FILED
June 3, 2025
INDIANA UTILITY
REGULATORY COMMISSION

VERIFIED DIRECT TESTIMONY

OF

MICHAEL E. RUSSO

SENIOR FORECAST CONSULTANT ITRON

ON BEHALF OF

INDIANAPOLIS POWER & LIGHT COMPANY

D/B/A AES INDIANA

Cause No. 46258

VERIFIED DIRECT TESTIMONY OF MICHAEL E. RUSSO

ON BEHALF OF AES INDIANA

1. INTRODUCTION

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

A1. My name is Michael E. Russo. My employer is Itron, Inc at 20 Park Plaza, Suite 428, Boston, Massachusetts 02116.

Q2. What is your position with Itron, Inc?

A2. I am a Senior Forecast Consultant with Itron.

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

A3. I am submitting this testimony on behalf of AES Indiana.

Q4. Please describe your duties as Senior Forecast Consultant.

A4. I am responsible for supporting utilities, independent system operators (ISO), and transmission companies' sales, and energy forecasting requirements. My work also includes providing forecast and modeling training, supporting Itron's Energy Forecasting Group (EFG), and providing regulatory support.

Q5. Please summarize your education and professional qualifications.

A5. I received a Master of Science in International Economics from Suffolk University and a Bachelor of Arts in Economics from the University of Massachusetts.

Q6. Please summarize your prior work experience.

A6. I began at Itron in 2013 as a forecast analyst. Since that time, I have been promoted to Senior Forecast Consultant. I provide forecast and analysis support for a wide range of utility operations and planning requirements, including revenue forecasting, load research, rate case support, and resource planning. Companies I have worked with 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. Recent project work includes developing and supporting the Integrated Resource Plan (IRP) forecast for the AES Indiana IRP and Centerpoint Energy Indiana (CEI) South IRP, developing a long-term forecasting process for Northwest Power and Conservation Council, developing a 5-year forecast for use in rate making for Hydro Ottawa, and developing the forecast and providing testimony CEI South's 2024 Rate Case. Prior projects include assisting with the Vermont long-term system load and planning area forecast (Vermont Electric Power Company), developing and presenting recommendations for improving the PJM system long-term load forecast, conducting commercial end-use analysis for the New York Independent System Operator, and implementing load research systems for Oncor Electric Delivery and El Paso Electric.

Q7. Have you testified previously before the Indiana Utility Regulatory Commission ("Commission") or any other regulatory agency?

A7. Yes. I have provided testimony supporting the forecast in Centerpoint Energy Indiana South's 2024 Rate Case, Cause No. 45990.

Q8. What is the purpose of your testimony in this proceeding?

A8. The purpose of my direct testimony is to support the projected 2026 test-year sales.

Q9. Are you sponsoring or co-sponsoring any financial exhibits or attachments?

A9. No.

Q10. Did you submit any workpapers?

A10. Yes. Model data, estimated coefficients, and model statistics for tariff average use and sales models are provided in the following workpapers:

- Workpaper_Russo_RS.xlsx
- Workpaper_Russo_RC.xlsx
- Workpaper_Russo_RH.xlsx
- Workpaper_Russo_SS.xlsx
- Workpaper_Russo_SH.xlsx
- Workpaper_Russo_SL.xlsx
- Workpaper_Russo_PL.xlsx
- Workpaper_Russo_PH.xlsx
- Workpaper_Russo_HL1.xlsx
- Workpaper_Russo_HL2.xlsx
- Workpaper_Russo_HL3.xlsx

The data for coincident and non-coincident monthly tariff peaks for cost-of-service analysis is provided in the Workpaper_Russo_COS.xlsx.

Q11. Were the exhibits, attachments, or workpapers, or portions thereof, that you are sponsoring or co-sponsoring prepared or assembled by you or under your direction and supervision?

A11. Yes.

Q12. Please describe the forecast approach.

A12. The test-year period is January 1, 2026, to December 31, 2026. The forecast is based on a set of linear regression models estimated for the tariff classes listed in Table 1 below:

