Exhibit No.: 22
Issue: Weather Normalization
Witness: Eric Fox
Type of Exhibit: Direct Testimony
Sponsoring Party: The Empire District Electric Company
Case No.: ER-2019-0374
Date Testimony Prepared: August 2019

Before the Public Service Commission of the State of Missouri

Direct Testimony

of

Eric Fox

on behalf of

The Empire District Electric Company a Liberty Utilities Company

August 2019

Liberty Utilities
EMPIRE DISTRICT

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OF
ERIC FOX
THE EMPIRE DISTRICT ELECTRIC COMPANY
BEFORE THE
MISSOURI PUBLIC SERVICE COMMISSION
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I. INTRODUCTION

Q. PLEASE STATE YOUR NAME AND BUSINESS ADDRESS.

A. My name is Eric Fox. My business address is 20 Park Plaza, Suite 428, Boston, Massachusetts, 02116.

Q. BY WHOM ARE YOU EMPLOYED AND IN WHAT CAPACITY?

A. I am employed by Itron, Inc. ("Itron") as Director, Forecast Solutions.

Q. PLEASE BRIEFLY DESCRIBE ITRON.

A. 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.

Q. ON WHOSE BEHALF ARE YOU TESTIFYING IN THIS PROCEEDING?

A. I am testifying on behalf of The Empire District Electric Company, a Liberty Utilities company ("Liberty-Empire" or the "Company").

Q. PLEASE DESCRIBE YOUR EDUCATIONAL AND PROFESSIONAL BACKGROUND.

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 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 in Schedule EF-1.

Q. HAVE YOU PREVIOUSLY TESTIFIED BEFORE THE MISSOURI PUBLIC SERVICE COMMISSION ("COMMISSION") OR ANY OTHER REGULATORY AGENCY?

A. I have not testified before the Commission but have provided testimony related to weather normalization and forecasting before other regulatory agencies. My regulatory experience is included in Schedule EF-1.

Q. WHAT IS THE PURPOSE OF YOUR DIRECT TESTIMONY IN THIS PROCEEDING?

A. The purpose of my testimony is to support test-year sales and system load weather normalization. I directed the development of rate class and system 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 SCHEDULES WITH YOUR TESTIMONY?

A. Yes. I am sponsoring Schedule EF-2 which shows calculated test-year weather normalized sales and Schedule EF-3 which includes the estimated weather response models and associated model statistics.

Q. WAS THE INFORMATION CONTAINED IN SCHEDULES 2 AND 3 OBTAINED OR DERIVED FROM THE BOOKS AND RECORDS OF THE COMPANY?

A. Yes. Normalized rate-class sales are based on historical load research data and billed sales and customer data provided by the Company. Historical weather data and an Excel file for calculating normal weather were provided by the Staff of the Commission ("Staff").

II. SUMMARY

Q. WHAT IS THE PURPOSE OF WEATHER NORMALIZATION?

A. The purpose of weather normalization is to adjust the test-year sales and energy for abnormal weather conditions. The objective is to establish test-year sales and energy requirements for determining revenue requirements and costs that reflect typical or expected weather conditions. The test-year includes the twelve-month period April 2018 through March 2019.

Q. PLEASE DESCRIBE THE TEST-YEAR WEATHER CONDITIONS.

A. The test-year is characterized by an extremely warm cooling season with cooling degree-days (CDD on a 65 degree temperature basis) 31% higher than normal and a colder than normal heating period with heating degree-days (HDD on a 55 degree temperature base) 9.5% above normal. Table 1 shows the test-year actual and normal CDD and HDD.

Table 1: Test-Year Actual and Normal Calendar-Month Degree-Days

Month	CDD65	Nrm CDD65	HDD55	Nrm HDD55
Apr-18	5.0	15.6	192.9	82.0
May-18	245.1	88.1	-	6.4
Jun-18	429.6	275.2	-	-
Jul-18	465.4	420.4	-	-
Aug-18	369.3	405.5	-	-
Sep-18	231.9	165.3	-	0.2
Oct-18	79.2	22.1	81.2	61.2
Nov-18	-	0.2	456.0	273.7
Dec-18	-	-	496.4	593.0
Jan-19	-	-	637.6	682.0
Feb-19	-	-	491.1	503.6
Mar-19	-	0.2	376.7	293.8
Total	**1,825.5**	**1,392.5**	**2,731.9**	**2,495.9**

Normal CDDs and HDDs are derived from temperature data for the Springfield-Branson National Airport using a 30-year average (1987 to 2016). Both actual and normal degree-days are based on the Staff temperature definition calculated as a weighted average of the current day (2/3 weighting) and prior day (1/3 weighting).

Q. WHAT IS THE WEATHER IMPACT ON TEST-YEAR SALES.

A. Table 2 shows the test-year weather impact for those customer classes whose usage is weather-sensitive.

Table 2: Test-Year Billed Sales (MWh)

Customer Class	Actual	Weather Normal
Residential	1,773,850	1,662,875
Commercial	326,813	316,026
General Power	863,434	844,956
Small Heating	88,132	84,898
Total Electric Building	368,651	357,178
Total	**3,420,879**	**3,265,934**

Total billed sales for the weather-sensitive classes are weather normalized down by 154,945 MWh – a 4.5% reduction.

III. WEATHER NORMALIZATION METHOD

Q. PLEASE DESCRIBE HOW SALES ARE WEATHER NORMALIZED.

A. Sales are weather normalized using a set of daily weather response models estimated from rate-class load research data. The estimated models and weather impact calculations are derived using the approach developed by the Staff; this results in reasonable weather impacts as well as consistent normalized daily peaks and hourly rate class load profiles. The same modeling approach is used in generating weather-normalized system energy, peak, and hourly loads.

HDD and CDD coefficients (B_{HDD} and B_{CDD}) derived from the weather response models are used to calculate daily weather impacts over the test-year period. The impacts are calculated by multiplying the degree-day coefficients with the difference between actual and normal degree-days:

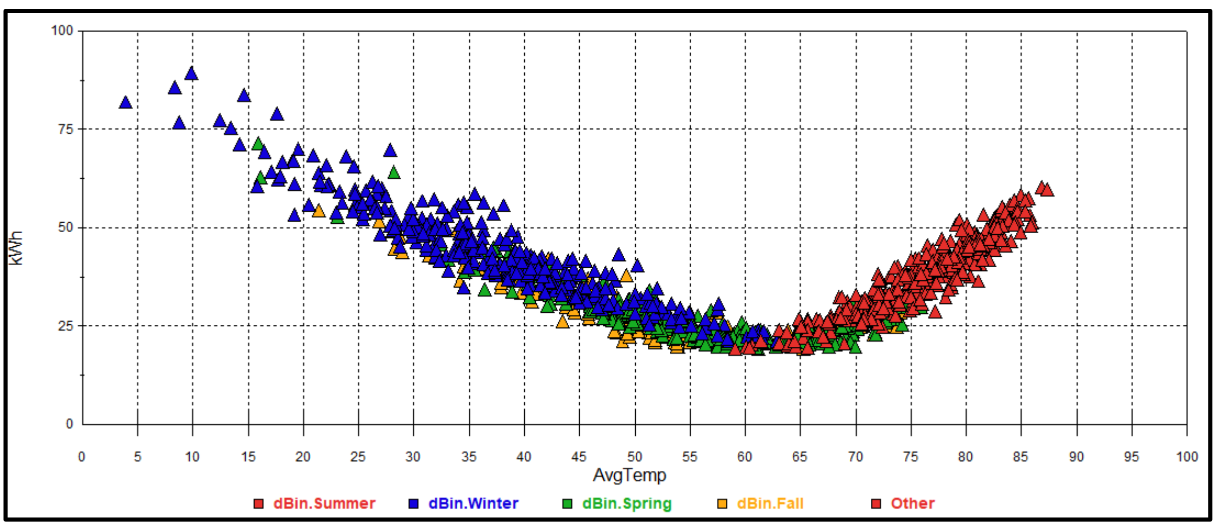
$$WthrImpact = B_{HDD} \times (HDD_{actual} - HDD_{normal}) + B_{CDD} \times (CDD_{actual} - CDD_{normal})$$

The daily impacts and load research data are weighted to reflect the meter read schedule and summed to generate monthly weather impacts consistent with the monthly billing periods. Given potential definition and measurement differences between load research sample data and revenue-class billed sales, the derived weather impacts are not directly used. The weather impacts are instead used to calculate monthly weather adjustment factors that are then applied to test-year billed-sales average use. The calculations of the weather adjustment factors are provided in Schedule EF-2.

Q. PLEASE DISCUSS ESTIMATION OF THE WEATHER NORMALIZATION MODELS.

A. Separate models are estimated for each rate class using linear regression. The models relate daily rate class usage to daily weather conditions and binary variables that account for non-weather variation across months, day of the week, and holidays. As daily load research data can be "noisy", large outliers (over 2.5 standard errors) are excluded from the estimation set. Models are estimated using three-years of data; annual binaries are incorporated to account for any difference in the sample expansion across years. The objective of the model estimation process is to estimate a set of strong weather response coefficients that captures the usage/temperature relationship. Figure 1 shows this relationship for the residential customer class with daily kWh on the y axis against average daily temperature (two-day weighted) on the x axis. The seasons are color-coded.

Figure 1: Residential Usage/Weather Relationship

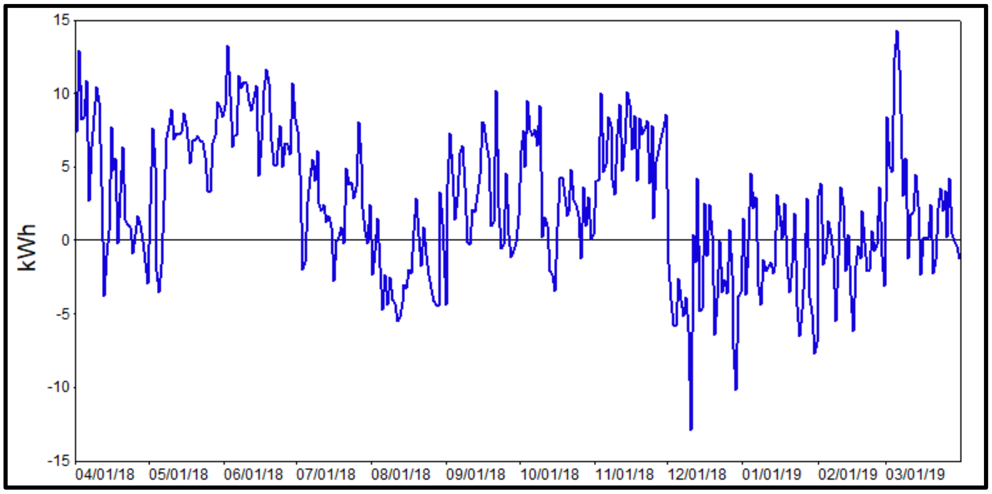


As shown, the relationship between usage and temperature is roughly U-shaped; the relationship between usage and temperature is nonlinear. As temperatures fall below 60 degree or increase above 65 degrees, usage begins to rise. HDD and CDD are a means to capture this non-linear relationship. HDD only takes on a value on the heating side of the curve; HDD defined with a 60-degree base is equal to 60 minus the temperature when the temperature is below 60 and equals 0 when the temperature is 60 degrees or higher. Similarly, on the cooling side, a CDD with a base temperature of 65 degrees is 0 until temperatures exceed 65 degrees and equals the temperature minus 65 degrees when the temperature is above 65 degrees. Often, the model fit can be improved by incorporating multiple degree-day variables with different temperature breakpoints; this allows us to capture the change in the steepness of the usage/temperature curve. The residential model, for example, includes HDD with a base of 60 degrees and 55 degrees and CDD with a base of 65 degrees and 75 degrees. The estimated weather coefficients are statistically strong across all the customer class models; T statistics (a measure of statistical strength) indicate that all the estimated weather coefficients are significant at the 95% level of confidence and higher. Estimated models and statistics are included in Schedule EF-3.

Q. PLEASE DESCRIBE HOW THE MODELS ARE USED TO CALCULATE TEST-YEAR WEATHER IMPACTS.

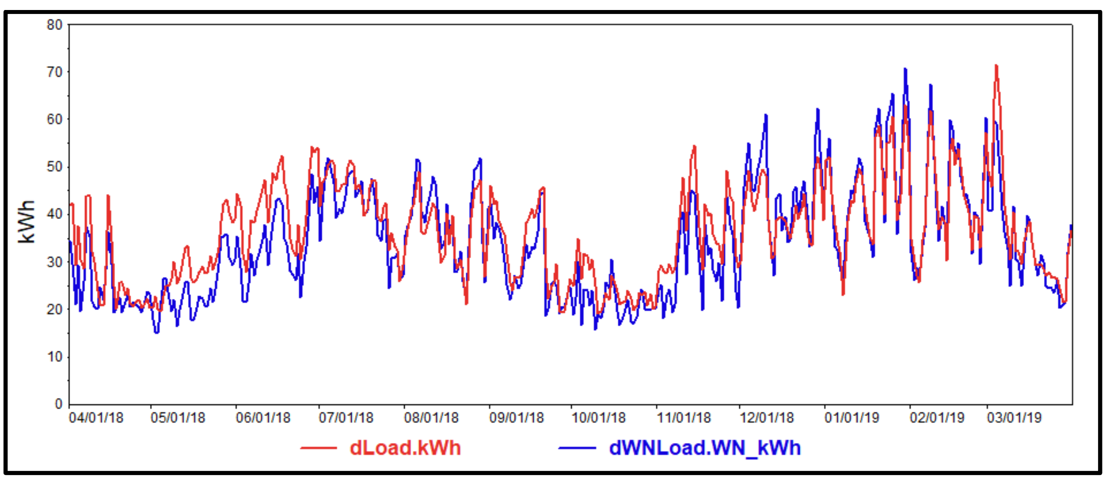
A. The estimated weather coefficients are used to calculate the daily weather impact over the test year period using the MetrixND *Simulation Object* (MetrixND is Itron's load modeling and analysis application). The Simulation Object returns the predicted daily use with actual weather and predicted daily use with normal weather. The difference between *predicted with actual* and *predicted with normal* is the daily weather impact. Figure 2 shows the resulting daily weather impact for the residential customer class for the test-year period.

