

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

Electric Management Group (EMG)

Alex Kozera

Timothy Lohr

Timothy McInerney

Anthony Pane



# Agenda

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# Introduction

# Background

Other utilities generate and transmit electricity

Power generation plant

Other Utilities

PJM brokers purchase agreements between generators and resellers of electricity

Purchase agreements



NOVEC distributes electricity using its own network

Commercial Customers

NOVEC sells electricity to commercial and residential customers

Residential Customers

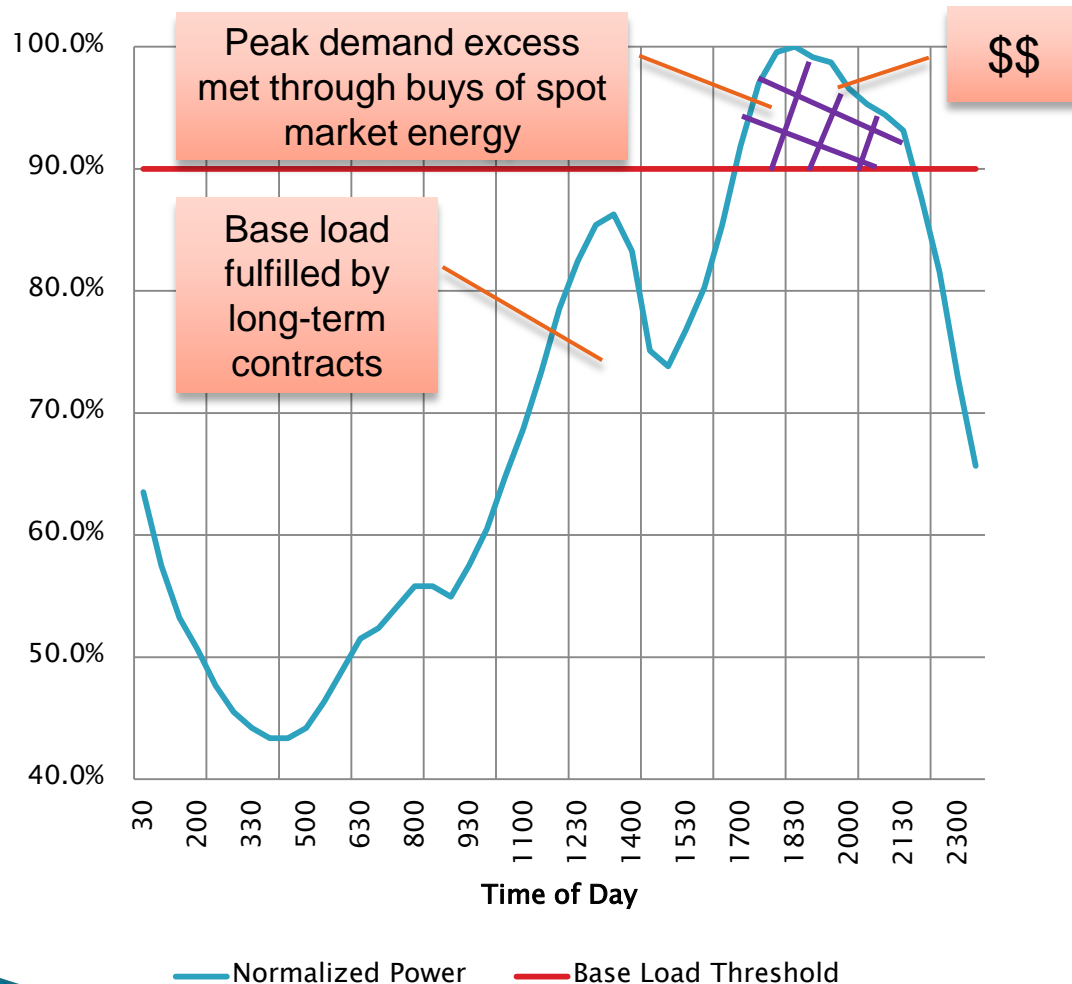
43,000 R/C load management switches installed

NOVEC buys electricity via PJM marketplace

Long-term & spot market energy purchases



# Problem Statement



- ▶ Spot market prices are expensive and volatile
- ▶ NOVEC must reserve generation capacity for worse case peak demand
- ▶ Demand peaks drive up costs to customers
- ▶ **How can the operation of load management system be improved?**
  - To maximally reduce peak demand
  - That improves the realized cost savings for NOVEC customers
  - While maintaining customer satisfaction

# Scope

- ▶ Develop load management control algorithms and utilization policies
  - More consistently reduce peak energy demand
  - Maintain customer satisfaction with NOVEC's service
- ▶ Demonstrate effectiveness of algorithms and policies
  - Create Load Management Director (LMD) prototype computer model
  - Assess LMD prototype using historical data sets of power demand and weather data provided by NOVEC
- ▶ Deliverables
  - Technical report that describes the research approach, the experiment design, obtained results, and conclusions
  - Developed simulations and load management director policies

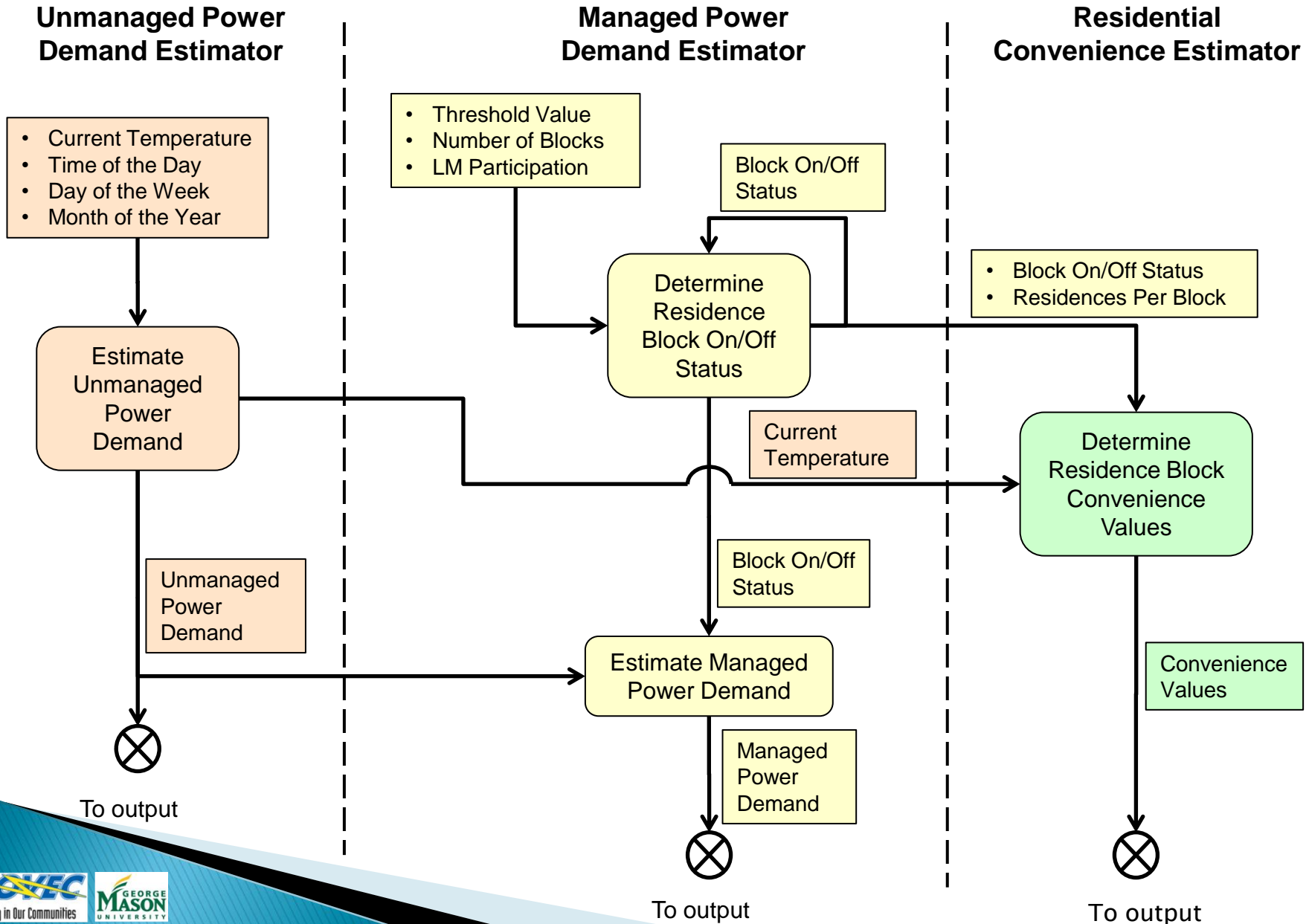


# Technical Requirements

- ▶ The Load Management Director (LMD) shall provide managed peak demand estimates every 15 minutes
  - Matches NOVEC power recording periodicity
- ▶ The LMD shall use temperature measurements for NOVEC's residential customer locales
  - NOVEC observations indicate power increases with outside temperature
  - Dulles airport temperature readings suffice for service region

Technical requirements developed with sponsor participation using series of meetings, written proposals, and teleconferences.

