Improving NOVEC's Load Management Control Using Temperature and Energy Demand Statistics

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OR-680/SYST-798 Capstone Project Report

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EXECUTIVE SUMMARY

Northern Virginia Electric Cooperative (NOVEC) is headquartered in Manassas, Virginia and is an electricity reseller serving residential, commercial, and industrial customers. NOVEC owns an electricity distribution network but does not currently own any electric generation. Consequently, NOVEC must purchase power from the wholesale power market which must be delivered through the PJM Interconnection (PJM). PJM is a regional transmission organization (RTO) that coordinates the movement of wholesale electricity in all or parts of 13 states, including Virginia and the District of Columbia.

Problem Statement

During times of peak energy demand, NOVEC has the ability to remotely control electric water heaters and HVAC systems for approximately 43,000 residential customers. Specifically NOVEC can shut these devices off during peak demand times to reduce the overall demand on both the NOVEC distribution system and regional electric grid. This technique is referred to as load management. An additional benefit to reducing consumption during peak demand is that energy is not consumed when the price of energy is the most expensive. Devices that are shut off for too long a period of time results in lost energy sales and lost revenue to NOVEC impacting NOVEC's ability to recovery plant investment costs. Devices that are not shut off long enough do not sufficiently reduce the on-peak energy consumption and thus do not benefit the NOVEC system, the regional energy grid and results in increased cost to the customer as a result of the high cost of on peak energy.

Technical Approach

The objective of this project is to use historical temperature and energy demand statistics to develop a set of algorithms and utilization policies that will improve load management operation by more consistently reducing peak energy demand while maintaining customer satisfaction. To achieve this, the Electric Management Group (EMG) has developed three models: the Unmanaged Power Demand Estimator (UPDE), the Managed Power Demand Estimator (MPDE), and the Residential Convenience Estimator (RCE). The UPDE uses regression analysis used to develop parametric equations for predicting power demand given the temperature, time of day, month, and day of the week. The MPDE uses an integer programming technique to reduce power by assigning certain blocks of customers to be in load management

and then maximizing the sum of the predicted power of the entire customer base, subject to several constraints that govern the amount of blocks that can be under load management at a time, the duration each block can be under load management, and the amount of power demand that is to be reduced. The RCE estimates the impact on customer convenience that the selected load management policy has by assigning calculating the probability that each customer under load management will be inconvenienced given the temperature and the duration of the policy. These models were integrated into the Load Management Director (LMD) prototype.

Findings

The LMD was evaluated against a test dataset provided by NOVEC comprised of data that was independent of the data used to develop the models. Findings from this evaluation indicate that the LMD performs adequately in months where the peak power threshold is exceeded often and by large amounts, but suffers in months where the peak power threshold is rarely exceeded. Additionally, customer convenience was found to stay above 80 percent for power demand reductions less than 15 percent. The EMG also tested the sensitivity of the results to the number of independently controlled blocks and found that increasing this number increases the probability that NOVEC's planned base power will satisfy the managed demand.

Conclusion

The EMG believes that this report successfully demonstrates the feasibility of improving load management system operation. The EMG recommends a continuation of this research to realize the potential benefits of the demonstrated concepts, including the extension of peak demand estimation model to work with winter heating months, an investigation into the sensitivity of LMD operation to different blocks presenting different energy demands, and the inclusion of convenience estimates in the computation of the load management schedule to increase the likelihood that high levels of customer convenience are maintained.

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1 INTRODUCTION

Northern Virginia Electric Cooperative (NOVEC) is headquartered in Manassas, Virginia and is an electricity reseller serving residential, commercial, and industrial customers. NOVEC owns an electricity distribution network but does not currently own any electric generation [1]. Consequently, NOVEC must purchase power from the wholesale power market which must be delivered through the PJM Interconnection (PJM) [2]. PJM is a regional transmission organization (RTO) that coordinates the movement of wholesale electricity in all or parts of 13 states, including Virginia and the District of Columbia. NOVEC's electricity purchase and distribution concept is portrayed in Figure 1.

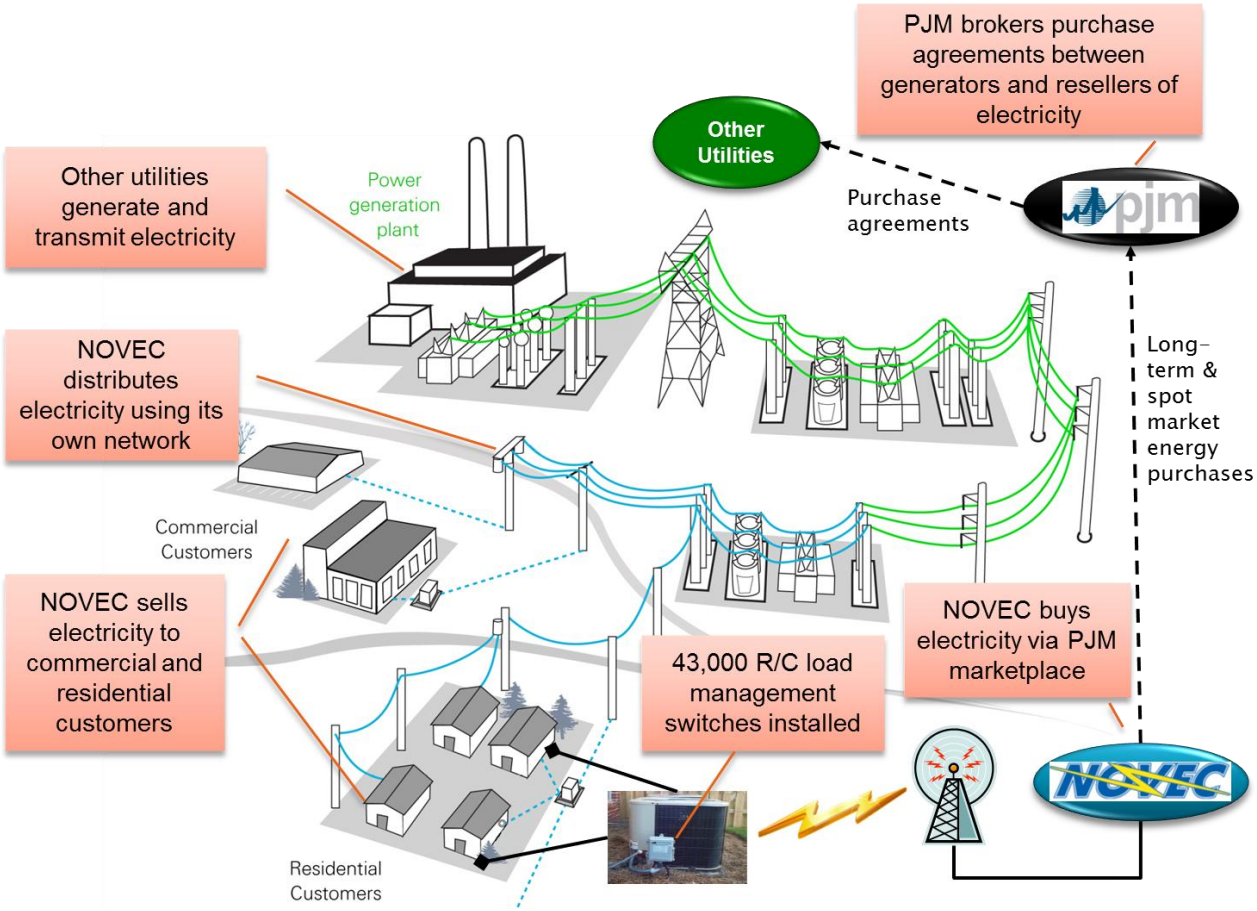

Figure 1 – NOVEC's Electricity Purchase and Distribution

1.1 NOVEC ELECTRICITY PURCHASE OVERVIEW

Generating capacity is the ability to provide electrical energy at certain rate, i.e., power. Capacity must be sized and acquired for the worst case demand which, for NOVEC, occurs during the summer period that spans June 1 through September 30 of each year. PJM assigns to

NOVEC its annual peak capacity requirement that is determined using a complex formula based predominately on NOVEC's previous summer peak demand and NOVEC's forecasted peak consumption for the upcoming summer period. It benefits NOVEC customers when NOVEC is able to control its customer peak hour usage and thus minimize its annual summer peak capacity requirements and energy purchases. NOVEC works hard to forecast and control its actual hourly peak demand that will occur during the summer period and uses this estimate to purchase capacity in advance. An advance purchase ahead of the summer is necessary because NOVEC must be sure that its meets its PJM assigned capacity obligation and has sufficient capacity to serve its customers' energy needs during summer peak hours. NOVEC must acquire and have available a level capacity equal to its peak hour demand for the entire summer period (June 1 through September 30) even if this peak demand is used only for single hour during this summer period. Accordingly it is to NOVEC's benefit to minimize customer usage during these few hours of high consumption in order to minimize its summer period capacity requirement and energy purchases. Effective use of a load management program designed to turn off selected customer loads during peak consumption periods is the current method employed by NOVEC to reduce its peak period consumption.

Energy is purchased using two methods that reflect both the average energy consumption (base load) and the deviations from the average (intermediate and peak loads). Base load consumption is satisfied by energy purchased using negotiated, firm price, bilateral contracts. These contracts are purchased one month to three years in advance of consumption and make up a majority of NOVEC's energy purchases and sales.

Peak load consumption is satisfied by spot market energy purchases made either on the same day, or up to one day before, the energy is consumed. The quantity of these purchases is determined by the number of kilowatt-hours used during peak electricity-use times. Spot market prices are volatile and high, particularly during periods of high energy consumption, due to the competition that occurs between utilities seeking purchases on the PJM marketplace. The PJM marketplace updates and posts its market energy prices every hour. Accordingly a second benefit of the effective use of a load management program is to reduce customer consumption of energy during periods of time when the price wholesale commodity price of electric energy is at the highest level.

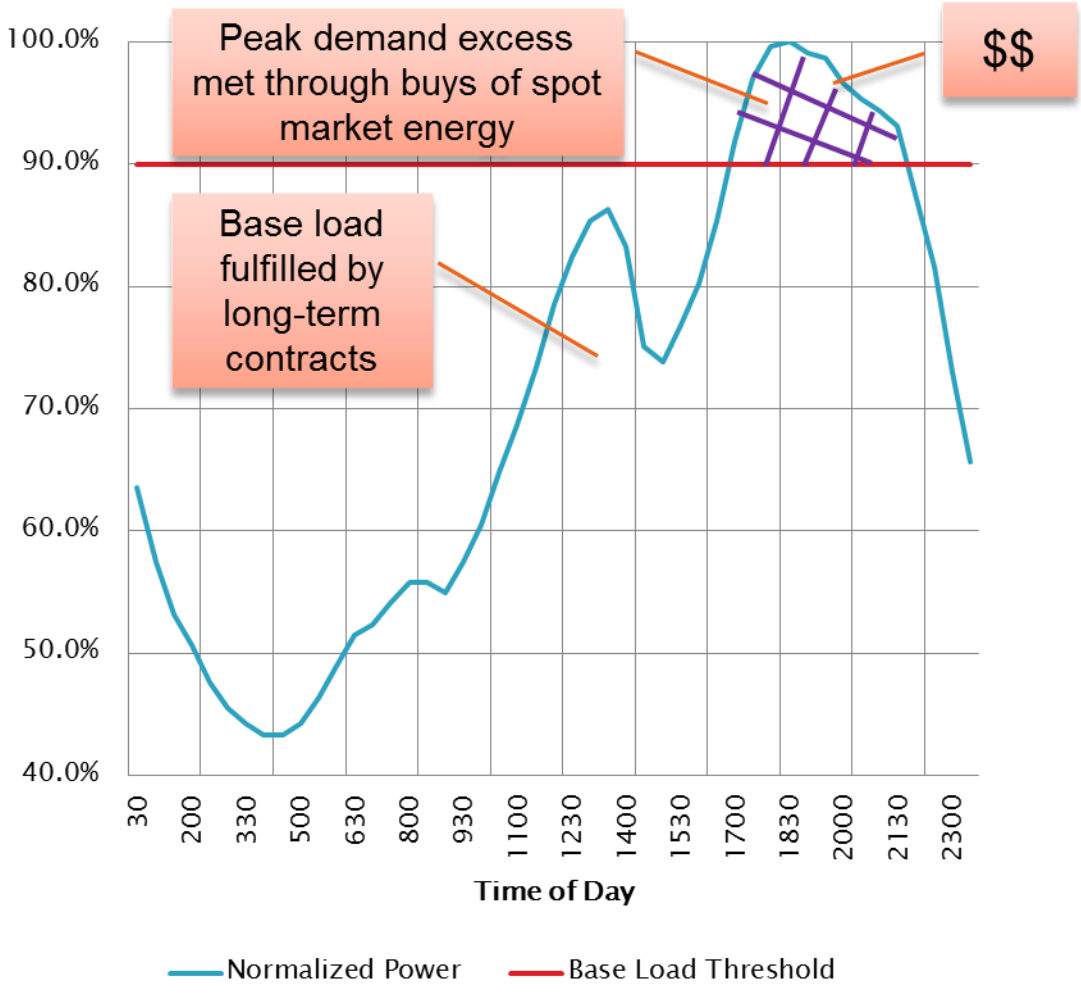

Figure 2 – Typical Day's Energy Fulfillment Purchase Needs

1.2 LOAD MANAGEMENT PROGRAM

NOVEC has instituted the voluntary Load Management Program (LMP) for its residential customers as a way to reduce peak power demand and thus reduce the purchase of expensive spot market purchases of the energy to satisfy the peak power demand. NOVEC utilizes a Load Management System (LMS) comprising a load management control center and remote controlled switches. Customers participating in the LMP allow NOVEC to install remote controlled switches on their hot water heaters and/or air conditioning compressor units. Customers then agree to allow NOVEC to switch off these appliances for a fraction of an hour during peak energy use times.

Participation in the program gives NOVEC the opportunity to better control the residential demand for peak power and potentially reduce NOVEC's energy purchase costs by a several million dollars each year.

2 PROBLEM STATEMENT

NOVEC would like to determine how the operation of LMS can be improved to maximize the benefit of reducing peak electricity demand. In particular, NOVEC has interest in the daily on/off scheduling of the load management switches as well as discovering if the current switch block size of 5,000 units is optimal. A successful improvement approach is one that simultaneously reduces peak electricity demand, reduces peak energy consumption but minimizes reductions in overall energy sales, and maintains customer satisfaction in the provided electricity service.

NOVEC has indicated the operation of the LMS is guided by an associated load management policy. As such, NOVEC seeks a recommended load management policy or set of policies that:

- Accommodate multiple peak load scenarios driven by seasonal and time of day influences
- Provide potential cost savings for NOVEC customers.

3 OBJECTIVES AND SCOPE

The scope of this project is the development and demonstration of an algorithm and associated load management policy that optimizes the operation of the LMS to reduce peak energy demand while minimizing the reduction of overall energy sales and customer satisfaction. Demonstration of the effectiveness of the algorithm and associated policy will be accomplished by computer simulation of an LMS optimization prototype driven by historical data sets of power demand and weather data provided by NOVEC. The project will provide a technical report that describes the research approach, the experiment design, obtained results, and conclusions. Furthermore, the developed simulations and load management policies will be made available to NOVEC.

4 TECHNICAL APPROACH

The project employed a methodical, systems engineering approach to develop a solution to be called the Load Management Director (LMD). The approach comprises the following steps listed below.

a) Determine Load Management Director (LMD) technical requirements by collaborating with the sponsor to understand the operational need. Sponsor collaboration included a project kickoff meeting; submission of a project proposal to the sponsor; and teleconferences as needed.

b) Define a top-level LMD system architecture that identifies the essential component algorithms of the LMD model and their interaction necessary to provide guidance to improve the operation of the NOVEC LMS.

c) Develop the LMD algorithms identified in the top-level architecture using solution forms (statistical, deterministic, etc.) that are appropriate to the nature of the problem spaces being addressed by the algorithms.

d) Assess effectiveness of LMD solution by testing the solution with historical power demand and temperature data that are independent of the data used to formulate the LMD algorithms.

5 TECHNICAL REQUIREMENTS

At the start of the project, the Electric Management Group (EMG) developed a set of top-level technical requirements as well as an operational concept of the Load Management Director (LMD) solution in accordance with the technical approach. Upon review of the NOVEC empirical data, it soon became clear that the EMG had been optimistic in its understanding of the load management problem. Consequently, uncertainty about the reasonableness of original set of technical requirements arose. In response, the EMG focused on the following fundamental requirements as follows:

a) The Load Management Director (LMD) shall provide managed peak demand estimates every 15 minutes.

b) The LMD shall use temperature measurements for NOVEC's residential customer locales

The rationale for requirement a) is that the 15 minute periodicity matches NOVEC's demand load measurement frequency. Thus, it is reasonable to assume that the LMD solution should provide load management control directions at the same frequency of occurrence.

The rationale for requirement b) is that NOVEC observations indicate power increases with outside temperature. This readily observable correlation between temperature and power demand indicates a dominant influence by the outside temperature. Thus, the LMD solution must take outside temperature into account if it is to improve the operation of NOVEC's LMS.

6 SPONSOR PROVIDED DATA

NOVEC provided historical power demand, weather, and load control data for the years 2009, 2010, and 2011. The structure of the NOVEC data is portrayed in Figure 3. The description of each illustrated data table is given in Table 1.

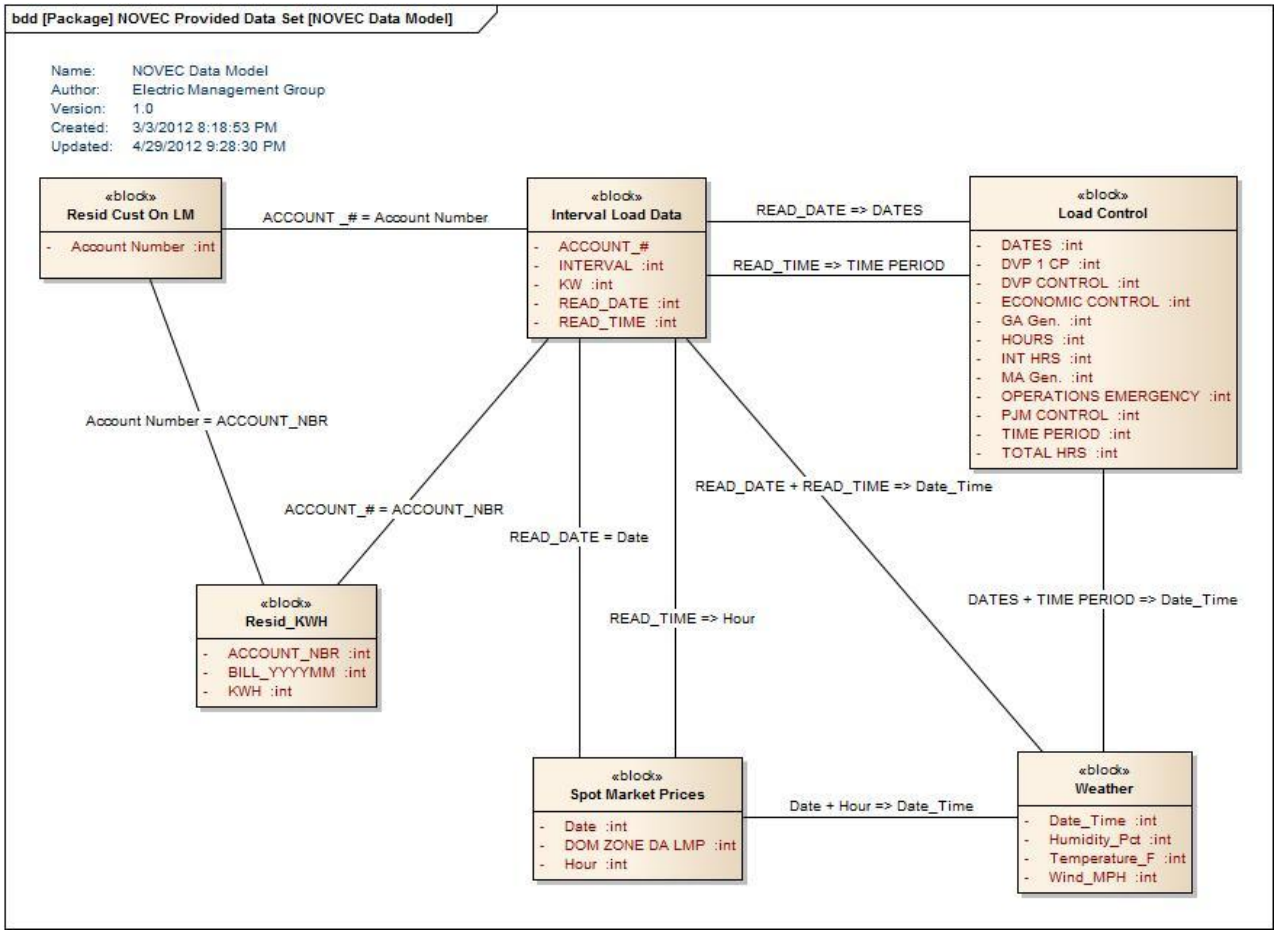

Figure 3 – Structure of NOVEC Provided Data

Table 1 – NOVEC Data Table Descriptions

Table Name	Description
Interval Load Data	Load data for instrumented accounts that are measured at a periodic interval
Load Control	List of dates and times when load control was activated during each year
Resid Cust On LM	List of residential account numbers that participate in the Load Management Program
Resid_KWH	Aggregate residential electrical energy usage per month
Spot Market Prices	Cost of power on the spot market
Weather	Weather data for the years provided

7 ASSUMPTIONS

The project performed the research using the following assumptions:

a) The research will focus on the summer months as power demand is highest and most volatile during these months. Furthermore, limiting the focus to the summer months will reduce the size of the data sets that NOVEC will need to provide.

b) The temperatures reported by Dulles Airport will stand as the temperatures for the NOVEC service region if it is not possible to obtain hourly temperature data on a municipality-scale basis. This is acceptable because the operation of the existing NOVEC LMS does not currently utilize temperatures at the locale of each participating residence.

c) Customer satisfaction is primarily perceived personal comfort within the home for a given outside temperature. Therefore the project team will examine ways to estimate customer satisfaction with NOVEC's Load Management Program as a function of temperature and possibly humidity.

