Cause No. 45990

SOUTHERN INDIANA GAS AND ELECTRIC COMPANY
d/b/a CENTERPOINT ENERGY INDIANA SOUTH
(CEI SOUTH)

DIRECT TESTIMONY
OF
MICHAEL E. RUSSO
SENIOR FORECAST CONSULTANT

ON

TEST-YEAR SALES AND CUSTOMER FORECASTS

SPONSORING PETITIONER'S EXHIBIT NO. 16,
ATTACHMENT MER-1

DIRECT TESTIMONY OF MICHAEL E. RUSSO

I. INTRODUCTION

Q. PLEASE STATE YOUR NAME AND BUSINESS ADDRESS.

A. My name is Michael E. Russo. 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 a Senior Forecast Consultant with Itron.

Q. ON WHOSE BEHALF ARE YOU SUBMITTING THIS DIRECT TESTIMONY?

A. I am submitting testimony on behalf of Southern Indiana Gas and Electric Company d/b/a CenterPoint Energy Indiana South ("CEI South", "Petitioner" or the "Company"), which is an indirect subsidiary of CenterPoint Energy, Inc.

Q. WHAT IS YOUR ROLE WITH RESPECT TO THIS CASE?

A. I provided CEI South with class-level 2025 Test-Year sales and customer forecasts.

Q. PLEASE DESCRIBE YOUR EDUCATIONAL BACKGROUND.

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

Q. PLEASE DESCRIBE YOUR PROFESSIONAL EXPERIENCE.

A. 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 CEI South IRP, assisting with the Vermont long-term system load and planning area forecast (Vermont Electric Power Company ("VELCO")), 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 ("ISO"), and implementing load research systems for Oncor Electric Delivery and El Paso Electric.

Q. WHAT ARE YOUR PRESENT DUTIES AND RESPONSIBILITIES AS SENIOR FORECAST CONSULTANT?

A. I am responsible for supporting utilities, ISOs, 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.

II. PURPOSE & SCOPE OF TESTIMONY

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

A. The purpose of my direct testimony is to support the projected 2025 Test-Year sales.

Q. ARE YOU SPONSORING ANY ATTACHMENTS IN THIS PROCEEDING?

A. Yes. I am sponsoring the following attachment in this proceeding:

- Petitioner's Exhibit No. 16, **Attachment MER-1**: IRP Forecast Report 2022_Appendix B C

This document provides a detailed description of the Statistically Adjusted End-Use ("SAE") modeling framework used for developing the 2025 Test-Year sales.

Q. WAS THIS ATTACHMENT PREPARED BY YOU OR UNDER YOUR SUPERVISION?

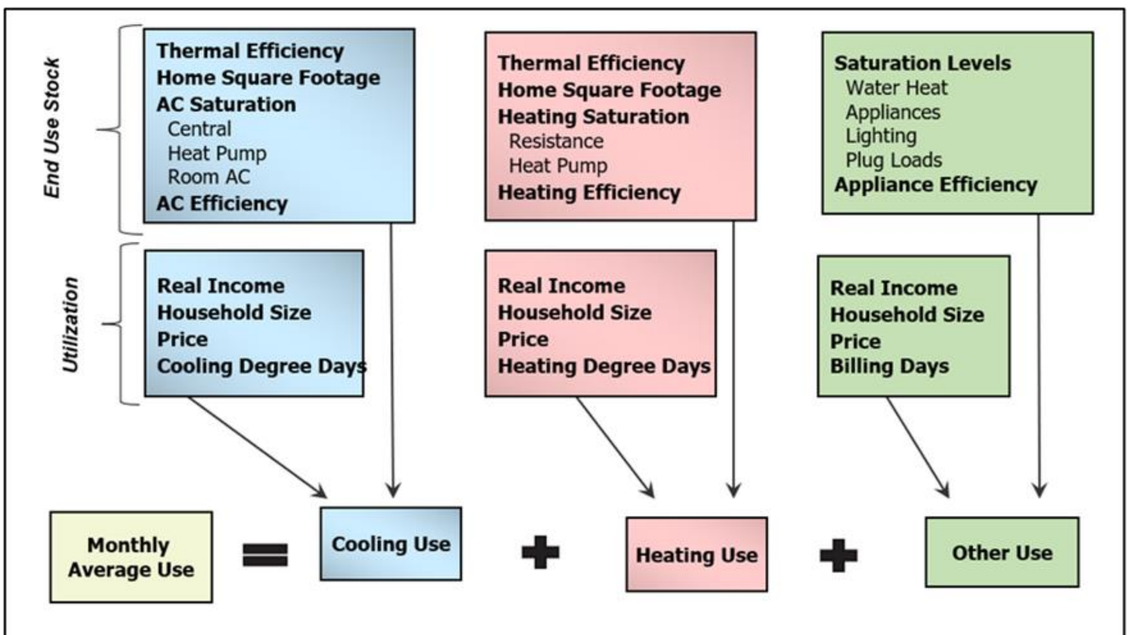
A. Yes, it was.

Q. PLEASE DESCRIBE THE FORECAST APPROACH.

A. The test-year period is January 1, 2025, to December 31, 2025. The forecast is based on a set of linear regression models estimated for each revenue class: residential, commercial, industrial, and street lighting. Models are estimated using historical monthly billed sales and customer data for the period January 2011 to June 2023. The model-derived forecasts capture the expected impact of customer growth, economic activity, regional end-use saturation and efficiency trends, and CEI South'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 and commercial sales models are estimated using what is called a Statistically Adjusted End-Use ("SAE") model. The idea 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 MER-1** below illustrates the Residential SAE model structure.

