Exhibit No.
Issue: Weather Normalization
Witness: Eric Fox
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Sponsoring Party: The Empire District Electric Company.
Docket No.19-EPDE-223-RTS
Date Testimony Prepared: December 2018

Before the Kansas Corporation Commission

Direct Testimony

of

Eric Fox

December 2018

Liberty Utilities
EMPIRE DISTRICT

**DIRECT TESTIMONY
OF
ERIC FOX
ON BEHALF OF
THE EMPIRE DISTRICT ELECTRIC COMPANY
BEFORE THE
KANSAS CORPORATION COMMISSION
DOCKET NO. 19-EPDE-___-RTS**

TABLE OF CONTENTS

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I. BACKGROUND AND INTRODUCTION

Q. PLEASE STATE YOUR NAME, TITLE, AND BUSINESS ADDRESS.

A. My name is Eric Fox. My business address is 20 Park Plaza, Suite 428, Boston, Massachusetts, 02116. I am employed by Itron, Inc. ("Itron"),[1] as Director, Forecast Solutions.

Q. ON WHOSE BEHALF ARE YOU TESTIFYING?

A. I am testifying on behalf of The Empire District Electric Company ("Empire" or "Company").

Q. PLEASE STATE YOUR EDUCATION, PROFESSIONAL AND WORK EXPERIENCE.

A. 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 Senior Analyst in the Rate Department. I also

[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.

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 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 Direct Exhibit EF-1.

Q. WHAT ARE YOUR RESPONSIBILITIES AS DIRECTOR, FORECAST SOLUTIONS?

A. 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.

Q. HAVE YOU PREVIOUSLY TESTIFIED BEFORE A REGULATORY COMMISSION?

A. Yes. I provided testimony related to weather normalization and forecasting in several regulatory proceedings. My regulatory experience is listed in Direct Exhibit EF-1 (*Regulatory Experience*).

Q. WHAT IS THE PURPOSE OF YOUR TESTIMONY?

A. 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, and estimation of test-year weather normal sales.

Q. ARE YOU SPONSORING ANY EXHIBITS IN SUPPORT OF YOUR TESTIMONY?

A. Yes. I am sponsoring the report *2019 Rate Case Sales Weather Normalization, October 2018* ("Itron Report"), which is included as Direct Exhibit EF-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 graphs.

Q. WERE THESE EXHIBITS PREPARED OR ASSEMBLED BY YOU OR UNDER YOUR DIRECTION AND SUPERVISION?

A. Yes.

II. WEATHER NORMALIZATION METHOD AND RESULTS

Q. PLEASE DESCRIBE THE APPROACH USED FOR WEATHER NORMALIZING TEST-YEAR SALES.

A. Weather normal sales are estimated for six (6) weather-sensitive rate classes. The weather-sensitive rate classes include:

- Residential General Service (RG)
- Residential Electric Space Heating (RH)
- Small Commercial (CB)
- General Power (GP)

- Small Heating (SH)
- Total Electric Building (TEB)

Sales are weather-normalized based on a set of weather adjustment coefficients that are estimated from monthly average use regression models; a separate model is estimated for each rate class. Weather-response models are used to estimate the relationship between monthly average use and monthly heating degree-days (HDD) and cooling degree-days (CDD). HDD are a measure of heating requirements and CDD are a measure of cooling requirements. The weather adjustment coefficients derived from the estimated regression models are applied to the difference between actual and normal monthly CDD and HDD; this gives 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. Models are estimated on an average use per customer basis using simple regression models that are fully replicable. 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 (Direct Exhibit EF-2).

Q. PLEASE DESCRIBE CALCULATION OF HDD AND CDD USED IN WEATHER-NORMALIZING SALES.

A. HDD and CDD are measures of temperature variance from a defined temperature reference point. Typical reported HDD and CDD use a 65-degree temperature reference point. For example, if the average temperature for the day is 70 degrees, the number of CDD (with a 65-degree temperature base (CDD65) is 5 (70 degrees – 65 degrees); at or below 65 degrees the CDD65 value is 0. CDD65 works well for weather normalizing cooling-related residential sales. In the commercial sector, weather normalization models can be improved by using a CDD with a reference temperature of 60 degrees (CDD60); with internal heat gains, commercial cooling generally starts at a lower temperature point than residential cooling; CDD60 takes on a positive value when the average daily temperature is above 60 degrees (temperature – 60 degrees) and equals 0 when temperatures are 60 degrees or lower. HDD is used in capturing heating requirements. HDD take on a positive value when temperatures are **below** a defined reference temperature point. While the National Oceanic Atmospheric Administration (NOAA) calculates monthly HDD for a 65-degree day base (HDD65), the relationship between heating requirements and temperature is much stronger using HDD with a 55-degree temperature reference point (HDD55); there is little measurable heating load until average temperature falls below 55 degrees. With a 55-degree basis a daily average temperature of 50 degrees translates into a HDD55 of 5 (55 degrees – 50 degrees); HDD55 is 0 if daily temperature is 55 degrees or higher. For each rate class, the degree-day break points are determined by evaluating the average use/temperature plots and model fit statistics with HDD and CDD of different temperature breakpoints.

Calendar-month HDD and CDD are derived by first calculating the daily HDD and CDD from daily average temperature; the daily HDD and CDD are then summed over the month. The calculation is a little more complex for weather-normalizing billed sales. The problem is that reported billed sales are based on a meter read schedule that spans two to sometimes three calendar months. Typically, billed sales include consumption for the first half of the current month and the second-half of the prior month; HDD and CDD must match this billing period. January billing-month HDD, for example, are calculated to capture heating requirements in the second half of December and the first half of

January while July CDD incorporates daily temperatures over the second-half of June and the first half of July. Billing-month CDD and HDD that are consistent with the billing period (sometimes referred to as cycle-weighted HDD and CDD) are calculated by combining daily CDD and HDD with daily weights based on the meter read schedule; the daily-weighted degree-days are then summed over the billing period. The process for calculating cycle-weighted HDD and CDD is explained in the *Itron Report*.

Q. PLEASE DESCRIBE THE CALCULATION OF NORMAL HDD AND CDD USED IN WEATHER-NORMALIZING SALES.

A. Normal HDD and CDD and designed to capture expected heating and cooling load requirements and reflect the average weather conditions over a defined historical period. Normal degree-days are calculated based on thirty-years of historical weather data from the Springfield-Branson National Airport (SGF). SGF is the closest primary weather station to the Company's Kansas service area. Normal HDD55, CDD60, and CDD65 are calculated from daily average temperature data over the period 1987 through 2017; 2017 is the most current full year of weather data. Using a 30-year rolling period vs. NOAA's fixed-year period of 1981 to 2010 incorporates more recent temperature data in calculating normal HDD and CDD. Normal degree-days are calculated by first calculating daily HDD55, CDD60, and CDD65 from daily average temperature and averaging the daily degree-days by date; this gives a daily normal weather series that when aggregated by month generates monthly HDD and CDD; this is consistent with the method used by NOAA. Cycle-weighted normal HDD and CDD are derived in a similar manner to that used for calculating actual cycle-weighted HDD and CDD; daily normal degree-days are combined with daily weights derived from the meter read schedule and summed over the billing month period.

Q. HOW DO TEST-YEAR DEGREE-DAYS COMPARE WITH NORMAL DEGREE-DAYS?

A. The test-year period includes the months July 2017 through June 2018. Table EF-1 compares actual and normal cycle-weighted HDD55 and CDD65 for this period.

Table EF-1: Comparison of Actual and Normal Cycle-Weighted Degree-Days

Month	CDD65	NrmCDD65	Difference	HDD55	NrmHDD55	Difference
Jul-17	355	356	(1)	-	-	-
Aug-17	367	386	(19)	-	-	-
Sep-17	213	288	(75)	-	1	(1)
Oct-17	162	74	88	11	29	(18)
Nov-17	19	9	10	159	163	(4)
Dec-17	-	-	-	289	414	(125)
Jan-18	-	-	-	811	691	120
Feb-18	1	-	1	573	577	(4)
Mar-18	1	1	-	319	412	(93)
Apr-18	5	12	(7)	254	194	60
May-18	93	44	49	63	46	17
Jun-18	361	177	184	-	3	(3)
Total	1,577	1,347	230	2,479	2,530	(51)

Over the test-year period, CDD65 are 230 or 17% above normal. While the beginning of the test-year is cooler than normal, October 2017 and May and June 2018 are significantly warmer than normal contributing overall to stronger than normal cooling requirements. The winter months are slightly warmer than normal with HDD55 51 degrees below normal (2.0% below normal).

Q. HOW DOES WEATHER IMPACT TEST-YEAR SALES?

A. **Table EF-2** shows test-year actual and weather normal billed sales by rate class.

Table EF-2: Test-Year Weather-Adjusted Sales (MWh)

Rate Class	Billed Sales	Wthr Normal Sales	Difference	Pct
Res General	74,767.8	73,098.2	1,669.7	2.2%
Res Space Heat	34,619.7	34,436.7	183.0	0.5%
Small Commercial	18,838.8	18,430.7	408.0	2.2%
General Power	38,550.8	38,200.7	350.2	0.9%
Electric Space Heat	2,823.7	2,779.4	44.3	1.6%
Total Electric Building	9,436.1	9,327.9	108.2	1.1%
Total	**179,037.0**	**176,273.5**	**2,763.5**	**1.5%**

Total test-year billed sales are adjusted down 1.5%. There are significant differences in normalized sales adjustments across rate schedules as each class responds differently to changes in temperature. The residential general rate class and small commercial rate class show the largest change in normalized sales as these rate classes are strongly sensitive to changes in CDD and while sensitive to changes in HDD, these classes are not nearly as sensitive as the electric heating rate classes. For the electric space heating rate classes, the positive adjustments due to lower than normal winter heating conditions mitigate some of the impact from the downward adjustment for higher than normal cooling requirements. General power includes some of the Company's largest C&I customers; this class is much less sensitive to changes in CDD and is not sensitive to changes in HDD. The monthly impacts for each rate class are included in the Itron report.

Q. ARE THERE ANY OTHER ADJUSTMENTS MADE TO TEST-YEAR SALES?

A. Yes. A small sales adjustment is also made for the number of ending customers in the test-year period (June 2018). The adjustment entails calculating test-year normal sales as if the number of customers in June 2018 were there in each of the test-period months. As there is little customer growth from the beginning to the end of the test-year period, total customer adjustment is 162.5 MWh – a 0.1% positive adjustment.

III. SUMMARY

Q. COULD YOU BRIEFLY SUMMARIZE YOUR TESTIMONY?

A. Yes. Rate class sales are weather adjusted using regression-based models that relate customer monthly average use to cycle-weighted HDD and CDD; the normalization method is the standard approach used by most electric and gas utilities. Sales are weather-normalized at the rate-class level (for those rate classes that are weather-sensitive) thus account for differences in rate specific weather/load relationship. Weather adjustment coefficients are derived from regression models based on billed sales and customer data; the weather coefficients are statistically significant and consistent with observed change in customer usage. Test-year monthly HDD and CDD calculations are based on best practice methods. Actual and normal HDD and CDD variables are defined with temperature break definitions that best explain the rate-class usage/weather relationship and are consistent with the billing-month period.

The test-year period is characterized by a winter that was slightly warmer than normal and cooling requirements significantly above normal in three of the test-year months (October 2017, May 2018, and June 2018). Rates that are sensitive to changes in HDD saw the smallest overall sales adjustments as positive winter adjustments mitigates some of the larger negative cooling adjustments. In total, test-year sales are adjusted down by 1.5%.

Q. DOES THIS CONCLUDE YOUR PRE-FILED DIRECT TESTIMONY?

A. Yes, it does.

Resume and Project Experience

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

Forecasting Methods, Model Development, and Training. WEC Energy Group, Milwaukee WI, September 20 -21.

Development of Budget Sales and Customer Forecast Models, Report, and Forecast Training. Alectra Utilities, July 2018

Electricity Forecasting in a Dynamic Market. Presentation and Panel Participant, Organization of MISO States, Forecast Workshop & Spring Seminar, Des Moines Iowa, March 21 -23, 2018.

Load Research Methods and Results, IPL and Indiana Office of Utility Consumer Counselor (OUCC), March 12, 2018

Sales Weather Normalization to Support the IPL 2018 Rate Case, with Richard Simons, Indianapolis Power & Light, December 2017

Dominion Long-Term Electricity Demand Forecast Review. Dominion Energy Virginia, September 15, 2017.

Dominion Long-Term Electricity Demand Forecast Review. Dominion Energy Virginia, September 15, 2017.

Vermont Long-Term Energy and Demand Forecast, with Mike Russo and Oleg Moskatov, Presented to the Vermont State Forecast Committee, August 1, 2017

Utility Forecasting Trends and Approaches, with Rich Simons and Mike Russo, Presented to the Energy Information Administration, July 27, 2017

Sales and Revenue Forecast Delivery and Presentation, with Mike Russo, Indianapolis Power & Light, July 13, 2017

Forecasting Gas Demand When GDP No Longer Works, Southern Gas Association Gas Forecasters Forum, June13 to 17, Ft Lauderdale, Florida

Behind the Meter Solar Forecasting, with Rudy Bombien, Duke Energy, Electric Utility Forecaster Forum, May 3 to 5, 2017, Orlando, Florida

Advanced Forecast Training Workshop, with Mike Russo, EFG Meeting, Chicago Illinois, April 25th, 2017

Budget-Year Electric Sales, Customer, and Revenue Forecast, with Oleg Moskatov and Mike Russo, Green Mountain Power Company, March 2017

Solar Load Modeling, Statistic Analysis, and Software Training, Duke Energy, March 1 to 3, 2017

Development of a Multi-Jurisdictional Electric Sales and Demand Forecast Application, with Mike Russo and Rich Simons, Wabash Valley Power Cooperative, January, 2017,

Net Energy Metered Customer Sample Design and Training, Nevada Energy, December 1 – 2, 2016

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

Regulatory Experience

December 2017: Provided testimony and support related to sales weather-normalization for the 2018 rate case. Indianapolis Power & Light.