8 LMD PROTOTYPE PROCESSING

A summary-level portrayal of the LMD prototype processing architecture is shown in Figure 4. As shown in the figure, the process begins with developing an estimate for the unmanaged power demand using the current temperature, time of day, day of the week, and the month. This unmanaged power demand estimate assumes that all residences in the NOVEC service region can draw electrical energy at will as if no load management system exists.

The unmanaged power demand estimate is then used in conjunction with an independently set peak demand reduction objective and knowledge of how many residences can be controlled en masse (a block) to determine the managed power demand estimate. This estimate uses the population of residences that participate in NOVEC's Load Management Program to compute the expected power demand that results from the selection of residences that will have their air conditioning shut off by the LMS. The to-be-commanded on/off state of each LMS block is also generated and saved for future calculation of the next block on/off states.

The on/off status of each block and the number of residences per block are used to estimate the aggregate customer convenience value that will result from the execution of the computed block on/off states. This estimate provides an indicator of customer satisfaction that results from air conditioning needs going unfulfilled due to the inhibiting action of the LMS operation.

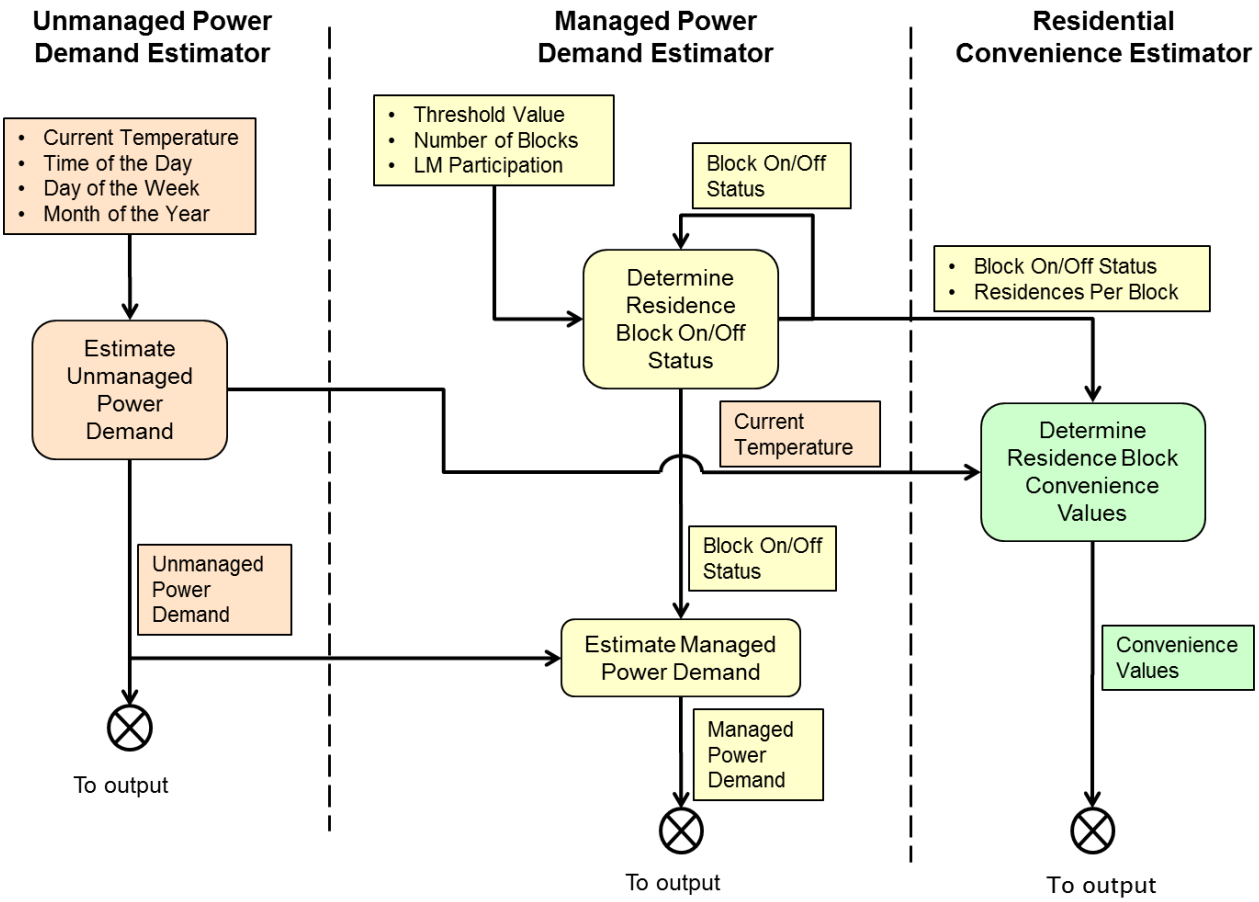

Figure 4 – LMD Prototype Processing Architecture

Detailed descriptions of the algorithms employed by the Unmanaged Power Demand Estimator, the Managed Power Demand Estimator, and the Residential Convenience Estimator are presented in the following sections.

8.1 UNMANAGED POWER DEMAND ESTIMATOR

The Unmanaged Power Demand Estimator (UPDE) is the upfront segment of the Load Management Director (LMD) that provides a prediction of the instantaneous Average Residential Load (ARL) without the influence of the Load Management System (LMS). The UPDE arrives at this estimate from a combination of factors to include temperature, time of day, day of the week and the month of summer, which are fed into a Statistical Residential Demand Model (SRDM) that computes the ARL. The SRDM is composed of a set of parametric equations that were developed using regression analysis which is discussed later in Section 8.1.6.

8.1.1 Data Collection and Normalization

To assist in conducting a regression analysis necessary to developing the SRDM, a set of historical data for the summer months of 2010 and 2011 (June-September) was provided by NOVEC. This dataset was comprised of a number of elements to include time, temperature and humidity at fifteen minute time intervals for approximately 250 NOVEC customer accounts. Due to the large quantity of data (over 15 million entries) SQL Server was used as the standardization and data formatting mechanism.

To properly normalize the dataset, customer accounts participating in NOVEC's load management program were removed in instances where their load management devices were activated. Unfortunately, removing these accounts in multiple places within the dataset caused an inconsistency in the number of readings for each interval across the entire dataset. For instance, for a given day during the summer there might be 230 readings taken at 2:00PM and only 205 taken at 2:15PM. To account for this irregularity, the Average Residential Load (ARL) was computed for each time interval by summing the total load across all readings and dividing by the number of readings taken. To provide an estimate of the total load for NOVEC's entire customer base for a specified point in time, the ARL is multiplied by the population size once it is provided to the Managed Power Demand Estimator (MPDE).

8.1.2 Relationships in the Dataset

Using the normalized dataset, scatter diagrams were developed to better understand the relationships between the ARL and potential drivers. These diagrams, which depict the relationship between the ARL and temperature, time of day, and humidity are depicted below in Figure 5, Figure 6, and Figure 7 respectively.

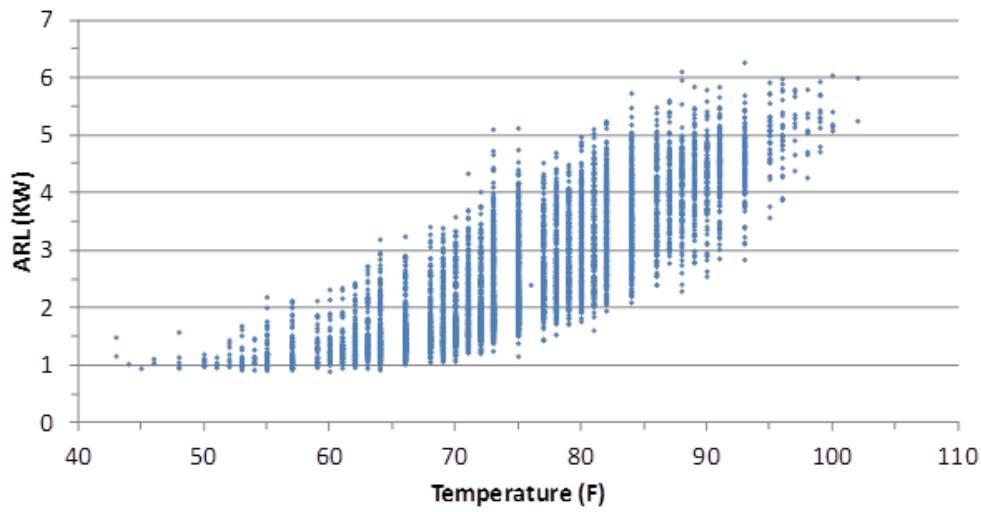

Figure 5 – ARL versus Temperature

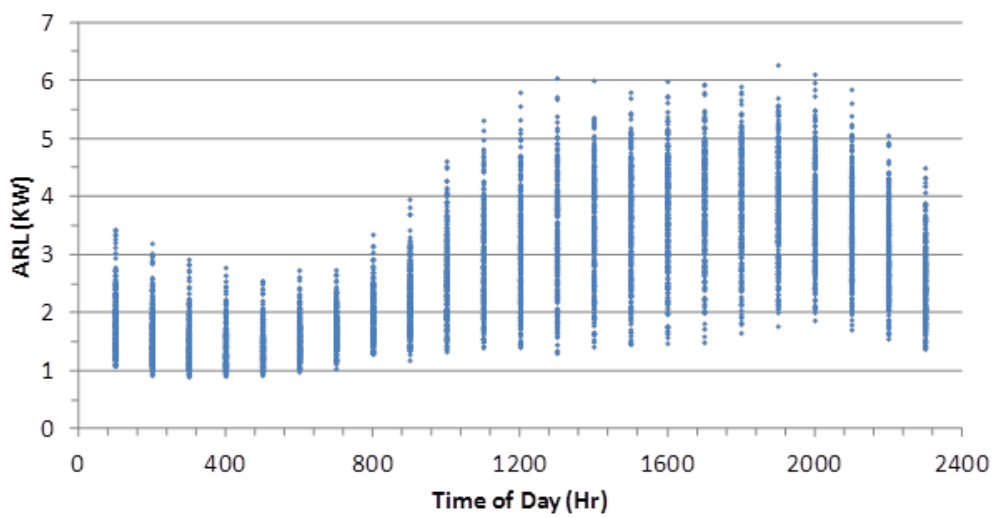

Figure 6 – ARL versus Time of Day

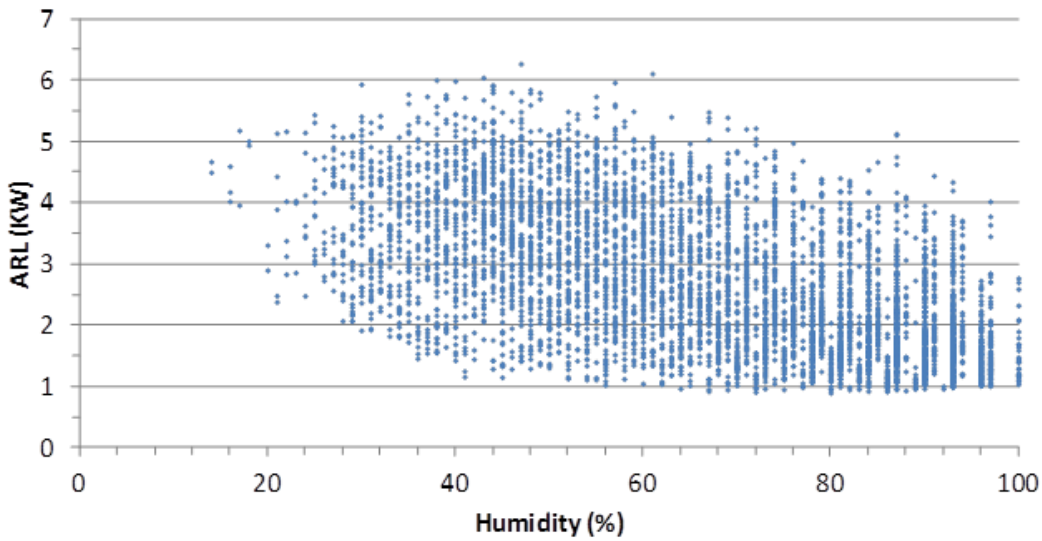

Figure 7 – ARL versus Humidity

Analysis of the relationships between the ARL and potential drivers reveal a clear positive correlation between the ARL and temperature. Conversely, observation of the relationship between the ARL and time of day indicates an association that varies periodically throughout the day while humidity shows almost no correlation at all. This upfront analysis clearly identified temperature and time of day as necessary components of the regression model. However, additional factors also needed to be considered such as day of the week and the month of summer.

8.1.3 Time of Day Analysis

To pull this information out of the dataset and to better understand how time of day might impact the relationship between the ARL and temperature, multiple views were constructed from the ARL vs. Temperature scatter diagram. First, the mean ARL and temperature were calculated for each hour of the day across the entire dataset and plotted as shown below in Figure 8.

The cyclical cycle depicted in the ARL vs. Time of Day scatter diagram from Figure 6 is clearly exposed in Figure 8 which illustrates that the relationship between ARL and temperature is bimodal depending on the time of day. For instance, for a temperature of 75°F, the average ARL is either approximately 2.2KW or 3.6KW depending on whether the time resides in the "Low Cycle" or the "High Cycle". The "Low Cycle" shown in Figure 8 generally falls in-between the hours of 3:00AM and 3:00PM while the "High Cycle" is comprised of the remaining times of the day.

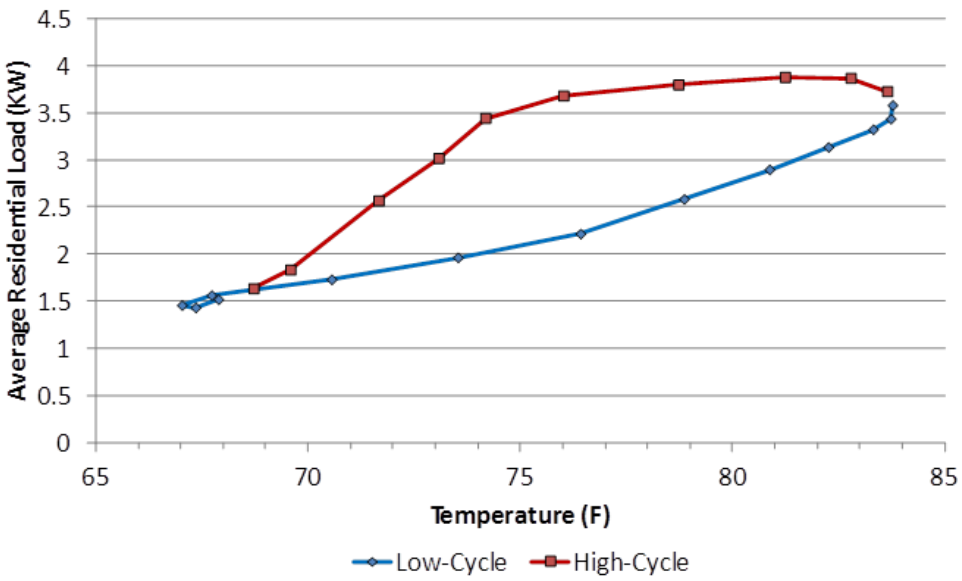

Figure 8 – Time of Day Impact on ARL

One hypothesis for this relationship between ARL, temperature and time of day is the difference between the temperature of the environment and the interior temperature of the residential homes. As external temperatures begin to rise during the morning hours, the internal temperature of residences should still be relatively cool due to lower temperatures experienced during the nighttime hours. Theoretically, this should translate into longer time intervals between A/C cycles during the morning hours. Once heat from the rising morning temperatures begins to transfer into residential homes, the time between A/C cycles should become shorter, which raises the ARL. As the outside temperature begins to decline during the evening hours, it is probable that the A/C units are still combating the large amount of heat generated during the afternoon hours. Therefore, for the same temperature, the ARL experience during the morning and early afternoon ("Low Cycle") should be much smaller than during the late afternoon and evening ("High Cycle").

In order to account for the bimodal condition that time of day creates, it was determined that two parametric models (one for both "low" and "high" cycles) needed to be developed in order to account for the phenomenon. These models are discussed in detail in Section 8.1.6 below.

8.1.4 Month of Summer Analysis

The second potential driver of ARL analyzed was the month of summer. It was theorized that at different points during the summer period the ARL experienced would be significantly different

for similar temperature levels. In order to characterize this, the dataset was split into four groups, one for each month of the summer period (i.e. June, July, August and September). To better understand this difference visually, ARL and temperature were calculated for each hour of the day for each grouping of data and plotted as shown in Figure 9. The enlarged data points represent the average ARL and temperature for 8:00AM, 12:00PM, and 8:00PM for each class of data.

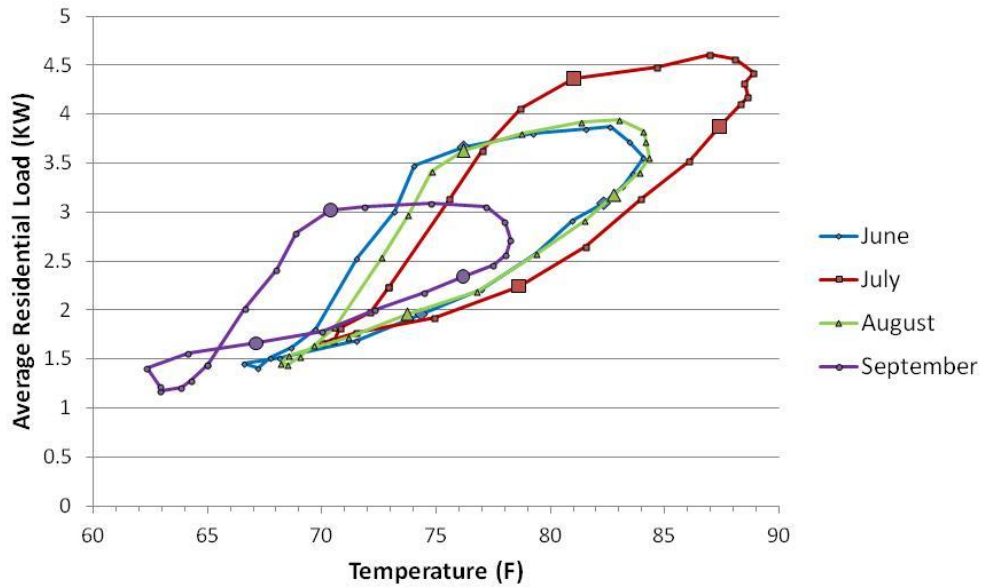

Figure 9 – Month of Summer Impact on ARL

There are a number of observations that can be derived from Figure 9. First, June and August tend to follow a very similar load pattern over the course of a day while September and July are noticeably different. The average temperature for the same time of day is generally higher during July and lower during September when compared to June and August. For September, the ARL is typically higher during the evening and morning hours while substantially lower during the later morning and afternoon hours when compared to June and August. Conversely, July is just the opposite when comparing its mean ARL over the course of the day with June and August. Further testing of the statistical significance of the month of summer as a driver of ARL is discussed below in Section 8.1.6.

8.1.5 Day of the Week Analysis

The last potential driver of ARL analyzed was day of the week. It was hypothesized that there might be a significant difference in the ARL experienced during the weekend versus a weekday

for a given temperature due to weekend in residential occupancy being different compared to the weekday. To analyze this, the dataset was split into two groups with the first attributed to readings taken on the weekend (Saturday/Sunday) and the second for readings taken during weekdays (Monday – Friday). Next, ARL and temperature were calculated for each hour of the day for each grouping of data and plotted as shown in Figure 10.