Figure MER-1 – Residential SAE Structure



$$AvgUse_m = a + b_c \times XCool_m + b_h \times XHeat_m + b_o \times XOther_m + b_e \times EE_m$$

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 and customer model coefficients, model statistics, and data inputs can be found in Petitioner's Exhibit No. 16, **Workpaper MER-1** and **Workpaper MER-2**. A similar SAE structured model is estimated for the commercial sector where total monthly sales are modeled instead of average use. The commercial sales and customer model coefficients, model statistics, and data inputs can be found in Petitioner's Exhibit No. 16, **Workpaper MER-3** and **Workpaper MER-4**. A more detailed description of the forecast approach is in the IRP Forecast Report 2022_Appendix B C, provided as Petitioner's Exhibit No. 16, **Attachment MER-1**. As discussed by Petitioner's Witness Justin L Forshey, projected industrial sales are based on a discrete forecast by customer with expected expansion or contraction activity. A street light forecast is derived using a simple seasonal and trend model.

Q. PLEASE DESCRIBE THE NEAR-TERM SALES OUTLOOK.

A. In the near-term, 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 S&P Global Market Intelligence June 2023 Outlook for Indiana and the Evansville Metropolitan Statistical Area ("MSA"). Households are expected to average 0.5% annual near-term growth with 0.8% real household income growth. In the commercial sector, S&P projects just 1.1% Real GSP annual growth over the next three years with a 0.3% annual decline in employment growth. Total sales, excluding industrial sales, decline 0.3% per year on average. This compares with weather normalized sales decline over the last five years of 0.4%. Industrial sales are forecasted to increase in 2024 due to the addition of one large customer. **Table MER-1** shows the class and total sales projections.

Table MER-1 – Sales Historical Data and Projections

Year	Residential Sales (MWh)	Commecial Sales (MWh)	Industrial Sales (MWh)	Streetlighting Sales (MWh)	Total Sales (MWH)
2018	1,520,086	1,272,303	2,183,160	21,361	4,996,909
2019	1,422,320	1,215,352	2,078,175	21,235	4,737,083
2020	1,386,440	1,126,229	1,971,320	21,000	4,504,989
2021	1,401,988	1,168,164	2,041,929	20,699	4,632,780
2022	1,452,409	1,168,055	1,972,273	20,244	4,612,981
2023	1,331,858	1,166,478	1,885,545	19,962	4,403,843
2024	1,405,673	1,177,542	2,354,511	20,085	4,957,811
2025	1,407,162	1,166,082	2,386,545	19,904	4,979,693

Sales are adjusted for PV and electric vehicles. With these adjustments, residential sales are virtually flat, averaging just 0.2% annual sales growth between 2023 and 2025 (weather normalized) and 0.5% annual customer growth.

The 0.5% customer growth is offset by efficiency gains from both new standards and EE program activity that contribute to a 0.3% average annual decline in average use. **Table MER-*2*** shows residential sales, customers, and average use forecast with historical weather-normalized data.

Table MER-2 – Residential Historical Data and Projections

Year	Wthr Norm Sales (MWh)	Customers	Wthr Norm Average Use (kWh)
2018	1,396,319	127,438	10,957
2019	1,388,736	128,343	10,820
2020	1,417,061	129,606	10,934
2021	1,404,747	130,607	10,756
2022	1,406,327	131,648	10,682
2023	1,402,276	132,357	10,595
2024	1,405,673	133,016	10,568
2025	1,407,162	133,577	10,534
Change			
2019	-0.5%	0.7%	-1.2%
2020	2.0%	1.0%	1.0%
2021	-0.9%	0.8%	-1.6%
2022	0.1%	0.8%	-0.7%
2023	-0.3%	0.5%	-0.8%
2024	0.2%	0.5%	-0.3%
2025	0.1%	0.4%	-0.3%
2018-23	**0.1%**	**0.8%**	**-0.7%**
2023-25	**0.2%**	**0.5%**	**-0.3%**

On a weather normalized basis, there is little difference in forecasted sales growth than that over the prior four years.

Commercial sales were significantly impacted by the COVID mandated shutdown that occurred in early April 2020. While there has been a significant business recovery coupled with school re-openings, sales never fully recovered. By end of 2023 normalized commercial sales are still 28,000 MWh below 2019 levels. From here, slow economic growth coupled with expected end-use efficiency gains, and PV adoption continue to put downward pressure on commercial sales with commercial sales declining 0.8% through 2025. **Table MER-3** shows the commercial customers and sales forecast with historical weather-normalized data.

Table MER-3 – Commercial Historical Data and Projections[1]

Year	Wthr Norm Sales (MWh)	Customers
2018	1,239,362	18,652
2019	1,208,012	18,734
2020	1,137,928	18,885
2021	1,169,527	19,017
2022	1,160,559	19,093
2023	1,185,192	19,118
2024	1,177,542	19,198
2025	1,166,082	19,248
Change		
2019	-2.5%	0.4%
2020	-5.8%	0.8%
2021	2.8%	0.7%
2022	-0.8%	0.4%
2023	2.1%	0.1%
2024	-0.6%	0.4%
2025	-1.0%	0.3%
2018-23	**-0.8%**	**0.5%**
2023-25	**-0.8%**	**0.3%**

In recent years, CEI South experienced a drop in industrial sales, partially the result of customer shutdowns from COVID impacts. This, however, is expected to turn around; as described by Witness Forshey, CEI South will be adding one large new customer in 2024. 2025 industrial sales are expected to be 26% higher than 2023 sales. **Table MER-4** shows industrial sales forecast with historical weather-normalized data.

[1] Commercial includes Small General Service, Off-Season Service, and Demand General Service.

