BEFORE THE CORPORATION COMMISSION OF THE STATE OF OKLAHOMA

APPLICATION OF THE EMPIRE DISTRICT ELECTRIC COMPANY, A KANSAS CORPORATION, FOR AN ADJUSTMENT IN ITS RATES AND CHARGES FOR ELECTRIC SERVICE IN THE STATE OF OKLAHOMA	)))))	CAUSE NO. PUD 202100163

Direct Testimony

of

Eric Fox

Submitted on behalf of

The Empire District Electric Company

February 28, 2022

Liberty™

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THE EMPIRE DISTRICT ELECTRIC COMPANY
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DIRECT TESTIMONY OF ERIC FOX
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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 ("Liberty-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 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

[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.

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 30 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 course of my career, 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 including Liberty-Empire's last Oklahoma rate case application in Cause No. PUD 201800133. My regulatory experience is listed in Direct Exhibit EF-1.

Q. What is the purpose of your testimony?

A. The purpose of my testimony is to support test-year sales and revenue 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 calculation of the revenue impact.

Q. Are you sponsoring any exhibits in support of your testimony?

A. Yes. I am sponsoring the report *2022 Rate Case Test-Year Weather-Normal Sales, January 2022* ("Itron Report"), which is included as Direct Exhibit EF-2 *(Itron Report)*. 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 attachments prepared or assembled by you or under your direction and supervision?

A. Yes.

II. WEATHER NORMALIZATION METHOD AND RESULTS

Q. Please describe the test-year weather conditions and impact on sales.

A. On an annual basis, billing-month heating degree days with a 55 degree temperature base (HDD55) are 1.3% above normal. CDD with a 65 degree base (CDD65) are 1.0% above normal and CDD with a 60 degree day basis (CDD60) are 0.4% below normal. The difference in CDD directions reflects more days of hot weather captured in CDD65 2020 and fewer days of moderate warm weather reflected in CDD60. CDD65 is used in weather normalizing residential sales and CDD60 is used in weather normalizing commercial sales. While total degree-days are close to normal there is significant variation across the year with higher than normal cooling requirements in billing-month July 2020 and significantly colder than normal weather in billing months February and March 2021. The impact on total sales is somewhat mitigated by milder than normal weather in December (2020), January (2021), and April (2021). Table EF-1 below shows actual, normal, and weather-related sales by rate class.

Table EF-1: Test-Year Sales by Month

Rate Class	Billed Sales	Wthr Normal Sales	Weather Sales	Pct Impact
Res General	34,292,860	34,092,625	200,235	0.6%
Res Space Heat	17,165,588	17,058,330	107,258	0.6%
Small Commerci	13,031,010	13,014,538	16,472	0.1%
General Power	23,042,291	23,029,701	12,590	0.1%
Total Electric Bu	3,697,315	3,691,659	5,656	0.2%
Total	**91,229,064**	**90,886,853**	**342,211**	0.4%

The residential rate classes show the largest change as these classes are more sensitive to winter heating and summer cooling temperatures.

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

A. Weather normal sales are estimated for five (5) 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)
- 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. Normalized average use is calculated by subtracting the weather impact from actual customer average use. Finally weather normal sales are derived by multiplying the weather-normal average use by number of customers. 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, provided as Direct Exhibit EF-2.

Q. Please describe the HDD and CDD variables used in estimating the weather response models.

A. HDD and CDD are measures of temperature variance from a defined temperature reference point. Residential weather response models are estimated using CDD with a 65 temperature breakpoint and HDD with a 55 temperature degree-break; while typically HDD are defined with a 65 degree breakpoint, there is no observable heating load until average temperatures fall to 55 degrees or lower. The commercial weather response models are estimated with CDD with a 60 degree day base rate classes as cooling in the commercial sector starts at a lower temperature point largely as a result of internal heat gains; commercial heating related load is also captured with an HDD using a 55 degree temperature base.

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 (or occasionally 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 incorporate 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,* provided in Direct Exhibit EF-2.

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 30-years of historical weather data from the Springfield-Branson National Airport (SGF). The 30-year normal period is January 1, 1991 to December 31, 2020. 2020 was the last full year of historical temperature data at the time the analysis was completed.

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 results in daily normal degree-day 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 billing-cycle 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 2020 through June 2021. Table EF-2 compares actual and normal cycle-weighted CDD65 and CDD60.

Table EF-2: Test-Year Cycle-Weighted Cooling Degree-Days

Month	CDD65	NrmCDD65	Difference	CDD60	NrmCDD60	Difference
Jul-20	428	379	49	588	537	51
Aug-20	408	411	(3)	563	565	(2)
Sep-20	300	297	3	449	440	9
Oct-20	85	96	(11)	176	183	(7)
Nov-20	22	12	10	56	39	16
Dec-20	1	0	1	10	3	6
Jan-21	-	0	(0)	-	1	(1)
Feb-21	-	0	(0)	-	1	(1)
Mar-21	-	1	(1)	3	7	(4)
Apr-21	4	14	(10)	23	44	(21)
May-21	32	50	(18)	84	116	(31)
Jun-21	187	193	(5)	298	322	(24)
Total	**1,468**	**1,453**	**14**	**2,250**	**2,259**	**(9)**

July is significantly warmer than normal but is largely mitigated by below normal CDD over the 2021 shoulder cooling months. CDD60 are even lower in the shoulder months indicating fewer days with moderate cooling temperatures than what would be expected. CDD65 are used in weather normalizing residential sales. CDD60 are used in weather normalizing commercial sales. On a total test-year basis, CDD65 are slightly higher than normal while CDD60 are slightly lower than normal. Table EF3 compares actual and normal cycle weighted HDD55.

Table EF3: Test-Year Cycle-Weighted HDD

Month	HDD55	NrmHDD55	Difference
Jul-20	-	0	(0)
Aug-20	-	-	-
Sep-20	-	1	(1)
Oct-20	24	25	(1)
Nov-20	159	159	1
Dec-20	364	431	(67)
Jan-21	628	676	(48)
Feb-21	668	551	117
Mar-21	481	405	76
Apr-21	122	191	(69)
May-21	62	40	22
Jun-21	5	3	2
Total	**2,513**	**2,481**	**32**

The test-year includes the cold wave triggered by the Polar Vortex's deep push south in the second half of February, known as Winter Storm Uri. The cold wave impacts both billing-month February and March HDD55 which are roughly 20% higher than normal. December, January, and April HDD55 are measurably lower than normal.

Q. How does weather impact test-year sales?

A. The impact of weather on sales varies across the year. February and March sales are significantly higher than normal as a result of the end-of-February cold wave. July sales are also significantly higher than normal while January, December, and April sales are significantly lower than expected sales. Table EF-3 shows total sales, normalized sales, and weather-related sales by month.

Table EF-4: Test-Year Sales by Month

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)	Weather Sales (kWh)	Impact
Jul-20	8,316,615	7,881,609	435,006	5.2%
Aug-20	8,655,825	8,680,499	-24,674	-0.3%
Sep-20	8,391,071	8,357,156	33,915	0.4%
Oct-20	6,134,913	6,212,445	-77,532	-1.3%
Nov-20	6,134,104	6,038,333	95,771	1.6%
Dec-20	6,341,516	6,803,893	-462,377	-7.3%
Jan-21	11,735,280	12,083,344	-348,064	-3.0%
Feb-21	10,055,825	9,215,550	840,275	8.4%
Mar-21	7,740,408	7,213,511	526,897	6.8%
Apr-21	5,330,201	5,926,312	-596,111	-11.2%
May-21	5,747,207	5,755,362	-8,155	-0.1%
Jun-21	6,646,099	6,718,838	-72,739	-1.1%
Total	**91,229,064**	**90,886,853**	342,211	0.4%

Months with large positive weather-related sales are highlighted in red and months with large negative weather sales are highlighted in Blue. The Itron report (Direct Exhibit EF-2) includes monthly normalized sales and weather sales for the individual rate classes. Total weather-related sales are 342,211 kWh resulting in normalized sales of 90,886,853 kWh – a 0.4% reduction from test-year billed sales.

Q. How is the revenue impact calculated?

A. The revenue impact is calculated for each rate class by multiplying the weather sales (difference between actual and weather-normal sales) by the current tariff's seasonal kWh marginal rates. This is the same approach that has been used in previous filings.

The marginal rates are the prices for the last blocks of energy use. The second-block kWh rates are lower than the initial block kWh rates. The assumption is that variation in weather is impacting the last block of kWh sales. This is somewhat conservative as there are likely customers who usage doesn't exceed the first block but still includes some weather-related sales. Table EF-5 shows the test-year revenue adjustment.

Table EF-5: WN Adjusted Test-Year Revenues

Test Year Ending June 30, 2021				
Tariff	**Rev by Tariff**	**WN Revenue Adjustment applied to final block rate only**	**WN Adjusted Revenue**	**Revenue Change**
RG-Residential Total	$ 2,944,593	$ (15,868)	$ 2,928,725	-0.5%
RH-Residential Total Elec Total	1,158,404	(7,121)	$ 1,151,283	-0.6%
CB-Commercial Total	1,392,691	(1,496)	$ 1,391,195	-0.1%
GP-General Power Total	1,732,220	(563)	$ 1,731,657	0.0%
TEB-Total Electric Bldg Total	260,076	(574)	$ 259,502	-0.2%
Total	**$ 7,487,984**	**$ (25,621)**	**$ 7,462,363**	**-0.3%**

Weather-related sales of 90,886,853 kWh, results in a test-year revenue adjustment of minus $25,621 – a 0.3% reduction.

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. The estimated models capture differences in weather response across the rate classes. Weather adjustment coefficients derived from regression models are statistically significant and result in predicted use that is consistent with observed change in customer usage. Actual and normal HDD and CDD variables are defined with temperature breakpoint definitions that best explain the rate-class usage/weather relationship. HDD and CDD variables are cycle-weighted based on the meter read schedule and as a result reflect the same period as the monthly reported billed sales.

The test-year period includes heating months that are significantly colder than normal (February and March (as a result of the Winter Storm Uri) and warmer than normal temperatures in December, January, and April. On the cooling side, July is warmer than normal contributing to strong weather related sales. The rest of the summer months temperatures are close to normal. In the commercial sector, July's hot weather is largely mitigated by lower than normal cooling requirements in the shoulder months. The result is total test-year sales are adjusted by -0.4% with a larger adjustment in the residential sectors (-0.6%); the commercial and general power rates are adjusted down 0.1%, and the TEB rate class is adjusted down 0.2%. Based on current tariffs, the total revenue impact is minus $25,621 a 0.3% reduction in test-year revenues.

Q. Does this conclude your 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

Long-Term Energy and Demand Outlook, Indiana Stakeholder Meeting, AES Indiana, with Mike Russo, January 24, 2022

Long-Term Energy and Demand Forecast, 2022 IRP, AES Indiana, with Mike Russo, December 2021

Delmarva Power & Light, Forecast Review, Delmarva Maryland, with Stuart McMenamin and Mike Russo, December 2021

Forecast Model Review and Recommendations, ISO New England, November 2021

Heat Pump Program Impact Study, Nova Scotia Power, with Rich Simons, August 2021

Sales, Customer, and Revenue Forecast Through 2040, Green Mountain Power Company, with Oleg Moskatov and Mike Russo, April 2021

Reacting to a Changing Environment: Trends in Estimated Load Impacts of COVID-19 Mitigation Policies, submitted to National Association of Regulatory Utility Commissioners, March 2021, with Frank Monforte, Ph.D.

