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VOLUME 3

LOAD ANALYSIS AND LOAD FORECASTING

THE EMPIRE DISTRICT ELECTRIC COMPANY

4 CSR 240-22.030

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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

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:

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. With the exception of the Variance Request described and approved in section 1.5 and the additional scenarios described in section 1.6, the forecast is consistent with the load forecast methods prescribed in the IRP Rule.

1.1 Purpose - Identification of End-Use Measures

(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;

1.2 Purpose - Derivation of Data Set of Historical Values

(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;

1.3 Purpose - Analysis of Impacts of Implemented DSM and Demand-Side Rates on 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

1.4 Purpose - Preservation of Load Analysis in Historical Database

(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.

1.5 Variance Request

On April 1, 2015, Empire filed a Variance Request identifying expected deviations from the IRP Rule. Two requests were included in the filing. These requests are identified below. On July 2, 2015, the variance request was granted.

<u>Request 1: Forecast by Major Class</u>

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

The Variance Request asked that the IRP forecast be developed by the following revenue classes:

- Residential
- Commercial
- Industrial

- Wholesale
- Street & Highway
- Interdepartmental
- Public Authority

The revenue class approach aggregates customers into groups that improve data stability and align with economic drivers. This request is consistent with Empire's 2013 IRP filing. A breakdown of revenue classes by rate classes 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 be exempt from the end-use analysis for the industrial class. While Empire includes end-use information for the residential and commercial class based on Energy Information Administration (EIA) data, no data are available for the industrial class. This request is consistent with Empire's 2013 IRP filing.

1.6 Additional Scenarios

4 CSR 240-22.030 (8)(A) requires that Empire produce at least two additional normal weather load forecast scenarios representing a high and low growth case. The high and low growth cases are presented in Section 8 in accordance with the Commission's rule.

In addition to these two scenarios, Empire includes two additional scenarios for informational purposes. These scenarios are created in response to a deficiency allegation from the 2013 IRP Joint Filing (Page 4, Paragraph 8) stating "Empire's forecast scenarios reflect too narrow a range of uncertainty regarding the economic series inputs." In 2013, Empire committed to consider scenario suggestions from stakeholders for this 2016 filing.

Based on comments from stakeholders in the November 20, 2015 stakeholder meeting, Empire created the "High-High" scenario. In addition, Empire created the "Aggressive Electric Vehicle" scenario. Both of these scenarios are included in Section 8. Empire believes these scenarios are useful for consideration, but beyond the requirements of the Commission's rules.

SECTION 2 HISTORICAL DATABASE FOR LOAD ANALYSIS

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

2.1 Customer Class Detail

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

Empire maintains historic data by major revenue class (i.e., Residential, Commercial, and Industrial). Empire's database 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).

The database is maintained with at least 10 years of data.

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;

Empire maintains actual customer and energy data by class. 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 would change under normal weather conditions.

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 1985 to 2014.

While weather normalization is performed by month, Table 3-1 and Figure 3-1 show annual summaries of the monthly results.

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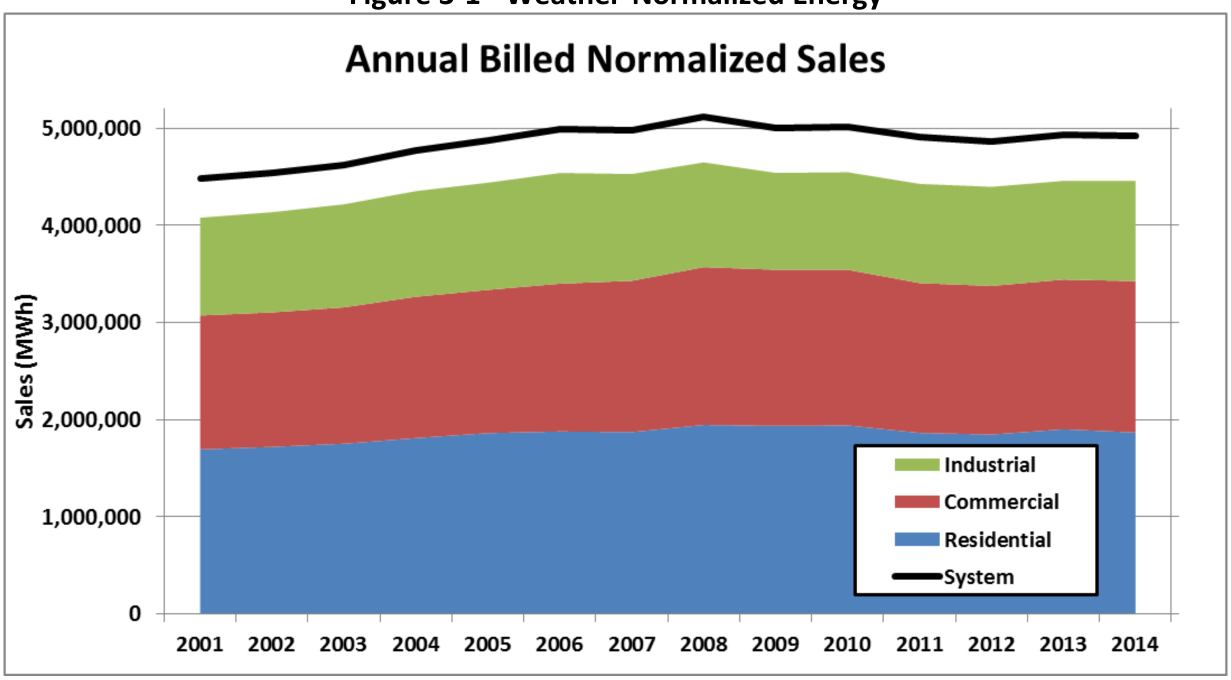
Table 3-1 - Historical Weather Normalized Energy (MWh)