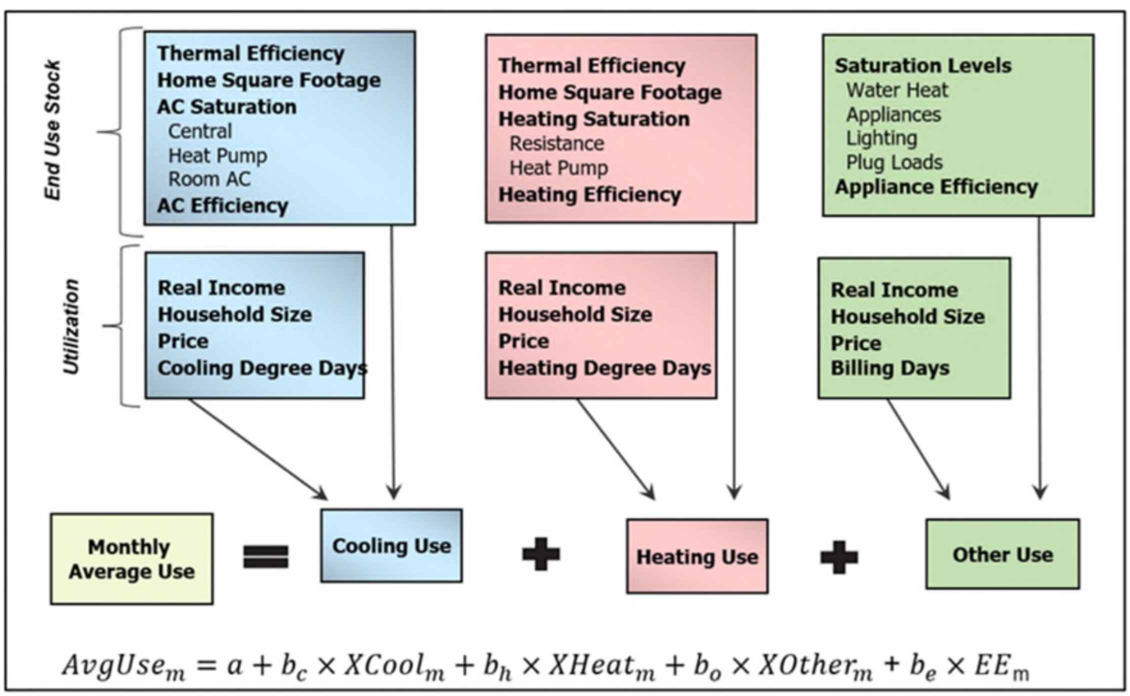
Table 1: Tariff Class Description

Sector	Tariff Code	Rate Description
Residential	RS	Residential Heating
Residential	RC	Residential General Service
Residential	RH	Residential Water Heating
Small Commercial	SS	Secondary Service Small
Small Commercial	SH	Secondary Service Heating
Large Commercial & Industrial	SL	Secondary Service Large
Large Commercial & Industrial	PL	Primary Service Large
Large Commercial & Industrial	PH	Process Heating
Large Commercial & Industrial	HL1	Primary Distribution
Large Commercial & Industrial	HL2	Sub Transmission
Large Commercial & Industrial	HL3	Transmission
Lighting & Other	StLight	Street Lighting
Lighting & Other	R_APL	Residential Outdoor Lighting
Lighting & Other	CB	Water Heating Controlled
Lighting & Other	UW	Water Heating Uncontrolled
Lighting & Other	C_APL	Commercial Outdoor Lighting
Lighting & Other	I_APL	Industrial Outdoor Lighting

Models are estimated using historical monthly billed sales and customer data for the period January 2011 to September 2024 for the residential, small commercial, and secondary service large tariffs. Models for the primary service large and primary distribution tariff are estimated using data for the period January 2018 to September 2024. The model-derived forecasts capture the expected impact of customer growth, economic activity, regional end-use saturation and efficiency trends, and AES Indiana's energy efficiency (EE) program savings. The forecast is then adjusted for customer-owned photovoltaic (PV) generation, and electric vehicles (EV).

The residential average use, small commercial sales, and secondary service models are estimated using a Statistically Adjusted End-Use (SAE) model. The purpose is to combine both long-term structural changes such as improving air conditioning efficiency and thermal shell integrity with the short-term drivers of end-use consumption, including temperature (cooling degree-days and heating degree-days), price, household income, and business activity (i.e., economic output and employment). Figure 1 illustrates the residential SAE model structure.

Figure 1: Residential SAE Framework



The data inputs are used to derive initial estimates of residential cooling ("XCool"), heating ("XHeat"), and other use ("XOther") energy requirements along with a variable to capture additional EE programs savings. The model coefficients (b_c, b_h, b_o, and b_e) are then estimated using residential average use derived from the historical billed sales and customer data. The residential average use models (RS, RC, and RH) coefficients, model statistics, and data inputs can be found in Workpaper_Russo_RS, Workpaper_Russo_RC, and Workpaper_Russo_RH. A similar SAE structured model is estimated for the small commercial and secondary service large tariffs where total monthly sales are modeled instead of average use. The small commercial and secondary service model coefficients, model statistics, and data inputs can be found in Workpaper_Russo_SS, Workpaper_Russo_SH, and Workpaper_Russo_SL.

The primary service large and primary distribution tariff models use a simple regression model approach which relates historical sales to weather conditions and monthly binaries. The lighting and water heating tariff models use a simple regression model approach which relates historical sales to monthly binaries, designed to capture the seasonal variation.

Q13. Please describe the sales forecast outlook from the end of model estimation period through the 2026 test-year period.

A13. In the next two years, sales will be driven by the number of new households, household income, electricity price, and regional economic activity reflected in regional output (Gross State Product or "GSP") and employment. The forecast is based on Moody's Analytics September 2024 Outlook for Marion County, Indiana, and the Indianapolis Metropolitan Statistical Area (MSA). Household growth is expected to average 1.6% annual near-term growth with 0.9% real household income growth. In the commercial sector, Moody's projects 2.1% real non-manufacturing GSP annual growth over the next two years with a 0.9% annual increase in non-manufacturing employment growth. The sale forecast includes the impact of new electric vehicle adoption and distributed solar adoption. Total sales increases 1.0% per year on average between 2024 and 2026. Table 2 shows the historical weather normalized sales and forecasted sales by sector.

Table 2: Annual Sector Sales

Year	Residential Sales (MWh)	Small Commercial Sales (MWh)	Large Commercial & Industrial Sales (MWh)	Lighting & Other Sales (MWh)	Total Sales (MWh)
2018	5,035,234	1,801,813	6,307,777	97,885	13,242,709
2019	5,053,770	1,796,855	6,268,397	87,507	13,206,528
2020	5,173,812	1,702,451	5,841,388	74,314	12,791,966
2021	5,186,637	1,745,544	5,963,100	63,637	12,958,918
2022	5,162,580	1,781,115	6,024,952	58,855	13,027,502
2023	5,140,619	1,774,113	5,945,728	60,610	12,921,070
2024	5,222,052	1,794,652	5,933,258	74,728	13,024,690
2025	5,321,756	1,816,983	5,996,460	69,128	13,204,328
2026	5,386,148	1,818,565	6,020,484	68,787	13,293,984

Q14. Please provide a detailed description of the residential sector forecast.

A14. The residential sector forecast is comprised of separate average use and customer models for the RS, RC, and RH tariff classes. The sales forecast is the product of the average use and customer forecasts. The average use forecast integrates end-use saturation and efficiency trends that capture energy trends with monthly weather, number of days, and economic drivers that capture the expected utilization of the end-use stock. The customer forecast captures new household formation. Each of the three residential classes has different historical and forecasted usage and customer trends. Customer growth increased significantly in 2024 compared to the prior five years. Total residential customers increased 1.6% in 2024, the average annual growth in the prior five years was 0.8%. Although the RC and RH classes currently have fewer customers than the RS class, the RC and RH classes are experiencing much stronger customer growth. Residential customers are forecasted using a composite economic variable which is comprised of Marion County and Indianapolis MSA household projections. Although the majority of AES Indiana's service territory lies within Marion County, residential customers are more highly correlated with Indianapolis households than Marion County households. For this reason, a composite customer variable was constructed which places a 75% weight on Indianapolis households and 25% weight on Marion County households. Table 3 shows the historical and forecasted average annual customer counts.