Accounting for COVID-19 in the Sales Forecast, March 2021, Itron Brownbag Presentation, with Andy Sukenik, and Mike Russo

Long-Term Data Center Demand Analysis and Forecast, Salt River Project, March 2021, with Mike Russo

Temperature Trend Study, Puget Sound Energy, November 2020, with Rich Simons

Vermont Long-Term Energy and Demand Forecast, Vermont Electric Power Company, October 2020, with Oleg Moskatov and Mike Russo

IRP Forecast Support and Data Center Forecast, Dominion Energy, September 2020

Long-Term Temperature Trend Analysis and Workshop, NV Energy, August 2020, with Rich Simons

Sales and Revenue Forecast for 2020 Rate Case, with Mike Russo, Hydro Ottawa, March 2020

New York ISO Climate Impact Study: Phase 1 Long-Term Load Impact, New York ISO, December 2019, with Rich Simons, Oleg Moskatov, and Mike Russo

Cold Climate Heat Pump Study, Sample Design, December 2019, with Rich Simons, Nova Scotia Power

Long-Term Energy and Demand Forecast, 2020 IRP, October 2019, with Mike Russo, Vectren (A CenterPoint Energy Company)

Fundamentals of Forecasting Workshop, October 2019, Washington DC

Development of Energy Efficiency Conservation Curves for Long-Term System Load Model, ISO New England, September 2019 with Mike Russo

Test-Year Weather Normalization and Filed Testimony, July 2019, with Oleg Moskotov, Liberty Utilities

Advanced Forecast Topics Workshop, Energy Forecasting Group 2019 Annual Meeting, April 2, 2019, Boston NA

*Long-Term Forecast Development and Modeling Worksho*p. Salt River Project, Tempe Arizona, March 26-27, 2019

Sales and Revenue Forecast for 2019 Rate Filing, with Oleg Moskatov and Mike Russo, Green Mountain Power Company, March 2019

Modeling Long-Term Peak Demand - Forecasting Workshop. ISO New England, December 19, 2018

Testimony and Supporting Sales Weather-Normalization for the 2018 Kansas Rate Case. Empire District Electric/Liberty Utilities, November 2018.

Load Research Training – Methods, Design, and LRS Applications. Colorado Springs Utilities. November 29-30, 2018

2018 Benchmark Survey – Energy Trends, Projections, and Methods. Electric Utility Forecaster Forum, November 13-14, 2018. Orlando, Florida

Forecasting Methods, Model Development, and Training. WEC Energy Group, Milwaukee WI, September 20 -21, 2018.

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

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

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

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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

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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

DIRECT TESTIMONY OF ERIC FOX
THE EMPIRE DISTRICT ELECTRIC COMPANY
BEFORE THE MISSOURI PUBLIC SERVICE COMMISSION
CASE NO. ER-2021-0312

May 2021: Provided testimony and supporting sales and weather-normalization for the 2022 Missouri rate case. Empire District Electric/Liberty Utilities.

June 2020: Provided testimony and supporting analysis of weather trends and analysis as part of Nevada Power's 2020 general rate review.

July 2019: Provided testimony and supporting sales and weather-normalization for the 2020 Missouri rate case. Empire District Electric/Liberty Utilities.

November 2018: Provided testimony and supporting sales weather-normalization for the 2018 Kansas rate case. Empire District Electric/Liberty Utilities.

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

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2022 Rate Case
Test-Year Weather-Normal Sales

Empire District Electric Company, Oklahoma

Submitted to:

The Empire District Electric Company
Joplin, Missouri

Submitted by:

Itron, Inc.
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January 2022

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Overview

The Empire District Electric Company (Empire) contracted Itron, Inc. (Itron) to develop weather normalized sales to support the Oklahoma 2022 rate case. Rate class normalized sales are estimated for the 2022 Test-Year Period. The Test-Year Period is July 2020 through June 2021.

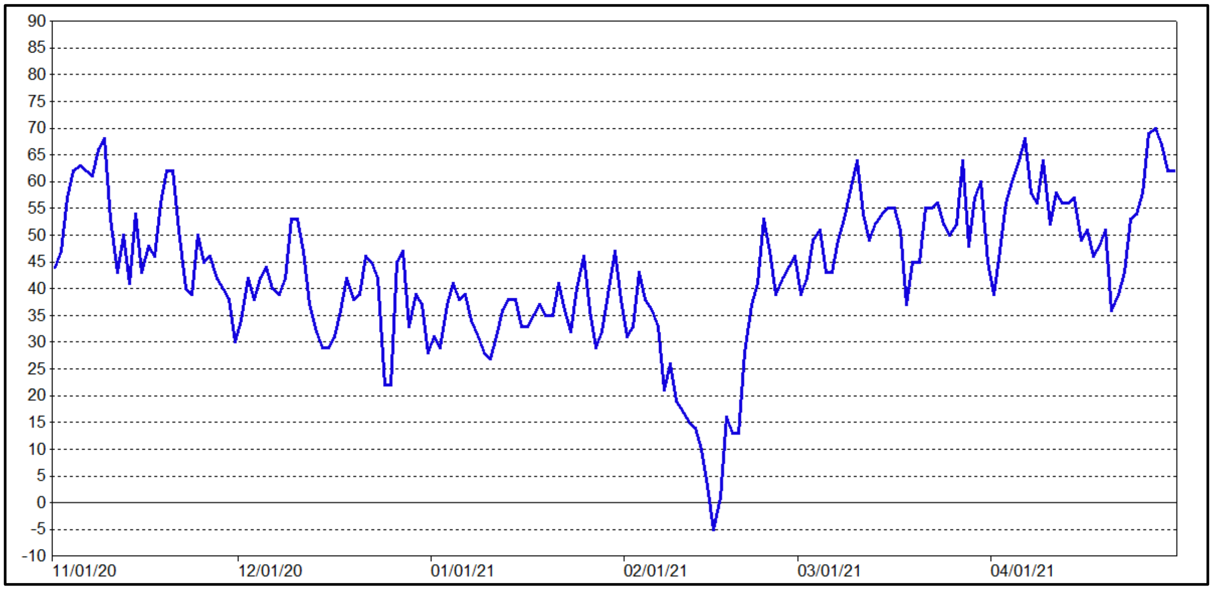
Utility revenues and costs can vary significantly from month to month, largely because of variations in weather conditions. In determining appropriate revenues and associated cost of service, it is important to minimize this variation. This process is known as weather-normalization and entails estimating sales for expected or normal weather conditions. Weather normalization entails first estimating the relationship between customer use and weather using linear regression models and then using the estimated regression model coefficients to translate the variation in weather from normal weather into weather-related sales. Normal sales are then calculated by subtracting weather sales from actual sales.

Weather normalization models are generally estimated using heating degree-days (HDD) which are correlated with heating electricity use and cooling degree-days (CDD) which are correlated with cooling requirements. Residential sales are weather normalized with CDD using a 65 degree-day base (CDD65) while commercial sales are weather normalized with a lower 60-degree day base (CDD60). Commercial cooling begins at lower temperature point than residential cooling. Both residential and commercial heating is weather normalized with an HDD that has a 55 degree temperature base (HDD55).

Test-year HDD55 are 1.3% higher than normal, CDD65 are 1.0% higher than normal, and CDD60 is 0.4% below normal. CDD65 is higher than normal as there are more hot days than expected, while CDD60 is below normal as there are fewer moderate cooling days (temperatures between 60 and 65 degrees) than normal.

While in total, degree-days are close to normal, there are significant variation in weather impacts across the year that impact sales. The test-year includes the February 2021 extreme cold weather event as a result of the Polar Vortex push through Oklahoma into Texas and as far south as Mexico. Between February 9th and February 20th, the average daily temperature was below 20 degrees. Temperatures declined from the 9th through the 15th reaching a record low of -5 degrees before climbing to a more normal temperature range. Figure 1 shows the winter average temperature for the test-year winter period.

Figure 1: Test-Year Winter Average Temperature



As there is significant electric heat in the Oklahoma service area, heating-related sales are higher than what would be expected with more typical weather conditions. Temperatures in the other heating-months are warmer than normal mitigating much of the February extreme weather impact.

On the cooling side, the test-year includes July 2020 which is measurably warmer than normal and contributes higher than expected cooling-related sales; the other summer cooling months are close to normal. For the summer cooling months (July through October) CDD65 are 3.2% higher than normal contributing to positive weather sales. CDD65 is lower than normal for the rest of the months. For the commercial rate classes using the lower 60-degree temperature breakpoint results in negative weather related sales across the non-summer months that mitigates the positive summer weather sales.

The relationship between customer use and weather varies by rate class and is captured in the estimated weather coefficients. Table 1 shows test-year sales, weather-normalized sales, and weather sales (difference between actual and normal sales).

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

Rate Class	Billed Sales	Wthr Normal Sales	Weather Sales	Pct Impact
Res General	34,292,860	34,092,625	200,235	0.6%
Res Space Heat	17,165,588	17,058,330	107,258	0.6%
Small Commercial	13,031,010	13,014,538	16,472	0.1%
General Power	23,042,291	23,029,701	12,590	0.1%
Total Electric Building	3,697,315	3,691,659	5,656	0.2%
Total	**91,229,064**	**90,886,853**	**342,211**	0.4%

In total, test-year sales are adjusted down 0.4% for weather impact. The largest adjustments are in the residential customer classes. Test-year residential sales are adjusted down 0.6%. The residential rate classes are generally more sensitive to changes in temperature. Commercial heating and cooling impacts balance out across the test-year period resulting in small adjustments in Small Commercial, General Power, and Total Electric Building.

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. Test-year sales are normalized using an industry-standard approach that involves estimating weather response model with linear regression. Linear regression is a statistical modeling approach where customer monthly average use is specified as a function of the number of HDD and CDD in the billing month cycle, number of billing days, and binary variables to account for variation in sales data that is not weather related. The objective is to isolate the impact changes in HDD and CDD have on monthly usage using the estimated HDD and CDD model coefficients.

The relationship between customer usage and temperature varies across rate schedules. Figure 2 through 5 illustrate the difference in temperature response function across the weather-sensitive rate classes. These curves show monthly use per customer against monthly average temperature.