Table MER-4 – Industrial Historical Data and Projections[2]

Year	Wthr Norm Sales (MWh)
2018	2,158,329
2019	2,072,537
2020	1,975,292
2021	2,038,958
2022	1,966,179
2023	1,886,843
2024	2,354,511
2025	2,386,545
Change	
2019	-4.0%
2020	-4.7%
2021	3.2%
2022	-3.6%
2023	-4.0%
2024	24.8%
2025	1.4%
2018-23	**-2.6%**
2023-25	**13.1%**

Street lighting sales are based on a simple trend model that captures usage decline as a result of the adoption of more efficient bulb technology. Sales for 2025 are projected to be 0.3% lower than 2023 sales.

Q. HOW DOES THE FORECAST DIFFER FROM THE 2022/2023 IRP FORECAST?

A. The estimated models are based on the same SAE framework as that used in the 2022/2023 IRP forecast. Models are updated to include sales and customer data through June 2023, S&P's most recent economic outlook, and updated end-use saturation and efficiency trends from the Energy Information Administration's ("EIA") 2023 Annual Energy Outlook. The industrial forecast is based on more recent industrial customer business activity information. Heating and cooling degree-days include updated actuals through June 2023, the normal heating and cooling degree-days remain the same. The PV forecast is updated to reflect current installed capacity, and EVs are updated to use the new residential customer forecast. The primary differences

[2] Industrial forecast includes Large Power and High Load Factor.

is how EE programs savings are treated. In the IRP forecast future EE program savings are required to be treated as a supply side resource and are not included in the class sales forecasts. Unlike the IRP forecast, the test-year models include the impact of future EE program savings as these savings reduce sales and associated test-year revenue.

Q. WHAT ARE THE PRIMARY FORECAST MODEL INPUTS AND ADJUSTMENTS?

A. The model inputs include weather, economic data, end-use efficiency and saturation projections, EE program savings, and PV and EV projections.

Q. HOW ARE WEATHER INPUTS CALCULATED?

A. Historical and normal heating degree-days ("HDD") and cooling degree-days ("CDD") are derived from daily temperature data for the Evansville airport. HDD and CDD are often 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 customer class. Commercial heating and cooling generally start 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. In the non-residential classes, HDD with a 60 degree reference point and CDD with a 60 degree reference point improve the overall model fit. Traditionally, utilities base their long-term forecast on what the industry calls normal weather. Normal weather is calculated by averaging historical weather usually 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. Recent studies that Itron and others have conducted have shown that this is probably not the best assumption; over the last fifty years, average temperatures have been increasing. In reviewing historical Evansville weather data, we found a statistically significant positive, but slow, increase in average temperature. Since 1988, 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. This results in HDDs decreasing 0.2% per year while CDDs are increasing 0.5% per year through 2025 Test-Year period.

Q. WHAT ARE THE ECONOMIC VARIABLES AND SOURCES USED IN THE FORECAST MODELS?

A. The residential and commercial sales forecasts use inputs from June 2023 S&P Global Market Intelligence economic forecast for the Evansville MSA and Indiana. The residential customer model uses household projections as an input, the residential average use model uses income per household and household size. The commercial sales model uses non-manufacturing GSP, non-manufacturing employment, and population as inputs. **Table MER-5** shows the economic variable projections.

Table MER-5 – Historical and Forecasted Economic Drivers

Year	Households ('000)	Household Income (Real '000 $)	Population ('000)	Non-Manufacturing GSP (Real Mil $)	Non-Manufacturing Employment ('000)
2018	129.8	116.8	313.5	243,939	2,597
2019	130.2	118.9	313.8	245,751	2,618
2020	129.8	128.9	314.2	240,114	2,489
2021	131.2	129.6	314.3	251,034	2,560
2022	132.2	123.7	314.0	257,248	2,653
2023	132.9	123.2	313.9	259,207	2,719
2024	133.7	123.7	313.9	262,775	2,729
2025	134.3	125.2	314.1	266,376	2,728

Q. WHAT ARE THE SOURCES FOR SAE MODEL INPUTS?

A. The SAE model inputs are derived from the EIA's 2023 Annual Energy Outlook for the East South Central census region. CEI South's service territory lies in the southernmost portion of the East North Central region, a region that includes Wisconsin and Michigan, which have different cooling requirements from southern Indiana. Because of these differences, the East South Central region was selected as a better representation of cooling equipment stock. Residential inputs are calibrated to end-use saturations estimates specific to CEI South's service territory. End-use energy intensities, expressed in kilowatt-hour ("kWh") per household for the residential sector and kWh per square foot for the commercial sectors, are incorporated into the constructed forecast model variables. Energy intensities reflect both change in ownership (saturation) and average stock efficiency. Total residential intensity increases 0.1% per year through the test-year period. Total commercial intensity declines 0.5% per year. **Table MER-6** and **Table MER-7 – C** show the residential and commercial intensity projections for heating, cooling, and all other end-uses.

Table MER-6 – Residential Energy Intensity

Year	Heating (Annual kWh per Cust)	Cooling (Annual kWh per Cust)	Other (Annual kWh per Cust)	Total (Annual kWh per Cust)
2018	1,612	2,404	7,158	11,173
2019	1,605	2,389	7,164	11,159
2020	1,599	2,375	7,172	11,146
2021	1,589	2,357	7,177	11,123
2022	1,599	2,343	7,203	11,146
2023	1,604	2,329	7,216	11,149
2024	1,613	2,326	7,201	11,140
2025	1,627	2,326	7,212	11,165

Table MER-7 – Commercial Energy Intensities

Year	Heating (Annual kWh per SqFt)	Cooling (Annual kWh per SqFt)	Other (Annual kWh per SqFt)	Total (Annual kWh per SqFt)
2018	0.44	1.70	11.13	13.28
2019	0.44	1.71	10.98	13.12
2020	0.43	1.71	10.85	12.99
2021	0.43	1.71	10.74	12.87
2022	0.42	1.71	10.59	12.72
2023	0.42	1.71	10.48	12.60
2024	0.42	1.71	10.40	12.53
2025	0.41	1.71	10.35	12.47

Q. WHAT EE SAVINGS PROJECTIONS WERE USED IN THE FORECAST?

A. The residential and commercial models incorporate historical and forecasted energy efficiency program savings. Forecasted future EE program savings reduce residential and commercial sales; this is a major distinction between the forecast models used in the 2022/23 IRP and the models used in developing the 2025 Test-Year sales. The EE variables are constructed based on annual verified EE savings and projected future saving based on the prior IRP forecast[3]. The annual numbers are converted to a monthly series for use in the monthly residential and commercial regression models.