# LMD Processing Architecture





# Algorithm Descriptions

# Unmanaged Power Demand Estimator (UPDE): Methodology

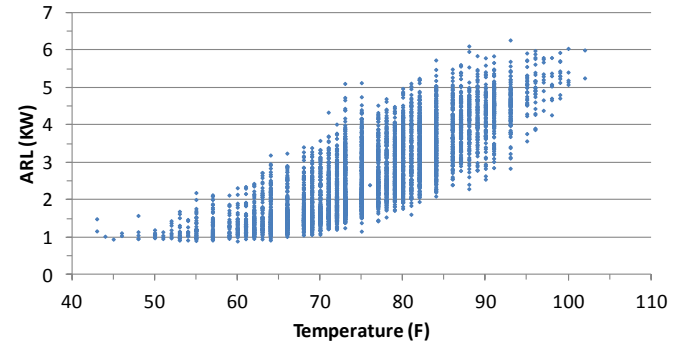
- ▶ Regression analysis used to develop parametric equation for predicting power demand
- ▶ Multiple drivers considered
  - **Temperature**, humidity, **time of day**, **month** and **day of the week**
- ▶ Many model types analyzed
  - **Ordinary Least Squares (OLS)**, Percent Least Squares, Generalized Least Squares
  - Regression Types Analyzed: **Polynomial ( $y = a+bx+cx^2$ )** , Power ( $y = ax^b$ ), Exponential ( $y=ae^{xb}$ )
- ▶ Stepwise Regression Approach
  - Implemented both forward and backward elimination techniques
    - Variables are inserted (forward) or removed (backward) until an appropriate regression is found

# UPDE: The Dataset and Underlying Relationships

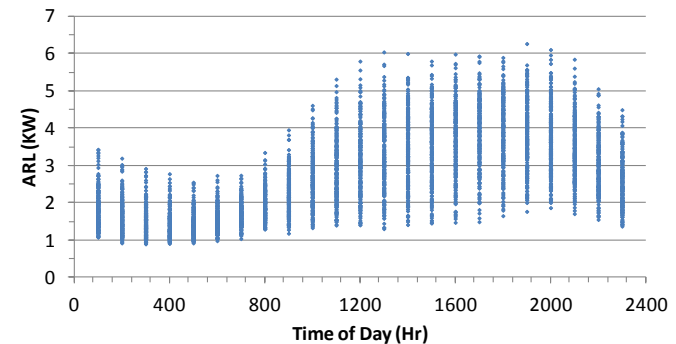
- ▶ The Dataset
  - NOVEC historical data from 2010 and 2011
  - Summer months (June-September)
  - Power readings from approximately 250 customer accounts for 15 minute intervals
  - Average Residential Load (ARL) used as the response variable
  - SQL Server and Excel used to normalize and format the raw data
- ▶ Underlying Relationships with ARL
  - Clear, positive correlation with temperature
  - Periodic relationship with time of day
  - Minimal correlation with humidity

Temperature possesses the strongest relationship with ARL

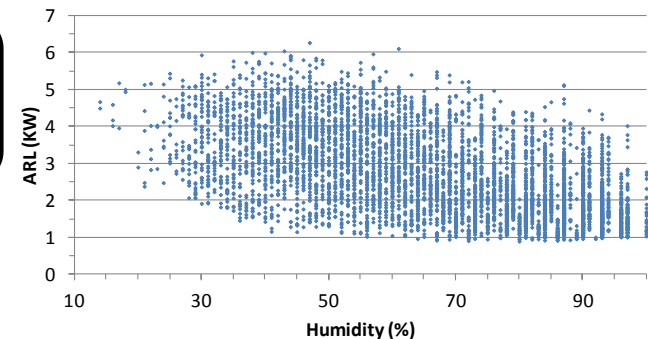
ARL vs. Temperature



ARL vs. Time of Day

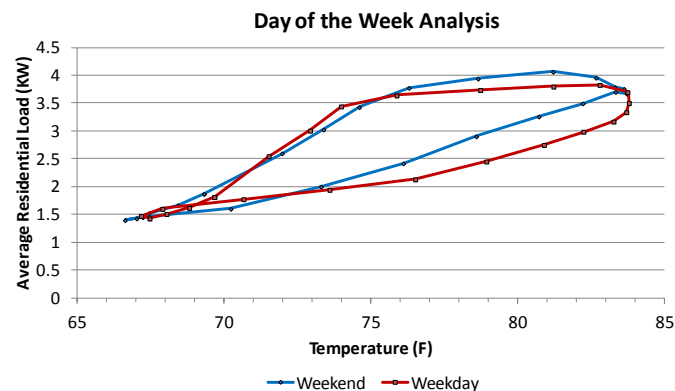
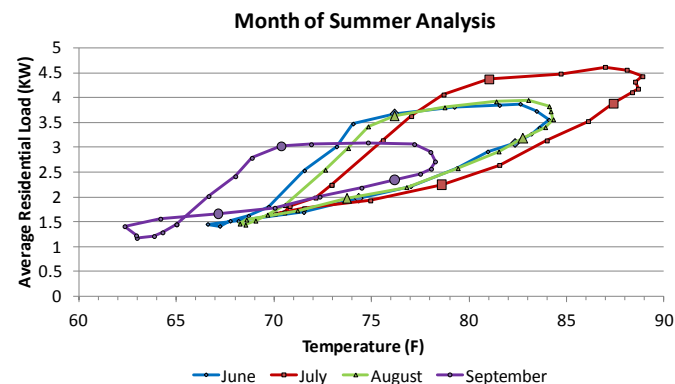
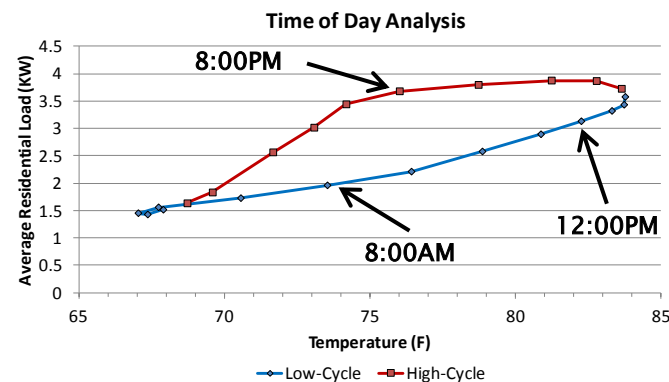


ARL vs. Humidity



# UPDE: ARL Drivers

- ▶ Time of Day
  - Relationship between ARL and temperature is bimodal and depends on the time of day
  - Drives the development of 2 distinct regression models: Low Cycle / High Cycle
- ▶ Month of Summer
  - June and August follow a similar load pattern throughout the day
  - Average temperature for the same time of day is generally higher during July and lower during September when compared to June and August
- ▶ Day of the Week
  - On average, the ARL is higher during the weekend from the morning through the mid-afternoon given the same temperature
  - During the night and early morning hours, the differences between the mean temperatures and ARLs are minimal



# UPDE: Regression Analysis – Final Model (1/2)

## Low Cycle Model

Regression Statistic	Value
R <sup>2</sup>	0.846
SE	0.406
SPE	17.4%
Observations	3149

Term	Coefficients	Standard Error	t Stat	P-value
Intercept	6.244	0.481	12.9	1.23E-37
Temp	-0.207	0.013	-16.6	2.79E-59
Temp <sup>2</sup>	0.002	8.07E-05	25.1	2.04E-126
Sep	-1.769	0.754	-2.35	0.019
Sep*Temp	0.065	0.021	3.18	0.002
Sep*Temp <sup>2</sup>	-5.68E04	1.42E04	-4.01	6.23E-05
Weekend	0.199	0.016	12.4	2.67E-34

## High Cycle Model

Regression Statistic	Value
R <sup>2</sup>	0.752
SE	0.563
SPE	24.6%
Observations	2420

Term	Coefficients	Standard Error	t Stat	P-value
Intercept	-4.17	0.781	-5.34	1.03E-07
Temp	0.073	0.020	3.68	2.60E04
Temp <sup>2</sup>	2.89E04	1.28E04	2.25	0.024
July*Temp	1.03E03	3.67E04	2.82	4.83E03
Sep	0.782	0.139	5.61	2.26E-08
Sep*Temp <sup>2</sup>	-1.51E04	2.54E-05	-5.94	3.29E-09
Weekend	0.085	0.026	3.33	8.7E04