Figure 2: Residential General Average Use vs. Temperature

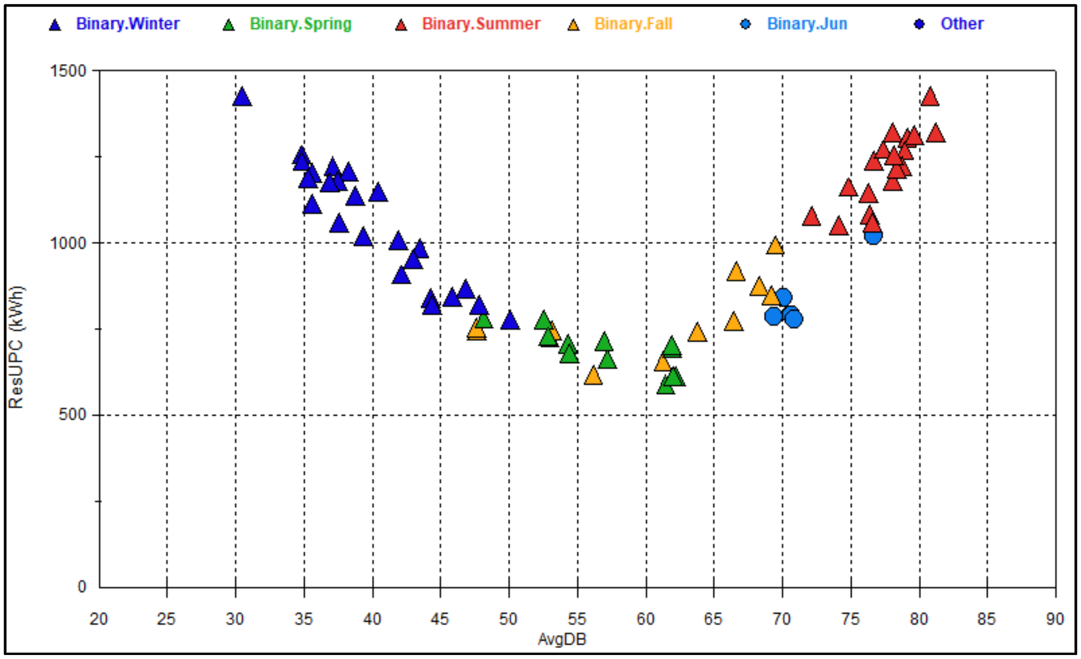


Figure 3: Residential Heating Average Use vs. Temperature

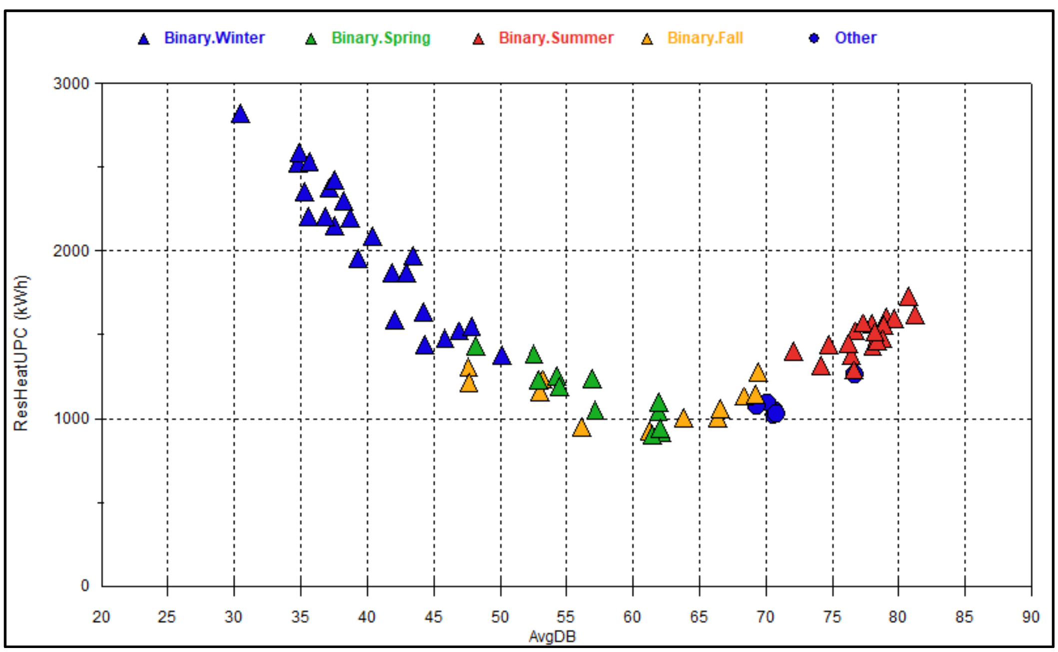


Figure 4: Commercial Average Use vs. Temperature

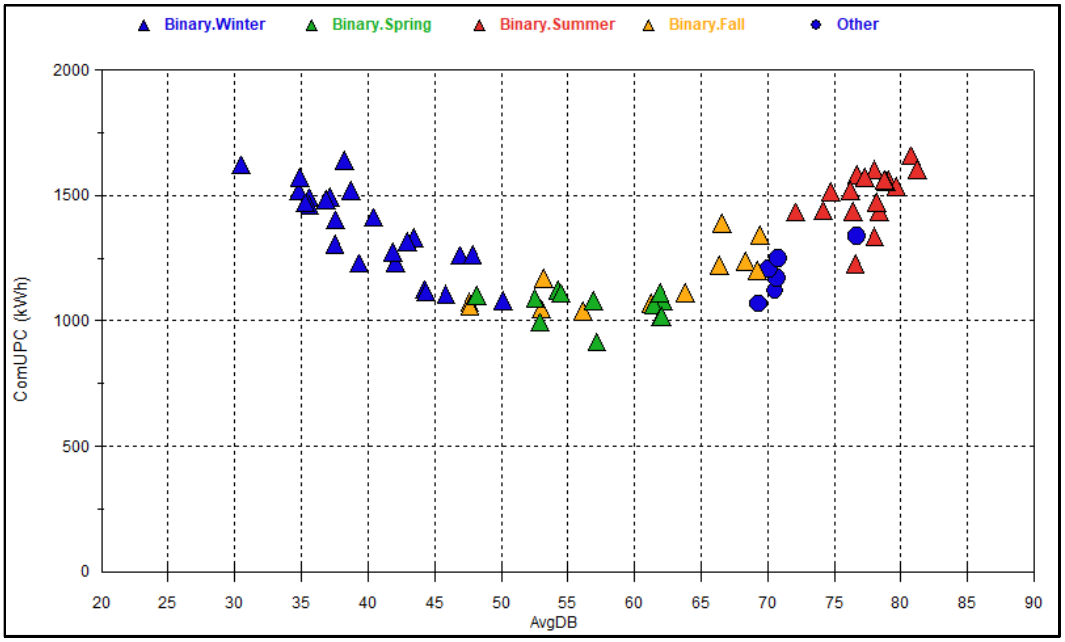


Figure 5: General Power Use per Customer vs. Temperature

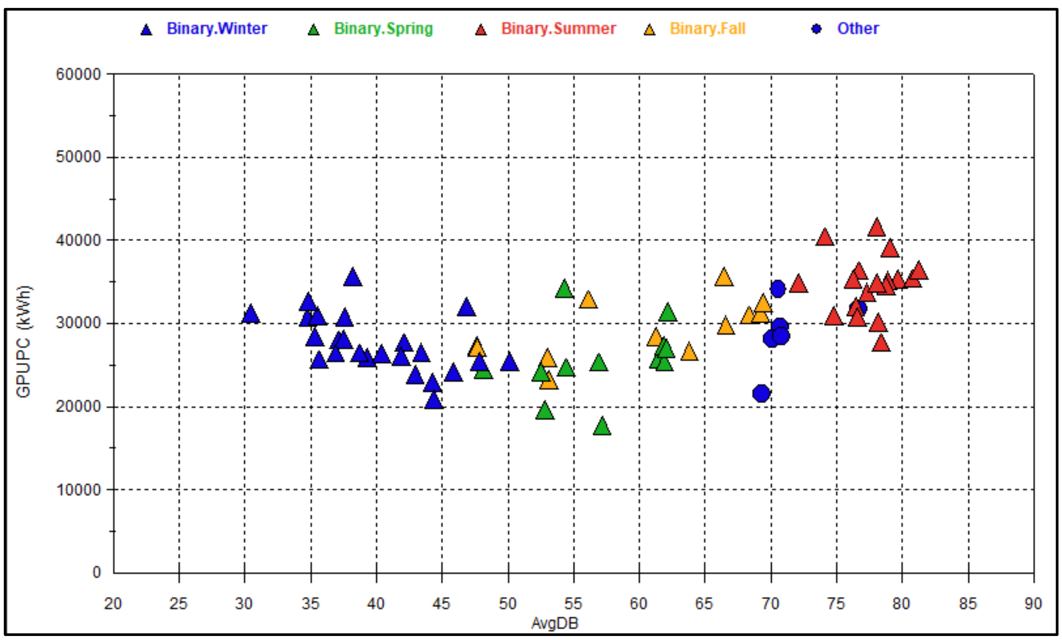
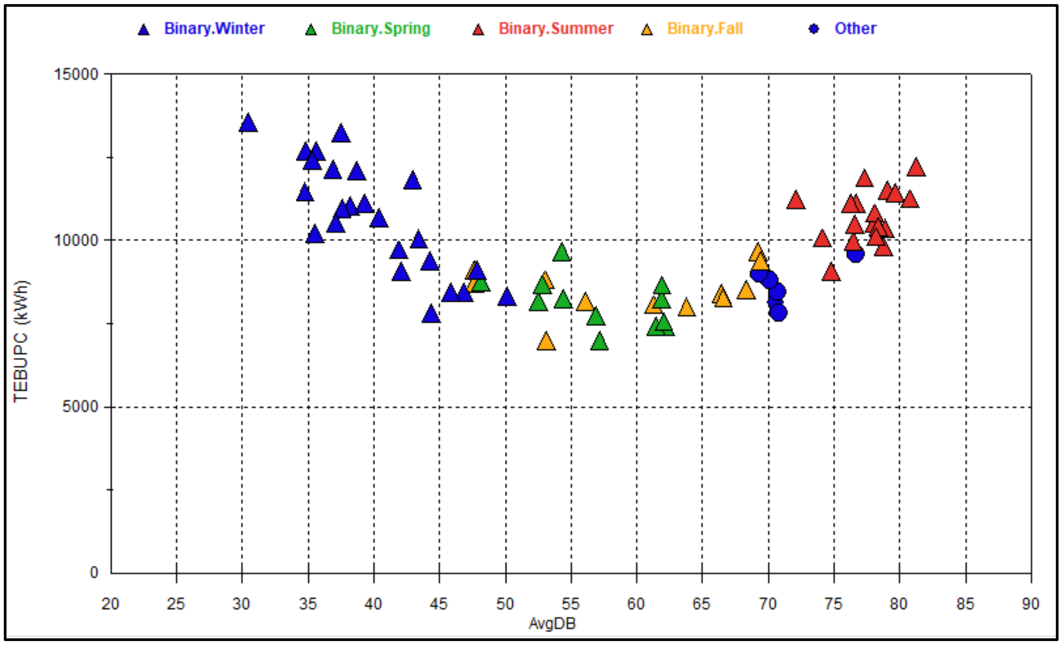