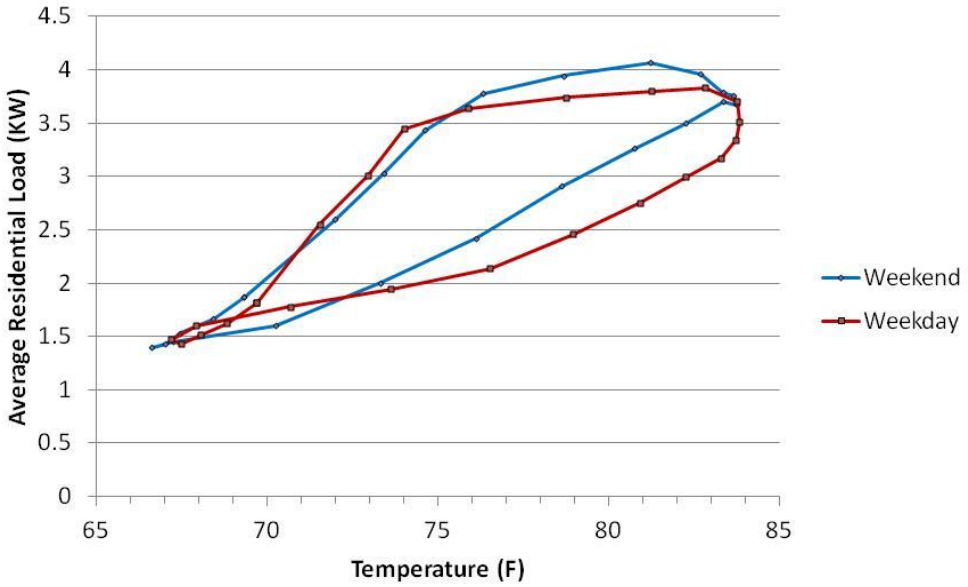

Figure 10 – Day of the Week Impact on ARL

The results indicate that on average, during the morning and afternoon hours, the ARL given the same temperature is higher during the weekend than during weekdays. However, the difference between the ARLs for both categories is relatively small during the evening and nighttime hours. Additional testing of the statistical significance of the day of the week as a driver of ARL is discussed below in Section 8.1.6.

8.1.6 Regression Analysis

8.1.6.1 Approach

To conduct the regression analysis, Microsoft Excel and Minitab, a powerful statistical software package, were used to more easily automate the process. As discussed in Section 8.1.3, due to the bimodal affect time of day has on the relationship between ARL and temperature, two regression analyses were performed. For the "Low Cycle", data between the hours of 3:00AM and 3:00PM was used to conduct the first regression analysis while data for all other times of the day ("high cycle") was used to perform the second regression analysis.

Using the ARL versus temperature scatter diagram from Figure 5 above, in conjunction with the plots developed in Figure 8 through Figure 10, a polynomial form was determined to be the best fit for both "Low Cycle" and "High Cycle" models when compared to linear, power and exponential regression forms. Ordinary Least Squares (OLS), which minimizes the sum of the squares of vertical deviations from the actual data points to the regression line, was selected as the primary regression methodology. Percent Least Square (PLS), General Least Squares (GLS) and Weighted Least Squares (WLS) were other methodologies also examined.

In order to determine the optimum subset of independent variables for each model, a stepwise regression approach was implemented. Both forward selection and backward elimination methods were used. Forward selection is based on the notion that variables should be inserted one at a time until a satisfactory regression equation is found while backward elimination involves the same concepts as forward selection except that one begins with all the variables in the model. Stepwise regression is accomplished by first selecting the independent variable that gives the largest value of R^2. The next variable inserted into the model is the one that gives the largest increase in R^2. This procedure is continued until the most recent variable inserted fails to induce a significant increase in the explained regression. The significance of the increase is determined using a t-test, which assesses whether the means of two groups are statistically different from each other [3]. The formula for the t-test is shown below

$$t - value = \frac{R^2(\beta_1,\beta_2) - R^2(\beta_1)}{SE(R^2(\beta_1,\beta_2) - R^2(\beta_1))}$$

where SE is the standard error and β1 and β2 are the independent variables. Using a t-table, the alpha level can located which provides the corresponding significance value. If this figure is less than the desired alpha value, the difference is considered significant [4]. A significance constraint of $\alpha \leq 0.05$ ($\geq$ 95% confidence level) was imposed when performing the stepwise regression approach.

8.1.6.2 "Low Cycle" Parametric Model

Using a basic polynomial form in tandem with a stepwise regression approach to determine the most appropriate set of independent variables, the following parametric model was produced for the "Low Cycle":

$$ARL = A + B(Temp) + C(Temp)^2 + D(Sep) + E(Temp * Sep) + F(Temp^2 * Sep) + G(WE)$$

Table 2 – "Low Cycle" Regression Statistics

Regression Statistic	Value
R^2	0.846
Standard Error (SE)	0.405
Standard Percent Error (SPE)	17.4%
Bias	-2.8%
Observations	3149

Table 3 – "Low Cycle" Equation Values

Term	Coefficient	Standard Error	t-Stat	P-Value
A	6.244852	0.48063	12.99318	1.22615E-37
B	-0.20739	0.01250	-16.58442	2.78569E-59
C	0.00202	8.069E-05	25.05019	2.03650E-126
D	-1.76971	0.75351	-2.34862	0.01890
E	0.065822	0.02072	3.17745	0.00150
F	-0.00057	0.00014	-4.00935	6.23008E-05
G	0.199579	0.01614	12.35989	2.665E-34

Sep and WE are indicator variables for the month of September and the weekend, respectively. Inspection of each component of the equation reveals how the month of September and the weekend affect the basic formula. When predicting the ARL in September the intercept, slope and curvature of the parametric model are all adjusted. Only the intercept is altered when estimating the ARL on weekends.

The regression statistics shown above in Table 2 and below in Figure 11 and in Figure 12 demonstrate that the regression model developed for the "Low Cycle" is satisfactory. The high R^2 value of 0.846 indicates that the model accounts for a majority of the variability found in the dataset and will be a good predictor of future outcomes. However, analysis of Figure 11 below reveals that the model has a slight tendency to overestimate lower ARLs and underestimate higher ARLs. This is most likely due to where the centroid of the data lies and a few outliers that

skew the regression in this direction. Subsequent analyses may wish to revisit the data points identified as outliers and examine the impact of removing them from the overall dataset.

The P-Values in Table 3 above signify that each independent variable used in the regression formula is statistically significant. This statistic indicates how likely it is that the coefficient for an independent variable emerged by chance and does not describe a real relationship [5]. For the analysis conducted, a confidence level of 95% (α=0.05) was used as the filter for significance.

Analysis of variance was conducted to validate the model assumptions. The three standard assumptions for a regression-based model are that the random errors have a constant variance, zero mean and be normally distributed [6].

The standardized residual and normality plots shown below in Figure 11, Figure 12, and Figure 13, respectively, confirm the validity of the model. The residual plot does not exhibit any distinct patterns and the random errors depicted in the diagram have a variance that is approximately constant with a mean of zero. The normality plot of the standardized residuals is reasonable straight (with some curvature towards the 95th percentile) and can be considered to be approximately normal.

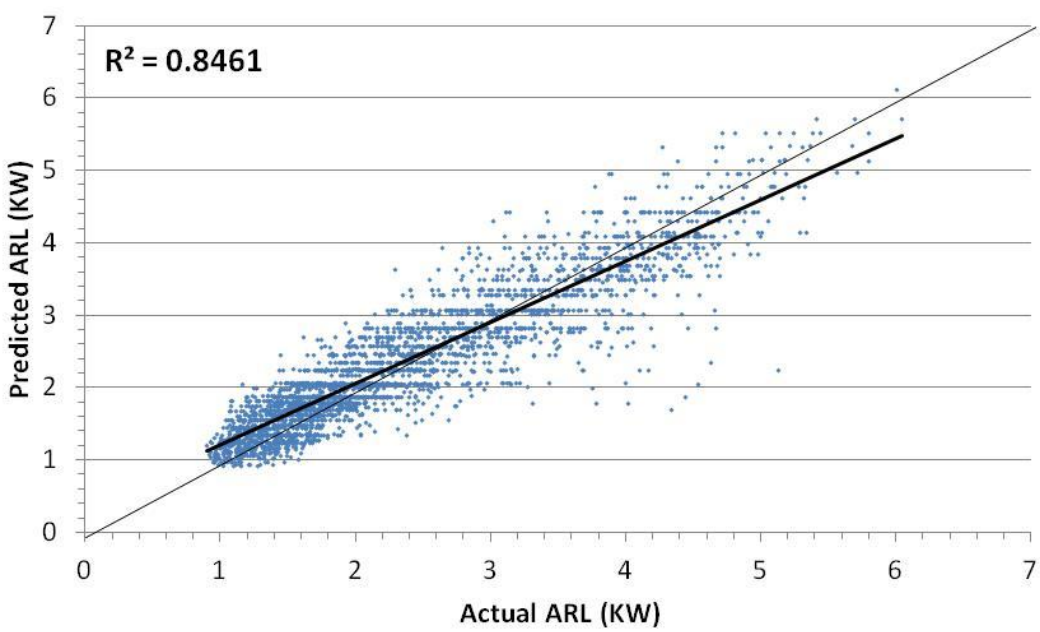

Figure 11 – "Low Cycle" ARL Predicted versus Actuals

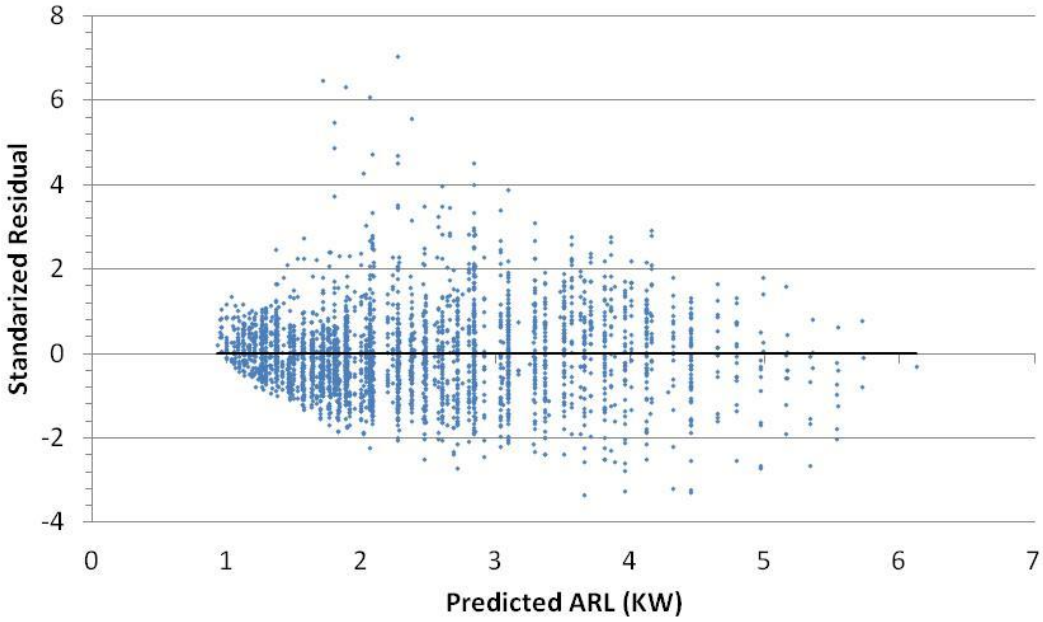

Figure 12 – "Low Cycle" ARL Standardized Residuals

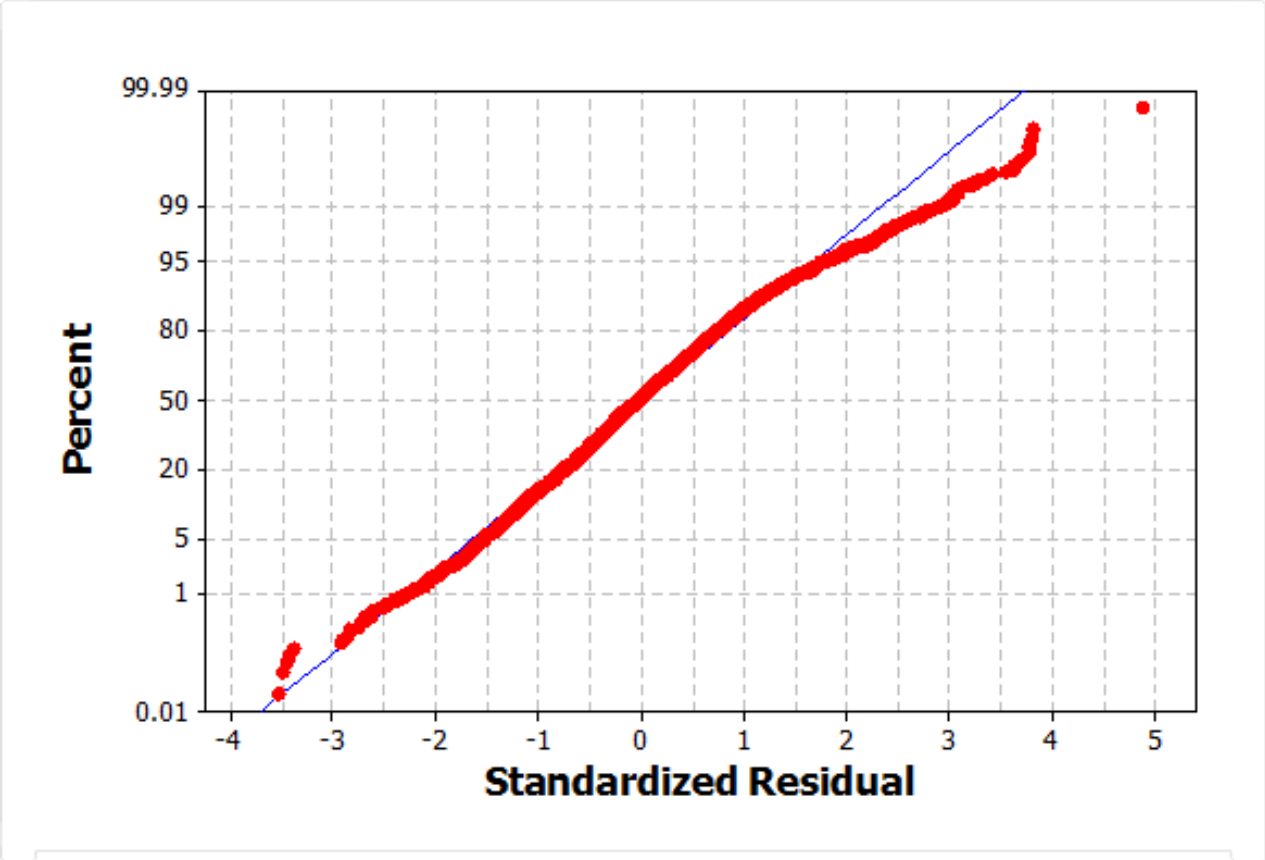

Figure 13 – "Low Cycle" Q-Q Normal Probability Plot (Response is ARL)

8.1.6.3 "High Cycle' Parametric Model

Using the same basic polynomial form used for the "Low Cycle" regression model and a stepwise regression approach to determine the most appropriate set of independent variables, the following parametric model was produced for the "High Cycle":

$$ARL = A + B(Temp) + C(Temp)^2 + D(Temp * July) + E(Sep) + F(Temp^2 * Sep) + G(WE)$$

Table 4 – "High Cycle" Regression Statistics

Regression Statistic	Value
R^2	0.752
Standard Error (SE)	0.563
Standard Percent Error (SPE)	24.6%
Bias	-4.5%
Observations	2420

Table 5 – "High Cycle" Equation Values

Term	Coefficient	Standard Error	t-Stat	P-Value
A	-4.17057	0.78140	-5.33731	1.03E-07
B	0.07335	0.02005	3.65758	0.00026
C	0.00029	0.00012	2.25150	0.024443
D	0.00103	0.00036	2.82065	0.004832
E	0.78243	0.13949	5.60921	2.26E-08
F	-0.00015	2.53915E-05	-5.93877	3.29E-09
G	0.08521	0.02556	3.33358	0.00087

July, Sep and WE are indicator variables for the months of July, September and the weekend, respectively. Inspection of each component of the equation reveals how the months of July, September and the weekend affect the basic formula. When predicting the ARL in September the intercept and curvature of the parametric model are all adjusted while only the slope is altered

when estimating the ARL in July. Similar to the "Low Cycle" model, when predicting the ARL on weekends, the intercept is increased.

The regression statistics shown above in Table 4 and Figure 14 below, demonstrate that the regression model created for the "High Cycle" is reasonable. The relatively high R^2 value of 0.752 and Predicted ARL versus Actual ARL plot in Figure 14 indicates that the regression equation fits the data reasonably well. For the same reasons as the "Low Cycle" model, the "High Cycle" model has a propensity to overestimate lower ARLs and underestimate higher ARLs. Additionally, the P-Values in Table 5 above indicate that each independent variable used in the regression formula is statistically significant as all the values are less than 0.05. Thus, there is less than a 5% chance that the relationships between the dependent and independent variables in the model emerged randomly and greater than a 95% chance that they are real.

The standardized residual and normality plots shown below in Figure 15 and Figure 16, respectively, substantiate the validity of the model. The residual plot does not exhibit any distinct patterns and the random errors depicted in the diagram have a variance that is approximately constant with a mean of zero. The normality plot of the standardized residuals is reasonable straight (with some curvature towards the 99th percentile) and can be considered to be approximately normal.

