Exhibit No.: _____
Issues: Weather Normalization
Witness: Eric Fox
Type of Exhibit: Direct Testimony
Sponsoring Party: The Empire District Electric Company d/b/a Liberty
Case No.: ER-2024-0261
Date Testimony Prepared: November 2024

Before the Public Service Commission
of the State of Missouri

Direct Testimony

of

Eric Fox

on behalf of

The Empire District Electric Company d/b/a Liberty

November 6, 2024

Liberty™

TABLE OF CONTENTS
FOR THE DIRECT TESTIMONY OF ERIC FOX
THE EMPIRE DISTRICT ELECTRIC COMPANY D/B/A LIBERTY
BEFORE THE MISSOURI PUBLIC SERVICE COMMISSION
CASE NO. ER-2024-0261

FOR THE DIRECT TESTIMONY OF ERIC FOX
THE EMPIRE DISTRICT ELECTRIC COMPANY D/B/A LIBERTY
BEFORE THE MISSOURI PUBLIC SERVICE COMMISSION
CASE NO. ER-2024-0261

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.

Q. On whose behalf are you testifying in this proceeding?

A. I am testifying on behalf of The Empire District Electric Company d/b/a Liberty ("Liberty" 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 an economic analyst where I assisted in developing a macro-economic model for San Diego County. 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 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.

Q. Have you previously testified before the Missouri Public Service Commission (“Commission”) or any other regulatory agency?

A. Yes. I have filed testimony before the Commission in previous Liberty electric rate cases, including testimony for the 2019 General Rate Case (Case No. ER-2019-0374) and 2021 General Rate Case (Case No. ER-2021-0312), and most recently I filed testimony for the Company's affiliate in the Liberty Utilities (Midstates Natural Gas) Corp. rate case (Case No. GR-2024-0106). I have also provided testimony supporting weather normalization and forecasting in other jurisdictions. My regulatory and other work experience is included in **Direct Schedule EF-1**.

Q. What is the purpose of your direct testimony in this proceeding?

A. The purpose of my testimony is to support the weather and customer sales normalization for the test year period October 2022 to September 2023. Sales weather normalization is the process of adjusting test year sales for "normal" or expected weather conditions. I begin my testimony by explaining the results of my analyses, and then describe the processes I used in my analyses.

II. RESULTS

Q. Please describe the test year weather conditions and resulting weather-normalized sales.

A. The test year period includes a mild winter and a warmer than normal summer; as a result, winter use is weather-normalized up and cooling use is weather-normalized down. Actual and normal weather conditions are measured in heating-degree-days (HDD) and cooling-degree-days (CDD). HDD are used in calculating heating-related sales and CDD are used in estimating cooling-related sales. Table 1 below shows the test year actual and normal HDD (with a reference temperature point of 60 degrees) and CDD (with a reference temperature point of 65 degrees).

Table 1: Calendar-Month Test Year Cooling and Heating Degree-Days

	HDD 60		CDD 65	
Month	**Actual**	**Normal**	**Actual**	**Normal**
October	138	148	20	33
November	473	419	10	1
December	739	713	-	0
January	649	814	-	-
February	494	642	-	0
March	457	420	1	4
April	144	173	22	22
May	26	42	118	100
June	-	1	293	285
July	-	-	453	418
August	-	0	421	387
September	-	13	188	179
Total	**3,120**	**3,387**	**1,526**	**1,430**

Test year HDD are 7.9% below normal, while test year CDD are 6.7% above normal. Actual and normal degree-days are derived from daily average temperature data for the Springfield-Branson National Airport ("SGF"). Normal degree-days are based on a thirty-year period from 1992 through 2021.

Sales are weather normalized for the three weather-sensitive revenue classes: Residential (three tariff schedules[1]), Small General Service (three tariff schedules[2]), and Large General Service (four tariff schedules[3]). With new tariffs starting in October 2022, sales and customers have been moving from non-TOU (nonstandard rates) to the TOU rates. In the first two months (October and November) of the test year, most of the billed sales and customer counts are on the non-standard rates and transition to the new TOU rates by December 2022. Table 2 shows the tariffs by revenue class.

