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VOLUME 3

LOAD ANALYSIS AND LOAD FORECASTING

THE EMPIRE DISTRICT
ELECTRIC COMPANY – A LIBERTY UTILITIES COMPANY
(LIBERTY-EMPIRE)

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LOAD ANALYSIS AND LOAD FORECASTING

4 CSR 240-22.30 Load Analysis and Load Forecasting

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

SECTION 1 SELECTING LOAD ANALYSIS METHODS

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

(A) To identify end-use measures that may be potential demand-side resources, generally, those end-use measures with an opportunity for energy and/or demand savings;

(B) To derive a data set of historical values from load research data that can be used as dependent and independent variables in the load forecasts;

(C) To facilitate the analysis of impacts of implemented demand-side programs and demand-side rates on the load forecasts and to augment measurement of the effectiveness of demand-side resources necessary for 4 CSR 240-22.070(8) in the

evaluation of the performance of the demand-side programs or rates after they are implemented; and

(D) To preserve, in a historical database, the results of the load analysis used to perform the demand-side analysis as described in 4 CSR 240-22.050, and the load forecasting described in 4 CSR 240-22.030.

The load forecast documented in this volume is intended to achieve the purposes of rule 4 CSR 240-22.30 ("IRP Rule"). These purposes are identified in Sections 1.1 through 1.4 below. Except for the approved Variance Request described in Section 1.5, the forecast is consistent with the load forecast methods prescribed in the IRP Rule. Special contemporary issues are described in Section 1.6.

1.1 Variance Request

On September 20, 2018, The Empire District Electric Company, A Liberty Utilities Company ("Liberty-Empire"), filed a Variance Request identifying expected deviations from the IRP Rule. The filing included two requests which are identified below. On November 25, 2018, the variance request was granted.

Request 1: Forecast by Major Class

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

The Variance Request called for the IRP forecast to be developed by the following revenue classes:

- Residential
- Commercial

- Industrial
- Wholesale
- Street and Highway
- Interdepartmental
- Public Authority

The revenue class approach aggregates customers into groups that improve data stability and align with economic drivers. In 2015, Liberty-Empire filed the same Variance Request, which was granted. This request is consistent with Liberty-Empire's 2013 and 2015 IRP filings. A breakdown of revenue classes by rate class appears in Table 3-40.

Request 2: End-Use Information for the Industrial Class

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

The Variance Request asked to exempt the industrial class from end-use analysis. While Liberty-Empire includes end-use information for the residential and commercial class based on Energy Information Administration ("EIA") data, no end-use data are available for the industrial class. In 2015, Liberty-Empire filed the same Variance Request, which was granted. This request is consistent with Liberty-Empire's 2013 and 2015 IRP filings.

1.2 Special Contemporary Issues

On October 24, 2018, the Commission issued the Order Establishing Special Contemporary Resource Planning Issues ("Order"). In this Order, the Commission required Liberty-Empire to analyze the impacts of electric vehicles in the low, base, and high growth cases. The Order states the following:

(C) When complying with 4 CSR 240-22.060(5)(A), analyze and document the impact of electric vehicle usage for the 20-year planning period upon the low-case, base-case, and high-case load forecasts.

Liberty-Empire included an electric vehicle forecast in the base, high, and load forecasts. Discussion of the electric vehicle forecast in the base case is included in Section 2.5. The implications of the electric vehicle forecast in the low and high growth cases are discussed in Section 8.

SECTION 2 HISTORICAL DATABASE FOR LOAD ANALYSIS

(2) 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;

Liberty-Empire maintains historic data by major revenue class (i.e., Residential, Commercial, and Industrial). Liberty-Empire's database is maintained with at least 10 years of data and includes historic load and customers for the following customer classes:

1. Residential
2. Commercial
3. Wholesale
4. Street and highway
5. Interdepartmental (company use)
6. Public authority
7. Industrial (Praxair, oil and pipeline, and others)

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;

Liberty-Empire maintains actual customer and energy data by class for each month. The historical database is maintained with at least 10 years of data.

Weather-normalized energy by class is developed each forecast cycle based on the final energy models. The weather normalization process determines how actual energy consumption changes under normal weather conditions.

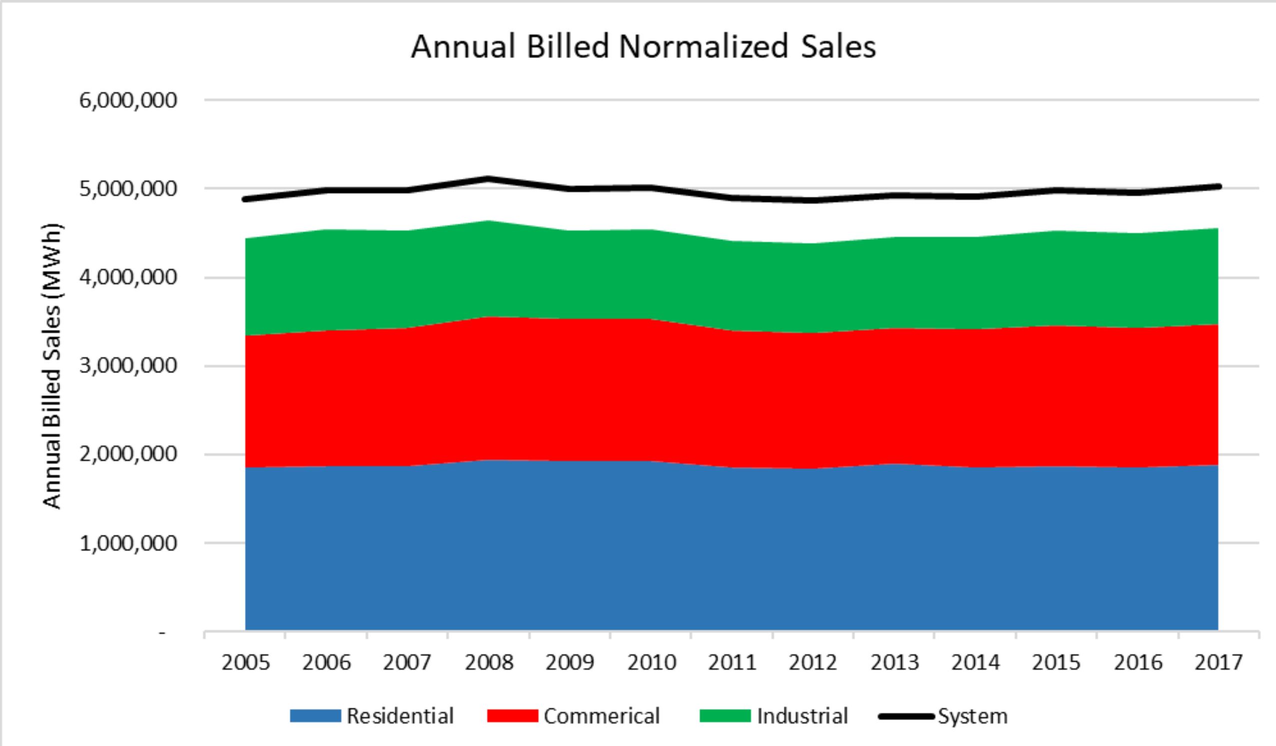
Liberty-Empire weather-normalizes energy sales using the energy models described in Section 6.1.2 and weather from the Springfield, Missouri airport. Normal weather is defined as the 30-year average from 1988 to 2017. Weather-normalization is performed by month.

Table 3-1 shows actual and normal energy sales for the major classes and system summarized by year. Figure 3-1 graphically displays normal energy sales. In these figures, the system includes additional classes such as Street and Highway, Public Authority, and Interdepartmental.

Table 3-1 - Historical Actual Weather-Normalized Energy (MWh)

Annual Sales (MWh) - Billed Sales Basis								
	Residential		Commercial		Industrial		System	
Year	Normal	Actual	Normal	Actual	Normal	Actual	Normal	Actual
2005	1,860,466	1,893,691	1,475,325	1,495,868	1,103,292	1,108,069	4,880,054	4,939,350
2006	1,872,058	1,880,028	1,524,685	1,532,371	1,139,157	1,144,016	4,987,667	5,006,800
2007	1,865,201	1,901,855	1,557,281	1,586,029	1,098,409	1,105,924	4,977,669	5,052,907
2008	1,937,208	1,934,723	1,622,156	1,615,030	1,078,494	1,075,254	5,113,883	5,093,341
2009	1,928,644	1,865,690	1,604,321	1,573,688	997,480	991,660	4,999,013	4,886,508
2010	1,929,129	2,069,460	1,603,203	1,652,292	1,003,064	1,007,518	5,011,579	5,211,531
2011	1,851,307	2,008,128	1,544,977	1,594,638	1,020,735	1,025,085	4,902,984	5,121,397
2012	1,837,636	1,838,353	1,531,365	1,544,380	1,019,294	1,026,864	4,864,270	4,886,854
2013	1,894,720	1,922,317	1,537,237	1,543,701	1,016,659	1,015,908	4,924,188	4,954,395
2014	1,858,739	1,957,659	1,559,982	1,583,796	1,030,393	1,030,770	4,913,701	5,036,558
2015	1,871,005	1,861,541	1,590,170	1,593,006	1,062,624	1,064,848	4,989,951	4,981,270
2016	1,858,825	1,814,242	1,570,455	1,581,255	1,064,971	1,072,627	4,958,553	4,931,840
2017	1,888,364	1,755,726	1,589,896	1,565,684	1,077,524	1,080,975	5,020,692	4,857,440

Figure 3-1 - Weather-Normalized Energy



2.2.2 Historical Estimated Actual and Weather-Normalized Demands at System Peaks

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

Class level estimated actual and normalized peaks are derived each forecast cycle using load research data and the net system loads.

Estimated actual class peaks are developed using a two-step process. First, class coincident peaks are identified by aggregating historic load research data into classes, calibrating the load research data to historic calendar month sales, and identifying the annual class coincident peak. Where historic load research data are missing, modeled values are substituted. Second, the coincident peaks are scaled based on the ratio of gross net system peak to the modeled system peak. Gross net system peaks have been adjusted to remove estimated curtailments. The estimated actual peaks are shown in Table 3-2.

Table 3-2 - Class Level Estimated Actual Peaks (MW)

Estimated Actual Peaks (MW)				
Year	**Residential**	**Commercial**	**Industrial**	**System Peak**
2005	582	268	152	1,095
2006	622	284	165	1,167
2007	606	308	164	1,181
2008	590	310	165	1,161
2009	536	290	162	1,093
2010	697	302	123	1,205
2011	639	278	167	1,209
2012	575	281	174	1,142
2013	450	358	170	1,080
2014	686	267	118	1,162
2015	643	280	141	1,149
2016	613	283	137	1,114
2017	486	330	173	1,075

Class-level normalized peaks are derived by multiplying the ratio of class coincident peak to gross net system peak by the weather-normalized system peak. Table 3-3 shows the weather-normalized peaks. In this table, the weather-normalized system peaks maintain the season in which the peak occurred. The system peak normalization process is described in Section 2.2.3.

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

Weather-Normalized Class Peaks (MW)				
	Residential	Commercial	Industrial	Weather-Normalized System Peak
2005	621	286	162	1,170
2006	623	284	165	1,169
2007	606	308	164	1,182
2008	595	313	166	1,172
2009	574	311	173	1,172
2010	658	285	116	1,137
2011	604	263	158	1,144
2012	580	283	176	1,151
2013	482	383	182	1,158
2014	682	266	117	1,155
2015	693	302	152	1,240
2016	655	302	146	1,191
2017	523	354	186	1,155

2.2.3 Weather-Normalized Net System Loads

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

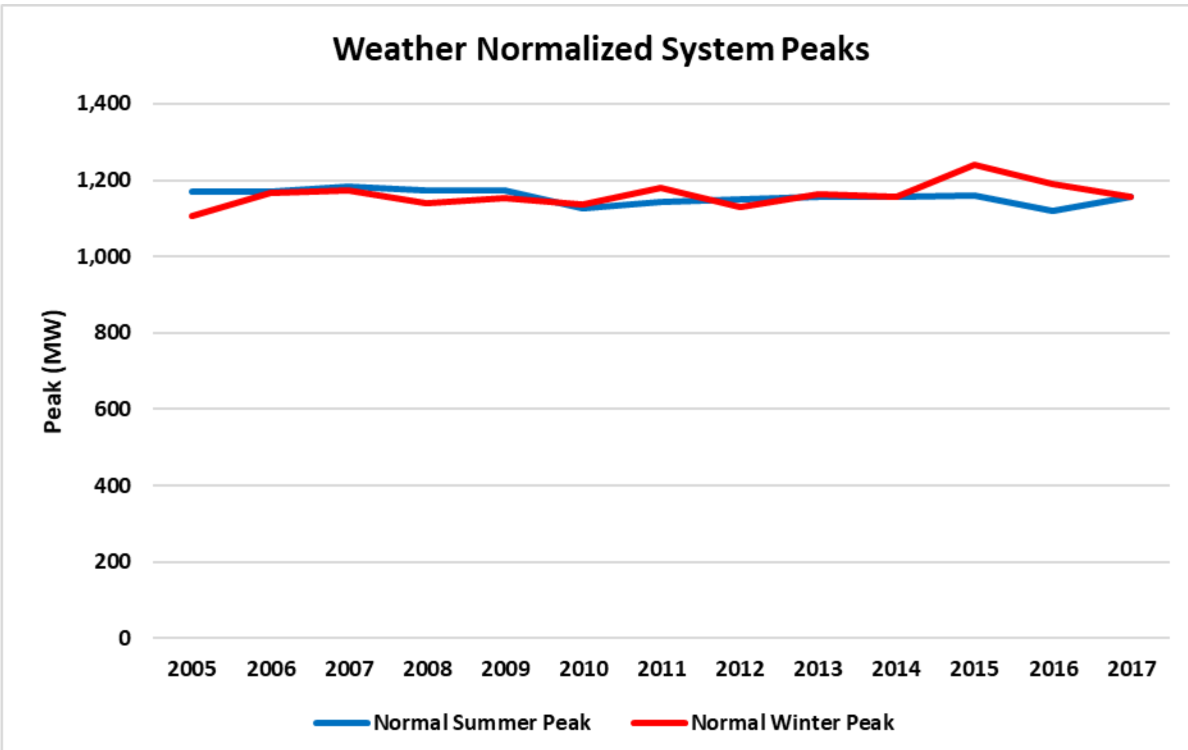
Liberty-Empire maintains actual hourly net system loads. The historical database is maintained with at least 10 years of data.

While Liberty-Empire does not weather-normalize hourly net system loads, Liberty-Empire does weather-normalize monthly sales and peaks. This level of weather-normalization identifies the major system load characteristics and may be used to develop normal load shapes. Weather-normalized sales are discussed in Section 2.2.1.

Weather-normalized peaks are developed using the peak model described in Section 6.1.2.8 and from normal peak-producing weather from the Springfield, Missouri airport. Normal peak-producing weather is defined as a 5-year average. Normal summer peak weather is defined from

2013 to 2017 by month and season. Normal winter peak weather is defined from 2014 to 2018 by month and by season. Using 2018 captures the last available winter system peak at the time of model development. Summer and winter weather-normalized net system peaks are shown in Figure 3-2.

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 "energy-per-customer." Use-per-customer is calculated by dividing energy by customers.

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's load forecast is revised annually. During each forecast cycle, the historic dataset is reviewed for data anomalies.

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 is produced using regression models that capture the effect of weather on electric loads. The regression models use multi-part splines to capture the nonlinear relationship between load and weather. The spline variable's statistical significance 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 and commercial 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 EIA 2018 Annual Energy Outlook ("AEO"). These data capture changing end-use saturation and energy efficiency trends for each census region based on known energy efficiency standards and codes.

Behind-the-meter solar and electric vehicles are included in the SAE modelling framework. These drivers are also generated based on the EIA's 2018 AEO forecast but calibrated into actual installed solar data and estimated electric vehicle registrations from the Auto Alliance.

2.4.2 Weather Sensitivity of Energy and Peak Demand

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

Liberty-Empire’s energy and peak demands are sensitive to weather. Weather sensitivity is modeled using historical weather data from the National Oceanic and Atmospheric Administration (“NOAA”) for the Springfield, Missouri airport. These data are transformed into monthly heating degree days (“HDD”), cooling degree days (“CDD”), and peak-producing weather variables. The variables are included in the forecast models to capture weather response. The models and relevant statistics are described in Section 6.1.2.

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. Included in the end-use trends are the forecasts for behind-the-meter solar and electric vehicles. Figure 3-3 through Figure 3-9 show annual summaries of the major trends used in the forecast models.

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

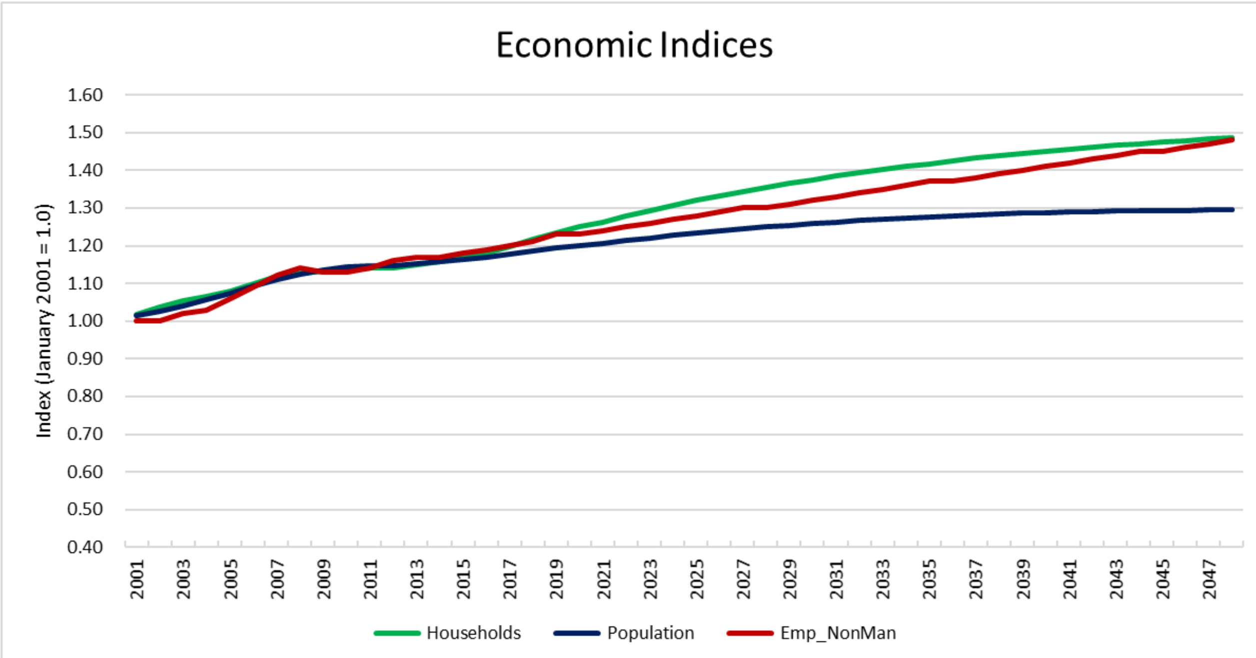


Figure 3-4 - Annual Summary of a Major Trend – Commercial vs. Residential Electric Prices

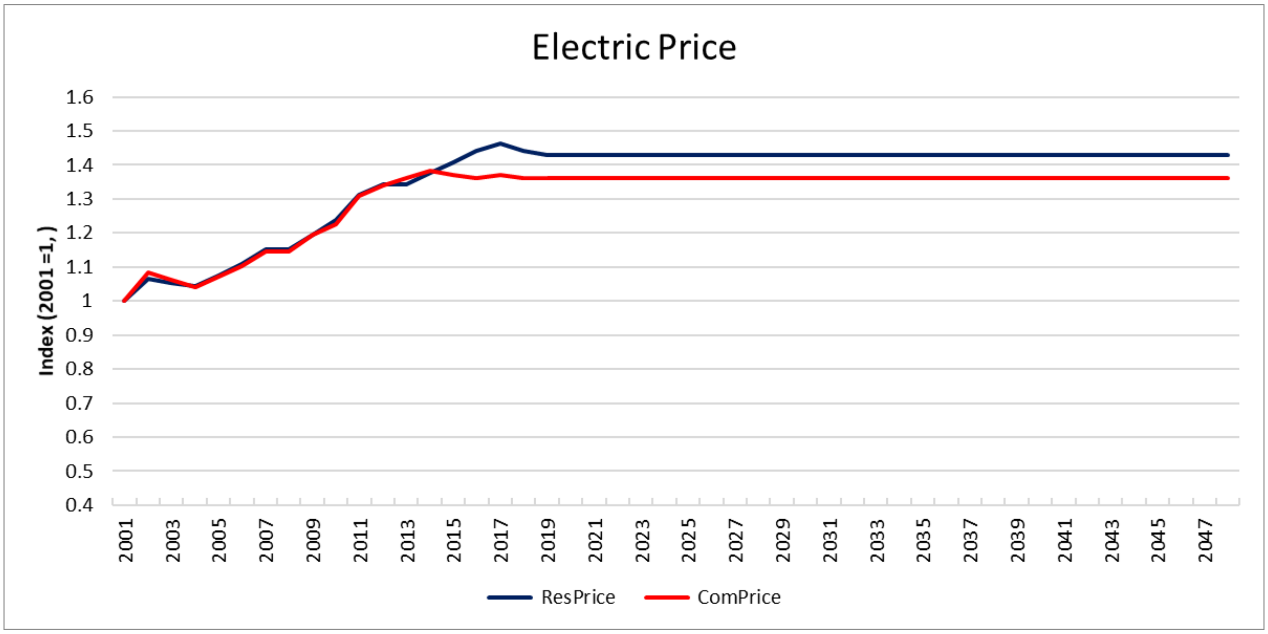


Figure 3-5 - Annual Summary of a Major Trend - Residential SAE Indices

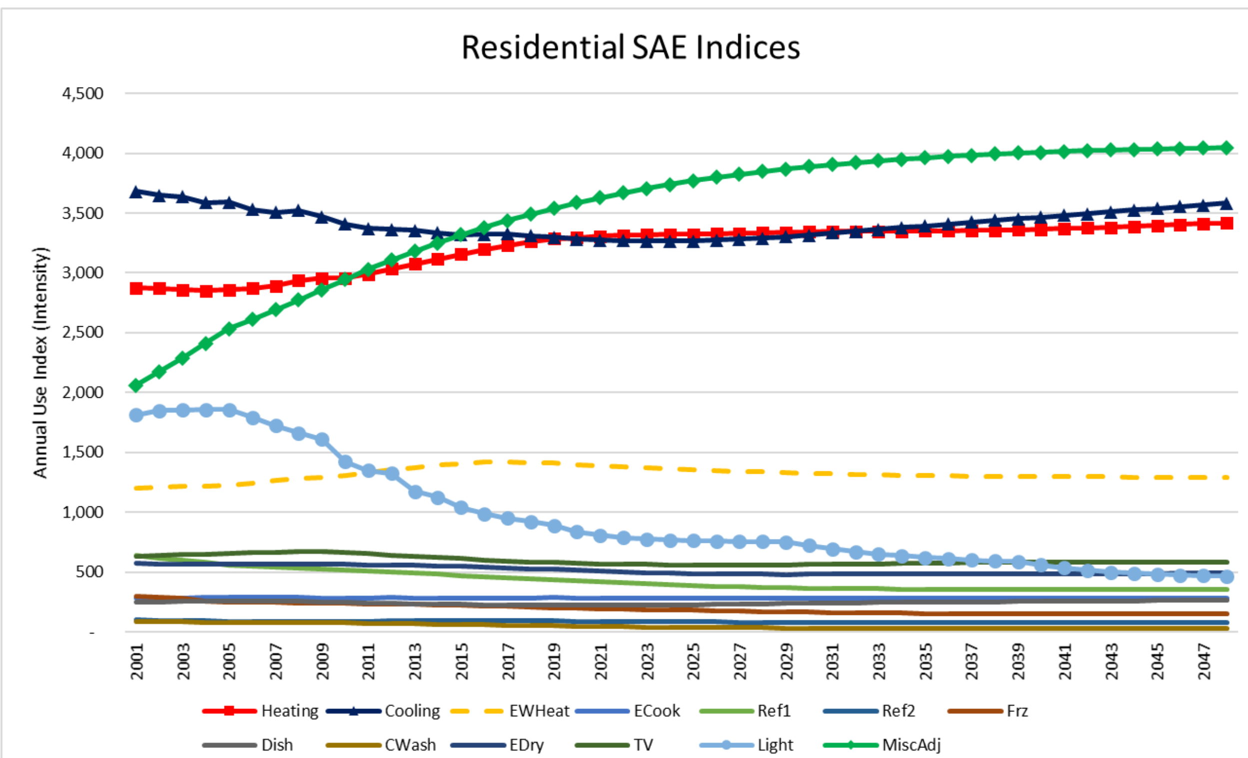


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Figure 3-6 - Annual Summary of a Major Trend - Heating and Cooling Degree Days

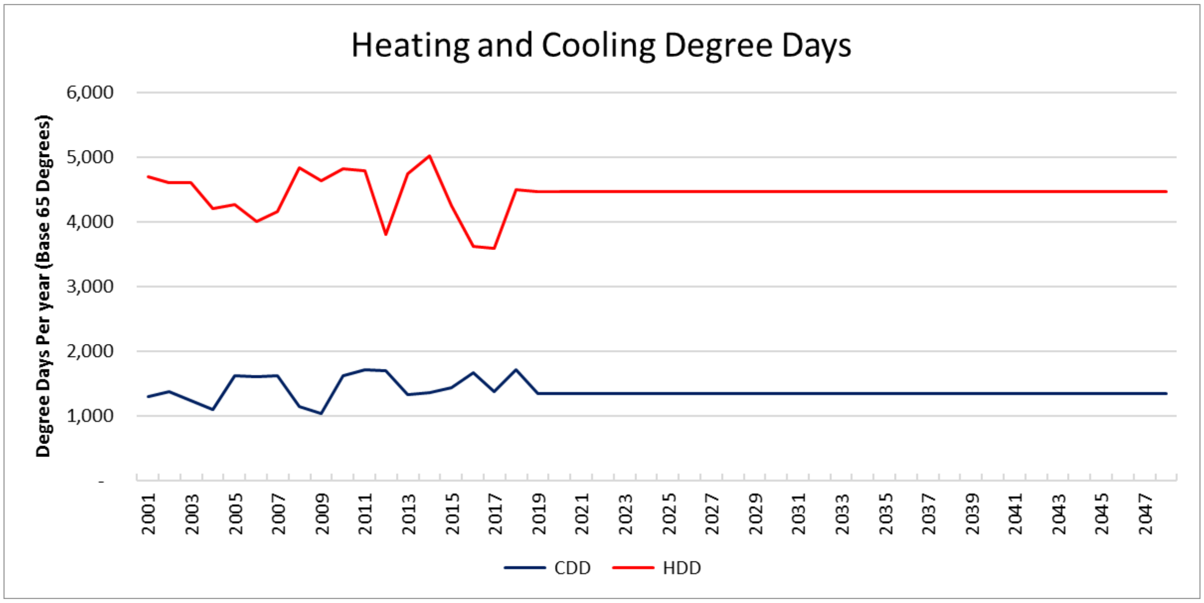


Figure 3-7 - Annual Summary of a Major Trend - Commercial SAE Indices

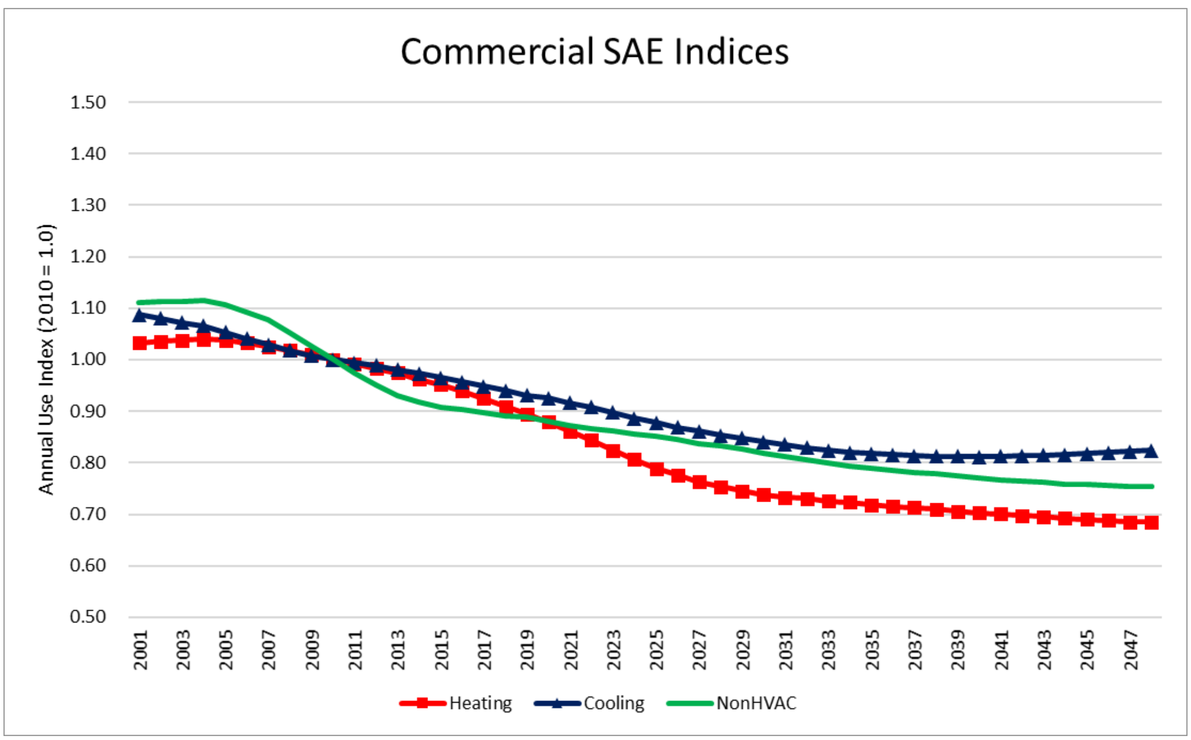


Figure 3-8 - Annual Summary of a Major Trend – Photovoltaics (Behind-the-Meter)

