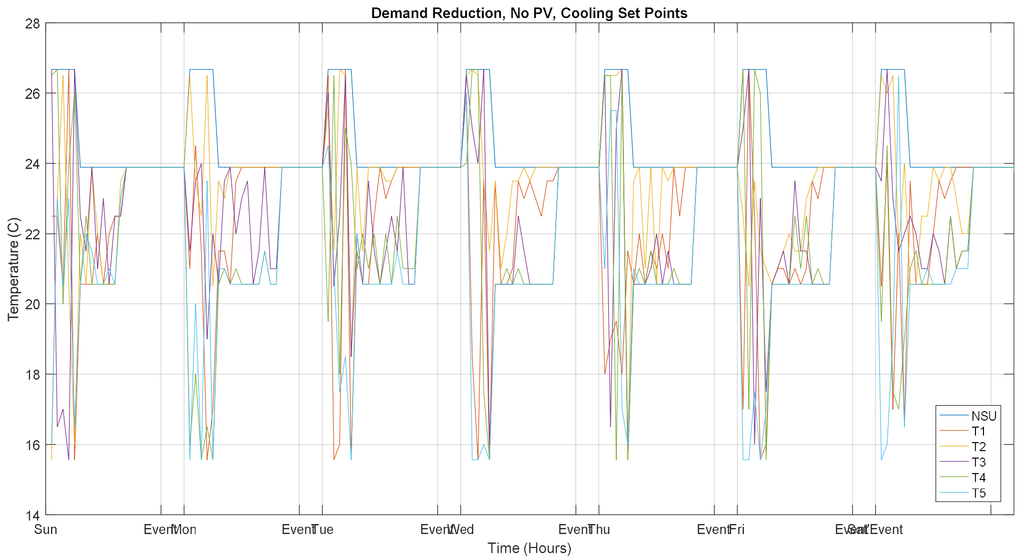


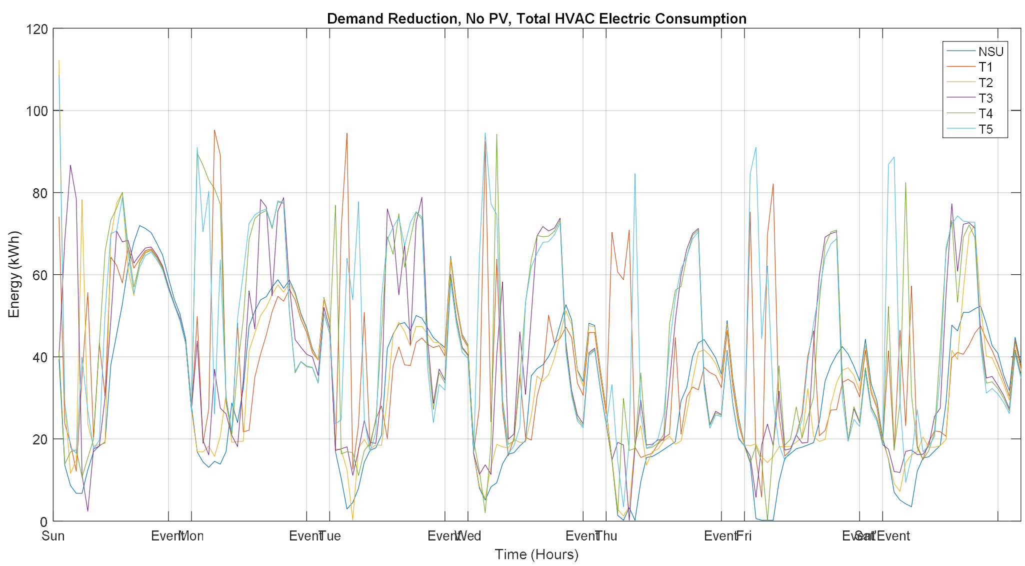

DAP, 154kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Peak
Mon
Peak
Tue
Peak
Wed
Peak
Thu
Peak
Fri
Peak
Sat
Peak
NSU
T1
T2
T3
T4
T5

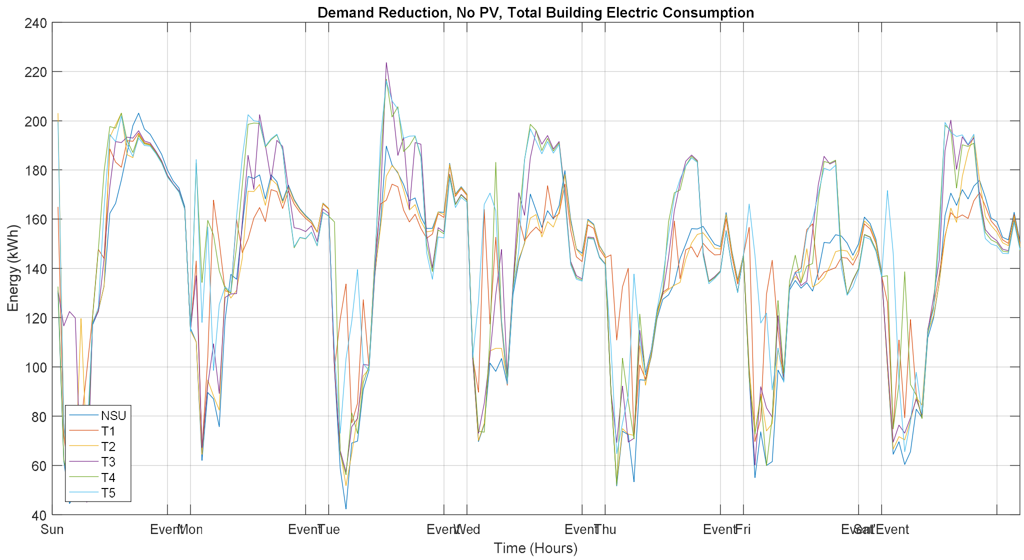

DAP, 154kW PV, Total Building Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Peak
Mon
Peak
Tue
Peak
Wed
Peak
Thu
Peak
Fri
Peak
Sat
Peak
NSU
T1
T2
T3
T4
T5

Hour 20 Demand Reduction Event

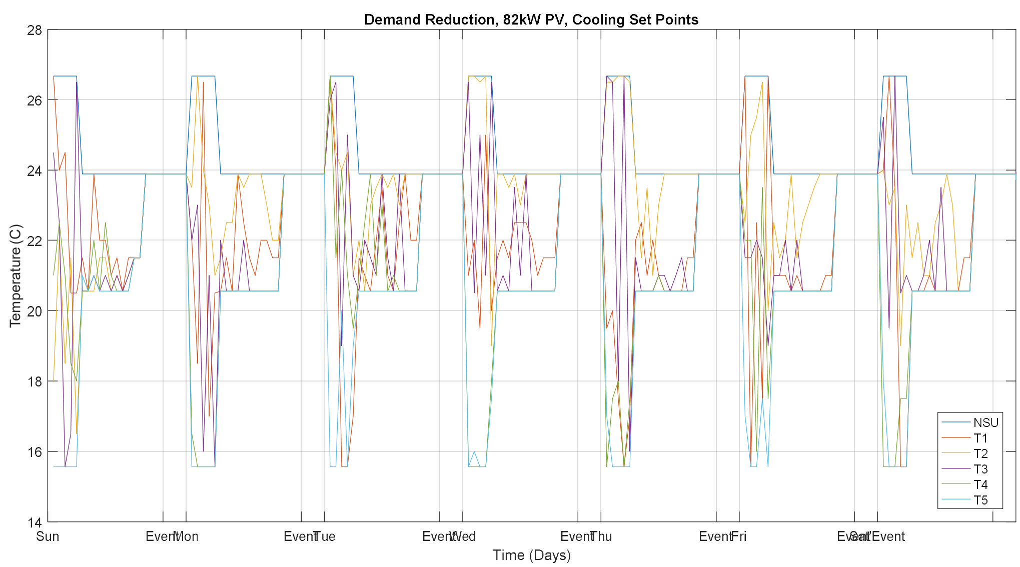
No PV

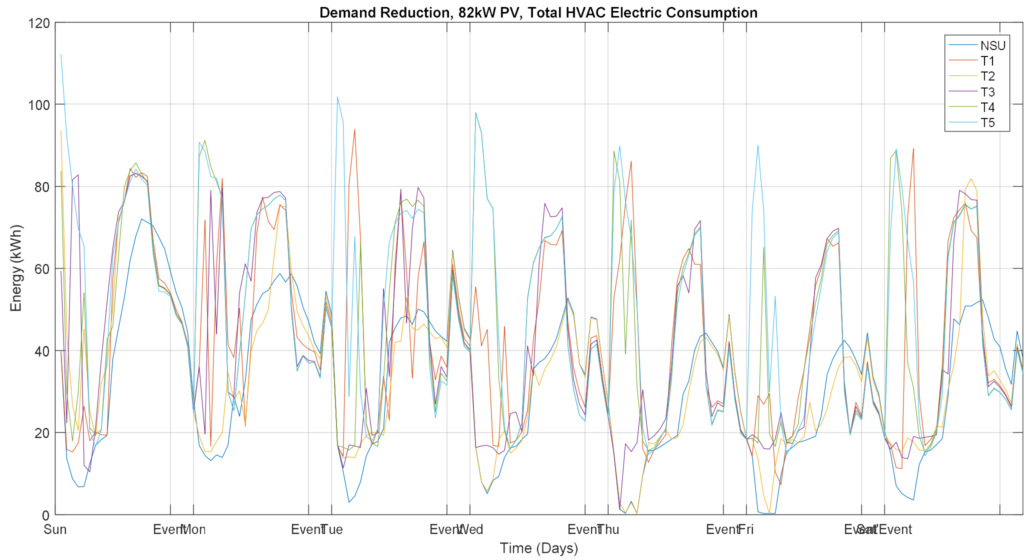




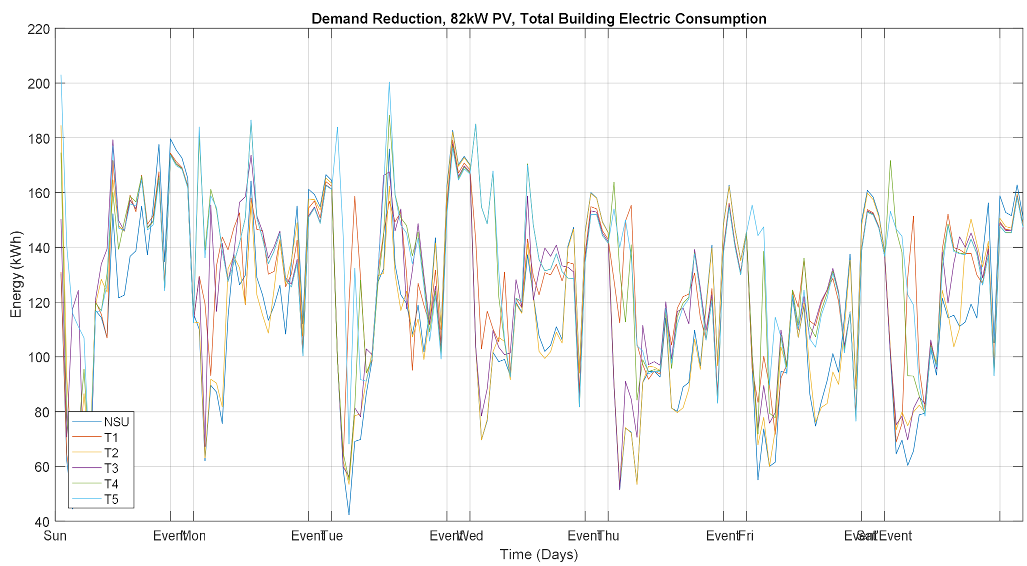

Demand Reduction, No PV, Total Building Electric Consumption
Energy (kWh)
240
220
200
180
160
140
120
100
80
60
40
NSU
T1
T2
T3
T4
T5
Sun
Event
Mon
Event
Tue
Event
Wed
Event
Thu
Event
Fri
Event
Sat
Event
Time (Hours)

82kW PV


Demand Reduction, 82kW PV, Cooling Set Points
Temperature (C)
28
26
24
22
20
18
16
14
NSU
T1
T2
T3
T4
T5
Sun
Event
Mon
Event
Tue
Event
Wed
Event
Thu
Event
Fri
Event
Sat
Event
Time (Days)