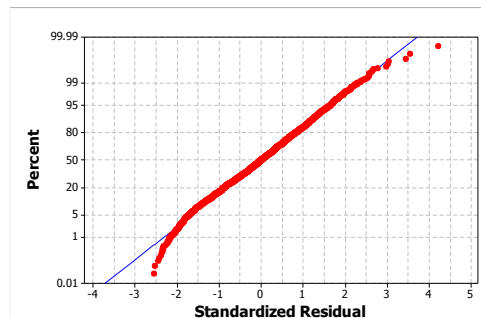
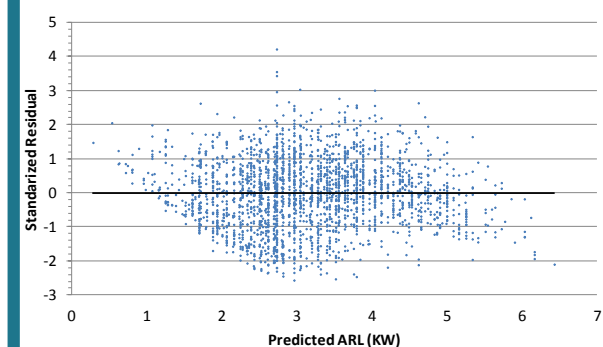
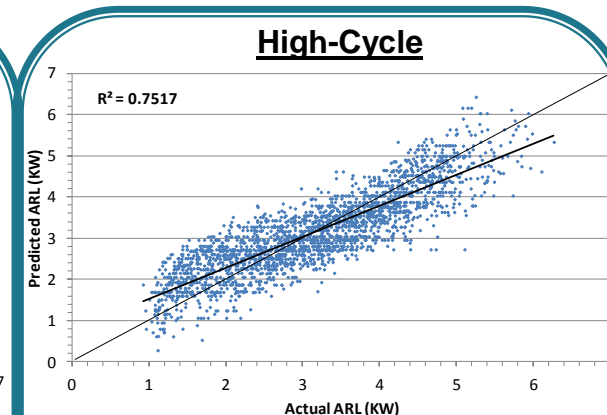
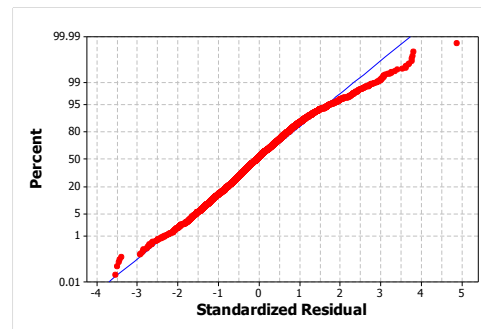
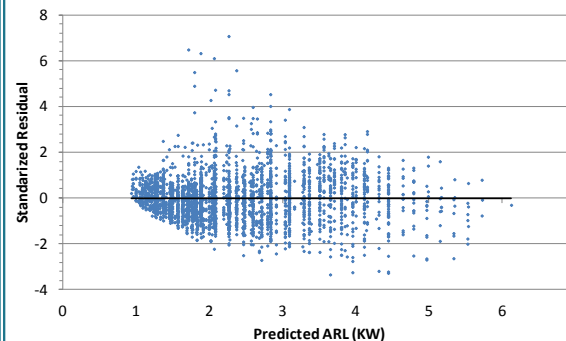
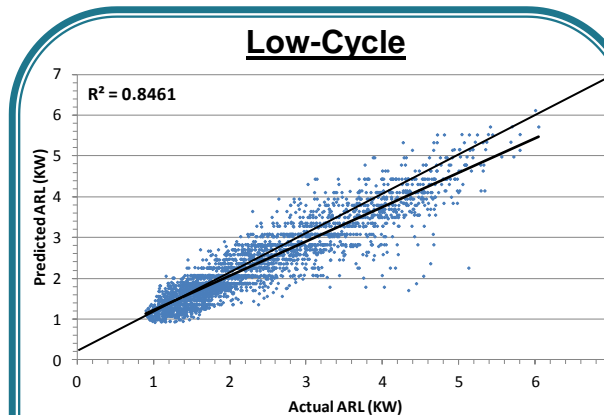
# UPDE: Regression Analysis – Final Model (2/2)

Plots of Estimates vs. Actuals show...

- Models are a reasonable predictor of the average residential load (good fit)
- Slight tendency to overestimate lower loads and underestimate higher loads

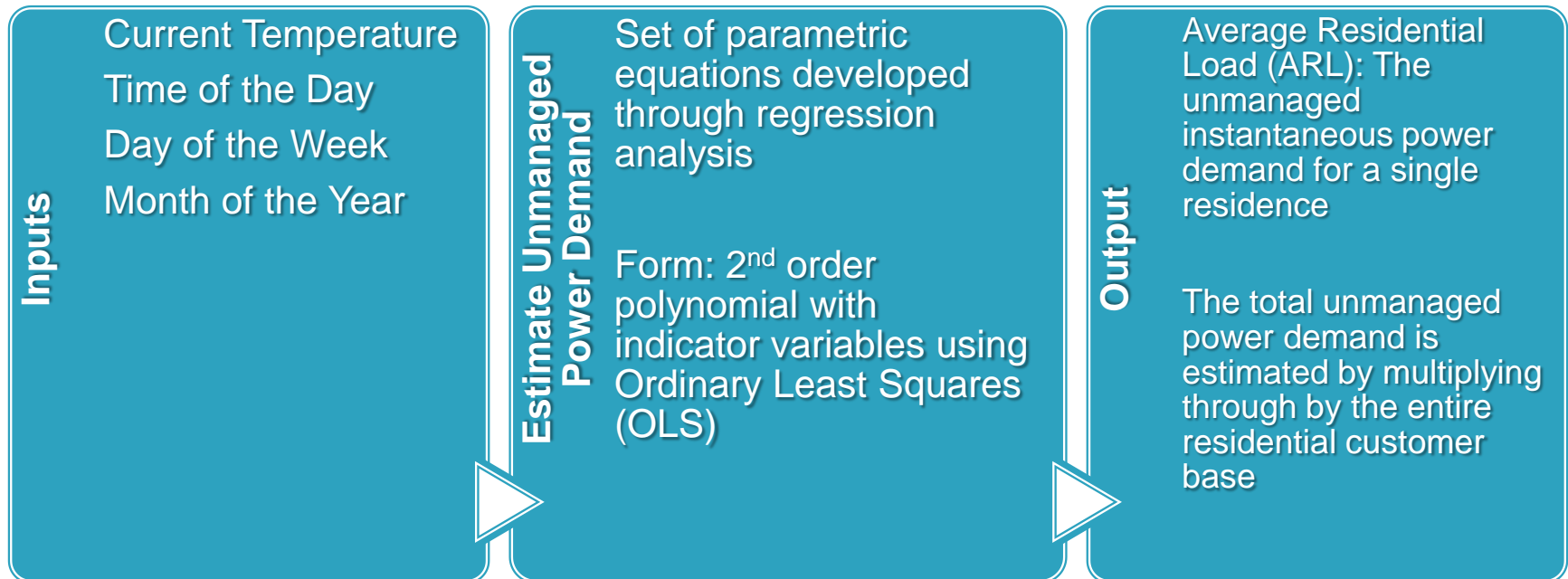
Analysis of Residuals show...

- Random errors have zero mean ✓
- Random errors are normally distributed ✓
- Random errors have an approximate constant variance ✓





# UPDE Algorithm



- ▶ ARL is updated in 15 minute time intervals
- ▶ Managed power demand is achieved when applying the load management policy to the unmanaged power demand

# UPDE Limitations

- ▶ Predictions outside the range of observed data are inaccurate and not valid for equations developed through regression analysis
- ▶ Model is only valid for...
  - Temperatures between 50-100°F
  - Summer months (June-September)
- ▶ Use of the model requires that the relationship between power demand and associated drivers is constant from year-to-year
- ▶ Lacking potentially significant drivers due to data shortfalls
  - House size, weather conditions (e.g. rain, clouds, sun), etc.

# Managed Power Demand Estimator (MPDE): Methodology

- ▶ Model realization : Integer Programming
- ▶ Objective function is to maximize power
- ▶ Set of constraints to limit the objective function
  - Constraint set 1: Power at any single time cannot exceed peak power threshold set by NOVEC
  - Constraint set 2: Limit the number of times a block of residences experience air conditioning shutoff in a given hour
  - Constraint set 3: Balances the loads by limiting the number of shutoffs experienced by each block of houses
- ▶ Definition of variables
  - Each block of houses is represented by a binary variable

# MPDE Assumptions

- ▶ The algorithm assumes that each block of residences demands an equal amount of power
  - E.g., Block 1 draws as much power as Block 2
- ▶ The model assumes that customers in each block will be equally impacted by having their system turned off
  - Does not distinguish amongst variability of individual residence air conditioning cycles

# Mathematical Representation

Maximize

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

Such That

Each Block uses an equal amount of power

Represents the power used by those residents not on the load management system

Reduction Constraint

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

Represents the power threshold that must be achieved

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

Shows that each block must be kept on for 3 of the last 4 times

$$\sum_{i=1}^n (BLOCK_{1i} - BLOCK_{2i}) \leq 1 : \sum_{i=1}^n (BLOCK_{2i} - BLOCK_{3i}) \leq 1 : \sum_{i=1}^n (BLOCK_{3i} - BLOCK_{4i}) \leq 1$$

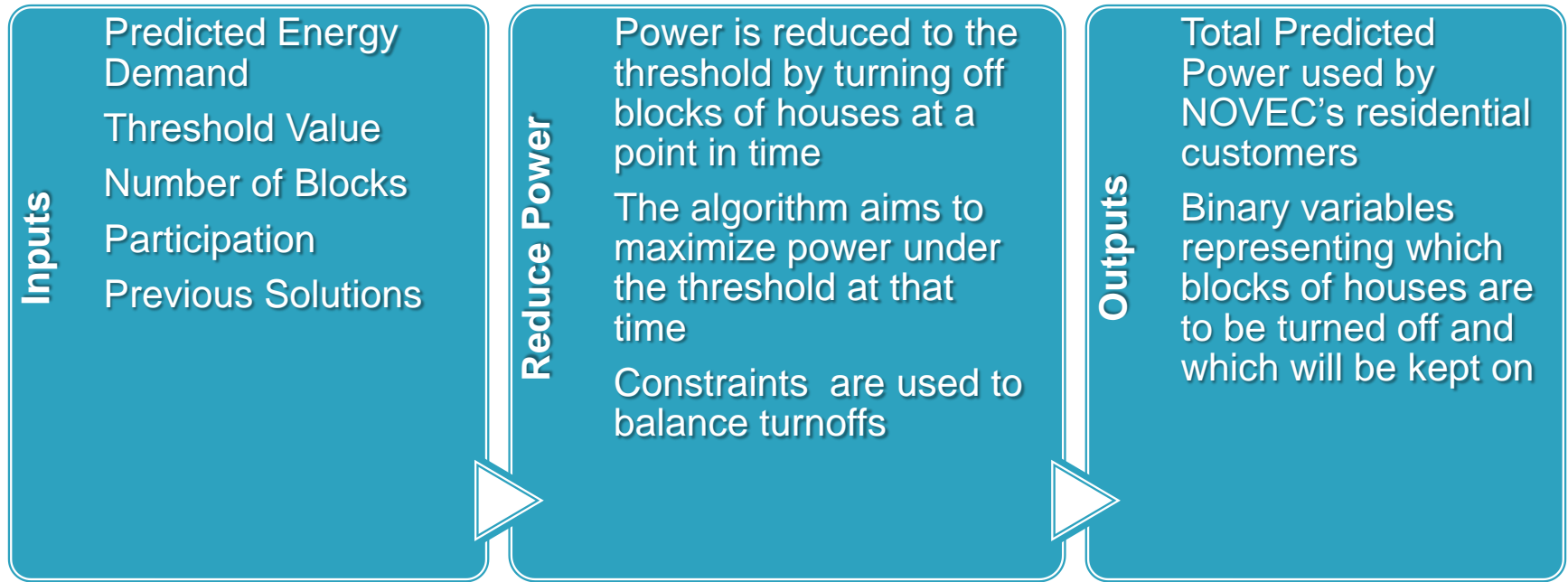
$$\sum_{i=1}^n (BLOCK_{1i} - BLOCK_{3i}) \leq 1 : \sum_{i=1}^n (BLOCK_{2i} - BLOCK_{4i}) \leq 1 : \sum_{i=1}^n (BLOCK_{1i} - BLOCK_{4i}) \leq 1$$