[3] The IRP Forecast report can be found starting on page 517 of the IRP volume II, https://midwest.centerpointenergy.com/assets/downloads/planning/irp/2022-2023%20IRP%20-%20Volume%202%20of%202.pdf.

The EE variable is expressed as savings per customer in the residential average use model as the dependent variable is sales per customer. The commercial EE variable is expressed as total saving as the dependent variable is total commercial sales.

Q. PLEASE DESCRIBE THE ADJUSTMENTS MADE FOR CUSTOMER OWNED PVS.

A. The forecast is adjusted for future customer-owned PV systems. Generation from incremental new PV systems is used to reduce future sales, the impact of existing systems is embedded in historical billed sales data.

PV adoption is based on a payback model that relates installed capacity to payback. Payback reflects the length of time needed to recover the cost of installing a solar system—the shorter the payback, the higher the system adoption rate. From the customer's perspective, this is the number of years until electricity is "free". Payback is calculated as a function of system costs, federal and state tax credits and incentive payments, retail electric rates, and treatment of excess generation (solar generation returned to the grid). The payback calculation incorporates the impact of switching from net metering to Excess Distributed Generation ("EDG"). Federal investment tax credits were extended in accordance with the Inflation Reduction Act. The solar adoption model relates monthly residential solar adoptions to payback, estimated with data from January 2014 to June 2023. In the commercial sector, there have been too few adoptions to estimate a robust model. Limited commercial adoption reflects higher investment hurdle rates, building ownership issues (i.e., the entity that owns the building often does not pay the electric bill), and physical constraints as to the placement of the system. As a result, the forecast assumes there continues to be some commercial rooftop adoption by allowing commercial adoption to increase over time, based on the current relationship between commercial and residential adoptions rates. **Table MER-7** shows the residential and commercial PV forecast.

Table MER-7 – PV Capacity Forecast

Year	New Residential Systems	New Residential Capacity (kW)	New Commercial Systems	New Commercial Capacity (kW)
2023	63	652	8	790
2024	207	2,143	28	2,595
2025	363	3,759	48	4,551

Capacity is transformed into generation using monthly load factors. The generation from the cumulative new capacity is then subtracted from residential and commercial sales. **Table MER-8** shows the annual reduction in class sales through the 2025 Test-Year.

Table MER-8 – PV Impact on Class Sales

Year	Residential MWh Reduction	Commercial MWh Reduction
2023	208	252
2024	1,901	2,301
2025	3,993	4,834

Q. PLEASE DESCRIBE THE ADJUSTMENTS MADE FOR ELECTRIC VEHICLES.

A. The 2025 Test-Year sales incorporate the impact of charging requirements from electric vehicles ("EV"). Incremental EV charging loads are added to future sales, the charging from existing vehicles is embedded in historical billed sales data. The EV forecast uses a consensus forecast, averaging a forecast produced by the EIA Annual Energy Outlook and BloombergNEF. The forecast estimates the share of registered light-duty vehicles that are all electric vehicles ("BEV") and plug-in hybrid electric vehicles ("PHEV"). Total light duty vehicles in CEI South's service territory are estimated as the product of residential customer forecast and EIA's projected vehicles per household. The number of BEV and PHEV are calculated by applying consensus projected BEV and PHEV saturation to the service area total vehicle forecast. Monthly charging requirements are based on 1,200 miles per month and a weighted average kWh per 100 miles. On an annual basis this equates to 3,752 kWh per BEV and 2,180 kWh per PHEV. **Table MER-9** shows year-end cumulative new EVs and total annual charging sales added to the residential sales projections.

Table MER-9 – Electric Vehicle Impact on Class Sales

Year	New BEV Count	New BEV Charging MWh	New PHEV Count	New PHEV Charging MWh
2023	115	122	72	44
2024	435	1,038	260	367
2025	930	2,572	529	868

Q. HOW ARE THE FORECASTED SALES AND CUSTOMER FORECAST USED IN THIS RATE PROCEEDING?

A. The customer class forecast (residential, commercial, and industrial) are allocated down to the rate class level using allocations factors based on historical values. Factors are specific for each month and rate class. For instance, the residential customer class forecast is divided into A (standard service), Residential (Transitional - electric space heating) and B (water heating). This then creates a forecast of the billing determinants for each rate class. The volumes and customers are then multiplied by the tariff rates for each rate schedule to determine the forecasted base margin by month by rate schedule. **Table MER-10** shows the mapping of customer class to rate class.

