FILED
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INDIANA UTILITY
REGULATORY COMMISSION

VERIFIED DIRECT TESTIMONY

OF

ERIC FOX

ITRON, INC.

ON BEHALF OF

INDIANAPOLIS POWER & LIGHT COMPANY

D/B/A AES INDIANA

Cause No. 45911

SPONSORING AES INDIANA ATTACHMENT EF-1

VERIFIED DIRECT TESTIMONY OF ERIC FOX

ON BEHALF OF AES INDIANA

1. BACKGROUND AND INTRODUCTION

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

A1. My name is Eric Fox. I am employed by Itron, Inc. ("Itron"). My business address is 20 Park Plaza, 4th Flr, Boston, Massachusetts, 02116.[1]

Q2. What is your position with Itron?

A2. I am Director, Forecast Solutions.

Q3. On whose behalf are you submitting this direct testimony?

A3. I am testifying on behalf of AES Indiana (the "Company").

Q4. Please describe your duties as Director, Forecast Solutions?

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

[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.

analysis topics. I am an active participant in forecasting and load analysis conferences and forums across the country.

Q5. Please state your education, professional and work experience.

A5. I received my M.A. in Economics from San Diego State University in 1984 and my B.A. in Economics from San Diego State University in 1981. While attending graduate school, I worked for Regional Economic Research, Inc. ("RER") as a SAS programmer. After graduating, I worked as an Analyst in the Forecasting Department of San Diego Gas & Electric. I was later promoted to Sr. Analyst in the Rate Department. I also taught statistics in the Economics Department of San Diego State University on a part-time basis.

In 1986, I was employed by RER as a Senior Analyst. I worked at RER for three years before moving to Boston and taking a position with New England Electric as a Senior 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 expected weather conditions that reflect long-term temperature trends to support sales and system hourly load forecasting. My resume is included as AES Indiana Attachment EF-1.

Q6. Have you previously testified before a regulatory commission?

A6. Yes. I provided testimony related to weather normalization and forecasting in several regulatory proceedings. This includes weather-normalization rebuttal testimony that I provided for Indianapolis Power & Light 2014 Rate Case (Cause No. 44576) and weather-normalization testimony in the Indianapolis Power & Light 2017 Rate case (Cause No. 45029). My work and regulatory experience are provided in my resume, AES Indiana Attachment EF-1 (***Work and Regulatory Experience***).

Q7. What is the purpose of your testimony in this proceeding?

A7. The purpose of my testimony is to support the 2022 test-year sales weather normalization and development of the test-year rate class hourly load profiles for determining customer class costs. 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, the weather adjustment factors that are inputs to the Company's Utility International (UI) Financial Planning Module, and rate class test-year hourly load estimates for both actual and expected weather conditions.

Q8. Did you submit supporting work papers?

A8. Yes. Calculations of weather normalized sales, sales adjustment factors, and inputs (estimated model statistics, coefficients, test-year weather, test-year customers, and test-year sales) are provided AES Indiana Workpaper EF-1. Model data is provided in AES Indiana Workpaper EF-2. Weather data and test-year meter read schedule are included in AES Indiana Workpaper EF-3.

Q9. Please describe the approach used for weather normalizing test-year sales.

A9. Weather normal sales are estimated for seven (7) weather-sensitive rates within three revenue classifications. The weather-normalized rates are:

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

3. Large C&I Services

- Rate SL (Large C&I, Secondary Service)

Large C&I Services also include PL (Primary Large), and three HL (High Load Factor) rate classes; these rate classes are primarily industrial load and on an aggregated rate-class basis show little weather-sensitivity.

Weather normalized sales are estimated based on a set of weather adjustment coefficients that are estimated from daily-use regression models; a separate model is estimated for each rate class. Models are estimated on a daily use per customer basis using simple regression analyses that are fully replicable. The weather adjustment coefficients are applied to the difference between actual and normal monthly degree-days to estimate a monthly per-customer weather impact. Total weather impacts are calculated by multiplying per-customer impacts by number of rate class customers. Weather normalized sales are derived by subtracting the weather impact from actual billed sales.

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

Q10. How do test-year weather conditions compare with normal weather conditions?

A10. The test-year period includes a slightly warmer than normal summer cooling period and slightly cooler than normal heating period. As a result, there is a small downward adjustment to test-year sales; total test-year sales are adjusted down 0.3%. Residential sales are adjusted down 0.5%, small commercial sales are adjusted down 0.3%, and there is a marginal .03% adjustment down for large C&I sales.

Sales are weather normalized based on the difference between actual and normal heating degree-days (“HDD”) and cooling degree-days (“CDD”) and estimated model coefficients that measure the sensitivity of each rate class to changes in degree-days. HDDs are a measure of heating requirements and CDDs are a measure of cooling requirements. Monthly reported sales are based on the meter read schedule (a period that overlaps calendar-months). For weather-normalization both actual and normal HDD and CDD must also reflect the same billing period as sales. These are called cycle weighted HDD and CDD. January cycle-weighted HDD, for example, will largely include temperature data from the first half of January and second half of December while July CDD will include temperatures from the first half of July and second half of June. Table 1 compares actual and normal cycle weighted CDD.

Table 1: Comparison of Actual and Normal Cycle-Weighted CDD

Cycle -Weighted CDD (65 Degree Base)			
Month	**Actual**	**Normal**	**Difference**
Jan-22	0.0	0.0	0.0
Feb-22	0.0	0.1	-0.1
Mar-22	0.0	1.1	-1.1
Apr-22	2.0	10.3	-8.4
May-22	50.0	38.2	11.7
Jun-22	194.6	172.9	21.6
Jul-22	373.5	331.7	41.8
Aug-22	348.8	341.8	7.0
Sep-22	259.7	262.8	-3.0
Oct-22	63.5	88.8	-25.3
Nov-22	2.0	8.0	-6.0
Dec-22	0.0	0.2	-0.2
Total	**1,294.0**	**1,255.8**	**38.2**

Over the test-year period, CDD (with a base temperature of 65 degrees) are 3% above normal. Table 2 compares actual and normal HDD.