October 2017: Provided testimony and support for the Dominion Energy Virginia 2017 Integrated Resource Plan

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

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

October 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

Knowledge to Shape Your Future

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2019 Rate Case
Sales Weather Normalization

Empire District Electric Company, Kansas

Submitted to:

The Empire District Electric Company
Joplin, Missouri

Submitted by:

Itron, Inc.
20 Park Plaza
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Boston, Massachusetts 02116
(617) 423-7660

November 2018

Table of Contents

Table of Figures

Table of Tables

Overview

The Empire District Electric Company (Empire) contracted Itron, Inc. (Itron) to develop weather and customer normalized sales to support their Kansas 2019 rate case. Revenue class normalized sales are estimated for the 2019 Rate Case Test-Period. The Test-Year is defined as the period July 2017 through June 2018.

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. To account for customer growth (or decline) sales are also normalized for number of customers; normalized sales are calculated as if customers in the last month of the test-year period (June 2018) are there for the entire test-year period.

The test-year period is characterized with winter temperatures that are slightly lower than normal with heating-degree-days 2.0% below normal. On the cooling side, overall temperatures are significantly higher than average. Billing-month cooling degree-days are 17% higher than normal, and on a calendar-month, basis 24% higher than normal. While the beginning of the test-year period (July through September 2017) is slightly cooler than normal, October 2017, and May and June 2018 are significantly warmer than normal. The impact is test-year sales for the weather-sensitive rate classes are normalized down by 1.5%. Table 1 summarizes the weather-normalization results.

Table 1: Test-Year Weather-Normal Billed Sales (MWh) by Rate Class

Rate Class	Billed Sales	Wthr Normal Sales	Difference	Pct
Res General	74,767.8	73,098.2	1,669.7	2.2%
Res Space Heat	34,619.7	34,436.7	183.0	0.5%
Small Commercial	18,838.8	18,430.7	408.0	2.2%
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Electric Space Heat	2,823.7	2,779.4	44.3	1.6%
Total Electric Building	9,436.1	9,327.9	108.2	1.1%
Total	**179,037.0**	**176,273.5**	**2,763.5**	**1.5%**

Detailed results of weather normalization process can be found in Appendix A: Weather Response Models, Data, and Results.

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; the general approach is to use Heating Degree-Days (HDD) and Cooling Degree-Days (CDD) to capture heating and cooling requirements. The industry-standard approach is to estimate a weather response model with linear regression. Linear regression is a statistical modeling approach where customer usage is specified as a function of temperature or HDD and CDD; the estimation process results in a set of weather coefficients that measure the change in customer usage given a change in HDD and CDD. With these coefficients we can then calculate the use per customer impact given variation of actual degree-days from normal degree-days.

The relationship between customer usage and temperature varies across rate schedules. Figure 1 through Figure 3 illustrate the difference in temperature response function. These curves show monthly use per customer against monthly average temperature.

Figure 1: Residential General Average Use vs. Temperature

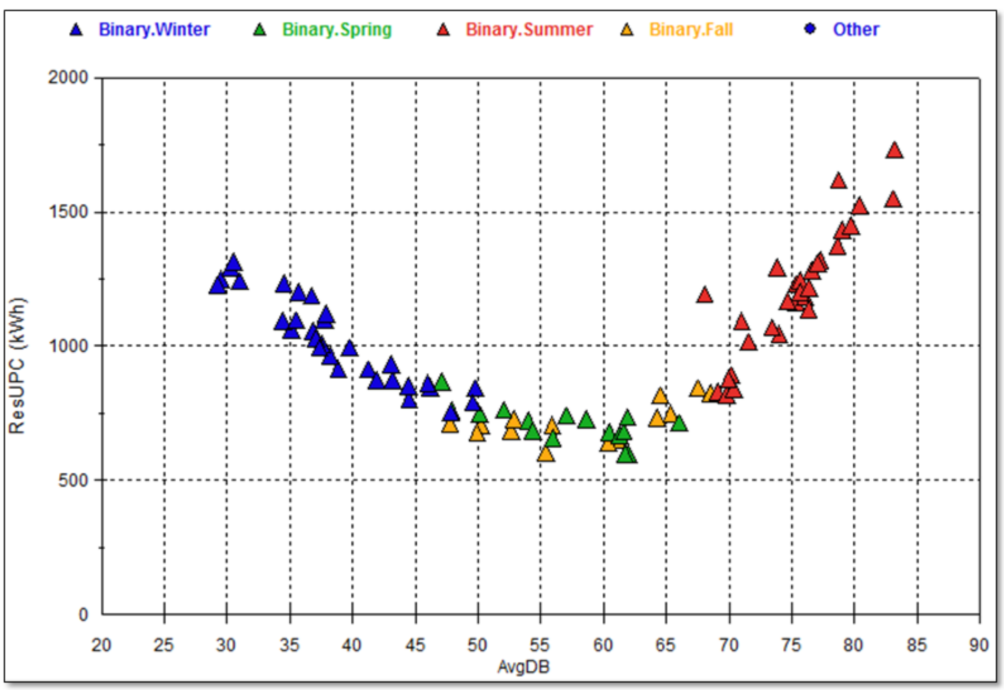

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Figure 2: Residential Heating Average Use vs. Temperature

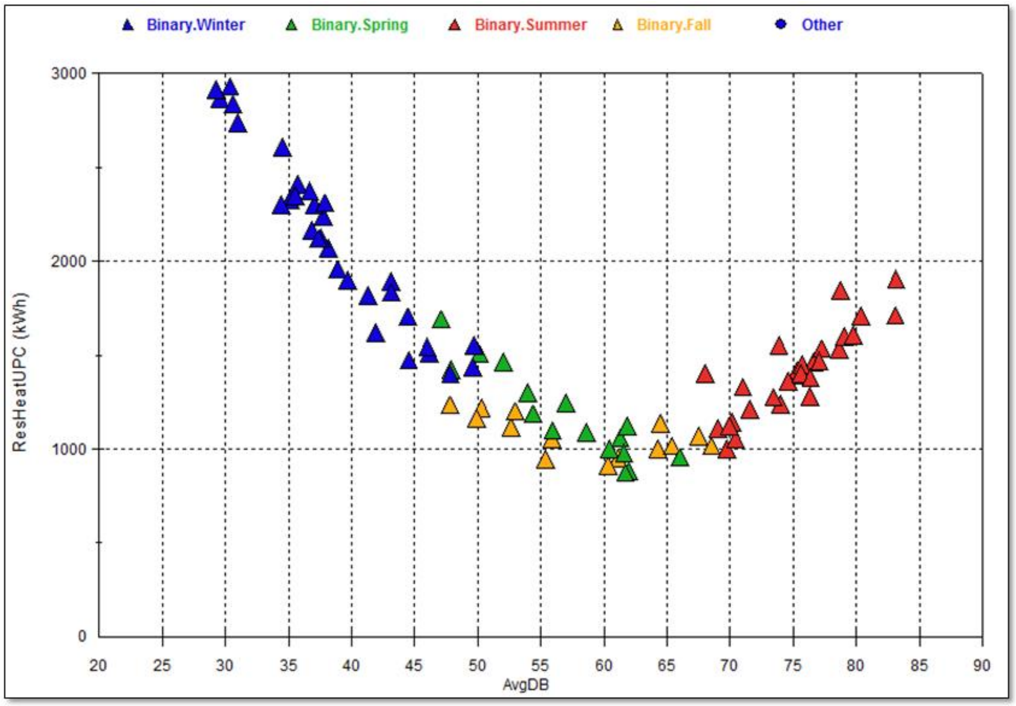


Figure 3: Commercial Average Use vs. Temperature

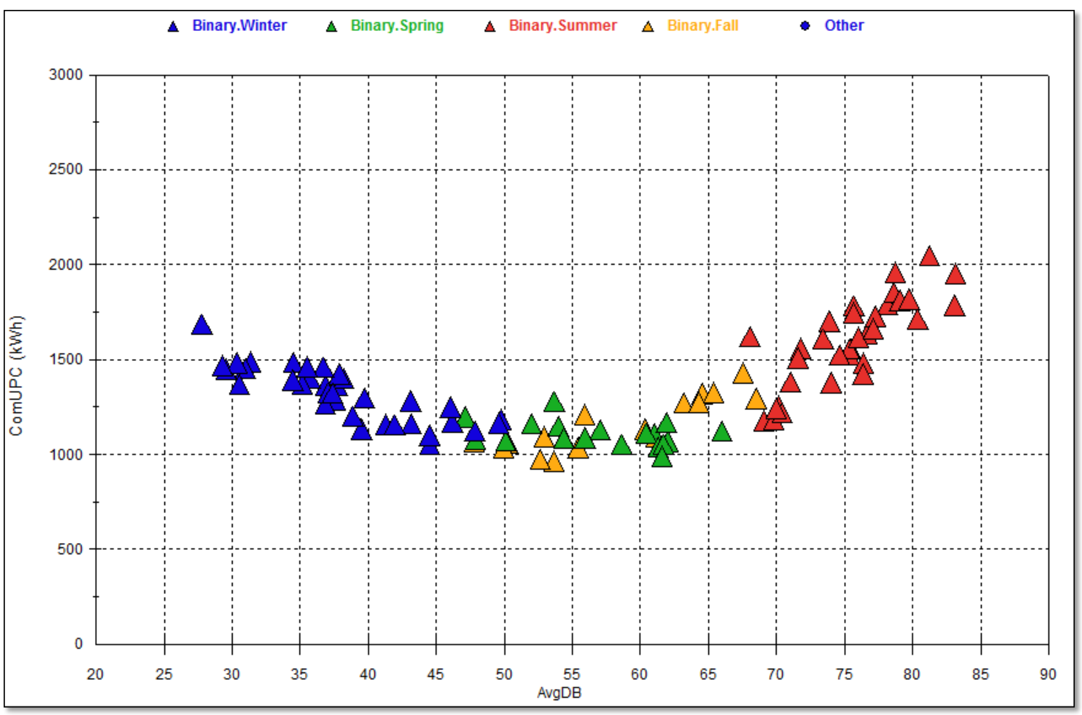
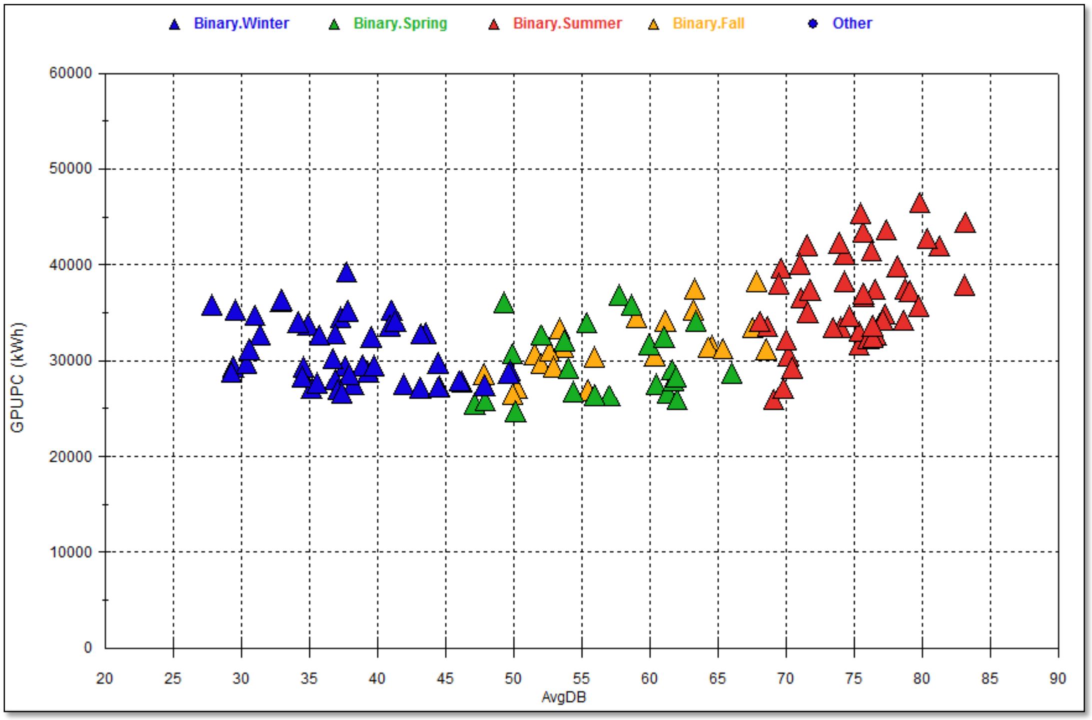


