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VOLUME 3

LOAD ANALYSIS AND LOAD FORECASTING

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

20 CSR 4240-22.030

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****Denotes Confidential****

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LOAD ANALYSIS AND LOAD FORECASTING

Commission Rule 20 CSR 4240-22.030, Load Analysis and Load Forecasting, provides in part as follows:

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 fulfill the requirements of 20 CSR 4240-22.30 ("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, 2021, Liberty-Empire filed a Variance Request identifying one load forecasting deviation and one load forecasting disclosure. The deviation and disclosure are identified below. On May 12, 2021, the variance request was granted in File No. EO-2021-0331.

Deviation Request: End-Use Information for the Industrial Class

20 CSR 4240-22.030 (4)(A)(1) requires that analysis for each major class include information by end-use to the extent possible.

The Variance Request asks to be exempt from the end-use analysis for the industrial class. While Liberty-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 Liberty-Empire's 2013, 2016, and 2019 IRP filings.

Disclosure: Forecast by Major Class

Various rules in 20 CSR 4240-22 identify the data and forecast should be performed by "major class." 20 CSR 4240-22.020 (37) defines "major class" as a cost-of-service class for the utility.

In Liberty-Empire's 2013, 2016, and 2019 IRP filings, Liberty-Empire requested and was granted variances allowing the IRP to be developed using the following revenue classes.

- Residential
- Commercial
- Industrial
- Wholesale
- Street & Highway
- Interdepartmental
- Public Authority

However, on November 15, 2018, the Commission issued an Order Granting Variances (in File No. EO-2019-0049) stating that Liberty-Empire and the Missouri Office of the Public Counsel ("OPC") agreed that Liberty-Empire would not seek the same forecast class variance request in its 2022 IRP filing unless OPC agreed that a variance is appropriate. On March 31, 2021, Liberty-Empire met with OPC for a technical discussion and the parties agreed that Liberty-Empire should define "major classes" for purposes of the 2022 IRP load forecast as the following:

- 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

Changing the definition of "major class" has two implications for this IRP forecast. First, Liberty-Empire redeveloped its historical databases to align with the new classes. The new database contains, at a minimum, historical data from 2010 forward. Second, Liberty-Empire developed a new set of forecast models which render class-level comparisons with prior IRP filings in appropriate. However, system level comparisons are still applicable.

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;

With the new major class definition, Liberty-Empire developed the historical modeling dataset to include historical sales and customer counts data for 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, PL, and SPL rates)
- Linde (formerly Praxair)
- Municipals

The database contains data from January 2010 through April 2021.

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 2010 through April 2021. Weather-normalized usage data by class is based on the final monthly sales models and developed from January 2011 through December 2020. Weather-normalized total sales are equal to the sum of weather-normalized class sales.

Table 3-1 shows actual billed sales summarized to annual sales. Table 3-2 and Figure 3-1 show weather-normalized billed sales summarized to weather-normalized annual sales.

Table 3-1 - Historical Weather Actual Sales (MWh)

Annual Normal Sales (MWh) - Billed Sales Basis					
Year	Residential	Small Commercial	Large Commercial	Industrial	Total Sales
2011	2,001,996	459,817	1,385,134	637,020	4,767,852
2012	1,832,376	440,916	1,312,128	669,829	4,544,952
2013	1,916,446	442,743	1,300,885	670,558	4,622,735
2014	1,951,949	459,212	1,322,393	678,996	4,711,810
2015	1,855,960	452,452	1,360,499	678,344	4,661,863
2016	1,809,679	444,102	1,321,291	725,647	4,612,677
2017	1,751,393	434,719	1,303,068	739,007	4,544,056
2018	2,005,777	468,311	1,356,778	718,898	4,843,370
2019	1,903,445	451,034	1,313,997	796,309	4,785,390
2020	1,843,101	421,402	1,210,646	755,211	4,514,396

Table 3-2 - Historical Weather-Normalized Sales (MWh)

Annual Normal Sales (MWh) - Billed Sales Basis					
Year	Residential	Small Commercial	Large Commercial	Industrial	Total Sales
2011	1,822,695	434,375	1,348,395	633,336	4,522,161
2012	1,831,288	439,335	1,302,017	661,526	4,523,663
2013	1,890,217	441,710	1,299,336	672,885	4,596,191
2014	1,846,351	444,407	1,303,932	679,707	4,573,552
2015	1,872,189	452,740	1,360,349	676,844	4,676,794
2016	1,856,740	446,906	1,314,487	717,353	4,647,322
2017	1,899,358	450,628	1,319,967	735,528	4,721,649
2018	1,821,140	443,127	1,315,874	711,278	4,584,442
2019	1,851,575	443,963	1,301,771	793,330	4,711,062
2020	1,923,562	431,977	1,227,350	757,074	4,624,159

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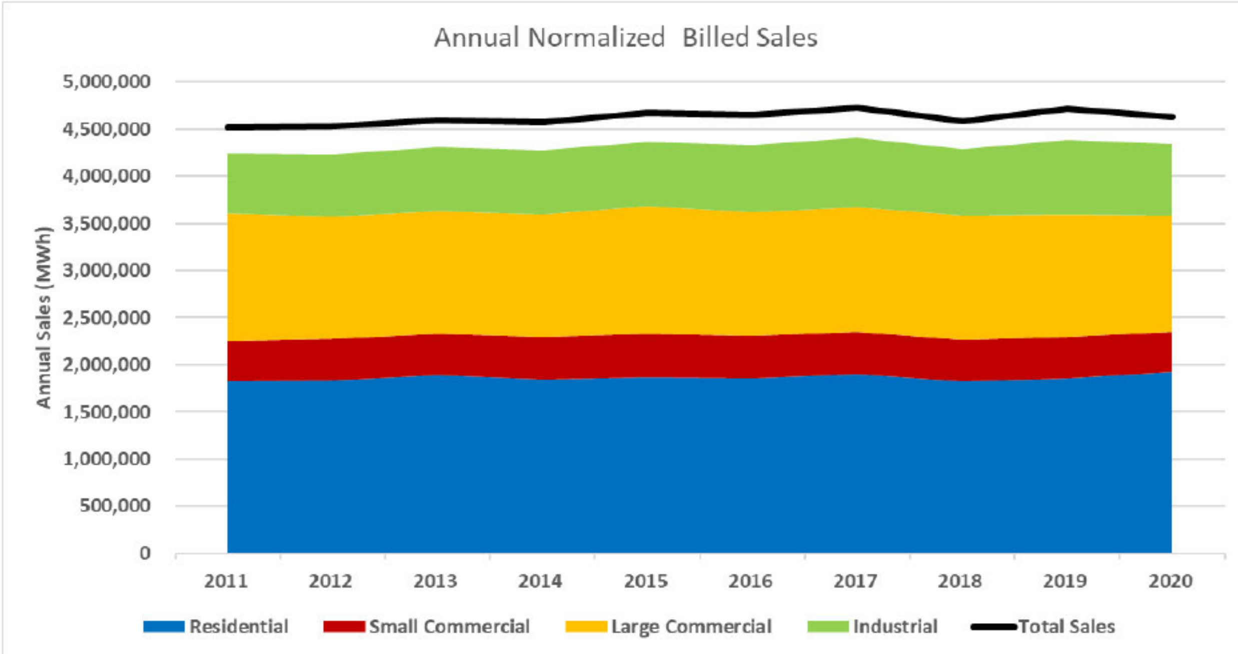
Figure 3-1 - Weather-Normalized Sales



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 research data and the net system loads excluding the on-system wholesale customers that left the system on June 1, 2020. Departing on-system wholesale customers include municipal electric customers Monett Missouri, Mount Vernon Missouri, and Chetopa Kansas. The city of Lockwood Missouri remains an on-system wholesale customer.

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

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

Estimated Actual Peaks (MW)					
	Residential	Small Commercial	Large Commercial	Industrial	System Peak*
2011	539	102	258	100	1,130
2012	493	108	250	100	1,078
2013	409	108	250	101	1,017
2014	647	96	230	71	1,111
2015	587	94	244	82	1,096
2016	569	82	233	83	1,063
2017	480	105	246	113	1,016
2018	639	98	233	81	1,158
2019	545	87	231	92	1,061
2020	456	103	229	113	994

*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 3-3. Class weather-normalized peaks are calculated using the ratio of the estimated class actual peak to the system peak and 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 3-4.

Table 3-4 - Historical Weather-Normalized Peaks (MW)

Weather-Normalized Class Peaks (MW)					
	Residential	Small Commercial	Large Commercial	Industrial	System Peak
2011	524	99	251	98	1,098
2012	507	111	257	103	1,108
2013	444	117	271	110	1,103
2014	669	99	238	73	1,149
2015	585	94	243	81	1,094
2016	582	84	238	85	1,088
2017	547	119	280	128	1,158
2018	628	96	229	80	1,139
2019	560	90	237	95	1,090
2020	501	113	252	124	1,090

2.2.3 Weather-Normalized Net System Loads

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

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

While Liberty-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 1991 to 2020.

Weather-normalized peaks are calculated based on the final peak model described in Section 6.1.2.10. Normal peak producing weather is developed using the most recent 20 years of peak producing weather. Summer and winter weather-normalized net system peaks are shown in Figure 3-2.

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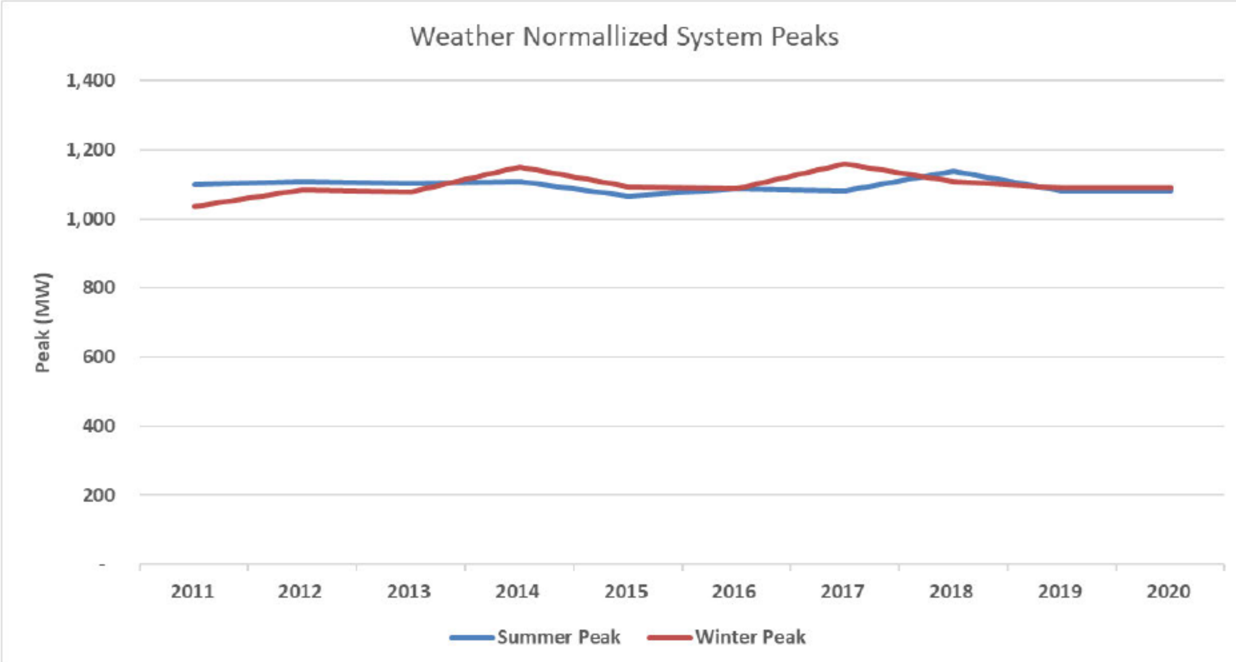
Figure 3-2 - Weather-Normalized Summer and Winter System Peaks



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 Liberty-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.

Liberty-Empire updates its load forecast each year. During each forecast cycle, Liberty-Empire reviews the historical dataset for data anomalies and updates its forecast models. Once the forecast is complete, Liberty-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 splines 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") 2021 Annual Energy Outlook ("AEO"). These data capture changing end-use saturation and energy efficiency trends for each census region based on adopted energy efficiency standards and codes.

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 3-3 through Figure 3-7 show annual plots summarizing the major trends used in the forecast models.

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

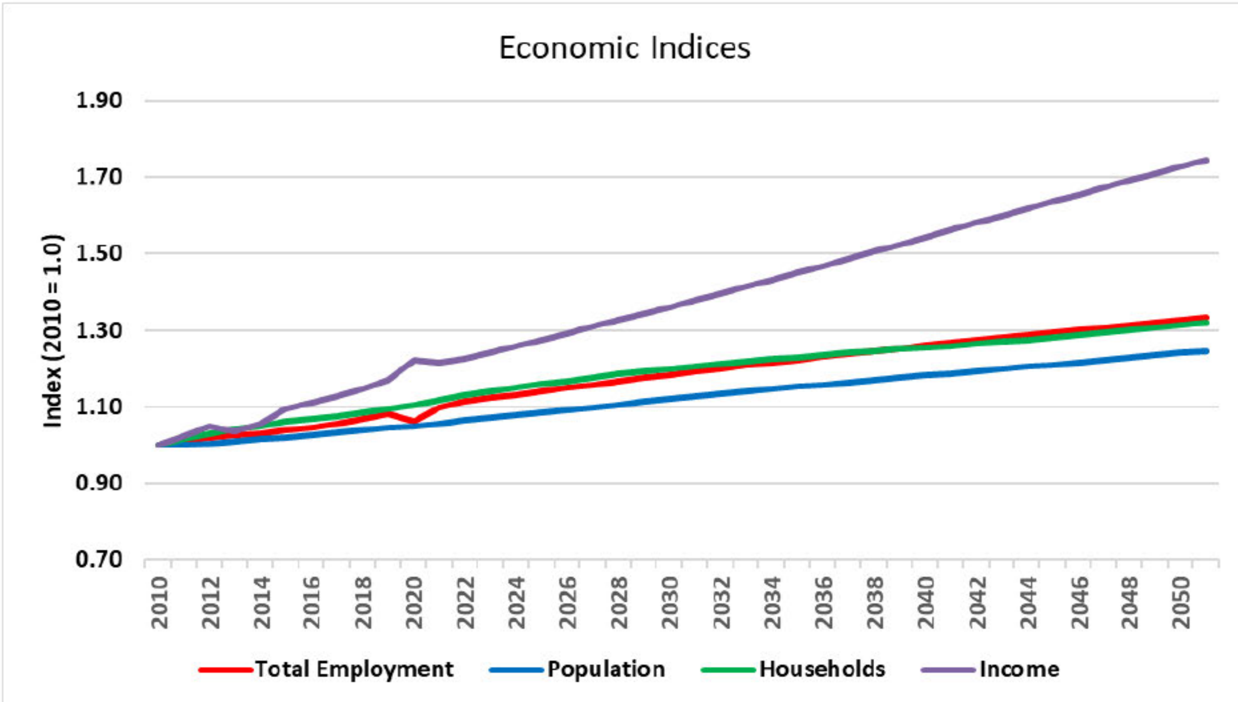


Figure 3-4 - Annual Summary of a Major Trend - Electric Prices

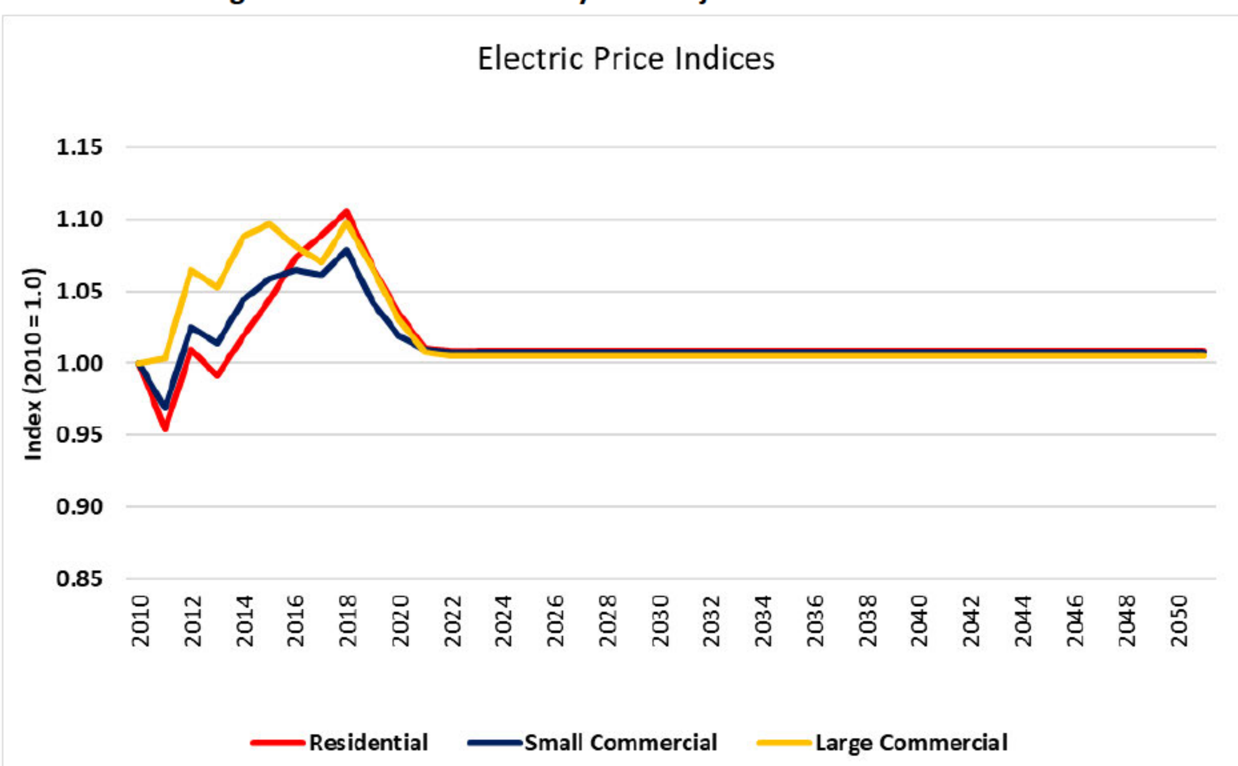


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Figure 3-5 - Annual Summary of a Major Trend - Residential SAE Indices