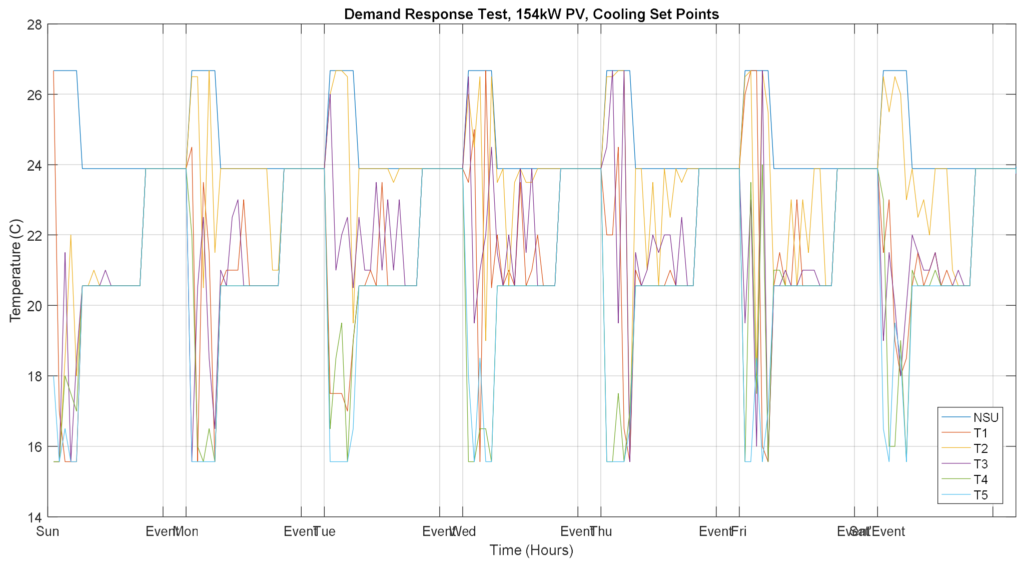


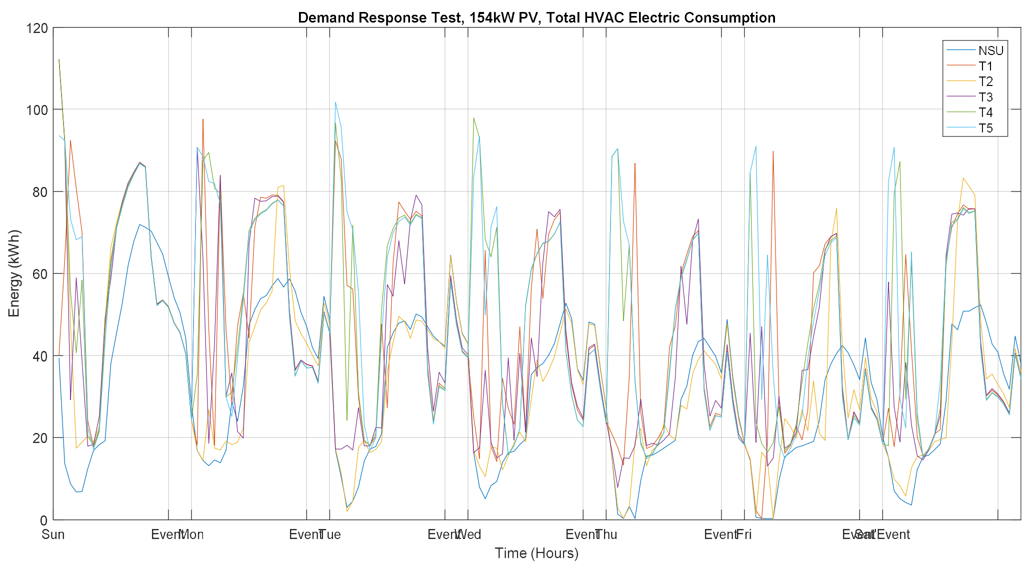
Demand Reduction, 82kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Days)
Sun
Event
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3
T4
T5

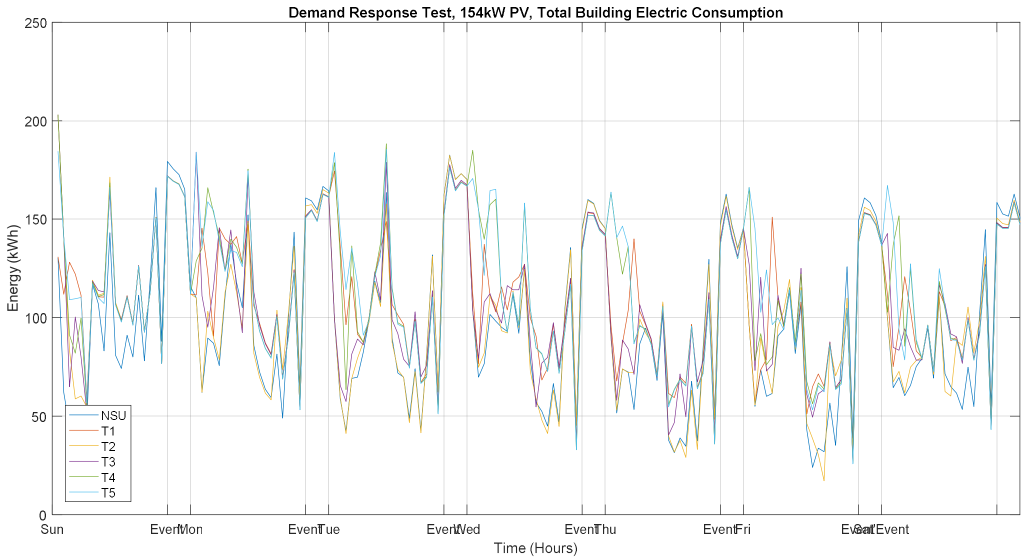


Demand Reduction, 82kW PV, Total Building Electric Consumption
Energy (kWh)
Time (Days)
Sun
Event
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3
T4
T5

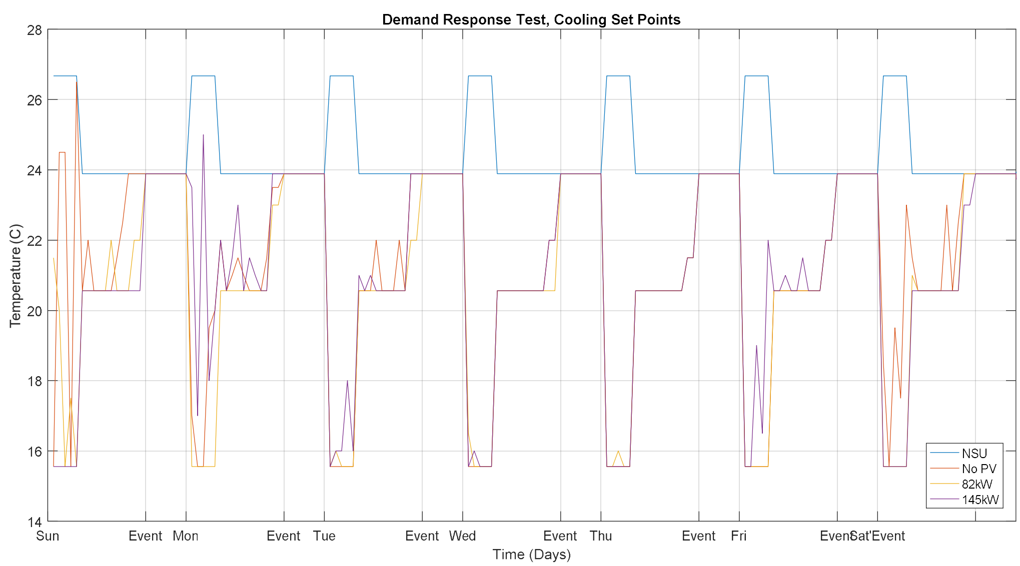
154kW PV

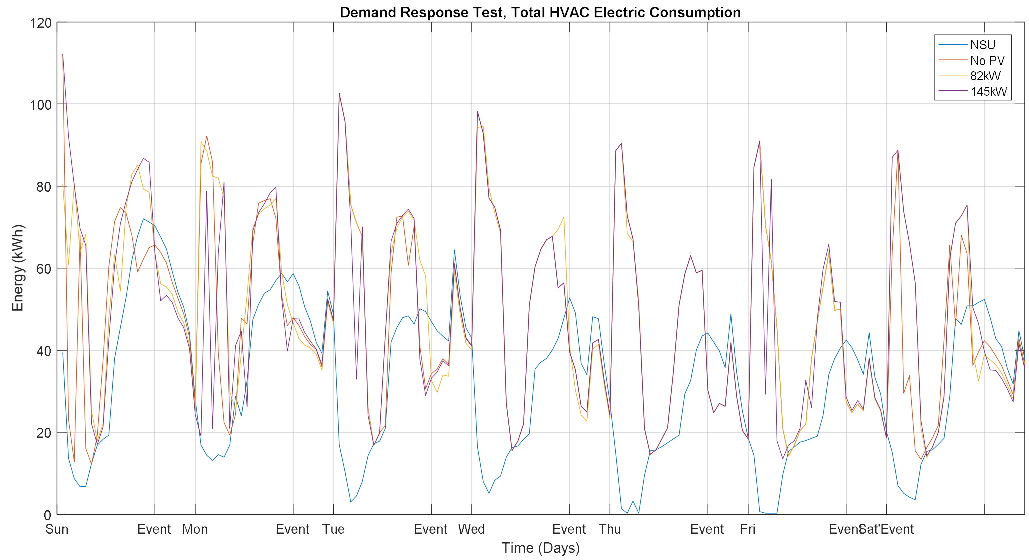

Demand Response Test, 154kW PV, Cooling Set Points
Temperature (C)
Time (Hours)
Sun
Event
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3
T4
T5


Demand Response Test, 154kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Event
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3
T4
T5