$$\sum_{i=1}^n (BLOCK_{4i} - BLOCK_{3i}) \leq 1 : \sum_{i=1}^n (BLOCK_{3i} - BLOCK_{2i}) \leq 1 : \sum_{i=1}^n (BLOCK_{2i} - BLOCK_{1i}) \leq 1$$

$$\sum_{i=1}^n (BLOCK_{4i} - BLOCK_{2i}) \leq 1 : \sum_{i=1}^n (BLOCK_{3i} - BLOCK_{1i}) \leq 1 : \sum_{i=1}^n (BLOCK_{4i} - BLOCK_{1i}) \leq 1$$

Balance constraints that compare the number of turnoffs that each blocks has experienced

# MPDE Algorithm



- ▶ When run at each read time, the algorithm will provide NOVEC with a schedule for turning off blocks of houses
- ▶ Algorithm can balance the number of turnoffs among the blocks
  - Takes into account the previous solutions for a day



# MPDE Limitations

- ▶ The algorithm looks only at the single time in which it is run
  - Therefore it does not decide the length of a block's turn-off duration
- ▶ The algorithm only takes into account the solutions from the previous 24 hours
- ▶ The algorithm must be run at each interval that power reduction is needed

# Residential Convenience Estimator (RCE): Methodology

- ▶ Important to consider load management effects on customer convenience
  - Power cutoff to customer A/C units may cause customer discomfort
- ▶ Residential Convenience Estimator (RCE) developed to estimate a customer's convenience level
  - Allows evaluation of demand reduction policies on customer convenience
- ▶ The estimator outputs is a number between 0 and 100
  - Value of 100 represents every customer is satisfied
  - Metric used to compare customer satisfaction to a convenience threshold that a load management policy must observe
  - Can also be used to compare customer satisfaction across multiple load management options

# RCE: Assumptions

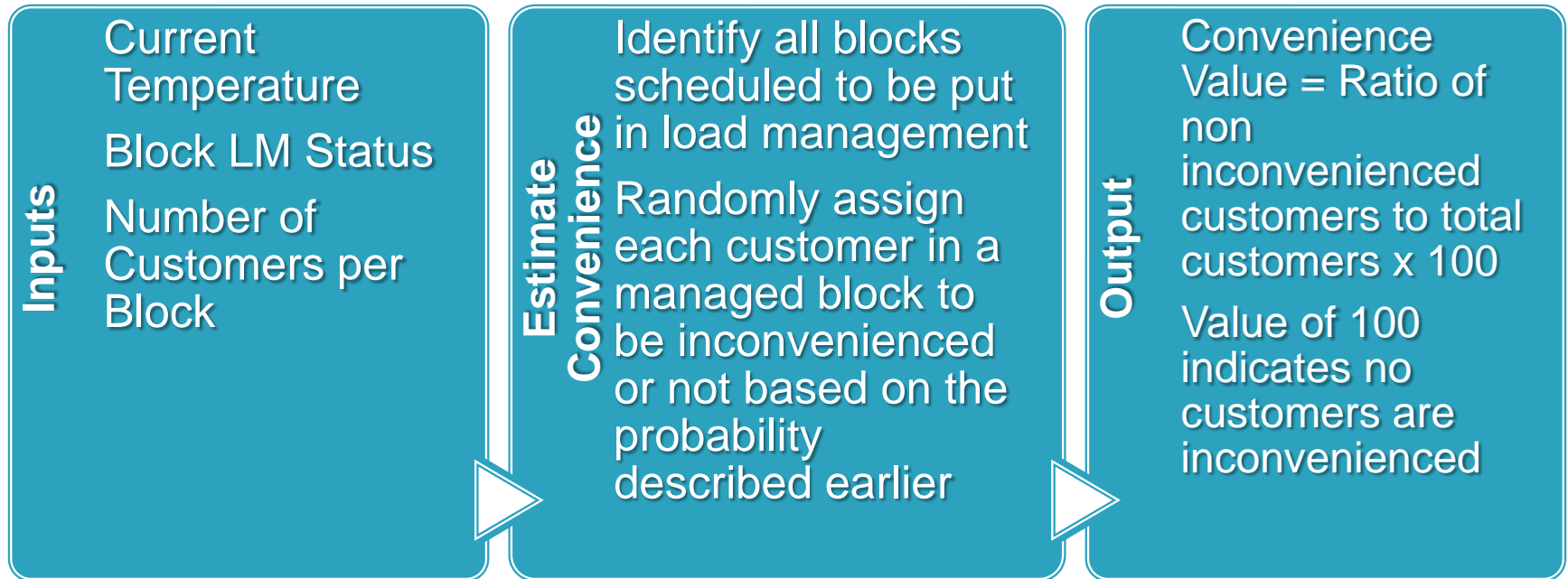
- ▶ A customer is inconvenienced when he or she desires to use the air conditioner in a given interval but is unable to because of load management
- ▶ The probability that a customer will want to use the air conditioner in an hour is a function of the outside temperature and is assumed to be:

$$\text{If Current Temperature} > 75^{\circ}, \quad p = 1 - \left( \frac{75}{\text{Current Temperature}} \right)$$

$$\text{If Current Temperature} \leq 75^{\circ}, \quad p = 0$$

- The probability increases as temperature increases
- At temperatures of 75° or lower, there will be no need to run the air conditioner

# RCE: Algorithm



- ▶ Convenience value for each customer is stored to be carried through to the next interval
- ▶ For each interval when a block is not in load management, 20% of inconvenienced customers in that block will return to full satisfaction

# RCE: Limitations

- ▶ Inputs and methodology are not based on data empirically derived from customer experience
- ▶ Individual customer convenience is represented as a binary value whereas in reality it is more likely to be a spectrum
- ▶ Algorithm ignores other factors that may drive customer need for air conditioner use
  - E.g., time of day

# LMD Assessment

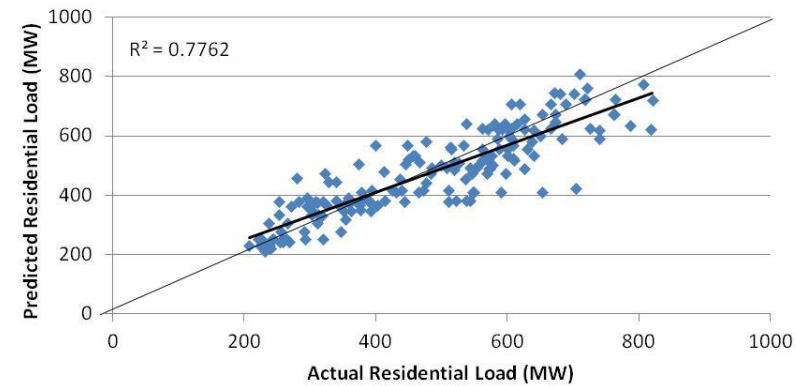
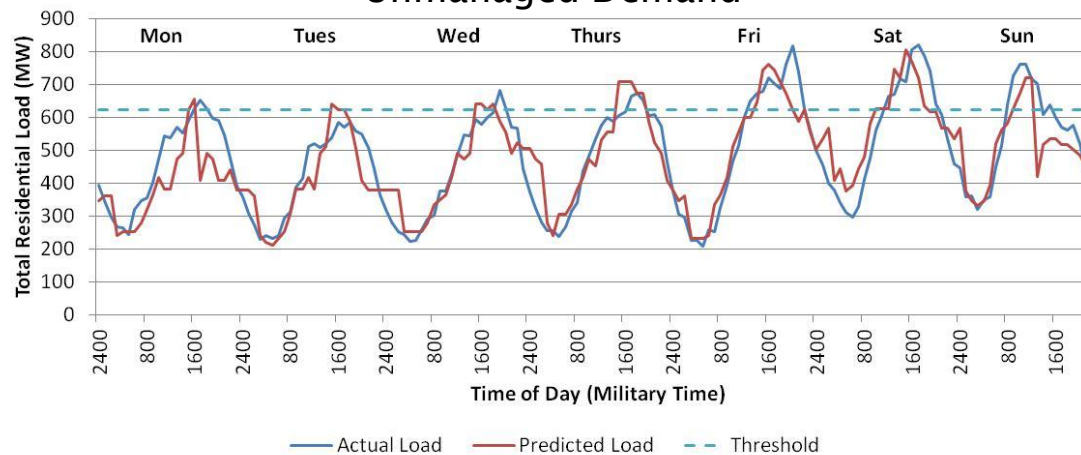


