Engineering 90 Final Report:
Adaptive Electricity Use Model
ADELUS

Swarthmore College, Department of Engineering

Advisor: Professor Carr Everbach, Ph.D

Omer M. Corluhan

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Abstract

An energy model has been developed to predict the electricity consumption at Swarthmore College. Factors such as historical weather data and the College's class schedule are considered as major decision variables for the model. The model is implemented through a Windows-based computer program. The College's Facilities Department plans to use the model to estimate the College's future electricity demand. The model will help Facilities managers to avoid potentially high electricity costs as a result of the coming deregulation of electricity prices in Pennsylvania in 2010. The model's feedback system will improve its results based on the deviations between predicted and actual data collected over time.

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[1] Please note that the Appendices will be provided upon request. The code and data for the Project can be provided in a CD.

Introduction

The Adaptive Electricity Use Model, "the Project", at Swarthmore College, "the Client" or "the College", was created in response to the energy challenge the College faces in future. It is a work of extensive data collection, analysis, formulation and real-time implementation. Three major objectives of the Project are: minimizing the College's energy cost, reducing greenhouse gas emissions and heightening students' awareness of wasteful practices.

The Project analyses, estimates and forecasts the College's electricity consumption. During 2005 – 2006, the College was charged for its electricity demand by local contractors PECO/Exelon at $0.08 per kWh[2], which cost in total $1,387,010.56 from August 2005 to July 2006. An additional demand charge for exceeding the allowable peak limit was charged at $25 per kW. The College paid approximately $52,000 for the excess demand.

The motivation for this Project is the final step in the deregulation of the electricity market in December, 2010. A competitive market for electricity will end the regulation of electricity prices. Current electricity prices at in Pennsylvania will change in 2010, when electricity prices will adjust every fifteen minutes based on the market price determined by supply and demand. Swarthmore College, "the Client", is concerned that its electricity bill will triple as a result of deregulated electricity prices. The Client's endowment has returned outstanding results while beating the market's return in past years. However, tripling the current electricity bill of approximately $1.4 million will squeeze the College budget in a significant way leading to cuts in other spending. In order to excel as the best undergraduate institution in the world, the Client must understand its electricity demand to avoid potentially high electricity prices in 2010.

The Adaptive Electricity Use Model, "the Project", at Swarthmore College, was developed in response to the Client's challenge of becoming a low-cost and environmentally-friendly energy consumer. An energy model has been designed to optimize the electricity consumption in terms of cost and environmental impact, and will be implemented at Swarthmore College. The model will predicts the Client's future electricity demand based on factors such as outside temperature and time by taking inputs through a Windows-based program. The Client plans to use the model to estimate its future demand and take precautions to avoid potentially high electricity prices. The academic goal for the author is to apply his knowledge from a broad range subjects such as optimization research, linear physical systems analysis, systems engineering, fluid mechanics, digital signal processing, thermodynamics and economics. The project is also aimed at raising environmental awareness among the campus community.

The College has a well-structured data gathering system for data such as electricity demand and temperature. Other experiments such as a hotbox experiment have been conducted to get a deeper understanding of College's electricity consumption. The extent of data collection has been the main constraint in the Project.

The model has been developed to forecast electricity demand based on selected decision variables. The decision variables range from class schedule to the performance of air handling units. Extensive data has been acquired from the Swarthmore College Facilities Management Department (FMD) through its established data-gathering system. The FMD will eventually send the raw data to an intermediate server. A Windows-based program will read the data from the server. An interface portion of the program will analyze the data and present it. After the data gathering and analysis phase is completed, the electricity model will digest this data to output tomorrow's predicted electricity

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[2] Current price for electricity is at constant dollars similar to 1991's electricity prices.

demand in terms of kWh. The user interface will help the user to choose among different forecasting models. The result will be displayed graphically. During the next day, the predicted result of the model will be compared to actual data. Through a feedback loop mechanism, the deviations will be minimized and the model will optimize over time[3]. The Client plans to use the model to estimate its future demand and take precautions to avoid the potentially high electricity prices by 2010.

Information about the Project space

The Campus Energy Analysis Project at Swarthmore College investigates Kohlberg Hall, "the building", in depth. Kohlberg is the home to Economics, Modern Languages and Literatures Departments, was completed in 1996. There is a language lab on its third floor. The ground floor includes a lounge with a coffee bar and fireplace, and the Scheuer Room. The coffee bar provides a community space for campus and it is a popular study and hang-out space for students. On the upper two floors are classrooms, seminar rooms and faculty offices. Kohlberg is a gathering point for the college community and it is located in the center of a group of other academic buildings.

Kohlberg is chosen as an exemplar building for the whole college. The rationale for choosing Kohlberg is because of its main usage, its average age compared to other buildings at campus, its size and location, its functionality at the college and its infrastructure for data gathering. The building has several classrooms and faculty offices. Since students leave their rooms for most of the day, a dormitory building is not the best choice for a campus-exemplar building. Kohlberg is neither new nor old compared to other building in campus. The building is located at the center of the college. With its coffee bar, it attracts student body every day. The most important feature of the building is the already built-in data gathering system. The Facilities Department can collect various types of data from the building. Once Kohlberg is understood, the model can be replicated for the rest of the campus.

Conversion Factors

The Campus Energy Analysis project heavily relies on quantitative data. In the Project, experimental data is compared to theoretical data. To analyze data, it is essential to convert the different units of data into the same units. The most common units are KW and KWh since the Project's main target is electricity consumption at the College. One KW equals to 1000 Joule per 1 second.

$$W = \frac{J}{s} = \frac{kg * m^2}{s^3} = \frac{Nm}{s} \text{ , \textbf{Equation 1}}$$

In terms of electrical definition, 1 watt is 1 volt times 1 ampere. In other words, 1 watt of power is dissipated, if 1 volt of potential difference is applied across a resistive load, and a current of 1 ampere flows through that resistor load. A watt-hour is a unit of energy. One thousand watt-hours equals one kilowatt-hour. One watt-hour is the amount of energy consumed operating a watt-power load for one hour. The next most common unit is the British Thermal Unit (Btu), since the Project is an energy project. Btu is defined as the amount of heat required to raise the temperature of one pound of water by one degree Fahrenheit. The table below shows useful conversion factors.

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[3] Please look at "Forecasting electricity demand at Swarthmore College" section for more information.

Table 1

Unit	Multiplication Factor	Obtained Unit
Btu	252	Calorie
Btu/sec	1.0545	KW
Btu	$1.05*10^3$	Joule

Information about the potential energy candidates for Swarthmore College

Table 1 displays several properties for commonly used energy sources[4]. These are fuel types that Swarthmore College is using or might be using in the future. Currently, the College uses electricity and #6 Oil oil as major sources of energy, whereas cooling machines that use natural gas exist.

Table 2

Fuel	Type	Unit Btu/unit	Efficiency	Cost/unit	Cost/mmBtu	Carbon Dioxide Emission (kg)
Gas	Therms	100,000	80%	$0.96	$12.00	
#2 Oil	Gallons	139,000	85%	$2.00	$16.93	
#4 Oil	Gallons	145,000	85%	$1.30	$10.55	
#6 Oil	Gallons	150,000	85%	$1.24	$9.73	
Electricity	kWh	3,143	100%	$0.08	$25.45	44

Electricity is the most expensive energy out of the possible fuel types, whereas #6 Oil is the least expensive energy source available. Although #6 oil has cost advantages, it is the dirtiest energy source among the listed fuels. It is not in the College's interest to pollute the environment. At the same time, the College has carbon dioxide caps imposed upon it by Pennsylvania law. If these limits are surpassed by the College's CO_2 – emission, the College has to pay a significant fine for the excess of pollutants.

The College uses #6 oil for heating purposes. Beside its regular use, electricity is also used for cooling, ventilation, distribution of heat and infiltration. The #6 oil is used to make steam in the College's heating plant and that is distributed to the rest of the campus through its central heating system. Some buildings have separate heating systems with their boilers such as Mary Lyons and PPR.

Electricity consumption at campus – How to choose decision variables?

A brief summary of the literature about forecasting electricity demand

Forecasting electricity has been an important topic since electricity has become a commodity that is traded much like oil in markets. Neural network systems and vector machines are the main approaches in the literature to forecast electricity demand or prices. In this project, I will choose not use these models since they do not require an understanding of the system for forecasting. With the rich data set I have, I would like to build more intuitive models that will help decision makers understand the electricity demand and forecast it.

Forecasting electricity demand at Swarthmore College

It is vital for the Project's success to choose appropriate decision variables for the forecasting model.

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[4] The information is obtained from Tom Sahagian and Betsy Jenkins from Power Concepts LLC.

Therefore, it is important to understand the electricity consumption at the College. Electricity consumption at Swarthmore can be broken down among three main electricity demand variables: controlled, uncontrolled, and HVAC variables. The controllable variables are the electricity consumption factors such as temporary lighting, computers and other plug loads. The uncontrollable variables are the fixed loads like emergency lights and pumps. The final variable is the HVAC variables, which represent the heating, ventilation and air conditioning of the buildings. Although HVAC is partly an uncontrollable and partly a controllable variable, it will be treated as a separate variable because of its extent of contribution to the total electricity demand at the College.

Controllable variables such as office equipment and additional plug loads like students' fan dryers or laptops are an important part of the electricity demand. These variables are the major factor for demand peaks that cost the College $52,925[5] in the 2005-2006 class year. Controllable variables are the hardest to forecast among the three decision variables because they strictly depend on human interactions and activities. Human interactions depend on various factors that are either hard to observe or not observable. Since a model's success depends on the ratio of factors that the model can observe out of the all possible factors that affect the model, it is a challenge to build a model to forecast electricity based on controllable variables.

The uncontrollable variables are factors that the College has no control to regulate. The College is mostly restricted by authorities on limits for these uncontrollable variables. For instance, pumps are used to heat the water that runs through the heating pipes across the buildings. The pumps will always be on as long as outside temperature is under 65 Fahrenheit. Shutting off the pumps is not feasible since this will decrease the inside temperature of the buildings so significantly that the low temperature will cause a discomfort to Kohlberg residents, students, faculty and staff. Similarly, turning off the fixed lighting is not possible since fixed lighting such as emergency lights is essential to provide safety on campus.

HVAC variables cover the biggest portion of the energy bill. As described above, the Collage uses #6 oil for heating. The HVAC system distributes this heat through air handling units to campus spaces. At the same time, HVAC variables include the cooling of campus space. Although electricity is the most expensive fuel type used on campus, it is the main source of cooling. The cooling plant at the north campus and McCabe chiller are two major cooling plants. Although there are some cooling units that run by natural gas, these units are additional units.

The remaining share of the electricity consumption can be identified as other variables. Other variables represent all the factors that affect the electricity demand at Kohlberg and are not observed by the three decision variables discussed above. Another name for these other variables is unobserved variables. These unobserved variables might be inefficiencies or unidentified energy demands. For instance, when the electrical demands of Kohlberg and Trotter are plotted against time, peaks in electricity demand are seen between midnight and early morning. These peaks do not belong to any of the three decision variables listed above, but they appear to be the result of Kohlberg's hydraulic elevator pump.

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[5] Demand cost is the additional electricity cost that the College has to pay to the electricity distributor as a punishment of its high electricity demand peaks in the summer. The College has a complicated agreement with the electricity distributor. Briefly, the College will be charged when its electricity demand falls below some certain percentage of its highest peak in the given year. More information is given about the demand cost in Appendix X, Swarthmore College Case Study.

Forecasting with decision variables

The three decision variables discussed above represent the observable factors that affect the electricity demand at Kohlberg. Although they are responsible for a part of the total electricity demand, their influence on the total demand is important. Therefore, three different models are built to forecast the total electricity demand based on each of these decision variables. These three models are combined by a linear function that is shown below.

$$X = \alpha * X_1 + \beta * X_2 + \gamma * X_3, \text{ **Equation 2**}$$

, where X_1 represents the uncontrollable variables model, X_2 is the controllable variables model and X_3 stands for the HVAC variables model. The coefficients multiplying the decision variable models are the weighting factors to finalize the forecasted electricity demand. Different approaches to finalize the forecasting model are presented toward the end of the project by comparing the results. Possible approaches to adaptive adjustment of the coefficients are a dynamic multivariable regression model and/or an adaptive filter method. A feedback loop mechanism is created through these methods. The final forecasting model predicts tomorrow's electricity demand. The forecast is compared to actual data the next day. Based on the deviations from actual data, weighting factors are reevaluated[6].

Since authorities set most of the uncontrollable variables, these variables are more easily observed compared to other decision variables. Unobserved variables might demand different loads of electricity at different times but they are expected to follow a specific schedule since they are predetermined. Therefore, their electricity demands repeat based on their specific demand schedules. It is essential to understand the cyclical behavior of the unobserved variables to build a forecasting model. In order to create an elaborate model, historical data were investigated.

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[6] If there are significant errors, the models will be changed accordingly.

Time Series Model – Models for decision variables

Theory

      Electricity demand at Kohlberg has been recorded every 30 minutes with Facilities Departments' loggers since Fall 2006. The failure of some loggers and other types of data lost are the limitations of this meticulous data gathering process. A snapshot of electricity demand at Kohlberg is provided below for the first three weeks of November 2007.
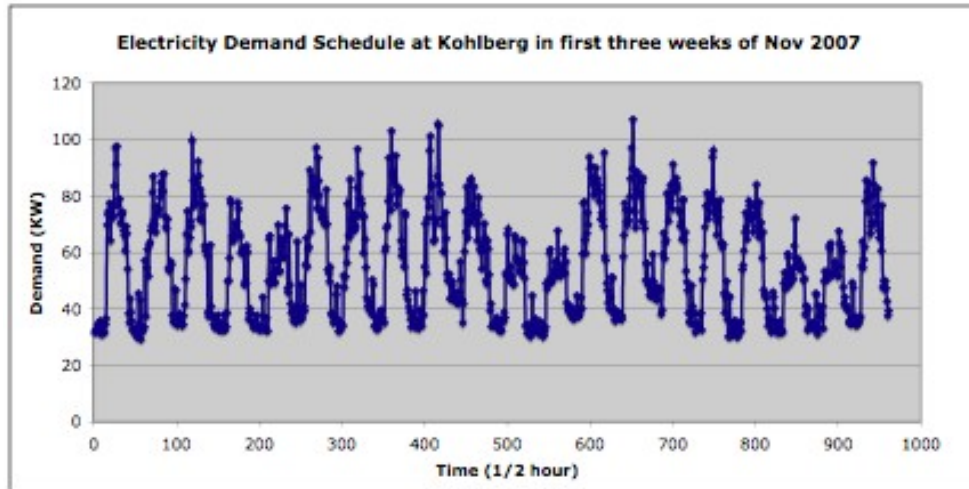

Figure 1

      Looking at the data above, it can be observed that the electricity demand fluctuates like a sinusoidal curve with smaller amplitudes on weekends and bigger amplitudes on weekdays. As a first step in data investigation, I separated the weekend data from the weekday data since the variables that affect them are different. For instance, because there are no classes on weekends, electricity demand at Kohlberg is considerably less compared to a weekday's electricity demand.

      The cyclical behavior of electricity demand can be generally attributed to uncontrollable variables. Although they each might have a different schedule for electricity consumption, I understand that their electricity demands depend on time. Since the weekday cycles have same periods and similar amplitudes, an average cycle for uncontrollable variables' electricity demand schedule can be chosen as any multiple of one day. Since the electricity demand depends on time, the idea of time series data is encountered. A time series is a sequence of data points that is gathered mostly with a uniform time interval.

