Economic Efficiency and Carbon Emissions in MES with Flexible Buildings

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ECONOMIC EFFICIENCY AND CARBON EMISSIONS IN MES WITH FLEXIBLE BUILDINGS

A Thesis Presented

by

Zachary L Hurwitz

to

The Faculty of the Graduate College

of

The University of Vermont

In Partial Fulfillment of the Requirements
for the Degree of Master of Science
Specializing in Mechanical Engineering

January, 2020

Defense Date: September 23rd, 2019
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Abstract

Multi-energy systems offer an opportunity to leverage energy conversion processes and temporary energy storage mechanisms to reduce costs and emissions during operation of campuses, cities, and buildings. With increasing options for flexibility in demand-side resources it is possible to meet demand without sacrificing comfort and convenience of MES occupants.

This Thesis develops a multi-period, linear optimization model of a MES with flexible buildings that captures nonlinearities in the efficiency of energy conversion processes. The flexible buildings are parametrized, in part, based on historical data from a college campus in Vermont, USA. The idea of the MES model is to investigate the role that flexibility plays in reducing costs and emissions for a small campus relative to that of a possible carbon tax. The operation of the MES is optimized to reduce costs based on representative seasons. Interestingly, it is found that when utilized optimally, flexible buildings allows for a more cost and energy effective method of not only meeting demand but also reducing carbon emissions in the process.
ACKNOWLEDGEMENTS

We would like to thank Mr. Mike Pelletier of UVM Physical Plant Department for assistant and support in data gathering and model verification. As well and Burlington electrical department and the Burlington airport for data collection.
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Chapter 1: Background and Motivation

While each generation has faced changes before it, the current generation will need to overcome the global fight against climate change. Climate change has already impacted the lives of millions of individuals around the world and will continue to impact many more. One way many aim to fight climate change is by achieving net zero emissions. However, this idea of net zero is loosely defined in the energy community, whether it represents zero total emissions or a net production of zero emissions [1, 2]. There are a variety of dials to turn when attempting to achieve net zero as seen in Fig. 1. From an environmental point of view, any reduction in the total emissions is a good start.

![Figure 1: Method of achieving net zero balance][2]

Smart energy technologies offer one method of moving towards a net zero future with our existing infrastructure. Unlike smart grid, which looks at only the electricity
sector, Smart energy looks at the larger picture working to unify all utilities and energy transmissions [3]. This means coupling electricity, heating, cooling, transport and even waste [4, 5]. This will give more storage options for the variability inherent to renewable generation as well as save overall costs and reduce emissions.

Smart energy systems also support the implementation of multi-energy systems (MES). These are processes like co-generation or tri-generation which involve the use of multiple sources of energy to meet the desired output of energy [6, 7]. For individual households this process may be automated, however for larger buildings, campuses and even entire cities the generation and delivery of these processes is a much larger and costly process that requires much more attention [8]. Fig. 2 shows an example of the energy variety and size variance in an MES.

Most single households use a conventional heating, cooling and electrical process with each of the three processes being fulfilled by an individual machine, some households have begun to vary the devices used, whether that be rooftop solar or anaerobic digesters, however many are too small for these to make a difference both monetarily and environmentally. Due to the increase in demand from scaling up from individual buildings to city blocks or campuses, operators are better able to take advantage of these processes to save money and energy.
Figure 2: Variation in size and application of MES systems [8]

MES utilize multiple types of energy in order to meet the necessary demand of the surrounding area. These systems are operated on different scales from city to city down to individual buildings however the larger the scale the larger the savings [9, 10]. While these multi-energy systems are more complex both in operation and construction then their single energy counter parts, the merging of multiple means of production can greatly reduce cost and emissions thought the plant [11].

With any process the waste products should be taken in to consideration and reused where possible, whether waste heat in a Rankin cycle [7] or biogases there are many waste-to-energy (WTE) processes and technologies that can be taken advantage of at all scales. [12, 13]

Renewables can always be used to help reduce emissions and achieve net zero however some problems do series from heavy reliance on renewable. The famous duck curve in California shows a problem that arose due to excess solar production.
Massive amounts of solar energy generated during the day were not fully used, while at night there was not enough solar being generated to meet the necessary demand. This problem was solved with the implementation of energy storage allowing excess daytime energy to be used at night [14, 15].

These problems can cause a serious problem for generating plants and without the available generation possible blackouts can occur, so instead of sizing the plant for the peak hour, storage can be used to reduce the amount of generation needed during these peak times by adding additional supply that had been stored previously.

Similar to the storage of electricity, thermal energy is able to be stored as well. Vermont Gas uses hot water heaters to store energy, instead of leaving the hot water heaters to operate themselves Vermont gas imposed mandatory shutoff and startup times for the hot water heaters to limit the demand for gas during high demand hours [16, 17, 18, 19].

The idea behind this study follows in line with energy storage. While batteries provide a huge bank for electricity there are no equivalent size or longevity storage units for thermal and chilled water in a commercial and residential environment. Ice storage takes much more space and can only be stored for a duration of hours, hot water storage is similar, and methods like molten salt or geothermal are unrealistic in these setting. However, buildings themselves are fairly large thermal masses and residential heating and cooling is a large pillar of energy usage in the US. For this reason, we wanted to look at the possibility of use a building as a thermal energy device and see how this would work. Studies have shown that there can be significant reductions in cost and environmental impact with the implementation of flexibility. [20, 21, 22, 23, 24, 25, 26]
However, no studies have shown this for the specific setup that commercial and residential buildings face in Vermont. Due to Burlington overwhelmingly green electricity supply gas usage, specifically Vermont gas is the largest player when it comes to environmental impacts.

This study will quantify the buildings as a whole taking into account building occupancy and simplifying the thermal circuit of the model. The effect building occupancy has on operation has been studied before. [11, 27, 28] However with the inclusion of an MES as well as an optimization around billing and scheduling of devices [29] is original in regards to Vermont. The simplification of the model does lead to some questions about how a more complex model would preform and where this model falls short. However, accounting for entity’s in the buildings as shown in Fig. 3 [30, 31] as well as the countless materials used in the building would lead to a parameter heavy study [32] whose impact would not greatly change the high level operations of the system.

Figure 3: 3D model of thermal heating in living room [31]
This Thesis will demonstrate the potential of building flexibility to reduce costs and emissions using a MES plant designed to operate optimally with cost savings with and without a carbon tax for a primary service electrical rate and High Usage gas rate building in Burlington thought three different billing seasons.
CHAPTER 2: JOURNAL ARTICLE

ECONOMIC EFFICIENCY & CARBON EMISSIONS IN MES WITH FLEXIBLE BUILDINGS

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0.1 Motivation & Introduction

Recently, climate change has intensified the focus on efficiency and methods to reduce carbon (and other harmful) emissions from human and engineering processes [33]. This has led to innovations in building and renewable energy technologies and significantly tightened efficiency standards. In fact, it is well-recognized that the passive nature of efficiency alone is not sufficient to enable the deep penetration of variable renewable generation required to reverse the trends of climate change. Thus, to go beyond efficiency, we need to leverage the flexibility that is available behind the natural gas and electric meters, which could come from homes [34], commercial buildings [35, 36], and large industrial sites, such as manufacturing and campuses [37, 38, 39]. This has even motivated organizations, such as LEED, to recently update their energy efficiency certification metrics to explicitly include and incentivize demandside flexibility [40].

The need for efficiency and flexibility includes multiple energy demand types, such as electric, (district) heating, and cooling. In fact, natural gas and electricity often supply C&I systems and buildings from vast networks of pipelines and transmission lines to physically couple the electric, heating, and cooling demands. Therefore, to improve efficiency and leverage flexibility requires a multi-energy systems (MES) approach that is cognizant of both the economics and the emissions in supplying the
demand, which is the focus of this paper. For a comprehensive overview of MES, please see [41]. In addition to innovations on efficiency and flexibility, there is also a growing popular demand for carbon tax policies, which alter the economics of energy. Within that context, this Thesis seeks to study and investigate the following question: for a realistic MES, what role can flexible buildings play in reducing costs and emissions relative to a carbon tax?

To answer this question, we:

1. analyze real data from buildings to develop a simplified first-order model of a thermodynamically flexible building;

2. develop a predictive model of a flexible MES, including nonlinear energy conversion processes inherent to realistic boilers, chillers, and combined heat and power plants;

3. optimize over the actual natural gas and electric energy and demand tariffs that promote “economic efficiency” and consider the role of a carbon tax; and

4. construct and analyze a realistic case-study based on a local university campus setting in Vermont, USA.

Most of the early work on MES focuses on combined natural gas and electrical optimal power flow (or GEOPF) on multi-carrier networks [42, 43]. This early work on MES optimization established the existence of new minimum cost solutions that were not achievable when studying the energy systems in isolation. In addition, these methods led to the MES modeling frameworks of so-called “Energy Hubs” and “Power Nodes” [44, 45, 46, 47]. The energy hub framework enabled innovative studies in:
distributed predictive modeling and control of energy hub systems, impact of hybrid-electric transportation, integration of energy storage, and multi-energy analysis of buildings [48]. Generalizing the energy hub models to manage flexible buildings as part of a MES has been presented, including [49], but was focused on control and short term operations rather than emissions and planning problems.

Herein, we build on concepts from university campus-scale MES [39], which developed a PWL framework and illustrated the value of considering the nonlinear energy conversion processes of boilers, chillers and combined heat and power (CHP) assets. That is, we employ a similar piece-wise linear (PWL) approximation of the underlying nonlinear energy efficiencies. However, the PWL approaches now more accurately capture the energy processes and we augment energy storage with available energy flexibility from buildings by allowed temperature set-points to deviate from their set-points. Much of the literature on flexible buildings focuses on feedback control or online optimization over at couple hours or up to a day [50]. However, we use historical MES demand data to construct representative seasonal demand profiles to consider average annual impacts of flexibility and carbon taxes. Similarly, we use historical data to estimate the thermodynamic parameters for building flexibility, in terms of the internal temperature set-points. The key contributions of this Thesis is the identification and integrating of flexible buildings (FB) within economic dispatch of a nonlinear MES (time-coupled PWL optimization), and the analysis of comparing the effects of FBs against that of a carbon-tax. Specifically, unlike very recent work from [47] that is also focused on campus-scale MES and carbon emissions, we focus on how flexibility in the thermal demand, in addition to a carbon tax, and separate from their energy hub coordination scheme can improve system performance. That is,
we show that flexibility in the proposed Vermont system (which has access to 100% renewable electricity) can achieve almost the same outcome with flexibility that it does with a carbon tax. That is, the incentives of economic efficiency almost align with those of the carbon tax in this system, which means that unlocking building-level flexibility in Vermont can lead to significant reductions in carbon without necessarily having a carbon tax in place.

