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VERIFIED DIRECT TESTIMONY

OF

ERIC FOX

ON BEHALF OF

INDIANAPOLIS POWER & LIGHT COMPANY

INCLUDING IPL WITNESS EF ATTACHMENTS 1 AND 2

DIRECT TESTIMONY OF ERIC FOX
ON BEHALF OF INDIANAPOLIS POWER & LIGHT COMPANY

I. BACKGROUND AND INTRODUCTION

Q1. Please state your name, title, and business address.

A1. My name is Eric Fox. My business address is 20 Park Plaza, Suite 910, Boston, Massachusetts, 02116. I am employed by Itron, Inc. ("Itron"),[1] as Director, Forecast Solutions.

Q2. On whose behalf are you testifying?

A2. I am testifying on behalf of Indianapolis Power & Light Company ("IPL" or the "Company").

Q3. Please state your education, professional and work experience.

A3. I received my M.A. in Economics from San Diego State University in 1984 and my B.A. in Economics from San Diego State University in 1981. While attending graduate school, I worked for Regional Economic Research, Inc. ("RER") as a SAS programmer. After graduating, I worked as an Analyst in the Forecasting Department of San Diego Gas & Electric. I was later promoted to Sr. Analyst in the Rate Department. I also taught statistics in the Economics Department of San Diego State University on a part-time basis.

In 1986, I was employed by RER as a Senior Analyst. I worked at RER for three years before moving to Boston and taking a position with New England Electric as a Senior

[1] Itron is a leading technology provider and critical source of knowledge to the global energy and water industries. More than 3,000 utilities worldwide rely on Itron technology to deliver the knowledge they require to optimize the delivery and use of energy and water. Itron provides industry-leading solutions for electricity metering; meter data collection; energy information management; demand response; load forecasting, analysis and consulting services; distribution system design and optimization; web based workforce automation; and enterprise and residential energy management.

Analyst in the Forecasting Group. I was later promoted to Manager of Load Research. In 1994, I left New England Electric to open the Boston office for RER which was acquired by Itron in 2002.

Over the last 25 years, I have provided support for a wide range of utility operations and planning requirements including forecasting, load research, weather normalization, rate design, financial analysis, and conservation and load management program evaluation. Clients include traditional integrated utilities, distribution companies, Independent System Operators, generation and power trading companies, and energy retailers. I have presented various forecasting and energy analysis topics at numerous forecasting conferences and forums. I also direct electric and gas forecasting workshops that focus on estimating econometric models and using statistical-based models for monthly sales and customer forecasting, weather normalization, and calculation of billed and unbilled sales. Over the last few years, I have provided forecast training to several hundred utility analysts and analysts in other businesses.

In the area of energy and load weather normalization, I have implemented and directed numerous weather normalization studies and applications used for utility sales and revenue variance analysis and reporting, and estimating booked and unbilled sales and revenue. Recent studies include developing weather normalized class profiles for cost allocation and rate design, estimating rate class hourly profile models to support retail settlement activity, weather normalizing historical billing sales for analyzing historical sales trends, developing customer class and weather normalized end-use profiles as part of a utility integrated resource plan, and developing normal daily and monthly weather data to support sales and system hourly load forecasting. My resume is included as IPL Witness EF Attachment 1.

Q4. What are your responsibilities as Director, Forecast Solutions?

A4. I am responsible for directing forecast and load analysis work to support electric and gas utility operations and planning. I manage the day-to-day work of Itron's Boston office. I work with utilities and regulatory organizations across the country and in Canada to address a range of long-term and short-term forecasting and load analysis issues. My work also includes directing the activity of Itron's Energy Forecasting Group (a long-term energy forecasting data and analysis service with over 60 participating utilities), conducting forecast workshops and web-based presentations on specific forecasting and analysis topics. I am an active participant in forecasting and load analysis conferences and forums across the country.

Q5. Have you previously testified before a regulatory commission?

A5. Yes. I provided testimony related to weather normalization and forecasting in several regulatory proceedings. This includes rebuttal testimony that I provided for IPL's 2014 Rate Case, Cause Nos. 44576/44602. My regulatory experience is listed in IPL Witness EF Attachment 1 (*Regulatory Experience*).

Q6. What is the purpose of your testimony?

A6. The purpose of my testimony is to support test-year sales weather normalization. I directed the development of rate class weather normalization models, calculation of actual and normal test-year weather variables, estimation of test-year weather normal sales, and the weather adjustment factors that are inputs to IPL's Utilities International Revenue Module.

Q7. Are you sponsoring any attachments in support of your testimony?

A7. Yes. In addition to IPL Witness EF Attachment 1, my resume, I am sponsoring the report *2016 Rate Case, Weather Normalization, September 2016* ("Itron Report"), which is included as IPL Witness EF Attachment 2. This report describes estimation of the weather response functions, weather normal sales calculations, derivation of the test-year actual and normal cooling degree days ("CDD") and heating degree days ("HDD"), and summarizes the results. The report also includes model statistics and related graphics.

Q8. Were these attachments prepared or assembled by you or under your direction and supervision?

A8. Yes.

Q9. Did you submit supporting work papers?

A9. Yes. Calculations of weather normalized sales, sales adjustment factors, and inputs (estimated model statistics, coefficients, test-year weather, test-year customers, and test-year sales) are provided in the Excel file IPL Witness *EF Workpaper 1 (FactorCalculations)*. Model data are provided in the Excel file IPL Witness *EF Workpaper 2 (ModelData)*. Weather data and test-year meter read schedule is included in the Excel file IPL Witness *EF Workpaper 3 (WeatherData)*.

II. WEATHER NORMALIZATION APPROACH

Q10. Please describe the approach used for weather normalizing test-year sales.

A10. Weather normal sales are estimated for 7 weather-sensitive rate classes within three revenue classifications. The weather-normalized rate classes are:

1. Residential Service:
    - Rate RS (Residential General Service)
    - Rate RH (Residential Electric Space Heating)
    - Rate RC (Residential Electric Water Heating)
2. Small C&I Services:
    - Rate SS (Small C&I, General Service)
    - Rate SH (Small C&I, Electric Space Heating)
    - Rate SE (Small C&I, Schools Electric Space Heating)
3. Large C&I Services
    - Rate SL (Large C&I, Secondary Service)

Large C&I Services also includes Primary Service, and three High Load Factor rate classes; these rate classes are primarily industrial load and are not weather-sensitive.

Weather normalized sales are estimated based on a set of weather adjustment coefficients that are estimated from daily-use regression models; a separate model is estimated for each rate class. Models are estimated on a daily use per customer basis using simple regression analyses that are fully replicable. The weather adjustment coefficients are applied to the difference between actual and normal monthly degree-days to estimate a monthly per-customer weather impact. Total weather impacts are calculated by multiplying per-customer impacts by number of rate class customers. Weather normalized sales are derived by subtracting the weather impact from actual billed sales. The weather-normalization method represents industry best practice and is used by most electric and gas utilities; the methodology is described in detail in the Itron Report (IPL Witness EF Attachment 2).

Normalized rate-class sales estimates are used in constructing a set of adjustment factors that are uploaded into IPL's Utilities International system. The adjustment factors are the ratio of the normalized sales to actual sales; the factors are used in the Customer Revenue Module to adjust model sales and revenues for test-year normal weather conditions.

Q11. Please describe the rate class weather normalization models.

A11. Separate daily regression-based weather normalization models are estimated for each rate class because each rate class has a distinct load/weather relationship. Models are estimated with average daily use derived from IPL's load research database and daily HDD and CDD variables constructed from average temperature data from the Indiana International Airport. The estimation dataset combines two test-year periods: the current test-year (July 1, 2015 to June 30, 2016) and IPL's prior rate case test-year (July 1, 2013 to June 30, 2014). Combining test-year periods provides more observations (366 in the current test-year and 365 in the prior-test year) and more variation in the load/temperature relationship than using just the current test-year period data. The current test-year includes a significantly warmer than normal winter, while the prior test-year includes a colder than normal winter. Weather response functions can also be estimated with monthly billed sales, but this requires a significantly longer historical data series in order to incorporate enough observations to estimate statistically strong regression models. As daily data is more current, weather coefficients estimated with the daily data will better reflect test-year weather impacts.

The estimated models also include monthly and day-of-the week binary variables; these variables are constructed to capture seasonal and weekly usage patterns that are not weather related. Some models also include binary variables for specific-holidays like *Thanksgiving, Christmas*, and *New Year's Day* where these variables are statistically significant. Binary variables (or sometimes called dummy variables) equal 1 when the condition is true and 0 otherwise. The January binary variable for example, equals 1 for all observations that fall in January and equals 0 for all other observations. The Sunday binary variable equals 1 for all Sunday observations and 0 otherwise. Daily rate class usage estimates will often have large outliers as a result of the "noisiness" of the underlying load research sample points. Some rate class models include binaries to address some of the largest outliers; this minimizes the impact the outliers have on the estimated weather coefficients. Models also include an auto-regressive term to correct for serial correlation (i.e., patterns in the residuals); serial correlation can result in overstated statistical significance of the estimated model coefficients. A more detail discussion of the rate class weather response models and results are included in the Itron Report (IPL Witness EF Attachment 2).

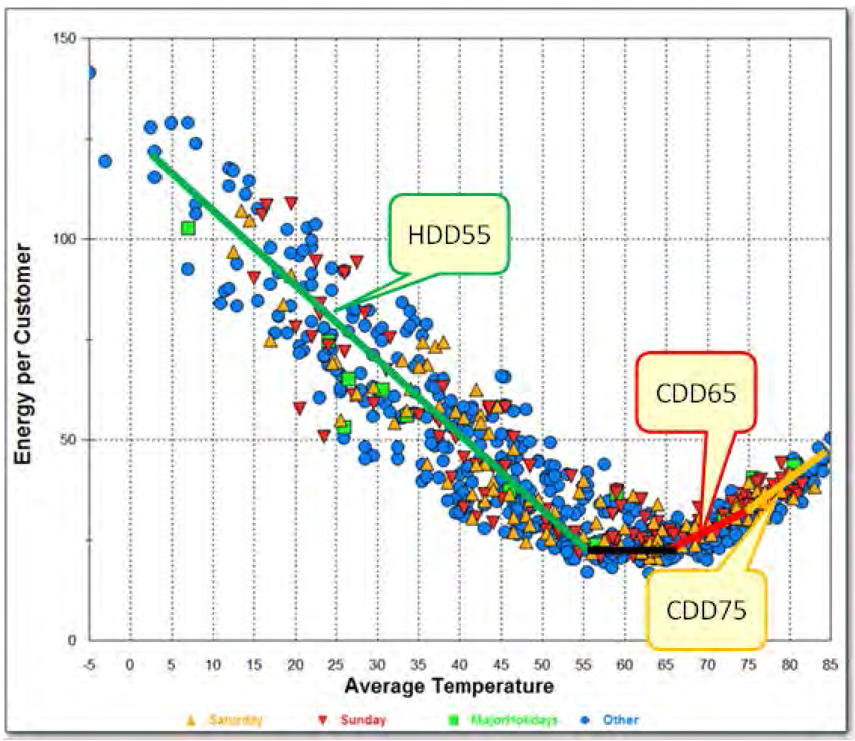
Q12. Please describe the construction of the model weather variables.

A12. The relationship between electric use and temperature is non-linear. In the heating season, when temperatures decline, usage increases. In the cooling season, when temperatures increase, usage increases. The standard approach for accounting for this relationship is to define daily use as a function of HDDs and CDDs. HDD and CDD are known as "spline" variables as they take on a value only when the temperature is above a specified temperature point (a CDD) or below a specified temperature point (a HDD).

The traditional degree-day breakpoint is 65 degree. Temperatures above 65 degrees generate a CDD, and temperatures below 65 degrees generate a HDD. NOAA reports HDD and CDD using a 65 degree-day base. While the 65 degree-day base allows for reasonable weather comparison between different years and to averages (or normal), it is not necessarily the best basis for weather normalizing sales. Weather normalization models can be improved by defining HDD and CDD temperature break points (other than 65 degrees) that better reflect heating and cooling conditions. For example, the commercial and industrial rate classes' weather response functions are specified using CDDs with a 60 degree temperature breakpoint (CDD60). The lower breakpoint captures the load/weather relationship better in the lower part of the curve as commercial and industrial cooling begins well before 65 degrees. This can be seen visually in the usage/temperature scatter plots (see the Itron Report Appendix B) and in the model statistics.

The non-residential rate class model standard errors (a measure of the average model error) and in-sample statistics (Adjusted R-Squared, Mean Absolute Deviation ("MAD"), and Mean Absolute Percent Error ("MAPE")) are generally better when estimated with CDD60 rather than CDD65. For example, IPL's Large Secondary Service (Rate SL) model's standard error with CDD65 is 56.77 kWh per day, while the standard error using the lower temperature breakpoint (CDD60) is 52.75; the standard error is 7.0% lower using a 60 degree-day breakpoint instead of using a 65 degree-day breakpoint. Similarly on the heating side, a HDD specified with a 55 degree-day temperature breakpoint (HDD55) fits the load/weather curve better than a HDD using a 65 degree-day temperature breakpoint (HDD65) as there is no significant heating load until the average daily temperature falls below 55 degrees. For residential and small commercial rate classes on the high side of the cooling curve, the fitted weather response function can be improved by adding an additional CDD term with a temperature breakpoint of 75 degrees (CDD75). Figure 1 shows IPL's Residential Heating Rate (Rate RH) average daily use against average daily temperature (for the combined test-year periods) and daily HDD and CDD variables that best explain the average use/weather relationship.

Figure 1: Residential Heating (Rate RH) Weather/Use Relationship



Daily HDD and CDD variables used in estimating the rate class models vary by revenue class. Degree-day variables include:

- Residential Rates (3): HDD55, CDD65, CDD75
- Small C&I Rates (3): HDD55, CDD60, CDD75

- Large C&I Secondary Service: CDD60, HDD55 (HDD55 is statistically significant, but the impact is very small)

The number following the HDD and CDD variable refers to the temperature break point used in constructing the degree-day variables. For example, HDD55 is based on a temperature breakpoint of 55 degrees. HDD55 equals 0 if the temperature is 55 degrees or higher and equals 55 degrees minus average temperature if temperatures are below 55 degrees. A CDD is just the opposite. CDD60 is 0 when temperatures are 60 degrees or lower and equals temperature minus 60 degrees when temperatures are above 60 degrees.

Q13. Please describe how the monthly test-year HDD and CDD are calculated.

A13. Meters are generally read and processed over a 21 day period in order to even out the work flow. Energy usage processed in the early billing cycles (at the beginning of the month) is mostly consumption from the prior calendar month. Energy usage processed in the later cycles (near the end of the month) is mostly consumption in the current month. As a result the sum of the 21-day consumption, often referred to as *billed* sales, reflects weather conditions in the current month, prior month, and sometimes two-month prior period. For weather normalization, it is necessary to construct monthly HDD and CDD that are consistent with the billing period; these are often referred to as billing-month or cycle-weighted HDD and CDD.

Test-year HDD and CDD variables are constructed using an industry-standard approach. The approach entails first estimating daily HDD and CDD and then multiplying the daily degree-days by daily weights based on the meter read schedule. The weighted daily degree-days are summed by month to get billing-month HDD and CDD.

Normal billing-month HDD and CDD are constructed in a similar manner. First, daily normal HDD and CDD are calculated by averaging actual HDD and CDD by date; all the January 1sts are averaged, January 2nds are averaged, and so forth through December 31st. The daily normal HDD and CDD series are based on a thirty-year historical period from January 1, 1986 to December 31, 2015. Normal billing-month HDD and CDD series are derived by multiplying the daily normal degree-day series by the daily cycle-read weights for the test-year period and summing the values for the test-year billing month. A more detailed discussion of the method used in constructing billing-month HDD and CDD is included in the Itron Report (IPL Witness EF Attachment 2).

III. SALES IMPACT

Q14. How does test-year weather conditions compare with normal weather conditions?

A14. Tables 1 to 3 compare actual and normal test-year degree-days for those concepts used in normalizing rate class sales.

Table 1 : Test-Year HDD55

(Billing-Month Basis)			
Month	**Actual**	**Normal**	**Difference**
July 2015	0.0	0.0	-
Aug	0.0	0.0	-
Sept	0.0	0.7	(0.7)
Oct	18.8	42.2	(23.4)
Nov	107.8	199.0	(91.2)
Dec	357.2	509.2	(152.0)
Jan 2016	604.3	782.7	(178.4)
Feb	709.8	758.1	(48.3)
Mar	431.0	579.0	(148.0)
Apr	213.3	276.3	(63.0)
May	64.5	75.2	(10.7)
June	14.2	8.1	6.1
Total	**2520.9**	**3230.5**	**(709.6)**

Table 2: Test-Year CDD65

(Billing-Month Basis)			
Month	**Actual**	**Normal**	**Difference**
July 2015	267.9	313.2	(45.3)
Aug	300.1	313.0	(12.9)
Sept	237.6	231.2	6.4
Oct	77.2	64.9	12.3
Nov	8.6	4.9	3.7
Dec	0.9	0.1	0.8
Jan 2016	0.0	0.0	-
Feb	0.0	0.0	-
Mar	0.0	0.9	(0.9)
Apr	3.4	7.1	(3.7)
May	21.3	32.5	(11.2)
June	186.5	146.5	40.0
Total	**1103.5**	**1114.3**	**(10.8)**

Table 3: Test-Year CDD75

(Billing-Month Basis)			
Month	**Actual**	**Normal**	**Difference**
July 2015	31.3	62.5	(31.2)
Aug	45.5	69.5	(24.0)
Sept	39.5	36.5	3.0
Oct	7.5	4.9	2.6
Nov	0.0	0.1	(0.1)
Dec	0.0	0.0	-
Jan 2016	0.0	0.0	-
Feb	0.0	0.0	-
Mar	0.0	0.0	-
Apr	0.0	0.1	(0.1)
May	0.0	0.5	(0.5)
June	21.3	16.5	4.8
Total	**145.1**	**190.6**	**(45.5)**

The test-year period includes very mild winter temperatures with HDD55 22% below normal. Test-year CDD65 is 1.0% below normal. Two of the primary cooling months (July and August 2015) are below normal, while June 2016 is significantly above normal. September 2015, another cooling month, is slightly above normal. While total test-year CDD65 is close to normal, there are fewer than expected hot days as measured by CDD75. There are 145.1

CDD75 compared with normal CDD75 of 190.6; this contributes to a small upward cooling sales adjustment for residential and small C&I rate classes. CDD75 is statistically insignificant in the SL (Secondary Large C&I) rate class.