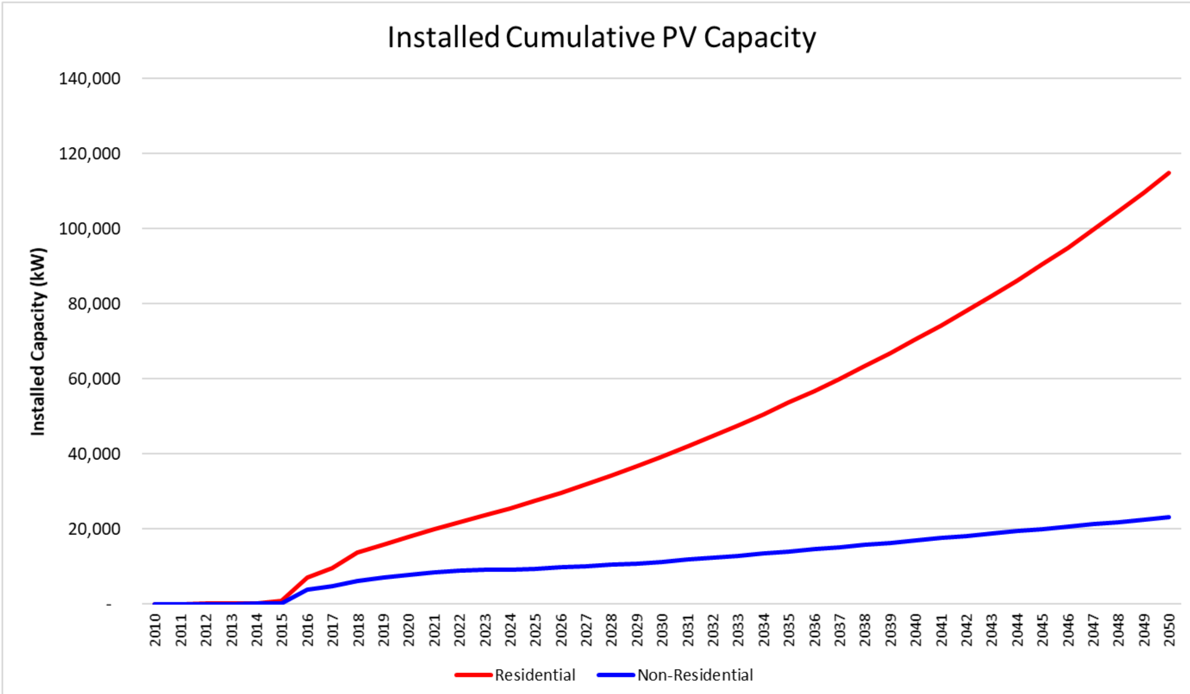
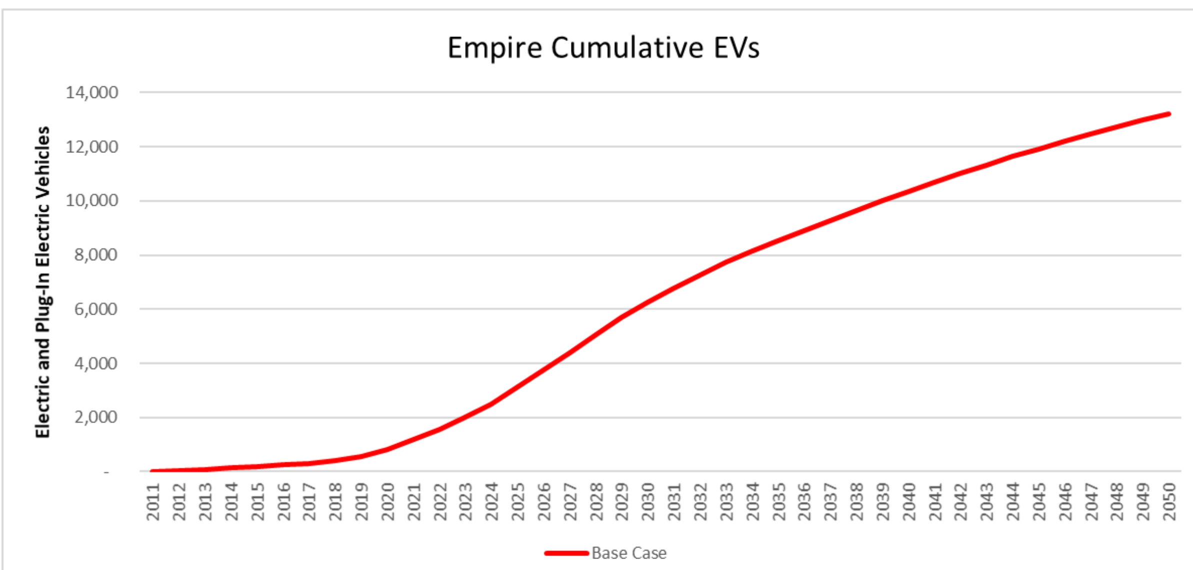


Figure 3-9 - Annual Summary of a Major Trend – Electric Vehicles



2.5 Adjustments to Historical Data Description and Documentation

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

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

Monthly peak data are derived from hourly net system loads. Hourly net system loads are reconstructed with estimated curtailment data prior to calculating the monthly peak data (gross peaks).

Economic data are provided by Moody's for Joplin and Springfield MSAs. These data are combined, applying 66% weight to the Joplin MSA and 34% weight to the Springfield MSA. These weights are consistent with Liberty-Empire's 2016 IRP filing and based on residential and commercial energy consumption between April 2014 and March 2015 for counties in the Liberty-Empire service territory and for the two MSAs. Non-manufacturing employment data between 2018 and 2020 is adjusted to remove the forecasted recession.

End-use data are provided from Itron's 2018 SAE data and adjusted to reflect Liberty-Empire's 2008 Potential Study and 2015 Saturation Survey. Further adjustments to historic and forecast saturations smooth the transition between known Liberty-Empire saturation levels and EIA trends.

Residential adjustments include changes to the saturation levels of heating, cooling, water heating, cooking, refrigeration, dishwashing, clothes washing, and clothes drying technologies.

Additional changes to end-use intensities for heating, cooling, and lighting reflect actual DSM programs and smooth transitions between years.

Commercial adjustments include changes to heating saturations and adjustments for the historical DSM program. Heating changes are made for consistency with Liberty-Empire's 2016 IRP filing and smooth anomalous historic data. DSM adjustments reflect implemented programs and savings for heating, cooling, and lighting.

The behind-the-meter solar forecast is derived for the residential and non-residential classes based on actual installations identified from Liberty-Empire's Solar Rebate program and the EIA's national solar forecast. 80% of the EIA's annual growth rates are applied to Liberty-Empire's actual installation base to create the solar forecast.

The electric vehicle forecast is derived based on EIA's vehicle sales per household for the West North Central region and the Auto Alliance's Missouri electric vehicle registration data. Data prior to 2018 is the average of the EIA's vehicle per household ratio applied to Liberty-Empire's residential customer count and the share of the Auto Alliance's Missouri electric vehicle registrations based on the ratio of Joplin's population to the state population. The long-term forecast of electric vehicles applies the EIA growth rates to the historical data.

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 retains the historical database for a minimum of 10 years.

SECTION 3 ANALYSIS OF NUMBER OF UNITS

(3) 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.

The key explanatory variables for each forecast model are listed and described in Table 3-4.

Table 3-4 - Key Drivers for Forecast Models

Key Drivers for Forecast Models			
Major Class	**Model**	**Key Explanatory Variable**	**Description**
Residential			
	Customer	Population	Historical and forecast population is based on Moody's forecasts for the Joplin and Springfield MSAs.

Key Drivers for Forecast Models			
Major Class	**Model**	**Key Explanatory Variable**	**Description**
	Average Use (SAE Model)	End Use Efficiency Trends	End-use efficiencies by technology type are based on 2018 EIA data.
		End Use Saturation Trends	End-use saturations by technology type are based on EIA data and calibrated to Liberty-Empire’s technology saturation information.
		Housing Stock	Housing information is based on EIA data calibrated to Liberty-Empire’s 2008 Potential Study and 2015 Saturation survey.
		Household Size & Income	Historical and forecast household size and income are based on Moody’s forecasts for the Joplin and Springfield MSAs.
		Price	Energy prices are based on historical revenues and kWh consumption. Energy price forecasts are forecast to be flat in real dollars.
		End Use Intensities	End-use intensities are based on the SAE West North Central region and adjusted to reflect Liberty-Empire’s 2008 Potential Study and 2015 Saturation Surveys.
		HDD and CDD	Heating and cooling degree days are based on NOAA data.
Commercial			
	Customer	Nonmanufacturing employment	Historical and forecast nonmanufacturing employment based on Moody’s forecasts for the Joplin and Springfield MSAs.

Key Drivers for Forecast Models			
Major Class	**Model**	**Key Explanatory Variable**	**Description**
	Average Use (SAE Model)	HDD and CDD	Heating and cooling degree days are based on NOAA data.
		End Use Efficiency Trends	End-use efficiencies by technology type are based on 2018 EIA data.
		End Use Saturation Trends	End-use saturations by technology type are based on 2018 EIA data.
		Price	Energy prices are based on historical revenues and kWh consumption. Energy price forecasts are forecast to be flat in real dollars.
		Employment	Historical and forecast employment are based on Moody's forecasts for the Joplin and Springfield MSAs.
Industrial			
	Energy - OPP - Praxair - Other Industrial	CDD	Heating and cooling degree days are based on NOAA data.
Municipals			
	Energy - Monett - Mt. Vernon - Lockwood - Chetopa	Population	Historical and forecast population is based on Moody's forecasts for the Joplin and Springfield MSAs.
		End Use Efficiency Trends	End-use efficiencies by technology type are based on 2018 EIA data.
		End Use Saturation Trends	End-use saturations by technology type are based on EIA data and

Key Drivers for Forecast Models			
Major Class	**Model**	**Key Explanatory Variable**	**Description**
			calibrated to Liberty-Empire's technology saturation information.
		Housing Stock	Housing information is based on EIA data, Liberty-Empire's 2008 Potential Study and Liberty-Empire's 2015 Saturation survey.
		Household Size and Income	Historical and forecast household size and household income are based on Moody's forecasts for the Joplin and Springfield MSAs.
		Price	Energy prices are based on historical revenues and kWh consumption. Energy price forecasts are forecast to be flat in real dollars.
		End Use Intensities	End-use intensities are derived based on the SAE West North Central zones and adjusted to reflect Liberty-Empire's 2008 Potential Study and 2015 Saturation Survey findings.
		HDD and CDD	Heating and cooling degree days are based on NOAA data.
Street Highway			
	Customer	Population and Non-Manufacturing Employment	The weighted index of population and non-manufacturing employment for the Joplin and Springfield MSA areas.
	Average Use	Outside Lighting Efficiency	The outside lighting efficiency index is based on the 2018 SAE West North Central zone commercial dataset developed by Itron based on EIA data.

Key Drivers for Forecast Models			
Major Class	**Model**	**Key Explanatory Variable**	**Description**
Interdepartmental			
	Average Use	HDD and CDD	Heating and cooling degree days are based on NOAA data.
Public Authority			
	Customer	Government Employment	Historical and forecast government employment is based on Moody's forecasts for the Joplin and Springfield MSAs.
	Average Use	HDD and CDD	Heating and cooling degree days are based on NOAA data.

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 Sections 6.1.2.

SECTION 4 USE PER UNIT ANALYSIS

(4) 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 energy forecast model uses the SAE modeling framework. This framework accounts for residential end-uses including space heating, space cooling, water heating, cooking, refrigeration, freezers, dishwashers, clothes washers, clothes dryers, televisions, lighting, electric vehicles, photovoltaics, and miscellaneous end-uses.

Except for photovoltaics and electric vehicles, these data are obtained from the 2018 EIA AEO for the West North Central region and developed by Itron. End-use saturations are modified by incorporating the Liberty-Empire 2008 Potential Study and 2015 Saturation Survey. Photovoltaic and electric vehicle forecasts are developed by Itron based on the EIA's long-term growth projections calibrated into Liberty-Empire district historic data.

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

The commercial energy forecast model uses the SAE modeling frameworks. This framework accounts for commercial end-uses including space heating, space cooling, water heating, cooking, refrigeration, outside lighting, inside lighting, office equipment and miscellaneous end-uses. These data are obtained from the 2018 EIA AEO for the West North Central region and developed by Itron. The photovoltaic forecast is developed by Itron based on the EIA's long-term growth projections calibrated into Liberty-Empire district historic data.

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 energy forecast is developed from three independent regression models. These models do not include end-use information. Liberty-Empire submitted a Variance Request specifying that end-use information was not available for the industrial class. The request was approved on November 25, 2018.

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.*

The SAE model consolidates end-use information into three explanatory variables: XHeat, XCool and XOther. Each variable is created to include end-use saturation and efficiency data, economic trends, and weather information. The aggregated variables describe the changes for each technology through time.

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.

End-use variable construction is maintained in Excel databases and the MetrixND forecasting software. End-use input data 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.

This is not applicable.

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 effects have a significant impact on most revenue classes. Weather is modeled with the XHeat and XCool variables. The XHeat and XCool variables include representations of heating and cooling degree days based on temperature reference points applicable to the residential and commercial classes. The model variables may be viewed 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 relies upon the equipment stock in the SAE dataset which is based on EIA's datasets.

4.2.2 End-Use Energy and Demand Estimates

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

End-use energy information is included in the residential, commercial, and wholesale SAE models. These models calibrate base, heating, and cooling end-use loads to historic billed sales (on a total sales or use per customer basis) through the model coefficients. For example, if the cooling end-use load estimate is larger than seen in the historic sales, the SAE model will calibrate to the historical sales (i.e. identify a coefficient that reduces the cooling end-use estimate to match historical sales).

The monthly demand forecast includes end-use information by incorporating the end-use sales trends into the peak model. Because the calibrated end-use data are included in the sales trends, the end-use data influences the peak model. Within the peak model, calibration is included by allowing the regression model coefficients to adjust the sales trends (which include end-use estimates) for base, summer, and winter loads to the historic peak values.

SECTION 5 SELECTING LOAD FORECASTING MODELS

(5) 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;

Liberty-Empire’s load forecast uses SAE models for the residential and commercial classes and econometric models for the remaining classes. The SAE models capture residential and commercial consumption patterns based on weather and end-use information. The econometric models capture consumption patterns based on historical use, economic drivers, and weather. The 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 contains three main modeling processes: (1) monthly class level sales; (2) monthly system peaks; and (3) class level hourly profiles, which are calibrated to the monthly sales and peak. The forecast model results in hourly load forecasts from 2019 through 2048. The process is summarized below.

Step 1 – Energy Models: The energy forecast models use Itron's SAE method for the residential and commercial classes and the econometric method for the remaining classes. Liberty-Empire models the following classes:

a. Residential.
b. Commercial.
c. Wholesale (Monett, Mt. Vernon, Lockwood, and Chetopa).
d. Street and highway.
e. Interdepartmental.
f. Public authority.
g. Industrial (oil and pipelines, Praxair, and other).

Step 2 – Peak Model: The peak model forecasts system monthly peaks (Net System). This econometric model uses the energy forecast as a primary driver.

Step 3 – Load Profile Models: Hourly load profile models are created for each class. The profile models are econometric models based on load research data. The load profiles are calibrated to the monthly energy and system peak forecasts resulting in an hourly forecast for each class. The aggregation of the hourly forecasts comprises the hourly net system load.

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 described above considers the impact of legal mandates, economic policies, and rate designs on future energy and demand requirements by including known changes in end-use codes and standards. These changes are included in the SAE dataset.

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.

Step 1 - Energy Models. Weather, end-use trends, and economic trends are critical in developing the energy models. These assumptions are described below.

a. *Weather Variables*. For each class, Liberty-Empire determined whether temperature is critical in the forecast model. After evaluating scatter plots and statistical model results, temperature is incorporated into most class energy models. When temperature is included, weather variables are constructed using multi-part HDD and CDD splines weighted to approximate billing cycle impacts. Forecasted HDD and CDD are based on 30-year normal temperatures for Springfield, Missouri.

b. *End-Use Variables*. For the residential and commercial classes, Liberty-Empire uses the SAE model. End-use trends calibrated to Liberty-Empire specific saturation and efficiency data are crucial in determining the change in average use 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 and energy models. Selection of these variables is based on statistical fit and the relationship between the economic driver and class consumption.

Step 2 – System Peak Models. In the system peak model, the peak dataset, weather, and growth trends are critical in developing the peak model. These assumptions are described below.

a. *Peak Dataset*. The peak dataset is developed by extracting historic monthly peaks and associated peak producing weather from the hourly system loads.

b. *Weather*. A key driver in the peak forecast is the forecasted (or normal) monthly peak producing weather. The weather calculation uses the following steps:

1) Average daily temperatures, prior day temperatures, and two-prior day temperatures for the monthly peak days from 2001 through 2017 are developed from the Peak Dataset.
2) The April average temperature is defined as a heating peak (i.e., driven by cold weather). This step removes historic peak producing weather occurrences above 65 degrees from the average.
3) The May average temperature is defined as a cooling peak (i.e. driven by hot weather). This step removes historic peak producing weather occurrences below 65 degrees from the average.
4) The October average temperature is defined as a cooling peak (i.e. driven by hot weather). This step removes historic peak producing weather occurrences below 65 degrees from the average.
5) January is defined as the winter seasonal peak month. The January average temperature is replaced with the seasonal average calculated over the last five (2014-2018) seasonal winter peak producing events.

The winter season peak event could occur in December, January, or February.

6) August is defined as the summer seasonal peak month. The August average temperature is replaced with the seasonal average calculated over the last five (2013-2017) seasonal summer peak producing events. The summer season peak event could occur in July, August, or September.
7) Calculate the three-day weighted average temperature ("TDWT") using 70 percent for the current day, 20 percent for the prior day, and 10 percent for the two days prior.

c. *Growth Trends*. Peak growth depends on the growth drivers included in the model. Liberty-Empire uses the energy forecast to drive the peaks. The energy forecast is decomposed into heating, cooling, and base load energy which allows the monthly peak growth to vary based on the underlying end-use changes. Statistical evaluation of the growth drivers is used to identify the most appropriate variables.

Step 3 – Load Profile Models. Load profile models are used to convert the energy and peak forecast to the hourly net system load shape and to calculate coincident class peaks. The key driver in the load profile models is the weather assumption. This assumption is described below.

a. *Weather*. The load profile models use daily average temperatures divided into HDD and CDD splines to capture the nonlinear weather response. The temperature forecast is calculated using a rank-and-average method with 30-years (1988 to 2017) of historic data. The rank-and-average result is mapped to the 2003 temperature calendar year.

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 applicability of historical explanatory variables is primarily driven by statistical significance. The key drivers included in each class model are summarized in Table 3-4. Detailed information about the driver's statistical significance is included in Section 6.1.2. This section summarizes the broad modeling method approach for each class.

Residential Class

Residential electric consumption is highly 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 forecast. These models are defined below:

1. *Customer Model*: This model forecasts the number of residential customers in each month. The customer model is designed to capture customer count growth based on a macroeconomic driver.
2. *UPC Model*: This model forecasts the average use-per-customer ("UPC") for a month. The UPC model is designed to capture how an average customer consumes electricity.

The class forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total energy 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").

Commercial Class

As with the residential class, commercial energy 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:

1. *Customer Model*: This model forecasts the number of commercial customers in each month. The customer model is designed to capture customer count growth based on a macroeconomic driver.
2. *UPC Model*: This model forecasts the average UPC for a month. The UPC model is designed to capture how an average customer consumes electricity.

The class forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total energy in each month. Using two models to develop the 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").

Wholesale Class

The wholesale class is composed of four municipal utilities (Monett, Mt. Vernon, Lockwood, and Chetopa). The forecast is developed with four energy models, one for each municipal utility. All wholesale models use the SAE model framework applied to total wholesale customer sales. The models in this class forecast are defined below:

1. *Monett Energy Model*: This model forecasts the total kWh for Monett in a month.
2. *Mt. Vernon Energy Model*: This model forecasts the total kWh for Mt. Vernon in a month.

3. *Lockwood Energy Model*: This model forecasts the total kWh for Lockwood in a month.
4. *Chetopa Energy Model*: This model forecasts the total kWh for Chetopa in a month.

The class forecast is calculated by summing the four energy model forecasts in each month.

Street and Highway Class

Street and highway class consists primarily of outside lighting accounts. Two models are used to forecast this class as defined below:

1. *Customer Model*: This model forecasts the number of street and highway customers in each month. The customer model is designed to capture customer count growth based on a macroeconomic driver.
2. *UPC Model*: This model forecasts the average UPC for a month. The UPC model is designed to capture how an average customer consumes electricity.

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

Interdepartmental Class

The interdepartmental class is modeled with two models:

1. *Customer Model*: This model forecasts the number of interdepartmental customers in each month. The forecast holds the number of customers constant

based on the last monthly customer count because this class is not correlated with a macroeconomic driver.

2. *UPC Model*: This model forecasts the average UPC for a month. This model is designed to capture variations in monthly usage through time based on weather.

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

Public Authority Class

The public authority class is modeled with the following two models:

1. *Customer Model*: This model forecasts the number of public authority customers in each month. The customer model is designed to capture customer count growth based on a macroeconomic driver.

2. *UPC Model*: This model forecasts the average UPC for a month. This model is designed to capture variations in monthly usage through time based on weather.

The class forecast is calculated by multiplying the customer forecast with the UPC forecast to obtain the total energy in each month. Using two models to develop the public authority class forecast captures both the class growth based on a changing number of customers and annual customer usage patterns.

Industrial Class

The industrial class is composed of large customers. The forecast for this class is developed with three separate models as described below:

1. *Praxair*: Praxair is a large individual customer. A single energy model is developed to forecast monthly energy based on the customer's most recent consumption.
2. *Oil and Pipeline*: The oil and pipeline segment has consisted of 12 customers since 2014. Two models are developed to forecast the oil and pipeline energy forecast. The customer model is designed to maintain the 12 customers in the planning period. The UPC model is created to capture the seasonal variations of the class.
3. *Other Industrial*: Two models are used to forecast the remaining industrial customers. A customer model is used to capture the existing number of customers and project those customers into the planning period. The UPC model is created to capture the monthly variations of the segment.

The class forecast is calculated by summing the energy forecast for Praxair, oil and pipeline, and other industrial energy forecasts.

System Peak Model

The system peak model is a regression model designed to forecast monthly peaks for the net system load. The peak model consists of two main drivers, energy growth and weather. The growth is driven by the energy forecast to maintain consistency between peak and energy. The weather drives monthly variation based on historical and forecast peak producing weather.

Profile Model

Twelve hourly profile models are developed as the basis for determining the class level monthly shapes. These models are hourly regression models and use similar structures to capture the load shape based on weather and time of year.

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;

Variable selection is reviewed each forecast cycle. Final variable selection is based on historical energy and customer data as well as available data (e.g. new economic regions). Model changes include updated estimation periods, new shift variables, altered construction of existing variables, or new economic drivers. Table 3-5 summarizes the main drivers in the 2016 IRP model and changes made in the 2019 IRP models. The 2019 IRP column briefly highlights the motivation for the change.

Table 3-5 - Variable Differences Between the 2016 and 2019 IRP Models

Key Drivers Changes for Forecast Models			
Class	**Model**	**2016 IRP**	**2019 IRP**
Residential			
	Customer	Population (Joplin and Springfield MSAs)	No change
	Average Use	2015 SAE Data	2018 SAE Data • Update end-use data

Key Drivers Changes for Forecast Models			
Class	**Model**	**2016 IRP**	**2019 IRP**
Commercial			
	Customer	Residential Customers	Nonmanufacturing Employment • Remove decelerating population trend.
	Average Use	2015 SAE Data	2018 SAE Data • Update end-use data Additional Binary Shifts • Add shift variables to adjust trends to recent data
Industrial			
	Energy - OPP - Praxair - Other	Binary Shifts	Additional Binary Shifts • Add shift variables to adjust level to recent data
Municipals			
	Energy - Monett - Mt. Vernon - Lockwood - Chetopa	2015 SAE Data	2018 SAE Data • Update end-use data
Street and Highway			
	Customer	Population and Non-Manufacturing Employment	No Change

Key Drivers Changes for Forecast Models			
Class	**Model**	**2016 IRP**	**2019 IRP**
	Average Use	Lighting efficiency	Add solar variable • Include behind-the-meter solar variable based on historic class penetration
Interdepartmental			
	Customer	Binary Shifts	Additional Binary Shifts • Added shift variables to adjust trends to recent data
	Average Use	Binary Shifts HDD and CDD	Additional Binary Shifts • Added shift variables to adjust trends to recent data
Public Authority			
	Customer	Government Employment	Additional Binary Shifts • Added shift variables to adjust trends to recent data
	Average Use	HDD Base 55 CDD Base 55	No change
System Peak		CDD Trend Interaction HDD Trend Interaction	Change CDD80 Spline to CDD85 Spine.

Key Drivers Changes for Forecast Models			
Class	**Model**	**2016 IRP**	**2019 IRP**
		Other (Baseload) Trend January 2012 Plus Winter Energy Trend CDD80 Spline	• Refine changing cooling slope for high temperatures Add Monthly Binaries • Add shoulder month binaries to adjust for low weather condition months.
Hourly Profile Models		Weighted Average HDD and CDD splines	No change

6.1.2 Mathematical or Statistical Equations

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

6.1.2.1 Residential Class

1. *Customer Mode*l: The customer model is a regression model estimated with historical data from July 2011 through July 2018. Table 3-6 shows the customer model specification and Table 3-7 shows the customer model statistics.

Table 3-6 - Residential Customer Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	8,526.543	8,066.329	1.057	29.41%
Index_Population	115,792.293	6,898.698	16.785	0.00%
March	-144.530	37.737	-3.830	0.03%
April	-481.530	50.073	-9.617	0.00%
May	-637.804	57.273	-11.136	0.00%
June	-581.003	61.353	-9.470	0.00%
July	-521.786	63.017	-8.280	0.00%
August	-569.622	60.852	-9.361	0.00%
September	-724.533	56.805	-12.755	0.00%
October	-613.251	49.794	-12.316	0.00%
November	-239.199	37.642	-6.355	0.00%
May2011Tornado	-164.742	109.417	-1.506	13.66%
AR(1)	0.870	0.025	35.016	0.00%

Table 3-7 - Residential Customer Model Statistics

Statistics	Residential Customer Model
Estimation	7/2011 – 7/2018
R2	0.997
Adj. R2	0.997
MAPE	0.05%
DW	1.425

a. Model Variables: The customer model's primary driver is population. A binary shift captures the impact of the Joplin tornado in 2011. Monthly binary variables capture the season pattern and the auto-regressive (AR) term corrects for serial correlation.