The outline of the Thesis is as follows: Section 0.2 presents the MES model for curating the objective function and PWL constraints. The FB parameters are identified and estimated in Section 0.3 based on real demand and weather data. Section 0.4 presents the case-study on flexibility in Vermont, while Section 0.5 presents the conclusion and directions for future work.

Figure 4: Right: System-level overview of the MES system considered in this Thesis with economic costs as the key output. Left: physical asset-level overview of the MES considered in this paper. The energy conversion processes are illustrated with color changes while energy storage is represented by a cylinder. Flexible buildings are internal to the cooling/heating demands at the bottom.
0.2 System Modeling

From Fig. 4, a somewhat general MES is presented (on the left) and is separated (on the right) into different blocks to represent devices and their corresponding physical energy processes (conversion and storage). Each device modeled could be categorized in one of three block types, source blocks, storage blocks, and conversion blocks. Source blocks are used to inject (at a cost) energy, which includes natural gas and electricity. These blocks are used to calculate costs of operation as well as carbon emissions and are further discussed in Section 0.2.1. Storage blocks store energy over multiple time-steps and could represent electric batteries or thermal energy storage tanks whose general form is explained in Section 0.2.2. Conversion blocks represent devices, such as chillers, boilers and CHPs that transform one energy input into one or more energy outputs. Of course, these conversions are subject to the physical reality of losses, which for converting energy and calculating the associated losses are in Sections 0.2.3.

0.2.1 Energy Economics

Almost all systems are driven by economic incentives and MES are no different. That is, the focus on operating an MES is always on economic efficiency (i.e., costs), which is why carbon taxes put a price on carbon. At the core of these costs are utility tariffs from natural gas and electricity, which are described next and make up the objective function of the MES optimization problem described in this paper.
Natural gas

Natural gas is one of the two resources that can be purchased by the MES. The rate structure used in this model from the energy plant’s actual rate in Vermont and is relatively low at $0.8227/CCF, which is due to the fact that the rate is interruptible. Being interruptible (or “flexible”) means that during times of peak regional demand and limited supply (in the Northeastern U.S.), the MES may be asked to switch to fuel oil in order to reduce natural gas demand for the surrounding region. However, the natural gas supply is not interrupted more than one to two weeks per year and it is, therefore, reasonable to consider the cost above as a valid annual value. For this reason, we are not considering the short term and temporary (required) switch to oil enacted by the utility, even if the oil has significant increase in carbon emissions.

In addition, the utility also offers a cleaner form of renewable natural gas or “trash gas.” Renewable natural gas is recovered from landfills or in other methane recovery systems. As a large consumer, renewable natural gas can be purchased as a percentage of the total gas used: 10%, 25%, 50% or 90% with the costs of the (100%) renewable gas and corresponding emissions in Table 1. Clearly, any convex combination of conventional and renewable natural gas results in a convex combination of the costs and emissions. Lastly the cost of natural gas can be augmented with a carbon tax, which is estimated to approximately $0.05/lb. of carbon [51].
Table 1: Natural Gas Rate Parameters

<table>
<thead>
<tr>
<th>Name/ Info</th>
<th>Value/Ref</th>
</tr>
</thead>
<tbody>
<tr>
<td>Usage + Distribution + Energy Efficiency</td>
<td>$0.8227/CCF</td>
</tr>
<tr>
<td>Renewable Natural Gas Cost</td>
<td>$1.174/CCF</td>
</tr>
<tr>
<td>CO2 from Natural Gas</td>
<td>117.1 lbs. of CO2/CCF</td>
</tr>
<tr>
<td>CO2 from Renewable Natural Gas</td>
<td>50.1 lbs. of CO2/CCF</td>
</tr>
</tbody>
</table>

Electricity

The other MES supply is electricity, which is supplied by the Burlington Electric Department (BED) from the grid. Each building has its own electric meter and depending on size, its own electric rate. The buildings used in this Thesis fall into two categories in terms of rate structure, primary service “Ps” and large general “Lg.” We have chosen to focus on the more expensive of the two, “Ps” to provide a conservative estimate on costs and savings. The rate structures include time-of-use (TOU) and seasonally varying energy and demand rates. In addition, we include the standard fixed account fee and energy efficiency charges and the time-varying demand ($/kW) and usage ($/kWh) charges as well as associated taxes. As expected, the majority of the costs come from demand and usage charges, which can vary significantly over the year depending on peak seasons and hours. The official peak hours are shown in Fig. 5 and Table 2.
Figure 5: Peak hours begin at 6:00am and end at 10:00pm for the winter months while in the summer peak hours go from 12:00pm until 6:00pm. Shoulder months (April, May, October, November) do not incur peak demand or usage charges.

BED’s power is supplied from a bio mass plant, distributed solar and wind farms, and hydro-power imports, which makes BED’s entire electric supply 100% certified renewable with no associated CO2 burden. In fact, in the U.S., BED was the first utility whose supply was fully certified as renewable [52].

Table 2: Electric Rate Parameters

<table>
<thead>
<tr>
<th>Description</th>
<th>Value(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy efficiency use</td>
<td>$0.00413/ kWh</td>
</tr>
<tr>
<td>Energy efficiency demand</td>
<td>$1.6614/kW</td>
</tr>
<tr>
<td>Peak demand (Winter, shoulder, summer)</td>
<td>$[25.17, 0, 25.17]/ kW-month</td>
</tr>
<tr>
<td>Peak usage (Winter, shoulder, summer)</td>
<td>$[0.103813, 0, 0.095552]/kWh</td>
</tr>
<tr>
<td>Off-peak demand charges</td>
<td>$3.45/kW-month</td>
</tr>
<tr>
<td>Off-peak usage charges</td>
<td>$0.067251/kWh-month</td>
</tr>
<tr>
<td>CO2 emissions from electricity</td>
<td>0.0 lbs. of CO2/kW</td>
</tr>
</tbody>
</table>

Next, we describe models and constraints on energy storage and energy conversion processes, which later become subject to the described energy supply costs above in the economic dispatch problem.
0.2.2 ENERGY STORAGE PROCESSES

Energy storage processes can be in the form of thermal energy storage (e.g., ice-storage, heated rocks, molten salt) and chemical energy storage (e.g., Lithium-ion electric batteries). In this Thesis we focus on electric batteries. Later, we will also describe flexible buildings as part of the demand, however, energy flexibility is another source of energy storage that we leverage in this work, but is not described in this section.

Battery Equations

The batteries main purpose is to store chemical energy and use it at a later time step. Energy can be supplied to the battery from either the grid or a CHP. We assume no standing losses from keeping energy in the battery, however, charging and discharging losses are included.

Energy storage devices, like batteries, operate using the same base set of equations. Let $X_{\text{Bat}}[t]$ denote the state of charge of the battery at time-step $t$. There are three different loss-terms associated with using the energy storage device, losses while adding energy (charging rate $X_{\text{in}}[t]$) $\eta_{\text{in}}$, losses when removing energy (discharging $X_{\text{out}}[t]$) $\eta_{\text{out}}$. From these terms, we can capture the discrete-time (first-order) dynamics of the state of charge relative to charging and discharging schedules and the energy capacities, $X_{\text{Bat Max}}$, of the storage device over time for $t \in [0, 1, \ldots, T]$

\[ X_{\text{Bat}}[t+1] = X_{\text{Bat}}[t] + \eta_{\text{in}}X_{\text{in}}[t] - \frac{1}{\eta_{\text{out}}}X_{\text{out}} \]

\[ 0 \leq X_{\text{Bat}}[t+1] \leq X_{\text{Bat Max}} \]
In addition, there is a charging and discharging rate limit, $X_{\text{Bat}}^{\text{Step}}$. These vary for each device and limit the amount of energy allowed in and out of the device per time step:

$$-X_{\text{Step}}^{\text{Bat}} \leq X^{\text{Bat}}[t + 1] - X^{\text{Bat}}[t] \leq X_{\text{Step}}^{\text{Bat}}$$

(3)

In addition, we enforce a sustainability condition on energy storage to ensure consistency between representative periods in the simulation. This condition ensures that the initial energy states and terminal energy states of the device are the same: $X^{\text{Bat}}[1] = X^{\text{Bat}}[T]$. Table 3 outlines the battery specifications used in this paper.

**Remark** (Simultaneous battery charging and discharging). *Note that while the formulation for the battery above does allow for simultaneous charging and discharging (i.e., $X_{\text{SCD}}[t] := X^{\text{in}}_{\text{Bat}}[t]X^{\text{out}}_{\text{Bat}}[t] \geq 0$), the strictly positive prices for electricity enforce that $X_{\text{SCD}}[t] \equiv 0, \forall t$. Thus, it is not necessary to create a separate binary variable to indicate charging/discharging state.*

**Table 3: Battery Parameters**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery Capacity, $X^{\text{Bat}}_{\text{Max}}$</td>
<td>308 kWh</td>
</tr>
<tr>
<td>Max Charge Rate, $X^{\text{Bat}}_{\text{Step}}$</td>
<td>82 kWh</td>
</tr>
<tr>
<td>Battery Charging Losses, $\eta_{\text{in}}$</td>
<td>97.5%</td>
</tr>
<tr>
<td>Battery Discharging Losses, $\eta_{\text{out}}$</td>
<td>97.5%</td>
</tr>
</tbody>
</table>
0.2.3 Energy Conversion Processes

Converting energy from natural gas to steam and electricity and from steam to chilled water for cooling loads is a lossy process. Losses depend on the assets and their operations. For example, operating two natural gas steam boilers (natural gas to steam) at low load relative to one at high load can yield significant efficiency improvements. Many plants operate under so-called “N+1 mode” where if any boiler or chiller were to fail, the remaining devices could pick up the slack. While these constraints could be added, they have been ignored in this work to focus on the relationship between flexible demand and economic efficiency and carbon emissions. First, we describe the two main thermal energy conversion processes (steam and chilled water) before providing their input-output models and the piece-wise-linear (PWL) formulation used in this paper.