      The series that we want to forecast vary over time. We often attribute that variation to unobserved underlying components such as trends, seasonal variations, and cycles. There are various possible approaches to analyze and forecast time series data. Before we investigate time series models, I present a linear regression analysis since it is essential for the models used in this paper.

Theory – Correlation coefficient and simple linear regression analysis

      A relationship between two data sets can be investigated by a simple linear regression analysis method. Linear Regression Analysis (LRA) is a fundamental statistical method used throughout the Project's data analysis.

As a first approach to data analysis in many engineering problems, data is investigated often by graphing the dependent and independent variables against each other. This helps the analyst to visualize the type of the relationship between the independent and dependent variables. "The correlation coefficient (ρ) of two random variables X_1 and X_2 is computed by dividing the covariance of X_1 and X_2 by their respective standard deviations."[7] We can write:

$$\rho = \frac{\text{Cov}(X_1, X_2)}{\sigma_1 * \sigma_2} = \frac{\text{E}(X_1, X_2) - \mu_1 * \mu_2}{\sigma_1 * \sigma_2}, \textbf{ Equation 3}$$

, where σ_1 and σ_2 are the standard deviations of X_1 and X_2, respectively. A positive or negative correlation will indicate whether there is a relationship between dependent and independent variables, while a correlation value of zero will indicate no relationship. A correlation number of -1 is a perfect negative linear correlation, whereas a value of 1 indicates a perfect positive linear correlation.

However, in most engineering problems the data is further investigated by regression analysis. In data analysis where there is only one independent variable involved, the regression analysis is called simple regression. Later in the paper, a more complicated regression analysis such as multivariable regression analysis will be discussed. Simple regression analysis has a dependent variable and an independent variable. We are interested in finding a relationship between these two variables to find the expected value of the dependent variable for any given number of independent variable. We can write:

$$\text{E}(Y \mid X) = a + b*X, \textbf{ Equation 4}$$

, in which a and b are constants. To find the estimates for constants "a" and "b", the method of least square analysis is used. The deviation of each estimated dependent value from the actual dependent value or, in other words, the difference between the estimated value and the experimental value, $\Delta_i = y^*_i - y_i$, is called the residue. In the least square method, the sum of the square values of residues is minimized to find the best-fit line for the given data[8]. The sum of squares of residues can be denoted as SSE or SS_E. Minimizing the sum of squared of residues can be described as:

$$SS_E = \sum_{i=1}^{n}\left(y^*_i - y_i\right)^2 = \sum_{i=1}^{n}(a + bx_i - y_i)^2, \textbf{ Equation 5}$$

Two equations below estimate the coefficients "a" and "b". These coefficients are described with symbols "a" and "b".

$$\frac{\partial SS_E}{\partial a} = 0, \textbf{ Equation 6}$$

$$\frac{\partial SS_E}{\partial b} = 0, \textbf{ Equation 7}$$

The linear regression analysis above can be taken one step further by minimizing the SS_E. This is called the least square estimation method. Equation 5 can be rewritten for the least square estimation method:

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[7] Fundamentals of Systems Engineering with Economics, Probability and Statistics, C. J. Khisty and J. Mohammadi, Prentice Hall
[8] In data gathering process, data is collected in Y and X pairs.

$$Min_{a,b} \sum_{i=1}^{n} (a + bx_i - y_i)^2 \text{ , \textbf{Equation 8}}$$

, where coefficients a and b are determined to minimize the sum of squared errors, SSE. The least square estimation method will be often used in time series modeling.

Procedure – Time series model

Some Forecasting Thoughts

There are ways to estimate and to forecast a selected time series data set. First, we need to understand the time series data to find the best approach possible. Let's investigate some possible approaches.

Constant Plot Approach

The simplest estimate for a time series is a constant estimate model. The set of unobserved factors includes everything but the average of the selected data set. As a result of these factors, the time series data varies along the plotted constant average of the data set.

$$y_t = a + \varepsilon_t \text{ , \textbf{where} } \varepsilon_t : N(0, \sigma^2) \text{ , \textbf{Equation 9}}$$

"a" is the estimate for the selected data. In this simple case, it is the average of the data set, which is plotted as a constant line below in Figure 2.
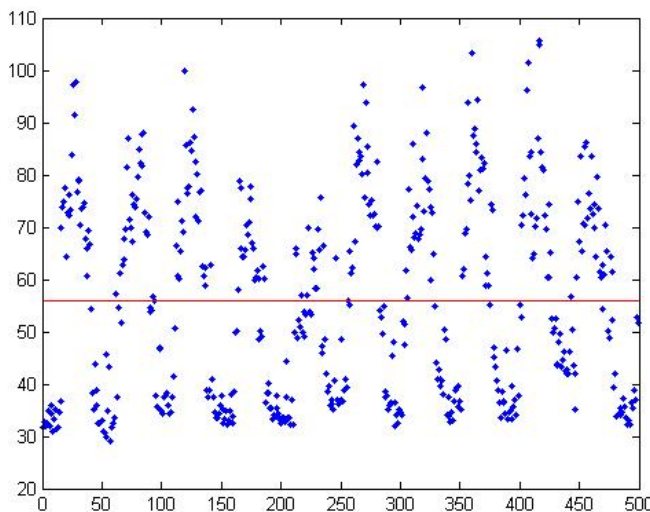

Figure 2

$\hat{a}$ is the estimate for the constant average number, a, for the data set. $\hat{a}$ can be found as following:

$$\hat{a} = \frac{\sum_{n=1}^{T} y_t}{T} \text{ , \textbf{Equation 10}}$$

T is the last time point that we have data for. In Figure 2 above, T corresponds to 500. This formula is nothing different than solving the following equation.

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$$Min_a = \sum_{n=1}^{T}(y_t - a)^2 \text{, \textbf{Equation 11}}$$

Let's assume that we get one more data point after T. Most likely our estimate of $\hat{a}$ will change with the additional data. To find the new estimate, we have to find $\hat{a}$ (T+1).

$$\hat{a}(T+1) = \frac{\sum_{n=1}^{T}y_t - y_{T+1}}{T+1} = \frac{y_{T+1}}{T+1} + \frac{\hat{a}(T)*T}{T+1} \text{, \textbf{Equation 12}}$$

Now we know how to find the estimate of the selected data set. We want to forecast future data points based on past data. $\hat{y}_{T+k}$ is the forecast for the data point y, k time intervals in the future.

$$\hat{y}_{T+k} = \hat{a}(T) \text{, \textbf{Equation 13}}$$

The constant model tells that the forecast data point y that is k time intervals in the future is equal to the estimate $\hat{a}$.

Exponential Smoothing:

Investigating $\hat{a}(T+1)$ further, we can rewrite the equation as following:

$$\hat{a}(T+1) = \left(\frac{1}{T+1}\right) * y_{T+1} + \left(\frac{T}{T+1}\right) * \hat{a}(T) \text{, \textbf{Equation 14}}$$

The sum of coefficients in front of the independent variable, $\left(\frac{1}{T+1}\right)$, and the estimate for the selected data set,

$\left(\frac{T}{T+1}\right)$, is 1. In other words, these coefficients are weighting factors for the two variables on the right side of

equation. We can rewrite the equation as:

$$\hat{a}(T+1) = \alpha * y_{T+1} + (1-\alpha) * \hat{a}(T) \text{, \textbf{Equation 15}}$$

The weighting factor α determines the importance of the variables on the right hand side of equation in finding the new estimate for the selected data set after the additional data point is added to the data set. This is called exponential smoothing. Even with exponential smoothing, the constant plot model does not fit our data well as a result of the variance of data from $\hat{a}$. A high Sum of Squared Error number is expected from this fit.

Linear Trend Model:

In linear trend models, not all the factors are unobserved. An upward or downward sloping trend is an observable factor. "Trend is slow, long-run, evolution in variables that we want to model and forecast."[9] When this

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[9] Diebold, Francis. "Elements of Forecasting." Department of Economics, University of Pennsylvania. Chapter 4, page 74. South-Western College Publishing.

trend evolves in a predictable way, then the model has a deterministic trend. Figure 2 below, has an upward sloping trend.
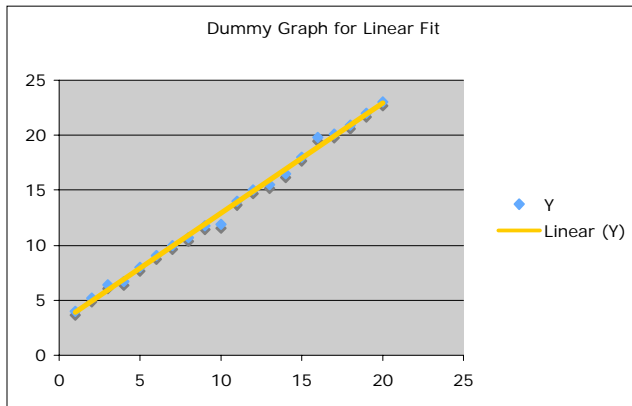

Figure 3

The time series graph in Figure 2 can be described with a simple linear function of time:

$$y_t = a + b*t + \varepsilon_t, \text{ where } \varepsilon_t : N(0,\sigma^2), \textbf{Equation 16}$$

Similarly, the estimates for a and b can be found by minimizing the following equation:

$$\underset{a,b}{Min} \sum_{n=1}^{T}(y_t - a - b*t)^2, \textbf{Equation 17}$$

a is the intercept while b presents the slope coefficient. $\hat{a}$ and $\hat{b}$ from Equation 18 are the estimates that minimizes the Sum of Squared Errors of the linear fit to the selected time series data set. Forecasting any data point in future can be found similarly with the following equation:

$$\hat{y}_{T+k} = \hat{a}(T) + \hat{b}(T)*(T+k), \textbf{Equation 18}$$

Quadratic Trend Model

Another time series model is Quadratic Trend Model. Figure 3 represents the time series data for United States' population from 1805 to 1975.This model is used when the time series data looks as following:
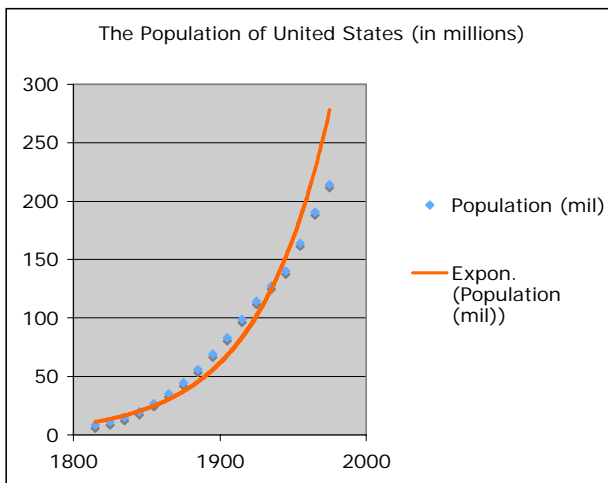

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Figure 4[10]

Quadratic Time Model can be described with the following equation.

$$y_t = a + b*t + c*t^2 + \varepsilon_t \text{, \textbf{Equation 19}}$$

Data above is has an exponential trend. To forecast this data set, quadratic model can be used

$$\hat{y}_{T+k} = \hat{a}(T) + \hat{b}(T)*(T+k) + \hat{c}(T)*(T+k)^2 \text{, \textbf{Equation 20}}$$

by minimizing the Sum of Squared Errors.

$$\underset{a,b,c}{Min} \sum_{n=1}^{T} (y_t - a - b*t - c*t^2)^2 \text{, \textbf{Equation 21}}$$

Autoregressive Model, AR(p)

In the previous models discussed above, time series data set y is only dependent on time. This is not the case for autoregressive model data, where correlation among the data themselves is expected. This model is mostly used for engineering problems in production systems. A model that works on a queuing problem such as predicting the number of customers in a grocery store has to use an auto-regressive model. The customers will wait or not wait the queue based on its length. Since the data depends on past data, an AR model is necessary. An estimate of time series model can be found as following:

$$y_t = a + b_1 y_{t-1} + b_2 y_{t-2} + ... + b_p y_{t-p} + \varepsilon_t \text{, \textbf{where} } \varepsilon_t : N(0, \sigma^2) \text{, \textbf{Equation 22}}$$

If we want to make the equation above look similar to our previous equations, we can rewrite it as:

$$Y = X_1 + X_2 + ... + X_p + \varepsilon_t \text{, \textbf{where} } \varepsilon_t : N(0, \sigma^2) \text{, \textbf{Equation 23}}$$

We don't see time variables on the right hand side of the equation but we observe that y_t is dependent on past variables such as y_{t-1}, y_{t-2},…,y_{t-p}, where p is the order of the auto-regressive model.

Forecasting is little more meticulous in this case. We have to follow a step-by-step approach since the y-values depend on the past y-values. To forecast y_{T+k}, we have to find the forecast for y_{T+1}, y_{T+2},…, until y_{T+k-1} in order to find $\hat{y}_{T+k}$. The forecast for y_{T+1} is equal to:

Code 1
```
for j = 1:1:48
count = 1;
        for index=(day_diff-((day_diff-40))):day_diff
         dayy = index;
         timee = j;
         % Wednesday
         day_act = dayy;
         dayy = dayy - 2;
         A1 = [demand(timee,dayy-1), demand(timee,dayy-2), demand(timee,dayy-3), demand(timee,dayy-
         4), demand(timee,dayy-5), ...
         demand(timee,dayy-6), demand(timee,dayy-7), demand(timee,dayy-14), demand(timee,dayy-21),
         demand(timee,dayy-28)];
         b1 = demand(timee,dayy);
         % I truncated some code here…
         …
         % Creating the matrix
         A = [A1; A2; A3; A4];
         b = [b1; b2; b3; b4];
         % Least Square Regression to find the Betas
```

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[10] http://www.mste.uiuc.edu/malcz/ExpFit/FIRST.html

```
    x = lsqr(A,b);
    end
end
```
Code 1 represents a portion of the auto-regression model, written in Matlab. This model searches for autocorrelation between the current data and historical data. In the code above, the user would like to forecast electricity demand on Friday. Based on visual autocorrelation detection and Matlab's "xcorr.m" function, it can be argued that an auto-correlation occurs every 24-hours occurs. As a result of the class schedule, different multiples of day-interval is used to find the historical auto-correlative data to forecast Friday's electricity demand. The model works as following:

Table 3

Weekday	T-1	T-2	T-3	T-4	T-5	T-6	T-7	T-14	T-21	T-28
Friday										
Wednesday	Tuesday	Monday	Sunday	Saturday	Friday	Thursday	Wednesday	Wednesday	Wednesday	Wednesday
Monday	Sunday	Saturday	Friday	Thursday	Wednesday	Tuesday	Monday	Monday	Monday	Monday
Last Friday	Thursday	Wednesday	Tuesday	Monday	Sunday	Saturday	Friday	Friday	Friday	Friday
Last Wednesday	Tuesday	Monday	Sunday	Saturday	Friday	Thursday	Wednesday	Wednesday	Wednesday	Wednesday

Four matrixes are created for Wednesday, Monday, last Friday, and last Wednesday. Each matrix has ten columns representing the past data from T-1 through T-28. The Least square estimation method is used to find the variable x in Code 1 that minimizes the sum of squared errors for function B = A*x. B is the raw data and A is the four matrixes created above. X is the forecasting matrix. By multiplying X with A_act, which is shown below, one can find $\hat{y}$ based on the auto-regressive model.