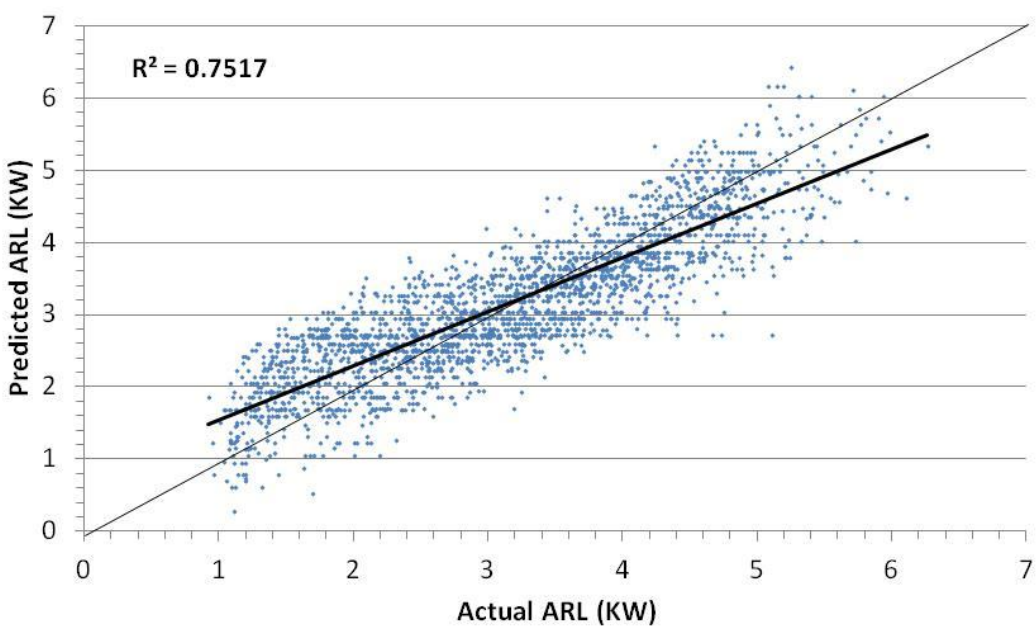

Figure 14 – "High Cycle" ARL Predicted versus Actuals

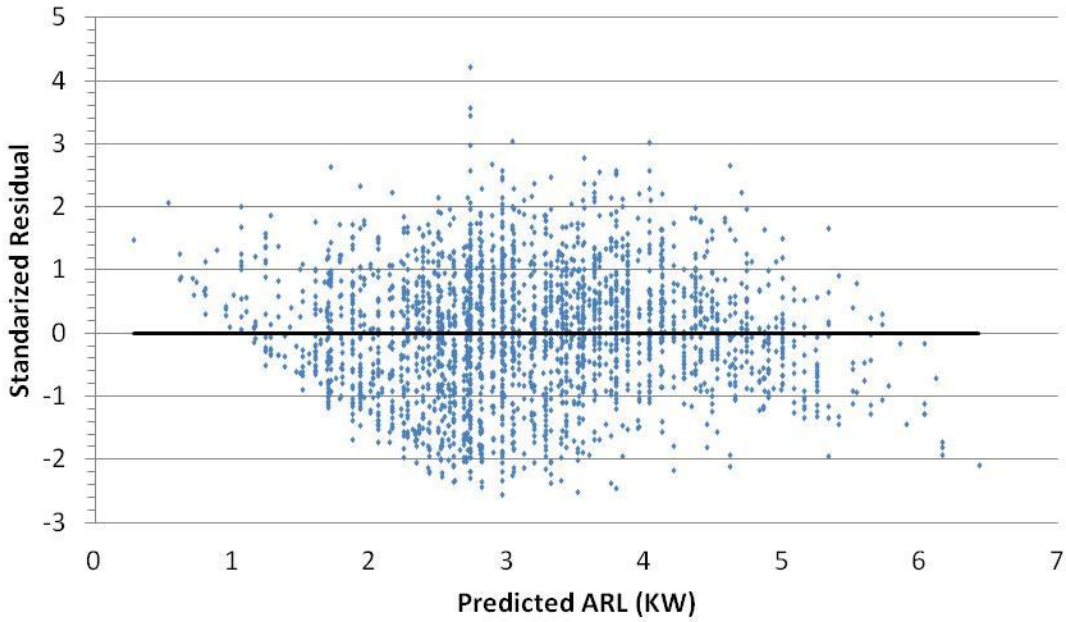

Figure 15 – "High Cycle" ARL Standardized Residuals

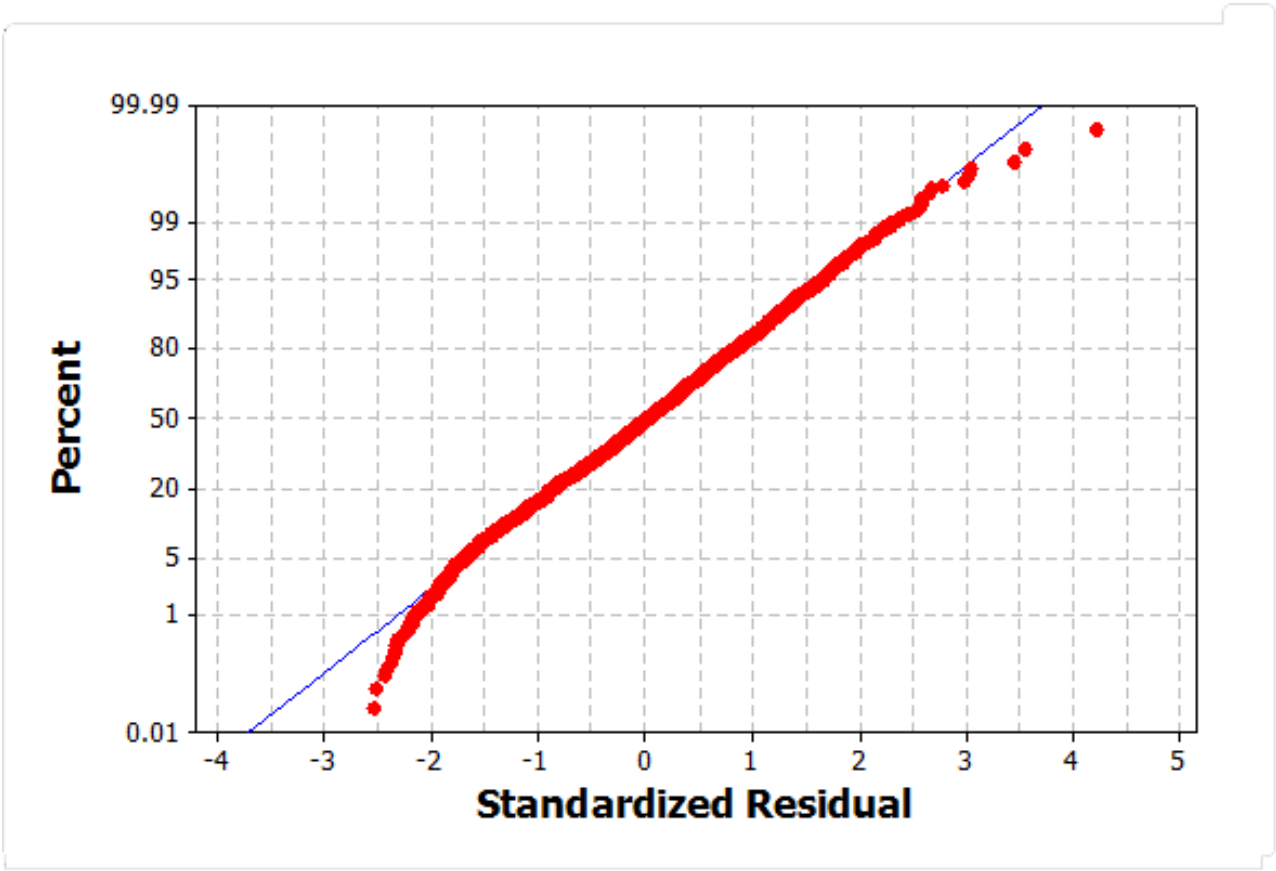

Figure 16 – "High Cycle" Q-Q Normal Probability Plot (Response is ARL)

8.1.7 UPDE Limitations

Although the UPDE has been developed to capture factors that are important in determining unmanaged power demand, it contains many underlying limitations that affect its overall utility. Due to the selection of regression analysis as the primary methodology, predictions outside the range of data used to develop the UPDE will potentially be inaccurate and invalid. In general, the model is only valid for temperatures ranging between 50-100°F and the summer months (June-September).

For example, temperatures 45°F and below will result in negative ARLs, which is obviously not possible. Also, using the model to estimate the ARL in winter would not be wise. This is because the relationship between ARL and temperature, which drove the fundamental form of the UPDE, has not been validated for the winter months. In addition, there is no guarantee the model will be a good predictor of the ARL for future summers.

If the relationship between the ARL and temperature (or any of the other drivers) changes, the model will no longer be a good predictor of the ARL. Additional historical data should be analyzed in future analyses for potential trends between the ARL and drivers selected for inclusion in the UPDE.

8.2 MANAGED POWER DEMAND ESTIMATOR

The MPDE utilizes an integer programming approach to provide NOVEC with a schedule for turning off blocks of houses. By turning off a block of houses, NOVEC will be able to reduce their peak demand and reduce their dependency on spot market purchases. In order to do this, the model must take in many factors that will influence how the houses will be managed. Among these factors are the unmanaged demand, the peak threshold, and previous solutions [14]. By utilizing previous solutions, the managed demand model can guarantee that blocks of houses are not turned off repeatedly and the impact of reducing load is spread throughout NOVEC's entire Load Management System. Once these inputs are considered, the MPDE provides an optimal solution to control NOVEC's Load Management System (LMS).

8.2.1 Inputs

The managed demand model takes in five input parameters to best provide a solution to managing NOVEC's residential demand. Each of these inputs is imported from Microsoft Excel and can be varied based on NOVECs needs. The first input is the estimated unmanaged demand

for the current temperature, time of day, day of the week and month of summer. This stands as the baseline POWER demand for NOVEC's customer base. It is the main focus of the managed demand model because it influences all decision made concerning how many and which of NOVEC's residents will have their power turned off at a given time. The second input is the demand threshold set by NOVEC. This marks the peak demand objective that NOVEC wants to stay under in order to stay out of the spot market. For the current model this threshold is set at 10% below the peak demand. The third input for the model is the number of blocks the NOVEC customers within the Load Management System are divided into. The blocks determine how many houses can be turned off at a given time and how much variation in management strategy can be achieved [13]. The next input is the percentage of participation in the Load Management System. This input determines how much of NOVEC's overall power demand can be influenced by the LMS. This input cannot be influenced by the model but is included to show NOVEC how increasing their participation will impact their ability to reduce peak demand. The last input is the solution to the model run at previous time intervals. These previous solutions come in two forms. First is the full solution for the previous three intervals. Since the model focuses on making decisions at each fifteen minute interval, using the three previous intervals completes an hour long cycle of load management decisions. This allows the model to take into account previous decisions and ensure that customers are not inconvenienced by having their houses turned off over and over. The second form of the previous solutions is the total number of turnoffs a block has experienced up to the present time. By taking the total turnoffs of each block into account, the MPDE can balance the burden of turnoffs equally among the blocks.

8.2.2 Model

The main focus of the MPDE model is to maximize the POWER demand under a set of demand constraints. This creates a solution that maximizes the amount of power used by NOVEC's customers without forcing NOVEC to enter the spot market. The maximization function sums both the managed demand of those residents in the load management program and the unmanaged demand of those not participating. To limit the maximization, a series of constraints control the solution. The first constraint limits the amount of POWER that can be used at any one time. The demand threshold drives this constraint and stands as the maximum amount of power to be used at a time. All remaining constraints concern the previous solutions to the model and are aimed at ensuring balance in the load management system. The first set of constraints is the

maintenance constraints. These constraints ensure that a single block of houses will not be turned off more than a set number of times in an hour. The number of shutoffs can be determined by NOVEC based on the aggressiveness of their load management policy. The next sets of constraints are the balance constraints. These aim to provide balance to which blocks are turned off. It requires that no block of houses is turned off two more times than another block of houses in a single day. By satisfying these constraints, the integer programming model provides an optimal solution to schedule NOVEC's LMS.

8.2.3 Output

The output of the managed demand model is a set of blocks that should be left on and a set that should be turned off as well as the total demand at the current time. To represent the blocks, a series of binary variables are used. If a block has a value of one, the block will remain on at that time. Conversely, if the block has a value of zero, it is turned off to reduce the overall POWER demand at that time. The total power is shown as a sum of the power used by all of NOVEC's residential customers regardless of whether they are participating in the LMS. By showing the NOVEC's total power demand it can be shown if the threshold is reached at any time. Once a solution is achieved, it is exported to Microsoft Excel and is presented in a tabular form [15]. The table is set to increment with each new solution, presenting a full day's worth of solutions in a single view. This allows users to examine how an entire day has been managed by knowing exactly which blocks of houses have been turned off at any time. It also allows NOVEC to adjust their strategy to be more or less aggressive depending on their objective.

8.2.4 Mathematical Formulation

The following is an example mathematical formulation of the problem. It portrays a system with four blocks of houses. The estimated demand for this example is 10 units and the demand threshold is 9 units. Also, there is a twenty percent participation in the NOVEC's LMS and a block can only be turned off one time per hour. With these constraints you can see that (Participation * Power) / Blocks equals (0.2 * 10) / 4 = 0.5 and Power * (1 – Participation) equals 10 * 0.8 = 8. In the following formulation, two subscripts are used to represent the binary block variables. The first subscript number determines which block the variable signifies and the second determines the time interval [13]. An example of this is the variable $BLOCK_{1i}$ which represents the state of block one at time i. If $BLOCK_{14}$ = 1 then the houses in block one are

turned on at time four and if $BLOCK_{14}$ = 0 then the houses in block one are turned off at time four. Because of the real time nature of the model, the only variables to manipulate are those block variables where i = n. These are the variables that represent the most recent time. All variables where i < n represent previous time solutions and will be treated as constants.

Maximize

$$(0.5) \times BLOCK_{1n} + (0.5) \times BLOCK_{2n} + (0.5) \times BLOCK_{3n} + (0.5) \times BLOCK_{4n} + 8$$

Such That

Reduction Constraint

$$(0.5) \times BLOCK_{1n} + (0.5) \times BLOCK_{2n} + (0.5) \times BLOCK_{3n} + (0.5) \times BLOCK_{4n} + 8 \leq 9$$

Maintenance Constraints

$$\sum_{i=n-4}^{n} BLOCK_{1i} \geq 3$$

$$\sum_{i=n-4}^{n} BLOCK_{2i} \geq 3$$

$$\sum_{i=n-4}^{n} BLOCK_{3i} \geq 3$$

$$\sum_{i=n-4}^{n} BLOCK_{4i} \geq 3$$

Balance Constraints

$$\sum_{i=1}^{n} (BLOCK_{1i} - BLOCK_{2i}) \leq 1$$

$$\sum_{i=1}^{n} (BLOCK_{2i} - BLOCK_{3i}) \leq 1$$

$$\sum_{i=1}^{n} (BLOCK_{3i} - BLOCK_{4i}) \leq 1$$

$$\sum_{i=1}^{n} (BLOCK_{1i} - BLOCK_{3i}) \leq 1$$

$$\sum_{i=1}^{n} (BLOCK_{2i} - BLOCK_{4i}) \leq 1$$

$$\sum_{i=1}^{n} (BLOCK_{1i} - BLOCK_{4i}) \leq 1$$

$$\sum_{i=1}^{n}(BLOCK_{4i} - BLOCK_{3i}) \leq 1$$

$$\sum_{i=1}^{n}(BLOCK_{3i} - BLOCK_{2i}) \leq 1$$

$$\sum_{i=1}^{n}(BLOCK_{2i} - BLOCK_{1i}) \leq 1$$

$$\sum_{i=1}^{n}(BLOCK_{4i} - BLOCK_{2i}) \leq 1$$

$$\sum_{i=1}^{n}(BLOCK_{3i} - BLOCK_{1i}) \leq 1$$

$$\sum_{i=1}^{n}(BLOCK_{4i} - BLOCK_{1i}) \leq 1$$

8.2.5 MPL Formulation

Below is the MPL formulation of the MPDE. It takes in a variety of values and arrays from Microsoft Excel and uses them to provide the best possible solution to the current conditions. By importing arrays of data, the model is scalable in its ability to provide a solution for any number of blocks. This will give NOVEC flexibility in analyzing different options for their LMS.

```
DATA
    DEMAND := EXCELRANGE("Real Time Model.xlsm", "Threshold");
    PART       := EXCELRANGE("Real Time Model.xlsm", "Participation");
    BLOCKS       := EXCELRANGE("Real Time Model.xlsm", "Blocks");
    POWER   := EXCELRANGE("Real Time Model.xlsm", "Power");
    SHUTOFFS   := EXCELRANGE("Real Time Model.xlsm", "Shutoffs");
INDEX
    i          := 1..BLOCKS;
DATA
    PREVIOUS3[i]    := EXCELRANGE("Real Time Model.xlsm",
"Previous3");
```

```
    PREVIOUS2[i]    := EXCELRANGE("Real Time Model.xlsm",
"Previous2");
    PREVIOUS1[i]    := EXCELRANGE("Real Time Model.xlsm",
"Previous1");
    TOTON[i]      := EXCELRANGE("RealTimeModel.xlsm", "TotOns");
DECISION VARIABLES
    LOAD[i] EXPORT TO EXCELRANGE("Real Time
Model.xlsm","Current");
MACRO
    MANAGE := SUM(i: LOAD * POWER * PART / BLOCKS);
    UNMANAGE := POWER * (1 - PART);
MAX
    MANAGE + UNMANAGE;
SUBJECT TO
    REDUCE : SUM(i: LOAD * POWER * PART / BLOCKS) + POWER * (1
- PART) < DEMAND;
    MAINTAIN[i]  : LOAD[i] + PREVIOUS3[i] + PREVIOUS2[i] +
PREVIOUS1[i] >= 4 - SHUTOFFS;
    BAL1[i]          : if(i < BLOCKS)     then TOTON[i] + LOAD[i] -
TOTON[i+1] - LOAD[i+1] endif <= 1;
    BAL2[i]          : if(i < BLOCKS - 1) then TOTON[i] + LOAD[i] -
TOTON[i+2] - LOAD[i+2] endif <= 1;
    BAL3[i]          : if(i < BLOCKS - 2) then TOTON[i] + LOAD[i] -
TOTON[i+3] - LOAD[i+3] endif <= 1;
    BAL4[i]          : if(i < BLOCKS - 3) then TOTON[i] + LOAD[i] -
TOTON[i+4] - LOAD[i+4] endif <= 1;
```

```
    BAL5[i]        : if(i < BLOCKS - 4) then TOTON[i] + LOAD[i] -
TOTON[i+5] - LOAD[i+5] endif <= 1;
    BAL6[i]        : if(i < BLOCKS - 5) then TOTON[i] + LOAD[i] -
TOTON[i+6] - LOAD[i+6] endif <= 1;
    BAL11[i]   : if(i > 1) then TOTON[i] + LOAD[i] - TOTON[i-1] - LOAD[i-1]
endif <= 1;
    BAL12[i]   : if(i > 2) then TOTON[i] + LOAD[i] - TOTON[i-2] - LOAD[i-2]
endif <= 1;
    BAL13[i]   : if(i > 3) then TOTON[i] + LOAD[i] - TOTON[i-3] - LOAD[i-3]
endif <= 1;
    BAL14[i]   : if(i > 4) then TOTON[i] + LOAD[i] - TOTON[i-4] - LOAD[i-4]
endif <= 1;
    BAL15[i]   : if(i > 5) then TOTON[i] + LOAD[i] - TOTON[i-5] - LOAD[i-5]
endif <= 1;
    BAL16[i]   : if(i > 6) then TOTON[i] + LOAD[i] - TOTON[i-6] - LOAD[i-6]
endif <= 1;
BINARY
        LOAD[i];
```

Table 6 shows a sample output of an MPDE solution set for a portion of an arbitrarily selected day. Temperature is in degrees Fahrenheit, the Managed Demand, Unmanaged Demand, and Reductions are in kilowatts.

Table 6 – Example MPDE Solution Output

Time	Temp	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7	Man. Demand	Unman. Demand	Reduc-tion
11:30	91	1	1	1	1	1	1	1	555080	555080	0
11:45	91	1	1	1	1	1	1	1	555080	555080	0
12:00	93	1	1	1	1	0	1	1	573776	599468	25691
12:15	93	1	1	1	1	1	1	0	573776	599468	25691
12:30	93	1	1	1	1	1	0	1	573776	599468	25691

Time	Temp	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7	Man. Demand	Unman. Demand	Reduc-tion
12:45	93	1	1	1	0	1	1	1	573776	599468	25691
13:00	93	1	1	0	1	1	1	1	573776	599468	25691
13:15	93	1	0	1	1	1	1	1	573776	599468	25691
13:30	93	0	1	1	1	1	1	1	573776	599468	25691
13:45	93	1	1	1	1	1	1	0	573776	599468	25691
14:00	93	1	1	1	1	1	0	1	573776	599468	25691
14:15	93	1	1	1	1	0	1	1	573776	599468	25691
14:30	93	1	1	1	0	1	1	1	573776	599468	25691
14:45	93	1	1	0	1	1	1	1	573776	599468	25691
15:00	93	0	0	1	0	0	0	1	546635	695717	149082
15:15	93	0	0	0	1	1	0	0	546635	695717	149082
15:30	93	0	0	0	0	0	1	1	546635	695717	149082
15:45	93	1	1	0	0	0	0	0	546635	695717	149082
16:00	87	1	1	1	1	1	1	0	568661	594123	254623
16:15	87	1	0	1	1	1	1	1	568661	594123	25462
16:30	87	0	1	1	1	1	1	1	568661	594123	25462
16:45	87	1	1	1	1	1	1	0	568661	594123	25462
17:00	89	0	0	1	1	1	1	1	573875	627675	53800

8.2.6 MPDE Limitations

The algorithm looks only at the single time in which it is run and must be run at each interval that power reduction is needed. Therefore, the algorithm does not decide the length of a block's turn-off duration. Instead, the turn-off duration is a function of the interval between MPDE runs which, for this study, is tied to the frequency that NOVEC takes system load readings, i.e., every 15 minutes.

The algorithm only takes into account the solutions from the previous 24 hours. It is not currently know if a 24 hour solution history length is appropriate for all conditions that would call for load management to be active.

8.3 RESIDENTIAL CONVENIENCE ESTIMATOR

8.3.1 Residential Convenience Estimator

As indicated in the problem statement, a successful load management operation would maintain customer satisfaction in the provided electricity service. It is therefore important that decisions about applying load management be made in such a way that considers whether customers are inconvenienced. The Residential Convenience Estimator (RCE) was developed as a way to estimate the inconvenience a customer could potentially experience under load management. The output of the estimator is a metric that could be used to compare customer satisfaction across multiple load management options or could be compared against some set threshold of inconvenience that a load management policy is not to exceed.

8.3.2 RCE Development Process

Research into how to estimate customer convenience began with an examination of how weather conditions translate into the actual comfort or discomfort felt by a person [7][8]. The initial concept for the RCE was to employ a well-established weather comfort index as the main driver of customer satisfaction. Research performed by the EMG produced two indexes that appeared to be suitable candidates: the Heat Index [9] and Thom's Discomfort Index [10]. Each of these indexes combines the air temperature and the humidity—data which were included in the NOVEC data files—to produce a single index number that maps to the relative comfort a person would feel under those conditions. Figure 17 shows the index values that result for different values of humidity and temperature using the Heat Index [9] formulation.

The proposed methodology using this approach was to compute the comfort index value given the current temperature and humidity statistics and determine what category of discomfort is mapped to that index value. The discomfort category would then determine what function is used by the convenience estimator to map the duration of the load management to the convenience level. For example, given a very low discomfort category a function would be chosen where the convenience level is relatively flat across changes in duration. However, given a high discomfort category the function would be such that the convenience level decreases more rapidly as the duration is extended. The result would be a convenience level that decreases with the duration of the load management and will vary given the current (or forecasted) temperature and humidity values.

NOAA's National Weather Service

Heat Index

Temperature (°F)

Relative Humidity (%)	80	82	84	86	88	90	92	94	96	98	100	102	104	106	108	110
40	80	81	83	85	88	91	94	97	101	105	109	114	119	124	130	136
45	80	82	84	87	89	93	96	100	104	109	114	119	124	130	137	
50	81	83	85	88	91	95	99	103	108	113	118	124	131	137		
55	81	84	86	89	93	97	101	106	112	117	124	130	137			
60	82	84	88	91	95	100	105	110	116	123	129	137				
65	82	85	89	93	98	103	108	114	121	128	136					
70	83	86	90	95	100	105	112	119	126	134						
75	84	88	92	97	103	109	116	124	132							
80	84	89	94	100	106	113	121	129								
85	85	90	96	102	110	117	126	135								
90	86	91	98	105	113	122	131									
95	86	93	100	108	117	127										
100	87	95	103	112	121	132										

Likelihood of Heat Disorders with Prolonged Exposure or Strenuous Activity

Caution Extreme Caution Danger Extreme Danger

Figure 17 – Heat Index Values

This approach was ultimately abandoned, however, as the EMG decided that customers would not be as affected by the outside heat index as they would be conditions within their own homes. Outside conditions may have already been somewhat neutralized within the home by the time load management goes into effect. Instead, customer satisfaction would depend on whether or not they would be able to run their air conditioner at the time they desired. This in turn depends on many factors such as the current temperature within the house, when the air conditioner was last run, and the rate at which the house heats up when the air conditioner is not running.