[1] The three Residential schedules are Non-Standard Residential (Schedule NS-RG), Time Choice Residential (Schedule TC-RG), and Time Choice Plus Residential (Schedule TP-RG).
[2] The three Small General Service schedules are Non-Standard General Service (Schedule NS-GS), Time Choice General Service (Schedule TC-GS), and Time Choice Plus General Service (Schedule TP-GS).
[3] The four Large General Service schedules are Non-Standard Large General Service (Schedule NS-LG), Time Choice Large General Service (Schedule TC-LG), Non-Standard Small Primary Service (Schedule NS-SP), and Time Choice Small Primary Service (Schedule TC-SP).

Table 2: Tariffs by Revenue Class

Residential	
NS-RG Residential	Non-Standard
TC-RG Time Choice	New TOU
TP-RG Time Choice Plus	New TOU
Small General Service	
NS-GS General Service	Non-Standard
TC-GS Time Choice	New TOU
TP-GS Time Choice Plus	New TOU
Large General Service	
NS-SP Small Primary	Non-Standard
NS-LG Large General	Non-Standard
TC-SP Time Choice	New TOU
TC-LG Time Choice	New TOU

Residential and Small General Service sales have positive weather adjustments as the positive heating adjustments are larger than the negative cooling adjustments. Large General Service sales are adjusted down slightly as this class is more sensitive to changes in CDD than HDD; the negative cooling adjustment is slightly larger than the positive heating adjustment. Residential sales have the largest positive adjustment as this class is most sensitive to changes in HDD. Table 3 below shows test year results.

Table 3: Test Year Actual and Weather Normalized MWh

Revenue Class	Actual	Weather Normal	Adjustment	Pct
Residential	1,730,898	1,749,766	18,868	1.1%
Sml General Service	415,265	416,373	1,108	0.3%
Lrg General Service	1,158,361	1,156,994	-1,367	-0.1%
Total	**3,304,523**	**3,323,133**	**18,610**	**0.6%**

The monthly test year adjustments are included in **Direct Schedule EF-2**.