Code 2
```
% From the historical raw data we have for the electricity demand.
A_act = [demand(timee,day_act-1) demand(timee,day_act-2) demand(timee,day_act-3)
        demand(timee,day_act-4) demand(timee,day_act-5) ...
        demand(timee,day_act-6) demand(timee,day_act-7) demand(timee,day_act-14)
        demand(timee,day_act-21) demand(timee,day_act-28)];
```
Clearly, the forecasted electricity demand depends on past data since historical electricity demand values are used to forecast tomorrow's electricity demand.

Holt Winter Model

Like the first three models, this model only depends on time. Therefore, any possible autocorrelation in the data ignored. Investigating our time series data from Kohlberg, one notices that the data set is strictly dependent on the time of day. The two big factors that affect the KW demand are outside temperature and human actions measured by class schedule. In general, these two factors vary based on the time of day. The Holt – Winter Model is the model for forecasting that is used to investigate data sets with similar properties. The model can be described by the following equation.

$$y_t = a * c_t + b + \varepsilon_t \text{, where } \varepsilon_t : N(0, \sigma^2) \text{, Equation 24}$$

, where we want to minimize:

$$Min_a = \sum_{n=1}^{T} (y_t - a * c_t - b)^2 \text{, Equation 25}$$

'C_t' is the adjustment factor that is essential for the success of the Holt – Winter Model. There are forty-eight 'c_t' that correspond to half-an-hours in a day. The number of constant 'a's equal to the number of days of time series data since

'a' represents the average electricity demand of a day in past data. 'B' is a constant number in the model. 'C_t' will suppress or magnify the estimated average number, 'a', based on the time of day.

Code 3: Part of the Holt – Winter Model Code

```
% Get the forty-eight Ct for the Holt - Winter Model. These Ct will be used
% to estimate and forecast the time series data based on the following
% equation: y = a*Ct + error.
% I got the average for every day (for the whole day). Then I found Ct
% variables for each half-an-hour by doing a least square estimate.
for i=1:1:48
    B = weekday_demand(i,:)'; % This is a column vector for y - values at 00:00
    A = weekday_mean_demand'; % To find the aver vector w/ same size.
    Ct(i) = lsqr(A,B);
end
```

For our purposes, 'b' is chosen as zero, since we do not need any constant for our time series data. 'C_t' is calculated by the least square estimation method. It is a 48x1 vector that minimizes sum of squared errors for $y - a * c_t$. By multiplying the 'c_t' array with (for instance) electricity demand averages of the last five weekdays, we can estimate tomorrow's electricity. The forecasting equation is as following:

$$\hat{y}_{T+k} = \hat{a}(T+k) * \hat{c}_{T+k} \text{ , Equation 26}$$

, where the estimates of 'a' and c_t are used as forecasting coefficient and variable, respectively. Kohlberg electricity data depends strictly on time. It can be argued that any autocorrelation in the data set can be ignored since electricity demand at each half an hour interval depends heavily on factors like temperature, class schedule, and very little on what has happened earlier in the day.

Class schedule is another way of understanding the human activity at Kohlberg since the building is used for education purposes. Controllable variables are the direct impact of human existence activity on the electricity bill. Although their effect is less compared to other variables, they are inevitable in modeling the electricity demand at Kohlberg.

The Class Schedule Model – Controllable Variables

Theory

The contribution of the controllable variables such as lights, computers and plug loads to total electricity demand is harder to investigate than the contribution of uncontrollable variables such as pumps and air handling units (AHU). They also represent the smallest portion of the electricity demand. Consequently, the contribution of controlled variables, computers and other plug loads, to electricity demand is often overlooked. At the same time, electricity demand by controllable variables is fairly large to neglect, approximately up to 22 KW on weekdays in Kohlberg in Fall 2006 and 17 KW on weekdays in Trotter in spring 2007 between 8:30 and 6:30 PM. At the same time, controllable variables are one of the main reasons for additional peak charges that the College paid in the past.

Based on documents produced by the US EPA, "office equipment accounts for 7% of all commercial electrical usage or several billion dollars annually."[11] Data from various electrical devices that are used in Kohlberg and other places on campus are gathered and presented in table below.

Table 4

Device Type	Type of Data	Location	Electricity Usage - peak (W)	Electricity Usage - regular (W)	Electricity Usage - idle (W)	Electricity Usage - off (W)	Data Discrepancy (%)

---

[11] Energy Star Power Management: http://www.microtech.doe.gov/energystar/

Device	Data type	Source	Peak (W)	Regular (W)			Annual KW
Apple Power Mac G4 Tower	Measured	Hicks 213	104.80	84.80		14 (standby), 8.4 (off but plugged in)	9.281
	Theoretical		115.00	90.00		2.00	
Nec Multisync P1150, 22"	Measured	Hicks 213	127.60	115.20	82	2.4	26.748
	Theoretical	Nec Co.	167.00		20.00	5.00	
Dell Flat Screen 15"	Measured	Hicks 213		29.20	28.80	2.40	
	Theoretical		NA	NA		0.70	
Dell OptiPlex GX280 Mini Tower	Measured	Hicks 310	120.8	58.4	78	3+/-1 (standby), 1 (off but plugged in)	1.392
Dell OptiPlex GX320 Mini Tower	Theoretical	Dell Co.	119.13	NA	79.43	2,4 (standby), 1,98 (hibernate)	
Dell OptiPlex GX280 Desktop	Measured	Hicks 213	164.08	101.20	101.20	2.8 (standby)	26.881
Dell OptiPlex GX320 Desktop	Theoretical	Dell Co.	125.20	NA	80.16	2,4 (standby), 1,87 (hibernate)	
60 Watts Light Bulb	Measured	Hicks 310	NA	57.20	NA	0.00	4.778
	Theoretical		NA	60	NA	0.00	

The tested devices are office equipment and they are either computer or computer-related peripherals. Measured data is from the existing electrical devices in building. Theoretical data is from the equipment user's manual or company websites of the listed devices. The average of the listed devices' peak and regular usage is calculated as:

$$\frac{104.8+127.6+120.8+164.08}{4}=129.3 \text{ Watts, } \textbf{Equation 27: } \text{Measured average peak usage}$$

$$\frac{115+167+119.13+125.2}{4}=131.6 \text{ Watts, } \textbf{Equation 28}: \text{Theoretical average peak usage}$$

Similarly, the measured and theoretical regular electricity usages are found. Making a conservative assumption, these devices are used three hours in their peak schedule and 21 hours in their regular schedule per day. It is known that these devices are not turned off overnight or they do not hibernate. Based on the measurements on campus, the annual electricity cost for a desktop computer (adjusted for Mac/PC) is calculated by:

$$\left(\frac{(129.3*3)+(89.9*21)}{1000}*365\right)=831KW \text{ , } \textbf{Equation 29}$$

Table 5 below displays the results for measured and theoretical averages for a desktop computer at the College. Assuming one KW costs 14 cents to college, the cost can also be calculated.

Table 5

Data type	Peak Use (W)	Regular Use (W)	Annual KW	Annual Cost in $ 14 cents per KWh	Average Use (W)
Measured Average	129.3	89.9	830.7	116.3	95
Theoretical Average	131.6	90	833.9	116.8	95.2

The average annual electrical demand and cost for Apple Power Mac, Nec monitor, Dell flat screen, Dell mini-tower and desktop are 95 W per hour and $116 per year. Hundreds of students that visit Kohlberg use these devices every day.

The human actions that demand electricity are very hard to predict since each individual has his or her own schedule unlike the uncontrollable variables' predetermined schedules. Along the path of understanding the controllable variables, I faced the challenge of understanding psychology and sociology in Kohlberg. From my talks

with Professor McGarity, I concluded that he also experienced a similar problem while conducting a similar research in Princeton. His work[12] was to understand the contribution of air conditioning to the electricity consumption and the outcome was "I always turn it on super!" This is what his colleague, an anthropologist, concluded after an interview-survey with the air conditioner users. Although human behaviors are extremely hard to predict, I believe that the College's student body and faculty alike share common characteristics with regard to electricity use.

Kohlberg is mainly occupied by classrooms and faculty offices. Comparing the winter-break data for these buildings to a regular weekday data revealed the electrical load contribution of controllable variables in these buildings. Investigating the class schedule, one can also find an approximate number for people in Kohlberg at a given time.

To see the difference in electricity load, two graphs with classes in session and without classes are presented below.
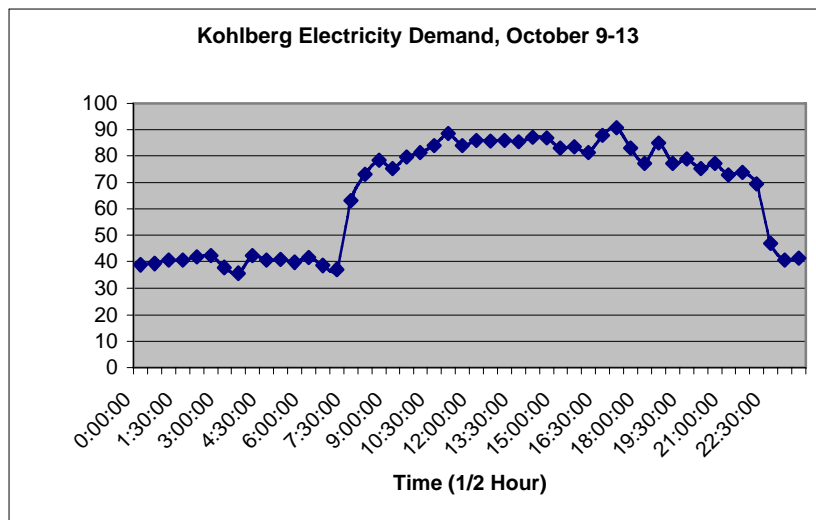

Figure 5

A similar rise in electricity demand is notable in Figure 6 below representing the demand over the fall break in 2006.

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[12] Energy and Buildings, 18 (1992) 177-191, "'I always turn it on super': user decisions about when and how to operate room air conditioners." W. Krempton, D. Feuermann, A. McGarity.
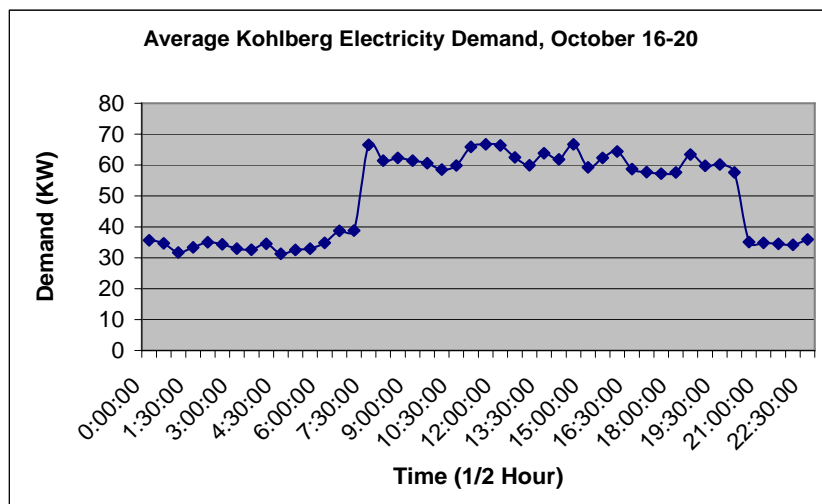
Average Kohlberg Electricity Demand, October 16-20

Figure 6

Air handling units start to operate at 6:55 AM and turn off at 8:00 PM on weekdays[13]. Consequently, in Figure 6 above, a significant increase in electricity demand is observed around 7 AM. After the rise in the electricity demand at 7:00 AM, the two figures diverge in terms of their load characteristics. The reason for this difference is the fall break. Figure 6 reflects the electricity consumption in Kohlberg without any human activities while Figure 5 represents a regular weekday for Kohlberg. Temperature setpoints were identical.

From 8:30 AM until 11:30 AM, the electricity consumption increases to its peak and it drops around 12:30 PM. The lunch break at this time of day causes this drop in electricity. As students and faculty members come back from lunch around 1:15 PM, electricity demand starts to increase again. However, for Kohlberg, the increase in demand after lunch will not be as strong as the increase in the morning's demand. The pattern will continue with small-amplitude fluctuations until around 7:00 PM.

To forecast electricity demand based on the human actions, we seek a relationship between the number of classes (which represents the building population) and electricity demand. A linear regression analysis is conducted among class schedule and electricity demand to search for any possible relationship. Any linear model will indicate a fixed load that results from the existence of building population and an additional load per class. Electricity demand is expected to be positively correlated with class schedule since the electricity consumption rises with the number of people in the building as a result of controllable variables like lights, computers, and plug loads.

Procedure for Class Schedule Model

I have two different class schedule models. The first Excel-based method was developed during my Campus Energy Analysis Project with Professor Carr Everbach[14]. The second Matlab-based model is designed for my E-90 Project. The first model returns good R^2 values (~0.75) while it is not flexible if the class schedule changes and it has built-in assumptions. The second, Matlab-based model, on the other side, is capable of downloading any reserved space

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[13] Please see the Appendix X, Swarthmore College Case Study for a detailed schedule of fan operations.
[14] Please find the Campus Energy Analysis Project's Class Schedule Model attached.

information or class schedule from the on-line Kohlberg space schedule and analyzing the information without any assumptions[15].

As the first step, the Matlab model takes the user input of the weekday that the user would like to forecast. The model does not accept any dates on weekends, winter break or summer breaks. After acquiring the input date, the model finds what weekday the user input corresponds to and calls one of the five weekday functions (for instance "ClassScheduleTue.m"). Each weekday function scans the Kohlberg reserved space schedule. A part of the code from "ClassScheduleTue.m" is provided below:

Code 4
```
elseif(datenum('2:29 PM')<datenum(R(index,6))) && (datenum(R(index,6))<datenum('3:29 PM'))
        if(datenum('2:29 PM')<datenum(R(index,7))) && (datenum(R(index,7))<datenum('3:29 PM'))
            n7=n7+1;
        elseif(datenum('3:29 PM')<datenum(R(index,7))) && (datenum(R(index,7))<datenum('4:29 PM'))
            n7=n7+1;n8=n8+1;
        elseif(datenum('4:29 PM')<datenum(R(index,7))) && (datenum(R(index,7))<datenum('5:29 PM'))
            n7=n7+1;n8=n8+1;n9=n9+1;
        elseif(datenum('5:29 PM')<datenum(R(index,7))) && (datenum(R(index,7))<datenum('6:29 PM'))
            n7=n7+1;n8=n8+1;n9=n9+1;n10=n10+1;
        else n7=n7+1;n8=n8+1;n9=n9+1;n10=n10+1;n11=n11+1;
end
```
The code initially divides the day from 8:30 to 9:30 into fourteen 1-hour intervals and creates buckets representing each interval. As "ClassScheduleTue.m" is scanning the reserved space schedule, it fills Tuesday's fourteen buckets. For instance, if a class starts at 2:30, the part of the code for Tuesday will find it. Based on the end time of the class, the program will increase the corresponding buckets. If the class ends at 4:00 PM, the code will increase bucket n7 and n8 by 1.

After getting the information from the reserved space schedule, the model will call the "ClassScheduleDemand.m" to find the corresponding electricity demand for the chosen date. The code scans an Excel file for electricity demand of the selected day profiles (here, it is Tuesdays).

