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VOLUME 3

LOAD ANALYSIS AND LOAD FORECASTING

THE EMPIRE DISTRICT ELECTRIC COMPANY D/B/A LIBERTY ("LIBERTY-EMPIRE")

4 CSR 240-22.030

File No. EO-2024-0280

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****Denotes Confidential****

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LOAD ANALYSIS AND LOAD FORECASTING

4 CSR 240-22.30 Load Analysis and Load Forecasting

Purpose: This rule sets minimum standards for the maintenance and updating of historical data, the level of detail required in analyzing loads, and the purposes to be accomplished by load analysis and by load forecast models. The load analysis discussed in this rule is intended to support both demand-side management efforts of 4 CSR 240-22.050 and the load forecast models of this rule. This rule also sets the minimum standards for the documentation of the inputs, components, and methods used to derive the load forecasts.

SECTION 1 SELECTING LOAD ANALYSIS METHODS

(1) The utility may choose multiple methods of load analysis if it deems doing so is necessary to achieve all of the purposes of load analysis and if the methods are consistent with, and calibrated to, one another. The utility shall describe and document its intended purposes for load analysis methods, why the selected load analysis methods best fulfill those purposes, and how the load analysis methods are consistent with one another and with the end-use consumption data used in the demand-side analysis as described in 4 CSR 240-22.050. At a minimum, the load analysis methods shall be selected to achieve the following purposes:

(A) To identify end-use measures that may be potential demand-side resources, generally, those end-use measures with an opportunity for energy and/or demand savings;
(B) To derive a data set of historical values from load research data that can be used as dependent and independent variables in the load forecasts;
(C) To facilitate the analysis of impacts of implemented demand-side programs and demand-side rates on the load forecasts and to augment measurement of the effectiveness of demand-side resources necessary for 4 CSR 240-22.070(8) in the evaluation of the performance of the demand-side programs or rates after they are implemented; and
(D) To preserve, in a historical database, the results of the load analysis used to perform the demand-side analysis as described in 4 CSR 240-22.050, and the load forecasting described in 4 CSR 240-22.030.

The load forecast documented in this volume is intended to achieve the purposes of rule 4 CSR 240-22.30 (IRP Rule). Except for the Variance Request described and approved in Section 1.1, the forecast is consistent with the load forecast methods prescribed in the IRP Rule.

1.1 Variance Request

On April 1, 2024, Liberty-Empire ("Empire") filed a Variance Request identifying one load forecasting deviation and one load forecasting disclosure. The deviation and disclosure are identified below. On June 29, 2024, the variance request was granted in File No. EO-2024-0280.

Deviation Request: End-Use Information for the Industrial Class

4 CSR 240-22.030 (4)(A)(1) requires that analysis for each major class includes information by end-use to the extent possible.

The Variance Request asks that Empire be exempt from the end-use analysis for the industrial class. While Empire includes end-use information for the residential, small commercial, and large commercial classes based on Energy Information Administration (EIA) data, no data are available for the industrial class. This request is consistent with Empire's 2016, 2019, and 2022 IRP filings.

Disclosure: Forecast by Major Class

Various rules in 4 CSR 240-22 identify the data and forecast should be performed by "major class". 4 CSR 240-22.020 (37) defines "major class" as a cost-of-service class for the utility.

In Empire's 2022 IRP filing, Empire worked with Missouri Office of the Public Counsel (OPC) to revise its forecast classes to include the following classes.

- Residential (RG rates)
- Small Commercial (CB and SH rates)
- Large Commercial (GP and TEB rates)
- Large Power (LP rate)
- Power Feed Mills (PFM rate)
- Transmission (PT rate)
- Lighting (LS and PL rates)
- Linde (formerly Praxair)
- Municipals

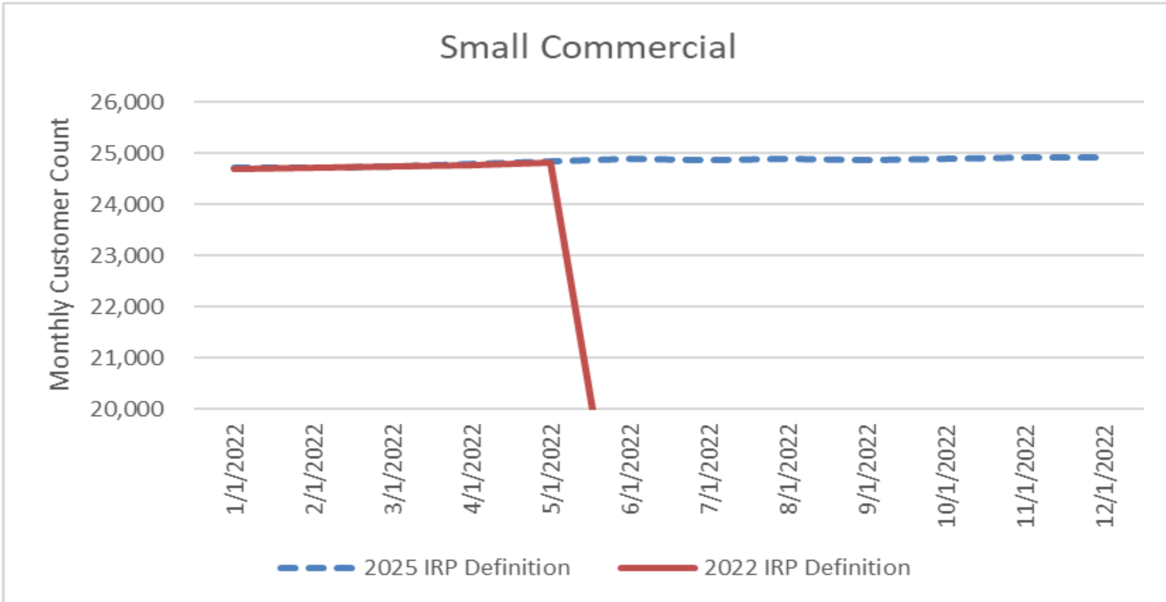
The Variance Request disclosed that Empire will retain the forecast classes but that new rate mappings are required to accommodate Empire's new rates which were implemented in 2022. The new rates are mapped to the classes to maintain consistency between the 2022 IRP data set and the 2025 IRP data set. Table 2-1 show the 2022 IRP and 2025 IRP rate mapping.

Table 2-1 - Rate to Rate Class Mapping

Class	2022 IRP	2025 IRP
Residential	RG Rates	RG, NS-RG, RG WH, RGL, RH, TC-RG, TP-RG, NEB
Small Commercial	CB, SH	CB, SH, NS-GS, PFM, TC-GS, TP-GS, TS-GS
Large Commercial	GP, TEB	GP, TEB, NS-SP, NS-LG, NS-SP TEB, OP GP, TC-SP, NS-SP Oil, TC-LG
Industrial	LP	LP, OP LP
Power Feed Mills	PFM	Class no longer exists
Transmission	PT	PT, OP PT
Lighting	LS, PL	LS, PL, SPL
[redacted]	**[redacted]*	**[redacted]**
Municipals	Lockwood	Lockwood

Figure 2-1 is an example of the rate change and the resulting consistency using the new mapping. In this figure, the 2022 IRP Small Commercial class consists of the two (2) tariffs (i.e., CB and SH tariffs). In April 2022, the class consisted of 24,775 customers. Using the 2022 IRP definition, the class is reduced to 3,080 customers in July 2022. However, these customers are simply moved to new tariffs. Using the 2025 IRP Small Commercial class definition, the July 2022 customer count is 24,868. Figure 2-1 shows that the rate class mapping maintains a consistent Small Commercial data series which is used as the basis for the IRP forecast models.

Figure 2-1 - Small Commercial Rate Mapping Example



SECTION 2 HISTORICAL DATABASE FOR LOAD ANALYSIS

The utility shall develop and maintain data on the actual historical patterns of energy usage within its service territory. The following information shall be maintained and updated on an ongoing basis and described and documented in the triennial compliance filings:

2.1 Customer Class Detail

(A) Customer Class Detail. At a minimum, the historical database shall be maintained for each of the major classes;

The 2025 IRP forecast uses the following major classes as the basis for forecasting. The classes are defined by aggregating multiple rate plans as shown below.

Table 3-2 - Rate Class Definitions

Class	Rate Plans
Residential	RG, NS-RG, RG WH, RGL, RH, TC-RG, TP-RG, NEB
Small Commercial	CB, SH, NS-GS, PFM, TC-GS, TP-GS, TS-GS
Large Commercial	GP, TEB, NS-SP, NS-LG, NS-SP TEB, OP GP, TC-SP, NS-SP Oil, TC-LG
Industrial	LP, OP LP
Transmission	PT, OP PT
Lighting	LS, PL, SPL
[redacted]	**[redacted]**
Municipals	Lockwood

The historical database contains data from January 2011 through March 2024.

2.2 Load Data Detail

(B) Load Data Detail. The historical load database shall contain the following data:

2.2.1 Actual and Weather-Normalized Energy, and Number of Customers

1. For each jurisdiction for which it prepares customer and energy and demand forecasts, for each major class, to the actual monthly energy usage and number of customers and weather-normalized monthly energy usage;

For each major class, the historical monthly customer and usage data is developed from January 2011 through March 2024. Weather normalized usage data by class is based on the final monthly sales models and developed from January 2012 through December 2023. Total weather normalized sales is the sum of the weather normalized class sales.

Table 3-3 shows actual class billed sales summarized to annual billed sales. Table 3-4 shows weather normalized class billed sales summarized to weather normalized total annual sales.

Table 3-3 - Historical Actual Sales (kWh)

Annual Sales (kWh) - Billed Sales Basis					
Year	Residential	Small Commercial	Large Commercial	Industrial	Total Sales
2011	2,001,996,981	460,203,945	1,385,132,954	637,020,442	5,121,413,908
2012	1,832,285,761	441,230,744	1,312,127,422	669,829,138	4,886,860,943
2013	1,916,446,402	443,172,734	1,300,885,179	670,558,006	4,954,398,174
2014	1,951,948,512	459,696,281	1,322,392,909	678,996,279	5,036,563,307
2015	1,855,960,401	453,079,862	1,360,499,114	678,344,314	4,981,347,051
2016	1,809,681,041	444,636,108	1,321,286,114	725,647,284	4,933,191,472
2017	1,751,393,503	435,145,075	1,303,067,407	739,007,184	4,859,063,754
2018	2,005,777,264	468,696,687	1,356,778,114	718,897,749	5,150,676,053
2019	1,903,445,282	451,551,320	1,313,996,651	796,309,305	5,108,941,551
2020	1,843,101,418	429,746,642	1,210,700,027	755,251,202	4,666,410,307
2021	1,927,968,064	449,663,204	1,266,239,606	814,956,278	4,762,207,149
2022	2,001,478,836	469,948,510	1,287,890,235	810,486,260	4,846,494,804
2023	1,929,214,265	465,140,697	1,264,797,642	824,460,323	4,772,462,799

Table 3-4 - Historical Weather Normalized Sales (kWh)

Annual Normal Sales (kWh) - Billed Sales Basis					
Year	Residential	Small Commercial	Large Commercial	Industrial	Total Sales
2012	1,866,594,730	445,010,395	1,306,968,431	662,198,409	4,911,066,264
2013	1,907,822,311	444,259,703	1,301,755,380	673,185,973	4,950,473,827
2014	1,824,812,612	441,392,984	1,302,063,269	680,062,837	4,871,553,592
2015	1,867,789,578	453,216,172	1,361,357,172	677,249,819	4,993,195,039
2016	1,878,371,886	450,854,129	1,319,511,099	718,031,396	4,998,085,003
2017	1,897,743,757	452,898,917	1,322,941,577	736,045,945	5,041,115,923
2018	1,821,449,436	443,330,493	1,316,437,277	712,335,849	4,892,077,184
2019	1,858,882,914	445,349,465	1,303,310,980	793,836,336	5,044,396,868
2020	1,943,293,184	443,004,417	1,229,353,465	757,456,238	4,801,072,527
2021	1,924,014,570	448,414,043	1,267,454,666	814,375,458	4,757,652,415
2022	1,909,387,357	455,034,789	1,259,178,321	804,146,459	4,704,001,751
2023	1,997,350,340	469,855,593	1,266,665,554	819,802,441	4,842,494,564

2.2.2 Historical Estimated Actual and Weather-Normalized System Peaks

2. For each jurisdiction and major class, estimated actual and weather-normalized demands at the time of monthly system peaks; and

Estimated class actual peaks and class weather normalized peaks are developed using load AMI data and the net system loads excluding the wholesale customers that left the system on June 1, 2020. Exiting wholesale customers include Monett, Missouri, Mount Vernon, Missouri, and Chetopa, Kansas (municipals). The city of Lockwood Missouri remains a wholesale customer until 2025.

Estimated actual class peaks are developed by calibrating historical hourly class AMI data to historical sales and identifying the coincident peak. The estimated class actual peaks compared with the system peak are shown in Table 3-5.

Table 3-5 - Estimated Class Actual Peaks (MW)

Estimated Actual Peaks (MW)					
	Residential	Small Commercial	Large Commercial	Industrial	System Peak*
2011	539	102	247	98	1,130
2012	493	108	241	128	1,078
2013	409	108	243	137	1,017
2014	647	96	225	48	1,111
2015	587	94	236	54	1,096
2016	569	83	228	60	1,063
2017	480	106	243	123	1,016
2018	639	96	228	85	1,158
2019	545	87	229	78	1,061
2020	456	105	228	99	994
2021	753	103	101	55	1,220
2022	761	96	390	174	1,249
2023	536	109	252	126	1,120

*System peaks exclude municipal data (Monett, Mount Vernon, and Chetopa).

Class weather normalized peaks are estimated based on the weather normalized system peak and the estimated class actual peaks from Table 3-5. Class weather normalized peaks are calculated using the ratio of the estimated class actual peak to the system peak and then applying the ratio to the weather normalized system peak. The system peak weather normalization is described in Section 2.2.3. Class weather normalized peaks are shown in Table 3-6.

Table 3-6 - Historical Weather-Normalized Peaks (MW)

Weather Normalized Class Peaks (MW)					
	Residential	Small Commercial	Large Commercial	Industrial	System Peak
2012	493	108	241	128	1,078
2013	437	116	259	146	1,085
2014	617	92	214	46	1,060
2015	611	98	246	57	1,142
2016	577	84	231	61	1,078
2017	504	111	255	129	1,068
2018	578	87	206	77	1,047
2019	566	90	237	81	1,101
2020	501	116	251	109	1,092
2021	690	95	93	50	1,118
2022	688	87	353	157	1,129
2023	531	108	249	125	1,109

2.2.3 Weather Normalized Net System Loads

3. *For the system, actual and weather-normalized hourly net system load;*

Empire maintains actual hourly net system loads. The historical database is maintained with at least 10 years of data.

While Empire does not weather normalize historical hourly net system loads, it does weather normalize monthly class sales and monthly peaks. The weather normalized sales and peaks characterize the net system loads. Section 2.2.1 shows the weather normalized sales and Section 2.2.2 shows the weather normalized peaks.

Weather normalized sales are calculated as the sum of the weather normalized class sales.

Weather normalized class sales are developed using the sales models described in Section 6.1.2 and weather from the Springfield, Missouri airport. Normal weather is defined as the 30-year average from 1994 to 2023.

Weather normalized peaks are calculated based on the final peak model described in Section 6.1.2.9. Normal peak producing weather is developed using the most recent 20 years of peak producing weather.

2.3 Load Component Detail

(C) Load Component Detail. The historical database for major class monthly energy usage and demands at time of monthly peaks shall be disaggregated into a number-of-units component and a use-per-unit component, for both actual and weather-normalized loads.

2.3.1 Units Component

1. The number-of-units component shall be the number of customers, square feet, devices, or other units as appropriate to the customer class and the load analysis method selected by the utility. The utility shall select the units component with the intent of providing meaningful load analysis for demand-side analysis and maintaining the integrity of the database over time.

The number-of-units component selected by Empire is “customers” and the use-per-unit is sales-per-customer. Sales-per-customer is calculated by dividing sales by customers. In this document, sales-per-customer will also be referred to as use-per-customer (UPC).

2.3.2 Update Procedure

2. The utility shall develop and implement a procedure to routinely measure and regularly update estimates of the effect of departures from normal weather on class and system electric loads. The estimates of the effect of weather on historical major class and system loads shall incorporate the nonlinear response of loads to daily weather and seasonal variations in loads.

Empire updates its load forecast each year. During each forecast cycle, Empire reviews the historical dataset for data anomalies and updates its forecast models. Once the forecast is complete, Empire reviews the forecast with senior management prior to its adoption. The update process ensures that the latest data and weather response information is included in the modeling process.

2.3.3 Weather Measures and Estimation of Weather Effects Description and Documentation

3. The utility shall describe and document the methods used to develop weather measures and the methods used to estimate the effect of weather on electric loads. If statistical models are used, the documentation shall include at least: the functional form of the models; the estimation techniques employed; and the relevant statistical results of the models, including parameter estimates and tests of statistical significance. The data used to estimate the models, including the development of model input data from basic data, shall be included in the work papers supplied at the time the compliance report is filed;

The load forecast uses regression models to capture the effect of weather on electric loads. The regression models use multipart spline variables to capture the nonlinear relationship between load and weather. The statistical significance of the spline variables is considered in the overall context of the regression model. The models and relevant statistics are described in Section 6.1.2.

2.4 Assessments

(D) For each major class specified pursuant to subsection (2)(A), the utility shall provide, on a seasonal and annual basis for each year of the historical period—

2.4.1 Historic End-Use Drivers of Energy Usage and Peak Demand

1. Its assessment of the historical end-use drivers of energy usage and peak demand, including trends in numbers of units and energy consumption per unit;

The residential, small commercial, and large commercial sales models use Itron’s Statistically Adjusted End-Use ("SAE") modeling framework. The SAE model includes annual end-use drivers obtained from Itron based on the Energy Information Administration’s ("EIA") 2023 Annual Energy Outlook ("AEO"). These data capture changing end-use saturation and energy efficiency trends for each census region based on adopted energy efficiency codes and standards.

The peak model uses inputs from the class sales models. By using the sales models, the peak model implicitly incorporates the impact of the changing end-uses embedded in the residential, small commercial, and large commercial models.

2.4.2 Weather Sensitivity of Energy and Peak Demand

2. Its assessment of the weather sensitivity of energy and peak demand.

Historic weather data are obtained from the National Oceanic and Atmospheric Administration ("NOAA") for the Springfield, Missouri airport. These data are used to develop monthly heating and cooling degree days and peak producing weather. The weather data are included in the sales and peak models to capture the weather sensitivity of electric consumption.

2.4.3 Plots Illustrating Trends

3. Plots illustrating trends materially affecting electricity consumption over the historical period;

The major trends affecting electric consumption are economic indicators, prices, weather, and end-use trends. Figure 3-2 through Figure 3-5 show annual plots summarizing the major trends used in the forecast models.