Figure 4: General Power Use per Customer vs. Temperature



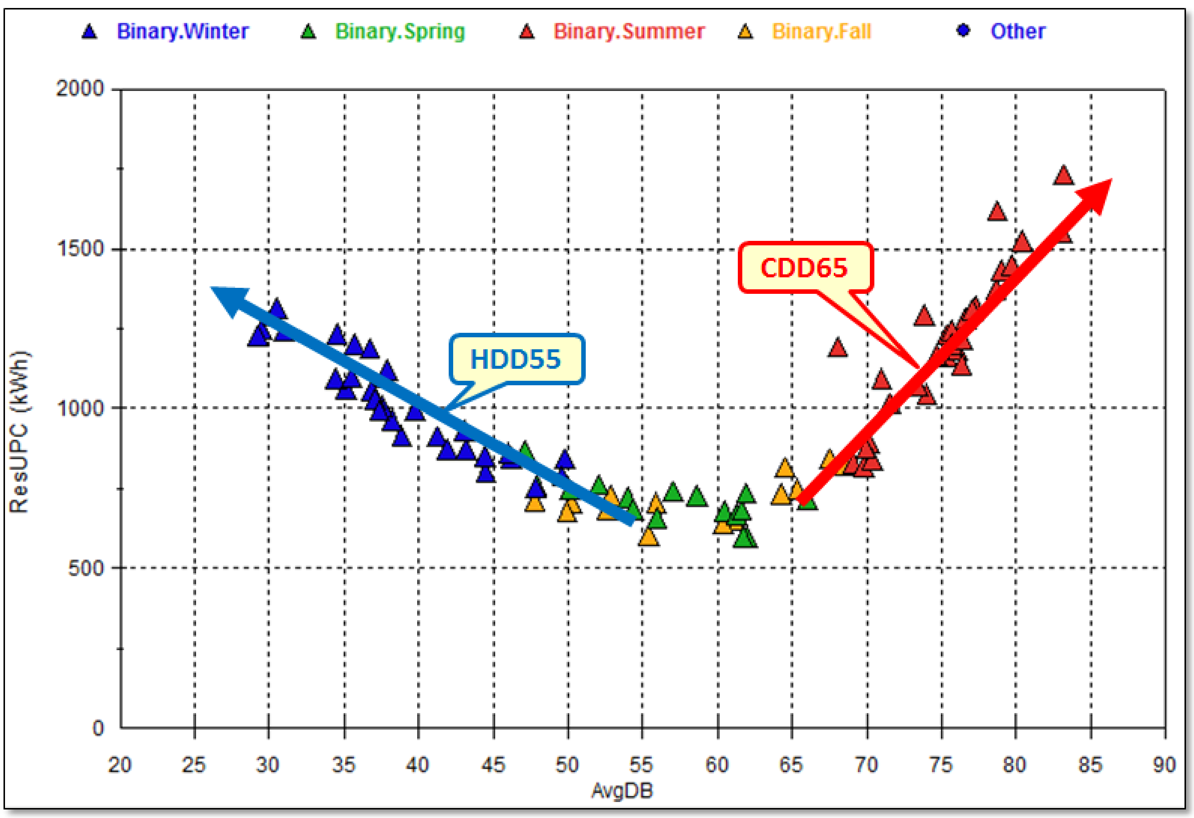
The general residential rate classes show strong sensitivity to changes in temperatures over the cooling months. Residential heating use is also strongly sensitive to changes in summer temperatures, but the slope of the curve is not as steep as the general service. Predictably, the residential heating rate class is more weather-sensitive to changes in temperatures on the heating-side of the curve.

While commercial usage is also sensitive to changes in temperature, the response to change in temperature on the cooling-side of the curve is not as large as the residential cooling response; the commercial cooling curve is not as steep. The flatter curve reflects the relatively high level of cooling use across all the late spring through early fall months to address internal as well as external heat gains; loads are not as sensitive to changes in external temperatures. Related, commercial cooling generally starts at a lower temperature point (around 60 degrees) where residential cooling loads are generally measurable when average monthly temperature is above 65 degrees. On the heating-side of the curve, while there is some sensitivity to changes in temperature in the small commercial sector, the curve is relatively flat. The General Power customer usage (which includes a little over 100 of the largest C&I customers) is even less sensitive to changes in CDD and is not sensitive to changes in HDD.

2. Use of Degree-Days for Weather Response Functions

The relationship between usage and temperature is non-linear; it is a curved relationship between temperature and use vs. a straight line. As temperatures increase above a certain temperature point usage increase, and for residential and small commercial class as temperatures falls below a certain temperature point usage also increases. The standard approach is to estimate the usage/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 usage and CDD is generally linear on the cooling side while the relationship between usage and HDD are generally linear on the heating side. The non-linear relationship can be modeled by combining these linear splines. This is illustrated in Figure 5 where HDD of base 55 degrees and CDD of base 65 degrees are fitted to the Residential General rate-class curve.

Figure 5: Residential Fitted Degree-Day Splines



As illustrated, HDD explains the left side of the curve, where load increases as temperature decreases, while CDD explains the right-side of the curve, where load increases as temperature increases. 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 degree breakpoint 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 cooling base (CDD65).

CDD with a base temperature of 60 degrees (CDD60) proved the best statistical fit for the non-residential revenue 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 commercial usage/temperature scatter-plot (Figure 3) shows usage increasing at 60 degrees. The degree-day breakpoints are determined by evaluating the usage/temperature scatter plots and statistically testing the HDD and CDD variables with different temperature break points.

3. Estimate Weather Response Functions

Use per customer weather response models are estimated for 5 customer classes:

1. Residential
2. Commercial
3. General Power
4. Small Heating
5. Total Electric Building

Models are estimated using linear regression using monthly use per customer (kWh) data derived from billed sales and customer counts. Models are estimated over the period January 2013 and June 2018 (the last month of available data); this gives 66 monthly observations per model. The estimation period is selected to provide enough historical data points to incorporate a wide variation in average use and average monthly weather conditions. But not too many historical points that we then need to account for the changes in underlying cooling and heating technologies.

In addition to HDD and CDD variables described above, models include monthly binaries to account for non-weather related variation and binaries for specific data points that are extreme outliers; the objective is to minimize the impact these outliers have on the estimated weather coefficients.

Model results are provided in Appendix A:
Weather Response Models, Data, and Results.

4. Weather Impact Calculations

As models are estimated on a use per customer basis, estimated HDD and CDD coefficients give the average use impact for a change in degree-day. 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 the shoulder months, heating and cooling often occur in the same month. Months such as May and October may have both heating and cooling load adjustments. In some months HDDs may be below normal, while CDDs are above normal.

Weather Normal Sales. Weather normal sales are calculated by multiplying the weather-normal average use by number of actual customers:

$$WthrNrmSales_{ymc} = WthrNrmAvgUse_{ymc} \times Customers_{ymc}$$

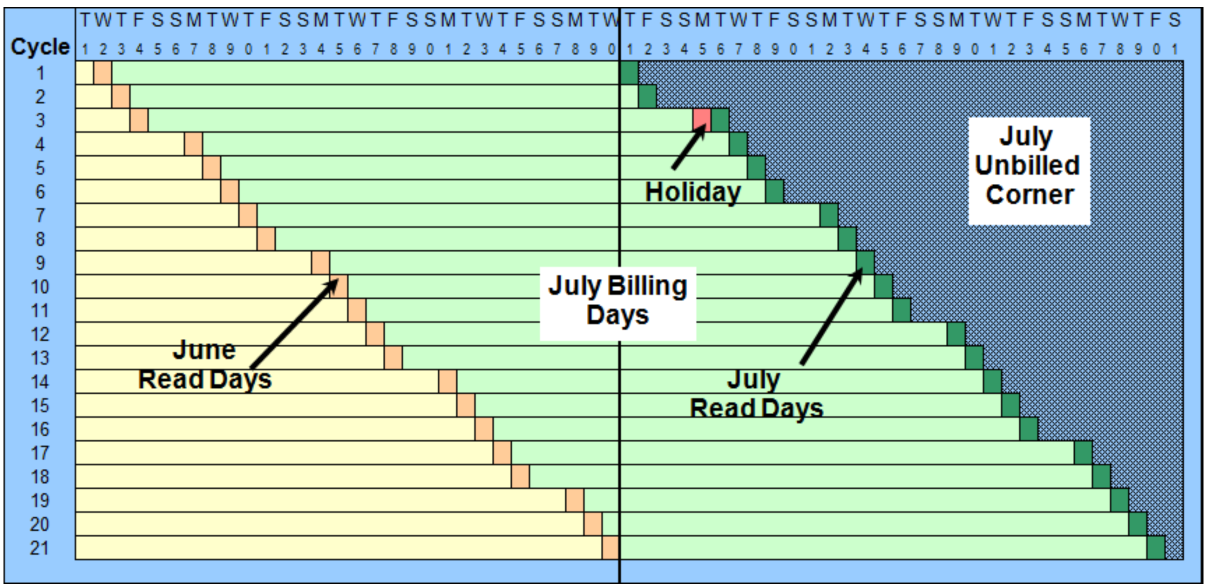
Where:

- y = year
- m = month
- c = customer class

5. Calculation of Cycle-Weighted HDD and CDD

The use per customer weather response models are estimated using historical billed sales and customer counts. Billed sales are read on a meter read schedule that distributes the reading process across the month. Empire 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. For example, September's billing-month sales include customer usage in August as well as September. As much as half or even more (depending on the weather conditions during the billing period) of September's billed sales is associated with August weather conditions; as a result September CDD may be minimally correlated with September billed sales. Figure 6 is a generalized representation of a billing-month with 21 cycles; the dates do not correspond to Empire's actual billing cycles, but the principles are consistent.

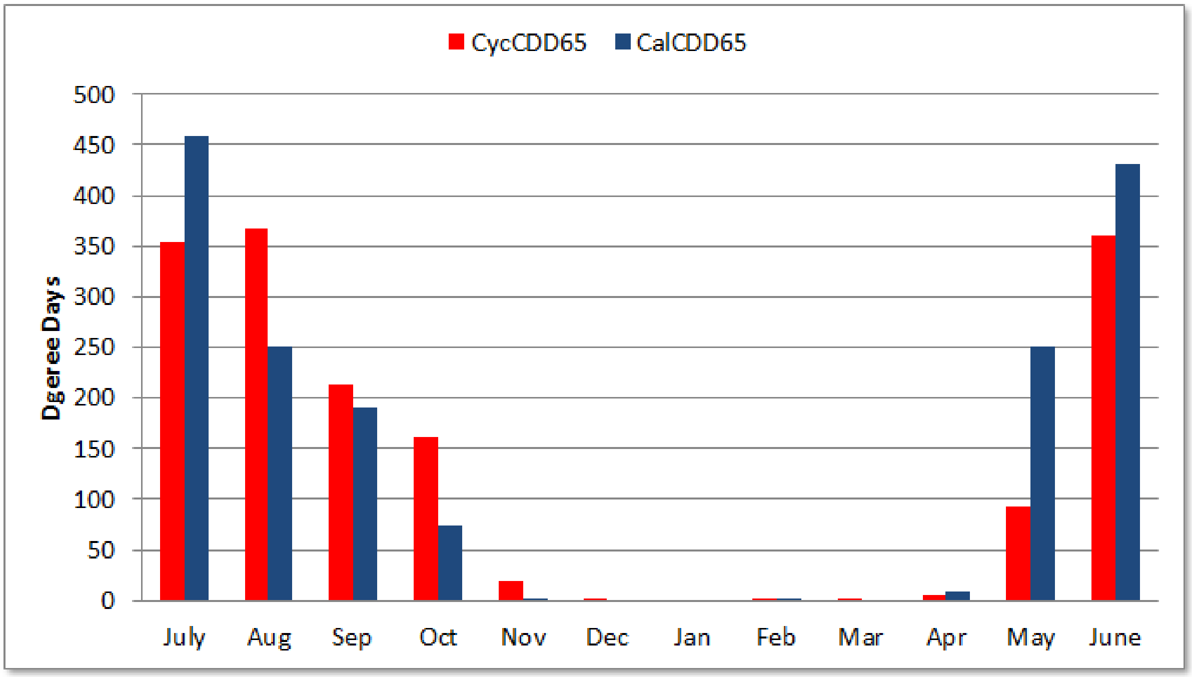
Figure 6: Billing Cycles



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. Cycle-weighted degree-days are calculated using a standard approach. 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 C provides a detailed description of this calculation.

Figure 7 compares calendar-month and billing-month CDD for the test-year.

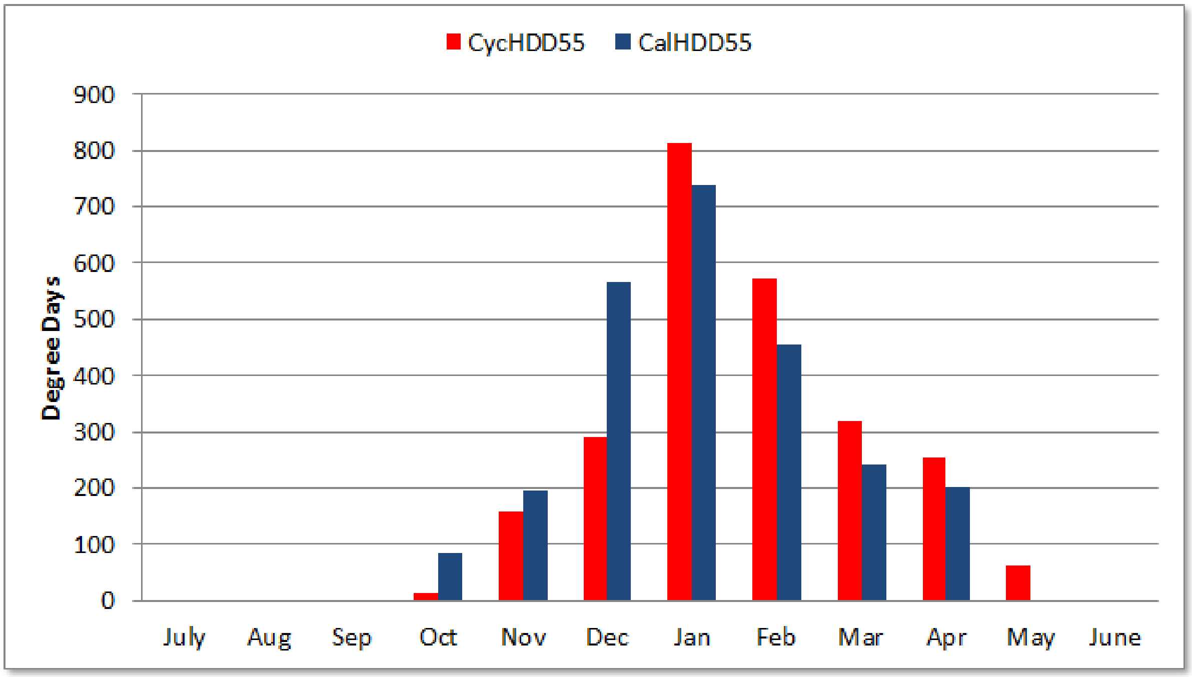
Figure 7: Test-Year Cycle-Weighted CDD vs. Calendar-Month CDD



Cycle-weighted CDD are shown in red and calendar-month CDD are in blue. As Figure 7 shows, there are significant differences between calendar-month and billing-month CDD on a monthly basis. For instance, June calendar-month CDD is significantly higher than the billing-month CDD as the billing-month includes cooler May temperatures.