Table 2: Comparison of Actual and Normal Cycle-Weighted HDD

Cycle -Weighted HDD (55 Degree Base)			
Month	**Actual**	**Normal**	**Difference**
Jan-22	629.4	720.2	-90.8
Feb-22	831.3	721.0	110.3
Mar-22	491.1	540.6	-49.5
Apr-22	285.4	254.0	31.4
May-22	79.2	63.3	15.9
Jun-22	0.4	8.9	-8.6
Jul-22	0.0	0.0	0.0
Aug-22	0.0	0.0	0.0
Sep-22	0.5	0.3	0.2
Oct-22	47.3	30.9	16.4
Nov-22	161.9	179.0	-17.1
Dec-22	507.3	481.9	25.3
Total	**3,033.8**	**3,000.2**	**33.6**

HDD (with a base temperature of 55 degrees) are 1.1% higher than test-year normal HDD. Typically, normal HDD and CDD are based on a simple 20-year or 30-year average of historical daily HDD and CDD. But as shown in the recent 2022 IRP Public Report (Volume 3 of 3), there has been a measurable increase in average annual temperature; between 1960 and 2020 average temperature increased 0.05 degrees per year (0.5 degrees per decade). A twenty-year average will underestimate cooling requirements and overestimate heating requirements. The 0.05-degree annual temperature trend is used in calculating trended-normal daily HDD and CDD for the IRP forecast. For consistency, the same normal daily trended HDD and CDD are used in normalizing 2022 test-year sales.

Test year sales are weather normalized by subtracting weather impact from monthly sales where the weather impact is calculated by multiplying the difference between normal and actual HDD and CDD by weather adjustment coefficients. The calculations are on a use-per-customer basis (UPC). This can be written as a simple equation:

Equation 1. $\boldsymbol{Wthr\ Nrm\ UPC_{rm} = UPC_{rm} - (CDD\ coef_r * (NrmCDD_m - ActCDD_m)}$

$\boldsymbol{+\ HDD\ coef_r * (NrmHDD_{rm} - ActHDD_m))}$

Where ***r*** is the rate class and ***m*** is the billing cycle month.

Sales weather impacts are calculated by multiplying the use per customer impact by number of customers. Table 3 shows test-year actual and weather normal billed sales by rate and revenue class.

Table 3: Actual and Weather-Normal Billed Sales

Rates	Sales (MWh)	Wthr Adj Sales	Adjustment	Sales Change
Residential				
RS	2,374,517	2,363,378	11,139	-0.47%
RH	2,412,350	2,398,105	14,245	-0.59%
RC	438,679	436,139	2,540	-0.58%
Total	**5,225,546**	**5,197,621**	**27,924**	**-0.53%**
Small C&I				
SS	1,260,777	1,258,880	1,898	-0.15%
SH	502,382	499,781	2,601	-0.52%
SE	15,415	15,415	-	
Total	**1,778,574**	**1,774,075**	**4,499**	**-0.25%**
Large C&I				
SL	3,264,549	3,262,888	1,660	-0.05%
PL	1,083,887	1,083,887	-	
H1	1,299,170	1,299,170	-	
H2	183,428	183,428	-	
H3	242,607	242,607	-	
PH	27,374	27,374	-	
Total	**6,101,015**	**6,099,355**	**1,660**	**-0.03%**
All Classes	**13,105,135**	**13,071,051**	**34,084**	**-0.26%**

Overall, weather had a small impact on test-year sales. Residential sales are weather-normalized down 0.5%, small commercial sales are weather-normalized down 0.3%, and large C&I sales are marginally adjusted down. Total sales are weather normalized down

0.3%.

Q11. Please describe how the weather adjustment coefficients are calculated.

A11. The weather adjustment coefficients are derived from a set of daily weather response functions that relate daily use per customer (UPC) to daily CDD and HDD and other binary variables that account for non-weather-related variation. Depending on the model, non-weather variables include weekend, and holiday variables, binaries for specific months, and binaries to mark off large residuals that impact the estimated weather coefficients. Separate models are estimated for the three residential rate classes (RS, RH, and RC), three of the small commercial rate classes (SL, SH, and SE), and the large C&I rate SL. Daily linear regression models are estimated using 2022 advanced metering infrastructure ("AMI")-based sample data. The relationship between UPC and temperature is nonlinear and varies across rate classes. Figures 1 and 2 show the relationship for RS and RH rate and Figure 3 shows the relationship for the small commercial rate SS.

Figure 1: RS UPC/Temperature Relationship (2022)

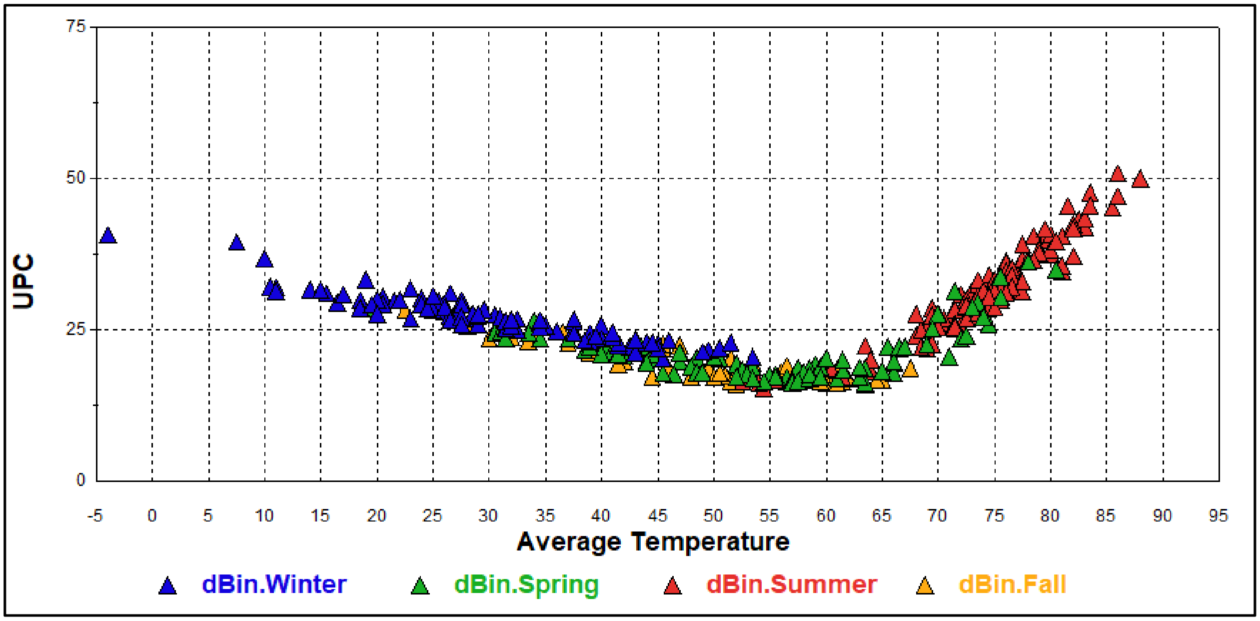


Figure 2 : RH UPC vs. Temperature (2022)