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Figure 3-2 - Annual Summary of a Major Trend - Economic Indices

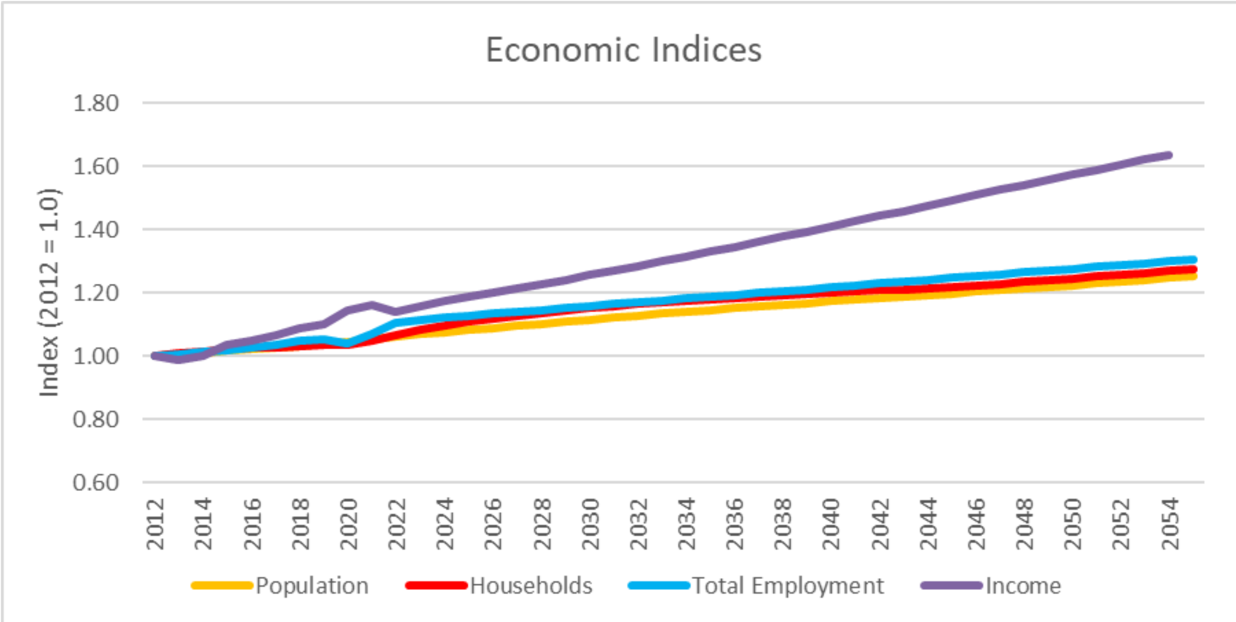


Figure 3-3 - Annual Summary of a Major Trend - Electric Prices

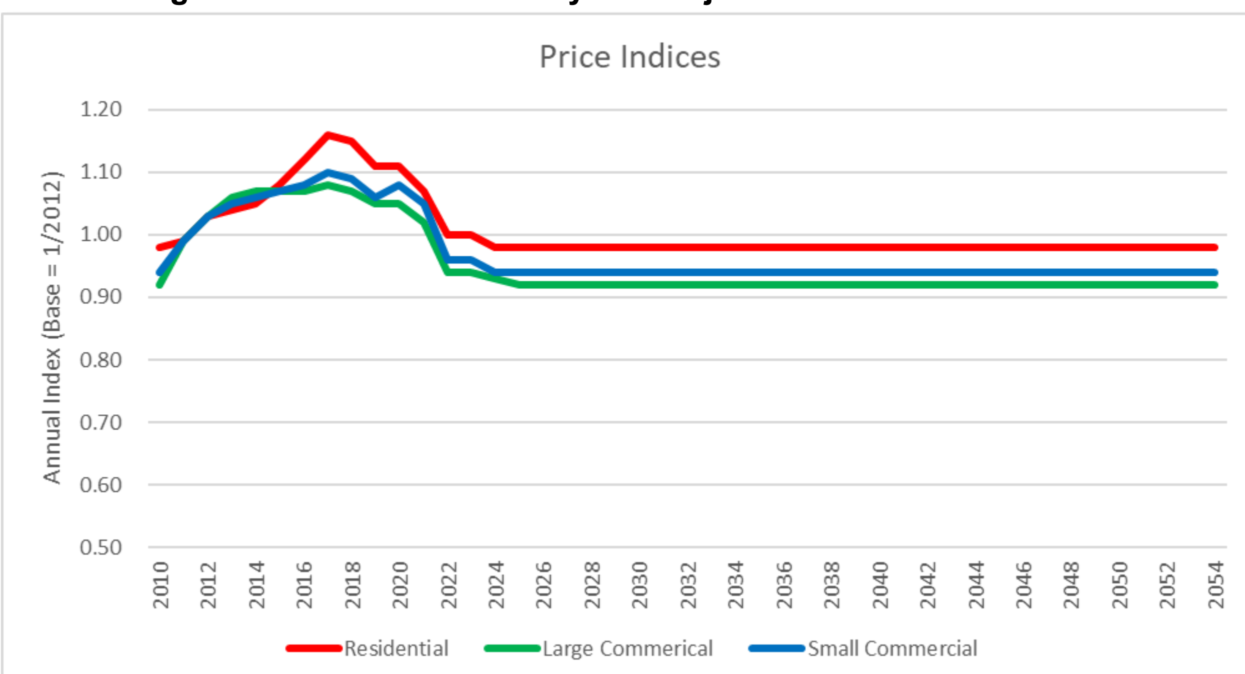


Figure 3-4 - Annual Summary of a Major Trend - Residential SAE Indices

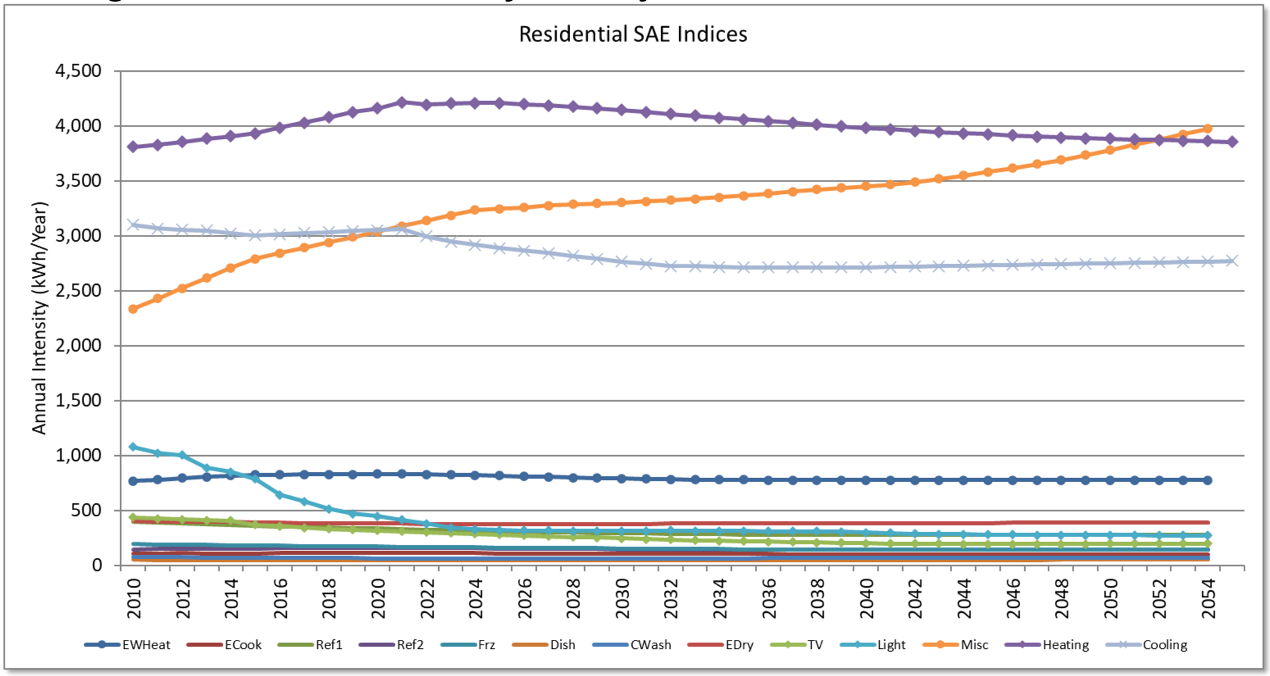


Figure 3-5 - Annual Summary of a Major Trend - Commercial SAE Indices

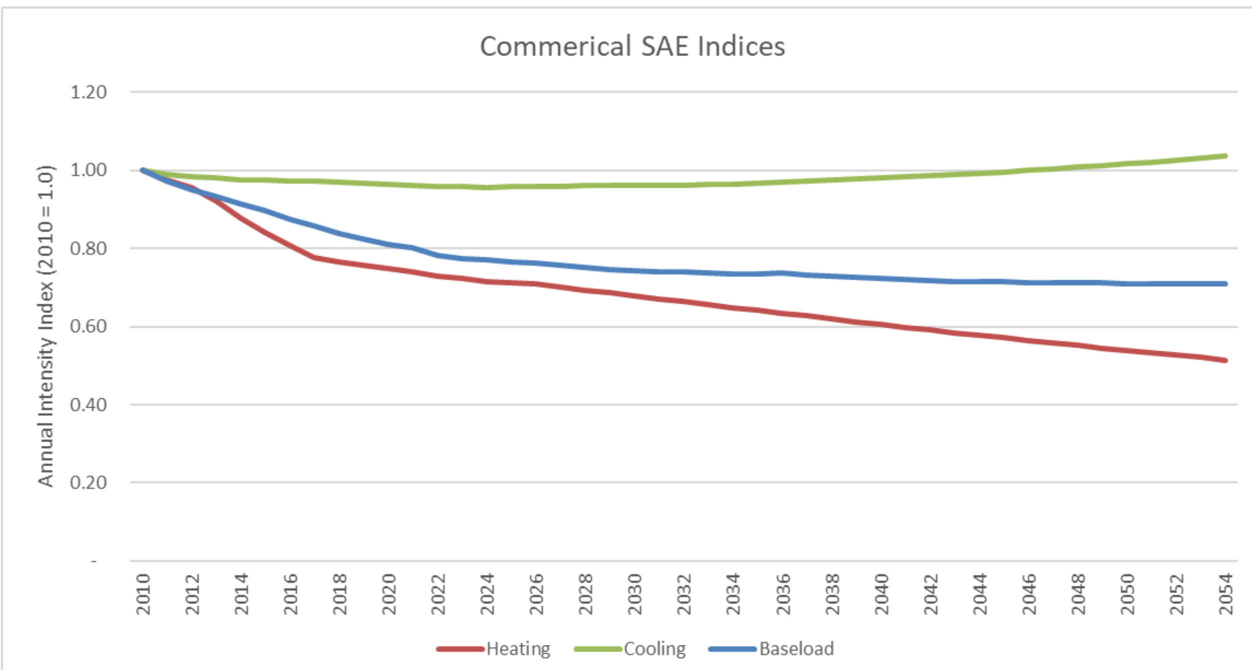
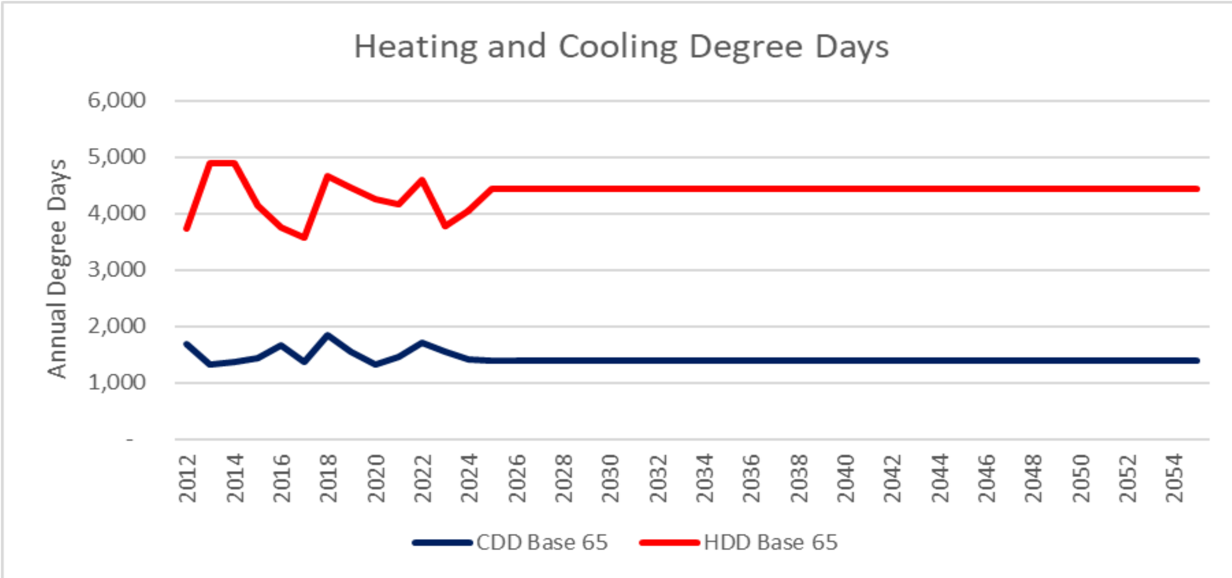


Figure 3-6 - Annual Summary of a Major Trend - Heating and Cooling Degree Days



2.5 Adjustments to Historical Data Description and Documentation

(E) The utility shall describe and document any adjustments that it made to historical data prior to using it in its development or interpretation of the forecasting models; and

The forecast uses historical sales, peak, customers, weather, economic, and end-use data in the forecast models. Of these data, no adjustments were made to the sales or customers data.

Monthly peak data are derived from hourly net system loads. Two modifications are made to the peak data. First, estimates of historical curtailments are added to historical peaks to model gross peaks. Second, municipal data (i.e., Monett, Mount Vernon, and Chetopa) are removed from the history.

Economic data are provided by Woods and Poole Inc. for the Joplin and Springfield metropolitan statistical areas (MSAs). The data are combined applying a 60% weight to the Joplin MSA and a 40% weight to the Springfield MSA. Weights are based on March

2021 residential customer counts for counties included in the Joplin and Springfield MSAs.

End-use data are provided by Itron and are adjusted to reflect Empire's 2008 Potential Study, 2015 Saturation Survey, and 2021 Market Research study. Calibrating Itron's data to Empire's historical saturation data includes smoothing the transitions between known Empire saturation levels and Itron's long-term trends. Both residential and commercial end-use data are also adjusted to include historical DSM savings.

2.6 Length of Historical Database

(F) Length of Historical Database. The utility shall develop and retain the historical database over the historical period.

Empire created the historical database to include, at a minimum, data from January 2011 through March 2024.

SECTION 3 ANALYSIS OF NUMBER OF UNITS

For each major class, the utility shall describe and document its analysis of the historical relationship between the number of units and the economic and/or demographic factors (explanatory variables) that affect the number of units for that major class. The analysis may incorporate or substitute the results of secondary analyses, with the proviso that the utility analyze and verify the applicability of those results to its service territory. If the utility develops primary analyses, or to the extent they are available from secondary analyses, these relationships shall be specified as statistical or mathematical models that relate the number of units to the explanatory variables.

3.1 Identification of Explanatory Variables

(A) Choice of Explanatory Variables. The utility shall identify appropriate explanatory variables as predictors of the number of units for each major class. The critical assumptions that influence the explanatory variables shall also be identified and documented.

Selection of the appropriate explanatory variables for the class number of units models (i.e., customer count models) is performed in model building process. The variable selection considers variables used in the prior IRP models and additional economic variables from the Woods and Poole dataset. The selection of the explanatory variable is based on statistical significance and industry accepted causality.

For classes with a small number of customers or relatively constant number of customers, a constant forecast is used. These classes do not show correlation with known economic drivers and statistical modelling is not appropriate. Instead, customer increases are included when specific customer projects are known.

The key explanatory variables for each customer count model are listed and described in Table 3-7.

Table 3-7 - Key Drivers for Customer Count Models

Major Class	Key Explanatory Variable	Description
Residential	Households	The number of households is the primary driver for the residential class. This driver is a common explanatory variable used by utilities to forecast residential customer growth. This driver's correlation coefficient with residential customer counts is 0.972.
Small Commercial	Total Employment	Total employment is the primary driver for the small commercial class. Employment is a common explanatory variable used by utilities to forecast commercial customer growth. This driver's correlation coefficient with small commercial customer counts is 0.944.
Large Commercial	Total Employment	Total employment is the primary driver for the large commercial class. Employment is a common explanatory variable used by utilities to forecast commercial customer growth. This driver's correlation coefficient with large commercial customer counts is 0.812.
Industrial	None	Between 2012 to 2024, the number of customers varies between 35 and 46. Because of the relatively constant number of customers, a constant forecast is used.
Transmission	None	Between 2012 and 2024, the number of customers varies between 13 and 15. Because of the relatively constant number of customers, a constant forecast is used.
Linde	None	Linde is a single customer.
Lighting	None	Lighting customers have declined from 569 in 2012 to 437 in 2024. Because no economic drivers correlate with the customer decline a constant forecast is used.
Municipal	None	The municipal class now consists of a single customer, the city of Lockwood. Lockwood will leave the Empire system in 2025.

3.2 Statistical Model Documentation

(B) Documentation of statistical models shall include the elements specified in sub-section (2)(C) of this rule. Documentation of mathematical models shall include a specification of the functional form of the equations if the utility develops primary analyses, or to the extent they are available if the utility incorporates secondary analyses.

The model functional form of equations and statistical results are shown in Section 6.1.2.

SECTION 4 USE PER UNIT ANALYSIS

For each major class, the utility shall describe and document its analysis of historical use per unit by end use.

4.1 End-Use Load Detail

(A) End-Use Load Detail. For each major class, use per unit shall be disaggregated, where information permits, by end-uses that contribute significantly to energy use or peak demand.
1. The utility shall consider developing information on at least the following end-use loads:

4.1.1 Residential Sector

A. For the residential sector: lighting, space cooling, space heating, ventilation, water heating, refrigerators, freezers, cooking, clothes washers, clothes dryers, television, personal computers, furnace fans, plug loads, and other uses;

The residential sales forecast uses Itron's SAE modeling framework. This framework models residential average usage based on end-use information. The model includes the following end-uses.

- Electric space heating
- Central air conditioning
- Room air conditioning
- Heat Pumps
- Electric water heating
- Electric cooking
- Refrigeration
- Freezers
- Dishwashers
- Clothes washers
- Clothes dryers
- Televisions
- Lighting
- Miscellaneous end-uses

End-use data are obtained from the 2023 EIA AEO forecast and developed by Itron for the West North Central region. End-use saturations are modified to include Empire's 2008 Potential Study, 2015 Saturation Survey, and 2021 Market Research study. End-use intensity data are modified to include estimates of Empire's historical DSM programs.

4.1.2 Commercial Sector

B. For the commercial sector: space heat, space cooling, ventilation, water heat, refrigeration, lighting, office equipment, cooking equipment, and other uses; and

Both small commercial and large commercial class sales use Itron's SAE modelling framework and Itron's commercial sector SAE data. The commercial sector SAE data includes the following end-uses.

- Electric heating
- Cooling
- Ventilation
- Electric water heating
- Electric cooking
- Refrigeration
- Lighting
- Office equipment
- Miscellaneous end-uses

End-use data are obtained from the 2023 EIA AEO forecast and developed by Itron for the West North Central region. End-use intensity data are modified to include estimates of Empire's historical DSM programs.

4.1.3 Industrial Sector

C. For the industrial sector: machine drives, space heat, space cooling, ventilation, lighting, process heating, and other uses.

The industrial sales forecast is developed using a regression model. This model does not include end-use information. Empire submitted a variance request specifying that end-use information was not available for the industrial class. The variance request was approved on June 29, 2024.

4.1.4 Modifications of End-Use Loads

2. The utility may modify the end-use loads specified in paragraph (4)(A)1.

4.1.4.1 Removal or Consolidation of End-Use Loads

A. The utility may remove or consolidate the specified end-use loads if it determines that a specified end-use load is not contributing, and is not likely to contribute in the future, significantly to energy use or peak demand in a major class.

Itron's SAE modelling framework consolidates end-use information into three explanatory variables, XHeat, XCool and XOther. Each variable aggregates technology information for heating, cooling, and base load end-uses and combines the aggregated information with economic variables that describe how customers use electricity.

4.1.4.2 Additions to End-Use Loads

B. The utility shall add to the specified end-use loads if it determines that an end-use load currently not specified is likely to contribute significantly to energy use or peak demand in a major class.

There were no additions to specified end-use loads.

4.1.4.3 Modification of End-Use Documentation

C. The utility shall provide documentation of its decision to modify the specified end-use loads for which information is developed, as well as an assessment of how the modifications can be made to best preserve the continuity and integrity of the end-use load database.

Construction of the end-use variables is maintained in the MetrixND forecasting software. Input data for the end-uses are obtained from Itron's annual SAE data updates. Modifications to the end-use data are described in Section 2.5.

4.1.5 Schedule for Acquiring End-Use Load Information

3. For each major class and each end-use load, including those listed in paragraph (4)(A)1., if information is not available, the utility shall provide a schedule for acquiring this end-use load information or demonstrate that either the expected costs of acquisition were found to outweigh *the expected benefits over the planning horizon or that gathering the end-use load information has proven to be infeasible.*

While Empire uses end-use data for the residential, small commercial, and large commercial classes developed by Itron, it does not use end-use data for the industrial class. As explained in Empire's Variance Request, Itron and Empire do not maintain end-use information for the industrial class.

End-use data is useful for classes with a large number of customers and where end-use saturation data can model equipment stock turnover and efficiency changes. Currently, the industrial class consists of 44 customers. Due to the class's low number of customers, equipment stock turnover will be "lumpy" and not yield strong statistical benefits. As a result, Empire does not intend to collect industrial end-use data in the future.

4.1.6 Weather Effects on Load

4. The utility shall determine the effect that weather has on the total load of each major class by disaggregating the load into its cooling, heating, and non-weather-sensitive components. If the cooling or heating components are a significant portion of the total load of the major class, then the cooling or heating components of that load shall be designated as end uses for that major class.

Weather has a significant impact on most major classes. The weather impact is modeled with the XHeat, XCool, HDD, and CDD variables. The model variables are defined in Section 6.1.2.

4.2 End-Use Development

(B) The database and historical analysis required for each end use shall be developed from a utility-specific survey or other primary data. The database and analysis may incorporate or substitute the results of secondary data, with the proviso that the utility analyze and verify the applicability of those results to its service territory. The database and historical analysis required for each end use shall include at least the following:

4.2.1 Measures of the Stock of Energy-Using Capital Goods

1. Measures of the stock of energy-using capital goods. For each major class and end-use load identified in subsection (4)(A), the utility shall implement a procedure to develop and maintain adequate data on the energy-related characteristics of the building, appliance, and equipment stock including saturation levels, efficiency levels, and sizes, where applicable. The utility shall update the data before each triennial compliance filing;

Empire does not maintain a database of equipment stock for use in the SAE model. Instead, Empire acquires equipment stock data through Itron's SAE datasets for each IRP forecast cycle. Itron's SAE datasets are based on the EIA's AEO equipment stock forecasts.