1) Population: Population is calculated as the weighted average of the Joplin and Springfield MSAs based on 2014 residential and commercial energy sales. The data are provided by Moody's Analytics.

2) May2011Tornado: This variable takes the value "1" from May 2011 through December 2011 and the value of "0" beginning in 2012.

3) Monthly Binary Variables: Binary variables for March through November are included to capture seasonal customer effects. These variables take the value of “1” in their month and a “0” for all other months.
4) AR1: The inclusion of the AR1 term corrects the serial correlation problems with the model and does not impact the strength of the population driver.

2. UPC Model: The UPC model is an SAE model estimated with historical data from January 2000 through July 2018. Table 3-8 shows the UPC model specification and Table 3-9 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 2018 SAE West North Central region modified for Liberty-Empires’ 2008 Potential Study and 2015 Saturation Survey. SAE data contains adjustments for DSM programs and includes forecasts of photovoltaics and electric vehicles.

Table 3-8 - Residential UPC Model

Variable	Coefficient	StdErr	T-Stat	P-Value
XHeat	1.036	0.029	36.044	0.00%
XCool	1.075	0.046	23.372	0.00%
XOther	1.007	0.013	74.752	0.00%
XHeatShift2007	0.108	0.024	4.455	0.00%
September	145.629	19.320	7.538	0.00%
January	112.593	16.376	6.875	0.00%
July	146.285	21.205	6.899	0.00%
August	115.564	25.343	4.560	0.00%
November	-86.988	13.768	-6.318	0.00%
Year2014Plus	-41.032	8.744	-4.693	0.00%
Year2012	-55.543	16.049	-3.461	0.07%
FebMar2013	-85.967	37.207	-2.311	2.18%

Variable	Coefficient	StdErr	T-Stat	P-Value
FebMar2015	-149.400	37.221	-4.014	0.01%
JanFeb2011	-108.683	38.075	-2.854	0.48%
JanFeb2010	128.508	38.097	3.373	0.09%
Dec2006Jan2007	165.022	53.143	3.105	0.22%

Table 3-9 - Residential UPC Model Statistics

Statistics	Residential Customer Model
Estimation	1/2000 – 7/2018
R2	0.966
Adj. R2	0.963
MAPE	3.71%
DW	2.041

b. Model Variables: The UPC model includes the three standard SAE variables (XHeat, XCool, and XOther) as well as monthly binary variables, shift variables, and trinary variables.

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 including photovoltaics and electric vehicles. The response includes the effects of hours of light, price, income, billing cycles, household size, and DSM programs.

4) XHeatShift2007: This variable is used to capture a general heating response shift beginning in 2007. The shift occurs near the end of the housing market boom in the mid-2000 time-frame and captures the rapid growth in new electric-heated homes.

4) September, January, July, August, and November: These binary variables are included to capture a patterned residual for each month.

5) Year2014Plus: This shift variable adjusts the model to ensure that the forecast is consistent with recent history beginning in 2014.

6) Year2012: This binary variable deduced consumption in 2012 capturing the residual effects of the 2011 tornado.

7) FebMar2013, FebMar2015, JanFeb2011, JanFec2010, Dec2006Jan2007: These variables are trinaries and take the form of a “1” in the first period and an “-1” in the second period. For example, FebMar2013 contains all “0” values except for February and March 2013. February 2013 is a “1” and March 2013 is a “-1”. Trinaries variables capture the offsetting effects of errant billing data.

6.1.2.2 Commercial Class

1. Customer Model: The customer model is a regression model estimated with historical data from July 2011 through July 2018. Table 3-10 shows the customer model specification and Table 3-11 shows the customer model statistics.

Table 3-10 - Commercial Customer Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	6,673.491	1,408.909	4.737	0.00%
Index_Nonmanufacturing employment	14,950.293	1,191.428	12.548	0.00%
AR(1)	0.805	0.058	13.760	0.00%

Table 3-11 - Commercial Customer Model Statistics

Statistics	Commercial Customer Model
Estimation	7/2011 – 7/2018
R2	0.980
Adj. R2	0.980
MAPE	0.10%
DW	2.581

a. Model Variables: The primary driver in the customer model is nonmanufacturing employment. The AR term corrects for serial correlation.

1) Index Nonmanufacturing Employment: Nonmanufacturing employment is calculated as the weighted average of the Joplin and Springfield MSAs based on 2014 residential and commercial energy sales. The data are provided by Moody's Analytics.

2) AR1: The inclusion of the AR1 term corrects the serial correlation problems with the model and does not impact the strength of the economic driver.

2. UPC Model: The UPC model is an SAE model estimated with historical data from January 2000 through July 2018. The SAE model is based on the same theoretical foundation as the residential SAE model but is modified for commercial end-use information. Table 3-12 shows the UPC model specification and Table 3-13 shows the UPC model statistics.

   a. Commercial SAE Model Summary: The SAE model contains end-use information for heating, cooling, and baseload technologies. The data for the SAE model is from Itron's 2018 SAE West North Central region. SAE data contains adjustments for DSM programs and includes a forecast of photovoltaics.

Table 3-12 - Commercial UPC Model

Variable	Coefficient	StdErr	T-Stat	P-Value
XHeat	1,150.885	49.808	23.106	0.00%
XCool	959.326	28.570	33.579	0.00%
XOtherPV	890.681	6.980	127.613	0.00%
Year2006	-419.118	59.687	-7.022	0.00%
Year2007	-369.580	59.556	-6.206	0.00%
Year2006Plus	441.008	32.635	13.514	0.00%
FebMar2015	-401.130	133.388	-3.007	0.30%
JanFeb2010	420.466	133.097	3.159	0.18%
Jul	238.597	52.962	4.505	0.00%
Sep	266.683	53.329	5.001	0.00%
Nov	-215.451	48.462	-4.446	0.00%
Year2013Plus	244.794	45.535	5.376	0.00%
Year2015Plus	140.964	48.106	2.930	0.38%

Table 3-13 - Commercial UPC Model Statistics

Statistics	Commercial UPC Model
Estimation	1/2000 – 7/2018
R2	0.925
Adj. R2	0.920

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Statistics	Commercial UPC Model
MAPE	2.70%
DW	1.755

b. Model Variables: The UPC model includes the three standard SAE variables (XHeat, XCool, and XOther) as well as monthly binary variables and annual shift 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, output indices, 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, output indices, and DSM programs.
3) XOtherPV: 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, output indices, DSM programs, and photovoltaics.
4) July, September, and November Binary: These binary variables are included to capture a patterned residual.
5) Year2006 and Year2007: These independent binary variables are included to capture the quick growth in average use during the high economic growth period.
6) Year2006Plus, Year2013Plus, and Year2015Plus: These binary variables are used to calibrate recent historical shifts into the planning period.

The binary variable consists of a "1" value beginning in the designated year and continues throughout the planning period.

6.1.2.3 Wholesale Class

1. Energy Models: The models forecast total energy and are not divided into a customer and UPC models. However, the energy models apply the SAE model framework to forecasting total energy by including an economic variable to capture customer growth. The SAE model variable construction is identical to the construction used in the residential class with two exceptions. First, the XOther variable includes Population as a growth driver. Second, the weather variables use temperature splines directly related to each municipal's weather response.

    a. Model Variables. The energy models include the three standard SAE variables (XHeat, XCool, and XOther) and an economic driver (population) as well as annual binary and shift variables. The general definitions of the variables are listed below:

        1) XHeat: This variable captures the general heating response for a typical wholesale customer. The response includes the effects of heating technology efficiencies, saturation, thermal shell, weather, price, income, and household size.
        2) XCool: This variable captures the general cooling response for a typical wholesale customer. The response includes the effects of cooling technology efficiencies, saturation, thermal shell, weather, price, income, and household size.
        3) XOther: This variable captures the general response for all non-heating and cooling technologies. The response includes the effects of hours of

light, price, income, billing cycles, and household size. XOther also includes population changes which capture the long-term growth in energy caused by economic expansion.

4) Annual Binaries: These binary variables (e.g., Year2004, Year2005) are included to capture variations in energy growth through the historical time period. In some cases, the set of binary variables capture rapid energy growth beyond the growth obtained by the SAE variables.

5) Annual Plus Binaries: These binary variables (e.g. Year2012Plus, Year2013Plus) capture an ongoing shift in base load which is expected to continue in the future.

6) Time Period Binaries: Time period binaries (e.g. JulToSep2001_2002 and JanDec2007Plus) capture month and year specific shifts in the data.

b. Monett Energy Model: The Monett energy model is summarized in Table 3-14 and Table 3-15.

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Table 3-14 - Monett Energy Model

**** Confidential in its Entirety**[1]**

[redacted]

Table 3-15 - Monett Energy Model Statistics

****Confidential in its Entirety**[1]**

[redacted]

c. Mt. Vernon Energy Model: The Mt. Vernon energy model is summarized in Table 3-16 and Table 3-17.

[1] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

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Table 3-16 - Mt. Vernon Energy Model

**** Confidential in its Entirety**[2]**

[redacted]

Table 3-17 - Mt. Vernon Energy Statistics

****Confidential in its Entirety**[2]**

[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]
[redacted]	[redacted]

[2] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

d.Lockwood Energy Model: The Lockwood energy model is summarized in Table 3-18 and Table 3-19.

Table 3-18 - Lockwood Energy Model

****Confidential in its Entirety**[3]**

[redacted]

Table 3-19 - Lockwood Energy Model Statistics

****Confidential in its Entirety**[3]**

[redacted]

e. Chetopa Energy Model: The Chetopa energy model is summarized in Table 3-20 and Table 3-21.

[3] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Table 3-20 - Chetopa Energy Model

****Confidential in its Entirety**[4]**

[redacted]

Table 3-21 - Chetopa Energy Model Statistics

****Confidential in its Entirety**[4]**

[redacted]

6.1.2.4 Street and Highway Class

1. Customer Model: The customer model is a regression model estimated with historical data from January 2001 through July 2018. Table 3-22 shows the customer model specification and Table 3-23 shows the customer model statistics.

[4] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Table 3-22 - Street and Highway Customer Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	192.461	7.877	24.432	0.00%
Oct2007ToDec2008 Binary	-19.515	1.491	-13.090	0.00%
Population & Non-Manufacturing Employment	247.839	7.139	34.718	0.00%
Year2016Plus	8.700	1.741	4.998	0.00%
Year2017Plus	7.446	2.230	3.339	0.10%
Year2018Plus	13.330	2.598	5.131	0.00%

Table 3-23 - Street and Highway Customer Model Statistics

Statistics	Street and Highway Customer Model
Estimation	1/2001 – 7/2018
R2	0.932
Adj. R2	0.930
MAPE	0.95%
DW	0.503

a. Model Variables: The street and highway model includes an economic driver, three data end-shift variables, and a binary variable. The primary driver is the weighted population and non-manufacturing employment index.

1) Population and Non-Manufacturing Employment Index: This variable is the weighted average of the population and non-manufacturing employment forecast for the Joplin and Springfield MSAs. The variable is constructed using 1/3 population index and 2/3 employment index.

2) Oct2007ToDec2008 Binary: This variable takes the value of "1" from October 2007 through December 2008. This binary variable captures the dramatic reduction in customer counts during the 2007 to 2008 timeframe.

3) Annual Plus Binaries: The annual binary plus variables (e.g. Year2016Plus, Year2017Plus, and year2018Plus) capture the accelerated customer increases after 2016. These shifts are expected to remain into the future.

2. UPC Model: The UPC model is a regression model estimated with historical data from January 2003 through July 2018. Table 3-24 shows the UPC model specification and Table 3-25 shows the UPC model statistics.

Table 3-24 - Street and Highway UPC Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	3,714.463	49.230	75.451	0.00%
January	1,421.059	45.136	31.484	0.00%
February	761.491	44.107	17.265	0.00%
March	613.067	42.084	14.568	0.00%
April	138.261	42.043	3.289	0.12%
May	22.064	40.450	0.545	58.62%
July	266.608	39.674	6.720	0.00%
August	426.756	40.313	10.586	0.00%
September	530.191	40.628	13.050	0.00%
October	913.823	41.879	21.821	0.00%
November	1,129.486	44.546	25.355	0.00%
December	1,452.219	45.570	31.868	0.00%
OutsideLightEfficiency	-41.300	11.387	-3.627	0.04%
Sep2007ToMay2008	147.876	39.379	3.755	0.02%
AprilMay2014	386.009	81.936	4.711	0.00%
OctNov2012	409.550	82.131	4.987	0.00%
Photovoltaic UPC	329.062	200.640	1.640	10.29%

Table 3-25 - Street and Highway UPC Model Statistics

Statistics	Street and Highway UPC Model
Estimation	1/2003 – 7/2018
R2	0.952
Adj. R2	0.948
MAPE	1.93%
DW	1.665

a. Model Variables: The UPC model captures both the reducing average usage of the class and the seasonal pattern. The following variables are used in the model:

1) Monthly Binaries: This set of binary variables captures the general seasonal response due to the changing sunrise and sunset times.

2) Outside Light Efficiency: This variable captures the increasing energy efficiency of outside lighting technology. The variable is derived from the commercial SAE model, outside lighting efficiency index provided by the EIA. The increasing value of the index implies that lighting technologies are becoming more efficient and use less energy over time.

3) Sep2007ToMay2008: This binary variable captures a residual pattern that shows a short-term increase in lighting energy through this time period.

4) Trinaries (AprMay2014, OctNov2012): Trinary and take the form of a "1" in the first period and an "-1" in the second period. For example, AprMay20142013 contains all "0" values except for April and May 2014.

April 2014 is a "1" and May2014 is a "-1". Trinaries variables capture the offsetting effects of errant billing data.

5) Photovoltaic UPC. This variable captures the installed behind-the-meter photovoltaic consumption for the street and highway class customers on a use-per-customer basis. The data values are negative which estimates energy savings due to installed solar systems.

6.1.2.5 Interdepartmental Class

1. Customer Model: The customer model is a regression model that is designed to provide a flat forecast based on the last actual value. The model uses end-shift binary variables to capture the value of the last actual data point and project that value through the planning period.

2. UPC Model: The UPC model is a regression model estimated with historical data from January 2001 through July 2018. This model is designed to capture seasonal fluctuations based on weather response and forecast loads based the recent history from 2014 forward. Table 3-26 shows the UPC model specification and Table 3-27 shows the UPC model statistics.

Table 3-26 - Interdepartmental UPC Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	10,622.575	331.170	32.076	0.00%
Year2008Plus	-4,879.925	454.818	-10.729	0.00%
Year2007Plus	-2,850.452	455.087	-6.264	0.00%
Year2014Plus	3,757.718	324.904	11.566	0.00%
May2016Plus	-2,886.754	394.931	-7.310	0.00%
HDD55	4.976	0.674	7.379	0.00%
CDD55	2.521	0.619	4.075	0.01%

Table 3-27 – Interdepartmental UPC Model Statistics

Statistics	Interdepartmental UPC Model
Estimation	1/2001 – 7/2018
R2	0.852
Adj. R2	0.881
MAPE	12.65
DW	1.800

a. Model Variables. The UPC model is designed to capture the seasonal variations of the usage. The variation is driven by the heating and cooling response. The remaining variables capture general shifts to the underlying average use:

1) Weather Variables: This set of variables (HDD55 and CDD55) capture the weather response of the interdepartmental class.

2) Annual Shift Variables: This set of variables (Year2007Plus, Year2008Plus, Year2014Plus, and May2016Plus) capture annual shifts in the average use which continue through the planning period. These shifts capture the rapid decline through 2008, the sudden increase in 2014, and decline in May 2016.

6.1.2.6 Public Authority Class

1. Customer Model: The customer model is a regression model designed to capture growth for the class. Table 3-28 shows the customer model specification and Table 3-29 shows the customer model statistics. The model is primarily driven by the government employment forecast and includes an end-shift binary variable to calibrate the forecast to the last actual data point.

Table 3-28 - Public Authority Customer Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	308.081	26.298	11.715	0.00%
Government Employment	980.421	21.036	46.607	0.00%
July 2012 to August 2014	171.473	2.608	65.759	0.00%
Year2018Plus	14.352	4.623	3.104	0.23%

Table 3-29 - Public Authority Customer Model Statistics

Statistics	Public Authority Customer Model
Estimation	1/2000 - 7/2018
R2	0.983
Adj. R2	0.982
MAPE	0.58%
DW	0.425

a. Model Variables: The customer model is primarily driven by the government employment forecast and calibrated to the last actual number of customers. The variables are discussed below:

1) Government Employment: This variable is the weighted Joplin and Springfield MSAs forecast for government employment.

2) Annual Shift Variables: This variables (Sept2018Plus) captures annual shifts in the average use and calibrates the forecast to the most recent data.
3) Binary Shift: This variable (Jul12toAug14) captures a dramatic shift in customer counts for the two-year period.

2. UPC Model: The UPC model is a regression model estimated with historical data from January 1999 through July 2018. This model captures seasonal fluctuations based on weather response but does not attempt to capture long-term changes in average use. Table 3-30 shows the UPC model specification and Table 3-31 shows the UPC model statistics.

Table 3-30 - Public Authority UPC Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	4,426.176	61.385	72.106	0.00%
Year2008Plus	308.919	44.941	6.874	0.00%
Year2002Plus	-201.215	49.953	-4.028	0.01%
Year2012Plus	-407.520	83.147	-4.901	0.00%
Year2015Plus	347.399	83.477	4.162	0.01%
HDD55	2.177	0.121	17.946	0.00%
CDD55	2.156	0.098	21.897	0.00%
February	-349.735	65.871	-5.309	0.00%
June	129.081	57.598	2.241	2.60%
July 2012 to August 2014	-267.064	88.826	-3.007	0.30%

Table 3-31 - Public Authority UPC Model Statistics

Statistics	Public Authority UPC Model
Estimation	1/1999 - 7/2018
R2	0.747
Adj. R2	0.737
MAPE	3.45%
DW	1.849

a. Model Variables: The UPC model is forecasts the monthly shape of the class. The following variables are used in the model:

1) Weather Variables: These variables (HDD55 and CDD55) capture the weather response of the public authority class.
2) Annual Shift Variables: These variables (Year2002Plus, Year2008Plus, Year2012Plus, and Year2015Plus) capture annual shifts in the average use which continue through the planning period.
3) Monthly Binaries: The February and June binary variables capture the patterned residuals which contribute to the seasonal shape.
4) Binary Shift: This variable (Jul12toAug14) matches the dramatic shift in customer counts for the two-year period.

6.1.2.7 Industrial Class

1. Praxair Model: The Praxair model is a regression model that forecasts monthly energy. The model provides a forecast based on the 2015 through 2018 average annual energy usage and the seasonal pattern created by the varying number of days in each month. The model results are shown in Table 3-32 and Table 3-33.

Table 3-32 - Praxair Model

****Confidential in its Entirety**[5]**

[redacted]

Table 3-33 - Praxair Model Statistics

****Confidential in its Entirety**[5]**

[redacted]

a. Model Variables: The Praxair model consists of five annual shift variables and monthly binary variables.

1) Annual Shift Variables: The annual shift variables (Year2008Plus, Year2009Plus, Year2010Plus, Year2011Plus, and Year2015Plus) are designed to capture the average energy load for the year and project the 2015 through 2018 average energy load through the planning period.

[5] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

2) Monthly Binaries: Monthly binary variables (February, April, June, September, and November) capture monthly variations due to the changing number of days per month.

2. Oil and Pipeline Model: The Oil and Pipeline model uses two regression models to forecast energy. Because there have been no recent changes to the number of customers, the customer model forecasts the existing 12 customers throughout the planning period. The UPC model captures the most recent average customer usage and monthly variation. The UPC model results are shown in Table 3-34 and Table 3-35.

Table 3-34 - Oil and Pipeline Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	369731.312	25311.533	14.607	0.00%
Year2003Plus	-206865.520	61828.338	-3.346	0.10%
Year2004Plus	477539.036	66311.832	7.201	0.00%
Year2005Plus	-79241.070	31958.744	-2.479	1.39%
Year2008Plus	-128125.525	22598.245	-5.670	0.00%
Year2011Plus	47840.686	22598.245	2.117	3.54%
Year2014Plus	67969.014	22598.245	3.008	0.30%
Year2003Trend	56943.439	8235.034	6.915	0.00%
January	34943.280	31128.538	1.123	26.29%
February	4595.809	31069.000	0.148	88.25%
March	58984.064	31014.815	1.902	5.85%
April	84018.768	30966.010	2.713	0.72%
May	122560.869	30922.612	3.963	0.01%
June	137706.229	30884.643	4.459	0.00%
July	163987.450	30852.122	5.315	0.00%
August	155282.409	31154.633	4.984	0.00%
September	119364.725	31133.521	3.834	0.02%
October	72488.768	31118.433	2.329	2.08%
November	32395.968	31109.377	1.041	29.89%
Year2017Plus	-128694.192	31958.744	-4.027	0.01%
Year2018Plus	103235.155	45925.719	2.248	2.56%

Table 3-35 - Oil and Pipeline UPC Model Statistics

Statistics	Oil and Pipeline UPC Model
Estimation	1/1999 – 7/2018
R2	0.575
Adj. R2	0.535
MAPE	14.10%
DW	1.378

a. Model Variables: The Oil and Pipeline UPC model consists of annual shift variables, monthly binary variables, and a trend variable.

1) Annual Shift Binary: These variables (Year2003Plus through Year2018Plus) capture the average energy load for the year and project the average energy shift through the planning period.
2) Year2003Trend: This variable is a trend variable that applies only in 2003. The variable is designed to capture the rapid consumption change in 2003.
3) Monthly Binary: These independent binary variables capture seasonality through the year.

3. Other Industrial Model: The remaining industrial customers ("other industrial") are modeled using two models to forecast energy. The customer model forecasts the existing 338 customers throughout the planning period. The UPC model captures monthly variation for these customers. The model results are shown in Table 3-36 and Table 3-37.

Table 3-36 - Other Industrial UPC Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	204662.613	1774.057	115.364	0.00%
January	10663.030	2177.844	4.896	0.00%
February	147.837	2171.677	0.068	94.58%
March	7837.981	2130.450	3.679	0.03%
April	4645.794	1978.630	2.348	1.98%
May	10086.847	2230.054	4.523	0.00%
June	11672.320	3652.330	3.196	0.16%
July	12910.480	5298.714	2.437	1.57%
August	15788.144	5897.125	2.677	0.80%
September	3007.096	4832.639	0.622	53.45%
October	6977.549	2773.653	2.516	1.27%
November	1433.068	2175.331	0.659	51.08%
CDD55	42.281	9.250	4.571	0.00%
Year2003	-8801.518	1809.958	-4.863	0.00%
Year2006	6168.166	1815.721	3.397	0.08%
Year2009	-12980.190	1842.920	-7.043	0.00%
Year2010Plus	-12552.666	1814.390	-6.918	0.00%
Year2011Plus	7119.268	1852.167	3.844	0.02%
MarApr2003	18452.843	4256.736	4.335	0.00%
NovDec2002	28425.377	4258.738	6.675	0.00%
MarApr2008	12649.758	4258.842	2.970	0.33%
Year2016Plus	7555.979	1869.310	4.042	0.01%
Year2017Plus	8734.687	2164.336	4.036	0.01%

Table 3-37 - Other Industrial UPC Model Statistics

Statistics	Other Industrial Model
Estimation	1/2000 – 7/2018
R2	0.896
Adj. R2	0.884
MAPE	2.01%
DW	1.687

a. Model Variables: The Other Industrial UPC model consists of annual shift variables, weather variables, annual binaries, monthly binaries, and a trinary variable

1) Annual Shift Binary: The shift variables (Year2010Plus, Year2011Plus, Year2016Plus, and Year2017Plus) capture the average energy load for the year and project the 2017 to 2018 average energy load through the planning period.
2) Weather Variables: This variable (CDD55) captures the cooling weather response of the industrial customers.
3) Annual Binaries: These binary variables (Year2003, Year2006, and Year2009) capture underlying shifts in the average use for industrial customers.
4) Monthly Binary: These independent binary variables capture the seasonality of the industrial class.
5) Trinaries (AprMay2003, OctNov2002, and MarApr2008): Trinary variables capture the offsetting effects of errant billing data.

6.1.2.8 System Peak Model

The system model forecasts monthly system peaks. The model is estimated with historical data from January 2004 through July 2018. The model is summarized in Table 3-38 and Table 3-39.

Table 3-38 - System Peak Model

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	346.129	142.472	2.429	1.63%
HDD x Heating Trend	9.957	0.359	27.746	0.00%
CDD x Cooling Trend	27.012	0.789	34.235	0.00%
Cooling Peak CDD 85	-19.527	4.077	-4.790	0.00%
Other Trend Index	328.126	129.758	2.529	1.25%
January 2012 Plus x Winter Energy Trend	12.226	13.536	0.903	36.79%
April	-30.180	12.128	-2.488	1.39%
May	-11.979	10.548	-1.136	25.79%
October	-26.381	12.157	-2.170	3.16%

Table 3-39 - System Peak Model Statistics

Statistics	Public Authority Customer Model
Estimation	1/2004 – 7/2018
R2	0.945
Adj. R2	0.942
MAPE	3.10%
DW	1.597

1. Model Variables: The system peak model is primarily driven by the energy forecast and peak producing weather. The variables are discussed below:

    a. HDD x Heating Trend: This is an interacted variable combining the effects of weather and changes in heating technologies. The weather effect is modeled as the number of degrees the three-day weighted average temperature falls below 45 degrees (HDD). The changes in heating technologies (Heating Trend) are obtained from the weather-normalized heating components of the class energy models. The Heating Trend is smoothed and interacted with the HDD variable.

b. CDD x Cooling Trend: This is an interacted variable combining the effects of weather and changes in cooling technologies. The weather effect is modeled as the number of degrees the three-day weighted average temperature exceeds 70 degrees (CDD). The changes in cooling technologies (Cooling Trend) are obtained from the weather-normalized cooling components of the class energy models. The Cooling Trend is smoothed and interacted with the CDD variable

c. Cooling Peak CDD85: The variable captures a flattening of the summer peak weather response when the three-day weighted average temperature exceeds 85 degrees.

d. Other Trend Index: The Other Trend Index captures the non-HVAC growth trends of the energy models.

e. January 2012 Plus x Winter Energy Trend: The winter energy trend variable is created by the interaction of the energy trend with a binary variable that is active in Januarys after 2012. This variable is designed to capture additional growth in the winter peak above the energy trend and maintain modeling consistency between the 2016 and 2019 IRP.

f. Monthly Binaries: The April, May, and October binaries capture minor seasonal shifts due to shoulder month impacts.

6.1.2.9 Profile Model

1. Data Development: Liberty-Empire maintains an active load research program. Unfortunately, the program is not designed to forecast load shapes by the classes identified in this forecast process. To obtain historical load shape data

for the profile models, the load research data are aggregated based on the annual average 2017 customer counts associated with each rate in the class.

Table 3-40 shows the class and the weights used for each load research profile.

Table 3-40 - Load Research to Class Profile Mapping

Class	Load Research	Weight
Residential	Residential	100.00%
Commercial	CB GP - Secondary SH TEB	77% 7% 13% 4%
Wholesale	Monett, Mt. Vernon, Lockwood, Chetopa	NA
Street Highway	CB Generic Lighting Shape SH	80% 19% 1%
Interdepartmental	CB GP - Secondary	85% 15%
Industrial: Other Industrial	CB GP - Secondary LP - Primary SH TEB	25% 56% 9% 5% 5%
Industrial: Praxair	Praxair	NA
Industrial: OPP	GP - Primary LP - Primary	55% 45%

2. Profile Models: The profile models consist of a standard set of variables that identify hourly shapes based on the time of the year and weather response. All models are regression models. Table 3-41 identifies the sets of variables used in each profile model. Definitions of the variables are summarized below:

Table 3-41 - Model Variable Classes

Class	HDD CDD	Day of Week	Month	Year	Holiday	Hours of Light
Residential	X	X	X	X	X	X
Commercial	X	X		X	X	X
Wholesale (Monett, Lockwood, Chetopa, Mt. Vernon)	X	X	X	X	X	
Street Highway	X	X	X	X	X	
Interdepartmental	X	X		X	X	
Industrial: Other Industrial	X	X		X	X	
Industrial: Praxair						
Industrial: OPP	X	X		X	X	

a. Heating and Cooling Splines: HDD and CDD spline variables are weighted multi-part variables used to capture the nonlinear load-weather response. For each class, 5-degree break points were examined to identify changes in the weather response. Statistically significant breakpoints are weighted together to create the weighted average HDD and CDD variables.