Q15. How does weather impact test-year sales?

A15. Overall test-year sales adjustments are positive as HDD are significantly below normal. Total test-year sales are weather normalized up 1.9%. Given sensitivity to HDD, the residential class accounts for the largest share of this adjustment; residential sales are weather normalized up 4.6%. Small C&I sales are adjusted up 1.4%. Large C&I sales are the least sensitive to changes in weather conditions with sales adjusted up just 0.01% for the SL rate. Monthly sales adjustment factors by rate class are summarized in the Itron Report (IPL Witness EF Attachment 2).

IV. SUMMARY

Q16. Could you briefly summarize your testimony?

A16. Yes. The weather normalization method adopted represents best industry practice. Sales are weather normalized at the rate level thus accounting for differences in rate specific weather/load responses. Weather adjustment coefficients are derived from daily use regression models that are statistically strong resulting in reasonable weather adjustment coefficients.

Test-year monthly HDD and CDD calculations are also based on best practice methods. Actual and normal HDD and CDD variables are defined with temperature break definitions that best explains the rate-class usage/weather relationship and are consistent with the billing-month period.

Test-year sales are weather adjusted upwards 1.9% primarily as a result of warm winter weather conditions over the test-year period. The residential rate class saw the largest adjustment, given the class' sensitivity to changes in HDD. There is also a small upward adjustment for residential and small C&I cooling loads as a result of fewer hot days over the test-year period.

Q17. Does this conclude your verified pre-filed direct testimony?

A17. Yes it does.

VERIFICATION

I, Eric Fox, Director, Forecast Solutions for Itron, Inc., affirm under penalties of perjury that the foregoing representations are true and correct to the best of my knowledge, information and belief.

Eric Fox

Eric Fox

Dated: December 22, 2016

Eric Fox

Director, Forecast Solutions
Itron, Inc.

Education

- M.A. in Economics, San Diego State University, 1984
- B.A. in Economics, San Diego State University, 1981

Employment History

- Director, Forecasting Solutions, Itron, Inc. 2002 - present
- Vice President, Regional Economic Research, Inc. (now part of Itron, Inc.), 1999 – 2002
- Project Manager, Regional Economic Research, Inc., 1994 – 1999
- New England Electric Service Power Company, 1990 – 1994
  Positions Held:
  - Principal Rate Analyst, Rates
  - Coordinator, Load Research
  - Senior Analyst, Forecasting
- Senior Economist, Regional Economic Research, Inc., 1987 – 1990
- San Diego Gas & Electric, 1984 – 1987
  Positions Held:
  - Senior Analyst, Rate Department
  - Analyst, Forecasting and Evaluation Department
- Instructor, Economics Department, San Diego State University, 1985 – 1986

Experience

Mr. Eric Fox is Director, Forecasting Solutions with Itron where he directs electric and gas analytics and forecasting projects and manages Itron's Boston office. Mr. Fox has over 30 years of forecasting experience with expertise in financial forecasting and analysis, long-term energy and demand forecasting, and load research.

Mr. Fox and his team focus on developing and implementing forecast applications to streamline and support utility business operations. This work includes directing development and implementation of Itron's integrated sales and revenue forecasting application (*ForecastManager.net*) and load research system (*LRS*). He also engages in forecast support work, which includes developing energy and demand forecasts for financial and long-term planning, billed and unbilled sales and revenue analysis, weather normalization for monthly sales variance analysis and rate case support, and analyzing technology and economic trends and their impact on long-term energy usage.

Mr. Fox has provided expert testimony and support in rate and regulatory related issues. This support has included developing forecasts for IRP and rate filings, weather normalizing sales and demand for rate filing cost of service studies, providing rate case support and direct testimony and conducting forecast workshops with regulatory staff. He is one of Itron's primary forecast instructors. He provides forecast training through workshops sponsored by Itron, utility on-site training programs, and workshops held by other utility organizations.

Prior to joining RER/Itron, Mr. Fox supervised the load research group at New England Electric where he oversaw systems development, directed load research programs, and customer load analysis. He also worked in the Rate Department as a Principal Analyst where he was responsible for DSM rate and incentive filings, and related cost studies. The position required providing testimony in regulatory proceedings.

Projects, Reports, and Presentations

Development of Long-Term Regional Energy and Demand Forecast Models, Tennessee Valley Authority, November 14, 2016

New York Energy Trends and Long-Term Energy Outlook, New York ISO Forecasting Conference, Albany New York, October 28, 2016

Fundamentals of Forecasting Workshop, with Mark Quan, Chicago, Illinois, September 26th – 28th, 2016

Building Long-Term Solar Capacity and Generation Model, Duke Energy, September 8 and 9th, Charlotte North Carolina

When GDP No Longer Works - Capturing End-Use Efficiency Trends in the Long-Term Forecast, EEI Forecast Conference, August 21 – 23rd, 2016, Boston Massachusetts

2016 Long-Term Electric Energy and Demand Forecast, Vectren Corporation, August 4, 2016

Forecasting Behind the Meter Solar Adoption and Load Impacts, with Mike Russo, Itron Brown Bag, July 12, 2016

2016 Long-Term Electric Energy and Demand Forecast, IPL, July 19, 2016

Long-Term Forecast Methodology, IPL Integrated Resource Plan Forecast, Presented to the Indiana Utility Regulatory Commission Staff, June 15, 2016

Long-Term Energy and Demand Forecast, Burlington Electric Vermont, May 2016

Statistical Mumbo Jumbo: It's Not Really, Understanding Basic Forecast Model Statistics, Electric Utility Forecasting Forum, Chattanooga, Tennessee, April 7 to 8, 2016

Solar Load Modeling and Forecast Review, NV Energy, Nevada Public Utilities Commission Staff, and Bureau of Consumer Protection, Reno Nevada, January 29, 2016

Statistically Adjusted End-Use Modeling Workshop, New York ISO, December 10, 2015

Long-Term Energy and Load Modeling Workshop, Chicago Illinois, October 29th – 30th

Integrating Energy Efficiency Program Impacts into the Forecast, Indiana Utility Regulatory Commission, Contemporary Issues Conference, September 1, 2015

Residential and Commercial End-Use Energy Trends (SAE Update), Itron Webinar for EFG Members, with Oleg Moskatov and Michael Russo, July 22, 2015

Capturing End-Use Efficiency Improvements through the SAE Model, 3rd CLD Meeting, Vaughan, Ontario, June 24 2015

Modeling New Technologies – When Regression Models Don't Work, Itron Webinar Brown Bag Series, with Oleg Moskatov and Michael Russo, June 9, 2015

Long-Term Demand Forecasting Overview and Training, KCP&L, April 2015

Budget Year 2016, Sales, Revenue, and Load Forecast, Green Mountain Power Company, March 2015

Forecast Review and Training for 2015 Rate Filing, PowerStream, January 2015

Rate Class Customer and Sales Forecast: 2015 Rate Filing, Hydro Ottawa, January 2015

Forecast Systems Implementation and Training, Entergy, January 2015

Long-Term Energy and Demand Forecasting, Ontario Ministry of Energy, January 2015

Load Research Sample Design, Nova Scotia Power, November 2014

Vermont Long-Term Energy and Demand Forecast, VELCO, November 2014

Energy Trends and Utility Survey Results, EUFF Meeting, October 2014

Fundamentals of Forecasting Workshop, Boston, MA, October 2014

Gas Forecasting Workshop with Minnesota PUC Staff, Integrys, September 2014

Load Research System Implementation and Training, NVEnergy, June 2014

Forecasting and Modeling Issues Workshop, Ontario, CA, July 2014

Unbilled Sales Analysis and System Implementation, KCP&L March 2014

Gas Sales and Revenue Forecast Model Development, TECo, December 2013

Forecast Model Development and Training, Duke Energy, October 2013

Sales and Revenue Forecast, GMP, August 2013

Forecast Support and Testimony, TECo, June 2013

Long-Term Energy and Demand Forecast, IRP Filing, GMP, May 2013

Long-Term Energy and Demand Forecast, IRP Filing, Vectren, March 2013

Statistical End-Use Model Implementation, Nova Scotia Power, December 2012

Fundamentals of Forecasting, Workshop, Boston, MA, November 2012

Rate Class Profile Development for Settlement Support, NYSEG and RGE (Iberdrola), September 2012

Budget Forecasting System Implementation, and Training, Horizon Utilities, August 2012

Commercial Sales Forecasting: Getting it Right, Itron Brownbag Web Presentation, June 2012

Long-Term Energy Trends and Budget Forecast Assessment, Tampa Electric Company, June 2012

Budget-Year 2013 Sales and Revenue Forecast, Green Mountain Power, April 2012

Long-Term Residential and Commercial Energy Trends and Forecast, Electric Utility Forecasting Week, Las Vegas, May 2012

NV Energy Forecast Workshop, with Terry Baxter, NV Energy, March 2012

Commercial Sales Forecasting, the Neglected Sector, Electric Utility Forecasting Forum, Orlando, November 2011

Vermont Long-Term Energy and Demand Forecast, Vermont Electric Transmission Company, November 2011

Fundamentals of Forecasting Workshop, Boston, September 2011

Forecasting Top 100 PPL Load-Hours, with David Woodruff, AEIC Summer Load Research Conference, Alexandra, VA, August 2011

Budget and Long-Term Energy and Demand Forecast Model Development, Central Electric Power Cooperative, April 2011

Development of an Integrated Revenue Forecasting Application, TVA, March 2011

Integrating Energy Efficiency Into Utility Load Forecasts, with Shawn Enterline, 2010 ACEE Summer Study on Energy Efficiency in Buildings, August 2010

Using Load Research Data to Develop Peak Demand Forecasts, AEIC Load Research Conference, Sandestin, FL, August 2010

Development of a Long-term Energy and Demand Forecasting Framework, Consumer Energy, October 2009

Review of Entergy Arkansas Weather Normalization Methodology for the 2009 Rate Case, Entergy Arkansas Inc., September 2009

Green Mountain Power Budget Year and Rate Case Sales and Revenue Forecast, Green Mountain Power, May 2009

Vectren Gas Peak-Day Design Day Load Forecast and Analysis, Vectren Energy, April 2009

Nevada Power, Long-Term Energy and Demand Forecast, NV Energy, March 2009

Estimating End-Use Load Profiles, Leveraging Off of Load Research Data, Western Load Research Conference, Atlanta, March 2009

Fundamentals of Load Forecasting Workshop, Orlando, March 2009

DPL Long-Term Energy and Demand Forecast, 2009 IRP Filing, Dayton Power & Light, February 2009

Development and Application of Long-Term End-Use Hourly Load Forecasting Model, AEP, October 2008

Load Research from the User's Perspective, AEIC Annual Load Research Conference, Oklahoma City, August 2008

OGE Weather Normalized Sales Study, Estimation of Weather Normalized Sales for 2007 Rate Case, July 2008

Vermont Long-Term and Zonal Demand Forecast, Vermont Power Company, July 2008

Budget Forecast System Implementation, Entergy June 2008

Approaches for Analyzing Electric Sales Trends, Electric Forecasting Group, Las Vegas, May 2008

2008 Budget Sales Forecast, NStar, August 2007

Long-Term Peak Demand Forecast, ITC, August 2007

Long-Term Forecasting Workshops, Ameren and Missouri Public Utilities Commission, April 2007

Fundamentals of Forecasting Workshop, March 2007, Orlando Florida

Statistically Adjusted End-Use Modeling Overview, Vermont Public Utilities Commission, December 2006

2007 Budget Sales and Revenue Forecast, Green Mountain Power Company, October 2006

Estimation of Long-Term Peak, Michigan Electric Transmission Company, August 2006

Review and Estimation of Gas Price Elasticities, with Dr. Stuart McMenamin, PSEG, March 2006

Implementation of Long-Term Energy and Hourly Load Forecasting Application, Project Manager, Florida Power & Light, March 2006

Development of Long-Term Energy and Demand Forecast, Orlando Utilities Commission, February 2006

Development of Long-Term Energy and Demand Forecast, Orlando Utilities Commission, February 2006

Regulatory Experience

September 2015: Provided testimony and support related to sales weather-normalization for the 2015 rate case. Indianapolis Power & Light

Jan 2015 – Dec 2016: Assisted Power Stream with developing and supporting the 2015 rate case sales and customer forecast before the Ontario Energy Board

Jan 2015 – Dec 2016: Assisted Hydro Ottawa with developing and supporting the 2015 rate case sales and customer forecast before the Ontario Energy Board

Oct 2014 – July 2015: Assisted Entergy Arkansas with developing and supporting weather adjusted sales and demand estimates for the 2015 rate case.

September 2014: Assisted with developing the budget sales and revenue forecast and provided regulatory support related Horizon Utilities 2014 rate filing before the Ontario Energy Board

August 2013: Reviewed and provided testimony supporting Sierra Pacific Power Company's forecast for the 2013 Energy Supply Plan before the Nevada Public Utilities Commission

July 2013: Reviewed and provided testimony supporting Tampa Electric's forecast for the 2013 rate case before the Florida Public Service Commission

March 2013: Reviewed and provided testimony supporting Entergy Arkansas sales weather normalization for the 2013 rate filing before the Arkansas Public Service Commission

June 2012: Reviewed and provided testimony supporting Nevada Power Company's 2012 Long-Term Energy and Demand Forecast before the Nevada Public Utilities Commission

May 2010: Provided testimony supporting Sierra Pacific Power's Company's 2010 Long-Term Energy and Demand Forecast before the Nevada Public Utilities Commission

March 2010: Assisted with development of the IRP forecast and provided testimony supporting Nevada Power Company's 2010 Long-Term Energy and Demand Forecast before the Nevada Public Utilities Commission

August 2009: Reviewed Entergy Arkansas weather normalization and provided supporting testimony before the Arkansas Public Service Commission

February 2006: Developed long-term forecast and provided testimony to support Orlando Utilities Commission *Need for PowerApplication* before the Florida Public Service Commission

July 2005: Developed sales and customer forecast and provided testimony to support Central Hudson's electric rate filing before the New York Public Service Commission

April 2004: Held Weather Normalization Workshop with the Missouri Public Service Commission Staff

July 2001: Conducted workshop on long-term forecasting with the Colorado Public Utilities Commission Staff

October 1993: Submitted testimony in support of DSM earned incentives and related rate design before the Massachusetts Department Public Utilities, and Rhode Island Public Utilities Commission. Position: Principal Analyst, Rate Department, New England Power Service Company. Supervisor: Mr. Larry Reilly.

June 1993: Testified in matters related to the annual Energy Conservation Services Charge before Massachusetts Department Public Utilities. Position: Principal Analyst, Rate Department, New England Power Service Company. Supervisor: Mr. Larry Reilly.

June 1990: Submitted testimony in Nevada Power's behalf in matters related to gas transportation rates proposed by Southwest Gas in Southwest Gas rate proceedings before Nevada Public Utilities Commission. Position: Sr. Analyst, Regional Economic Research, Inc.

October 1988: Testified to development and application of a Gas Marginal Cost of Service Study for unbundling natural gas rates as part of a generic hearing to restructure the natural gas industry in California before the California Public Utilities Commission. Position: Sr. Analyst, Rate Department, San Diego Gas & Electric. Supervisor: Mr. Douglas Hansen

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2016 Rate Case
Sales Weather Normalization

Indianapolis Power & Light

Submitted to:

Indianapolis Power & Light
Indianapolis, IN

Submitted by:

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September 2016

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Overview

Indianapolis Power & Light Company (IPL) contracted Itron, Inc. (Itron) to develop rate class weather-adjustment factors for IPL's 2016 Rate Case. Weather-adjustment factors are used to weather normalize monthly sales by rate for the test-year period.

Utility revenues and costs can vary significantly from month to month, largely as a result of variations in weather conditions. In determining appropriate revenues and associated cost of service, it is important to minimize this variation. This process is known as weather-normalization and entails estimating sales for expected or normal weather conditions. For IPL's 2016 Rate Case, the test-year period is July 2015 to June 2016.

1. Weather Response Functions

The first task in weather-normalizing sales is to estimate weather-response functions. Weather-response functions measure customers' usage sensitivity to changes in weather conditions. The industry-standard approach is to estimate weather response models using linear regression. Linear regression is a statistical modeling approach that allows us to relate customer electricity usage to weather conditions and other factors that impact usage such as seasonal changes, hours of light, weekends and holidays, and customer usage trends over the estimation period; the resulting model's weather-coefficients measure how usage changes as weather conditions change.

The relationship between usage and weather varies by rate class as the response to weather depends on the type of heating and cooling equipment in place and seasonal/daily usage patterns. Over the long-term, economic activity, end-use standards and utility-sponsored efficiency programs also impact responsiveness to temperature. We would expect, for example the per-customer response to changes in cooling-degree days would decline as overall air conditioning equipment efficiency improves. Figure 1 and Figure 2 illustrate the difference in temperature response function; Figure 1 shows the residential heating rate (Rate RH) response function and Figure 2 shows the weather response function for large C&I secondary service (Rate SL) rate class. These curves show daily use per customer against daily average temperature. Daily use per customer data is derived from load research data; data includes the current test-year period (July 1, 2015 to June 30, 2016) and prior test-year period (July 1, 2013 to June 30, 2014). As illustrated, RH is significantly more sensitive to changes in winter temperatures than SL.