4.2.2 End-Use Energy and Demand Estimates

2. Estimates of end-use energy and demand. For the end-use loads identified in subsection (4)(A), the utility shall estimate monthly energies and demands at the time of monthly system peaks and shall calibrate these energies and demands to equal the weather-normalized monthly energies and demands at the time of monthly peaks for each major class for the most recently available data.

End-use sales estimates are embedded in the SAE models used for the residential, small commercial, and large commercial classes. By design, the SAE models calibrate historical billed sales to the end-use data through the model coefficients. Using these model coefficients, the end-use sales may be calculated by multiplying the model coefficients by their input end-use data.

Estimates for end-use demand are embedded in the peak model. The key inputs to the peak demand model are the end-use sales components. Like the SAE models, end-use demand components may be calculated using the model coefficients and their input data.

SECTION 5 SELECTING LOAD FORECASTING MODELS

The utility shall select load forecast models and develop the historical database needed to support the selected models. The selected load forecast models will include a method of end-use load analysis for at least the residential and small commercial classes, unless the utility demonstrates that end-use load methods are not practicable and provides documentation that other methods are at a minimum comparable to end-use methods. The utility may choose multiple models and methods if it deems doing so is necessary to achieve all of the purposes of load forecasting and if the methods and models are consistent with, and calibrated to, one another. The utility shall describe and document its intended purposes for load forecast models, why the selected load forecast models best fulfill those purposes, and how the load forecast models are consistent with one another and with the end-use usage data used in the demand-side analysis as described in 4 CSR 240-22.050. As a minimum, the load forecast models shall be selected to achieve the following purposes:

5.1 Consumption Drivers and Usage Patterns

(A) Assessment of consumption drivers and customer usage patterns—to better understand customer preferences and their impacts on future energy and demand requirements, including weather sensitivity of load;

Consumption drivers and usage patterns are analyzed in the model development process. The residential, small commercial, and large commercial classes use Itron's SAE modelling framework to incorporate end-use saturation and efficiency patterns. The remaining classes use a mix of econometric models and exponential smoothing models to forecast class sales trends. When classes do not show significant growth over the historical period, forecast trends are projected to be "flat" or "constant". The forecast models are described in 6.1.2.

5.2 Long-Term Load Forecasts

(B) Long-term load forecasts—to serve as a basis for planning capacity and energy service needs. This can be served by any forecasting method or methods that produce reasonable projections (based on comparing model projections of loads to actual loads) of future demand and energy loads;

The forecast is developed using three main modeling processes: (1) monthly class sales models, (2) monthly system peak model, and (3) hourly profiles models. When these three processes are combined, the result is a long-term hourly load forecast from 2025 through 2054.

The process is summarized below:

1. Monthly Class Sales Models: The sales models use Itron's SAE method for the residential, small commercial, and large commercial, and traditional econometric or exponential smoothing methods for the remaining classes.

   The following rate classes are modeled.

   - Residential
   - Small Commercial
   - Large Commercial
   - Industrial
   - Transmission
   - Linde
   - Lighting
   - Municipal (Lockwood)

   The sales models are based on historical monthly rate class data and include the impacts of historical DSM programs and behind-the-meter photovoltaic (PV) generation.

2. Monthly System Peak Model: The peak model forecasts monthly gross system peaks. The peak model is an econometric model and based on historical and forecast sales.

3. Hourly Load Models: The system hourly load forecast is developed by aggregating hourly class forecasts, calibrating it to the peak model forecast, and then adjusting the hourly forecast for future electric vehicles (EV) and behind-the-meter photovoltaics (PV). The hourly class forecasts are developed using the

sales model forecast scaled for losses and shaped with hourly profile models. The EV forecast calibrates an hourly charging profiles to forecasted monthly EV sales. The PV forecast calibrates an hourly PV generation profile to forecasted monthly PV generation.

5.3 Policy Analysis

(C) Policy analysis—to assess the impact of legal mandates, economic policies, and rate designs on future energy and demand requirements. The utility may use any load forecasting method or methods that it demonstrates can adequately analyze the impacts of legal mandates, economic policies, and rate designs.

The load forecasting method includes the impacts of legal mandates and economic policies through the input variables. The models are specifically designed to capture adopted changes in end-use codes and standards. Future price effects are assumed to be constant in real dollars. And finally, economic policy is embedded in the long-term economic forecast.

SECTION 6 LOAD FORECASTING MODEL SPECIFICATIONS

6.1 Description and Documentation

(A) For each load forecasting model selected by the utility pursuant to section 4 CSR 240-22.030(5), the utility shall describe and document its—

6.1.1 Determination of Independent Variables

1. Determination of appropriate independent variables as predictors of energy and peak demand for each major class. The critical assumptions that influence the independent variables shall also be identified.

As described in Section 5.2, the forecast is developed in three steps. This section describes the critical assumptions in each step. Appendix A contains Itron's report summarizing the modeling method, model, and results.

Step 1 - Monthly Class Sales Models. Three classes of independent variables are used in the monthly class sales models – weather, end-use, and economic variables. These variables are described below.

a. Weather Variables. For each class, Empire determines whether temperature is critical in the forecast model by examining scatter plots and statistical models. Temperature is incorporated into most class sales models. When temperature is included, weather variables are constructed using multipart weather splines (HDD and CDD) and weighted current and prior month weather data that approximate billing cycle impacts. Weather forecasts use 30-year normal temperatures for Springfield, Missouri.

b. End-Use Variables. For residential, small commercial, and large commercial classes, Empire uses the SAE model framework. The SAE framework captures changing end-use saturation and efficiency trends over time. The statistical fit is used to determine the appropriateness of the model calibration.

c. Economic Variables. Economic variables are selected based on statistical fit and the relationship between the economic and class growth.

Step 2 – Monthly System Peak Model. The peak model uses the peak dataset, weather, and growth trends. These inputs are described below.

a. Peak Dataset. The peak dataset is developed using historical monthly peaks restored with estimated curtailments from January 2010 to April 2024. The data removes the municipal data (i.e., Monett, Mount Vernon, and Chetopa).

b. Weather. Historical weather data are derived from the historical weather conditions on past monthly peak days. Normal weather is used to create the long-term peak forecast. The normal weather calculation uses the following steps:

    1) Historical peak temperature is calculated as a three-day weighted average. The weighted average consists of 70% of the current day temperature, 20% of the prior day temperature, and 10% of the two-day prior temperature.

2) The normal peak weather is the average of historical peak weather over the prior 20 years (or 21 years) calculated as the average from January 2004 through April 2024.

3) Shoulder month peaks may be driven by hot or cold weather. For instance, April peaks are driven by hot weather in 8 of the 21 historical years. For normal peak weather in April, May and October, the normal weather is modified by removing historical years from the average that do not match the primary weather effect. In April, the predominate peak weather effect is heating. As a result, the cooling peak weather is removed from the April normal weather calculation. May is designated as a cooling month, and October is designated as a heating month.

4) Because January and August are the seasonal peaks, their normal values are replaced using the seasonal peak averages.

c. Growth Trends. Peak growth is related to the underlying changes in end-use equipment. For example, if electric space heating is growing faster than space cooling, winter peaks should grow at a faster rate than summer peaks. This differentiated peak growth is captured by decomposing the sales models into their heating, cooling, and base load components and using these components to drive winter and summer peak growth. Statistical evaluation of the growth drivers is used to identify the most appropriate variables.

Step 3 – Hourly Load Models. The hourly load forecast is developed using a bottom-up approach, then calibrating the hourly load forecast to the system peak forecast. The approach begins by developing hourly rate class profile models based on Empire's AMI data. The hourly profiles are forecast using daily normal weather. Next, the hourly profiles are calibrated to their respective class sales forecasts from Step 1 and scaled for losses to obtain the hourly class loads. The hourly class loads are summed to obtain the hourly system loads and calibrated to the system peak forecast from Step 2. Finally, independent forecasts for EVs and PVs are used to modify the hourly system load forecast. The key assumptions in this step are described below.

a. Daily Normal Weather. Normal daily average temperatures are calculated using a 30-year period (1994-2023) and the rank-and-average method. In the forecast period, the rank-and-average results are mapped to the 2003 temperature calendar and scaled to be consistent with the 30-year monthly normal HDDs and CDDs.

b. PV Model. Behind-the-meter solar is forecast based on the EIA's 2023 AEO PV forecast calibrated to historical Empire solar adoption. The hourly profiles are based on the National Renewable Energy Laboratory's (NREL) PVWatts Calculator for Springfield, Missouri.

c. EV Model. The EV forecast is based on an estimate of EVs currently active in Empire's service territory and the EIA's 2023 AEO forecast growth rates. The current number of EVs is derived from the Alternative Fuel Data Center (AFDC) 2022 estimates, modified based on Empire's population relative to the state population, and escalated based on the EIA's 2023 AEO forecast. The hourly profiles are based on AFDC charging profiles assuming a "delayed – finish by departure" charging strategy for residential charging and "immediate" charging strategy for workplace and fast charging stations.

6.1.1.1 Historical Explanatory Variables by Class

A. The utility shall assess the applicability of the historical explanatory variables pursuant to subsection (3)(A) to its selected forecast model.

The key variables included in each class model are summarized in Table 3-7. This section summarizes the modeling method for each class.

Residential Class

Residential electric sales are weather sensitive and subject to changing usage patterns over time based on the saturation and efficiency of end-use appliances. To capture these changes, two models are used to develop the residential electric sales forecast. These models are defined below:

- Customer Model: This model forecasts the number of residential customers in each month.
- UPC Model: This model forecasts the average use-per-customer (UPC) for each month.

The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month. Using two models to develop the residential class forecast captures both the class growth based on a changing number of customers (customer model) and changes in customer usage patterns (UPC model).

Small Commercial Class

The Small Commercial class consists of customers with the CB, SH, NS-GS, PFM, TC-GS, TP-GS, and TS-GS rates. As with the residential class, small commercial sales are modeled using two models. These models capture both the growth based on the number of customers and the changing usage of the average customer based on end-use information.

These models are defined below:

- Customer Model: This model forecasts the number of small commercial customers in each month.
- UPC Model: This model forecasts the average UPC for each month.

The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month. Using two models to develop the small commercial class forecast captures both the class growth based on a changing number of customers (customer model) and changes in customer usage patterns (UPC model).

Large Commercial Class

The Large Commercial class consists of customers with the GP, TEB, NS-SP, NS-LG, NS-SP TEB, OP GP, TC-SP, NS-SP Oil, and TC-LG rates. This class is modeled using two models. These models capture both the growth based on the number of customers and the changing usage of the average customer based on end-use information. These models are defined below:

- Customer Model: This model forecasts the number of large commercial customers in each month.
- UPC Model: This model forecasts the average UPC for each month.

The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month. Using two models to develop the large commercial class forecast captures both the class growth based on a changing number of customers (customer model) and changes in customer usage patterns (UPC model).

Industrial Class

The Industrial class consists of customers with the LP and OP LP rate. This class is modeled using a customer count forecast and a UPC Model. The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month.

- Customer Forecast: Between January 2012 and March 2024, the class varied between 35 and 44 customers. The low number of customers cannot be reliability forecast using a statistical model. Instead, the industrial customer forecast is based on known customer expansions and projects.
- UPC Model: This model forecasts the average UPC for each month.

The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month.

Transmission Class

The Transmission class consists of customers with the transmission rates. This class is modeled using a customer count forecast and a UPC Model. The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month.

- Customer Forecast: Between January 2012 and March 2024, the number of customers varies between 13 and 15. Since the number of customers has not dramatically changed since 2020, the forecast assumes the existing 13 customers continue through the forecast period with no new additions.
- UPC Model: This model forecasts the average UPC for each month.

The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month.

Linde Class

[redacted].

Lighting Class

The Lighting class consists of customers with the LS, PL, and SPL rates. This class is modeled using two models. These models capture both the growth based on the number of customers and the changing usage of the average customer based on end-use information. These models are defined below:

- Customer Model: This model forecasts the number of lighting customers in each month.
- UPC Model: This model forecasts the average UPC for each month.

The class sales forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total sales in each month.

Municipal Class

The Municipal class consists of the city of Lockwood, a wholesale customer. This class is modeled using total Lockwood sales in each month. Because the Lockwood will no longer be an Empire customer beginning in June 2025, the forecast model is simplified from the prior IPR models, and the forecast is set to “0” beginning in June 2025.

System Peak Model

The system peak model is a regression model designed to forecast monthly peaks. Monthly peaks are restored for estimated curtailments and modified to remove historical municipal data (i.e., Monett, Mount Vernon, and Chetopa).

Profile Models

Eight hourly profile models are developed to create the class hourly loads. The profile models are hourly regression models and use similar structures to capture the load shape based on time of year and weather.

6.1.1.2 Independent and Historical Explanatory Variable Difference

B. To the extent that the independent variables selected by the utility differ from the historical explanatory variables, the utility shall describe and document those differences.

The 2025 forecast models are consistent with the 2022 forecast models. Table 3-8 highlights the 2025 and 2022 IRP drivers.

Table 3-8 - Variable Differences Between the 2022 and 2025 IRP Models

Key Drivers Changes for Forecast Models			
Class	**Model**	**2025 IRP**	**2022 IRP**
Residential			
	Customer	• Households (Joplin and Springfield MSAs)	• Households (Joplin and Springfield MSAs)
	Average Use (SAE Model)	• 2023 SAE Data	• 2021 SAE Data
Small Commercial			
	Customer	• Total Employment	• Total Employment
	Average Use (SAE Model)	• 2023 SAE Data	• 2021 SAE Data
Large Commercial			
	Customer	• Total Employment	• Total Employment
	Average Use (SAE Model)	• 2023 SAE Data	• 2021 SAE Data
Industrial			

Key Drivers Changes for Forecast Models			
Class	**Model**	**2025 IRP**	**2022 IRP**
	Customer	• Known Customer Additions	• Known Customer Additions
	Average Use	• Historical Average UPC	• Historical Average UPC
Transmission			
	Customer	• Flat Forecast	• Flat Forecast
	Average Use	• Historical Average UPC	• Historical Average UPC
Linde			
	Sales	• Historical Average	• Historical Average plus known additions
Lighting			
	Customer	• Flat Forecast	• Flat Forecast
	Average Use	• Lighting Customer Forecast	• Lighting Customer Forecast
Municipals			
	Sales	• Heating and Cooling Degree days	• 2021 SAE
System Peak			
	Peak Model	• CDD65 Trend Interaction • CDD85 Trend Interaction • HDD40 Trend Interaction • Baseload Trend • Seasonal Winter Peak Trend	• CDD65 Trend Interaction • CDD85 Trend Interaction • HDD40 Trend Interaction • Baseload Trend • Seasonal Winter Peak Trend
Profile Models			
	9 Hourly Models	• HDD Splines • CDD Splines • Months • Days • Years • Holidays • Hours of Light	• HDD Splines • CDD Splines • Months • Days • Years • Holidays • Hours of Light

6.1.2 Mathematical or Statistical Equations

2. Development of any mathematical or statistical equations comprising the load forecast models, including a specification of the functional form of the equations; and

6.1.2.1 Residential Class

The residential class is modelled with two models, a customer model and a UPC model.

1. Customer Model: The Customer Model is a regression model estimated with historical data from January 2012 through March 2024. Table 3-9

shows the customer model specification and Table 3-10 shows the customer model statistics.

Table 3-9 - Residential Customer Model

Variable	Coefficient	StdErr	T-Stat
Constant	6066.161	4473.484	1.356
Household Index	133525.640	4398.696	30.356
Year2017Plus	1279.096	146.078	8.756
Year2021Plus	2851.052	215.147	13.252
Oct2019toMar2020	1498.130	200.076	7.488
Apr2020toDec2020	2753.007	203.213	13.547
MA(1)	0.946	0.080	11.838
MA(2)	0.431	0.080	5.362

Table 3-10 - Residential Customer Model Statistics

Statistics	Residential Customer Model
Estimation	**1/2012 – 3/2024**
R2	**0.997**
Adj. R2	**0.997**
MAPE	**0.14%**
DW	**1.823**

The customer model is driven by households and incorporates adjustments for Covid and the recent acceleration of residential customer formation. The variables included in the model are described below.

1) Households: Households is calculated as the weighted average of the Joplin and Springfield MSAs.

2) Binary Variables. The Year2021Plus and Year2017Plus variables capture the pre-Covid and post-Covid acceleration in customer formation.

3) Covid: Four model adjustments are included to capture the Covid impact, two binary variables (Oct2019toMar2020 and Apr202toDec2020) and two MA terms. The adjustments correct for the conversion of annual economic data to monthly data which distorts the timing of Covid.

2. UPC Model: The UPC Model is an SAE model estimated with historical data from January 2012 through March 2024. Table 3-11 shows the UPC model specification and Table 3-12 shows the UPC model statistics.

The SAE model contains end-use information for heating, cooling, and other technologies. The data for the SAE model is from Itron's 2023 SAE West North Central region modified for Empires' 2008 Potential Study, 2015 Saturation Survey, and 2021 Market Research study. End-use intensities are modified to account for Empire's historical demand-side management (DSM) programs.

Table 3-11 - Residential UPC Model

Variable	Coefficient	StdErr	T-Stat
XHeat	1.103	0.025	44.971
XCool	1.103	0.027	41.366
XOther	1.109	0.028	39.115
ResSolar_UPC_Hist	-2.635	0.587	-4.490
Apr2020toFeb2021	49.436	21.398	2.310
Mar2021	-349.419	66.402	-5.262
Year2023Plus	48.709	23.173	2.102

Table 3-12 - Residential UPC Model Statistics

Statistics	Residential UPC Model
Estimation	1/2012 – 3/2024
R2	0.942
Adj. R2	0.939
MAPE	4.76%
DW	2.220

The UPC model includes SAE variables (XHeat, XCool, and XOther), a solar variable, and Covid variables.

1) XHeat: XHeat captures the heating response for a typical residential customer. The response includes the effects of heating technology efficiencies, saturation, thermal shell, weather, price, income, household size, and DSM programs.

2) XCool: XCool captures the cooling response for a typical residential customer. The response includes the effects of cooling technology efficiencies, saturation, thermal shell, weather, price, income, household size, and DSM programs.

3) XOther: XOther captures the response for all non-heating and cooling technologies. The variable includes the effects of hours of light, price, income, household size, and DSM programs.

4) Solar: The ResSolar_UPC_Hist variable captures the historical impact of behind-the-meter solar installations based on Empire's solar rebate program. Annual historical installed capacity is converted to monthly generation and then divided by customers to obtain solar generation per customer. The model assumes no changes in historical solar generation in the forecast. New solar generation is forecast externally and added to the forecast after the statistical modeling is complete.

5) Covid: Three variables capture variations in usage caused by Covid. The Apr2020toFeb2021, Mar2021 and Year2023Plus model usage changes and adjust the forecast for slightly higher average use after the Covid.

6.1.2.2 Small Commercial Class

The small commercial class is modelled with two models, a customer model and a UPC model.

1. Customer Model: The customer model is a regression model estimated with historical data from January 2012 through March 2024. Table 3-13 shows the customer model specification and Table 3-14 shows the customer model statistics.

Table 3-13 - Small Commercial Customer Model

Variable	Coefficient	StdErr	T-Stat
Constant	6514.732	282.468	23.064
Total Employment	16580.550	269.347	61.558
Apr2020toDec2020	258.084	35.026	7.368
Jan2021toSep2021	209.881	34.317	6.116
Oct2019	1978.181	39.552	50.015
MA(1)	0.809	0.078	10.354
MA(2)	0.504	0.078	6.463

Table 3-14 - Small Commercial Customer Model Statistics

Statistics	Small Commercial Customer Model
Estimation	1/2012 – 3/2024
R2	0.994

Statistics	Small Commercial Customer Model
Adj. R2	0.993
MAPE	0.17%
DW	1.698

The primary driver in the customer model is total employment. The additional variables capture an errant historical data point and Covid.

1) Total Employment: The Total Employment variable is the historical and forecast total employment for the Springfield and Joplin MSAs.

2) Binary Variable. The binary variable (Oct2019) removes outlier data.

3) Covid. Four variables capture the Covid impact. Two binary variables (Apr2020toDec2020 and Jan2021toSep2021) and two MA terms. The adjustments correct for the conversion of annual employment data to monthly data which distorts the timing of Covid.

2. UPC Model: The UPC model is an SAE model estimated with historical data from January 2012 through March 2024. The SAE model uses the same theoretical foundation as the residential SAE model but is modified for commercial end-use information. Table 3-15 shows the UPC model specification and Table 3-16 shows the UPC model statistics.

The SAE model contains end-use information for heating, cooling, and other technologies. The data for the SAE model is from Itron's 2023 SAE West North Central region.

Table 3-15 - Small Commercial UPC Model

Variable	Coefficient	StdErr	T-Stat
XHeat	0.911	0.043	20.965
XCool	0.651	0.025	25.986
XOther	0.020	0.000	56.836
SComSolar_UPC_Hist	-1.889	0.924	-2.044
Feb	-85.958	32.503	-2.645
Sep	95.073	28.870	3.293
OctNov2020	121.344	27.748	4.373

Table 3-16 - Small Commercial UPC Model Statistics

Statistics	Small Commercial UPC Model

Estimation	1/2012 – 3/2024
R2	0.867
Adj. R2	0.860
MAPE	4.33%
DW	1.896

The UPC model includes SAE variables (XHeat, XCool, and XOther), a solar variable, and binary variables.