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

c. Annual Binaries: Annual binaries capture load growth contained in the load research data. When modeling load shape over the long-term horizon, the profile models assume no load growth in the profile shape. As such, the annual binary variables capture historic changes so that these changes do not influence the other variables.

d. Holidays: Key holidays are identified using this set of binary variables. These holidays capture the unique shape for specific holidays.

e. Monthly Binaries: Monthly binary variables are used to capture the underlying load shape variation through the seasons of the year.

f. Hours of Light: This variable is calculated based on the sunrise and sunset time at Springfield, Missouri. The hours of light variable contain the number of sunlight hours in each day.

3. Model Exceptions: The following three exceptions are made in the profile modeling process:

   a. Wholesale Class: Each wholesale customer is modeled separately based on their actual load data, not load research data.

   b. Street Highway Class: The street and highway class includes a large percentage of outside lighting accounts. Because no load research data were available for lighting accounts, a generic commercial outside light shape from Itron's shape library was used in developing the historical data.

   c. Industrial - Praxair: Praxair is a single large industrial customer. Because historical data were available for this customer, no load research data were used. Due to the unpredictable nature of the Praxair hourly consumption, a flat profile is used as an approximation of the load profile.

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;

Liberty-Empire maintains a historical data set of more than 10 years of historical values for independent variables.

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 12 years, Liberty-Empire has filed IRP forecasts in 2007, 2010, 2013, and 2016. Because the 2007 and 2010 IRP filings employed a substantially different method than the 2013, 2016 and 2019 filings, key driver comparisons are not possible. However, the 2013 through 2019 filings use a similar structure and class definitions which provide a reasonable basis for comparisons.

For the economic data, comparisons of employment, households, and population drivers are shown in Figure 3-10 through Figure 3-12. In 2013, the economic drivers are based on state-level economics. In 2016 and 2019, the economics drivers are based on Joplin and Springfield MSA-level economics. All drivers are indexed for comparative purposes.

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Figure 3-10 - Comparison 2013, 2016, and 2019 IRP Employment Index

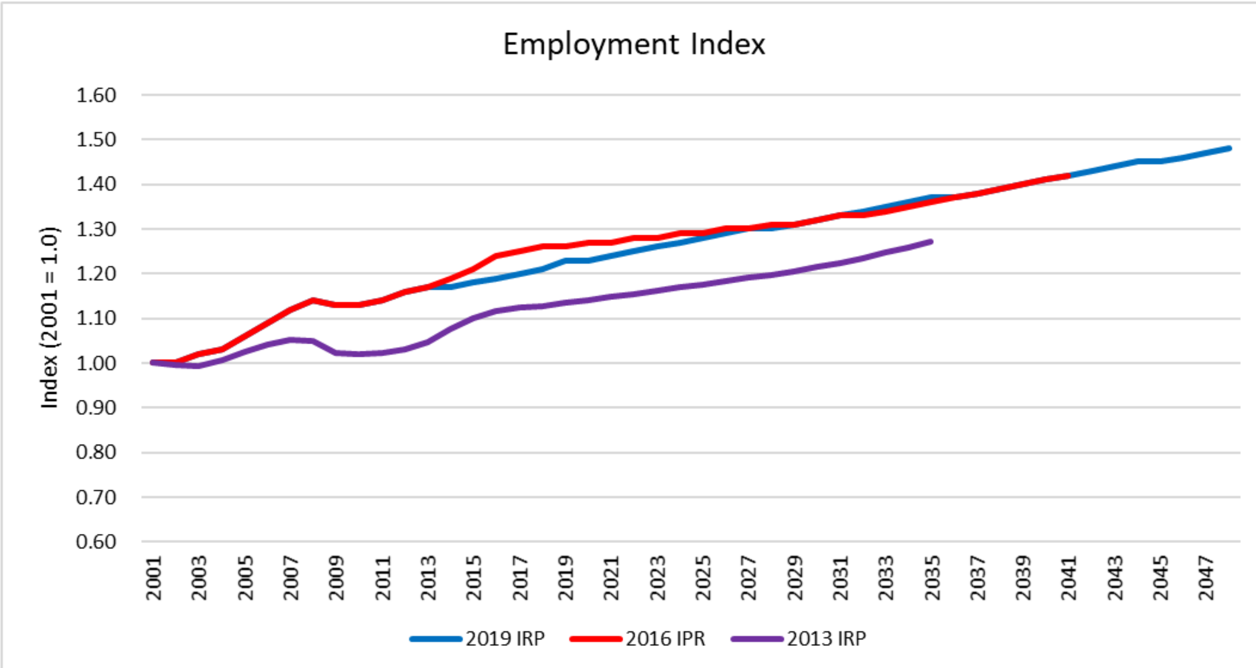


Figure 3-11 - Comparison 2013, 2016, and 2019 IRP Population Index

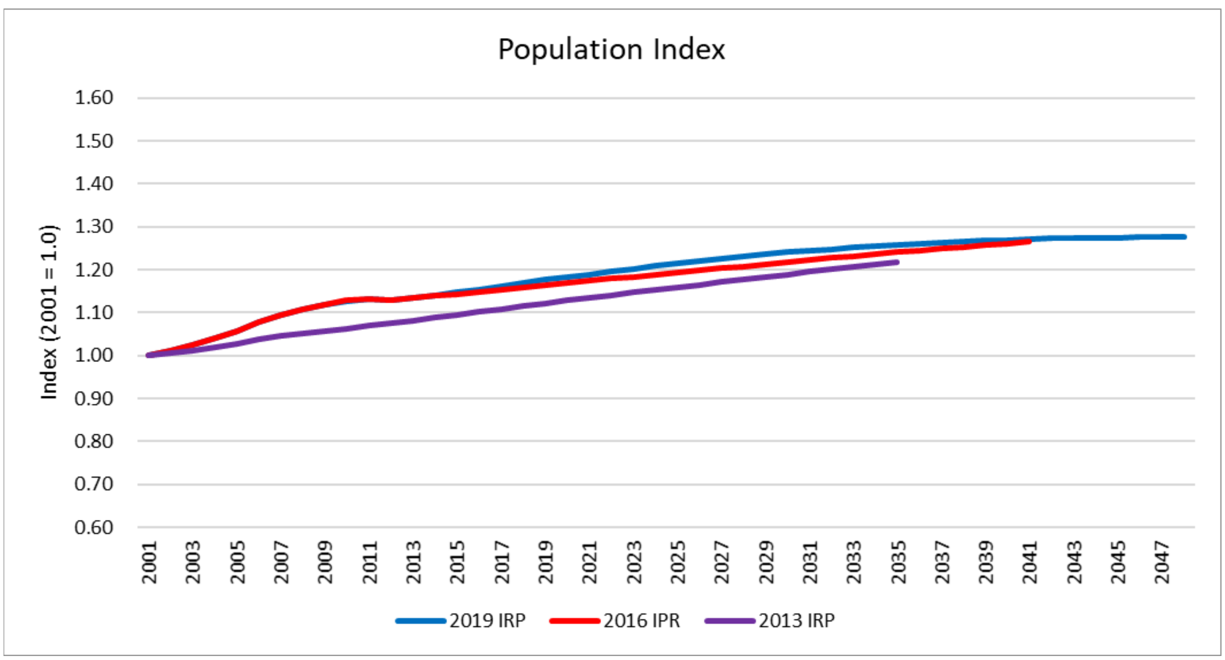
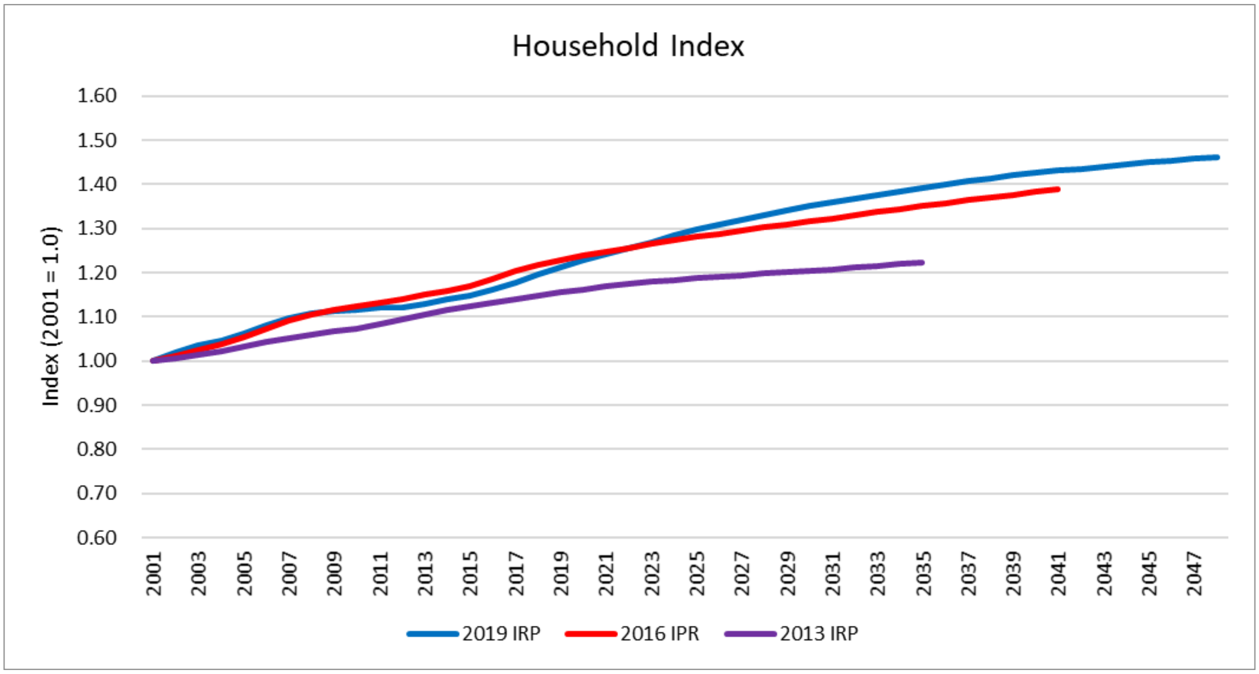


Figure 3-12 - Comparison 2013, 2016, and 2019 IRP Household Index



The SAE data captures end-use changes in technology saturation and efficiencies. These data are obtained from Itron and developed into the end-use driver variables for the models. The 2013 IRP uses data from Itron's 2011 SAE database. The 2016 IRP uses data from Itron's 2015 SAE database, and the 2019 IRP uses data from Itron's 2018 SAE database. Figure 3-13 through Figure 3-15 compare the SAE intensity indexes for residential heating, cooling, and other (baseload). The residential other index includes electric vehicles and behind-the-meter solar. Figure 3-16 through Figure 3-18 compare SAE indices for commercial heating, cooling, and other (non-HVAC). The commercial other includes behind-the-meter solar.

Figure 3-13 - Comparison 2013, 2016, and 2019 IRP Residential Heating Index

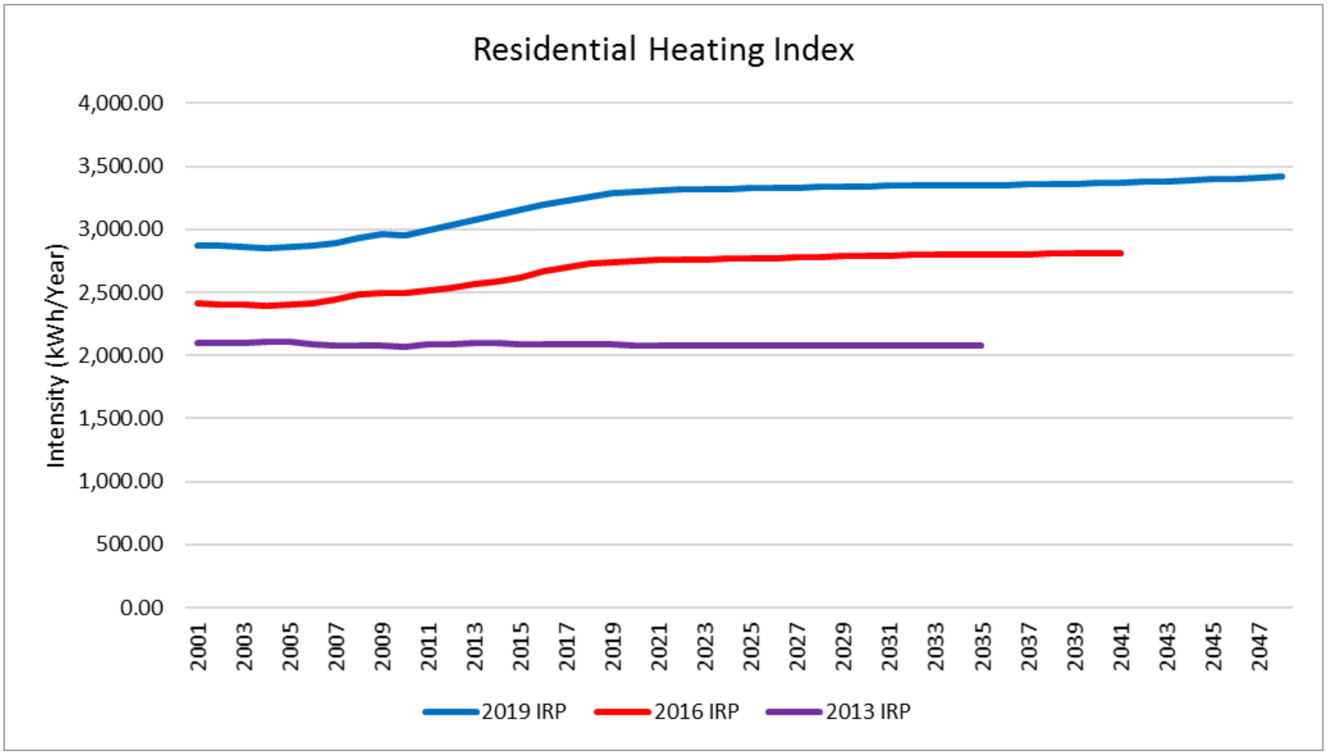


Figure 3-14 - Comparison 2013, 2016, and 2019 IRP Residential Cooling Index

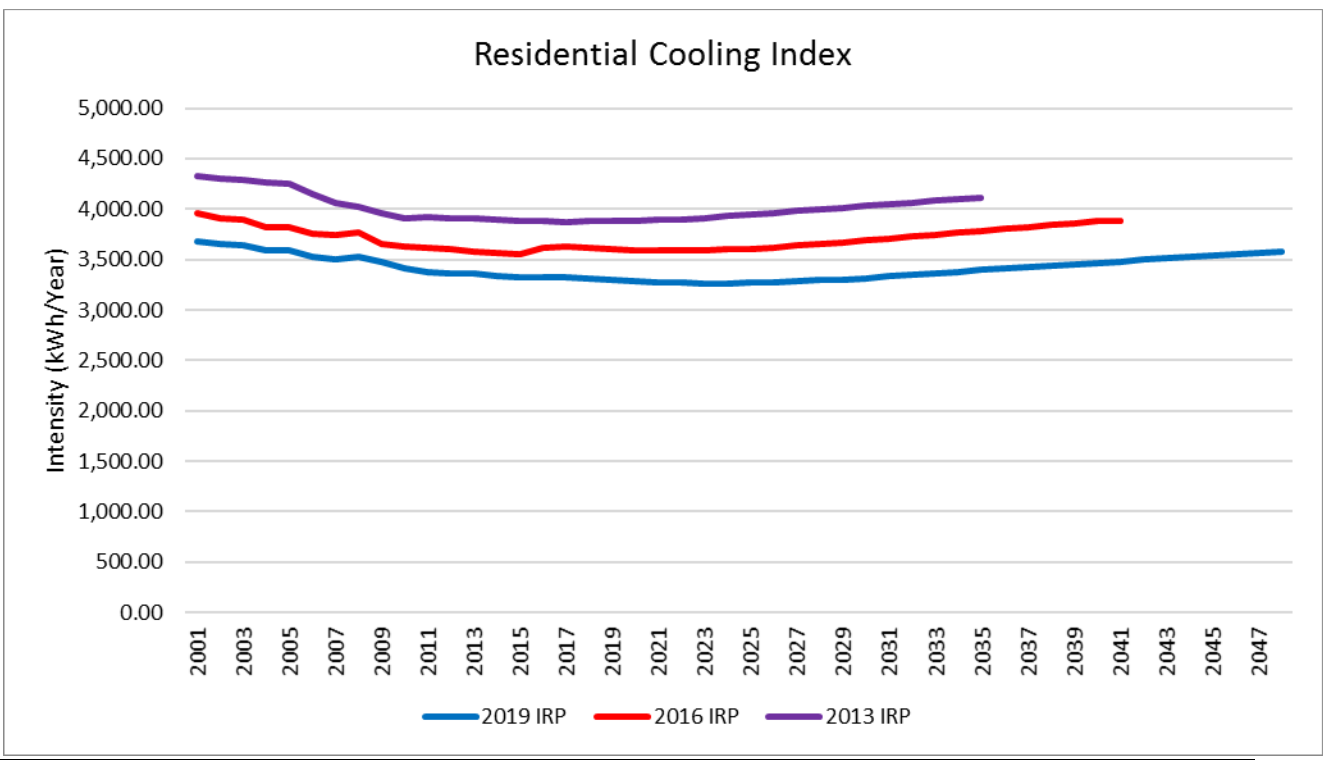


Figure 3-15 - Comparison 2013, 2016 IRP, and 2019 Residential Other Index

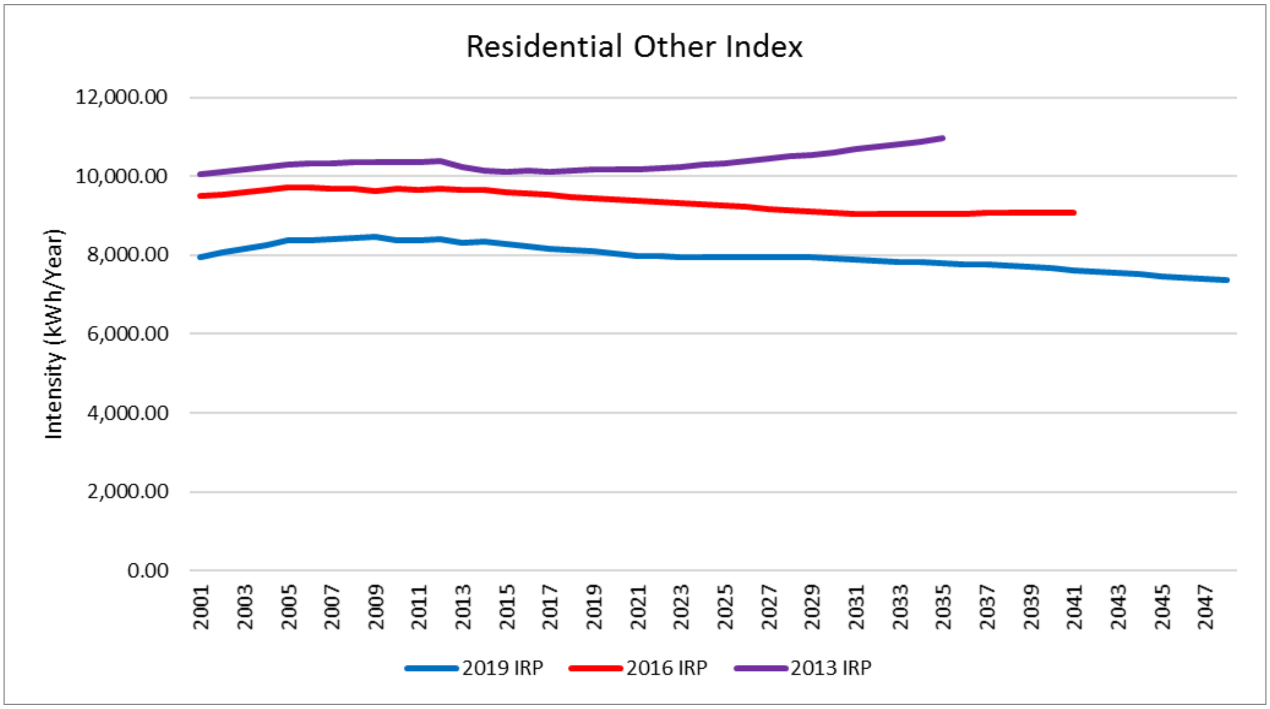


Figure 3-16 - Comparison 2013, 2016, and 2019 IRP Commercial Heating Index

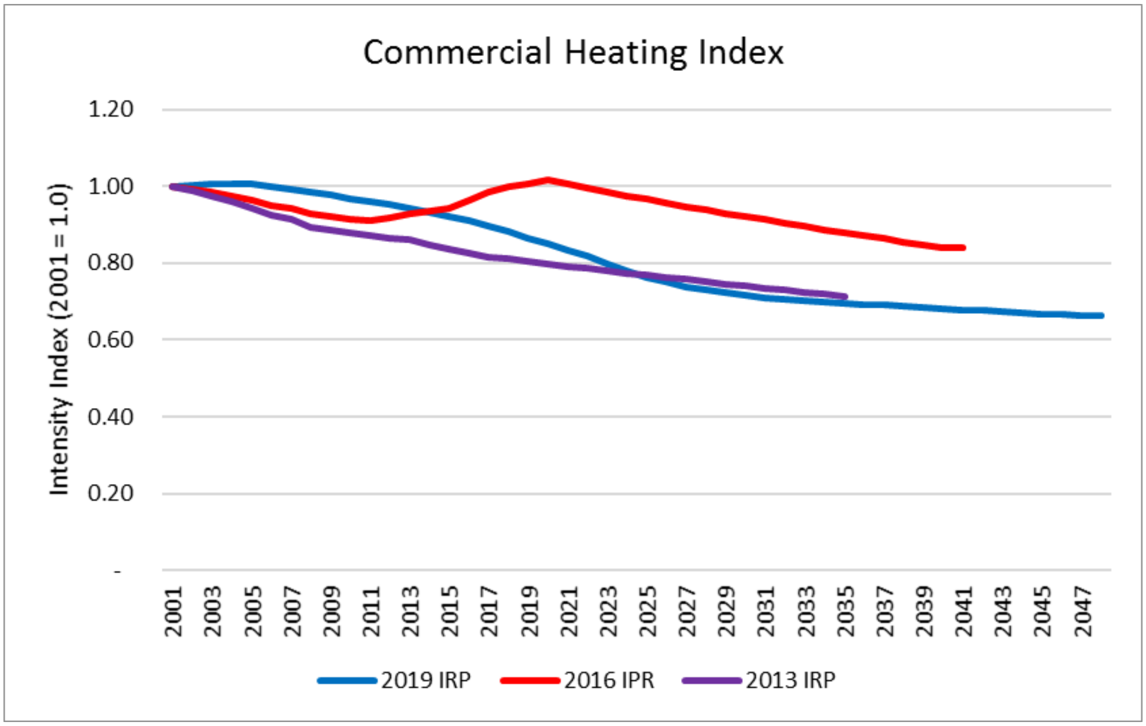


Figure 3-17 - Comparison 2013, 2016, and 2019 IRP Commercial Cooling Index

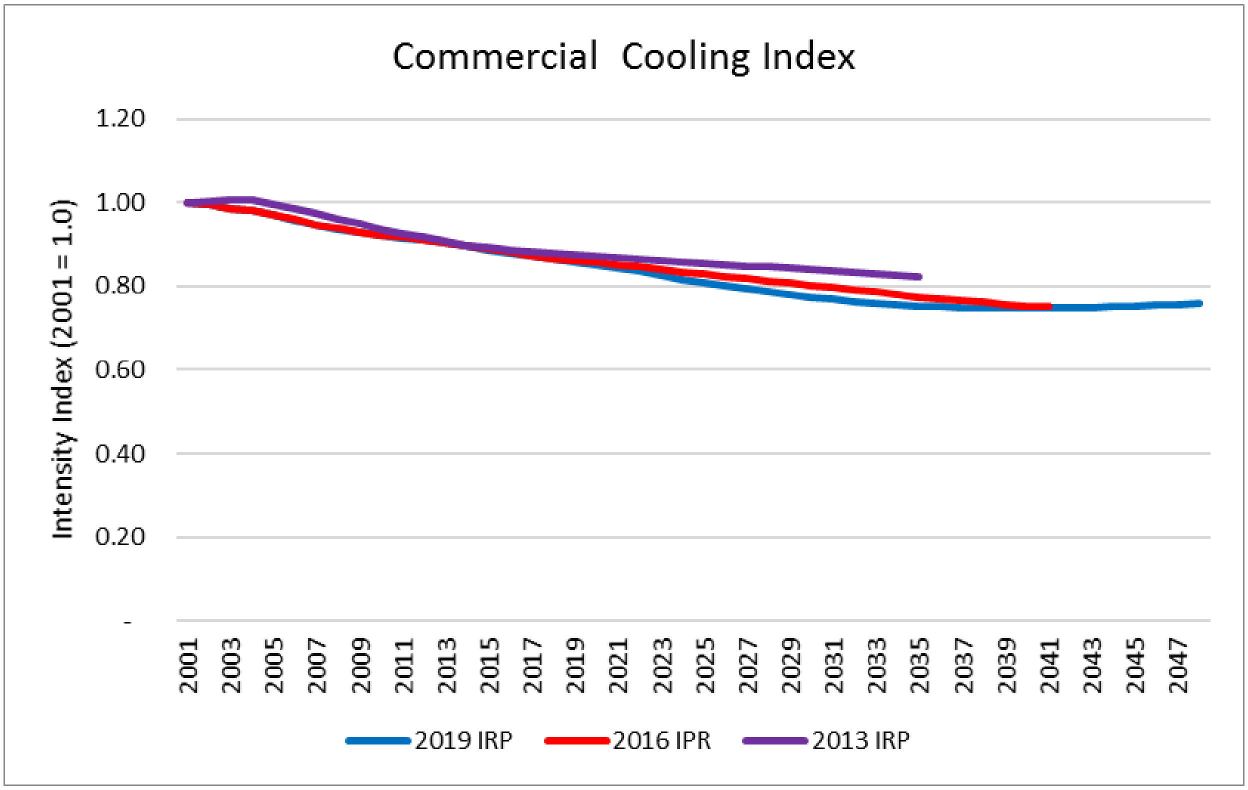
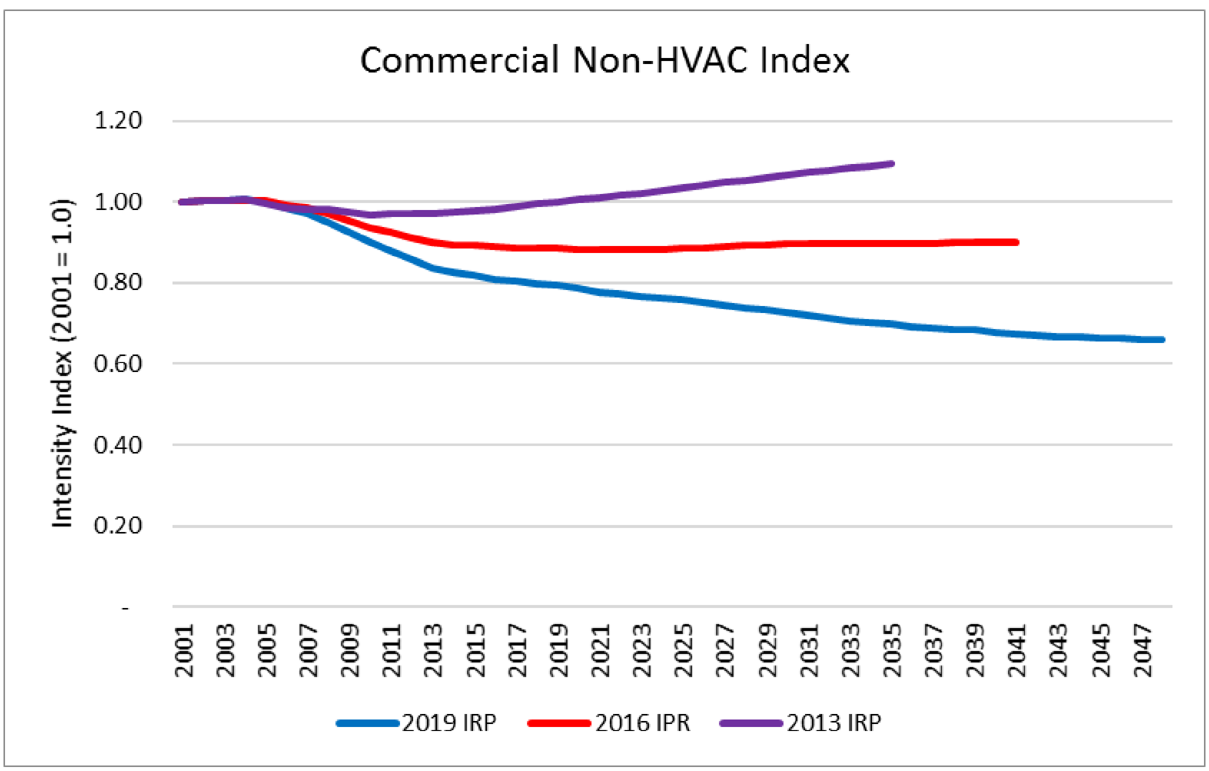


Figure 3-18 - Comparison 2013, 2016, and 2019 IRP Commercial Other Index



The weather assumptions for the 2019 IRP is updated to reflect a new historic period for normal weather. Table 3-42 shows historic annual heating and cooling degree days from 2001 through 2017 compared with the 2013, 2016, and 2019 normal assumptions. Heating and cooling degree days are based on a 65-degree reference point.