Generating steam

Both the boiler and CHP blocks employ combustion to convert natural gas to steam. The main difference between the two blocks lies with the CHP doing the conversion indirectly. Specifically, the CHP combusts natural gas (with compressed air) to create hot, high-pressure gas, which drive a gas generator to produce electricity. The resulting hot exhaust gas from the generator is the used along with a heat-exchanger (and/or heat-recovery steam generator) to generate steam [53]. Both the boiler and CHP have a variable efficiency. The boilers efficiency is a nonlinear, nonconvex function of the steam output while the CHP’s efficiency is a nonlinear, nonconvex function of the electricity output while the resulting available hot gas is
converted to steam at an (assumed) constant efficiency. For simplicity and owing to our non-operational planning purposes in this paper, we have chosen to ignore the complexities of mass flow rates of flues, steam loops, pumps, and air compressors and instead focus on the input-output relations between the different devices. Similarly, if steam is needed for a process, such as the absorption chiller described next, it is assumed that operations ensure that steam is at the desired temperatures and pressures.

**Chilled Water Generation**

There are two different types of chillers used in the model, electric and absorption chillers. The electric chiller converts electricity to chilled water while the absorption chiller converts steam input to chilled water output. Both devices operate in a similar manner besides the different inputs and have the same general operating assumptions. For each of them, heat transfer between the condenser, evaporator and cooling towers are neglected. Instead energy in and out are taken at a variable efficiency based on the devices coefficient of performance (COP; or EEF). That is, as was done with boilers and CHP, we have neglected the chilled water mass flows, pumps, and valves and deal solely with energy flows and lumped thermal demands, which is reasonable for the planning purposes of this paper.

Next, we describe the input-output relations of these devices and formulate the piece-wise linear (PWL) model to turn the nonlinear, non-convex efficiency curves into a computational tractable formulation (albeit by introducing integer variables). Nonetheless, given the maturity of MIP solvers and the underlying MILP formulation, we can solve to (near) optimality as will be discussed in the results section.
0.2.4 **Piece-wise linear (PWL) formulation**

The mapping between the input and the output for the boilers, chillers, and CHP are nonlinear and non-convex. To ensure a formulation that has a tractable global (near) optimal solution but avoids the oversimplification of a constant efficiency, we follow the work in [39] to replace the nonlinear input-output curves with their PWL approximations. The empirical\(^3\) nonlinear input-output curves are provided in Table 4 for representative devices in this Thesis while Table 5 outlines the devices specific parameters. When there are multiples of the same device type, the performance curves have been de-rated slightly to differentiate their dispatch.

<table>
<thead>
<tr>
<th>Device</th>
<th>Performance curve (based on [39])</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boiler</td>
<td>(Y = -0.155X^3 + 0.587X^2 + 0.267X)</td>
</tr>
<tr>
<td>CHP (Steam)</td>
<td>(Y = 0.45X)</td>
</tr>
<tr>
<td>CHP (Electric)</td>
<td>(Y = -1.026X^3 + 2.6084X^2 - 0.0293X)</td>
</tr>
<tr>
<td>Absorption Chiller</td>
<td>(Y = 0.3X^3 + 1.2X^2 + 0.03X)</td>
</tr>
<tr>
<td>Electric Chiller</td>
<td>(Y = 0.32X^3 + 1.4X^2 + 0.03X)</td>
</tr>
</tbody>
</table>

To generate the PWL approximation, we mostly follow [39] by first defining the maximum input/output operating ranges for each device. The original nonlinear input-output curves are a function of historical performance data and original manufacturer data.

---

\(^3\)The input-output curves are a function of historical performance data and original manufacturer data.
The curve is limited between those operating points. Next, we select $M + 1$ input-output pairs from the nonlinear curve, which define $M$ PWL segments. Each segment is defined by a linear expression of the slope and intercept $(m, b)$, respectively: $Y = m_i X + b_i$, $\forall i = 1, \ldots, M$, where $i$ represents the $i$-th segment (or bin).

Thus, at time $t$ and for each device, the input, $X[t]$, and output, $Y[t]$, variables are created. Each device also has static input limits $X_{Min}$ and $X_{Max}$, as well as a binary ON/OFF variables, $X_1^t \in \{0, 1\}$. If the device in ON, then (4) ensures that it operates within its limits, while (5) ensures that the device does not ramp up faster than the static ramping limit, $X_{Ramp}$. Equation (6) keeps track of how many times the device starts up throughout the day because each start-up event requires consuming a non-trivial startup energy portion to get started, $X_{Start}$.

\begin{align*}
X_{Max}X_1^t[t] & \geq X[t] \geq X_{Min}X_1^t[t] & (4) \\
X[t] - X[t - 1] & \geq X_{Ramp} & (5) \\
X_{Start}[t] = X_1^t[t] - X_1^t[t - 1] & (6)
\end{align*}

From the PWL setup, we then need to segment the input and output variables. Starting with the input, we define $X[t]$ to defined as a collection of $M$ binned variables that cover the entire input range as shown next.

$$X[t] = \sum_{i=1}^{M} B_i[t].$$

(7)

In (7), the binning of the input is achieved by introducing the binned input variables, $B_i$ for PWL segment $i = 1, \ldots, M$. Recall, these $M$ segments are generated from the nonlinear curve ranging from the minimum operation of the device to the
maximum. However, to ensure that at most one input bin is active to represent the admissible input range of segment $i$, we need to limit the number of active bins to at most one:

$$\sum_{i=1}^{M} B_{i,t} \leq 1,$$

(8)

where $B_{i,t}$ is the binary (0/1) segment indicator variable for PWL segment $i$. This ensures that the device is either OFF or operating within its input range and at the efficiency determined by the active PWL segment $i$.

Next, the binary segment indicator values are used to capture the admissible range of input bin $B_{i,t}$ with the segment’s upper and lower limits:

$$B_{i,t}B_{i} \leq B_{i,t} \leq B_{i,t}B_{i},$$

(9)

Note that these upper and lower segment bounds are defined by the consecutive input point pairs that make up PWL segment $i$. Finally, with PWL segment $i$’s input range defined, we can define the output in terms of the input bins and the PWL segment line expressions as:

$$Y[t] = \sum_{i=1}^{M} m_i B_{i,t} + B_{i,t}b_i$$

(10)

which ensures that that the output $Y$ is always represented by a single active PWL segment (or none at all, if all binary segment indicator variables are zero). Figure 6 presents an example for a PWL approximation of a nonlinear, input-output curve with $M = 4$ segments.
Figure 6: Example of using the PWL approximation for a general device with $M = 4$ segments and the corresponding input bins and binary segment indicator variables. Note that the third segment is active in this example (i.e., $B^3_{1,0} \equiv 1$).

0.2.5 Demand

Through the energy storage and conversion processes, the goal of any MES is to supply the (multi-energy) demand while minimizing economic costs as illustrated in Fig. 4. In this section, we describe the demand types and highlight the nature of the flexibility in thermal (building) demand.

Electric Demand

Electrical demand was recorded from the meters of each building, and aggregated to create one representative week-day and weekend-day for each season. From these representative seasonal days, we can construct seasonal weeks and months as needed. To meet the electric demand, electricity is either supplied by the grid $E_{\text{Grid}}$ (subject
to the electric rate) or generated in via a CHP $E_{chp}$ (subject to conversion process and natural gas rate). The electricity supply can go to either meet the electric demand $E_d^{Tot}$, charging the battery $E_s^{Tot}$ or run an electric chiller, $E_{Chw}^{Tot}$. That is, from electric power balance requirements:

$$E_{chp}[t] + E_{Grid}[t] = E_s^{Tot}[t] + E_d^{Tot}[t] + E_{Chw}^{Tot}[t], \quad (11)$$

where $E_s^{Tot}[t] := E_{in}^{Bat}[t] - E_{out}^{Bat}[t]$ is the battery’s net-charging effect.

**Heating Cooling and Flexibility**

Heating and cooling do not necessarily have a meter to pull data from, but more require a level of comfort. Ambient temperature for the area has been recorded by the local Burlington Airport and this data was averaged in a similar manner to the electrical data to provide a representative dataset for each season. This data was then used together with the building management system’s (BMS’s) setpoint and a one dimensional heat transfer model approximation of the building to simulate heating, cooling, and ambient losses for the building. The model then assumed that the set-point temperature was maintained at the BMS’s set-point since the building was not operated in a flexible manner. Equation (12) relates the energy supplied to the building, $E_{in}[t]$, to the demand-serving assets (heating and cooling) at a given time $t$. Boilers and the CHP can supply steam for heating, $S_d^{Tot}$, increasing the internal temperature while chillers $Chw_d^{Tot}$ supply the energy for cooling the building (i.e., reducing the temperature). This is capture as follows:

$$E_{in}[t] = S_d^{Tot}[t] - Chw_d^{Tot}[t] \quad (12)$$
The one-dimensional heat transfer in (13) governs the temperature inside the buildings [54]. On the left side is the building temperature $\theta$ and thermal mass $M_{th}$, while on the right side of the equation the energy in from the physical plant $E_{in}$, as well as energy in or out due to ambient forcing terms, $\theta_{ambi}$ and building activity $U[t] \in \{0, 1\}$ is equal to one if the building is populated (during normal hours) and else is zero. That is, the building usage term represent the impact of human activity on the building (e.g., an energy loss from opening/closing windows). The terms $M_{th}, Cp, R, U_{use}[t] \eta_{use}$ are further explained in Table 9 and detailed in Section 0.3, where they are estimated from historical demand and weather data.

$$\frac{M_{th}Cp(\theta[t+1]-\theta[t])}{\Delta t} = (1 - \eta_{use}U[t]) \frac{E_{in}[t]}{\Delta t} - \frac{R(\theta[t]-\theta_{ambi}[t])}{\Delta t}$$ (13)

The temperature inside the building can vary around the setpoint by some fixed dead band, $\theta_{flex}$ (e.g., 2, 5, or 10 degrees) as long as over the course of the day, the temperatures average value is close to the set-point to ensure average comfort. This is the idea of energy flexibility within buildings and is defined next.