Figure 6: TEB Use Per Customer vs. Temperature

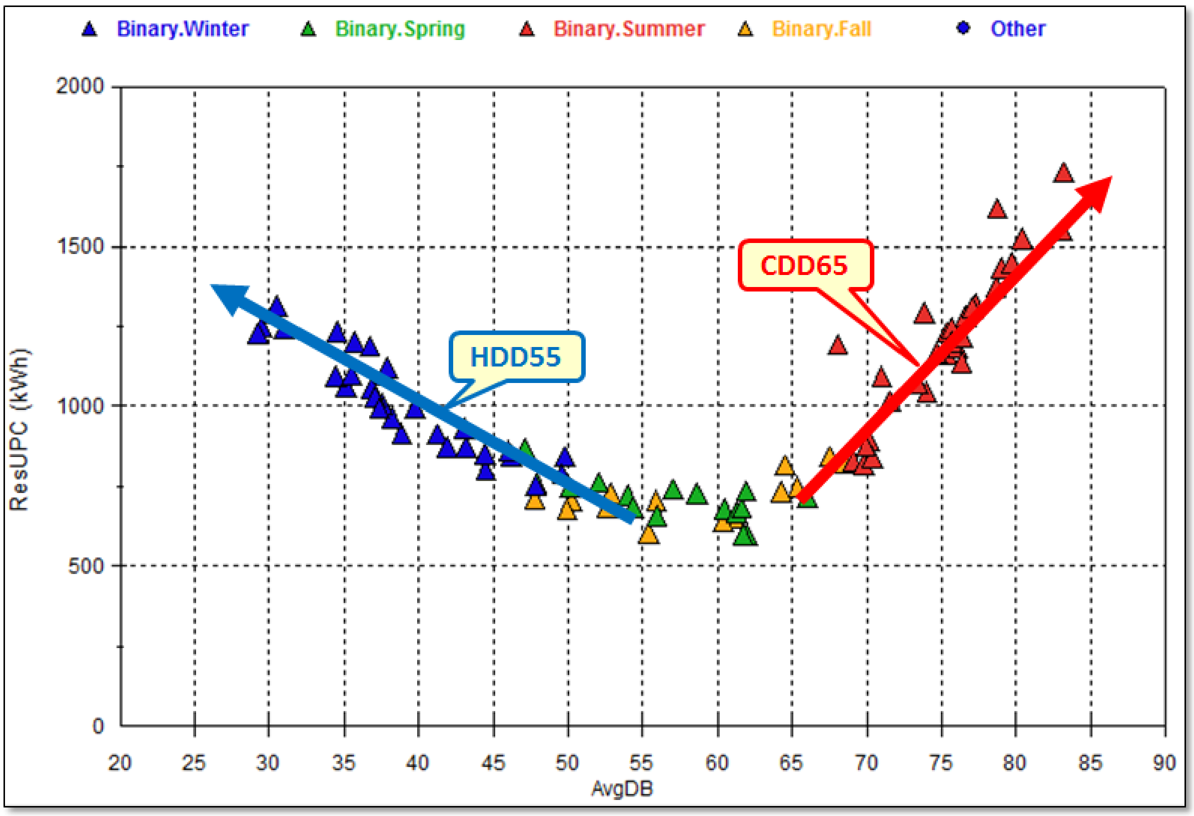


As depicted in Figure 1, the residential general service rate class is strongly sensitive to changes in winter temperatures as well as summer temperatures indicating a high level of electric heat saturation. Not surprisingly as Figure 2 shows, average use in residential electric rate class is higher across the winter months and shoulder months; cooling use per customer is roughly the same as general service rate class. The commercial profile shows a similar pattern as residential with sensitivity to both changes in winter and summer temperatures. The curve is not as steep as residential general service and 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. The General Power customer usage (which includes a 73 of the largest C&I customers) is less sensitive to changes in summer temperatures and is not sensitive to changes in temperatures across the heating months.

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 6 where HDD of base 55 degrees and CDD of base 65 degrees are fitted to the Residential General rate-class curve.

Figure 7: 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 fall 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 commercial rate class models. Commercial cooling is observable at a lower average temperature than residential as commercial buildings tend to have more internal heat build-up. The commercial usage/temperature scatterplot (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 General
2. Residential Heating
3. Commercial
4. General Power
4. 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 2015 to June 2021 (the last month of available data); this gives 78 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:

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

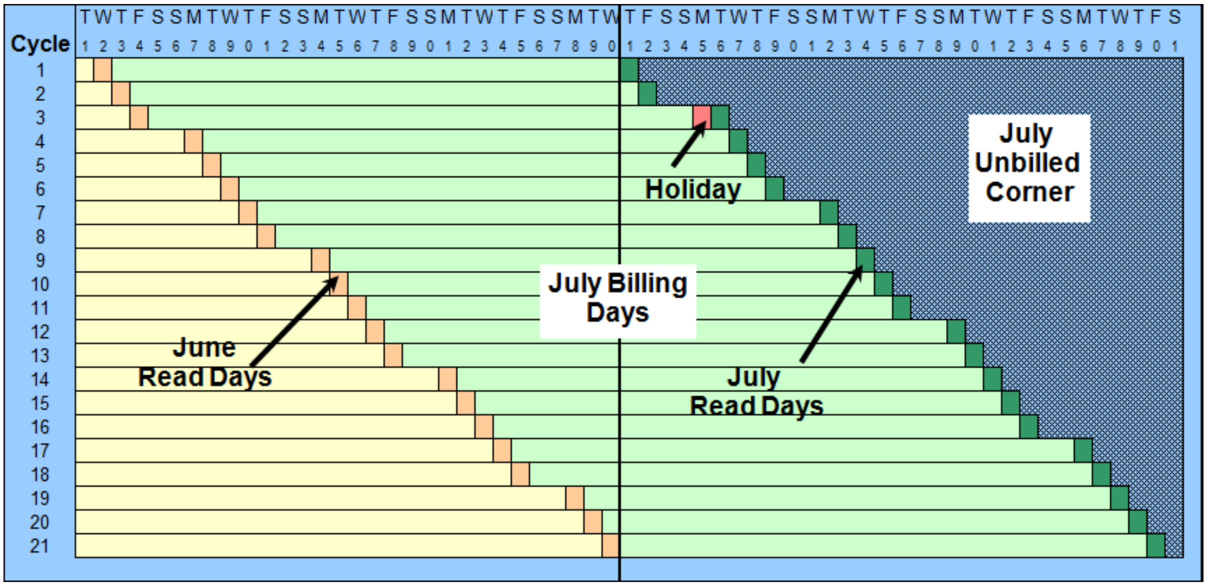
Where:

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

5. Calculation of Cycle-Weighted HDD and CDD

The 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 7 is a generalized representation of a billing-month with 21 cycles; the dates do not correspond to actual billing cycles, but the principles are consistent.

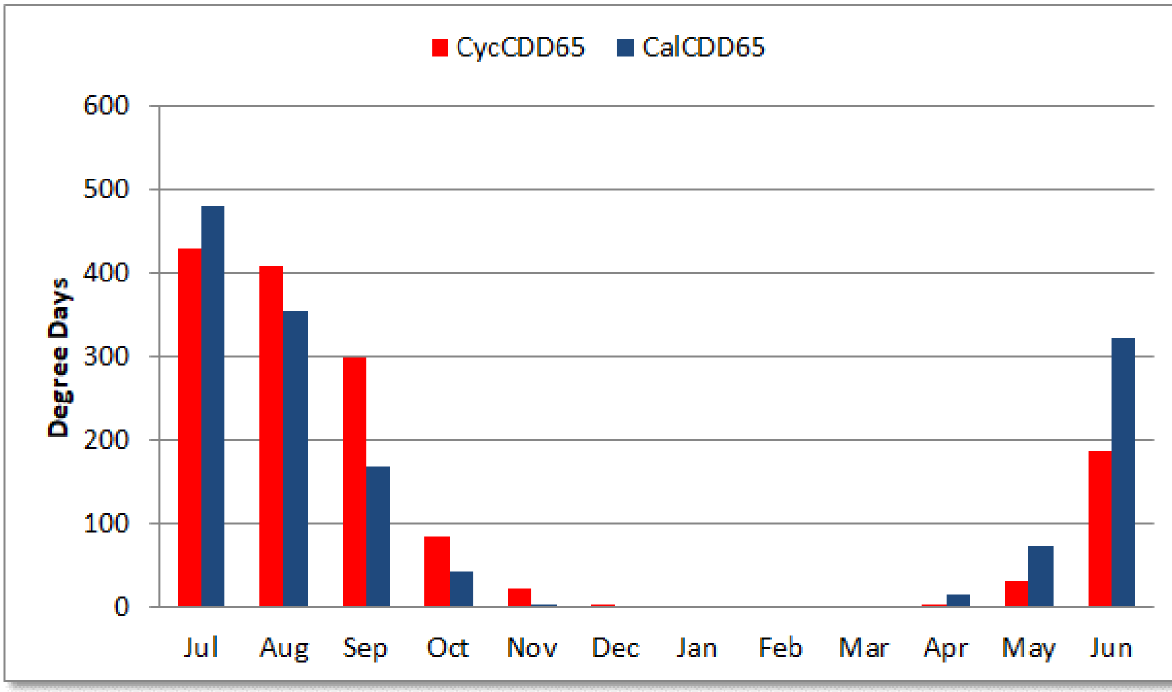
Figure 8: Billing Cycles



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

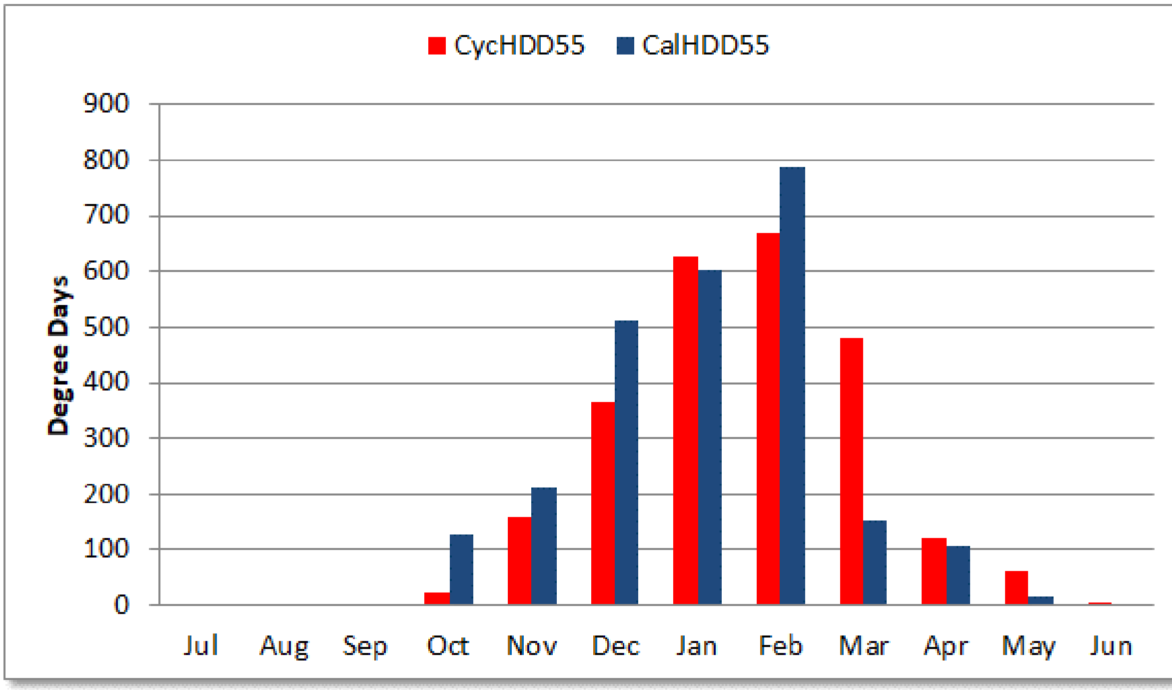
Figure 9: Test-Year Cycle-Weighted CDD vs. Calendar-Month CDD



Cycle-weighted CDD are shown in red and calendar-month CDD are in blue. As Figure 8 shows, there are significant differences between calendar-month and billing-month CDD month-to-month. For instance, July calendar-month CDD (in blue) is higher than Jul billing-month CDD (in red) as the billing-month includes cooler June temperatures. On an annual basis, cycle-weighted CDD and calendar-month CDD are close; differences are result of the timing in the meter read schedule.