Annual Normal Sales (MWh) - Billed Sales Basis				
Year	Residential	Commercial	Industrial	System
2001	1,694,114	1,378,620	1,006,347	4,485,799
2002	1,719,720	1,384,910	1,031,571	4,543,113
2003	1,752,543	1,404,282	1,060,803	4,625,198
2004	1,810,128	1,455,426	1,088,011	4,775,836
2005	1,861,643	1,474,686	1,103,791	4,875,642
2006	1,878,544	1,522,043	1,139,665	4,986,756
2007	1,872,538	1,557,656	1,099,195	4,981,141
2008	1,944,937	1,625,837	1,078,155	5,120,592
2009	1,935,641	1,607,878	996,872	5,004,388
2010	1,940,320	1,603,016	1,003,529	5,019,011
2011	1,863,597	1,542,932	1,021,190	4,909,736
2012	1,847,508	1,529,734	1,020,086	4,868,380
2013	1,901,250	1,540,850	1,016,580	4,929,899
2014	1,867,906	1,558,779	1,030,432	4,917,640

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 peaks and normalized peaks are derived for each forecast cycle using load research data and the net system loads.

Estimated actual class peaks are developed by summing class profiles from available load research data and calculating coincident peak ratios based on the time of the system peak. The coincident peak ratios are applied to the net system loads to obtain the estimated actual class peaks. The estimated actual peaks are show in Table 3-2.

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

Estimated Actual Peaks (MW)				
	Residential	Commercial	Industrial	System Peak
2003	526	268	170	1,049
2004	496	247	181	1,014
2005	564	266	173	1,095
2006	587	285	192	1,167
2007	575	319	184	1,181
2008	600	310	158	1,161
2009	485	296	189	1,093
2010	582	299	170	1,156
2011	656	287	161	1,209
2012	616	280	152	1,142
2013	424	356	187	1,080
2014	521	292	170	1,083

Class level normalized peaks are derived by multiplying the coincident peak ratios by the normalized system peak. The system peak normalization is described in Section 2.2.3. Class level normalized peaks are contained in Table 3-3.

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

Weather Normalized Class Peaks (MW)				
	Residential	Commercial	Industrial	Weather Normalized System Peak
2003	491	346	160	1,120
2004	558	300	166	1,134
2005	588	300	173	1,172
2006	582	290	204	1,191
2007	618	291	179	1,199
2008	591	287	181	1,174
2009	572	318	172	1,174
2010	594	307	151	1,150
2011	507	309	195	1,142
2012	584	300	162	1,160
2013	627	275	149	1,155
2014	620	282	149	1,149

2.2.3 Weather Normalized Net System Loads

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

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

Weather normalized net system loads are characterized by weather normal peaks and energy. Weather normalized energy is developed by class as discussed in Section 2.2.1, and weather normalized peaks are discussed in Section 2.2.2.

Empire weather normalizes peaks using the peak model described in Section 6.1.2.8 and normal peak producing weather from the Springfield, Missouri airport. Normal weather is defined as the 10 year average from 2005 to 2014 by month and season. Summer and winter weather normalized net system peaks are shown in Figure 3-2.