One of the key contributions of this Thesis is the parametrization of a flexible building, which includes the ability of the building to operate within a dead band around the BMS’s temperature set-point. The larger the dead band, the more flexibility the building has. This allows the building to behave similarly to a thermal energy storage device. The building can be charged by raising or lowering the temperature relative to the ambient temperature, and then discharge by not supplying as much heating or cooling and allowing the indoor temperature to move towards the upper or lower dead band bound (depending on the season). This can allow for preheating or pre-cooling based on a predicted increase in demand, change in ambient
temperature, or to reduce peak demand. In (14), and (15), the temperature bounds and the averaging constraint on temperature excursions from the set-point ensure that the comfort levels are satisfied on average.

\[
\theta_{\text{Set}} - \frac{\theta_{\text{flex}}}{2} \leq \theta[t] \leq \theta_{\text{Set}} + \frac{\theta_{\text{flex}}}{2}
\]

\[
\frac{1}{T} \sum_{t=1}^{T} \theta[t] = \theta_{\text{Set}}
\]

As with energy storage, we impose a terminal consistency constraint on the temperature that together with the above constraints ensure that comfort is achieved on average and that every day starts and ends at the same temperature set-point: \(\theta_{\text{Set}} = \theta[1] = \theta[T]\).

Next, we leverage building-level data to estimated parameters that enable flexible buildings.

0.3 Identifying Flexible Building Parameters

0.3.1 One Dimensional Heat Transfer Model Parameters

The one dimensional building model presented above assumes a single wall with a thermal resistance and a mass of air on one side at ambient temperature and a mass of air on the other side equal to the equivalent thermal mass inside the building. To
make this approximation useful, we need to approximate the equivalent weight and amount of air inside the building as well as an equivalent thermal resistivity of the building. Sections 0.3.1 and 0.3.1 discuss how these parameters are calculated using data from the physical plant.

**Approximating thermal mass $M_{th}$ and 1-D Approximation**

To determine the thermal mass for the model, data was collected for the available buildings involved in the paper. These data include the number of floors, rooms, active and inactive floor-space as well as the wall height and thickness, which vary within the buildings. Using this data, we were able to determine the total volume of air within these buildings, and easily convert that to a thermal mass of air using its density. Walls, windows, doors and air vents are all lumped together in the thermal resistant term $R$.

**Calculating Thermal Loss Term $R$**

The 1D approximation used for the heat transfer equation inside the buildings not only simplifies the models but also the necessary parameters needed in order
to solve the model. Thermal resistivity was needed to calculate the energy transfer between the buildings to the ambient surroundings. Using heat transfer relation in (12), it is reasonable to assume a constant indoor temperature throughout the day (i.e., \((\theta[t + 1] - \theta[t]) \equiv 0\)), which allows us to drop the left-hand side of (13) and get:

\[
0 = E_{in} - R(\theta[t] - \theta[t]_{ambi})
\]

This form then states that the losses must be equal to the energy added, as there is no change in temperature inside the building. From this we can then solve for the thermal resistivity \(R\) in terms of the energy in (which we have from metered data) and the difference in temperature inside the building (i.e., the BMS’s set-point) and ambient conditions (i.e., data from the local airport).

\[
R = \frac{E_{in}}{(\theta[t] - \theta[t]_{ambi})}
\]

From the available metered interval data we can then set up a large set of equations and estimate \(R\). Figure 7 shows the distribution of calculated \(R\) values for 7 months of data.
Since the mean value are consistent for the different distributions of the $R$-estimates and we are focusing on an annual average outcome in the simulations, we average the monthly averages for the 7 months of estimates. This yields an estimated $R = 0.01392 \text{ ft}^2 \text{F}/(\text{MMBtu/hr})$.

**Building usage term, $U$**

At a university, there can be a significant difference in utilization of the campus buildings between seasons (e.g., holidays, summer break, teaching semesters) and weekdays and weekends (e.g., lectures are on weekdays). This led us to consider estimating a correction factor for increased/reduced building utilization during day/night and weekend/weekday and gave rise to the notion of the building usage term, $U[t]$, which is a time-dependent binary parameter and not a variable that reflect internal building usage and corresponding energy usage disturbances (or losses) to account for the additional individuals and activity within the building during semester weekdays.

*Figure 7: Distribution of estimated thermal resistivity $R$ for different seasons based on data.*

![Calculated R Value For Constant Building Temperature](image.png)
as well as the reduction during nights and weekends outside of teaching semesters.

On average, ambient temperatures are similar for a representative weekday and weekend in a given season, so the only real change between these periods is building activity. A similar change can be found between daytime and nighttime however nights consistently have lower temperatures. In a given season, the temperature setpoints are also held constant by the BMS. This means that the same setpoint is used during the day and night as well as weekday and weekend. Thus, from steam flow and pressure data, as well as, the corresponding ambient temperature data collected over the past five years, we separated the data into day and night bins and also weekday and weekend bins, which led to four data classes and clusters. The usage term can then be approximated from the centroids of each of the four day-time cluster, which are shown in Tables 7 and 8 for steam pressure and steam flow. For day and night, there are a larger temperature drops as well as a smaller drops in the usage term. Between weekday and weekend daytime usage there is a much smaller drop in temperature but still a noticeable change in usage.

<table>
<thead>
<tr>
<th>Day/Time</th>
<th>Steam Psi</th>
<th>Temp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekend-Night</td>
<td>954.84</td>
<td>47.05</td>
</tr>
<tr>
<td>WeekDay-Night</td>
<td>963.37</td>
<td>47.20</td>
</tr>
<tr>
<td>Weekend-Day</td>
<td>965.93</td>
<td>51.17</td>
</tr>
<tr>
<td>WeekDay-Day</td>
<td>969.75</td>
<td>52.03</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Day/Time</th>
<th>Steam Flow</th>
<th>Temp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekend-Night</td>
<td>7.54</td>
<td>47.05</td>
</tr>
<tr>
<td>WeekDay-Night</td>
<td>7.51</td>
<td>47.20</td>
</tr>
<tr>
<td>Weekend-Day</td>
<td>7.51</td>
<td>51.17</td>
</tr>
<tr>
<td>WeekDay-Day</td>
<td>7.42</td>
<td>52.01</td>
</tr>
</tbody>
</table>

From this we can estimate that the effect of the the internal building activity (not energy usage) during the weekday leads to approximately $\eta_{use} = 1\%$ more energy.
consumed than for inactive times at the same temperature. This may be due to doors and windows being opened as well as more rooms being occupied and requiring additional energy to support. To be clear, this loss term is only present during weekday and day-time hours of the simulations and represents an additional (small) forcing term on the buildings to account for increased activity (relative to other times/days).

Combining the estimates of building parameters allows us to complete our flexible building parametrization, which is presented in Table 9. Next, we combine the MES model presented above with the flexible building model presented here to look at the high-level role that flexible buildings can play on MES and compare it to that of a carbon tax.

Table 9: Building Heat Transfer Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass and Cp of Air, $M_{th}C_p$</td>
<td>0.3 MMBTU/F$^\circ$</td>
</tr>
<tr>
<td>Thermal Resistance of System, $R$</td>
<td>0.01392 MMBTU/F$^\circ$</td>
</tr>
<tr>
<td>Usage Energy Loss Term, $\eta_{use}$</td>
<td>1%</td>
</tr>
<tr>
<td>Usage Time Steps, $U_{use}$</td>
<td>Weekdays[8:00am 10:00pm]</td>
</tr>
<tr>
<td>Flexibility, $\theta_{flex}$</td>
<td>[0.5, 2.5, 5.0, 10, 20]F$^\circ$</td>
</tr>
</tbody>
</table>
0.4 MES Case-Study: Economics & Flexible Buildings

Combining the models above with representative data and utility energy supply rates, we performed a number of tests under different assumptions on the available flexibility from buildings and on carbon prices. The MES in question is presented in Fig. 4 and utilizes one electric chiller, one absorption chiller, one large battery, one CHP, and two boilers. Each energy conversion process is represented by $M = 8$ PWL segments. The building temperature setpoint was set to 72 for the winter and 62 for the summer and 70 for the shoulder months. Five different flexibility levels were considered:

$$\theta_{\text{flex}} \in \{0.5(\text{none}), 2.5(\text{low}), 5(\text{medium}), 10(\text{high}), 20(\text{extreme})\}$$

and tested under two carbon pricing scenarios: with and without a carbon tax. Each season is a month from summer, winter, and shoulder, and the seasonal period is composed of representative weekdays ($\times 22$) and weekends ($\times 8$).

The MES system was formulated as a multi-period, mixed-integer linear program (MP-MILP) and run for one hour or to within a 2% optimally (MIP) gap using Julia Pro version 6.4.1 with GUROBI’s MILP solver (v8.0.1) on an Intel core i7 with 16GB memory. All solutions achieved the 2% MIP gap, which was deemed reasonable in the context of the averaged representative periods and other model approximations. The average MP-MILP run time for representative {Winter, Shoulder, Summer} weekend and weekday solutions were less than {30, 25, 520} seconds.
Figures 8-10 show the main results: each representative season (Winter, Summer, Shoulder) and the total predicted operating costs and carbon emissions resulting from each case of flexibility, $\theta_{\text{flex}}$. Each pairing of points represents an evaluation of the MES for one seasonal month made from evaluations of the weekday and weekend at the given flexibility. Within each figure, the top plot is the result without a carbon tax, while the bottom plot includes the carbon tax. The x-axis of all plots shows the increasing levels of building flexibility (from none to extreme), and the y-axis of all plots correspond to the optimized operating costs (black) and resulting carbon emissions (blue).