Figure 1: Residential Heat (RH) User per Customer vs. Temperature

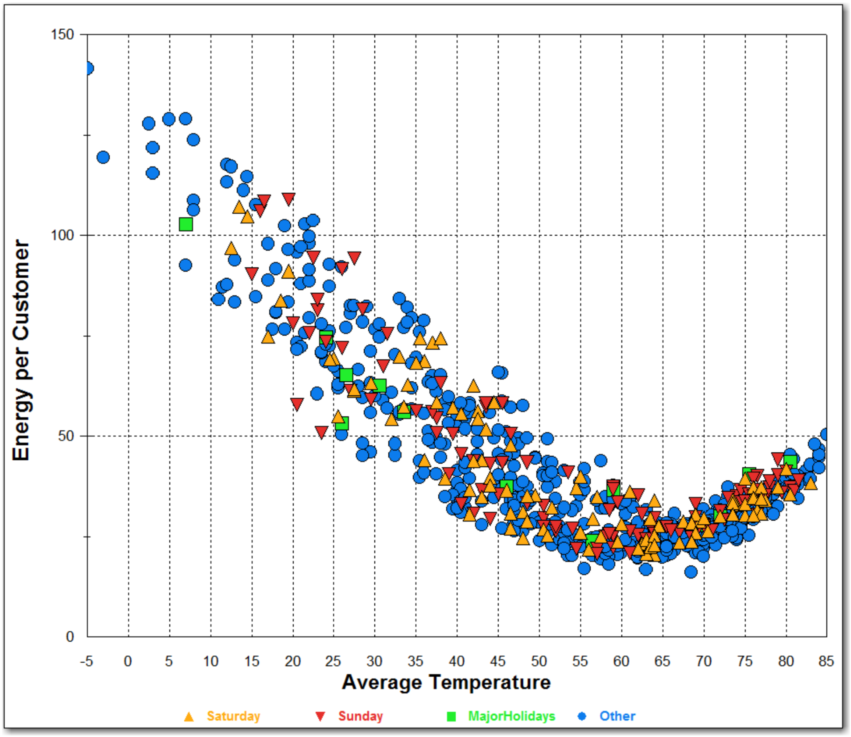
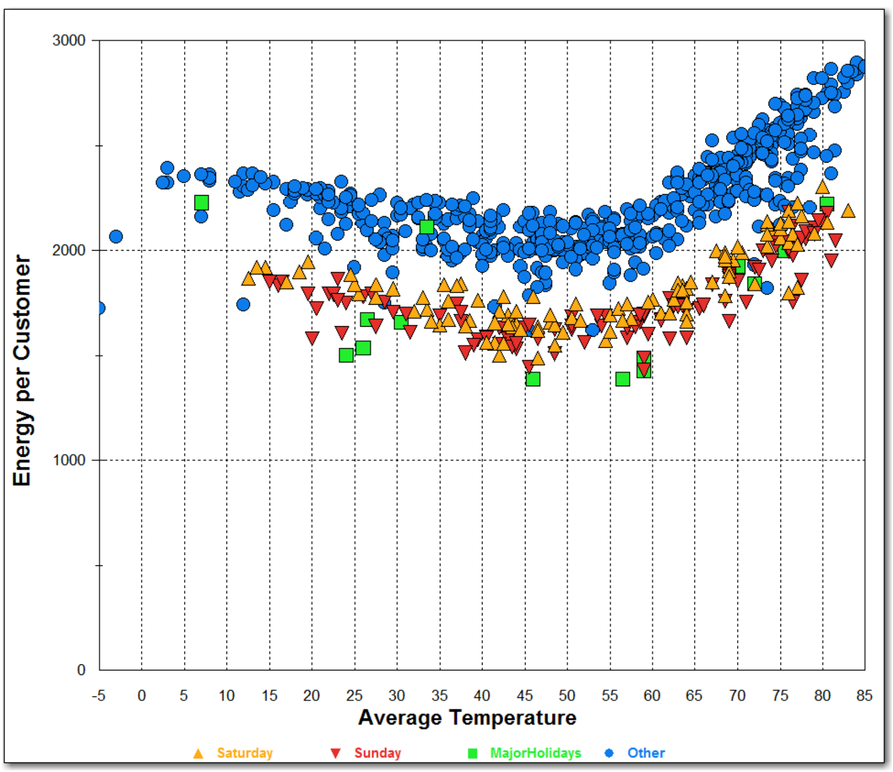


Figure 2: Large C&I Secondary (SL) Use per Customer vs. Temperature

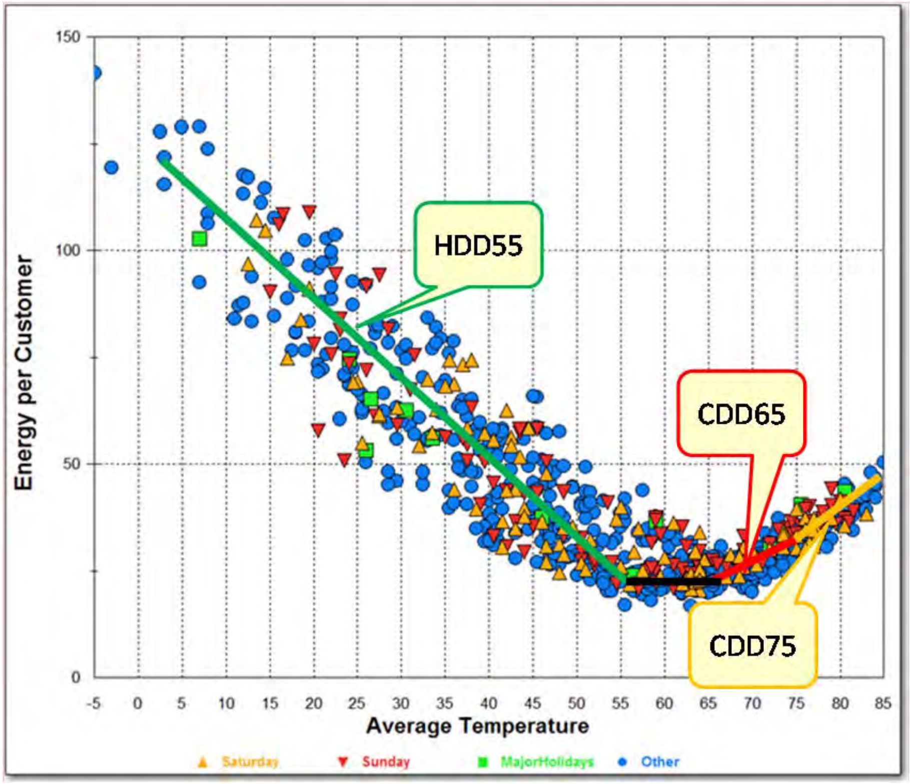


The other noticeable difference between the RH and SL is that the SL load is markedly lower on weekends than weekdays, reflecting business hours of operation. In estimating weather-response functions, we want to account for these shifts in usage as well as other non-weather factors (e.g., holidays and fewer hours of light in the winter months) in order to isolate the variation in load that is due to changes in weather conditions.

Figure 1 and Figure 2 also show that the relationship between customer usage and temperature is non-linear. During the heating season when temperatures decline, usage increases and during the cooling season as temperatures increases usage increases. Given this relationship, it's impossible to fit a meaningful regression model that directly relates average daily use to temperature without using a quadratic (temperature and temperature$^{\wedge 2}$) or more likely a cubic (temperature, temperature$^{\wedge 2}$, and temperature $^{\wedge 3}$) model specification.

Using Degree-Days. The more traditional approach is to estimate the weather/temperature relationship using heating and cooling degree-days (HDD and CDD). Heating and cooling degree days are constructed from daily average temperature data. In regression modeling, HDD and CDD are referred to as spline variables, as they only take on a value above or below a critical temperature value, otherwise they take on a value of 0; the relationship between degree-days and usage is linear for the defined degree-day temperature range. The non-linear relationship can be modeled by combining these linear splines. This is illustrated in Figure 3 where HDD of base 55 degrees and CDD of base 65 and 75 degrees are fitted to the RH curve.

Figure 3: RH Fitted Degree-Day Splines



As illustrated, HDD explains the left side of the curve, where load increases as temperatures decrease, while CDD explains the right-side of the curve, where load increases as temperatures increase. HDD and CDD are constructed using actual (i.e., observed) daily temperature and a defined temperature base.

Defining HDD and CDD Temperature Breakpoints. The National Oceanic and Atmospheric Administration (NOAA) define CDD and HDD using a base temperature of 65 degrees. A daily CDD of 65 degree-day base is calculated as:

CDD65 = IF (Average Temperature > 65)
THEN (Average Temperature – 65)
ELSE 0

And HDD as:

HDD65 = IF (Average Temperature < 65)
THEN (65 – Average Temperature)
ELSE 0

While a 65 degree-day base is a useful standard for comparing heating and cooling seasons against reference or normal weather conditions, the 65 degrees is not necessarily the best base temperature for weather normalizing electric or gas sales. Generally, 65 degrees works well on the cooling side. Daily use on the cooling side begins to rise when average daily temperature is above 65 degrees. A 65-degree base does not work as well on the heating side as there is little heating until average daily temperatures falls below 55 degrees.

In developing the weather response models, the objective is to fit the best possible curve with HDD and CDD. In the residential rates, the best model statistical fit is with HDD defined for a 55 degree temperature base (HDD55) and CDD with a 65 degree-day cooling base (CDD65). Model statistical fit and resulting weather response curve can be improved by including a 75 degree-day based CDD (CDD75) in addition to the CDD65. The relationship between residential usage and temperature is slightly steeper when daily average temperature exceeds 75 degrees. That is, a one-degree increase above 75 degrees has a larger kWh impact that a one-degree increase below 75 degrees.

CDD with a base temperature of 60 degrees (CDD60) proved the best statistical fit for the C&I rate-class models. In general, commercial cooling is observable at a lower average temperature than residential because commercial buildings tend to have more internal heat build-up. The SL usage/temperature scatter-plot (Figure 2) shows usage increasing at 60 degrees. While each rate class is has slightly different temperature breakpoints that best fit the data, to simplify the analysis, we used consistent degree-day break points for Residential, Small C&I, and Large C&I rate classes. The degree-day basis is determined by evaluating the usage/temperature scatter plots and statistically testing the HDD and CDD variables with different temperature break points. The defined degree-days are:

- Residential Rate Classes: HDD55, CDD65, CDD75
- Small C&I Rate Classes: HDD55, CDD60, CDD75
- Large C& Rate Classes: HDD55, CDD60

Within the Large C&I revenue class only SL is weather normalized; the other rates including Large Primary and the High Load Factor rates are primarily industrial sales that are not weather-sensitive.

Weather response models are estimated for 7 weather-sensitive rates:

Residential Service:

1. Rate RS (Residential General Service)
2. Rate RH (Residential Electric Space Heating)

3. Rate RC (Residential Electric Water Heating)

Small C&I Services:

4. Rate SS (Small C&I, General Service)
5. Rate SH (Small C&I, Electric Space Heating)
6. Rate SE (Small C&I, Schools Electric Space Heating)

Large C&I Services

7. Rate SL (Large C&I, Secondary Service)

Model results are provided in Appendix A and B.

Models are estimated using daily use per customer estimates derived from IPL's load research data. Models are estimated using the current and prior-test year periods. We elected to use two years of daily rate-class level data (July 1, 2013 to June 30, 2014 and July 1, 2015 to June 30, 2016) as the two-year period provides more data points (than a single test-year, and greater load/weather variation; the current test-year includes one of the warmest weather on record and the prior test-year period includes a very cold winter. The models include a test-year binary to account for any difference between the test-year data series resulting from the sample expansion process, reclassification, and changes in average use growth between the test-years. The model specifications are relatively simple and are similar in structure across the rate classes. In addition to HDD and CDD variables described above, models include monthly binaries to account for non-weather related seasonal variation such as month, day of the week, and specific holiday binaries where they proved to be statistically significant. Models also include binaries for specific data points that are extreme outliers; the objective is to minimize the impact these outliers have on the estimated weather coefficients. Models include an AR(1) auto-regressive term to correct for serial correlation (i.e., residual pattern). Model results are included in Appendix B.

2. Weather Impact Calculations

As models are estimated on a use per customer basis, estimated HDD and CDD coefficients give the impact for a change in HDD or CDD on average customer use. The coefficients can be used to calculate monthly weather impacts where the weather impact is a measure of the change in sales that can be attributed to differences between actual and normal weather conditions. The weather impact in any given month is calculated as:

$$WthrImpact = B_{HDD} \times (HDD_{actual} - HDD_{normal}) + B_{CDD} \times (CDD_{actual} - CDD_{normal})$$

Where:

- B_{HDD} is the estimated coefficient on the HDD variable
- B_{CDD} is the estimated coefficient on the CDD variable
- HDD_{actual} is the actual HDD over the billing month period
- HDD_{normal} is the normal HDD for the billing month
- CDD_{actual} is the actual CDD over the billing month period
- CDD_{normal} is the normal CDD for the billing month

Weather normal average use is then calculated as:

$$WthrNrmAvgUse = ActualAvgUse - WthrImpact$$

If actual degree days are higher than normal, the weather impact is positive and sales are adjusted downward. If actual degree days are lower than normal, the impact is negative and sales are adjusted upward.

In models with two CDD variables, the cooling weather impact is the sum of the impact of the first CDD term (CDD1) plus the impact of the second CDD term (CDD2). The monthly impact is calculated as:

$$\begin{aligned} WthrImpact = {} & B_{HDD} \times (HDD_{actual} - HDD_{normal}) + \\ & B_{CDD1} \times (CDD1_{actual} - CDD1_{normal}) + \\ & B_{CDD2} \times (CDD2_{actual} - CDD2_{normal}) \end{aligned}$$

Where:

- B_{HDD} is the estimated coefficient on the HDD variable
- B_{CDD1} is the estimated coefficient on the CDD1 variable (e.g., CDD65)
- B_{CDD2} is the estimated coefficient on the CDD2 variable (e.g., CDD75)
- HDD_{actual} is the actual HDD over the billing month period
- HDD_{normal} is the normal HDD for the billing month
- $CDD1_{actual}$ is the actual CDD1 over the billing month period
- $CDD1_{normal}$ is the normal CDD1 for the billing month
- $CDD2_{actual}$ is the actual CDD2 over the billing month period
- $CDD2_{normal}$ is the normal CDD2 for the billing month

In Indiana, heating and cooling often occur during the same month. Consequently, months such as May and October may have both heating and cooling load adjustments. As a complicating factor, it is mathematically possible that the actual HDD in a given month may be below normal HDD, while actual CDD is above normal CDD.

As discussed earlier, the relationship between electricity usage and temperature is non-linear. To better fit the non-linear relationship on the cooling side, the residential and small C&I rate classes include CDD with a 65 degree-day base (CDD65) and a CDD with a 75 degree-day base (CDD75). Both CDD variables and HDD variable are statistically significant in the estimated weather response functions. The impact of CDD75 is additive to the impact of CDD65. If average daily temperature is below 75 degrees, there is no additive impact as CDD75 = 0. If the average daily temperature is for example 78 degrees then CDD65 has a value of 8 (78 – 65) and CDD75 equals 3 (78– 75). The weather impact is then:

$$WthrImpact = (B_{CDD65} \times 8) + (B_{CDD75} \times 3)$$

The impact of CDD75 is relatively small, but statistically significant. Figure 4 and Figure 5 show the contribution of CDD65 and CDD75 to predicted average daily RS usage.