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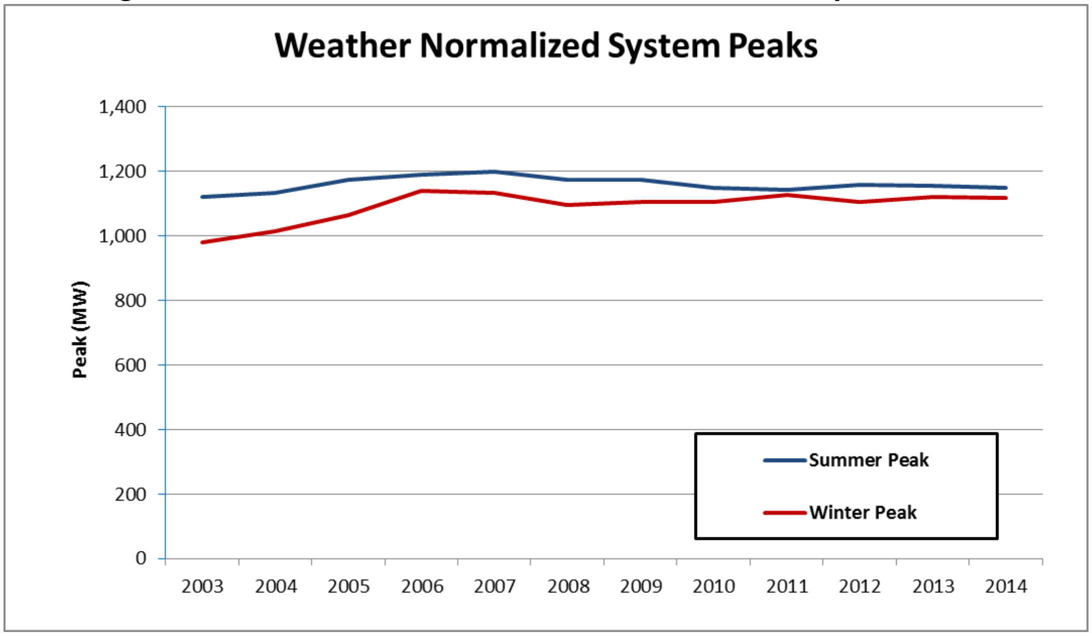
Figure 3-2 - Weather-Normalized Summer and Winter System Peaks



2.3 Load Component Detail

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

2.3.1 Units Component

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

The number-of-units component selected by 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.

Empire's load forecast is revised annually. During each forecast cycle, the historic dataset is reviewed for data anomalies. Scheduled reviews of the load forecast are held with senior management.

2.3.3 Weather Measures and Estimation of Weather Effects Description and Documentation

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

The load forecast uses regression models to capture the effect of weather on electric loads. The regression models use multipart splines to capture the nonlinear relationship between load and weather. The statistical significance of the spline variables are 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 2015 Annual Energy Outlook. These data capture changing end-use saturation and energy efficiency trends for each census region based on known energy efficiency standards and codes.

2.4.2 Weather Sensitivity of Energy and Peak Demand

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

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

2.4.3 Plots Illustrating Trends

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

The major trends affecting electric consumption are economic indicators, prices, weather, and end-use trends. Figure 3-3 through Figure 3-7 show annual summaries of the major trends used in the forecast models.