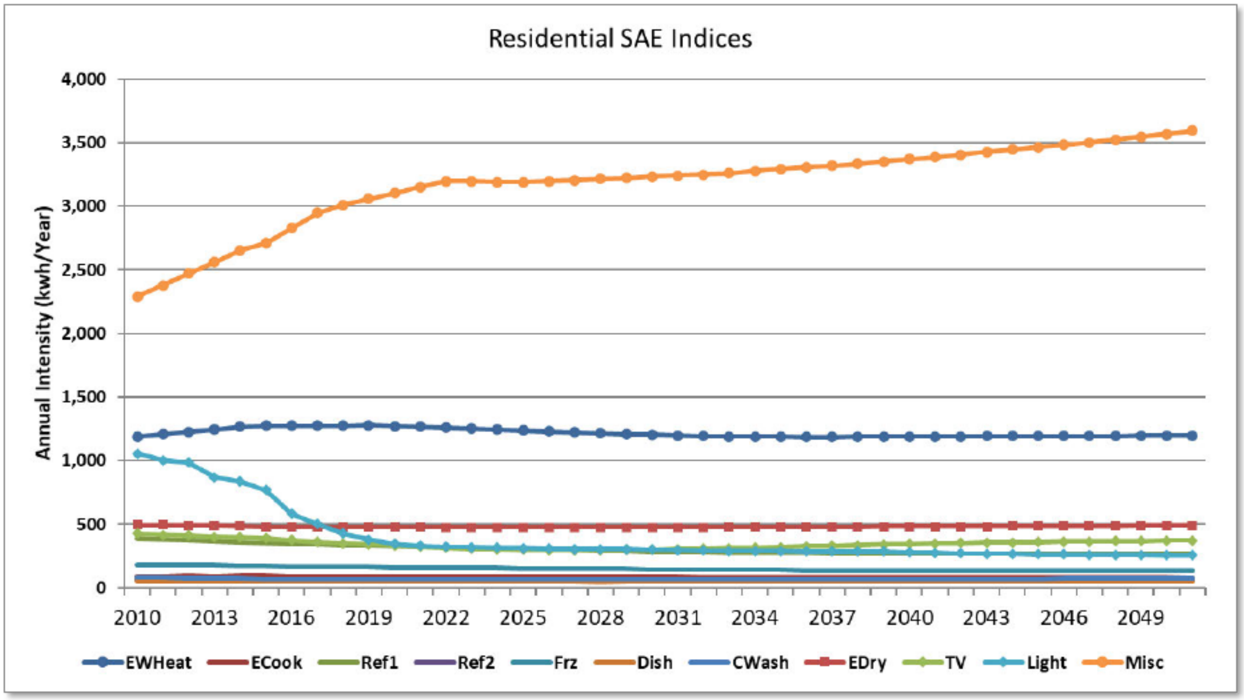


Figure 3-6 - Annual Summary of a Major Trend - Heating and Cooling Degree Days

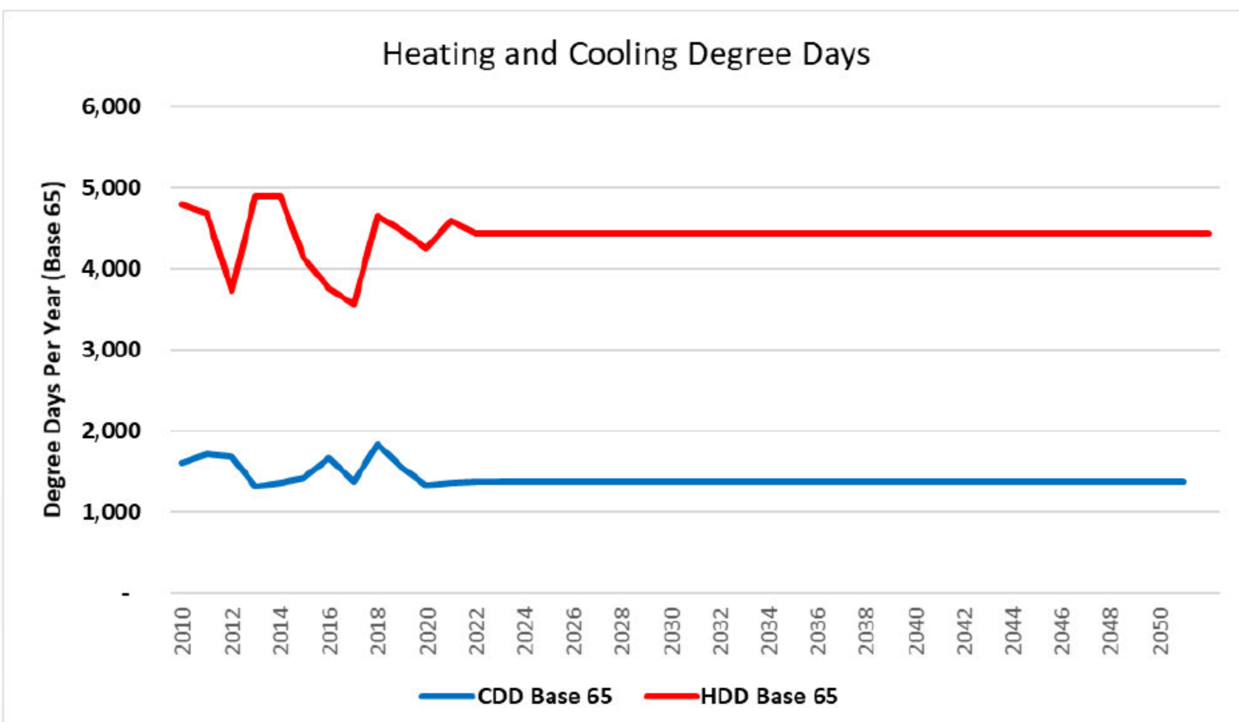
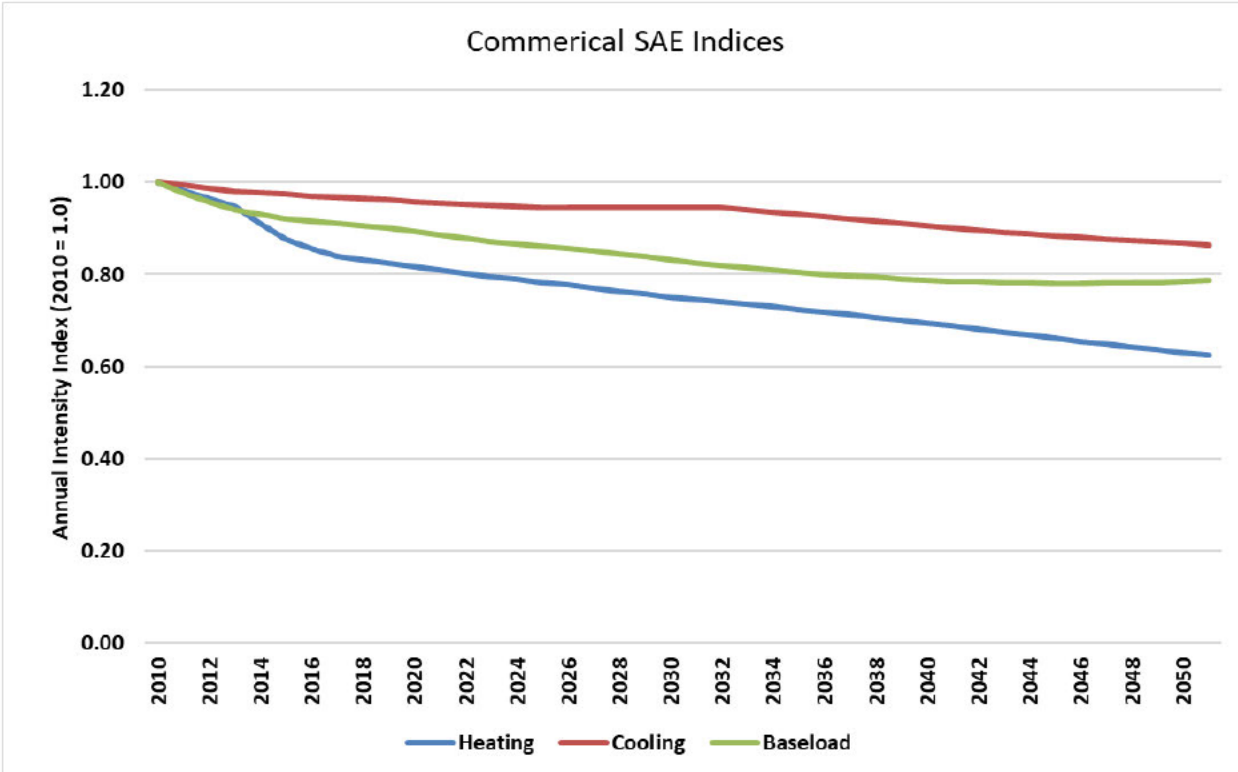


Figure 3-7 - Annual Summary of a Major Trend - Commercial SAE Indices



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 2022 IRP uses historical sales, peak, customers, weather, economic, and end-use data in the development of the load 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, data associated with municipals that have left the Liberty-Empire system (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 ("MSA"). 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 Liberty-Empire's 2008 Potential Study and 2015 Saturation Survey. Calibrating Itron's data to Liberty-Empire's historical saturation data includes smoothing the transitions between known Liberty-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.

Liberty-Empire created the historical database to include, at a minimum, data from January 2010 through April 2021.

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 the 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 modeling 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 3-5.

Table 3-5 - 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 0.873.
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 0.845.
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 0.580.
Industrial	None	The number of customers varies between 38 and 40 from 2011 through 2019. Because of the relatively constant number of customers, a constant forecast is used.
Power Feed Mills	None	The number of customers has remained constant since 2015 (10 customers). Because of the constant number of customers, a constant forecast is used.
Transmission	None	The number of customers varies between 12 and 14 from 2011 through 2019. Because of the relatively constant number of customers, a constant forecast is used.
Linde	None	Linde is a single customer. This customer was previously named "Praxair".
Lighting	None	Lighting customers have declined from 613 in 2011 to 469 in 2019. The customer count has remained 469 through 2020. Because of the constant number of customers since 2019, a constant forecast is used.
Municipal	None	The municipal class now consists of a single customer, the city of Lockwood.

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

These data are obtained from the 2021 EIA AEO and developed by Itron for the West North Central region. End-use saturations are modified to include Liberty-Empire's 2008 Potential Study and 2015 Saturation Survey. End-use intensity data are modified to include estimates of Liberty-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 modeling 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

These data are obtained from the 2021 EIA AEO and developed by Itron for the West North Central region. End-use intensity data are modified to include estimates of Liberty-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. Liberty-Empire submitted a variance request specifying that end-use information was not available for the industrial class. The variance request was approved on May 12, 2021 in File No. EO-2021-0331.

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 modeling 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 Liberty-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 Liberty-Empire's April 1, 2021, Variance Request, Itron and Liberty-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 be used to model equipment stock turnover and efficiency changes. Currently, the industrial class consists of 44 customers. Due to the low number of customers in this class, equipment stock turn over will be "lumpy" and not yield strong statistical benefits. As a result, Liberty-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, Heating Degree Days ("HDD"), and Cooling Degree Days ("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;

Liberty-Empire does not maintain a database of equipment stock for use in the SAE model. Instead, Liberty-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.

Estimates of end-use sales are embedded in the SAE models used for the residential, small commercial, large commercial, and municipal 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, large commercial, and municipal classes use Itron's SAE modeling 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 2022 through 2051.

The process is summarized below:

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

   The following rate classes are modeled:
   - Residential
   - Small Commercial
   - Large Commercial
   - Industrial
   - Power Feed Mills
   - Transmission
   - Linde (formerly Praxair)
   - Lighting
   - Municipal (Lockwood)

   The sales models are based on historical monthly rate class data and include the impacts of historical DSM programs, behind-the-meter photovoltaic ("PV") generation, and Covid-19 heathcare orders.

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 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 profile 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, and historical Covid-19 impacts. Future price effects are assumed to be constant in real dollars. 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 variables, end-use variables, and economic trend variables. These classes of variables are described below.

a. Weather Variables. For each class, Liberty-Empire determined whether temperature is critical in the forecast model. Through the examination of 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 that approximate billing cycle impacts. Weather forecasts use 30-year normal temperatures for Springfield, Missouri.

b. End-Use Variables. For residential, small commercial, large commercial and municipal classes, Liberty-Empire uses the SAE model framework. In this framework, end-use trends calibrated to Liberty-Empire specific saturation and efficiency data are used to model the changing usage over time. An evaluation of statistical fit is used to determine the appropriateness of the model calibration.

c. Economic Variables. Economic variables are used in the customer count models. The selection of these variables is based on statistical fit and the relationship between the economic driver 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 2021. Historical peaks remove 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 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 2001 through April 2021.

3) Shoulder month peaks may be driven by hot or cold weather. For instance, April peaks are driven by hot weather in 9 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 in the customer classes. For example, if electric space heating is growing faster than space cooling, summer peaks should grow at a different rate than winter 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, summer, and baseload 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 Liberty-Empire's load research 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 (1991-2020) 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 2021 AEO PV forecast calibrated to historical Liberty-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 Liberty-Empire's 2020 electric vehicle study and extended using EIA's 2021 AEO EV growth rates. The hourly profiles are based on Los Angeles Department of Water and Power's (LADWP) published energy charging profiles.

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 3-5. 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 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, and MS 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 and TEB 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 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 2011 and April 2021, this class increased from 38 customers to 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.

Power Feed Mill Class

The Power Feed Mill ("PFM") class consists of customers with the PFM 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 2011 and April 2021, the class increased from 7 customers to 10 customers. Since the number of customers has remained constant since 2015, the forecast assumes no additional customers through the forecast period.
- 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 2011 and April 2021, the number of customers varies between 10 and 13. 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.
- 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

The Linde forecast is for a single customer. This customer was previously named "Praxair". The forecast for Linde is constructed using the historical average monthly consumption and information about the customer's planned expansion.

Before the customer's planned expansion, the forecast is the average of the historical monthly consumption from January 2015 through April 2021, removing October 2018 as a data outlier. The planned expansion **[redacted]**.

Lighting Class

The Lighting class consists of customer 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 wholesale customer. This class is modeled using total Lockwood sales in each month. The Lockwood sales model uses Itron's SAE model framework and assumes that Lockwood's sales are dominated by residential customers.

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

Nine 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.

As discussed in Liberty-Empire's Variance Request, the change in the major class definition generally renders documenting the difference in the class model independent variables inapplicable. While Table 3-6 highlights the 2022 and 2019 IRP drivers, the comparisons should be used with caution as the class definitions have changed.

Table 3-6 - Variable Differences Between the 2022 and 2019 IRP Models

Key Drivers Changes for Forecast Models			
Class	**Model**	**2022 IRP**	**2019 IRP**
Residential			
	Customer	• Households (Joplin and Springfield MSAs)	Old Residential Class Definition • Population (Joplin and Springfield MSAs)
	Average Use (SAE Model)	• 2021 SAE Data	Old Residential Class Definition • 2018 SAE Data
Small Commercial			
	Customer	• Total Employment	Old Commercial Class Definition • Nonmanufacturing Employment
	Average Use (SAE Model)	• 2021 SAE Data	Old Commercial Class Definition • 2018 SAE Data
Large Commercial			

Key Drivers Changes for Forecast Models			
Class	**Model**	**2022 IRP**	**2019 IRP**
	Customer	• Total Employment	Old Commercial Class Definition • Nonmanufacturing Employment
	Average Use (SAE Model)	• 2021 SAE Data	Old Commercial Class Definition • 2018 SAE Data
Industrial			
	Customer	• Know Customer Additions	Old Industrial Class Definition Industrial Class modeled using 3 separate sales models (OPP, Linde, and Other)
	Average Use	• Historical Average UPC	
PFM			
	Customer	• Flat Forecast	Not Applicable
	Average Use	• Historical Average UPC	
Transmission			
	Customer	• Flat Forecast	Not Applicable
	Average Use	• Historical Average UPC	
Linde (formerly Praxair)			
	Sales	• Historical Average plus known additions	Old Industrial Class Definition • Historical Average
Lighting			
	Customer	• Flat Forecast	Not Applicable
	Average Use	• Lighting Customer Forecast	
Municipals			
	Sales (Lockwood Only)	• 2021 SAE	Old Municipal Class Definition 4 Sales Models (Monett, Mount Vernon, Lockwood, Chetopa) • 2018 SAE Data
System Peak			
	Peak Model	• CDD65 Trend Interaction • CDD85 Trend Interaction • HDD40 Trend Interaction • Baseload Trend • Seasonal Winter Peak Trend	• CDD70 Trend Interaction • CDD85 Trend Interaction • HDD45 Trend Interaction • Baseload Trend • Seasonal Winter Peak Trend
Profile Models			
	9 Hourly Models	• HDD Splines • CDD Splines • Months • Days • Years • Holidays • Hours of Light	8 Hourly Models • 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 modeled 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 2011 through April 2021. Table 3-7 shows the customer model specification and Table 3-8 shows the customer model statistics.