Figure 10 compares test-year calendar and cycle-weighted HDD.

Figure 10: Test-Year Cycle-Weighted HDD vs. Calendar-Month HDD



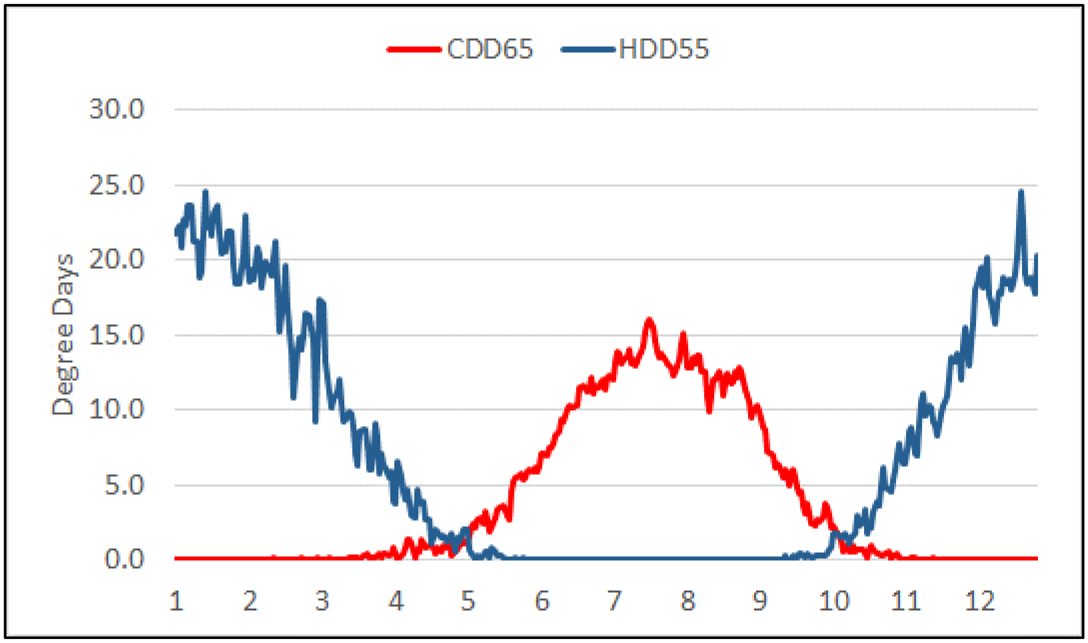
At the start of the heating season, calendar-month HDD tend to exceed the billing-month HDD as the year transitions into colder weather. November billing-month HDD, for example, will lag calendar-month November HDD as the billing-month carries warmer temperatures from October. The converse is true at the end of the heating season, where the billing-month HDD tend to exceed the calendar-month HDD. While there are significant differences between cycle-weighted and calendar-month HDD month-to-month on an annual basis, test-year cycle-weighted and calendar-month HDD are the same.

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, 1991 to December 31, 2020. Temperature data is from the Springfield-Branson National Airport (SGF). SGF is the closest primary weather station.

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 10 shows the resulting daily 30-year average HDD55 (in blue) and CDD65 profiles (in red).

Figure 11: Daily Normal HDD55 and CDD65 (1991 - 2020)



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.

Figure 11 and Figure 12 compare actual and normal CDD and HDD for the test-year period from July 2020 to June 2021.

Figure 12: Comparison of Actual and Normal Cycle-Weighted CDD65

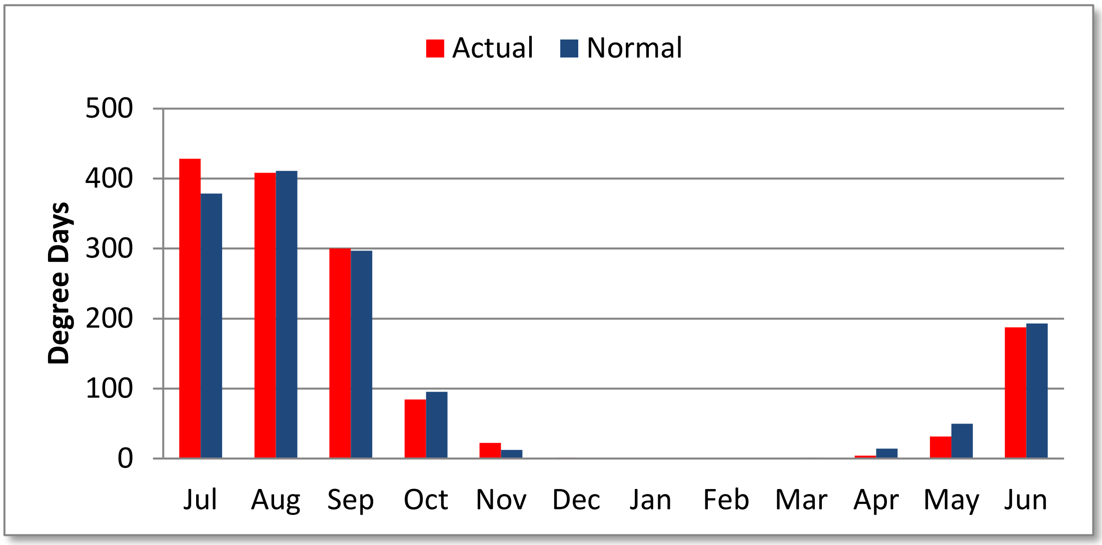
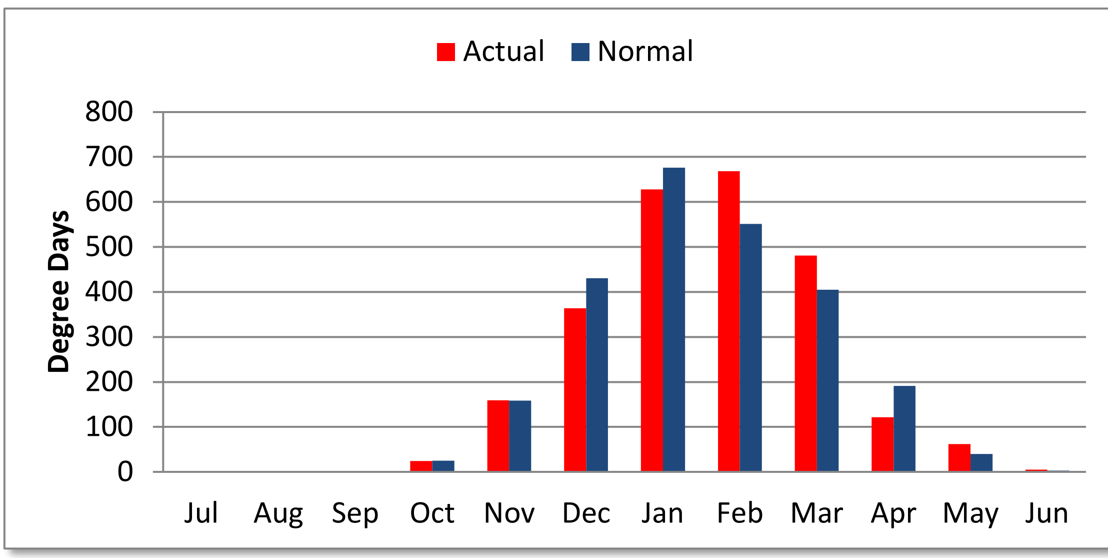


Figure 13: Comparison of Actual and Normal Cycle-Weighted HDD55



3. Weather Normalization Example

The estimated Residential Heat (RH) model weather coefficients are:

- HDD55: 2.393 (55 degrees - avg monthly temp)
- CDD65: 1.014 (avg monthly temp – 65 degrees)

- CDD65_Summer: 0.529 (CDD65 * Summer Month Binary)

The CDD_Summer interactive variable is statistically significant and reflects that the response to changes in CDD is a little stronger in the summer months (defined as July, August, and September) than in the non-peak cooling months. The coefficient is additive to the CDD65 coefficient in the peak cooling months and has no impact in the shoulder months; June is treated as shoulder month as the June billing period includes sales over the late May and early June. Normalized sales are calculated for month in test-year period. The examples below show the calculation for July.

For July, the weather adjustment coefficient is 1.543 (1.014 + 0.529).

The weather impact is calculated as:

- *kWh impact = 1.543 * (428.2 Actual CDD65 – 378.2 Normal CDD65) = 76.31 kWh*

Normal average use is then calculated as:

- *normal avg use = 1,467.4 kWh Average Use – 76.31 kWh Impact = 1,391.12 kWh*

Finally, June weather-normal sales are calculated by multiplying June customer counts with the June normalized average use:

- *normal sales = 1,391.12 kWh normal average use* 915 customers = 1,272,875 kWh*

July weather sales are:

- *weather sales = 76.31 kWh * 915 customers = 69,822 kWh*

4. Summary

Total test-year sales are slightly higher than what would be expected for normal weather conditions as a result sales are adjusted down 342,211 kWh or -0.4% for weather impacts. Adjustments vary across rate classes and months reflecting differences in rate class responses to change in temperatures and differences between actual and normal degree-days. The largest adjustment is in the residential class (-0.6%) as a result of the extreme cold weather experienced in the second-half of February (impacting both cycle-weighted HDD in February and March), and summer cooling period with higher than normal CDD. The commercial customer class impacts are relatively small as higher summer-month cooling requirements are mitigated by lower cooling requirements across the rest of the year. Monthly rate-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.

Appendix A: Weather Response Models, Data, and Results

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

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

Model Data

Usage Data. Empire provided historical monthly billed sales data and customer counts used in constructing the average use data series.

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 August 31, 2021. 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, 2020. The meter read schedule used in constructing the cycle-weighted HDD and CDD was provided by Empire. Tables 2 through Table 4 show Test-Year actual and normal cycle-weighted degree-days.