Code 5: A part of the code from "ClassScheduleDemand.m"
```
if((strcmp(weekday1,'Tue'))&&(strcmp(weekday2,'Tue')))
        for subindex=1:48
            count = count + 1;
            dates(day , count) = R(subindex+index-1,2);  % copy cell contents to dates array
            times(day , count) = cell2mat(R(subindex+index-1,3));  % copy cell contents to time array
            demand(day , count) = cell2mat(R(subindex+index-1,4)); % convert time number and save
        end
        day = day + 1;
end
```
After it gathers all Tuesdays from the Excel file, the code averages the day profiles. Similarly, the code imports the electricity demand profile from winter break in order to get Tuesday data without having any people at Kohlberg. To understand the effect of people in the building, the code finds the difference between mean electricity demand of regular days and of winter break days. At the end, the model uses Matlab's "polyfit" function to find best fit line for the new data set consisting of the obtained electricity demand and class schedule data.

Code 6: A part of the code from "ClassScheduleDemand.m"
```
P_coeff = polyfit(n,d,1); % Searching for the best fit line and its coefficients
for i=1:1:14
    classsch_KW(i) = P_coeff(2)+ P_coeff(1)*n(i)+Mean_Demand_Ave_Select(i); % The forecasted demand
end
```
The linear equation's coefficients are used to estimate the electricity demand. By adding the basic building electricity load, which is obtained from the winter break, the electricity demand is forecasted. The model returns an array of 48x1.

---

[15] There is only one assumption about lunch-time.

Although the Excel and Matlab models are similar in principle, the Excel model has built-in assumptions to smooth data sets for class schedule in order to lower sum of squared errors and a higher R^2 value. The assumptions from the Excel model can be listed as following[16]:

1. All of the one-time activities are neglected since the class schedule model returns specific class schedules for the chosen day.

2. The Excel model uses a snap-shot method where it only cares about the number of classes at specific times in day. These times correspond to class start times based on class schedule.

3. The data points are collected based on daily class schedule. Monday, Wednesday and Friday follows a different model than Tuesday and Thursday since their class schedules are different.

4. First classes start at 8:30 AM but electricity demand does not increase like a step function as the number of classes does. To avoid a sharp increase in the electricity forecast, the first class is assumed to start at 9:00 AM.

5. Because of a similar reasoning for the first assumption, the sharp decrease at 12:30 in terms of number of classes is compensated by adding 20% of the number of classes from the previous period. The idea is that 20 % of the classes that start at 11:30 AM continue at 12:30 because of the Tuesday and Thursday class schedule.

Although some of these assumptions are useful in terms of decreasing the sum of squared errors and therefore providing a better fit and forecast, they tend to limit the flexibility of the code. For instance, taking only the start times for each class limits the code's ability of correctly determining how long each class lasts. An incorrect estimation of the class duration will provide incorrect estimates for the number of people at Kohlberg and therefore give a weak forecast for electricity demand. Therefore I used the Matlab model for class schedule. The class schedule model test results are shown below:

Table 6: Based on class schedule model result from Monday, November 5, 2007

Results	
Sum of squared errors, SS_E	1.9588e+004
R^2	0.704
Degrees of freedom error, dfe	142
Adjusted R^2	0.702
Root mean square error, rmse[17]	11.7449

The goodness of the "polyfit" function does not return a R^2 value as high as the Excel model did. This might be due to the small number of data points (14 data points) in the best-fit curve and/or the assumptions listed above. In future work, some of the assumptions might be integrated into the Matlab model and tested. Based on the results, the Matlab model can be improved.

Heat Loss Model

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[16] Please find the Excel model in Appendix attached.
[17] Root mean square error: The square root of the mean square error.

Historical data has been a fundamental source for understanding, modeling and predicting electricity demand. Other organizations and institutions such as PJM rely heavily on historical data to predict tomorrow's electricity demand in order to shape the current real time electricity market. However, a physical understanding of the electricity demand will enrich our understanding.

A Heat loss model is created as a third approach to forecast tomorrow's electricity demand based on ambient temperature and time. The model looks for a relationship between the heat loss of Kohlberg and its electricity consumption.

Heat loss model uses principles from thermodynamics and heat transfer. Heat transfer can be defined as "the transmission of energy from one region to another as a result of a temperature difference between them"[18]. Generally, three types of heat transmission are recognized by the literature: conduction, radiation, and convection. From a thermodynamic point of view, the amount of heat transferred during a process simply equals to the difference between system's energy change and work done. The heat loss model incorporates these three types of heat transmission and thermodynamics.

The basic procedures for estimating heating load (loss) of Kohlberg are developed. The procedures can be summarized among three categories: external heat gain, internal heat gain, and ventilation and infiltration. The total heat loss of the building is the sum of the partial heat losses discussed below.

Theory

External Heat Gain

External heat gain is the heat gain by conduction and convection through exterior walls, windows and roofs. Conduction is described as "a process by which heat flows from a higher temperature to a region with lower temperature within a medium"[19], whereas convection is "a process of energy transport by the combined action of heat conduction, energy storage, and mixing motion"[20]. The heat loss due to conduction and convection can be calculated as following:

$$Q = U * A * \Delta T \text{ , Equation 30}$$

, where U is one over thermal resistance (R), A is the area of element under analysis and ΔT is the temperature difference between Kohlberg's temperature and ambient temperature. In order to find the heat loss, I have to find the thermal resistance, R, and surface area, A. I will collect Kohlberg temperature and ambient temperature by placing data loggers in the building and using Facilities infrastructure to collect data. To find the thermal resistance, R, first, the layers of roof, exterior walls, and windows need to be identified.

The Walls:

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[18] Kreith, Frank. "Principles of Heat Transfer". 3rd Edition. Intext Educational Publishers. New York.
[19] Kreith, Frank. "Principles of Heat Transfer". 3rd Edition. Chapeter 1-2, pg: 4. Intext Educational Publishers. New York.
[20] Kreith, Frank. "Principles of Heat Transfer". 3rd Edition. Chapeter 1-2, pg: 5. Intext Educational Publishers. New York.

To identify the layers of wall construction, Kohlberg's blueprints from the College's Facilities Department are obtained. Kohlberg has several variations for exterior walls. After investigating all the exterior walls, a typical wall cross section is chosen for simplicity and coherence in calculations.
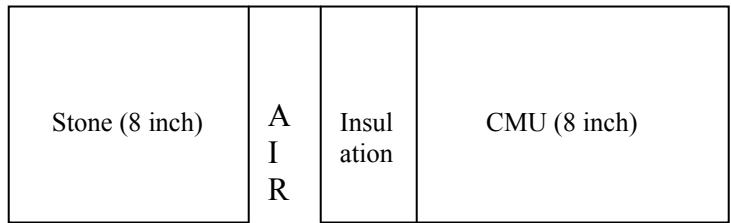

Figure 7: A schematic display of Kohlberg's typical exterior wall.

The typical exterior wall of Kohlberg consists of four parts: stone, air gap, insulation, concrete masonry unit (CMU). Individual lengths of each component are shown in Table 1. These lengths are determined by investigating corresponding blueprints.

Table 7

Kind	Length (inches)
Total wall length	19
Stone	8
Air space	1
Rigged insulation	2
CMU	8

The stone component of the wall consists of different types of stones[21]. For simplicity, the eight-inch stone component is treated as filled CMU. The R-values of each part of the wall is calculated based on the ASHRAE's Fundamentals Handbook. The R-values are shown in Table 8 below.

Table 8[22]: Thermal resistance properties used in typical wall at Kohlberg.

Exterior Wall Component (in 1 in unit)	Resistance, R, (F*Ft*Hour^2/BTU)
8 inch heavy weight concrete block filled	1.96
Air	0.91
2 inch insulation	6.67
8 inch block (CMU)	2
Internal resistance	0.69
External resistance	0.17

The thermal resistance of the exterior wall can be modeled as resistors in series. Each components resistance (per inch) is multiplied by its length and added together to find the total resistance of the typical wall.

$$R_{wall} = R_{Stone} + R_{Air} + R_{Insulation} + R_{CMU}$$ **, Equation 31**

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[21] Please see the Appendix for Kohlberg's stone schedule.
[22] 1997 ASHRAE Fundamentals Handbook, Nonresidential Cooling and Heating Calculations, Table 11: Thermal Properties and Code Numbers of Layers Used in Wall and Roof Description. Chapter 28, page 18.

The typical wall's resistance is found as 12.4 (F*Ft*Hour^2/BTU). Since the U-factor is one over the thermal resistance, the U-factor is found as 0.080646 BTU/ (F*Ft*Hour^2) for Kohlberg's walls.

The portion of walls on Kohlberg's facet is determined with the help of the blueprints. For each floor, the surface area of exterior walls is given as following:

Table 9: Surface area for walls.

Walls	Feet^2
Floor 1	8038
Floor 2	7318
Floor 3	7215
Total	22572

Knowing U-factor and wall areas, Q_{Wall} can be found by multiplying the constant, U*A, with ΔT .

$$Q_{Wall} = U * A_{Total,Wall} * \Delta T \text{ , Equation 32}$$

, where $U * A_{Total,Wall} = 22572 * 0.080646 = 1820.3$ BTU/(F*Hour^2).

The Windows:

The conduction and convection through windows is important for Kohlberg since the area of windows is approximately one fourth of the total building's facet area. There are four types of windows in Kohlberg: Small size, double small size, medium size and large size. The areas of each window type are shown below. These numbers are also obtained from Kohlberg's blueprints.

Table 10

Windows	Kind	Type	Square Inch
	Large size	Type 1	3318
	Small size	Type 2	6636
	Double the small size	Type 3	11664
	Medium size	Type 4	8258

Kohlberg's windows have double-glazing. I choose ½ inch air space between the panes. From ASHRAE Fundamentals Handbook, various U-factors for different types of windows are obtained. To find the correct U-factor, I averaged center of glass and edge of glass for glass only. The U-factor for Kohlberg window is determined as 0.535 (BTU/(h*ft^2*F)).

Table 11: U Factors for Various Fenestration Products in BTU/(h*ft^2*F)

Product Type	Glass only		Operable glass (including sliding glass doors)	
	Center of glass	Edge of glass	Aluminum w/o thermal break	Aluminum w/ thermal break
Double Glazing				
¼ air space	0.55	0.64	0.87	0.65
½ air space	0.48	0.59	0.81	0.6
¼ argon space	0.51	0.61	0.84	0.62
½ argon space	0.45	0.57	0.79	0.58

Similarly, I found the surface area for windows, which is shown in the table below.

Table 12

Windows	Feet^2
Floor 1	3184
Floor 2	2094
Floor 3	2197
Total	7475

Knowing U-factor and wall areas Q_{Window} can be found as following:

$$Q_{Window} = U * A_{Total,Window} * \Delta T \text{ , Equation 33}$$

, where $U * A_{Total,Window} = 7475 * 0.535 = 3999.1$ BTU/(F*Hour^2).

The Roof:

A typical cross-section for Kohlberg's roof is determined that is presented below.

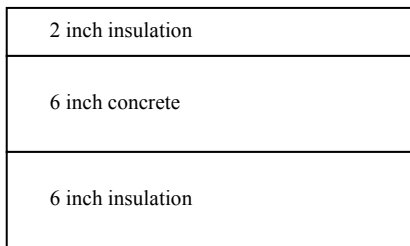| 2 inch insulation |
| 6 inch concrete |
| 6 inch insulation |

Figure 8: Typical Roof schematic

The resistance values for each part of the cross section are found from ASHAE Fundamentals Handbook 1997. The results are displayed below.

Table 13

A typical roof at Kohlberg	R, (F*ft^2)/Btu	U, (F*ft^2)/Btu
2 inch Insulation	6.67	0.149925037
6 inch concrete	5.00	0.2
6 inch Insulation	20.01	0.049975012
Outside surface resistance	0.33	3.03030303
Inside surface resistance	0.69	1.449275362
Total	32.7	0.030581039

The net area for third floor is determined as 11917 ft^2 from Kohlberg's blueprint. It is assumed that third floor has the same area with the roof. It is also assumed that the roof is flat and does not have downward sliding sections. Therefore, the heat loss through the roof is determined as following.

$$Q_{Window} = U * A_{Total,Roof} * \Delta T$$
$$U * A_{Total,Roof} = 0.030581*11917 = 364.43 \text{ , Equation 34}$$

, where $U * A_{Total,Roof} = 0.030581*11917 = 364.43$ BTU/(F*Hour^2), and ΔT is the temperature difference

between Kohlberg's inside air and ambient temperatures.

Total Heat Loss through Conduction and Convection

The total heat loss through conduction and convection from walls, windows and roof can be summarized by the following equation.

$$Q_{Conduction,Convection} = Q_{Total,Wall} + Q_{Total,Window} + Q_{Total,Roof} \text{ , Equation 35}$$

, which results in:

$$Q_{Conduction,Convection} = 1820.3\left(\frac{Btu}{Hour}\right) + 3999.1\left(\frac{Btu}{Hour}\right) + 364.43\left(\frac{Btu}{Hour}\right) = 6183.83\left(\frac{Btu}{Hour}\right) \text{, Equation 36.}$$

The Matlab code below shows how conduction and convection part of the heat loss model gathers information from roof, windows, and walls.

Code 7: Part of the Conduction and Convection model

```
% Calculating the heat loss for each section.
Q_wall = UA_wall*Temp;
Q_windows = UA_windows*Temp;
Q_roof = UA_roof*Temp;
% Calculating the final heat loss through conduction and convection
QCC = Q_wall + Q_windows + Q_roof;
```

Solar Gain

Radiation is third type of heat transmission in heat transfer literature. It is the primary weather related variable influencing the heat gain of the building. Based on ASHRAE Fundamentals Handbook, solar heat gain at any instant can be modeled as following:

$$E_t + U(t_0 - t_i) = q_R + q_S + q_T + q_{RCo} + q_{RCi} \text{ , Equation 37}$$

, where q_R, q_S , and q_T are the heat reflected, stored in the glass, and transmitted, respectively. The terms q_{RCo} and q_{RCi} represent outward and inward heat flux rates by radiation and convection. In other words, the heat gain can be expressed as:

Table 14

Total heat admission through glass	=	Solar heat gain	+	Heat gain through conduction and convection

This can be written as:

$$q_A = SHGC * E_t + U(t_0 - t_i) \text{, Equation 38}$$

, where q_A is the instantaneous rate of heat gain through fenestration in units of BTU/(Hour*ft^2) and $SHGC$ is the solar heat gain coefficient.

I have just discussed the conduction through windows above in Windows section. Therefore, I can leave out the conduction part when calculating q_A. Simplified heat gain calculation can be made using the following solar gain equation:

$$q_i = SC * SHGC \text{ , Equation 39}$$

, where SC represents the shading coefficient.

To find the correct solar heat gain coefficient (SHGC), I need correct location of the College. I found out that Swarthmore College is located in 39°54'18"N and 75°21'15"W coordinates[23]. According to Duffie and Beckman[24], a

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[23] Google Earth

60° surface at 40° North latitude from 9 AM – 10 AM on February 20th receives about $1.29 \dfrac{MJ}{m^2 \cdot Hour}$, which can be

converted to $113.6 \dfrac{BTU}{ft^2 \cdot Hour}$. Assuming that we have a shading coefficient of 50%, we calculate q_i as

$56.8 \dfrac{BTU}{ft^2 \cdot Hour}$. Then the heat gain through solar radiation is:

$$Q_{Solar} = SC * SHGC * A_{Total,Window}$$, **Equation 40**

Kohlberg's exterior window area is presented as 7475 ft^2 in Table 6 above. Therefore, $A_{Total,Window}$ is equal to 7475 ft^2.