Table 3: Annual Residential Customer Counts

Year	RS Customers	Annual Diff	RC Customers	Annual Diff	RH Customers	Annual Diff	Total Residential	
2018	249,335		32,845		158,408		440,588	
2019	250,703	0.5%	33,657	2.5%	161,399	1.9%	445,760	1.2%
2020	252,027	0.5%	34,556	2.7%	163,784	1.5%	450,367	1.0%
2021	252,980	0.4%	35,274	2.1%	165,547	1.1%	453,800	0.8%
2022	253,405	0.2%	36,266	2.8%	166,724	0.7%	456,394	0.6%
2023	253,698	0.1%	37,612	3.7%	168,267	0.9%	459,577	0.7%
2024	255,233	0.6%	38,753	3.0%	172,823	2.7%	466,809	1.6%
2025	256,755	0.6%	40,053	3.4%	176,992	2.4%	473,800	1.5%
2026	258,442	0.7%	41,120	2.7%	180,360	1.9%	479,923	1.3%

Federal codes and standards, combined with AES Indiana EE program savings, have resulted in historical declines in residential usage per customer. Forecasted usage is driven by forecasted energy intensity trends and AES Indiana EE program savings. Forecasted energy intensity trends decline at a slower rate in 2025 and 2026 compared to the prior five years. Forecasted annual residential AES Indiana EE program savings in 2025 and 2026 are on average lower compared to the prior five years. Table 4 shows the usage forecast and weather normalized historical usage.

Table 4: Annual Residential Average Use

Year	RS Avg Annual kWh	Annual Diff	RC Avg Annual kWh	Annual Diff	RH Avg Annual kWh	Annual Diff
2018	9,299		12,303		14,596	
2019	9,227	-0.8%	12,169	-1.1%	14,454	-1.0%
2020	9,431	2.2%	12,322	1.3%	14,482	0.2%
2021	9,366	-0.7%	12,230	-0.7%	14,419	-0.4%
2022	9,244	-1.3%	12,050	-1.5%	14,291	-0.9%
2023	9,169	-0.8%	11,856	-1.6%	14,075	-1.5%
2024	9,217	0.5%	12,058	1.7%	13,922	-1.1%
2025	9,277	0.6%	12,097	0.3%	13,884	-0.3%
2026	9,278	0.0%	12,070	-0.2%	13,826	-0.4%

The Workpaper_Russo_RS, Workpaper_Russo_RC, and Workpaper_Russo_RH show all model data inputs, coefficients and model statistics.

Q15. Please provide a detailed description of the small commercial sector forecast.

A15. The small commercial sales forecast is comprised of total sales forecasts for the SS and SH tariff classes. Customer forecasts are developed but they do not directly impact the sales forecast. Like the residential models, SAE specified models are used, forecasting monthly sales as a function of heating requirements (XHeat), cooling requirements (XCool), other use (XOther), and AES Indiana energy efficiency program savings. The small commercial classes were significantly impacted by the reduced economic activity and mandated shutdowns brought on by the COVID-19 pandemic. On a weather normalized basis sales dropped 4.9% in 2020, by 2022 sales had rebounded to 2019 levels. Over this course of time federal codes and standards, combined with AES Indiana EE program savings have put downward pressure on small commercial sales. In contrast to residential, forecasted annual small commercial AES Indiana EE program savings in 2025 and 2026 are on average higher compared to the prior five years. Table 5 shows the historical weather normalized and forecast sales.

Table 5: Annual Small Commercial Sales

Year	SS Sales (MWh)	Annual Diff	SH Sales (MWh)	Annual Diff	Total Small Commercial	Annual Diff
2018	1,246,517		539,996		1,786,513	
2019	1,251,182	0.4%	529,502	-1.9%	1,780,684	-0.3%
2020	1,189,609	-4.9%	497,358	-6.1%	1,686,967	-5.3%
2021	1,228,242	3.2%	501,352	0.8%	1,729,594	2.5%
2022	1,254,938	2.2%	510,227	1.8%	1,765,166	2.1%
2023	1,259,428	0.4%	501,169	-1.8%	1,760,597	-0.3%
2024	1,297,237	3.0%	497,415	-0.7%	1,794,652	1.9%
2025	1,303,305	0.5%	513,678	3.3%	1,816,983	1.2%
2026	1,305,556	0.2%	513,009	-0.1%	1,818,565	0.1%

The Workpaper_Russo_SS, and Workpaper_Russo_SH show all model data inputs, coefficients, and model statistics.

Q16. Please provide a detailed description of the large commercial and industrial sector forecast.

A16. The large commercial and industrial sales forecast is comprised of total sales forecasts for the SL, PL, PH, HL1, HL2, and HL3 tariff classes. Customer forecasts are developed but they do not directly impact the sales forecast. Like the residential and small commercial models, the SL sales model uses an SAE specification, forecasting monthly sales as a function of heating requirements (XHeat), cooling requirements (XCool), other use (XOther), and AES Indiana energy efficiency program savings. These tariff classes use econometric models with CDDs and binary to account for changes in shifts in sales which are not due to weather or economics. Table 6 shows the historical weather normalized and forecast sales. Only the SL historical sales are weather normalized. HL sales are the summation of HL1, HL2, and HL3.

Table 6: Large Commercial & Industrial Sales

Year	SL Sales MWh	Annual Diff	PL Sales MWh	Annual Diff	PH Sales MWh	Annual Diff	HL Sales MWh	Annual Diff
2018	3,459,164		1,047,496		38,531		1,846,019	
2019	3,439,642	-0.6%	1,030,055	-1.7%	35,114	-8.9%	1,773,533	-3.9%
2020	3,131,312	-9.0%	1,047,135	1.7%	31,115	-11.4%	1,650,476	-6.9%
2021	3,242,918	3.6%	1,098,253	4.9%	29,106	-6.5%	1,653,803	0.2%
2022	3,230,209	-0.4%	1,081,267	-1.5%	27,374	-6.0%	1,723,233	4.2%
2023	3,243,556	0.4%	1,039,698	-3.8%	23,639	-13.6%	1,630,157	-5.4%
2024	3,192,354	-1.6%	1,017,105	-2.2%	23,907	1.1%	1,697,374	4.1%
2025	3,225,766	1.0%	1,027,026	1.0%	22,970	-3.9%	1,720,698	1.4%
2026	3,234,223	0.3%	1,024,030	-0.3%	22,970	0.0%	1,739,261	1.1%

The Workpaper_Russo_SL, Workpaper_Russo_PL, Workpaper_Russo_PH, Workpaper_Russo_HL1, Workpaper_RussoHL2, and Workpaper_Russo_HL3 show all model data inputs, coefficients, and model statistics.

Q17. Please provide a detailed description of the lighting and other sector forecasts.

A17. The remaining tariffs are comprised of outdoor lighting, street lighting, and water heating tariffs. Econometric regression models are used to forecast the sales for these tariff classes. The models include monthly binaries to capture the seasonal usage patterns, they do not include weather or economic variables. The residential outdoor lighting tariff model (R_APL) includes a linear trend to capture the historical decline in sales, this results in a forecast which declines in 2025 and 2026.