Figure 8 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 8: Test-Year Cycle-Weighted HDD vs. Calendar-Month HDD



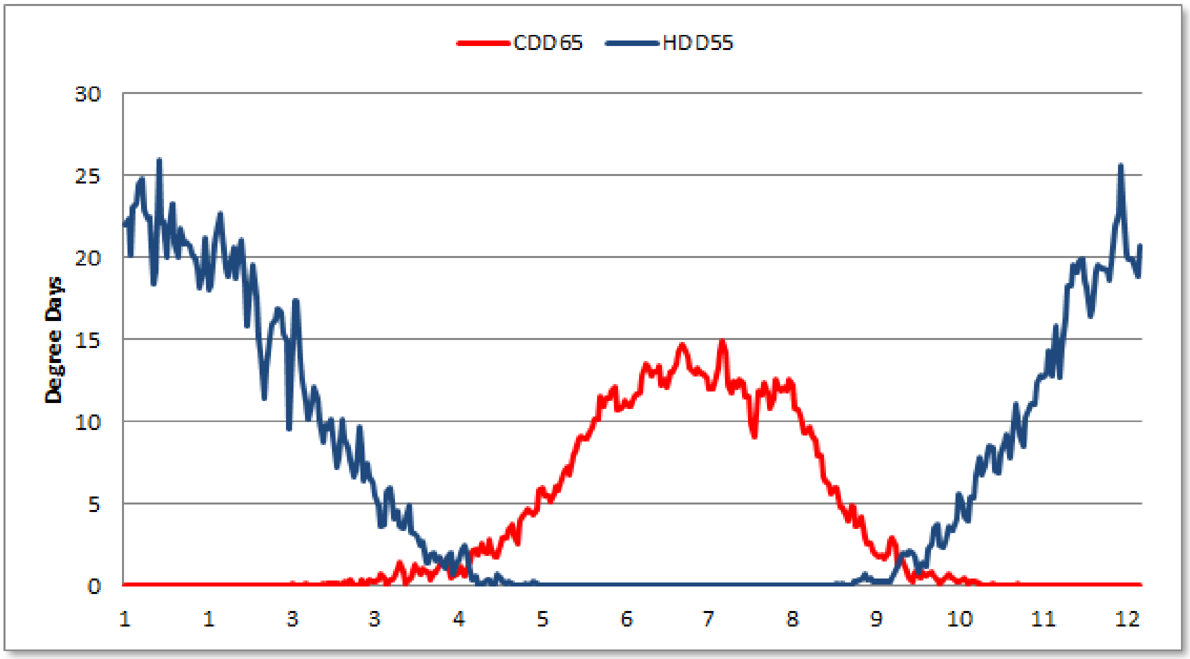
Again, on a monthly basis, there are significant differences between cycle-weighted and calendar-month HDD.

6. Calculation of 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, 1988 to December 31, 2017. Temperature data is from the Springfield-Branson National Airport (SGF). SGF is the closest primary weather station for the three jurisdictions – Kansas, Oklahoma, and Arkansas.

The first step is to calculate historical daily HDD and CDD for each degree-day concept – HDD55, CDD60, and CDD65. The daily degree-day series is then averaged by date. To construct a daily normal HDD55 series, all January 1st HDD55 are averaged, all January 2nd HDD55 are averaged, all January 3rd HDD55 are averaged, etc. all the way through the December 31st HDD55. Daily normal CDD60 and CDD65 are calculated in a similar manner. This method is consistent with that used by NOAA. Figure 9 shows the resulting daily 30-year average HDD55 (in blue) and CDD65 profiles (in red).

Figure 9: Daily Normal HDD55 and CDD65 (1988 - 2017)



Normal cycle-weighted HDD and CDD are calculated by multiplying the daily normal HDD55, CDD60, and CDD65 by the meter-cycle daily weights and summing the weighted normal daily degree-days over the billing month period.

The test-year period from July 2017 to June 2018 included a winter period that was slightly warmer than normal with cycle-weighted HDD55 (base 55-degree temperature) 2% below normal. Cycle-weighted CDD65 (base 65 degree temperature) that are 17% above normal with most of the above normal deviation occurring in October, May, and June. Figure 10 and Figure 11 compare test-year actual and normal CDD and HDD.

Figure 10: Comparison of Actual and Normal Cycle-Weighted CDD65

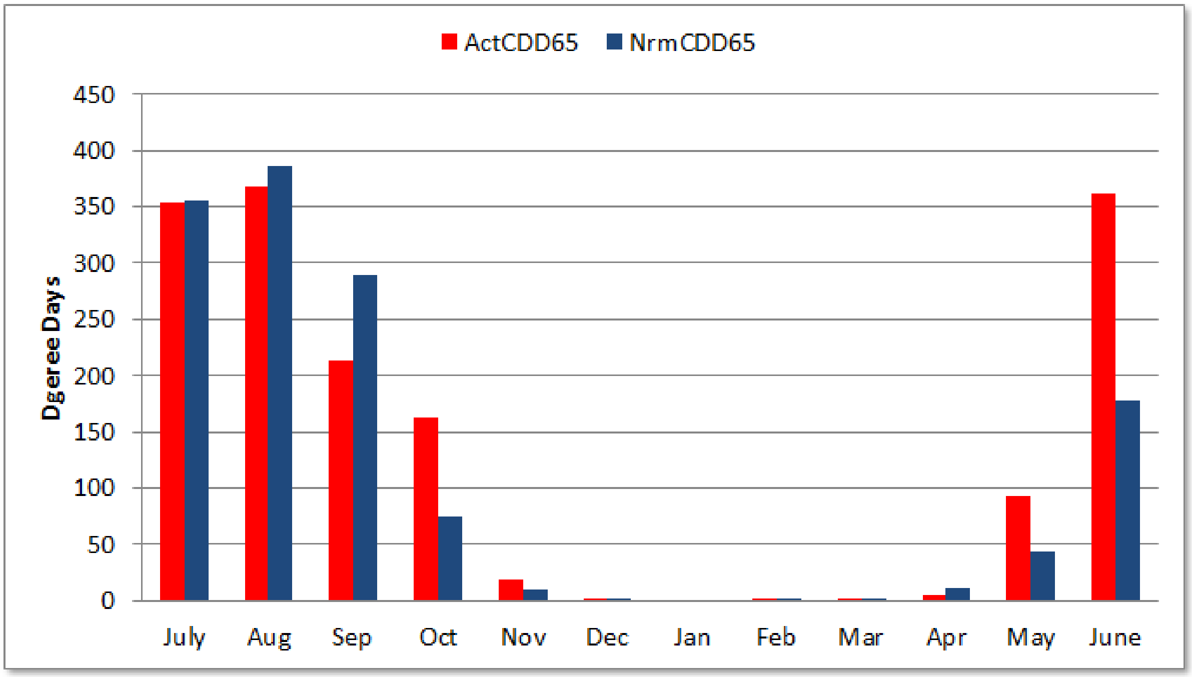
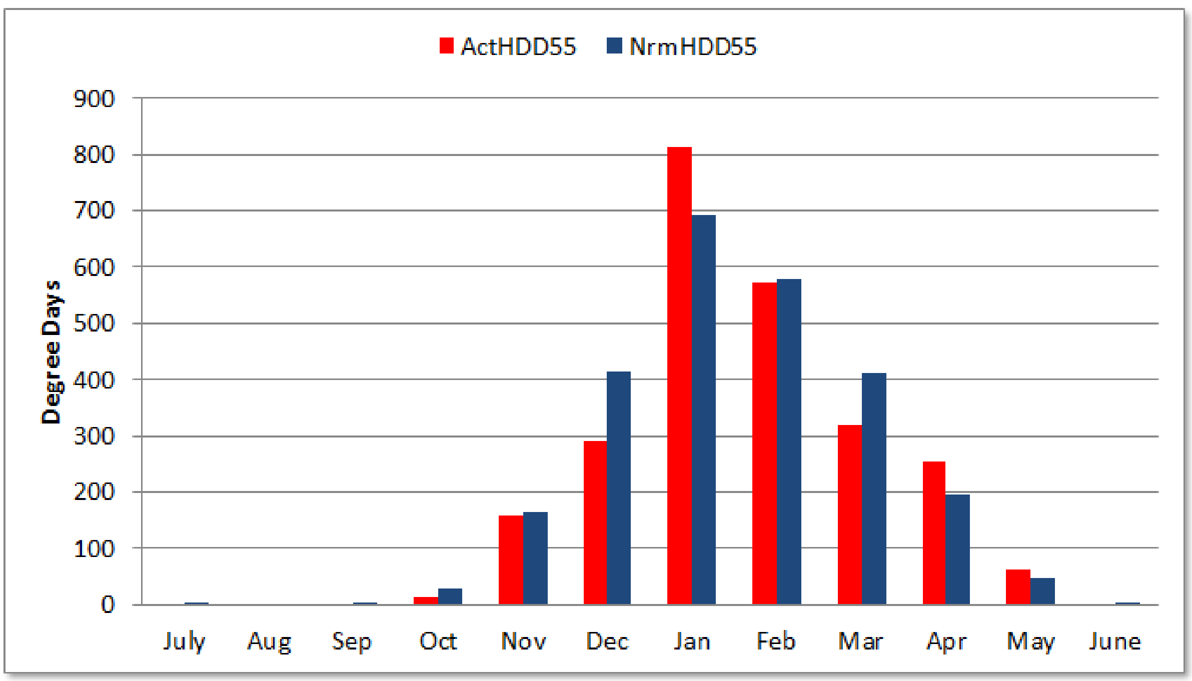


Figure 11: Comparison of Actual and Normal Cycle-Weighted HDD55



7. Summary

In total, weather-sensitive sales are adjusted down by 2,763.5 MWh or 1.6%. Cooling weather conditions in October 2017, and May and June 2018 are the primary contributors to this adjustment. Adjustments vary significantly across rate classes reflecting differences in rate class responses to change in temperature or degree-days. General residential service for example is adjusted down 2.3% while residential heating is adjusted down just 0.5%. The lower residential heating adjustment reflects compensating positive adjustments in winter heating load and less sensitivity to changes in CDD. Detailed monthly class adjustments are provided in Appendix A: Weather Response Models, Data, and Results.

The regression-based model approach is the most common approach for weather normalizing electric sales; it represents the industry best practice. The degree-day model coefficients are statistically significant and are consistent with expected differences in weather responses across rate classes. Best practice methods are also used in determining HDD and CDD temperature break points and calculating actual and normal HDD and CDD that are consistent with the billing month period.

A small adjustment for test-year sales is also made for change in customers over the test-year period. Customer adjusted normalized sales are calculated by multiplying the normalized rate class monthly average use by the customer count in the last month of the test-year (June 2018). Adjustment for year-end customer growth adds 162.5 MWh or 0.1% to normalized sales.

Appendix A:
Weather Response Models, Data, and Results

Daily weather response models are estimated for 5 rates. The rates include:

- Residential
- Commercial
- General Power
- Small Heating
- Total Electric Building

Model Data

Usage Data. Monthly data is received from Liberty. Data includes sales and customers by revenue class.

Weather Data. Daily actual and normal HDD and CDD are derived from hourly temperature data for Springfield-Branson National Airport. Daily temperature data is from January 1, 1980 to July 31, 2018. 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, 2017.

Estimated Models

Models are estimated for monthly use per customer for each class. Models are estimated over the period January 1, 2013 to June 30, 2018. The model specifications are relatively simple with a single HDD value (based on 55 degrees) and CDD value (based on the weather-responsiveness of the class). The residential models include a summer binary interactive with the CDD variable; summer includes the billing months July, August, and September. The purpose of the Summer/CDD interactive terms is to capture the stronger impact CDD have on load in the summer cooling period than in the shoulder months. Without the summer interactive the weather adjustment for the June and October test-year months are too high. While Summer/CDD term was tested in the non-residential models, the model variable either had no impact on normalized sales or was statistically insignificant. term, Estimated models also include the number of billing days and monthly binaries to capture load variation that is not weather-related. General Power model also includes 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. Model statistics are provided in Appendix B: Model Statistics.

Weather Normalization Results

Table 2 through Table 7 shows test-year billed and weather normal sales for the weather-sensitive rate classes.