Internal Heat Gain

Humans

Internal heat gain, Q_{Source}, is the result of humans and electrical loads in the building that generate additional heat. The table below shows heat input by human in different states of activity.

Table 15: Rates of Heat Gain from Occupants of Conditioned Spaces[25]

Degree of Activity	Total Heat, Btu/hour			
	Adult, male	Adjusted, M/F	Sensible Heat, Btu/h	Latent Heat, Btu/h
Seated at theater	390	330	225	105
Seater at theater, night	390	350	245	105
Seated, very light work	450	400	245	155
Moderately active office work	475	450	250	200

I choose adjusted female/male heat input of very light work since the students and the faculty in Kohlberg are expected to be working in classes. Consequently, the heat input per human in Kohlberg is 400 BTU/Hour. This heat input can be divided into two subsections: sensible heat and latent heat. I choose to use the total heat input since I think it is the best estimate of students' activities in Kohlberg. By multiplying the number of humans in the building by the heat input of one person, the total heat input by humans is determined.

$$Q_{Human} = N_{Students} * q_{AdjM/F}$$, **Equation 41**

, where $q_{AdjM/F}$ is the adjusted heat input of 400 BTU/Hour and $N_{Students}$ is the number of people in Kohlberg that are mostly students and teachers. To find the building population, class schedule is investigated since teachers' and students' schedule depends on their classes. This is nothing but the class schedule model I discussed above. Assuming that there are 15 students per class (Liberal Arts College!), an estimate for building population, $N_{Students}$, is found. A part of the dedicated Matlab code can be found below:

---

[24] Duffie and Beckman. Solar Engineering of Thermal Processes. John Wiley & Sons: 1991. pg. 95. (Conlton's Project)

[25] This table above is from ASHRAE Fundamentals Handbook 1997, Chapter 28, page 8. Please note that the tabulated values are based on 75 F room dry-bulb temperature.

Code 8
```
Q_in_perhuman = 400; %BTU/Hour
% There are approximately 15 students per class room and a teacher.
N_human_perclass = 15;
% Finds the heat input generated by humans.
Q_human = NumberOfClasses.*Q_in_perhuman.*N_human_perclass; %BTU/Hour
% Displaying the heat input to space for each hour interval.
```

Electrical Loads – Equipment

As we can see from Table 4 in class schedule above, the electricity demands of various devices on campus are calculated. Based on the measurements on campus, the annual electricity for a desktop computer (adjusted for Mac/PC) is calculated. 1 watt equals 3.41214163 Btu / hour. The average Btu consumption can be calculated for a typical desktop computer at Swarthmore College as:

$$\left(\frac{(129.3*3)+(89.9*21)}{1000*24} * 3412.14163 \right) = 323.6 \frac{Btu}{Hour} \text{ , Equation 42}$$

The table 7 below displays the results for measured and theoretical averages for a desktop computer at the College.

Table 16

Data type	Annual Btu/Hour	Average Btu per hour
Measured Average	2834466	323.6
Theoretical Average	2845385	324.8

These calculations are an approximation of the big picture for the rest of the electrical devices, especially computers, at the College. Printers, scanners, fax machines, and other peripherals and related devices should be included if a more detailed estimation is made. Many of these devices are never turned off. They continuously consume electricity and generate heat. The heat gain, Q_{Device}, is calculated as following:

$$Q_{Device} = q_{Device} * N_{Device} \text{ , Equation 43}$$

, where N_{Device} is the number of computers in the building and q_{Device} is the average heat input by electrical devices that equals to $323.6 \frac{Btu}{Hour}$. Adding the internal heat generation sources together, humans and electrical devices, I can find total Q_{Source}.

$$Q_{Source} = Q_{Human} + Q_{Device} = N_{Students} * q_{AdjM/F} + q_{Device} * N_{Devices} \text{ , Equation 44}$$

, where $N_{Students}$ is the building population, $q_{AdjM/F}$ is the adjusted heat input by each people, q_{Device} is the average heat input by electrical devices, and N_{Device} is the number of electrical devices in building.

Recommendation to decrease the electricity demand

This high cost of one controllable variable is the result of two factors. These factors are continuous operation of these devices and high regional electricity price of 14 cents for 1 KWh. According to the EPA, nearly 44 percent of computer users do not use the power-saving features of their equipments. I did a survey about computer usage at Kohlberg in 2006. The qualitative results of the survey indicate that more than one half of the professors leave their computers on over night in order to save time when they come back to their office the other morning. However, 90% of these professors are willing to turn their devices off or use power saving features such as hibernation after the survey.

The second best thing after turning off the computer is using computers' power saving features. Based on EPA, computers can power down to as little as 14 watts in hibernation feature. In other words, if the power saving mode is used, computers consume significantly less electricity. Assuming 90% of professors turn off their computers, $50 per computer can be saved.

$$\left(\frac{89.9 * 12}{1000} * 365 \right) * 0.14 * 0.90 = \$49.6 \text{ , \textbf{Equation 45}}$$

Considering the annual estimation for a computer's cost is $116.3, this is a remarkable saving in the College's electricity bill.

Ventilation and Infiltration Air

To understand ventilation and infiltration, I consider the College's HVAC system and its air-handling units (AHUs) that affect the heat gain of the building directly by inputting conditioned air into the building space.

The HVAC system is responsible for the biggest portion of the College's electricity bill. The HVAC system can distribute heat to space, ventilates air and, if necessary, air-conditions the space. The picture below belongs to Trotter's HVAC, which is the same as Kohlberg's system.
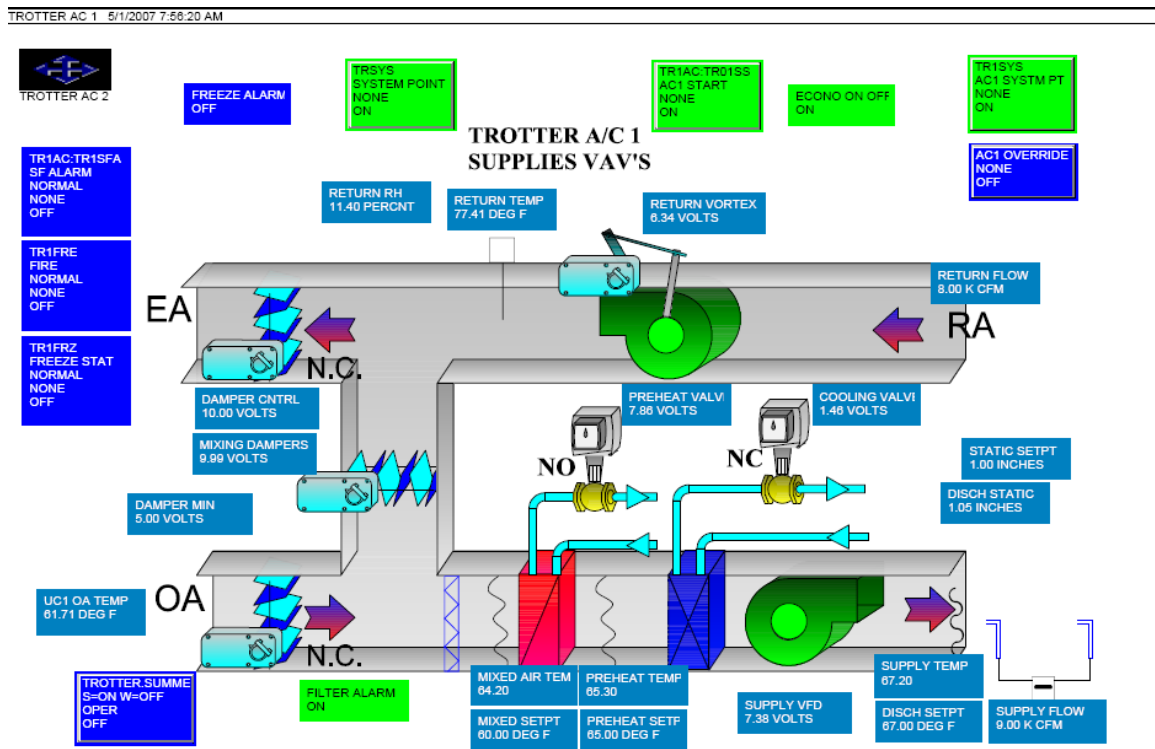

Figure 9: HVAC system at Trotter is very similar to Kohlberg's system.

There are various abbreviations used in HVAC systems at the College. Table 17 below explains the most common abbreviations:

Table 17: Explanation of Abbreviations for HVAC operating system at Swarthmore College

AHU1 Discharge Temp (F^O)	56 – 68 for operating	Temperature of air discharged to Kohlberg spaces
AHU1 Mix Temp (F^O)	Ranges roughly from 40 – 60 depending on conditions	Air entering the system from outside to be heated or used for cooling
AHU1 Preheat Temp (F^O)	Ranges roughly from 60 – 75 depending on conditions	Temperature of heated or cooled air ready for distribution
AHU1 Return Temp (F^O)	70 – 80 roughly	Air temperature returned from public spaces and sent to outside
AHU1 Return Flow (KCFM)	0 – 7 roughly	Flow rate of air returned from public spaces and released to the outside
AHU1 Supply Fan	ON/OFF	Fan blowing air to supply all public spaces

The College uses a HVAC system, called INSIGHT 3.7, by Siemens. The system has 49 panels in 26 buildings that monitor 24,484 points over the campus fiber optic system. The panels operate as stand-alone units. The College has a server in Beardsley that collects data from various panels and sends scheduling information out to various panels. This infrastructure has helped me remarkably in collecting the required data for my Project. This infrastructure can create a database that might be very useful to continue with the project in future.

Theory – Air Handling Units

The HVAC is the abbreviation for heating, ventilation and air-conditioning. Heating is supplied by central heating system by burning #6 oil. The hot steam is distributed to rest of the campus by underground steam tunnels. The air handling units in each separate building distribute the heat to the building space. Similarly, air-conditioning is provided through the cooling plants. The cool air is distributed through the air handling units to the buildings. A building like Kohlberg has a two pipe system, where the Facilities can only heat or cool the building. This system is less useful but at the same time, less expensive compared to a three pipe system. The newly built Science Center has a three pipe system, allowing feeding of hot steam and air-conditioned cool air into the building at the same time. The remaining third pipe is for returning air.

HVAC variables at the College can be divided into two groups based on their usage patterns. First group consists of distribution of cooled and/or heated air into the campus space. The second group cools campus space through air-conditioning. It should be noted that air-conditioning is switched off for approximately seven months per year, whereas HVAC first group has a significant contribution to electrical demand based on its daily schedule all year around.

The campus space internal temperature is regulated based on a weekday-weekend schedule. For our purposes in the Project, only the weekdays will be considered. The main air handling unit at Kohlberg starts to operate at 6:55 AM and stops at 8:00 PM. In the mean time, the allowable range of interior temperature is 70 F to 75 F. The temperature is brought back to the allowable range around 7:00 AM with the start of air handling units. The building's resistance, the R-value of the walls, secures the inside temperature for a while until it drops after the air handling units are switched off around 8:00 PM.

If classes are not in session, the classroom temperature gradually increase and decrease based on factors like outside temperature and solar radiance. However, if the classes are in session, then the inside temperature increases

with a steeper slope in morning due to additional heat sources such as computer, light and humans[26]. It should be noted that for the rest of the day, the air handling units' main operation is to keep inside air temperature in the range of 70 to 75 F. Most of the time, Kohlberg is overheated as a result of additional heat sources. Therefore, the air handling units bring outside air to decrease inside air temperature at Kohlberg.

One of the major heat losses at Kohlberg is due to ventilation and infiltration of the space. I will focus on the main air handling unit at Kohlberg, AHU1, to build a model for the heat loss due to ventilation and infiltration. To calculate $Q_{Ventilation, Infiltration}$, I need to find AHU1 discharge temperature and mass flow, AHU1 return temperature and mass flow, specific air constant (C_p). These variables of merit are tracked and recorded in Kohlberg in several experiments. The figure below presents the AHU1 discharge temperature, AHU1 return temperature, and Kohlberg outside temperature.
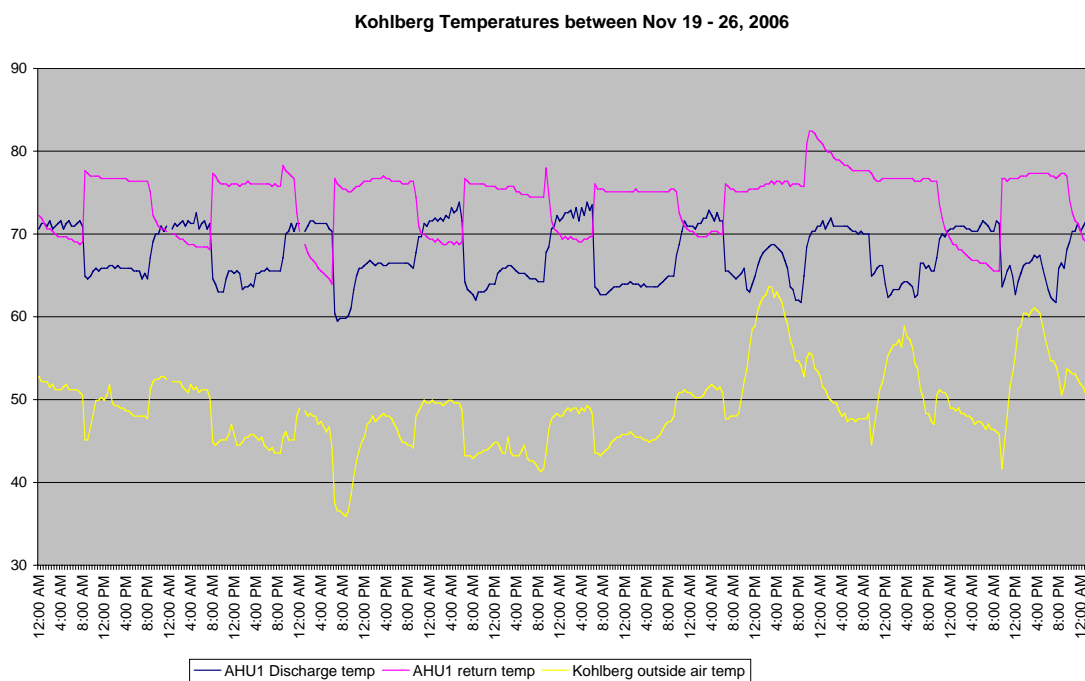

Figure 10

As it can be seen from Figure 14, AHU1 discharge temperature is lower than the AHU1 return temperature that means the air-handling units are technically cooling the space while the air-conditioning is off and the building is in heating schedule. At the same time, this conclusion can be misleading. The mass flow of air through AHU1 discharge is almost twice the amount of return air flow. Therefore it is misleading to say that AHU1 is cooling the building in heating schedule. AHU1 is regulating the conditioned air temperature in the building. Although AHU1 discharge temperature is lower than AHU1 return temperature, AHU1 discharge's heat input into Kohlberg per hour is bigger than AHU1 return's heat output from the building per hour.