Figure 4: RS Model – Contribution of CDD65 (kWh per Customer)

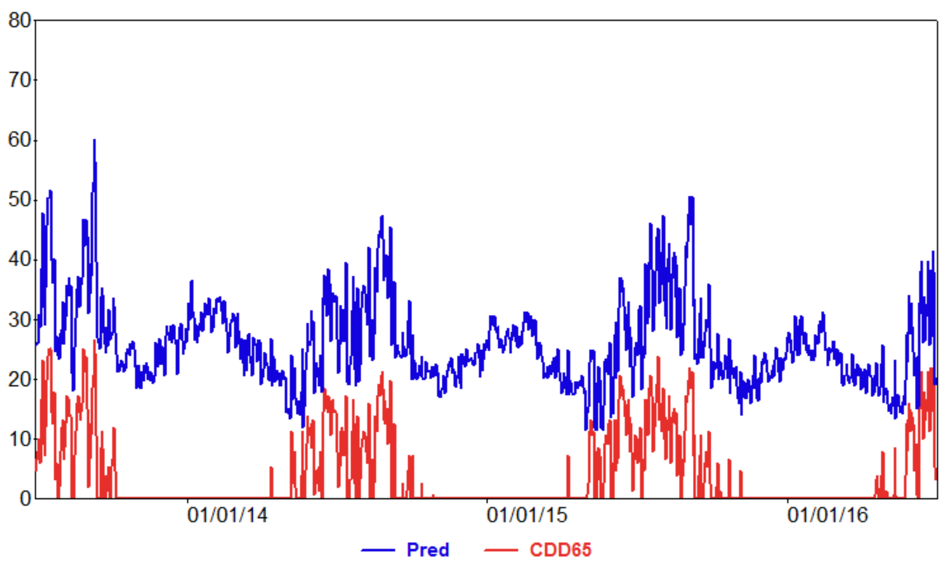
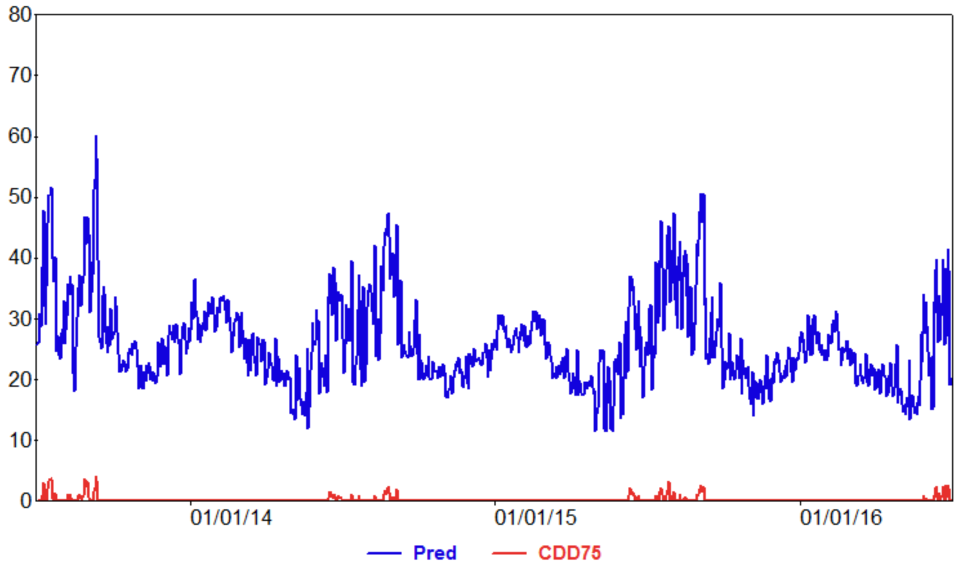
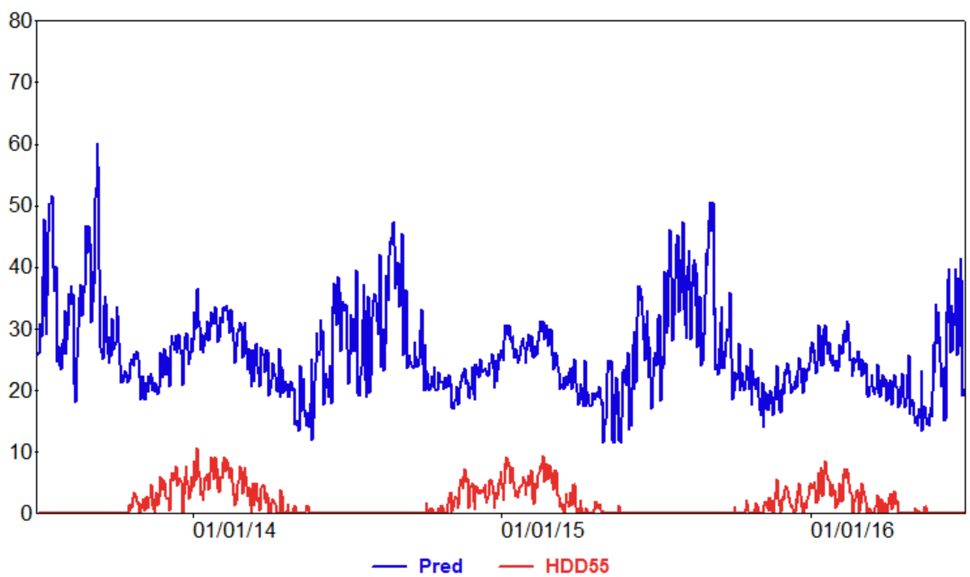


Figure 5: RS Model – Contribution of CDD75 (kWh per Customer)



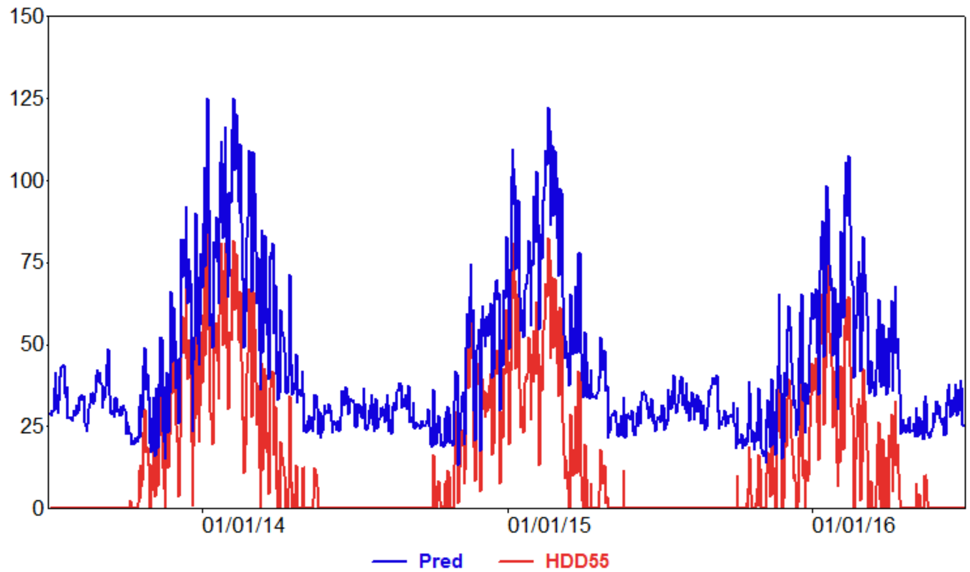
The contribution of HDD55 is analogous to the contribution of the two CDD variables. In this case however, there is only one HDD variable (HDD55) as the relationship between usage and temperature on the heating side of the curve is linear. The impact of HDD55 on RS average daily use is depicted in Figure 6.

Figure 6: RS Model – Contribution of HDD55 (kWh per Customer)



By way of contrast, the RH class usage is significantly more sensitive to changes in HDD. Figure 7 shows the contribution of HDD55 to RH predicted average use.

Figure 7: RH Model – Contribution of HDD5



Weather Normal Sales. Weather normal billed sales are calculated by subtracting the weather impact from billed sales:

$$WthrNrmSales_{ymc} = ActualSales_{ymc} - (WthrImpact_{ymc} \times Customers_{ymc})$$

Where:

- y = year
- m = billing month
- c = rate class

The revenue model requires weather adjustment factors for each rate class and month for the test-year period (July 2015 to June 2016). The weather adjustment factors are calculated as the ratio of weather normal sales estimates to actual sales:

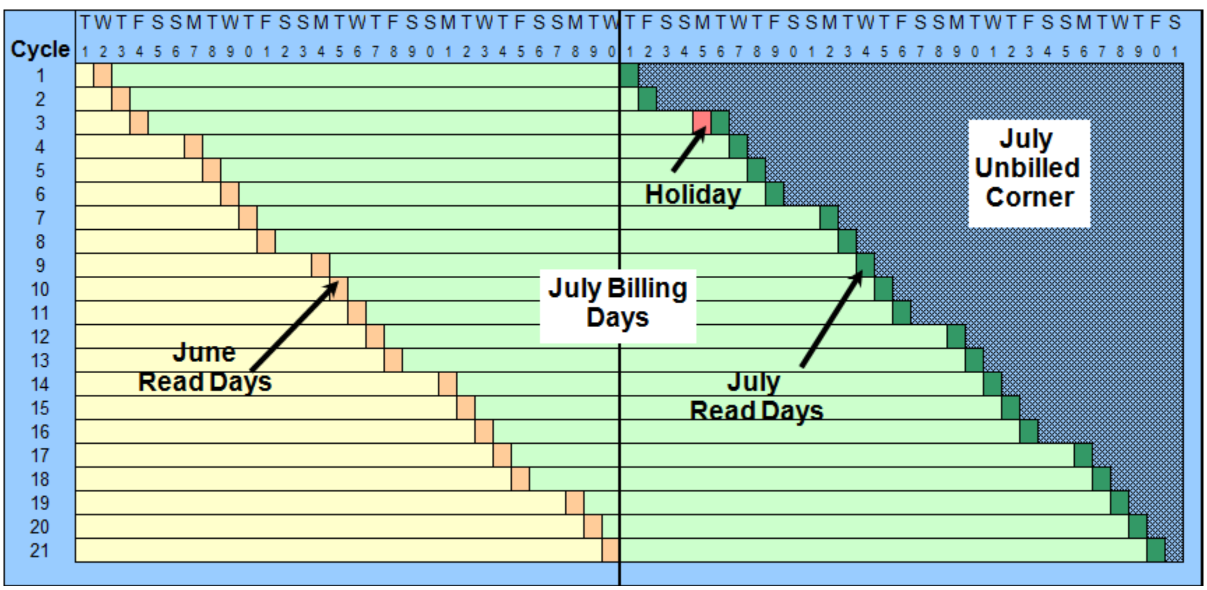
$$AdjFactor_{ymc} = {WthrNrmSales_{ymc}}\Big/{ActualSales_{ymc}}$$

The resulting adjustment factors will vary around 1.0. Adjustment factors above 1.0 will adjust billed sales upward as sales are below weather-normal sales estimates. Adjustment factors below 1.0 will adjust sales downward as actual sales are above weather normal sales.

3. Cycle-Weighted HDD and CDD

Like most utilities, IPL processes its customers over a 21-cycle billing period; approximately 1/21 of the customers' meters are processed each read date. Typically, the first cycle starts on or near the first working day of the month. Most of first cycle's usage occurs in the prior month and is associated with prior-month weather conditions. The last cycle is read at the end of the month; most of cycle 21 usage occurs in the current calendar month and is associated with current month weather conditions. Billing cycles 2 through 20 will have some usage in both the prior and current calendar months. The early billing cycles will have more of their usage in the prior month; the later cycles will have more of their usage in the current month. For example, May's billing-month sales include customer usage in April as well as May. As much as half or even more (depending on the weather conditions during the billing period) of May's billed sales is associated with April weather conditions. Calendar-month HDD and CDD may be minimally correlated with May billed sales. Figure 8 is a generalized representation of a billing-month with 21 cycles; the dates do not correspond to IPL's actual billing cycles, but the principles are consistent.

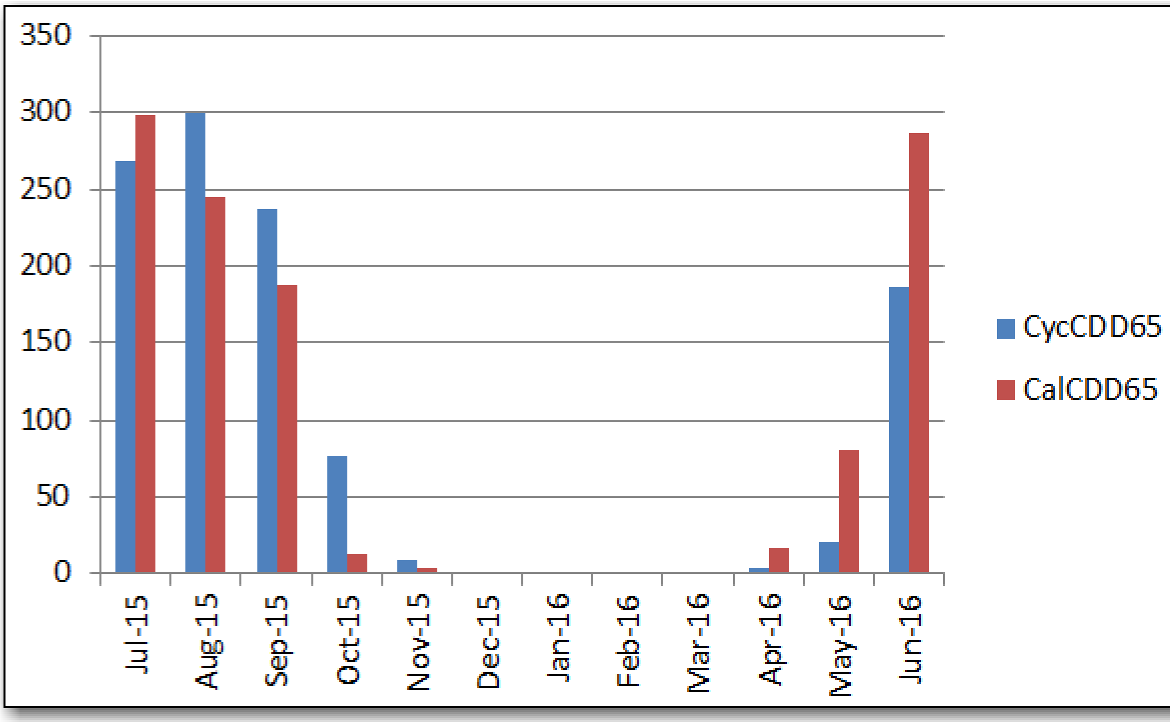
Figure 8: Billing Cycles



Test-year billed sales are appropriately weather-normalized using billing month (i.e., cycle-weighted) HDD and CDD rather than calendar-month HDD and CDD. IPL uses a standard approach for calculating cycle-weighted HDD and CDD. This approach entails developing daily weights from the historical meter-read schedule and applying these weights to daily HDD and CDD. The daily weighted HDD and CDD are then summed across the billing period. Normal cycle-weighted HDD and CDD are calculated in a similar manner; the difference is that the meter-read schedule is applied to daily normal HDD and CDD; the cycle-weighted daily normal degree days are then summed over the month. Appendix B provides a detailed description of this calculation.

Figure 9 compares calendar-month and billing-month CDD for the test-year.

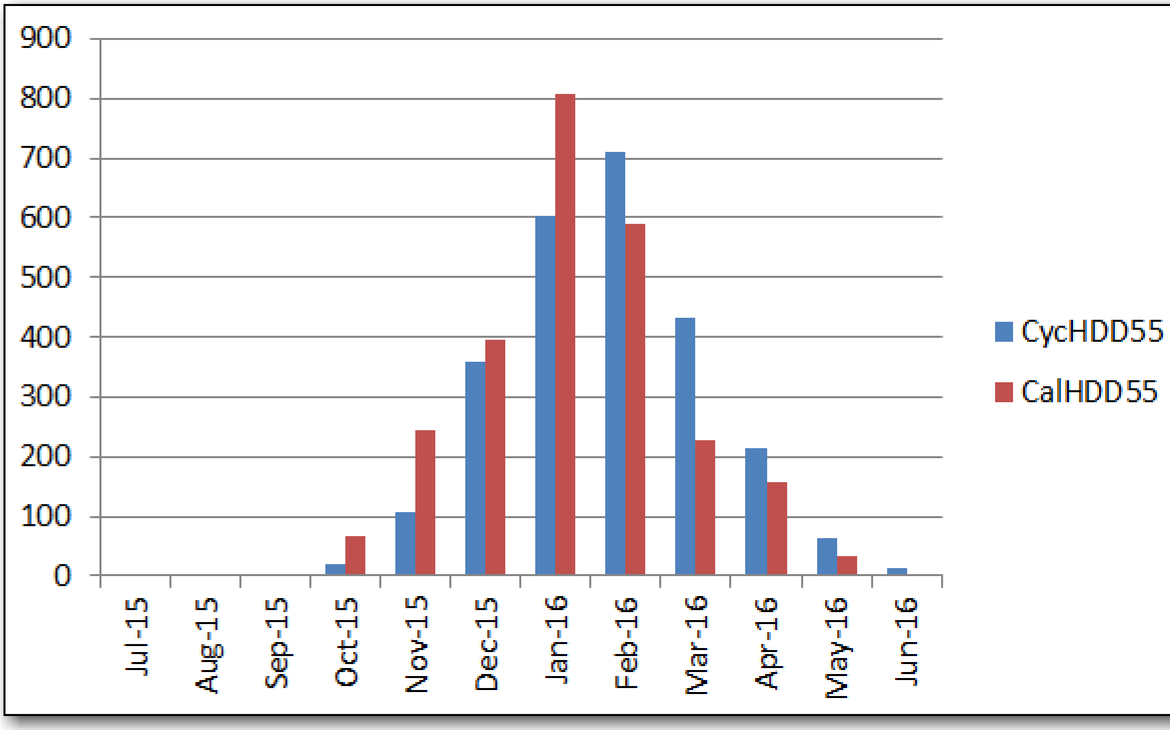
Figure 9: Test-Year Calendar Month vs. Billing Month CDD



As Figure 9 shows, there are significant differences between calendar-month and billing-month CDD. For instance, May calendar-month CDD is significantly higher than the billing-month CDD as the billing-month includes cooler April temperatures.

Figure 10 compares test-year calendar and cycle-weighted HDD. At the start of the heating season in October and November, the calendar-month HDD tend to exceed the billing-month HDD. This is the expected behavior as the calendar-month of November will generally include more cold days than the billing-month of November, which includes days in October and November. The converse is true at the end of the heating season, where the billing-month HDD tend to exceed the calendar-month HDD.

Figure 10: Test-Year Calendar vs. Billing-Month HDD



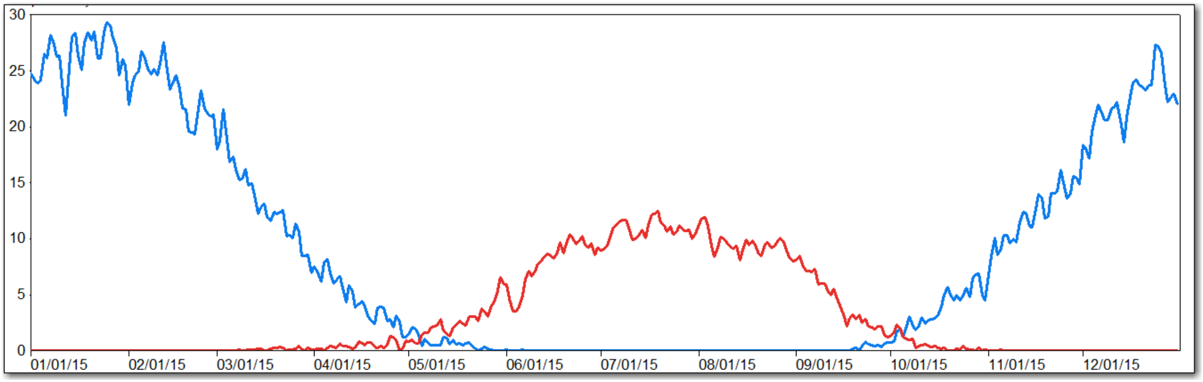
Again, on a monthly basis, there are significant differences between calendar-month and billing-month HDD. Cycle-weighted degree-days are calculated for CDD60, CDD65, CDD75 and HDD55.