Table MER-10 – Customer Class to Rate Class Mapping

Customer Class	Rate Class
Residential	Rate RS - Standard Rate RS - Transitional Rate B - Electric water heating
Commercial	Rate DGS- Demand General Service Rate SGS- Small General Service Rate OSS- Off Season Service
Industrial	Rate LP- Large Power Rate HLF- High Load Factor

III. <u>CONCLUSION</u>

Q. DOES THIS CONCLUDE YOUR PREPARED DIRECT TESTIMONY?

A. Yes, it does.

VERIFICATION

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

SOUTHERN INDIANA GAS AND ELECTRIC COMPANY D/B/A CENTERPOINT ENERGY INDIANA SOUTH

Michael E. Russo
Senior Forecast Consultant, Itron

12/1/2023
Date

APPENDIX B: RESIDENTIAL SAE MODELING FRAMEWORK

The traditional approach to forecasting monthly sales for a customer class is to develop an econometric model that relates monthly sales to weather, seasonal variables, and economic conditions. From a forecasting perspective, econometric models are well suited to identify historical trends and to project these trends into the future. In contrast, the strength of the end-use modeling approach is the ability to identify the end-use factors that drive energy use. By incorporating end-use structure into an econometric model, the statistically adjusted end-use (SAE) modeling framework exploits the strengths of both approaches.

There are several advantages to this approach.

- The equipment efficiency and saturation trends, dwelling square footage, and thermal shell integrity changes embodied in the long-run end-use forecasts are introduced explicitly into the short-term monthly sales forecast. This provides a strong bridge between the two forecasts.
- By explicitly introducing trends in equipment saturations, equipment efficiency, dwelling square footage, and thermal integrity levels, it is easier to explain changes in usage levels and changes in weather-sensitivity over time.
- Data for short-term models are often not sufficiently robust to support estimation of a full set of price, economic, and demographic effects. By bundling these factors with equipment-oriented drivers, a rich set of elasticities can be incorporated into the final model.

This section describes the SAE approach, the associated supporting SAE spreadsheets, and the *MetrixND* project files that are used in the implementation. The source for the SAE spreadsheets is the 2021 Annual Energy Outlook (AEO) database provided by the Energy Information Administration (EIA).

RESIDENTIAL STATISTICALLY ADJUSTED END-USE MODELING FRAMEWORK

The statistically adjusted end-use modeling framework begins by defining energy use ($USE_{y,m}$) in year (y) and month (m) as the sum of energy used by heating equipment ($Heat_{y,m}$), cooling equipment ($Cool_{y,m}$), and other equipment ($Other_{y,m}$). Formally,

$$\mathrm{USE}_{y,m} = \mathrm{Heat}_{y,m} + \mathrm{Cool}_{y,m} + \mathrm{Other}_{y,m} \qquad (1)$$

Although monthly sales are measured for individual customers, the end-use components are not. Substituting estimates for the end-use elements gives the following econometric equation.

$$USE_m = a + b_1 \times XHeat_m + b_2 \times XCool_m + b_3 \times XOther_m + \varepsilon_m \quad (2)$$

$XHeat_m$, $XCool_m$, and $XOther_m$ are explanatory variables constructed from end-use information, dwelling data, weather data, and market data. As will be shown below, the equations used to construct these X-variables are simplified end-use models, and the X-variables are the estimated usage levels for each of the major end uses based on these models. The estimated model can then be thought of as a statistically adjusted end-use model, where the estimated slopes are the adjustment factors.

Constructing XHeat

As represented in the SAE spreadsheets, energy use by space heating systems depends on the following types of variables.

- Heating degree days
- Heating equipment saturation levels
- Heating equipment operating efficiencies
- Thermal integrity and footage of homes
- Average household size, household income, and energy prices

The heating variable is represented as the product of an annual equipment index and a monthly usage multiplier. That is,

$$XHeat_{y,m} = HeatIndex_{y,m} \times HeatUse_{y,m} \quad (3)$$

Where:

- $XHeat_{y,m}$ is estimated heating energy use in year (y) and month (m)
- $HeatIndex_{y,m}$ is the monthly index of heating equipment
- $HeatUse_{y,m}$ is the monthly usage multiplier

The heating equipment index is defined as a weighted average across equipment types of equipment saturation levels normalized by operating efficiency levels. Given a set of fixed weights, the index will change over time with changes in equipment saturations (*Sat*), operating efficiencies (*Eff*), building structural index (*StructuralIndex*), and energy prices. Formally, the equipment index is defined as:

$$HeatIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \Big/ Eff_y^{Type} \right)}{\left(Sat_{base\,yr}^{Type} \Big/ Eff_{base\,yr}^{Type} \right)} \quad (4)$$

The *StructuralIndex* is constructed by combining the EIA's building shell efficiency index trends with surface area estimates:

$$StructuralIndex_y = \frac{BuildingShellEfficiencyIndex_y \times SurfaceArea_y}{BuildingShellEfficiencyIndex_{base\ yr} \times SurfaceArea_{base\ yr}} \tag{5}$$

The *StructuralIndex* is defined on the *StructuralVars* tab of the SAE spreadsheets. Surface area is derived to account for roof and wall area of a standard dwelling based on the regional average square footage data obtained from EIA. The relationship between the square footage and surface area is constructed assuming an aspect ratio of 0.75 and an average of 25% two-story and 75% single-story. Given these assumptions, the approximate linear relationship for surface area is:

$$SurfaceArea_y = 892 + 1.44 \times Footage_y \tag{6}$$

For electric heating equipment, the SAE spreadsheets contain two equipment types: electric resistance furnaces/room units and electric space heating heat pumps. Examples of weights for these two equipment types for the U.S. are given in Table 0-1.

TABLE 0-1: ELECTRIC SPACE HEATING EQUIPMENT WEIGHTS

Equipment Type	Weight (kWh)
Electric Resistance Furnace/Room units	767
Electric Space Heating Heat Pump	127

Data for the equipment saturation and efficiency trends are presented on the *Shares* and *Efficiencies* tabs of the SAE spreadsheets. The efficiency for electric space heating heat pumps is given in terms of Heating Seasonal Performance Factor [BTU/Wh], and the efficiencies for electric furnaces and room units are estimated as 100%, which is equivalent to 3.41 BTU/Wh.