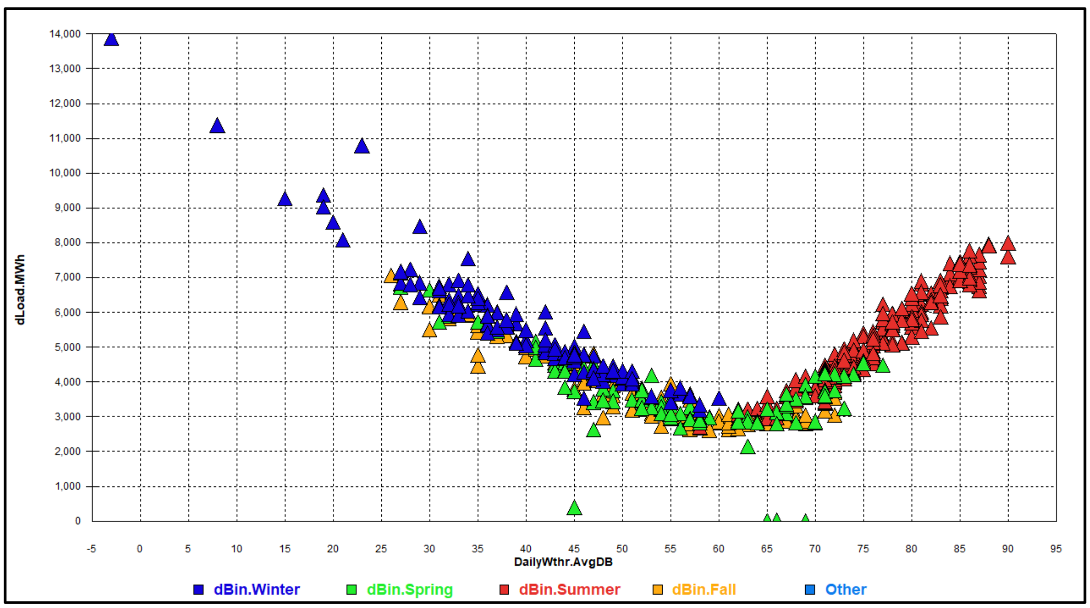
III. WEATHER-NORMALIZATION PROCESS

Q. Please explain how sales are weather-normalized.

A. Sales are weather-normalized using weather response models estimated with revenue class AMI data, that for the first time, are replacing weather models that have been estimated with load research data. Given AMI data is available for almost every customer, AMI-based models provide a high level of confidence in how specific customer classes respond to changes in weather. The modeling approach is like that used in past rate cases by both Liberty and Commission Staff; daily sales linear regression models are estimated that relate daily use to daily CDD and HDD. The coefficient on CDD and HDD combined with test year actual and normal weather are used in calculating billing-month weather adjustment factors.

The estimation process starts with evaluating the load weather relation. Figure 1 below shows the Residential temperature (on the X axis) and sales (Y axis) relationship; each point represents a day.

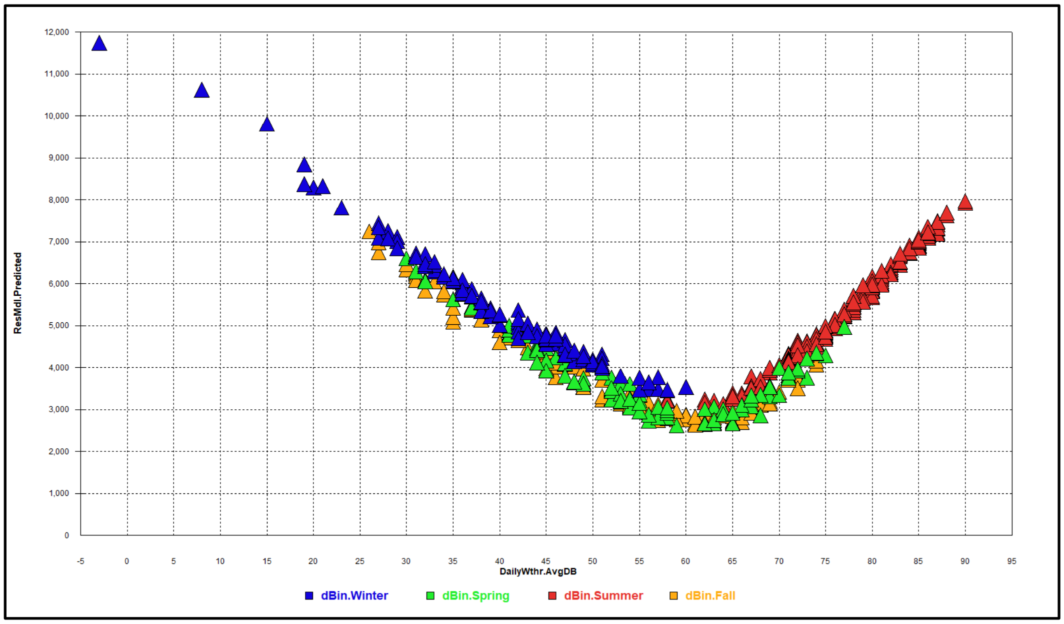
Figure 1: Residential Daily Sales (MWh) vs Daily Average Temperature



The data covers the period July 2022 through December 2023 which includes all the available AMI data at the time the models were estimated. The relationship between sales and weather is non-linear and U-shaped. When temperatures increase on the cooling side, sales increase, and when temperatures decrease on the heating side, sales also increase. The nonlinearity is addressed with HDD and CDD. HDD takes on a positive value when there is heating load (temperatures below 60 degrees) and CDD have positive values on the other side where cooling begins (above 65 degrees). The scatter plot also shows that the curve (on both heating and cooling sides) is steeper as temperatures decline on the heating side and increase on the cooling side. The weather response models address the change in the sales/temperature relationship by including HDD and CDD with multiple breakpoints. The Residential model for example includes HDD with a 60 degree breakpoint, a 55 degree breakpoint, and a 40 degree breakpoint. On the cooling side, the model includes CDD with a 65 degree base and CDD with a 75 degree base; the additional degree-day splines improve the overall model fit. As shown in the scatter plot, there are a few large outliers; the outliers on the zero line are due to missing interval data and are excluded from the modeling data set. The extreme value (December 23, 2022) is also excluded as this represented a unique extreme cold weather event not likely to be experienced in a typical weather year.