Q18. How does the forecast account for electric vehicles and solar?

A18. The 2026 test-year forecast includes the impact of electric vehicles (EV) and customer solar (PV). The EV and PV forecast were provided to Itron by AES Indiana and developed in conjunction with the 2025 Integrated Resource Plan (IRP) process by Carnegie Mellon University. Base, Low, and High EV/PV forecasts were generated for the IRP. The Base forecast is used in the test-year sales forecast. The EV/PV forecasts developed for the IRP are segmented into residential and non-residential but not by tariff class. The residential and non-residential forecast are allocated to tariffs based on tariff customer and sales forecasts. The residential EV/PV forecasts are allocated to the RS, RC, and RH tariffs based on those tariff class customer forecasts. The non-residential EV/PV forecasts are allocated to the SS, SH, and SL tariffs based on those tariff sales forecasts. Only the incremental new MWh associated with EV charging and PV solar generation are added (EV) to and subtracted (PV) from the tariff sales forecast. The net impact of the EV/PV forecast is negative in the 2026 test-year sales for the residential tariffs, which implies PV is greater than EV. The net impact is positive for the non-residential classes. Table 7 shows the EV MWh added to the tariff forecast. Table 8 shows the PV MWh subtracted from the tariff forecast.

Table 7: Annual EV Forecast

Year	RS EV MWh	RC EV MWh	RH EV MWh	SS EV MWh	SH EV MWh	SL EV MWh
2025	2,601	1,792	399	469	185	1,161
2026	5,184	3,601	798	938	369	2,324

Table 8: Annual PV Forecast

Year	RS PV MWh	RC PV MWh	RH PV MWh	SS PV MWh	SH PV MWh	SL PV MWh
2025	4,616	3,181	708	317	125	784
2026	9,202	6,392	1,416	633	249	1,569

Q19. Were other adjustments made to the tariff class sales forecast?

A19. The SL, PL, and HL tariff classes include adjustments for known customer expansion or contraction. The monthly estimates are based on discussions AES Indiana has with specific customers in these classes. The 2026 test-year sales include 169,000 MWh of additional sales due to customer expansion.

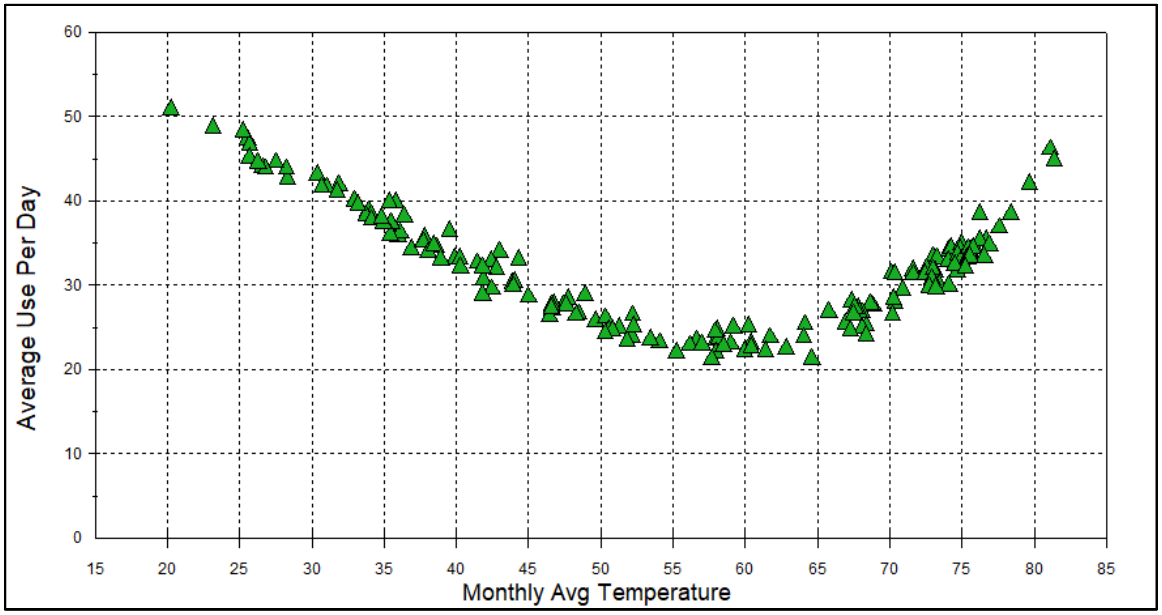
Q20. Do the test-year sales include adjusts for future large loads such as datacenters?

A20. No. The 2026 sales do not include adjustments for datacenters.

Q21. How are weather inputs calculated?

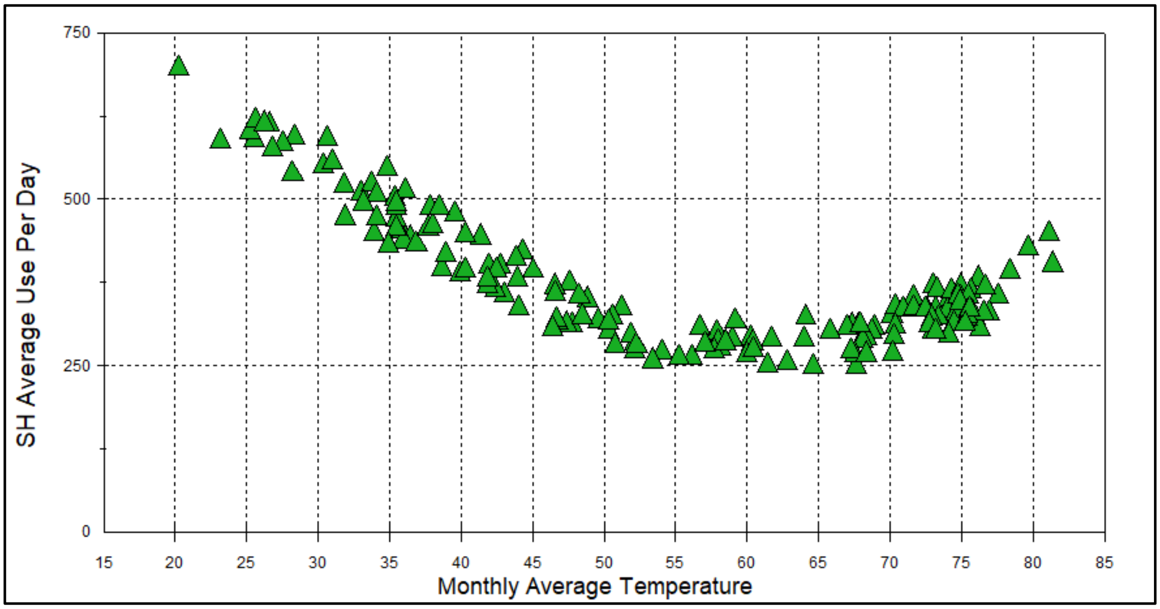
A21. Historical and normal heating degree-days (HDD) and cooling degree-days (CDD) are derived from daily temperature data for Indianapolis. HDD and CDD can be referred to as spline variables as they either take on a positive value or are zero. HDD are positive when temperatures are below a specified temperature reference point and are zero when temperatures are at or above the temperature reference point. CDD are positive when temperatures are above a temperature reference point and are zero when temperatures are at or below the temperature reference point. The best temperature breakpoints in terms of statistical model fit varies by tariff class. Non-residential heating and cooling generally starts at lower temperature points than residential. Temperature breakpoints are evaluated as part of the model estimation process. For the residential rate classes, the best temperature breakpoints are 60 degrees for HDD and 65 degrees for CDD. Figure 2 shows a scatter plot of monthly residential average use per day and monthly average temperature.