Figure 2: Residential Daily Weather Impact



The daily weather impact is then subtracted from actual daily use to derive normal daily use. Figure 3 compares actual daily use and weather-normal daily use. Actual daily use is red; normalized daily use is blue.

Figure 3: Residential Test-Year Daily Average Use



Actual and weather normal daily use are aggregated to the test-year billing months. Because the billing-month period overlaps calendar months (billing-month July for example includes the second half of June and the first half of July), the daily data is first weight to reflect the meter read schedule and then summed over the billing-month period. A monthly weather-adjustment ratio is calculated for each rate class as the ratio of monthly weather-normal average use to actual average use; both data series are derived from the load research data. Table 3 shows the resulting monthly adjustment factors.

Table 3: Monthly Weather Adjustment Factors

	2018									2019		
Rates	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
Res	0.926	0.871	0.790	0.884	0.995	0.982	0.880	0.857	0.948	1.048	1.030	0.954
Com	0.982	0.944	0.881	0.930	0.997	0.989	0.938	0.958	0.982	1.019	1.012	0.982
GP	1.002	0.957	0.914	0.958	0.997	0.990	0.952	0.990	0.998	1.007	1.004	0.994
SH	0.946	0.929	0.887	0.934	0.997	0.990	0.938	0.898	0.959	1.043	1.025	0.961
TEB	0.966	0.942	0.900	0.944	0.997	0.990	0.947	0.932	0.971	1.034	1.021	0.969

The adjustment factors are applied to average use derived from billed sales data. Factors below 1.00 weather adjust billed-sales average use down. Factors above 1.00 weather adjust billed-sales average use up. In most months, average use is adjusted down as the billing-month CDD and HDD in most months are above normal. Table 4 shows actual and weather-normal billed sales average use.

Table 4: Actual and Normalized Billed Sales Average Use (kWh)

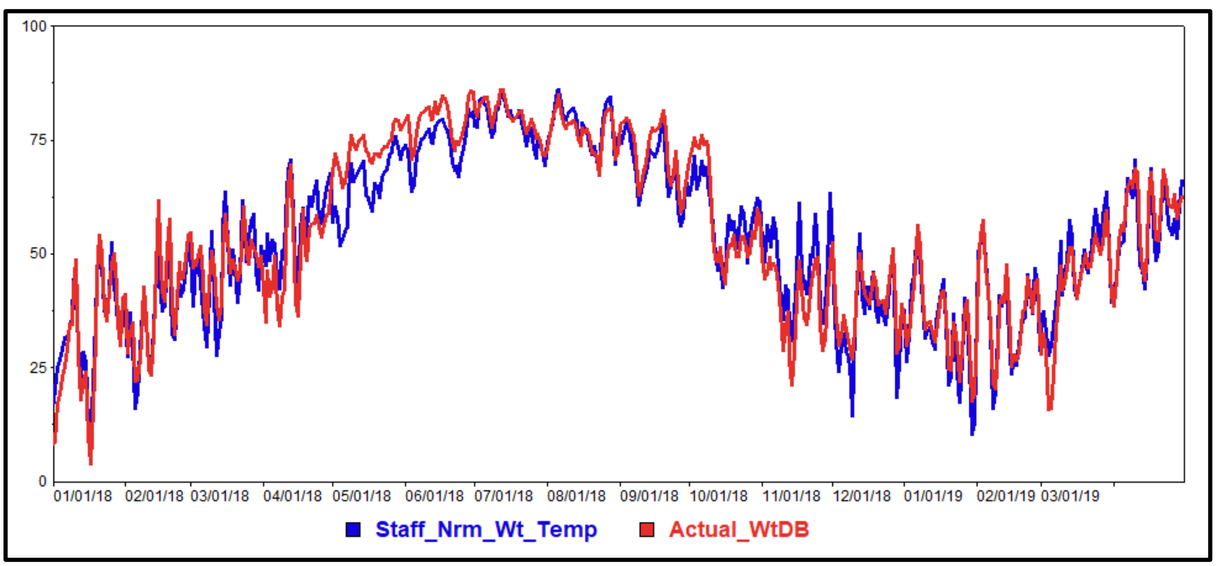
	2018									2019			
	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Total
Residential													
kWh per Cust	976.7	794.6	1,117.0	1,329.3	1,202.2	1,088.9	904.8	943.2	1,218.8	1,298.1	1,393.7	1,358.9	**13,626**
WN kWh per Cust	904.8	692.3	882.6	1,174.6	1,196.2	1,069.2	795.9	808.3	1,154.9	1,360.5	1,436.0	1,296.2	**12,771**
Commercial (CB)													
kWh per Cust	1,316	1,262	1,646	1,871	1,670	1,596	1,495	1,345	1,402	1,498	1,495	1,527	**18,122**
WN kWh per Cust	1,291	1,191	1,450	1,741	1,665	1,578	1,403	1,289	1,377	1,527	1,513	1,500	**17,524**
General Power													
kWh per Cust	36,850	38,068	45,909	49,213	46,202	45,118	42,967	36,920	36,447	36,243	36,756	36,528	**487,222**
WN kWh per Cust	36,908	36,441	41,964	47,167	46,050	44,684	40,894	36,556	36,365	36,499	36,914	36,314	**476,755**
Small Heating													
kWh per Cust	2,105	1,808	2,282	2,670	2,450	2,260	2,025	2,127	2,655	2,849	3,070	2,836	**29,136**
WN kWh per Cust	1,991	1,679	2,023	2,493	2,443	2,236	1,899	1,911	2,547	2,972	3,147	2,726	**28,067**
Total Electric Building													
kWh per Cust	29,309	27,330	32,308	37,616	35,665	32,265	31,359	30,130	33,436	34,115	33,968	33,191	**390,694**
WN kWh per Cust	28,305	25,752	29,088	35,507	35,550	31,953	29,699	28,096	32,455	35,279	34,680	32,158	**378,522**

Normalized sales are calculated by multiplying weather normal average use by the number of customers in each test-year month. Normalized billed sales by month are provided in Schedule EF-2.