# Test Conditions

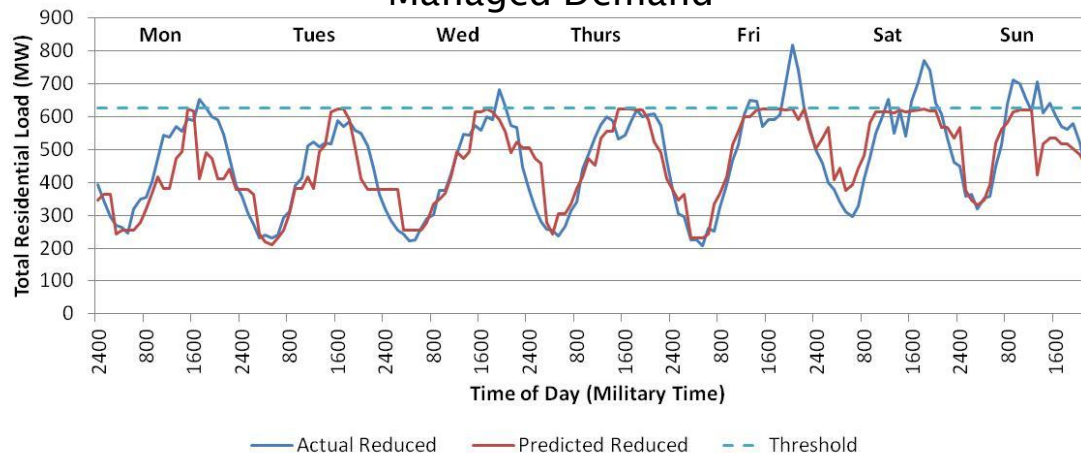
- ▶ LMD Evaluated Using Test Dataset
  - June-September 2009
  - Test data independent of data set used to develop parametric models
- ▶ Intervals sampled every 15 minutes for 7 days
- ▶ Prediction results represent the mean residential power demand for a given set of conditions
- ▶ Objective threshold levels
  - Similar to percent load NOVEC satisfies with long term contract energy purchases
  - Set to the 90th percentile of the ARL dataset for August and July
  - Set to the 85th percentile of the ARL dataset for June and September

# July LMD Operation Results

## Unmanaged Demand



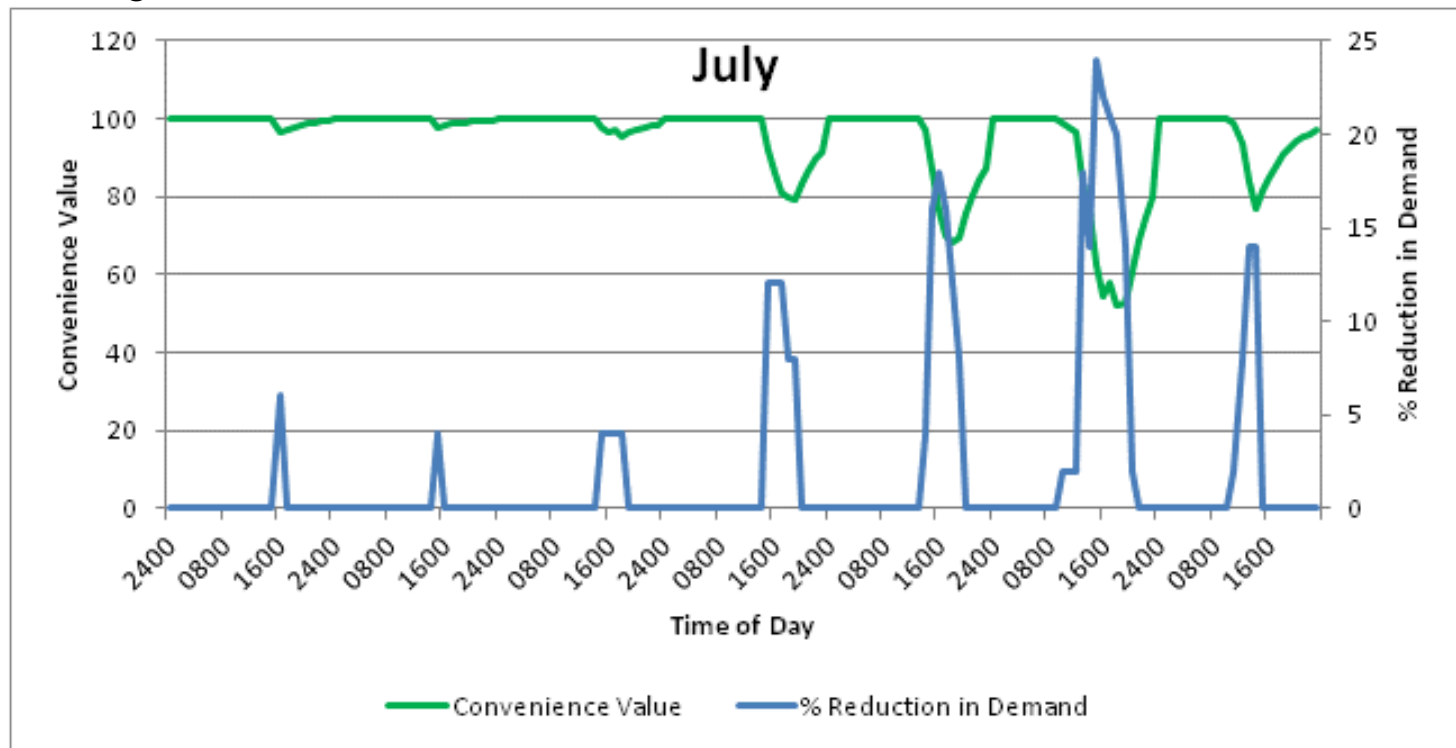
## Managed Demand



Unmanaged MOEs	Peak Prediction Success Rate	62%
	False Positive Rate	28%
Managed MOEs	% of Peak Power Occurrences Eliminated	35%
	% of Peak Power Reduced	51%
	% of Baseline Power Reduced	1.2%

# July Convenience Results

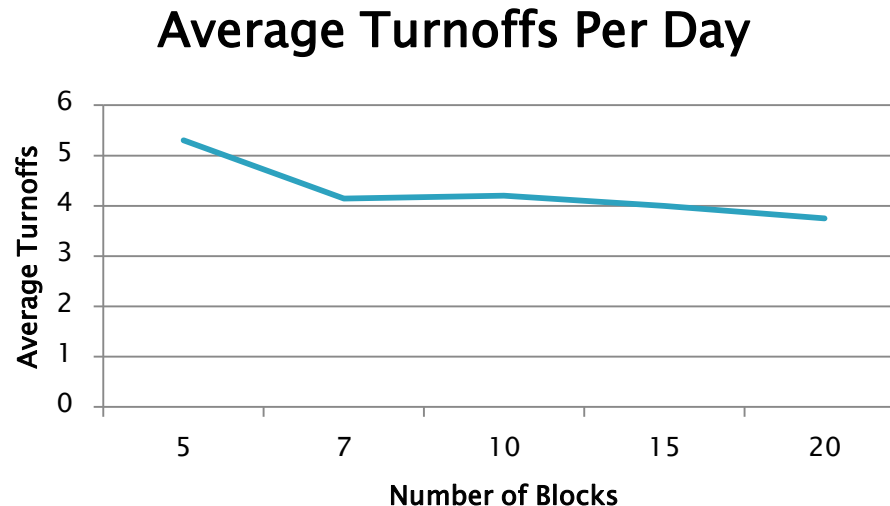
- ▶ Convenience value remains above 80 for reductions of 15% or less, but drops to nearly 50 in the most extreme case
  - Indicates a policy this aggressive runs the risk of potentially reducing satisfaction to a large number of customers



# Sensitivity Analysis: Number of Blocks

- ▶ NOVEC requested study include change in block size
  - NOVEC Load Management System operates on blocks of residences
  - Participating residences are divided into a number of load management control blocks
  - Load switches within a block are turned on/off en-masse
  - Residences within a block may be scattered through service region
- ▶ Study changed the number of blocks used for a fixed number of residences
  - More blocks implies less residences per block
- ▶ With smaller / larger number of blocks
  - Power should be reduced in smaller/larger increments
  - Blocks get turned off more / less times per day
- ▶ These impacts occur because power reduction burden is spread across multiple blocks
  - If only one block is used, it must be turned off any time reduction occurs
  - If multiple blocks are used, there are many options for turning off blocks based on how much energy must be reduced and what customers are inconvenienced

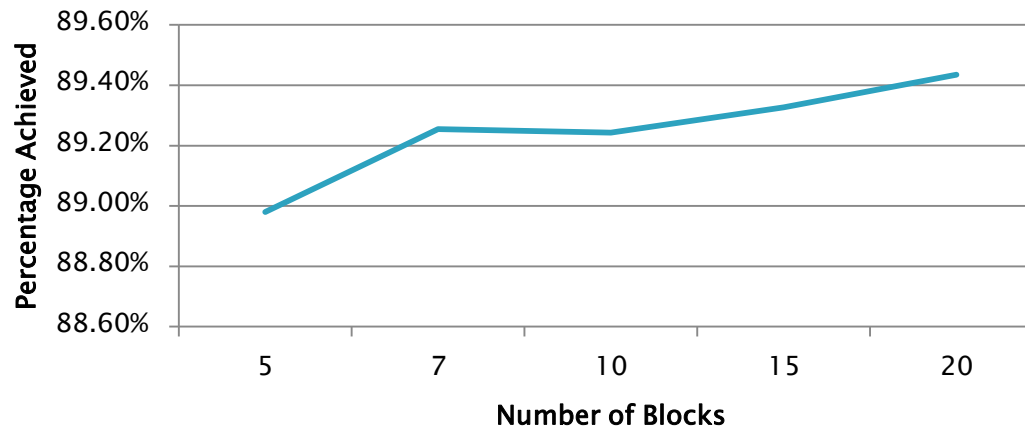
# Sensitivity Analysis Results: Average Turnoffs