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[26] It should be noted that taking this additional source of heat into account, it is possible to save some energy by starting the air handling units later than their scheduled time.

I would like to talk about how I modeled Q_{diff}, or $Q_{Heating}$, in order to clarify my model. Later, I will develop

the current model to find $Q_{Ventilation.Infiltration}$ for Kohlberg. $Q_{Heating}$ is calculated by the following equation:

$$Q_{Heating} = C_p \left(\overset{\bullet}{m}_{Discharge} * T_{Discharge} - \overset{\bullet}{m}_{Return} * T_{Return} \right), \textbf{Equation 46}$$

, where $\overset{\bullet}{m}_{Discharge}$ and $T_{Discharge}$ are the mass flow and temperature at the discharge unit at Kohlberg. Similarly,

$\overset{\bullet}{m}_{Return}$ and T_{Return} are the mass flow and temperature at the return unit. The results for $Q_{Heating}$ are shown in Figure 13

below. Because each of the variables on the right hand side of the equation change with time based on variables such as

temperature and mass flow, there are various different results for $Q_{Heating}$ when the air-handling units are on. I also

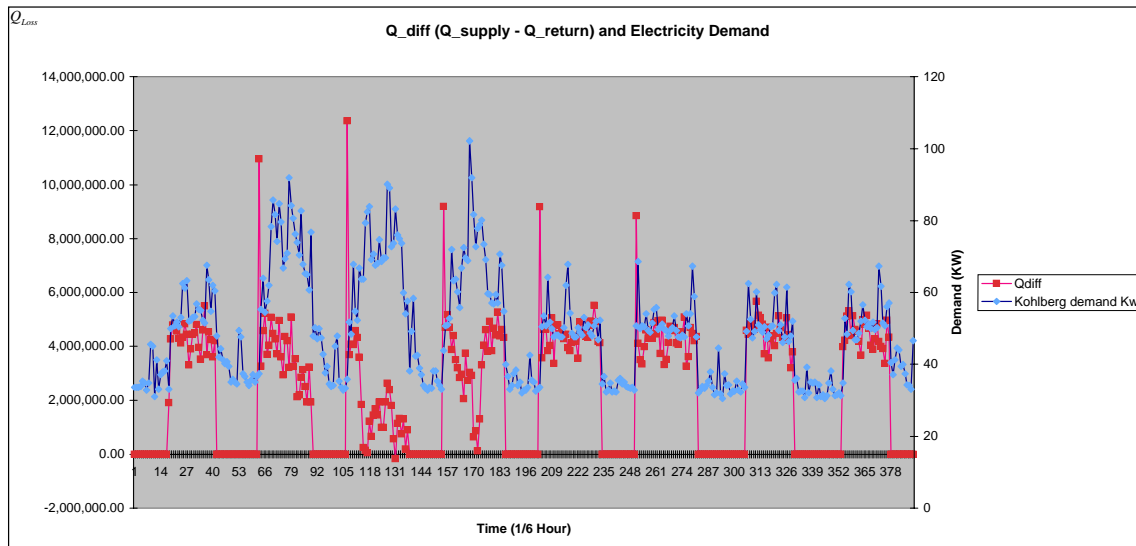included the electricity demand schedule in the same graph.

Figure 11: The data for electricity demand and heat input is from Nov 19 to 26, 2006.

Figure 13 shows a time span starting and ending on Sunday. AHU1 is not operating from 8 PM to 7 AM. Therefore,

there are zero values for $Q_{Heating}$, which is also called as Q_{Diff} since it is the difference between heat input and output.

When the blowers turn on and AHU1 starts operating there is a large heat input to building to warm up the space for

early classes. Although this warm-up period is short, it can be seen in Figure 15 as early peaks in every weekday

morning.

The average numbers for heat input, $Q_{Heating}$, for each weekday are presented in table 11 below. These

numbers represent the heat difference between the Q_{supply} and Q_{return}.

Table 18: Q_{diff} Values

Day of the week	Average Heat in - Q (Btu/Hour)
Monday	3,861,217
Tuesday	2,067,690
Wednesday	3,680,998

Thursday	4,535,253
Friday	4,394,652

Looking at Figure 13 and Equation 46 will give us an understanding about how we calculated daily averages for $Q_{Heating}$. Figure 13 represents the HVAC system at Trotter, which is the same as the HVAC system at Kohlberg. The HVAC system regulates Kohlberg's inside temperature through its discharge and return units. The temperature and air flow data at these units are recorded from April 1 to April 8 at Kohlberg. The air flow data in units of cubic feet per minute (cfm) is converted to mass flow data in units of lb_m per hour, and then multiplied by the temperature (F) to find final results in Btu per hour. Mass flow is equal to volumetric flow times the air density. At 70 F and 14.696 psia, dry air has a density of $0.074887 \dfrac{lb_m}{ft^3}$.[27] To calculate the heat input above, I need to use some conversion factors. This calculation is presented in Equation 47 below:

$$\frac{Btu}{hour} = F° * 1000 * \frac{ft^3}{\min} * 60 * \frac{\min}{hour} * 0.074887 * \frac{lb_m}{ft^3} \text{, \textbf{Equation 47}}$$

The schematic below in Figure 14 will give a better understanding about my $Q_{Heating}$ model. Equation 46 represents $Q_{Heating}$ model, and the variables on the right hand side of the equation are temperatures and air flows at "supply air" and "return air" stations shown below.
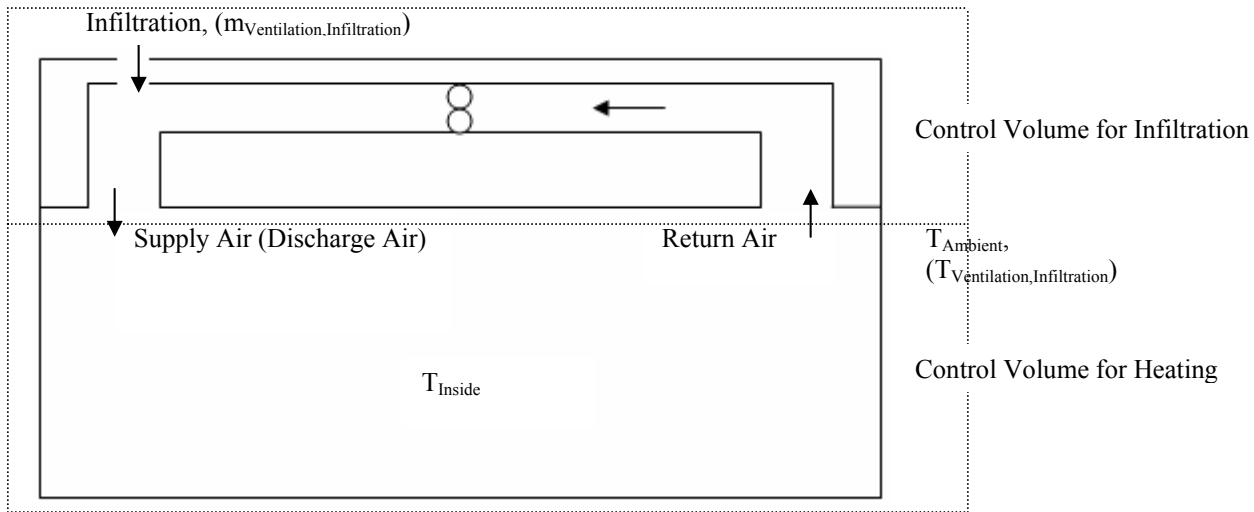

Figure 12: Schematic for Infiltration model.

Although $Q_{Heating}$ and $Q_{Ventilation,Infiltration}$ models look similar, they are completely different models. $Q_{Ventilation,Infiltration}$ is a part of a model that finds the heat loss of Kohlberg, whereas $Q_{Heating}$ is a totally new approach and a model by itself to find the heat gain of the building. At this point, it is essential to find $Q_{Ventilation,Infiltration}$ to complete the heat loss model.

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[27] Wikipedia. "http://en.wikipedia.org/wiki/Density_of_air".

Kohlberg losses heat through ventilation and infiltration. Federal laws determine the minimum required heat ventilation in buildings. Heat loss due to ventilation and infiltration in Kohlberg can be found as an extension of the discussion above. $Q_{Ventilation,Infiltration}$ can be calculated by the following equation:

$$Q_{Ventilation,Infiltration} = C_p \left(\dot{m}_{Ventilation,Infiltration} * (T_{Ventilation,Infiltration} - *T_{Inside}) \right) \text{, } \textbf{Equation 48}$$

, where C_p is the specific heat constant for air, $\dot{m}_{Ventilation,Infiltration}$ is the difference between AHU1 discharge mass flow

and AHU1 return mass flow[28], $T_{Ventilation,Infiltration}$ is ambient temperature since AHU1 takes outside air for ventilating

Kohlberg and cooling the building in heating schedule. The daily averages for $Q_{Ventilation,Infiltration}$ is presented below.

Table 19: $Q_{Ventilation,Infiltration}$ Values

Day of the week	Average Heat in - Q (Btu/Hour)
Monday	3,778,332
Tuesday	2,042,398
Wednesday	3,597,066
Thursday	4,445,477
Friday	4,380,260

"Program Q_VI2.m" is the Matlab model designed to calculate the heat loss through Ventilation and infiltration at Kohlberg. As inputs, the program needs time (for instance: "11/1/2007"), AHU1 discharge temperature and airflow, return temperature and return airflow. A part of the Matlab code, used to calculate the $Q_{Ventilation.Infiltration}$, can be found below.

Code 9: VI stands for ventilation and infiltration[29].
```
% Mass flow for infiltration is the difference between supply and return mass flows.
M_infiltration = M_supply - M_return;
% Temperature is the difference between inside temp and ambient (outside) temperatures.
T_infiltration = T_inside - T_ambient;
% Calculating the infiltration and ventilation heat loss.
% The fundamental equation is Q = m*Cp*delta(T).
QVI_All = M_infiltration.*T_infiltration*Cp;
```

Heat Loss Model

The heat loss model combines external, internal heat gains, and ventilation and infiltration. The total heat input to the building is the result of all of the heat gains and losses mentioned above. The total heat loss is the sum of partial heat losses that are discussed above. Since the Project is designed for winter and Swarthmore is located in 39°54'18"N and 75°21'15"W coordinates, the heat gain from Solar radiation can be neglected. Consequently, the heat loss can be modeled as following:

$$Q_{Loss} = Q_{Conduction,Convection} - Q_{Source} + Q_{Ventilation,Infiltration} \text{, } \textbf{Equation 49}$$

, where variables on the right hand side depend on factors such as ambient temperature, AHU1 discharge air-flow, AHU1 return air-flow, AHU1 discharge temperature, and AHU1 return temperature that vary based on time of the day and day of the week. $Q_{Conduction,Convection}$ depends on the ambient temperature and inside temperature. Currently, the

---

[28] $\dot{m}_{Ventilation,Infiltration}$ is true assuming that there is no remarkable loss through conduction through the walls.

[29] These tables are the product of an Excel file that digested November 2006 data. The Matlab model will run on April 2008 data to be consistent with class schedule and time series models.

model is designed to take forecasted outside temperature and average inside temperature as inputs to calculate the heat loss through conduction and convection. Q_{Source} depends on the class schedule to determine the heat input by humans to Kohlberg, whereas $Q_{Ventilation,Infiltration,NET}$ depends on ambient temperature, inside temperature, AHU1 discharge and return airflows.

A regression analysis is conducted between the final heat loss, Q_{Loss}, and electricity demand. The result will provide a model to estimate the electricity demand based on past data and forecast tomorrow's electricity demand.

Discussion

The disadvantage of $Q_{Ventilation,Infiltration}$ model is the limited data for AHU1 discharge temperature, discharge airflow, return temperature, and return airflow. I have only data from a week in 2006 and a week in April 2008 to build my model on. Consequently, I got sizeable differences among my results for average Btu/hour calculations. As presented in Table 18 above, average heat input for weekdays vary considerably with a standard deviation of 46,322.

An important assumption in the infiltration model is that the difference between the discharge mass flow and return mass flow is equal to infiltration mass flow. This assumption neglects the fact that the HVAC system leaves some potion of the return air back to environment. From the Trotter HVAC system, it can be observed that some potion of the return air is mixed with outside air and the rest is sent outside. Another assumption is that the amount of infiltration enters the building is the same as the amount of infiltration that leaves the space. This is not the same way for heating model where the input mass flow through the discharge unit is almost twice as the return mass flow. Although we do not expect any heat accumulation in the building since the building temperature is around 72 F, we understand there are all types of other losses due to other infiltration through doors and windows or conductivity.

As mentioned in the introduction section of the model, the College burns #6 oil since it is a cheap energy source. In Table 20 below, the cost of burning #6 fuel oil to produce 1 million Btu is presented. One also notices the significant rise in the energy prices when one compares the November 2006's price to last months' price.

Table 20[30]

Fuel	Type	Unit Btu/unit	Efficiency	Cost/unit	Cost/mmBtu November, 2006	Cost/mmBtu March, 2008
#6 Oil	Gallons	150,000	85%	$1.24	$9.73	$11.81

Table 20 shows Kohlberg's average Btu per hour consumption and what the College paid in March 2008 and November 2006 for one million Btu. Based on the cost of one million Btu in March 2008, the College's heating cost for Kohlberg is calculated. The results are displayed in the table below:

Table 21: Cost of Heating Kohlberg using March 2008 rates for ($/mmBtu)

Day of the week	Average Heat in - Q (Btu/Hour)	Average Cost per day – ($)
March (Actual), Campus	10,558,000,000	124,756
March[31] (Calculated), Kohlberg	1,346,278,916	15,908

Equation 46 above to find the heating load for Kohlberg is used to find an average Btu consumption for each weekday and weekend. After finding a typical week, the numbers are multiplied by four to find the Btu consumption per month.

---

[30] Tom Sahagian and Betsy Jenkins from Power Concepts LLC.
[31] One month is assumed to be four weeks.

The results are based on the fact that air handling units work approximately 13 hours per weekdays and 11.5 hours on weekends. Table 21 represent the actual heating bill and consumption for March 2008. If the calculations are correct, the numbers indicated that Kohlberg consumes approximately 1/8 of the total heating at campus. I find this result high. I would expect a ratio of 1/27, which is the number of sizeable buildings on campus. Figure 13 below shows the heat losses from conductivity and convection, ventilation and infiltration. It also displays the heat gains from equipment (electrical loads) and humans.

QuickTime™ and a
decompressor
are needed to see this picture.

Figure 13

Hot Box Model – An alternative approach to energy modeling

There are various ways of modeling the effect of HVAC system and ambient temperature on the electricity demand. The hotbox model is an alternative approach to heat loss model discussed above. A hotbox model is developed and tested at Kohlberg with several experiments.

<u>Theory</u>

Thermal systems can be explained by mathematical models that can calculate heat gain, loss and accumulation. A hotbox experiment in Kohlberg 115 is conducted to calculate the thermal resistance value, R, and thermal capacitance value, C.