Table 3-7 - Residential Customer Model

Variable	Coefficient	StdErr	T-Stat
Constant	8235.470	10302.170	0.799
Household Index	126573.569	9532.334	13.278
JanApr2011	2300.280	257.327	8.939
Sep2018	-9836.228	219.605	-44.791
Oct2018	-7498.524	269.278	-27.847
Nov2018	-5030.580	271.467	-18.531
Dec2018	-2972.441	227.738	-13.052
Feb2019	-2972.285	182.400	-16.295
Jan	195.352	77.475	2.521
Feb	192.586	67.145	2.868
Dec	194.371	69.648	2.791
AR(1)	0.905	0.030	30.632

Table 3-8 - Residential Customer Model Statistics

Statistics	Residential Customer Model
Estimation	1/2011 – 4/2021
R2	0.995
Adj. R2	0.995
MAPE	0.10%
DW	1.653

Model Variables: The primary driver of the customer model is households. Binary variables are included to capture data anomalies and seasonality. The autoregressive (AR) term corrects for serial correlation.

1) Households: Households is calculated as the weighted average of the Joplin and Springfield MSAs based the Woods and Poole economic forecast.

2) Binary Variables. The JanApr2011 binary variable captures the change in customers resulting from the 2011 Joplin tornado. The Sep2018, Oct2018, Nov2018, Dec2018, and Feb2019 binary variables capture data anomalies. The Jan, Feb, and Dec binary variables capture seasonality.

3) AR1: The AR1 term corrects for serial correlation and does not impact the strength of the household's driver.

2. UPC Model: The UPC Model is an SAE model estimated with historical data from January 2011 through April 2021. Table 3-9 shows the UPC model specification and Table 3-10 shows the UPC model statistics.

   a. Residential SAE Model Summary: The SAE model contains end-use information for heating, cooling, and other technologies. The data for the SAE model is from Itron's 2021 SAE West North Central region modified for Liberty-Empires' 2008 Potential Study, 2015 Saturation Survey, and DSM programs.

Table 3-9 - Residential UPC Model

Variable	Coefficient	StdErr	T-Stat
XHeat	1.135	0.028	40.039
XCool	1.132	0.030	37.751
XOther	1.136	0.028	39.939
ResSolar_UPC_Hist	-2.783	0.943	-2.952
JanFeb2011	-121.513	47.343	-2.567
JanFeb2019	-112.542	47.339	-2.377
Covid_Res	63.537	25.574	2.484

Table 3-10 - Residential UPC Model Statistics

Statistics	Residential UPC Model
Estimation	1/2011 – 4/2021
R2	0.941
Adj. R2	0.938
MAPE	4.88%
DW	2.429

b. Model Variables: The UPC model includes the standard SAE variables (XHeat, XCool, and XOther), binary variables, a solar variable, and a Covid-19 variable.

1) XHeat: This variable captures the general 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: This variable captures the general 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: This variable captures the general 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) Binary Variables: The JanFeb2011 and JanFeb2019 binary variables remove data anomalies.

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

6) Covid-19: The Covid_Res variable is a binary variable that begins in April 2020 and ends in February 2021. The variable captures the increase in residential usage resulting from Covid-19 health care policy orders. The Covid-19 impact on residential customers ends in February 2021 and no further Covid-19 impacts are expected.

6.1.2.2 Small Commercial Class

The small commercial class is modeled 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 2011 through April 2021. Table 3-11 shows the customer model specification and Table 3-12 shows the customer model statistics.

Table 3-11 - Small Commercial Customer Model

Variable	Coefficient	StdErr	T-Stat
Constant	8072.120	509.582	15.841
Total Employment	14899.047	490.453	30.378
JanApr2011	416.233	54.270	7.670
Sep2018	340.992	38.488	8.860
Oct2018	-813.147	76.201	-10.671
Nov2018	-698.516	87.746	-7.961
Dec2018	-541.389	87.863	-6.162
Feb2019	-335.618	78.628	-4.268
MA(1)	-211.260	66.496	-3.177

Table 3-12 - Small Commercial Customer Model Statistics

Statistics	Small Commercial Customer Model
Estimation	1/2002 – 3/2015
R2	0.997
Adj. R2	0.996
MAPE	0.10%
DW	2.037

Model Variables: The primary driver in the customer model is total employment. Binary variables are included to capture data anomalies. The moving average ("MA") term corrects for 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: The JanApr2011 binary variable captures the change in customers resulting from the 2011 Joplin tornado. The Sep2018, Oct2018, Nov2018, Dec2018, and Feb2019 binary variables capture data anomalies.

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 2011 through April 2021. The SAE model is based on the same theoretical foundation as the residential SAE model but is modified for commercial end-use information. Table 3-13 shows the UPC model specification and Table 3-14 shows the UPC model statistics.

    a. Small Commercial SAE Model Summary: The SAE model contains end-use information for heating, cooling, and other technologies. The data for the SAE model is from Itron's 2021 SAE West North Central region.

Table 3-13 - Small Commercial UPC Model

Variable	Coefficient	StdErr	T-Stat
XHeat	0.111	0.005	23.932
XCool	0.097	0.003	28.149
XOther	0.003	0.000	67.388
SComSolar_UPC_Hist	-1.574	0.699	-2.253
OctNov2020	-483.642	57.144	-8.464
Covid_SCom	-138.698	59.976	-2.313
Year2011	-95.119	26.086	-3.646

Table 3-14 - Small Commercial UPC Model Statistics

Statistics	Small Commercial UPC Model
Estimation	1/2011 – 4/2021
R2	0.894
Adj. R2	0.889
MAPE	3.83%
DW	1.955

b. Model Variables: The UPC model includes the standard SAE variables (XHeat, XCool, and XOther), binary variables, a solar variable, and a Covid-19 variable.

1) XHeat: This 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: This 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: This 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: The Year2011 variable captures the usage shift from the 2011 Joplin tornado. The OctNov2020 variable captures billing data errors in the historical dataset.

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

6) Covid-19: The Covid_SCom variable is binary variable from April 2020 to May 2020 and approximates the decline in small commercial usage from Covid-19 health care policy orders. The Covid-19 impact on small commercial customers ends in May 2020 and no further Covid-19 impacts are expected.

6.1.2.3 Large Commercial Class

The large commercial class is modeled 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 2011 through April 2021. Table 3-15 shows the

customer model specification and Table 3-16 shows the customer model statistics.

Table 3-15 - Large Commercial Customer Model

Variable	Coefficient	StdErr	T-Stat
Constant	1890.207	81.853	23.093
Total Employment	1070.328	78.268	13.675
JanApr2011	30.274	8.273	3.659
April2013Dec2013	50.217	6.016	8.347
April2020Dec2020	24.480	5.745	4.261
Year2014	-88.998	5.449	-16.332
Year2015	-60.124	5.309	-11.325
Year2016	-28.138	5.175	-5.437
MA(1)	0.636	0.074	8.553

Table 3-16 - Large Commercial Customer Model Statistics

Statistics	Large Commercial Customer Model
Estimation	1/2011 – 4/2021
R2	0.954
Adj. R2	0.951
MAPE	0.26%
DW	1.614

Model Variables: The primary driver in the customer model is total employment. Binary variables are included to capture data anomalies and major customer count shifts. The MA term corrects for 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: The JanApr2011 binary variable captures the change in customers resulting from the 2011 Joplin tornado. The April2013Dec2013, April2020Dec2020, Year2014, Year2015, and Year2016 binary variables capture larger changes in 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 2011 through April 2021. Table 3-17 shows the UPC model specification and Table 3-18 shows the UPC model statistics.

   a. Large Commercial SAE Model Summary: The SAE model contains end-use information for heating, cooling, and other technologies. The data for the SAE model is from Itron's 2021 SAE West North Central region.

Table 3-17 - Large Commercial UPC Model

Variable	Coefficient	StdErr	T-Stat
XHeat	1.127	0.075	15.069
XCool	1.666	0.056	29.657
XOther	0.078	0.001	97.048
Covid_LCom1_AprJul	-3657.407	709.905	-5.152
Covid_LCom2_AugDec	-913.223	616.483	-1.481
SepOct2019	2741.111	885.968	3.094
OctNov2020	3760.633	885.218	4.248
LComSolar_UPC_Hist	-3.005	2.035	-1.477
Year2016	1163.928	389.354	2.989
Year2015	2775.380	405.968	6.836
Year2014	1486.408	407.737	3.646

Table 3-18 - Large Commercial UPC Model Statistics

Statistics	Large Commercial UPC Model
Estimation	1/2011 – 4/2021
R2	0.912
Adj. R2	0.904
MAPE	2.53%
DW	1.778

b. Model Variables: The UPC model includes the standard SAE variables (XHeat, XCool, and XOther), binary variables, a solar variable, and Covid-19 variables.

1) XHeat: This 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: This 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: This 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: The SepOct2019 and OctNov2020 variables capture offsetting data anomalies. The Year2014, Year2015, and Year2016 binary variables capture short term usage shifts.

5) Solar: The LComSolar_UPC_Hist variable is the estimated historical behind-the-meter solar installation sales associated with Liberty-Empire's solar rebate program. The historical installed capacity is converted to monthly generation using monthly load factors and then divided by customers to obtain solar generate per customer. The model assumes no changes in solar generation in the forecast. New

solar installations are externally forecast and added to the final forecast after the statistical modeling is complete

6) Covid-19: The Covid_LCom1_AprJul and Covid_LCom2_AugDec variables approximate the decline in large commercial usage from Covid-19 health care policy orders. Two variables are used to model the changing declining impact from April 2020 through December 2020. The Covid-19 impact on large commercial customers ends in December 2020 and no further Covid-19 impacts are expected.

6.1.2.4 Industrial Class

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

1. Customer Count Forecast: Between January 2011 and April 2021, the class increased from 38 customers to 44 customers. The low number of customers and slow growth cannot be reliability forecast using a statistical model. Instead, the industrial customer forecast is based on known customer expansions and projects. From 2021 through 2023, the class is expected to increase by 8 customers with an estimated annual consumption of 61,101 MWh and annual coincident peak demand of 10.5 MW.

2. UPC Model: The existing 44 customers' usage is modeled with a UPC model. The model captures the recent usage patterns and Covid-19 impacts. Table 3-19 shows the UPC model specification and Table 3-20 shows the UPC model statistics.

Table 3-19 - Industrial UPC Model

Variable	Coefficient	StdErr	T-Stat
Constant	1482550.945	10267.787	144.389
CDD55	452.141	22.837	19.799

Variable	Coefficient	StdErr	T-Stat
Covid_Ind	-153457.476	36747.897	-4.176
Year2011	-149216.153	22199.640	-6.722
Year2012	-160974.620	22215.291	-7.246
Year2013	-124334.163	22194.145	-5.602
Year2014	-93505.711	22193.439	-4.213
Oct2018	-1436648.054	71623.796	-20.058

Table 3-20 - Industrial UPC Model Statistics

Statistics	Industrial UPC Model
Estimation	1/2011 – 4/2021
R2	0.883
Adj. R2	0.876
MAPE	3.50%
DW	1.613

Model Variables: The UPC model includes a weather variable, binary variables, and a Covid-19 variable.

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

2) Binary Variables: The Year2011, Year2011, Year2013, and Year2014 binary variables capture higher average usage associated with a lower number of customers. Between 2015 and 2021, usage is stable requiring no further binary shift variables. The Oct2018 binary variable removes the outlier data in October 2018.

3) Covid-19: The Covid_Ind variable is binary variable from April 2020 to July 2020 and approximates the decline in industrial usage from Covid-19 health care policy orders. The model does not expect future changes resulting from Covid-19.

6.1.2.5 Power Feed Mill (PFM) Class

The PFM class is modeled with manual customer count forecast and a UPC model.

1. Customer Count Forecast: Between January 2011 and April 2021, the class increased from 7 customers to 10 customers. The low number of customers cannot be reliability forecast using a statistical model. Since the number of customers has remained constant since 2015, the forecast assumes no additional customers through the forecast period.

2. UPC Model: The existing 10 customers' usage is modeled with a UPC model. The model captures the recent usage patterns and Covid-19 impacts. Table 3-21 shows the UPC model specification and Table 3-22 shows the UPC model statistics.

Table 3-21 - PFM UPC Model
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[redacted]

Table 3-22 - PFM UPC Model Statistics
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[redacted]

[redacted]

Model Variables: The UPC model includes a weather variable, binary variables, and a Covid-19 variable.

1) Weather: The class's weather response is modeled using an HDD variable with a temperature reference point of 65 degrees.

2) Binary Variables: The Jul, Aug, Sep, Oct, and Nov binary variables model the seasonal usage pattern. The Dec2019Jan2020 variable captures the offsetting data anomalies for these two months. The Year2016Plus variable models the usage stabilization after 2016.

3) Covid-19: The Covid_PFM variable from March 2020 to December 2020 and approximates the decline in PFM usage from Covid-19 health care policy orders. While the variable is not statistically significant, the variable captures the minor reduction in usage and has a P-value of 22.18%. The model does not expect future changes resulting from Covid-19.

4) MA1: The MA1 term corrects for serial correlation.

6.1.2.6 Transmission Class

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

1. Customer Count Forecast: Between January 2011 and April 2021, the number of customers varies between 10 and 13. The low number of customers cannot

be reliability forecast 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 modeled 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	1138678.721	9580.894	118.849
Jan	-66072.890	19091.933	-3.461
Feb	-96012.973	19091.933	-5.029
Mar	-86194.816	19091.933	-4.515
Apr	-59549.641	19091.933	-3.119

Table 3-23 (Cont'd) - Transmission UPC Model

Variable	Coefficient	StdErr	T-Stat
Jul	78047.649	19818.637	3.938
Aug	100599.176	19818.637	5.076
Nov	-100064.212	19818.637	-5.049
Dec	-113461.536	19818.637	-5.725
Oct2018	-916670.936	56726.808	-16.159
Year2015	58845.751	17221.538	3.417
Year2019	74273.680	17221.538	4.313
Year2011	56358.710	17221.538	3.273

Table 3-24 - Transmission UPC Model Statistics

Statistics	Transmission UPC Model
Estimation	1/2011 – 4/2021
R2	0.883
Adj. R2	0.876
MAPE	3.50%

Statistics	Transmission UPC Model
DW	1.613

Model Variables: The UPC model consists of binary variables that capture seasonality, temporary usage shifts, and data anomaly.

1) Binary Variables: the Jan through Dec binary variables model the seasonal usage pattern. The Year2011, Year2015, and Year2019 binary variables capture short-term usage shifts. The Oct2018 binary variable captures a data anomaly.

6.1.2.7 Linde Class

The Linde class is a forecast for a single customer (formerly named "Praxair"). The forecast uses a regression model to forecast a monthly average consumption. The average is calculated from January 2015 through April 2021, removing October 2018 as a data outlier. Table 3-25 shows the model specification and Table 3-26 shows the UPC model statistics.

Table 3-25 - Linde Model

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[redacted]

Table 3-26 - Linde Model Statistics

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[redacted]

[redacted]

The Linde model consists of three variables. These variables are shown below.

a. Dec2020Jan2021: This variable captures the offsetting data anomalies for December 2020 and January 2021.

b. Oct2018: This variable removes October 2018 as a data anomaly.

c. Year2015Plus. This variable causes the regression model to forecast the monthly average usage from January 2015 through April 2021 with the exception of the October 2018 data anomaly.

The Linde model forecast results are adjusted for a known facility expansion. **[redacted].**

6.1.2.8 Lighting Class

The lighting class is modeled 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 2011 through April 2021 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	460.517	2.220	207.398

Variable	Coefficient	StdErr	T-Stat
Year2011	143.999	3.550	40.558
Year2012	107.666	3.550	30.325
Year2013	86.499	3.550	24.363
Year2014	64.666	3.550	18.213
Year2015	47.166	3.550	13.284
Year2016	47.666	3.550	13.425
Year2017	27.666	3.550	7.792
Year2018	11.499	3.550	3.239
Mar	10.045	3.414	2.942
Apr	16.863	3.414	4.940
May	20.601	3.551	5.801
Jun	21.301	3.551	5.998
Jul	11.501	3.551	3.239
Aug	8.701	3.551	2.450
Sep	9.801	3.551	2.760

Table 3-28 - Lighting Customer Model Statistics

Statistics	Lighting Customer Model
Estimation	1/2011 – 4/2021
R2	0.959
Adj. R2	0.953
MAPE	1.44%
DW	1.302

Model Variables: The model is designed to forecast a constant number of customers based on the 2019 and 2020 customer counts. The model uses binary variables.

1) Binary Variables. The annual binary variables (Year2011, Year2012, …, Year2018) model the decreasing number of customers. The number of customers stabilizes in 2019. The monthly binary variables (Mar, Apr, …, Sep) model seasonality.