EMPIRE DISTRICT ELECTRIC COMPANY

Table 2: Test-Year Cycle-Weighted HDD55

Year	Month	Actual	Normal	Difference
2020	Jul	0.0	0.0	0.0
2020	Aug	0.0	0.0	0.0
2020	Sep	0.0	0.8	-0.8
2020	Oct	24.1	24.9	-0.8
2020	Nov	159.5	158.8	0.7
2020	Dec	363.7	430.8	-67.1
2021	Jan	627.7	675.9	-48.2
2021	Feb	668.3	551.1	117.2
2021	Mar	481.0	405.3	75.7
2021	Apr	121.7	190.9	-69.2
2021	May	62.2	39.9	22.3
2021	Jun	4.9	2.9	2.0
		2513.0	**2481.1**	**31.9**

Table 3: Test Year Cycle-Weighted CDD65

Year	Month	Actual	Normal	Difference
2020	Jul	428.2	378.7	49.5
2020	Aug	408.0	411.0	-3.0
2020	Sep	300.0	297.0	3.0
2020	Oct	84.5	95.6	-11.0
2020	Nov	22.3	12.3	10.1
2020	Dec	1.3	0.3	1.1
2021	Jan	0.0	0.0	0.0
2021	Feb	0.0	0.1	-0.1
2021	Mar	0.0	1.5	-1.5
2021	Apr	4.4	14.2	-9.8
2021	May	31.5	50.0	-18.4
2021	Jun	187.4	192.8	-5.4
Total		**1467.7**	**1453.4**	**14.4**

Table 4: Test-Year Cycle-Weighted CDD60

Year	Month	Actual	Normal	Difference
2020	Jul	588.2	537.4	50.8
2020	Aug	562.8	565.1	-2.4
2020	Sep	449.0	440.5	8.5
2020	Oct	176.1	182.8	-6.8
2020	Nov	55.9	39.4	16.4
2020	Dec	9.7	3.3	6.4
2021	Jan	0.0	0.6	-0.6
2021	Feb	0.0	0.8	-0.8
2021	Mar	2.9	6.9	-4.0
2021	Apr	23.3	44.0	-20.6
2021	May	84.1	115.5	-31.4
2021	Jun	297.9	322.2	-24.3
Total		**2249.7**	**2258.6**	**-8.8**

Estimated Models

Models are estimated for monthly use per customer for each class. Models are estimated over the period January 2015 to June 2021. The model specifications are relatively simple with an HDD variable with a temperature base of 55 degrees and CDD with a 65-degree-day base for the residential rates and a 60 degree-day CDD base for the nonresidential rates. 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. 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. Estimated models also include the number of billing days and monthly binaries to capture load variation that is not weather-related.

Overall, the estimated models explain variation in daily use relatively well. Model statistics are provided in Appendix B: Model Statistics.

Weather Normalization Results

Tables 5 through Table 9 show test-year billed and weather normal sales for the weather-sensitive rate classes.

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Table 5: Residential (General) Test-Year Sales

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)
Jul-20	3,507,329	3,266,316
Aug-20	3,599,857	3,614,486
Sep-20	3,343,908	3,331,918
Oct-20	2,146,791	2,194,357
Nov-20	2,162,431	2,119,202
Dec-20	2,382,737	2,593,509
Jan-21	4,241,390	4,395,921
Feb-21	4,244,710	3,869,254
Mar-21	2,683,518	2,447,431
Apr-21	1,908,383	2,169,176
May-21	1,770,714	1,774,517
Jun-21	2,301,092	2,316,538
Total	**34,292,860**	**34,092,625**

Table 6: Residential (Heating) Test-Year Sales

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)
Jul-20	1,342,697	1,272,875
Aug-20	1,383,348	1,387,598
Sep-20	1,309,288	1,306,810
Oct-20	916,145	928,100
Nov-20	1,125,195	1,114,429
Dec-20	1,310,803	1,455,953
Jan-21	2,548,316	2,653,518
Feb-21	2,368,815	2,113,050
Mar-21	1,938,624	1,774,406
Apr-21	1,008,994	1,169,566
May-21	923,995	892,075
Jun-21	989,368	989,951
Total	**17,165,588**	**17,058,330**

Table 7: Commercial Test-Year Sales

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)
Jul-20	1,146,892	1,106,367
Aug-20	1,176,518	1,178,410
Sep-20	1,216,390	1,210,166
Oct-20	890,849	896,891
Nov-20	934,485	920,822
Dec-20	903,653	950,864
Jan-21	1,591,067	1,629,229
Feb-21	1,189,053	1,098,162
Mar-21	1,338,041	1,282,152
Apr-21	687,928	758,758
May-21	904,524	912,620
Jun-21	1,051,610	1,070,096
Total	**13,031,010**	**13,014,538**

Table 8: General Power Test-Year Sales

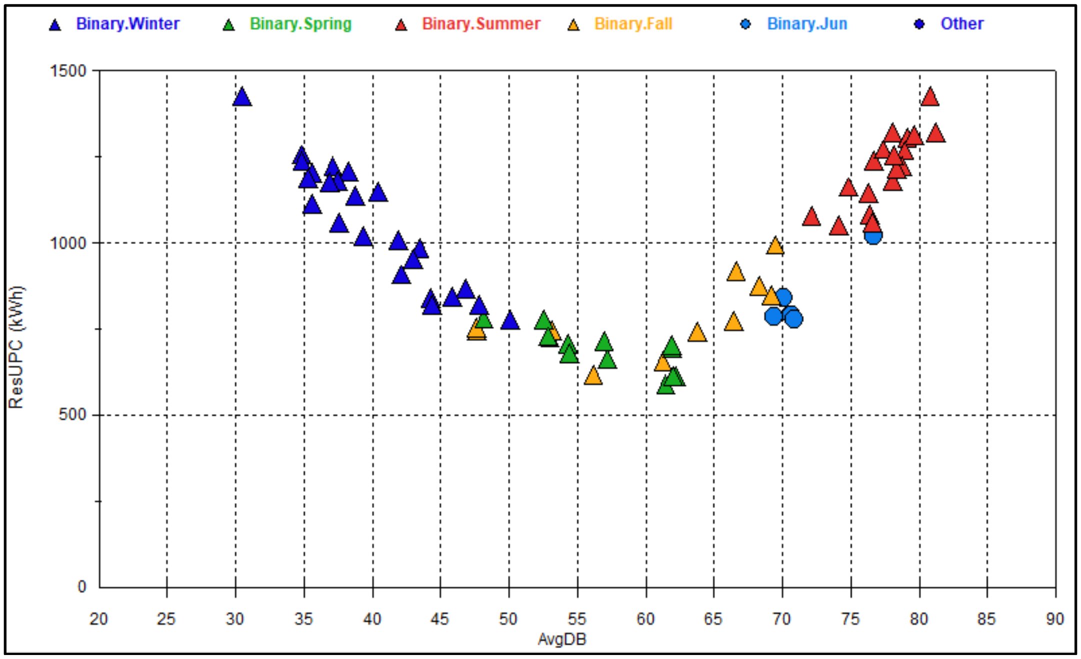
Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)
Jul-20	2,048,847	1,977,837
Aug-20	2,233,361	2,236,676
Sep-20	2,285,841	2,274,514
Oct-20	1,973,269	1,983,326
Nov-20	1,716,291	1,692,793
Dec-20	1,525,877	1,566,345
Jan-21	2,806,315	2,842,122
Feb-21	1,843,428	1,759,579
Mar-21	1,343,788	1,294,348
Apr-21	1,449,451	1,527,660
May-21	1,830,068	1,856,643
Jun-21	1,985,755	2,017,858
Total	**23,042,291**	**23,029,701**

Table 9: Total Electric Building Test-Year Sales

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)
Jul-20	270,850	258,214
Aug-20	262,741	263,331
Sep-20	235,644	233,747
Oct-20	207,859	209,771
Nov-20	195,702	191,088
Dec-20	218,446	237,222
Jan-21	548,192	562,553
Feb-21	409,819	375,504
Mar-21	436,437	415,173
Apr-21	275,445	301,152
May-21	317,906	319,507
Jun-21	318,274	324,395
Total	**3,697,315**	**3,691,659**

Appendix B: Model Statistics

Figure 14: Residential (General) Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mCycWthr.BDays	18.043	0.798	22.611	0.00%
mCycWthr.HDD55	1.106	0.05	22.292	0.00%
mCycWthr.CDD65	1.412	0.138	10.244	0.00%
WthrTrans.CDD65_Summer	0.274	0.113	2.43	1.76%
Binary.LTrend	-1.249	4.138	-0.302	76.36%
Binary.Jan21	176.235	70.837	2.488	1.52%

Model Statistics	
Adjusted Observations	78
Deg. of Freedom for Error	72
R-Squared	0.928
Adjusted R-Squared	0.923
Std. Error of Regression	67.93
Mean Abs. Dev. (MAD)	51.3
Mean Abs. % Err. (MAPE)	5.28%
Durbin-Watson Statistic	1.939

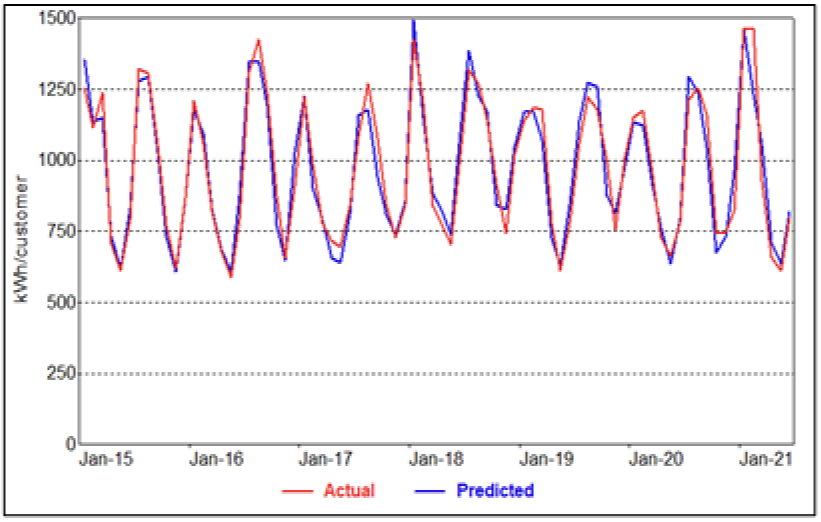
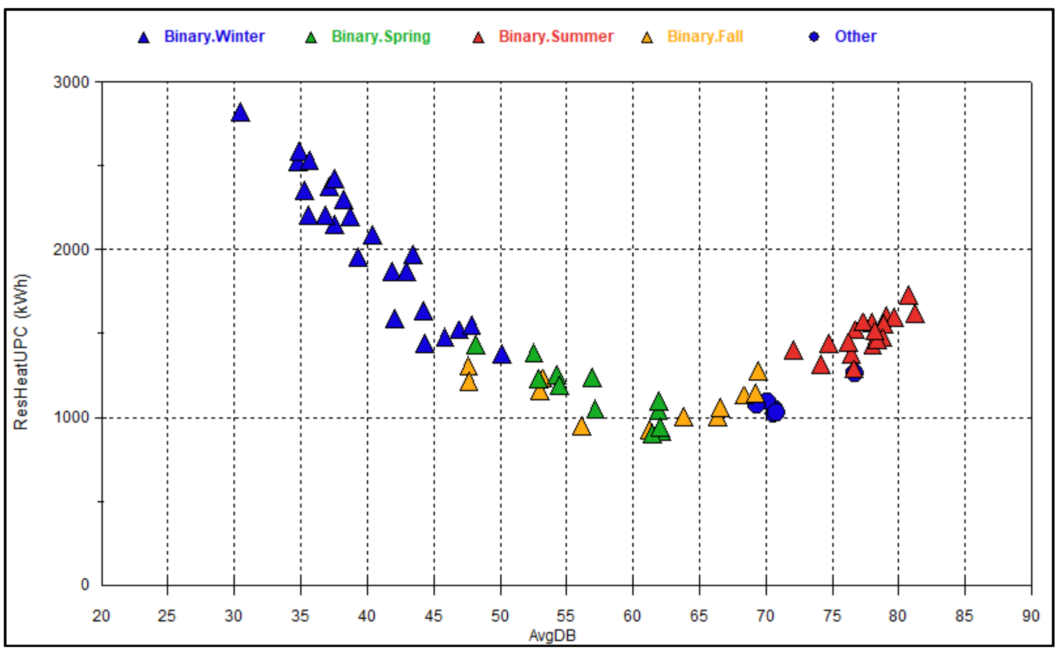