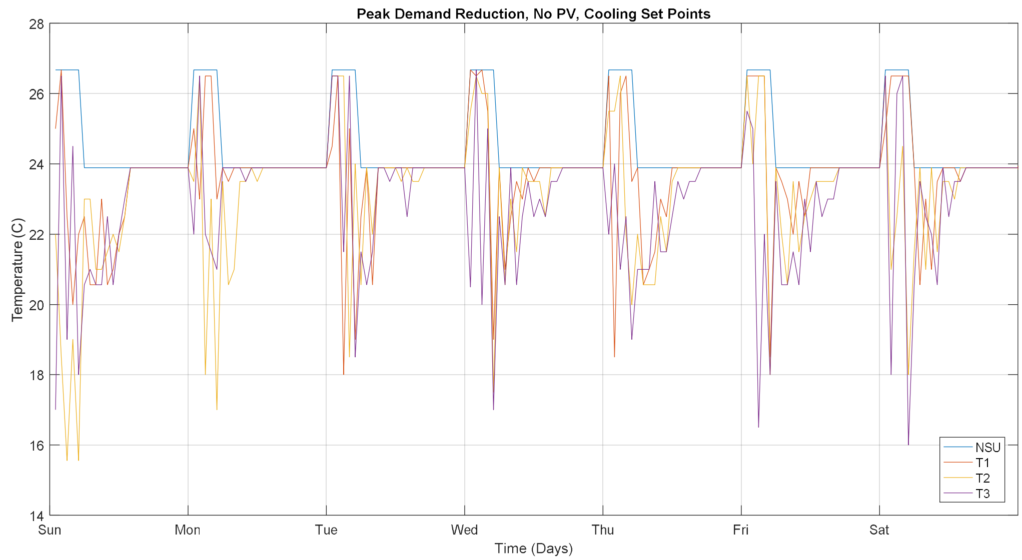
Hour 17 Demand Reduction Event

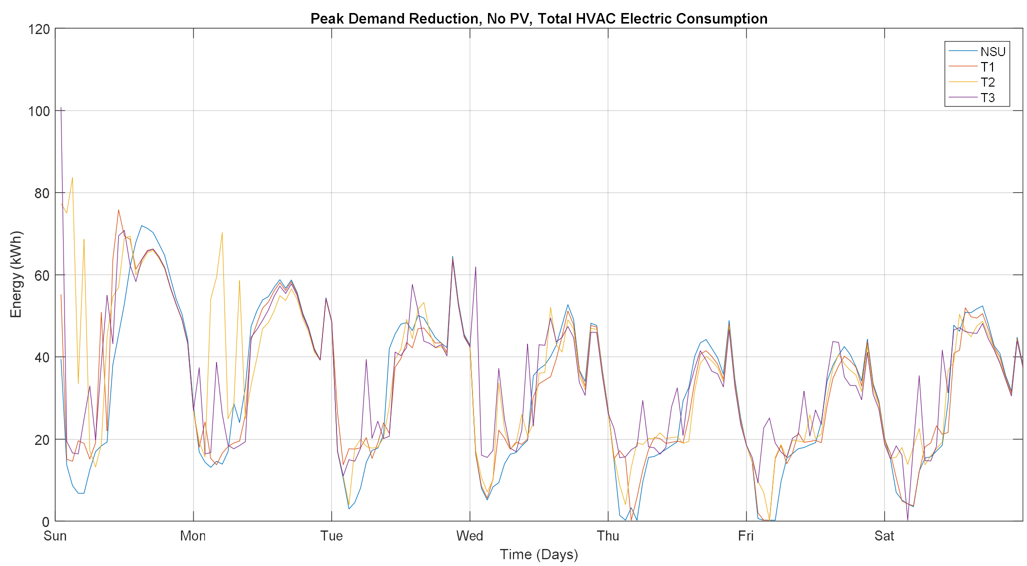


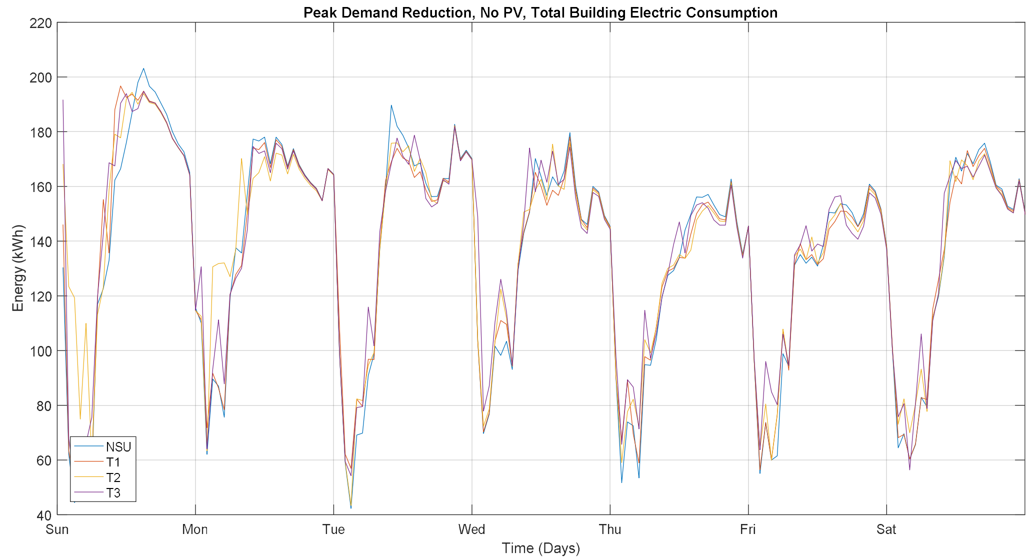

Demand Response Test, Total HVAC Electric Consumption
Energy (kWh)
Time (Days)
Sun
Event
Mon
Event
Tue
Event
Wed
Event
Thu
Event
Fri
Event
Sat
Event
NSU
No PV
82kW
145kW

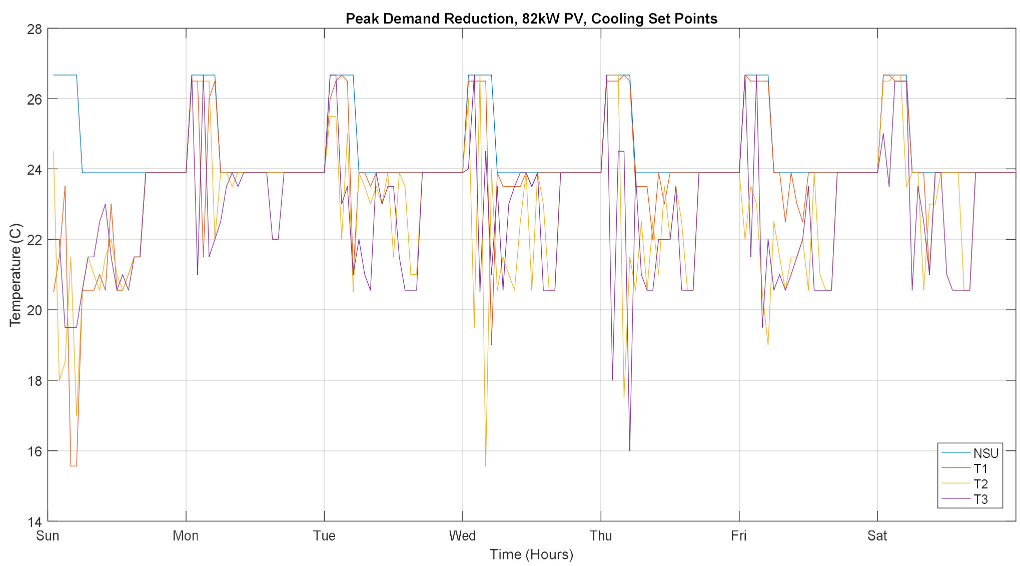

Demand Response Test, Total Building Electric Consumption
Energy (kWh)
Time (Days)
Sun
Event
Mon
Event
Tue
Event
Wed
Event
Thu
Event
Fri
Event
Sat
Event
NSU
No PV
82kW
145kW

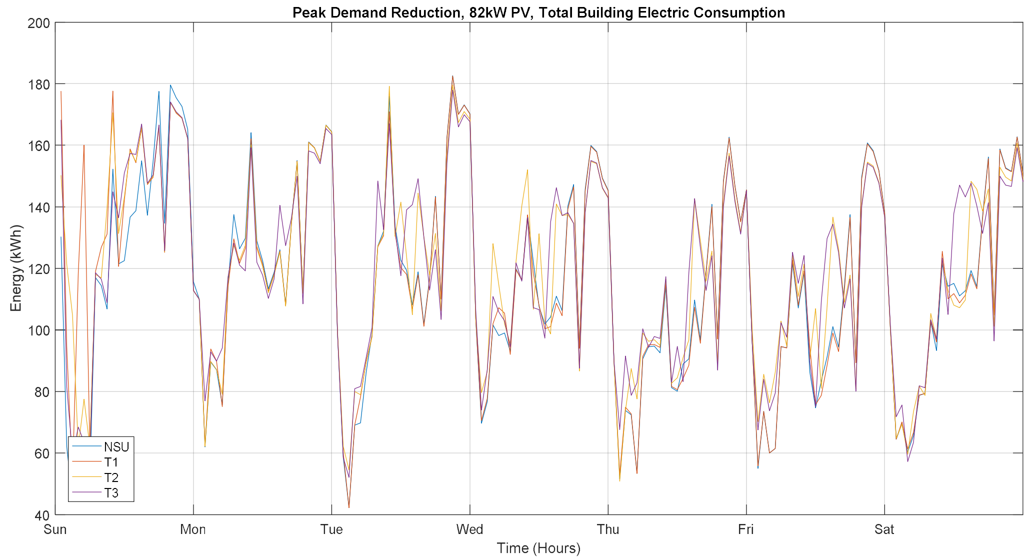
Peak Demand Reduction

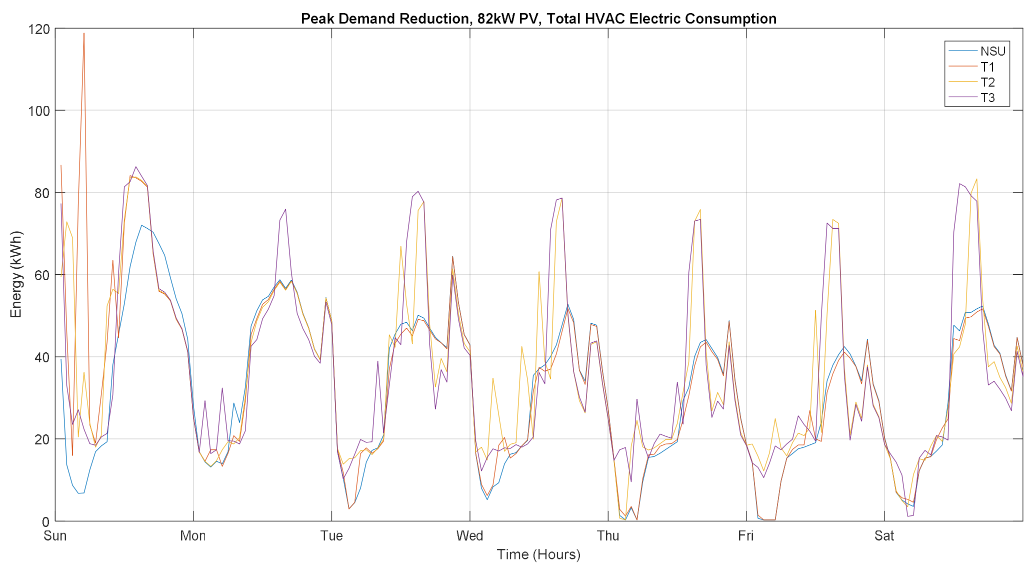


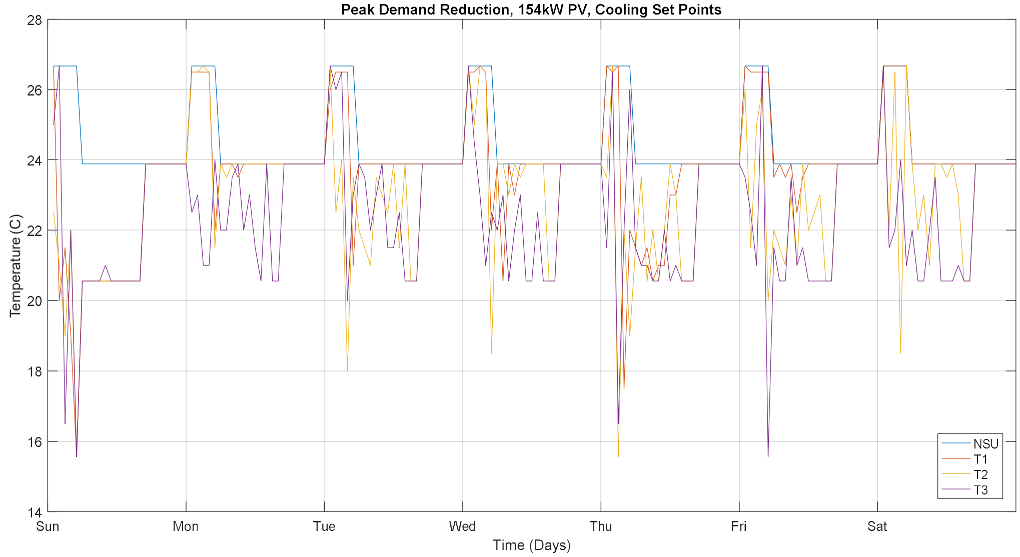


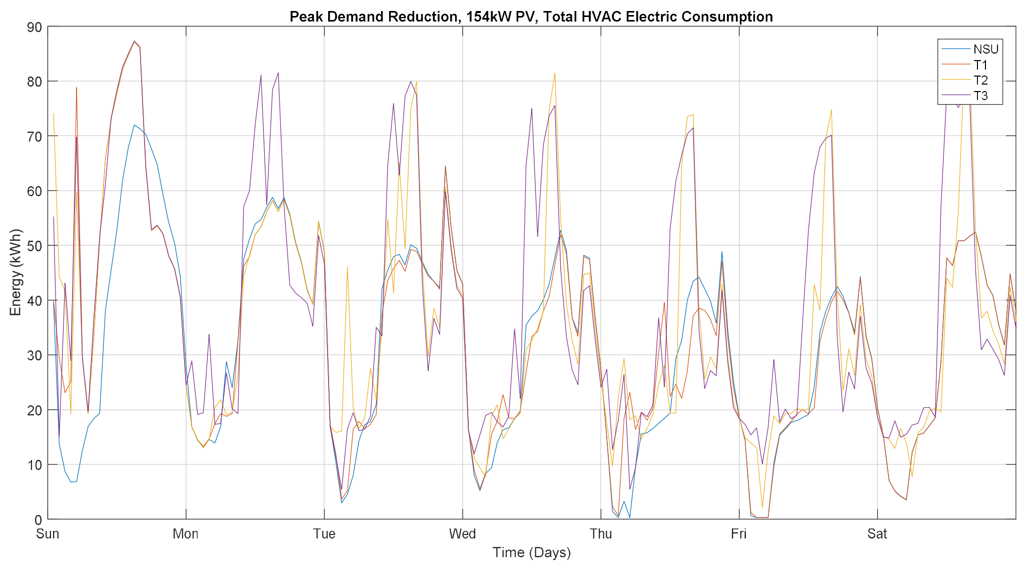

Peak Demand Reduction, No PV, Total Building Electric Consumption
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3

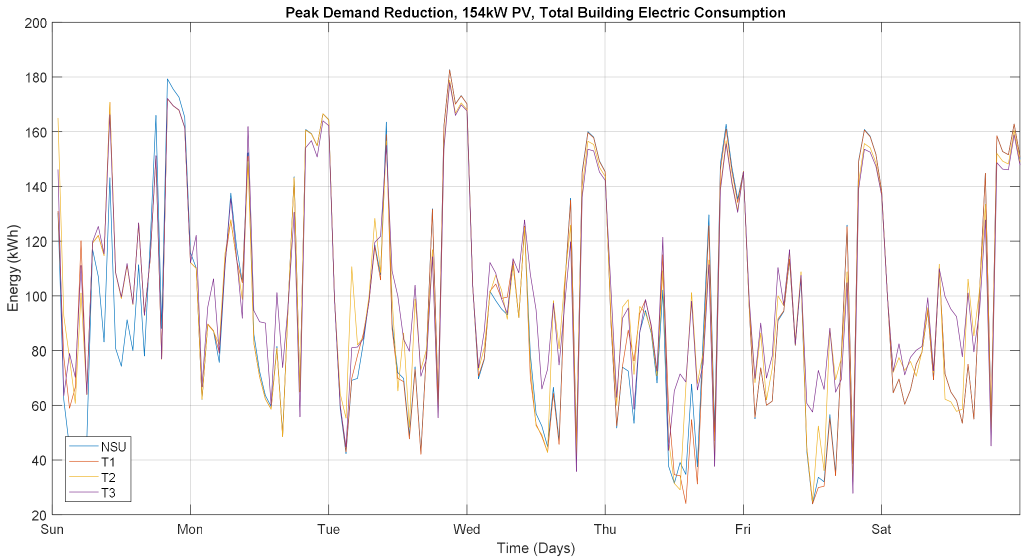

Peak Demand Reduction, 82kW PV, Cooling Set Points
Temperature (C)
Time (Hours)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3