2. UPC Model: The UPC Model is a regression model estimated with historical data from January 2011 through April 2021. 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
XHeat	1.135	0.028	40.039
XCool	1.132	0.030	37.751
XOther	1.136	0.028	39.939
ResSolar_UPC_Hist	-2.783	0.943	-2.952
JanFeb2011	-121.513	47.343	-2.567
JanFeb2019	-112.542	47.339	-2.377
Covid_Res	63.537	25.574	2.484

Table 3-30 - Lighting UPC Model Statistics

Statistics	Lighting UPC Model
Estimation	1/2011 – 4/2021
R2	0.941
Adj. R2	0.938
MAPE	4.88%
DW	2.429

Model Variables: The UPC model is primarily driven by the customer count forecast and include 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 (Jan, Feb, ..., Dec) model seasonality. The Oct2018 binary variable removes a data anomaly.

6.1.2.9 Municipal Class

The municipal class is a forecast for a single customer, the city of Lockwood. The sales model is an SAE model estimated with historical data from January 2011 through April 2021. Table 3-31 shows the model specification and Table 3-32 shows the model statistics.

Table 3-31 - Municipal Model

Variable	Coefficient	StdErr	T-Stat
XHeat	258.046	13.625	18.939
XCool	578.750	27.790	20.826
XOther	1305.236	19.041	68.548
Oct2018	-820256.858	37973.546	-21.601
Covid_Muni	-80251.566	29030.324	-2.764
Year2013Plus	45742.889	8861.444	5.162
Jun	66482.753	17435.379	3.813
Jul	86073.159	22413.645	3.840
Aug	114021.733	20328.722	5.609
Sep	103354.808	15046.208	6.869
Year2019Plus	-41928.372	8655.887	-4.844

Table 3-32 - Municipal Model Statistics

Statistics	Municipal Model
Estimation	1/2011 – 4/2021
R2	0.961
Adj. R2	0.957
MAPE	2.79%
DW	1.759

The municipal model consists of SAE variables, binary variables, and a Covid-19 variable. These variables are shown below.

a. SAE: Like the residential UPC model, the SAE variables consist of the XHeat, XCool, and XOther variables. These variables are based Itron's 2021 SAE West North Central region modified for Liberty-Empires' 2008 Potential Study, 2015 Saturation Survey, and DSM programs.

b. Binary Variables: The Jun, Jul, Aug, and Sep binary variables capture seasonality. The Oct2018 binary variable removes October 2018 as a data anomaly. The Year2013Plus and Year2019Plus binary variables model usage shifts beginning in 2013 and 2019.

c. Covid-19: The Covid_Muni variable is binary variable from May 2020 to June 2020 and models the decline in municipal sales from Covid-19 health care policy orders. The Covid-19 impact ends in June 2020 and no further impacts from Covid-19 are expected.

6.1.2.10 System Peak Model

The System Peak Model is a regression model that is designed to forecast 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 2012 through April 2021. 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	679.457	8.194	82.921
HDD40_HeatIndex	13.794	0.679	20.303
CDD65_CoolIndex	8.445	1.292	6.538
CDD75_CoolIndex	18.061	2.490	7.253
Covid_Peak	-109.488	26.535	-4.126
JanFebDec2014	-74.805	25.016	-2.990
WinterPeakTrend2015Plus	40.539	20.061	2.021
Apr15Apr16Apr17	-113.159	22.166	-5.105

Table 3-34 - System Peak Model Statistics

Statistics	Peak Model
Estimation	1/2012 – 4/21

Statistics	Peak Model
R2	0.935
Adj. R2	0.931
MAPE	3.23%
DW	1.721

Model Variables: The System Peak Model is driven by the sales forecast and peak producing weather with adjustments for Covid-19 and short-term data shifts. The variables are discussed below.

a. 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.

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

c. 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.

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

e. Covid-19. Covid_Peak is binary variable from April 2020 to May 2020 and approximates the decline in peak from Covid-19 health care policy orders. The model does not expect future changes resulting from Covid-19.

f. WinterPeakTrend2015Plus. This variable captures the seasonal winter peak trend beginning in 2015 and continuing 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.

g. Binaries. 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.

6.1.2.11 Profile Models

The hourly profile models are developed as hourly regression models using historical load research data. The models are estimated with data from 2016 through 2021 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	Covid19
Residential	X	X	X				
Small Commercial	X	X	X		X	X	X

Class	HDD CDD	Day of Week	Month	Year	Holiday	Hours of Light	Covid19
Large Commercial	X	X	X	X	X	X	X
Industrial	X	X	X	X	X	X	
PFM	X	X		X	X		
Transmission			X	X			
Linde (formerly Praxair)			X				
Lighting			X				
Municipal	X	X	X		X	X	X

a. 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.

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

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

d. Year: Annual binary variables capture load growth or annual sampling changes in the Load Research data.

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

f. 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.

g. Covid19. This binary variable models the Covid-19 healthcare policy impacts.

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 Liberty-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 fore-casted over the entire planning horizon;

Empire maintains, at a minimum, a 10-year data set of historical values for independent variables. 2021 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, Liberty-Empire has filed IRP forecasts in 2013, 2016, and 2019. This section compares the key independent variables used in the 2022 IRP with the prior IRP variables. All variables are converted to indices for ease of comparison.

The economic data includes two definitional changes. First, the 2013 IRP economic data are based on state-level economic forecasts. In the 2016 through 2022 IRPs, the economic data are based on the Joplin and Springfield MSAs economic forecasts. Second, in the 2022 IRP, employment is based on total employment. In the 2013 through 2019 IRPs, employment is based on non-manufacturing employment. The economic driver comparisons are shown in Figure 3-8 through Figure 3-10.

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Figure 3-8 - Employment Index Comparison

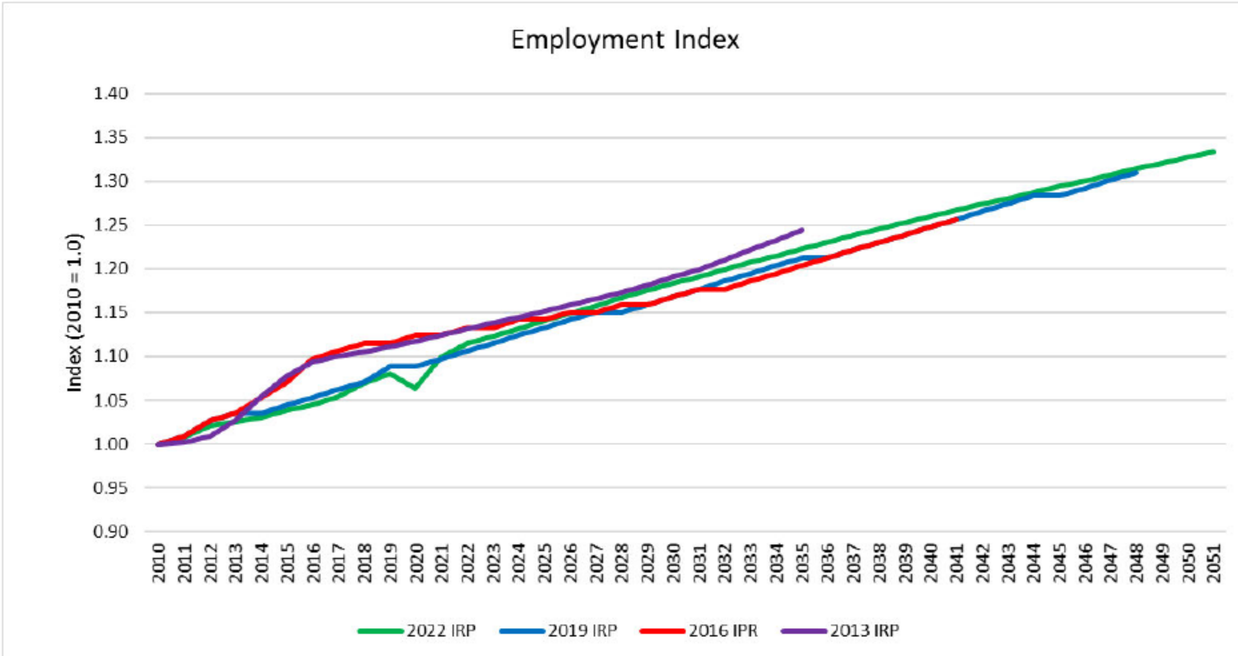


Figure 3-9 - Population Index Comparison

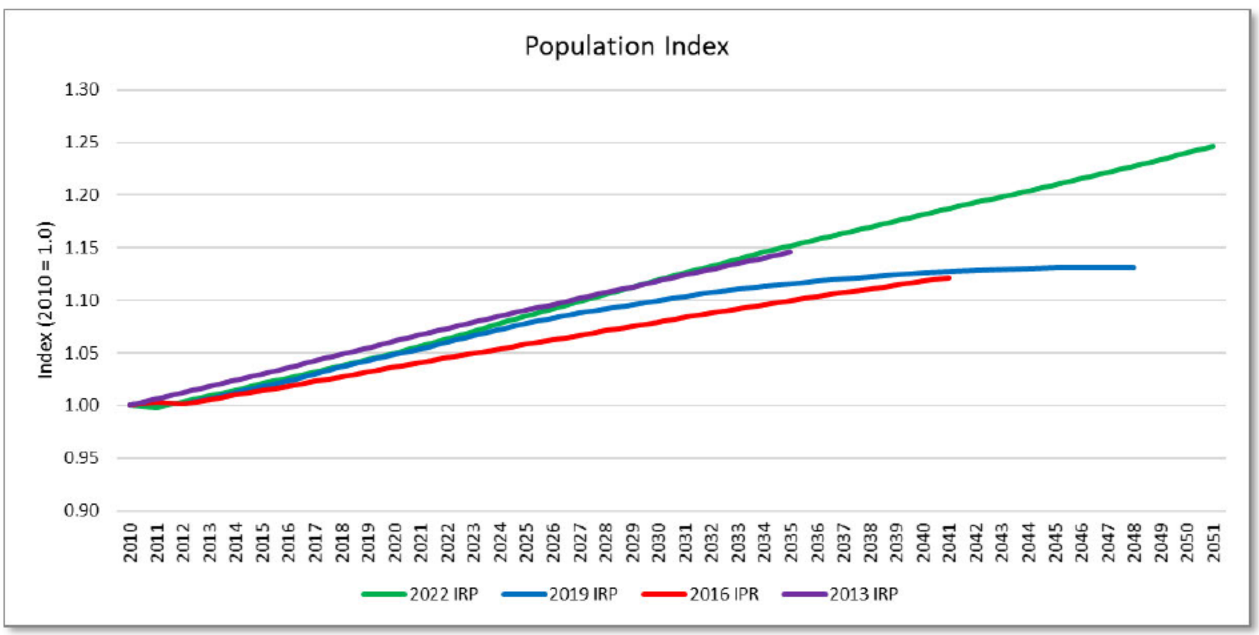
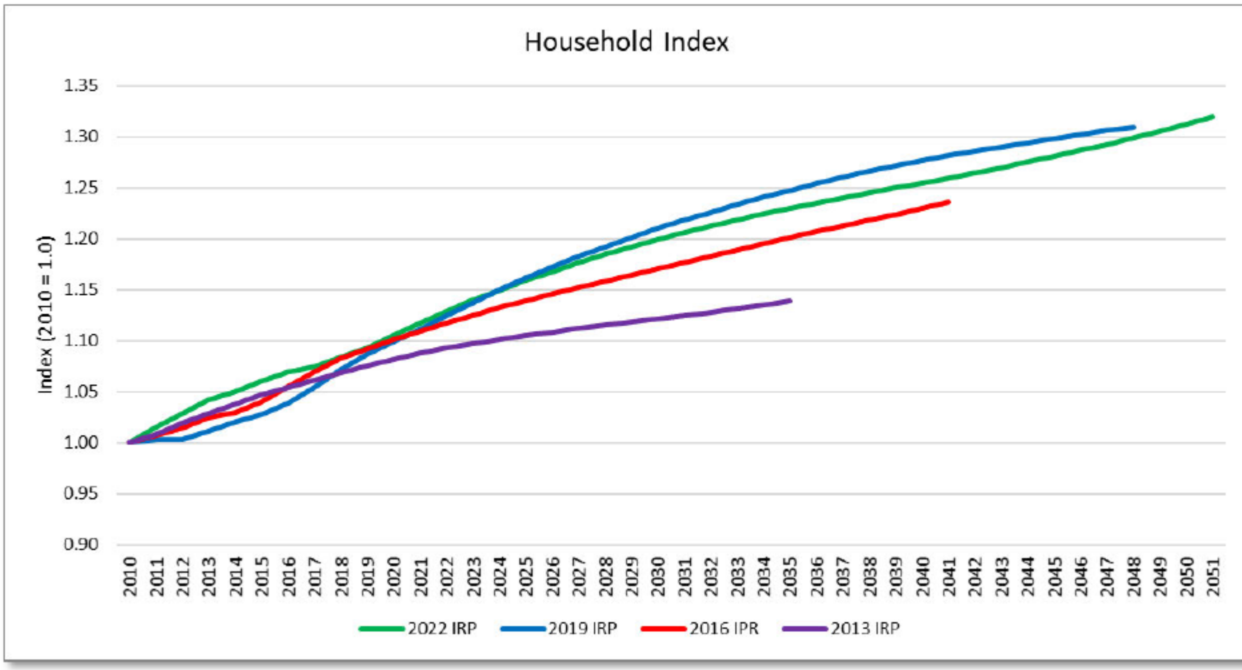


Figure 3-10 - Household Index Comparison



The SAE data is developed by Itron. Figure 3-11 through Figure 3-13 compare the residential SAE indices for residential heating, cooling, and other (baseload). Figure 3-14 through Figure 3-16 compare the commercial SAE indices for heating, cooling, and other (baseload).

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Figure 3-11 - Residential SAE Heating Index