Table 3-42 - Historical and IRP Normal Heating Degree Days and Cooling Degree Days

Year	HDD Base 65	CDD Base 65
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	1,666
2017	3,566	1,365
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 input (MWh) and system peak (MW) to forecasts in the 2007 through 2019 IRPs are shown in Table 3-43 through Table 3-45. In these tables, actual values are not weather-normalized. Figure 3-19 through Figure 3-21 compare the five IRP forecasts against actual values.

The range of historic forecasts captures the evolution of customer usage and the changing economic and end-use assumptions over the past 12 years. Specific modeling differences between the 2016 and 2019 IRP forecasts can be seen in Table 3-5. Assumption differences can be viewed in Section 6.3.3.

Table 3-43 - Historical and Base Forecasts for 2007 through 2019 IRPs - Total Customers

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[redacted]

[6] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-19 - Comparison of Total Electric Customers Actual Historical and 2007 through 2019 IRP Base Forecasts

****Confidential in its Entirety**[7]**

[redacted]

[7] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Table 3-44 - Historical and Base Forecasts for 2007 through 2019 IRPs - Energy Net System Input (MWh)

Year	Actual	2019 IRP	2016 IRP	2013 IRP	2010 IRP	2007 IRP
1990	3,029,425					
1991	3,208,554					
1992	3,151,977					
1993	3,552,901					
1994	3,720,515					
1995	3,937,177					
1996	4,204,598					
1997	4,250,155					
1998	4,471,314					
1999	4,473,229					
2000	4,794,585					
2001	4,800,756					
2002	4,917,875					
2003	4,950,161					
2004	4,972,159					
2005	5,293,643					
2006	5,330,214					
2007	5,485,658					5,537,354
2008	5,493,653					5,702,917
2009	5,263,206					5,864,927
2010	5,584,282				5,475,998	6,044,727
2011	5,452,111				5,572,170	6,219,337
2012	5,221,481				5,681,231	6,398,012
2013	5,314,210			5,324,210	5,795,281	6,579,619
2014	5,379,836			5,354,520	5,911,622	6,764,775
2015	5,281,346			5,388,547	6,038,721	6,953,604
2016	5,290,273		5,374,142	5,429,509	6,171,573	7,145,991
2017	5,143,008		5,396,328	5,473,270	6,313,519	7,341,880
2018		5,612,302	5,406,325	5,519,525	6,465,044	7,540,943
2019		5,484,665	5,413,159	5,568,083	6,626,670	7,743,765
2020		5,279,656	5,415,984	5,612,778	6,792,337	7,951,030
2021		5,154,776	5,420,751	5,659,982	6,962,145	8,162,735
2022		5,177,325	5,429,974	5,708,978	7,136,199	8,379,486
2023		5,200,864	5,440,860	5,759,197	7,314,604	8,600,629
2024		5,228,965	5,454,227	5,812,596	7,497,469	8,826,436
2025		5,255,290	5,468,732	5,864,549	7,684,905	9,056,088

Year	Actual	2019 IRP	2016 IRP	2013 IRP	2010 IRP	2007 IRP
2026		5,274,228	5,481,519	5,919,206	7,877,028	9,290,588
2027		5,293,576	5,496,648	5,976,005	8,073,954	
2028		5,315,110	5,513,520	6,037,165	8,275,802	
2029		5,338,465	5,531,126	6,096,783	8,482,698	
2030		5,351,778	5,546,889	6,158,261		
2031		5,365,222	5,564,385	6,220,513		
2032		5,378,583	5,583,240	6,285,480		
2033		5,392,921	5,603,514			
2034		5,409,641	5,624,242			
2035		5,427,969	5,646,261			
2036		5,446,817				
2037		5,466,466				
2038		5,486,734				
2039		5,507,074				
2040		5,520,090				
2041		5,533,929				
2042		5,546,660				
2043		5,560,309				
2044		5,574,524				
2045		5,589,007				
2046		5,604,316				
2047		5,621,303				
2048		5,638,809				

Figure 3-20 - Comparison of Energy Net System Input (MWh)

Actual Historical and 2007 through 2019 Base Forecasts

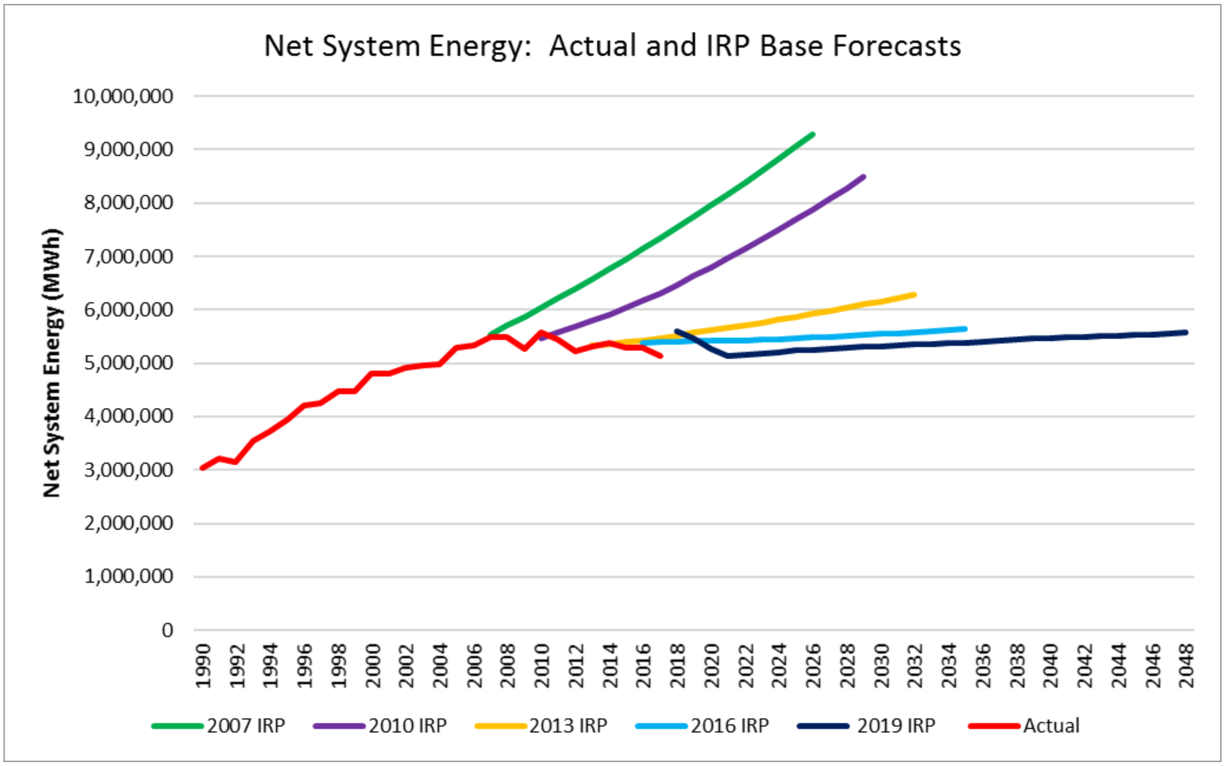


Table 3-45 - Historical and Base Forecasts for 2007 through 2019 IRPs - Net Peak (MW)

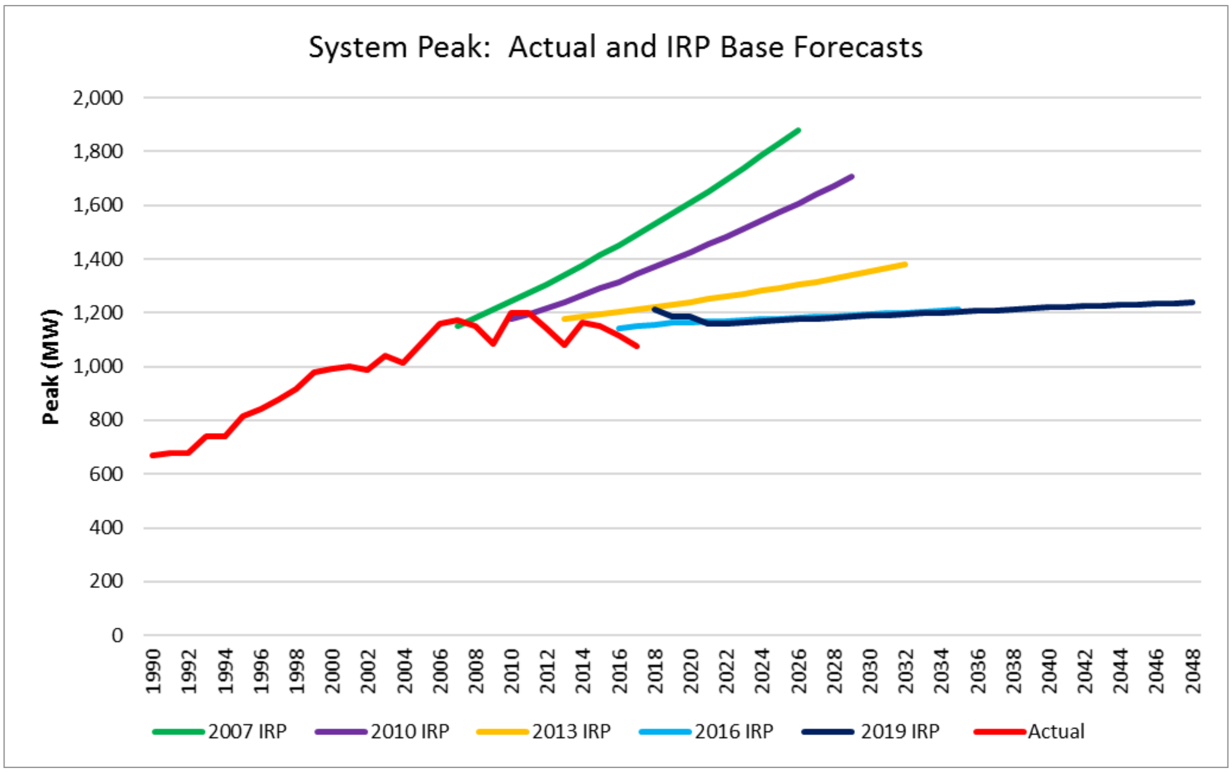
Year	Actual	2019 IRP	2016 IRP	2013 IRP	2010 IRP	2007 IRP
1990	668					
1991	678					
1992	680					
1993	739					
1994	741					
1995	815					
1996	842					
1997	876					
1998	916					
1999	979					
2000	993					
2001	1,001					
2002	987					

Year	Actual	2019 IRP	2016 IRP	2013 IRP	2010 IRP	2007 IRP
2003	1,041					
2004	1,014					
2005	1,087					
2006	1,159					
2007	1,173					1,149
2008	1,152					1,180
2009	1,085					1,211
2010	1,199				1,179	1,242
2011	1,198				1,196	1,273
2012	1,142				1,216	1,306
2013	1,080			1,179	1,240	1,341
2014	1,162			1,187	1,265	1,377
2015	1,149			1,194	1,290	1,414
2016	1,114		1,143	1,203	1,316	1,451
2017	1,075		1,151	1,212	1,343	1,490
2018		1,211	1,157	1,221	1,370	1,529
2019		1,185	1,162	1,231	1,397	1,569
2020		1,188	1,165	1,240	1,426	1,610
2021		1,158	1,168	1,250	1,454	1,651
2022		1,161	1,170	1,260	1,483	1,694
2023		1,165	1,172	1,270	1,513	1,739
2024		1,169	1,175	1,281	1,544	1,785
2025		1,173	1,178	1,292	1,575	1,832
2026		1,176	1,181	1,303	1,606	1,881
2027		1,179	1,184	1,315	1,639	
2028		1,183	1,187	1,327	1,672	
2029		1,186	1,191	1,339	1,705	
2030		1,189	1,194	1,352		
2031		1,192	1,198	1,365		
2032		1,195	1,201	1,378		
2033		1,198	1,204			
2034		1,201	1,208			
2035		1,204	1,212			
2036		1,207				
2037		1,210				
2038		1,213				
2039		1,216				
2040		1,219				
2041		1,221				

Year	Actual	2019 IRP	2016 IRP	2013 IRP	2010 IRP	2007 IRP
2042		1,224				
2043		1,226				
2044		1,229				
2045		1,231				
2046		1,234				
2047		1,236				
2048		1,239				

Figure 3-21 - Comparison of System Peak (MW) Actual Historical

2007, 2010, and 2013 IRP Base Forecasts



SECTION 7 BASE-CASE LOAD FORECAST

(7) 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 in 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 the SAE model for the residential and commercial classes. The SAE model uses the EIA AEO 2018 as the foundation for long term energy efficiency trends. The EIA AEO accounts for 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 by estimating statistical models over a historical time period. Consistency with historical consumption patterns is shown in the model statistical fit. The statistics for each model are shown in Section 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, commercial and industrial classes are obtained by applying the weather variable coefficient from the statistical models to the normal weather data. The results of this calculation are the energy associated with heating and cooling. Non-heating and cooling loads are assumed to be base load (non-weather-sensitive load). Table 3-46 summarizes the monthly data heating and cooling data for the major classes into annual values.

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Table 3-46 - Annual Heating, Cooling, and Base Load Components

of the R, C, and I Classes MWh (Billed Year Basis)

Confidential in its Entirety[8]

[redacted]

[8]4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

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.

The final industrial forecast is adjusted to reflect known customer expansions. Beginning in 2018, the forecast is increased by 89,959 kWh to reflect additional sales after July 2018 from customer expansions. The full impact of these customer expansions results in an increase of 111,155 kWh above the sales reflected through 2030. This increase is shown in Table 3-47. After 2030, the increase continues at the same level through the planning period.

Table 3-47 - Industrial Forecast Adjustment

Year	Energy (kWh)	Capacity (kW)
2018	89,959	9,263
2019	111,155	9,263
2020	111,155	9,263
2021	111,155	9,263
2022	111,155	9,263
2023	111,155	9,263
2024	111,155	9,263
2025	111,155	9,263
2026	111,155	9,263
2027	111,155	9,263
2028	111,155	9,263
2029	111,155	9,263
2030	111,155	9,263

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 Energy Forecast: Residential Annual

The residential energy forecast is developed as the product of the customer model and UPC forecast. Figure 3-22 through Figure 3-24 show the annual energy forecast, customer forecast, and UPC forecast. Both the energy and UPC figures show normalized energy and UPC for comparative purposes. Table 3-48 and Table 3-49 summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates. In the tables, 2017 is the last full year of actual data, and 2019 is the first full year of forecast data. When shown, 2018 values consist of actual values through July and forecast values from August through December.

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Figure 3-22 - Residential Energy Annual Forecast
****Confidential in its Entirety**[9]**

[redacted]

Figure 3-23 - Residential Customer Forecast
****Confidential in its Entirety**[9]**

[redacted]

[9] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

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Figure 3-24 - Residential UPC Forecast

****Confidential in its Entirety**[10]**

[redacted]

Table 3-48 - Residential Energy Forecast Summary

****Confidential in its Entirety**[10]**

[redacted]

[10]4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Table 3-49 - Residential Energy Forecast Average Annual Growth Rates

****Confidential in its Entirety**[11]**

[redacted]

7.1.6.1.2 Energy Forecast: Commercial Energy Annual

The commercial energy forecast is developed as the product of the customer model and UPC forecast. Table 3-25 through Table 3-27 show the annual energy forecast, customer forecast, and UPC forecast. Both the energy and UPC figures show normalized energy and UPC for comparative purposes.

Table 3-50 and Table 3-51 summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates. In the tables, 2017 is the last full year of actual data, and 2019 is the first full year of forecast data. When shown, 2018 values consist of actual values through July and forecast values from August through December.

[11] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-25 - Commercial Energy Forecast
****Confidential in its Entirety**[12]**

[redacted]

Figure 3-26 - Commercial Customer Forecast
****Confidential in its Entirety**[12]**

[redacted]

[12] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-27 - Commercial UPC Forecast

****Confidential in its Entirety**[13]**

[redacted]

Table 3-50 - Commercial Energy Forecast Summary

****Confidential in its Entirety**[13]**

[redacted]

[13] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Table 3-51 - Commercial Energy Forecast Average Annual Growth Rates

****Confidential in its Entirety**[14]**

[redacted]

7.1.6.1.3 Energy Forecast: Wholesale Energy Annual

The wholesale energy forecast is developed as the sum of the four municipal utility energy models. In July 2020, the contracts with Monett, Mt. Vernon, and Chetopa will end. This forecast removes these three municipals from the forecast beginning in August 2020. As a result, the 2020 sales show a significant decrease with no sales to these three municipals beginning in 2021. Figure 3-28 shows the total energy forecast is shown. Table 3-52 and Table 3-53 summarize the annual energy forecast and show the forecasts for each municipal utility for comparative purposes.

[14] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

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Figure 3-28 - Wholesale Energy Forecast

****Confidential in its Entirety**[15]**

[redacted]

Table 3-52 - Wholesale Energy Forecast Summary

**** Confidential in its Entirety**[15]**

[redacted]

[15] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Table 3-53 - Wholesale Energy Forecast Average Annual Growth Rates

****Confidential in its Entirety**[16]**

[redacted]

7.1.6.1.4 Energy Forecast: Street and Highway Annual

The street and highway energy forecast is developed as the product of the customer model and UPC forecast. Figure 3-29 through Figure 3-31 show the annual energy forecast, customer forecast, and UPC forecast. Table 3-54 and Table 3-55 summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates.

Figure 3-29 - Street and Highway Annual Energy Forecast

****Confidential in its Entirety**[16]**

[redacted]

[16] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-30 - Street and Highway Customer Forecast
****Confidential in its Entirety**[17]**

[redacted]

Figure 3-31 - Street and Highway UPC Forecast
****Confidential in its Entirety**[17]**

[redacted]

[17] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Table 3-54 - Street and Highway Energy Forecast Summary

****Confidential in its Entirety**[18]**

[redacted]

Table 3-55 - Street and Highway Energy Forecast Average Annual Growth Rates

****Confidential in its Entirety**[18]**

[redacted]

7.1.6.1.5 Energy Forecast: Interdepartmental Annual

The interdepartmental energy forecast is developed as the product of the customer model and the UPC forecast. The forecast is designed to be flat with no expected addition of customers or change in annual UPC. Figure 3-32 through Figure 3-34 shows the annual energy forecast, customer forecast, and UPC forecast. Table 3-56 and Table 3-57 summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates.

[18] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

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Figure 3-32 - Interdepartmental Annual Energy Forecast
****Confidential in its Entirety**[19]**

[redacted]

Figure 3-33 - Interdepartmental Customer Forecast
****Confidential in its Entirety**[19]**

[redacted]

[19] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information

Figure 3-34 - Interdepartmental UPC Forecast
****Confidential in its Entirety**[20]**

[redacted]

Table 3-56 – Interdepartmental Energy Forecast Summary
****Confidential in its Entirety**[20]**

[redacted]

[20] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information

Table 3-57 - Interdepartmental Energy Forecast Average Annual Growth Rates

****Confidential in its Entirety**[21]**

[redacted]

7.1.6.1.6 Energy Forecast: Public Authority Annual

The public authority energy forecast is developed as the product of the customer model and the UPC forecast. The forecast grows based on government employment. However, average usage remains. Figure 3-35 through Figure 3-37 show the annual energy forecast, customer forecast, and UPC forecast. Table 3-58 and Table 3-59 summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates.

[21] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information

Figure 3-35 - Public Authority Annual Energy Forecast

****Confidential in its Entirety**[22]**

[redacted]

Figure 3-36 - Public Authority Customer Forecast

****Confidential in its Entirety**[22]**

[redacted]

[22] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information

Figure 3-37 - Public Authority UPC Forecast

****Confidential in its Entirety**[23]**

[redacted]

Table 3-58 - Public Authority Energy Forecast Summary

****Confidential in its Entirety**[23]**

[redacted]

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[23] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Table 3-59 - Public Authority Energy Forecast Annual Growth Rates
****Confidential in its Entirety**[24]**

[redacted]

7.1.6.1.7 Energy Forecast: Industrial Energy Forecast

The industrial energy forecast is the sum of the Praxair, the oil and pipelines, and other industrial forecasts. For all sectors, the forecast models are designed to hold the number of customers and use-per-customer constant through the planning period. However, the other industrial segment forecast is increased by customer expansions totaling 111,155 MWh/year by 2019.

Figure 3-38 through Figure 3-40 show the annual energy forecast, customer forecast, and UPC forecast. Table 3-60 and Table 3-61 summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates.

[24] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-38 - Industrial Energy Annual Forecast
****Confidential in its Entirety**[25]**

[redacted]

Figure 3-39 - Industrial Customer Forecast
****Confidential in its Entirety**[25]**

[redacted]

[25] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-40 - Industrial UPC Forecast

****Confidential in its Entirety**[26]**

[redacted]

Table 3-60 - Industrial Energy Forecast Summary
****Confidential in its Entirety**[26]**

[redacted]

[26] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Table 3-61 - Industrial Energy Forecast Average Annual Growth Rates
****Confidential in its Entirety**[27]**

[redacted]

7.1.6.1.8 Peak Summer/Winter Month Energy

The peak summer and winter month energy forecast, coincident with the seasonal peak, by residential, commercial, industrial, and other classes are shown in Figure 3-41 and Figure 3-42, respectively. Other classes consist of municipals, public authority, interdepartmental, and streets/highways. These classes are aggregated due to the small sizes.

Figure 3-41 - Peak Summer Calendar Month Energy (MWh)
****Confidential in its Entirety**[27]**

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[redacted]

27 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-42 - Peak Winter Calendar Month Energy (MWh)

****Confidential in its Entirety**[28]**

[redacted]

7.1.6.2 Class Level Coincident Peak Forecasts: System Level Peak

System level peaks are shown in Figure 3-43 and Figure 3-44 for each season.

[28] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-43 - System Summer Peak Forecast

****Confidential in its Entirety**[29]**

[redacted]

Figure 3-44 - System Winter Peak Forecast
****Confidential in its Entirety**[29]**

[redacted]

[29] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

7.1.6.2.2 Class Level Coincident Peaks

Class level coincident peaks are estimated by calibrating an hourly profile model forecast to the monthly energy and peak forecast. The models used are described in Section 6.1.2. The results are shown in Figure 3-45 through Figure 3-50 for the residential, commercial, and industrial classes. Coincident peak values are shown in Table 3-62 and Table 3-63. Year-to-year variations in class peaks occur based on class growth and variations in the consumption patterns based on the days of the week.

Figure 3-45 - Residential Coincident Summer Peak Forecast

****Confidential in its Entirety**[30]**

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[redacted]

30 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-46 - Residential Coincident Winter Peak Forecast

****Confidential in its Entirety**[31]**

[redacted]

Figure 3-47 - Commercial Coincident Summer Peak Forecast

****Confidential in its Entirety**[31]**

[redacted]

[31] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

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Figure 3-48 - Commercial Coincident Winter Peak Forecast
****Confidential in its Entirety**[32]**

[redacted]

Figure 3-49 - Industrial Coincident Summer Peak Forecast

****Confidential in its Entirety**[32]**

[redacted]

[32]4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-50 - Industrial Coincident Winter Peak Forecast
****Confidential in its Entirety**[33]**

[redacted]

[33] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

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Table 3-62 – Summer Coincident Peak by Class
****Confidential in its Entirety**[34]**

[redacted]

[34] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

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Table 3-63 - Winter Coincident Peak by Class

****Confidential in its Entirety**[35]**

[redacted]

[35] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

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.*

Forecasted hourly load profiles for the base, 5th, 10th, and 20th years broken out by summer and winter peak days for each major class and system level are shown in Figure 3-51 through Figure 3-58.

Figure 3-51 - Forecasted Residential Summer Peak Day Profiles

****Confidential in its Entirety****[36]

[redacted]

[36] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-52 - Forecasted Residential Winter Peak Day Profiles

****Confidential in its Entirety**[37]**

[redacted]

Figure 3-53 - Forecasted Commercial Summer Peak Day Profiles

****Confidential in its Entirety**[37]**

[redacted]

[37] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-54 - Forecasted Commercial Winter Peak Day Profiles

****Confidential in its Entirety**[38]**

[redacted]

Figure 3-55 - Forecasted Industrial Summer Peak Day Profiles

****Confidential in its Entirety**[38]**

[redacted]

[38] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-56 - Forecasted Industrial Winter Peak Day Profiles

****Confidential in its Entirety**[39]**

[redacted]

Figure 3-57 - Forecasted System Summer Peak Day Profiles

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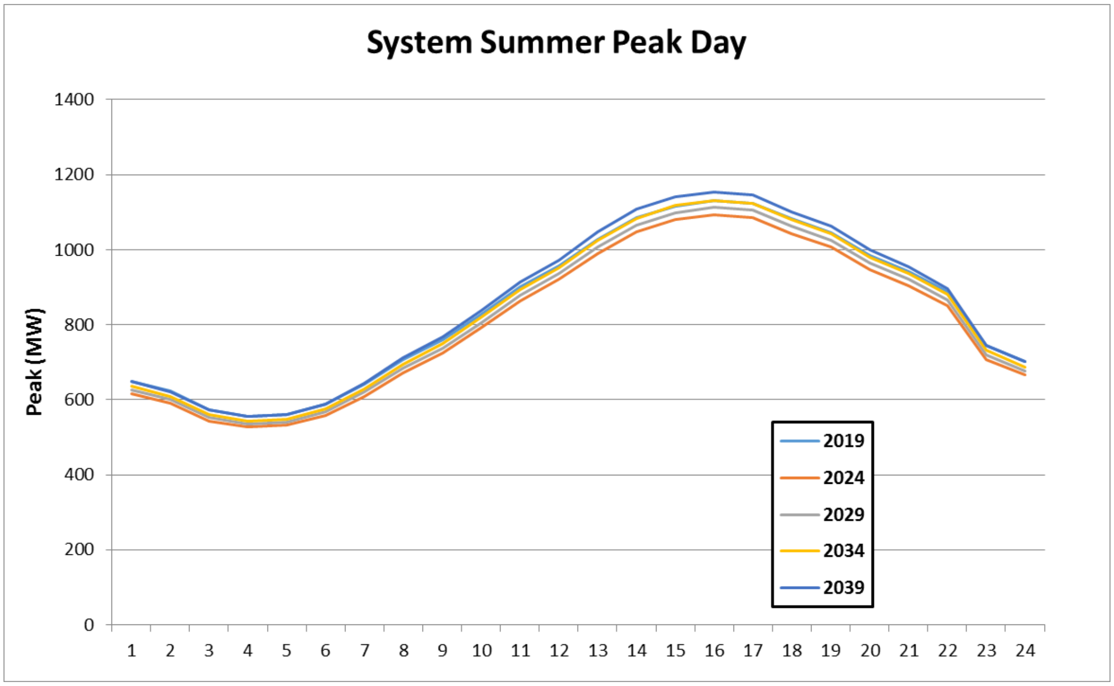
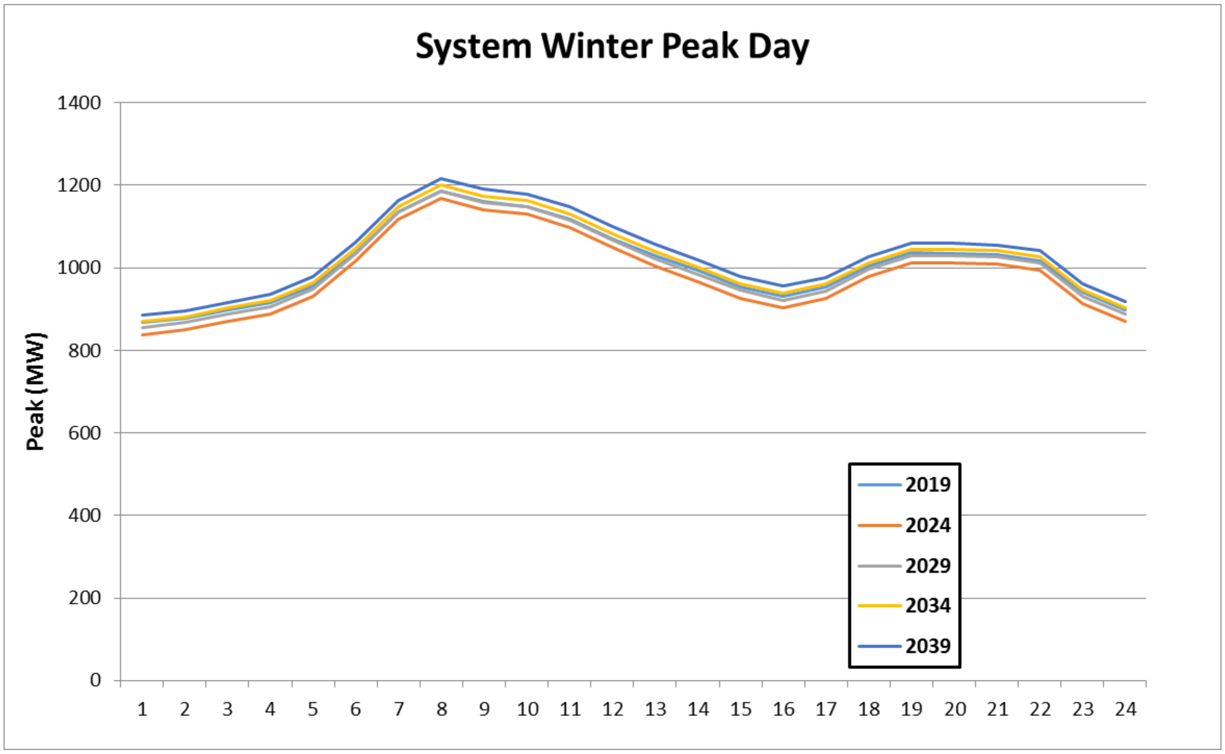


[39] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when it is customer specific information.