4. Cycle-Weighted Normal Monthly Degree-Days

Test-year Normal HDD and CDD are based on daily average temperatures for the thirty-year period January 1, 1986 to December 31, 2015. Temperature data is from the Indianapolis International Airport.

The first step is to calculate historical daily HDD and CDD for each degree-day concept – HDD55, CDD60, CDD65, and CDD75. The daily degree-day series is then averaged by date. To construct the daily normal HDD series, all January 1st HDD are averaged, all January 2nd HDD are averaged, all January 3rd HDD are averaged, etc. all the way through the December 31st HDDs. Daily normal CDD are calculated in a similar manner. This method is consistent with that used by NOAA. Figure 11 shows the resulting daily 30-year average HDD55 (in blue) and CDD65 profiles (in red).

Figure 11: Daily Normal HDD55 and CDD65 (1986 - 2015)



Normal calendar-month HDD and CDD are derived by summing up the daily normal degree days over the calendar month. Normal billing-month HDD and CDD are calculated by first multiplying the daily normal HDD and CDD by the meter-cycle daily weights and summing the weighted normal daily degree-days over the billing month period. Table 1 compares billing-month and calendar-month normal HDD55 and Table 2 compares billing month and calendar-month normal CDD65.

Table 1: Normal Billing-Month and Calendar-Month HDD55

Dt	NCycHDD55	NCalHDD55	Difference
Jul-15	0.1	0.0	0.1
Aug-15	0.0	0.0	0.0
Sep-15	0.7	5.5	-4.8
Oct-15	42.2	113.7	-71.5
Nov-15	199.0	362.3	-163.3
Dec-15	509.2	688.0	-178.8
Jan-16	782.7	817.7	-35.0
Feb-16	758.1	673.3	84.8
Mar-16	579.0	415.1	163.9
Apr-16	276.3	135.6	140.7
May-16	75.2	19.8	55.4
Jun-16	8.1	0.4	7.7
Total	**3,230.6**	**3,231.3**	**-0.7**

Table 2: Normal Billing-Month and Calendar-Month CDD65

Dt	NCycCDD65	NCalCDD65	Difference
Jul-15	313.2	334.3	-21.1
Aug-15	313.0	296.1	17.0
Sep-15	231.2	131.4	99.8
Oct-15	64.9	16.6	48.4
Nov-15	4.9	0.3	4.6
Dec-15	0.1	0.0	0.1
Jan-16	0.0	0.0	0.0
Feb-16	0.0	0.0	0.0
Mar-16	0.9	3.4	-2.5
Apr-16	7.1	13.8	-6.7
May-16	32.5	81.6	-49.0
Jun-16	146.5	236.3	-89.8
Total	**1,114.3**	**1,113.6**	**0.7**

5. Results

The test-year period from July 2015 to June 2016 included a winter period that was one of the warmest on record with normal HDD exceeding actual HDD55 by 28%. The summer period was much closer to normal, with total normal CDD exceeding actual by 1%. However, two of the primary cooling months (July and August) were significantly below normal and there were also significantly fewer hot days as captured by the CDD75 variable. Figure 12 and Figure 13 compare test-year actual and normal CDD and HDD.

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Figure 12: Comparison of Actual and Normal Billing-Month CDD

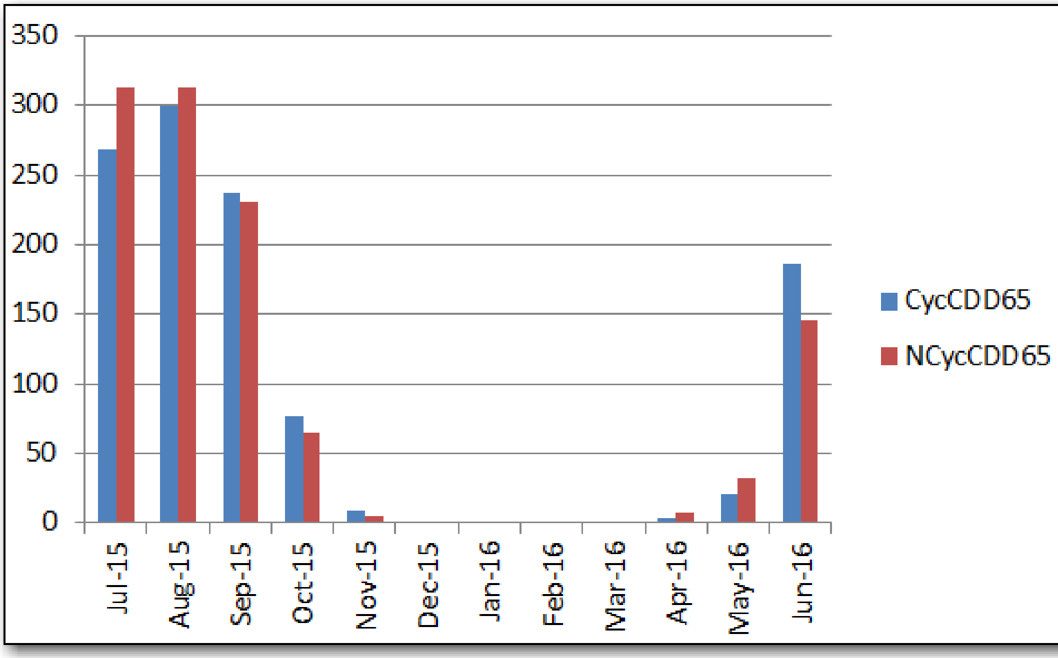

Figure 13: Comparison of Actual and Normal Bill-Month HDD

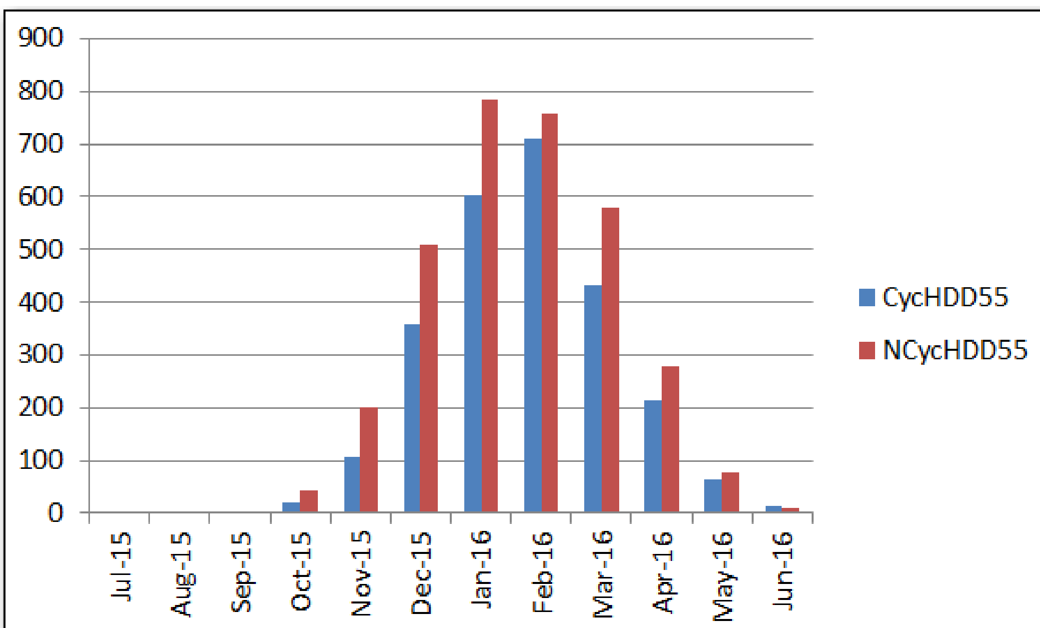

Table 3 provides the test-year actual and normal cycle-weighted degree-days.

Table 3: Actual and Normal Billing Month CDD and HDD

Dt	CycCDD65	NCycCDD65	Diff	CycHDD55	NCycHDD55	Diff
Jul-15	267.9	313.2	-45.3	0.0	0.1	-0.1
Aug-15	300.1	313.0	-12.9	0.0	0.0	0.0
Sep-15	237.6	231.2	6.4	0.0	0.7	-0.7
Oct-15	77.2	64.9	12.2	18.8	42.2	-23.4
Nov-15	8.6	4.9	3.7	107.8	199.0	-91.2
Dec-15	0.9	0.1	0.8	357.2	509.2	-152.0
Jan-16	0.0	0.0	0.0	604.3	782.7	-178.4
Feb-16	0.0	0.0	0.0	709.8	758.1	-48.3
Mar-16	0.0	0.9	-0.9	431.0	579.0	-147.9
Apr-16	3.4	7.1	-3.7	213.3	276.3	-63.0
May-16	21.3	32.5	-11.3	64.5	75.2	-10.7
Jun-16	186.5	146.5	40.0	14.2	8.1	6.0
Total	**1,103.3**	**1,114.3**	**-11.0**	**2,520.8**	**3,230.6**	**-709.8**

Test-year sales are weather normalized up as a result of the extremely warm winter and temperate peak cooling-months (July and August). Residential sales (RES), which are the most-sensitive to variation in winter temperatures, are adjusted up 4.6% for the test-year. Small C&I (SCI) sales are adjusted up 1.4%, and the Large C&I classes which are the least sensitive to changes in degree-days are adjusted up less than 0.1% in the SL rate. Total sales across all rate classes are adjusted up 1.9%. Table 4 shows test-year actual and weather normal billed sales by revenue class.

Table 4: Test-Year Billed Sales by Class

Actual Sales (MWh)	July	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June	Total
Res	443,599	452,921	410,780	313,357	289,302	412,951	534,255	535,472	425,967	337,847	291,599	379,820	4,827,871
SCI	161,731	161,519	152,950	134,613	115,211	138,350	163,826	171,411	152,089	129,506	126,043	145,308	1,752,557
LCI	643,762	601,684	629,088	558,554	497,019	525,884	534,806	509,652	519,970	509,027	522,666	577,679	6,629,791
Total	1,249,092	1,216,124	1,192,818	1,006,524	901,532	1,077,185	1,232,887	1,216,534	1,098,026	976,380	940,308	1,102,808	13,210,218
Wthr Adj Sales (MWh)													
Res	470,969	463,587	407,173	313,868	314,277	457,193	586,823	549,703	470,037	358,240	300,208	357,997	5,050,074
SCI	165,193	162,622	152,245	132,945	117,776	144,065	170,650	173,294	157,689	132,385	127,026	141,525	1,777,415
LCI	648,120	602,868	628,158	555,189	496,295	526,662	535,897	509,998	520,860	510,063	523,528	572,771	6,630,411
Total	1,284,282	1,229,077	1,187,577	1,002,002	928,348	1,127,920	1,293,370	1,232,996	1,148,586	1,000,688	950,762	1,072,293	13,457,900
Chg in WthrAdj Sales													
Res	6.2%	2.4%	-0.9%	0.2%	8.6%	10.7%	9.8%	2.7%	10.3%	6.0%	3.0%	-5.7%	4.6%
SCI	2.1%	0.7%	-0.5%	-1.2%	2.2%	4.1%	4.2%	1.1%	3.7%	2.2%	0.8%	-2.6%	1.4%
LCI	0.7%	0.2%	-0.1%	-0.6%	-0.1%	0.1%	0.2%	0.1%	0.2%	0.2%	0.2%	-0.8%	0.0%
Total	2.8%	1.1%	-0.4%	-0.4%	3.0%	4.7%	4.9%	1.4%	4.6%	2.5%	1.1%	-2.8%	1.9%

Summary

The regression-based approach for generating weather-normalized sales represents the best practice and is used by most electric utilities in North America. The availability of rate-class hourly/daily usage data provides greater clarity of the load/weather relationship (when compared with using monthly data) and allows us to construct degree-day variables that best explains the relationship between customer usage and weather conditions. The data set provides a large number of observations with variation in load and weather conditions allowing us to estimate robust models and statistically strong weather adjustment coefficients.

Appendix A:
Weather Response Models, Data, and Results

Daily weather response models are estimated for 7 rates. The rates include:

- RS (Residential General Service)
- RH (Residential Electric Space Heating)
- RC (Residential Electric Water Heating)
- SS (Small C&I, General Service)
- SH (Small C&I, Electric Space Heating)
- SE (Small C&I, Schools Electric Space Heating)
- Rate SL (Large C&I, Secondary Service)

Model Data

Usage Data. Daily rate class use data is derived from IPL's hourly load research data. The data set includes two test-year periods. July 1, 2013 to June 30, 2014 and July 1, 2015 to June 30, 2016. Daily per-customer use is calculated by summing the rate class hourly loads across the day and dividing by the monthly customer counts (using the same monthly value for each day during a month).

Weather Data. Daily actual and normal HDD and CDD are derived from daily maximum and minimum temperature data for Indianapolis International Airport. Daily temperature data is from January 1, 1986 to July 31, 2016. Billing-month actual and normal HDD and CDD calculations are based on the meter read schedule over the test-year period. Normal HDD and CDD are based on a thirty-year period ending December 31, 2015.

Estimated Models

Models are estimated for daily use per customer for each rate. Models are estimated over the period July 1, 2013 to June 30, 2016, with the exception of the SE model, which was estimated from July 1, 2015 to June 30, 2016. The model specifications are relatively simple with a single HDD value (based on 55 degrees) and one or two CDD value (based on the weather-responsiveness of the class). Models also include monthly binaries to capture load variation that are not weather-related; this includes, monthly, day-of-the week, and holiday binaries, specific daily binaries to account for large daily load variation that cannot be explained by weather, and a test-year binary to account for any differences due to test-year sample expansion and change in load growth between the test years. The models also include an auto-regressive term (AR1) to account for serial correlation resulting from the complexity inherent in load/weather response models.

Overall, the estimated models explain variation in daily use relatively well. Excluding the SE models, Adjusted R-Squared (a measure of the model's statistical fit) varies from 0.94 to 0.97. The SE rate (Schools, Electric Heat) is the smallest of the weather-normalized rate classes. The Adjusted R-Squared is 0.84 as result of significant variation in the day-to-day data series that can't be explained by weather, day of the week, or seasonal factors. While the SE overall model fit is not as strong, the weather variables (HDD55 and CDD60) are statistically strong with t-Statistics over 8.0.

Model statistics are provided in Appendix B.

Weather Normalization Results

Table 5 shows test-year billed and weather normal sales by rate. The large industrial rates (PL, PH, H1, H2, and H3) are not weather normalized.

Table 5: Test Year Billed Sales by Rate

Actual Sales (MWh)	July	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June	Total
RS	255,409	264,917	236,826	169,861	137,659	173,946	200,889	188,302	166,058	146,481	143,364	209,885	2,293,598
RH	149,161	148,139	138,108	116,044	127,018	206,372	294,398	309,368	227,747	163,686	122,879	136,747	2,139,667
RC	39,029	39,865	35,846	27,452	24,625	32,634	38,968	37,801	32,162	27,680	25,356	33,187	394,606
SS	117,162	115,834	111,314	98,329	83,257	95,207	105,663	104,409	97,955	90,450	90,981	106,649	1,217,211
SH	43,058	44,057	39,977	34,823	30,697	41,722	56,493	65,119	52,555	37,736	33,725	37,137	517,098
SE	1,511	1,628	1,660	1,461	1,257	1,421	1,670	1,883	1,579	1,320	1,337	1,521	18,247
SL	335,164	325,540	318,456	294,908	260,534	273,566	283,967	274,673	275,085	269,474	276,485	308,230	3,496,081
PL	124,183	119,422	121,928	105,954	94,843	100,401	98,231	93,851	95,558	88,146	96,883	103,890	1,243,291
H1	128,752	118,907	118,108	108,470	96,870	105,901	107,003	99,870	103,685	109,379	107,736	114,699	1,319,381
H2	21,340	7,687	35,841	17,774	15,919	19,151	17,077	16,931	18,703	17,111	16,048	20,861	224,442
H3	30,623	27,086	31,424	28,049	26,127	23,454	25,666	21,175	23,888	21,915	22,251	26,899	308,556
PH	3,699	3,043	3,330	3,398	2,726	3,412	2,861	3,153	3,051	3,000	3,264	3,102	38,039
Total	1,249,092	1,216,124	1,192,818	1,006,524	901,532	1,077,185	1,232,887	1,216,534	1,098,026	976,380	940,308	1,102,808	13,210,218
Wthr Adj Sales (MWh)													
RS	273,222	271,471	234,446	166,614	140,428	180,303	208,713	190,420	172,842	150,472	147,556	196,038	2,332,524
RH	156,222	151,128	137,197	119,997	148,095	242,177	336,661	320,810	262,947	179,076	126,724	130,452	2,311,485
RC	41,525	40,988	35,531	27,256	25,754	34,712	41,449	38,473	34,248	28,693	25,928	31,506	406,065
SS	119,200	116,549	110,914	97,070	83,354	96,159	106,852	104,751	98,915	91,130	91,372	104,632	1,220,896
SH	44,468	44,442	39,675	34,421	33,148	46,449	62,087	66,648	57,160	39,918	34,312	35,389	538,116
SE	1,525	1,632	1,656	1,454	1,275	1,457	1,711	1,895	1,614	1,337	1,342	1,504	18,403
SL	339,523	326,723	317,526	291,543	259,810	274,344	285,059	275,019	275,975	270,511	277,347	303,321	3,496,701
PL	124,183	119,422	121,928	105,954	94,843	100,401	98,231	93,851	95,558	88,146	96,883	103,890	1,243,291
H1	128,752	118,907	118,108	108,470	96,870	105,901	107,003	99,870	103,685	109,379	107,736	114,699	1,319,381
H2	21,340	7,687	35,841	17,774	15,919	19,151	17,077	16,931	18,703	17,111	16,048	20,861	224,442
H3	30,623	27,086	31,424	28,049	26,127	23,454	25,666	21,175	23,888	21,915	22,251	26,899	308,556
PH	3,699	3,043	3,330	3,398	2,726	3,412	2,861	3,153	3,051	3,000	3,264	3,102	38,039
Total	1,284,282	1,229,077	1,187,577	1,002,002	928,348	1,127,920	1,293,370	1,232,996	1,148,586	1,000,688	950,762	1,072,293	13,457,900
Chg in Wthr Adj Sales (MWh)													
RS	7.0%	2.5%	-1.0%	-1.9%	2.0%	3.7%	3.9%	1.1%	4.1%	2.7%	2.9%	-6.6%	1.7%
RH	4.7%	2.0%	-0.7%	3.4%	16.6%	17.4%	14.4%	3.7%	15.5%	9.4%	3.1%	-4.6%	8.0%
RC	6.4%	2.8%	-0.9%	-0.7%	4.6%	6.4%	6.4%	1.8%	6.5%	3.7%	2.3%	-5.1%	2.9%
SS	1.7%	0.6%	-0.4%	-1.3%	0.1%	1.0%	1.1%	0.3%	1.0%	0.8%	0.4%	-1.9%	0.3%
SH	3.3%	0.9%	-0.8%	-1.2%	8.0%	11.3%	9.9%	2.3%	8.8%	5.8%	1.7%	-4.7%	4.1%
SE	1.0%	0.2%	-0.2%	-0.4%	1.4%	2.5%	2.5%	0.6%	2.2%	1.3%	0.4%	-1.2%	0.9%
SL	1.3%	0.4%	-0.3%	-1.1%	-0.3%	0.3%	0.4%	0.1%	0.3%	0.4%	0.3%	-1.6%	0.0%
PL	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
H1	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
H2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
H3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
PH	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Total	2.8%	1.1%	-0.4%	-0.4%	3.0%	4.7%	4.9%	1.4%	4.6%	2.5%	1.1%	-2.8%	1.9%

Results from the weather normalization process are used in calculating weather adjustment factors. The weather adjustment factors are inputs into IPL's Utility International revenue model. The factors are used in calculating weather normal revenues. The adjustment factors are calculated as the ratio of weather-normal sales to actual sales. Table 5 shows the weather adjustment factors.