- ▶ Ran tests for 5, 7, 10, 15, and 20 blocks
  - Respective block sizes: 8.6K, 6.1K, 4.3K, 2.9K, and 2.2K residences
- ▶ Ran 1 day from each month through the each of the block variations
- ▶ As the number of blocks increased, average turnoffs for any one block decreased
- ▶ No change from 7 to 10 blocks caused by border cases in one day of the test reduction
  - Achieving the reduction threshold causes an extra block to be turned on when more blocks are introduced

# Sensitivity Analysis Results: Percentage of Threshold

## Percentage of Best Possible Per Day



- ▶ Best possible solution is where the threshold value is substituted for the power demand whenever the predicted unmanaged power exceeds the threshold
- ▶ As the number of blocks increases the system gets closer to the best possible solution
- ▶ The maximization aspect of the managed demand algorithm leads to the increase as the model aims to attain the exact threshold at any time



# Evaluation

- ▶ LMD performs adequately in months where
  - Peak power often exceeds objective threshold
  - Peak power exceeds threshold by large amounts (e.g., July)
- ▶ LMD performance suffers in months where
  - Peak power rarely exceeds objective threshold
  - Peak power exceeds threshold by small amounts (e.g., Sep.)
  - Unless the objective threshold is lowered, load management might not be necessary for these months
- ▶ Aggressive peak demand (>15%) policies are risky
  - Large potential of reduced service satisfaction with customers participating in load management program
- ▶ Increasing the number of controlled blocks increases probability that NOVEC's planned base power will satisfy the managed demand

# Recommendations

- ▶ Feasibility of improving load management system operation has been successfully demonstrated
  - 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
- ▶ Recommend continuation of research to realize the potential benefits of the demonstrated concepts

# Future Work

- ▶ 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
  - Increase the likelihood that high levels of customer convenience are maintained
  - Allow automatic evaluation of alternative peak demand reduction objectives

# Acknowledgements

- ▶ Electric Management Group would like to recognize the following individuals who contributed to the success of this project
- ▶ NOVEC Sponsor
  - Angie Thomas
  - Robert Bisson
  - Bryan Barfield
- ▶ GMU Capstone Project Instructor
  - Dr. Kathryn Laskey
  - Dr. Karla Hoffman

# Backup

# 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<sup>2</sup>:** 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 **does not** 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)

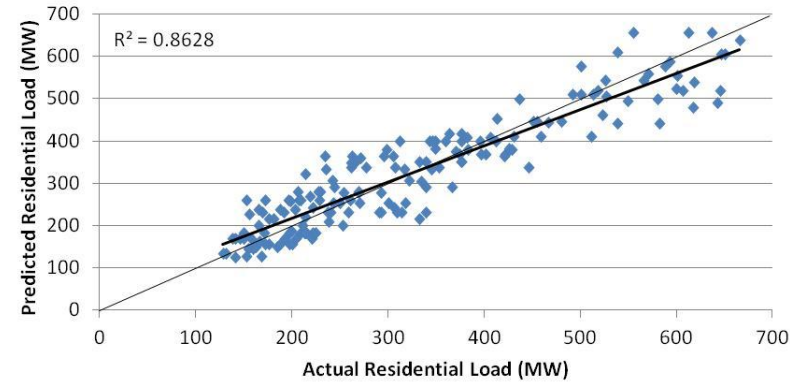
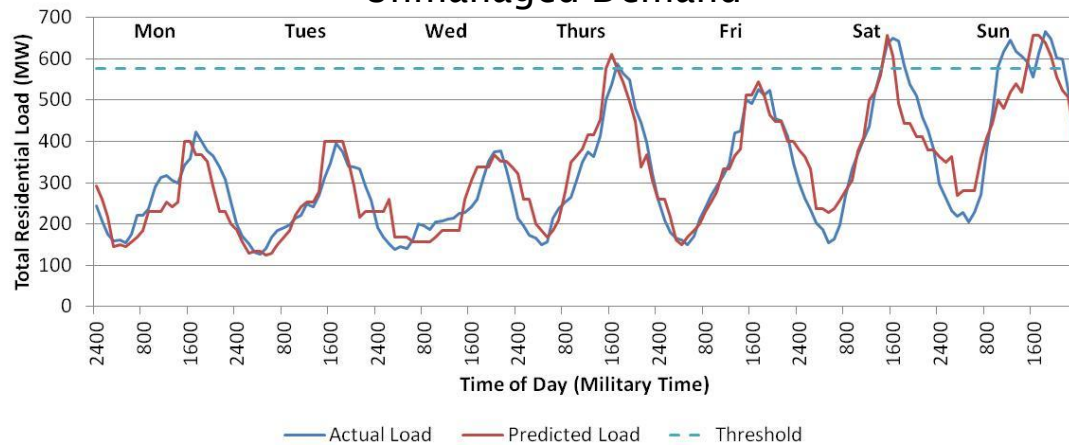
# Results: Measures of Effectiveness

Measure of Effectiveness (MOE)	Description
Peak Prediction Success Rate	$\frac{\# \text{ of Occurences where Actual and Predicted Power Exceed Threshold}}{\# \text{ of Occurences where Actual Power Exceeds Threshold}}$
False Positive Rate	$\frac{\# \text{ of Occurences where Predicted Power Exceeds Threshold but Actual Power Does Not}}{\# \text{ of Occurences where Predicted Power Exceeds Threshold}}$
% of Peak Power Occurences Eliminated	$\frac{\# \text{ of Occurences where Actual Power Exceeds Threshold} - \# \text{ of Occurences where Reduced Actual Power Exceeds Threshold}}{\# \text{ of Occurences where Actual Power Exceeds Threshold}}$
% of Peak Power Reduced	$\frac{\text{Total Actual Power Under the Threshold} - (\text{Total Power Under the Threshold Removed Under Managed Demand Policies})}{\text{Total Actual Power Under the Threshold}}$
% of Baseline Power Reduced	$\frac{\text{Total Actual Power above Threshold} - \text{Total Reduced Power above Threshold}}{\text{Total Actual Power Over the Threshold}}$

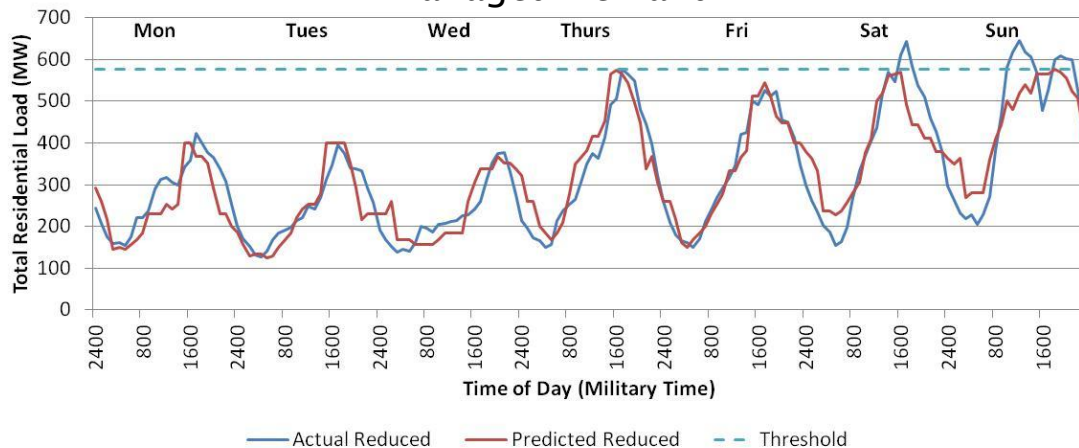


# June LMD Operation Results

## Unmanaged Demand



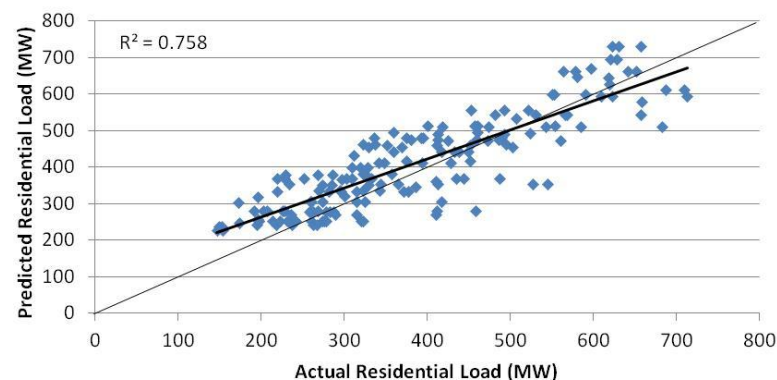
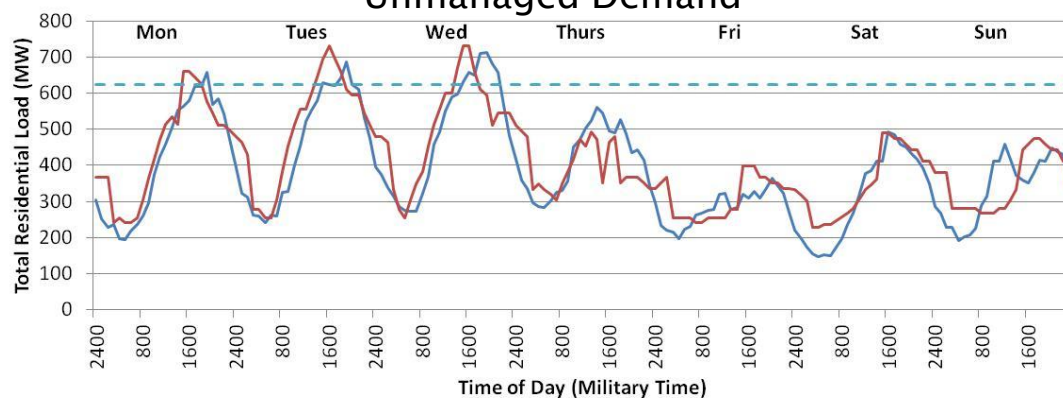
## Managed Demand