1) XHeat: XHeat captures the heating response for a typical commercial customer. The response includes the effects of heating technology efficiencies, saturation by technology and building types, weather, price, employment, and DSM programs.

2) XCool: XCool captures the cooling response for a typical commercial customer. The response includes the effects of cooling technology efficiencies, saturation by technology and building types, weather, price, employment, and DSM programs.

3) XOther: XOther captures the response for all non-heating and cooling technologies. The response includes the effects of other base load technology efficiencies, saturation by technology and building types, price, employment, and DSM programs.

4) Binary Variables: Two monthly binary variables (Feb and Sep) capture additional seasonality. The OctNov2020 binary variable captures billing data errors in the historical dataset

5) Solar: SComSolar_UPC_Hist models the historical impact of behind-the-meter solar generation based on Empire's solar rebate program. Historical installed capacity is converted to monthly generation and then divided by customers to obtain solar generation per customer. The model assumes no changes in historical solar generation in the forecast. New solar installations are forecast externally and added to the forecast after the statistical modelling is complete.

6.1.2.3 Large Commercial Class

The large commercial class is modelled with two models, a customer model and a UPC model.

1. Customer Model: The customer model is a regression model estimated with historical data from January 2012 through March 2024. Table 3-17 shows the customer model specification and Table 3-18 shows the customer model statistics.

Table 3-17 - Large Commercial Customer Model

Variable	Coefficient	StdErr	T-Stat
Constant	1790.268	48.701	36.761
Total Employment	1177.443	45.767	25.727
Apr2013Dec2013	54.198	6.204	8.736
Apr2020Dec2020	34.433	5.847	5.890
Year2014	-87.871	5.578	-15.753
Year2015	-59.782	5.447	-10.975
Year2016	-28.205	5.328	-5.294
MA(1)	0.437	0.078	5.629

Table 3-18 - Large Commercial Customer Model Statistics

Statistics	Large Commercial Customer Model
Estimation	1/2012 – 3/2024
R2	0.965
Adj. R2	0.963
MAPE	0.28%
DW	1.659

The primary driver is total employment. The additional variables capture short-term data shifts and address serial correlation.

1) Total Employment: The Total Employment variable is the historical and forecast total employment for the Springfield and Joplin MSAs.

2) Binary Variables: Five binary variables capture short-term shifts in the number of customers. The April2013Dec2013 and April2020Dec2020 binary variables capture 9 month shifts in the customer counts. Year2014, Year2015, and Year2016 capture 12 month shifts in the customer counts.

3) MA1: The MA1 term corrects for serial correlation and does not impact the strength of the total employment driver.

2. UPC Model: The UPC model is an SAE model estimated with historical data from January 2012 through March 2024. Table 3-19 shows the UPC model specification and Table 3-20 shows the UPC model statistics.

The SAE model contains end-use information for heating, cooling, and other technologies. The data for the SAE model is from Itron's 2023 SAE West North Central region.

Table 3-19 - Large Commercial UPC Model

Variable	Coefficient	StdErr	T-Stat
XHeat	9.713	0.756	12.848
XCool	11.573	0.494	23.419
XOther	0.543	0.007	75.747
Apr2020toJul2020	-2389.941	852.955	-2.802
LComSolar_UPC_Hist	-0.355	1.108	-0.321
SepOct2019	2725.318	1174.431	2.321
OctNov2020	3822.864	1172.609	3.260
Year2016	1241.267	516.233	2.404
Year2015	2158.178	529.279	4.078
XHeat	9.713	0.756	12.848

Table 3-20 - Large Commercial UPC Model Statistics

Statistics	Large Commercial UPC Model
Estimation	1/2012 – 3/2024
R2	0.836
Adj. R2	0.826
MAPE	3.53%
DW	1.223

The UPC model includes SAE variables (XHeat, XCool, and XOther), binary variables, a solar variable, and Covid variables.

1) XHeat: XHeat variable captures the general heating response for a typical commercial customer. The response includes the effects of heating technology efficiencies, saturation by technology and building types, weather, price, employment, and DSM programs.

2) XCool: XCool variable captures the general cooling response for a typical commercial customer. The response includes the effects of cooling technology efficiencies, saturation by technology and building types, weather, price, employment, and DSM programs.

3) XOther: XOther variable captures the general response for all non-heating and cooling technologies. The response includes the

effects of other base load technology efficiencies, saturation by technology and building types, price, employment, and DSM programs.

4) Binary Variables: Four binary variables capture short-term data shifts and data errors. The annual binaries (Year2015, and Year2016) capture higher than expected usage in 2015 and 2016. Two trinary variables (SepOct2019 and OctNov2020) capture offsetting data errors in consecutive months.

5) Solar: The LComSolar_UPC_Hist variable is the estimated historical behind-the-meter solar installation sales associated with Empire's solar rebate program. The historical installed capacity is converted to monthly generation and then divided by customers to obtain solar generation per customer. The model assumes no changes in historical solar generation in the forecast. New solar installations are externally forecast and added to the final forecast after the statistical modelling is complete.

6) Covid: The binary variable (Apr2020toJul2020) captures the short-term Covid impact.

6.1.2.4 Industrial Class

The industrial class is modelled with manual customer count forecast and a UPC model.

1. Customer Count Forecast: Between January 2012 and March 2024, the class increased from 38 customers to 44 customers. The low number of customers and slow growth cannot reliably be forecasted using a statistical model. Instead, the industrial customer forecast is based on known customer expansions and projects. In April 2024, one (1) customer is removed from the forecast. Between May 2024 and December 2024, seven (7) new customers are added to the forecast increasing peak demand by 8.2 MW.

2. UPC Model: The existing 44 customers' usage is modelled with a UPC model. The model captures the recent usage patterns and Covid impacts. Table 3-21 shows the UPC model specification and Table 3-22 shows the UPC model statistics.

Table 3-21 - Industrial UPC Model

Variable	Coefficient	StdErr	T-Stat
Constant	1486388.637	9747.643	152.487
CDD55	436.363	21.103	20.678
Apr2020toJul2020	-150561.596	36542.465	-4.120
JantoJul 2021Plus	-102965.835	16781.191	-6.136
Year2012	-160090.437	21977.624	-7.284
Year2013	-124252.937	21977.618	-5.654
Year2014	-93299.771	21974.176	-4.246
Oct2018	-559724.534	71543.347	-7.824
Jan2024	1382362.591	72804.642	18.987

Table 3-22 - Industrial UPC Model Statistics

Statistics	Industrial UPC Model
Estimation	1/2012 – 3/2024
R2	0.865
Adj. R2	0.857
MAPE	3.52%
DW	1.655

The UPC model forecasts constant usage based on recent usage patterns after accounting for Covid and outlier data impacts.

1) Weather: The weather response is modelled using a CDD variable with a temperature reference point of 55 degrees.

2) Binary Variables: Five binary variables capture the increasing usage from the changing number of customers and remove outlier data points. The Year2012, Year2013 and Year2014 variables capture the increasing average usage. The Oct2018 and Jan2024 binary variables remove outlier data. The JantoJul2021Plus variable captures a consistent shift in the first half of the year beginning in 2021.

3) Covid: The Apr2020toJul2020 variable is binary variable from April 2020 to July 2020 and approximates the decline in industrial usage from Covid.

6.1.2.5 Transmission Class

The transmission class is modelled with manual customer count forecast and a UPC model.

1. Customer Count Forecast: Between January 2012 and March 2024, the number of customers varies between 13 and 15. The low number of customers cannot reliably be forecasted using a statistical model. Since the number of customers has not dramatically changed, the forecast assumes the existing 13 customers continue through the forecast period with no new additions.

2. UPC Model: The existing 13 customers' usage is modelled with a UPC model. The model captures the recent usage patterns. Table 3-23 shows the UPC model specification and Table 3-24 shows the UPC model statistics.

Table 3-23 - Transmission UPC Model

Variable	Coefficient	StdErr	T-Stat
Constant	1145912.151	9692.198	118.230
Jan	-89423.535	20015.987	-4.468
Feb	-105334.425	19392.702	-5.432
Mar	-112699.408	19392.702	-5.811
Apr	-69183.089	20015.987	-3.456
Jul	82661.712	20015.987	4.130
Aug	89591.911	20015.987	4.476
Nov	-99793.666	20764.707	-4.806
Dec	-127524.786	20015.987	-6.371
Year2015	59028.658	18924.713	3.119
Year2019	74456.587	18924.713	3.934
Year2021	49628.334	20612.471	2.408
Year2022	-73561.114	18924.713	-3.887
Oct2021	380769.592	65368.117	5.825
Nov2021	997017.076	64506.066	15.456
Jan2024	241353.720	67755.317	3.562

Table 3-24 - Transmission UPC Model Statistics

Statistics	Transmission UPC Model
Estimation	1/2012 – 3/2024
R2	0.804
Adj. R2	0.782
MAPE	3.88%
DW	1.640

The UPC model consists of binary variables that capture seasonality and remove data anomalies.

1) Binary Variables: The Jan through Dec binary variables model the seasonal usage pattern. The Oct2021, Nov2021, and Jan2024 binary variables remove outlier data. Four annual binary shift variables (Year2015, Year2019, Year2021, and Year2022) capture short-term usage shifts.

6.1.2.6 Linde Class

[redacted].

Table 3-25 - Linde Model
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[redacted]

Table 3-26 - Linde Model Statistics
****Confidential in Its Entirety****

[redacted]

The Linde model consists of five variables designed to capture the historical average usage from 2015 forward. These variables are shown below.

1) Binary Variables: Four binary variables (Dec2020Jan2021, Oct2018, Dec2020, and Jan2024 remove data anomalies.

2) Year2015Plus. This variable causes the regression model to forecast the monthly average usage from January 2015 through March 2024 with the exception of the binary variables.

6.1.2.7 Lighting Class

The lighting class is modelled with two models, a customer model and a UPC model.

1. Customer Model: The Customer Model is a regression model estimated with historical data from January 2012 through March 2024 and designed to generate a constant forecast. Table 3-27 shows the customer model specification and Table 3-28 shows the customer model statistics.

Table 3-27 - Lighting Customer Model

Variable	Coefficient	StdErr	T-Stat
Constant	459.991	1.933	237.992
Year2012	110.667	3.337	33.165
Year2013	89.500	3.337	26.822
Year2014	67.667	3.337	20.279
Year2015	50.167	3.337	15.034
Year2016	50.583	3.337	15.159
Year2017	30.667	3.337	9.190
Year2018	18.667	3.337	5.594
Mar	8.147	3.066	2.657
Apr	12.778	3.163	4.040
May	13.361	3.163	4.224
Jun	14.394	3.163	4.550
Jul	7.477	3.163	2.364
Aug	5.061	3.163	1.600
Sep	7.894	3.163	2.496
Year2022Plus	-32.568	2.806	-11.606
Jun2023toDec2023	27.602	4.470	6.175

Table 3-28 - Lighting Customer Model Statistics

Statistics	Lighting Customer Model
Estimation	1/2012 – 3/2024
R2	0.955
Adj. R2	0.949
MAPE	1.51%
DW	1.072

The model is designed to forecast a constant number of customers based on the 2022 to 2024 customer counts. The model uses binary variables.

1) Binary Variables. The annual binary variables (Year2012, Year2013, …, Year2018) model the decreasing number of customers. The Year2022Plus variable captures the stabilized number of customers after 2022. The remaining variables capture seasonality and remove data anomalies.

2. UPC Model: The UPC model is a regression model estimated with historical data from January 2012 through March 2024. The model is designed to capture the increasing usage based on the declining number of customers. Table 3-29 shows the UPC model specification and Table 3-30 shows the UPC model statistics.

Table 3-29 - Lighting UPC Model

Variable	Coefficient	StdErr	T-Stat
Constant	9458.900	260.894	36.256
Jan	1398.008	87.595	15.960
Feb	965.529	85.033	11.355
Mar	642.837	84.798	7.581
Apr	368.179	87.421	4.212
Aug	343.378	87.424	3.928
Sep	652.732	90.577	7.206
Oct	977.191	87.609	11.154
Nov	1333.629	87.742	15.199
Dec	-3601.096	282.954	-12.727
Oct2018	4092.621	283.687	14.427
Jan2024	-7.501	0.515	-14.574
LightingCustomers	9458.900	260.894	36.256

Table 3-30 - Lighting UPC Model Statistics

Statistics	Lighting UPC Model
Estimation	1/2012 – 3/2024
R2	0.945
Adj. R2	0.940
MAPE	2.10%
DW	1.647

The UPC model is driven by the customer count forecast and includes binary variables.

1) Customer Counts: The increase in average use is highly correlated with the decreasing number of customers. The customer count variable is the historical and forecast number of lighting customers.

2) Binary Variables: The monthly binary variables (Mar, Apr, …, Sep) capture the customer seasonality. The Oct2018 and Jan2024 binary variables remove outlier data.

6.1.2.8 Municipal Class

**[redacted]. **

Table 3-31 - Municipal Model
****Confidential in Its Entirety****

[redacted]

Table 3-32 - Municipal Model Statistics
****Confidential in Its Entirety****

[redacted]

The municipal model consists of weather and binary variables. These variables are shown below.

1) Weather: The wtHDD and wtCDD variables are heating and cooling degree day variables that capture the weather response. The

wtHDD uses 55 degrees as its temperature reference point. The wtCDD variables is a multipart-spline variable using two temperature reference points, 65 degrees and 75 degrees.

2) Binary Variables: The model uses 5 binary variables to remove outlier data points and data shifts. These variables are Jan2024, Aug2023, JanFeb2022, Mar2021, and JantoApr2019.

6.1.2.9 System Peak Model

The System Peak Model is a regression model that forecasts monthly system peaks. Historical monthly peaks are obtained from the historical hourly Net System Loads adjusted to remove historical municipal loads (e.g., Chetopa, Monett, and Mount Vernon) and restored with estimated curtailments. The model is estimated with data from January 2013 through April 2024. The model is summarized in Table 3-33 and Table 3-34.

Table 3-33 - System Peak Model

Variable	Coefficient	StdErr	T-Stat
Base_Index	58.002	0.695	83.445
HDD40_HeatIndex	13.114	0.680	19.287
CDD65_CoolIndex	8.280	1.310	6.321
CDD75_CoolIndex	16.886	2.532	6.668
Apr2020toMay2020	-117.376	31.043	-3.781
JanFebDec2014	-62.562	28.265	-2.213
Apr15Apr16Apr17	-124.168	25.785	-4.815
WinterPeakTrend2015Plus	43.481	19.070	2.280

Table 3-34 - System Peak Model Statistics

Statistics	Peak Model
Estimation	1/2013 – 4/2024
R2	0.916
Adj. R2	0.911
MAPE	3.73%
DW	1.780

The System Peak Model is driven by the sales forecast and peak producing weather with adjustments for Covid and short-term data shifts. The variables are discussed below.

1) Base_Index. The Base_Index variable is created using the non-heating and non-cooling sales from class sales models. The sales results are smoothed using a 12-month moving average. This variable captures the base load contribution to peak growth.

2) HDD40_HeatIndex. This variable is created as an interaction between the three-day weighted average temperatures below 40 degrees and the sales model's heating components. The heating components are derived by multiplying the model's heating variable coefficients with normal heating degree days. The results are smoothed using a 12-month moving average. This variable captures the heating contribution to peak growth.

3) CDD65_CoolIndex. This variable is created as the interaction between the three-day weighted average temperature above 65 degrees and the sales models' cooling components. The cooling components are derived by multiplying the model's cooling variable coefficients with normal cooling degree days. The results are then smoothed using a 12-month moving average. This variable captures the cooling contribution to peak growth.

4) CDD75_CoolIndex. This variable is the same as the CDD65_CoolIndex variable except that the temperature refence point is 75 degrees.

5) Covid. Apr2020toMay2020 is binary variable from April 2020 to May 2020 and approximates the decline in peak from Covid-19 health care policy orders.

6) WinterPeakTrend2015Plus. This variable captures the seasonal winter peak trend beginning in 2015 and continues the trend through the forecast period. The variable is created by interacting the HeatIndex with the seasonal peak month. This variable captures additional winter peak growth since 2015.

7) Binaries Variables. Two binary variables are used to capture short-term shifts in the historical data series. The JanFebDec2014 variable captures errant data for the winter of 2014. The Apr15Apr16Apr17 variable captures lower than expected April peaks from 2015 through 2017.

6.1.2.10 Profile Models

The hourly profile models are developed as hourly regression models using historical AMI data. The models are estimated with data from July 2022 through December 2023 to forecast the most recent load shapes. While all these models use a similar set of variables, the variable classes are adjusted for each profile to capture the main load shape drivers. Table 3-35 identifies the variable classes used in each profile model. Definitions of the variables are summarized below.

Table 3-35 - Profile Model Variable Classes

Class	HDD CDD	Day of Week	Month	Year	Holiday	Hours of Light
Residential	X	X	X			
Small Commercial	X	X	X		X	X
Large Commercial	X	X	X	X	X	X
Industrial	X	X	X	X	X	X
Transmission			X	X		
Linde			X			
Lighting			X			
Municipal	X	X	X		X	X

1) HDD and CDD. HDD and CDD spline variables are used to capture the nonlinear weather response. The splines are created by examining multiple HDD and CDD variables with different temperature reference points. Based on the analysis, the temperature splines are weighted together to create weighted average HDD and CDD variables.

2) Day of Week: Day of week binary variables capture variations in the profile shape based on the day of the week.

3) Month: Monthly binary variables capture variations in the profile shape based on the months.

4) Year: Annual binary variables capture load growth.

5) Holiday: Key holidays are identified using a set of binary variables. These holidays capture the unique shape for specific holidays.

6) Hours of Light: Hours of light is calculated based on the sunrise and sunset times in Springfield, Missouri. This variable captures changes in lighting load throughout the year.

6.1.3 Models by Others

3. Assessment of the applicability of any load forecast models or portions of models that were utilized by the utility but developed by others, including a specification of the functional forms of any equations or models, to the extent they are available.

The forecast models were developed by Itron for Empire.

6.2 Deviations

(B) If the utility selects load forecast models that include end-use load methods, the utility shall describe and document any deviations in the independent variables or functional forms of the equations from those derived from load analysis in sections (3) and (4).

There were no deviations in the independent variables or functional forms of the equations.

6.3 Historical Database

(C) Historical Database for Load Forecasting. In addition to the load analysis database, the utility shall develop and maintain a database consistent with and as needed to run each forecast model utilized by the utility. The utility shall describe and document its load forecasting historical database in the triennial compliance filings. As a minimum, the utility shall—

6.3.1 Independent Variables

1. Develop and maintain a data set of historical values for each independent variable of each forecast model. The historical values for each independent variable shall be collected for a period of ten (10) years, or such period deemed sufficient to allow the independent variables to be accurately forecasted over the entire planning horizon;

Empire maintains, at a minimum, a 10-year data set of historical values for independent variables. 2024 is the first year of forecast driver values.

6.3.2 Adjustments

2. Explain any adjustments that it made to historical data prior to using it in its development of the forecasting models;

Adjustments to the historical data are described in Section 2.5.

6.3.3 Comparison of Historical Independent Variable Projections

3. Archive previous projections of all independent variables used in the energy usage and peak load forecasts made in at least the past ten (10) years and provide a comparison of the historical projected values in prior plan filings to actual historical values and to projected values in the current compliance filing; and

Over the past 10 years, Empire has filed IRP forecasts in 2016, 2019, and 2022. This section compares the key independent variables used in the 2025 IRP with the prior IRP variables. All variables are converted to indices for ease of comparison.

The economic data includes one definitional change. In the 2022 IRP, employment is based on total employment. In the 2016 through 2019 IRPs, employment is based on non-manufacturing employment. The economic driver comparisons are shown in Figure 3-7 through Figure 3-9.