In any given thermodynamic system, the change in total energy can be explained by the following equation:

$$\partial E = \partial U + \partial KE + \partial PE\text{, \textbf{Equation 50}}$$

, where U is the internal energy (related to temperature), KE is the kinetic energy (related to motion) and PE is the potential energy (related to position). If kinetic energy and potential energy are ignored for the hotbox model, we only change the internal energy, U. Internal energy is related to temperature changes by $\partial U = m*C_p*\partial T$, where "m" is the mass (in kg or lb_m) of material with specific heat at constant pressure C_p, and ∂T is the change in temperature (in Kelvin or Fahrenheit) giving rise to the change in U.
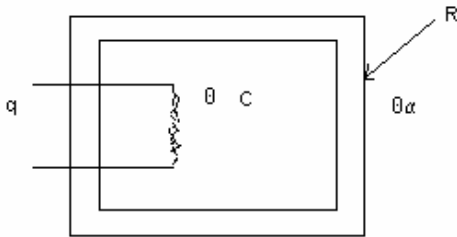

Figure 14: Hotbox Schematic

In hotbox model above, q resembles the heat flow in/ out of system. θ_{in} is the inside temperature and θ_a is the ambient (outside) temperature. R represents the thermal resistance factor of the box, whereas C is the thermal capacitance of the air inside the hotbox.

For heat flow into and out of a box, the time rate of change of total energy dE/dt is just the difference in power q_{in} - q_{out}, where q_{in} is the heat energy per second deposited into hotbox and q_{out} is the heat energy per second flowing out through the walls of hotbox. The change in total energy of hotbox is given as:

$$\frac{dE}{dt} = m*C_p*\frac{dT}{dt}\text{ , \textbf{Equation 51}}$$

The law of thermodynamics are associated generally with two types of thermal elements: thermal capacitance and thermal resistance. Thermal capacitance is the mathematical relationship between a system and the heat stored in

the given system. The relationship can be considered as linear and the constant C is known as the thermal capacitance. It has units of joules per kelvin (J/K or Btu/F). Assuming $q_{in}(t)$ is the heat flowing into the system and $q_{out}(t)$ is the heat flowing out of the system, the net heat supplied to system between time t_0 and t is

$$\int_{t_0}^{t}(q_{in}(\lambda) - q_{out}(\lambda))d\lambda \text{ , \textbf{Equation 52}}$$

It is assumend that net heat supplied to hotbox during the time interval equals the thermal capacitance, C, times the change in temperature. The temperature of system at t_0 is given as $\theta(t_0)$, then

$$\theta(t) = \theta(t_0) + \frac{1}{C}\int_{t_0}^{t}(q_{in}(\lambda) - q_{out}(\lambda))d\lambda \text{ , \textbf{Equation 53}}$$

Differentiating Equation 21 above, an equation for the rate of temperature change to the rate of net heat flow into system is obtained:

$$\dot{\theta}(t) = \frac{1}{C}\left(q_{in}(t) - q_{out}(t)\right) \text{ , \textbf{Equation 54}}$$

The second important element of laws of thermodynamics is the thermal resistance, R. Thermal resistance is the proportinality factor of conduction and convection, where net heat flows from one part of system to another through a medium. The realtionship below shows the functionality of the thermal resistance, R.

$$q(t) = \frac{1}{R}\left(\theta_1(t) - \theta_2(t)\right) \text{ , \textbf{Equation 55}}$$

Thermal systems are analagous to electrical systems. The relationship is described in table below:

Table 22[32]

Electrical System	Thermal System
Voltage	Temperature (Kelvin) as θ
Current	Heat flow (Watts) as q
Resistance	Thermal resistance (Kelvin/ Watts) as R
Capacitance	Thermal capacitance (Joules/ Kelvin) as C

We assume that the thermal resistance of the walls of hotbox is given by R, and is defined by a kind of "thermal Ohms Law (V = I*R)", in which the temperature difference across the walls of the box is like the voltage V.

---

[32] This information is obtained from the following website:
http://www.swarthmore.edu/NatSci/echeeve1/Class/e12/Lecture/L20_Thermal/L20.html

The current, I, is represented by the energy flow through the walls q_{out}. Thus, the temperature loss to ambient is $\theta = q_{out}*R$. Let the thermal capacitance of the air in hotbox be given by $C = m*C_p$, and the equation governing the heat flow out of the box looks like that of an R-C circuit:

$$q_{in} - \frac{\theta}{R} = C * \frac{d\theta}{dt} \text{, \textbf{Equation 56}}$$

, because $\partial T/\partial t$ is the same as $\partial\theta/\partial t$ if we reference ∂T to the outside temperature. To solve this first-order differential equation, it may be easier to let $A = \dfrac{q_{in}}{C}$ and $B = \dfrac{1}{R*C}$ so we have:

$$\frac{d\theta}{dt} = A - \left(B*\theta\right) \text{, \textbf{Equation 57}}$$

,or

$$\frac{d\theta}{d(A-B*\theta)} = dt \text{ , \textbf{Equation 58}}$$

Integrating both sides gives will give us:

$$\frac{-\ln\left(A-\left(B*\theta\right)\right)}{B} = t + K \text{ , \textbf{Equation 59}}$$

, where K is the unknown constant of integration. At t=0, we assume $\theta = 0$. In other words, no temperature difference between the temperature inside and outside hotbox exists because we have not started to put heat in yet. Thus, setting θ=0 and t=0 into the solution and solving for k gives: $\ln\left(A-\left(B*\theta\right)\right) = \ln(A) - B*t$

$$k = \frac{-\ln(A)}{B} \text{ , \textbf{Equation 60}}$$

Putting this result for K back in gives:

$$\frac{-\ln(A-B*\theta)}{B} = t - \frac{\ln(A)}{B} \text{ , \textbf{Equation 61}}$$

, or

$$\ln\left(A - (B * \theta)\right) = \ln(A) - B*t \quad \textbf{, Equation 62}$$

Taking exponential of both sides yields:

$$A - (B * \theta) = A * e^{(-B*t)} \textbf{, Equation 63}$$

, or

$$\theta = \left(\frac{A}{B}\right) * \left(1 - e^{(-B*t)}\right) \textbf{, Equation 64}$$

and putting back in the definitions of A and B:

$$\theta = q_{in} * R\left(1 - e^{-\left(\frac{t}{RC}\right)}\right) = T - T_{ambient} \textbf{, Equation 65}$$

, where T is the inside temperture and $T_{ambient}$ is the ambient temperature. All we need to do now is solve for T:

$$T = q_{in} * R\left(1 - e^{-\left(\frac{t}{RC}\right)}\right) + T_{ambient} \textbf{, Equation 66}$$

This is our solution, which represents an exponentially-saturating rise to an asymptotic value given as t goes to infinity as:

$$T_{eventually} = P_{in} * R + T_{ambient} \textbf{, Equation 67}$$

To find the thermal resistance of the box, we can simply rewrite the equation above.

$$R = \frac{\left(T_{eventually} - T_{ambient}\right)}{q_{in}} \textbf{, Equation 68}$$

Equation 68 is a method of calculating thermal resistance, R, if you wait long enough until the inside temperature levels off with a known heat source inside the box. Once you know the thermal resistance of the box, we can calculate the power input for any temperature with the following equation:

$$q_{in} = \frac{\left(T_{eventually} - T_{ambient}\right)}{R} \textbf{, Equation 69}$$

Knowing R, one can solve for C via the R*C time constant if that is determined from an exponential fit to the rising inside temperature.

Procedure – Experiment at Kohlberg 115

Several hotbox experiments are conducted at Kohlberg. The final experiment that I will focus on is located at Kohlberg 115. Kohlberg 115 is chosen for experiment location since it bears a general resemblance to the whole building in terms of its average size and wall-window ratio. Kohlberg's walls' area is approximately three times its windows' area. Kohlberg 115 has two large windows that covers almost one third of internal walls.

Hotbox experiment is designed to find the thermal resistance of Kohlberg 115's walls and windows. The wall-window ratio is important since this will affect the thermal resistance of the room directly. The experiment started on 1:15 AM and ran until 7:00 AM when the air handling units start to operate at 6:50 AM. This time interval is chosen so that Kohlberg residents and community are not disturbed and air handling units don't intervene the experiment. Data was collected through data loggers and College's data gathering system. Since the data by the College's system is enough to continue with the experiment, I will not use my data from temperature data loggers.

At 1:15 AM, three heaters and a fan were placed in Kohlberg 115. Before the experiment, room's windows and door were opened for fifteen minutes to decrease the inside temperature through ventilation. The power input by each heater is as following:

Table 23: Power input to Kohlberg 115

Fan (low speed)	0.159 KW
Hot air blower	1.164 KW
Delonghi heater	1.057 KW
Sears heater	1.035 KW
Total power input	3.414 KW

After the cooling, the doors and windows were closed. Starting at 1:30 AM, Kohlberg 115 was heated until 7:00 AM. The purpose of the project is to find the thermal resistance at Kohlberg 115. Equation 68 above shows how we can find the thermal resistance. Therefore, we need to find the inside temperature, $T_{eventually}$ and P. Inside temperature is recorded by the data loggers. To find $T_{eventually}$, Kohlberg 115 is heated until the inside temperature levels off. The maximum temperature or the final temperature where inside temperature levels off is called $T_{eventual}$. This is the maximum temperature that the room can bear given the properties of the room and the heat source inside. The figure below shows the heating process at Kohlberg 115 on April 8, 2008.
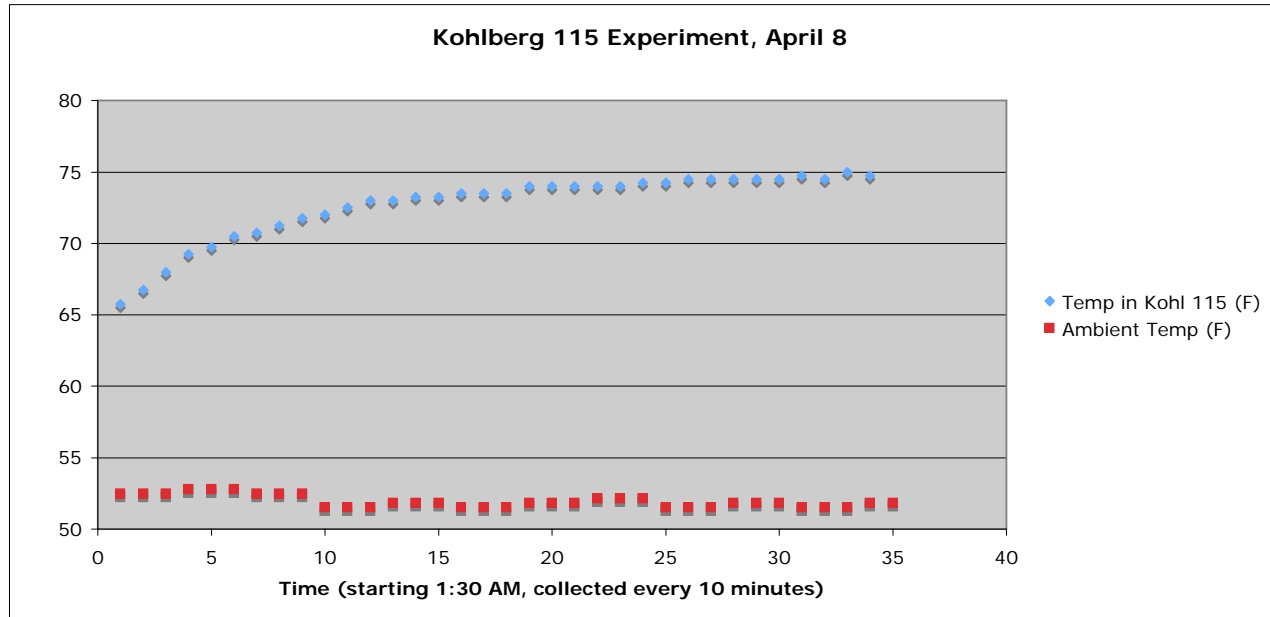
Figure 15

Results, Discussion and Future Work

      With the experiment on April 8, 2008, the variables on the right hand side of Equation 68, $T_{Eventually}$, T_{inside}, and power input are measured. Based on this data, the thermal resistance of Kohlberg is calculated as 6.75 ($F*ft^2*Hour/Btu$). Inputting this thermal resistance into Equation 69, the electricity demand due to heating load for different days can be calculated. I applied Equation 69 to the period of time between April 1 and April 9. The electricity load due to heating in Kohlberg 115 is interpolated for the whole building by calculating the volume of the room and the whole building. Kohlberg 115 is 932 ft^3, whereas the whole building without the basement is 34,828 ft^3. I choose to not include the basement since the thermal resistance of basement walls has no importance because it is assumed that there is no heat loss from basement. The volumetric ratio between the room and the building is calculated as 33.2. Since the ratio between the room and the building is known, calculated electricity demand at Kohlberg can be found. The result is presented in Figure 17 below with yellow data line.

      It was surprising to observe that the calculated electricity demand to be higher than the total electricity demand. I would expect the calculated electricity load due to heating to be lower than the total electricity demand of the college since it is only a part of it. I think that the volumetric assumption I made to find the heating load for the whole building from the heating load of Kohlberg 115 is to high. For future work, I will only count the classrooms' volumes and find a new ratio. Another reason for the overestimation of the heating load might be de to the thermal resistance calculation. I think that I might have underestimated the $T_{eventually}$. I believe I would have gotten a larger number if I waited for a much longer period heating Kohlberg 115. A higher $T_{eventually}$ will give a higher thermal resistance number that will lower the calculated electricity load due to heating.

      We can adjust the electricity load due to heating by multiplying the thermal resistance with adjustment factors. Let's assume that the whole electricity demand at Kohlberg is due to heating. In other words, we want to have no

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difference between electricity load due to heating and actual electricity load. We can find the electricity demand due to heating of Kohlberg 115 at a given time by using Equation 69 above.
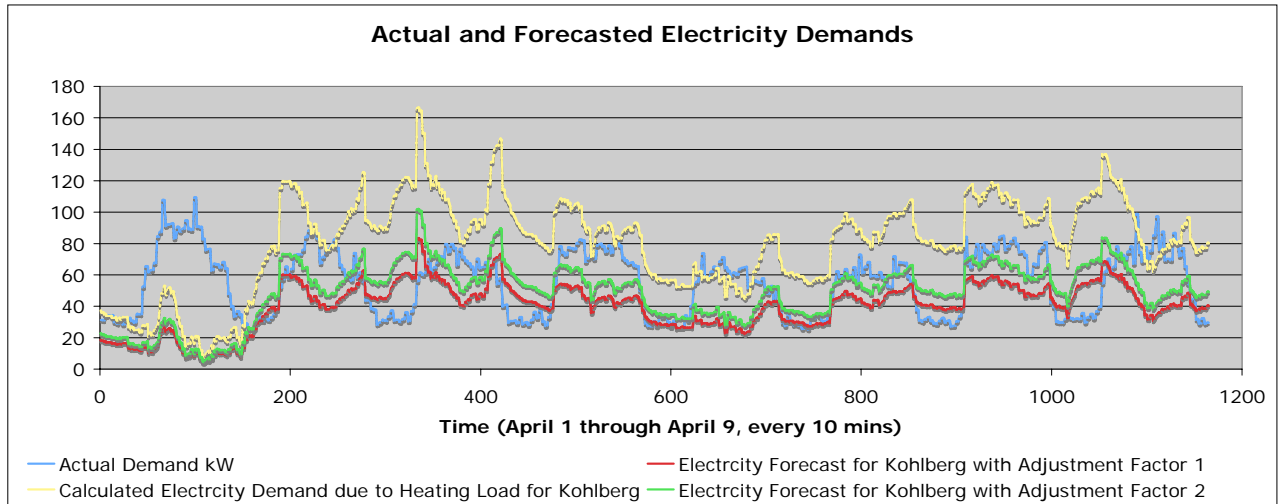

Figure 16

Calculated electricity demand for Kohlberg is adjusted with two different adjustment factors. Electricity forecast 1 and 2 belongs to adjustment factors 1 and 2, respectively, where adjusted thermal resistances, R_2 and R_3, become 13.51 and 11.04 ($F*ft^2*Hour/Btu$) respectively. Thermal resistance R_3 is found by minimizing the mean squared error. Testing these two adjustment factors between April 1 and April 9, following results are obtained.