Table 2: Residential (General) Test-Year Sales

Month	Actual Billed Sales (MWh)	Normal Billed Sales (MWh)	Customer-Adjusted Normal Billed Sales (MWh)
Jul-17	7,685.6	7,704.9	7,697.6
Aug-17	8,256.8	8,481.8	8,477.8
Sep-17	6,402.4	7,317.6	7,314.1
Oct-17	5,189.4	4,444.7	4,449.0
Nov-17	4,578.2	4,506.1	4,503.2
Dec-17	5,458.5	6,162.3	6,145.7
Jan-18	8,298.8	7,618.4	7,610.0
Feb-18	6,934.3	6,954.4	6,931.3
Mar-18	5,392.9	5,925.0	5,903.4
Apr-18	4,792.6	4,516.1	4,520.4
May-18	4,611.5	4,049.5	4,066.9
Jun-18	7,166.7	5,417.3	5,417.3
Total	**74,767.8**	**73,098.2**	**73,036.8**

Table 3: Residential (Heating) Test-Year Sales

Month	Actual Billed Sales (MWh)	Normal Billed Sales (MWh)	Customer-Adjusted Normal Billed Sales (MWh)
Jul-17	2,561.7	2,566.6	2,588.8
Aug-17	2,733.7	2,790.6	2,804.1
Sep-17	2,252.8	2,487.0	2,501.8
Oct-17	1,899.6	1,789.6	1,792.5
Nov-17	2,241.6	2,239.4	2,246.6
Dec-17	2,892.4	3,475.8	3,475.8
Jan-18	5,297.1	4,733.6	4,741.2
Feb-18	4,394.9	4,414.9	4,410.2
Mar-18	3,191.2	3,630.4	3,626.5
Apr-18	2,657.1	2,389.8	2,396.2
May-18	2,102.8	1,915.7	1,917.8
Jun-18	2,394.7	2,003.1	2,003.1
Total	**34,619.7**	**34,436.7**	**34,504.5**

Table 4: Commercial Test-Year Sales

Month	Actual Billed Sales (MWh)	Normal Billed Sales (MWh)	Customer-Adjusted Normal Billed Sales (MWh)
Jul-17	1,765.2	1,765.3	1,755.0
Aug-17	1,975.0	2,001.3	1,994.6
Sep-17	1,791.8	1,900.5	1,895.7
Oct-17	1,534.6	1,360.1	1,360.1
Nov-17	1,294.5	1,275.4	1,275.4
Dec-17	1,475.0	1,549.6	1,552.2
Jan-18	1,620.1	1,547.1	1,547.1
Feb-18	1,727.2	1,726.5	1,730.8
Mar-18	1,302.2	1,362.8	1,366.3
Apr-18	1,277.3	1,278.9	1,282.1
May-18	1,388.1	1,285.4	1,281.1
Jun-18	1,688.0	1,377.9	1,377.9
Total	**18,838.8**	**18,430.7**	**18,418.2**

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Table 5: General Power Test-Year Sales

Month	Actual Billed Sales (MWh)	Normal Billed Sales (MWh)	Customer-Adjusted Normal Billed Sales (MWh)
Jul-17	3,411.8	3,411.9	3,444.4
Aug-17	3,604.1	3,624.8	3,659.3
Sep-17	3,714.5	3,800.5	3,800.5
Oct-17	3,309.4	3,161.5	3,161.5
Nov-17	3,111.1	3,093.8	3,093.8
Dec-17	2,954.9	2,953.9	2,953.9
Jan-18	3,308.9	3,309.3	3,309.3
Feb-18	2,938.4	2,935.6	2,935.6
Mar-18	2,889.4	2,892.3	2,892.3
Apr-18	2,734.6	2,765.2	2,765.2
May-18	3,005.9	2,932.6	2,932.6
Jun-18	3,567.9	3,319.2	3,319.2
Total	**38,550.8**	**38,200.7**	**38,267.7**

Table 6: Small Heating Test-Year Sales

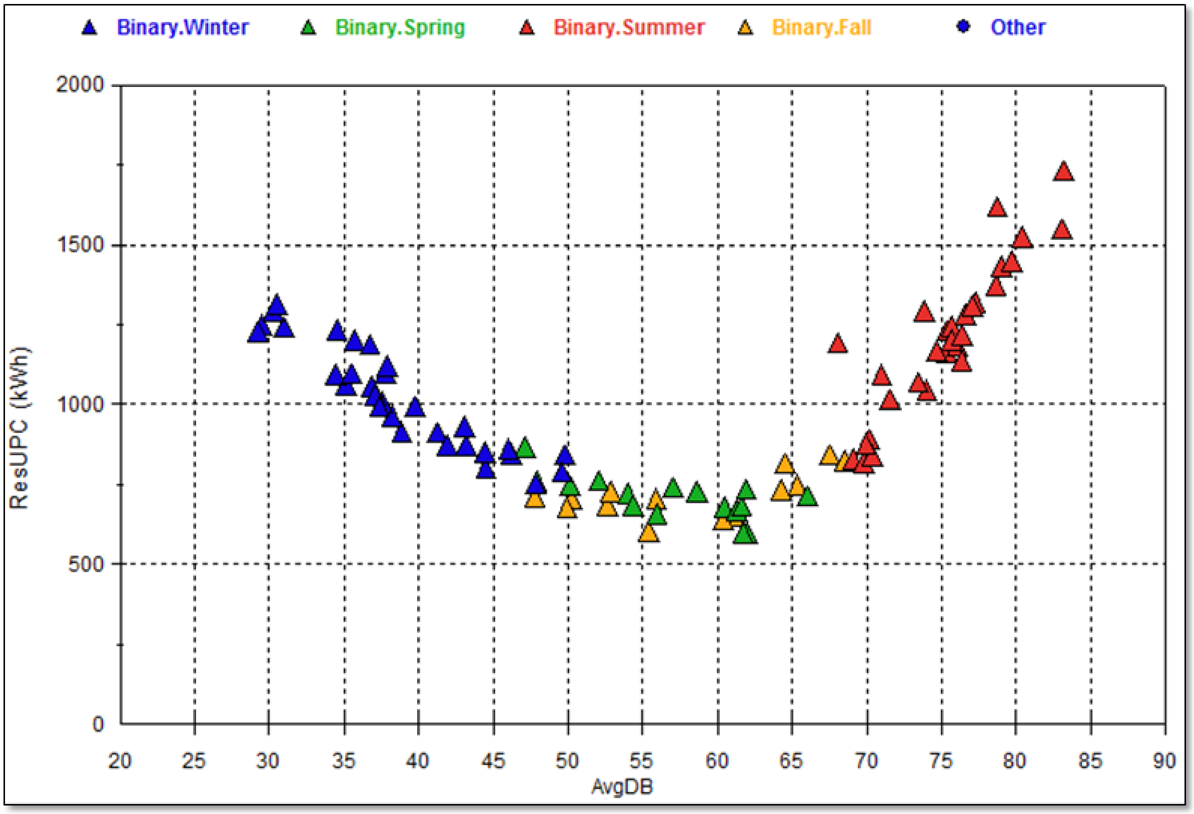
Month	Actual Billed Sales (MWh)	Normal Billed Sales (MWh)	Customer-Adjusted Normal Billed Sales (MWh)
Jul-17	243.2	243.6	245.8
Aug-17	230.4	235.3	235.3
Sep-17	210.7	230.7	230.7
Oct-17	179.8	162.2	162.2
Nov-17	174.7	173.4	173.4
Dec-17	211.0	248.2	250.5
Jan-18	338.2	302.2	305.0
Feb-18	316.8	318.1	318.1
Mar-18	230.2	258.4	258.4
Apr-18	207.3	190.8	190.8
May-18	270.8	253.0	253.0
Jun-18	210.6	163.6	163.6
Total	**2,823.7**	**2,779.4**	**2,786.7**

Table 7: Total Electric Building Test-Year Sales

Month	Actual Billed Sales (MWh)	Normal Billed Sales (MWh)	Customer-Adjusted Normal Billed Sales (MWh)
Jul-17	724.6	724.6	743.2
Aug-17	828.2	836.3	857.8
Sep-17	774.2	808.4	829.1
Oct-17	728.6	681.7	699.2
Nov-17	628.4	624.2	640.2
Dec-17	711.0	787.6	787.6
Jan-18	1,041.1	966.8	966.8
Feb-18	1,054.3	1,056.0	1,056.0
Mar-18	816.3	875.3	875.3
Apr-18	702.9	677.8	677.8
May-18	685.8	645.9	645.9
Jun-18	740.7	643.1	643.1
Total	**9,436.1**	**9,327.9**	**9,422.1**

Appendix B: Model Statistics (Update)

Figure 12: Residential (General) Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mCycWthr.BDays	18.609	0.328	56.793	0.00%
mCycWthr.HDD55	0.897	0.023	39.627	0.00%
mCycWthr.CDD65	1.527	0.075	20.328	0.00%
WthrTrans.CDD65_Summer	0.389	0.061	6.331	0.00%
Binary.Mar	31.47	15.165	2.075	4.23%
Binary.Mar16	-70.341	34.676	-2.029	4.70%
Binary.Dec16	-89.928	31.952	-2.814	0.66%

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Model Statistics	
Iterations	1
Adjusted Observations	66
Deg. of Freedom for Error	59
R-Squared	0.984
Adjusted R-Squared	0.982
AIC	6.994
BIC	7.226
Log-Likelihood	-317.45
Model Sum of Squares	3,575,664.82
Sum of Squared Errors	58189.07
Mean Squared Error	986.26
Std. Error of Regression	31.4
Mean Abs. Dev. (MAD)	22.25
Mean Abs. % Err. (MAPE)	2.41%
Durbin-Watson Statistic	2.037
Ljung-Box Statistic	23.05
Prob (Ljung-Box)	0.5168
Skewness	0.242
Kurtosis	3.306
Jarque-Bera	0.903
Prob (Jarque-Bera)	0.6366

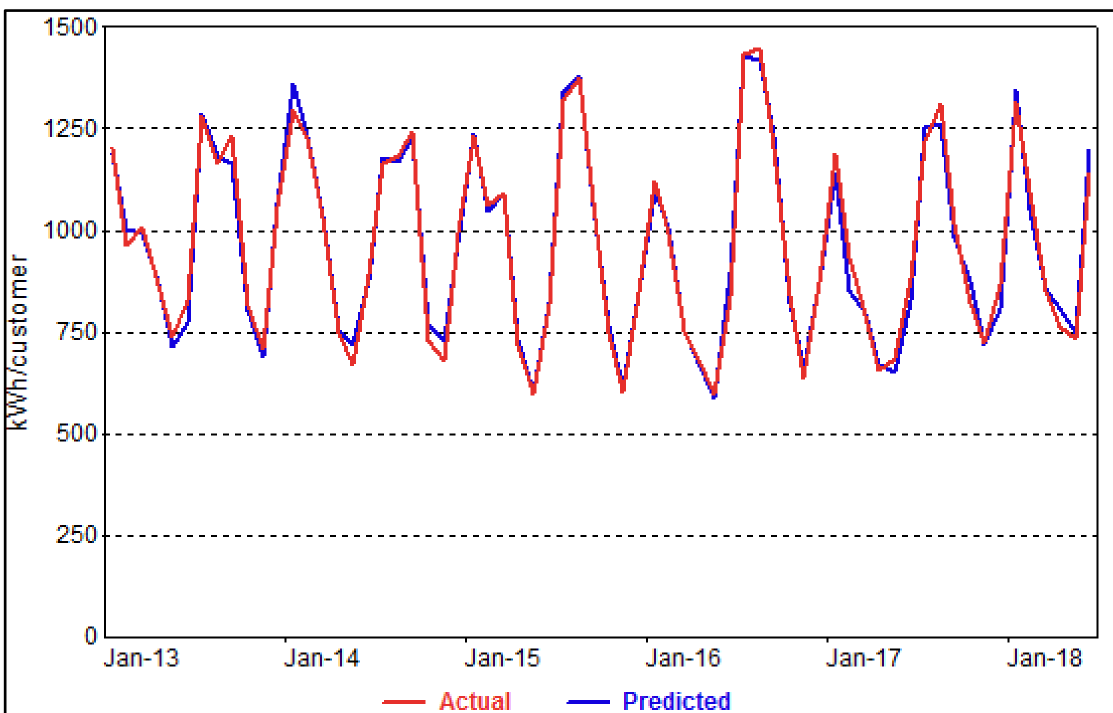
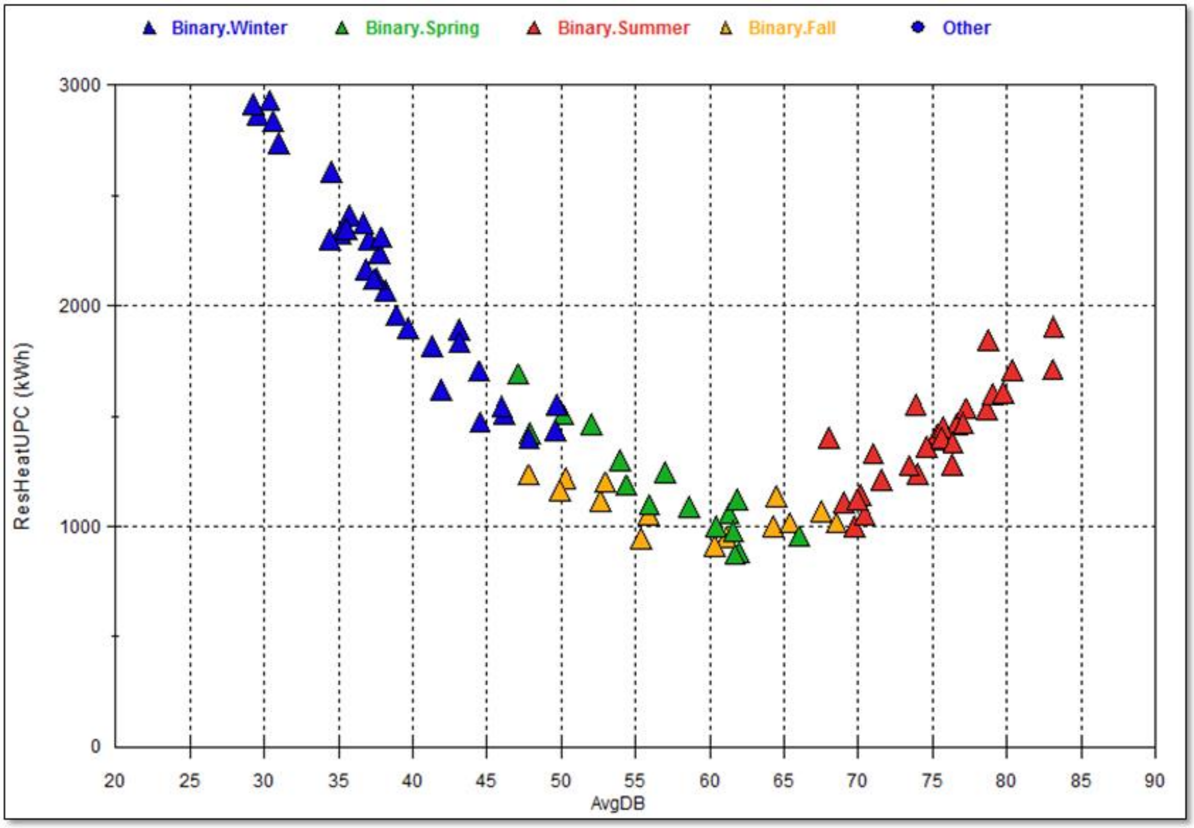