Figure 3-7 - Employment Index Comparison

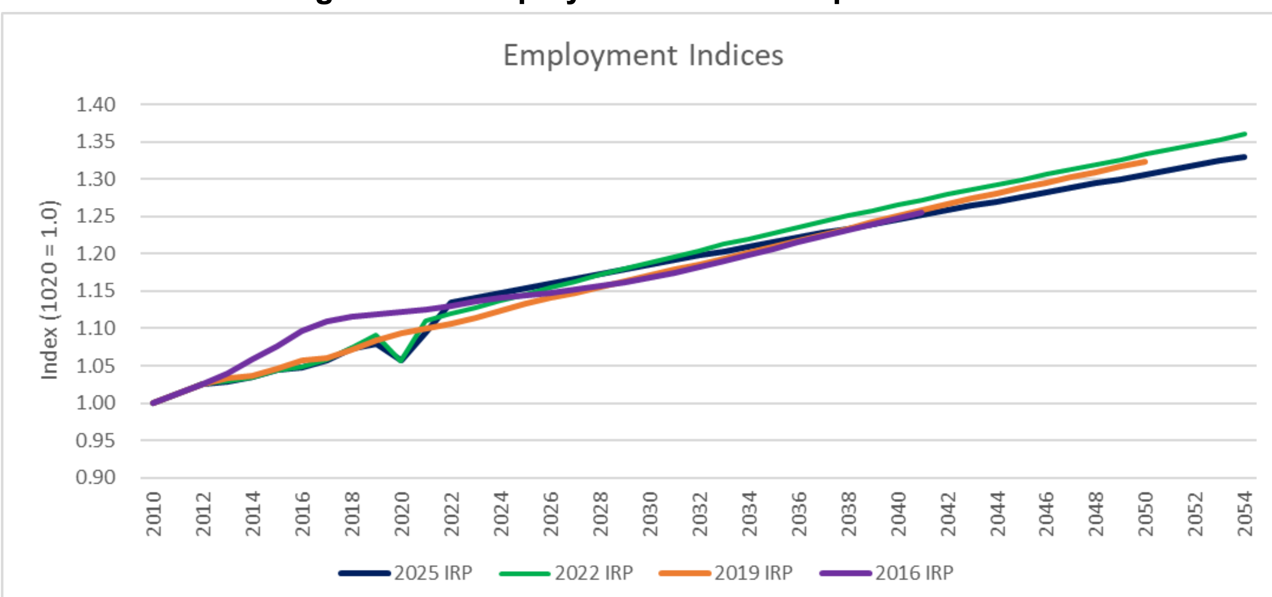


Figure 3-8 - Population Index Comparison

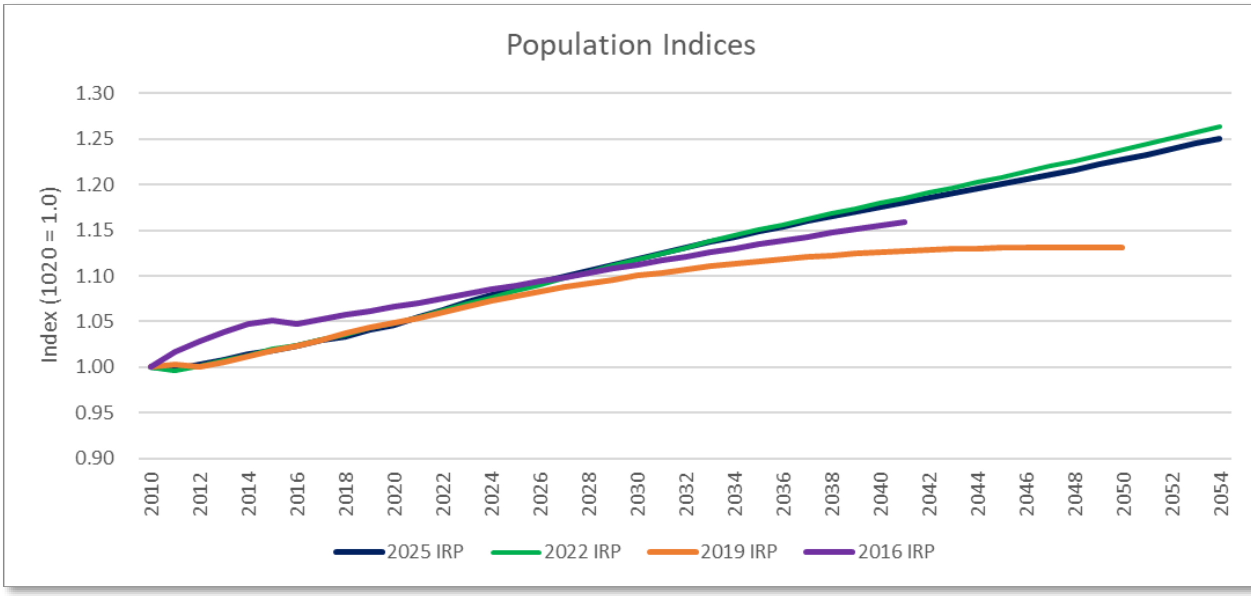
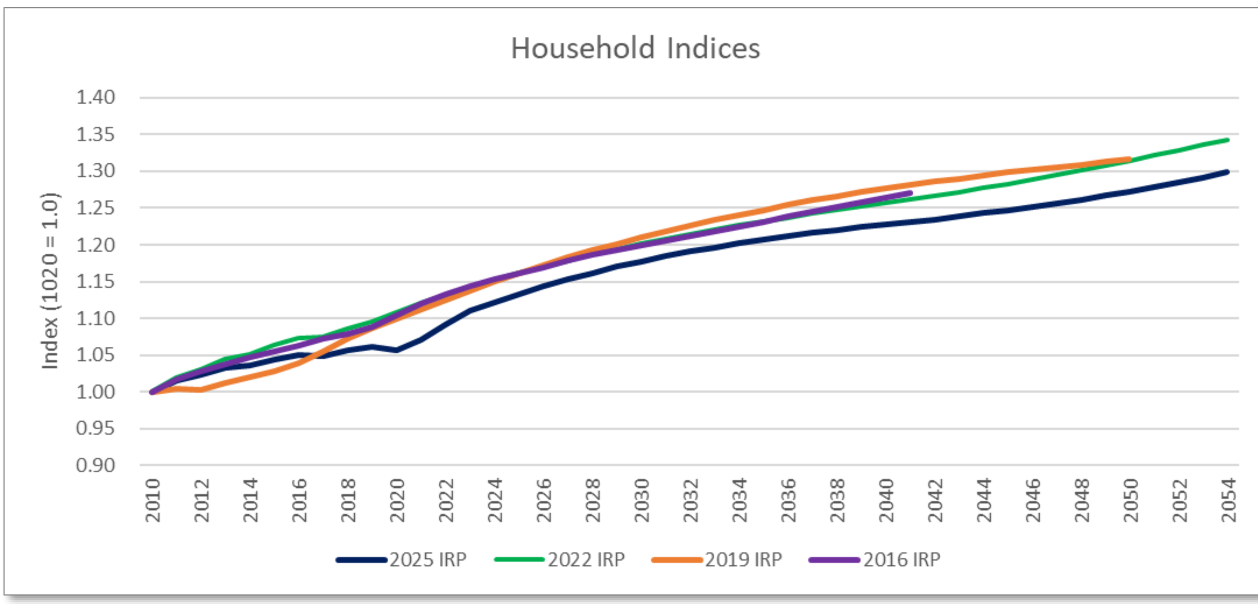


Figure 3-9 - Household Index Comparison



The SAE data is developed by Itron. Figure 3-10 through Figure 3-12 compare the residential SAE indices for residential heating, cooling, and other (baseload). Figure 3-13 through Figure 3-15 compare the commercial SAE indices for heating, cooling, and other (baseload).

Figure 3-10 - Residential SAE Heating Index

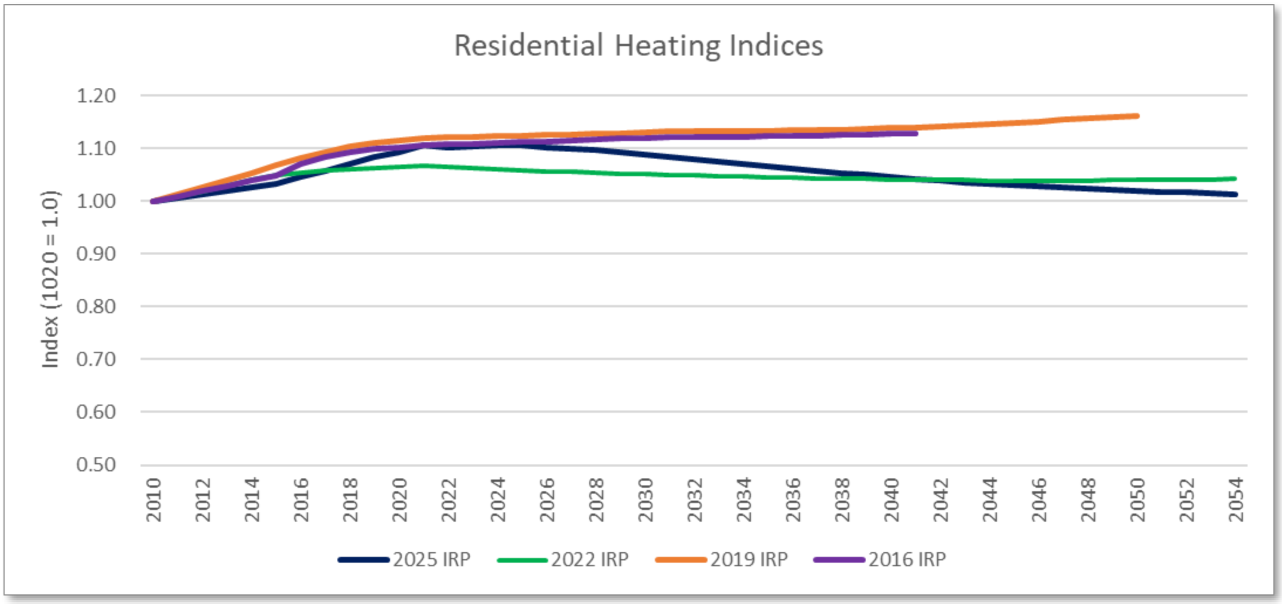


Figure 3-11 - Residential SAE Cooling Index

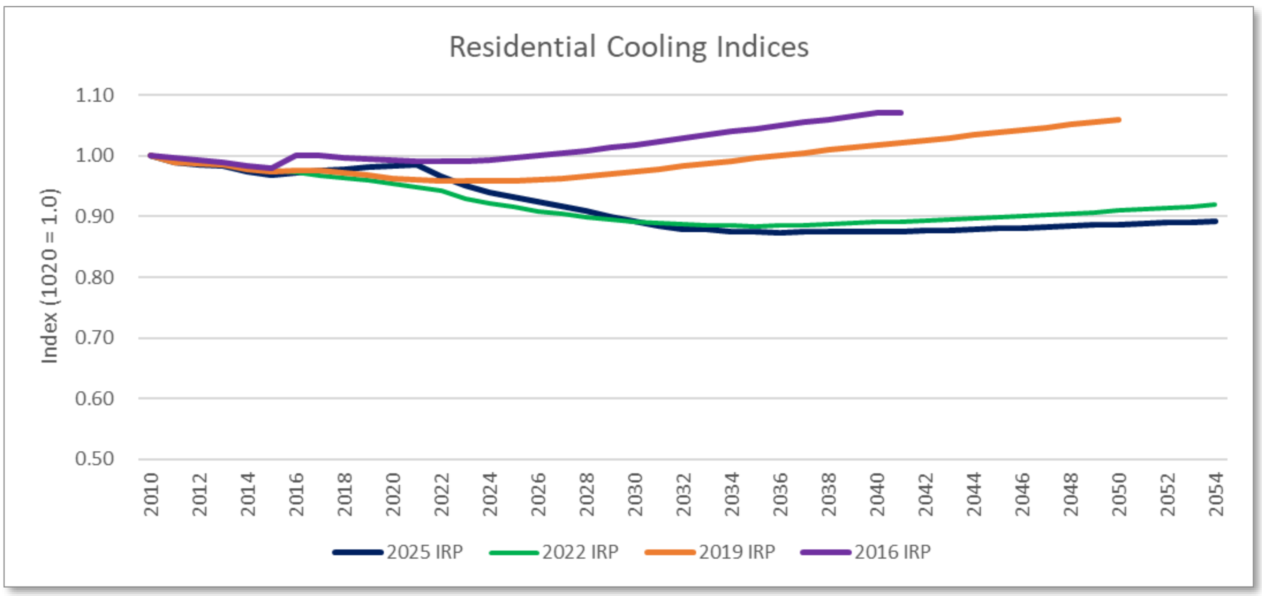


Figure 3-12 - Residential SAE Other Index

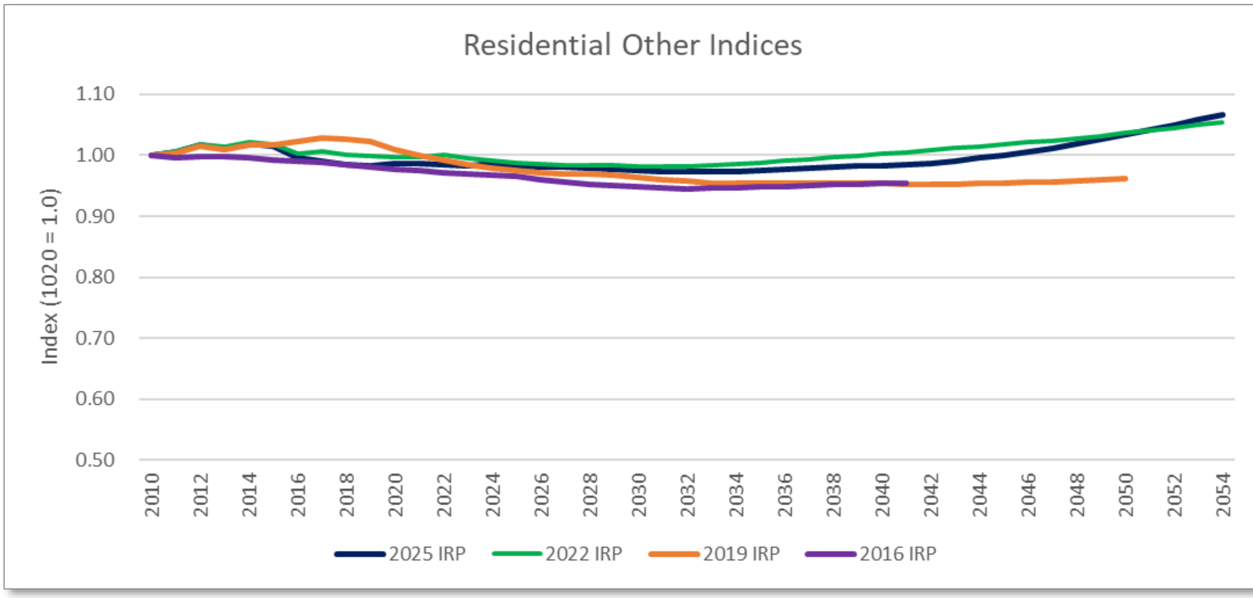


Figure 3-13 - Commercial SAE Heating Index

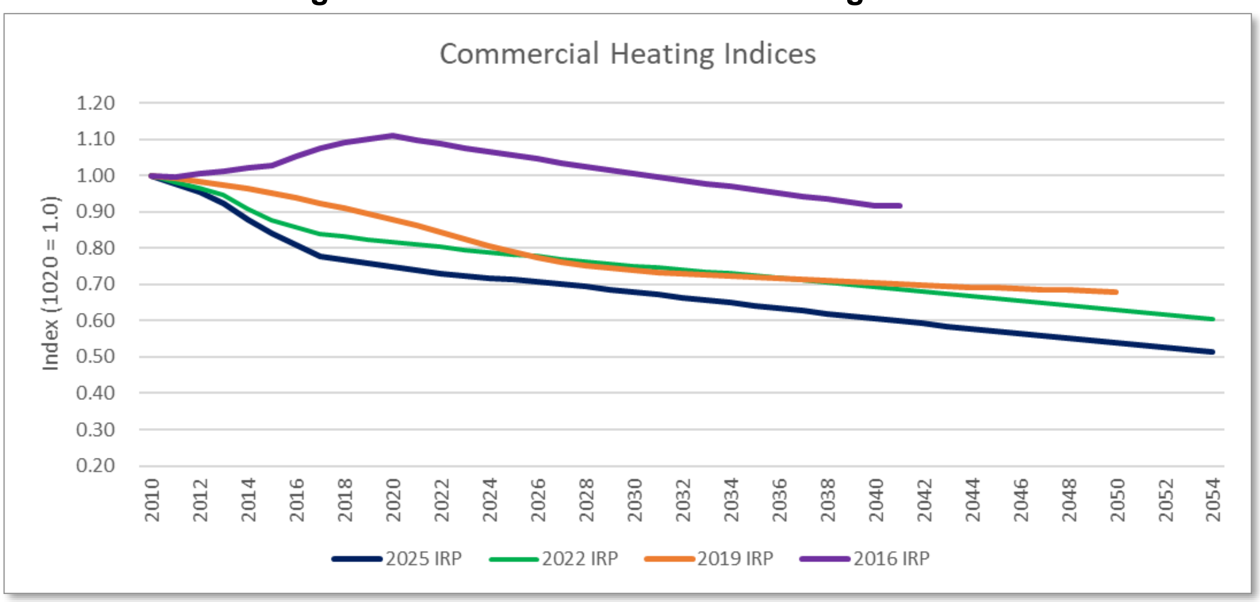


Figure 3-14 - Commercial SAE Cooling Index

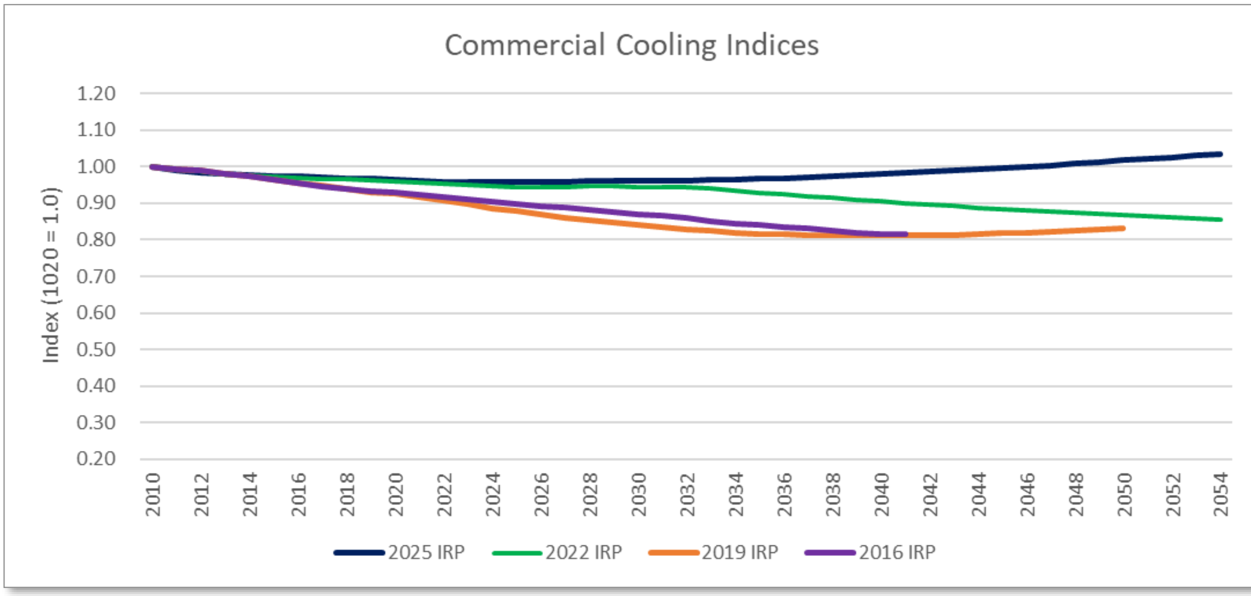
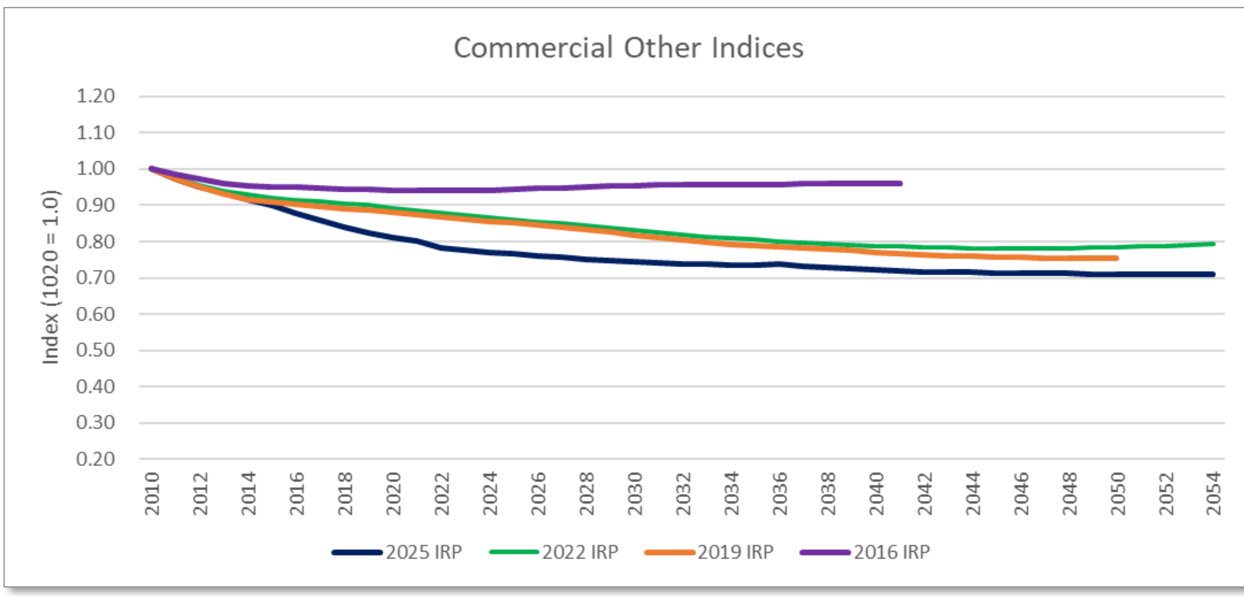


Figure 3-15 - Commercial SAE Other Index



The normal weather assumptions are updated each IRP cycle to reflect the most recent 30 -year average. Table 3-36 shows historical heating and cooling degree days per year and prior IRP assumptions. Heating and cooling degree days are based on a 65-degree reference point.