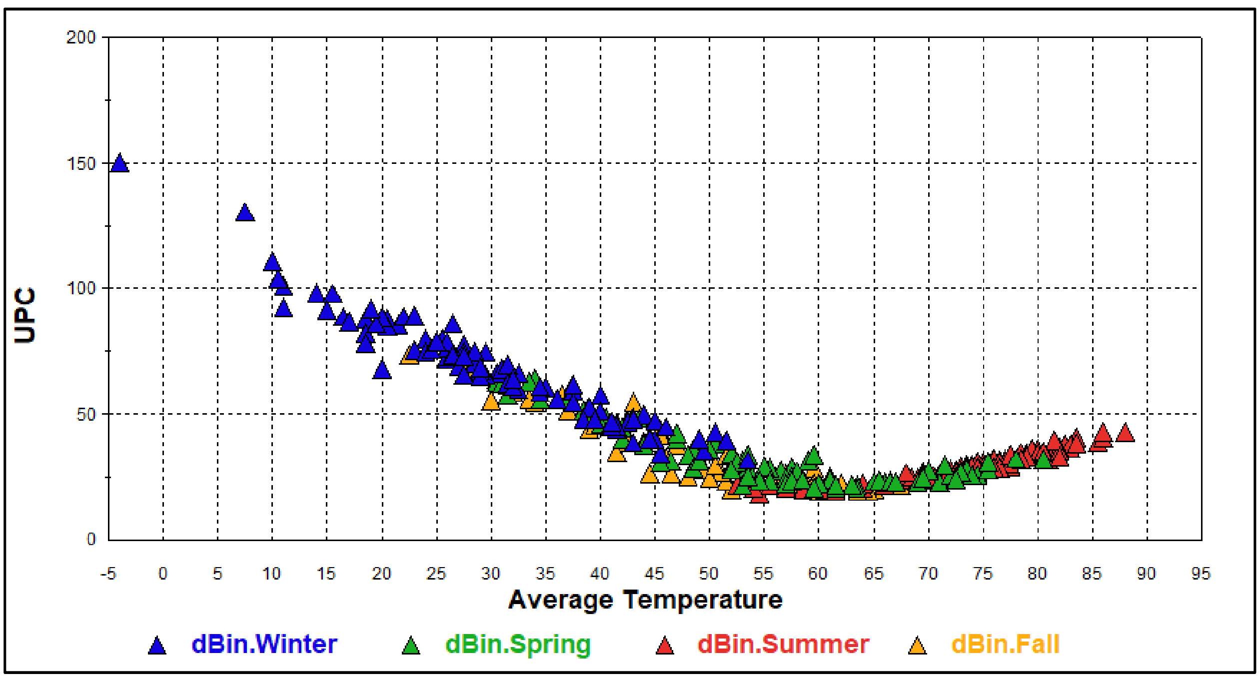
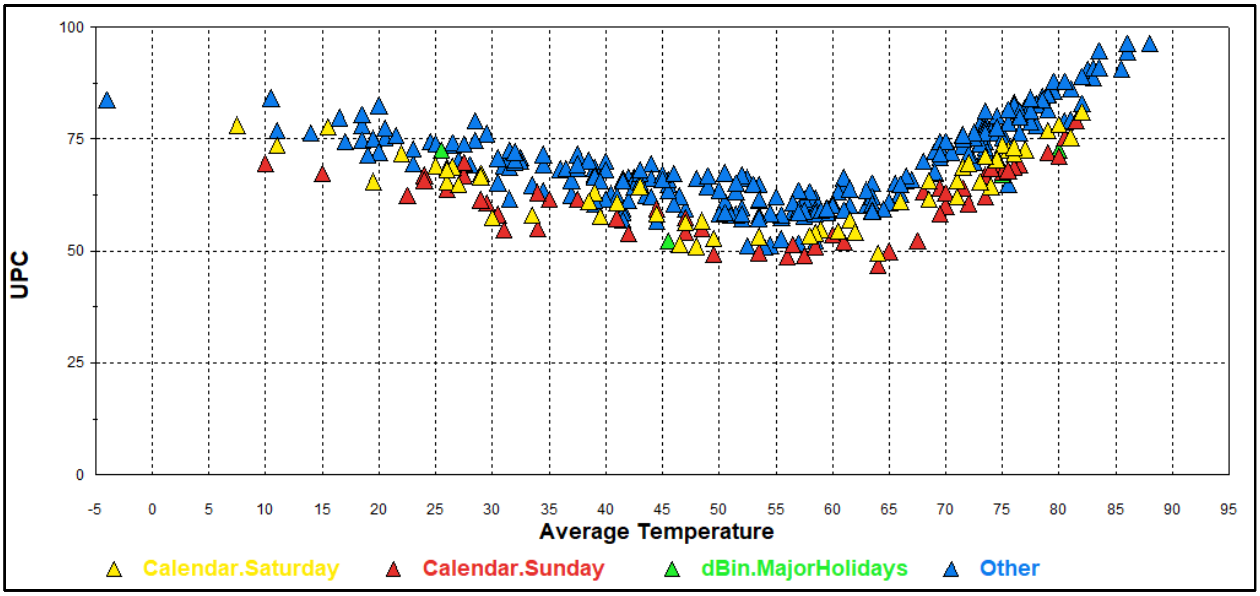


Figure 3: SS UPC vs. Temperature (2022)