*Figure 8: Winter Flexibility Runs*
As expected, seasonally Winter has the highest cost and emissions due to high heating demand in Vermont, while the shoulder months have the lowest (neither hot nor cold). The Summer falls in the middle of both, leaning closer to Winter in terms of cost, and closer to the shoulder months in terms of emissions.

### 0.4.1 Role of Flexibility

Increasing flexibility decreases overall costs in both carbon scenarios (with/without carbon tax). In all of but two cases did the emissions decrease with increasing
flexibility as well, which highlights the alignment between economic efficiency and reduced emissions. Summer without a carbon tax from 0.5 to 2.5 saw carbon increased by 0.03 and shoulder months with carbon tax from 10 to 20 flexibility. The reason for this had been determined as excess CHP usage to generate electricity, this cuts electric costs but uses excess natural gas. With the implementation of the carbon tax, the system sees on average 20\% higher costs but only 3\% decrease in overall emissions.

**Remark** (Flexibility and carbon emissions). *Table 10 shows the reduction in emissions due to a carbon tax (without flexibility) versus no carbon tax (with flexibility). Remarkably, in this case, increasing flexibility in winter to just 2.5 degrees sees a larger reduction than the carbon tax (without flexibility). Summer takes until 5 degrees of flexibility and the shoulder months see flexibility overtake a carbon tax at 20 degrees of flexibility. This shows that for a system like the one in Vermont where electricity is already clean, thermal flexibility alone can have similar (or greater) impact that a carbon tax. And this system is not even particularly complex (i.e., limited options for dispatching assets).

**Table 10: Flexibility (and no carbon tax) vs. Carbon tax (and no flexibility)**

<table>
<thead>
<tr>
<th>Flexibility</th>
<th>0.5</th>
<th>2.5</th>
<th>5</th>
<th>10</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Winter</strong></td>
<td>439.79</td>
<td>-3052.1</td>
<td>-5601</td>
<td>-7519.8</td>
<td>-11342</td>
</tr>
<tr>
<td><strong>Shoulder</strong></td>
<td>2580.1</td>
<td>2200.1</td>
<td>1215.6</td>
<td>403.81</td>
<td>-361.39</td>
</tr>
<tr>
<td><strong>Summer</strong></td>
<td>1292</td>
<td>1358.2</td>
<td>-2094.9</td>
<td>-7330.6</td>
<td>-22512</td>
</tr>
</tbody>
</table>
Building flexibility alters how the system chooses to dispatch its assets. Figures 11a and 11b show the ambient and internal temperature of the buildings with 0.5 and 10 degrees of flexibility respectively while figures 12a and 12b show the corresponding energy supplied. With little to no flexibility the boilers are forced to ramp up and down in order to maintain a temperature within a few degrees of the set point. Only with added flexibility does this dose the system take advantage of the buildings innate storage properties and use it like a battery. This is continued into the summer and shoulder months in Figures 13-16. The summer months pre-cool the buildings using the steam driven chiller, as it is more cost-effective than to utilizes the electric chiller. While the shoulder seasons operate in a less-extreme version of winter, only utilizing one boiler and the CHP as needed.

Table 11: Percent reduction of Carbon

<table>
<thead>
<tr>
<th>Flexibility</th>
<th>2.5</th>
<th>5</th>
<th>10</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Tax</td>
<td>0.90</td>
<td>1.56</td>
<td>2.06</td>
<td>3.04</td>
</tr>
<tr>
<td>Tax</td>
<td>0.94</td>
<td>1.51</td>
<td>3.85</td>
<td>5.09</td>
</tr>
<tr>
<td>Shoulder</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Tax</td>
<td>0.19</td>
<td>0.68</td>
<td>1.09</td>
<td>1.47</td>
</tr>
<tr>
<td>Tax</td>
<td>7.46</td>
<td>8.00</td>
<td>8.14</td>
<td>5.76</td>
</tr>
<tr>
<td>Summer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Tax</td>
<td>-0.035</td>
<td>1.78</td>
<td>4.54</td>
<td>12.53</td>
</tr>
<tr>
<td>Tax</td>
<td>0.67</td>
<td>1.76</td>
<td>3.75</td>
<td>14.38</td>
</tr>
</tbody>
</table>

Table 12: Percent reduction of Cost

<table>
<thead>
<tr>
<th>Flexibility</th>
<th>2.5</th>
<th>5</th>
<th>10</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Tax</td>
<td>0.71</td>
<td>1.14</td>
<td>1.53</td>
<td>1.56</td>
</tr>
<tr>
<td>Tax</td>
<td>0.61</td>
<td>0.86</td>
<td>1.83</td>
<td>2.10</td>
</tr>
<tr>
<td>Shoulder</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Tax</td>
<td>1.01</td>
<td>1.63</td>
<td>1.81</td>
<td>1.94</td>
</tr>
<tr>
<td>Tax</td>
<td>0.46</td>
<td>1.79</td>
<td>1.90</td>
<td>2.17</td>
</tr>
<tr>
<td>Summer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Tax</td>
<td>1.92</td>
<td>2.78</td>
<td>3.69</td>
<td>3.86</td>
</tr>
<tr>
<td>Tax</td>
<td>1.34</td>
<td>3.63</td>
<td>4.91</td>
<td>5.23</td>
</tr>
</tbody>
</table>
(a) Winter temperature with no flexibility  
(b) Winter temperature with high flexibility  

Figure 11: Winter indoor and ambient temperatures

(a) Winter with no flexibility  
(b) Winter with high flexibility  

Figure 12: Optimal dispatch for winter

(a) Summer without flexibility  
(b) Summer with flexibility  

Figure 13: Summer indoor and ambient temperature

37
Figure 14: Optimal dispatch for summer

(a) Summer with no flexibility  
(b) Summer with high flexibility

Figure 15: Shoulder Heating for buildings

(a) Shoulder with no flexibility  
(b) Shoulder with high flexibility

Figure 16: Optimal dispatch for shoulder month

(a) With no flexibility  
(b) With high flexibility
Finally, it is worth pointing out that the amount of energy saved is relative to the ambient temperature and the base amount of energy needed without flexibility. In winter, a 10 degree increase in building flexibility (high) sees an equivalent of 40,000 BTUs of thermal energy storage. While in the summer 10 degrees of flexibility is the equivalent of reducing load by 4,000 BTUs throughout the day.

Unfortunately, the flexibility does not carry over to the electrical side. Due to the high cost of electric rate’s demand charges compared with natural gas, it is always be more cost effective to run the CHP and use the battery to reduced peak usage as much as possible independent of what happens on the cooling and heating side. The battery early in the day to then use the stored energy during peak hours to cut the peak demand and usage from the grid, this is the largest cost saver and the strategy does not change with added flexibility, but instead incentivizes the system to run the CHP more throughout the day.

Figure 17: Electric Usage
0.4.2 The need for policy and flexible building technology

The carbon tax does not significantly change the operation strategy for the plant. While the CHP does not have to generate electricity and the electric chiller could be used instead of the steam driven to minimize cost, even with a carbon tax, the best strategy is to cut electricity purchased from the grid. Further increasing the carbon tax would eventually cause the system to switch to focus on mitigating natural gas consumption. However, increasing flexibility not only reduces cost and emissions but does so by lowering the demand instead of increasing the cost of the supply. Increased flexibility means less cooling or heating is required thereby less resources are used and, more importantly, the resources are used more efficiently to ensure less fuel is used to supply demand. Furthermore adding more flexible buildings to the system would give plants more options as they could not only per heat and cool with regards to weather, and peak hours, but also to other buildings. However, these gains from flexibility come at the cost of convenience, so there is a need to develop technologies that surreptitiously unlock temporary flexibility without sacrificing comfort in the home or work place. This puts the onus on design and operation of modern buildings, especially those with energy conscious design, to take full advantage of this intrinsic storage property to potentially save even more energy, reduce emissions further, and control costs.
0.5 Conclusion and Future Work

In this paper, we aimed to identify the effects of flexibility within buildings on a Vermont-based campus. The demand as well thermal and physical parameters for the model were derived using historical data while the internal, nonlinear energy processes that drive the results were modeled using PWL approximations to estimate MES performance. This MES was then formulated as a multi-period MILP problem and tested seasonally for different flexibility scenarios with and without a carbon tax. It was then determined that increased flexibility not only reduces costs of operation but also significantly reduces emissions. For this reason, flexibility may be more valuable in Vermont (and other high renewable electric settings) than a carbon tax if especially if the technology in place or the building design is constructed in a manner that can take the fullest advantage of flexibility.

For future work, we seek to expand on the asset models to include more detailed asset models, including cooling towers and fully validated building models (rather than the first order model used). We are also interested in more advanced building control schemes to expand flexibility without directly affecting occupants. Finally, we would be excited to pursue testing with the physical plant division at the university or elsewhere to validate these flexibility results in a realistic setting to quantify the CO2 reductions and savings.
CHAPTER 3: CONCLUSION

The climb towards net zero will not be an easy one and there is no clear path on how to get there. We can take an in depth look into individual rooms and individual actions and try to squeeze every bit of savings out, or we may look at a much larger scale of cities and districts and find ways to save energy there. Both are valid and both have been proven to make a difference. Building flexibility falls right in between the two scales and with wider use in multiple buildings could see dramatic changes both monetarily and environmentally.