Table 3-36 - Historical and IRP Normal
Heating Degree Days and Cooling Degree Days

Year	Heating Degree Days Base 65	Cooling Degree Days Base 65
1991	4,309	1,436
1992	4,193	907
1993	5,063	1,289
1994	4,262	1,282
1995	4,584	1,319
1996	5,050	1,100
1997	4,900	1,051
1998	4,226	1,590
1999	4,048	1,249
2000	4,722	1,371
2001	4,407	1,294
2002	4,650	1,369
2003	4,575	1,231
2004	4,219	1,095
2005	4,316	1,616
2006	3,889	1,609
2007	4,229	1,612
2008	4,889	1,145
2009	4,673	1,036
2010	4,788	1,612
2011	4,693	1,716
2012	3,736	1,695
2013	4,899	1,319
2014	4,900	1,360
2015	4,142	1,434
2016	3,768	1,672
2017	3,570	1,378
2018	4,661	1,847
2019	4,471	1,553
2020	4,265	1,334
2021	4,162	1,463
2022	4,596	1,703
2023	3,784	1,556
2025 IRP	**4,403**	**1,420**
2022 IRP	**4,437**	**1,384**
2019 IRP	**4,458**	**1,345**
2016 IRP	**4,428**	**1,333**

6.3.4 Comparison of Historical Energy and Peak Demand Projections

4. Archive all previous forecasts of energy and peak demand, including the final data sets used to develop the forecasts, made in at least the past ten (10) years. Provide a comparison of the historical final forecasts to the actual historical energy and peak demands and to the current forecasts in the current triennial compliance filing.

A comparison of historical customers, net system energy (MWh) and system peaks (MW) to forecasts from the 2016 through 2025 IRPs are shown in Table 3-37 through Table 3-39. In these tables actual values are not weather normalized. 2024 actual values include actual values through March 2024 and forecast values from April to December 2024. Figure 3-16 through Figure 3-18 compare the four IRP forecasts.

Table 3-37 - IRP Comparison - Total Customers
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[redacted]

Figure 3-16 - IRP Comparison - Total Customers
****Confidential in Its Entirety****

[redacted]

Table 3-38 - IRP Comparison - Net System Energy (MWh)
****Confidential in Its Entirety****

[redacted]

[redacted]

Figure 3-17 - IRP Comparison - Net System Energy (MWh)
****Confidential in Its Entirety****

[redacted]

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Table 3-39 - IRP Comparison – Summer System Peaks (MW)
****Confidential in Its Entirety****

[redacted]

Figure 3-18 - IRP Comparison - System Summer Peaks (MW)
****Confidential in Its Entirety****

[redacted]

Table 3-40 - IRP Comparison – Winter System Peaks (MW)
****Confidential in Its Entirety****

[redacted]

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[redacted]

Figure 3-19 - IRP Comparison - System Winter Peaks (MW)
****Confidential in Its Entirety****

[redacted]

SECTION 7 BASE-CASE LOAD FORECAST

The utility's base-case load forecast shall be based on projections of the independent variables that utility decision-makers believe to be most likely. All components of the base-case load forecast shall assume normal weather conditions. The load impacts of implemented demand-side programs and rates shall be incorporated in the base-case load forecast, but the load impacts of proposed demand-side programs and rates shall not be included in the base-case forecast.

7.1 Major Class and Total Load Detail

(A) Major Class and Total Load Detail. The utility shall produce forecasts of monthly energy usage and demands at the time of the summer and winter system peaks by major class for each year of the planning horizon, and shall describe and document those forecasts in its triennial compliance filings. Where applicable, these major class forecasts shall be separated into their jurisdictional components.

7.1.1 Describe and Document Relevant Economic and Demographics

1. The utility shall describe and document how the base-case forecasts of energy usage and demands have taken into account the effects of real prices of electricity, real prices of competitive energy sources, real incomes, and any other relevant economic and demographic factors. If the methodology does not incorporate economic and demographic factors, the utility shall explain how it accounted for the effects of these factors.

The forecast models include the effects of real electricity prices, demographic factors, and economic factors. These components are documented in the model variables, Section 6.1.2.

7.1.2 Describe and Document Effects of Legal Mandates

2. The utility shall describe and document how the forecasts of energy usage and demands have taken into account the effects of legal mandates affecting the consumption of electricity.

Empire uses Itron's SAE modelling framework for the residential, small commercial, and large commercial classes. The SAE model uses the EIA's 2023 AEO as the foundation for long term energy efficiency trends. The EIA's AEO includes legally mandated appliance efficiency standards and building codes.

7.1.3 Describe and Document Consistency

3. The utility shall describe and document how the forecasts of energy usage and demands are consistent with trends in historical consumption patterns, end uses, and end-use efficiency in the utility's service area as identified pursuant to sections 4 CSR 240-22.030(2), (3), and (4).

The forecast models are developed using statistical models. The statistical models are estimated over a historical period which capture the relationship between past usage with key driver variables. Consistency with historical consumption patterns is shown in the model statistical fit. The statistics for each model are show in 6.1.2.

7.1.4 Describe and Document Weather-Normalized Class Loads

4. For at least the base year of the forecast, the utility shall describe and document its estimates of the monthly cooling, heating, and non-weather-sensitive components of the weather-normalized major class loads.

The residential, small commercial, large commercial and industrial class weather sensitive components are obtained by applying the models' weather variable coefficient to normal weather data. The calculation results in the estimated heating and cooling sales components. Other sales components are assumed to be baseload (i.e., non-heating and cooling). Table 3-41 summarizes the monthly data heating and cooling data for the major classes into annual values. These values exclude the impact of electric vehicles and behind-the-meter solar.

Table 3-41 - Annual Heating, Cooling, and Base Load Components of the Major Classes MWh (Billed Year Basis)
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[redacted]

7.1.5 Describe and Document Modification of Modules

5. Where judgment has been applied to modify the results of its energy and peak forecast models, the utility shall describe and document the factors which caused the modification and how those factors were quantified.

Empire makes two adjustments to the forecast model results. The first adjustment removes one large customer from the Empire system. Because the large customer includes multiple metered accounts in the small commercial, large commercial, and industrial classes, the forecast for these classes is adjusted downward. In total, 8 metered accounts are removed totaling approximately 2,000 MWh/year. The second adjustment impacts the industrial class. In this adjustment seven known customer projects totaling 8.1 MW and approximately 43,500 MWh/year are added beginning in 2024. Empire is not aware of any additional projects after 2025.

7.1.6 Plots of Class Monthly Energy and Coincident Peak Demand

6. For each major class specified pursuant to subsection (2)(A), the utility shall provide plots of class monthly energy and coincident peak demand at the time of summer and winter system peaks. The plots shall cover the historical database period and the forecast period of at least twenty (20) years. The plots of coincident peak demands for the historical period shall include both actual and weather-normalized peak demands at the time of summer and winter system peaks. The plots of coincident peak demand for the forecast period shall show the class coincident demands for the base-case forecast at the time of summer and winter system peaks.

7.1.6.1 Sales Forecast

7.1.6.1.1 Residential Annual Summary

The residential sales forecast is developed using the models described in Section 6.1.2.1. Figure 3-20 through Figure 3-22 show the annual sales forecast, customer forecast, and UPC forecast. Both the sales and UPC figures show normalized values for comparative purposes. Table 3-42 and Table 3-43 summarize the sales, customer, and UPC forecasts and average annual growth rates for selected years. In the tables, 2023 is the last full year of actual data, and 2025 is the first full year of forecast data. 2024 values are actual values through March and forecast values from April through December.

Figure 3-20 - Residential Sales Annual Forecast
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[redacted]

Figure 3-21 - Residential Customer Forecast
****Confidential in Its Entirety****

[redacted]

Figure 3-22 - Residential UPC Forecast
****Confidential in Its Entirety****

[redacted]

Table 3-42 - Residential Forecast Summary
****Confidential in Its Entirety****

[redacted]

Table 3-43 - Residential Forecast Summary -- Annual Average Growth Rates
****Confidential in Its Entirety****

[redacted]

7.1.6.1.2 Small Commercial Annual Summary

The small commercial sales forecast is developed using the models described in Section 6.1.2.2. Figure 3-23 through Figure 3-25 show the annual sales forecast, customer forecast, and UPC forecast. Table 3-44 and Table 3-45 summarize the sales, customer, and UPC forecasts and average annual growth rates for selected years. In the tables, 2023 is the last full year of actual data, and 2025 is the first full year of forecast data. 2024 values are actual values through March and forecast values from April through December.

Figure 3-23 - Small Commercial Sales Forecast
****Confidential in Its Entirety****

[redacted]

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Figure 3-24 - Small Commercial Customer Forecast
****Confidential in Its Entirety****

[redacted]

Figure 3-25 - Small Commercial UPC Forecast
****Confidential in Its Entirety****

[redacted]

Table 3-44 - Small Commercial Forecast Summary
****Confidential in Its Entirety****

[redacted]

Table 3-45 - Small Commercial Forecast - Average Annual Growth Rates
****Confidential in Its Entirety****

[redacted]

7.1.6.1.3 Large Commercial Annual Summary

The large commercial sales forecast is developed using the models described in Section 6.1.2.3. Figure 3-26 through Figure 3-28 show the annual sales forecast, customer forecast, and UPC forecast. Table 3-46 and Table 3-47 summarize the sales, customer, and UPC forecasts and average annual growth rates for selected years. In the tables, 2023 is the last full year of actual data, and 2025 is the first full year of forecast data. When shown, 2024 values are actual values through March and forecast values from April through December.

Figure 3-26 - Large Commercial Sales Forecast
****Confidential in Its Entirety****

[redacted]

Figure 3-27 - Large Commercial Customer Forecast
****Confidential in Its Entirety****

[redacted]

Figure 3-28 - Large Commercial UPC Forecast
****Confidential in Its Entirety****

[redacted]

Table 3-46 - Large Commercial Forecast Summary
****Confidential in Its Entirety****

[redacted]

Table 3-47 - Large Commercial Forecast - Average Annual Growth Rates
****Confidential in Its Entirety****

[redacted]

7.1.6.1.4 Industrial Annual Summary

The industrial sales forecast is developed using the models described in Section 6.1.2.3 and the manual forecast additions described in Section 7.1.5. Figure 3-29 through Figure 3-31 show the annual sales forecast, customer forecast, and UPC forecast. Table 3-48 and Table 3-49 summarize the sales, customer, and UPC forecasts and average annual growth rates for selected years. In the tables, 2023 is the last full year of actual data, and 2025 is the first full year of forecast data. 2024 values are actual values through March and forecast values from April through December.

Figure 3-29 - Industrial Sales Forecast
****Confidential in Its Entirety****

[redacted]

Figure 3-30 - Industrial Customer Forecast
****Confidential in Its Entirety****

[redacted]

Figure 3-31 - Industrial UPC Forecast
****Confidential in Its Entirety****

[redacted]

Table 3-48 - Industrial Forecast Summary
****Confidential in Its Entirety****

[redacted]

Table 3-49 - Industrial Forecast - Average Annual Growth Rates
****Confidential in Its Entirety****

[redacted]

7.1.6.1.5 Transmission Annual Summary

The transmission sales forecast is developed using the models described in Section 6.1.2.5. Figure 3-32 through Figure 3-34 show the annual sales forecast, customer forecast, and UPC forecast. Table 3-50 and Table 3-51 summarize the sales, customer, and UPC forecasts and average annual growth rates for selected years. In the tables, 2023 is the last full year of actual data, and 2025 is the first full year of forecast data. 2024 values are actual values through March and forecast values from April through December.

Figure 3-32 - Transmission Sales Forecast
****Confidential in Its Entirety****

[redacted]

Figure 3-33 - Transmission Customer Forecast
****Confidential in Its Entirety****

[redacted]

Figure 3-34 - Transmission UPC Forecast
****Confidential in Its Entirety****

[redacted]

Table 3-50 - Transmission Forecast Summary
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[redacted]

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Table 3-51 - Transmission Forecast - Average Annual Growth Rates
Confidential in Its Entirety

[redacted]

7.1.6.1.6 Linde Annual Summary

[redacted].

Figure 3-35 - Linde Sales Forecast
** Confidential in its Entirety **

[redacted]

Table 3-52 - Linde Forecast Summary
**** Confidential in its Entirety ****

[redacted]

7.1.6.1.7 Lighting Annual Summary

The lighting sales forecast is developed using the models described in Section 6.1.2.7. Figure 3-36 through Figure 3-38 show the annual sales forecast, customer forecast, and UPC forecast. Table 3-53 and Table 3-54 summarize the sales, customer, and UPC forecasts and average annual growth rates for selected years. In the tables, 2023 is the last full year of actual data, and 2025 is the first full year of forecast data. 2024 values are actual values through March and forecast values from April through December.

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Figure 3-36 - Lighting Sales Forecast
**** Confidential in its Entirety ****

[redacted]

Figure 3-37 - Lighting Customer Forecast
**** Confidential in its Entirety ****

[redacted]

Figure 3-38 - Lighting UPC Forecast
**** Confidential in its Entirety ****

[redacted]

Table 3-53 - Lighting Forecast Summary
**** Confidential in its Entirety ****

[redacted]

Table 3-54 - Lighting Forecast - Average Annual Growth Rates
**** Confidential in its Entirety ****

[redacted]

7.1.6.1.8 Municipal Annual Summary

The municipal sales forecast is developed using the models described in Section 6.1.2.8. Figure 3-39 shows the annual sales forecast. Table 3-55 show the annual sales forecast for selected years. Historical municipal data includes the former municipal customers (Monett, Mount Vernon and Chetopa) which left the system as of June 1, 2020. Lockwood is forecast to leave the system on June 1, 2025. In the tables, 2023 is the last full year of actual data, and 2025 is the first full year of forecast data. 2024 values are actual values through March and forecast values from April through December.

Figure 3-39 - Municipal Sales Forecast
**** Confidential in its Entirety ****

[redacted]

Table 3-55 - Municipal Forecast Summary
**** Confidential in its Entirety ****

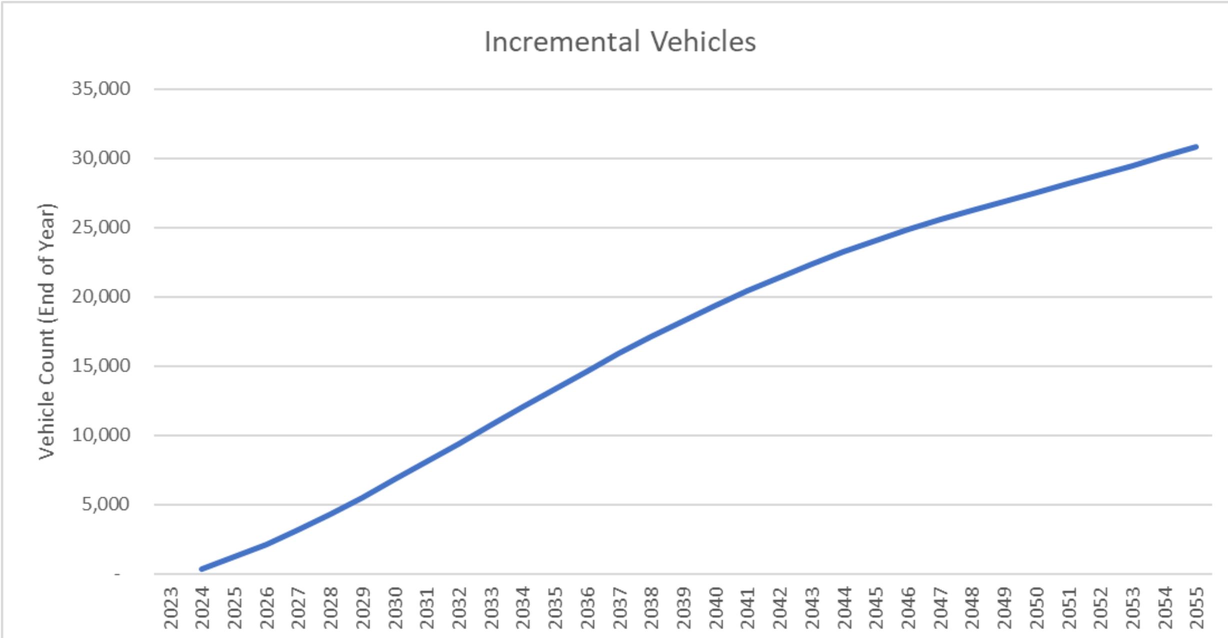
[redacted]

7.1.6.1.9 Electric Vehicle Adjustment

Like the 2022 IRP, the incremental electric vehicle forecast is excluded from the class forecasts so that the coincident load shape impact may be integrated into the hourly load forecast. The electric vehicle forecast is included in Step 3 of the load forecast process as described in Section 6.1.1.

The EV forecast is based on an estimate of EVs in Empire's service territory and the EIA's 2023 AEO forecast growth rates. The current number of EVs is derived from the Alternative Fuel Data Center (AFDC) 2022 estimates, modified based on Empire's population relative to the state population, and escalated based on the EIA's 2023 AEO forecast. Figure 3-40 shows the incremental electric vehicle count forecast.

Figure 3-40 - Incremental Electric Vehicle Adoption Forecast



The incremental electric vehicle forecast is converted to energy using the following conversion assumptions.

- Annual Miles:12,000
- kWh/Mile: 0.30
- Loss Factor: 6.45%

Table 3-56 and Table 3-57 show a summary of the electric vehicle counts and incremental energy included the forecast for selected years.

Table 3-56 - Electric Vehicle Incremental Forecast Summary

Year	Vehicles (End of Year)	Energy (MWh)
2024	390	420
2025	1,210	3,216
2030	6,805	23,931
2035	13,333	49,017
2040	19,380	72,634
2045	24,016	91,006
2050	27,529	104,843

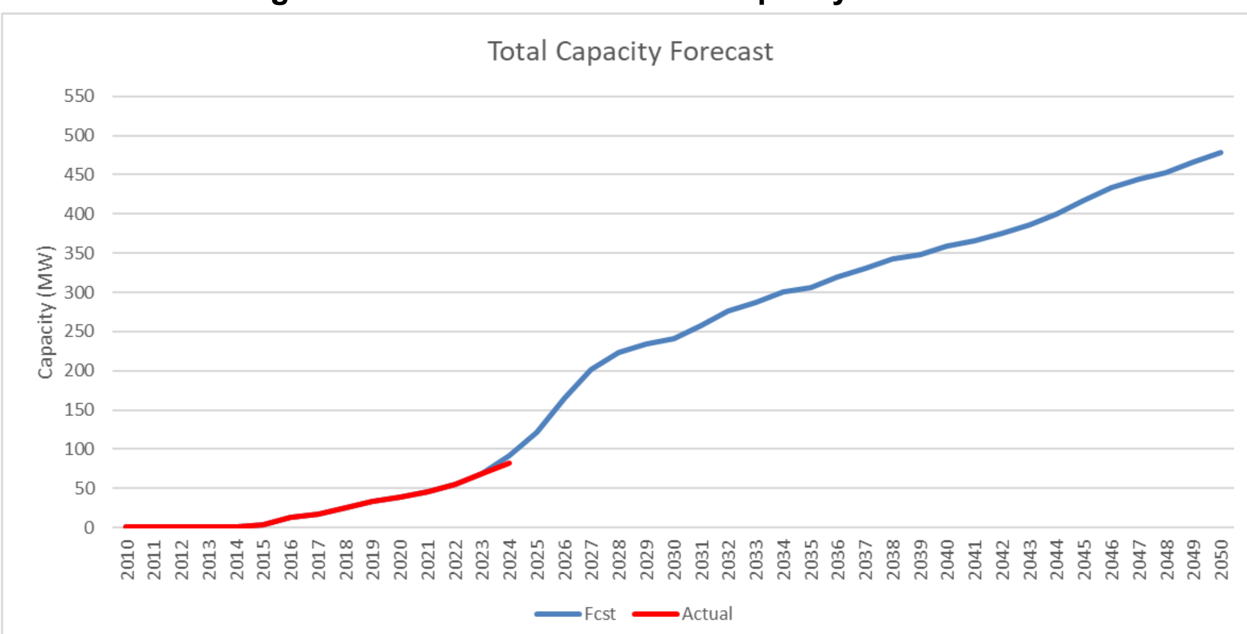
Table 3-57 - Electric Vehicle Forecast - Average Annual Growth Rates

Time Period	Sales
2012-2023 (Historical)	NA
2025-2034 (10 Year Forecast)	36.14%
2025-2044 (20 Year Forecast)	20.90%
2025-2054 (30 Year Forecast)	14.63%

7.1.6.1.10 Solar Adjustment

Like the 2022 IRP forecast, the incremental behind-the-meter photovoltaic solar (PV) forecast is excluded from the class forecasts so that the coincident load shape impact may be integrated into the hourly load forecast. The PV forecast based on the EIA's 2023 AEO forecast calibrated to historical Empire solar adoption. The PV forecast is included in Step 3 of the load forecast process as described in Section 6.1.1.