Figure 13: Residential (Heating) Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mCycWthr.BDays	27.825	0.716	38.876	0.00%
mCycWthr.HDD55	2.509	0.049	51.269	0.00%
mCycWthr.CDD65	1.183	0.164	7.236	0.00%
WthrTrans.CDD65_Summer	0.458	0.133	3.429	0.11%
Binary.Mar	64.4	30.396	2.119	3.83%
Binary.Nov14	-154.568	69.256	-2.232	2.94%
Binary.Dec16	-311.915	69.421	-4.493	0.00%

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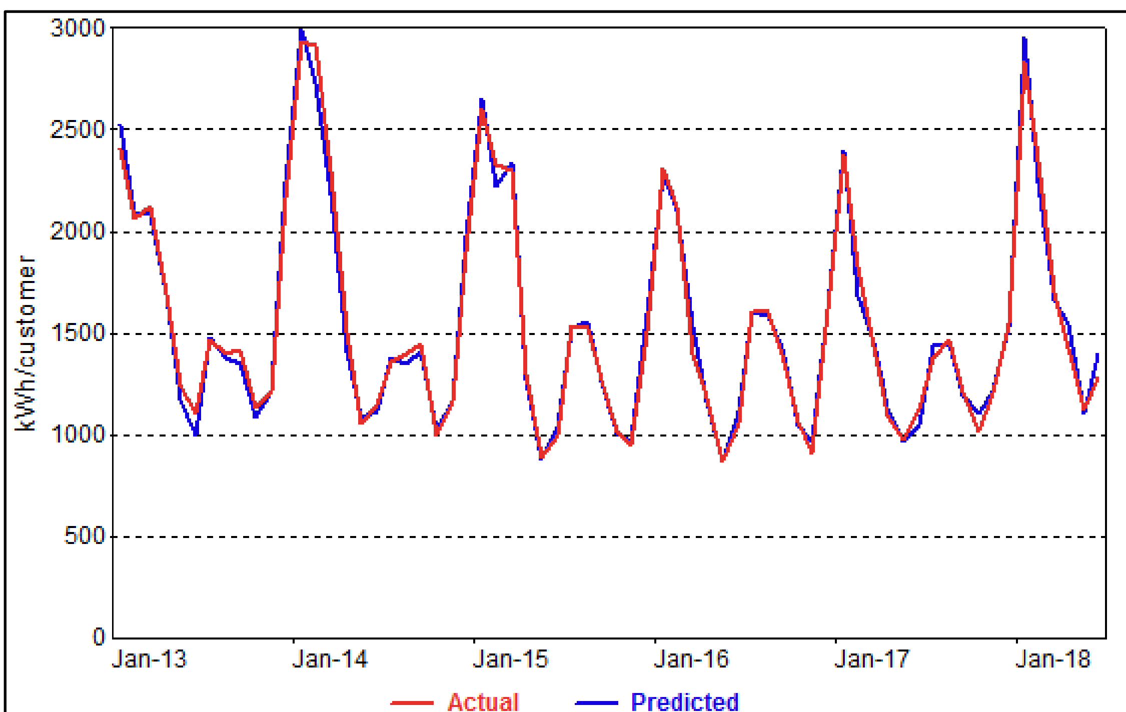
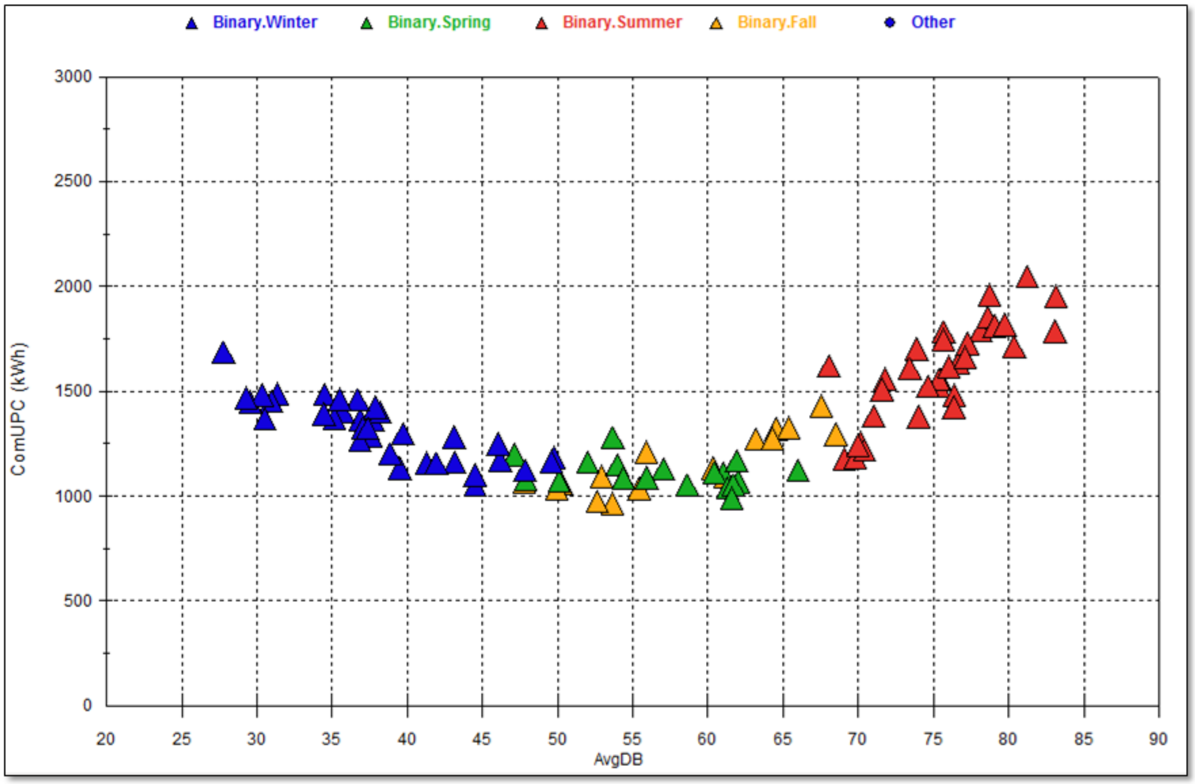
Model Statistics	
Iterations	1
Adjusted Observations	66
Deg. of Freedom for Error	59
R-Squared	0.985
Adjusted R-Squared	0.984
AIC	8.545
BIC	8.777
Log-Likelihood	-368.64
Model Sum of Squares	18,347,617.01
Sum of Squared Errors	274509.84
Mean Squared Error	4652.71
Std. Error of Regression	68.21
Mean Abs. Dev. (MAD)	49.35
Mean Abs. % Err. (MAPE)	3.22%
Durbin-Watson Statistic	1.929
Ljung-Box Statistic	26.64
Prob (Ljung-Box)	0.3215
Skewness	0.419
Kurtosis	3.506
Jarque-Bera	2.636
Prob (Jarque-Bera)	0.2677



EMPIRE DISTRICT ELECTRIC COMPANY

Figure 14: Commercial Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mCycWthr.BDays	32.742	0.819	40.002	0.00%
mCycWthr.HDD55	0.516	0.057	9.027	0.00%
mCycWthr.CDD60	1.243	0.066	18.828	0.00%
Binary.Feb	148.023	32.996	4.486	0.00%
Binary.Mar	65.558	30.94	2.119	3.84%
Binary.May	-90.263	32.061	-2.815	0.66%
Binary.Jun	-189.756	31.289	-6.065	0.00%
Binary.Sep	79.953	34.71	2.303	2.49%

EMPIRE DISTRICT ELECTRIC COMPANY

Model Statistics	
Iterations	1
Adjusted Observations	66
Deg. of Freedom for Error	58
R-Squared	0.919
Adjusted R-Squared	0.909
AIC	8.545
BIC	8.81
Log-Likelihood	-367.62
Model Sum of Squares	3,022,424.17
Sum of Squared Errors	266,163.19
Mean Squared Error	4,589.02
Std. Error of Regression	6774.00%
Mean Abs. Dev. (MAD)	5132.00%
Mean Abs. % Err. (MAPE)	3.86%
Durbin-Watson Statistic	2.268
Ljung-Box Statistic	21.46
Prob (Ljung-Box)	0.6115
Skewness	-0.174
Kurtosis	2.851
Jarque-Bera	0.395
Prob (Jarque-Bera)	0.8207