Figure 3-58 - Forecasted System Winter Peak Day Profiles



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. Six classes of independent variables are used in the forecast. Two classes (economic data and end-use data), are obtained from external vendors. Economic data are obtained from Moody's Analytics. End-use data are obtained from Itron. The remaining four classes (prices, weather, solar, and electric vehicles) are calculated internal to the forecasting process. Prices are assumed flat in real dollars. Temperatures are calculated as 30-year normal values. Solar and electric vehicle forecasts are developed based on EIA growth rates. 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 in Section 2.4.3.

7.2.4 Judgment 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.

Judgment is applied to the industrial class forecast. After developing the industrial forecast models, the industrial forecast is increased to known project expansions. The customer expansions are added to the customer counts and industrial energy forecast. Table 3-64 shows the additions to the industrial class.

Table 3-64 - Industrial Post Forecast Adjustments

Year	Energy (kWh)	Capacity (kW)
2018	89,959	9,263
2019	111,155	9,263
2020	111,155	9,263
2021	111,155	9,263
2022	111,155	9,263
2023	111,155	9,263
2024	111,155	9,263
2025	111,155	9,263
2026	111,155	9,263
2027	111,155	9,263
2028	111,155	9,263
2029	111,155	9,263
2030	111,155	9,263

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 constructed by calibrating hourly load profiles with monthly peaks and energy. This calibration step ensures that the net system load forecast is consistent with the overall energy and peak forecast.

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).

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 8.1.1. The extreme and mild scenarios capture changes to weather and use base case economic assumptions. The weather scenarios are discussed in Section 8.2. In addition, Liberty-Empire reviewed the implications of the electric vehicle forecast included in the high and low scenarios. The electric vehicle review is in Section 8.1.2 and includes a discussion of alternative adoption cases.

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.

Two normal-weather scenarios are created to construct 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 are created to capture economic uncertainty. The subjective probabilities assigned to these scenarios are listed below.

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

8.1.1 High and Low Case

The high and low case bounds are created by increasing or decreasing the annual growth rate for each economic driver by 50%. For instance, if the annual population growth rate in 2020 is 0.53%, the high case growth rate for 2020 is increased to 0.79% and the low case growth rate for 2020 is decreased to 0.25%. Figure 3-59 through Figure 3-62 show the key economic drivers for the high and low scenarios.

Figure 3-59 - High and Low Scenario – GDP Scenarios

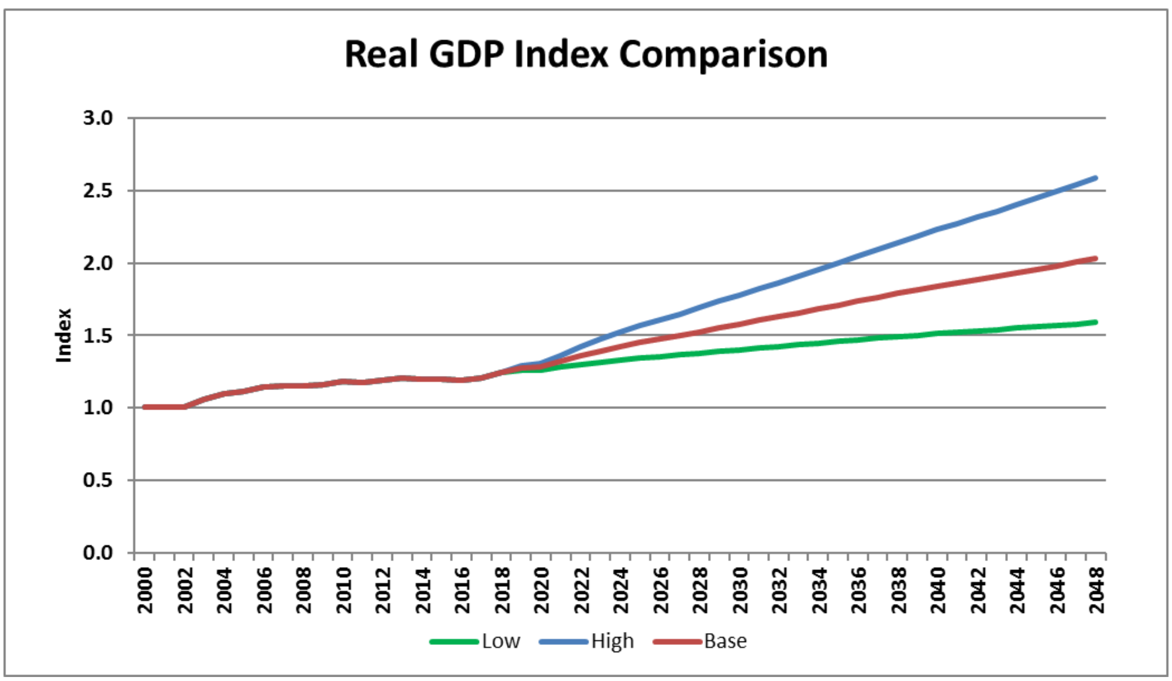


Figure 3-60 - High and Low Scenario – Non-Manufacturing Employment

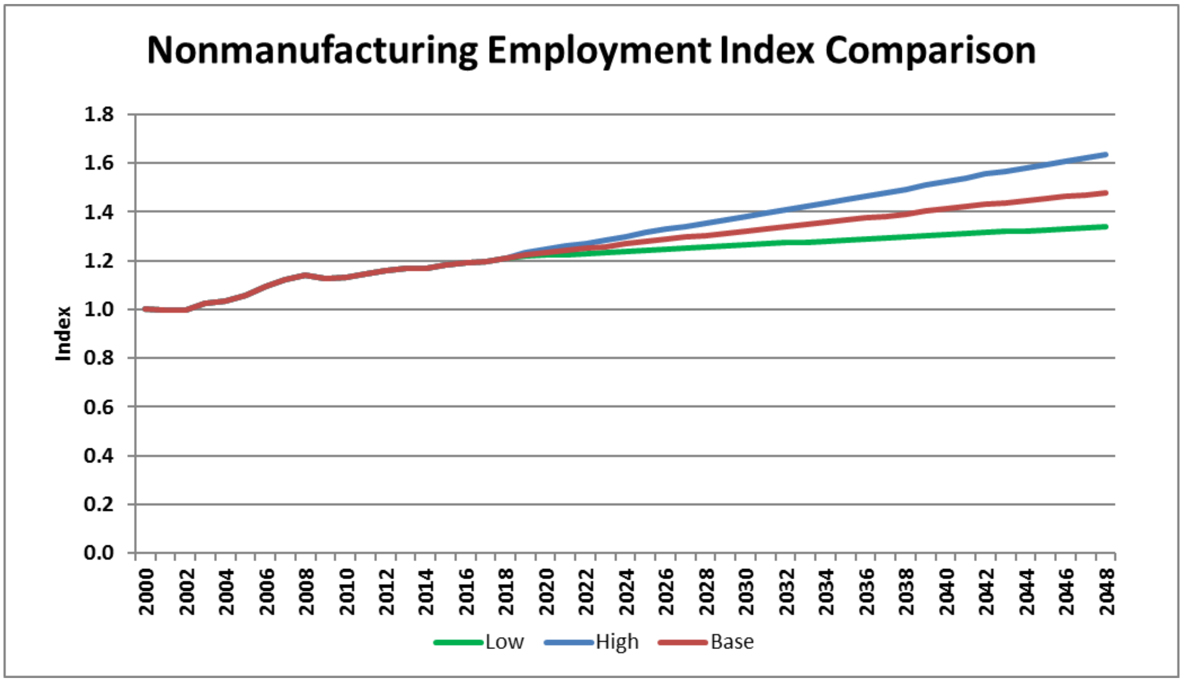


Figure 3-61 - High and Low Scenario – Population

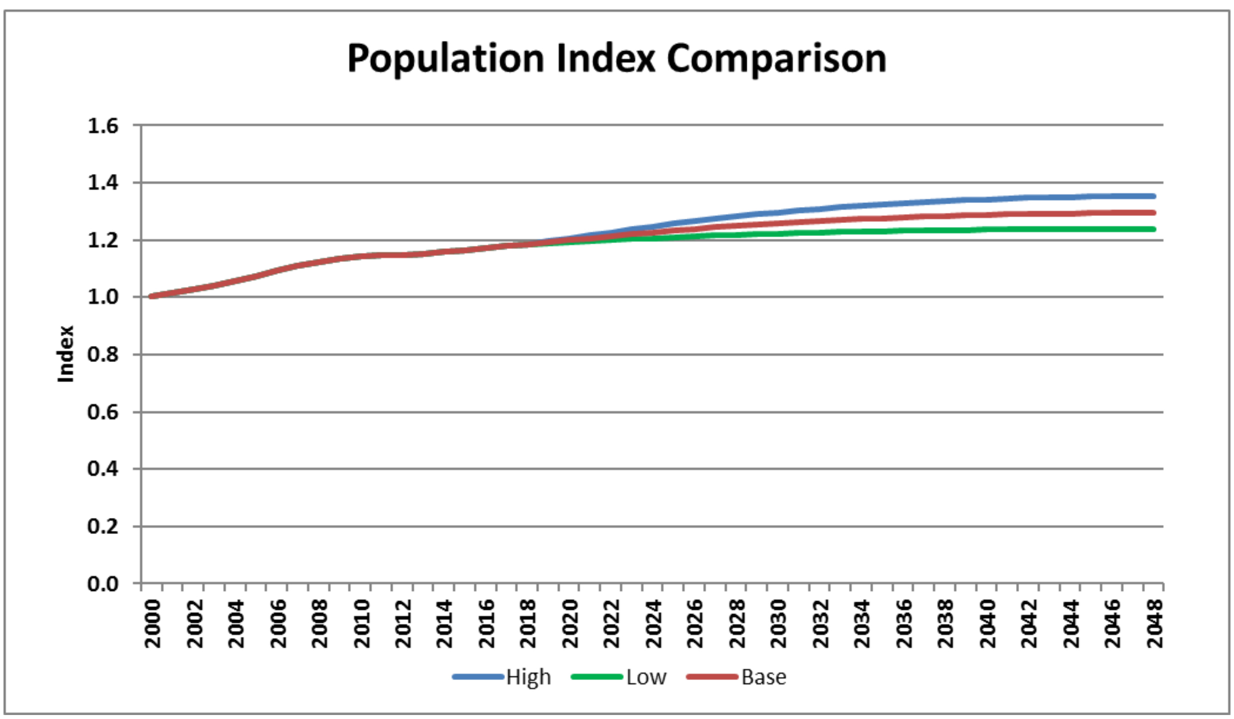
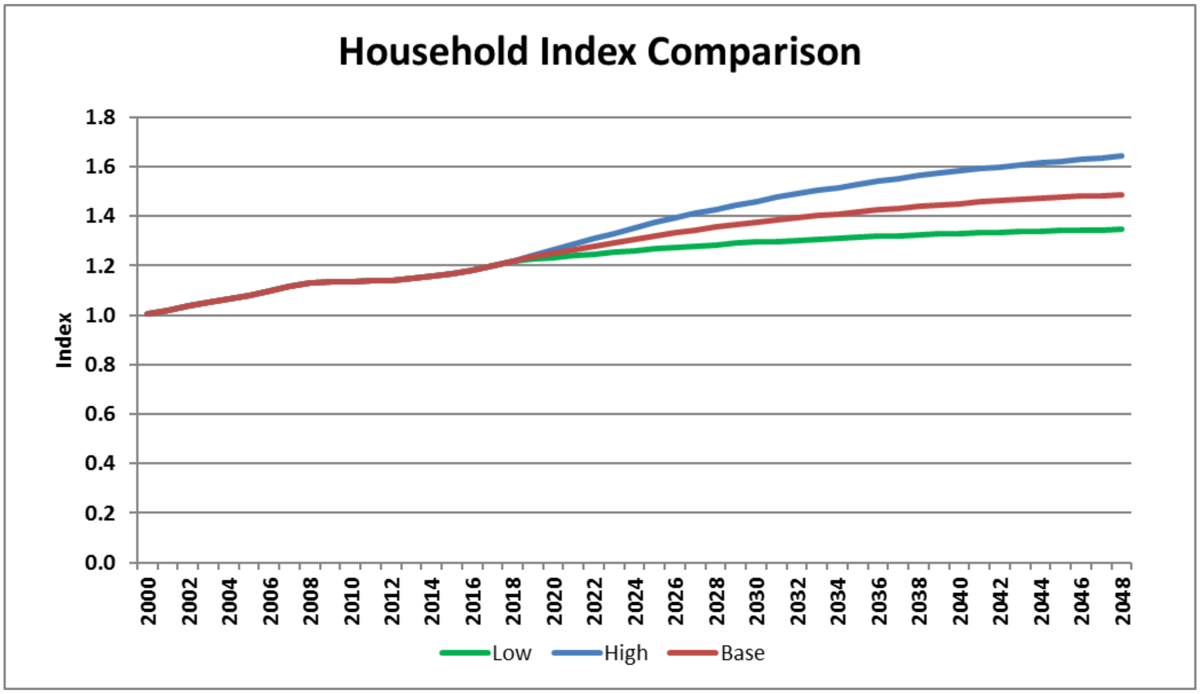


Figure 3-62 - High and Low Scenario – Households



8.1.2 Electric Vehicle Adoption Cases

On October 24, 2018, the Commission issued its Order Establishing Special Contemporary Resource Planning. In this Order, the Commission states:

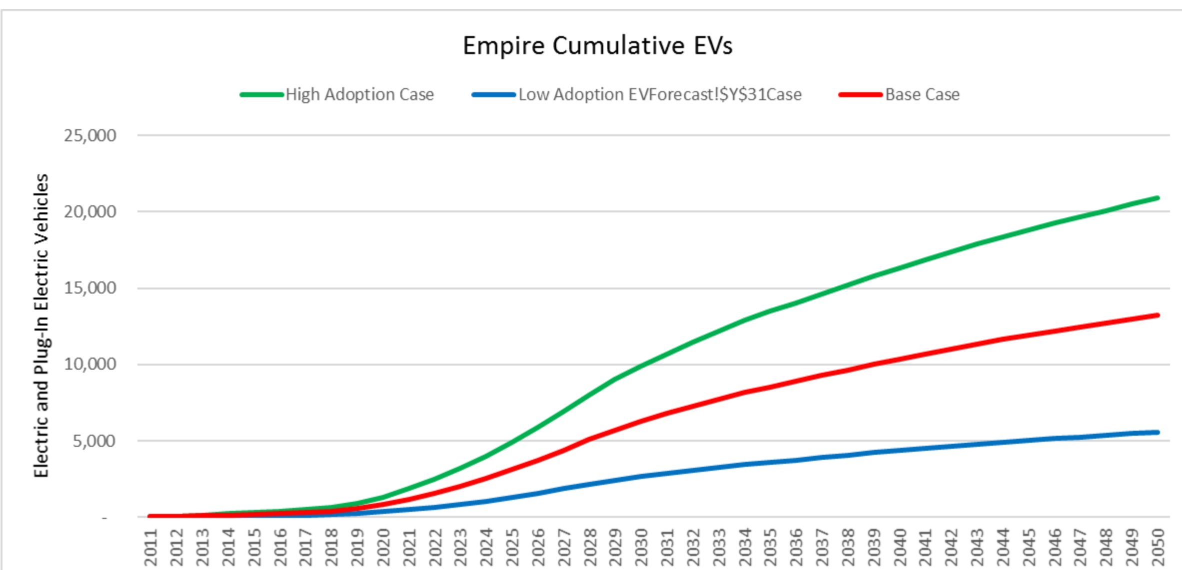
> *(C) When complying with 4 CSR 240-22.060(5)(A), analyze and document the impact of electric vehicle usage for the 20-year planning period upon the low-case, base-case, and high-case load forecasts.*

Liberty-Empire included an electric vehicle forecast in the base, high, and load forecasts. The electric vehicle forecast is summarized in Section 2.5 and shown in Figure 3-9. The impact of the electric vehicle forecast is included in Figure 3-79 through Figure 3-81 and Table 3-65 through Table 3-68.

In addition to including the electric vehicle forecast into the base, high, and low forecasts, Liberty-Empire explored alternative adoption cases to understand the sensitivity of the electric vehicle forecast. The adoption cases are shown in Figure 3-63. In this figure, the high adoption case assumes that the EIA vehicle per household ratio applied to Liberty-Empire's residential customers yields the correct starting vehicle count in 2018. This high adoption case assumes 633 vehicles in 2018 growing to 20,081 vehicles in 2048. The low adoption case assumes the Auto Alliance ratio of registered electric vehicles is correct in 2018. The low adoption case assumes 169 vehicles in 2018 growing to 5,364 in 2048. Both adoption cases grow at the EIA's annual growth rates.

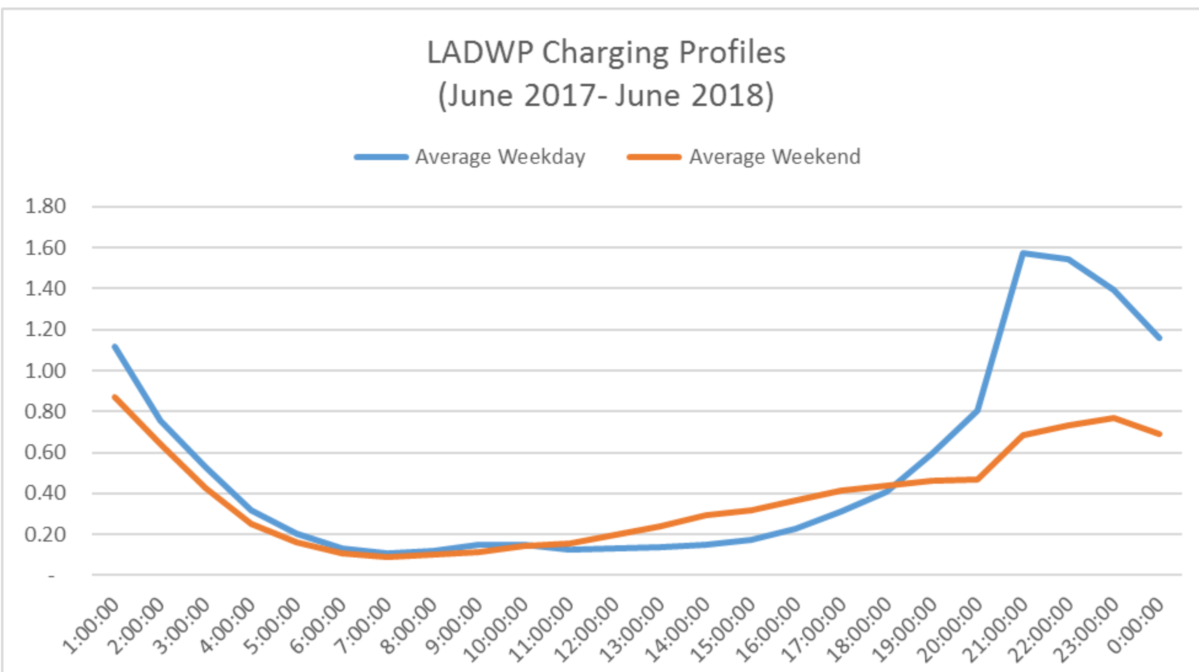
In 2048, the difference between high and base adoption cases is 7,358 vehicles, which amounts to approximately 350 GWh/year. The difference is the same between the low and base adoption cases. These differences are well within the bounds set by the high and low case scenarios and do not warrant a specific set of scenarios.

Figure 3-63 – Electric Vehicle Scenarios



While electric vehicles do not require new scenarios, monitoring advances in electric vehicle technology and charging patterns is important as this technology grows. Currently, the electric vehicle forecast is not expected to impact the peak forecast. Incentive charging programs tend to move peak charging hours to after midnight. Non-incentive charging tends to follow residential consumption patterns with charging after people return home from work. As an example, Figure 3-64 shows Los Angeles Department of Water and Power's ("LADWP") actual electric vehicle charging shape aggregated into weekday and weekend patterns. These patterns include both incentive and non-incentive charging and show the main load impact is in the evening and after midnight away from system peak hours. While these patterns are indicative of today's market, they cannot be assumed in the future during mass market adoption. As the market evolves, Liberty-Empire expects to update this analysis to improve its understanding of electric vehicle system impacts.

Figure 3-64 – Electric Vehicle Charging Profile



8.1.4 Normal Weather Scenario Results

Scenario results for billed sales of energy are shown in Figure 3-65 and Table 3-65. Scenario results for Net System Input ("NSI") are shown in Table 3-66. NSI energy is calculated as class-level billed sales multiplied by an annual average loss factor. Scenario system peaks are shown in Table 3-67, Table 3-68, Figure 3-66, and Figure 3-67.

Figure 3-65 - Base, High, and Low, Scenario System Annual Billed Sales

****Confidential in its Entirety**[40]**

[redacted]

[40] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when using reports, work papers, or other documentation related to work produced by internal or external auditors or consultants.

Table 3-65 - Base, High, and Low Scenario

Annual Billed Sales (MWh)

****Confidential in its Entirety**[41]**

[redacted]

[41]4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when using reports, work papers, or other documentation related to work produced by internal or external auditors or consultants.