Figure 15: Residential (Heating) Model



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Variable	Coefficient	StdErr	T-Stat	P-Value
mCycWthr.BDays	29.246	1.157	25.267	0.00%
mCycWthr.HDD55	2.393	0.08	29.766	0.00%
mCycWthr.CDD65	1.014	0.197	5.16	0.00%
WthrTrans.CDD65_Summer	0.529	0.156	3.395	0.12%
Binary.LTrend	-4.824	5.752	-0.839	40.47%
Binary.Feb	165.129	45.179	3.655	0.05%
Binary.Mar	165.847	40.736	4.071	0.01%
Binary.Nov	-102.661	41.874	-2.452	1.68%
Binary.Dec16	-314.221	95.541	-3.289	0.16%
Binary.Dec20	-317.18	96.318	-3.293	0.16%
Binary.Jan21	348.186	99.712	3.492	0.09%

Model Statistics	
Observations	78
Deg. of Freedom for Error	67
R-Squared	0.971
Adjusted R-Squared	0.967
Std. Error of Regression	92.7
Mean Abs. Dev. (MAD)	66.55
Mean Abs. % Err. (MAPE)	4.46%
Durbin-Watson Statistic	2.172

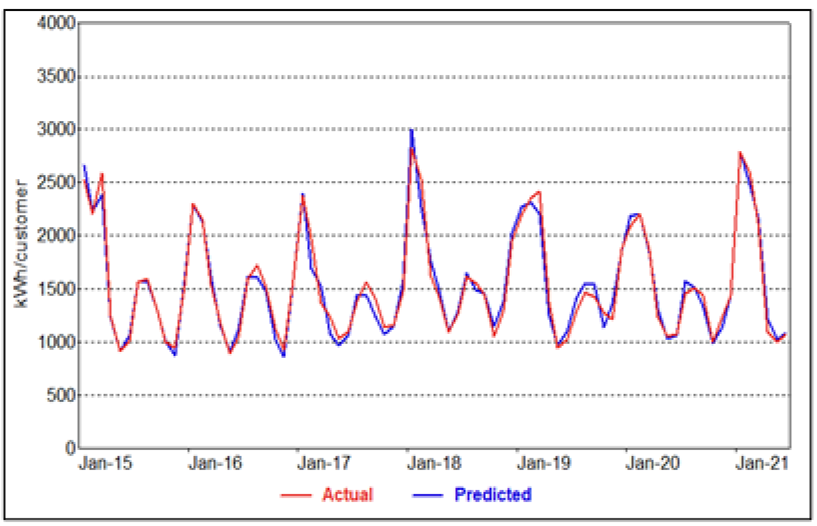
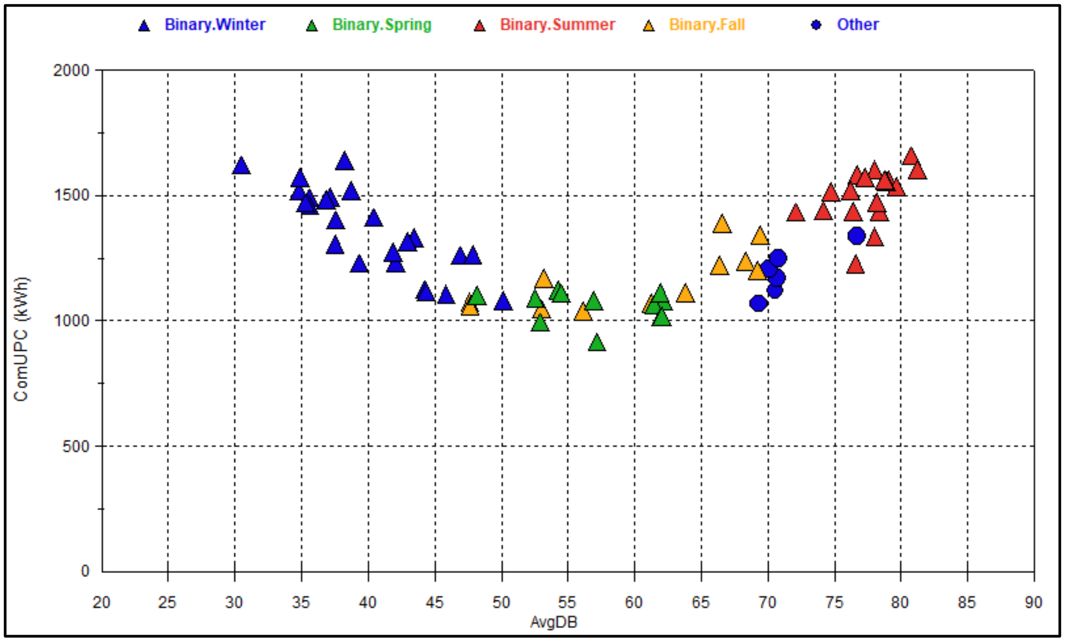


Figure 16: Commercial Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mCycWthr.BDays	30.963	1.086	28.521	0.00%
mCycWthr.HDD55	0.963	0.068	14.209	0.00%
mCycWthr.CDD60	0.999	0.07	14.27	0.00%
Binary.LTrend	-12.22	5.633	-2.169	3.35%
Binary.Jan21	401.328	93.41	4.296	0.01%
Binary.Mar21	349.218	92.686	3.768	0.03%
Binary.Apr21	-212.566	93.258	-2.279	2.57%
Binary.Sep	68.783	41.086	1.674	9.86%
Binary.Oct	75.233	39.535	1.903	6.12%

Model Statistics	
Observations	78
Deg. of Freedom for Error	69
R-Squared	0.853
Adjusted R-Squared	0.836
Std. Error of Regression	89.29
Mean Abs. Dev. (MAD)	68.42
Mean Abs. % Err. (MAPE)	5.33%
Durbin-Watson Statistic	2.07

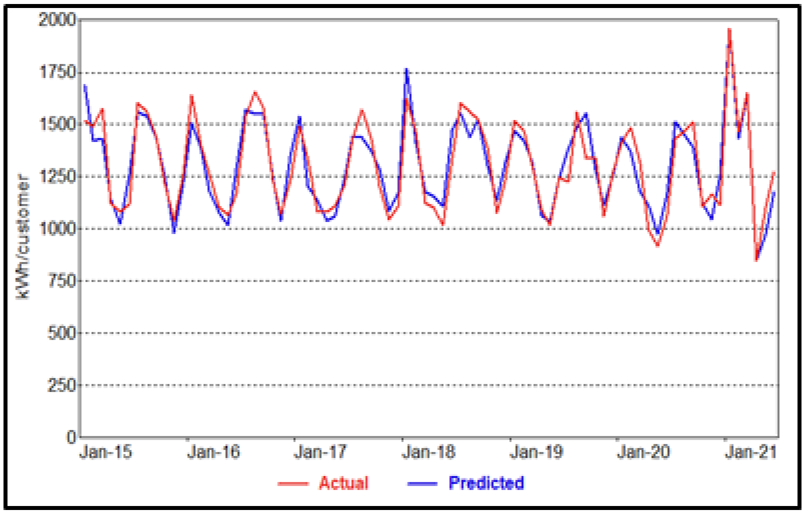
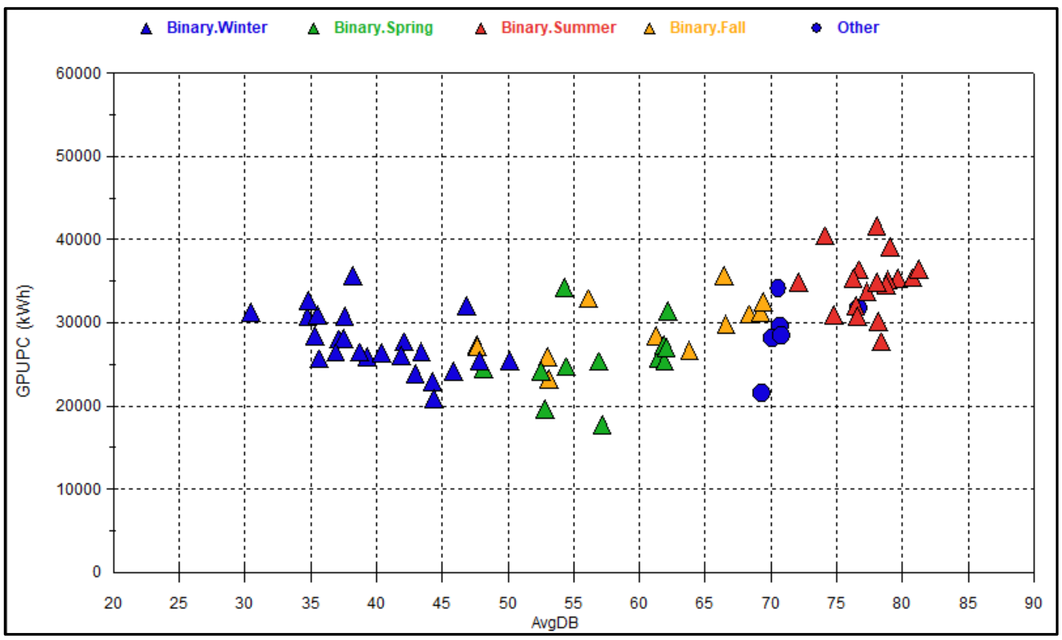


Figure 17: General Power Model



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Variable	Coefficient	StdErr	T-Stat	P-Value
mCycWthr.BDays	895.116	33.714	26.55	0.00%
mCycWthr.HDD55	10.067	1.953	5.155	0.00%
mCycWthr.CDD60	18.899	2.049	9.223	0.00%
Binary.LTrend	-1414.03	182.56	-7.746	0.00%
Binary.Sep	2739.201	887.548	3.086	0.30%
Binary.Oct	3635.109	1026.322	3.542	0.07%
Binary.Nov	3239.153	884.857	3.661	0.05%
Binary.Jan15	-5655.951	1880.125	-3.008	0.37%
Binary.Jan21	11349.492	1798.072	6.312	0.00%
Binary.Mar21	-4228.312	1851.597	-2.284	2.56%
Binary.May21	5317.512	1844.177	2.883	0.53%
MA(1)	0.504	0.108	4.651	0.00%

Model Statistics	
Adjusted Observations	78
Deg. of Freedom for Error	66
R-Squared	0.871
Adjusted R-Squared	0.85
Std. Error of Regression	1,979.16
Mean Abs. Dev. (MAD)	1,506.00
Mean Abs. % Err. (MAPE)	5.30%
Durbin-Watson Statistic	1.873