Q. PLEASE DESCRIBE HOW NORMAL WEATHER IS CALCULATED.

A. Normal daily HDD and CDD are derived from normal daily average temperature series generated by the Staff's weather-normal Excel application. Calculations are based on 30 years of historical daily temperature data (1987 to 2016) for Springfield-Branson National Airport. Normal temperatures are calculated using a rank and average approach. This entails first sorting (or ranking) the two-day weighted temperature (2/3 current day, 1/3 prior-day) within each year from the lowest to the highest daily temperature. Next the annual rankings are averaged starting with the lowest temperature in each year to the highest temperature; the process generates a normal temperature duration curve with 365 normalized daily temperature estimates. In the final step, the normalized temperature data is mapped to the test-year weather pattern. Figure 4 shows resulting daily normal average temperature (in blue) against test-year actual temperatures (in red).

Figure 4: Actual and Normal Test-Year Daily Average Temperature

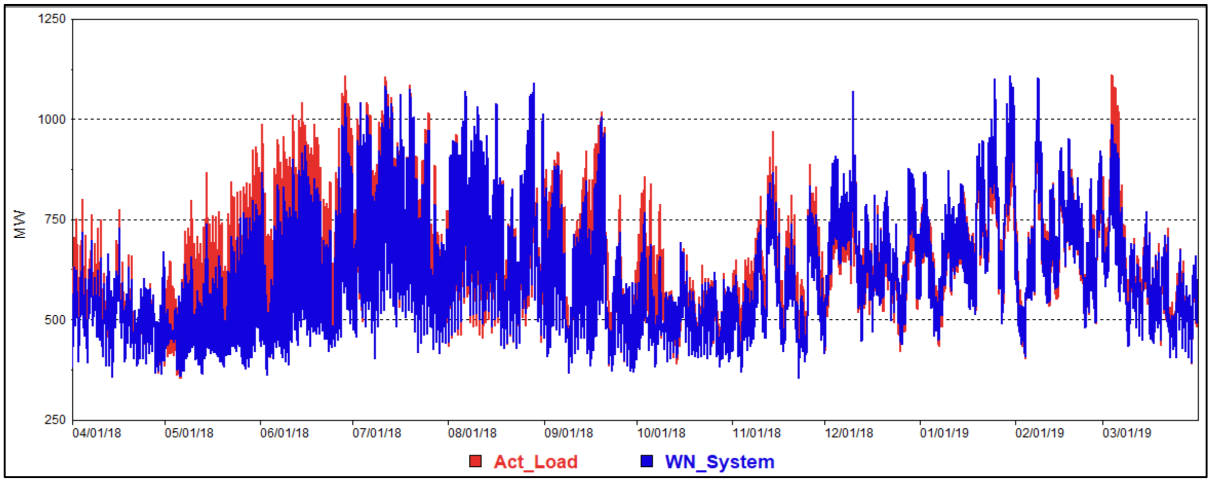


The test-year daily temperature series (actual and normal) are used in calculating daily HDD and CDD for different temperature breakpoints. Daily degree-days are generated for HDD with 55 and 60 degree breakpoints and for CDD with 60, 65, and 75 degree breakpoints. Actual daily degree-days are used in estimating the weather response models and generating daily predicted use for actual weather. Test-year normal daily degree days are used in calculating predicted use for normal weather.

Q. DID YOU ALSO GENERATE WEATHER NORMAL SYSTEM ENERGY, PEAK, AND HOURLY LOAD?

A. Yes. System normalized load for the test-year period is estimated using the same approach as that used in normalizing customer class sales. Daily system energy and peak weather response models are estimated that relate energy requirements to degree-days and binary variables to account for non-weather related load shifts, lower weekend and statistically significant holiday loads, and a trend variable to account for increase in loads over the estimation period (April 1, 2016 through March 31, 2019). Estimated weather coefficients, combined with the MetrixND Simulation Object, are used to calculate daily energy and peak weather impacts. Normal daily energy and peak estimates are then calculated by subtracting the weather impacts from actually daily energy and peak. Normalized energy and peak are combined with system profile to generate weather-normal system hourly load. Figure 5 shows actual and weather normal load for the test-year period. System energy weather response model and statistics are included in Schedule EF-3.

Figure 5: Test-Year Actual and Weather Normal System Load



IV. CONCLUSION

Q. DO YOU RECOMMEND USING THE NORMALIZED TEST-YEAR SALES FOR DETERMINING THE COMPANY'S REVENUE REQUIREMENTS?

A. Yes. The test-year normalized sales should be adopted for determining the Company's revenue requirements. Normalized sales are based on the Staff's weather normalization approach and Staff's calculated daily normal temperatures. The approach is well thought-out and results in reasonable test-year weather impacts.

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

Climate Impact Long-Term Demand Impacts - Modeling Approach, New York ISO Load Forecasting Task Force, June 18, 2019

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

Long-Term Forecast Development and Modeling Workshop. 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

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

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

Table 1: Actual and Normal Degree Days

Month	CDD65	Nrm CDD65	HDD55	Nrm HDD55
Apr-18	5.0	15.6	192.9	82.0
May-18	245.1	88.1	-	6.4
Jun-18	429.6	275.2	-	-
Jul-18	465.4	420.4	-	-
Aug-18	369.3	405.5	-	-
Sep-18	231.9	165.3	-	0.2
Oct-18	79.2	22.1	81.2	61.2
Nov-18	-	0.2	456.0	273.7
Dec-18	-	-	496.4	593.0
Jan-19	-	-	637.6	682.0
Feb-19	-	-	491.1	503.6
Mar-19	-	0.2	376.7	293.8
Total	**1,825.5**	**1,392.5**	**2,731.9**	**2,495.9**

Table 2: Normalized Sales

Customer Class	Actual	Weather Normal
Residential	1,773,850	1,662,875
Commercial	326,813	316,026
General Power	863,434	844,956
Small Heating	88,132	84,898
Total Electric Building	368,651	357,178
Total	**3,420,879**	**3,265,934**
		154,945
		4.5%

Table 3 Monthly Weather Adjustment Factors

	2018									2019		
Rates	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
Res	0.926	0.871	0.790	0.884	0.995	0.982	0.880	0.857	0.948	1.048	1.030	0.954
Com	0.982	0.944	0.881	0.930	0.997	0.989	0.938	0.958	0.982	1.019	1.012	0.982
GP	1.002	0.957	0.914	0.958	0.997	0.990	0.952	0.990	0.998	1.007	1.004	0.994
SH	0.946	0.929	0.887	0.934	0.997	0.990	0.938	0.898	0.959	1.043	1.025	0.961
TEB	0.966	0.942	0.900	0.944	0.997	0.990	0.947	0.932	0.971	1.034	1.021	0.969