Peak Demand Reduction, 82kW PV, Total Building Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3

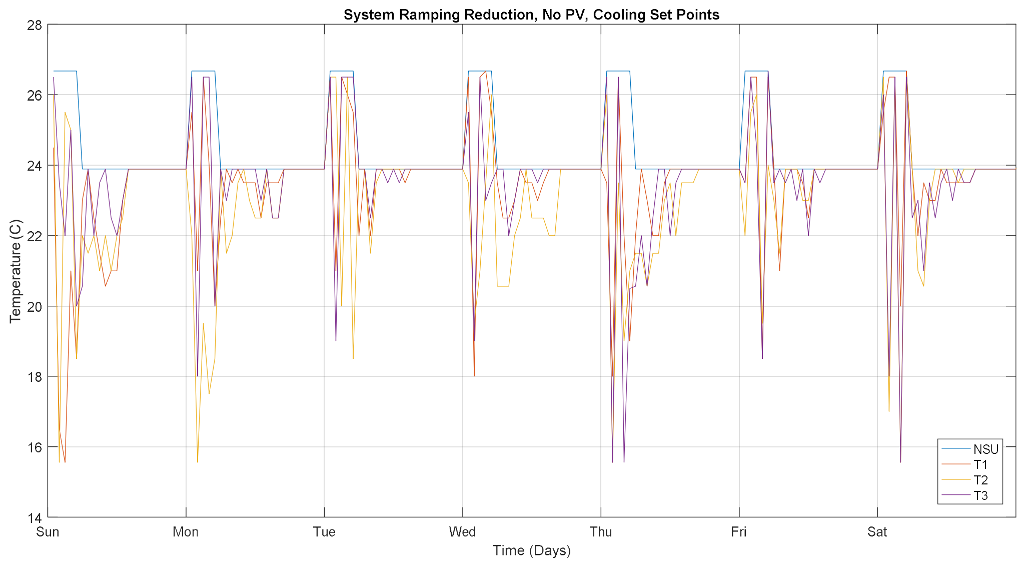

Peak Demand Reduction, 82kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3

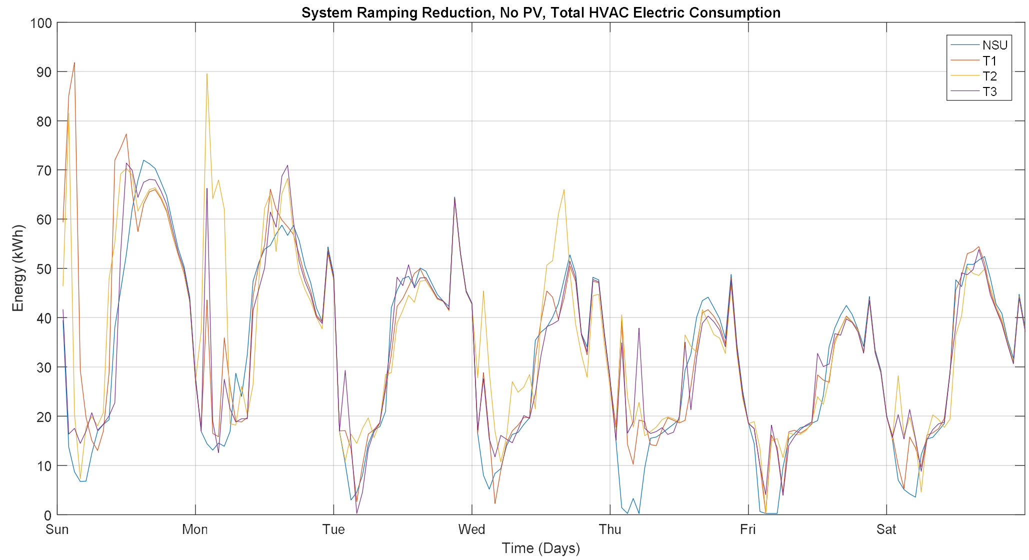

Peak Demand Reduction, 154kW PV, Cooling Set Points
Temperature (C)
28
26
24
22
20
18
16
14
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Days)
NSU
T1
T2
T3


Peak Demand Reduction, 154kW PV, Total HVAC Electric Consumption
Energy (kWh)
90
80
70
60
50
40
30
20
10
0
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Days)
NSU
T1
T2
T3

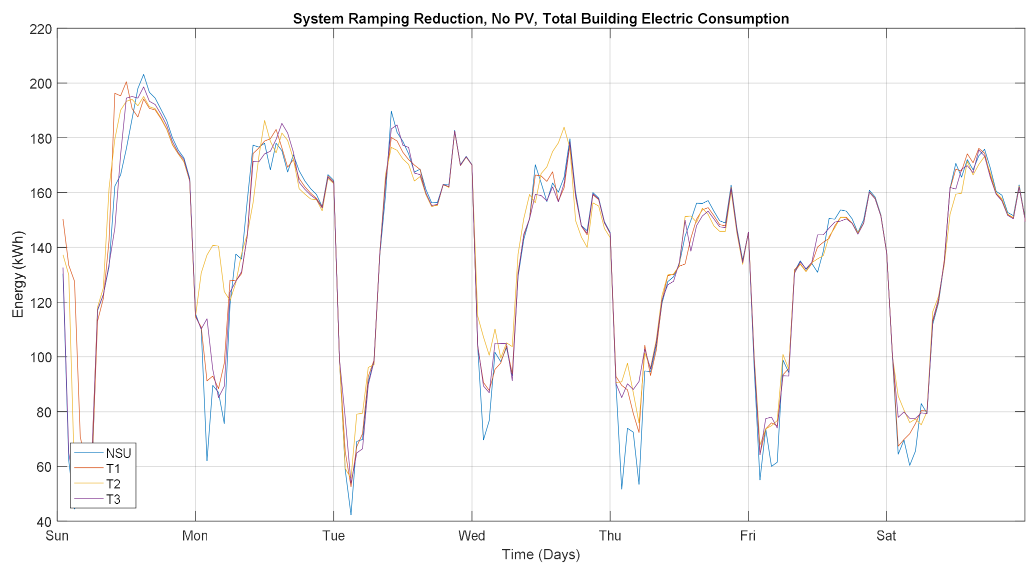


System Ramping Reduction

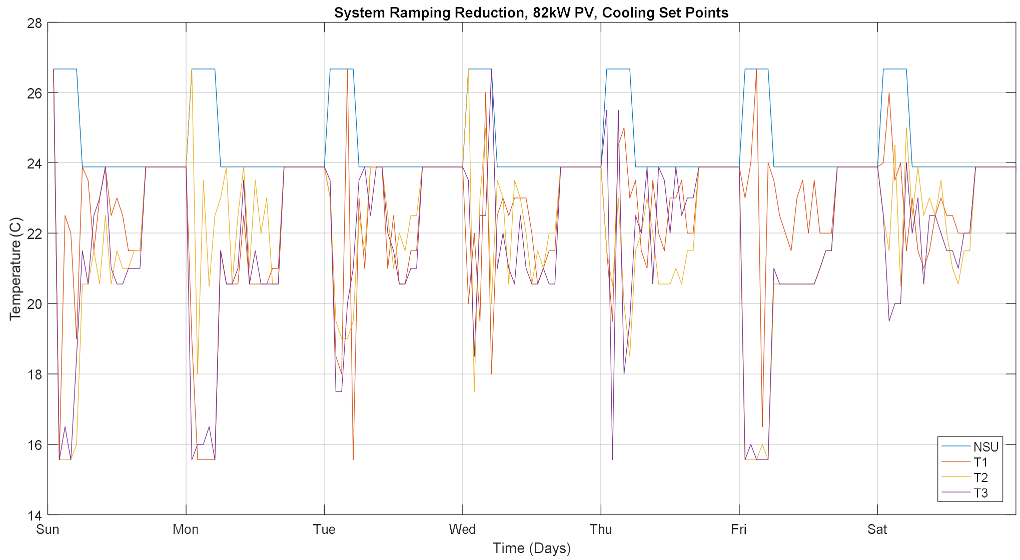


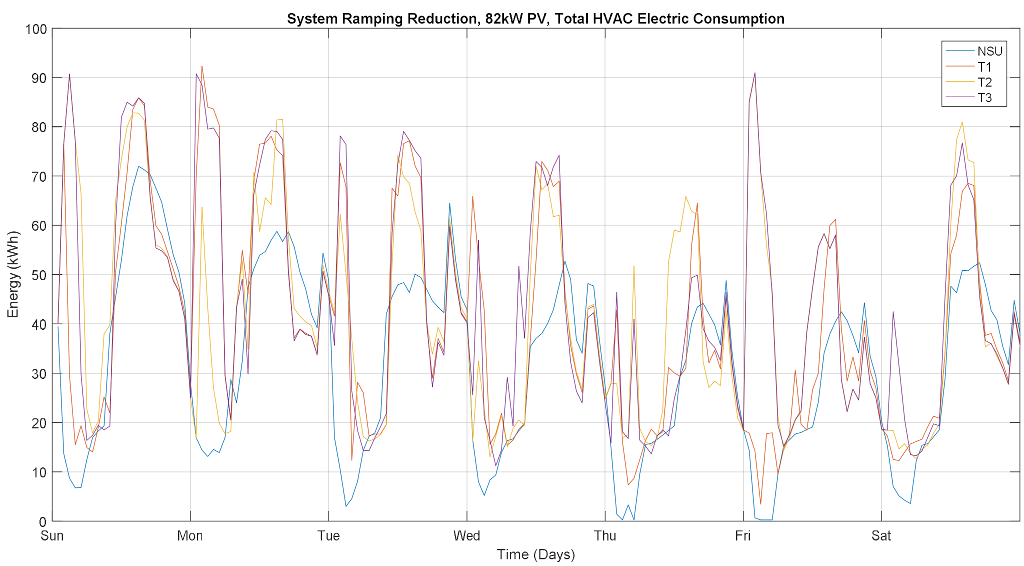


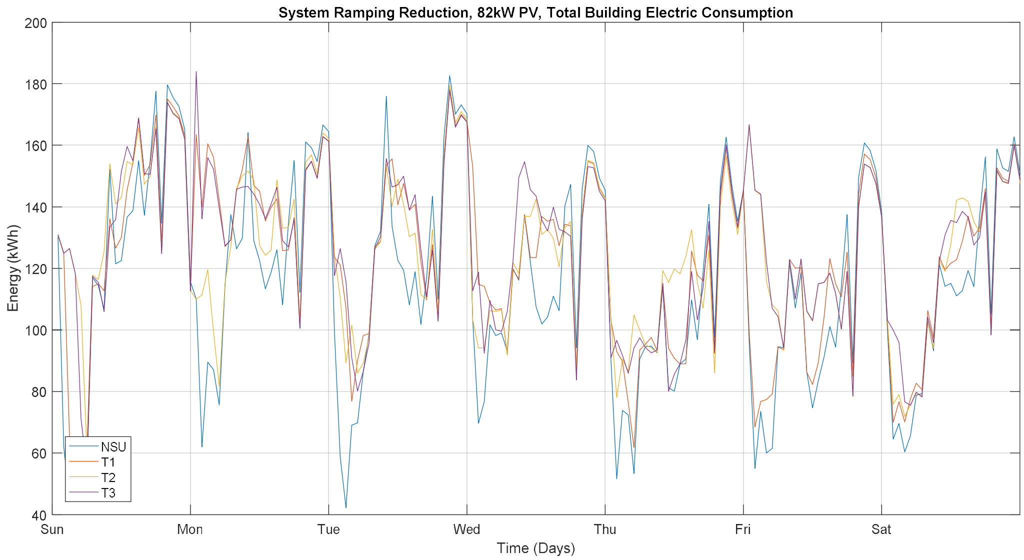
System Ramping Reduction, No PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3