Each point on the graphs represents the average daily use and the average daily temperature. Each plot shows a different relationship between daily use and temperature. Our objective is to find the best model fit using CDD to explain the "hot" side relationship on the right and HDD to explain the "cold" side relationship on the left. The best model fit in terms of model statistics can have one or more HDD and CDD variables with HDD and CDD defined for different temperature breakpoints. For example, the best fit for the RS model has a HDD with a temperature base of 55-degrees (a positive value when temperatures are below 55, otherwise equals 0) and three CDD variables that have temperature reference points of 60 degrees (a positive value when temperatures are above 60 degrees), 65 degrees, and 75 degrees that are all statistically significant at the 95 percent confidence level. The RH model is less complex with HDD with a 55-degree temperature base and CDD with a temperature base of 65-degrees. The SS model does not show heating loads until average temperatures are below 50 degrees (HDD with a 50-degree temperature base) and CDD with a 60- degree and 70-degree temperature base. Estimated models explain the UPC/temperature relationship relatively well with Adjusted R-Squared over 0.90; the Adjusted R-Squared measures the amount of variance the model can explain with 1.0 indicating perfect explanation. The weather coefficients are statistically strong with T statistics indicating 95% level of statistical confidence (a test that indicates the impact of the degree-day variables on customer use). Model and variable statistics, actual and predicted plots, and scatter plots showing the predicted use per temperature point are included in AES Indiana Workpaper EF-1. Table 4 shows the degree-day coefficients, associated T-Statistics, and model Adjusted R-Squared. The coefficients measure the change in UPC for a change in one degree-day.

Table 4: Estimated Degree-Day Coefficients and Model Fit

Rate	HDD50	HDD55	CDD60	CDD65	CDD70	CDD75		Adjusted R-Squared
RS		0.328	0.304	0.847		0.265		0.952
T-Stat		29.81	3.34	6.19		2.77		
RH		1.778		0.052				0.967
T-Stat		78.38		12.81				
RC		0.619		1.294				0.93
T-Stat		78.38		37.15				
SS	0.464		0.868		0.474			0.917
T-Stat	19.84		12.38		3.96			
SH		11.004		8.526				0.952
T-Stat		43.09		18.22				
SL	3.642		21.146		6.218			0.948
T-Stat	7.78		14.01		2.41			

Q12. How are the billed sales adjustment ratios calculated?

A12. The estimated degree-day coefficients are used to calculate the weather impacts and normalized use per customer as shown in Equation 1 above. AES Indiana Workpaper EF-1 shows how the coefficients are used to calculate the weather impact, normalized average use, and normalized sales. Sales adjustment ratios are derived as the ratio of normalized monthly sales to actual monthly sales. The sales adjustment ratios are inputs to the UI Financial Planning Model.

Q13. As part of the rate case work, you developed rate class and system hourly loads for actual and normal weather. Please explain how the load shapes are developed.

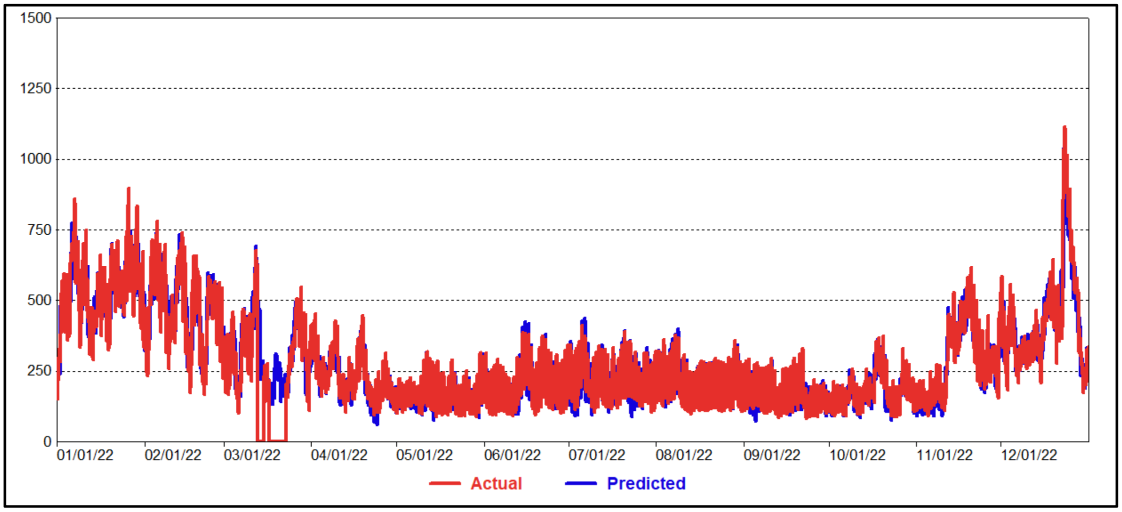
A13. Test-year rate class 8,760 load estimates are developed for actual and normal weather conditions. Table 5 lists the rate classes that are included.

Table 5 : Rate Classes

Residential	**Code**
Residential Heating	RH
Residential General Service	RS
Residential Water Heating	RC
Residential Outdoor Lighting	R_APL
Small Commercial	**Code**
Secondary Service Small	SS
Secondary Service Heating	SH
Schools Electric Heat	SE
Commercial Outdoor Lighting	C_APL
Large C&I	**Code**
Secondary Service Large	SL
Process Heating	PH
Primary Distribution	HL1
Primary Distribution	HL2
Primary Distribution	HL3
Primary Distribution	HL4
Primary Service Large	PL
Industrial Outdoor Lighting	I_APL
Other	**Code**
Water Heating Controlled	CB
Water Heating Uncontrolled	UW
Street Lighting	StLight
Traffic Control	TrafficLight
DPW Meters	Muni Devices