Figure 3-41 - Total PV Installed Capacity Forecast



The incremental PV forecast is converted to using load factors and load shapes based on the National Renewable Energy Laboratory's (NREL) PVWatts Calculator for Springfield, Missouri. Table 3-58 and Table 3-59 show a summary of the PV capacity and energy forecasts for selected years.

Table 3-58 - PV Incremental Forecast Summary

Year	Total Installed Capacity (MW)	Incremental Installed Capacity (MW)	Incremental Energy (MWh)
2012	0.2		
2015	3.4		
2020	39.1		
2023	68.6		
2025	121.2	50.0	42,831
2030	241.6	170.4	195,000
2035	305.8	234.6	271,328
2040	359.3	288.1	331,238
2045	417.5	346.3	395,674
2050	478.6	407.4	469,885

Table 3-59 - PV Forecast -- Average Annual Growth Rates

Time Period	Sales
2025-2034 (10 Year Forecast)	11.0%
2025-2044 (20 Year Forecast)	6.8%
2025-2054 (30 Year Forecast)	5.4%

7.1.6.2 Peak Annual Summary

The system peak forecast is developed using the models described in Section 6.1.2.9. Figure 3-42 and Figure 3-43 show historical, weather normalized and forecast seasonal peaks. Table 3-60 and Table 3-61 show the seasonal peaks and their growth rates for selected years. Historical peaks exclude municipal data for Monett, Mount Vernon, and Chetopa which left the Empire system on June 1, 2020.

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Figure 3-42 - System Summer Peak Forecast
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[redacted]

Figure 3-43 - System Winter Peak Forecast
**** Confidential in its Entirety ****

[redacted]

Table 3-60 - System Peak Forecast Summary
**** Confidential in its Entirety ****

[redacted]

Table 3-61 - System Peak Forecast - Average Annual Growth Rates
**** Confidential in its Entirety ****

[redacted]

7.1.6.2.1 Coincident Class Peak Forecasts

Coincident class peaks are estimated by calibrating the class hourly profile model forecast to the monthly energy forecast (including EV and PV energy) and identifying the coincident peak hour. Historical peaks are estimated weather normalized peaks. The models used are described in Section 6.1.2. Figure 3-44 through Figure 3-51 show the residential, small commercial, large commercial, and industrial class seasonal coincident peaks. Table 3-62 and Table 3-63 show historical coincident peaks by class for selected years. Historical system peak data excludes municipal data (i.e., Monett, Mount Vernon, and Chetopa).

Figure 3-44 - Residential Coincident Summer Peak Forecast
**** Confidential in its Entirety ****

[redacted]

Figure 3-45 - Residential Coincident Winter Peak Forecast
**** Confidential in its Entirety ****

[redacted]

Figure 3-46 - Small Commercial Coincident Summer Peak Forecast
** Confidential in its Entirety **

[redacted]

Figure 3-47 - Small Commercial Coincident Winter Peak Forecast
** Confidential in its Entirety **

[redacted]

Figure 3-48 - Large Commercial Coincident Summer Peak Forecast
** Confidential in its Entirety **

[redacted]

Figure 3-49 - Large Commercial Coincident Winter Peak Forecast
** Confidential in its Entirety **

[redacted]

Figure 3-50 - Industrial Coincident Summer Peak Forecast
**** Confidential in its Entirety ****

[redacted]

Figure 3-51 - Industrial Coincident Summer Peak Forecast
**** Confidential in its Entirety ****

[redacted]

Table 3-62 - Summer Coincident Peak by Class
**** Confidential in its Entirety ****

[redacted]

Table 3-63 - Winter Coincident Peak by Class
**** Confidential in its Entirety ****

[redacted]

7.1.6.2.2 Class Level Coincident Energy at the System Peaks

Table 3-64 and Table 3-65 show the class energy in the seasonal peak month for selected years. Summer peak months are August. Winter peak months are January.

Table 3-64 - Summer Peak Month Energy by Class
**** Confidential in its Entirety ****

[redacted]

Table 3-65 - Winter Peak Month Energy by Class
**** Confidential in its Entirety ****

[redacted]

7.1.7 Plots of Net System Load Profiles

7. The utility shall provide plots of the net system load profiles for the summer peak day and the winter peak day showing the contribution of each major class. The plots shall be provided in the triennial filing for the base year of the forecast and for the fifth, tenth, and twentieth years of the forecast. Plots for all years shall be included in the work papers supplied at the time of the triennial filing.

Figure 3-52 through Figure 3-61 show the forecast hourly load profiles for the base, 5th, 10th, 15th, and 20th forecast years. All profiles include the load shape changes from the electric vehicle and behind-the-meter solar forecast.

Figure 3-52 - Forecasted Residential Summer Peak Day Profiles
**** Confidential in its Entirety ****

[redacted]

Figure 3-53 - Forecasted Residential Winter Peak Day Profiles
**** Confidential in its Entirety ****

[redacted]

Figure 3-54 - Forecasted Small Commercial Summer Peak Day Profiles
**** Confidential in its Entirety ****

[redacted]

Figure 3-55 - Forecasted Small Commercial Winter Peak Day Profiles
**** Confidential in its Entirety ****

[redacted]

Figure 3-56 - Forecasted Large Commercial Summer Peak Day Profiles
**** Confidential in its Entirety ****

[redacted]

Figure 3-57 - Forecasted Large Commercial Winter Peak Day Profiles
** Confidential in its Entirety **

[redacted]

Figure 3-58 - Forecasted Industrial Peak Day Profiles
** Confidential in its Entirety **

[redacted]

Figure 3-59 - Forecasted Industrial Winter Peak Day Profiles
** Confidential in its Entirety **

[redacted]

Figure 3-60 - Forecasted System Peak Day Profiles
** Confidential in its Entirety **

[redacted]

Figure 3-61 - Forecasted System Peak Day Profiles
**** Confidential in its Entirety ****

[redacted]

7.2 Describe and Document Forecasts of Independent Variables

(B) Forecasts of Independent Variables.

The forecasts of independent variables shall be specified, described, and documented.

The independent variables used in the model are documented in Section 6.1.2. Four classes of independent variables are used in the forecast. Two classes, economics and end-use data, are obtained from external vendors. The economic data are obtained from Woods and Poole. The end-use data are obtained from Itron. The remaining two classes, prices and weather, are calculated internal to the forecasting process. Prices are assumed in constant real dollars. Temperatures are calculated as 30-year normal values. Plots of the variables are shown in Section 2.4.3.

7.2.1 Documentation of Mathematical Models

1. Documentation of mathematical models developed by the utility to forecast the independent variables shall include the reasons the utility selected the models as well as specification of the functional form of the equations.

Documentation of the forecast models is shown in Section 6.1.2. Models are selected based on statistical fit and overall descriptive power of the independent variables.

7.2.2 Documentation of Adopted Forecasts Developed by Another Entity

2. If the utility adopted forecasts of independent variables developed by another entity, documentation shall include the reasons the utility selected those forecasts, an analysis showing that the forecasts are applicable to the utility's service territory, and, if available, a specification of the functional form of the equations used to forecast the independent variables.

The forecast is developed by Itron on behalf of Empire.

7.2.3 Comparison of Forecast from Independent Variables to Historical Trends

3. These forecasts of independent variables shall be compared to historical trends in the variables, and significant differences between the forecasts and long-term and recent trends shall be analyzed and explained.

The forecasts of independent variables are shown in Section 2.4.3.

7.2.4 Applied to Modify Results

4. Where judgment has been applied to modify the results of a statistical or mathematical model, the utility shall specify the factors which caused the modification and shall explain how those factors were quantified.

Post forecast adjustments are discussed in Section 7.1.5.

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7.3 Net System Load Forecast

> *(C) Net System Load Forecast. The utility shall produce a forecast of net system load profiles for each year of the planning horizon. The net system load forecast shall be consistent with the utility's forecasts of monthly energy and peak demands at time of summer and winter system peaks for each major class.*

The net system load forecast is developed using the steps described in Section 5.2. Figure 3-62 shows the annual net system load forecast. Table 3-66 and Table 3-67 show the net system load forecast and growth rates for selected years. Historical data excludes municipal data (i.e., Monett, Mount Vernon, and Chetopa). 2024 values are actual values through March and forecast values from April through December.

Figure 3-62 - Forecasted Net System Load
**** Confidential in its Entirety ****

[redacted]

Table 3-66 - Net System Load Forecast Summary
**** Confidential in its Entirety ****

[redacted]

Table 3-67 - Net System Load Forecast - Average Annual Growth Rates
**** Confidential in its Entirety ****

[redacted]

SECTION 8 LOAD FORECAST SENSITIVITY ANALYSIS

(8) Load Forecast Sensitivity Analysis.

The utility shall describe and document its analysis of the sensitivity of the dependent variables of the base-case forecast for each major class to variations in the independent variables identified in subsection 4 CSR 240-22.030(6)(A).

Empire created five scenarios. The high and low scenarios capture changes to the economic assumptions and use normal weather. The high and low scenarios are discussed in Section 8.1. The extreme and mild scenarios capture changes to weather and use baseline economics assumptions. The weather scenarios are discussed in Section 8.2. The high-high scenario captures high economic growth with high electric vehicle growth. The high-high scenario is discussed in Section 8.3. The scenario results are presented in this section.

8.1 Normal Weather Load Forecast Scenarios

(A) The utility shall produce at least two (2) additional normal weather load forecasts (a high-growth case and a low-growth case) that bracket the base-case load forecast. Subjective probabilities shall be assigned to each of the load forecast cases. These forecasts and associated subjective probabilities shall be used as inputs to the risk analysis required by 4 CSR 240-22.060.

The high and low scenarios are created in compliance to the Commission's rule directing Empire to create two additional normal weather load forecasts. These forecasts capture economic uncertainty.

The subjective probabilities assigned to these scenarios are listed below.

- High Case 25%
- Base Case 45%
- Low Case 20%

(a high-high case, discussed later, is assigned a 10% probability)

The high scenario consists of high economic indices. The high indices are based on the ratio of the historical annual average population growth rate to the forecast annual average population growth rate. The historical annual average population growth rate (2004-2023) is 0.77%. The forecast annual average growth rate (2023-2054) is 0.50%. The ratio is 1.54 (0.77%/0.50%). Each high economic index is created by scaling the index's annual average growth rate by the ratio and then redeveloping the forecast using the new growth rate.

The low scenario consists of low economic indices. The low economic indices are created by subtracting the difference between the high and base scenario indices from the base scenario index. By subtracting the difference, the low economic indices mirror the high economic indices around the base scenario.

Figure 3-63 through Figure 3-66 show the high, base, and low scenario economic indices for employment, population, households, and real income.

Figure 3-63 - High and Low Scenario - Total Employment

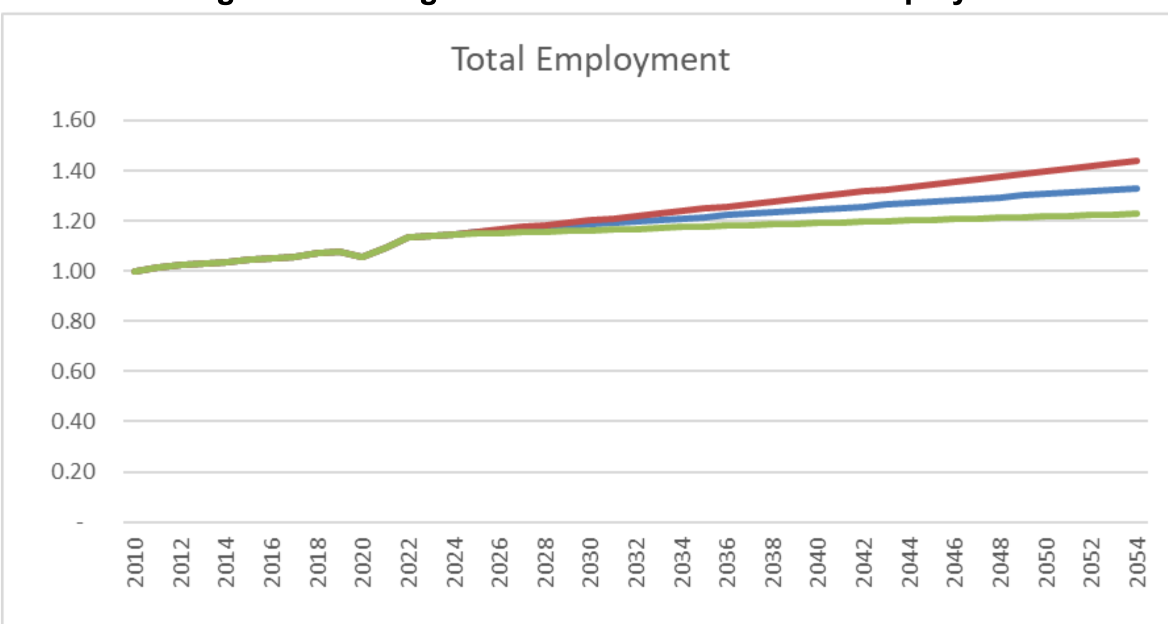

Figure 3-64 - High and Low Scenario - Population

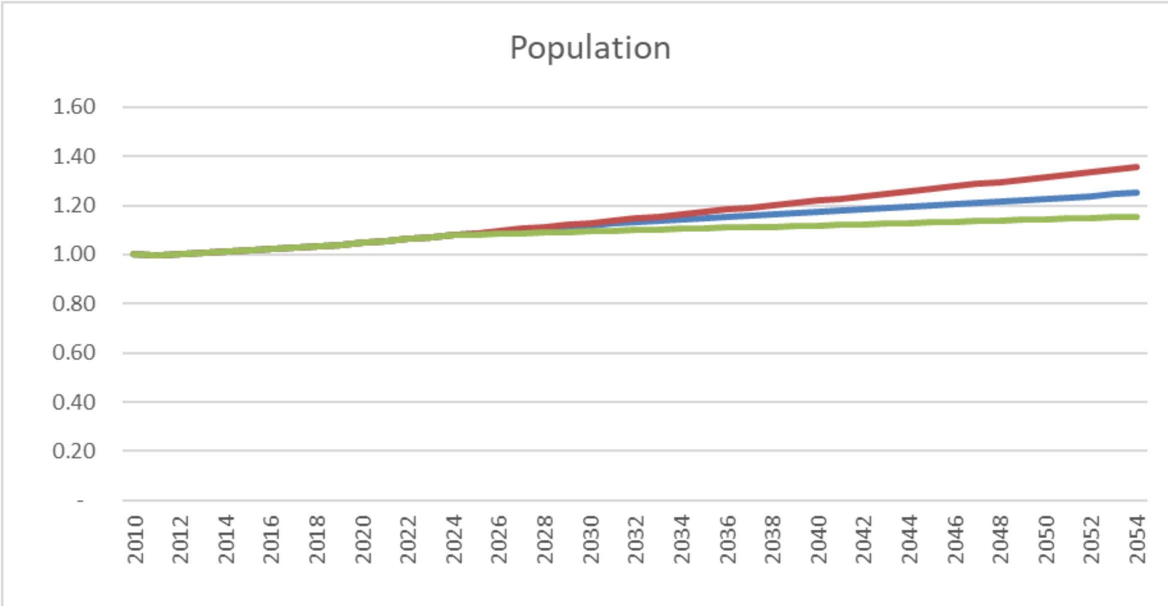

Figure 3-65 - High and Low Scenario - Households

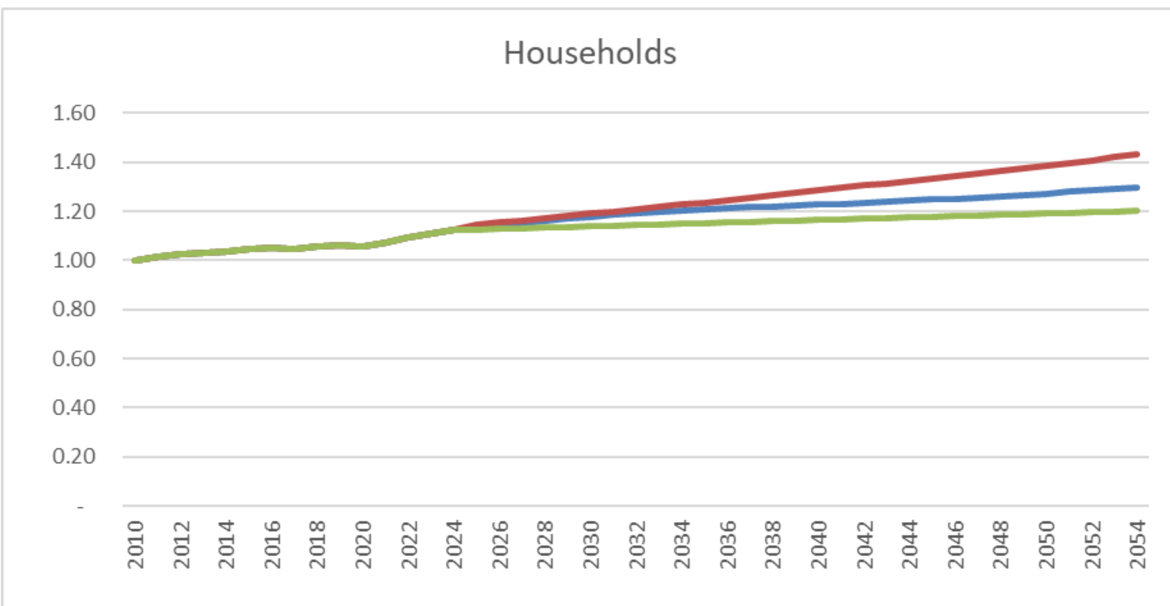

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Figure 3-66 - High and Low Scenario - Real Income

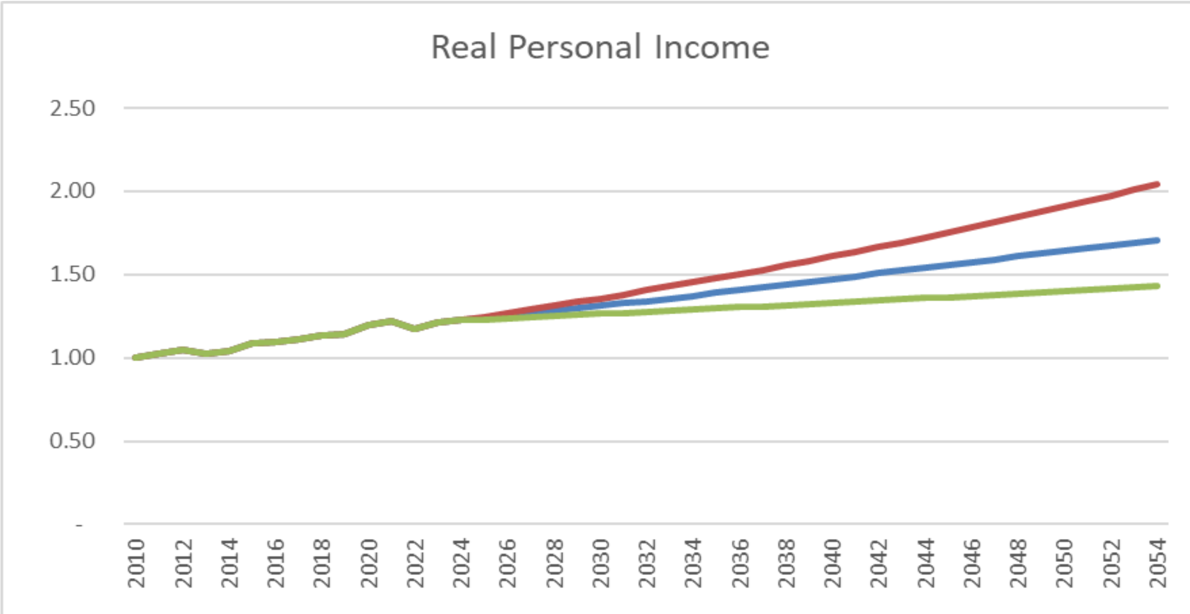


Figure 3-67 through Figure 3-69 show the base, high, and low scenarios for energy, summer peaks, and winter peaks. Table 3-68 through Table 3-70 show selected base, high, and low scenario forecast values for energy, summer peaks, and winter peaks. Historical data excludes municipals (Monett, Mount Vernon, and Chetopa).