Figure 2: Residential Use Per Day vs. Average Temperature



In the non-residential classes, HDD with a 55 degree reference point and CDD with a 60 degree reference point improves the overall model fit. Figure 3 shows a scatter plot of monthly SH tariff average use per day and monthly average temperature.

Figure 3: SH Use Per Day vs. Average Temperature



Normal weather is used to forecast 2025 and 2026 sales. Traditionally, normal weather is calculated by averaging historical weather over a period of years. Given the large variation in month-to-month and year-over-year weather conditions, it seemed reasonable to assume that the best representation of current and forecast weather is an average of the past. Studies that Itron and others have conducted have shown that this may not be the best assumption. Over the last sixty years, average temperatures have been increasing. In reviewing historical Indianapolis weather data, we found a statistically significant positive, but slow, increase in average temperature. Since 1960, average annual temperatures have been increasing 0.05 degrees per year, or 0.5 degrees per decade. The trend coefficient is highly statistically significant, indicating a high probability of increasing temperatures. Temperatures are not increasing uniformly; analysis of annual minimum and maximum temperatures show the minimum temperatures are increasing much faster at 1.2 degree per decade while maximums show no statistically significant trend. This results in HDDs decreasing 0.4% per year while CDDs are increasing 0.3% per year through 2026 Test-Year period.

Q22. What economic variables are used in the forecast?

A22. The average use, sales, and customer forecasts use input from September 2024 Moody's Analytics economic forecast for Marion County, Indianapolis MSA, and Indiana. The residential customer models use Marion County and Indianapolis MSA household projections as an input, the residential average use models use real household income and household size. The small and large commercial tariff sales models use non-manufacturing GSP and non-manufacturing employment as inputs. Table 9 shows the historical and forecasted economic concepts.

Table 9: Annual Economic Forecast

Year	Marion County Households (Thous)	Annual Diff	Indianapolis MSA Households (Thous)	Annual Diff	Indianapolis Household Income (Real $ Thous)	Annual Diff	Non-Manufacturing GSP (Real $ Thous)	Annual Diff	Non-Manufacturing Employment (Thous)	Annual Diff
2018	400.9		823.0		132.2		272,182.9		981.6	
2019	403.1	0.6%	830.0	0.9%	137.5	4.0%	274,561.8	0.9%	998.7	1.7%
2020	397.7	-1.4%	827.6	-0.3%	147.5	7.3%	267,773.2	-2.5%	955.9	-4.3%
2021	396.6	-0.3%	837.7	1.2%	155.8	5.6%	283,454.4	5.9%	993.9	4.0%
2022	397.0	0.1%	847.3	1.1%	149.7	-3.9%	289,977.1	2.3%	1,036.1	4.2%
2023	394.7	-0.6%	856.4	1.1%	147.0	-1.8%	295,947.9	2.1%	1,063.4	2.6%
2024	397.1	0.6%	869.5	1.5%	148.2	0.8%	302,992.9	2.4%	1,085.5	2.1%
2025	400.1	0.8%	884.3	1.7%	149.7	1.0%	309,441.5	2.1%	1,098.3	1.2%
2026	402.4	0.6%	897.9	1.5%	150.9	0.8%	315,903.4	2.1%	1,104.7	0.6%

Q23. What are the sources for the end-use saturation and efficiency data used in the SAE model inputs?

A23. The SAE model inputs are derived from the EIA's 2023 Annual Energy Outlook for the East North Central census region. Residential inputs are calibrated to end-use saturation estimates specific to AES Indiana and specific to the RS, RC, and RH tariff classes. SS, SH, and SL SAE inputs are calibrated based on annual sales. End-use energy intensities, expressed in kilowatt-hour (kWh) per household for the residential sector and kWh per square foot for the small and large commercial sectors, are incorporated into the constructed forecast model variables. Energy intensities reflect both the change in ownership (saturation) and average stock efficiency. Residential, weather sensitive end-use intensities also incorporate a thermal shell efficiency index and home size index. The average annual change in total residential intensity in 2025 and 2026 varies across the RS, RC, and RH tariff classes. RH intensity declines 0.3% per year, RS declines 0.1% and RC declines 0.2%. This variation is due to the calibration of end-use saturations. Total small and large commercial intensity declines 0.7% per year in 2025 and 2026. Table 10 shows the historical and forecasted total intensities for RS, RC, RH, and small and large commercial tariffs.

Table 10: Residential Energy Intensities

Year	RS (kWk Per Household)	RC (kWk Per Household)	RH (kWk Per Household)	Commercial (kWk Per SqFt)
2018	9,470	12,589	15,167	11.57
2019	9,437	12,540	15,096	11.45
2020	9,436	12,524	15,055	11.33
2021	9,412	12,483	14,983	11.23
2022	9,374	12,421	14,878	11.08
2023	9,349	12,376	14,793	10.94
2024	9,351	12,361	14,749	10.84
2025	9,341	12,335	14,700	10.77
2026	9,336	12,313	14,655	10.70

Q24. How are AES Indiana sponsored energy efficiency savings incorporated into the forecast?