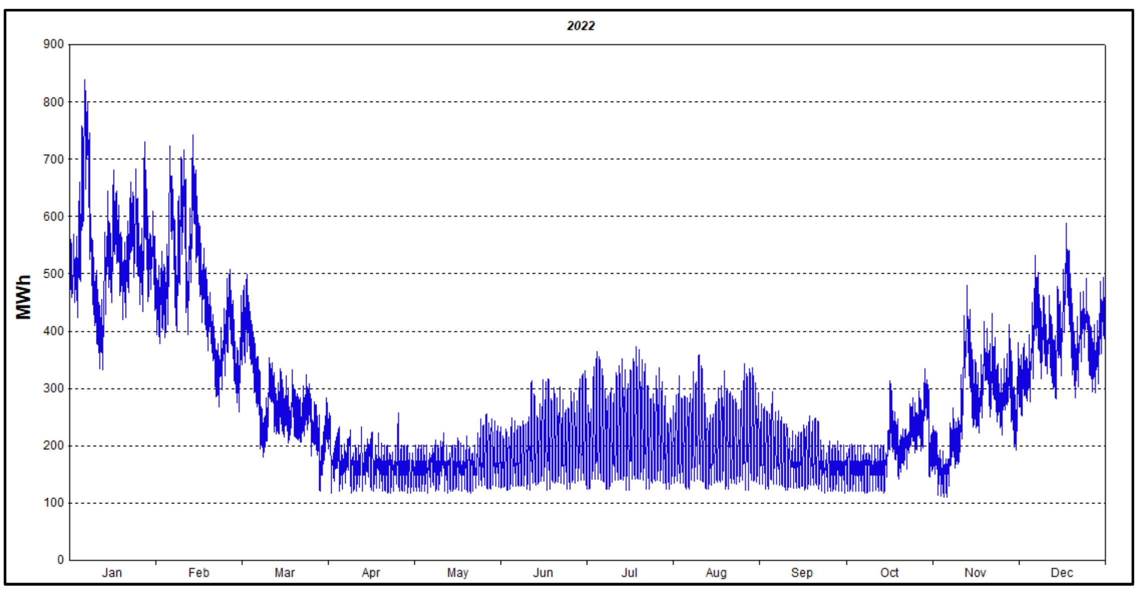
The DPW Meters (Rate MD) is a new relatively small rate class proposed for municipal devices, as explained further by Company witness Aliff. The profile is based on high load factor SS customers (over 80% load factor) with low annual use (less than 2,400 kWh per year). The profile is combined with expected sales of 869 MWh which is approximately 0.1% of system sales. There are two customers in the current HL3 rate that have been split with one customer moved to the new HL4 rate. Test-year hourly load estimates are used to derive customer class maximum and coincident peaks and calendar month energy (loss adjusted) that are inputs to the ***Cost-of-Service Study***. Hourly rate class models are estimated using the 2022 AMI sample data (same data set used to estimate the sales weather adjustment factors) and census (aggregation of all customers) for the Largest C&I rates including PH, PL, and the high load factor rates HL1, HL2, HL3, and HL4. Rate class load profiles are derived for both actual and normal weather; for consistency, the hourly load models are relatively simple using the same specification as that used in the daily UPC models. The models fit the data relatively well; as an example, Figure 4: RH Test-Year Load Estimate shows the RH predicted hourly load profile (in blue) against AMI sample expansion load (in red).

Figure 4: RH Test-Year Load Estimate



To calculate weather-normal profiles, estimated models are simulated with daily normal degree-days - the same data set used in constructing the monthly normal HDD and CDD variables. Figure 5 shows the weather-normal RH load profile.

Figure 5: RH Weather-Normal Profile



Typically, the RH rate class peaks in January when the coldest weather generally occurs. Test-year rate class load estimates are generated by combining actual sales with rate class estimated profiles and adjusting the loads for line losses. To validate test-year load estimates, rate class loads are aggregated (***Buildup***) and compared with system load (***System***). Figure 6 compares the test-year Buildup hourly load (in blue) with the System actual load (in red).

Figure 6: Buildup Load Comparison

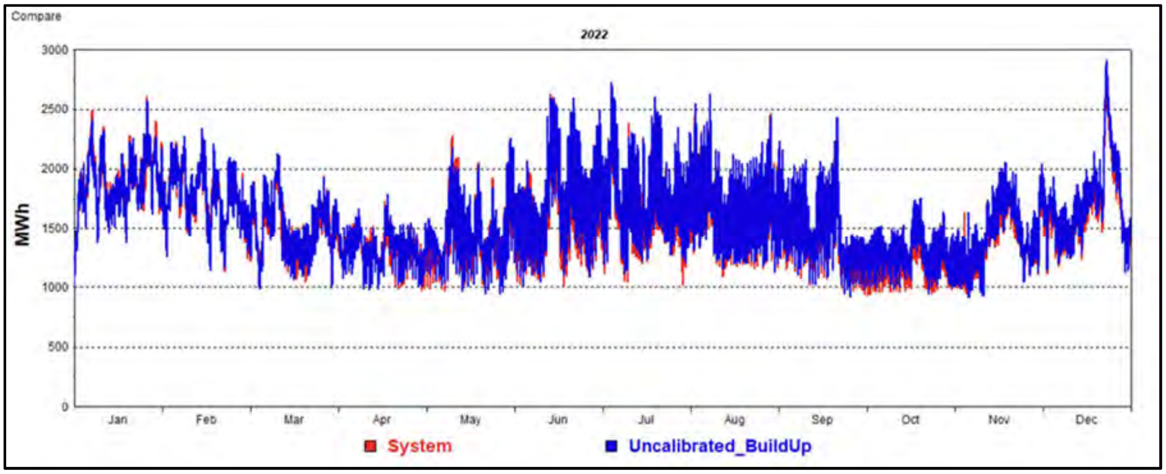
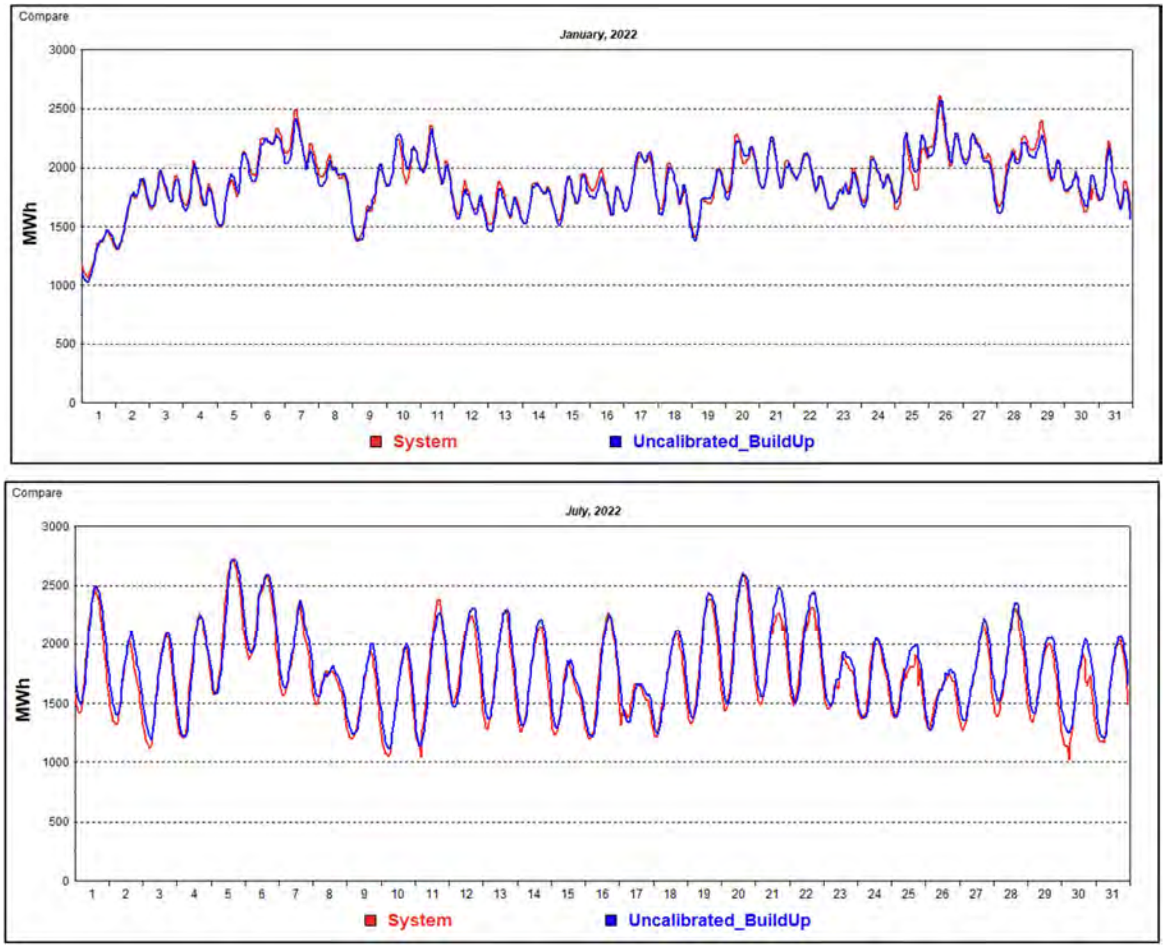