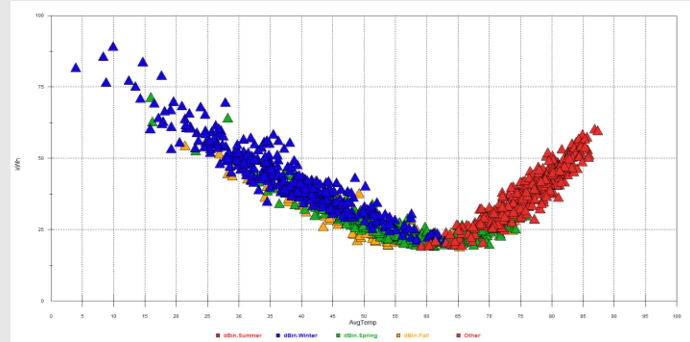
Table 4 Normalized Average Use

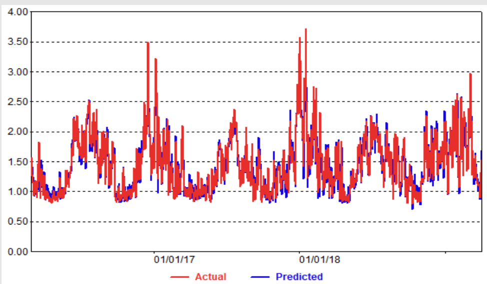
	2018									2019			
	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Total
Residential													
kWh per Cust	976.7	794.6	1,117.0	1,329.3	1,202.2	1,088.9	904.8	943.2	1,218.8	1,298.1	1,393.7	1,358.9	**13,626**
WN kWh per Cust	904.8	692.3	882.6	1,174.6	1,196.2	1,069.2	795.9	808.3	1,154.9	1,360.5	1,436.0	1,296.2	**12,771**
Commercial (CB)													
kWh per Cust	1,316	1,262	1,646	1,871	1,670	1,596	1,495	1,345	1,402	1,498	1,495	1,527	**18,122**
WN kWh per Cust	1,291	1,191	1,450	1,741	1,665	1,578	1,403	1,289	1,377	1,527	1,513	1,500	**17,524**
General Power													
kWh per Cust	36,850	38,068	45,909	49,213	46,202	45,118	42,967	36,920	36,447	36,243	36,756	36,528	**487,222**
WN kWh per Cust	36,908	36,441	41,964	47,167	46,050	44,684	40,894	36,556	36,365	36,499	36,914	36,314	**476,755**
Small Heating													
kWh per Cust	2,105	1,808	2,282	2,670	2,450	2,260	2,025	2,127	2,655	2,849	3,070	2,836	**29,136**
WN kWh per Cust	1,991	1,679	2,023	2,493	2,443	2,236	1,899	1,911	2,547	2,972	3,147	2,726	**28,067**
Total Electric Building													
kWh per Cust	29,309	27,330	32,308	37,616	35,665	32,265	31,359	30,130	33,436	34,115	33,968	33,191	**390,694**
WN kWh per Cust	28,305	25,752	29,088	35,507	35,550	31,953	29,699	28,096	32,455	35,279	34,680	32,158	**378,522**

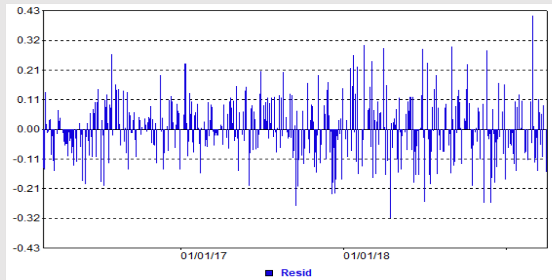
Residential Average MW Weather Normalization Model. Estimated March 2016 to March 2019

Model Statistics	
Iterations	11
Adjusted Observations	1108
Deg. of Freedom for Error	1093
R-Squared	0.962
Adjusted R-Squared	0.961
AIC	1.502
BIC	1.570
F-Statistic	1968.474
Prob (F-Statistic)	0.0000
Log-Likelihood	-2,389.21
Model Sum of Squares	122,085.64
Sum of Squared Errors	4,842.03
Mean Squared Error	4.43
Std. Error of Regression	2.10
Mean Abs. Dev. (MAD)	1.66
Mean Abs. % Err. (MAPE)	3.08%
Durbin-Watson Statistic	2.203

Variable	Coefficient	StdErr	T-Stat	P-Value	Units	Definition
CONST	0.905	0.016	57.546	0.00%		Constant term
Daily_DD.HDD55	0.029	0.003	9.191	0.00%		
Daily_DD.HDD60	0.014	0.003	4.865	0.00%		
Daily_DD.CDD65	0.047	0.002	26.536	0.00%		
Daily_DD.CDD75	0.034	0.004	9.378	0.00%		
dBin.Yr2016	0.086	0.011	7.739	0.00%		
dBin.Yr2017	0.062	0.011	5.836	0.00%		
dBin.Mar	-0.047	0.016	-3.004	0.27%		binary variable true if March false if not
dBin.Apr	-0.118	0.018	-6.674	0.00%		binary variable true if April false if not
dBin.May	-0.105	0.017	-6.220	0.00%		binary variable true if May false if not
dBin.Oct	-0.156	0.017	-9.191	0.00%		binary variable true if October false if not
dBin.Nov	-0.113	0.017	-6.492	0.00%		binary variable true if November false if not
dBin.WkEnd	0.055	0.008	7.155	0.00%		binary variable true if Saturaday or Sunday
Calendar.XMasWk	0.078	0.034	2.314	2.09%		Christmas week binary Variable
Calendar.NYDay	0.270	0.058	4.664	0.00%		New Years day binary Variable
MA(1)	0.362	0.029	12.491	0.00%		