For this reason, we would like to see this idea tested at different scales, studying the effects of flexibility on individual rooms as well as the effect of districts and city’s implementing flexibility. The race to net zero is one that could as easily be won with large steps as it could with small ones.
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Appendix

Optimization Code

```
using DataFrames
using MAT
using JuMP
using Gurobi
using JLD2

MIPTIME = 1
MIPGAP = .05

MinRun = .25
Gstart = .25
RampPerct = .30
XX = 8
TestRuns = 2
Flex = [.5]

HowManyDays = 1
Mnth = [1 7 11]
Rate = "PS";

numEChil = 1
numAChil = 1
numChp= 1
numBat= 1
numBlr= 2
SizeBatS = 0
SizeBatChw = 0

nuflx = length(Flex)
numnth = length(Mnth)

k = 1; n = 1; N = 96;
ps= 1;
pl = N;
UVM = matread("UVMGivenDataWaterman.mat");
```
X = UVM["WatermanE"]; ElectricFull = X[n:N,:];
X = UVM["WatermanCool"]; CoolingFull = X[n:N,:];
X = UVM["WatermanHeat"]; HeatDemandFull = X[n:N,:];

Usageindx = matread("BuildingUsageIndex.mat"); X = Usageindx["Active_Index"]; Uindex = X[n:N,:];
X = readtable("PriceData.csv") PriceData = X[n:N,:];
UVMTout = matread("OutdoorAirTemp.mat"); X = UVMTout["WeatherWeek"] UVMT = X[::]

Cf2Btu = .1027; kw2BTU = 0.00341214; CF2KW = 30.4/4 ;

x_B = XX; Steamout_Blr_Max = 3
Gasin_b_Max = Steamout_Blr_Max*2.434274586

x_Chp = XX
Gasin_chp_Max = 3*2.434274586

x_CHW = XX; EEFA = 1.2; A_ch = EEFA-.8

x_CHWE = XX EEFe = 1.1 MaxEChwTons = 500 A_che = EEFe-.8

Data_Electric2Bld = zeros(numnth,nuflx,TestRuns,HowManyDays)
Data_Eng2Bld = zeros(numnth,nuflx,TestRuns,HowManyDays)
Data_GMon = zeros(numnth,nuflx,TestRuns,HowManyDays)
Data_EMon = zeros(numnth,nuflx,TestRuns,HowManyDays)
Data_EC02 = zeros(numnth,nuflx,TestRuns,HowManyDays)
Data_GC02 = zeros(numnth,nuflx,TestRuns,HowManyDays)
Data_OBJ = zeros(numnth,nuflx,TestRuns,HowManyDays)
Data_Gap = zeros(numnth,nuflx,TestRuns,HowManyDays)

for mo = 1:numnth
  for flx = 1:nuflx
    for Obj = 1:TestRuns
      for dow = 1:HowManyDays
        Electric = ElectricFull[n:N,Mnth[mo]];  
        Limit_percent_gap = Flex[flx]
        USlim = (Limit_percent_gap)/2;
        LSlim = (Limit_percent_gap)/2;

        Setpoints = [72 66 70 ]
        Setpoint = Setpoints[Mnth[mo]]

        TambiWeekday = (UVMT[1:96,Mnth[mo]]);  
        TambiWeekend = (UVMT[481:576,Mnth[mo]]);
        DOW = [TambiWeekday TambiWeekend]
        Tambi = DOW[:,dow]

        MCp = .03; R = .01392; Dt = .25

        DperC02 = .05

        EU = 0.00413
        ED = 1.66140

        offW = find(PriceData[:,5].==0)
        peakW = find(PriceData[:,5].==1)
        offS = find(PriceData[:,6].==0)
        peakS = find(PriceData[:,6].==1)
        All = find(PriceData[:,6].!=2)
        Allind = round.(Int,[All])
PD  =  [25.17  25.17  0  ]
PU  =  [0.095552  0.103813  0.0]

OPD  =  3.45
OPU  =  0.067251  0.0764180  0.067251

SholderOff  =  ones(length(PriceData[:,1]))
Sholder    =  zeros(length(PriceData[:,1]))
Season=  "W","S","O"
off    =  round.(Int,[offW,offS,SholderOff];)
peak   =  round.(Int,[peakW,peakS,Sholder])

EDisChargeCeloss  =  .050
EChargeCeloss =  0
GridMax    =  1050
BatEMax    =  308
BatEStart  =  0
BatStep    =  BatEMax*.15

Csloss=  .025
BatStart    =  0
BatSMax     =  30*SizeBatS

# CHP PLW Constrains#
inVal  =  linspace(0, Gasin_chp_Max, x_Chp+1);
Chp5   =  -1.026*(inVal/Gasin_chp_Max).^3 + 2.6084*
         (inVal/Gasin_chp_Max).^2-0.0293* (inVal/Gasin_chp_Max);
         \( \rightarrow (inVal/Gasin\_chp\_Max).^2-0.0293* (inVal/Gasin\_chp\_Max); \\
Chp5   =  -1.846*(inVal/Gasin_chp_Max).^3 + 2.7084*
         (inVal/Gasin_chp_Max).^2-0.0293* (inVal/Gasin_chp_Max);
         \( \rightarrow (inVal/Gasin\_chp\_Max).^2-0.0293* (inVal/Gasin\_chp\_Max); \\

Gchp\_slope  =  zeros(x_Chp,numChp);
be\_chp =  zeros(x_Chp,numChp)
for i = 1:numChp
  for s = 1:x_Chp
    Gchp\_slope[s,i] = (1.1-.1*i)*(Chp5[s+1]-Chp5[s])
         \( \rightarrow /(inVal[s+1]/Gasin\_chp\_Max-inVal[s]/Gasin\_chp\_Max); \\
  end
end
deltaIn = diff(inVal);
deltaInCHW = sum(deltaIn)/length(deltaIn);
Bin_IndexU = [1:x_Chp;];
Bin_IndexL = [0:x_Chp-1;]
Bin2UseSchpU = (deltaInCHW*Bin_IndexU);
Bin2UseSchpL = (deltaInCHW*Bin_IndexL)

for i = 1:numChp
    for s = 1:x_Chp-1
        be_chp[s+1,i] = ((Gchp_slope[s,i]*Bin2UseSchpU[s]) + 
                        (be_chp[s,i]) - ((Gchp_slope[s+1,i]*Bin2UseSchpL[s+1])))
    end
end

EffE_chp = .40

inVal = linspace(0, Gasin_b_Max, x_B+1);
B_slope = zeros(x_B,numBlr); b_B = zeros(x_B,numBlr)

for i = 1:numBlr
    for s = 1:x_B
        B_slope[s,i] = (1.1-.1*i)*(B5[s+1]-B5[s])/(inVal[s+1]/Gasin_b_Max-inVal[s]/Gasin_b_Max);
    end
end

deltaIn = diff(inVal);
deltablr = sum(deltaIn)/length(deltaIn)

Bin_Index = [1:x_B;]
Bin2UseU = (deltablr*Bin_Index)
Bin_Index = [0:x_B-1;]
Bin2UseL = (deltablr*Bin_Index)
for i = 1:numBlr
    for s = 1:x_B-1
        ...
    end
end
\[ b_B[s+1,i] = ((B_{slope}[s,i]*Bin2UseU[s]) + (b_B[s,i]) - ((B_{slope}[s+1,i])*Bin2UseL[s+1])) \]

end

end

if numBlr == 0; BBGasCalc = 0; else; BBGasCalc = numBlr* (Gasin_b_Max*B_{slope}[x_B]+b_B[x_B])*Cf2Btu; endif

if numChp == 0; CHPGasCal = 0; else; CHPGasCal = numChp*(Gasin_chp_Max*Gchp_{slope}[x_Chp]+be_chp[x_Chp])*Cf2Btu; endif

MaxBTU_per_15Min_Heating = BBGasCalc + CHPGasCal

GUsageCost = (0.4176+0.3697+0.0354) \times 11.710

GasMax= (Gasin_chp_Max + Gasin_b_Max)\times N

RewnGCost = 1.1749\# Cost of renewable Natural Gas

G_C02R = 5.010 \# lbs of CO2 /hundred cubic feet

RenwGasPercent = [.10, .25, .50 ,1]

CHWCsloss = .001

BatCHWMax = 1.944*SizeBatChw

BatCHWStart = 0

CHWEMax = 30

EFF_CHE = .8

CHWSMax = 40

kw2BTU = 0.003412141633128

if numEChil ==0; CHWEMax = 0; CHWe_slop=0; else; CHWEMax = 0.879213125*MaxEChwTons; CHWe_slope = zeros(x_CHWE,numEChil); endif

MAXMBTUof1Chiller = MaxEChwTons*0.003

inVal = linspace(0, CHWEMax, x_CHWE+1);

C1 = A_che*(inVal/CHWEMax).^3+1.2*(inVal/CHWEMax).^2+.03*(inVal/CHWEMax)
\[
C1 = -1.8*(\text{inVal}/\text{CHWMax})^3 + 2.65*(\text{inVal}/\text{CHWMax})^2 + 0.03*(\text{inVal}/\text{CHWMax})
\]