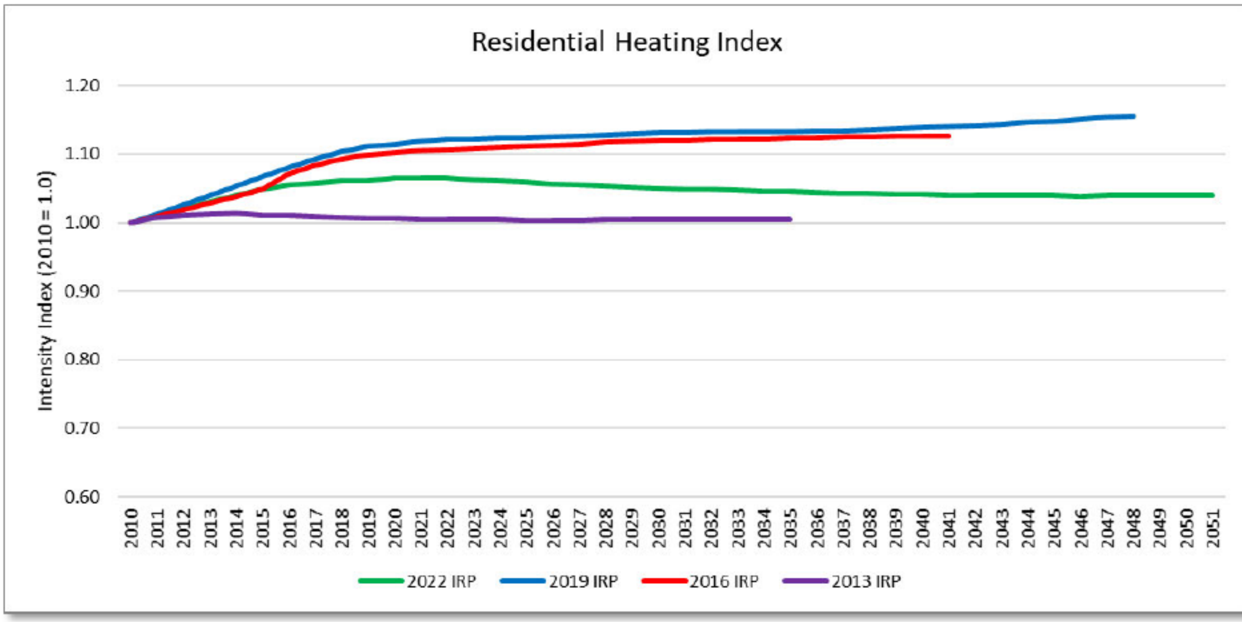


Figure 3-12 - Residential SAE Cooling Index

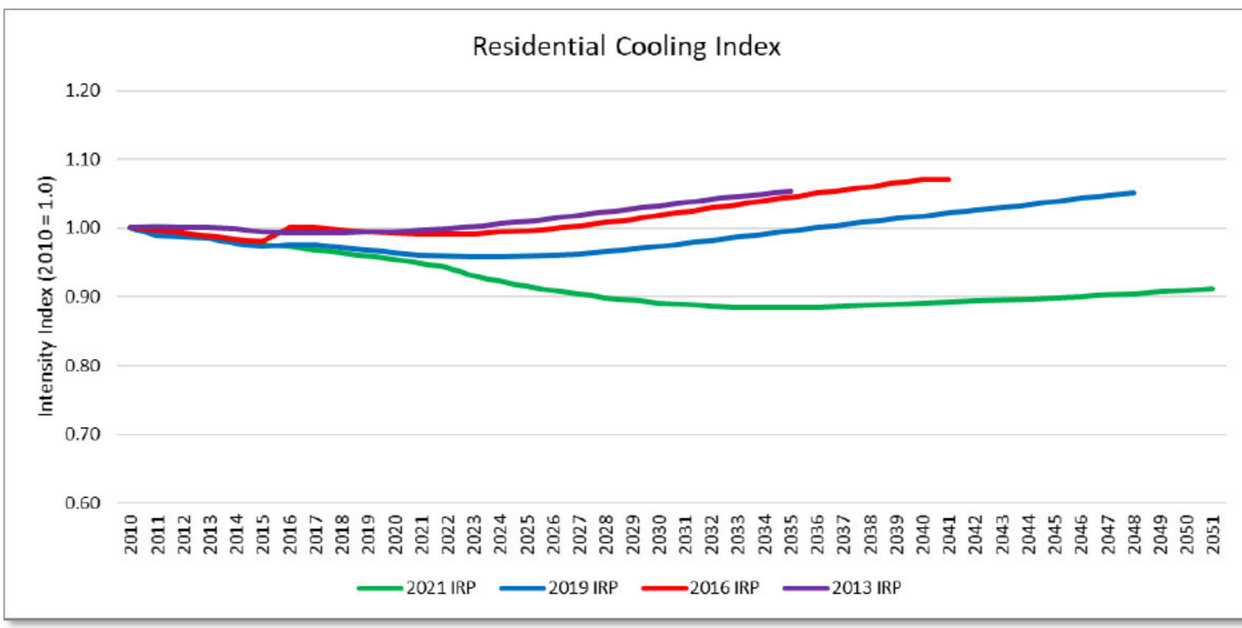


Figure 3-13 - Residential SAE Other Index

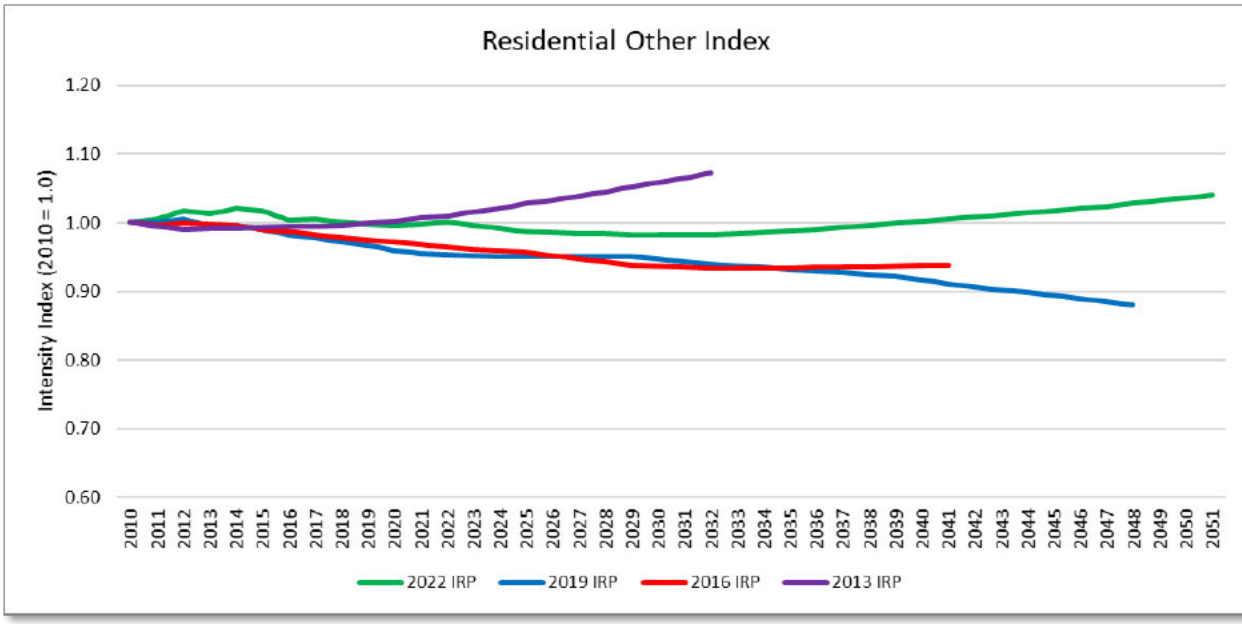


Figure 3-14 - Commercial SAE Heating Index

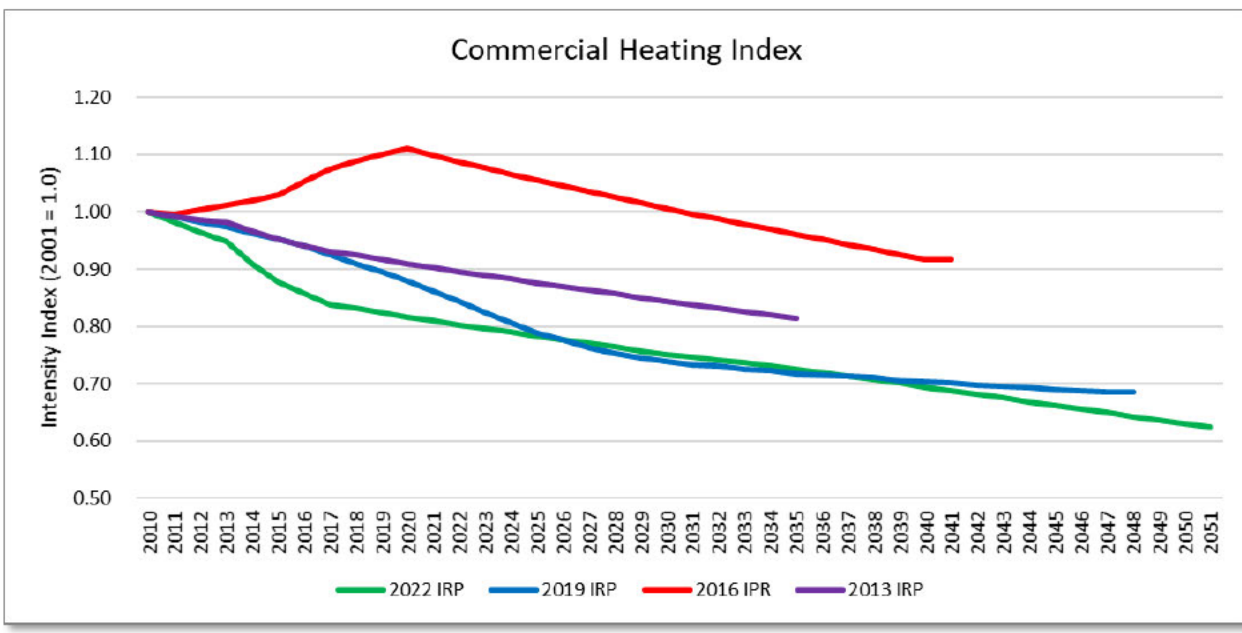


Figure 3-15 - Commercial SAE Cooling Index

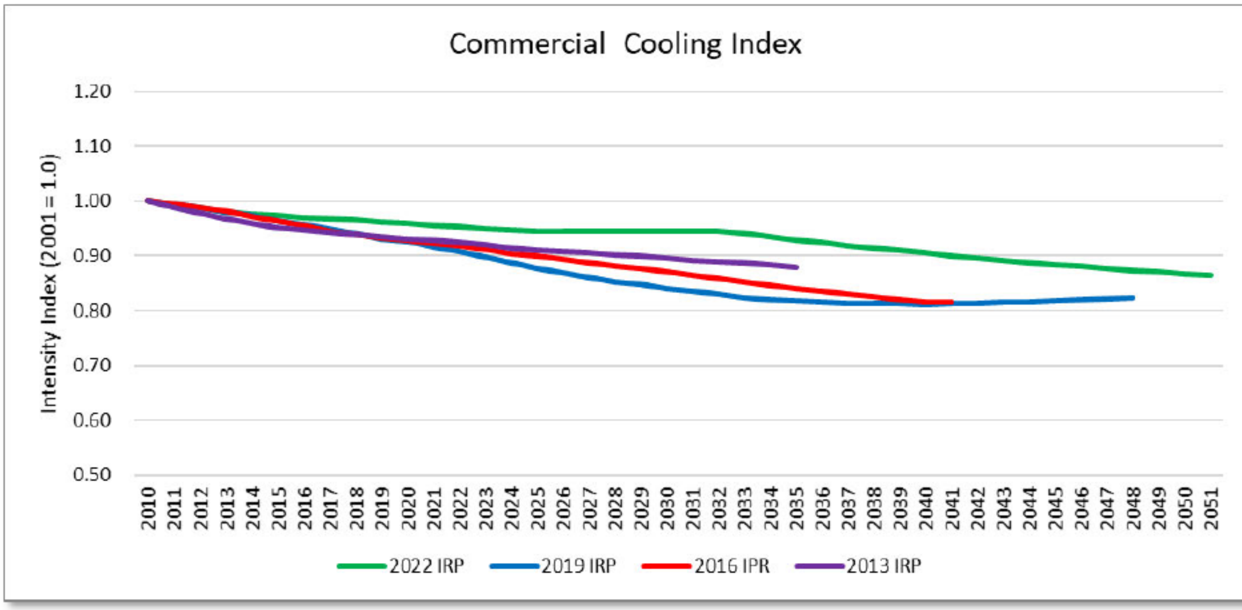
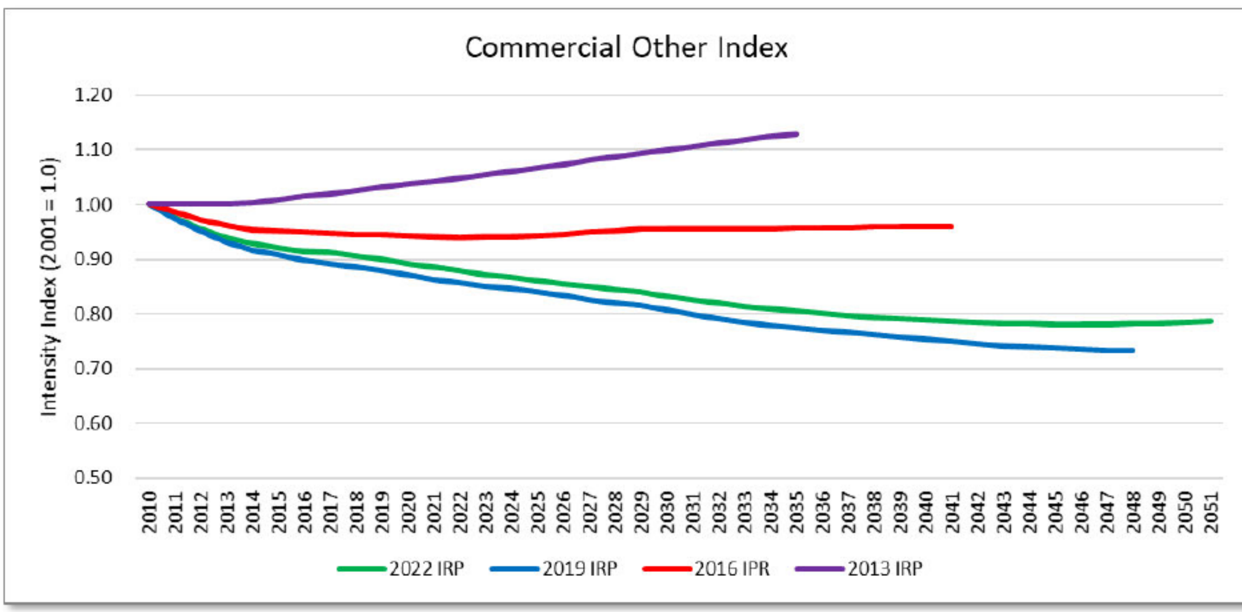


Figure 3-16 - Commercial SAE Other Index



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	1,434
2022 IRP	**4,437**	**1,384**
2019 IRP	**4,458**	**1,345**
2016 IRP	**4,528**	**1,333**
2013 IRP	**4,510**	**1,305**

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, energy net system (MWh) and system peaks (MW) to forecasts in the 2013 through 2019 IRPs are shown in Table 3-37 through Table 3-39. In these tables actual values are not weather-normalized and contain municipal data (i.e., Monett, Mount Vernon, and Chetopa). The 2022 IRP forecast values include partial actual values through April 2021. Figure 3-17 through Figure 3-19 compare the four IRP forecasts.

Table 3-37 - IRP Comparison - Total Customers

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[redacted]

Year	Actual	2013 IRP	2016 IRP	2019 IRP	2022 IRP
2035			177,512	185,720	194,322
2036				186,190	195,118
2037				186,634	195,889
2038				187,054	196,632
2039				187,446	197,348
2040				187,810	198,058
2041				188,140	198,783
2042				188,434	199,541
2043				188,688	200,327
2044				188,910	201,135
2045				189,103	201,947
2046				189,273	202,775
2047				189,430	203,636
2048				189,577	204,543
2049					205,500
2050					206,490
2051					207,492

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Figure 3-17 - IRP Comparison - Total Customers

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[redacted]

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

[redacted]

[redacted]

Figure 3-18 - IRP Comparison - Net System Energy (MWh)

[redacted]

Table 3-39 - IRP Comparison - System Peaks (MW)
****Confidential in its Entirety****

[redacted]

Figure 3-19 - IRP Comparison - System Peaks (MW)
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[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.

Liberty-Empire uses Itron's SAE modeling framework for the residential, small commercial, large commercial, and municipal classes. The SAE model uses the EIA's 2021 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.

Weather sensitive components of the residential, small commercial, large commercial and industrial classes are obtained by applying the models' weather variable coefficient to normal weather data. The results of this calculation are the sales associated with heating and cooling. Non-heating and cooling loads are assumed to be base load (non-weather-sensitive load). Table 3-40 summarizes the monthly data heating and cooling data for the major classes into annual values.

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Table 3-40 - Annual Heating, Cooling, and Base Load Components of the Major Classes MWh (Billed Year Basis)

****Confidential in its Entirety****

[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.

Liberty-Empire makes two adjustments to the forecast models. These adjustments impact the Industrial and Linde (formerly Praxair) classes. In both classes, the forecast models are designed to forecast a constant number of customers. These models are described in Section 6.1.2.4 and 6.1.2.7. The adjustments to these classes are made to capture known customer projects from 2021 through 2022. Liberty-Empire is not aware of any additional projects after 2022.

Table 3-41 shows the estimated customer, sales, and coincident peak additions by month through 2023. The monthly pattern of 2023 additions continues through 2051.

Table 3-41 - Forecast Adjustments

		Industrial			Praxair		
Year	Month	Customers (Count)	Sales (kWh)	Coincident Peak (MW)	Customers (Count)	Sales (kWh)	Coincident Peak (MW)
2021	1	1	967,200	2.0	0	0	0.0
2021	2	1	873,600	2.0	0	0	0.0
2021	3	2	1,264,800	2.5	0	1,696,320	2.4
2021	4	2	1,224,000	2.5	0	1,641,600	2.4
2021	5	2	1,264,800	2.5	0	1,696,320	2.4
2021	6	2	1,224,000	2.5	0	1,641,600	2.4
2021	7	3	2,008,800	4.0	0	1,696,320	2.4
2021	8	3	2,008,800	4.0	0	1,696,320	2.4
2021	9	3	2,880,000	6.0	0	1,641,600	2.4
2021	10	4	2,976,000	6.0	0	1,696,320	2.4
2021	11	4	2,880,000	6.0	0	1,641,600	2.4
2021	12	4	2,976,000	6.0	0	1,696,320	2.4
2022	1	4	2,976,000	6.0	0	3,392,640	4.8
2022	2	4	2,688,000	6.0	0	3,064,320	4.8
2022	3	5	3,459,600	7.0	0	3,392,640	4.8
2022	4	6	4,050,000	8.5	0	3,283,200	4.8
2022	5	6	4,185,000	8.5	0	3,392,640	4.8
2022	6	6	4,050,000	8.5	0	3,283,200	4.8
2022	7	6	4,185,000	8.5	0	3,392,640	4.8
2022	8	6	4,185,000	8.5	0	3,392,640	4.8
2022	9	6	4,050,000	8.5	0	3,283,200	4.8
2022	10	7	4,668,600	9.5	0	3,392,640	4.8
2022	11	8	5,022,000	10.5	0	3,283,200	4.8
2022	12	8	5,189,400	10.5	0	3,392,640	4.8
2023	1	8	5,189,400	10.5	0	3,392,640	4.8
2023	2	8	4,687,200	10.5	0	3,064,320	4.8
2023	3	8	5,189,400	10.5	0	3,392,640	4.8
2023	4	8	5,022,000	10.5	0	3,283,200	4.8
2023	5	8	5,189,400	10.5	0	3,392,640	4.8
2023	6	8	5,022,000	10.5	0	3,283,200	4.8
2023	7	8	5,189,400	10.5	0	3,392,640	4.8
2023	8	8	5,189,400	10.5	0	3,392,640	4.8
2023	9	8	5,022,000	10.5	0	3,283,200	4.8
2023	10	8	5,189,400	10.5	0	3,392,640	4.8
2023	11	8	5,022,000	10.5	0	3,283,200	4.8
2023	12	8	5,189,400	10.5	0	3,392,640	4.8

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, 2020 is the last full year of actual data, and 2022 is the first full year of forecast data. 2021 values are actual values through April and forecast values from May through December.

Figure 3-20 - Residential Sales Annual Forecast

****Confidential in its Entirety****

[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, 2020 is the last full year of actual data, and 2022 is the first full year of forecast data. 2021 values are actual values through April and forecast values from May through December.

Figure 3-23 - Small Commercial Sales Forecast

Confidential in its Entirety

[redacted]

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, 2020 is the last full year of actual data, and 2022 is the first full year of forecast data. When shown, 2021 values are actual values through April and forecast values from May through December.