Heating system usage levels are impacted on a monthly basis by several factors, including weather, household size, income levels, prices, and billing days. The estimates for space heating equipment usage levels are computed as follows:

$$HeatUse_{y,m} = \left(\frac{HDD_{y,m}}{HDD_{base\ yr}}\right) \times \left(\frac{HHSize_y}{HHSize_{base\ yr,m}}\right)^{0.25} \times \left(\frac{Income_y}{Income_{base\ yr,m}}\right)^{0.15} \times \left(\frac{ElecPrice_{y,m}}{ElecPrice_{base\ yr,m}}\right)^{-0.1} \tag{7}$$

Where:

- *HDD* is the number of heating degree days in year (y) and month (m).
- *HHSize* is average household size in a year (y)
- *Income* is average real income per household in year (y)
- *ElecPrice* is the average real price of electricity in month (m) and year (y)

By construction, the $HeatUse_{y,m}$ variable has an annual sum that is close to 1.0 in the base year. The first term, which involves heating degree days, serve to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will reflect changes in the economic drivers, as transformed through the end-use elasticity parameters. The price impacts captured by the Usage equation represent short-term price response.

Constructing XCool

The explanatory variable for cooling loads is constructed in a similar manner. The amount of energy used by cooling systems depends on the following types of variables.

- Cooling degree days
- Cooling equipment saturation levels
- Cooling equipment operating efficiencies
- Thermal integrity and footage of homes
- Average household size, household income, and energy prices

The cooling variable is represented as the product of an equipment-based index and monthly usage multiplier. That is,

$$XCool_{y,m} = CoolIndex_y \times CoolUse_{y,m} \qquad (8)$$

Where

- $XCool_{y,m}$ is estimated cooling energy use in year (y) and month (m)
- $CoolIndex_y$ is an index of cooling equipment
- $CoolUse_{y,m}$ is the monthly usage multiplier

As with heating, the cooling equipment index is defined as a weighted average across equipment types of equipment saturation levels normalized by operating efficiency levels. Formally, the cooling equipment index is defined as:

$$CoolIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \big/ Eff_y^{Type} \right)}{\left(Sat_{base\ yr}^{Type} \big/ Eff_{base\ yr}^{Type} \right)} \quad (9)$$

For cooling equipment, the SAE spreadsheets contain three equipment types: central air conditioning, space cooling heat pump, and room air conditioning. Examples of weights for these three equipment types for the U.S. are given in Table 0-2.

TABLE 0-2: SPACE COOLING EQUIPMENT WEIGHTS

Equipment Type	Weight (kWh)
Central Air Conditioning	1,219
Space Cooling Heat Pump	240
Room Air Conditioning	177

The equipment saturation and efficiency trends data are presented on the *Shares* and *Efficiencies* tabs of the SAE spreadsheets. The efficiency for space cooling heat pumps and central air conditioning (A/C) units are given in terms of Seasonal Energy Efficiency Ratio [BTU/Wh], and room A/C units efficiencies are given in terms of Energy Efficiency Ratio [BTU/Wh].

Cooling system usage levels are impacted on a monthly basis by several factors, including weather, household size, income levels, and prices. The estimates of cooling equipment usage levels are computed as follows:

$$CoolUse_{y,m} = \left(\frac{CDD_{y,m}}{CDD_{base\ yr}}\right) \times \left(\frac{HHSize_y}{HHSize_{base\ yr,m}}\right)^{0.25} \times \left(\frac{Income_y}{Income_{base\ yr,m}}\right)^{0.15} \times \left(\frac{Elec\,Price_{y,m}}{Elec\,Price_{base\ yr,m}}\right)^{-0.1} \quad (10)$$

Where:

- *CDD* is the number of cooling degree days in year (*y*) and month (*m*).
- *HHSize* is average household size in a year (*y*)
- *Income* is average real income per household in year (*y*)
- *ElecPrice* is the average real price of electricity in month (*m*) and year (*y*)

By construction, the *CoolUse* variable has an annual sum that is close to 1.0 in the base year. The first term, which involves cooling degree days, serves to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will change to reflect changes in the economic driver changes.

Constructing XOther

Monthly estimates of non-weather sensitive sales can be derived in a similar fashion to space heating and cooling. Based on end-use concepts, other sales are driven by:

- Appliance and equipment saturation levels
- Appliance efficiency levels
- Average number of days in the billing cycle for each month
- Average household size, real income, and real prices

The explanatory variable for other uses is defined as follows:

$$XOther_{y,m} = OtherEqpIndex_{y,m} \times OtherUse_{y,m} \tag{11}$$

The first term on the right-hand side of this expression (*OtherEqpIndex*$_y$) embodies information about appliance saturation and efficiency levels and monthly usage multipliers. The second term (*OtherUse*) captures the impact of changes in prices, income, household size, and number of billing-days on appliance utilization.

End-use indices are constructed in the SAE models. A separate end-use index is constructed for each end-use equipment type using the following function form.

$$ApplianceIndex_{y,m} = Weight^{Type} \times \frac{\left(Sat_y^{Type} \Big/ \frac{1}{UEC_y^{Type}} \right)}{\left(Sat_{base\,yr}^{Type} \Big/ \frac{1}{UEC_{base\,yr}^{Type}} \right)} \times MoMult_m^{Type} \times \tag{12}$$

Where:

- *Weight* is the weight for each appliance type
- *Sat* represents the fraction of households, who own an appliance type
- $MoMult_m$ is a monthly multiplier for the appliance type in month (m)
- *Eff* is the average operating efficiency the appliance
- *UEC* is the unit energy consumption for appliances

This index combines information about trends in saturation levels and efficiency levels for the main appliance categories with monthly multipliers for lighting, water heating, and refrigeration.