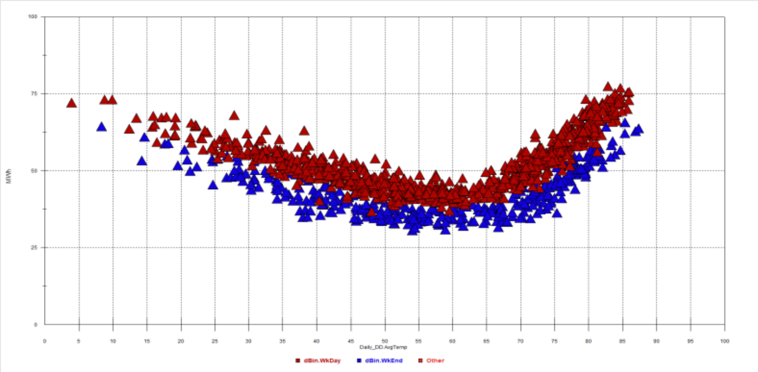


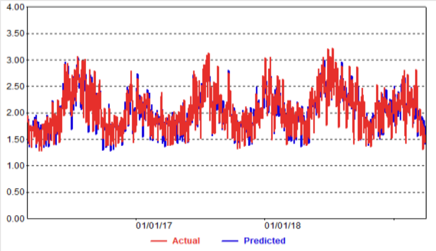


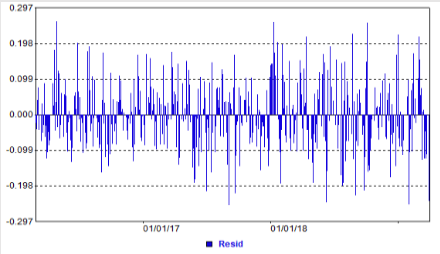
Commercial Average MW Weather Normalization Model. Estimated March 2016 to March 2019

Model Statistics	
Iterations	11
Adjusted Observations	1103
Deg. of Freedom for Error	1084
R-Squared	0.937
Adjusted R-Squared	0.936
AIC	-4.608
BIC	-4.522
F-Statistic	900.004
Prob (F-Statistic)	0.0000
Log-Likelihood	995.43
Model Sum of Squares	158.75
Sum of Squared Errors	10.62
Mean Squared Error	0.01
Std. Error of Regression	0.10
Mean Abs. Dev. (MAD)	0.08
Mean Abs. % Err. (MAPE)	3.92%
Durbin-Watson Statistic	1.903

Variable	Coefficient	StdErr	T-Stat	P-Value	Units	Definition
CONST	1.905	0.012	153.855	0.00%		Constant term
Daily_DD.HDD55	0.020	0.001	38.142	0.00%		
Daily_DD.CDD65	0.044	0.001	30.017	0.00%		
Daily_DD.CDD75	0.027	0.003	8.180	0.00%		
dBin.Yr2016	-0.073	0.010	-7.028	0.00%		
dBin.Yr2017	-0.024	0.010	-2.439	1.49%		
dBin.Mar	-0.114	0.014	-7.893	0.00%		binary variable true if March false if not
dBin.Apr	-0.088	0.017	-5.331	0.00%		binary variable true if April false if not
dBin.May	-0.041	0.016	-2.611	0.92%		binary variable true if May false if not
dBin.Oct	-0.134	0.016	-8.446	0.00%		binary variable true if October false if not
dBin.Nov	-0.103	0.016	-6.335	0.00%		binary variable true if November false if not
dBin.WkEnd	-0.371	0.007	-51.080	0.00%		binary variable true if Saturday or Sunday
Calendar.Thanks	-0.158	0.058	-2.730	0.64%		Thanksgiving day binary Variable
Calendar.FriAThanks	-0.334	0.058	-5.805	0.00%		Friday after Thanks Giving binary Variable
Calendar.XMasHol	-0.196	0.053	-3.729	0.02%		Christmas holiday binary Variable
Calendar.MemDay	-0.171	0.053	-3.210	0.14%		Memorial Day binary Variable
Calendar.July4thHol	-0.163	0.053	-3.084	0.21%		July 4th holiday binary Variable
Calendar.LaborDay	-0.095	0.053	-1.799	7.24%		Labor Day binary Variable
MA(1)	0.376	0.029	12.924	0.00%		



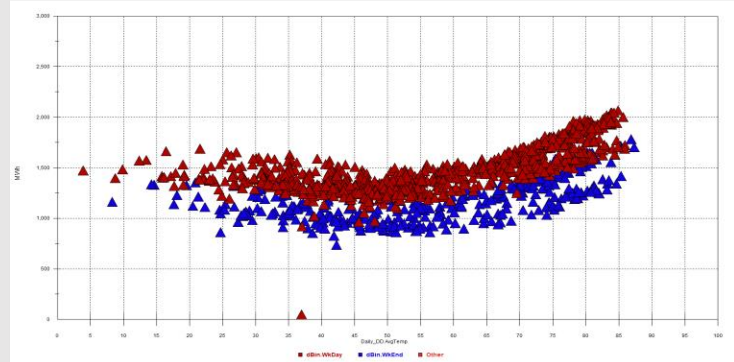


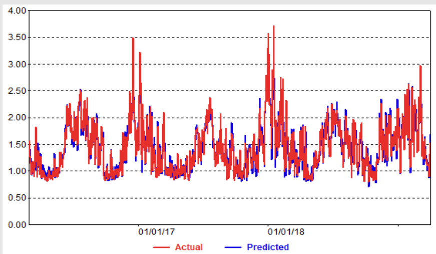


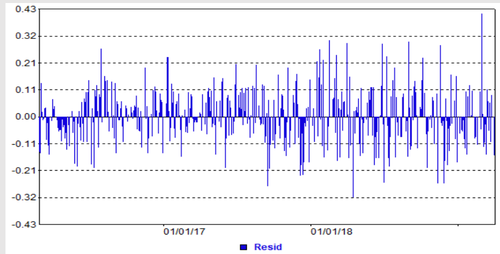
General Power Average MW Weather Normalization Model. Estimated March 2016 to March 2019

Model Statistics	
Iterations	11
Adjusted Observations	1108
Deg. of Freedom for Error	1093
R-Squared	0.962
Adjusted R-Squared	0.961
AIC	1.502
BIC	1.570
F-Statistic	1968.474
Prob (F-Statistic)	0.0000
Log-Likelihood	-2,389.21
Model Sum of Squares	122,085.64
Sum of Squared Errors	4,842.03
Mean Squared Error	4.43
Std. Error of Regression	2.10
Mean Abs. Dev. (MAD)	1.66
Mean Abs. % Err. (MAPE)	3.08%
Durbin-Watson Statistic	2.203

Variable	Coefficient	StdErr	T-Stat	P-Value	Units	Definition
CONST	68.267	7.291	9.363	0.00%		Constant term
Daily_DD.HDD55	0.160	0.013	11.936	0.00%		
Daily_DD.CDD60	0.890	0.018	49.262	0.00%		
dBin.Yr2016	6.425	1.089	5.898	0.00%		
dBin.Yr2017	4.003	0.656	6.102	0.00%		
dBin.WkEnd	-12.508	0.140	-89.167	0.00%		value = 1 if Saturday or Sunday
Calendar.Thanks	-3.622	1.175	-3.082	0.21%		Thanksgiving day binary Variable
Calendar.FriAThanks	-10.659	1.172	-9.094	0.00%		Friday after Thanks Giving binary Variable
Calendar.XMasDay	-6.753	1.153	-5.855	0.00%		Christmas Day binary Variable
Calendar.XMasWk	-4.207	0.935	-4.501	0.00%		Christmas week binary Variable
dBin.TrendVar	-1.168	0.501	-2.331	1.99%		
dOutliers.Dec01_16	-58.725	1.838	-31.958	0.00%		
dBin.Oct	-2.516	0.507	-4.966	0.00%		binary variable true if October false if not
dBin.Nov	-2.650	0.534	-4.962	0.00%		binary variable true if November false if not
AR(1)	0.564	0.025	22.136	0.00%		