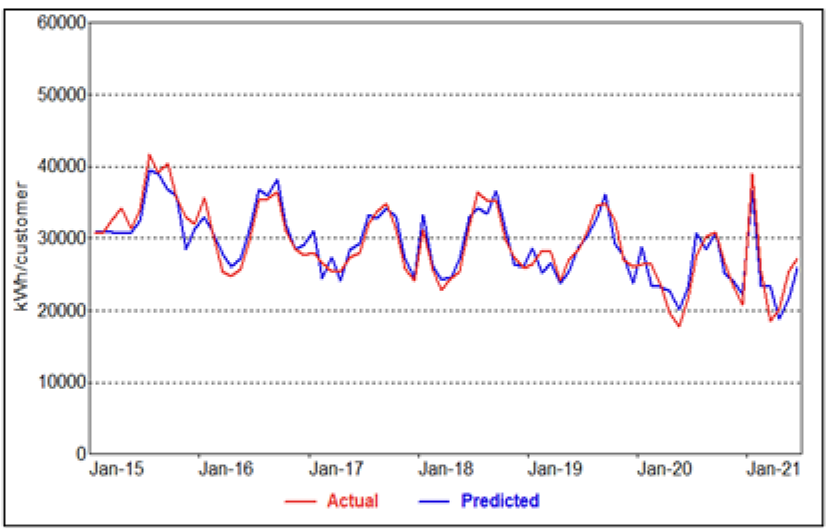
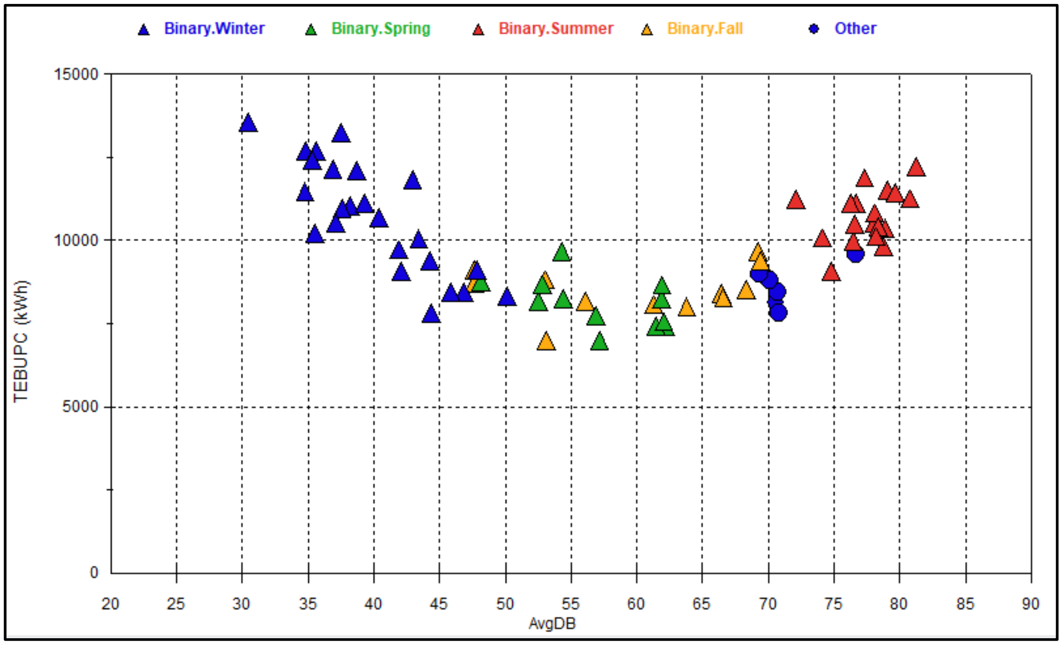


Figure 18: Total Electric Building Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mCycWthr.BDays	171.238	17.231	9.938	0.00%
mCycWthr.HDD55	10.908	0.972	11.226	0.00%
mCycWthr.CDD60	9.573	1.03	9.292	0.00%
Binary.LTrend	-23.01	56.925	-0.404	68.74%
Binary.Yr21Plus	3246.01	442.159	7.341	0.00%
Binary.Jan21	4650.348	936.419	4.966	0.00%
Binary.Mar	1814.756	366.466	4.952	0.00%
Binary.Apr	1159.688	471.583	2.459	1.66%
Binary.May	1266.323	470.357	2.692	0.90%
Binary.Sep	729.434	388.036	1.88	6.46%
Binary.Oct	890.103	421.222	2.113	3.84%
Binary.Nov	1169.446	450.086	2.598	1.15%

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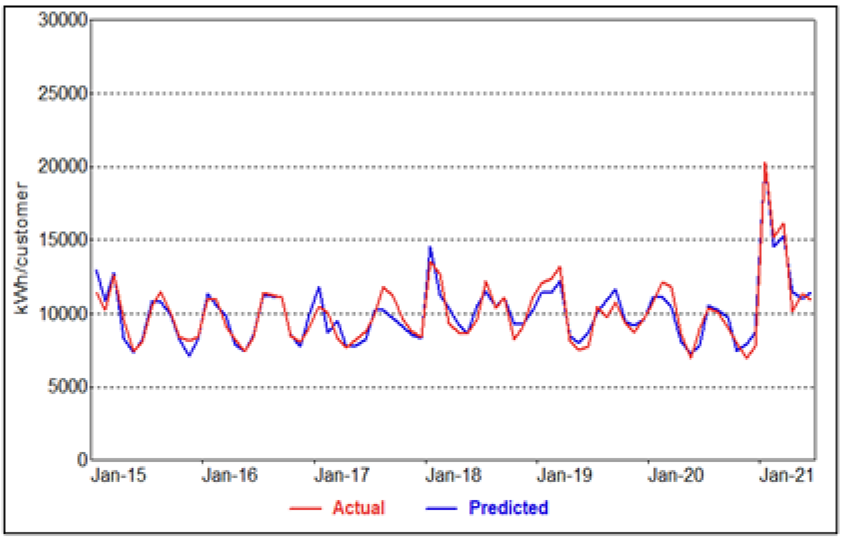
Model Statistics	
Observations	78
Deg. of Freedom for Error	66
R-Squared	0.874
Adjusted R-Squared	0.853
Std. Error of Regression	833.46
Mean Abs. Dev. (MAD)	595.3
Mean Abs. % Err. (MAPE)	5.95%
Durbin-Watson Statistic	1.894



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*

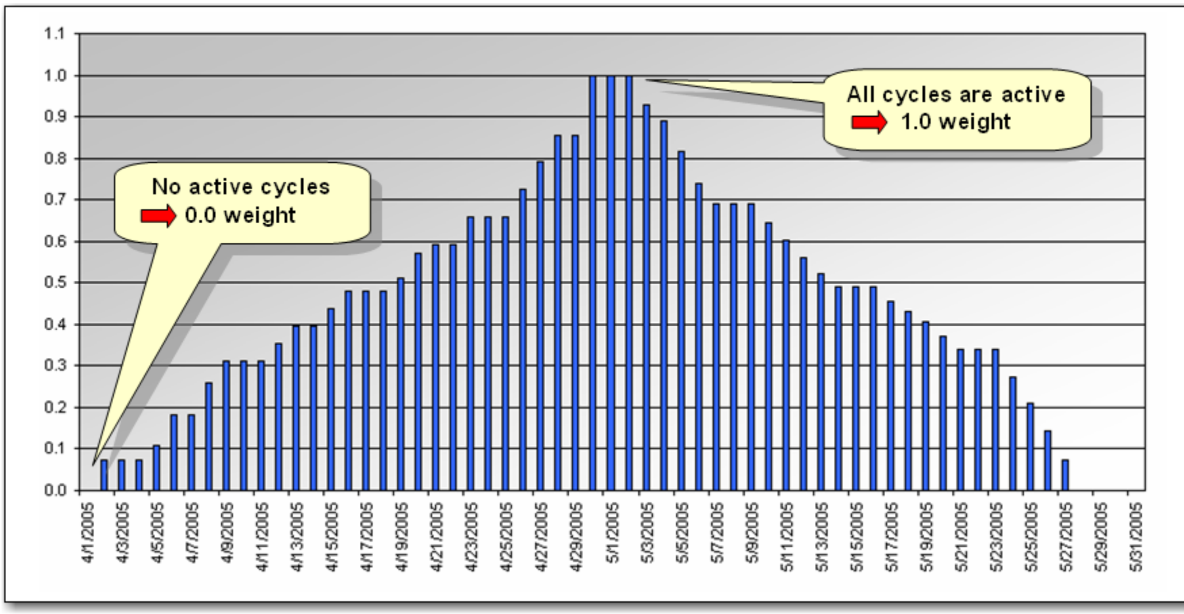
On the first day of the billing month, only 1 cycle is *On*; $ActiveCycles_{dm}$ has a value of 1.0. On the second day, cycle 2 is *On*; $ActiveCycles_{dm}$ has a value of 2. This process continues through the billing period. Assuming there are 21 billing cycles, the highest daily value for $Active\ Cycles_{dm}$ 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 19: 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.

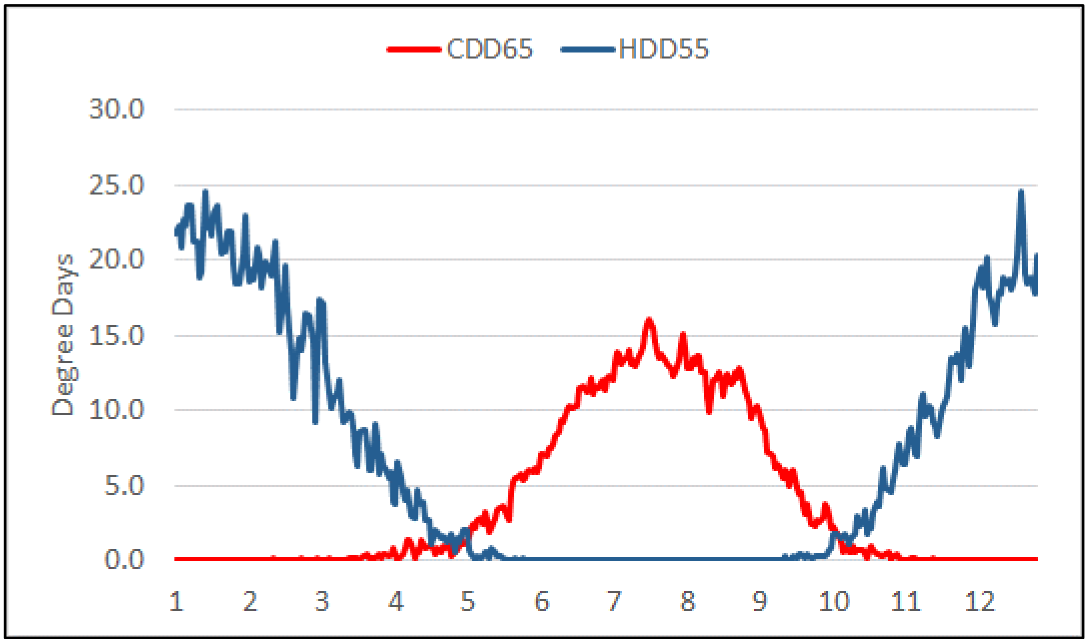
Step 1: Calculate Daily Degree-Days. The first step is to calculate historical daily degree days. Daily heating and cooling degree days are calculated for the Springfield, MO from January 1, 1991 to December 31, 2020 (i.e., 30-years). Daily degree days are calculated as:

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

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 20: 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 because of changes in the meter-read schedule. HDD and CDD used in normalizing Test-Year sales are based on the 2020 and 2021 meter read schedule.

CERTIFICATION

The undersigned, Eric Fox, deposes and states that he is Director, Forecast Solutions of Itron, that he has personal knowledge of the matters set forth in the foregoing responses and the information contained therein is true and accurate to the best of his information, knowledge and belief after reasonable inquiry.

/s/ Eric Fox

Eric Fox