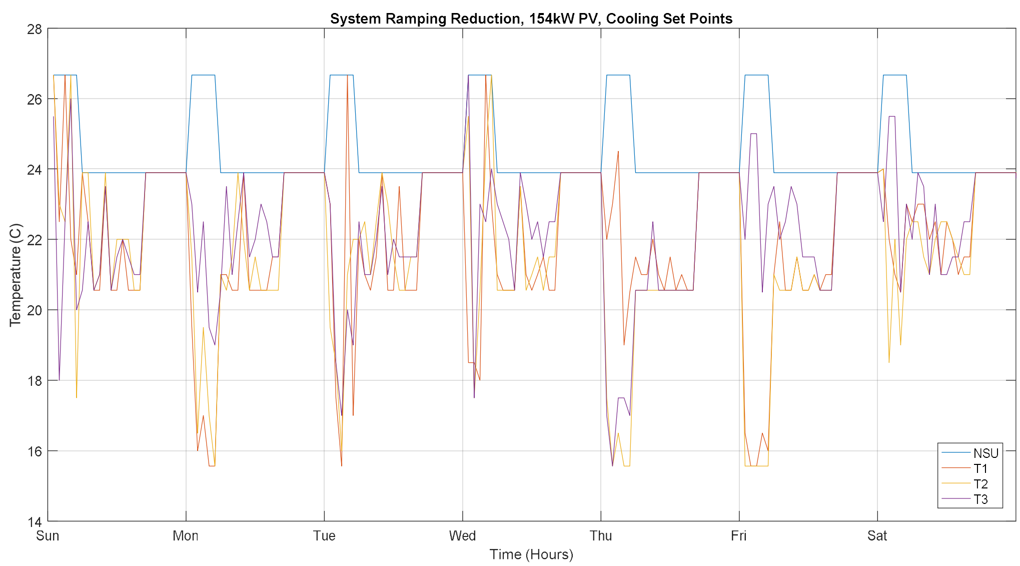
System Ramping Reduction, No PV, Total Building Electric Consumption
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3


System Ramping Reduction, 82kW PV, Cooling Set Points
Temperature (C)
28
26
24
22
20
18
16
14
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Days)
NSU
T1
T2
T3

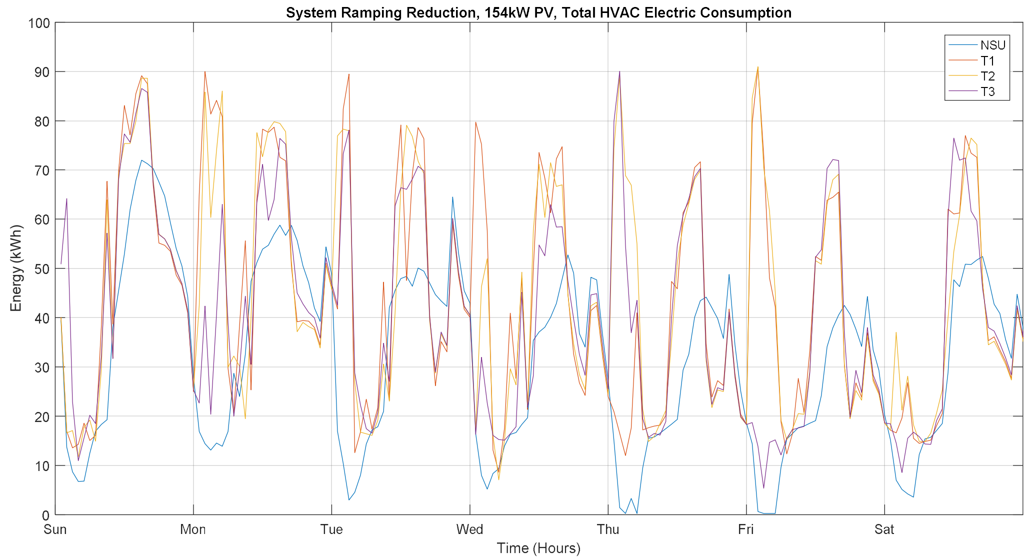

System Ramping Reduction, 82kW PV, Total HVAC Electric Consumption
Energy (kWh)
100
90
80
70
60
50
40
30
20
10
0
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Days)
NSU
T1
T2
T3

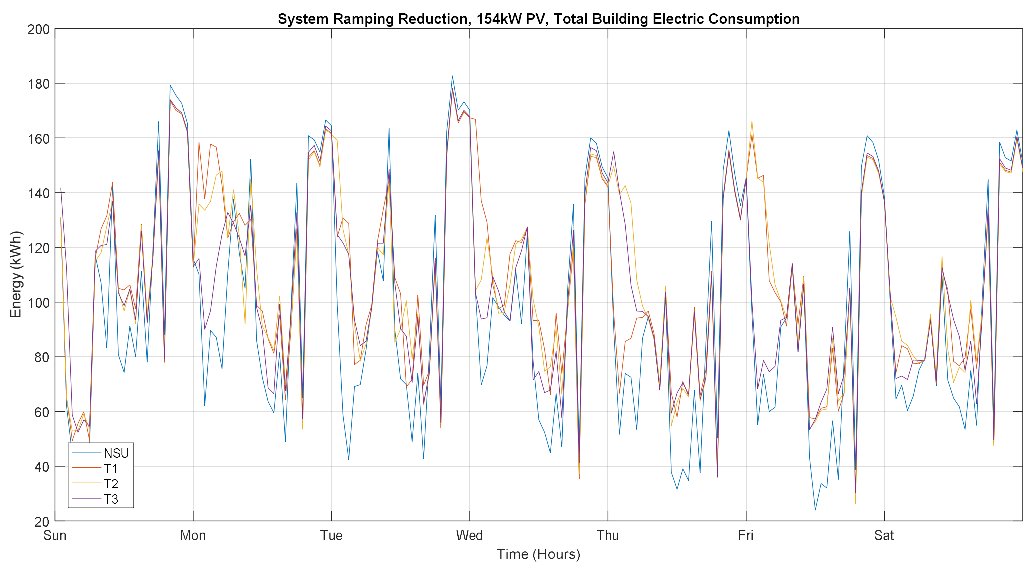


System Ramping Reduction, 82kW PV, Total Building Electric Consumption
Energy (kWh)
200
180
160
140
120
100
80
60
40
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Days)
NSU
T1
T2
T3

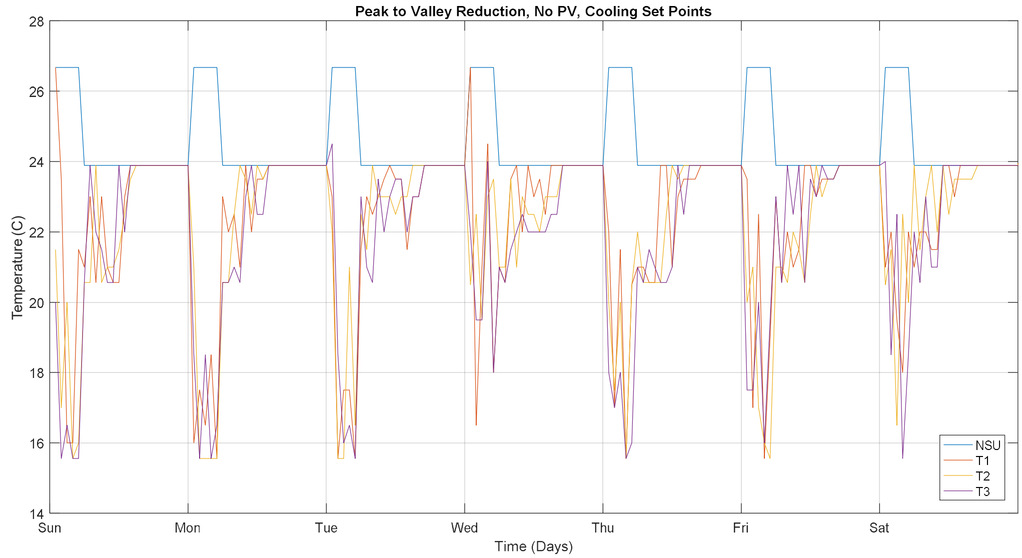


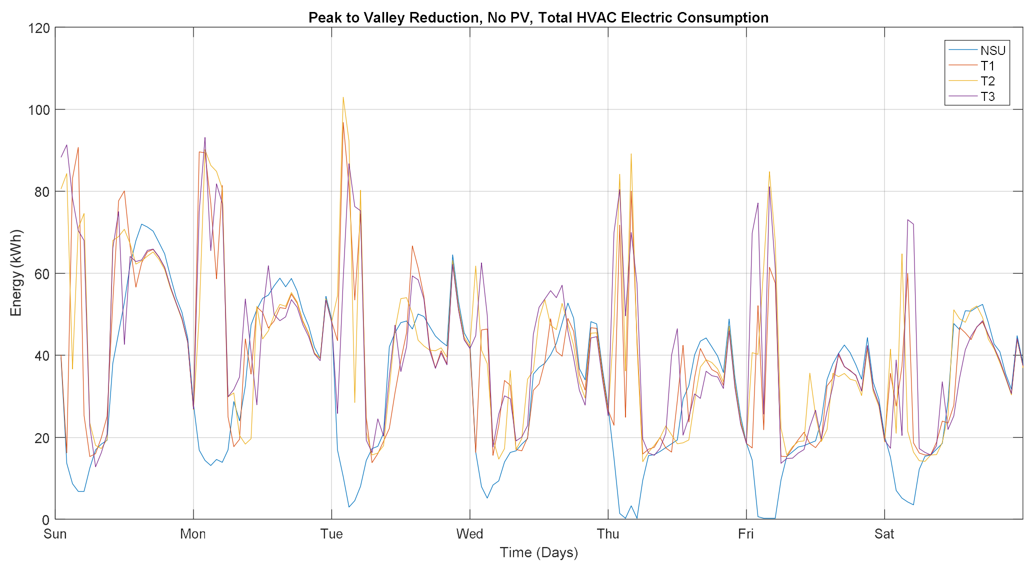
System Ramping Reduction, 154kW PV, Cooling Set Points
Temperature (C)
28
26
24
22
20
18
16
14
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Hours)
NSU
T1
T2
T3

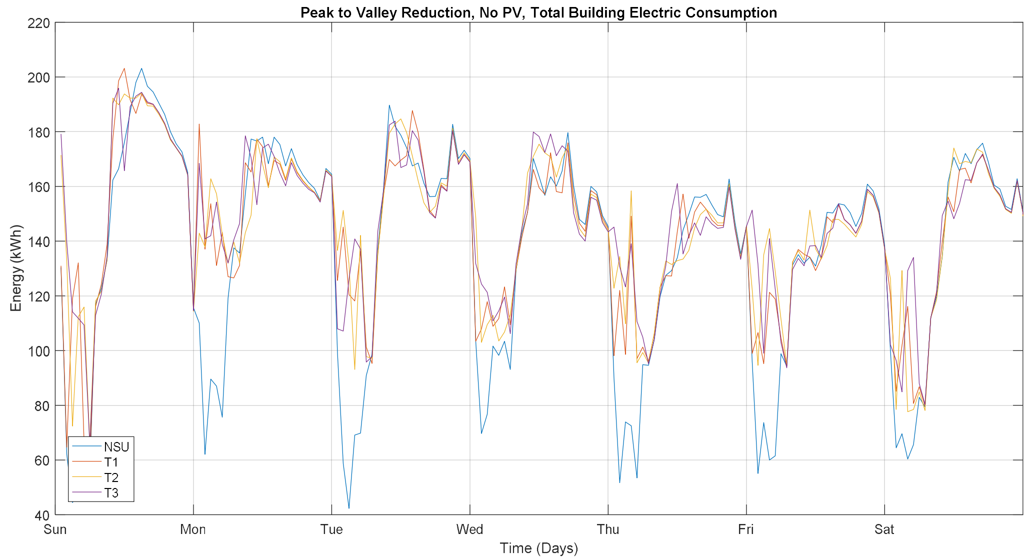

System Ramping Reduction, 154kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3

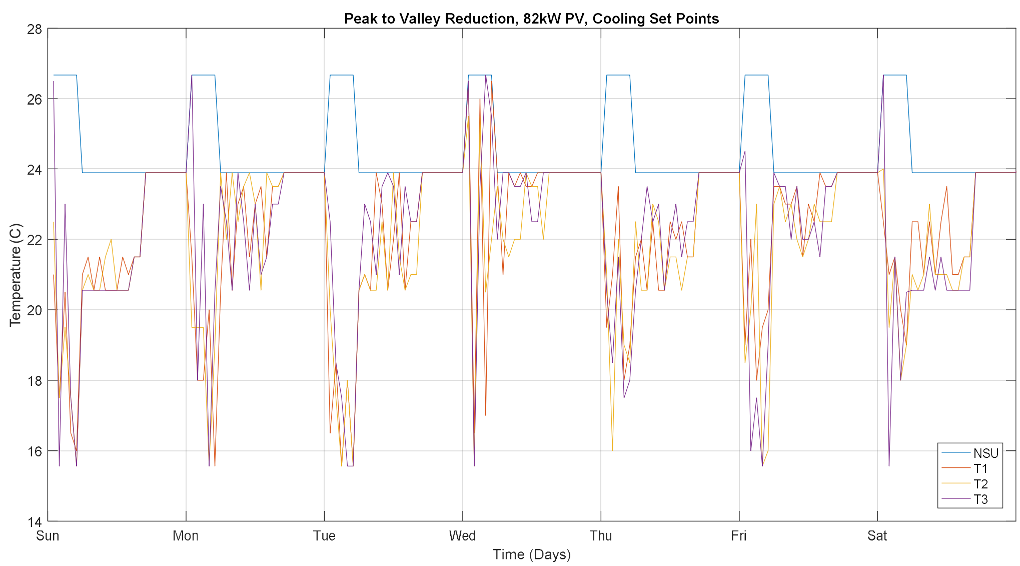

System Ramping Reduction, 154kW PV, Total Building Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3