Table 3-66 - Base, High, and Low Scenario – Net System Input (MWh)

Year	Base	Low	High
2019	5,484,665	5,457,802	5,507,244
2020	5,279,656	5,238,081	5,323,040
2021	5,154,776	5,095,203	5,217,190
2022	5,177,325	5,095,826	5,260,949
2023	5,200,864	5,098,278	5,307,476
2024	5,228,965	5,103,919	5,358,413
2025	5,255,290	5,109,719	5,407,008
2026	5,274,228	5,110,629	5,446,542
2027	5,293,576	5,112,828	5,485,889
2028	5,315,110	5,116,398	5,527,686
2029	5,338,465	5,121,306	5,571,846
2030	5,351,778	5,117,229	5,605,244
2031	5,365,222	5,114,171	5,638,264
2032	5,378,583	5,111,730	5,670,890
2033	5,392,921	5,110,116	5,704,664
2034	5,409,641	5,110,383	5,741,409
2035	5,427,969	5,111,985	5,780,306
2036	5,446,817	5,114,263	5,819,942
2037	5,466,466	5,117,518	5,860,471
2038	5,486,734	5,121,434	5,901,712
2039	5,507,074	5,125,539	5,943,168
2040	5,520,090	5,123,017	5,976,352
2041	5,533,929	5,121,931	6,009,966
2042	5,546,660	5,120,867	6,041,636
2043	5,560,309	5,121,083	6,073,840
2044	5,574,524	5,122,139	6,106,544
2045	5,589,007	5,123,490	6,139,803
2046	5,604,316	5,125,254	6,174,532
2047	5,621,303	5,128,006	6,211,724
2048	5,638,809	5,131,302	6,249,983

Figure 3-66 - Base, High, and Low Scenario – System Winter Peak

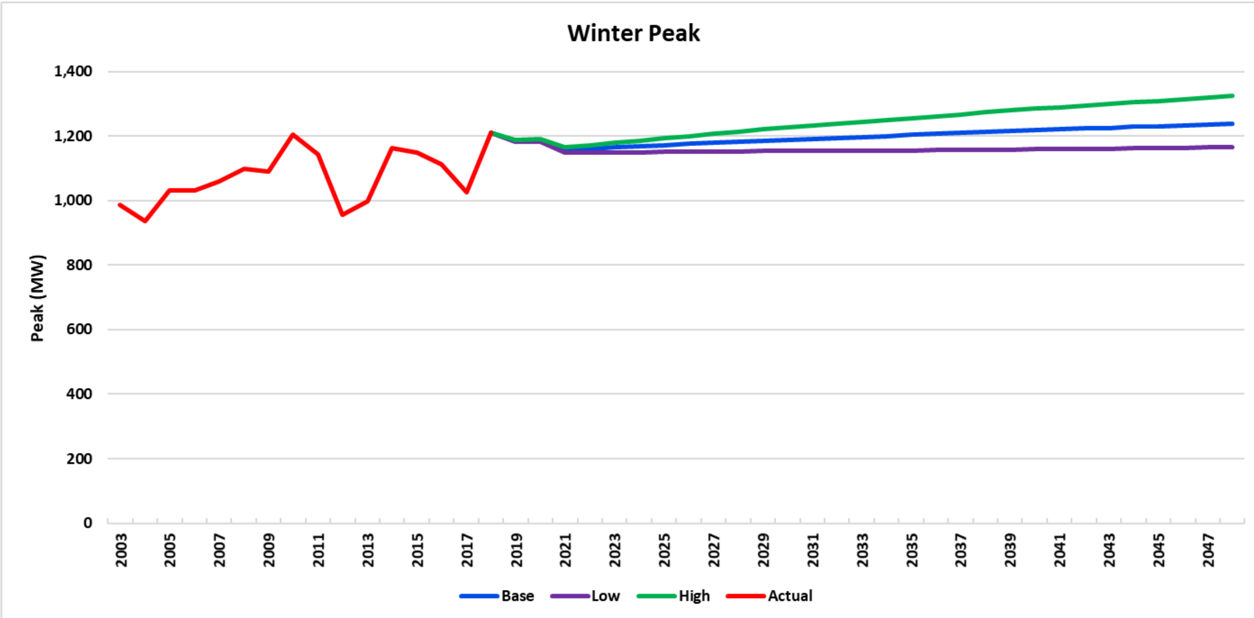


Table 3-67 - Base, High, and Low Scenario – Winter Peak (MW)

Year	Base	Low	High
2019	1,185	1,183	1,188
2020	1,188	1,184	1,191
2021	1,158	1,149	1,167
2022	1,161	1,149	1,172
2023	1,165	1,150	1,180
2024	1,169	1,150	1,187
2025	1,173	1,151	1,195
2026	1,176	1,152	1,201
2027	1,179	1,152	1,207
2028	1,183	1,153	1,214
2029	1,186	1,154	1,221
2030	1,189	1,154	1,227
2031	1,192	1,154	1,233
2032	1,195	1,155	1,238
2033	1,198	1,155	1,244
2034	1,201	1,156	1,250
2035	1,204	1,156	1,256
2036	1,207	1,157	1,262
2037	1,210	1,158	1,268
2038	1,213	1,159	1,274
2039	1,216	1,159	1,280
2040	1,219	1,160	1,285
2041	1,221	1,160	1,290
2042	1,224	1,161	1,295
2043	1,226	1,161	1,300
2044	1,229	1,162	1,305
2045	1,231	1,163	1,310
2046	1,234	1,164	1,314
2047	1,236	1,165	1,320
2048	1,239	1,166	1,325

Figure 3-67 - Base, High, and Low Scenario – System Summer Peak

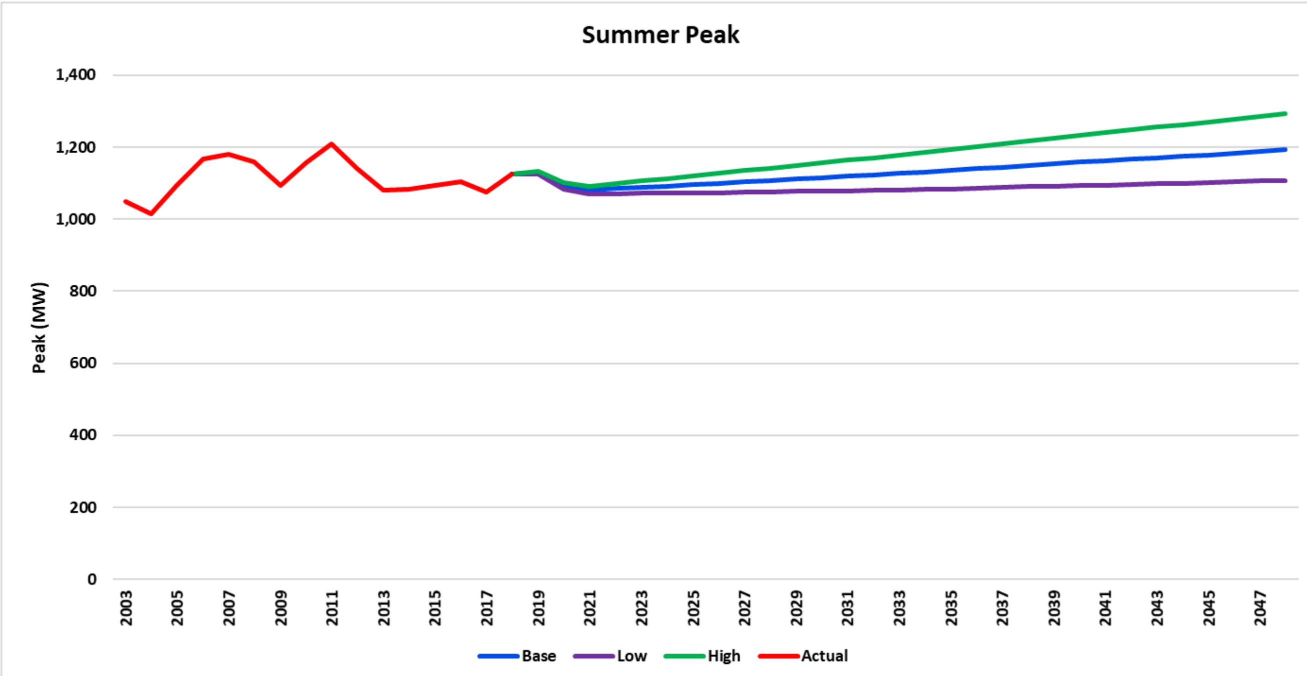


Table 3-68 - Base, High, and Low Scenario – Summer Peaks (MW)

Year	Base	Low	High
2019	1,130	1,126	1,134
2020	1,092	1,084	1,101
2021	1,081	1,071	1,091
2022	1,085	1,071	1,098
2023	1,088	1,072	1,106
2024	1,092	1,072	1,113
2025	1,097	1,073	1,121
2026	1,100	1,074	1,128
2027	1,104	1,075	1,135
2028	1,108	1,076	1,142
2029	1,112	1,077	1,150
2030	1,116	1,078	1,157
2031	1,120	1,079	1,164
2032	1,123	1,080	1,170
2033	1,127	1,081	1,178
2034	1,131	1,083	1,185
2035	1,136	1,084	1,193
2036	1,140	1,086	1,201
2037	1,145	1,088	1,209
2038	1,150	1,090	1,218
2039	1,155	1,092	1,226
2040	1,159	1,094	1,234
2041	1,163	1,095	1,241
2042	1,167	1,097	1,248
2043	1,171	1,099	1,256
2044	1,175	1,100	1,263
2045	1,179	1,102	1,270
2046	1,184	1,104	1,278
2047	1,188	1,106	1,286
2048	1,193	1,108	1,294

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 is driven by normal monthly HDDs and CDDs based on a 30-year average (1988 to 2017) using Springfield, Missouri daily average temperatures. The mild and extreme weather scenarios are developed using the same historical weather data but identify a 1-in-10 scenario above and below the base forecast normal temperatures.

Monthly HDD and CDD scenarios are created by ranking historic 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 3-68 and Figure 3-69 show the ordered annual HDD and CDD with the mild and extreme scenarios. Table 3-69 shows the annual HDD and CDD scenario values.

Figure 3-68 - Mild and Extreme Annual HDD Base 65 Scenarios

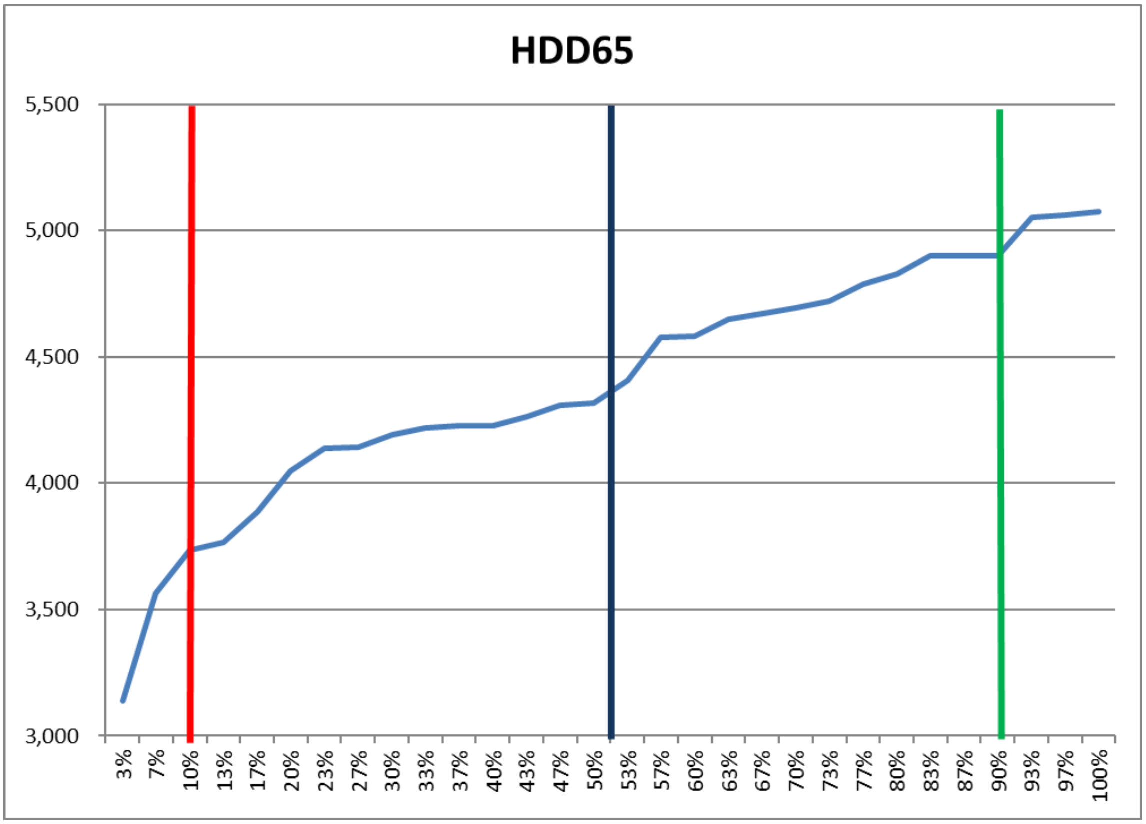


Figure 3-69 - Mild and Extreme Annual CDD Base 65 Scenarios

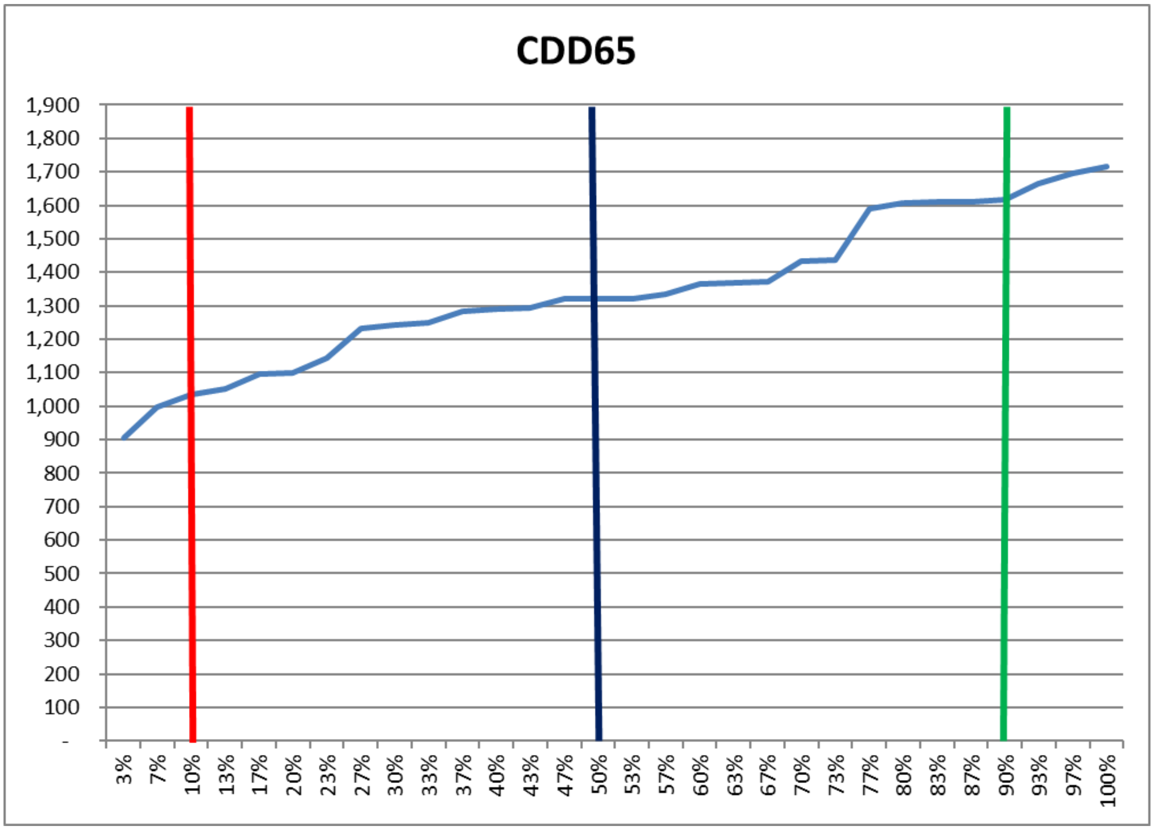


Table 3-69 - Scenario Annual Degree Days

Scenario	HDD65	CDD65
Base	4,458	1,345
Mild	3,736	1,035
Extreme	4,901	1,616

Annual HDD and CDD scenario values are converted to monthly HDD and CDD scenarios by calibrating the distributing the annual HDD and CDD values based on the normal monthly pattern. Figure 3-70 and Figure 3-71 show the monthly HDD and CDD scenarios.

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

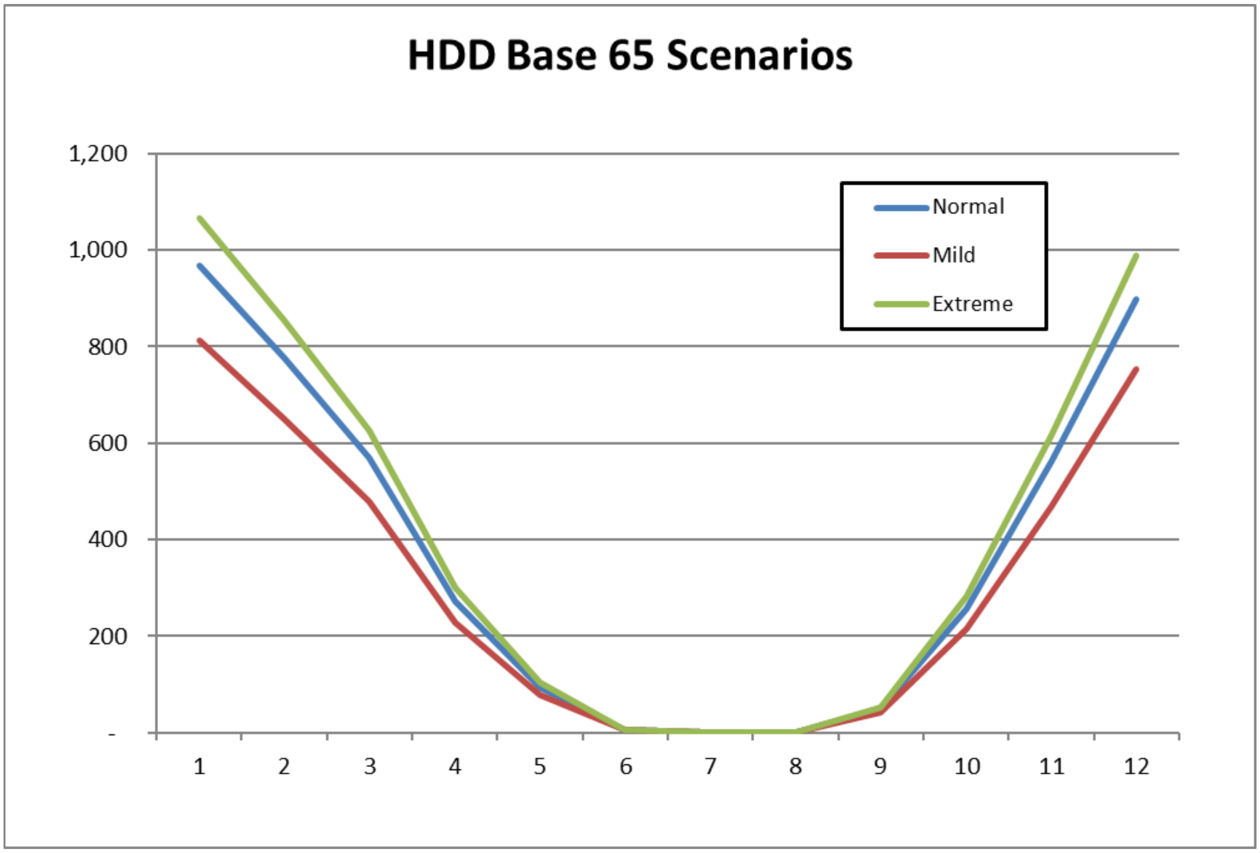
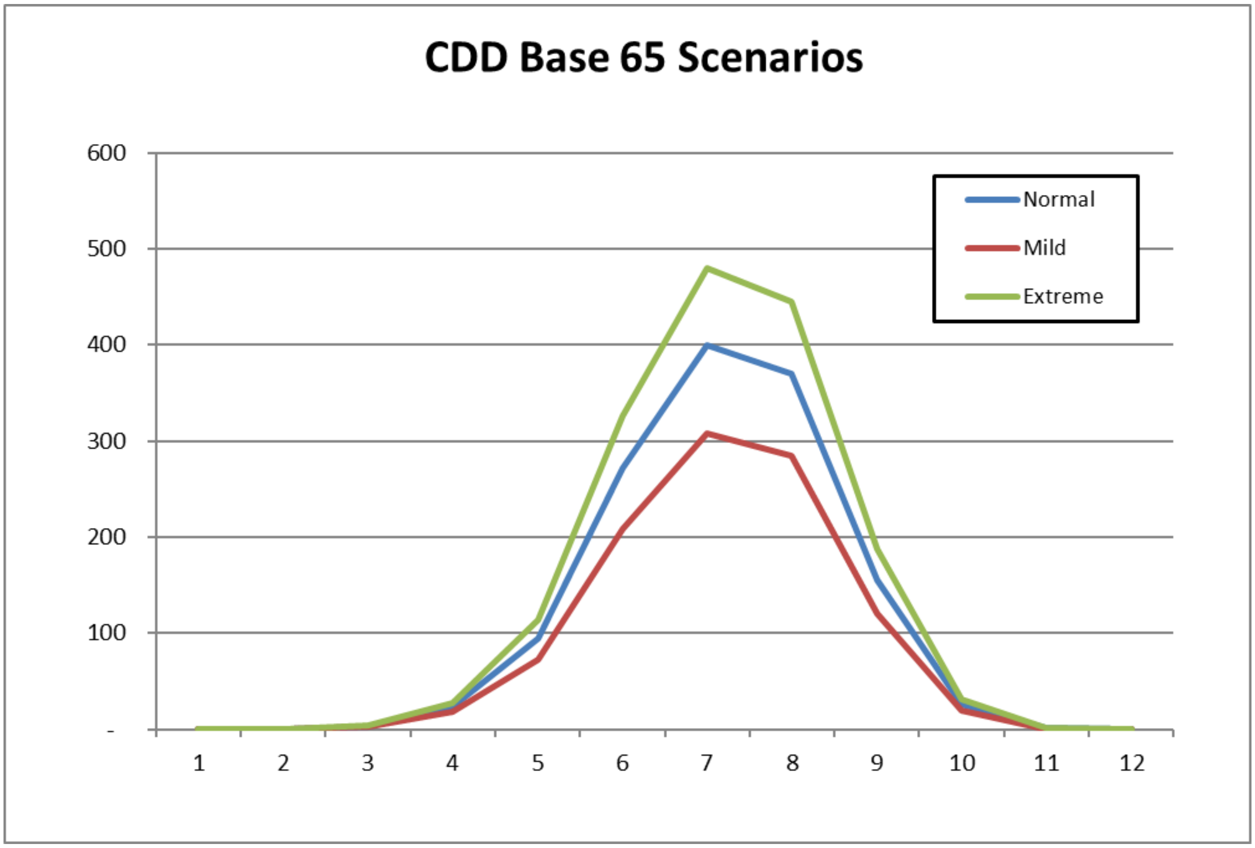


Figure 3-71 - Mild and Extreme Monthly CDD Base 65 Scenarios



Peak Producing Temperatures: The mild and extreme monthly peak scenarios are derived from 17 years of historical peak producing weather (2001 to 2017). The extreme case is obtained by selecting the lowest temperatures in the winter months and the highest temperatures in the summer months. The mild case is obtained by selecting the highest temperatures in the winter month and the lowest temperatures in the summer months.

Four exceptions were made in the mild scenario. In January, the 2006 year is removed due to its extreme mild temperature. April is defined as a heating month and the mild scenario is based on temperatures that produce a heating peak. October is defined as a cooling month and the mild scenario is based on temperatures that produce a cooling peak. Finally, May is defined as a cooling month and created to be two degrees lower than the base case due to the lack of variation in the historic data. Figure 3-72 and Table 3-70 show the extreme and mild peak temperature scenarios.

Figure 3-72 - Mild and Extreme Peak Temperature Scenarios

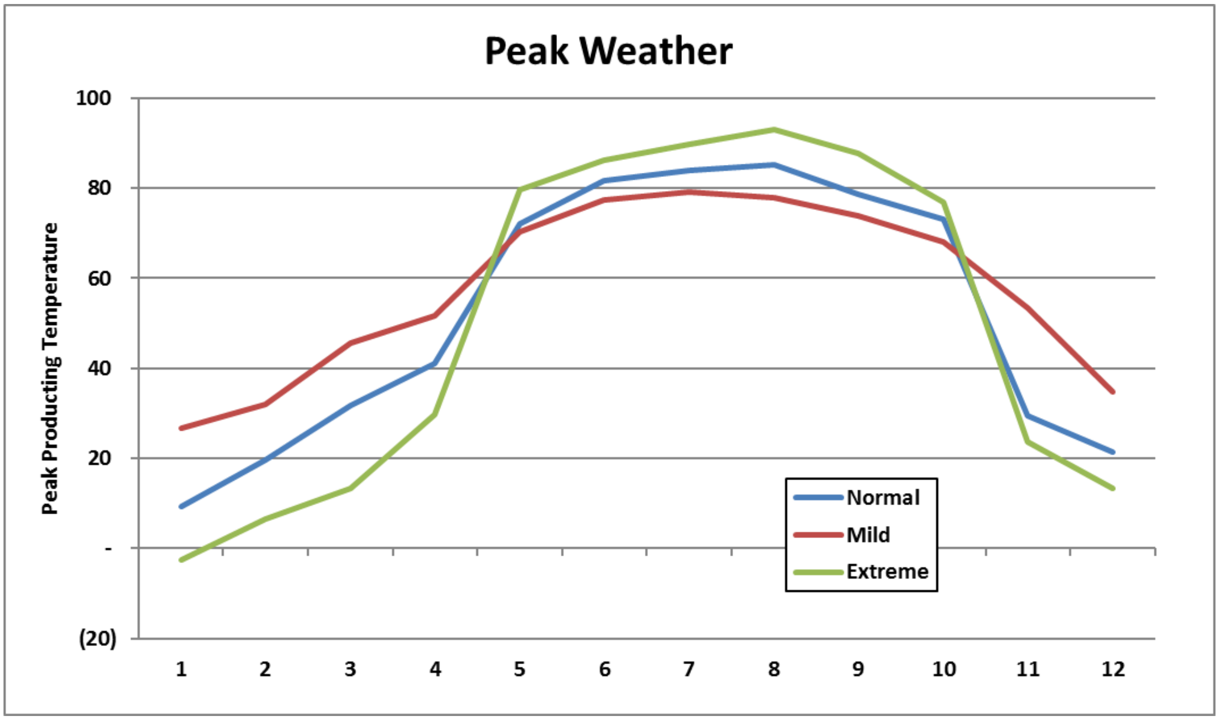


Table 3-70 - Scenario Monthly Peak Producing Temperatures

Month	Base	Extreme	Mild
Jan	9.37	(2.58)	26.75
Feb	19.69	6.54	31.88
Mar	31.85	13.25	45.71
Apr	41.02	29.83	51.54
May	72.21	79.58	70.21
Jun	81.69	86.13	77.26
Jul	83.90	89.71	79.23
Aug	85.11	93.04	77.83
Sep	78.70	87.79	73.79
Oct	72.99	76.83	68.17
Nov	29.50	23.58	53.38
Dec	21.38	13.33	34.75

Scenario results for billed sales of energy are shown in Figure 3-73 and Table 3-71. Scenario results for NSI are shown in Table 3-72. NSI energy is calculated as class-level billed sales multiplied by an annual average loss factor. Scenario results for peaks are shown in Figure 3-74 and Figure 3-75. Numerical values for the peaks are shown in Table 3-73 and Table 3-74.

Figure 3-73 - Base, Mild and Extreme Weather Scenario: System Annual Billed Sales

****Confidential in its Entirety**[42]**

[redacted]

[42] 4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when using reports, work papers, or other documentation related to work produced by internal or external auditors or consultants.

Table 3-71 – Base, Mild and Extreme Weather Scenario – Annual Billed Sales (MWh)
****Confidential in its Entirety**[43]**

[redacted]

[43]4 CSR 240-2.135(2)(A)1 allows information to be marked as confidential when using marketing analyses or other market-specific information relating to services offered in competition with others.