The appliance saturation and efficiency trends data are presented on the *Shares* and *Efficiencies* tabs of the SAE spreadsheets.

Further monthly variation is introduced by multiplying by usage factors that cut across all end uses, constructed as follows:

$$ApplianceUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{HHSize_{y}}{HHSize_{base\ yr,m}}\right)^{0.26} \times \left(\frac{Income_{y}}{Income_{base\ yr,m}}\right)^{0.15} \times \left(\frac{Elec\ Price_{y,m}}{Elec\ Price_{base\ yr,m}}\right)^{-0.1} \qquad (13)$$

The index for other uses is derived then by summing across the appliances:

$$OtherEqpIndex_{y,m} = \sum_{k} ApplianceIndex_{y,m} \times ApplianceUse_{y,m} \qquad (14)$$

APPENDIX C: COMMERCIAL SAE MODELING FRAMEWORK

The traditional approach to forecasting monthly sales for a customer class is to develop an econometric model that relates monthly sales to weather, seasonal variables, and economic conditions. From a forecasting perspective, the strength of econometric models is that they are well suited to identifying historical trends and to projecting these trends into the future. In contrast, the strength of the end-use modeling approach is the ability to identify the end-use factors that are driving energy use. By incorporating end-use structure into an econometric model, the statistically adjusted end-use (SAE) modeling framework exploits the strengths of both approaches.

There are several advantages to this approach.

- The equipment efficiency trends and saturation changes embodied in the long-run end-use forecasts are introduced explicitly into the short-term monthly sales forecast. This provides a strong bridge between the two forecasts.
- By explicitly introducing trends in equipment saturations and equipment efficiency levels, it is easier to explain changes in usage levels and changes in weather-sensitivity over time.
- Data for short-term models are often not sufficiently robust to support estimation of a full set of price, economic, and demographic effects. By bundling these factors with equipment-oriented drivers, a rich set of elasticities can be built into the final model.

This document describes this approach, the associated supporting Commercial SAE spreadsheets, and *MetrixND* project files that are used in the implementation. The source for the commercial SAE spreadsheets is the 2021 Annual Energy Outlook (AEO) database provided by the Energy Information Administration (EIA).

COMMERCIAL STATISTICALLY ADJUSTED END-USE MODEL FRAMEWORK

The commercial statistically adjusted end-use model framework begins by defining energy use ($USE_{y,m}$) in year (y) and month (m) as the sum of energy used by heating equipment ($Heat_{y,m}$), cooling equipment ($Cool_{y,m}$) and other equipment ($Other_{y,m}$). Formally,

$$USE_{y,m} = Heat_{y,m} + Cool_{y,m} + Other_{y,m} \quad (1)$$

Although monthly sales are measured for individual customers, the end-use components are not. Substituting estimates for the end-use elements gives the following econometric equation.

$$USE_{m} = a + b_1 \times XHeat_{m} + b_2 \times XCool_{m} + b_3 \times XOther_{m} + \varepsilon_{m} \quad (2)$$

Here, $XHeat_m$, $XCool_m$, and $XOther_m$ are explanatory variables constructed from end-use information, weather data, and market data. As will be shown below, the equations used to construct these X-variables are simplified end-use models, and the X-variables are the estimated usage levels for each of the major end uses based on these models. The estimated model can then be thought of as a statistically adjusted end-use model, where the estimated slopes are the adjustment factors.

Constructing XHeat

As represented in the Commercial SAE spreadsheets, energy use by space heating systems depends on the following types of variables.

- Heating degree days,
- Heating equipment saturation levels,
- Heating equipment operating efficiencies,
- Commercial output, employment, population, and energy price.

The heating variable is represented as the product of an annual equipment index and a monthly usage multiplier. That is,

$$\mathrm{XHeat}_{y,m} = \mathrm{HeatIndex}_y \times \mathrm{HeatUse}_{y,m} \tag{3}$$

Where:

- *$XHeat_{y,m}$ is estimated heating energy use in year (y) and month (m),*
- *$HeatInde_{xy}$ is the annual index of heating equipment, and*
- *$HeatUse_{y,m}$ is the monthly usage multiplier.*

The heating equipment index is composed of electric space heating equipment saturation levels normalized by operating efficiency levels. The index will change over time with changes in heating equipment saturations (*HeatShare*) and operating efficiencies (*Eff*). Formally, the equipment index is defined as:

$$HeatIndex_y = HeatSales_{base\ yr} \times \frac{\left(^{HeatShare_y}/_{Eff_y}\right)}{\left(^{HeatShare_{base\ yr}}/_{Eff_{base\ yr}}\right)} \tag{4}$$

The ratio on the right is equal to 1.0 in the base year. In other years, it will be greater than one if equipment saturation levels are above their base year level. This will be counteracted by higher efficiency levels, which will drive the index downward. Base year space heating sales are defined as follows.

$$HeatSales_{base\ yr} = \left(\frac{kWh}{Sqft}\right)_{Heating} \times \left(\frac{CommercialSales_{base\ yr}}{\sum_e {}^{kWh}/_{Sqft_e}}\right) \tag{5}$$

Here, base-year sales for space heating is the product of the average space heating intensity value and the ratio of total commercial sales in the base year over the sum of the end-use intensity values. In the Commercial SAE Spreadsheets, the space heating sales value is defined on the *BaseYrInput* tab. The resulting $HeatIndex_y$ value in the base year will be equal to the estimated annual heating sales in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

Heating system usage levels are impacted on a monthly basis by several factors, including weather, commercial level economic activity, prices and billing days. Using the COMMEND default elasticity parameters, the estimates for space heating equipment usage levels are computed as follows:

$$HeatUse_{y,m} = \left(\frac{HDD_{y,m}}{HDD_{base\ yr}}\right) \times \left(\frac{EconVar_{y,m}}{EconVar_{base\ yr,m}}\right) \times \left(\frac{Price_{y,m}}{Price_{base\ yr,m}}\right)^{-0.10} \tag{6}$$

Where:

- *HDD* is the number of heating degree days in month (m) and year (y).
- *EconVar* is the weighted commercial economic variable that blends Output, Employment, and Population in month (m), and year (y).
- *Price* is the average real price of electricity in month (m) and year (y).