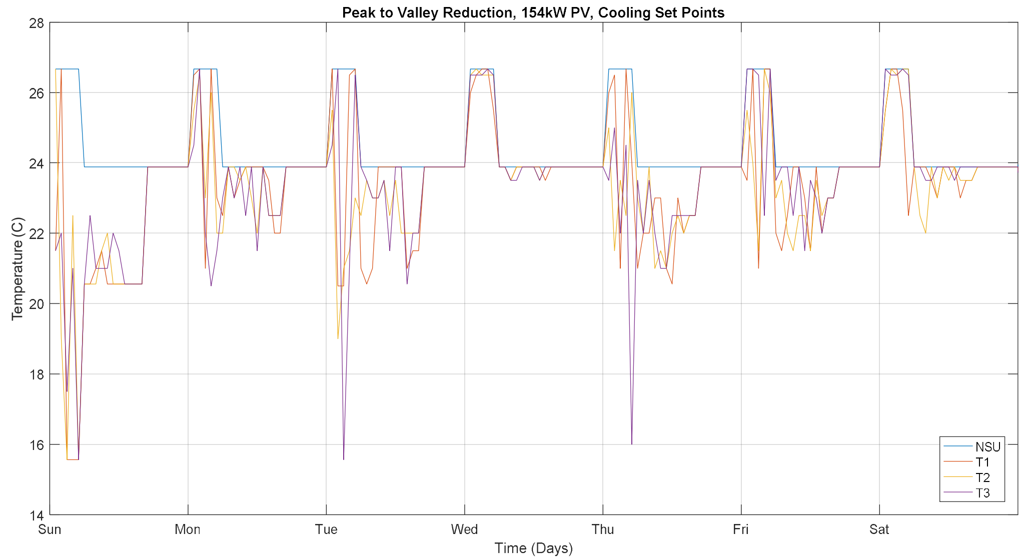
Peak to Valley Reduction

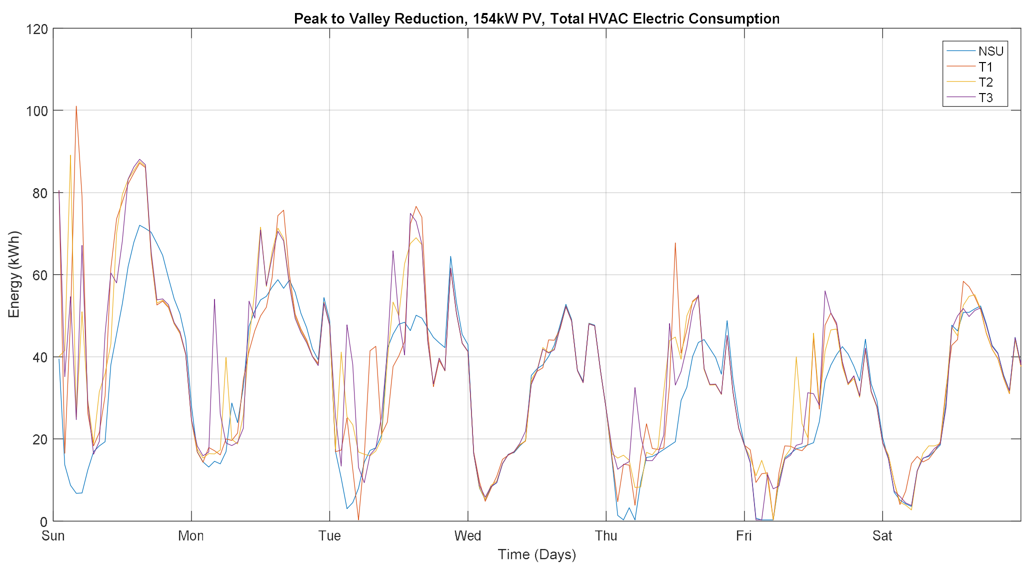


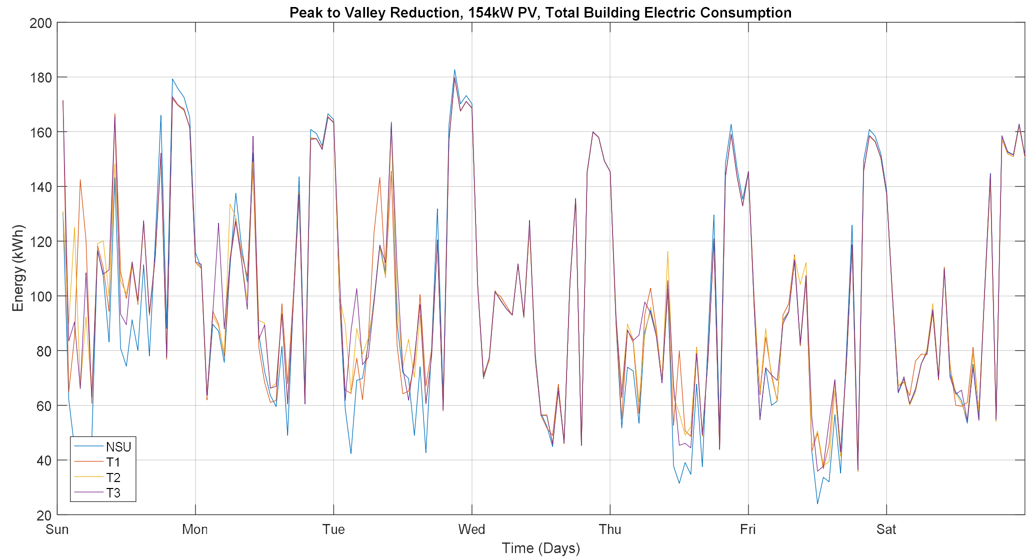


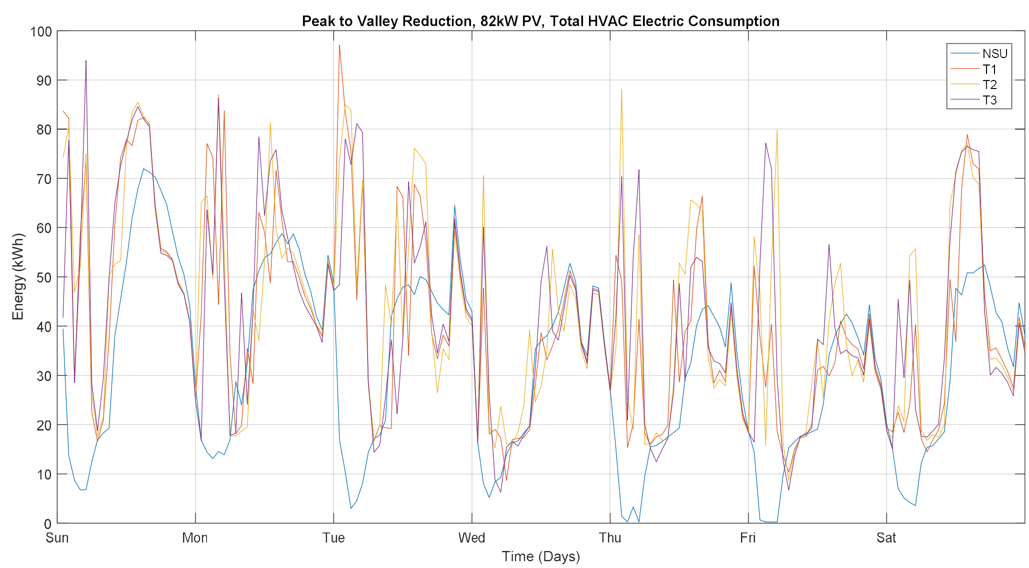

Peak to Valley Reduction, No PV, Total Building Electric Consumption
Energy (kWh)
220
200
180
160
140
120
100
80
60
40
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Days)
NSU
T1
T2
T3

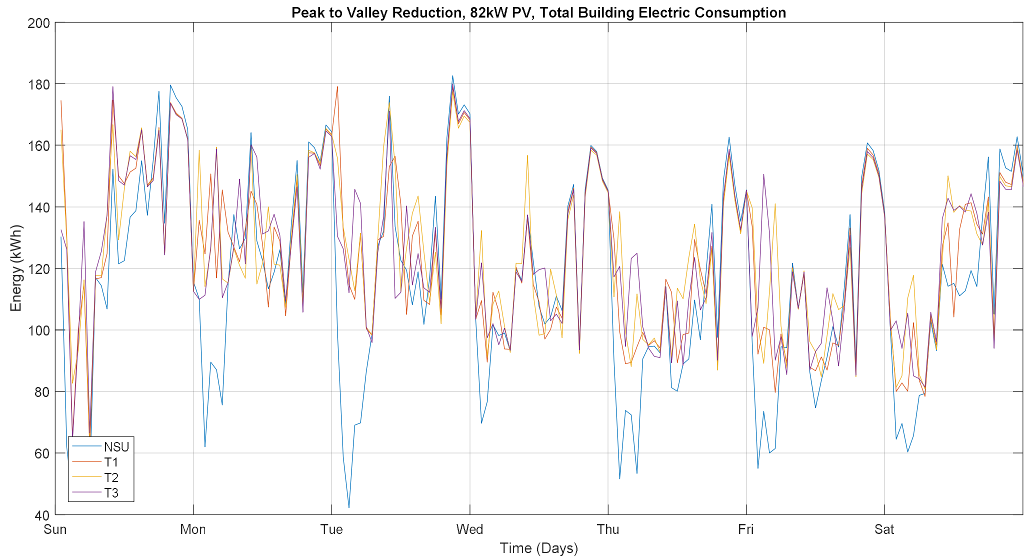

Peak to Valley Reduction, 82kW PV, Cooling Set Points
Temperature (C)
28
26
24
22
20
18
16
14
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Days)
NSU
T1
T2
T3


Peak to Valley Reduction, 154kW PV, Cooling Set Points
Temperature (C)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
28
26
24
22
20
18
16
14
NSU
T1
T2
T3

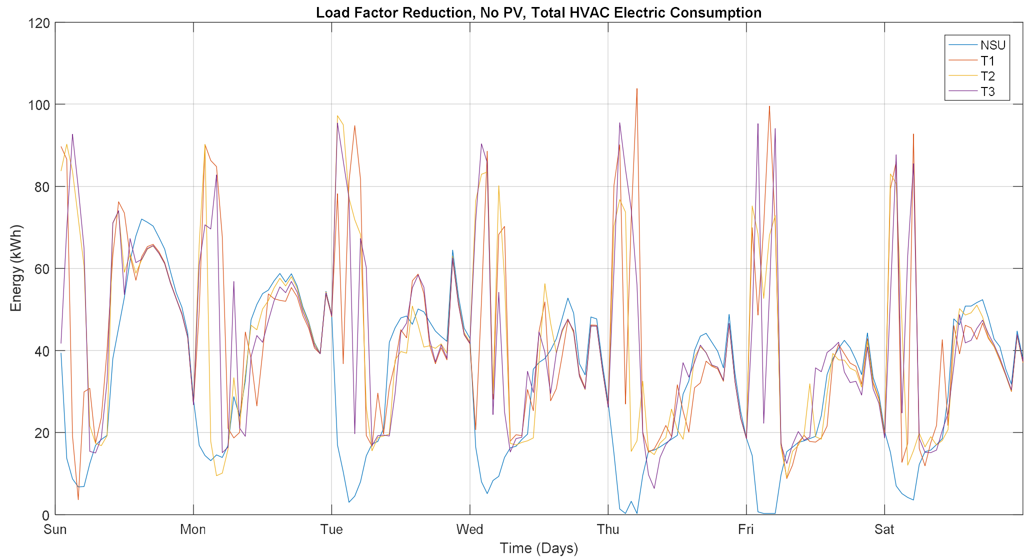

Peak to Valley Reduction, 154kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
120
100
80
60
40
20
0
NSU
T1
T2
T3


Peak to Valley Reduction, 154kW PV, Total Building Electric Consumption
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3