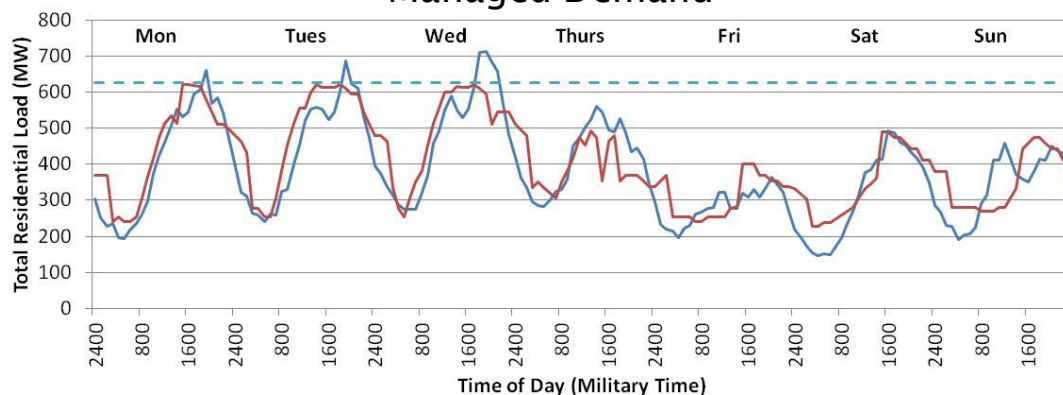
Unmanaged MOEs	Peak Prediction Success Rate	43%
	False Positive Rate	25%
Managed MOEs	% of Peak Power Occurrences Eliminated	20%
	% of Peak Power Reduced	40%
	% of Baseline Power Reduced	0.45%

# August LMD Operation Results

## Unmanaged Demand



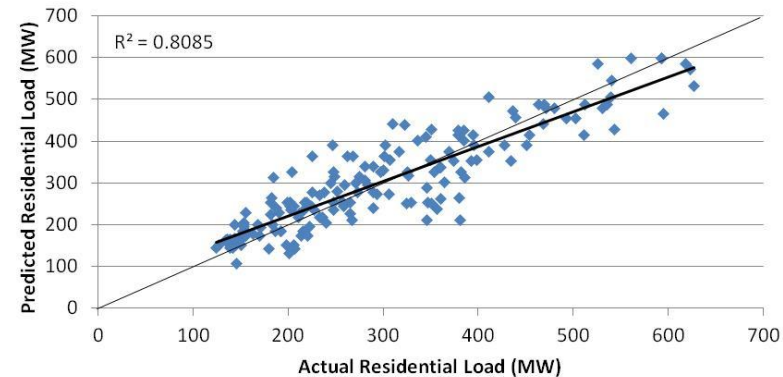
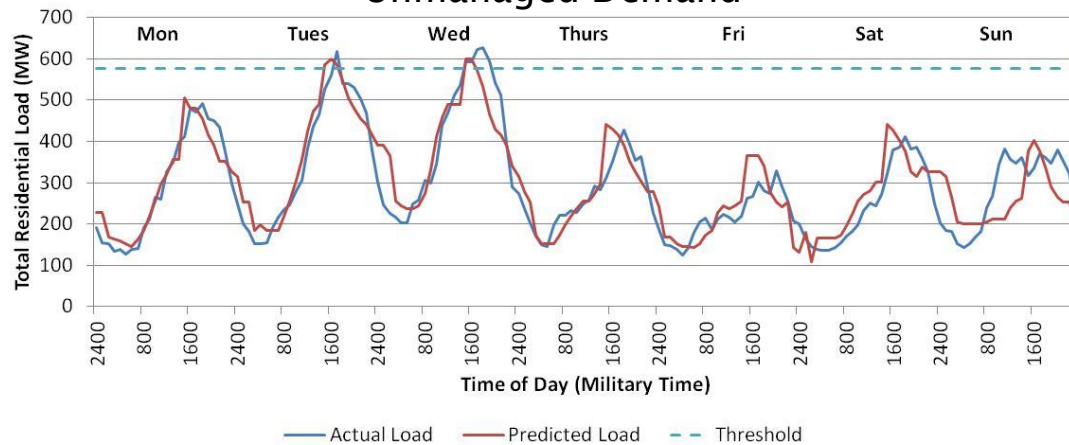
## Managed Demand



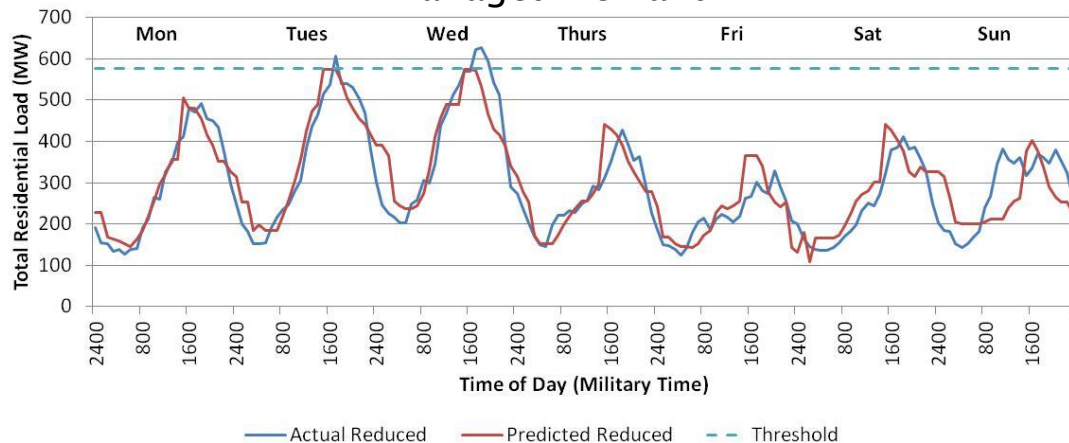
Unmanaged MOEs	Peak Prediction Success Rate	45%
	False Positive Rate	62%
Managed MOEs	% of Peak Power Occurrences Eliminated	45%
	% of Peak Power Reduced	19%
	% of Baseline Power Reduced	1.1%

# September LMD Operation Results

## Unmanaged Demand



## Managed Demand



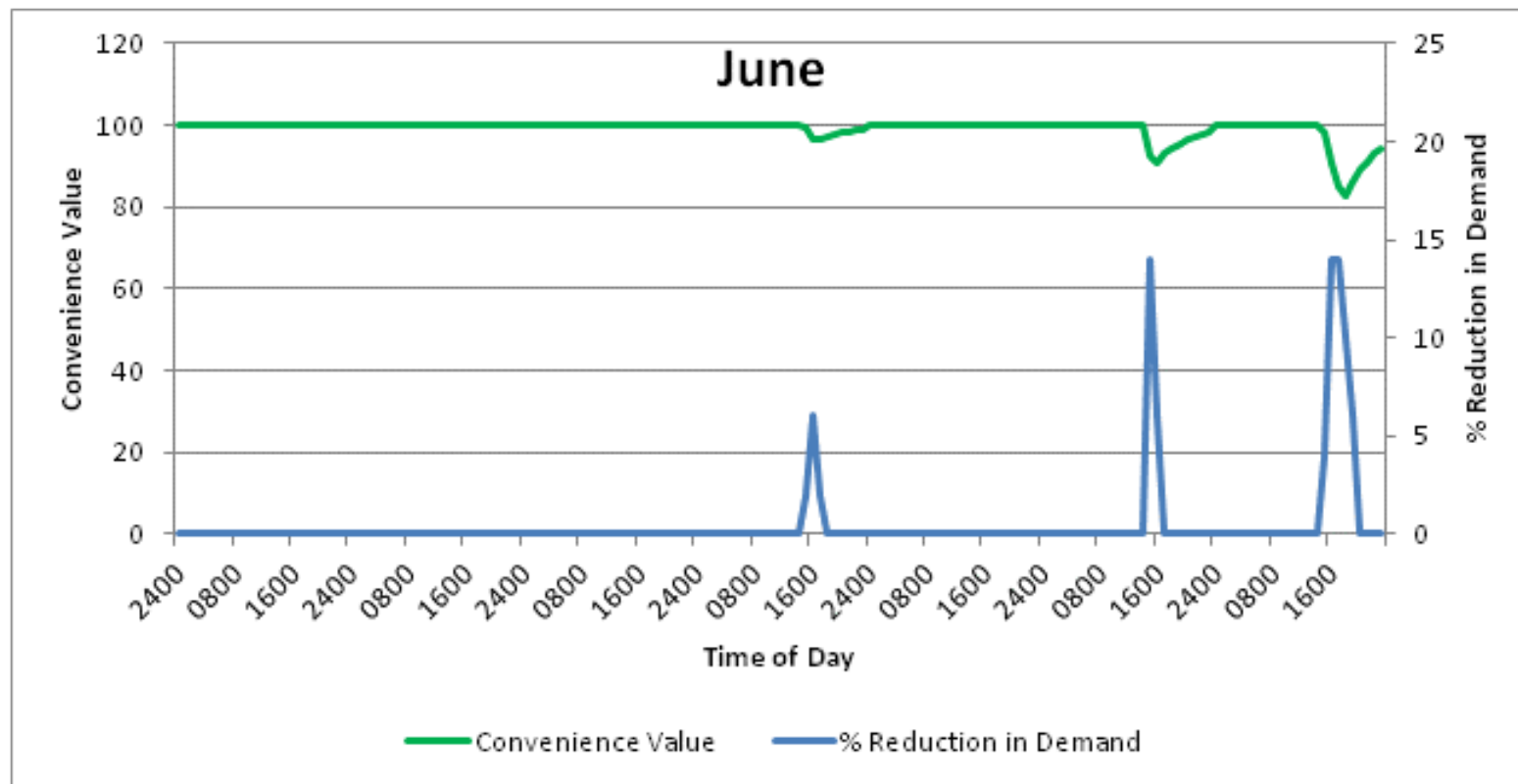
Unmanaged MOEs	Peak Prediction Success Rate	50%
	False Positive Rate	40%
Managed MOEs	% of Peak Power Occurrences Eliminated	33%
	% of Peak Power Reduced	24%
	% of Baseline Power Reduced	0.1%