Degree-day breakpoints are selected by first visually identifying where the sales/temperature relationship appears to change and then evaluating the degree-day model coefficient statistical significance and overall model fit statistics. Other model variables include prior-day HDD and CDD where statistically significant, and month, weekend, and holiday binary variables used to capture non-weather-related sales variation. Figure 2 below shows the resulting Residential weather model fit.

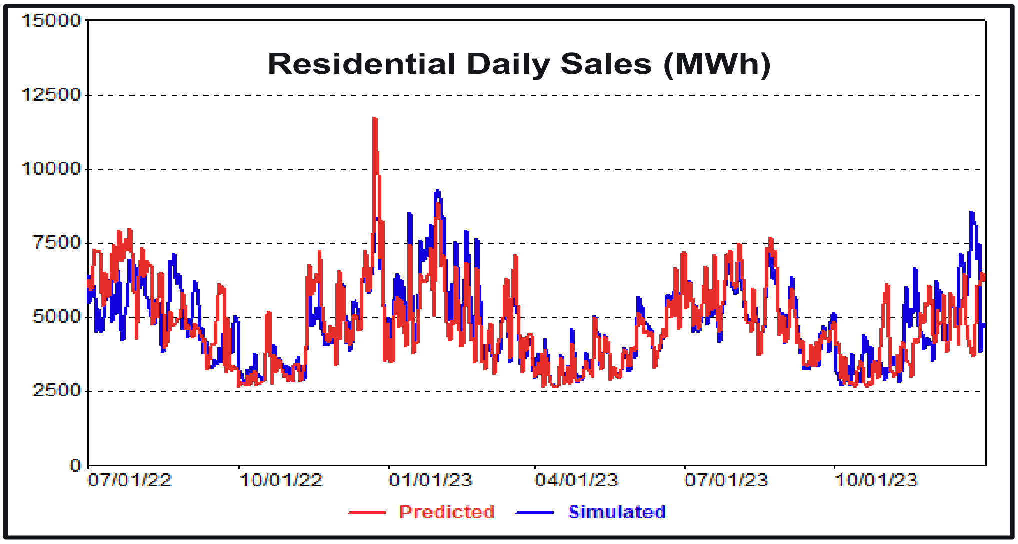
Figure 2: Predicted Residential Sales (MWh) vs Daily Average Temperature



Models are estimated for the period July 1, 2022, through December 31, 2023. The weather variable coefficients are statistically strong, and when combined with the binary variables, explains load variation sufficiently as measured by the model fit statistics. Estimated model statistics, actual and predicted plots, and scatter plot graphs are provided in **<u>Direct Schedule EF-3</u>** for all three models.

Once estimated, the models are used to predict daily sales with actual weather (predicted) and daily sales with normal weather (simulated). Figure 3 below shows the Residential results.

Figure 3: Predicted (Actual Weather) and Simulated (Normal Weather)



Simulation results are used in calculating monthly billing adjustment factors for each rate class. Daily predicted sales with actual weather and predicted with normal weather are summed across the meter read schedule. Billing weather adjustment factors are then calculated as the ratio of predicted with normal weather to predicted with actual weather. Billing-month sales are adjusted up if the adjustment factor is greater than 1.0 and adjusted down if the adjustment factor is less than 1.0. Calculations and resulting billing adjustment factors are also included in **<u>Direct Schedule EF-2.</u>**

MetrixND (Itron's energy forecasting and analysis application) is used for evaluating load weather relationship, estimating weather response models, and deriving daily predicted (with actual weather) and normal daily sales. MetrixLT (Itron's hourly load and weather modeling application) is used in calculating monthly billing adjustment factors.