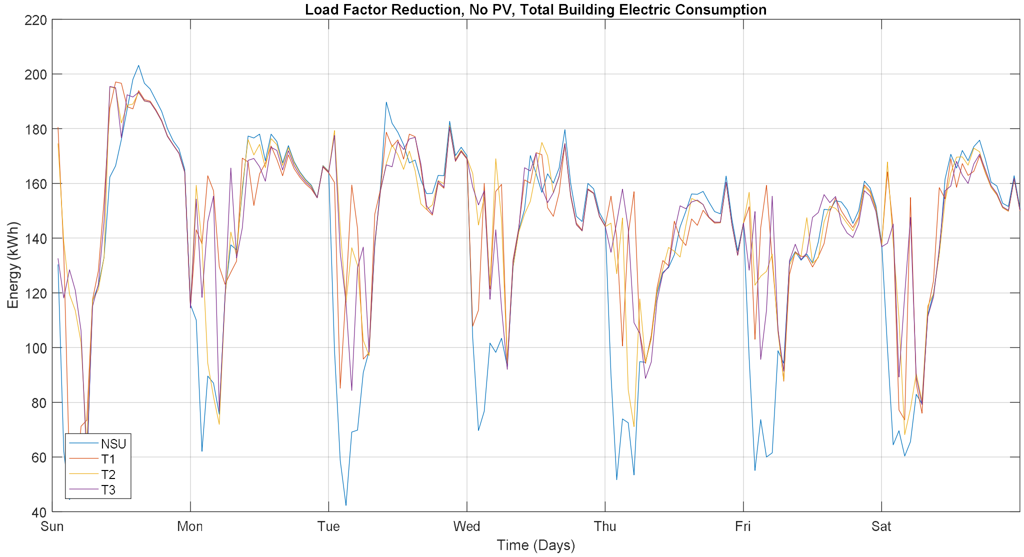

Peak to Valley Reduction, 82kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3

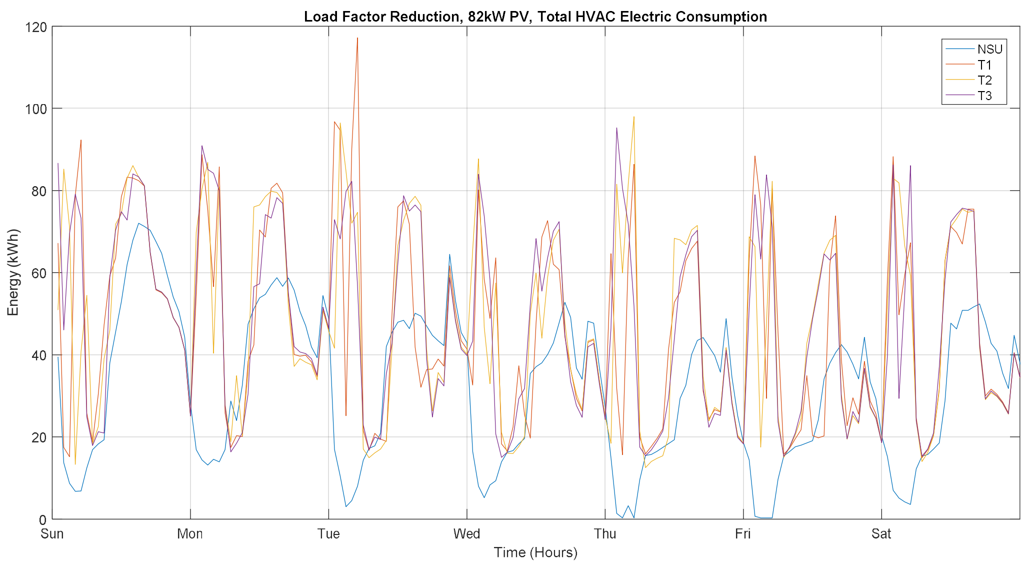


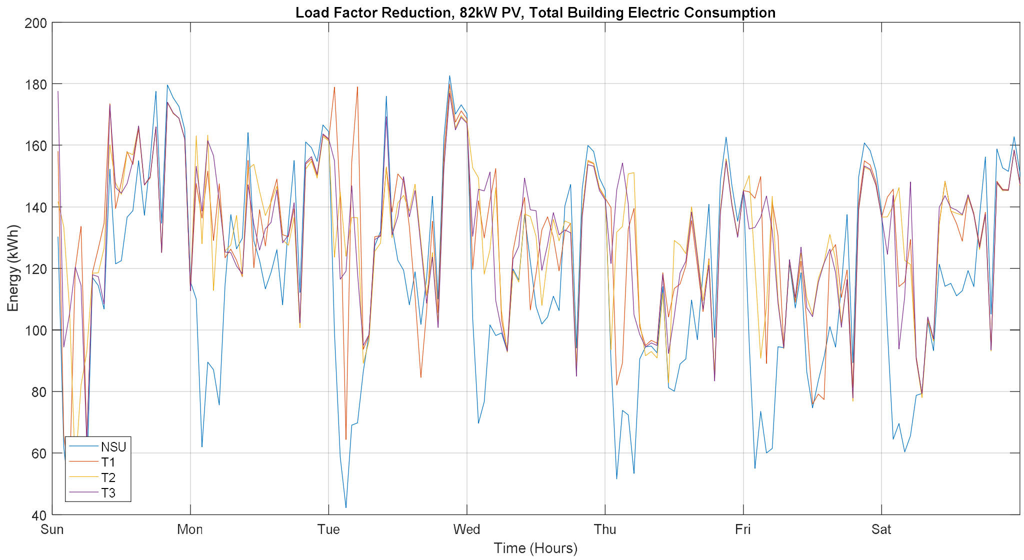
Load Factor Improvement


Load Factor Reduction, No PV, Total HVAC Electric Consumption
Energy (kWh)
0
20
40
60
80
100
120
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Days)
NSU
T1
T2
T3

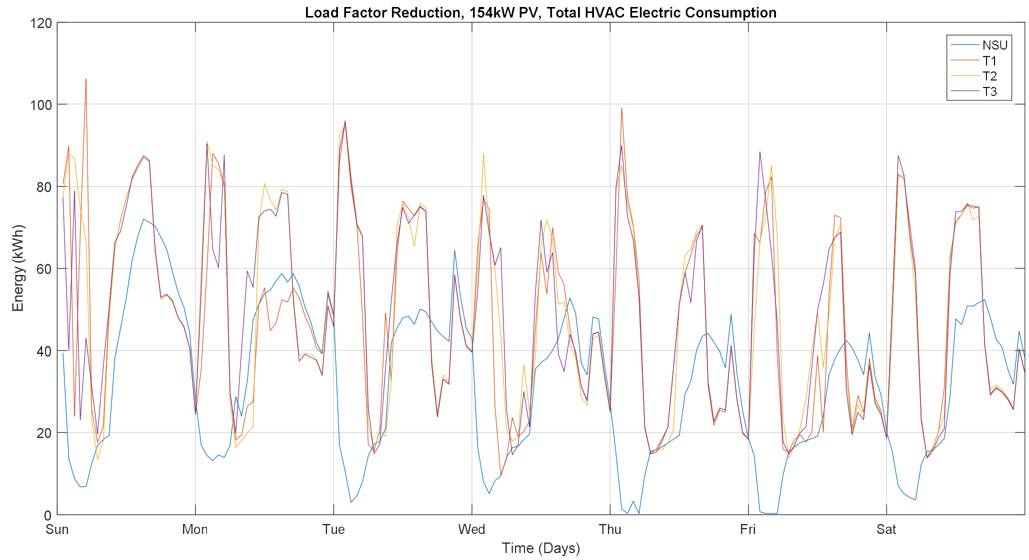

Load Factor Reduction, 82kW PV, Cooling Set Points
Temperature (C)
14
16
18
20
22
24
26
28
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Hours)
NSU
T1
T2
T3


Load Factor Reduction, No PV, Total Building Electric Consumption
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3

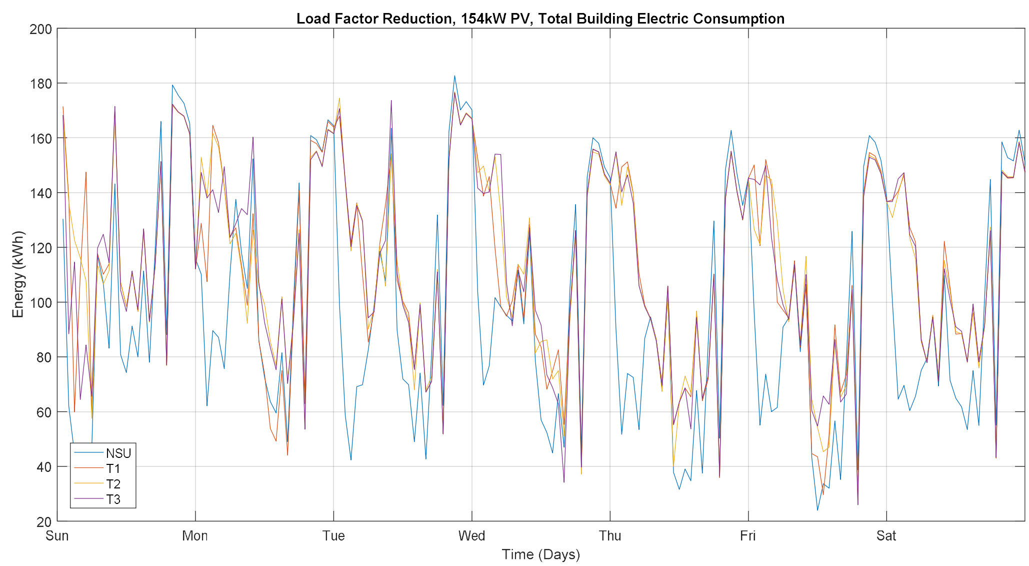

Load Factor Reduction, 82kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3


Load Factor Reduction, 82kW PV, Total Building Electric Consumption
200
180
160
140
120
100
80
60
40
Energy (kWh)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Hours)
NSU
T1
T2
T3


Load Factor Reduction, 154kW PV, Cooling Set Points
28
26
24
22
20
18
16
14
Temperature (C)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Days)
NSU
T1
T2
T3

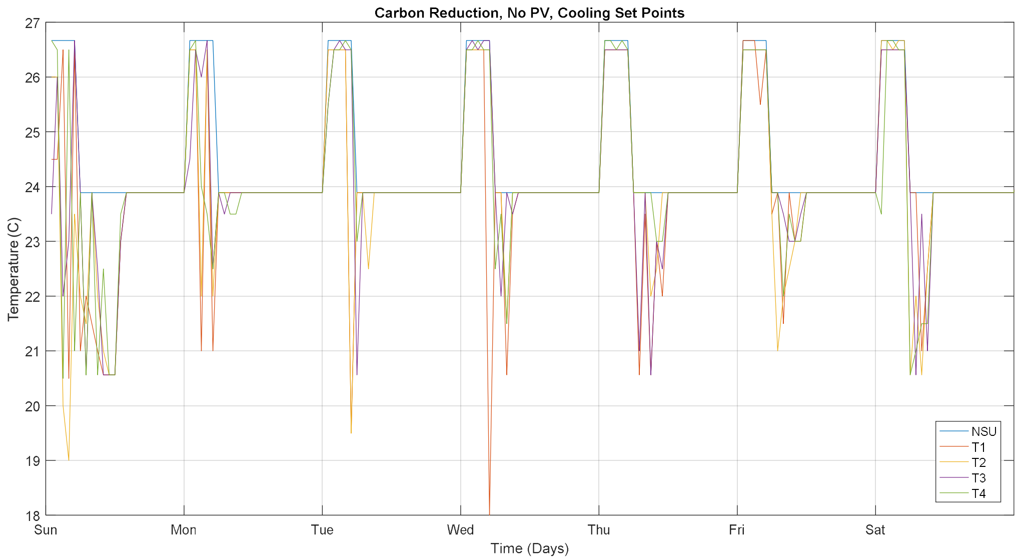


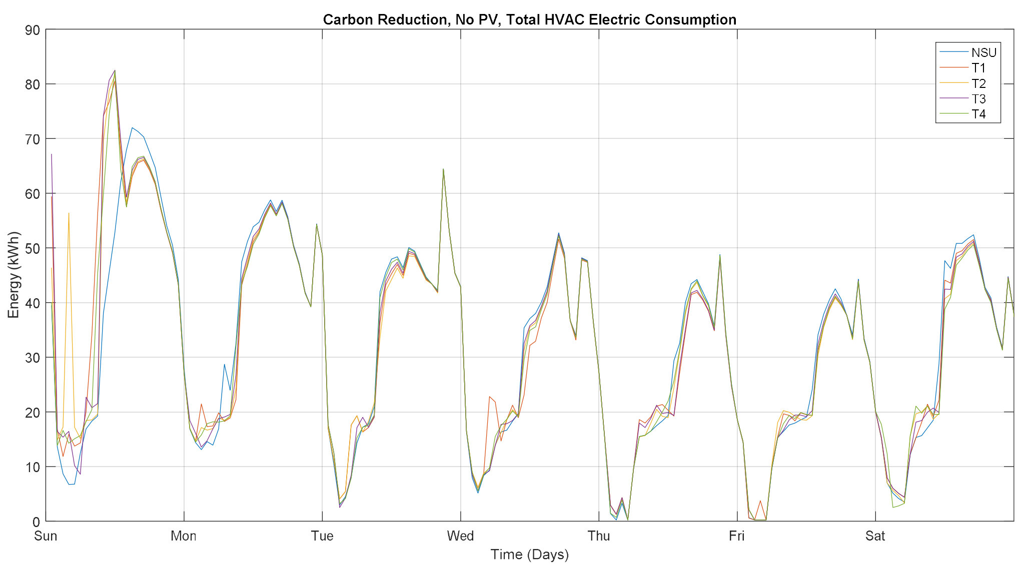
Load Factor Reduction, 154kW PV, Total HVAC Electric Consumption
NSU
T1
T2
T3
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat