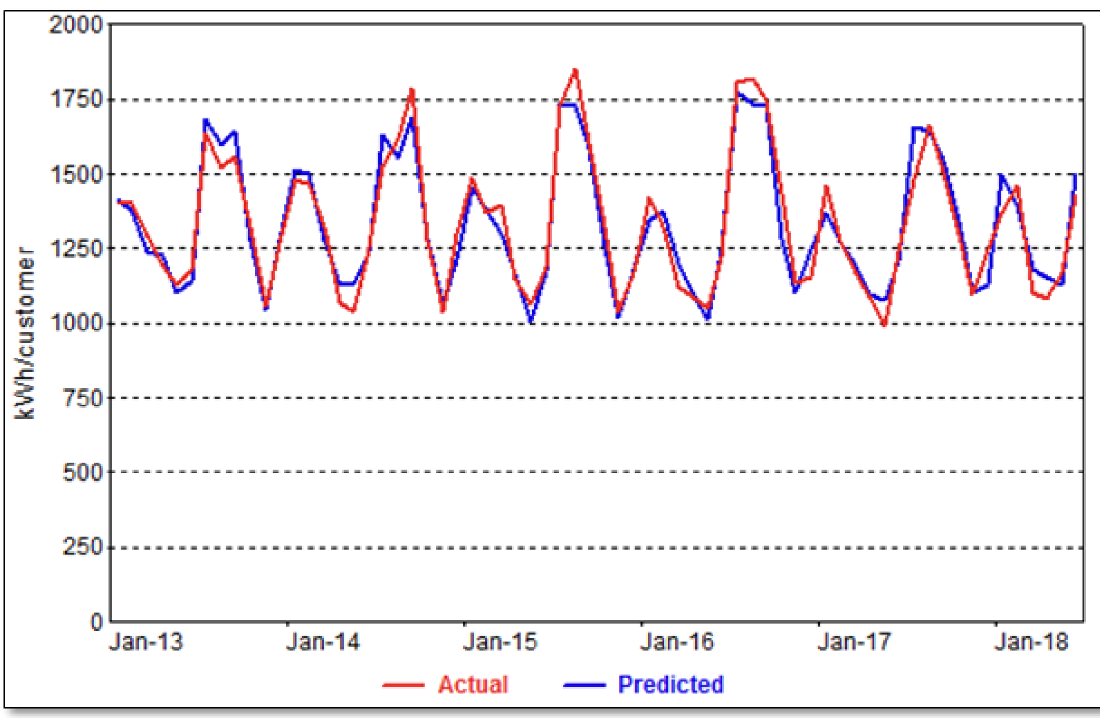


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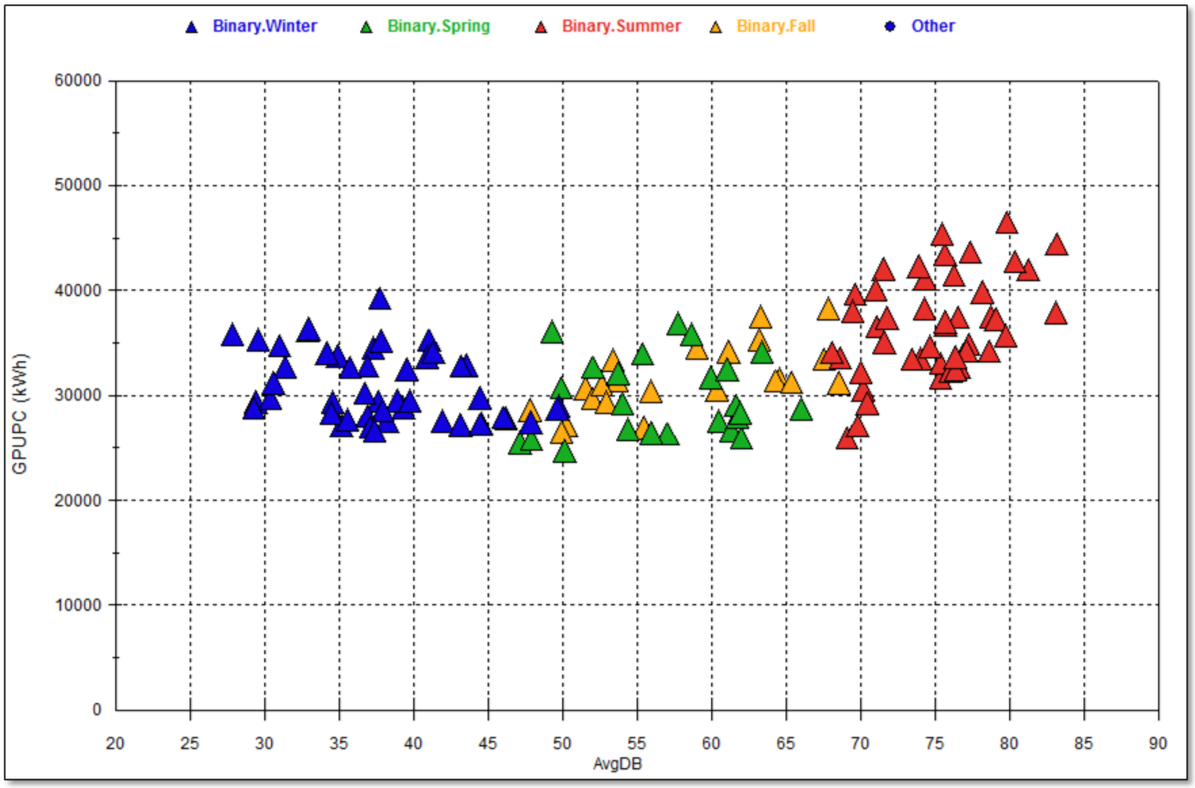
Figure 15: General Power Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mCycWthr.BDays	799.036	37.85	21.11	0.00%
mCycWthr.CDD60	11.067	0.928	11.925	0.00%
Binary.LTrend	469.326	123.686	3.794	0.04%
Binary.Apr	-2722.455	459.835	-5.921	0.00%
Binary.May	-2130.315	479.564	-4.442	0.00%
Binary.Jun	-2762.711	455.275	-6.068	0.00%
Binary.Mar13	3859.745	975.618	3.956	0.02%
Binary.Sep14	3102.054	972.488	3.19	0.24%
Binary.Dec16	-2502.044	970.767	-2.577	1.27%
Binary.Jul17	-3456.733	1016.21	-3.402	0.13%
AR(1)	0.373	0.123	3.033	0.37%

EMPIRE DISTRICT ELECTRIC COMPANY

Model Statistics	
Iterations	11
Adjusted Observations	65
Deg. of Freedom for Error	54
R-Squared	0.913
Adjusted R-Squared	0.897
AIC	14.017
BIC	14.385
Log-Likelihood	-536.79
Model Sum of Squares	593,244,318.31
Sum of Squared Errors	56,688,604.88
Mean Squared Error	1,049,788.98
Std. Error of Regression	102459.00%
Mean Abs. Dev. (MAD)	753.83
Mean Abs. % Err. (MAPE)	2.53%
Durbin-Watson Statistic	1.973
Ljung-Box Statistic	17.57
Prob (Ljung-Box)	0.8232
Skewness	0.4
Kurtosis	2.344
Jarque-Bera	2.894
Prob (Jarque-Bera)	0.2352

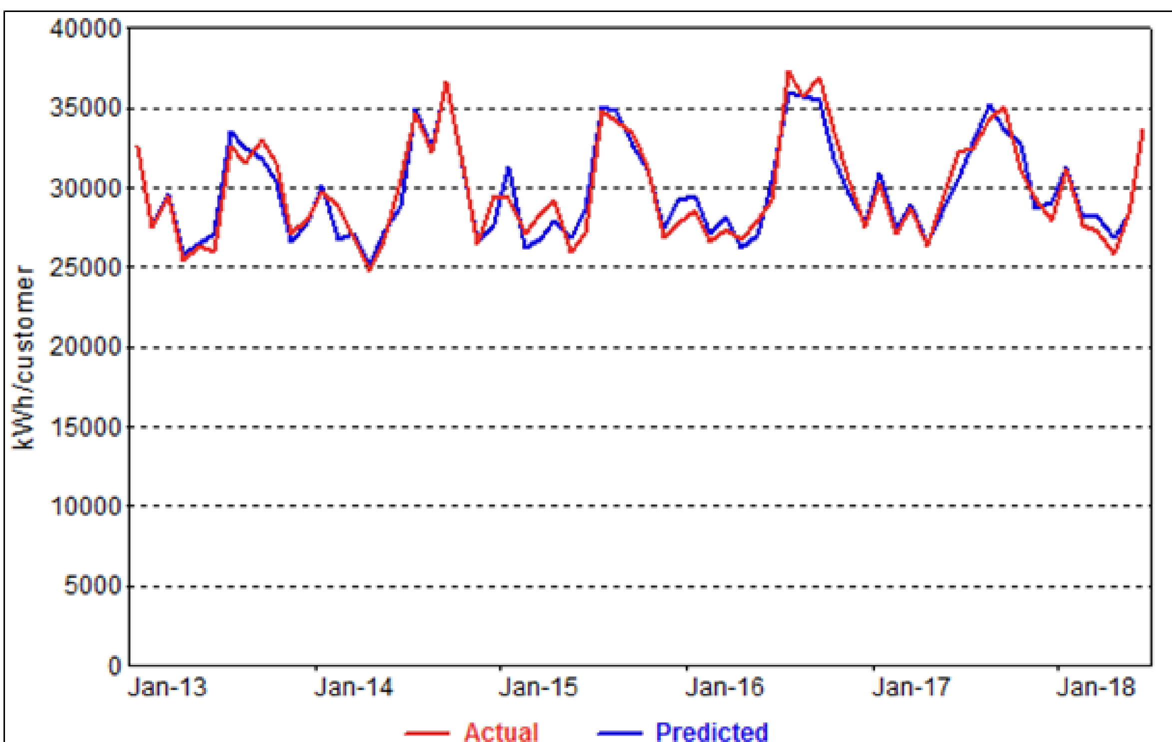
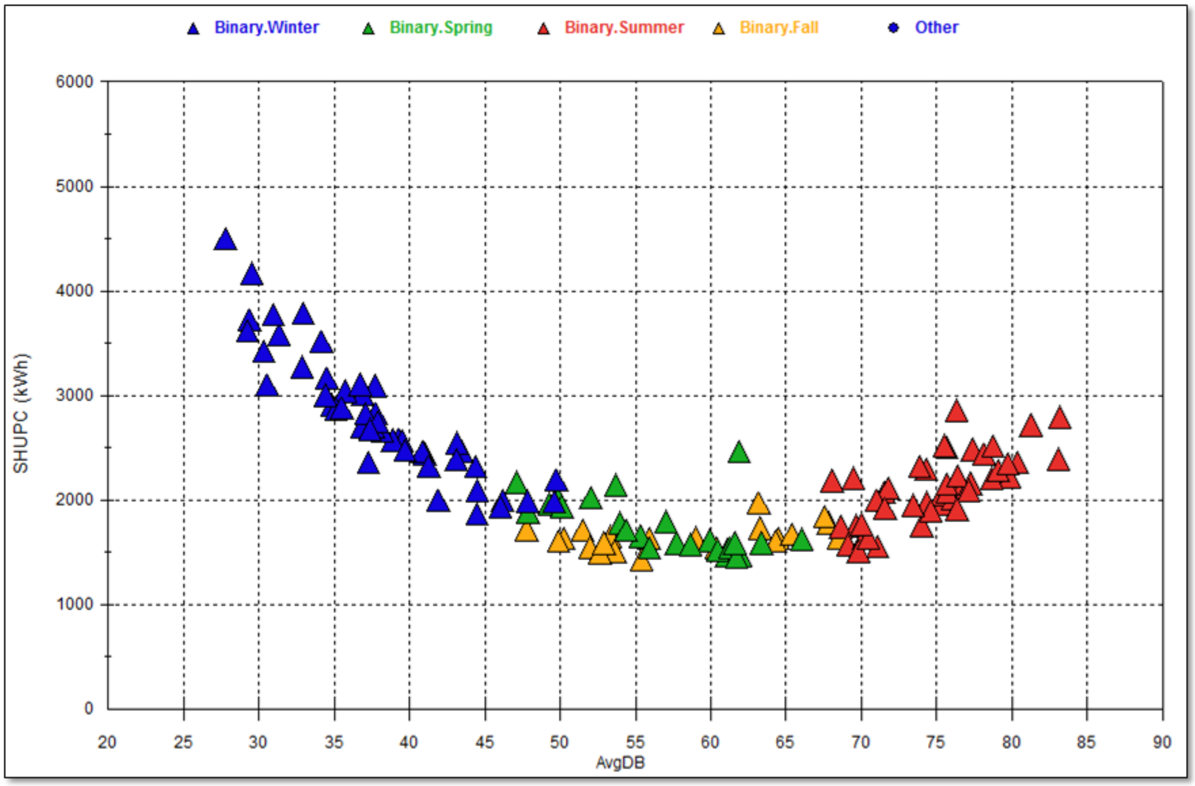


Figure 16: Small Heating Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mCycWthr.BDays	39.171	1.344	29.143	0.00%
mCycWthr.HDD55	2.744	0.088	31.075	0.00%
mCycWthr.CDD65	2.376	0.14	17.021	0.00%
Binary.Feb	208.832	46.588	4.483	0.00%
Binary.Mar	192.955	43.733	4.412	0.01%
Binary.Apr	105.011	47.12	2.229	3.00%
Binary.May	151.786	51.607	2.941	0.48%
Binary.Sep	120.955	46.135	2.622	1.13%
Binary.Oct	150.921	49.182	3.069	0.34%
Binary.Dec16	-387.489	94.745	-4.09	0.01%
Binary.May18	754.266	100.663	7.493	0.00%
Binary.Jan18	-416.339	101.448	-4.104	0.01%

EMPIRE DISTRICT ELECTRIC COMPANY

Model Statistics	
Iterations	1
Adjusted Observations	66
Deg. of Freedom for Error	54
R-Squared	0.976
Adjusted R-Squared	0.971
AIC	9.198
BIC	9.597
Log-Likelihood	-385.20
Model Sum of Squares	18,334,178.79
Sum of Squared Errors	453,392.25
Mean Squared Error	8,396.15
Std. Error of Regression	9163.00%
Mean Abs. Dev. (MAD)	64.74
Mean Abs. % Err. (MAPE)	3.24%
Durbin-Watson Statistic	1.529
Ljung-Box Statistic	30.01
Prob (Ljung-Box)	0.1845
Skewness	0.28
Kurtosis	2.881
Jarque-Bera	0.904
Prob (Jarque-Bera)	0.6362