\(\text{be}_{\text{cw}} = \text{zeros}(x_{\text{CHWE}}, \text{numEChil})\);

\[
\begin{align*}
\text{for } i &= 1: \text{numEChil} \\
\text{for } s &= 1: x_{\text{CHWE}} \\
\text{CHWe\_slope}[s, i] &= (1.04 - 0.04*i) \times (C1[s+1] - C1[s]) \\
&\quad / (\text{inVal}[s+1]/\text{CHWMax} - \text{inVal}[s]/\text{CHWMax})
\end{align*}
\]

\[
\text{deltaIn} = \text{diff}(\text{inVal});
\]

\[
\text{deltaInCHW} = \text{sum}(\text{deltaIn})/\text{length}(\text{deltaIn})
\]

\[
\text{Bin\_IndexU} = [1:x_{\text{CHWE}}]; \quad \text{Bin\_IndexL} = [0:x_{\text{CHWE}} - 1];
\]

\[
\begin{align*}
\text{Bin2UseCHWeU} &= \text{deltaInCHW} \times \text{Bin\_IndexU} \\
\text{Bin2UseCHWeL} &= \text{deltaInCHW} \times \text{Bin\_IndexL}
\end{align*}
\]

\[
\begin{align*}
\text{for } i &= 1: \text{numEChil} \\
\text{for } s &= 1: x_{\text{CHWE}} - 1 \\
\text{be\_cw}[s+1, i] &= ((\text{CHWe\_slope}[s, i] \times \text{Bin2UseCHWeU}[s]) + \\
&\quad (\text{be\_cw}[s, i]) - ((\text{CHWe\_slope}[s+1, i] \times \text{Bin2UseCHWeL}[s+1]))
\end{align*}
\]

\[
\text{if } \text{numAChil} == 0; \\
\text{CHWS\_Tot\_Max} = 0; \quad \text{CHW\_slope} = 0;
\]

\[
\text{else;}
\quad \text{CHWS\_Tot\_Max} = \text{MaxBTU\_per\_15Min\_Heating} / \text{numAChil}; \quad \text{CHW\_slope} = \\
\quad \text{zeros}(x_{\text{CHW}}, \text{numAChil});
\]

\[
\text{end}
\]

\[
\text{CHWS\_Tot\_Max} = 1.2
\]

\[
\text{inVal} = \text{linspace}(0, \text{CHWS\_Tot\_Max}, x_{\text{CHW}+1});
\]

\[
C1 = A_{\text{ch}} \times (\text{inVal}/\text{CHWS\_Tot\_Max})^3 + 1.2 \times (\text{inVal}/\text{CHWS\_Tot\_Max})^2 + 0.03 \times (\text{inVal}/\text{CHWS\_Tot\_Max})
\]

\[
\text{b\_cw} = \text{zeros}(x_{\text{CHW}}, \text{numAChil});
\]

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for i = 1:numAChil
    for s = 1:x_CHW
        CHW_slope[s,i] = (1.04-.04*i)* (C1[s+1]-C1[s])/(inVal[s+1]/CHWS_Tot_Max-inVal[s]/CHWS_Tot_Max);
    end
end

deltaIn = diff(inVal);
deltaInCHW = sum(deltaIn)/length(deltaIn)
Bin_IndexU = [1:x_CHW]; Bin_IndexL = [0:x_CHW-1];
Bin2UseCHWU = (deltaInCHW*Bin_IndexU); Bin2UseCHWL = (deltaInCHW*Bin_IndexL)

for i = 1:numAChil
    for s = 1:x_CHW-1
        b_cw[s+1,i] = ((CHW_slope[s,i]*Bin2UseCHWU[s]) + (b_cw[s,i]) -((CHW_slope[s+1,i]) *Bin2UseCHWL[s+1]))
    end
end

RampCHP = RampPerct*Gasin_chp_Max
RampBlr = RampPerct*Gasin_b_Max
RampEchw = RampPerct*CHWEMax
RampAchw = RampPerct*CHWS_Tot_Max

CHWS_Tot_Min = CHWS_Tot_Max*MinRun;
CHWEMin = CHWEMax*MinRun;
Gasin_b_Min = Gasin_b_Max*MinRun;
Gchp_Tot_Min = Gasin_chp_Max*MinRun;

# Optimization#
# Grid #
@variable(ed, GridMax >= E_Grid[n:N] >= 0)
@variable(ed, ETot[n:N] >= 0)
@variable(ed, ETot_d[n:N] >= 0)
@variable(ed, ETot_s[n:N,1:numBat] >= 0)
@variable(ed, CHWEMax >= ETot_CHW[n:N,1:numEChil] >= 0)

# CHP Electric #
@variable(ed, Echp[n:N,1:numChp] >= 0)

# Battery #
@variable(ed, BatStep >= BatEout[n:N,1:numBat] >= 0)
@variable(ed, BatEMax >= BatE[n:N,1:numBat] >= 0)

# PWL Steam Boiler#
@variable(ed, Gasin_b_Max*.95 >= Gasin_b[n:N,1:numBlr] >= 0)
@variable(ed, B_deltaP[n:N,1:x_B,1:numBlr] >= 0);
@variable(ed, Yk_b[n:N,1:x_B,1:numBlr], Bin)
@variable(ed, BlrMinBin[n:N,1:numBlr], Bin)

@variable(ed, Sb[n:N,1:numBlr] >= 0)
@variable(ed, StmTot[n:N] >= 0)
@variable(ed, StmTot_s[n:N] >= 0)
@variable(ed, StmTot_d[n:N] >= 0)
@variable(ed, StmTot_CHW[n:N,1:numAChil] >= 0)

@variable(ed, Gasin_chp_Max >= Gasin_chp[n:N,1:numChp] >= 0)
@variable(ed, Gasin_chp_S[n:N,1:numChp] >= 0)
@variable(ed, Gasin_chp_E[n:N,1:numChp] >= 0)

@variable(ed, GCHP_deltaP[n:N,1:x_Chp,1:numChp] >= 0);
@variable(ed, Yk_chp[n:N,1:x_Chp,1:numChp], Bin)
@variable(ed, Schp[n:N,1:numChp] >= 0)  Chilled water
@variable(ed, ChpMinBin[n:N,1:numChp], Bin)

@variable(ed, BatSMax >= BatS[n:N] >= 0)
@constraint(ed, BatS[1] == BatStart)
@variable(ed, BatSMax >= BatSout[n:N] >= 0)

@variable(ed, ChwTot_s[n:N] >= 0)
@variable(ed, ChwTot_d[n:N] >= 0)
@variable(ed, CHWE[n:N,1:numEChil] >= 0)
@variable(ed, CHW_deltaPE[n:N,1:x_CHWE,1:numEChil] >= 0);
@variable(ed, Yk_chE[n:N,1:x_CHWE,1:numEChil], Bin)
@variable(ed, CwEMinBin[n:N,1:numEChil], Bin)

@variable(ed, CHW_deltaP[n:N,1:x_CHW,1:numAChil] >= 0);
@variable(ed, Yk_ch[n:N,1:x_CHW,1:numAChil], Bin)
@variable(ed, CwSMinBin[n:N,1:numAChil], Bin)

@variable(ed, CHWS_Tot[n:N,1:numAChil] >= 0)
@variable(ed, CHWS[n:N,1:numAChil] >= 0)

@variable(ed, BatCHWMax >= BatCHW[n:N] >= 0)
@constraint(ed, BatCHW[1] == BatCHWStart)
@variable(ed, BatCHWMax >= BatCHWOut[n:N] >= 0)

@variable(ed, ES[n:N])
@variable(ed, Temp[n:N] >= 0)
@variable(ed, CoH[n:N], Bin)

@variable(ed, suChp[n:N,1:numChp] >= 0)
@variable(ed, suB[n:N,1:numBlr] >= 0)

@constraint(ed, suB[1:N-1,1:numBlr] .>=
    -> BlrMinBin[2:N,1:numBlr]-BlrMinBin[1:N-1,1:numBlr])
@constraint(ed, suChp[1:N-1,1:numChp] .>=
    -> ChpMinBin[2:N,1:numChp]-ChpMinBin[1:N-1,1:numChp])

@constraint(ed, sum(ETot_s[n:N,k] for k =
    1:numBat)+ETot_d[n:N]+sum(ETot_CHW[n:N,k] for k = 1:numEChil)
   .== sum(Echp[n:N,k] for k = 1:numChp)+E_Grid[n:N])
if numBat == 0
    @constraint(ed, Electric[n:N] .== ETot_d[n:N])
else
    for v = 1:numBat
        @constraint(ed, BatE[1,v] == BatEStart)
        @constraint(ed, BatE[n:N,v]-BatEOut[n:N,v] .>= 0)
        @constraint(ed, BatE[n,v] >= BatE[n,v])

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end

for t n+1:N
  @constraint(ed,BatE[t,1:numBat] .== ETot_s[t,1:numBat]*
  (1-EChargeCeloss)+BatE[t-1,1:numBat]-(BatEout[t,1:numBat]))
end

for j in n:N-1
  @constraint(ed,BatStep .>=
  (BatE[j+1,1:numBat]-BatE[j,1:numBat]))
  @constraint(ed,(BatE[j+1,1:numBat]-BatE[j,1:numBat]).>=
  (-1)*BatStep)
end

@constraint(ed,Electric[n:N] .==
  ETot_d[n:N]+sum(BatEout[n:N,k]for k =
  1:numBat).*(1-EDisChargeCeloss))

@constraint(ed,Gasin_b[n:N,1:numBlr] .==
  sum(B_deltaP[n:N,s,1:numBlr] for s=1:x_B) );
@constraint(ed,Gasin_b[n:N,1:numBlr] .>=
  Gasin_b_MIN*BlrMinBin[n:N,1:numBlr]);
@constraint(ed,Gasin_b[n:N,1:numBlr] .<=
  Gasin_b_MAX*BlrMinBin[n:N,1:numBlr]);

@constraint(ed,sum(Yk_b[n:N,s,1:numBlr] for s =1:x_B) .<= 1);

for s = 1:x_B
  @constraint(ed,B_deltaP[n:N,s,1:numBlr] .<=
  Yk_b[n:N,s,1:numBlr]*Bin2UseU[s]);
  @constraint(ed,Yk_b[n:N,s,1:numBlr]*Bin2UseL[s] .<=
  B_deltaP[n:N,s,1:numBlr] )
end

for j = 1:numBlr
  @constraint(ed,Sb[n:N,j] .==
  (sum(B_slope[s,j].*B_deltaP[n:N,s,j] for s=1:x_B)
  +sum(b_B[s,j]*Yk_b[n:N,s,j] for s=1:x_B)))*Cf2Btu); # PLW Output
  in BTUs Based on PWL Curve
end