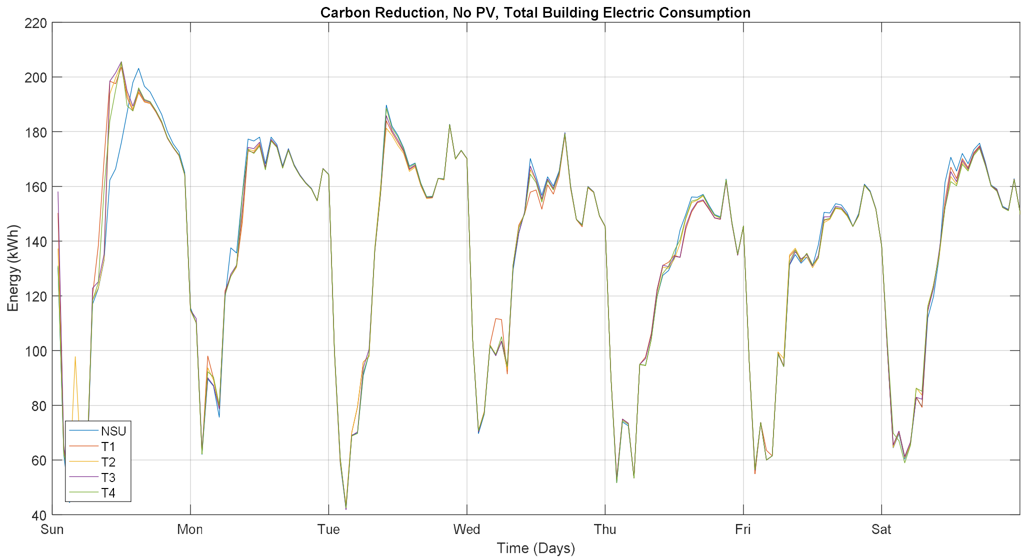


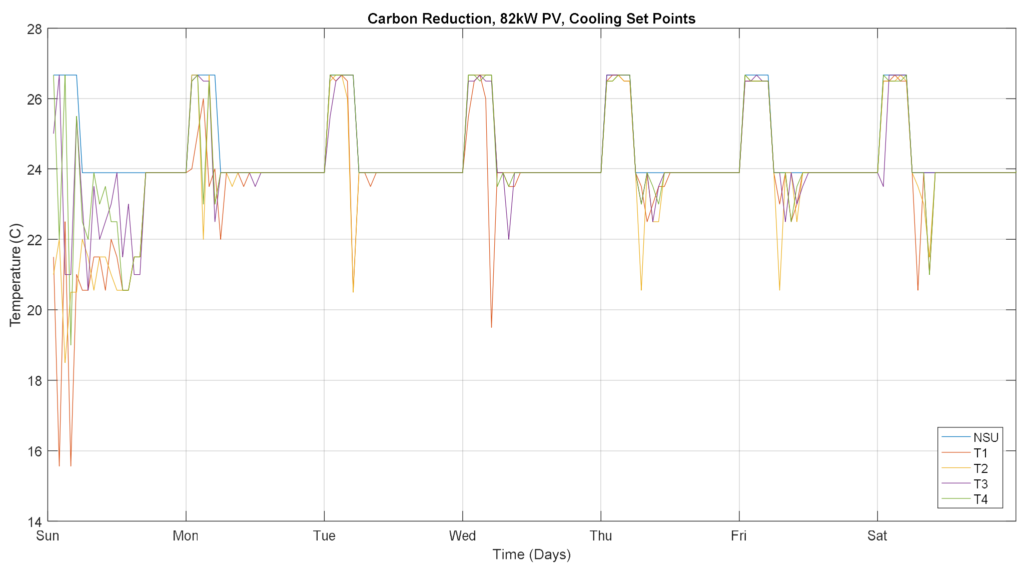
Load Factor Reduction, 154kW PV, Total Building Electric Consumption
NSU
T1
T2
T3
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat

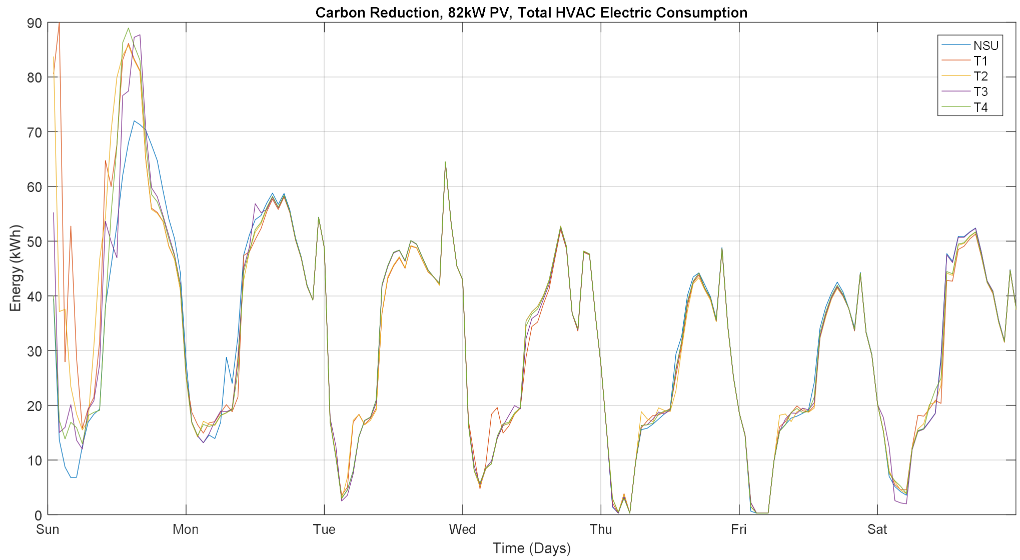
Carbon Reduction Test



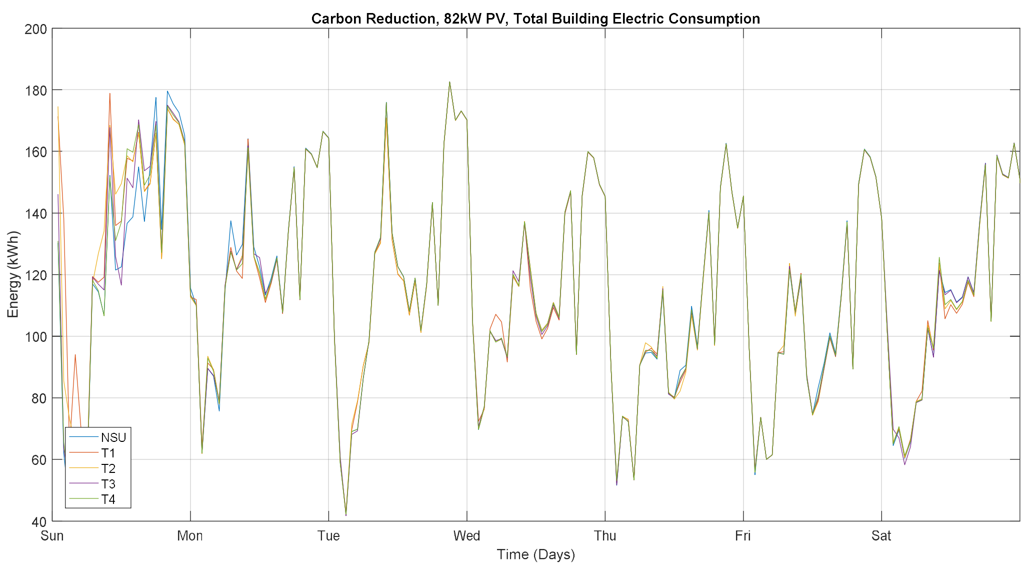



Carbon Reduction, No PV, Total Building Electric Consumption
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
220
200
180
160
140
120
100
80
60
40
NSU
T1
T2
T3
T4


Carbon Reduction, 82kW PV, Cooling Set Points
Temperature (C)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
28
26
24
22
20
18
16
14
NSU
T1
T2
T3
T4

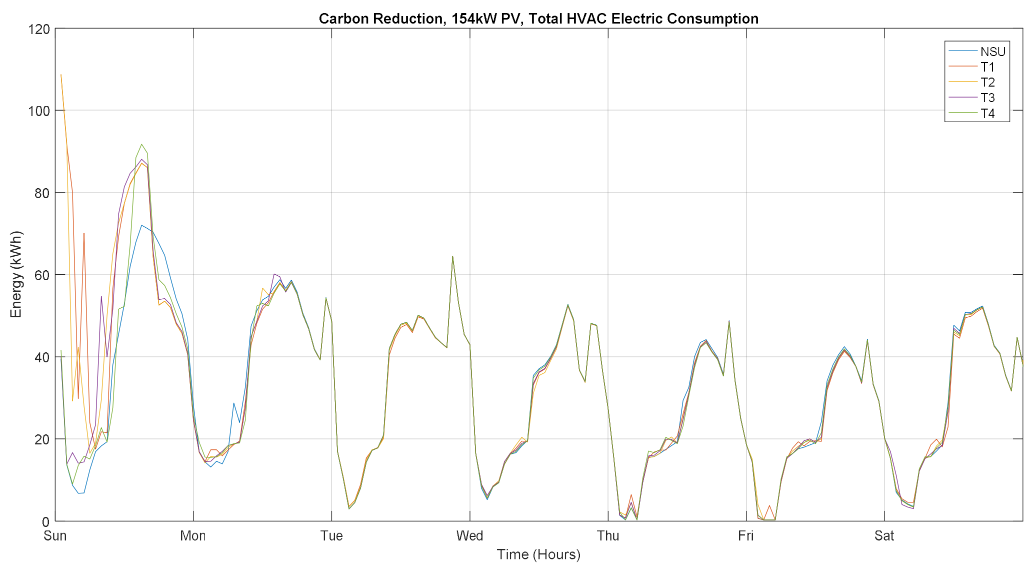


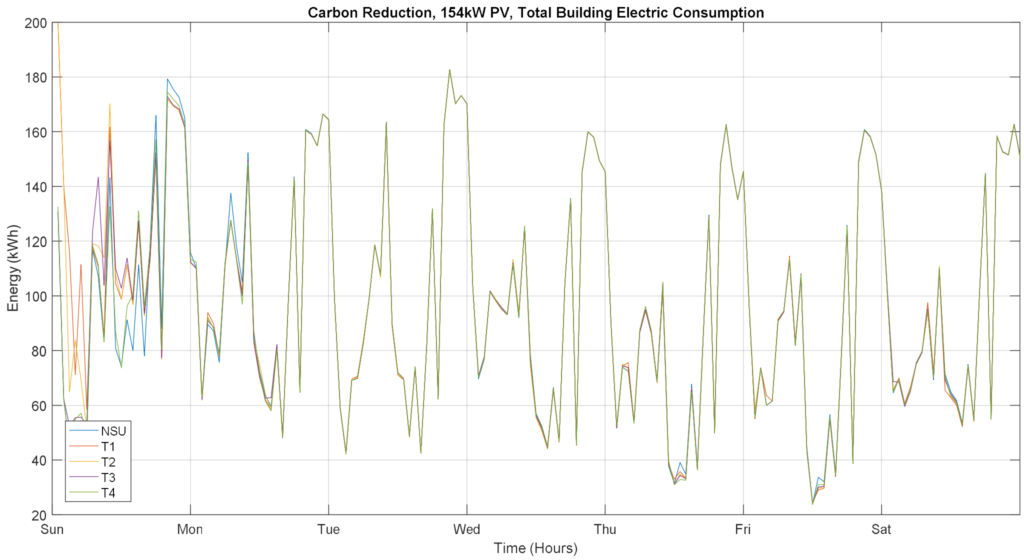
Carbon Reduction, 82kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3
T4



Carbon Reduction, 82kW PV, Total Building Electric Consumption
Energy (kWh)
Time (Days)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3
T4


Carbon Reduction, 154kW PV, Cooling Set Points
Temperature (C)
Time (Hours)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3
T4


Carbon Reduction, 154kW PV, Total HVAC Electric Consumption
Energy (kWh)
Time (Hours)
Sun
Mon
Tue
Wed
Thu
Fri
Sat
NSU
T1
T2
T3
T4


Carbon Reduction, 154kW PV, Total Building Electric Consumption
Energy (kWh)
200
180
160
140
120
100
80
60
40
20
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Time (Hours)
NSU
T1
T2
T3
T4