By construction, the $HeatUse_{y,m}$ variable has an annual sum that is close to one in the base year. The first term, which involves heating degree days, serves to allocate annual values to months of the year. The remaining terms average to one in the base year. In other years, the values will reflect changes in commercial output and prices, as transformed through the end-use elasticity parameters. For example, if the real price of electricity goes up 10% relative to the base year value, the price term will contribute a multiplier of about .98 (computed as 1.10 to the -0.18 power).

Constructing XCool

The explanatory variable for cooling loads is constructed in a similar manner. The amount of energy used by cooling systems depends on the following types of variables.

- Cooling degree days,
- Cooling equipment saturation levels,

- Cooling equipment operating efficiencies,
- Commercial output, employment, population, and energy price.

The cooling variable is represented as the product of an equipment-based index and monthly usage multiplier. That is,

$$\mathrm{XCool}_{y,m} = \mathrm{CoolIndex}_{y} \times \mathrm{CoolUse}_{y,m} \tag{7}$$

Where:

- $XCool_{y,m}$ is estimated cooling energy use in year (y) and month (m),
- $CoolIndex_y$ is an index of cooling equipment, and
- $CoolUse_{y,m}$ is the monthly usage multiplier.

As with heating, the cooling equipment index depends on equipment saturation levels (*CoolShare*) normalized by operating efficiency levels (*Eff*). Formally, the cooling equipment index is defined as:

$$CoolIndex_y = CoolSales_{base\ yr} \times \frac{\left({CoolShare_y}/{Eff_y}\right)}{\left({CoolShare_{base\ yr}}/{Eff_{base\ yr}}\right)} \tag{8}$$

Data values in 2004 are used as a base year for normalizing the index, and the ratio on the right is equal to 1.0 in the base year. In other years, it will be greater than one if equipment saturation levels are above their base year level. This will be counteracted by higher efficiency levels, which will drive the index downward. Estimates of base year cooling sales are defined as follows.

$$CoolSales_{base\ yr} = \left(\frac{kWh}{Sqft}\right)_{Cooling} \times \left(\frac{CommercialSales_{base\ yr}}{\sum_e {kWh}/{Sqft_e}}\right) \tag{9}$$

Here, base-year sales for space cooling is the product of the average space cooling intensity value and the ratio of total commercial sales in the base year over the sum of the end-use intensity values. In the Commercial SAE Spreadsheets, the space cooling sales value is defined on the *BaseYrInput* tab. The resulting *CoolIndex* value in the base year will be equal to the estimated annual cooling sales in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

Cooling system usage levels are impacted on a monthly basis by several factors, including weather, economic activity levels and prices. Using the COMMEND default parameters, the estimates of cooling equipment usage levels are computed as follows:

$$CoolUse_{y,m} = \left(\frac{CDD_{y,m}}{CDD_{base\ yr}}\right) \times \left(\frac{EconVar_{y,m}}{EconVar_{base\ yr,m}}\right) \times \left(\frac{Price_{y,m}}{Price_{base\ yr,m}}\right)^{-0.15} \quad (10)$$

Where:

- *HDD* is the number of heating degree days in month (m) and year (y).
- *EconVar* is the weighted commercial economic variable that blends Output, Employment, and Population in month (m), and year (y).
- *Price* is the average real price of electricity in month (m) and year (y).

By construction, the *CoolUse* variable has an annual sum that is close to one in the base year. The first term, which involves cooling degree days, serves to allocate annual values to months of the year. The remaining terms average to one in the base year. In other years, the values will change to reflect changes in commercial output and prices.

Constructing XOther

Monthly estimates of non-weather sensitive sales can be derived in a similar fashion to space heating and cooling. Based on end-use concepts, other sales are driven by:

- Equipment saturation levels,
- Equipment efficiency levels,
- Average number of days in the billing cycle for each month, and
- Real commercial output and real prices.

The explanatory variable for other uses is defined as follows:

$$\mathrm{XOther}_{y,m} = \mathrm{OtherIndex}_{y,m} \times \mathrm{OtherUse}_{y,m} \quad (11)$$

The second term on the right-hand side of this expression embodies information about equipment saturation levels and efficiency levels. The equipment index for other uses is defined as follows:

$$OtherIndex_{y,m} = \sum_{Type} Weight_{base\ yr}^{Type} \times \left(\frac{Share_y^{Type} / Eff_y^{Type}}{Share_{base\ yr}^{Type} / Eff_{base\ yr}^{Type}}\right) \quad (12)$$

Where:

- *Weight* is the weight for each equipment type,

- *Share* represents the fraction of floor stock with an equipment type, and
- *Eff* is the average operating efficiency.

This index combines information about trends in saturation levels and efficiency levels for the main equipment categories. The weights are defined as follows.

$$Weight_{base\ yr}^{Type} = \left(\frac{kWh}{Sqft}\right)_{Type} \times \left(\frac{CommercialSales_{04}}{\sum_e {}^{kWh}/_{Sqft_e}}\right) \tag{13}$$

Further monthly variation is introduced by multiplying by usage factors that cut across all end-uses, constructed as follows:

$$OtherUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{EconVar_{y,m}}{EconVar_{base\ yr,m}}\right) \times \left(\frac{Price_{y.m}}{Price_{base\ yr,m}}\right)^{-0.15} \tag{14}$$