Table 6: Weather Adjustment Coefficients

Rate Class	July	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June	Average
RS	1.070	1.025	0.990	0.981	1.020	1.037	1.039	1.011	1.041	1.027	1.029	0.934	1.024
RH	1.047	1.020	0.993	1.034	1.166	1.174	1.144	1.037	1.155	1.094	1.031	0.954	1.086
RC	1.064	1.028	0.991	0.993	1.046	1.064	1.064	1.018	1.065	1.037	1.023	0.949	1.037
SS	1.017	1.006	0.996	0.987	1.001	1.010	1.011	1.003	1.010	1.008	1.004	0.981	1.005
SH	1.033	1.009	0.992	0.988	1.080	1.113	1.099	1.023	1.088	1.058	1.017	0.953	1.047
SE	1.010	1.002	0.998	0.996	1.014	1.025	1.025	1.006	1.022	1.013	1.004	0.988	1.011
SL	1.013	1.004	0.997	0.989	0.997	1.003	1.004	1.001	1.003	1.004	1.003	0.984	1.001

Appendix B: Model Statistics

Figure 14: RS Model

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	21.131	0.289	73.21	0.00%
Calendar.January	2.249	0.421	5.344	0.00%
Calendar.February	2.646	0.419	6.314	0.00%
Calendar.April	-1.565	0.395	-3.961	0.01%
Calendar.May	-7.509	0.531	-14.135	0.00%
Calendar.June	-4.794	0.42	-11.418	0.00%
Calendar.August	4.233	0.536	7.904	0.00%
Calendar.September	4.678	0.404	11.589	0.00%
Calendar.October	0.916	0.395	2.318	2.07%
Calendar.November	-3.21	0.391	-8.202	0.00%
Calendar.Monday	-0.876	0.185	-4.734	0.00%
Calendar.Tuesday	-1.59	0.219	-7.247	0.00%
Calendar.Wednesday	-2.046	0.23	-8.911	0.00%
Calendar.Thursday	-1.963	0.231	-8.503	0.00%
Calendar.Friday	-2.125	0.22	-9.673	0.00%
Calendar.Saturday	-0.67	0.185	-3.616	0.03%
Calendar.Thanksgiving	2.984	1.052	2.836	0.47%
Calendar.XMasDay	2.326	1.044	2.229	2.61%
Wthr.HDD55	0.177	0.01	17.943	0.00%
Wthr.CDD65	1.325	0.031	42.154	0.00%
Wthr.CDD75	0.398	0.078	5.123	0.00%
BinT.Aug13	-7.376	0.7	-10.535	0.00%
BinT.May16	3.191	0.695	4.593	0.00%
BinT.Period1	2.149	0.224	9.578	0.00%
AR(1)	0.414	0.029	14.464	0.00%

Model Statistics	
Iterations	15
Adjusted Observations	730
Deg. of Freedom for Error	705
R-Squared	0.941
Adjusted R-Squared	0.939
AIC	1.375
BIC	1.532
F-Statistic	464.666
Prob (F-Statistic)	0
Log-Likelihood	-1,512.75
Model Sum of Squares	42,653.14
Sum of Squared Errors	2,696.42
Mean Squared Error	3.82
Std. Error of Regression	1.96
Mean Abs. Dev. (MAD)	1.41
Mean Abs. % Err. (MAPE)	5.41%
Durbin-Watson Statistic	2.087

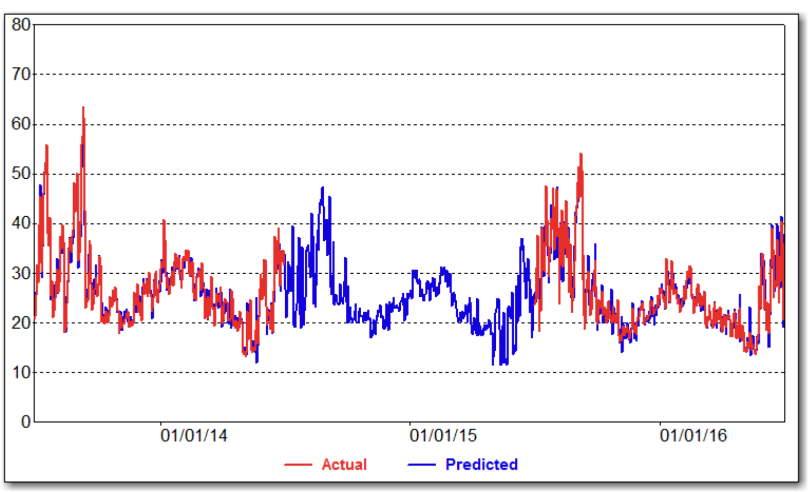

Figure 15: RS Energy per Customer vs. Temperature

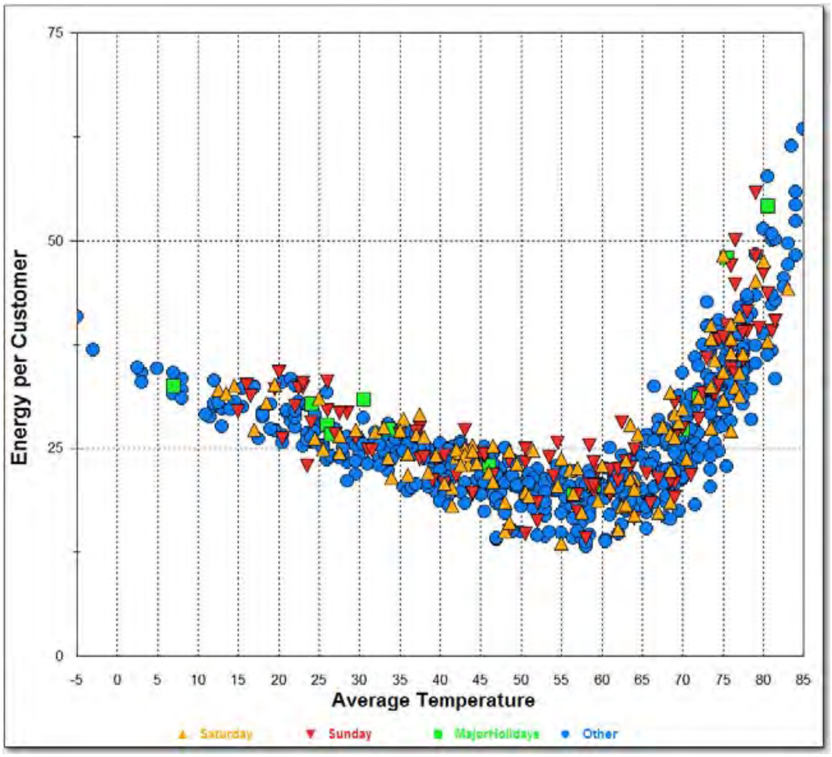

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Figure 16: RH Model

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	23.687	0.54	43.846	0.00%
Calendar.January	6.51	1.025	6.353	0.00%
Calendar.February	17.79	0.787	22.618	0.00%
Calendar.March	14.353	0.701	20.478	0.00%
Calendar.April	11.909	0.779	15.283	0.00%
Calendar.July	2.068	0.726	2.85	0.45%
Calendar.August	1.385	0.719	1.927	5.43%
Calendar.September	2.743	0.929	2.953	0.33%
Calendar.October	-2.849	0.692	-4.117	0.00%
Calendar.November	-11.351	0.939	-12.086	0.00%
Calendar.Monday	-0.696	0.407	-1.709	8.80%
Calendar.Tuesday	-1.436	0.462	-3.109	0.20%
Calendar.Wednesday	-1.333	0.473	-2.815	0.50%
Calendar.Thursday	-1.774	0.474	-3.745	0.02%
Calendar.Friday	-2.124	0.462	-4.602	0.00%
Calendar.Saturday	-1.01	0.408	-2.475	1.35%
Wthr.HDD55	1.556	0.019	81.021	0.00%
Wthr.CDD65	0.743	0.063	11.863	0.00%
Wthr.CDD75	0.426	0.156	2.74	0.63%
BinT.Apr16to30_2016	-9.972	1.354	-7.364	0.00%
BinT.Sep13	2.795	1.243	2.249	2.48%
BinT.Nov15	4.15	1.242	3.342	0.09%
BinT.Jan16	-7.111	1.225	-5.806	0.00%
BinT.Period1	1.069	0.408	2.619	0.90%
AR(1)	0.283	0.031	9.249	0.00%

Model Statistics	
Iterations	7
Adjusted Observations	730
Deg. of Freedom for Error	705
R-Squared	0.969
Adjusted R-Squared	0.967
AIC	2.855
BIC	3.012
F-Statistic	904.972
Prob (F-Statistic)	0
Log-Likelihood	-2,052.87
Model Sum of Squares	364,845.49
Sum of Squared Errors	11,842.73
Mean Squared Error	16.8
Std. Error of Regression	4.1
Mean Abs. Dev. (MAD)	2.82
Mean Abs. % Err. (MAPE)	6.76%
Durbin-Watson Statistic	2.062

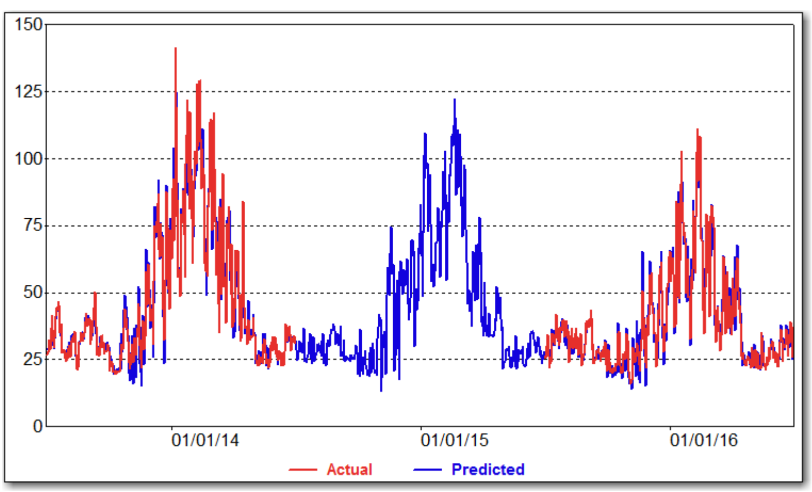

Figure 17: RH User per Customer vs. Temperature

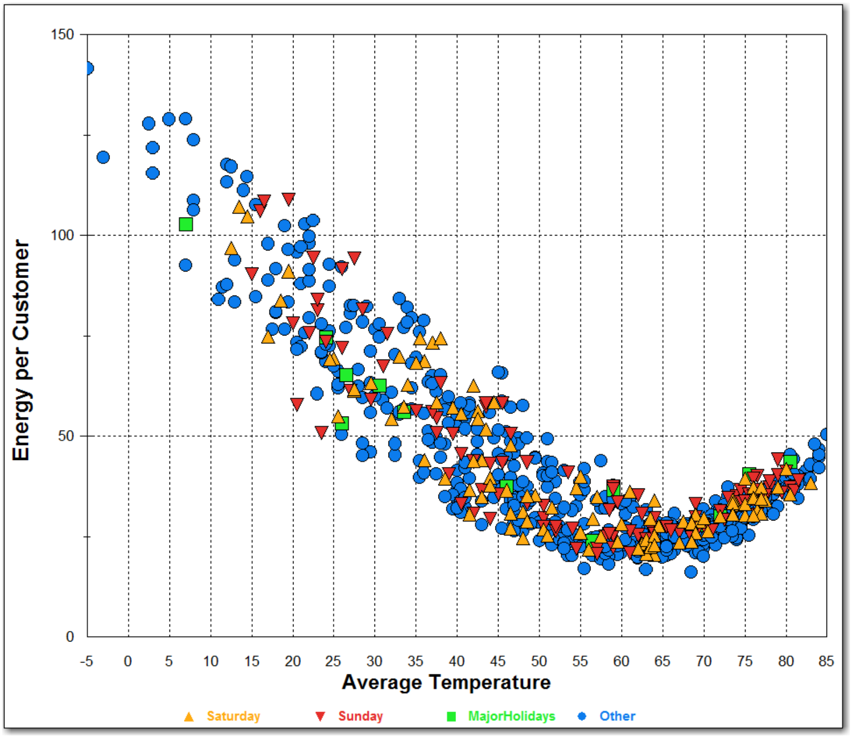

Figure 18: RC Model

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	27.276	0.66	41.315	0.00%
Calendar.January	3.584	0.667	5.374	0.00%
Calendar.February	6.485	0.678	9.564	0.00%
Calendar.March	3.592	0.678	5.301	0.00%
Calendar.April	1.736	0.705	2.462	1.40%
Calendar.May	-5.816	0.818	-7.107	0.00%
Calendar.June	-2.908	0.773	-3.763	0.02%
Calendar.July	1.774	0.779	2.279	2.29%
Calendar.August	5.741	0.876	6.551	0.00%
Calendar.September	5.404	0.744	7.261	0.00%
Calendar.October	0.341	0.708	0.482	62.98%
Calendar.November	-3.529	0.677	-5.215	0.00%
Calendar.Monday	-1.909	0.219	-8.715	0.00%
Calendar.Tuesday	-3.12	0.258	-12.078	0.00%
Calendar.Wednesday	-3.014	0.269	-11.185	0.00%
Calendar.Thursday	-3.428	0.27	-12.695	0.00%
Calendar.Friday	-3.555	0.258	-13.763	0.00%
Calendar.Saturday	-1.827	0.22	-8.323	0.00%
Wthr.HDD55	0.431	0.012	34.926	0.00%
Wthr.CDD65	1.137	0.041	28.02	0.00%
Wthr.CDD75	0.851	0.093	9.191	0.00%
BinT.Aug13	-7.997	0.805	-9.932	0.00%
BinT.May16	3.053	0.799	3.823	0.02%
BinT.Dec15	2.318	0.801	2.894	0.39%
BinT.Period1	2.622	0.268	9.799	0.00%
AR(1)	0.395	0.029	13.618	0.00%

Model Statistics	
Iterations	13
Adjusted Observations	730
Deg. of Freedom for Error	704
R-Squared	0.936
Adjusted R-Squared	0.934
AIC	1.701
BIC	1.865
F-Statistic	414.086
Prob (F-Statistic)	0
Log-Likelihood	-1,630.71
Model Sum of Squares	54,778.30
Sum of Squared Errors	3,725.21
Mean Squared Error	5.29
Std. Error of Regression	2.3
Mean Abs. Dev. (MAD)	1.75
Mean Abs. % Err. (MAPE)	5.06%
Durbin-Watson Statistic	2.105