Data were not available on the first two factors. For the third factor, the EMG did research to attempt to find a heat-gain rate for a typical household, but our findings indicated that this would vary significantly depending on house size; building material, number of windows, etc. (for example, see [11] and [12]). However, most equations governing heat gain consisted of some constant multiplied by the difference between the outside and inside temperatures. With this relationship in mind, we constructed a model where the probability that a customer would want to run the air conditioner is dependent on the relationship between the outside temperature and

the inside temperature. Without precise data on the inside temperature, we assumed it would be 75 degrees Fahrenheit, roughly room temperature. The rest of this section describes this model.

8.3.3 Assumptions

NOVEC does not keep direct data relating load management to customer convenience and conducting a survey of customers was deemed to be beyond the scope of this project. Therefore, the model had to be based on some assumptions of what was likely to lead to decreases in customer satisfaction. In discussions with NOVEC, they identified what they believed to be the two most common factors leading to complaints about load management: 1) the amount of time spent without power and 2) the outside temperature at the time the customer is without power. With these factors in mind, the RCE uses the following assumptions:

- A customer is inconvenienced when he or she desires to use the air conditioner in a given interval but is unable to because of load management;
- The probability that a customer will want to use the air conditioner in a given interval increases as the outside temperature increases relative to the inside temperature;
- For a previously inconvenienced customer, the level of inconvenience will decrease by 20% for each hour in which their block is not under load management (that is, customer satisfaction will start to increase again once they are no longer in load management).

8.3.4 Inputs and Outputs

For each time interval examined, the RCE requires three inputs. First is the outside temperature from the selected interval, the same value used as an input for the UPDE. Second is the status of each block in the load management program during the interval; each block is either switched on or switched off as determined by the Managed Demand Model. Third is the number of customers in each block; however this input should not be interval-specific.

As an output, the RCE produces a convenience value for each block. The convenience value is a number corresponding to the level inconvenience that each block is predicted to experience within the interval given the selected load management policy. The maximum convenience value is 100, which corresponds to a block experiencing no inconvenience. As the convenience value decreases, the level of inconvenience the block is predicted to experience increases. A lower convenience value represents higher inconvenience.

8.3.5 Methodology

The RCE measures customer satisfaction at the level of individual customers controlled by the load management system. The individual customer is assigned either a convenience value of 0 or 1; 0 for the customer that is inconvenienced by load management and 1 for the customer that is not inconvenienced. These numbers can then be aggregated to measure the satisfaction of blocks of managed houses or of the entire system by comparing the number of inconvenienced customers to the total number of customers in the block or system, respectively. When no load management has been performed, all blocks have a convenience rating of 100. That is, it is assumed that customer satisfaction will not be any different than normal. The following paragraphs describe the process used by the RCE when examining an interval.

First, for the given interval the RCE reads in the status of each block from the Managed Demand Model and the current temperature. If a given block is set to be shut off during this interval, the RCE estimates the number of customers within that block that will be inconvenienced as a result. The probability, p, that an individual customer will be inconvenienced in an hour is defined as follows:

$$p = \begin{cases} 1 - \left(\dfrac{75}{CurrentTemp}\right), CurrentTemp > 75°\text{F} \\ 0, CurrentTemp \leq 75°\text{F} \end{cases}$$

Because this represents the probability for one hour, if the interval is 15 minutes then the probability is divided by four. This value represents the probability that the customer will want to use the air conditioner during this interval. It is based on the idea that that the rate at which a house heats up is proportional to the difference between the inside temperature and the outside temperature. In this formulation, as the current outside temperature increases, the probability of wanting to use the air conditioner increases as well. However, because the interval itself is relatively small the probability does not get too high. The base temperature of 75 degrees was chosen as an approximation of room temperature. When the outside temperature is less than 75 degrees, we assume there is no need for the air conditioner and the probability of inconvenience is zero.

The RCE randomly assigns each customer in the switched-off block a convenience value of 0 or 1 based on the probability computed above. Customers in the switched-off block that already have a convenience value of 0 from being on load management earlier in the day are assumed to

stay inconvenienced regardless of what probability they are assigned. The ratio of non-inconvenienced customers (i.e., customers with a convenience value of 1) to the total number of customers within the block times 100 is considered the overall convenience value for the block at the given interval.

When the interval being examined is the first in which load management has been performed, the RCE's calculations end after the steps described above and it moves onto the next interval. However, if load management has already occurred at some point earlier in the day then it is likely that there are customers still experiencing residual inconvenience from prior intervals. One of the assumptions of the RCE is that customer inconvenience will decrease the more time they spend out of load management. To model this, the RCE also examines the convenience values of the blocks that are scheduled to be free from load management in the given interval. If the convenience value of a given block is 100 then maximum convenience is already achieved and nothing further is done. However, if the convenience value is less than 100, then the RCE loops through all of the currently inconvenienced customers and assigns them a convenience value of 1 with 25 percent probability. This has the result of reducing the predicted inconvenience of each block that is not in load management.

8.3.6 Limitations

While the RCE has been developed to capture factors that we believe are important in determining customer satisfaction, it contains many assumptions that limit its potential utility. These assumptions have not been validated—particularly the assumption describing the probability that a customer will be inconvenienced—and therefore it is not known how well this model corresponds to reality. The biggest limitation is that the inputs and methodology are not based on empirically-derived data on customer experience. More information obtained directly from customers would be extremely useful for updating the model and improving its validity. Additionally, individual customer convenience is represented as a binary value whereas in reality it is more likely to be a spectrum. Also, the probability of a customer being inconvenienced is dependent entirely on the outside temperature. Other factors, such as time of day, are likely to be relevant as well. Furthermore, the estimator treats each customer the same way rather than attempting to model variability across the different customers. More data on individual customers (or groups of customers) could help make the model more realistic.

9 RESULTS

NOVEC provided an independent dataset from 2009, which was used to test the performance and overall effectiveness of the LMD. The examples provided in following sections analyze the model's performance for one week during each summer month. July is the first month presented because it happens to be the period where peak power occurs most often and with the largest magnitudes. Therefore, it is the month where the most benefit can be derived from load management.

Demand estimates were calculated in 15 minute time intervals to support spot market power purchase planning decisions that NOVEC makes on an hourly basis. An objective peak demand threshold was set to the 90th percentile of the power demand experienced during the 2010-2011 summer timeframe. All power demand experienced under this threshold was considered part of the base load satisfied through NOVEC's long term contracts. The remaining power demand exceeding the threshold was considered peak demand and was the fraction of demand the LMD attempted to reduce. The 90th percentile was determined to be a reasonable objective threshold because it is similar to the percent load NOVEC satisfies with long term contract energy purchases.

The detailed discussions for each of the summer months begin on the next page.

9.1 UNMANAGED POWER DEMAND - JULY PERFORMANCE

Figure 18 depicts the unmanaged demand observed for both actual and predicted values for one week in July 2009. It is clear that the majority of peak power demand occurs later in the week, which is consistent with the weekday analysis conducted in 8.1.5 above. The predicted versus actual plot in Figure 19 indicates the UPDE models are potentially a good overall predictor of power demand even for time periods outside of the dataset used for their development.

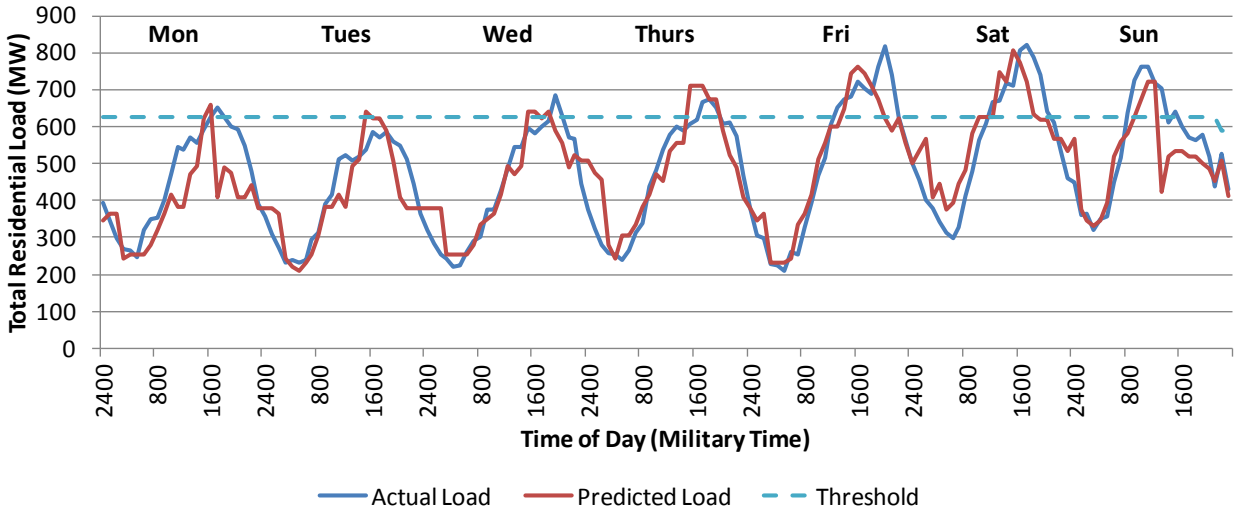

Figure 18 – Actual and Predicted Unmanaged Power Demand (1 Week, July 2009)

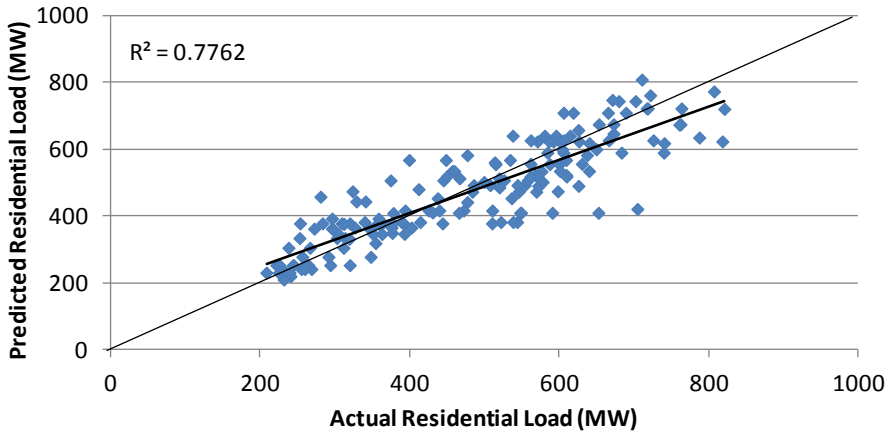

Figure 19 – Predicted versus Actual Unmanaged Power Demand Residuals (1 Week, July 2009)

Table 7 below provides a set of measures that better illustrate how well the UPDE performs at predicting the actual power demand.

Table 7 – MOEs for Unmanaged Power Demand (1 Week, July 2009)

MOE	Value
Peak Prediction Success Rate	62%
False Positive Rate	28%

The first Measure of Effectiveness (MOE), Peak Prediction Success Rate, calculates how often the UPDE successfully predicts the actual power demand exceeding the objective threshold. Higher Peak Prediction Success Rates are desired and indicate the UPDE is performing well. The formula for computing the Peak Prediction Success Rate is shown below.

$$Peak\ Prediction\ Success\ Rate = \frac{\begin{array}{c}\#\ of\ Occurences\ where\ Actual \\ and\ Predicted\ Power\ Exceed\ Threshold\end{array}}{\begin{array}{c}\#\ of\ Occurences\ where\ Actual \\ Power\ Exceeds\ Threshold\end{array}}$$

For July, the actual power demand exceeded the objective threshold on 34 occasions. The UPDE was able to predict 21 of these occurrences, demonstrating a Peak Prediction Success Rate of 62%.

The second MOE, False Positive Rate, describes how often the UPDE mistakenly predicts the objective demand threshold to be exceeded. For one week in July, the UPDE incorrectly estimated the objective threshold to be exceeded on 8 of 21 instances for a False Positive Rate of 28%. Lower False Prediction rates are desired. Higher False Prediction Rates will result in the LMD activating load management when it is not required, eating into potential sales. The formula for calculating this MOE is depicted below.

$$False\ Positive\ Rate = \frac{\begin{array}{c}\#\ of\ Occurences\ where\ Predicted\ Power\ Exceeds \\ Threshold\ but\ Actual\ Power\ Does\ Not\end{array}}{\begin{array}{c}\#\ of\ Occurences\ where\ Predicted \\ Power\ Exceeds\ Threshold\end{array}}$$

9.2 MANAGED POWER DEMAND - JULY PERFORMANCE

Figure 20 below depicts the power demand observed for both actual and predicted loads for one week in July 2009 after load management has been applied by the MPDE. The MPDE works by reducing the predicted power demand to levels near the threshold should it be exceeded. Assuming the UPDE correctly predicts the actual power demand (from Figure 18 above), it should be reduced to levels approximating the objective demand threshold. Figure 20 illustrates this is not always the case since the UPDE does not accurately predict the actual power demand in all instances. Thus, for certain intervals, the actual power demand is not reduced at all or by enough. At other times it is reduced when it is not necessary to do so.

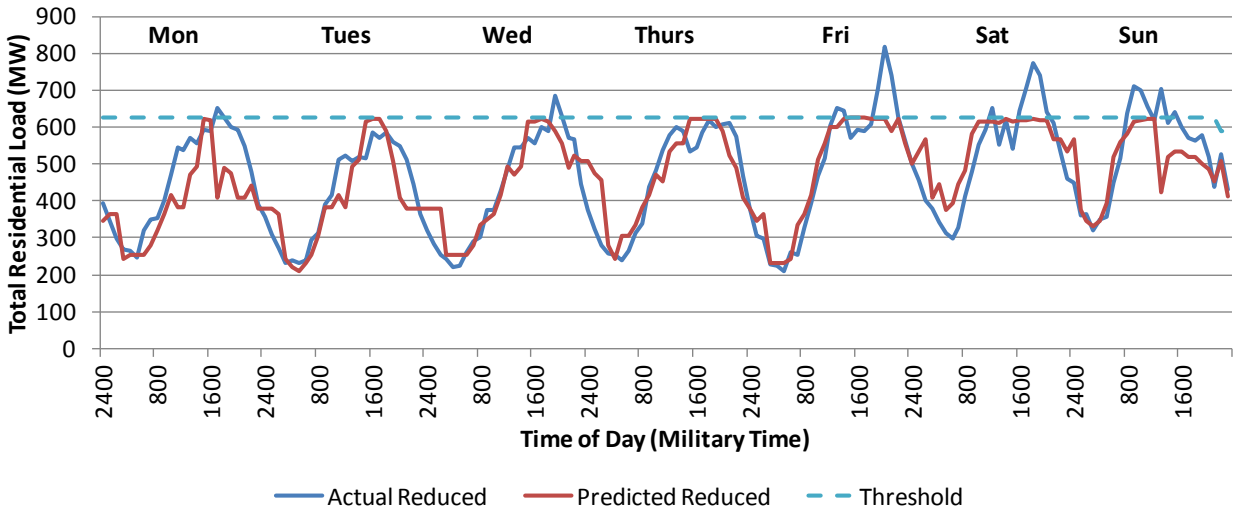

Figure 20 – Actual and Predicted Managed Demand (1 Week, July 2009)

Table 8 provides a set of measures that better illustrate how well the LMD performs at managing the actual power demand.

Table 8 – MOEs for Managed Power Demand for 1 Week in July 2009

MOE	Value
% of Peak Power Occurrences Eliminated	35%
% of Peak Power Reduced	51%
% of Baseline Power Reduced	1.2%

The first MOE, % of Peak Power Occurrences Eliminated, calculates the percentage of instances the actual power demand is reduced to levels below the objective threshold from the total number of times it exceeds the objective threshold when unmanaged. A higher percentage indicates the LMD is successfully removing peak demand under load management. For July, the LMD was able to eliminate 35% of instances where actual power demand exceeded the objective threshold. The formula for computing the % of Peak Power Occurrences Eliminated is shown below.

$$\%\ of\ Peak\ Power\ Occurences\ Eliminated$$
$$= \frac{\#\ of\ Times\ Actual\ Power\ Exceeds\ Threshold - \#\ of\ Times\ Reduced\ Actual\ Power\ Execeeds\ Threshold}{\#\ of\ Times\ Actual\ Power\ Exceeds\ Threshold}$$

The second MOE, % of Peak Power Reduced, describes the total amount of actual power exceeding the objective threshold that is eliminated. For the week examined in July 2009, the LMD eliminated 51% of the actual power demand exceeding the objective threshold. Higher percentages indicate the LMD is successfully removing peak power demand under load management, which in turn helps lower the electric bill for NOVEC customers. The formula for calculating this MOE is depicted below.

$$\%\ of\ Peak\ Power\ Reduced$$
$$= \frac{Total\ Actual\ Power\ Under\ \ Threshold - Total\ Power\ Under\ Threshold\ Removed\ Under\ Managed\ Demand\ Policies}{Total\ Actual\ Power\ Under\ Threshold}$$

The last MOE, % of Baseline Power Reduced, describes the total amount of baseline power removed due to instances where the actual power is reduced past the objective demand threshold. For the week analyzed in July 2009, the LMD eliminated 1.2% of the baseline power demand. Higher percentages indicate the LMD is incorrectly reducing the baseline power demand, which reduces NOVECs total sales. Ideally, this figure should remain very small. The formula for calculating this MOE is depicted below.

$$\%\ of\ Peak\ Power\ Reduced = \frac{Total\ Actual\ Power\ Above\ \ Threshold - Total\ Reducded\ Power\ Above\ Threshold}{Total\ Actual\ Power\ Over\ \ Threshold}$$

9.3 UNMANAGED POWER DEMAND - JUNE PERFORMANCE

Figure 21 below depicts the unmanaged demand observed for both actual and predicted values for one week in June 2009. The predicted versus actual plot in Figure 22 indicates the UPDE model did an exceptional job (R2 = 0.86, SPE = 19%) of predicting the overall power demand profile for the week analyzed.

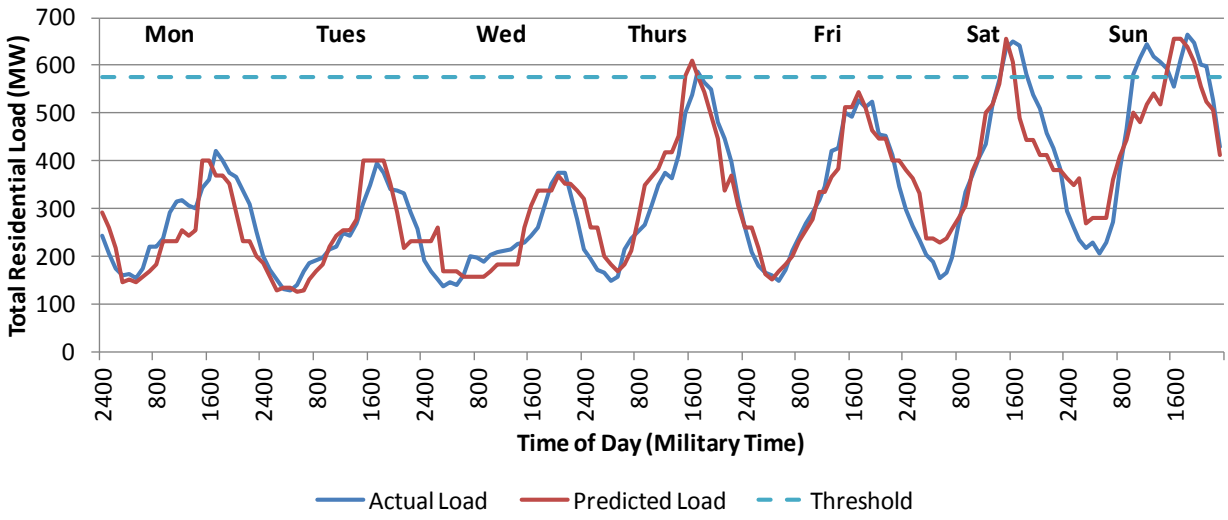

Figure 21 – Actual and Predicted Unmanaged Demand (1 Week, June 2009)

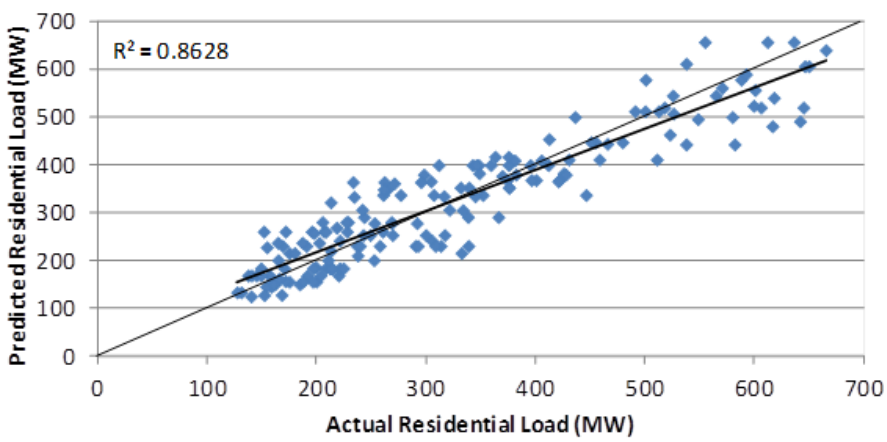

Figure 22 – Actual and Predicted Unmanaged Demand Residuals (1 Week, June 2009)

However, the unmanaged power demand MOEs listed below in Table 9 indicate the UPDE had some difficulty in predicting when the objective threshold would be exceeded. This is most likely due to the infrequency with which power demand actually exceeded the objective threshold in June. For example, the number of times the objective threshold was exceeded was more than twice the amount in July than in June (34 versus 16). Additionally, the objective

threshold was exceeded by an average of 14MW in July compared to only 4MW in June. With SPEs of 17.4% and 24.6% for the "Low Cycle" and "High Cycle" UPDE models respectively, peak power occurrences were much more difficult to predict in June given the objective threshold level.