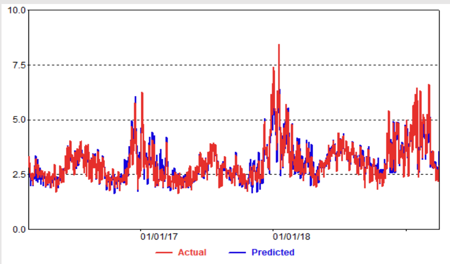


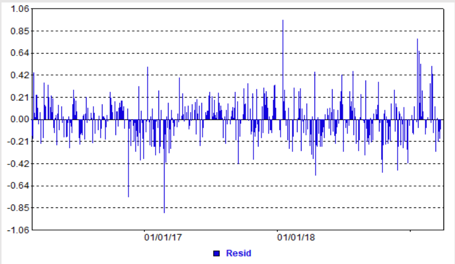


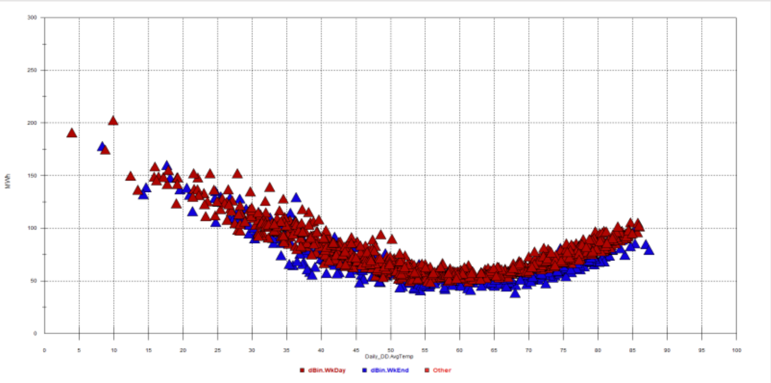
Small Heat Average MW Weather Normalization Model. Estimated March 2016 to March 2019

Model Statistics	
Iterations	13
Adjusted Observations	1104
Deg. of Freedom for Error	1086
R-Squared	0.940
Adjusted R-Squared	0.939
AIC	-3.088
BIC	-3.007
F-Statistic	998.641
Prob (F-Statistic)	0.0000
Log-Likelihood	156.32
Model Sum of Squares	761.27
Sum of Squared Errors	48.70
Mean Squared Error	0.04
Std. Error of Regression	0.21
Mean Abs. Dev. (MAD)	0.16
Mean Abs. % Err. (MAPE)	5.38%
Durbin-Watson Statistic	1.670

Variable	Coefficient	StdErr	T-Stat	P-Value	Units	Definition
CONST	2.602	0.028	92.871	0.00%		Constant term
Daily_DD.HDD55	0.086	0.001	71.217	0.00%		
Daily_DD.CDD65	0.062	0.003	19.067	0.00%		
Daily_DD.CDD75	0.029	0.007	3.959	0.01%		
dBin.Yr2016	-0.254	0.024	-10.709	0.00%		
dBin.Yr2017	-0.305	0.023	-13.500	0.00%		
dBin.Mar	-0.122	0.033	-3.700	0.02%		binary variable true if March false if not
dBin.Apr	-0.092	0.038	-2.442	1.47%		binary variable true if April false if not
dBin.May	-0.085	0.036	-2.400	1.65%		binary variable true if May false if not
dBin.Oct	-0.216	0.036	-5.999	0.00%		binary variable true if October false if not
dBin.Nov	-0.253	0.037	-6.842	0.00%		binary variable true if November false if not
dBin.WkEnd	-0.338	0.016	-21.200	0.00%		
Calendar.Thanks	-0.476	0.124	-3.834	0.01%		Thanksgiving day binary Variable
Calendar.FriAThanks	-0.256	0.124	-2.066	3.91%		Friday after Thanks Giving binary Variable
Calendar.XMasEve	-0.222	0.122	-1.824	6.84%		Christmas Eve binary Variable
Calendar.XMasDay	-0.409	0.122	-3.346	0.09%		Christmas Day binary Variable
Calendar.NYDay	0.513	0.108	4.735	0.00%		New Years day binary Variable
MA(1)	0.475	0.028	17.244	0.00%		



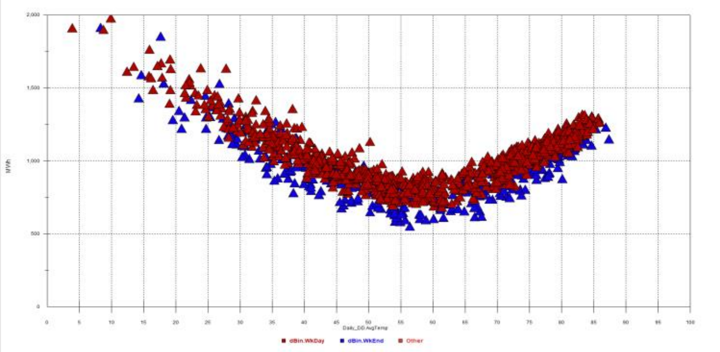


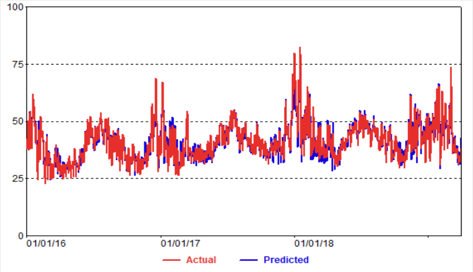


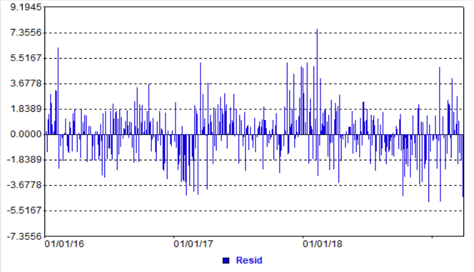
TEB Average MW Weather Normalization Model. Estimated January 2016 to March 2019

Model Statistics	
Iterations	12
Adjusted Observations	1156
Deg. of Freedom for Error	1135
R-Squared	0.946
Adjusted R-Squared	0.945
AIC	1.236
BIC	1.328
F-Statistic	988.726
Prob (F-Statistic)	0.0000
Log-Likelihood	-2,333.90
Model Sum of Squares	66,868.79
Sum of Squared Errors	3,838.07
Mean Squared Error	3.38
Std. Error of Regression	1.84
Mean Abs. Dev. (MAD)	1.41
Mean Abs. % Err. (MAPE)	3.52%
Durbin-Watson Statistic	1.912