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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, 2020 is the last full year of actual data, and 2022 is the first full year of forecast data. 2021 values are actual values through April and forecast values from May through December.

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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 PFM Annual Summary

The PFM 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, 2020 is the last full year of actual data, and 2022 is the first full year of forecast data. 2021 values are actual values through April and forecast values from May through December.

Figure 3-32 - PFM Sales Forecast

****Confidential in its Entirety****

[redacted]

Figure 3-33 - PFM Customer Forecast

****Confidential in its Entirety****

[redacted]

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Figure 3-34 - PFM UPC Forecast

****Confidential in its Entirety****

[redacted]

Table 3-50 - PFM Forecast Summary

****Confidential in its Entirety****

[redacted]

Table 3-51 - PFM Forecast - Average Annual Growth Rates

****Confidential in its Entirety****

[redacted]

7.1.6.1.6 Transmission Annual Summary

The transmission sales forecast is developed using the models described in Section 6.1.2.6. Figure 3-35 through Figure 3-37 show the annual sales forecast, customer forecast, and UPC forecast. Table 3-52 and Table 3-53 summarize the sales, customer, and UPC forecasts and average annual growth rates for selected years. In the tables, 2020 is the last full year of actual data, and 2022 is the first full year of forecast data. 2021 values are actual values through April and forecast values from May through December.

Figure 3-35 - Transmission Sales Forecast

****Confidential in its Entirety****

[redacted]

Figure 3-36 - Transmission Customer Forecast

****Confidential in its Entirety****

[redacted]

Figure 3-37 - Transmission UPC Forecast

****Confidential in its Entirety****

[redacted]

Table 3-52 - Transmission Forecast Summary

****Confidential in its Entirety****

[redacted]

Table 3-53 - Transmission Forecast - Average Annual Growth Rates

****Confidential in its Entirety****

[redacted]

7.1.6.1.7 Linde Annual Summary

The Linde (formerly named “Praxair”) sales forecast is developed using the models described in Section 6.1.2.7 and the estimated expansion described in Section 7.1.5. Figure 3-38 shows the annual sales forecast and Table 3-54 show the annual sales forecast for selected years. In the tables, 2020 is the last full year of actual data, and 2022 is the first full year of forecast data. 2021 values are actual values through April and forecast values from May through December.

Figure 3-38 - Linde Sales Forecast
****Confidential in its Entirety****

[redacted]

Table 3-54 - Linde Forecast Summary

****Confidential in its Entirety****

[redacted]

7.1.6.1.8 Lighting Annual Summary

The lighting sales forecast is developed using the models described in Section 6.1.2.8. Figure 3-39 through Figure 3-41 show the annual sales forecast, customer forecast, and UPC forecast.

Table 3-55 and Table 3-56 summarize the sales, customer, and UPC forecasts and average annual growth rates for selected years. In the tables, 2020 is the last full year of actual data, and 2022 is the first full year of forecast data. 2021 values are actual values through April and forecast values from May through December.

Figure 3-39 - Lighting Sales Forecast

****Confidential in its Entirety****

[redacted]

Figure 3-40 - Lighting Customer Forecast

****Confidential in its Entirety****

[redacted]

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Figure 3-41 - Lighting UPC Forecast

****Confidential in its Entirety****

[redacted]

Table 3-55 - Lighting Forecast Summary

****Confidential in its Entirety****

[redacted]

Table 3-56 - Lighting Forecast - Average Annual Growth Rates

Confidential in its Entirety

[redacted]

7.1.6.1.9 Municipal Annual Summary

The municipal sales forecast is developed using the models described in Section 6.1.2.9. Figure 3-42 shows the annual sales forecast. Table 3-57 and Table 3-58 show the annual sales forecast and growth rates for selected years. Historical and forecasted municipal data only includes data for the city of Lockwood and does not include the former municipal customers (Monett, Mount Vernon and Chetopa) which left the system as of June 1, 2020. In the tables, 2020 is the last full year of actual data, and 2022 is the first full year of forecast data. 2021 values are actual values through April and forecast values from May through December.

Figure 3-42 - Municipal Sales Forecast
Confidential in its Entirety

[redacted]

Table 3-57 - Municipal Forecast Summary

****Confidential in its Entirety****

[redacted]

Table 3-58 - Municipal Forecast - Average Annual Growth Rates

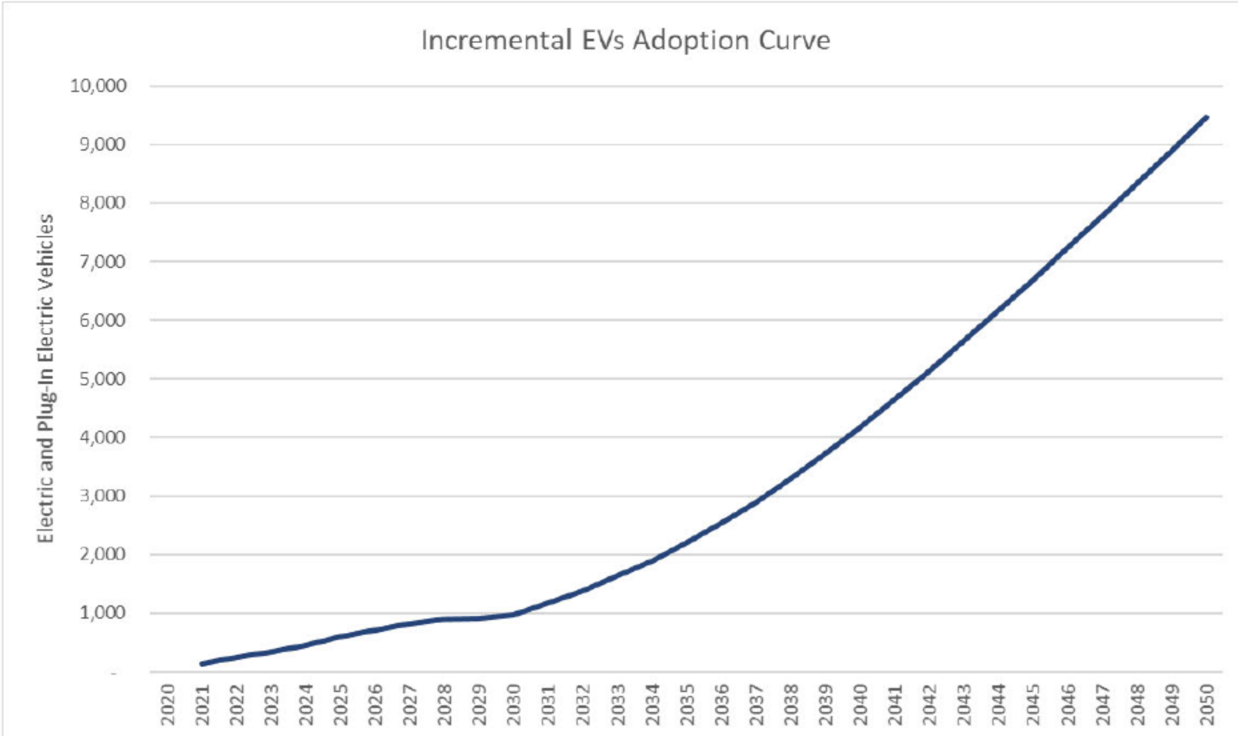
****Confidential in its Entirety****

[redacted]

7.1.6.1.10 Electric Vehicle Adjustment

Unlike prior IRP forecasts, the incremental EV forecast is excluded from the class forecasts so that the coincident load shape impact may be integrated into the load forecast. The EV forecast is included in Step 3 of the load forecast process as described in Section 6.1.1. The EV forecast is based on Liberty-Empire's 2020 EV study base case assuming Covid-19 scenario. The study forecasts EV adoption through 2030. After 2030, the EV forecast is extended by applying the EIA's AEO 2021 EV adoption growth rates. Figure 3-43 shows the incremental EV count forecast.

Figure 3-43 - Incremental Electric Vehicle Adoption Forecast



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

- Annual Miles: 12,000
- kWh/Mile: 0.30
- Loss Factor: 6.8%

Table 3-59 and Table 3-60 show a summary of the EV counts and incremental energy included the forecast for selected years.

Table 3-59 - Electric Vehicle Incremental Forecast Summary

Year	Vehicles (End of Year)	Energy (MWh)
2022	242	742
2025	595	2,058
2030	974	3,652
2035	2,205	7,979
2040	4,169	15,305
2045	6,682	24,873
2050	9,457	35,537

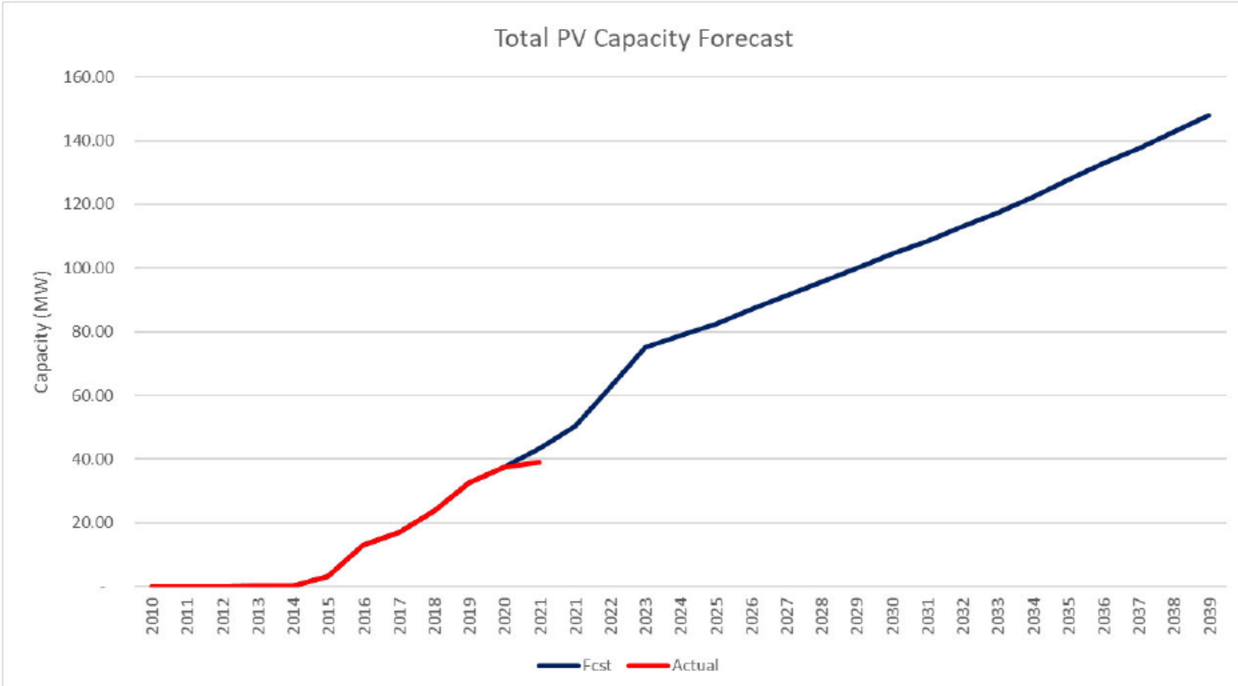
Table 3-60 - Electric Vehicle Forecast - Average Annual Growth Rates

Time Period	Sales
2011-2019 (Historical)	NA
2022-2031 (10 Year Forecast)	22.09%
2022-2041 (20 Year Forecast)	18.46%
2022-2051 (30 Year Forecast)	14.94%

7.1.6.1.11 Solar Adjustment

Unlike prior IRP forecasts, the incremental behind-the-meter PV forecast is excluded from the class forecasts so that the coincident load shape impact may be integrated into the load forecast. The PV forecast is included in Step 3 of the load forecast process as described in Section 6.1.1. The PV forecast is based the EIA's AEO 2021 growth rates applied to Liberty-Empire's historical installed PV capacity.

Figure 3-44 - Total PV Installed Capacity Forecast



The incremental PV forecast is converted to energy using load factors and load shapes based on the National Renewable Energy Laboratory's ("NREL") PVWatts Calculator for Springfield, Missouri. Table 3-61 and Table 3-62 show a summary of the PV capacity and energy forecasts for selected years.

Table 3-61 - PV Incremental Forecast Summary

Year	Total Installed Capacity (MW)	Incremental Installed Capacity (MW)	Incremental Energy (MWh)
2011	0.04		
2015	3.33		
2019	32.78		
2022	50.37	11.32	457
2025	78.70	39.65	2,412
2030	100.05	61.01	3,745
2035	122.41	83.36	5,147
2040	148.01	108.97	6,766
2045	174.97	135.92	8,482
2050	203.32	164.28	10,271

Table 3-62 - PV Forecast -- Average Annual Growth Rates

Time Period	Sales
2022-2031 (10 Year Forecast)	32.98%
2022-2041 (20 Year Forecast)	18.69%
2022-2051 (30 Year Forecast)	13.67%

7.1.6.2 Peak Annual Summary

The system peak forecast is developed using the models described in Section 6.1.2.10. Figure 3-45 and Figure 3-46 show historical, weather-normalized and forecast seasonal peaks. Table 3-63 and Table 3-64 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 Liberty-Empire system on June 1, 2020.

Figure 3-45 - System Summer Peak Forecast
****Confidential in its Entirety****

[redacted]

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Figure 3-46 - System Winter Peak Forecast
****Confidential in its Entirety****

[redacted]

Table 3-63 - System Peak Forecast Summary
****Confidential in its Entirety****

[redacted]

Table 3-64 - 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 and identifying the coincident peak hour. The models used are described in Section 6.1.2. Figure 3-47 through Figure 3-54 show the residential, small commercial, large commercial, and industrial class seasonal coincident peaks. Table 3-65 and Table 3-66 show historical coincident peak values by class for selected years. Historical system peak data excludes municipal data (i.e., Monett, Mount Vernon, and Chetopa).

Figure 3-47 - Residential Coincident Summer Peak Forecast
Confidential in its Entirety

[redacted]

Figure 3-48 - Residential Coincident Winter Peak Forecast

****Confidential in its Entirety****

[redacted]

Figure 3-49 - Small Commercial Coincident Summer Peak Forecast

****Confidential in its Entirety****

[redacted]

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Figure 3-50 - Small Commercial Coincident Winter Peak Forecast

Confidential in its Entirety

[redacted]

Figure 3-51 - Large Commercial Coincident Summer Peak Forecast

Confidential in its Entirety

[redacted]

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Figure 3-52 - Large Commercial Coincident Winter Peak Forecast

Confidential in its Entirety

[redacted]

Figure 3-53 - Industrial Coincident Summer Peak Forecast

Confidential in its Entirety

[redacted]

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Figure 3-54 - Industrial Coincident Summer Peak Forecast

****Confidential in its Entirety****

[redacted]

Table 3-65 - Summer Coincident Peak by Class

****Confidential in its Entirety****

[redacted]

Table 3-66 - Winter Coincident Peak by Class

****Confidential in its Entirety****

[redacted]

7.1.6.2.2 Class Level Coincident Energy at the System Peaks

Table 3-67 and Table 3-68 show the monthly class energy in the month of the seasonal peak for selected years.

Table 3-67 - Summer Peak Month Energy by Class

****Confidential in its Entirety****

[redacted]

Table 3-68 - 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 3-55 through Figure 3-64 show the forecast hourly load profiles for the base, 5th, 10th, 15th, and 20th forecast years. The system profile includes the load shape changes from the electric vehicle and behind-the-meter solar forecast. Class load shapes exclude load shape impacts from the electric vehicle and behind-the-meter solar forecast.

Figure 3-55 - Forecasted Residential Summer Peak Day Profiles

****Confidential in its Entirety****

[redacted]

Figure 3-56 - Forecasted Residential Winter Peak Day Profiles

****Confidential in its Entirety****

[redacted]

Figure 3-57 - Forecasted Small Commercial Summer Peak Day Profiles

****Confidential in its Entirety****

[redacted]

Figure 3-58 - Forecasted Small Commercial Winter Peak Day Profiles

****Confidential in its Entirety****

[redacted]

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Figure 3-59 - Forecasted Large Commercial Summer Peak Day Profiles

****Confidential in its Entirety****

[redacted]

Figure 3-60 - Forecasted Large Commercial Winter Peak Day Profiles

****Confidential in its Entirety****

[redacted]

Figure 3-61 - Forecasted Industrial Peak Day Profiles

Confidential in its Entirety

[redacted]

Figure 3-62 - Forecasted Industrial Winter Peak Day Profiles

Confidential in its Entirety

[redacted]

Figure 3-63 - Forecasted System Peak Day Profiles
****Confidential in its Entirety****

[redacted]

Figure 3-64 - 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 constant in 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 are 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 Liberty-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 are compared to historical trends are shown in the figures contained 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 included in the industrial and Linde (formerly Praxair) classes. These adjustments are discussed in Section 7.1.5.

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 detailed in Section 5.2. Figure 3-65 shows the annual net system load forecast. Table 3-69 and Table 3-70 show the net system load forecast and growth rates for selected years. Historical data excludes municipal data (i.e., Monett, Mount Vernon, and Chetopa). 2021 values are actual values through April and forecast values from May through December.

Figure 3-65 - Forecasted Net System Load

****Confidential in its Entirety****

[redacted]

Table 3-69 - Net System Load Forecast Summary

****Confidential in its Entirety****

[redacted]

Table 3-70 - 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).