Table 24: Test results for thermal resistances

Electricity forecast type	Average error per data point in (%)
Type 1, adjusted thermal resistance 2	36.40
Type 2, adjusted thermal resistance 3	0

As I mentioned in our discussion above, if we assume that the Kohlberg's electricity demand is a result of only heating, then to get a good forecast for electricity demand we have to adjust the thermal resistance or change our volumetric expansion assumption. Another valid reason for the overestimated heating electricity demand calculation might be as a result of the limited data set we have. This data set does not allow me to test the results for a bigger time span. Therefore, I would like to be conservative in my discussion since the test results and errors I get here might change with additional data.

Another useful property – the thermal capacitance

To find the thermal capacitance at Kohlberg, we need to fit an exponential curve to the existing data set. The time constant, RC, will equal to thermal resistance times thermal capacitance. Since we can find the thermal resistance from equation 68 as discussed above, the thermal capacitance can be easily determined. An exponential fit to the data set from April 8, 2008 is presented below. The temperature range is from the minimum inside temperature to the maximum inside temperature.

QuickTime™ and a
decompressor
are needed to see this picture.

Figure 17: The graph shows the temperature rise from the minimum inside temperature to maximum inside temperature at Kohlberg 115. The thermal capacitance times thermal resistance is 4657 and the increase in inside temperature is 9.8 F.

Assuming that the thermal resistance of 6.75 ($F*ft^2*Hour/Btu$) is calculated correctly, the thermal capacitance is calculated as 690 ($Btu/(lb_m*F)$).

The Forecasting Model – Combining everything together

<u>Theory</u>

The forecasting model is created to combine the three forecasting models, time series model, class schedule model and heat loss model, in order to get the best possible forecasted results and minimize the sum of squared errors. As I mentioned at the beginning of this paper, there are different approaches to combine the models that represent the decision variables. A multi variable linear regression model might be the simplest and perhaps the most effective way to do so. Given the nature of the final forecasting model, a linear regression is a good start. Let me recall the final forecasting model for one more time:

$$X = \alpha * X_1 + \beta * X_2 + \gamma * X_3 \text{, Equation 70}$$

, where X_1, X_2, and X_3 represent the uncontrollable variables, the controllable variables, and the HVAC variables, respectively. The forecasting models that calculate these decision variables are discussed above. I use Holt – Winter Model to forecast electricity demand based on uncontrollable variables, Class Schedule Model to forecast electricity demand based on controllable variables, and I use Heat Loss Model to forecast electricity demand based on HVAC variables (air handling units).

The coefficients in front of the decision variables are the weighting factors to finalize the forecasted electricity demand. These coefficients display how much each model contribute to final forecast. The higher its weighting factor, the more a model affects the forecasted electricity demand.

<u>Procedure</u>

The forecasting model, "FM.m", creates paths to each models' folders and calls them separately. A portion of the code to call the time series model is presented below:

Code 10
```
% Time Series Model
    addpath('\\data-software\Class Folders\Natural Sciences +
Engineering\Engineering\ENGR015.F07\AndresAbhayOmer\omer\e90e\ceap4\Time Series Model');
    load kohlberg_cleaned_data_Sep1_Dec14
    R = cleaned_data(:,1);
    [Elec_Forecast,raw_data] = HoltWinterModel(wday,R);
```

Raw data is imported to compare the forecasted results with actual electricity demand data. After calculating the forecasted electricity demand based on three different models, the forecasting model places the results in an array. The forecasting model is ready to estimate the factors, α, β, and γ, with a regression analysis. Least square estimate method is used to run the multivariable linear regression as it can be seen in Code 11 below.

Code 11
```
    A = [Elec_Forecast' classsch_weekday' Demand_KW'];
    size(A);
    B = One_Day_Data1';
    size(B);
    X = lsqr(A,B);
```

Matrix "B" represents the raw data and matrix "A" stands for the forecasted electricity demand by the three models. "FM.m" returns the coefficient numbers, α, β, and γ, for one day. Using an extension of this code, "FM2.m", the multivariable regression is run for multiple days or even for weeks. The Code 12 is rewritten slightly for this purpose:

Code 12[33]
```
wday = '11/2/2007';
number_date = datenum(wday);
i = 1;
while number_date < datenum('11/25/2007')
…
A = [Elec_Forecast' classsch_weekday' Demand_KW'];
    size(A);
    B = One_Day_Data1';
    size(B);
    X = lsqr(A,B);
…
    K(:,i) = X;
    [num_date string_date]=weekday(datestr(number_date));
    if(strcmp(string_date,'Fri'))
        number_date = number_date + 3; % to jump the weekend.
    else
        number_date = number_date + 1; % to go to next day.
    End
    % Don't forget to increase the index.
    i = i+1;
end
```

The essential parts of the code are displayed above. The variable "K" will accumulate all the factors over the course of the selected time interval. The final values for factors, α, β, and γ, can be determined by taking an average or a moving average of the regression results from variable "K". The model is run from Friday, November 2, 2007 until Friday, November 9, 2007 only on the weekdays. The results are presented below:

Table 25: The weighting factors obtained from the regression analysis between November 2, 2007 and November 9, 2007

Weighting	November 2	November 5	November 6	November 7	November 8	November 9	Average

---

[33] The code is designed to avoid the weekends and only forecast the weekdays. Therefore, the last rows are written to jump over the weekends.

Factors							
α	0.936	1.813	1.199	1.720	1.657	1.607	1.599
β	0.106	-0.465	-0.252	-0.425	-0.744	-0.482	-0.474
γ	-0.062	-0.340	0.037	-0.268	0.079	-0.192	-0.137

The same procedure is repeated for April 2008. The forecasting model is run for five days between April 21 and 25, 2008. The weighting factors are averaged in the last column in Table 26 below.

Table 26: The weighting factors obtained from the regression analysis between April 21 and 25, 2008

Weighting Factors	Monday	Tuesday	Wednesday	Thursday	Friday	Average
α	1.2210	1.1052	1.6474	0.8164	0.5571	1.0694
β	-0.0448	0.1360	-0.2808	0.3511	0.2853	0.0893
γ	-0.2107	-0.1744	-0.2665	-0.0419	0.0776	-0.1232

The goodness of the fit between actual data and forecasted data is tested by a R^2 analysis. R^2 is the coefficient of determination, which is the proportion of variability in a data set that is accounted by a model. The high numbers for R^2 below proves the success of the forecasting model.

	Monday	Tuesday	Wednesday	Thursday	Friday	Average
R	0.95	0.93	0.95	0.94	0.87	0.93

The results indicate that the forecasting model heavily relies on the time series model while the class schedule model and the heat loss model are less relevant. This result is expected since the time series model is devoted to forecast regular days. In other words, time series model returns good results if tomorrow resembles similar characteristics like past data. Class schedule model, on the other hand, becomes important when there are more classes scheduled at the forecasted calendar day. Finally, heat loss model forecasts electricity based on ambient temperature. If there is a significant change in ambient temperature, the model's weighting factor will increase[34].

Discussion and Future Work

The multivariable regression model above is a dynamic model. The forecasting model will run multi-variable regression with least square estimate method for a selected period of time each time it forecasts the electricity demand for Kohlberg. At the end, the forecasting model finds the average weighting factors needed to forecast the requested calendar day's one day electricity demand profile. With additional data, the weighting factors' averages will improve and the model is expected to return better results with higher R^2 values.

Collecting data is essential for the project's success. Although I have been tedious about data gathering and collected data for this project since October 2006, I still had difficulty of finding extensive data for variables in heat loss model. I only had one week in November 2006 and another week in April 2008 to build my heat loss model on. I calculated heat loss model with both weeks but used April 2008 for airflow and temperature data since it is the most recent set of data. Any additional data will decrease the sum of squared errors and improve the models.

---

[34] Since the data for AHU1 airflows and temperatures is limited, I ran the model based on the first week of April 2008.

As a future work, I would like to include a feedback loop to the final forecasting model. The feedback loop can be an adaptive filter design to find the weighting coefficients through a linear combiner. At this point, a feedback loop discussed above is not possible as a results of the limited data. This forecasting model has to be tested for a significant period of time before such a model can be developed.

Once there is more data, an additional artificial intelligence code can be developed. This code looks for any extraordinary fluctuations in input data such as huge drops in ambient temperature. If there are remarkable changes in ambient temperature in a short period of time (overnight), the code will warn the final forecasting model so that the model will weight heat loss model's factor the heaviest compared to other weighting factors. Similarly, the code will increase the weighting factor for Class Schedule Model if there are other classes scheduled for the requested day besides the regular class schedule.

Another important reason for the discrepancy between the forecasted and actual results is that not all the factors that affect the electricity at Kohlberg are (or can be) observed. This takes us back to my early discussion of fourth variable, other variables. Other variables represent all the other factors that affect the electricity but they are not explained with the models presented above.

Graphical User Interface (GUI)

A graphical user interface (GUI) is built in Matlab to serve two purposes. The first rationale is to create a Windows based interface so that the Facilities can improve its energy management with the help of this Project. By using this GUI, the Facilities can decrease the total electricity demand or shave down the peaks that result in penalties. Since the GUI is designed to be user-friendly, its users with any level of computer knowledge can plot raw data, forecast future data using different models and compare the results.
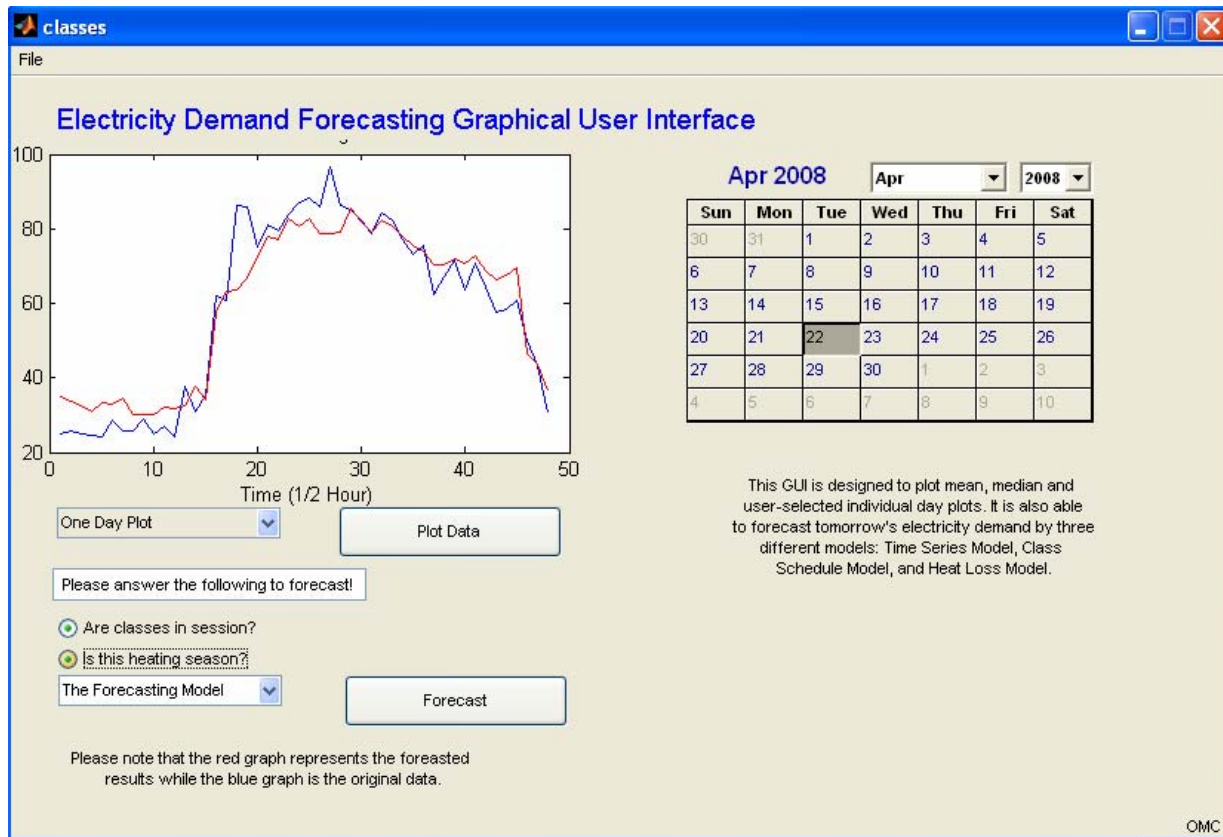
Figure 18: A snapshot from the graphical user interface

The second rationale is the Project's educational goal. The Project aims to increase community awareness about energy consumption. As a future work, the GUI can be uploaded to the College's website. Student body and faculty can display electricity demand for a day in the past and/ or forecast electricity demand for a day in the future. It is expected that the student body and faculty will become more environmentally friendly with this feedback mechanism and they will change their consumption behaviors accordingly. For instance, the faculty might turn off their computers over night after seeing that they can decrease the electricity demand and reduce carbon footprint by a simple push on their computers' turn-off button.

As it can be seen from Figure 18, the GUI has a calendar. If the user wants to display a day in the past, he or she can select a day in the past from the calendar and choose "One Day Plot" from the drop-down menu. By clicking "Plot" GUI will display one day profile of electricity demand for the selected day. The user can also choose to display the average for weekdays or weekends from the same drop-down menu. If the user wants to forecast a day in the future, he or she can choose a day in the future from the calendar and choose a forecasting model from the second drop-down menu. By clicking "Forecast", the forested electricity demand for the requested day will be displayed. The GUI code behind the "Forecast" pushbutton is displayed below:

Code 13

```
% --- Executes on selection change in ForecastChoicePopup.
function ForecastChoicePopup_Callback(hObject, eventdata, handles)
% hObject    handle to ForecastChoicePopup (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
```

```matlab
% Hints: contents = get(hObject,'String') returns ForecastChoicePopup contents as cell array
% contents{get(hObject,'Value')} returns selected item from ForecastChoicePopup
% Determine the selected data set
str = get(hObject, 'String');
val = get(hObject, 'Value');
% Set the current data to selected data set.
switch str{val};
    case 'AR Model' % User selects Auto Regressive Model.
        handles.current_data = handles.day;
    case 'Time Series Model' % User selects Time Series Model.
        handles.current_data = handles.day;
    case 'Class Schedule Model' % User selects Class Schedule Model.
        handles.current_data = handles.day;
    case 'Heat Loss Model' % User selects Heat Loss Model.
        handles.current_data = handles.day;
    case 'The Forecasting Model' % User selects the Forecasting Model.
        handles.current_data = handles.day;
end
% Save the handles structure.
guidata(hObject, handles)
```

The user can also forecast a day in the past to compare actual data to forecasted results.

Project Cost

The Project's cost was minimal since no additional hardware or software was needed. I took advantage of the already installed infrastructure and software during my Project. For my hotbox experiment at Kohlberg, I used Engineering Department's and my personal devices.

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