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

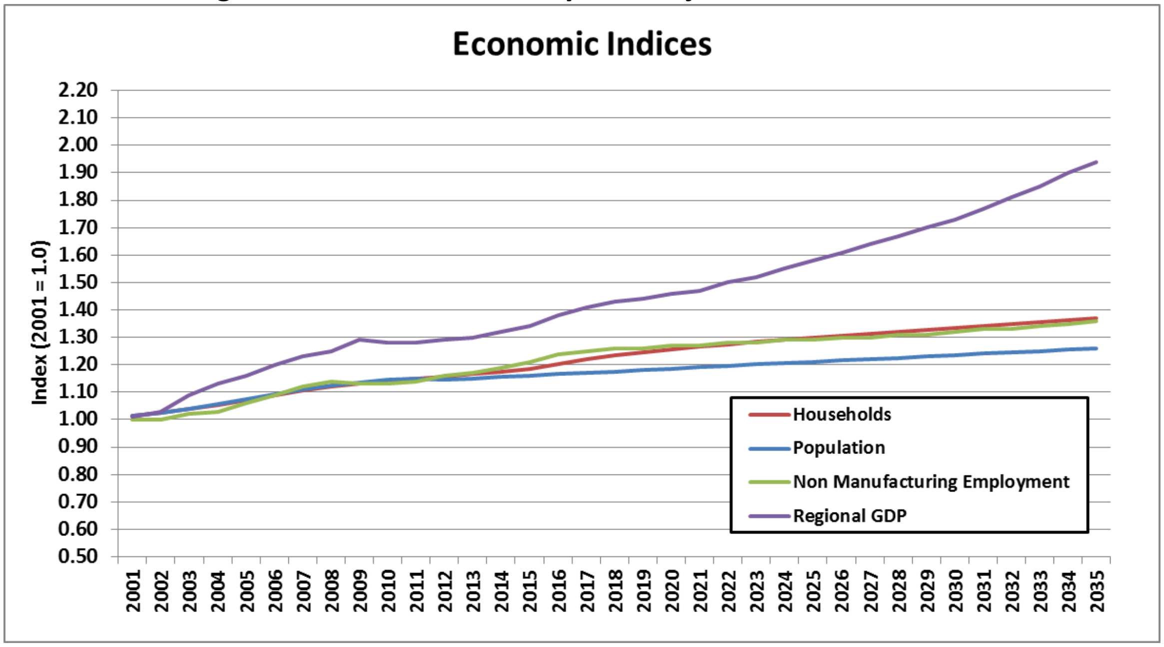


Figure 3-4 - Annual Summary of a Major Trend - Electric Prices

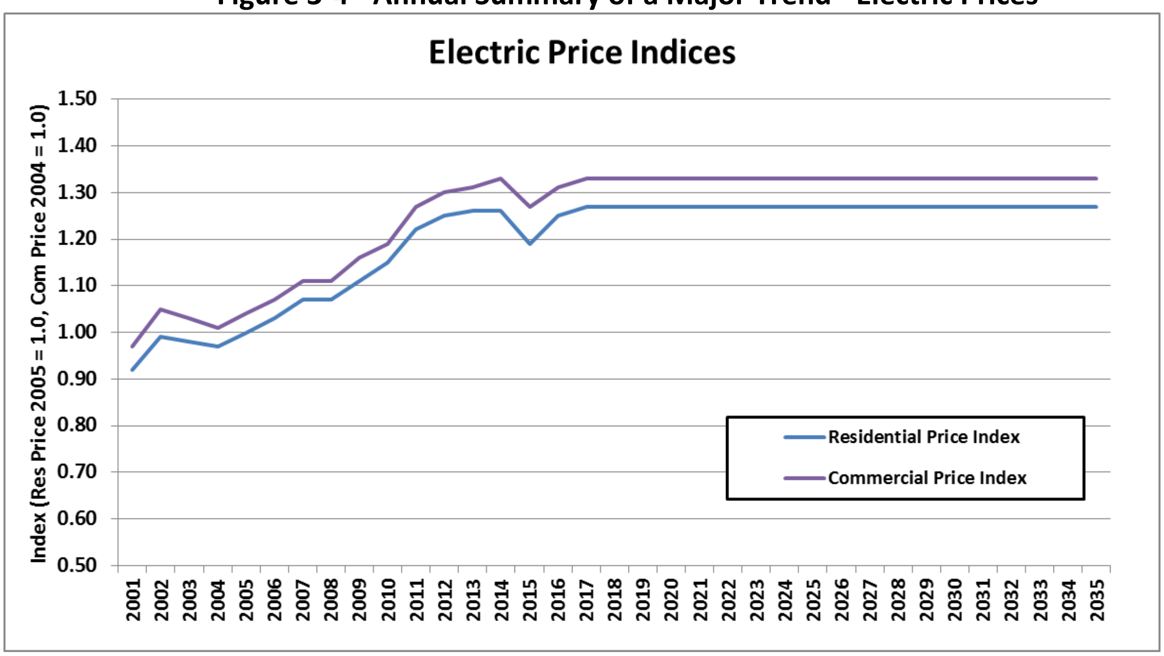