For the 2022 IRP, Liberty-Empire created four 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 results of the scenarios and analysis 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 two normal weather scenarios create reasonable planning bounds around the base forecast. The high and low scenarios are created in direct compliance to the Commission's rule directing Liberty-Empire to create two additional normal weather load forecasts. These forecasts capture economic uncertainty.

The subjective probabilities were assigned to these scenarios by the utility decision-makers, as further described in Volume 6. The subjective probabilities were assigned are as follows:

- High Case 25%
- Base Case 50%
- Low Case 25%

8.1.1 High and Low Case

The high scenario consists of high economic indices, a high EV forecast, and a low PV forecast. These assumptions are described below.

- The high scenario economic 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 (2000-2021) is 0.89%. The forecast annual average growth rate (2022-2051) is 0.55%. The ratio is 1.618 (0.89%/0.55%). 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 high EV forecast is developed like the base EV forecast except that the forecast uses the highest forecast included in Liberty-Empire's 2020 electric vehicle study (i.e., Liberty High Scenario).
- The low PV forecast assumes no incremental adoption of PV after 2023.

The low scenario consists of low economic indices. The EV and PV forecasts are the same as the base scenario forecasts. The economic assumption is described below.

- 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 3-66 through Figure 3-70 show the high, base, and low scenario economic indices for employment, population, households, and real income. Figure 3-70 shows the base and high increment EV forecasts. Figure 3-71 shows the low and base PV forecasts.

Figure 3-66 - High and Low Scenario - Total Employment

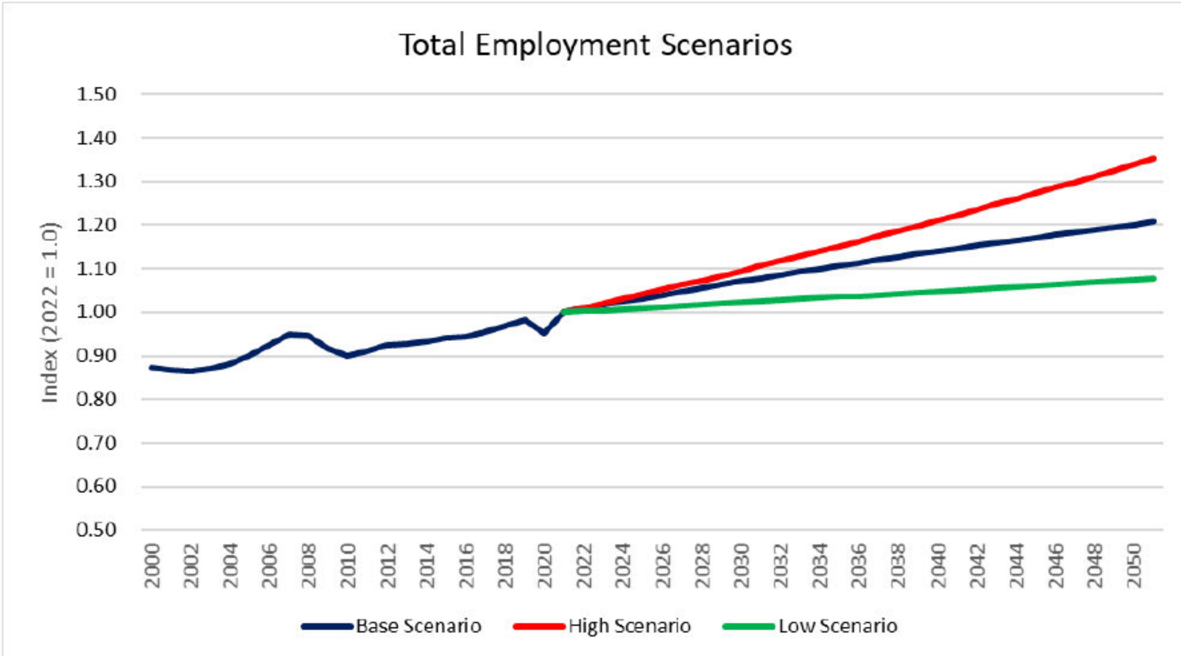

Figure 3-67 - High and Low Scenario - Population

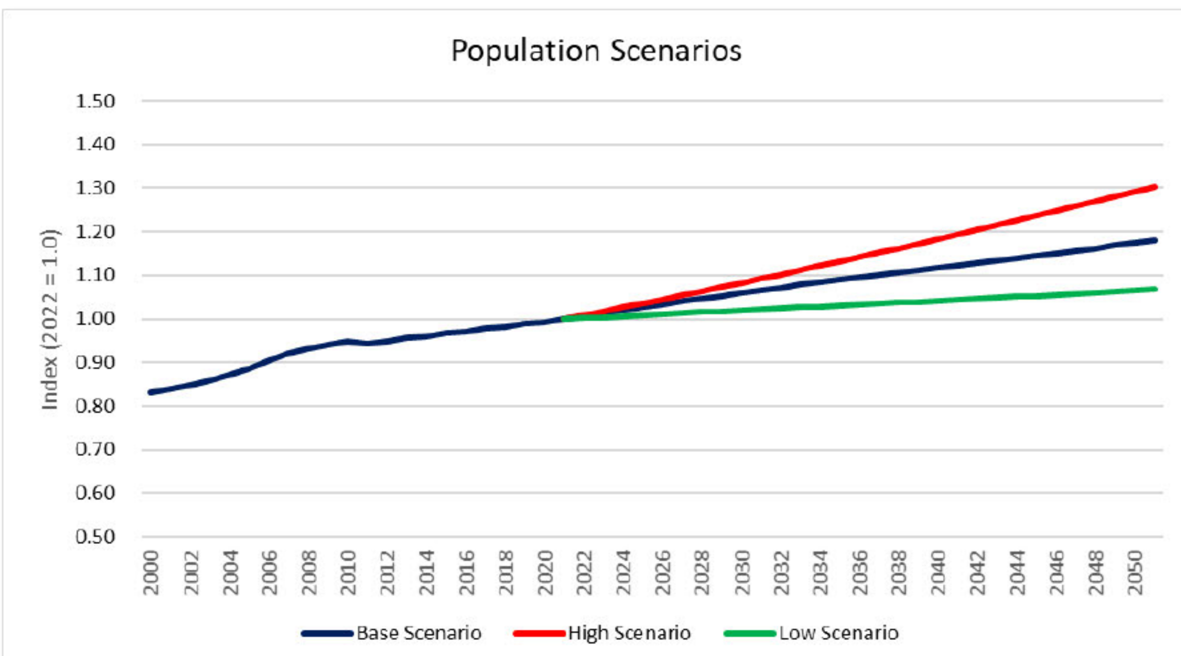

Figure 3-68 - High and Low Scenario - Households

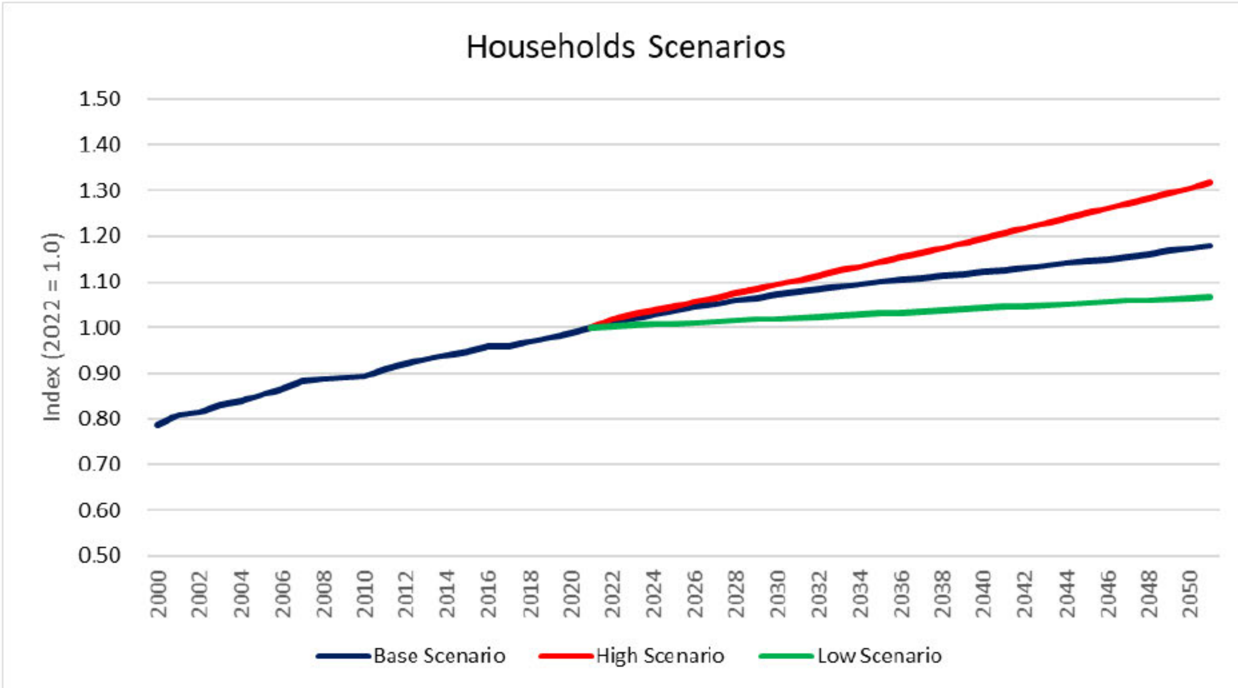

Figure 3-69 - High and Low Scenario - Real Income

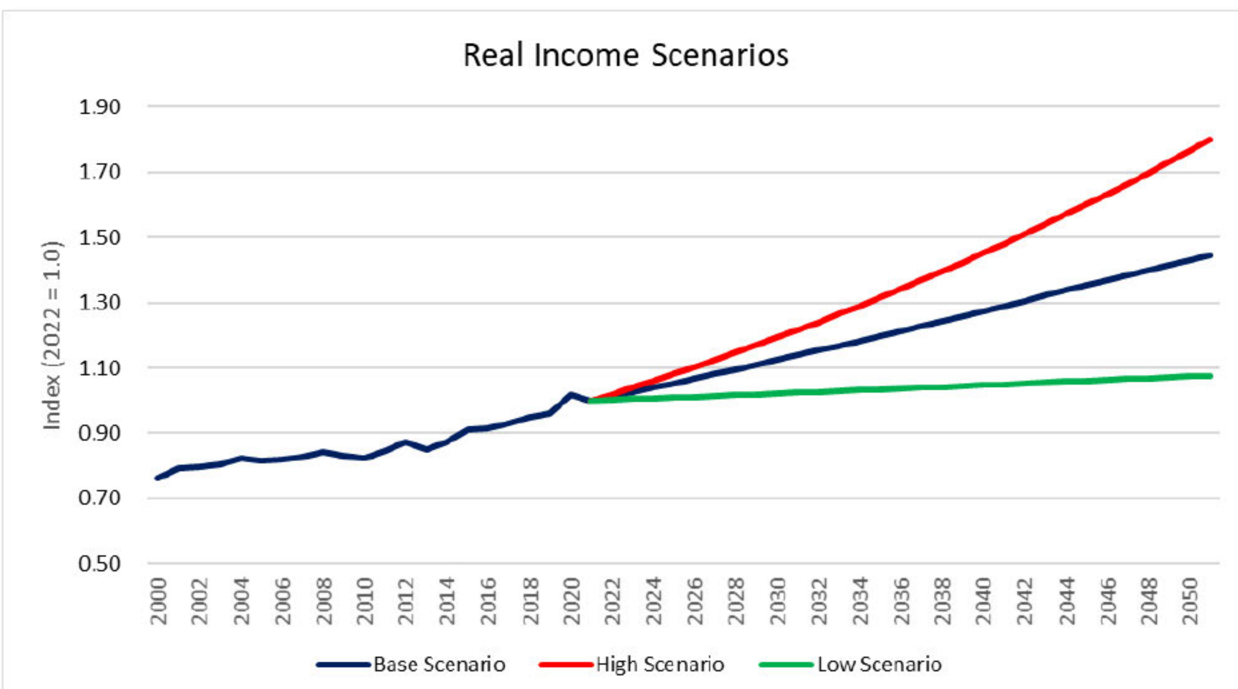

Figure 3-70 - High and Base Scenario - EV Adoption

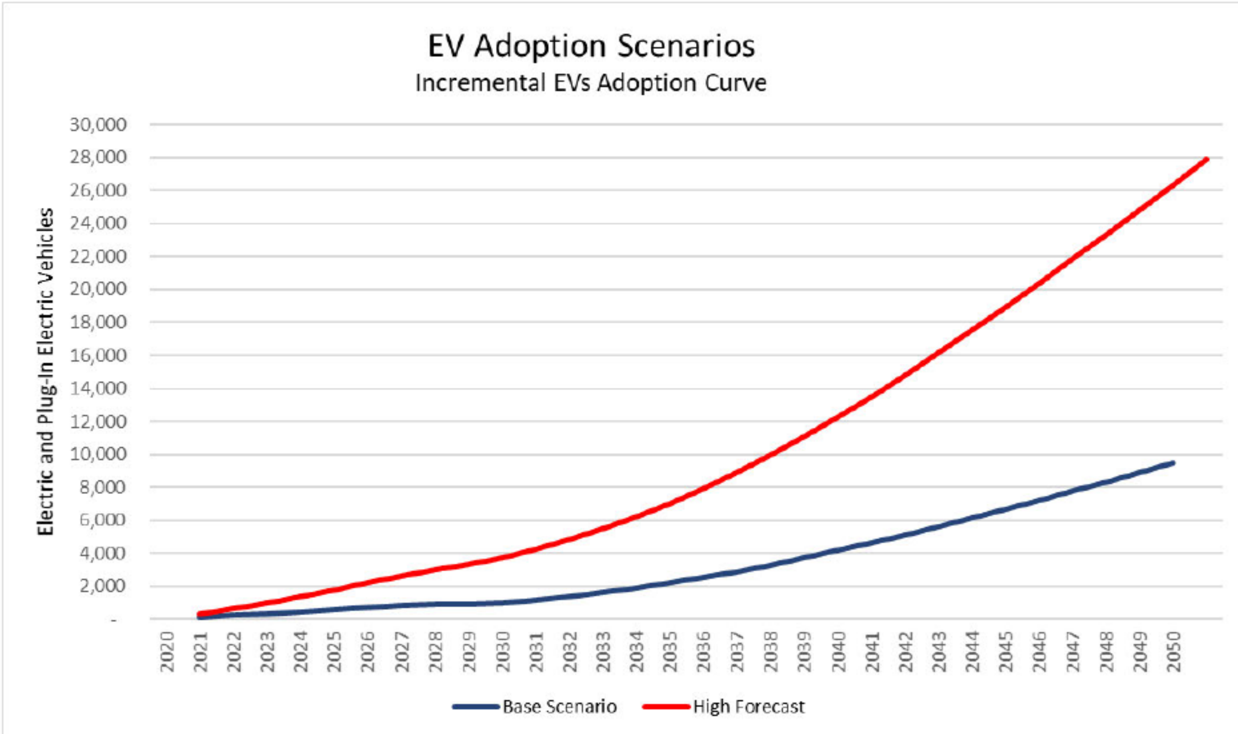

Figure 3-71 - High and Base Scenario - PV Sales

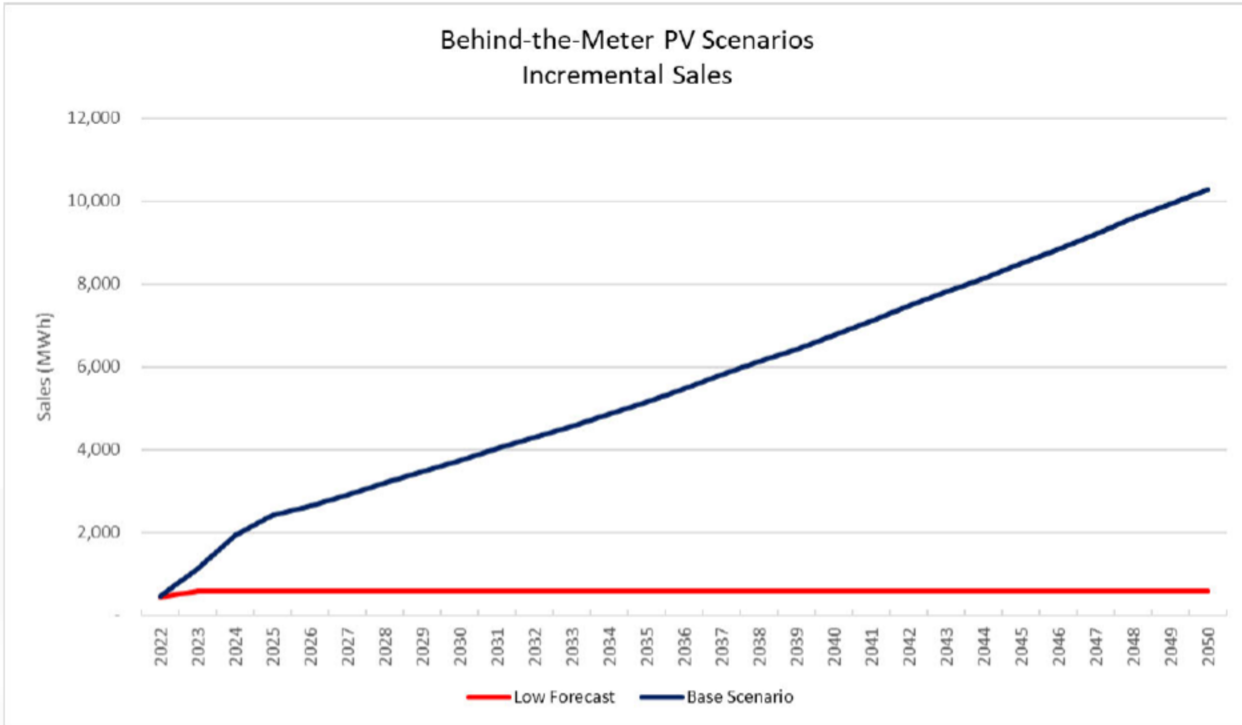

Figure 3-72 through

Figure 3-74 show the base, high, and low scenarios for energy, summer peaks, and winter peaks. Table 3-71 through Table 3-73 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 3-72 - Base, High, and Low, Scenarios - Annual Energy

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[redacted]

Table 3-71 - Base, High, and Low, Scenarios - Annual Energy (MWh)

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[redacted]

Figure 3-73 - Base, High, and Low Scenarios - Summer Peaks
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[redacted]

Table 3-72 - Base, High, and Low Scenarios - Summer Peak (MW)
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[redacted]

Figure 3-74 - Base, High, and Low Scenarios - Winter Peaks
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[redacted]

Table 3-73 - Base, High, and Low, Scenarios - Winter Peaks (MW)
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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 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 (1991 to 2020) 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 3-75 and Figure 3-76 show the ordered annual HDD and CDD with the mild and extreme scenarios. Table 3-74 shows the annual HDD and CDD scenario values.