Variable	Coefficient	StdErr	T-Stat	P-Value	Units	Definition
CONST	29.149	6.032	4.832	0.00%		Constant term
Daily_DD.HDD55	0.770	0.011	68.118	0.00%		
Daily_DD.CDD60	0.327	0.064	5.090	0.00%		
Daily_DD.CDD65	0.274	0.090	3.044	0.24%		
Daily_DD.CDD75	0.297	0.076	3.908	0.01%		
dBin.WkEnd	-3.867	0.119	-32.520	0.00%		
Calendar.Thanks	-2.577	1.010	-2.550	1.09%		Thanksgiving day binary Variable
Calendar.FriAThanks	-2.892	1.008	-2.868	0.42%		Friday after Thanks Giving binary Variable
Calendar.XMasHol	-4.038	0.904	-4.466	0.00%		Christmas holiday binary Variable
Calendar.NYEve	1.365	1.730	0.789	43.02%		New Years eve binary Variable
Calendar.NYDay	5.777	1.049	5.508	0.00%		New Years day binary Variable
dBin.Yr2016	-2.739	0.929	-2.949	0.33%		
dBin.Yr2017	0.636	0.566	1.124	26.14%		
dBin.Feb	-1.157	0.418	-2.764	0.58%		binary variable true if February false if not
dBin.Mar	-0.886	0.410	-2.160	3.10%		binary variable true if March false if not
dBin.Jun	2.571	0.537	4.783	0.00%		binary variable true if June false if not
dBin.Jul	2.985	0.577	5.178	0.00%		binary variable true if July false if not
dBin.Aug	2.109	0.544	3.877	0.01%		binary variable true if August false if not
dBin.Sep	1.486	0.499	2.977	0.30%		binary variable true if September false if not
dBin.TrendVar	0.363	0.411	0.884	37.69%		
AR(1)	0.591	0.025	24.059	0.00%		



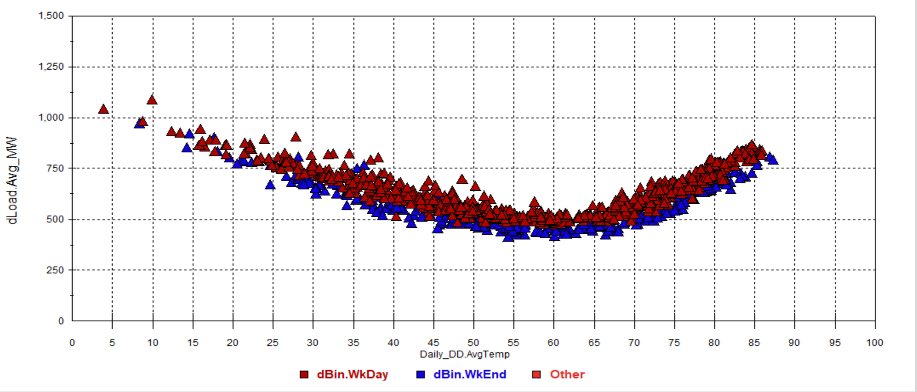


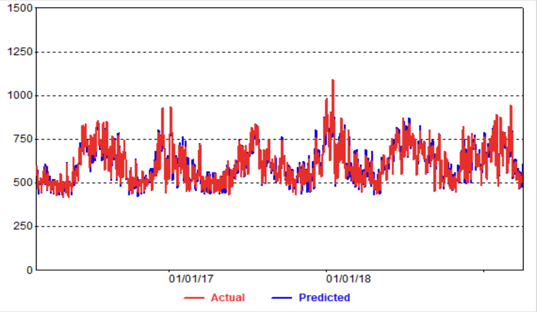


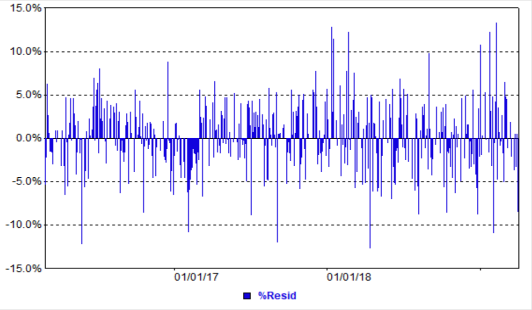
System Average MW Weather Normalization Model. Estimated March 2016 to March 2019

Model Statistics	
Iterations	12
Adjusted Observations	1126
Deg. of Freedom for Error	1105
R-Squared	0.946
Adjusted R-Squared	0.945
AIC	6.509
BIC	6.603
F-Statistic	965.464
Prob (F-Statistic)	0.0000
Log-Likelihood	-5,241.26
Model Sum of Squares	12,721,528.47
Sum of Squared Errors	728,006.70
Mean Squared Error	658.83
Std. Error of Regression	25.67
Mean Abs. Dev. (MAD)	19.12
Mean Abs. % Err. (MAPE)	3.11%

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	462.017	17.410	26.537	0.00%
dBin.TrendVar	4.666	1.267	3.682	0.03%
Daily_DD.HDD55	9.008	0.142	63.289	0.00%
Daily_DD.CDD65	12.608	0.388	32.515	0.00%
Daily_DD.CDD75	5.673	0.865	6.560	0.00%
dBin.Mar	-22.273	3.819	-5.833	0.00%
dBin.Apr	-28.949	4.419	-6.551	0.00%
dBin.May	-24.604	4.158	-5.917	0.00%
dBin.Oct	-24.582	4.213	-5.835	0.00%
dBin.Nov	-24.016	4.306	-5.577	0.00%
dBin.WkEnd	-58.140	1.876	-30.983	0.00%
Calendar.Thanks	-56.601	15.170	-3.731	0.02%
Calendar.FriAThanks	-73.058	15.092	-4.841	0.00%
Calendar.XMasHol	-57.988	14.032	-4.133	0.00%
dBin.Jan02_17	-81.374	23.589	-3.450	0.06%
dBin.Jan11_18	72.575	23.602	3.075	0.22%
dBin.Feb10_18	93.015	23.588	3.943	0.01%
dBin.Apr14_18	62.157	23.710	2.622	0.89%
dBin.Dec24_18	-76.912	24.310	-3.164	0.16%
dBin.Jan19_19	134.323	23.601	5.692	0.00%
MA(1)	0.398	0.029	13.881	0.00%







AFFIDAVIT OF ERIC FOX

STATE OF MASSACHUSETTS)
) ss
COUNTY OF SUFFOLK)

On the 8th day of August, 2019, 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 8 day of August, 2019

Notary Public

My commission expires:

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