Q. Please explain how daily normal weather is calculated.

A. The approach used for calculating daily normal degree-days is similar to the previous Commission Staff method. Daily normal degree-days are first calculated from average temperatures for the SGF. The normal weather period is 1992 through 2021. Normal daily temperatures are calculated for each month using a rank and average approach. This entails ranking the daily degree-days in each month and year from the highest daily degree-day to the lowest daily degree-day value. The daily rankings within each month are then averaged across the years. This is illustrated in Figure 4 below which shows the rank and average for January HDD 55. Each line represents a year; the line in the lower graph shows the average of 30-year ranking.

Figure 4: January Rank and Average (HDD 55)

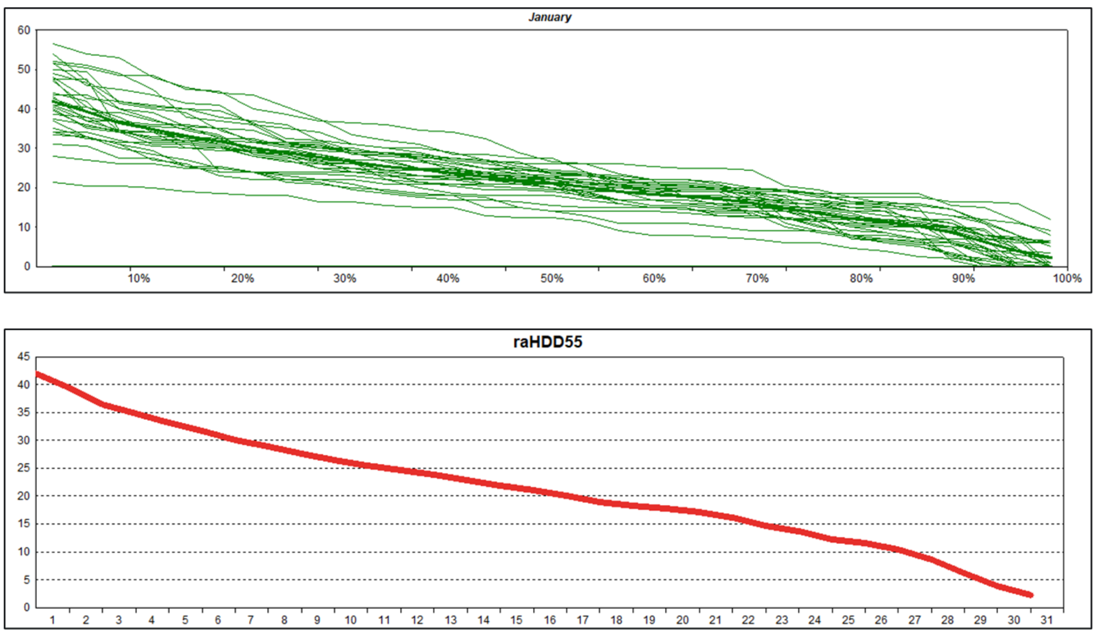
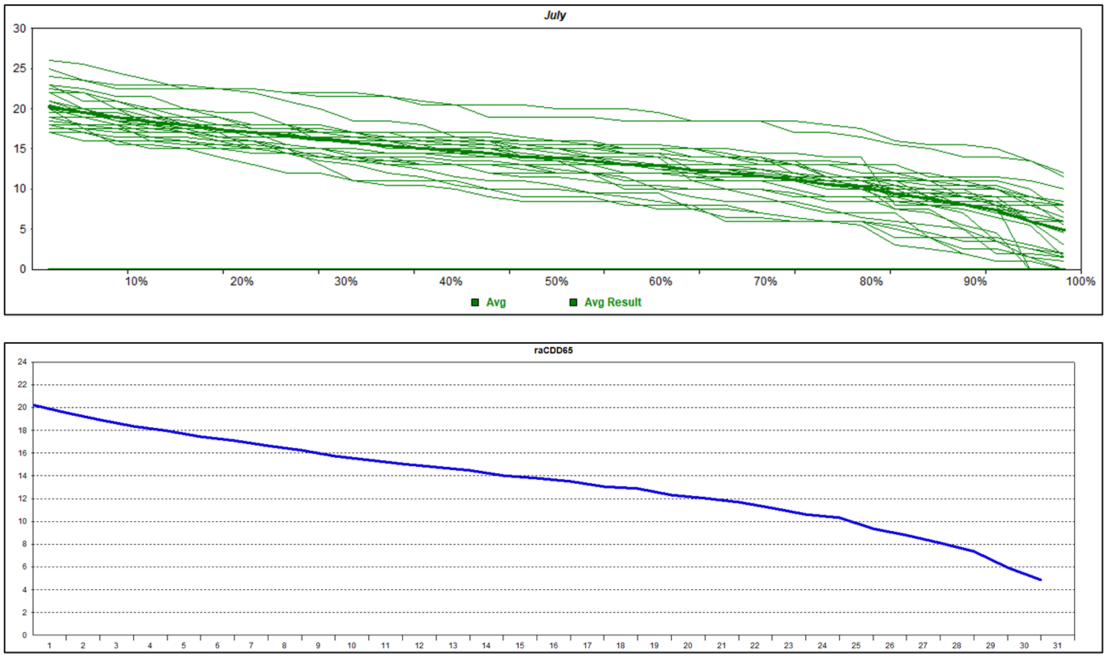