# MPDE: Sample Solution

- ▶ Run model iteratively at each 15 minute interval to get daily load management schedule
- ▶ At each interval the model will aim to reduce energy demand to the threshold
- ▶ Process contained memory constraints to balance load by taking into account previous solutions even when temperature remains constant
- ▶ Solutions are exported to Excel to produce daily schedule

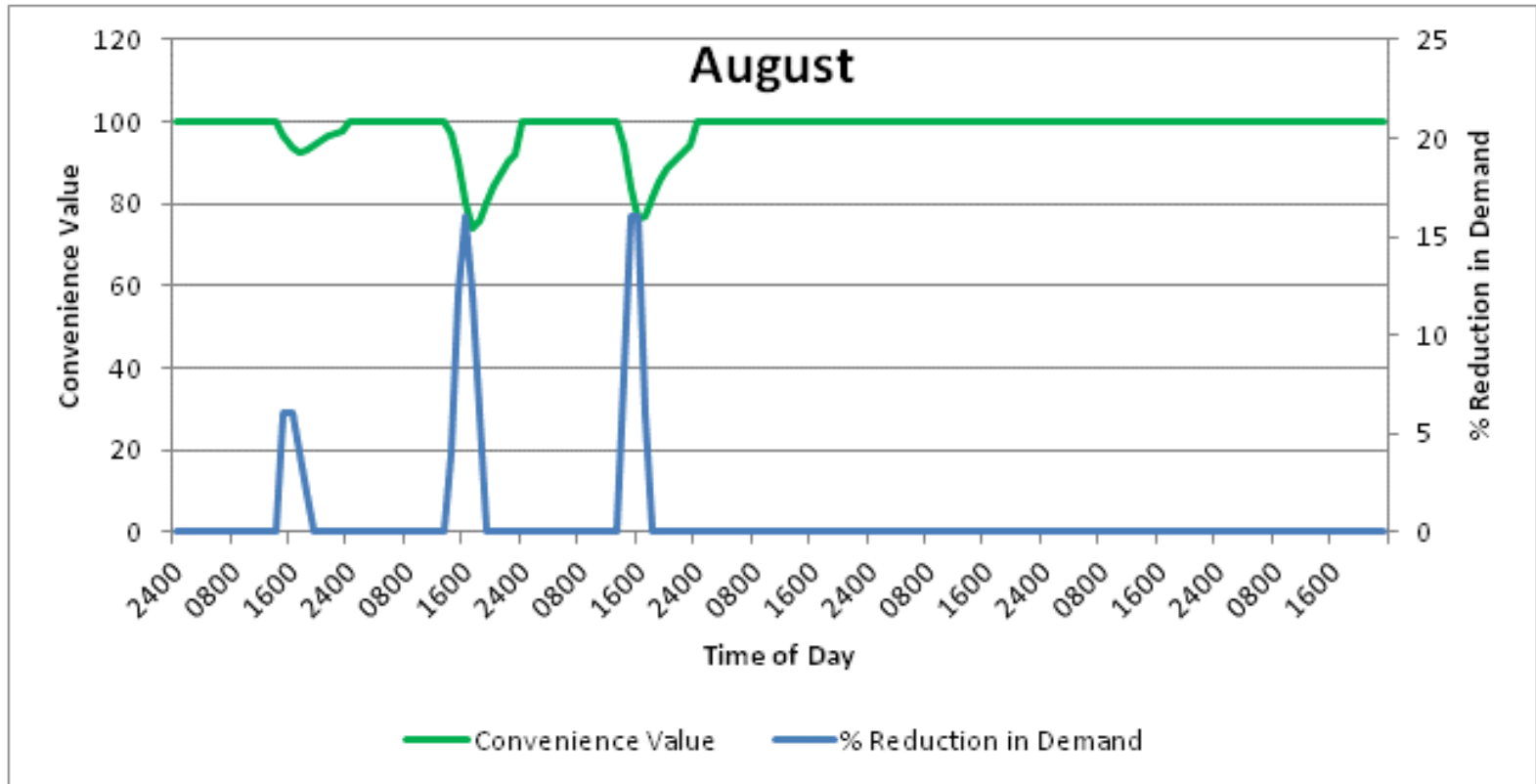
Time of Day	Temperature	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7	Total Energy
15:00	93	1	1	1	1	0	0	0	617592.6
15:15	93	0	0	0	1	1	1	1	617592.6
15:30	93	1	0	0	0	1	1	1	617592.6
15:45	93	0	1	1	1	0	0	1	617592.6
16:00	93	1	0	1	0	1	1	0	617592.6
16:15	93	1	1	1	1	0	0	0	617592.6
16:30	93	0	0	0	1	1	1	1	617592.6
16:45	93	1	0	0	0	1	1	1	617592.6
17:00	93	0	1	1	1	0	0	1	617592.6

# June Convenience Results

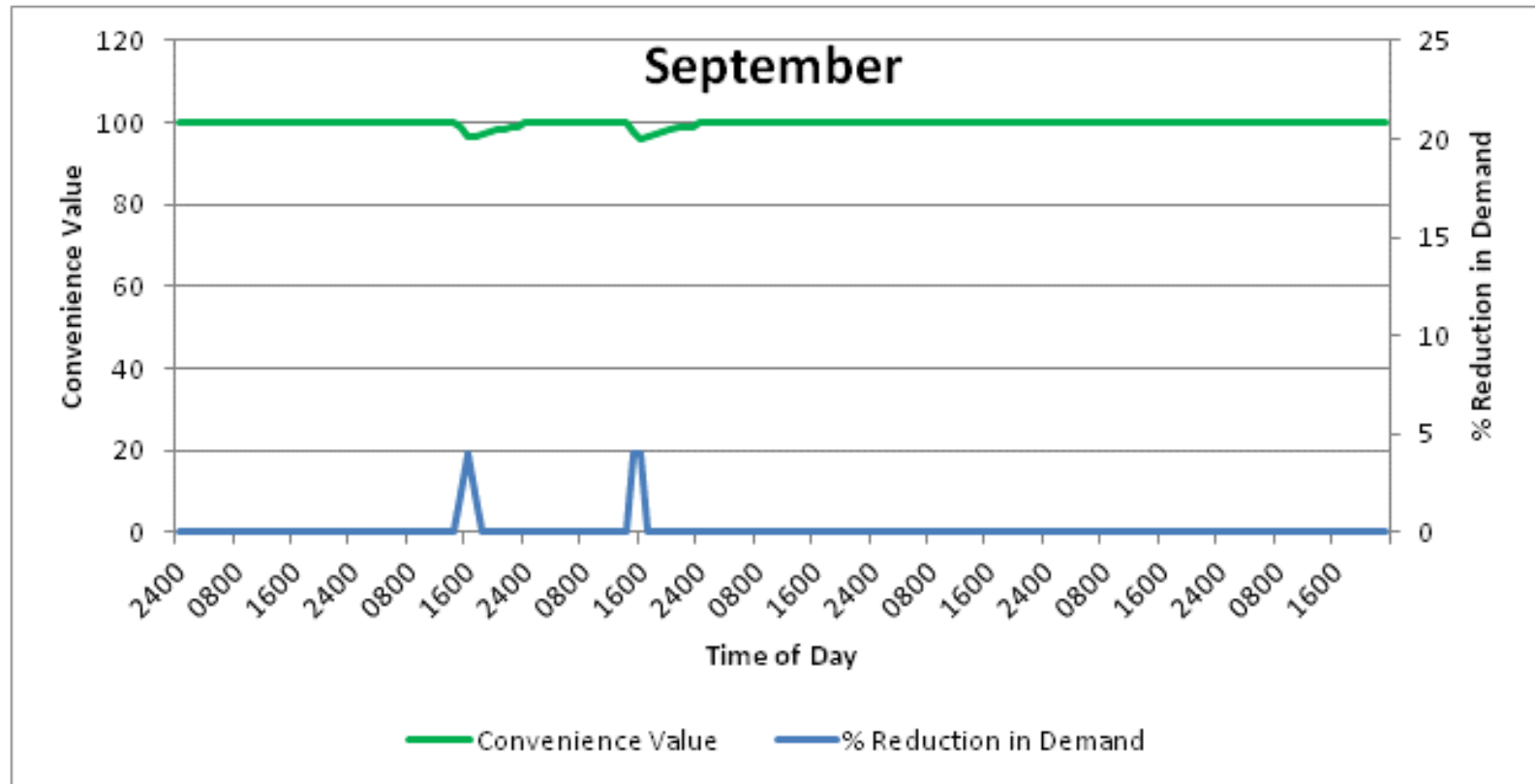




# Convenience Results – August



# Convenience Results – September





# NOVEC Data Model