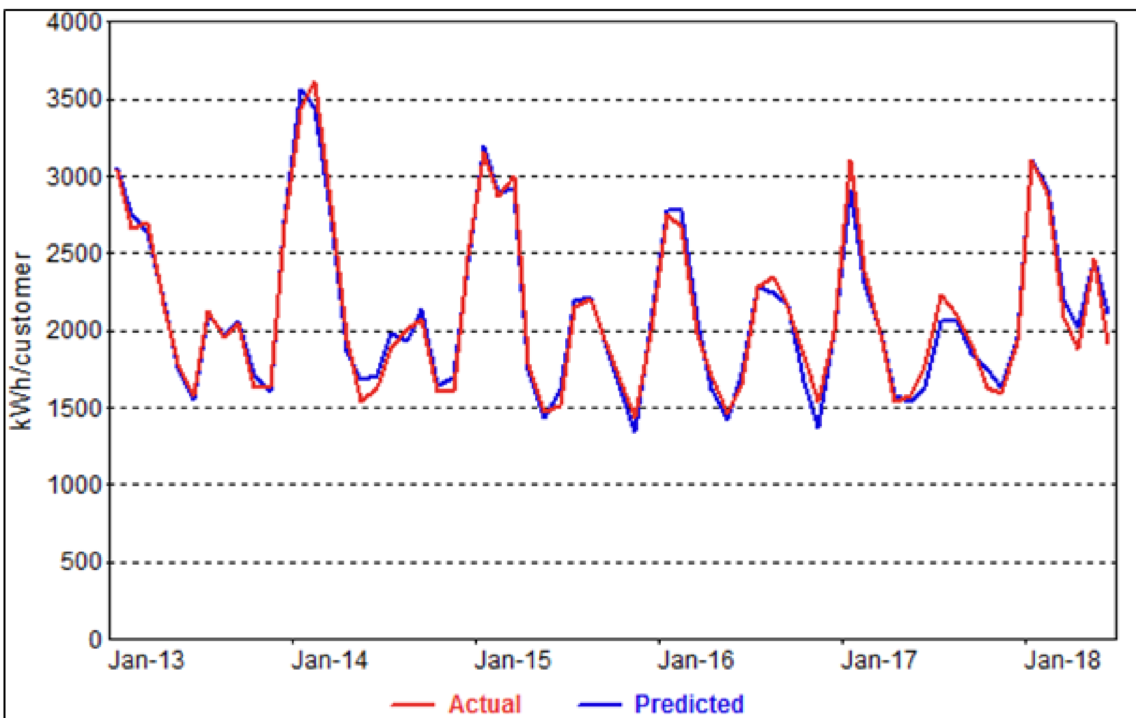
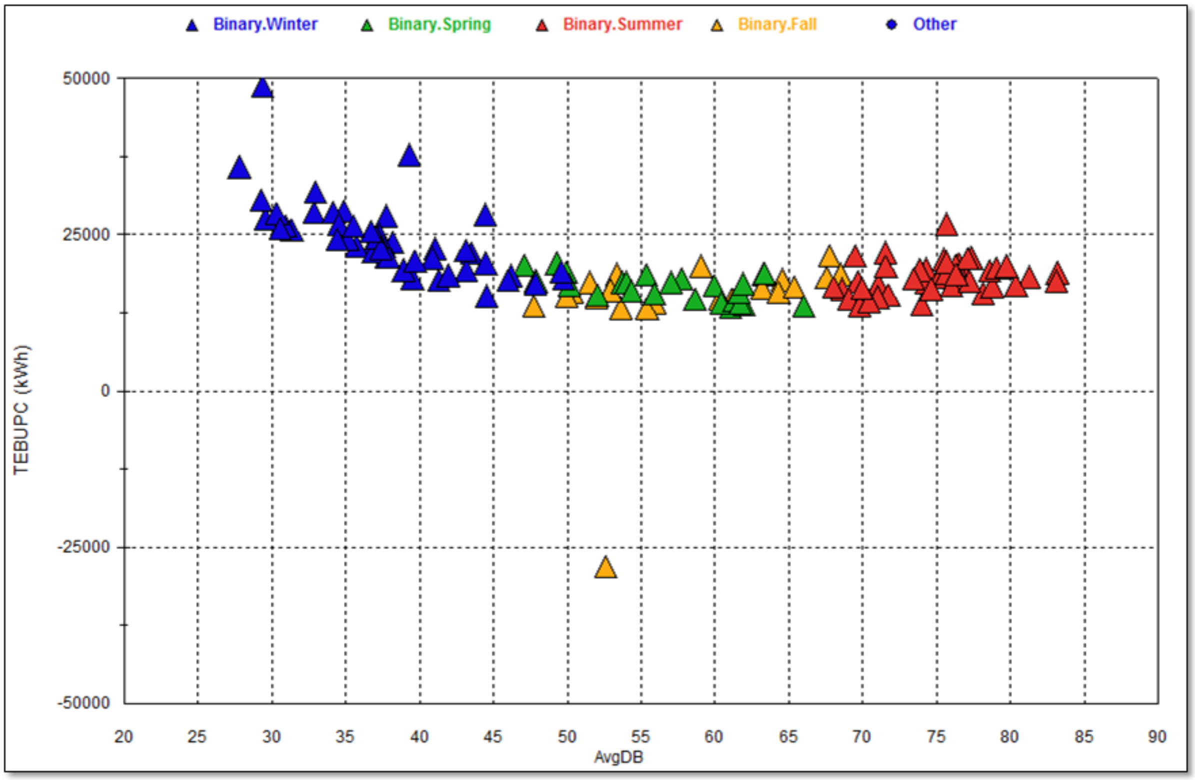


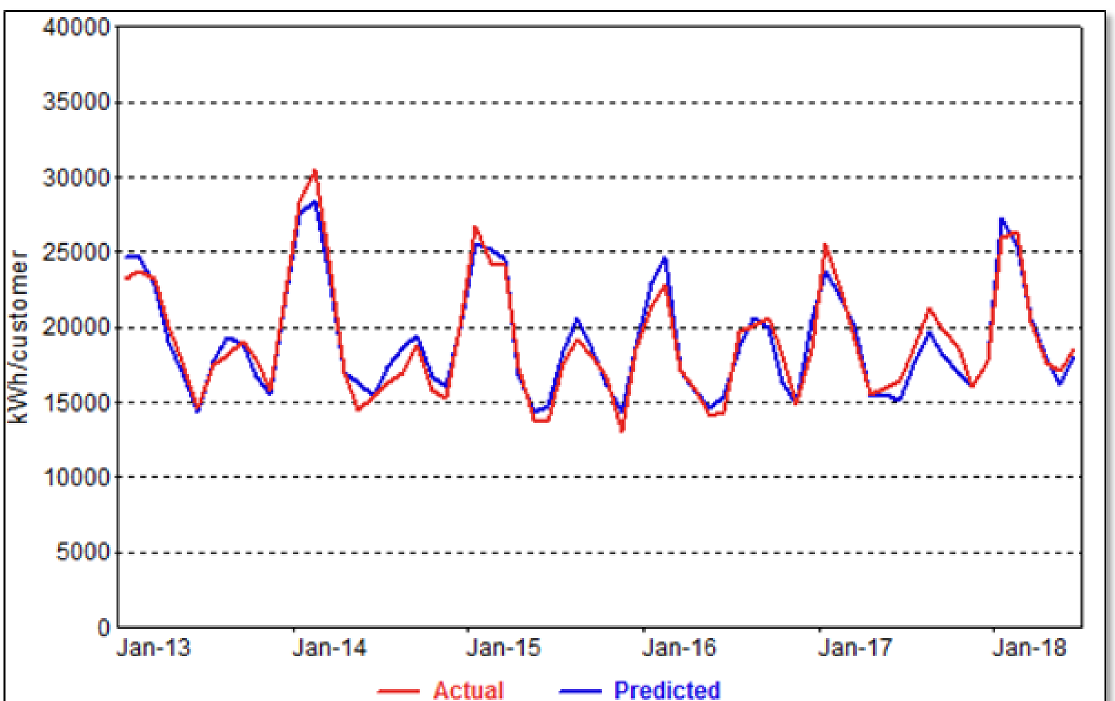
Figure 17: Total Electric Building Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mCycWthr.BDays	445.688	11.607	38.399	0.00%
mCycWthr.HDD55	15.484	0.857	18.066	0.00%
mCycWthr.CDD60	11.744	1.082	10.855	0.00%
Binary.Mar16	-3075.982	1187.732	-2.59	1.21%
Binary.Feb	3575.43	523.906	6.825	0.00%
Binary.Mar	2721.735	530.684	5.129	0.00%
Binary.Jun	-2340.389	494.409	-4.734	0.00%
Binary.Jul	-2384.921	595.945	-4.002	0.02%

EMPIRE DISTRICT ELECTRIC COMPANY

Model Statistics	
Iterations	1
Adjusted Observations	66
Deg. of Freedom for Error	58
R-Squared	0.93
Adjusted R-Squared	0.922
AIC	14.072
BIC	14.338
Log-Likelihood	-550.03
Model Sum of Squares	889,963,977.52
Sum of Squared Errors	66,941,148.57
Mean Squared Error	1,154,157.73
Std. Error of Regression	107432.00%
Mean Abs. Dev. (MAD)	825.15
Mean Abs. % Err. (MAPE)	4.32%
Durbin-Watson Statistic	1.372
Ljung-Box Statistic	30.43
Prob (Ljung-Box)	0.1709
Skewness	0.042
Kurtosis	2.251
Jarque-Bera	1.562
Prob (Jarque-Bera)	0.458



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*

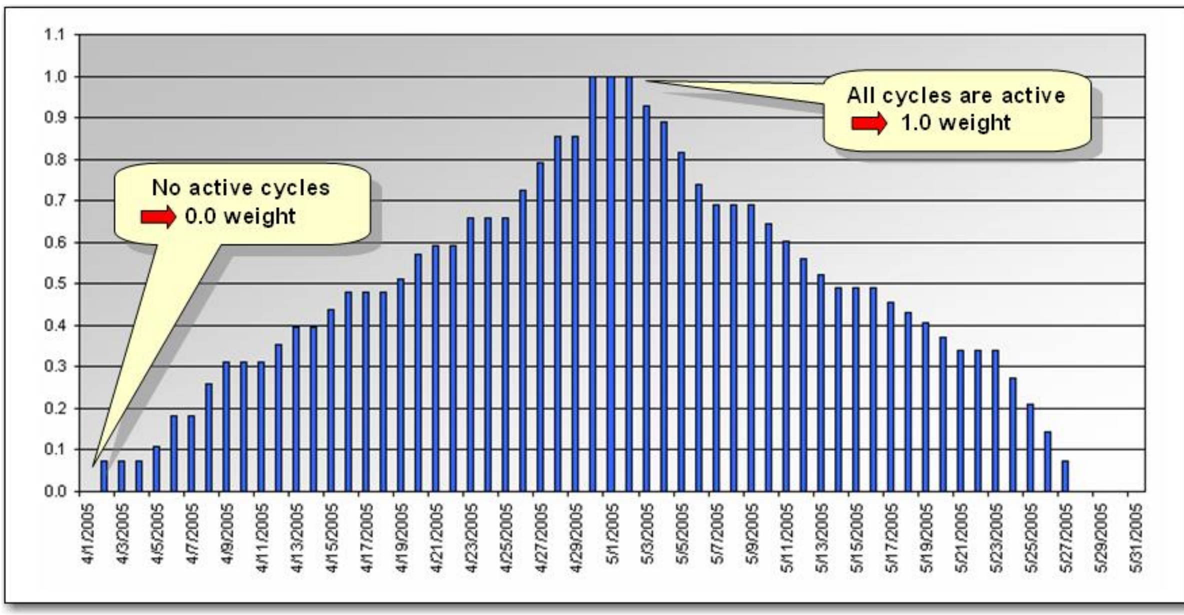
On the first day of the billing month, only 1 cycle is *On*; $ActiveCycles_{dm}$ has a value of 1.0. On the second day, cycle 2 is *On*; $ActiveCycles_{dm}$ has a value of 2. This process continues through the billing period. Assuming there are 21 billing cycles, the highest daily value for $Active\ Cycles_{dm}$ 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 18 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 18: 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.

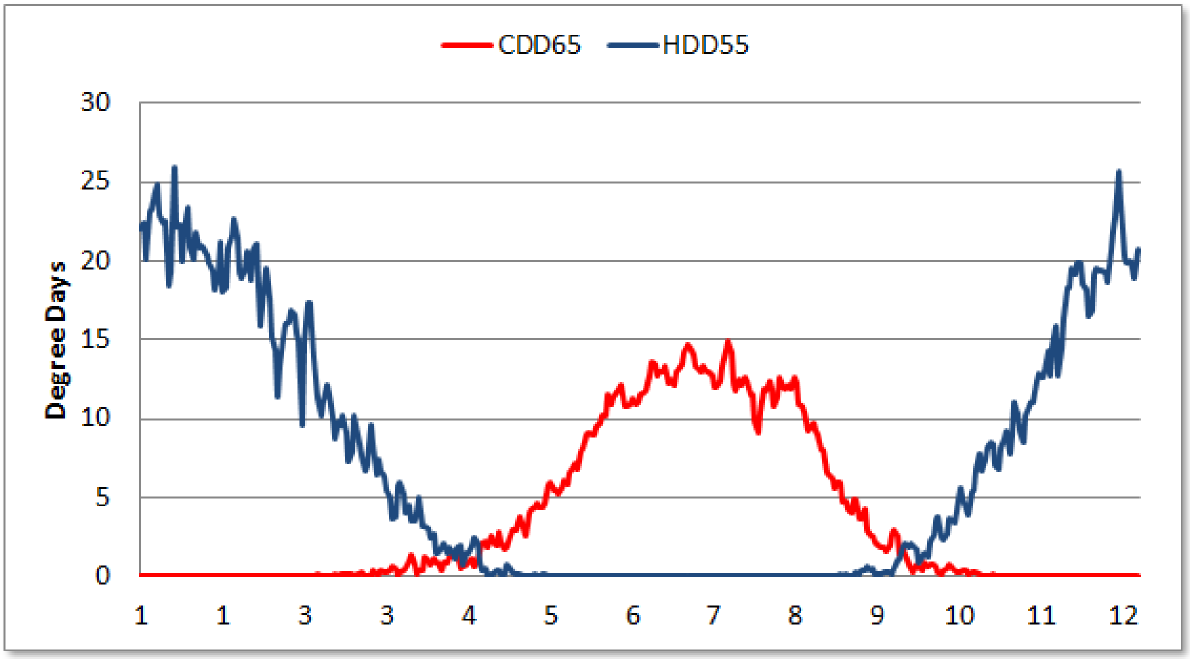
Step 1: Calculate Daily Degree-Days. The first step is to calculate historical daily degree days. Daily heating and cooling degree days are calculated for the Springfield, MO from January 1, 1988 to December 31, 2017 (i.e., 30-years). Daily degree days are calculated as:

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

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 19: 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 used in normalizing Test-Year sales are based on the 2017 and 2018 meter read schedule.

AFFIDAVIT OF ERIC FOX

STATE OF MASSACHUSETTS)
) ss
COUNTY OF SUFFOLK)

On the 4th day of December, 2018, before me appeared Eric Fox, to me personally known, who, being by me first duly sworn, states that he is Director of Forecast Solutions of Itron and acknowledges that he has read the above and foregoing document and believes that the statements therein are true and correct to the best of his information, knowledge and belief.

____
Eric Fox

Subscribed and sworn to before me this 4th day of December, 2018

____
Notary Public

My commission expires:

JENNIFER A. KELLY
Notary Public
COMMONWEALTH OF MASSACHUSETTS
My Commission Expires
May 31, 2024