Figure 7 shows the January and July Buildup comparison.

Figure 7: January and July Buildup Load Comparison



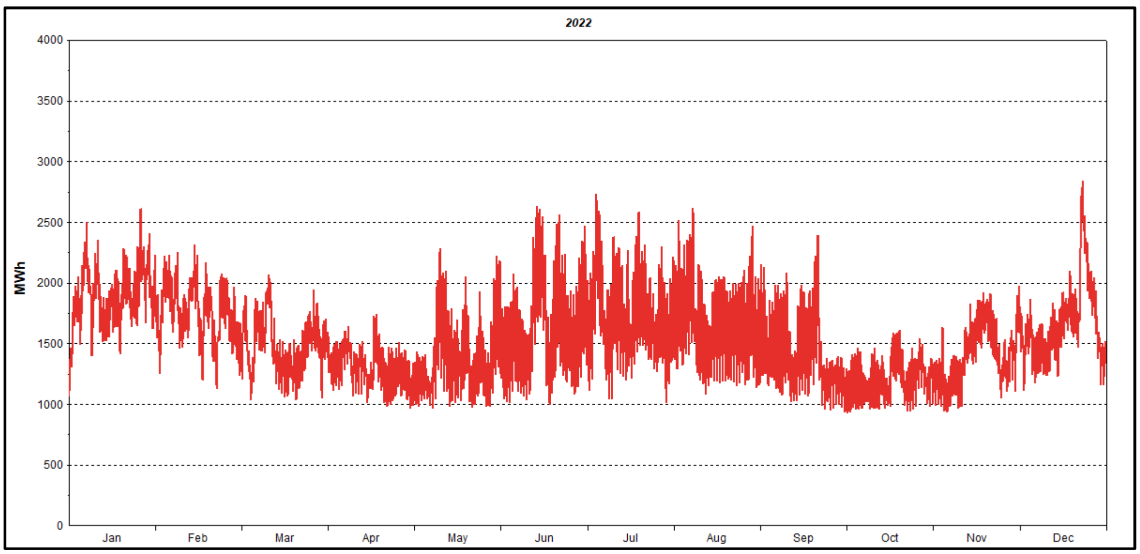
Overall, the Buildup load is relatively close to actual system loads indicating that load estimation process results in reasonable test-year rate class loads. Final test-year rate class loads are generated by calibrating the initial rate class loads (loss adjusted) to system hourly loads.

Weather-normal test-year loads are derived in a similar manner by combining weather-normal class sales with weather-normal rate class hourly load profiles. The weather-normal profiles are also adjusted for line losses and calibrated to system weather-normal load estimate.

Q14. Why are rate class profiles weather normalized?