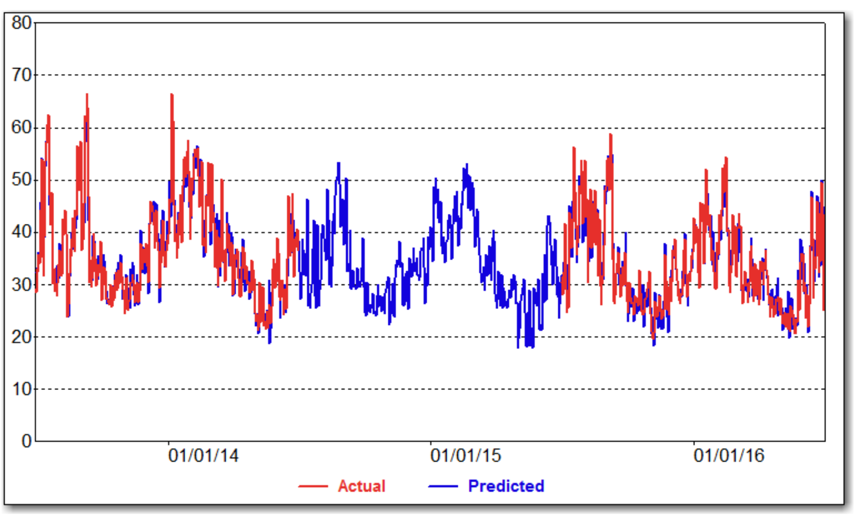

Figure 19: RC Use per Customer vs. Temperature

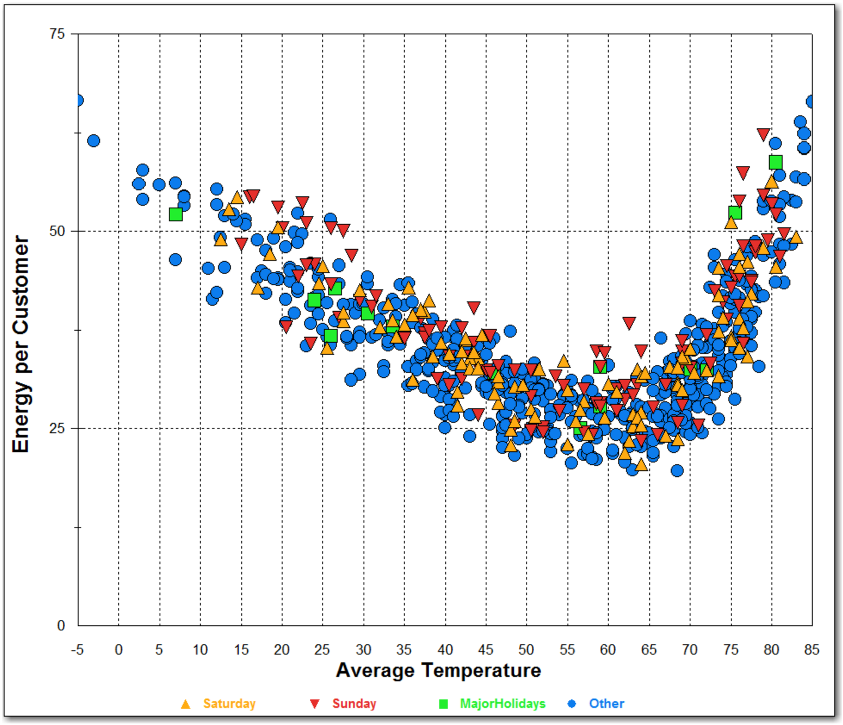

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Figure 20: SS Model

Variable	Coefficie	StdErr	T-Stat	P-Value
CONST	50.993	0.539	94.636	0.00%
Calendar.January	5.888	0.658	8.948	0.00%
Calendar.February	9.72	0.655	14.844	0.00%
Calendar.March	1.418	0.639	2.219	2.68%
Calendar.April	-2.522	0.661	-3.817	0.02%
Calendar.May	-11.188	0.835	-13.403	0.00%
Calendar.June	-3.028	0.755	-4.01	0.01%
Calendar.July	1.932	0.768	2.517	1.21%
Calendar.August	4.681	0.872	5.371	0.00%
Calendar.September	5.961	0.716	8.328	0.00%
Calendar.October	-2.026	0.81	-2.5	1.26%
Calendar.November	-4.531	0.623	-7.269	0.00%
Calendar.Monday	16.036	0.195	82.24	0.00%
Calendar.Tuesday	16.676	0.237	70.399	0.00%
Calendar.Wednesday	16.946	0.252	67.292	0.00%
Calendar.Thursday	16.58	0.254	65.353	0.00%
Calendar.Friday	15.241	0.238	64.038	0.00%
Calendar.Saturday	3.159	0.193	16.365	0.00%
Calendar.NYEve	-5.033	1.215	-4.141	0.00%
Calendar.NYDay	-15.453	1.213	-12.739	0.00%
Calendar.MemorialDay	-14.831	1.089	-13.614	0.00%
Calendar.July3rd	-5.72	1.194	-4.792	0.00%
Calendar.July4th	-10.418	1.194	-8.727	0.00%
Calendar.LaborDay	-17.03	1.091	-15.605	0.00%
Calendar.Thanksgivin	-16.574	1.205	-13.754	0.00%
Calendar.FriAftThanks	-9.106	1.203	-7.572	0.00%
Calendar.XMasEve	-12.512	1.199	-10.436	0.00%
Calendar.XMasDay	-18.483	1.194	-15.48	0.00%
BinT.Jan6_2014	-14.29	1.715	-8.335	0.00%
BinT.Jan7_2014	-6.936	1.706	-4.066	0.01%
Wthr.HDD55	0.146	0.012	11.864	0.00%
Wthr.CDD60	0.83	0.029	28.232	0.00%
Wthr.CDD75	0.214	0.077	2.765	0.59%
BinT.Period1	4.374	0.318	13.74	0.00%
BinT.Aug13	-6.788	0.928	-7.315	0.00%
BinT.May16	5.857	0.92	6.365	0.00%
BinT.Oct15	3.278	0.919	3.565	0.04%
AR(1)	0.537	0.027	20.21	0.00%

Model Statistics	
Iterations	13
Adjusted Observations	730
Deg. of Freedom for Error	692
R-Squared	0.964
Adjusted R-Squared	0.962
AIC	1.565
BIC	1.804
F-Statistic	496.556
Prob (F-Statistic)	0
Log-Likelihood	-1,568.89
Model Sum of Squares	83,493.01
Sum of Squared Errors	3,144.75
Mean Squared Error	4.54
Std. Error of Regression	2.13
Mean Abs. Dev. (MAD)	1.58
Mean Abs. % Err. (MAPE	2.27%
Durbin-Watson Statistic	2.098

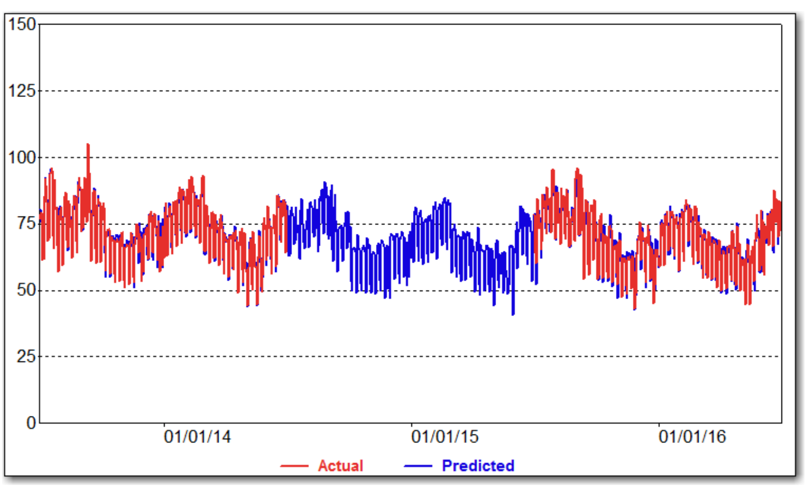

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Figure 21: SS Use per Customer vs. Temperature

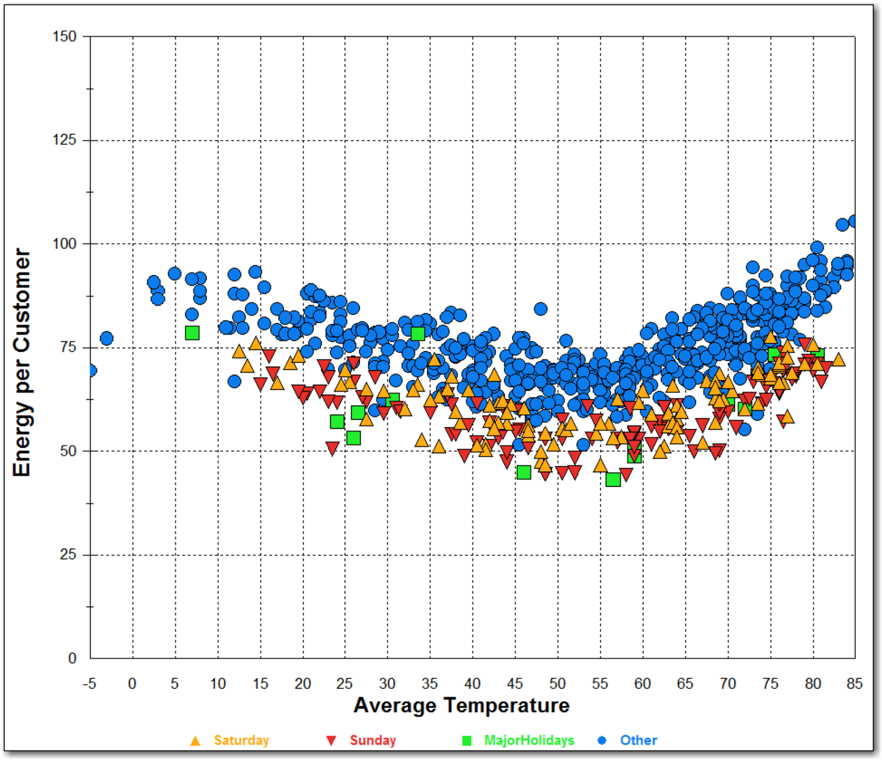

Figure 22: SH Model

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	182.35	5.36	34.023	0.00%
Calendar.January	89.97	7.444	12.086	0.00%
Calendar.February	192.527	5.93	32.466	0.00%
Calendar.March	142.981	5.753	24.855	0.00%
Calendar.April	34.048	7.421	4.588	0.00%
Calendar.May	-31.353	8.033	-3.903	0.01%
Calendar.June	-35.328	7.63	-4.63	0.00%
Calendar.July	-8.718	7.707	-1.131	25.84%
Calendar.August	26.194	8.456	3.098	0.20%
Calendar.September	25.435	7.12	3.572	0.04%
Calendar.October	14.64	6.233	2.349	1.91%
Calendar.November	-81.577	7.33	-11.13	0.00%
Calendar.Monday	63.656	3.793	16.782	0.00%
Calendar.Tuesday	60.385	3.811	15.844	0.00%
Calendar.Wednesday	61.021	3.795	16.08	0.00%
Calendar.Thursday	58.776	3.794	15.492	0.00%
Calendar.Friday	50.644	3.804	13.312	0.00%
Wthr.HDD55	7.872	0.162	48.56	0.00%
Wthr.CDD60	8.071	0.31	26.058	0.00%
BinT.Nov17_2013	82.835	32.327	2.562	1.06%
BinT.Aug13	-45.706	8.683	-5.264	0.00%
BinT.Apr14	71.254	8.796	8.1	0.00%
BinT.Nov15	43.886	8.804	4.985	0.00%
BinT.Jan16	-63.175	8.622	-7.327	0.00%
BinT.May16	31.275	8.653	3.614	0.03%
BinT.Period1	29.267	3.2	9.146	0.00%

Model Statistics	
Iterations	1
Adjusted Observations	731
Deg. of Freedom for Error	705
R-Squared	0.948
Adjusted R-Squared	0.946
AIC	6.943
BIC	7.106
F-Statistic	516.128
Prob (F-Statistic)	0
Log-Likelihood	-3,548.86
Model Sum of Squares	12,905,503.33
Sum of Squared Errors	705,125.19
Mean Squared Error	1,000.18
Std. Error of Regression	31.63
Mean Abs. Dev. (MAD)	23.6
Mean Abs. % Err. (MAPE)	6.52%
Durbin-Watson Statistic	1.085

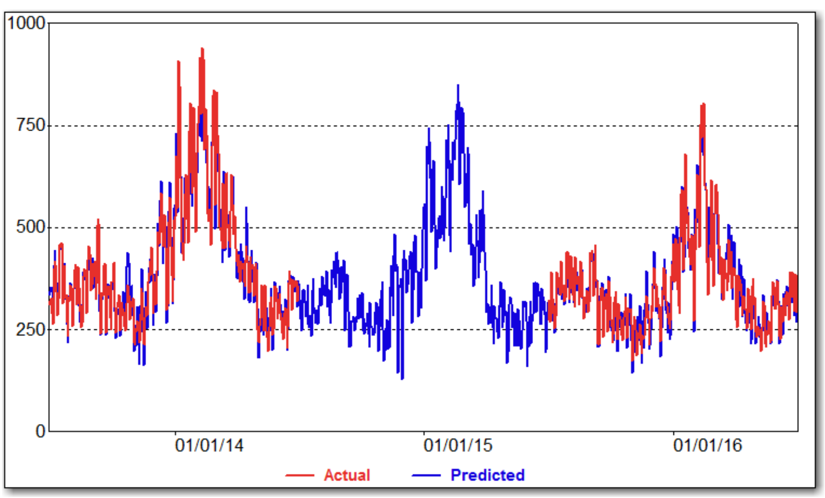

Figure 23: SH Use per Customer vs. Temperature

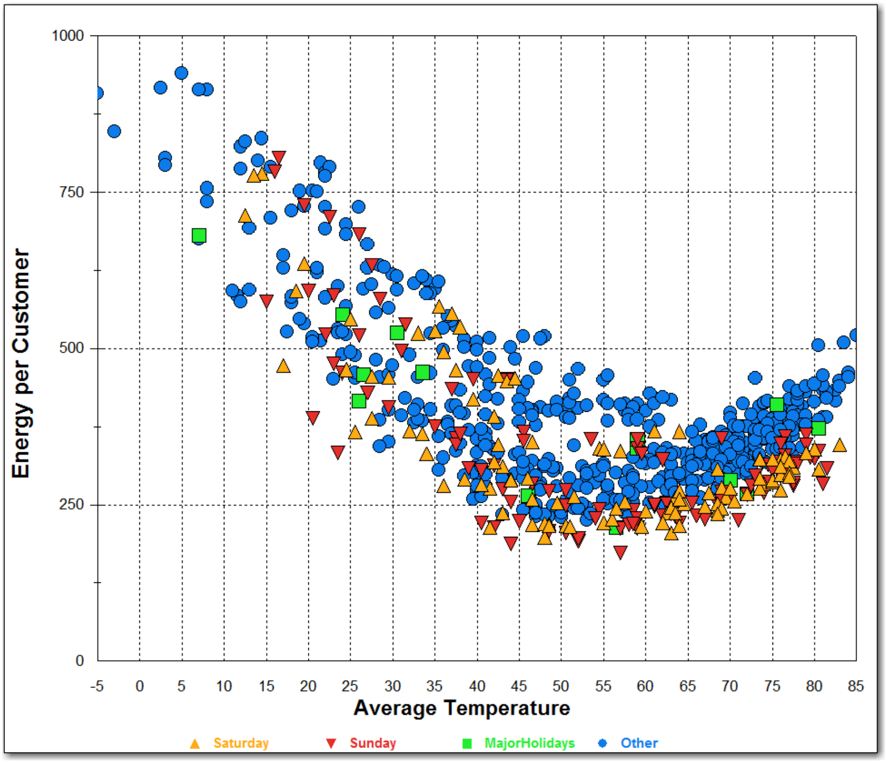

Figure 24: SE Model

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	479.392	20.734	23.121	0.00%
Calendar.January	178.643	43.333	4.123	0.01%
Calendar.February	162.79	41.343	3.938	0.01%
Calendar.April	53.116	38.471	1.381	16.83%
Calendar.May	114.283	37.98	3.009	0.28%
Calendar.August	142.116	41.223	3.447	0.06%
Calendar.September	108.735	39.188	2.775	0.58%
Calendar.Monday	339.811	14.974	22.694	0.00%
Calendar.Tuesday	371.824	17.663	21.051	0.00%
Calendar.Wednesday	357.038	18.413	19.39	0.00%
Calendar.Thursday	351.756	17.619	19.964	0.00%
Calendar.Friday	298.677	14.889	20.06	0.00%
BinT.AugWkEnd	-102.665	38.67	-2.655	0.83%
Calendar.NYDay	-143.609	86.567	-1.659	9.80%
Calendar.LaborDay	-273.308	83.938	-3.256	0.13%
Wthr.HDD55	8.984	1.013	8.866	0.00%
Wthr.CDD60	12.448	1.494	8.334	0.00%
AR(1)	0.552	0.045	12.341	0.00%

Model Statistics	
Iterations	9
Adjusted Observations	365
Deg. of Freedom for Error	347
R-Squared	0.846
Adjusted R-Squared	0.839
AIC	9.15
BIC	9.343
F-Statistic	112.354
Prob (F-Statistic)	0
Log-Likelihood	-2,169.87
Model Sum of Squares	17,145,936.62
Sum of Squared Errors	3,114,976.74
Mean Squared Error	8,976.88
Std. Error of Regression	94.75
Mean Abs. Dev. (MAD)	67.41
Mean Abs. % Err. (MAPE)	8.00%
Durbin-Watson Statistic	2.096