A24. The RS, RC, RH, SS, SH, SL, and PL tariff classes incorporate historical and forecasted energy efficiency program savings. Historical EE helps explain historical sales and improves the statistical fit of the tariff average use and sales models. The tariff models include an EE variable which are constructed based on annual verified EE savings and projected future saving based on the prior IRP. EE variables are unique for each tariff class. The EE variable is expressed as savings per customer in the residential average use models as the dependent variable is sales per customer. The small and large commercial EE variable is expressed as total saving as the dependent variable is total sales.

Q25. How does the rate case forecast differ from the IRP forecast?

A25. The primary difference is how EE programs savings are treated. In the IRP forecast future EE program savings are treated as a supply side resource and are not included in the class sales forecasts. The rate case test-year models include the impact of future EE program savings.

Q26. How are forecasted billing month sales converted to calendar month sales?

A26. All tariff models use historical billed sales and customer counts. Billed sales represent the sales over the billing month period, dictated by the number of billing cycles and the dates on which those cycles are read. The billing month of January encompasses sales in December and January. The January bill of a customer who falls into the first cycle may be based on that consumption which occurs almost entirely in December. By contrast, the January bill of a customer who falls into the last cycle may be based on that consumption which occurs almost entirely in January. The billing meter read schedule is used to calculate billing month weighted HDDs and CDDs, which are used in the monthly tariff usage and sales models. The resulting forecast is on a billing month basis. The billing month forecast is converted to calendar month by applying a billed to calendar ratio, this ratio is unique by month and tariff class. The ratio is calculated based on the monthly historical average billed to calendar sales estimates, calendar sales estimates are provided by the AES Indiana accounting group.

Q27. Hourly tariff class and system hourly load profiles were generated for cost-of-service analysis. Please explain how the load shapes are developed.

A27. Tariff class hourly load profiles are estimated for the 2026 test-year period from advanced metering infrastructure (AMI) based load research samples for the residential, small and large commercial tariffs. The primary tariff profiles are derived by aggregating all available customer interval data. Lighting and other rate classes are based on end-use load profiles. The AMI based profiles are based on large AMI samples selected randomly within four usage stratums for the residential rate classes and three stratums for the small and large commercial tariff classes; this is known as a stratified random sample. Data from January 1, 2022, to August 31, 2024, are used for the AMI based profiles. Hourly total AES Indiana system load data from January 1, 2021, to August 31, 2024 are used to estimate the system profile. Hourly models are estimated for each tariff class which relates hourly load to daily HDD and CDD using multiple breakpoints. The increased number of observations and variation of weather conditions allows for the use of multiple HDD and CDD breakpoints, something often not possible with monthly models. Models also include HDD/CCD interacted with a weekend binary to allow the impact of a HDD/CDD to be different on a weekend opposed to a weekday. Day type binaries are included to account for day of week, monthly and holiday impacts. Figure 4 to Figure 6 shows the daily load versus daily average temperature scatter plots, highlighting the unique weather and day type relation for three tariff classes, RH, SS, and SL.