Table 9 – MOEs for Unmanaged Power Demand (1 Week, June 2009)

MOE	Value
Peak Prediction Success Rate	44%
False Positive Rate	25%

9.4 MANAGED POWER DEMAND – JUNE PERFORMANCE

Figure 23 below depicts the power demand observed for both actual and predicted loads for one week in June 2009 after load management was applied by the MPDE. It is evident from the graph that the MDPE failed to completely reduce power demand exceeding the objective threshold for some of the weekend period.

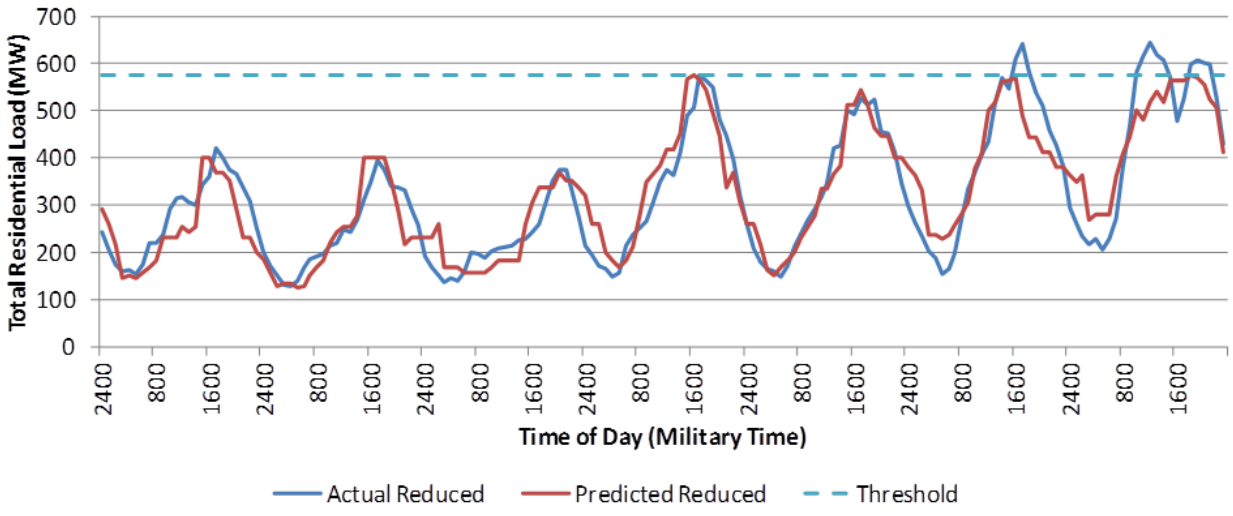

Figure 23 – Actual and Predicted Managed Demand (1 Week, June 2009)

Table 10 provides a set of measures that better illustrate how well the LMD performed at managing the actual power demand for one week in June 2009.

Table 10 – MOEs for Managed Power Demand (1 Week, June 2009)

MOE	Value
% of Peak Power Occurrences Eliminated	20%
% of Peak Power Reduced	40%
% of Baseline Power Reduced	0.45%

Although the MPDE was only able to completely eliminate 20% of peak power demand occurrences, it removed nearly 40% of the overall power demand exceeding the objective threshold for the week analyzed. Additionally, load management employed by the MPDE only impacted 0.45% of the base power demand, minimally affecting NOVEC's overall sales for the week in June.

9.5 UNMANAGED POWER DEMAND – AUGUST PERFORMANCE

Figure 24 below depicts the unmanaged demand observed for both actual and predicted values for one week in August 2009. The predicted versus actual plot in Figure 25 indicates the UPDE model did reasonably well (R2 = 0.76, SPE = 24%) at predicting the overall power demand profile for the week analyzed. Most of the error can be accounted for during the weekend period where temperatures and power demand were uncharacteristically low when compared to the dataset used to develop the UPDE.

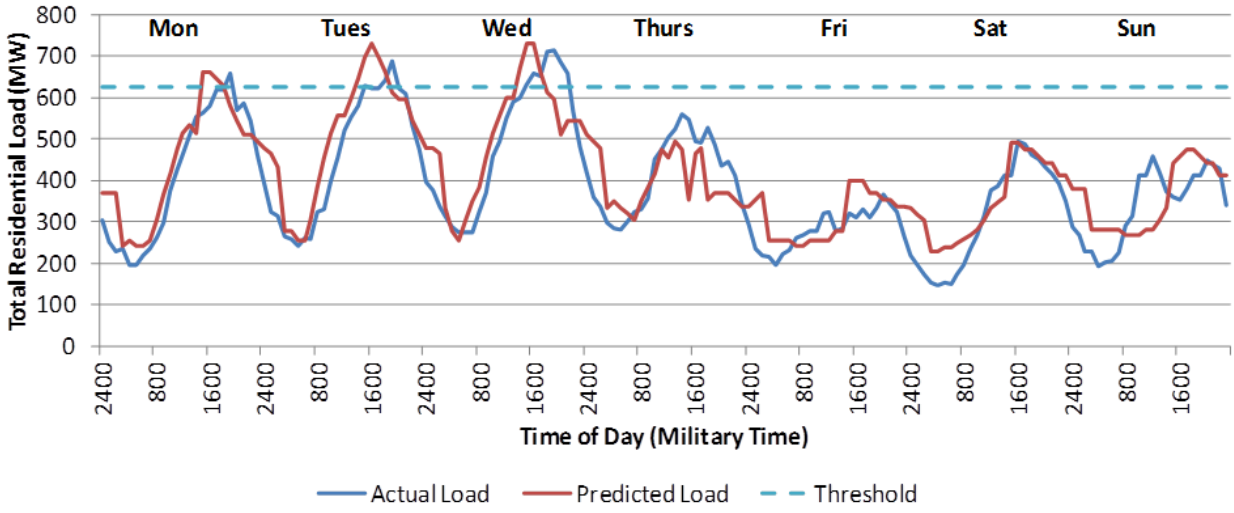

Figure 24 – Actual and Predicted Unmanaged Demand (1 Week, August 2009)

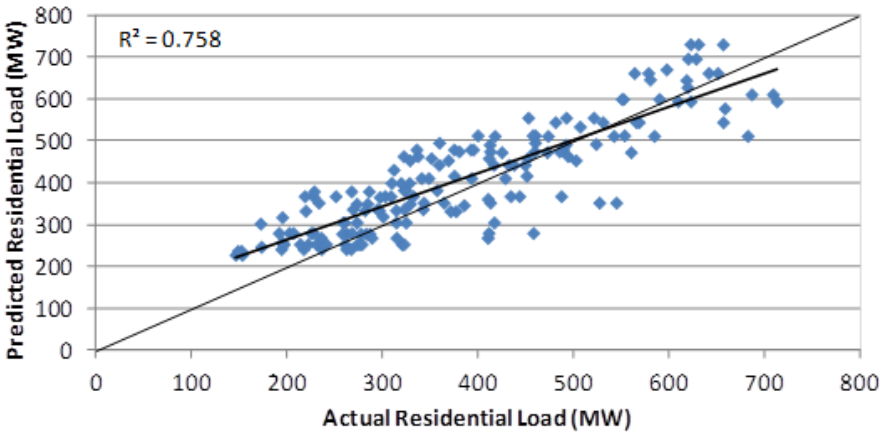

Figure 25 – Actual and Predicted Unmanaged Demand Residuals (1 Week, August 2009)

The unmanaged power demand MOEs listed below in Table 11 indicate the UPDE largely over-predicted the number of instances the objective threshold would be exceeded. Similar to June, this is likely due to the infrequency and level at which power demand actually exceeded the objective threshold. For instance, the number of times the objective threshold was exceeded for the week in August was less than three times the amount it was exceeded in July (34 versus 11). Additionally, the objective threshold was exceeded by an average of 14MW in July compared to only 2MW in August. With SPEs of 17.4% and 24.6% for the "Low Cycle" and "High Cycle" UPDE models respectively, peak power occurrences were much more difficult to predict in August given the objective threshold level.

Table 11 – MOEs for Unmanaged Power Demand (1 Week, August 2009)

MOE	Value
Peak Prediction Success Rate	45%
False Positive Rate	62%

9.6 MANAGED POWER DEMAND – AUGUST PERFORMANCE

Figure 26 below depicts the power demand observed for both actual and predicted loads for one week in August 2009 after load management was applied by the MPDE. It is evident from the graph that the MDPE reduced some of, but not all power demand exceeding the objective threshold for some intervals between Monday and Wednesday.

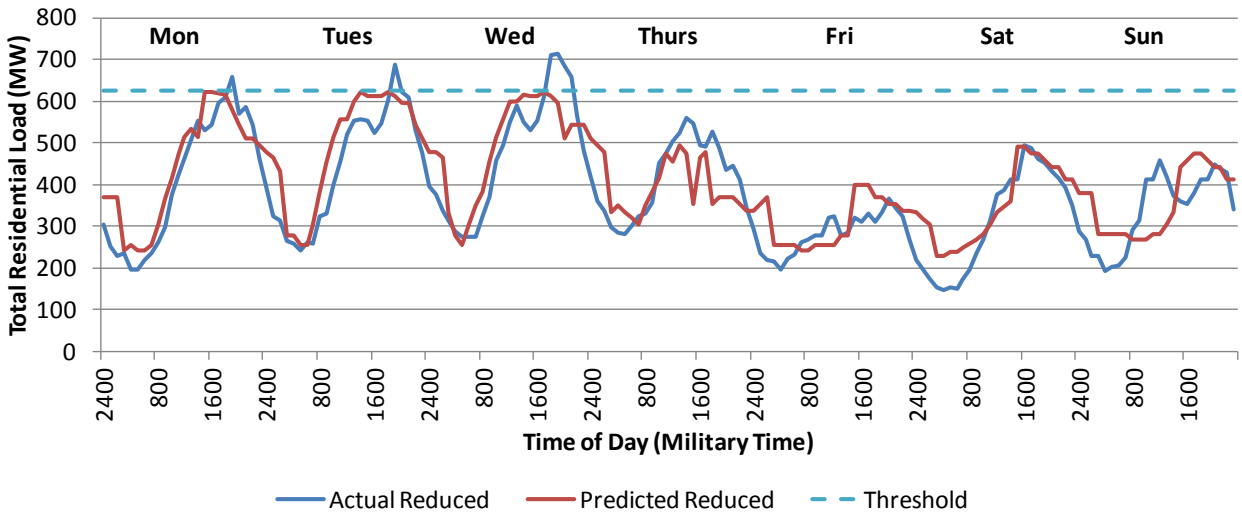

Figure 26 – Actual and Predicted Managed Demand (1 Week, August 2009)

Table 12 below provides a set of measures that better illustrate how well the LMD performed at managing the actual power demand for one week in August 2009.

Table 12 – MOEs for Managed Power Demand (1 Week, August 2009)

MOE	Value
% of Peak Power Occurrences Eliminated	45%
% of Peak Power Reduced	19%
% of Baseline Power Reduced	1.1%

Although the MPDE was able to completely eliminate all peak power demand occurrences predicted by the UPDE, it only removed 19% of the overall demand exceeding the objective threshold for the week in August analyzed. Additionally, load management employed by the MPDE negatively impacted 1.1% of the base power demand, primarily due to the high False Positive Rate illustrated in Table 11 above.

9.7 UNMANAGED POWER DEMAND – SEPTEMBER PERFORMANCE

Figure 27 below depicts the unmanaged demand observed for both actual and predicted values for one week in September 2009. From observation, it is clear that the objective threshold was rarely exceeded during this time period. Additionally, when the objective threshold was exceeded, it was only by small amounts (1.2MW average) when compared to the other three summer months. The predicted versus actual plot in Figure 28 indicates the UPDE models did well (R2 = 0.80, SPE = 21%) at predicting the overall power demand profile for the week analyzed. Most of the error can be accounted for during the weekend period where temperatures and power demand were uncharacteristically low when compared to the dataset used to develop the UPDE.

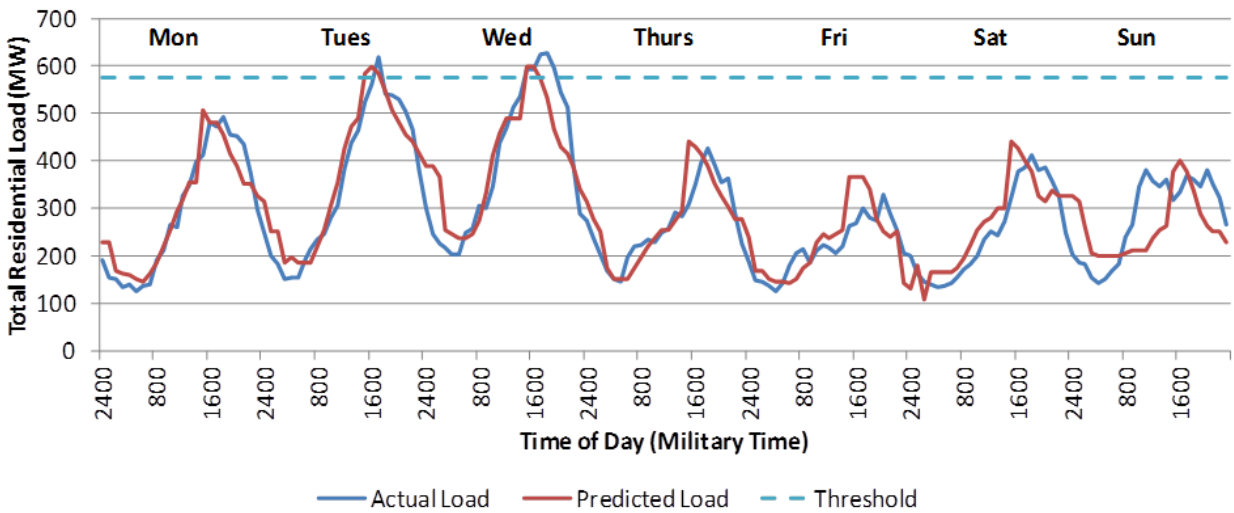

Figure 27 – Actual and Predicted Unmanaged Demand (1 Week, September 2009)

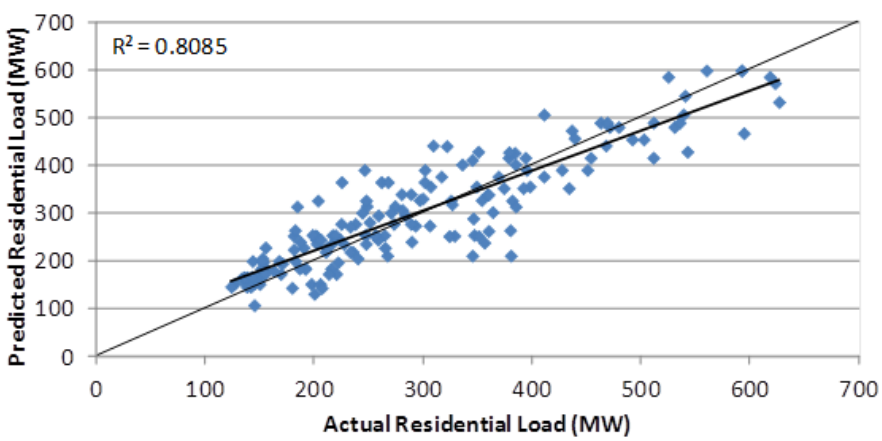

Figure 28 – Actual and Predicted Unmanaged Demand Residuals (1 Week, September 2009)

The unmanaged power demand MOEs listed below in Table 13 demonstrate that the UPDE was able to reasonably predict the number of instances the objective threshold was exceeded despite the relative infrequency of them occurring. However, nearly 40% of the peak power occurrences predicted by the UPDE were incorrectly identified. This is likely due to the infrequency and level at which power demand actually exceeded the objective threshold. For instance, the number of times the objective threshold was exceeded for the week in September was less than five times the amount it was exceeded in July (34 versus 6). Additionally, the objective threshold was exceeded by an average of 14MW in July compared to only 1.2MW in August. With SPEs of 17.4% and 24.6% for the "Low Cycle" and "High Cycle" UPDE models respectively, peak power occurrences are much more difficult to predict in August given the objective threshold level.

Table 13 – MOEs for Unmanaged Power Demand (1 Week, September 2009)

MOE	Value
Peak Prediction Success Rate	50%
False Positive Rate	40%

9.8 MANAGED POWER DEMAND – SEPTEMBER PERFORMANCE

Figure 29 below depicts the power demand observed for both actual and predicted loads for one week in September 2009 after load management was applied by the MPDE. It is evident from the graph that the MDPE reduced some of, but not all power demand exceeding the objective threshold for some intervals between Tuesday and Wednesday.

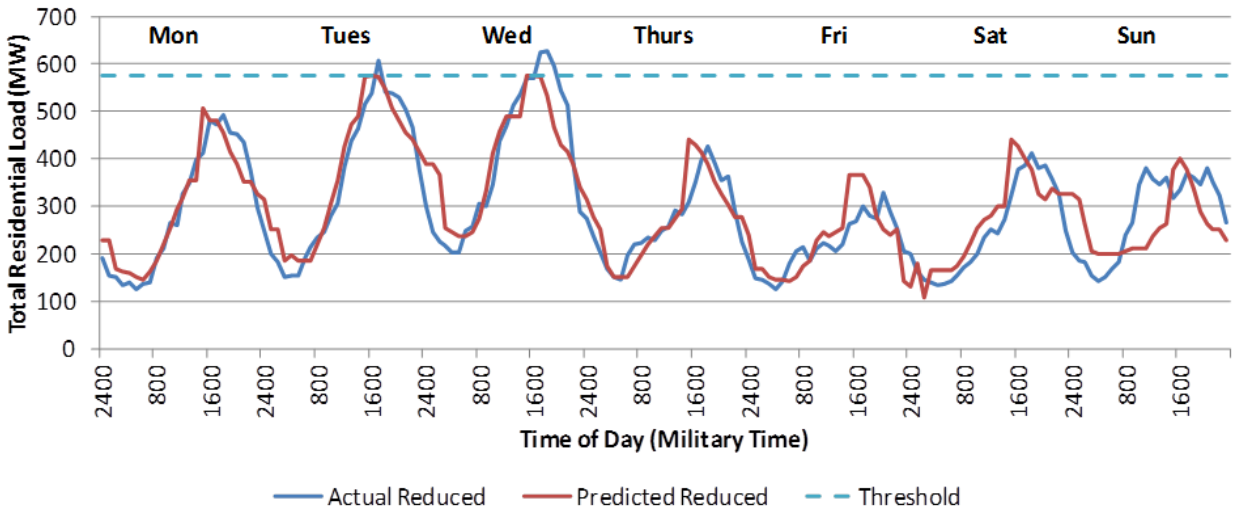

Figure 29 – Actual and Predicted Managed Demand (1 Week, September 2009)

Table 14 below provides a set of measures that better illustrate how well the LMD performed at managing the actual power demand for one week in September 2009.

Table 14 – MOEs for Managed Power Demand (1 Week, September 2009)

MOE	Value
% of Peak Power Occurrences Eliminated	33%
% of Peak Power Reduced	24%
% of Baseline Power Reduced	0.1%

The MPDE was able to eliminate some of the peak power demand occurrences predicted by the UPDE and a quarter of the overall demand exceeding the objective threshold for the week in September analyzed. Load management employed by the MPDE negatively impacted only 0.1% of the base power demand, minimally affecting NOVEC's overall sales for the week in September.

10 CUSTOMER CONVENIENCE RESULTS

The Residential Convenience Estimator (RCE), described in Section 8.3, was applied to the sample weeks of the summer months in order to evaluate the impact that the selected load management objectives might have on customer convenience. The results are presented in the figures below starting with July (Figure 30) and then proceeding with June (Figure 31), August (Figure 32) and September (Figure 33). This order matches the presentation of the monthly power management results from the previous section to aid comparing the results the two sections.

In each graph, the convenience value (green) is plotted against the percent of electricity demand reduced (blue). Convenience values are represented on the left vertical axis and electricity demand percent reduction values are on the right vertical axis. The horizontal axis is the time of day.