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Figure 3-75 - Mild and Extreme Annual HDD Base 65 Scenarios

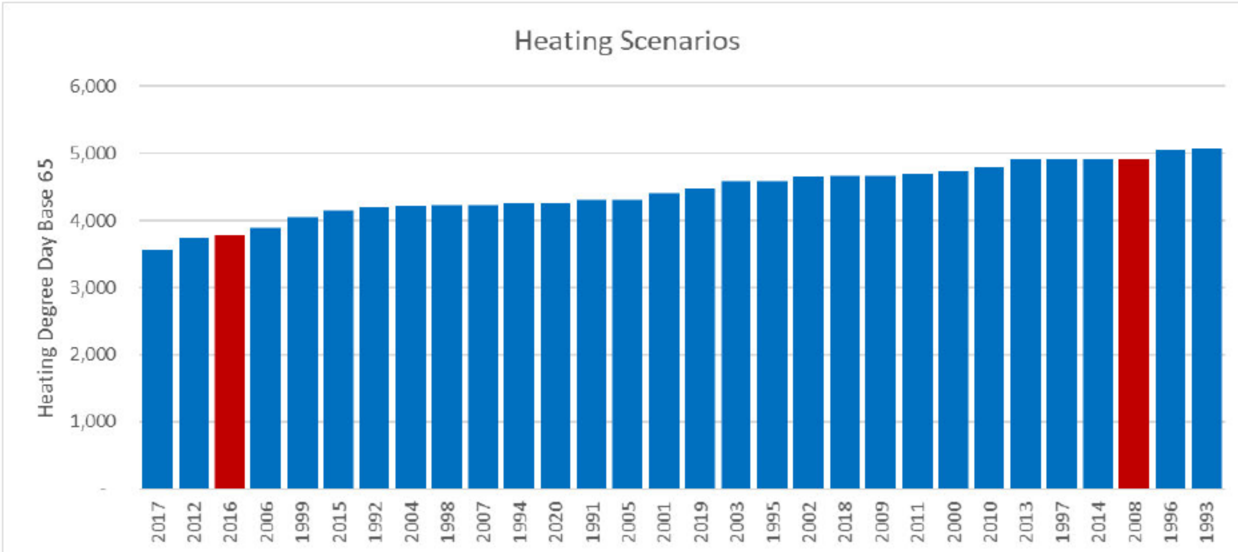

Figure 3-76 - Mild and Extreme Annual CDD Base 65 Scenarios

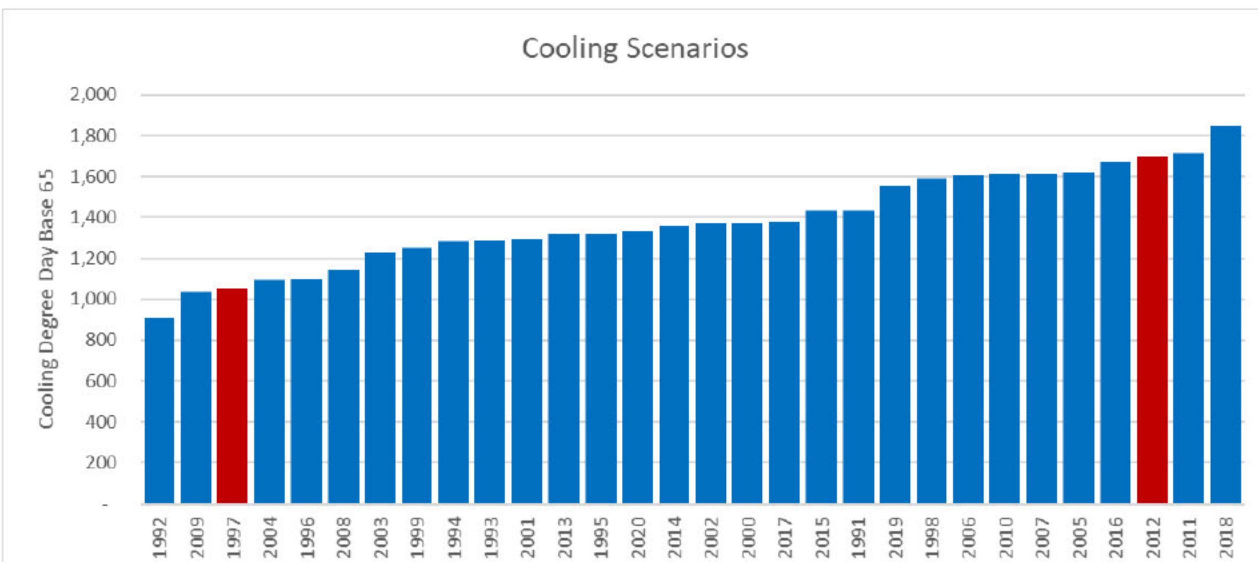

Table 3-74 - Scenario Annual Degree Days

Scenario	HDD65	CDD65
Base	4,437	1,384
Mild	3,768	1,051
Extreme	4,901	1,695

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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 3-77 and Figure 3-78 show the monthly HDD and CDD scenarios.

Figure 3-77 - Mild and Extreme Monthly HDD Base 65 Scenarios

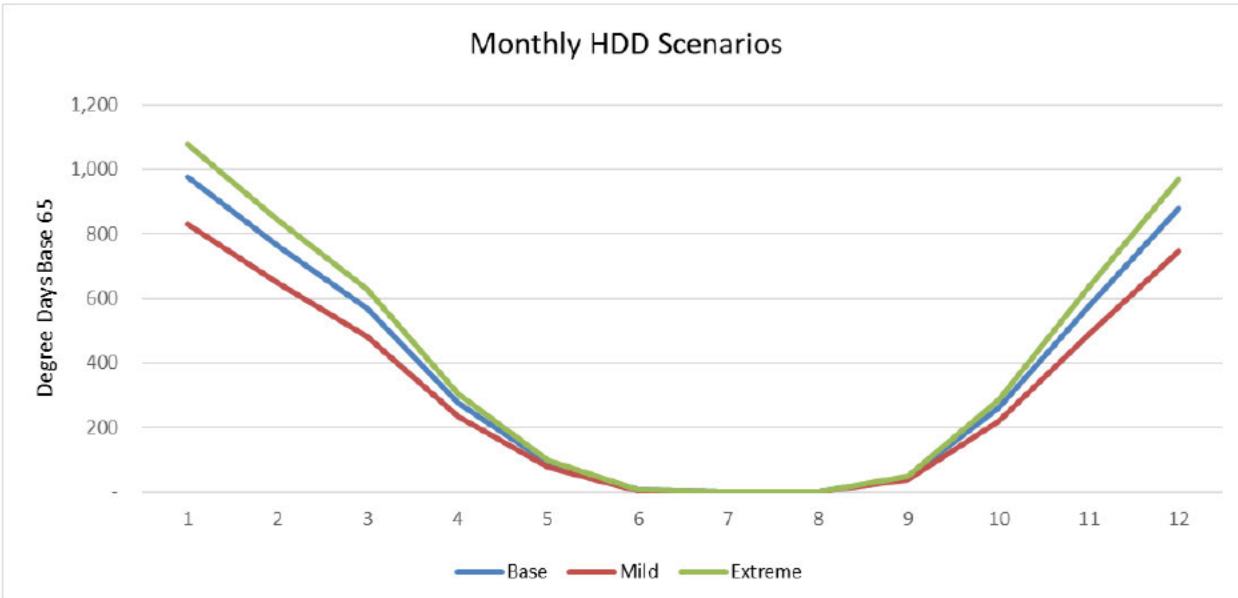
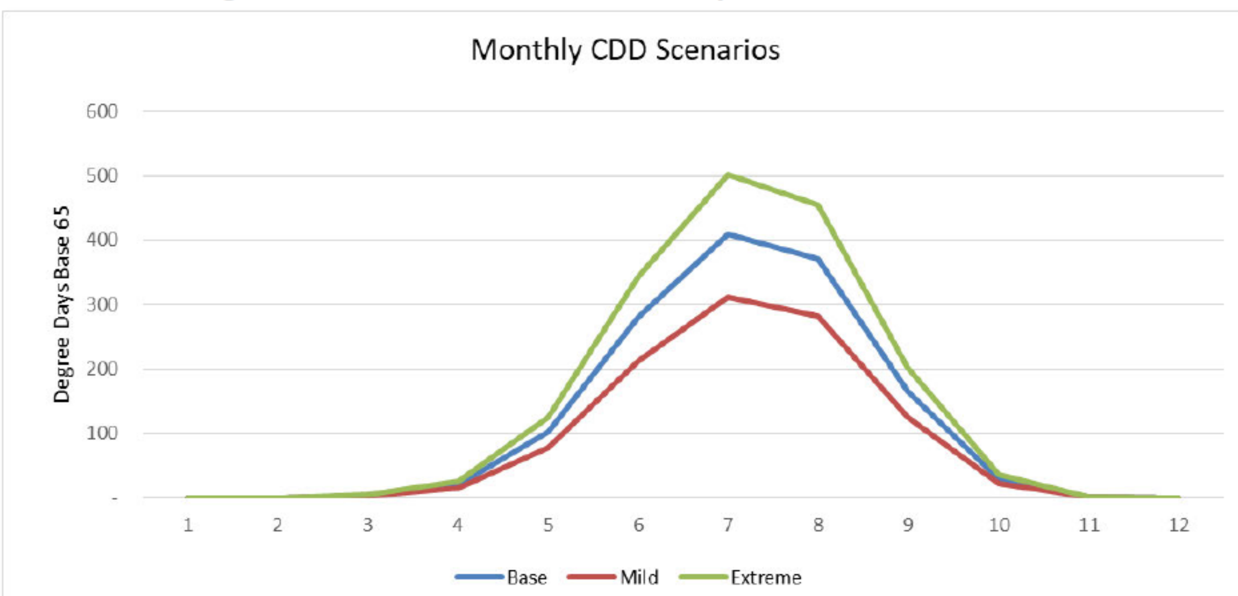


Figure 3-78 - Mild and Extreme Monthly CDD Base 65 Scenarios



Peak Producing Temperatures. The mild and extreme peak scenarios are derived based on 21 years of historical (2001 to 2021) 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 month and the 2nd lowest average temperatures in the summer months. Figure 3-79 and Table 3-75 show the extreme and mild peak temperature scenarios.

Figure 3-79 - Mild and Extreme Peak Temperature Scenarios

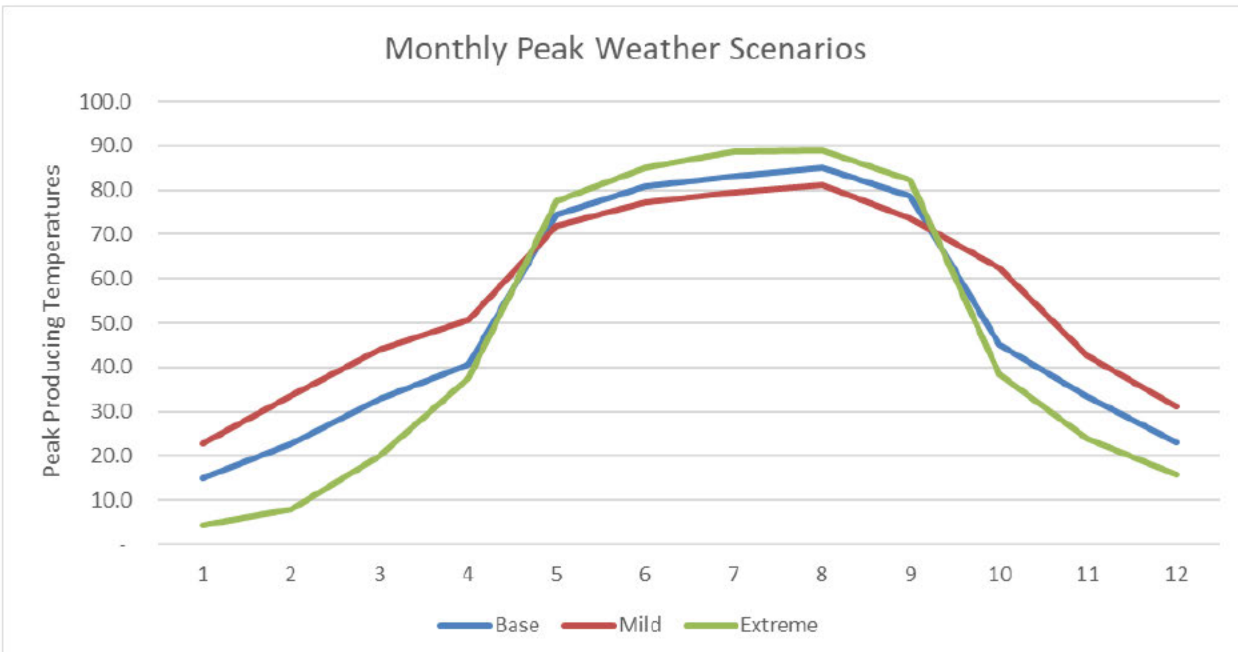


Table 3-75 - Scenario Monthly Peak Producing Temperatures

Month	Base	Extreme	Mild
Jan	14.99	4.42	22.77
Feb	22.77	7.96	33.67
Mar	32.79	19.90	44.10
Apr	40.77	37.51	50.59
May	74.32	77.53	71.88
Jun	80.82	85.00	77.16
Jul	83.21	88.83	79.51

Month	Base	Extreme	Mild
Aug	84.94	88.98	81.21
Sep	78.52	82.14	73.59
Oct	45.05	38.43	62.50
Nov	33.43	23.79	42.67
Dec	22.94	15.68	31.04

Figure 3-80 through Figure 3-82 show the weather scenario annual energy, summer peak and winter peaks. Table 3-76 through

Table 3-78 show selected forecast values for the weather scenarios.

Figure 3-80 - Base, Mild and Extreme Weather Scenario: System Annual Energy

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Table 3-76 - Base. Mild and Extreme Weather Scenario - Annual Energy (MWh)

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[redacted]

Figure 3-81 - Base, Mild and Extreme Weather Scenario - Summer Peak
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[redacted]

Table 3-77 - Base, Mild and Extreme Weather Scenario - Summer Peak (MW)
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[redacted]

Figure 3-82 - Base, Mild and Extreme Weather Scenario – Winter Peak
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[redacted]

Table 3-78 - Base, Mild and Extreme Weather Scenario - Winter Peak (MW)
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8.3 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.

8.3.1 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 3-79 and Table 3-80. 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 April 2021 and include municipal (Monett, Mount Vernon, and Chetopa) values until they leave the system in mid-2020. Historical peaks are not restored for estimated curtailments. Figure 3-83 through Figure 3-85 plot the historical and forecast energy and peaks.

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Table 3-79 - Historical and Forecast Summer, Winter, and Total Energy
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[redacted]

Table 3-80 - Historical and Forecast Summer and Winter Peaks
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[redacted]

Figure 3-83 - Historical and Forecast Summer and Winter Energy
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[redacted]

Figure 3-84 - Historical and Forecast System Energy
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[redacted]

Figure 3-85 - Historical and Forecast Summer and Winter Peaks
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[redacted]

8.3.2 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 3-86 through Figure 3-88 compare the seasonal and total energy forecasts for the four 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. Historical energy excludes the municipals (i.e., Monett, Mount Vernon, and Chetopa).

Figure 3-86 - Historical and Forecast Summer Energy - All Scenarios
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[redacted]

Figure 3-87 - Historical and Forecast Winter Energy - All Scenarios
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[redacted]

Figure 3-88 - Historical and Forecast Annual Energy - All Scenarios
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[redacted]

Figure 3-89 through Figure 3-91 compare the seasonal and total peak forecasts for the four scenarios. Historical peak excludes the municipals (i.e., Monett, Mount Vernon, and Chetopa).

Figure 3-89 - Historical and Forecast Summer Peak - All Scenarios
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Figure 3-90 - Historical and Forecast Winter Peak - All Scenarios
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[redacted]

Figure 3-91 - Historical and Forecast Annual Peak - All Scenarios
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[redacted]

APPENDIX A: Forecast Model Report for 2022 IRP