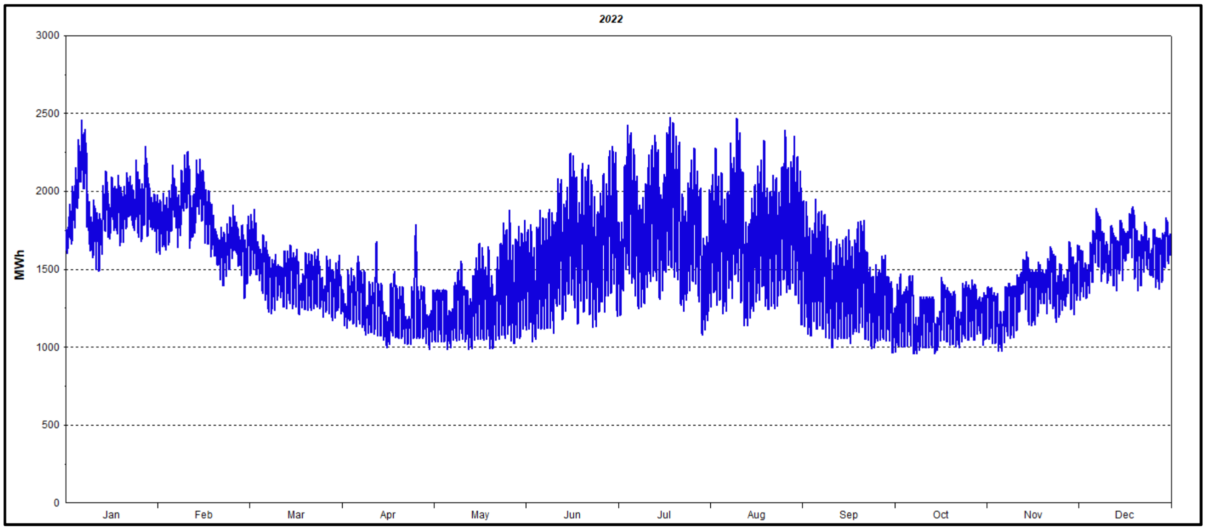
A14. In past filings, hourly load estimates based on actual test-year weather were used in developing rate class cost allocation factors with the system typically peaking in the summer months; test-year loads for actual weather generally provide reasonable coincident and noncoincident peak demand estimates for allocating costs. The 2022 system hourly load, however, was not typical largely because of winter storm Elliot that resulted in extreme cold temperatures just before Christmas with the system peaking on December 23rd. Figure 8 shows the 2022 system load.

Figure 8: 2022 Test-Year System Load



Utilizing actual test-year loads would result in rate allocation factors that would not necessarily reflect rate class imposed costs. Further as test-year sales are weather normalized for revenues it is reasonable to also weather-normalize rate class and system hourly loads on the cost side. Figure 9 shows the weather normal system hourly load profile based on a 20-year weather pattern.

Figure 9: Test-Year Weather Normal System Load



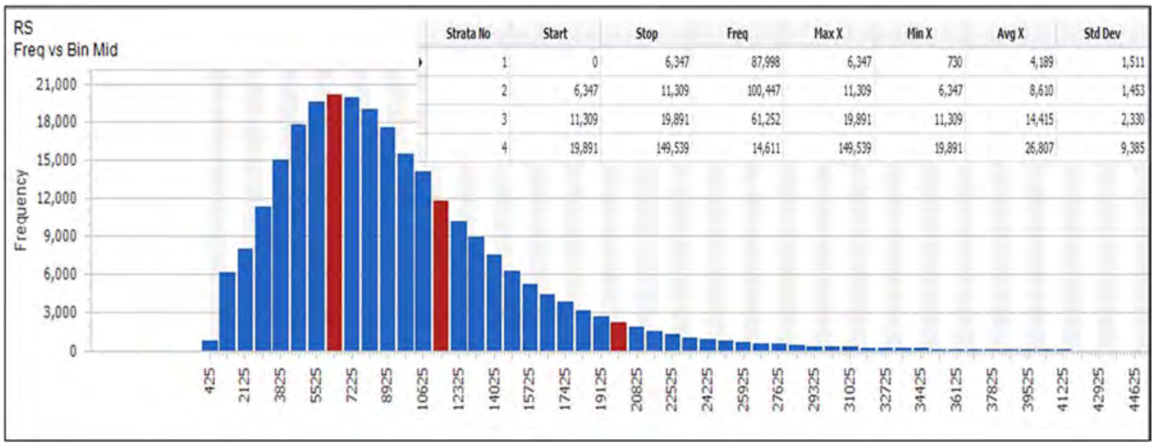
Q15. How are rate class coincident and non-coincident peaks calculated?

A15. MetrixLT (Itron's hourly load modeling and analysis application) ***Frequency Transform*** is used to find rate class coincident (with system) and noncoincident peaks for both actual and weather normal calibrated rate class hourly loads. The Frequency Transform generates reports by day, month, or year for coincident loads, peak time, non-coincident loads, minimum loads, monthly energy, and load factor. The Frequency Transform is used to calculate monthly coincident, non-coincident, and monthly energy for each rate class. Results are exported to the Excel file ***RateClassPeakandEnergy_2022.xlsx***.

Q16. What are the data sources used in developing the rate class hourly loads?

A16. Rate class hourly load profiles are estimated from AMI data for all but the industrial rate classes. The industrial rate class profiles are derived by aggregating all available customer interval data from the load research database. Profiles are based on large AMI samples selected randomly within four usage stratums for the residential rate classes and three stratums for the commercial rate classes; this is known as a stratified random sample. Stratum/usage breakpoints are determined using a standard Dalenius-Hodges (DH) breakpoint method that calculates stratum breakpoints that are designed to minimize the overall sample variance. Stratums are based on customers' 2022 annual kWh use. The DH method works well for distributions that are not normally distributed; DH considers the customer size (in terms of usage) as well as the number of customers. As an example, **Error! Reference source not found.** shows the DH breakpoints calculated for the RS rate class.

Figure 10: RS Frequency



Strata No	Start	Stop	Freq	Max X	Min X	Avg X	Std Dev
1	0	6,347	87,998	6,347	730	4,189	1,511
2	6,347	11,309	100,447	11,309	6,347	8,610	1,453
3	11,309	19,891	61,252	19,891	11,309	14,415	2,330
4	19,891	149,539	14,611	149,539	19,891	26,807	9,385

The Company randomly pulled 15-minute interval data for 250 customers within each stratum for a total of 1,000 customers in each residential rate class and 500 customers in the small commercial rate classes. The number of sample points was based both on achieving standard load research precision targets (10% at the 90% level of confidence) and LRS's (Itron's load research application) processing capacity. A few customers were ultimately excluded as a result of missing interval data. A mean per unit expansion (which is based on the ratio of population to sample customer counts) is used to develop sample loads for the residential rate classes and combined ratio expansion (which is based on population average use to sample average use) for the commercial rate classes. Table 6:

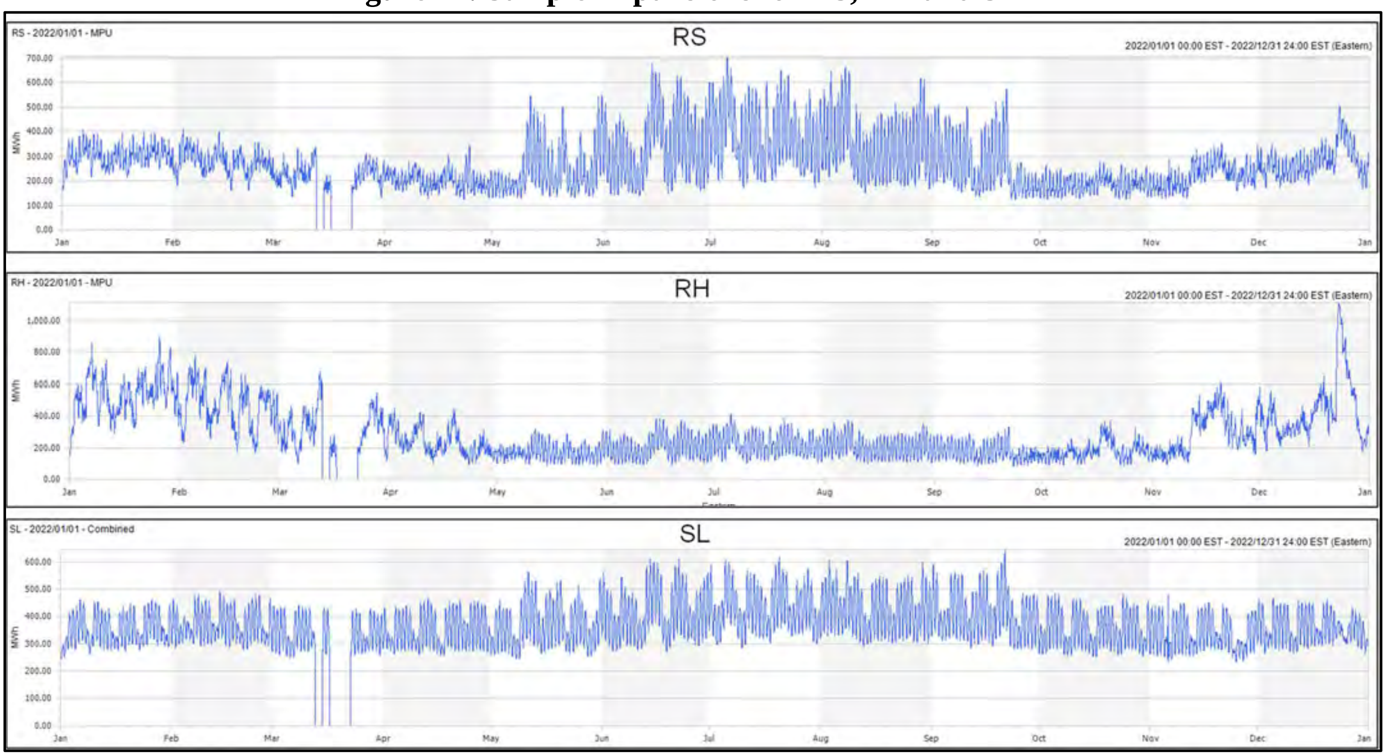
Sample Statistics shows total customer counts and billed sales (2022), sample size, number of stratums, and measured precision at time of the July and January system peak.

Table 6: Sample Statistics

Rate Class	Customers	MWh Billed	Sample Size	Number of Stratums	July Pk Precision	Jan Pk Precision
RS	253,405	2,374,517	999	4	3.39%	5.79%
RH	166,724	2,412,350	913	4	3.99%	4.00%
RC	36,266	438,679	994	4	3.41%	6.28%
SS	51,249	1,260,777	470	3	8.68%	5.01%
SH	3,752	502,382	459	3	2.10%	3.32%
SL	4,331	3,264,549	422	3	1.86%	2.03%

Sample precisions are within the desired range. As an example, shows the resulting RS, RH, and SL sample expansions.

Figure 11: Sample Expansions for RS, RH and SL



As shown in Figure 11, March is missing eight days of AMI data. For modeling, the missing days are filled with predicted hourly values from the rate class hourly load models.

2. SUMMARY AND RECOMMENDATIONS

Q17. Please summarize your testimony.

A.17. For the first time, AMI data is used for developing rate class loads for weather normalization and estimating rate class load profiles. Estimated rate class profiles are within acceptable accuracy ranges (as measured by coincident peak precision statistics) and when combined with sales and adjusted for losses are extremely close to actual system load. Weather normalization models estimated with the AMI data result in strong weather adjustment coefficients (as measured by their T Statistics) and as a result reasonable estimates of weather-normal sales.

The trended normal HDD and CDD appropriately reflects expected test-year weather conditions. Given warming temperature trends there are likely to be more CDD and fewer HDD than that of the twenty-year average. Normal daily and monthly degree-days were developed as part of the recent IRP filing. A statistically strong temperature trend coefficient indicates that average annual temperature has been increasing 0.05 degrees per year (0.5 degrees per decade); a linear trend model was estimated with annual temperature data from 1960 through 2020 from the Indianapolis International Airport.

Results of the load shape development work and weather-normalization provides reasonable normalized sales for calculating test-year revenues and actual and normalized customer load estimates for equitably allocating costs across rate classes.

Q18. Does this conclude your testimony?

A.18. Yes.

VERIFICATION

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

Eric Fox

Eric Fox
Dated: June 28, 2023

Work and Regulatory 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

Commercial Data Development for Long-Term Forecasting and Electrification Study, NYISO, with Mike Russo, Oleg Moskatov, and Rich Simons, December 2022

Forecast Model Development and Training, ISO New England, with Mike Russo, November 2022

2022 Long-term Residential and Commercial Energy Intensity Trends Presentation, Itron Energy Forecasting Group, with Oleg Moskatov and Mike Russo, September 20th, 2022

2022 Model Review Report and Presentation, PJM, with Michael Russo, Dr. Stuart McMenamin, and Dr. Frank Monforte, September 2022

Modeling Climate Change, Itron Brownbag Presentation, with Mike Russo and Dr. Frank Monforte, July 12, 2022

Forecast Review and Presentation to the SRP Power Committee, Salt River Project, with Mark Quan, April 24, 2022

Cold Climate Heat Pump Study, Nova Scotia Power, July 2022, with Rich Simons

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,

Regulatory Experience

June 2022: Provided testimony and supporting sales and weather-normalization for the 2022 Sierra Pacific Power Company (NV Energy) general rate case.

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

May 2021: Provided testimony and supporting sales and weather-normalization for the 2021 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