Figure 4: RH Daily Load vs Daily Average Temperature

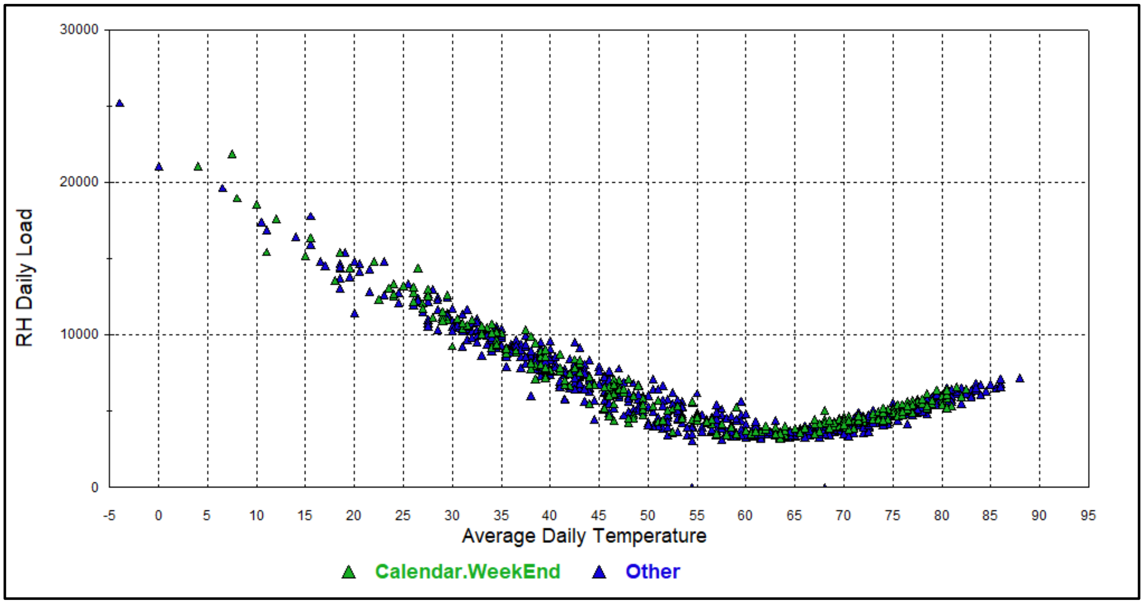


Figure 5: SS Daily Load vs Daily Average Temperature

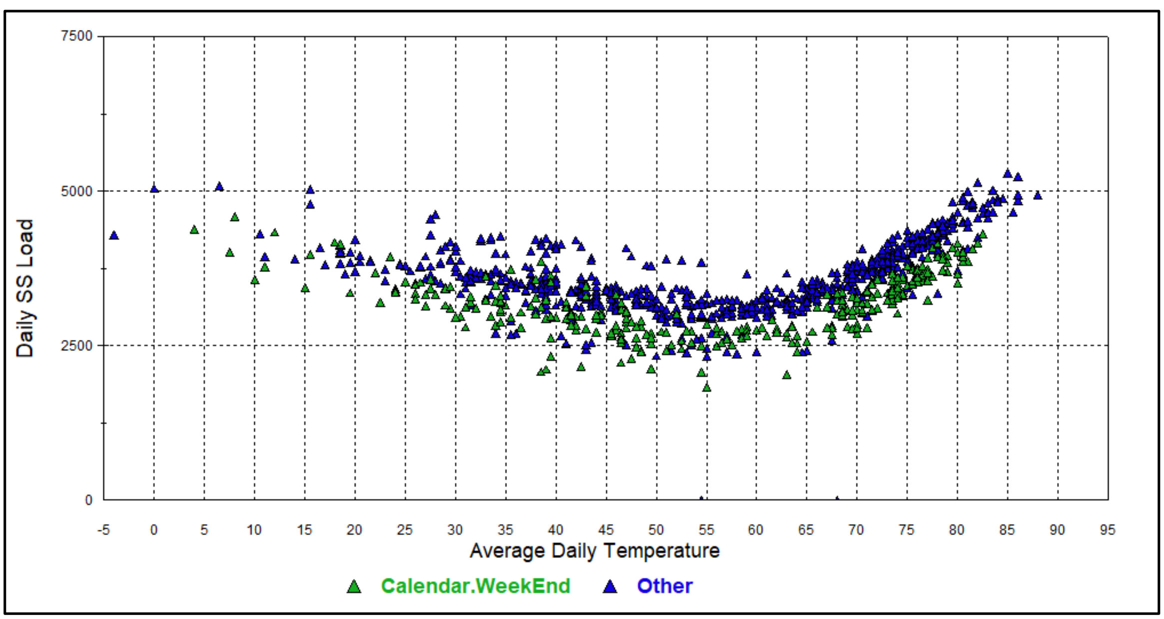
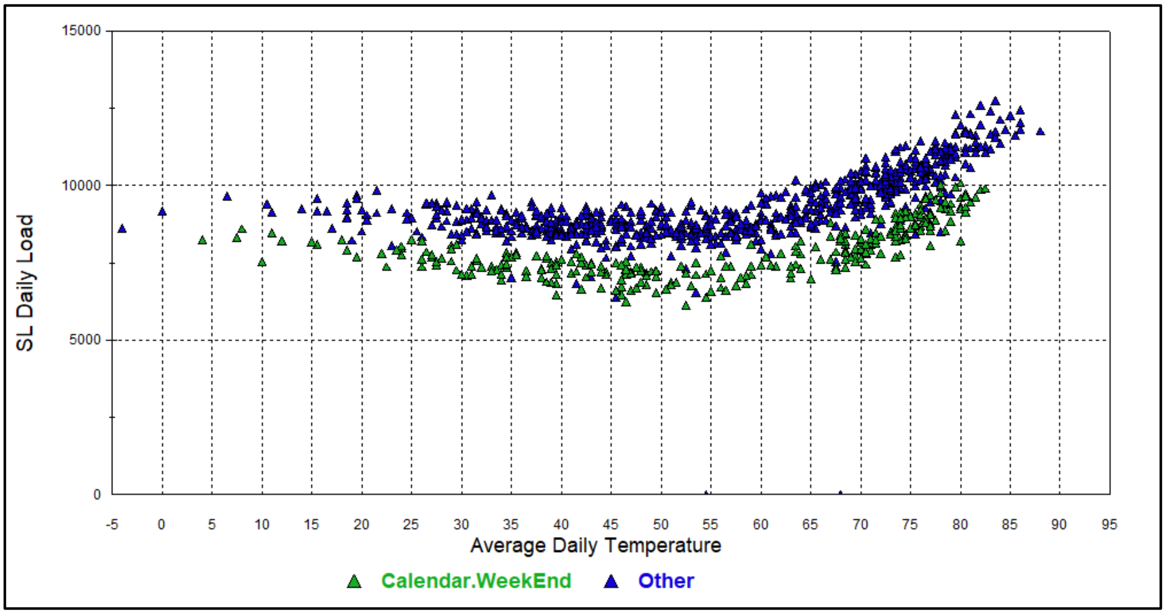


Figure 6: SL Daily Load vs Daily Average Temperature



The hourly tariff models generate hourly forecasts for the 2026 test-year. The daily normal HDD and CDD used in the forecast period are based on the same trended normal used to develop the test year sales forecast. The resulting 2026 hourly profiles reflect typical hourly usage patterns and sensitivity to heating and cooling requirements. The hourly profiles for tariffs which use electricity to heat will peak on the morning of the coldest winter day while non-electric heating customers will peak in the late afternoon of the hottest summer day. Figure 7 shows the hourly profile for the RH tariff class, who’s customers heat with electricity, and the Figure 8 shows the hourly profile for the RS tariff class, where customers typically do not heat with electricity.