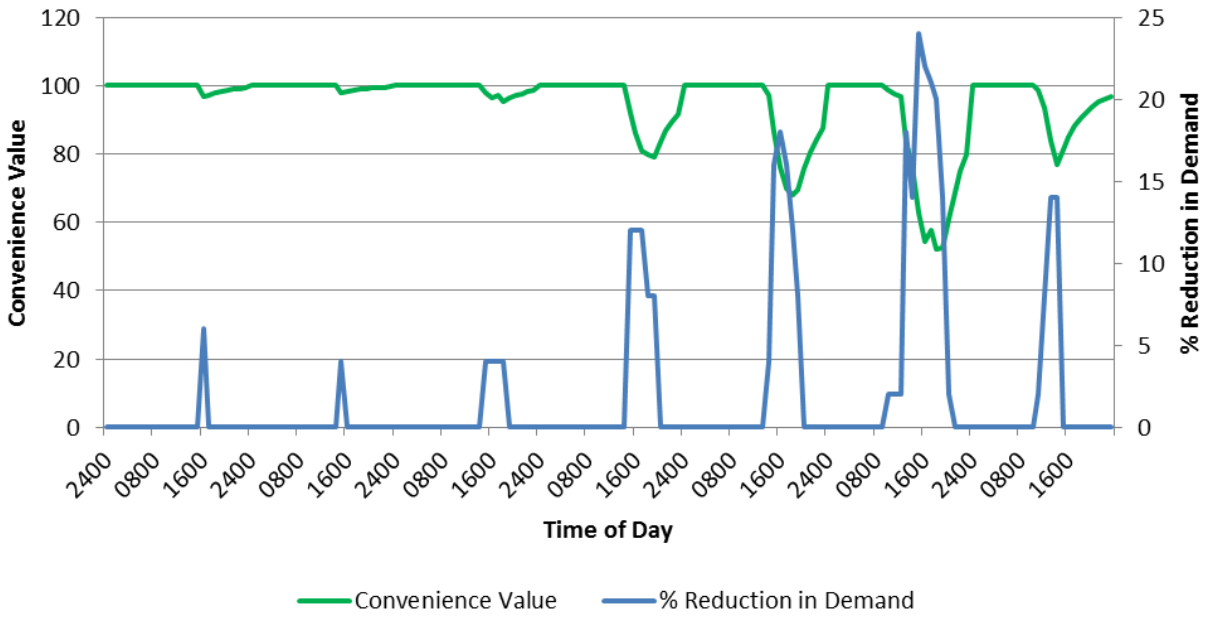

Figure 30 – Customer Convenience Values (1 Week, July 2009)

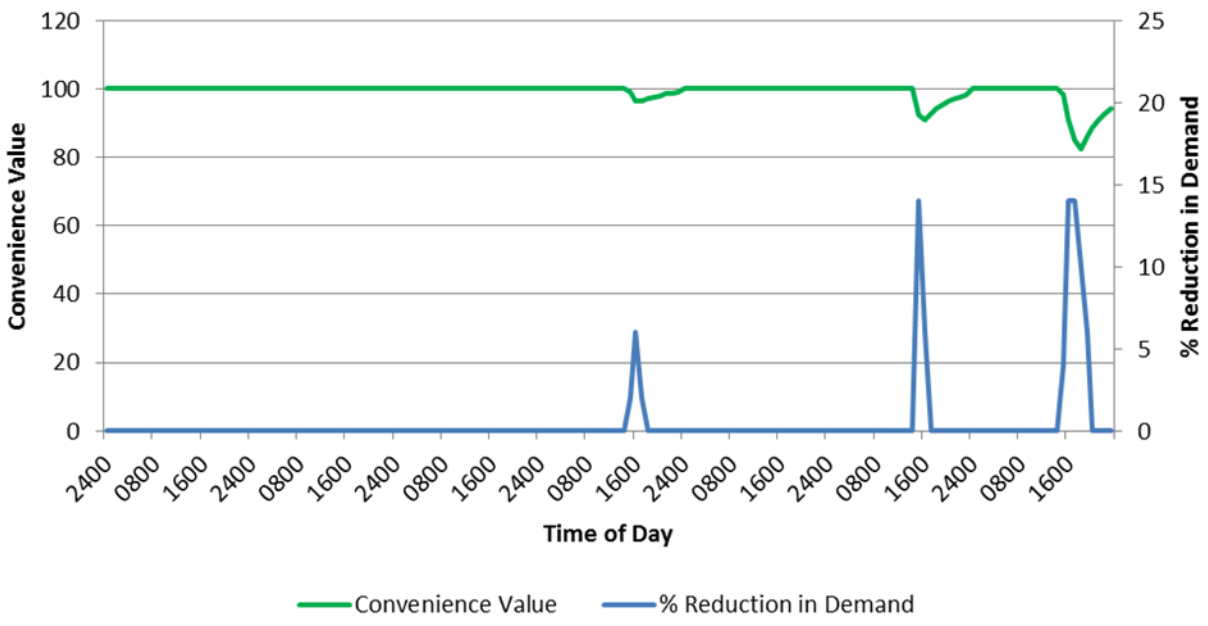

Figure 31 – Customer Convenience Values (1 Week, June 2009)

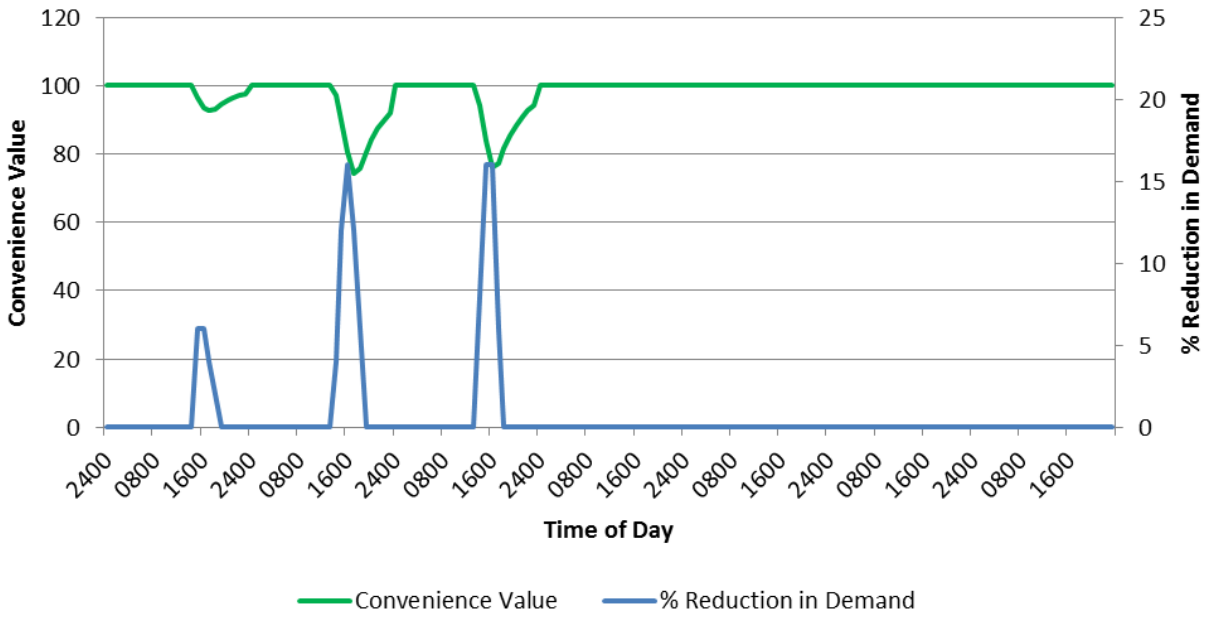

Figure 32 – Customer Convenience Values (1 Week, August 2009)

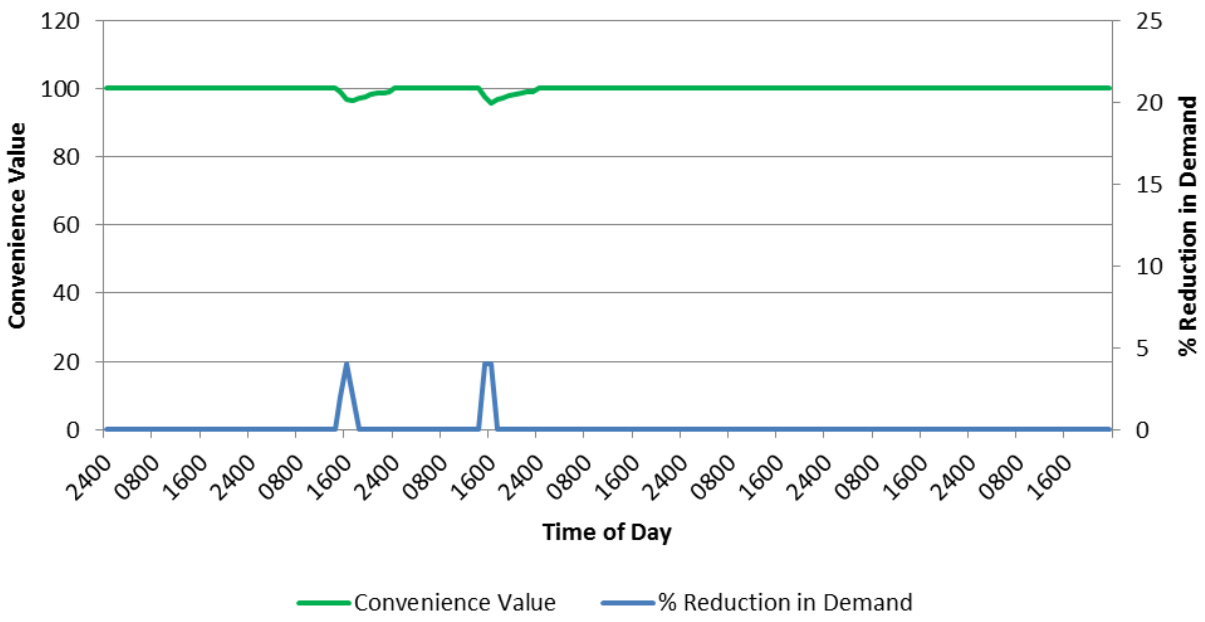

Figure 33 – Customer Convenience Values (1 Week, September 2009)

Neither June nor September required much in the way of load management according to our models so the impact on customer convenience was relatively small. Load management was higher for the week in August, with two cases where the convenience value dropped below 80. The week for July showed an even higher amount of load management and, as expected, this is reflected in generally lower convenience values. In one particularly extreme case, load management lasted for several hours and peaked at a nearly 25 percent demand reduction. The convenience values during this time hit a minimum of just over 50, indicating a potentially large number of unsatisfied customers.

11 SENSITIVITY ANALYSIS

A sensitivity analysis was performed to examine how changing the number of controlled blocks will affect the LMS. NOVEC is very interested knowing the ideal number of blocks because the LMS manages power by turning on and off blocks of houses instead of individual houses. Changing the number of blocks changes the number of houses within each block. In other words, increasing number of blocks decreases number of houses within each block. Increasing the number of blocks also has the impact of reducing the amount of power that each block consumes. These two relationships form the basis of the sensitivity analysis.

To perform this analysis, the model was tested with five, seven, ten, fifteen, and twenty blocks. Each of these block configurations was run through four days' worth of historical data, one day for each of the four summer months.

The first aspect of the analysis examines the average number of turnoffs experienced by each block during a day. This showed that as the number of blocks increased, the number of average turnoffs decreased. This is due to the fact that there are now more options of blocks to turn off. This becomes obvious by considering a simple example. If power is trying to be reduced by a small amount and there is only one block, then that block must be still be turned off at all times. If, on the other hand, there exist ten blocks of houses, then one or two blocks may be turned off to reach the small reduction. This leaves the remaining nine or ten of the blocks on.

This relationship is shown in Figure 34 below. As can be seen, the line is not strictly decreasing. The average turnoffs per day using ten blocks are actually higher than the average with seven blocks. This is due to border cases of power reduction. Border cases are defined as those instances when an increase in number of blocks causes more blocks to be turned off to reach a reduction threshold.

Another example can be used to understand this situation. Take the example of having a system demanding seven units of power and there is a need to reduce power by one unit. Now, if the system contains seven blocks, each block consumes one unit of power and only one must be turned off to reach the threshold. But, if there are ten blocks, each block now consumes less than one unit of power and two blocks must be turned off to meet the reduction goal. This doubles the amount of blocks to be turned off whenever that power reduction is needed. Since, there are not twice as many blocks; blocks will have to be turned off more often.

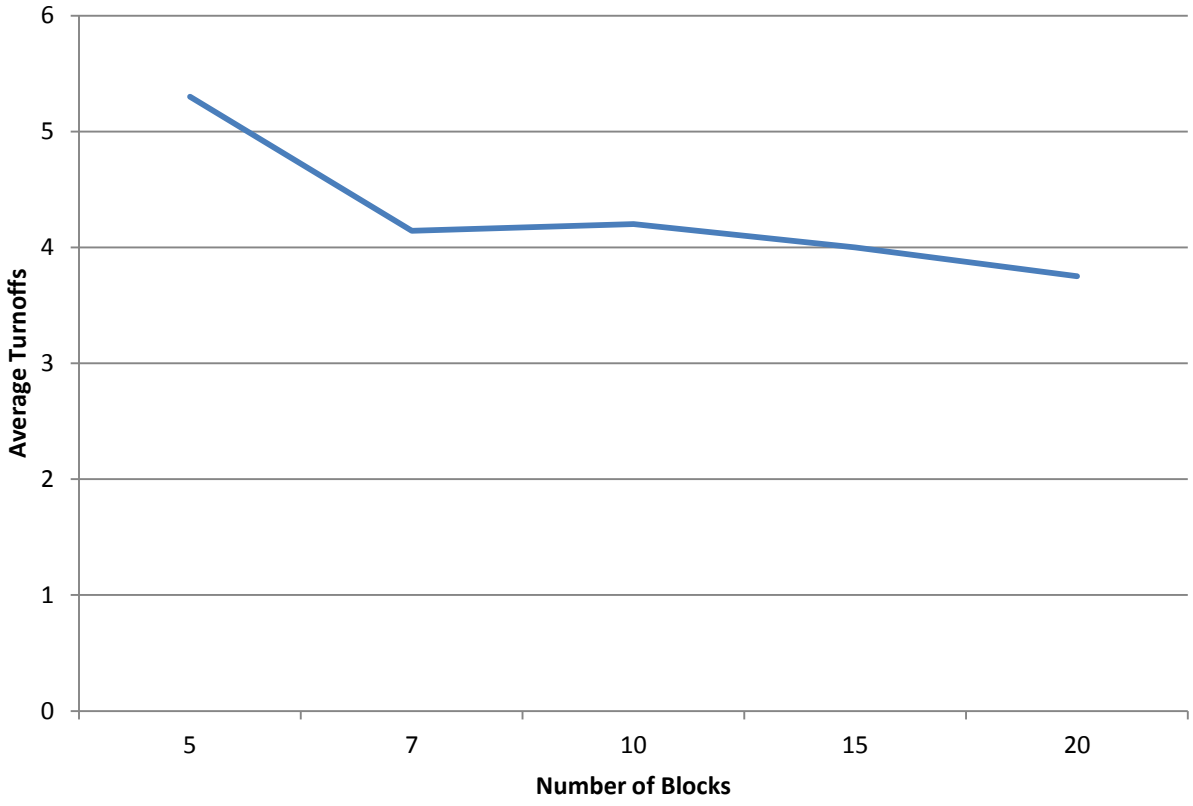

Figure 34 – Average Turnoffs Versus Number of Blocks

The next section of the sensitivity analysis concerns the relationship of number of blocks to amount of power consumed by each block. Increasing the number of blocks decreases the power each block consumes assuming a fixed total power consumed by all residences. Thus, turning off a block reduces the total power in a smaller increment which allows more precise control of the power reductions.

To examine the impacts of more precise control, an ideal solution to the model was established. This ideal solution represents the case where whenever the predicted power exceeds the demand objective threshold, the value of the threshold is substituted in for the power. This approach allows the model to guarantee that NOVEC's load always stays below the threshold, but also minimizes the chance of reducing power unnecessarily. Therefore, the question for this analysis becomes, how close will the model get to the ideal solution by changing the number of blocks?

As can be seen in Figure 35 below, increasing the number of blocks generally achieves more advantageous solutions. In the graph, the influence of border cases is again seen. This influence arises due to the fact that even though the blocks have less power associated to them, when more

are introduced, the difference is not significant enough to make up for the doubling of the turnoffs.

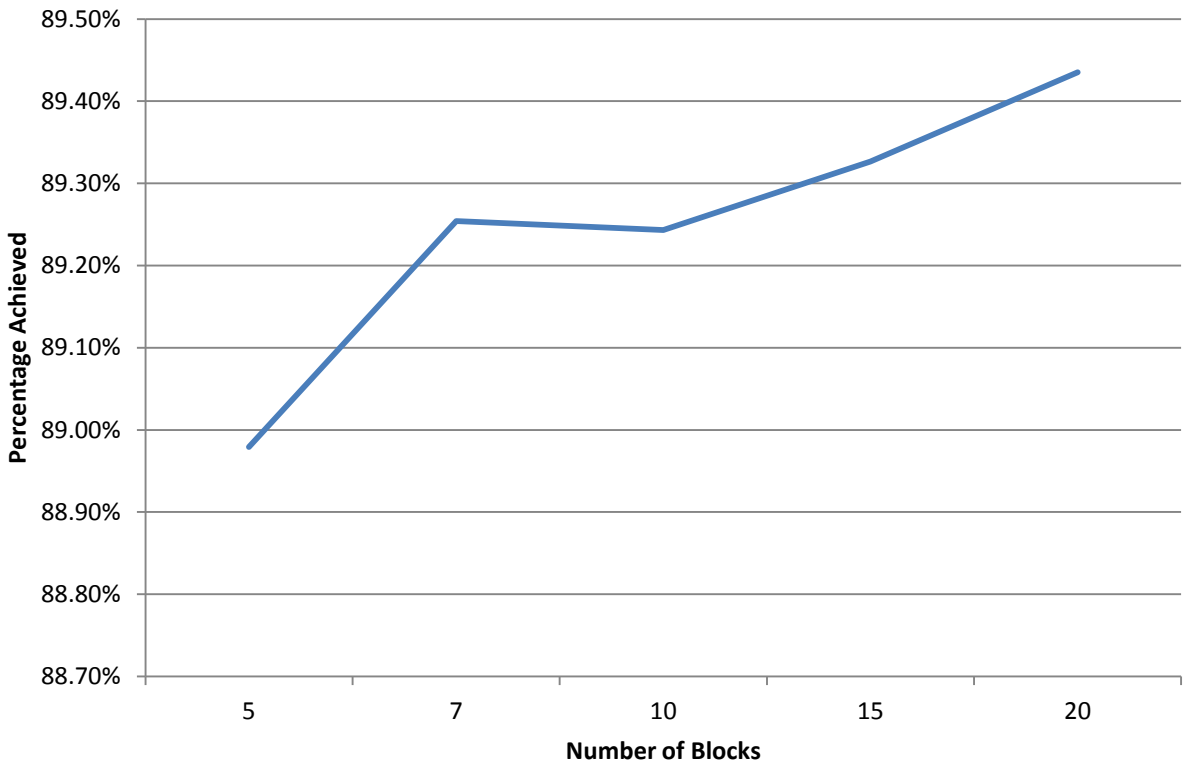

Figure 35 – Best Possible Solution Achievement

As is shown by these two areas of analysis, increasing the number of blocks improves MPDE performance. This conclusion is more clearly seen when the analysis examines the entire summer month period (120 days). The difference between using five blocks and twenty blocks amounts to 186 turnoffs throughout the summer. Also, the one percent difference in the second phase of the block analysis becomes significant when examined in the large quantities. Therefore, it is shown that in general increasing the number of blocks will improve the effectiveness of the MPDE.

12 EVALUATIONS

12.1 POWER MANAGEMENT EVALUATION

The LMD performs adequately in months where the peak power often exceeds the objective threshold and the excess is a large amount. The plots of LMD performance for the month of July exemplify these conditions.

Conversely, LMD performance suffers in months where the peak power rarely exceeds the objective threshold and/or the peak power exceeds the threshold by only small amounts. The plots of LMD performance for the month of September exemplify these conditions. Unless the objective threshold is lowered, load management might not be necessary for these conditions.

12.2 CONVENIENCE EVALUATION

In general, these results show that the convenience value tends to stay at 80 or above when load management is kept to a 15 percent reduction or below. More aggressive policies, like the one in the July example, run the risk of potentially reducing satisfaction for many customers. It must be noted this evaluation relies on a simple temperature formula to estimate customer convenience. More detailed study is needed to better determine the conditions that cause residential customers to perceive diminished convenience when their air conditioning is prevented from running due to load management action. It is possible that the upper limit on the objective demand reduction threshold is substantially lower than the 15% observed in the convenience results.

12.3 BLOCK SENSITIVITY EVALUATION

Increasing the number of controlled blocks (decreasing the block size) has two benefits. The first benefit is that more blocks provide more possible solutions to achieving the objective demand reduction of the peak load. This reduces the probability that a given residence will experience multiple load management actions within a given day. The net effect will be to maintain customer convenience during the portions of the day that load management is in effect.