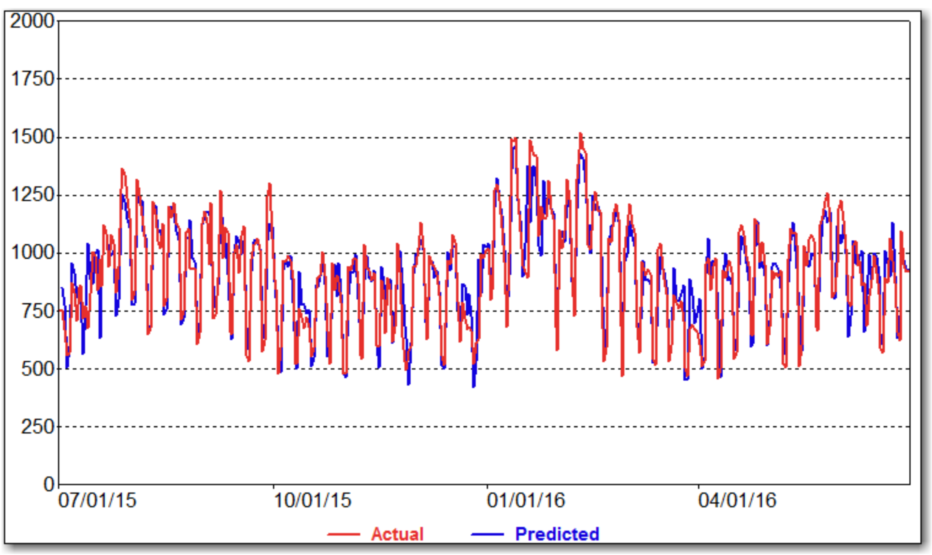

Figure 25: SE Use per Customer vs. Temperature

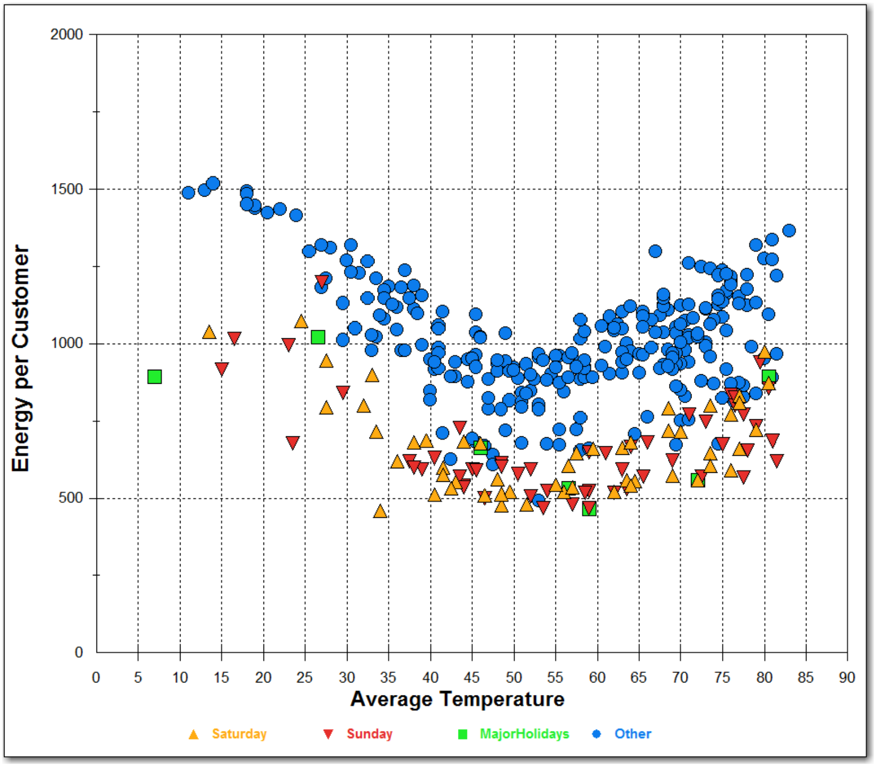

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Figure 26: SL Model

Variable	Coefficie	StdErr	T-Stat	P-Value
CONST	1568.347	12.253	127.99	0.00%
Calendar.January	115.08	19.595	5.873	0.00%
Calendar.February	100.512	19.25	5.221	0.00%
Calendar.March	-43.527	17.824	-2.442	1.48%
Calendar.June	-71.922	25.033	-2.873	0.42%
Calendar.July	139.172	20.35	6.839	0.00%
Calendar.August	177.582	24.498	7.249	0.00%
Calendar.September	122.726	18.982	6.465	0.00%
Calendar.October	31.016	18.272	1.697	9.01%
Calendar.November	-12.791	17.429	-0.734	46.32%
Calendar.Monday	475.959	4.547	104.68	0.00%
Calendar.Tuesday	501.516	5.692	88.108	0.00%
Calendar.Wednesday	506.801	6.145	82.47	0.00%
Calendar.Thursday	499.669	6.179	80.865	0.00%
Calendar.Friday	441.283	5.731	76.995	0.00%
Calendar.Saturday	68.048	4.485	15.172	0.00%
Calendar.NYEve	-151.992	28.785	-5.28	0.00%
Calendar.NYDay	-462.834	29.026	-15.945	0.00%
Calendar.MemorialDay	-430.93	24.995	-17.24	0.00%
Calendar.July4thMonF	-82.893	37.417	-2.215	2.70%
Calendar.July4thHol	-363.124	26.38	-13.765	0.00%
Calendar.LaborDay	-459.295	25.049	-18.336	0.00%
Calendar.Thanksgivir	-531.484	28.393	-18.719	0.00%
Calendar.FriAftThank	-279.997	28.369	-9.87	0.00%
Calendar.XMasEve	-363.898	28.299	-12.859	0.00%
Calendar.XMasDay	-558.294	28.154	-19.83	0.00%
Wthr.HDD55	1.537	0.306	5.021	0.00%
Wthr.CDD60	22.033	0.614	35.884	0.00%
BinT.Period1	45.526	11.589	3.928	0.01%
BinT.Aug13	-41.282	30.685	-1.345	17.90%
BinT.Apr14	-120.388	23.423	-5.14	0.00%
BinT.Jun14	134.482	33.502	4.014	0.01%
BinT.Jan5_2014	-181.703	41.574	-4.371	0.00%
BinT.Jan6_2014	-532.542	47.804	-11.14	0.00%
BinT.Jan7_2014	-184.788	42.078	-4.392	0.00%
BinT.Jun30_2014	-184.726	43.422	-4.254	0.00%
AR(1)	0.701	0.022	31.398	0.00%

Model Statistics	
Iterations	13
Adjusted Observations	730
Deg. of Freedom for Errc	693
R-Squared	0.972
Adjusted R-Squared	0.97
AIC	7.98
BIC	8.213
F-Statistic	659.549
Prob (F-Statistic)	0
Log-Likelihood	-3,911.71
Model Sum of Squares	66,069,226.75
Sum of Squared Errors	1,928,336.13
Mean Squared Error	2,782.59
Std. Error of Regression	52.75
Mean Abs. Dev. (MAD)	39.64
Mean Abs. % Err. (MAPI	1.90%
Durbin-Watson Statistic	2.021

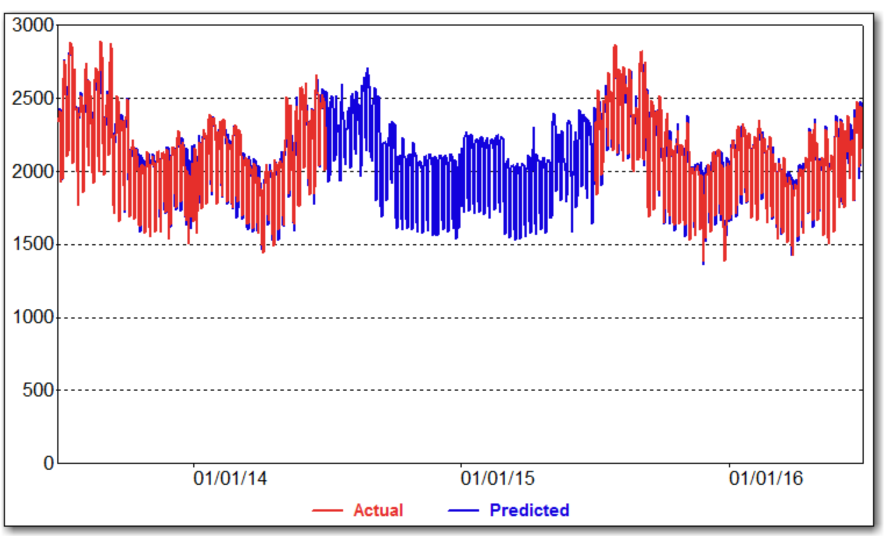
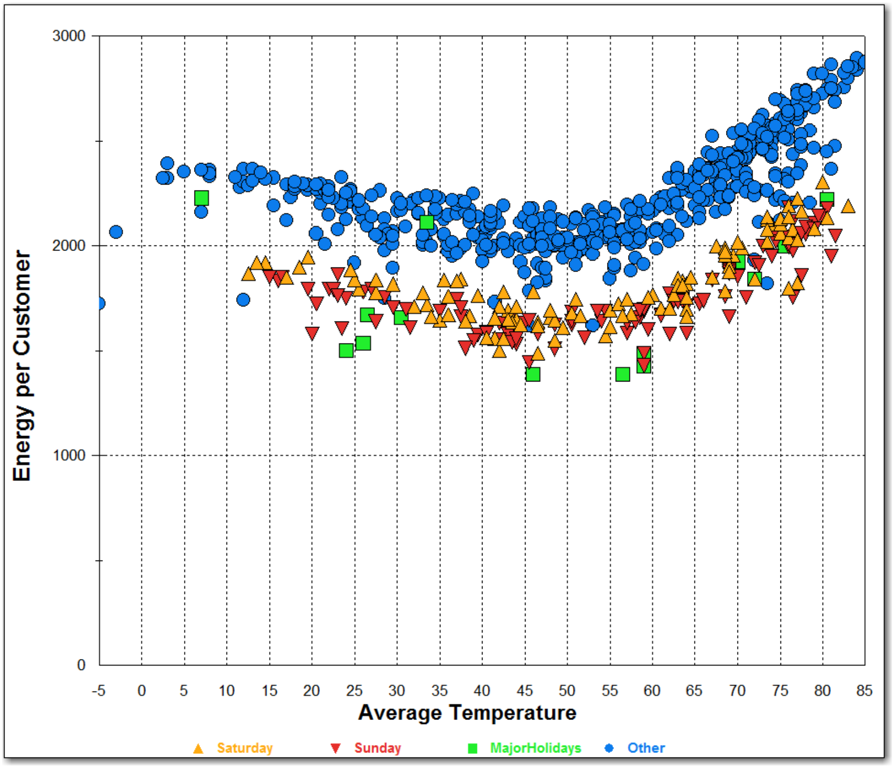


Figure 27: SL Use per Customer vs. Temperature



Appendix C: Billing-Month Degree Days

In modeling monthly sales, one of the first tasks is to align the weather data with the billing data. This section describes the methodology used to calculate billing month heating and cooling degree days (HDD and CDD).

1. Derive Actual Billing-Month Degree Days

Billing month HDD and CDD are generated to correspond with the start date and the end-date of the meter read schedule. In general, there are 21 billing cycles and each cycle has a different start date and different end date.

Step 1: Calculate the number of active billing cycles. The first task is to calculate the number of cycles that are active on each day. A cycle is *On* if the calendar day falls between (and includes) the first read date and the last read date. For each day of the billing month, we count the number of billing cycles that are *On*:

$$ActiveCycles_{dm} = \sum_{dm} CycleOn_{cdm}$$

Where:

$CycleOn_{cdm}$ = *1 if cycle c is active on day d in billing month m*
= *0 otherwise*

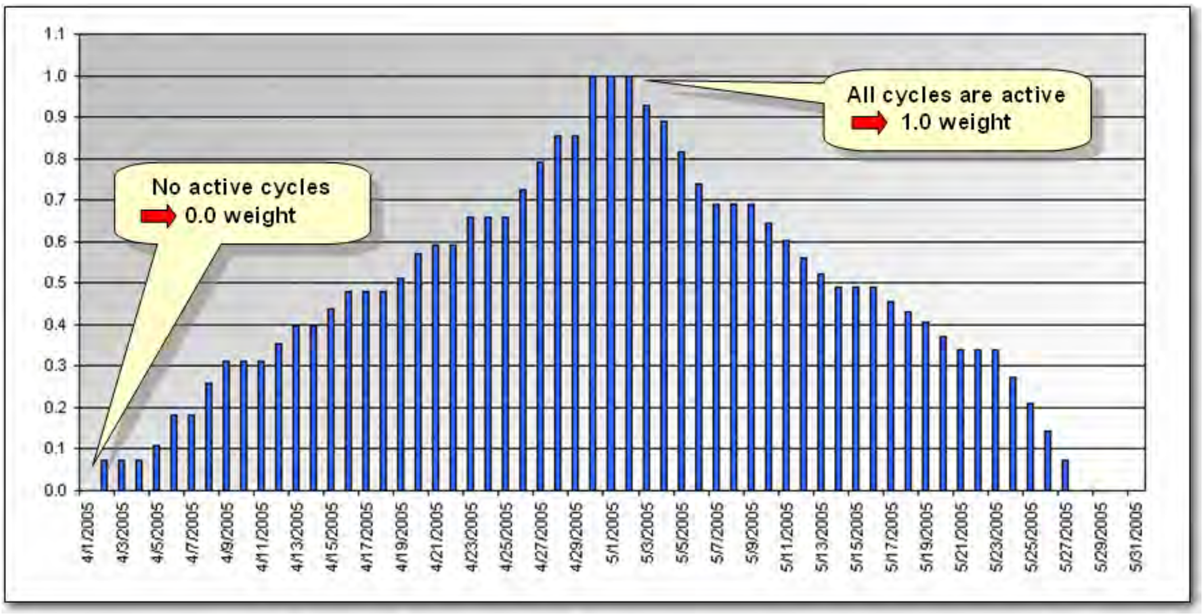
On the first day of the billing month, only 1 cycle is *On*; $ActiveCycles_{dm}$ has a value of 1.0. On the second day, cycle 2 is *On*; $ActiveCycles_{dm}$ has a value of 2. This process continues through the billing period. Assuming there are 21 billing cycles, the highest daily value for $Active\ Cycles_{dm}$ is 21; on that day all 21 cycles are on.

Step 2: Calculate the daily cycle weights. The daily cycle weight is calculated by dividing the number of active cycles by total number of billing cycles ($MaxCycles_m$). For most utilities, there are 21 billing cycles. The daily weight is calculated as:

$$Weight_{dm} = {}^{ActiveCycles_{dm}}/_{MaxCycles_m}$$

On the first day of billing month, the cycle weight = 1/21 (the number of active cycles divided by total billing cycles). On the second day when the read starts for cycle 2, two cycles are *On*, and the cycle weight is 2/21. By the middle of the billing-month (which is generally close to the start of the calendar month), all 21 billing cycles are *On*; the weight on these days would be 21/21, or 1. Figure 28 illustrates the daily weight calculation. With a relatively even meter-read schedule (in terms of number of days), the weights start at 0 at the beginning of the billing period, increases to 1.0 in the middle of the billing period (when all cycles are active), and then decreases back to 0 in a relatively smooth fashion.

Figure 28: Daily Billing-Month Weights (May)



In the example above, nearly half the billing days are in April, even though it is reported as May billed sales.

Step 3: Calculate Billing Month HDD and CDD. Once daily weights are calculated, billing-month CDD and HDD are generated by multiplying the daily degree days (CDD_d, HDD_d) by the daily cycle weight ($WEIGHT_{dm}$) and summing over billing month *m*:

$$CDD_m = \sum_m Weight_{dm} \times CDD_d$$

$$HDD_m = \sum_m Weight_{dm} \times HDD_d$$

Where:

m = The billing-month
d = A day during billing-month m

2. Normal Degree-Day Calculations

Normal billing-month HDD and CDD are calculated for each CDD and HDD breakpoint. In this example, CDD have a base of 65 degrees and HDD have a base of 55 degrees.

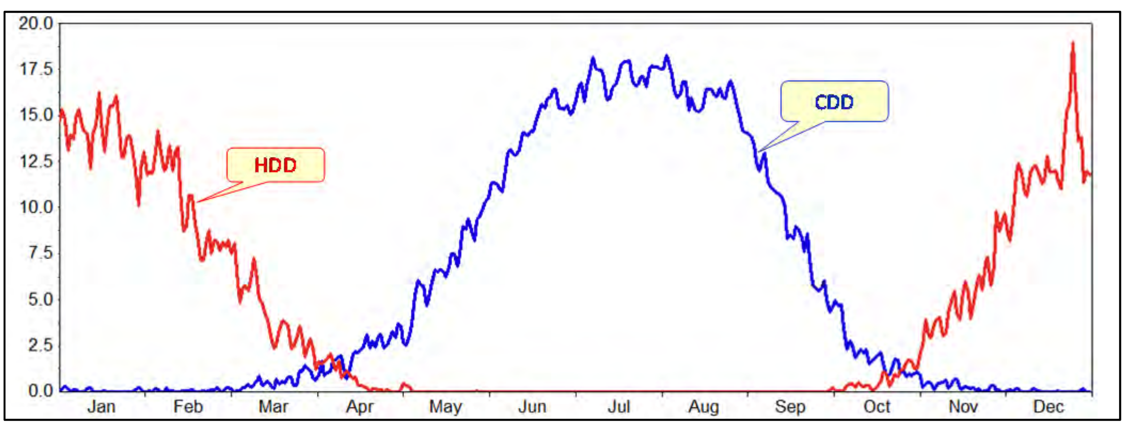
Step 1: Calculate Daily Degree-Days. The first step is to calculate historical daily degree days. Daily heating and cooling degree days are calculated for the Indianapolis, IND from January 1, 1986 to December 31, 2015 (i.e., 30-years). Daily degree days are calculated as:

$$CDD_d = Max(Temperature - 65, 0)$$
$$HDD_d = Max(55 - Temperature, 0)$$

The daily CDD is positive when temperatures are above 65 and 0 otherwise. The daily HDD is positive when temperatures are below 55 degrees and 0 otherwise.

Step 2: Calculate Average Daily Degree-Days: The daily degree days are averaged by date. All January 1st are averaged, all January 2nd's are averaged, and so forth through December 31st. This results in 366 (one extra day for February 29th) average daily degree-day values. Calculated daily HDD and CDD are depicted below.

Figure 29: Daily Normal HDD and CDD



Step 3: Calculate Normal Billing-Month Degree-Days. Normal degree days are calculated from the daily normal degree days generated in Step 2. Billing month normal degree-days ($NCDD_m$ and $NHDD_m$) are calculated by multiplying the daily cycle weights

($WEIGHT_{dm}$) with the daily normal degree days ($NCDD_{dm}$ and NHDD_{dm}) and then summing the weighted daily normal temperatures over the billing-month period m:

$$NCDD_m = \sum_m Weight_{dm} \times NCDD_d$$

$$NHDD_m = \sum_m Weight_{dm} \times NHDD_d$$

Billing month normal degree-days will differ from year to year as a result of changes in the meter-read schedule. HDD and CDD use in normalizing Test-Year sales are based on the 2015 and 2016 meter read schedule.