@constraint(ed, Gasin_chp[n:N,1:numChp].sum(GCHP_deltaP[n:N,s,1:numChp] for s=1:x_Chp));
@constraint(ed, sum(Yk_chp[n:N,s,1:numChp] for s=1:x_Chp) <= 1);

for s = 1:x_Chp
    @constraint(ed, GCHP_deltaP[n:N,s,1:numChp] <= Yk_chp[n:N,s,1:numChp]*Bin2UseSchpU[s]);
    @constraint(ed, Yk_chp[n:N,s,1:numChp]*Bin2UseSchpL[s] <= GCHP_deltaP[n:N,s,1:numChp]);
end

for j = 1:numChp
    @constraint(ed, Echp[n:N,j] == (sum(Gchp_slope[s]*GCHP_deltaP[n:N,s,j] for s=1:x_Chp) + sum(be_chp[s,j]*Yk_chp[n:N,s,j] for s=1:x_Chp) + CF2KW);
end

@constraint(ed, Schp[n:N,1:numChp] == (Gasin_chp[n:N,1:numChp].*EffE_chp) * Cf2Btu)

for t = n+1:N
    @constraint(ed, BatS[t] .== StmTot_s[n:N] - BatSout[t] + Csloss.*BatS[t-1])
end

@constraint(ed, BatS[n:N] - BatSout[n:N] .>= 0)
@constraint(ed, BatS[N] >= BatS[n])

@constraint(ed, StmTot_d[n:N] + StmTot_s[n:N] + sum(StmTot_CHW[n:N,k] for k = 1:numAChil) .== sum(Sb[n:N,k] for k = 1:numBlr) + sum(Schp[n:N,k] for k = 1:numChp))

@constraint(ed, ETot_CHW[n:N,1:numEChil] .>= CHWEMin*CwEMinBin[n:N,1:numEChil]);
@constraint(ed, ETot_CHW[n:N,1:numEChil] .<= CHWEMax*CwEMinBin[n:N,1:numEChil]);

@constraint(ed, ETot_CHW[n:N,1:numEChil] .== sum(CHW_deltaPE[n:N,s,1:numEChil] for s=1:x_CHWE));
@constraint(ed, sum(Yk_chE[n:N,s,1:numEChil] for s =1:x_CHWE) .<= 1);
for s = 1:x_CHWE
    @constraint(ed, CHW_deltaPE[n:N,s,1:numEChil] .<= Yk_chE[n:N,s,1:numEChil]*Bin2UseCHWeU[s]);
    @constraint(ed, Yk_chE[n:N,s,1:numEChil]*Bin2UseCHWeL[s] .<= CHW_deltaPE[n:N,s,1:numEChil]);
end
for j = 1:numEChil
    @constraint(ed, CHWE[n:N,j] .== (sum(CHWe_slope[s]*CHW_deltaPE[n:N,s,j] for s=1:x_CHWE) + sum(be_cw[s,j]*Yk_chE[n:N,s,j] for s=1:x_CHWE))*kw2BTU);
@constraint(ed, ETot_CHW[n+1:N,1:numEChil] - ETot_CHW[n:N-1,1:numEChil].<= RampEchw)
@constraint(ed, ETot_CHW[n+1:N,1:numEChil] - ETot_CHW[n:N-1,1:numEChil].>= -RampEchw)

@constraint(ed, StmTot_CHW[n:N,1:numAChil] == sum(CHW_deltaP[n:N,s,1:numAChil] for s=1:x_CHW));
@constraint(ed, StmTot_CHW[n:N,1:numAChil] .>= CHWS_Tot_Min*CwSMinBin[n:N,1:numAChil]);
@constraint(ed, StmTot_CHW[n:N,1:numAChil] .<= CHWS_Tot_Max*CwSMinBin[n:N,1:numAChil]);

@constraint(ed, sum(Yk_ch[n:N,s,1:numAChil] for s=1:x_CHW) .<= 1);

for s = 1:x_CHW
    @constraint(ed, CHW_deltaP[n:N,s,1:numAChil] <= Yk_ch[n:N,s,1:numAChil]*Bin2UseCHWU[s]);
    @constraint(ed, Yk_ch[n:N,s,1:numAChil]*Bin2UseCHWL[s] .<= CHW_deltaP[n:N,s,1:numAChil]);
end

for j = 1:numAChil
    @constraint(ed, CHWS[n:N,j] == sum(CHW_slope[s]*CHW_deltaP[n:N,s,j] for s=1:x_CHW)+sum(b cw[s,j]*Yk_ch[n:N,s,j] for s=1:x_CHW));
end

@constraint(ed, StmTot_CHW[n+1:N,1:numAChil] - StmTot_CHW[n:N-1,1:numAChil].<= RampAchw)
@constraint(ed, StmTot_CHW[n+1:N,1:numAChil] - StmTot_CHW[n:N-1,1:numAChil].>= -RampAchw)

for t = n+1:N
    @constraint(ed, BatCHW[t] == ChwTot_s[t]-BatCHWout[t]+CHWCsloss.*BatCHW[t-1])
end

@constraint(ed,BatCHW[n:N] - BatCHWout[n:N] .>= 0)
@constraint(ed,BatCHW[N] >= BatCHW[n])

    sum(CHWE[n:N,k] for k = 1:numEChil) + sum(CHWS[n:N,k] for k =
    1:numAChil)

@constraint(ed,(CoH[n:N])*10000 .>=
    StmTot_d[n:N]+(Csloss*BatSout[n:N]))

@constraint(ed,(CoH[n:N]-1)*-10000 .>=
    (ChwTot_d[n:N]+BatCHWout[n:N]))
@constraint(ed,(Temp[1]==Setpoint))

for t = 1:N-1
    @constraint(ed,ES[t] == StmTot_d[t]+(Csloss*BatSout[t])
            -.8(ChwTot_d[t]+BatCHWout[t]))

    @constraint(ed,MCp*(Temp[t+1]-Temp[t])/Dt ==
            (ES[t]) - R*(Temp[t]-Tambi[t]) - (Uindex[t]*.01*ES[t]))
end

@constraint(ed,ES[N] == StmTot_d[N]+
            (Csloss*BatSout[N])-.8(ChwTot_d[N]+BatCHWout[N]))

@constraint(ed,0 ==
            (ES[N]) - R*(Temp[N]-Tambi[N]) - (Uindex[N]*.01*ES[N])) U

@constraint(ed,(Temp[1]==Temp[N])
            @constraint(ed,(Setpoint+USlim).>= Temp[n:N])
            @constraint(ed,(Setpoint-LSlim).<= Temp[n:N])

@constraint(ed,sum(Temp[1:96])/N <= Setpoint )
@constraint(ed,sum(Temp[1:96])/N >= Setpoint)

@variable(ed,GDol[1]>=0)
@variable(ed, GC02[1] >= 0)
@variable(ed, G_Nat[1] >= 0)
@variable(ed, G_Ren[1] >= 0)
@variable(ed, G_ToT[1] >= 0)
@variable(ed, Gas_delta[1:4] >= 0)

@variable(ed, PickGas_R_N[1:4], Bin)

@constraint(ed, G_ToT[1] == (sum(Gasin_b[n:N,1:numBlr])
+ sum(Gasin_chp[n:N,1:numChp])
+ sum(suChp[:,,:] * Gasin_chp_Max * Gstart)
+ sum(suB[:,,:] * Gasin_b_Max * Gstart)))

@constraint(ed, G_ToT[1] >= sum(Gas_delta[j] for j=1:4);
for j=1:4
  @constraint(ed, Gas_delta[j] <= GasMax * PickGas_R_N[j]);
end

@constraint(ed, sum(PickGas_R_N[1:4]) <= 1);
@constraint(ed, G_Ren[1] == sum(RenwGasPercent[j] * Gas_delta[j] for j=1:4);

@constraint(ed, GDol[1] == GUsageCost * G_Nat[1] + RewnGCost * G_Ren[1])

@variable(ed, EC02[1]);
@variable(ed, EDol[1])
@variable(ed, EE_DE[1]);
@variable(ed, EE_Max[1])
@variable(ed, D_peak[1]);
@variable(ed, Usage_peak[1])
@variable(ed, D_off[1]);
@variable(ed, Usage_off[1])

if Rate == "PS"
  @constraint(ed, EE_Max[1] .>= E_Grid[n:N])
  @constraint(ed, EE_DE[1] == sum(E_Grid[n:N]))
    @constraint(ed, Usage_off[1] == sum(E_Grid[j] for j in off[Mnth[mo]]))
    for j in off[Mnth[mo]]
        @constraint(ed, D_off[1] >= E_Grid[j])
    end
@constraint(ed, Usage_peak[1] == sum(E_Grid[j] for j in peak[Mnth[mo]]))
    for j in peak[Mnth[mo]]
        @constraint(ed, D_peak[1] >= E_Grid[j])
    end
@constraint(ed, EDol[1] == EE_DE[1]*EU + EE_Max[1]*ED + Usage_peak[1]*PU[Mnth[mo]] + Usage_off[1]*OPU[Mnth[mo]] + D_peak[1]*PD[Mnth[mo]] + D_off[1]*OPD[Mnth[mo]])
else
    @constraint(ed, EDol[1] == EE_DE[1]*EU + EE_Max[1]*ED + EE_DE[1]*OPU[Mnth[mo]] + EE_Max[1]*OPD[Mnth[mo]])
end
elseif Rate == "LG"
    @variable(ed, D_all[1])
    @variable(ed, U_all[1])
    @constraint(ed, EE_Max[1] .>= E_Grid[n:N])
    @constraint(ed, EE_DE[1] == sum(E_Grid[n:N]))
    @constraint(ed, D_all[1] .>= E_Grid[n:N])
    @constraint(ed, U_all[1] == sum(E_Grid))
    @constraint(ed, EDol[1] == EE_DE[1]*EU + EE_Max[1]*ED + D_all[1]*20.03 + U_all[1]*0.083003)
end
@constraint(ed, EC02[1] == sum(E_Grid[1])*0.001)
if Obj == 1
@objective(ed, Min, EDol[1]+GDol[1])
solve(ed)
Data_OBJ[mo, flx, Obj, dow] = getobjbound(ed)

elseif Obj==2
  @objective(ed, Min, EDol[1]+GDol[1]+(EC02[1]+GC02[1])•DperC02)
  # Dollars + C02
  solve(ed)
  Data_OBJ[mo, flx, Obj, dow] = getobjbound(ed)
end