Table 3-72 - Base, Mild and Extreme Scenario – Net System Input (MWh)

Year	Base	Mild	Extreme
2019	5,484,665	5,262,972	5,652,429
2020	5,279,656	5,063,942	5,442,208
2021	5,154,776	4,939,828	5,316,805
2022	5,177,325	4,961,027	5,340,363
2023	5,200,864	4,983,578	5,364,663
2024	5,228,965	5,010,450	5,393,709
2025	5,255,290	5,035,599	5,420,943
2026	5,274,228	5,053,390	5,440,767
2027	5,293,576	5,071,536	5,461,045
2028	5,315,110	5,091,712	5,483,635
2029	5,338,465	5,113,637	5,508,113
2030	5,351,778	5,125,515	5,522,543
2031	5,365,222	5,137,453	5,537,167
2032	5,378,583	5,149,439	5,551,609
2033	5,392,921	5,162,387	5,567,048
2034	5,409,641	5,177,663	5,584,919
2035	5,427,969	5,194,463	5,604,464
2036	5,446,817	5,211,787	5,624,531
2037	5,466,466	5,229,885	5,645,421
2038	5,486,734	5,248,592	5,666,939
2039	5,507,074	5,267,353	5,688,547
2040	5,520,090	5,278,848	5,702,779
2041	5,533,929	5,291,173	5,717,833
2042	5,546,660	5,302,455	5,731,729
2043	5,560,309	5,314,648	5,746,544
2044	5,574,524	5,327,416	5,761,926
2045	5,589,007	5,340,473	5,777,559
2046	5,604,316	5,354,347	5,794,024
2047	5,621,303	5,369,836	5,812,220
2048	5,638,809	5,385,819	5,830,956

Figure 3-74 – Base, Mild and Extreme Weather Scenario – System Annual Winter Peak (MW)

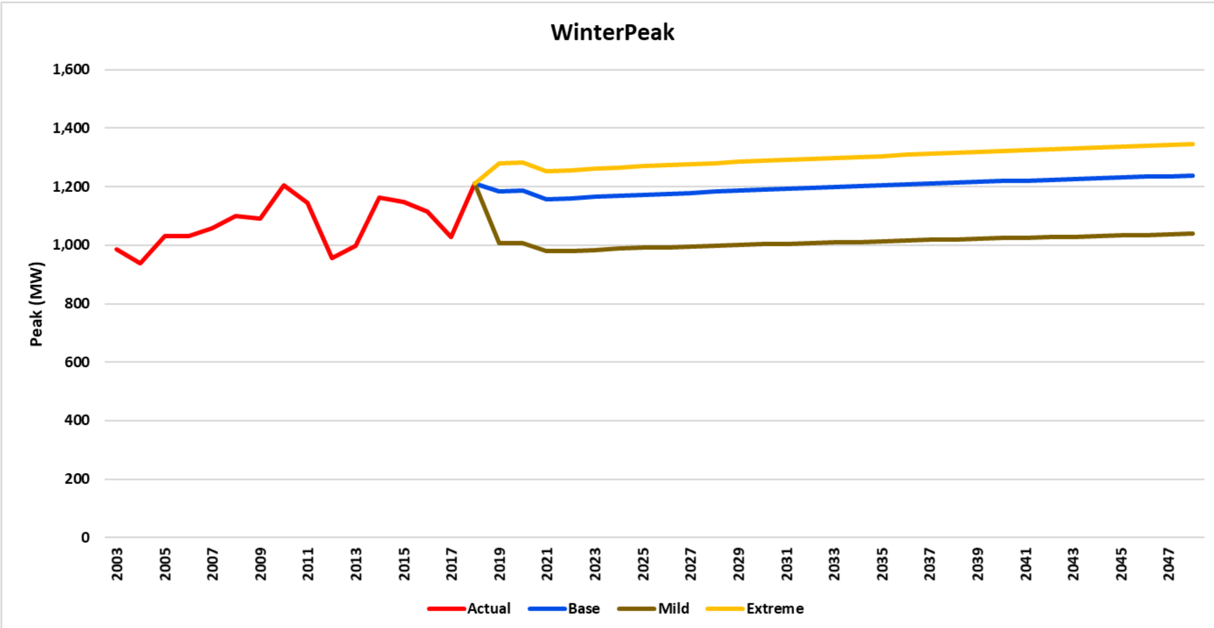


Table 3-73 - Base, Mild and Extreme Weather Scenario – System Annual Winter Peak (MW)

Year	Base	Mild	Extreme
2019	1,185	1,006	1,281
2020	1,188	1,008	1,284
2021	1,158	979	1,254
2022	1,161	981	1,256
2023	1,165	984	1,261
2024	1,169	988	1,265
2025	1,173	991	1,270
2026	1,176	993	1,273
2027	1,179	996	1,277
2028	1,183	998	1,281
2029	1,186	1,001	1,285
2030	1,189	1,003	1,289
2031	1,192	1,005	1,292
2032	1,195	1,007	1,295
2033	1,198	1,009	1,299
2034	1,201	1,011	1,302
2035	1,204	1,013	1,305
2036	1,207	1,015	1,309
2037	1,210	1,018	1,312
2038	1,213	1,020	1,316
2039	1,216	1,022	1,320
2040	1,219	1,024	1,323
2041	1,221	1,026	1,326
2042	1,224	1,028	1,328
2043	1,226	1,029	1,331
2044	1,229	1,031	1,334
2045	1,231	1,033	1,337
2046	1,234	1,035	1,340
2047	1,236	1,037	1,343
2048	1,239	1,039	1,346

Figure 3-75 - Base, Mild and Extreme Weather Scenario – System Annual Summer Peak

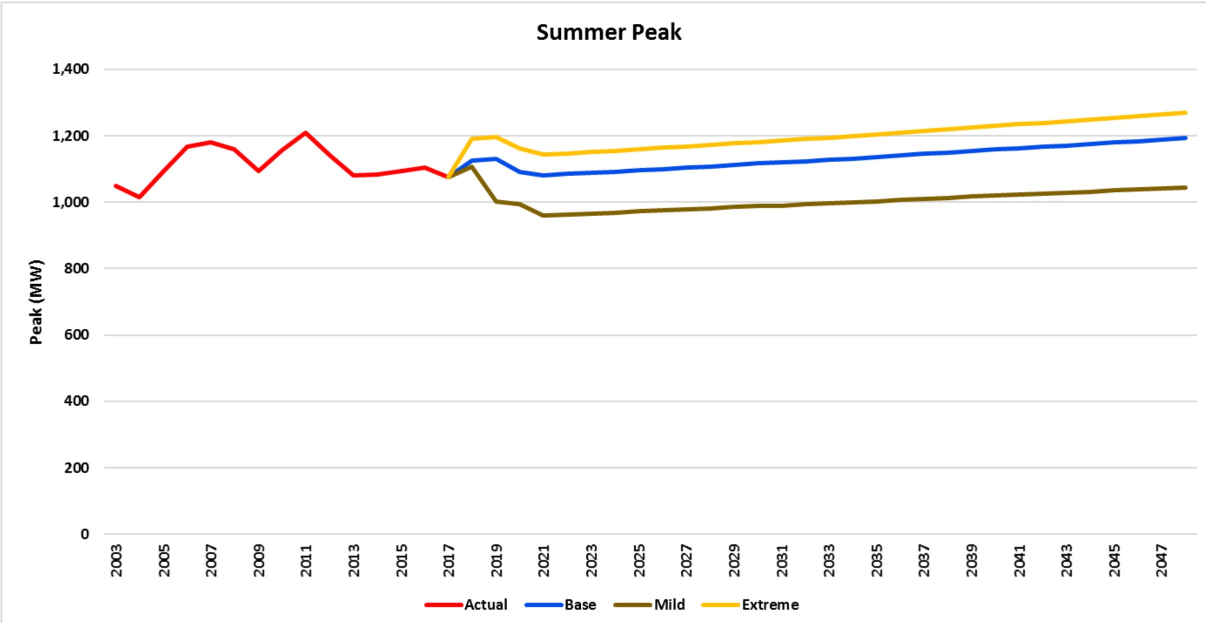


Table 3-74 – Base, Mild and Extreme Weather Scenario – System Annual Summer Peak (MW)

Year	Base	Mild	Extreme
2019	1,130	1,002	1,195
2020	1,092	995	1,163
2021	1,081	960	1,143
2022	1,085	963	1,147
2023	1,088	966	1,151
2024	1,092	969	1,155
2025	1,097	973	1,160
2026	1,100	976	1,164
2027	1,104	978	1,168
2028	1,108	982	1,172
2029	1,112	985	1,177
2030	1,116	988	1,181
2031	1,120	990	1,186
2032	1,123	993	1,190
2033	1,127	996	1,194
2034	1,131	999	1,199
2035	1,136	1,002	1,204
2036	1,140	1,006	1,209
2037	1,145	1,009	1,214
2038	1,150	1,013	1,220
2039	1,155	1,017	1,225
2040	1,159	1,020	1,230
2041	1,163	1,023	1,235
2042	1,167	1,026	1,239
2043	1,171	1,029	1,244
2044	1,175	1,032	1,249
2045	1,179	1,035	1,253
2046	1,184	1,038	1,258
2047	1,188	1,041	1,263
2048	1,193	1,045	1,269

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 use (sales) are listed in Table 3-75 and Table 3-76 and shown in Figure 3-76 and Figure 3-77. Summer is defined as June, July and August. Winter is defined as January, February, and December. Figure 3-78 shows the historical and forecast summer and winter peak demands.

Table 3-75 – Historical and Forecast Summer, Winter, and System Energy (Calendar)

Year	Winter	Summer	Total
2005	450,236	507,265	4,914,330
2006	447,699	548,459	4,996,412
2007	429,822	543,824	5,092,994
2008	490,485	478,894	5,169,158
2009	531,165	440,778	4,934,310
2010	568,300	536,786	5,206,974
2011	513,915	520,053	5,165,865
2012	451,432	469,910	4,863,689
2013	401,103	420,430	5,033,823
2014	521,069	490,876	4,993,530
2015	488,618	512,439	4,949,948
2016	462,396	493,295	5,037,660
2017	467,671	530,587	4,895,203
2018	535,368	485,231	5,254,849
2019	515,876	488,104	5,135,497
2020	517,427	456,987	4,943,547
2021	490,402	458,295	4,826,451
2022	492,743	460,364	4,847,731
2023	494,846	462,563	4,869,755
2024	497,459	465,154	4,895,980
2025	500,075	467,589	4,920,805
2026	502,053	469,388	4,938,385
2027	503,940	471,277	4,956,416
2028	505,991	473,444	4,976,781
2029	508,160	475,786	4,998,519
2030	509,608	477,337	5,011,072
2031	511,044	478,946	5,023,696
2032	512,408	480,506	5,036,077
2033	513,772	482,205	5,049,511
2034	515,337	484,125	5,065,244
2035	517,036	486,187	5,082,324
2036	518,798	488,313	5,100,105
2037	520,593	490,492	5,118,413
2038	522,424	492,724	5,137,276
2039	524,297	494,986	5,156,485
2040	525,535	496,646	5,168,613
2041	526,900	498,360	5,181,624
2042	528,165	499,956	5,193,589
2043	529,471	501,604	5,206,247
2044	530,818	503,305	5,219,523

Year	Winter	Summer	Total
2045	532,172	505,034	5,233,190
2046	533,542	506,817	5,247,438
2047	535,082	508,770	5,263,435
2048	536,702	510,747	5,279,845

Table 3-76 - Historical and Forecast Summer and Winter Peaks

Year	Winter Peak	Summer Peak
2005	1,032	1,095
2006	1,031	1,167
2007	1,059	1,181
2008	1,100	1,161
2009	1,090	1,093
2010	1,205	1,156
2011	1,145	1,209
2012	955	1,142
2013	997	1,080
2014	1,162	1,083
2015	1,149	1,094
2016	1,114	1,104
2017	1,027	1,075
2018	1,211	1,126
2019	1,185	1,130
2020	1,188	1,092
2021	1,158	1,081
2022	1,161	1,085
2023	1,165	1,088
2024	1,169	1,092
2025	1,173	1,097
2026	1,176	1,100
2027	1,179	1,104
2028	1,183	1,108
2029	1,186	1,112
2030	1,189	1,116
2031	1,192	1,120
2032	1,195	1,123
2033	1,198	1,127
2034	1,201	1,131
2035	1,204	1,136
2036	1,207	1,140
2037	1,210	1,145
2038	1,213	1,150
2039	1,216	1,155
2040	1,219	1,159
2041	1,221	1,163
2042	1,224	1,167
2043	1,226	1,171
2044	1,229	1,175

Year	Winter Peak	Summer Peak
2045	1,231	1,179
2046	1,234	1,184
2047	1,236	1,188
2048	1,239	1,193

Figure 3-76 - Historical and Forecast Summer and Winter Calendar Energy Use

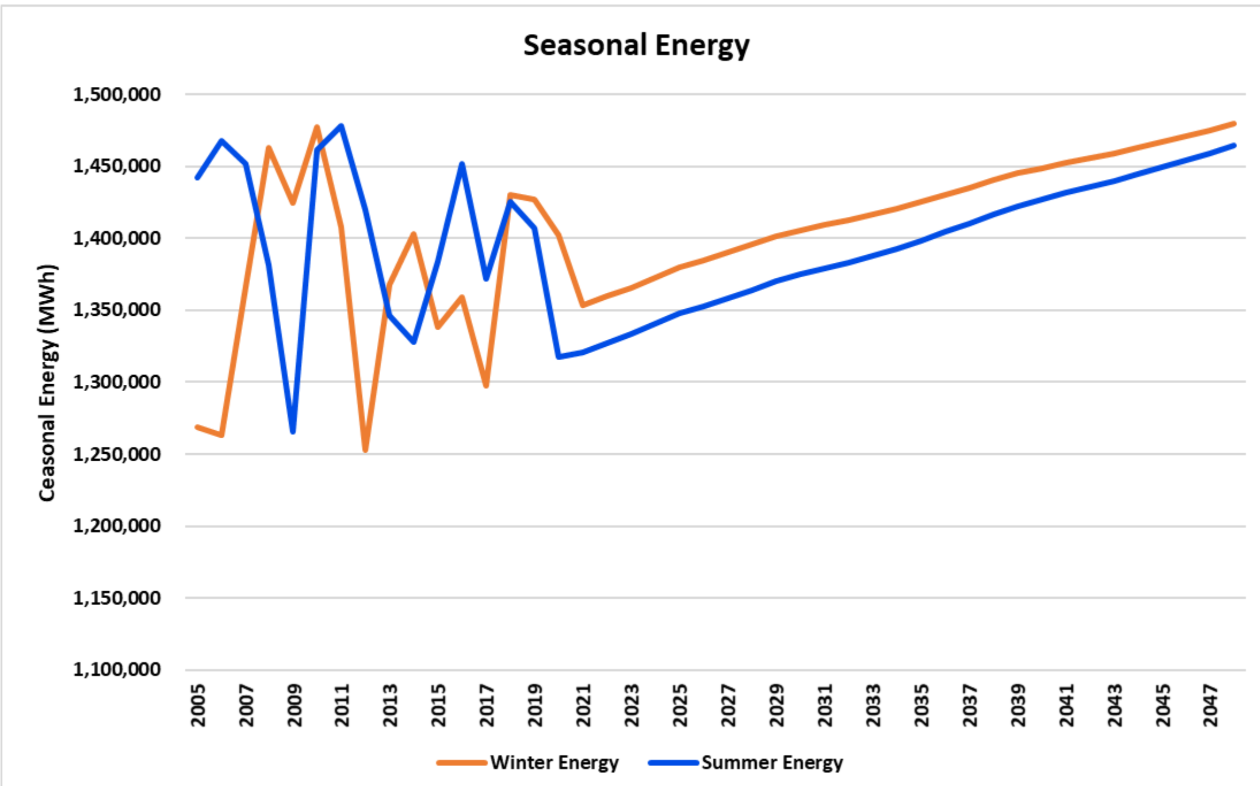


Figure 3-77 - Historical and Forecast Total Calendar Energy Use

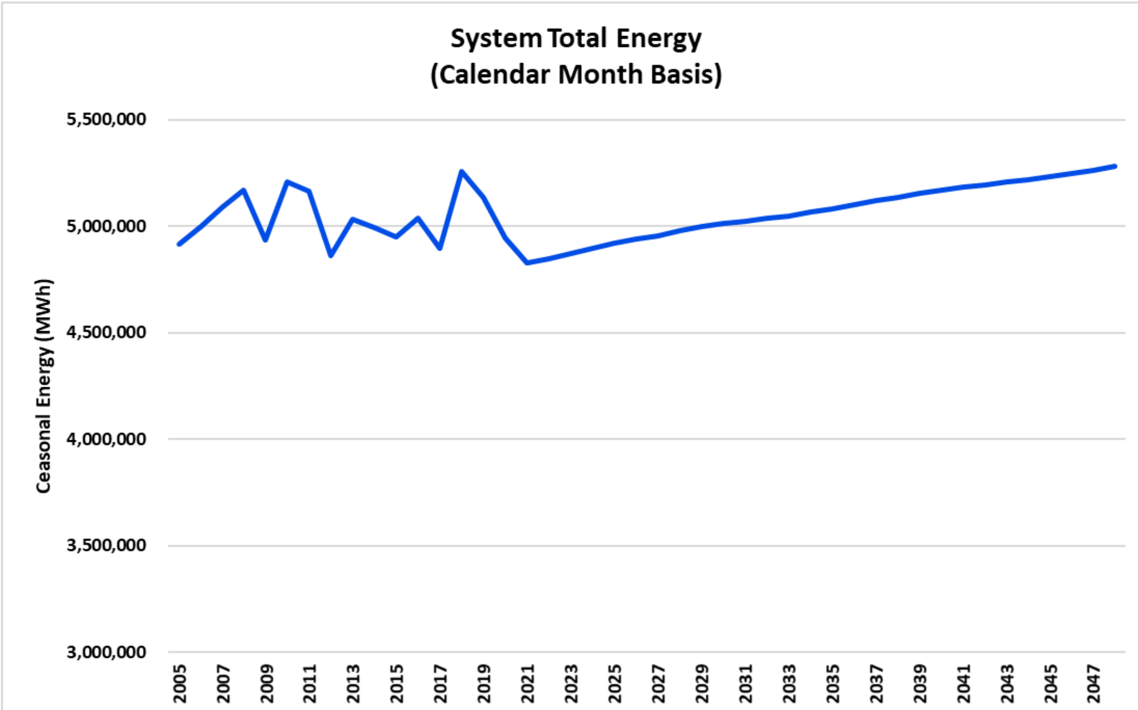
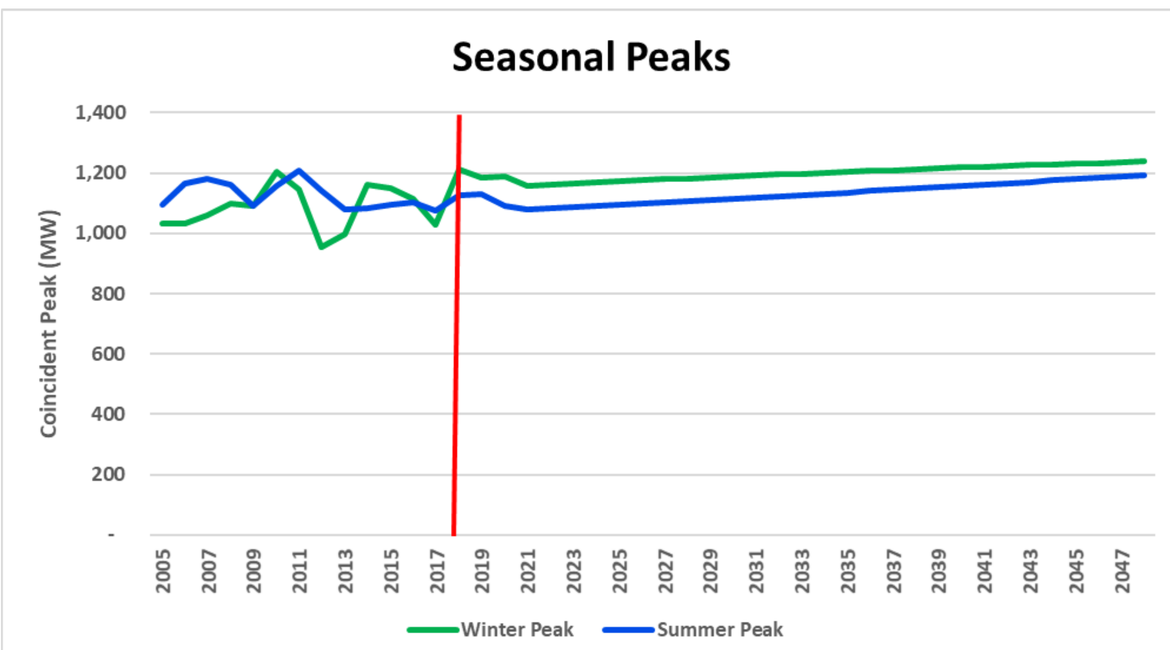


Figure 3-78 - Historical and Forecast Summer and Winter Peaks



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.

The historical (actual and normalized) and forecast for summer, winter, and annual energy under the four scenarios are shown in Figure 3-79 through Figure 3-81. The extreme and mild cases are weather scenarios using the base case economic forecast. The high and low cases are economic scenarios using the normal weather. Data are revenue month sales. The historic and forecast for the summer, winter, and system peak demands for all four scenarios are shown in Figure 3-82 and Figure 3-83.

Figure 3-79 - Historical and Forecast Summer Billed Energy for Base, Low, High, High-High, Aggressive EV, Mild, and Extreme Scenarios

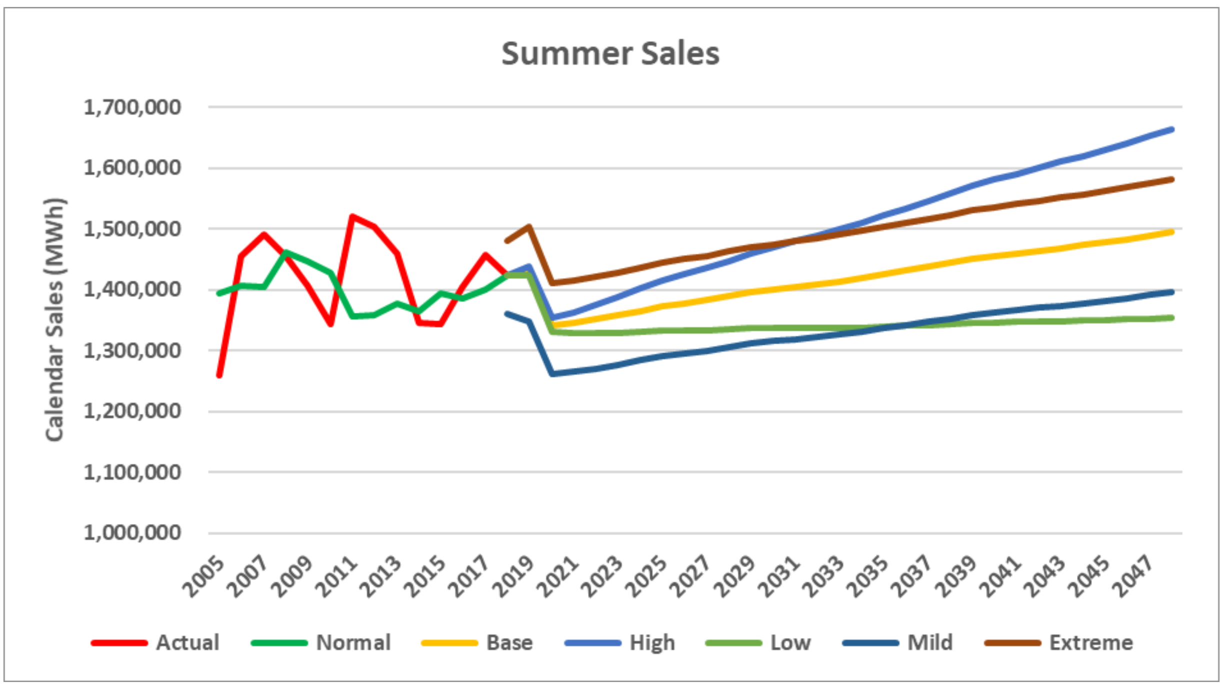


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Figure 3-80 - Historical and Forecast Winter Billed Energy for Base, Low, High, Mild, and Extreme Scenarios

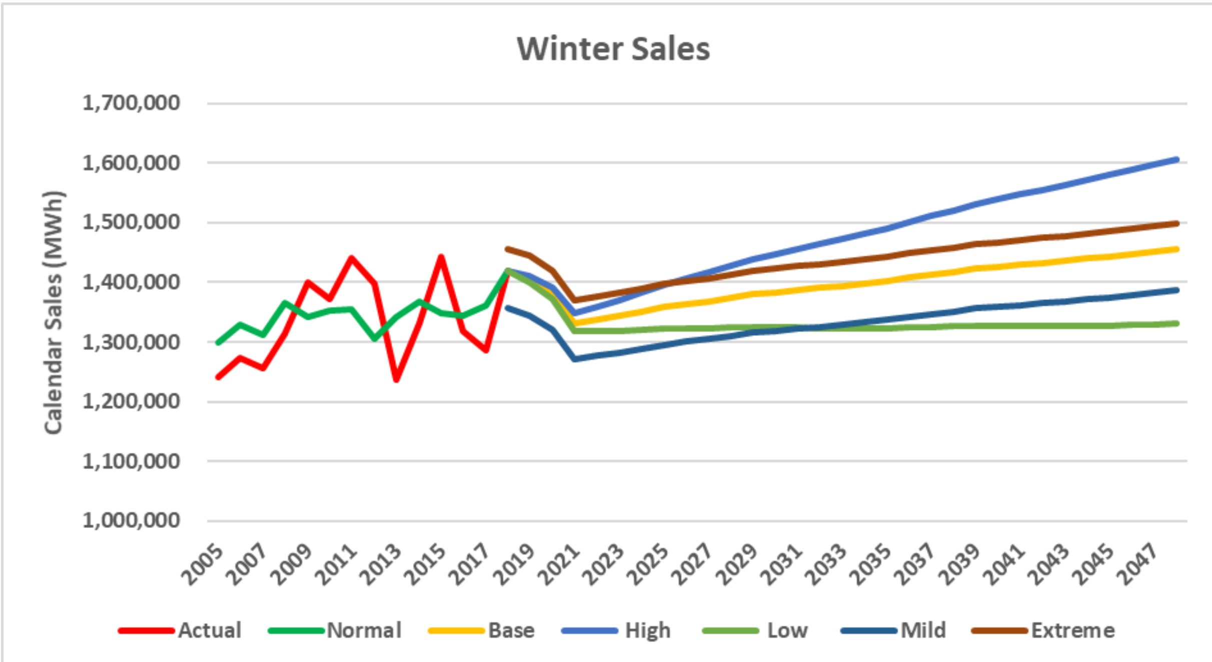

Figure 3-81 - Historical and Forecast Annual Billed Energy for Base, Low, High, Mild, and Extreme Scenarios

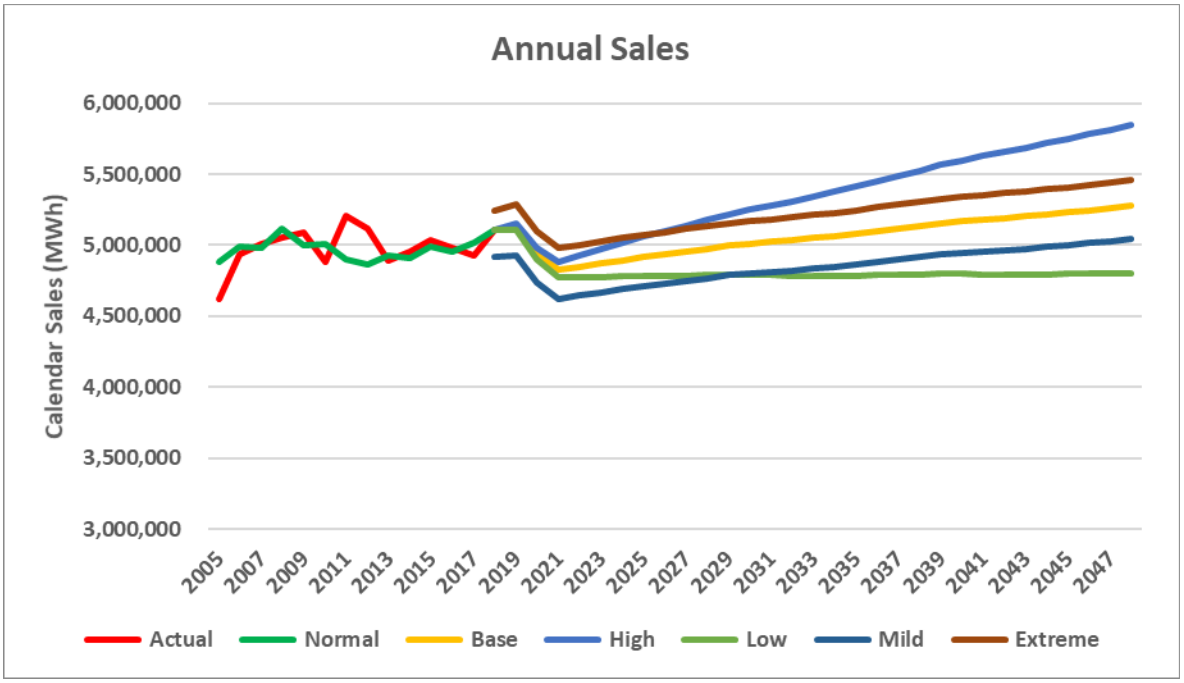

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Figure 3-82 - Historical and Forecast Summer Peak for Base, Low, High, Mild, and Extreme Scenarios

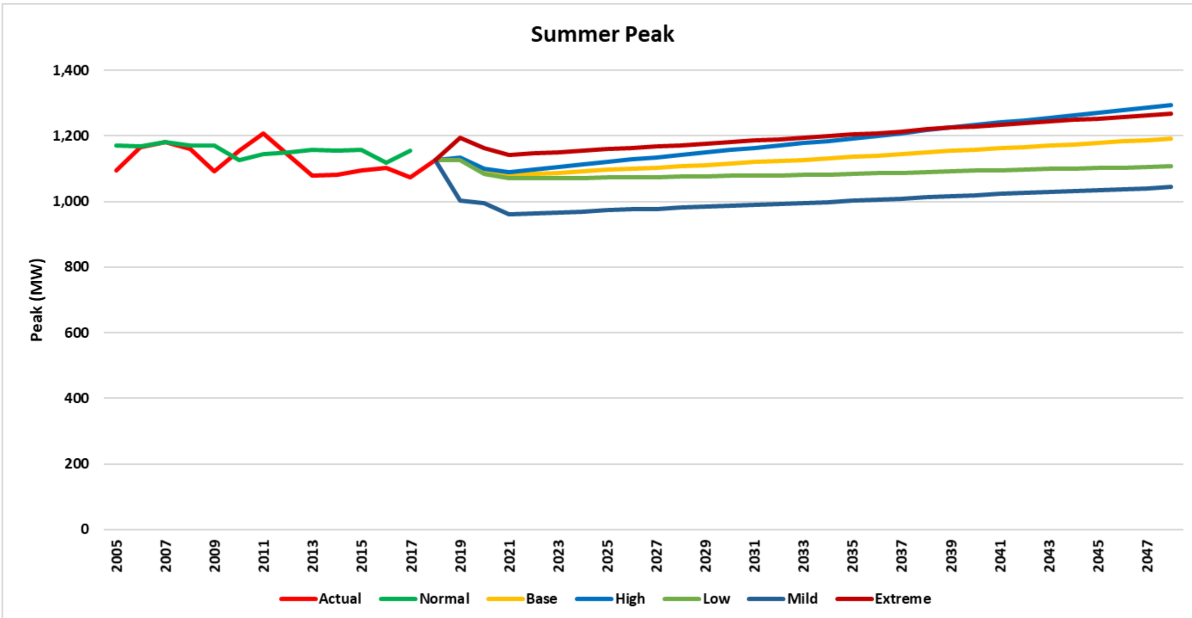

Figure 3-83 - Historical and Forecast Winter Peak for Base, Low, High, Mild, and Extreme Scenarios