Figure 7: RH Hourly Profile

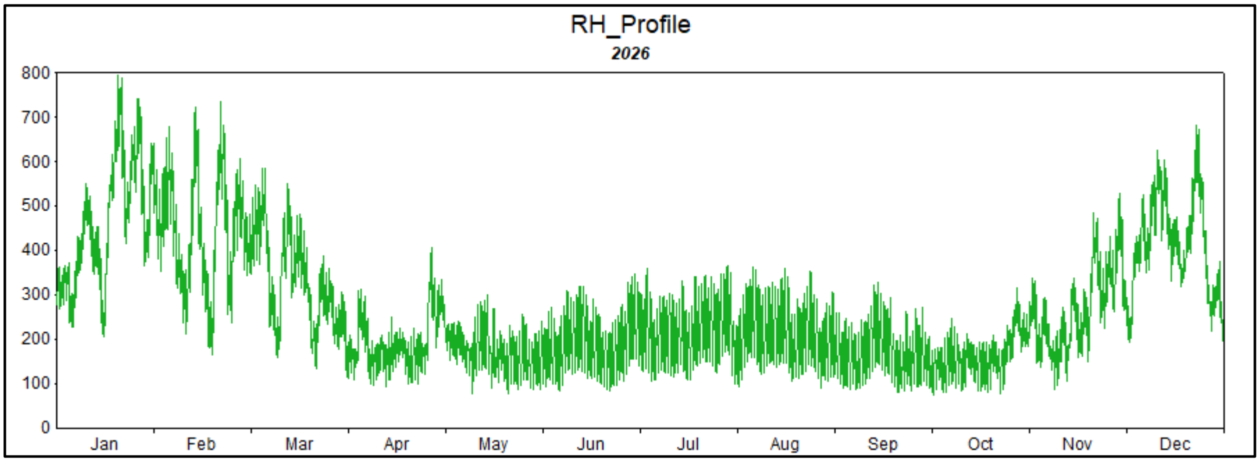
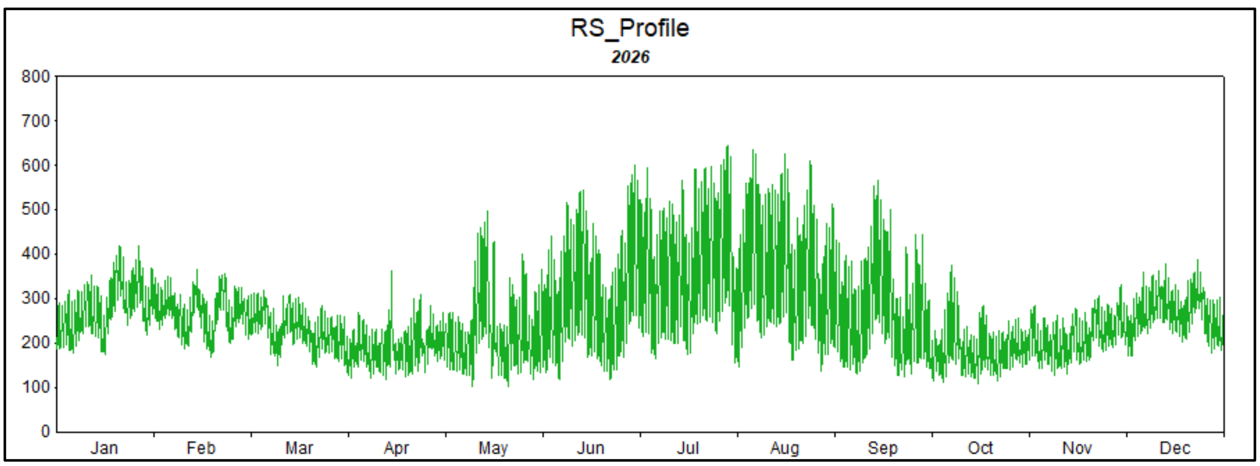
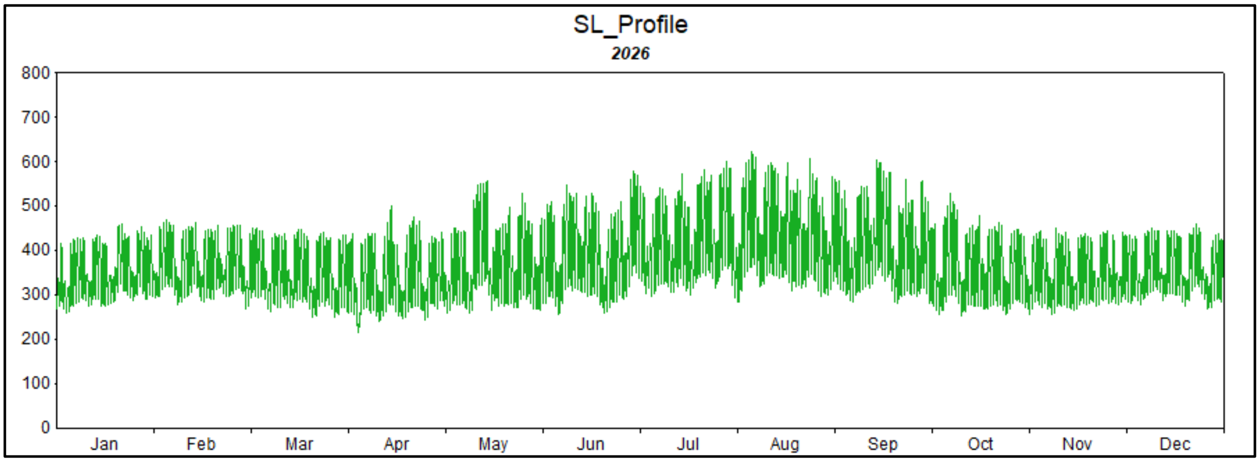


Figure 8: RS Hourly Profile



The SL profile peaks in the summer, driven by cooling requirements. The model does incorporate HDD but the SL class is much less sensitive to heating and even cooling compared to the residential and small commercial classes. Figure 9 shows the hourly profile for the SL tariff class.

Figure 9: SL Hourly Profile



The non-AMI sample based hourly profiles for the large primary class customers are based on all available interval data. The HL1 and HL2 tariff profiles are based on data from January 1st, 2022, to December 31st, 2022. The HL3 tariff profile, which currently consists of just two customers, is based on data from January 1, 2024, to December 31, 2024.

Q28. How was the AMI based load research sample created?

A28. The sample design was developed in 2022 for AES Indiana's 2023 rate case. The sample has not changed since 2022, only updated to include interval data through August 31,2024. The 2022 sample used large AMI samples selected randomly within four usage stratums for the residential rate classes and three stratums for small and large commercial classes. The stratums are based on customers' 2022 annual kWh use. The sample was designed to use 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 and large commercial classes. Some sample points may not be used in the final expansion if they do not meet the minimum number of data intervals required. Two expansion methodologies are used to estimate the total tariff class profiles. 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 small and large commercial classes. Table 11 shows number total number of tariff customers as of August 2024, the number of sample points used in the expansion, and measured precision at the time of the January and August 2024 system peak.

Table 11: Load Research Sample Size & Precision

Tariff Class	Customer Count	Sample Size	January Peak Precision	August Peak Precision
RS	255,129	948	6.11%	3.70%
RH	173,655	861	3.43%	4.24%
RC	38,868	717	5.70%	3.78%
SS	51,714	395	5.00%	5.04%
SH	3,700	444	2.32%	2.32%
SL	4,314	410	2.10%	1.79%

Q29. How are tariff class coincident and non-coincident peaks calculated?

A29. Hourly tariff profiles are combined with monthly tariff sales to generate test-year hourly forecasts which sum to the monthly test-year sales forecasts. This process occurs in Itron's long-term hourly load forecasting software, MetrixLT. These tariff profiles are adjusted for tariff specific line losses. All tariffs are aggregated and calibrated to a top-stem system hourly profile. Once calibrated and loss adjusted tariff hourly forecasts for the 2026 test-year are generated, tariff coincident (with system) and noncoincident peaks are derived. Peak time, non-coincident loads, minimum loads, monthly energy, and load factors can also be derived from the hourly load forecast. These outputs are used to populate the values seen in Workpaper_Russo_Tariff_COS.

Q30. Does this conclude your testimony?

A30. Yes

VERIFICATION

I, Michael Russo, Sr, Forecast Consultant, affirm under penalties for perjury that the foregoing representations are true to the best of my knowledge, information, and belief.

Michael Russo
Dated: May 30, 2025