Figure 5 below shows CDD 65 rank and average for July.

Figure 5: July Rank and Average (CDD 65)



The daily normal degree-day curves are then mapped to the test year weather pattern within each month. For example, the December daily normal HDD curve is mapped to the December test year HDD weather pattern, while the July CDD daily normal curve is mapped to the test year July CDD weather pattern. Figure 6 below shows the resulting test year normal HDD pattern, and Figure 7 below shows the daily normal CDD pattern.

Figure 6: Test Year Normal Daily HDD 55

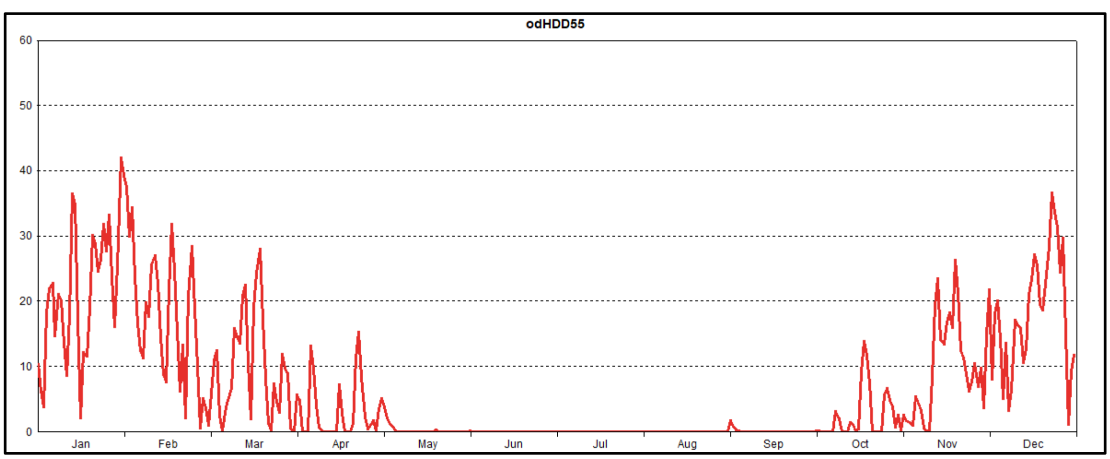
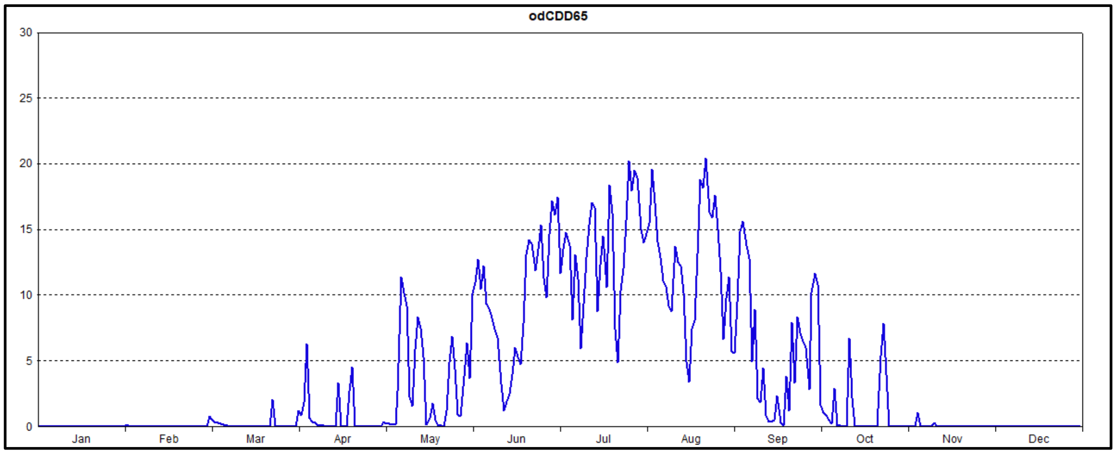