Figure 3-67 - Base, High, and Low, Scenarios - Annual Energy
**** Confidential in its Entirety ****

[redacted]

Table 3-68 - Base, High, and Low, Scenarios - Annual Energy (MWh)
** Confidential in its Entirety **

[redacted]

Figure 3-68 - Base, High, and Low Scenarios - Summer Peaks
** Confidential in its Entirety **

[redacted]

Table 3-69 - Base, High, and Low Scenarios - Summer Peak (MW)
**** Confidential in its Entirety ****

[redacted]

Figure 3-69 - Base, High, and Low Scenarios - Winter Peaks
**** Confidential in its Entirety ****

[redacted]

Table 3-70 - Base, High, and Low, Scenarios - Winter Peaks (MW)
**** Confidential in its Entirety ****

[redacted]

8.2 Estimate of Sensitivity of System Peak Load Forecasts to Extreme Weather

(B) The utility shall estimate the sensitivity of system peak load forecasts to extreme weather conditions. This information shall be considered by utility decision-makers to assess the ability of alternative resource plans to serve load under extreme weather conditions when selecting the preferred resource plan pursuant to 4 CSR 240-22.070(1).

The two normal weather scenarios create reasonable planning bounds around the base forecast. The mild and extreme weather scenarios capture the uncertainty associated with weather conditions. The weather scenarios are based on a 1 in 10 occurrence.

The base case uses normal monthly HDDs and CDDs based on a 30-year average (1994 to 2023) using Springfield, Missouri daily average temperatures. The mild and extreme weather scenarios are developed using the same historical weather data but identify the 1 in 10 scenarios above and below the base forecast normal temperatures.

Monthly Weather. Monthly HDD and CDD scenarios are created by ranking historical annual HDD and CDD values (base 65 degrees) from lowest to highest values. The mild case is determined by using the 3rd lowest year in the ranked list (i.e., 1 in 10 occurrences). The extreme case is determined by using the 3rd highest year in the ranked list. Figure 3-70 and Figure 3-71 show the ordered annual HDD and CDD with the mild and extreme scenarios. Table 3-71 shows the annual HDD and CDD scenario values.

Figure 3-70 - Mild and Extreme Annual HDD Base 65 Scenarios

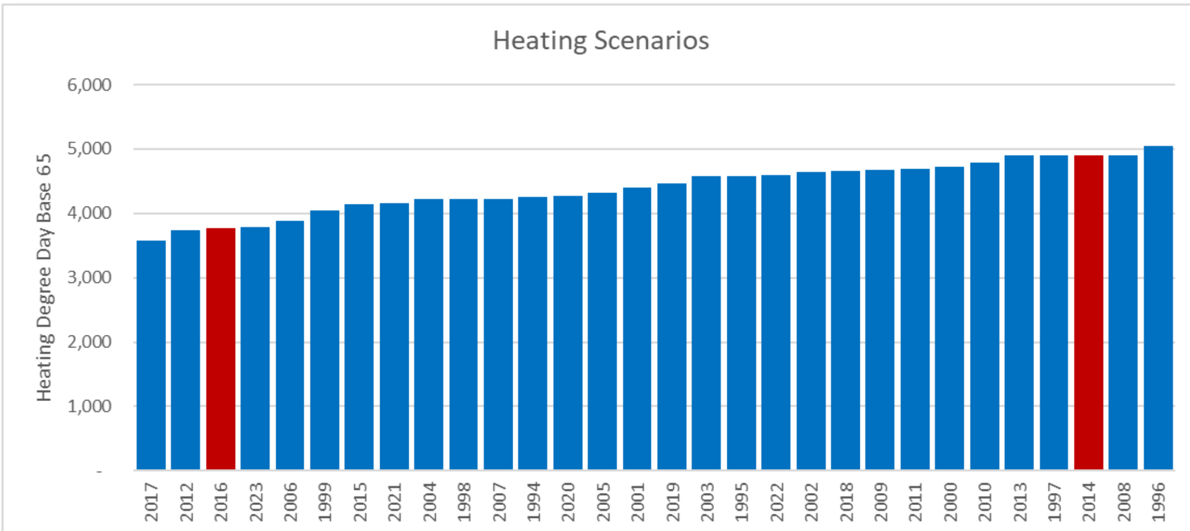


Figure 3-71 - Mild and Extreme Annual CDD Base 65 Scenarios

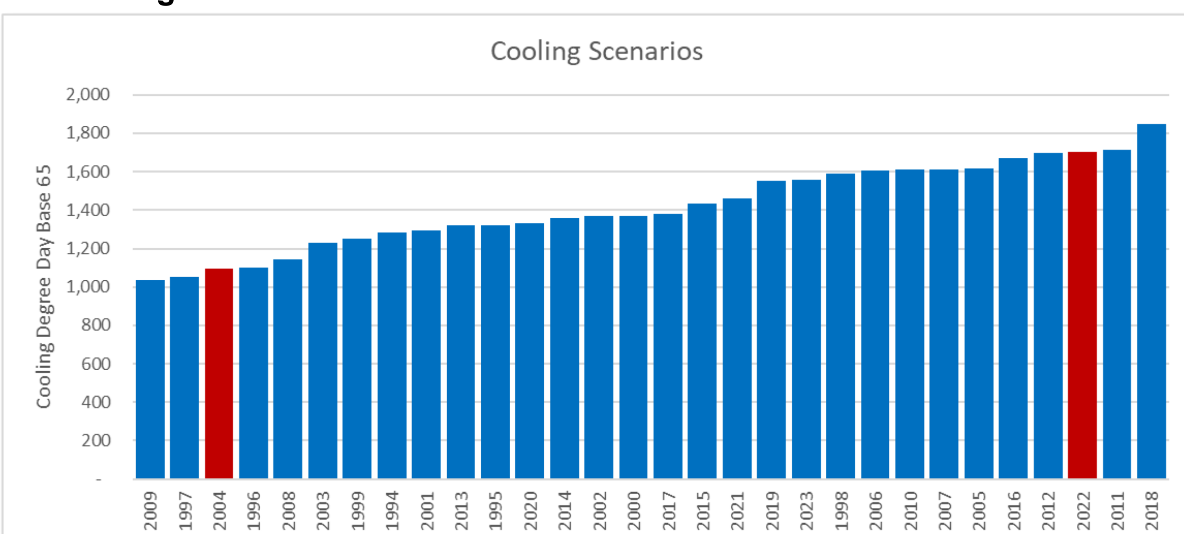


Table 3-71 - Scenario Annual Degree Days

Scenario	HDD65	CDD65
Base	4,403	1,420
Mild	3,793	1,081
Extreme	4,934	1,682

Annual HDD and CDD scenario values are converted to monthly HDD and CDD scenarios by calibrating the base case monthly HDD and CDD values to the annual extreme and mild annual HDD and CDD values. Figure 3-72 and Figure 3-73 show the monthly HDD and CDD scenarios.

Figure 3-72 - Mild and Extreme Monthly HDD Base 65 Scenarios

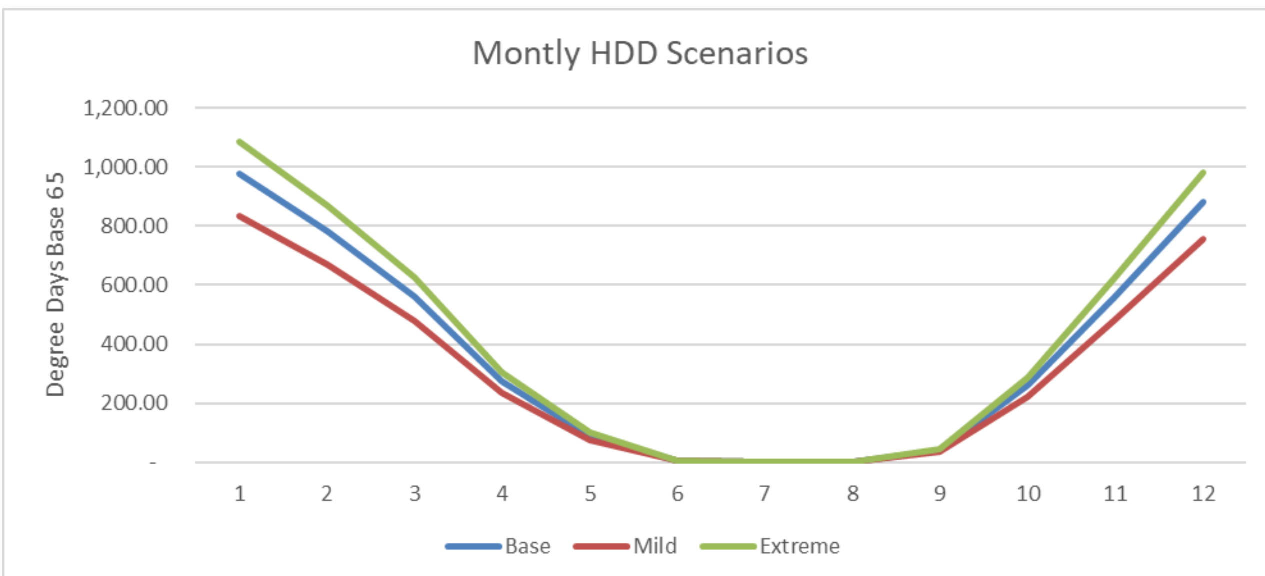
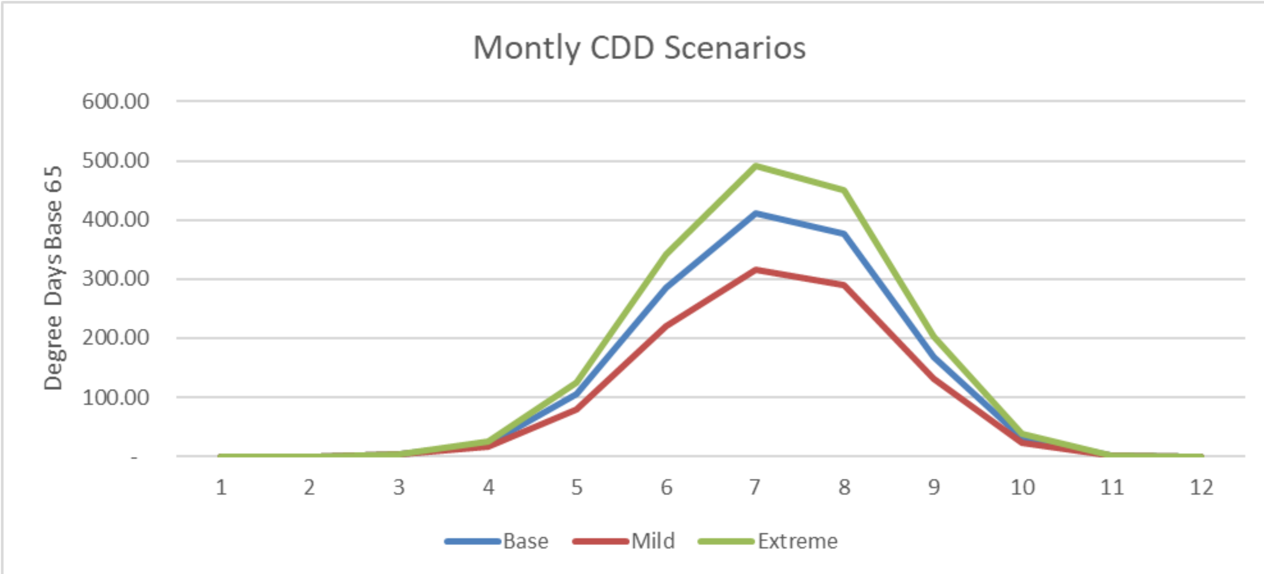


Figure 3-73 - Mild and Extreme Monthly CDD Base 65 Scenarios



<u>Peak Producing Temperatures</u>. The mild and extreme peak scenarios are derived based on 21 years of historical (2004 to 2024) peak producing weather. The extreme cases are obtained by selecting the 2nd lowest average temperatures in the winter months and the 2nd highest average temperatures in the summer months. The mild case is obtained by selecting the 2nd highest average temperatures in the winter months and the 2nd lowest average temperatures in the summer months. Figure 3-74 and Table 3-72 show the extreme and mild peak temperature scenarios.

Figure 3-74 - Mild and Extreme Peak Temperature Scenarios

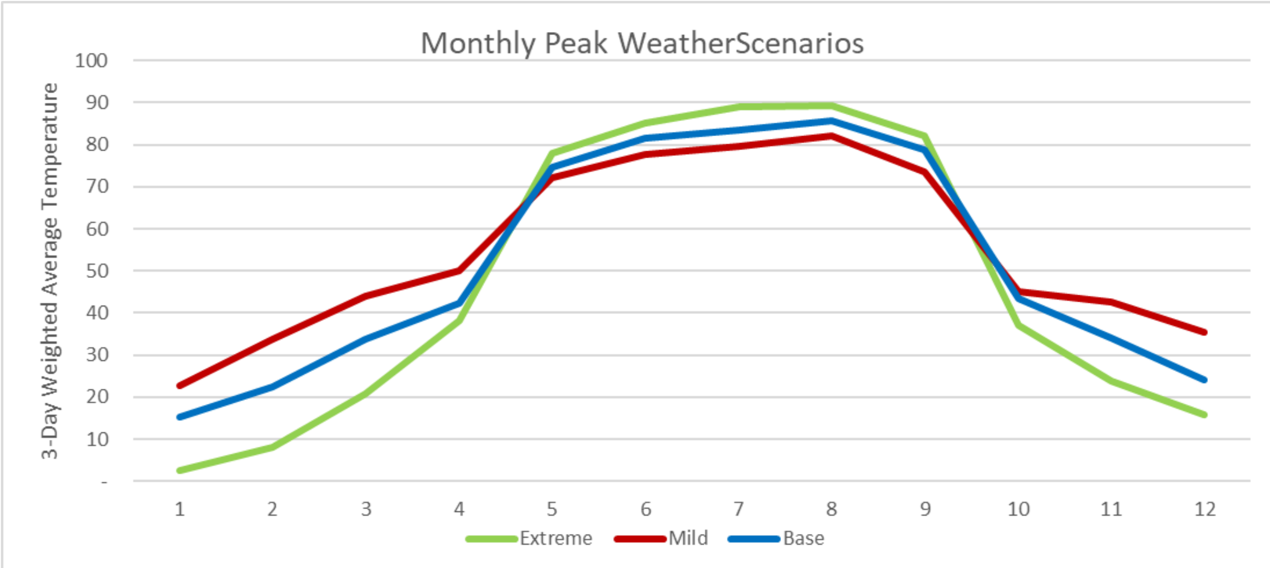


Table 3-72 - Scenario Monthly Peak Producing Temperatures

Month	Base	Extreme	Mild
Jan	15.22	2.64	22.77
Feb	22.33	7.96	33.67
Mar	33.83	20.63	44.10
Apr	42.44	38.24	50.05
May	74.70	77.97	72.01
Jun	81.58	85.00	77.53
Jul	83.55	88.98	79.51
Aug	85.58	89.36	81.97
Sep	78.74	82.14	73.59
Oct	43.55	37.00	45.03
Nov	34.15	23.79	42.67
Dec	24.09	15.68	35.30

Figure 3-75 through Figure 3-77 show the weather scenario annual energy, summer peak and winter peaks. Table 3-73 through Table 3-75 show selected forecast values for the weather scenarios.

Figure 3-75 - Base, Mild and Extreme Weather Scenario: System Annual Energy
**** Confidential in its Entirety ****

[redacted]

Table 3-73 - Base, Mild and Extreme Weather Scenario - Annual Energy (MWh)
**** Confidential in its Entirety ****

[redacted]

Figure 3-76 - Base, Mild and Extreme Weather Scenario -Summer Peak
**** Confidential in its Entirety ****

[redacted]

Table 3-74 - Base, Mild and Extreme Weather Scenario - Summer Peak (MW)
**** Confidential in its Entirety ****

[redacted]

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Figure 3-77 - Base, Mild and Extreme Weather Scenario -Winter Peak
**** Confidential in its Entirety ****

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Table 3-75 - Base, Mild and Extreme Weather Scenario - Winter Peak (MW)
**** Confidential in its Entirety ****

[redacted]

8.3 High-High Scenario

In addition to the required four scenarios (i.e., high, low, extreme, and mild), Empire constructed an additional scenario that captures high economic growth and high electric vehicle growth. Empire assigns this scenario a 10% probability of occurrence. The scenario represents strong economic and electric vehicle growth. The electric vehicle growth assumes 100% of new vehicle purchases are electric by 2045.

The electric vehicle forecast considers the current mandates for 100% vehicle purchases to be electric by 2035 but delays the implementation to 2045 allowing a 20-year transition from the beginning of the forecast period. While there are no specific goals or mandates that target 2045, the scenario imagines that the current electric vehicle policy environment will ultimately succeed but in a delayed form.

Figure 3-78 shows the High-High scenario's energy compared to the base forecast, high scenario, and extreme scenario. Table 3-76 compares the High-High scenario's energy compared to the base forecast for selected years. Historical data excludes municipals (Monett, Mount Vernon, and Chetopa).

Figure 3-78 - High-High Scenario - Annual Energy
**** Confidential in its Entirety ****

[redacted]

Table 3-76 - High-High Scenario - Annual Energy (MWh)
**** Confidential in its Entirety ****

[redacted]

[redacted]

Figure 3-79 and Figure 3-80 shows the High-High scenario's summer and winter peaks compared to the base forecast, high scenario, and extreme scenario. Table 3-77 compares the High-High scenario's summer and winter peaks compared to the base forecast for selected years.

Figure 3-79 - High-High Scenario – Summer Peak
**** Confidential in its Entirety ****

[redacted]

Figure 3-80 - High-High Scenario – Winter Peak
**** Confidential in its Entirety ****

[redacted]

Table 3-77 - High-High Scenario Summer and Winter Peaks (MW)
**** Confidential in its Entirety ****

[redacted]

8.4 Special Contemporary Issues Scenarios

On October 23, 2024, the Missouri Public Service Commission issued the “Order Establishing Special Contemporary Resource Planning Issues”. In this order, the Commission made two decisions that impact the load forecasting process. These decisions (Section 1B and 1C) are listed below.

> *B. Conduct a literature review of best practices on how other utilities are accounting for the addition of data centers in their IRPs and how risks can be minimized.*
> *C. Model large load growth scenarios stemming from: 1) data centers with a demand of 30 megawatts or greater; 2) potential re-shoring of industries, specifically manufacturing or materials refinement; and 3) electrification of buildings and vehicles as a result of federal mandates changes in the marketplace, or evolving consumer preference.*

Section 1B directs Empire to conduct a literature review of best practices of how other utilities are accounting for data center additions and how risks can be minimized. In the context of load forecasting, the load forecast is responsible for predicting load additions. Risk minimization is not part of the load forecasting process.

Section 1C directs Empire to model large growth scenarios. Empire believes that the High-High scenario subsumes the impact of these large growth scenarios because it envisions strong economic growth with high electric vehicle demand. However, Empire developed additional scenarios to address these cases. The additional scenarios are included in Volume 6 of this filing.

8.5 Energy Usage and Peak Demand Plots

(C) The utility shall provide plots of energy usage and peak demand covering the historical database period and the forecast period of at least twenty (20) years.

8.5.1 Energy and Peak Plots

1. The energy plots shall include the summer, non-summer, and total energy usage for each calendar year. The peak demand plots shall include the summer and winter peak demands.

The historical and forecast summer, winter, and total energy and seasonal peaks are listed in Table 3-78 and Table 3-79. Summer energy is defined as energy from May through October. Winter energy is defined as energy from January through April and November through December. Historical values include data through March 2024 and exclude municipal (Monett, Mount Vernon, and Chetopa) values. Historical peaks are not restored for estimated curtailments. Figure 3-81 through Figure 3-83 plot the historical and forecast energy and peaks.

Table 3-78 - Historical and Forecast Summer, Winter, and Total Energy
**** Confidential in its Entirety ****

[redacted]

NP

Table 3-79 - Historical and Forecast Summer and Winter Peaks
** Confidential in its Entirety **

[redacted]

Figure 3-81 - Historical and Forecast Summer and Winter Energy
** Confidential in its Entirety **

[redacted]

Figure 3-82 - Historical and Forecast System Energy
** Confidential in its Entirety **

[redacted]

Figure 3-83 - Historical and Forecast Summer and Winter Peaks
**** Confidential in its Entirety ****

[redacted]

8.5.2 Scenario Forecast Results Summary

2. The historical period shall include both actual and weather-normalized values. The forecast period shall include the base-case, low-case, and high-case forecasts.

Figure 3-84 through Figure 3-86 compare the energy and peak forecasts for the five scenarios. The extreme and mild scenarios use the base scenario forecast economics but change the forecast normal weather. The high and low scenarios use forecast normal weather, but change the base scenario forecast economics. The high-high scenario uses normal weather, but high forecast economics and high forecast electric vehicles. Historical energy excludes the municipals (i.e., Monett, Mount Vernon, and Chetopa).

Figure 3-84 - Historical and Forecast Energy - All Scenarios
**** Confidential in its Entirety ****

[redacted]

Figure 3-85 and Figure 3-86 compare the seasonal and total peak forecasts for the four scenarios. Historical peak excludes the municipals (i.e., Monett, Mount Vernon, and Chetopa).

Figure 3-85 - Historical and Forecast Summer Peak - All Scenarios
**** Confidential in its Entirety ****

[redacted]

Figure 3-86 - Historical and Forecast Winter Peak - All Scenarios
**** Confidential in its Entirety ****

[redacted]

SECTION 9 APPENDIX A: FORECAST MODEL REPORT FOR 2025 IRP