The second benefit is that more controlled blocks increases the ability of the load management to control the peak load to be closer to the objective threshold. The net effect is that the demand will be maintained at levels that are closer to the base power levels being supplied under long term contract and hence lower cost.

13 RECOMMENDATIONS

The feasibility of improving the operation of the NOVEC Load Management System has been successfully demonstrated as evidenced by the following:

- Peak demand predictions using energy demand statistics management and in-situ temperature measurements;
- Computation of block load management schedule using predicted peak and reduction thresholds as inputs to a constraint model;
- Estimates of customer convenience levels as a function of load management schedule for current temperature

It is recommended that the research should continue to realize the potential benefits of the demonstrated concepts. Such research should first broaden out the knowledgebase of load management phenomena as described in Section 14 below. Secondly, the broadened foundation of knowledge should be utilized to develop a realizable system design concept for the Load Management Director. The LMD conceptual system design should then be used to better understand the costs and benefits of the LMD in sufficient detail to allow NOVEC to make a decision to acquire and operate the LMD.

14 FUTURE WORK

The realization of the Load Management Director and its integration with NOVEC's current Load Management System is an undertaking requiring a more thorough understanding and modeling of the influences that drive peak demands for electrical energy. The LMD prototype that resulted from this project examined just the core aspect of these influences namely summertime temperatures. As such, the following future work is seen as a way to extend the knowledgebase to become a foundation for a realizable design.

- Extend peak demand estimation model to work with winter heating months
- Investigate the sensitivity of LMD operation to different blocks presenting different energy demands
- Refine residential convenience estimation to include other factors such as time of day, hot water demand

- Adapt load management schedule computation to include convenience estimates to
  - Increase the likelihood that high levels of customer convenience are maintained
  - Allow automatic evaluation of alternative peak demand reduction objectives

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16 APPENDICES

16.1 APPENDIX A – PROJECT MANAGEMENT

16.1.1 Project Planning

To more efficiently manage project assignments, primary tasks were broken down into a high-level Work Breakdown Structure (WBS) depicted in Figure 36. Project tasks were aligned under four main categories to include Project Management and Reporting, Research, Modeling and Simulation, and Analysis and Recommendations. Project Management and Reporting included activities such as schedule monitoring and control and deliverable development (e.g. proposal, final report and presentation). The Research task involved the collection of background data to better understand the problem and raw data to be used as the basis for model development. Modeling and Simulation contained all activities related to the design and development of the Load Management Director (LMD). Finally, Analysis and Recommendations concerned tasks that dealt with model testing against a set of pre-determined scenarios and analysis of the results.

The schedule shown below in Figure 37 provides further detail regarding tasks and milestones that were critical to the project's success, to include task durations and start/stop dates. Care was taken to avoid developing a schedule that would place the majority of tasks on the critical path (overly sequential), or one which would overburden the team for any given period of time (too many concurrent tasks). Using a mix of both approaches allowed for some schedule flexibility while ensuring team members were consistently assigned to work approximately 10 hours a week (+/- 10%) to complete the project within time, performance, and effort expectations.

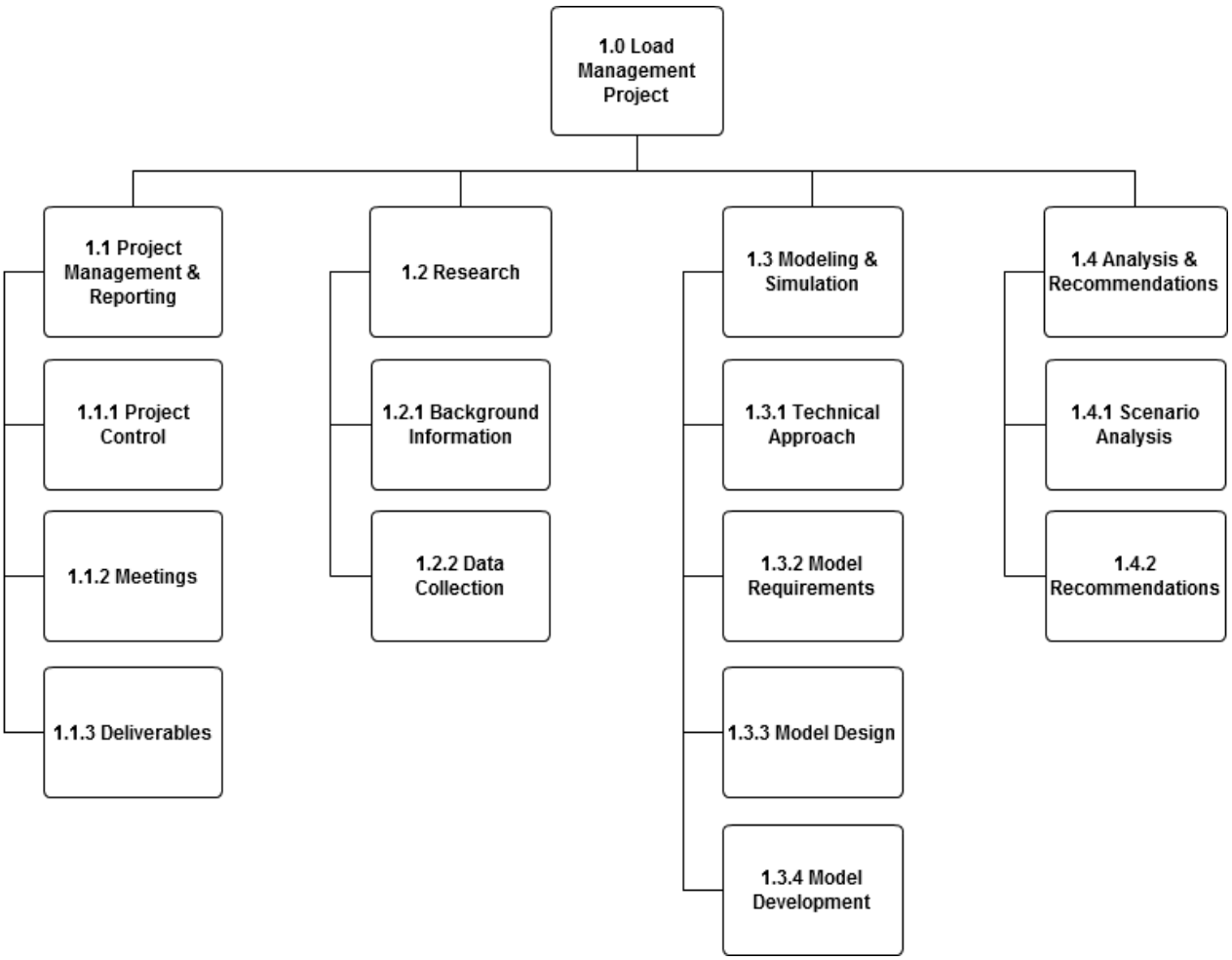

Figure 36 – Project WBS

ID	WBS	Task Name	Duration	Start
1	**1**	**Load Management Project**	**76 days**	**Thu 1/26/1**
2	**1.1**	**Project Management & Reportir**	**76 days**	**Thu 1/26/1**
3	**1.1.1**	**Project Control**	**68 days**	**Fri 2/3/12**
4	1.1.1.1	Activity Definition & Sequenc	7 days	Fri 2/3/12
5	1.1.1.2	Resource Loading	6 days	Tue 2/14/12
6	1.1.1.3	Schedule Control	55 days	Wed 2/22/1
7	**1.1.2**	**Meetings**	**65 days**	**Mon 2/6/1**
8	**1.1.2.1**	**Team Meetings**	**65 days**	**Mon 2/6/1**
23	**1.1.2.2**	**Sponsor Meetings**	**45 days**	**Fri 2/10/12**
24	1.1.2.2.	Sponsor Meetings 1	0 days	Fri 2/10/12
25	1.1.2.2.	Sponsor Meetings 2	0 days	Fri 3/9/12
26	1.1.2.2.	Sponsor Meetings 3	0 days	Fri 4/13/12
27	**1.1.3**	**Deliverables**	**76 days**	**Thu 1/26/1**
28	**1.1.3.1**	**Project Proposal**	**15 days**	**Thu 1/26/1**
29	1.1.3.1.	Preliminary Project Definiti	6 days	Thu 1/26/12
30	1.1.3.1.	Project Definition & Scope	5 days	Fri 2/3/12
31	1.1.3.1.	Final Proposal	4 days	Fri 2/10/12
32	1.1.3.1.	Final Proposal Complete	0 days	Thu 2/16/12
33	**1.1.3.2**	**Website**	**64 days**	**Mon 2/13/**
34	1.1.3.2.	Draft Webpage	5 days	Mon 2/13/1
35	1.1.3.2.	Maintain/Update Webpage	59 days	Mon 2/20/1
36	1.1.3.2.	Webpage Complete	0 days	Fri 5/11/12
37	**1.1.3.3**	**Progress Reports**	**16 days**	**Thu 3/8/12**
38	1.1.3.3.	Progress Report 1	1 day	Thu 3/8/12
39	1.1.3.3.	Progress Report 2	1 day	Thu 3/29/12
40	**1.1.3.4**	**Final Report**	**29 days**	**Mon 4/2/1**
41	1.1.3.4.	Report Template	5 days	Mon 4/2/12
42	1.1.3.4.	Draft Document	10 days	Mon 4/9/12
43	1.1.3.4.	Redline Document	10 days	Mon 4/23/1
44	1.1.3.4.	Finalize Document	4 days	Mon 5/7/12
45	1.1.3.4.	Final Report Complete	0 days	Fri 5/11/12
46	**1.1.3.5**	**Final Presentation**	**29 days**	**Mon 4/2/1**
47	1.1.3.5.	Presentation Template	5 days	Mon 4/2/12
48	1.1.3.5.	Draft Presentation	10 days	Mon 4/9/12
49	1.1.3.5.	Redline Presentation	10 days	Mon 4/23/1
50	1.1.3.5.	Finalize Presentation	4 days	Mon 5/7/12
51	1.1.3.5.	Final Presentation Complet	0 days	Fri 5/11/12
52	**1.2**	**Research**	**20 days**	**Mon 1/30/**
53	**1.2.1**	**Background Information**	**10 days**	**Mon 1/30/**
54	1.2.1.1	NOVEC/PJM Website Resear	10 days	Mon 1/30/1
55	1.2.1.2	Electricity Market Research	10 days	Mon 1/30/1
56	**1.2.2**	**Data Collection**	**10 days**	**Mon 2/13/**
57	1.2.2.1	List of Data Needs from Spon	5 days	Mon 2/13/1
58	1.2.2.2	Data Organization/Normaliza	5 days	Mon 2/20/1
59	**1.3**	**Modeling & Simulation**	**37 days**	**Thu 2/2/12**
60	**1.3.1**	**Technical Approach**	**16 days**	**Fri 2/3/12**
61	1.3.1.1	CONOPS Definition	10 days	Fri 2/3/12
62	1.3.1.2	Modeling Tools & Techniques Selection	6 days	Fri 2/17/12
63	**1.3.2**	**Model Requirements**	**17 days**	**Thu 2/2/12**
64	1.3.2.1	Needs Analysis	7 days	Thu 2/2/12
65	1.3.2.2	Preliminary Requirements	5 days	Mon 2/13/1
66	1.3.2.3	Incorporate Feedback From Sponsor	5 days	Mon 2/20/12
67	1.3.2.4	Model Requirements Comple	0 days	Sun 2/26/12
68	**1.3.3**	**Model Design**	**25 days**	**Mon 2/13/**
69	1.3.3.1	Functional Decomposition	25 days	Mon 2/13/1
70	1.3.3.2	UML Diagrams	25 days	Mon 2/13/1
71	**1.3.4**	**Model Development**	**20 days**	**Mon 2/27/**
72	1.3.4.1	Unmanaged Peak Demand Estimator	15 days	Mon 2/27/12
73	1.3.4.2	Managed Peak Demand Estin	5 days	Mon 3/19/1
74	1.3.4.3	Load Management Policy Sel	5 days	Mon 3/19/1
75	**1.4**	**Analysis & Recommendations**	**24 days**	**Mon 3/19/**
76	**1.4.1**	**Scenario Analysis**	**20 days**	**Mon 3/19/**
77	1.4.1.1	Define Baseline Scenario(s) & Assumptions	5 days	Mon 3/19/12
78	1.4.1.2	Conduct Baseline Analysis	5 days	Mon 3/26/1
79	1.4.1.3	Model and Output V&V	5 days	Mon 4/2/12
80	1.4.1.4	Sensitivity Analysis	5 days	Mon 4/9/12
81	**1.4.2**	**Recommendations**	**9 days**	**Mon 4/9/1**
82	1.4.2.1	Results Documentations	9 days	Mon 4/9/12
83	1.4.2.2	Recommendations Complete	0 days	Fri 4/20/12

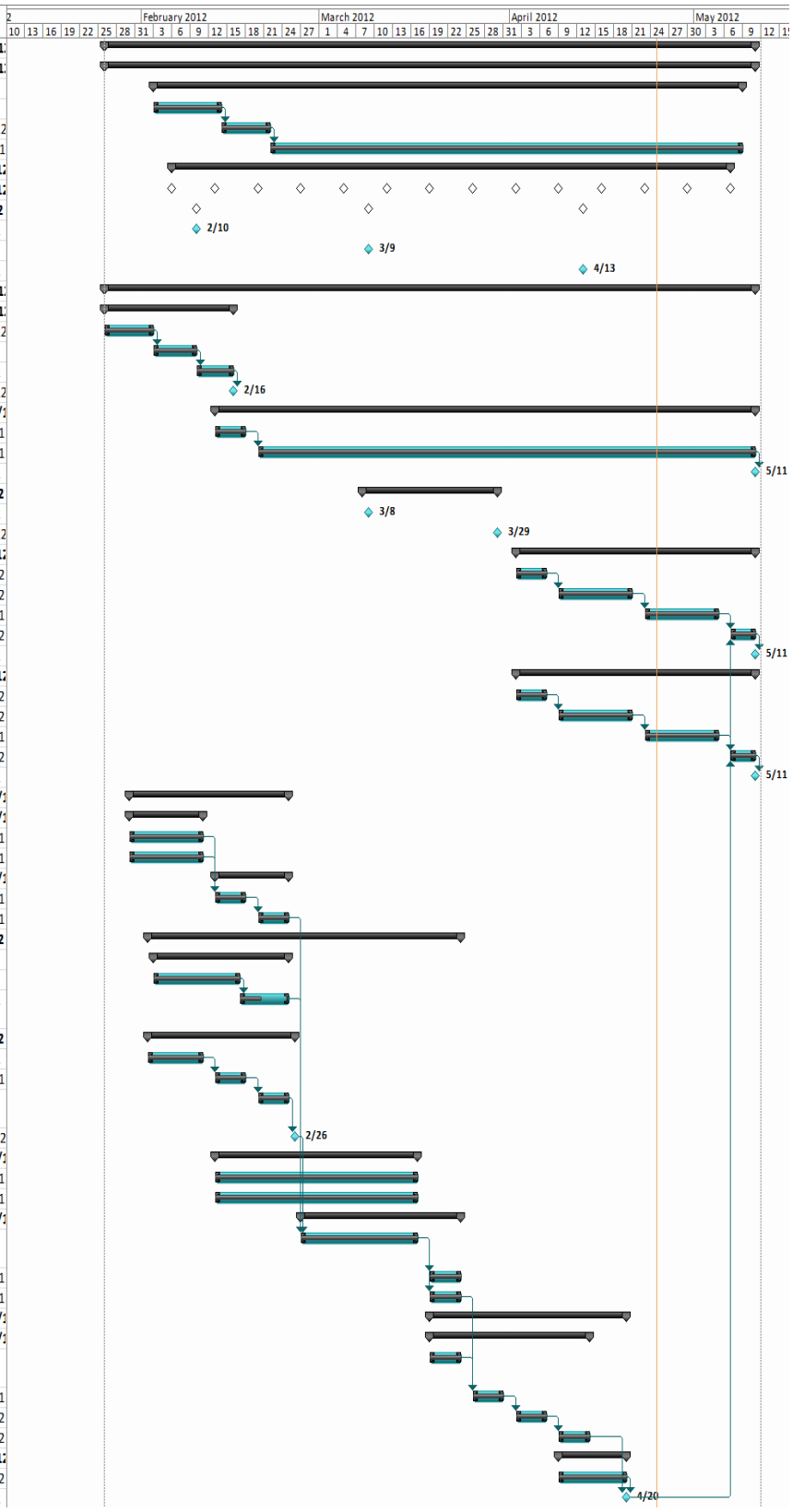

Figure 37 – Project Schedule

16.1.2 Project Execution / Earned Value Management (EVM)

EMG tracked project progress starting on Jan 30th up to successful completion on May 10th. Earned Value (EV) and Actual Cost (AC) were tracked on a weekly basis and updated every Saturday. Microsoft Project was used to develop the master schedule and perform EVM. Hours worked were used instead of cost as the EV metric since there was no actual monetary project. The Budget at Completion (BAC) was estimated to be 598 hours given the methods discussed above.

The project's progress over the course of the semester and final results are depicted below in Figure 38 and Table 15. Through the first 4 weeks, the project tracked very closely to the planned schedule. However, there was some schedule slippage starting in Week 4 due to the delayed start and completion of a task involving the collection and normalization of data necessary for the development of the Load Management Director (LMD).

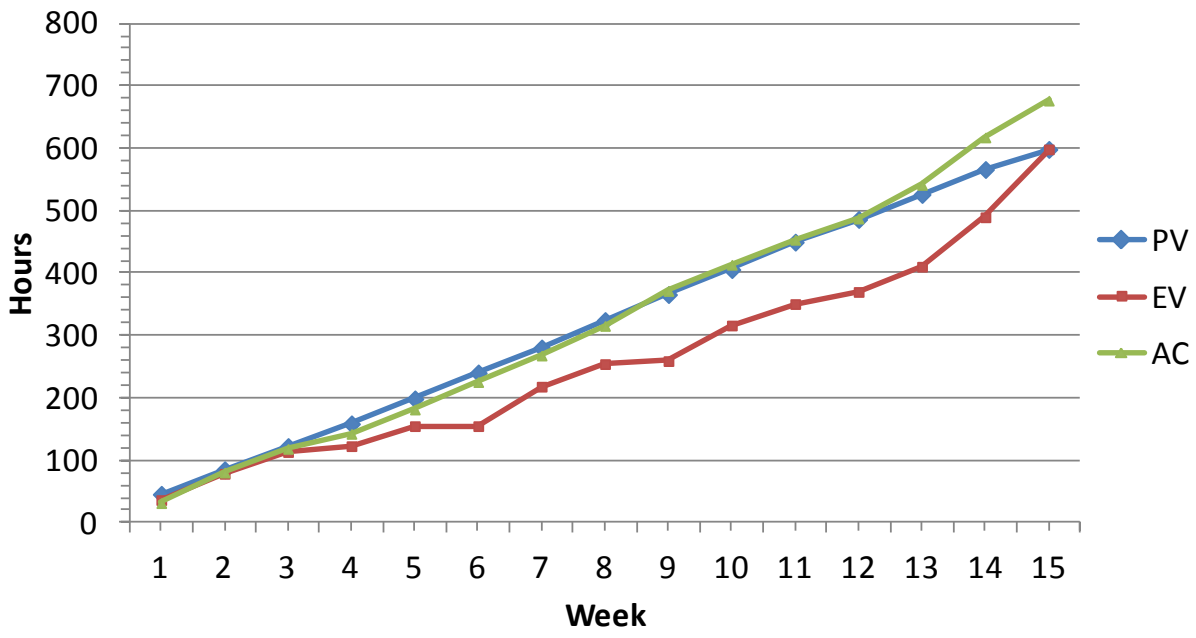

Figure 38 – Earned Value Performance

Table 15 – EVM Metrics

Metric	Value
SPI	1.00
CPI	0.88
BAC	598
CAC	676

The slippage was primarily due to an underestimation of the effort needed, which was driven by a larger than expected quantity of data requiring formatting and standardization. Additionally, the data collection and normalization task was on the critical path and caused the delay of subsequent model development activities.

In an attempt to recover schedule, later tasks that were originally scheduled to be sequential were restructured to reflect a more concurrent approach. It is evident from Figure 38 that this new approach did not produce positive results until approximately Week 13 when model development, testing and verification and validation were completed. Getting the project back on schedule required team members to work in excess of their budgeted hours for the final three weeks of the semester. This resulted in a final cost surpassing the budgeted amount by 13%.

16.2 APPENDIX B – GLOSSARY

- **Standard Error (SE)**: Refers to an estimate of the standard deviation of the overall regression or the coefficients that are found within the regression
- **Standard Percent Error (SPE)**: SE expressed as a percentage
- **Bias**: Difference between an estimator's expectation and the true value of the parameter being estimated
- **R^2**: Provides a measure of how well future outcomes are likely to be predicted by the regression model; Measures the goodness of fit with a scale from 0-1 with 1 representing a "perfect" fit
- **T-Statistic**: Ratio of the departure of an estimated parameter from its notional value and its standard error (regression coefficient divided by its respective standard error)
- **P-Value**: Indicates how likely it is that the coefficient for that independent variable emerged by chance and <u>does not</u> describe a real relationship (e.g. A P-value of .05 means that there is a 5% chance that the relationship emerged randomly and a 95% that it is real)