Figure 7: Test Year Normal Daily CDD 65



Daily normal degree-days are calculated using the MetrixLT weather objects including the *Rank and Average Transform* and the *Ordered Daily Transform*.

Q. How does the transition to AMI-based rates and data impact sales weather normalization?

A. New time of use rates went into effect in the first month (October 2022) of the test year period. Where there was historically one main Residential rate, there are now three Residential rates. Similarly, there are now three Small General Service rates and four Large General Service rates. The majority of Residential customers have transitioned to the new Time Choice rate schedule, but in the first two months (October and November 2022) most of the sales are in the Non-Standard ("NS") rate. Small General Service and Large General Service showed the same rate migration pattern. Given the sales transition, we assumed the weather response is the same across rate schedules within each revenue class as there is not enough data to determine if transitioning from the NS rate to the Time Choice rate has impacted how customer sales respond to temperature.

Transitioning to AMI data posed another challenge: AMI data was not available until July 2022 resulting in a somewhat short estimation period (through December 2023). Further, there are a few days in both March and April 2023 where data is missing.

This is not surprising considering the collection and processing of AMI interval data is relatively new; the longer customer usage is measured utilizing AMI data, its quality is expected to improve. Another more generalized issue is AMI interval data does not provide 100% coverage (this is true with most AMI interval data Itron has evaluated). For example, there are customers who opt out of the installation of AMI meters, meter read intervals are sometimes missing due to storms or various other reasons, and the aggregation process is not perfect.

Despite these nominal data issues, we are able to estimate statistically strong weather adjustment coefficients as there are still over 530 daily sales/weather observations. And given the breadth of AMI coverage, it is a significant improvement over the much smaller load research samples previously employed. The weather adjustment process addresses any issues related to the difference in AMI and billed sales. Models are not directly used to calculate weather impacts, but instead are used in constructing sales adjustment factors that reflect the difference in normal and actual weather over the billing-month period that are then applied to actual billed sales.

IV. CONCLUSION

Q. Please summarize your testimony.

A. As also experienced in the last several years, the test year winter heating months temperatures are generally below normal resulting in positive weather adjustments. In contrast, the summer months temperatures are on average above normal and are weather normalized downward. The positive winter adjustments outweigh the negative summer adjustments resulting in a 0.6% overall positive sales adjustment. The calculation of daily normal weather data is similar to the method adopted by Staff, and combined with estimated weather model coefficients, generate reasonable daily normal sales estimates that reflect the test year monthly weather patterns.

Despite minor data issues, the AMI data allowed us to estimate statistically strong customer class weather response models that reflect the current sales/weather relationship. The approach used for calculating billed sales adjustment factors and the application of these factors to actual billed sales addresses any issue related to differences in billed sales and AMI data coverage.

Q. Does this conclude your direct testimony at this time?

A. Yes.

VERIFICATION

I, Eric Fox, under penalty of perjury, on this 6th day of November, 2024, declare that the foregoing is true and correct to the best of my knowledge and belief.

/s/ Eric Fox