Figure 3-5 - Annual Summary of a Major Trend - Residential SAE Indices

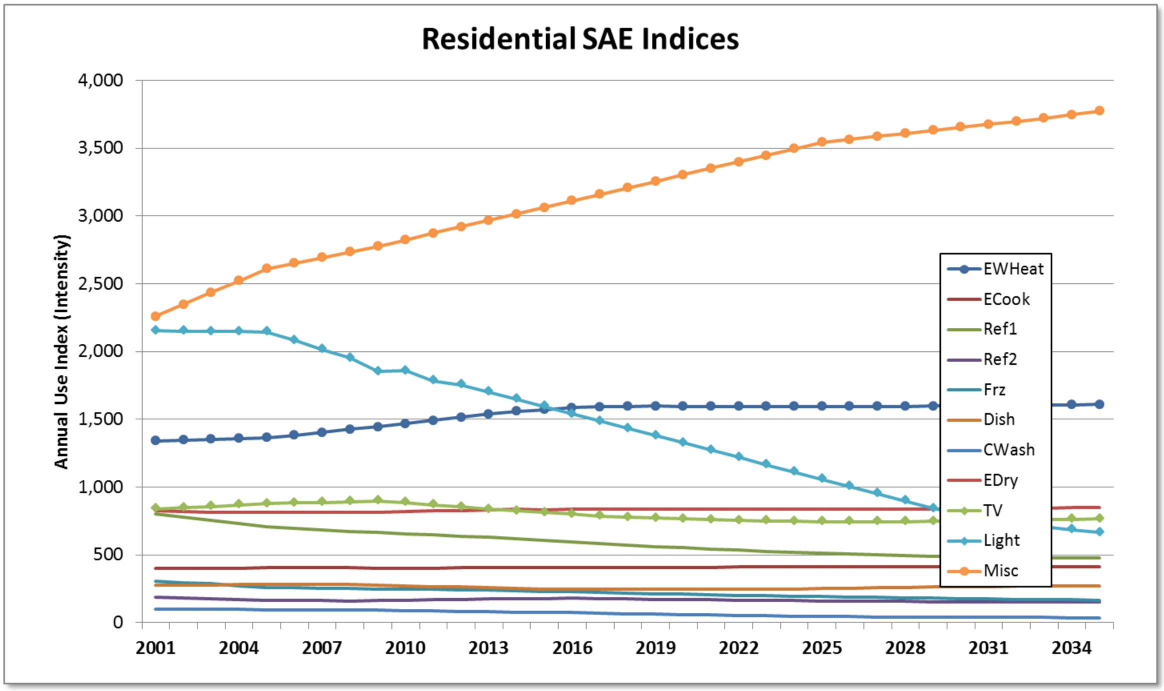


Figure 3-6 - Annual Summary of a Major Trend - Heating and Cooling Degree Days

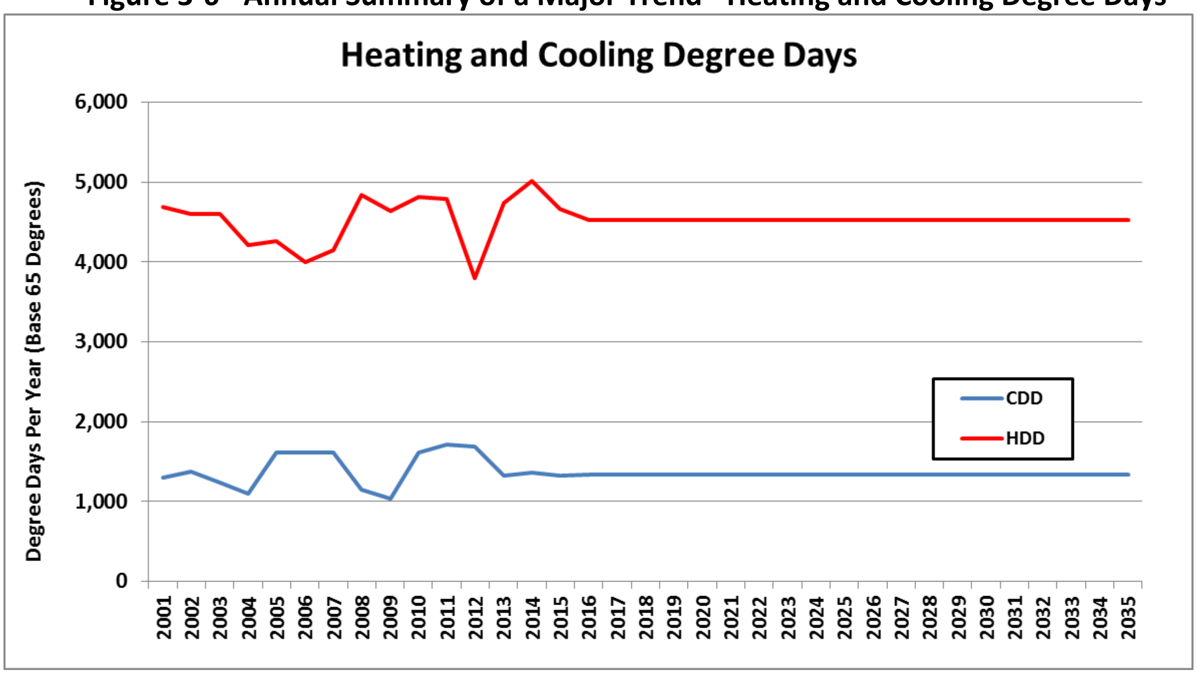
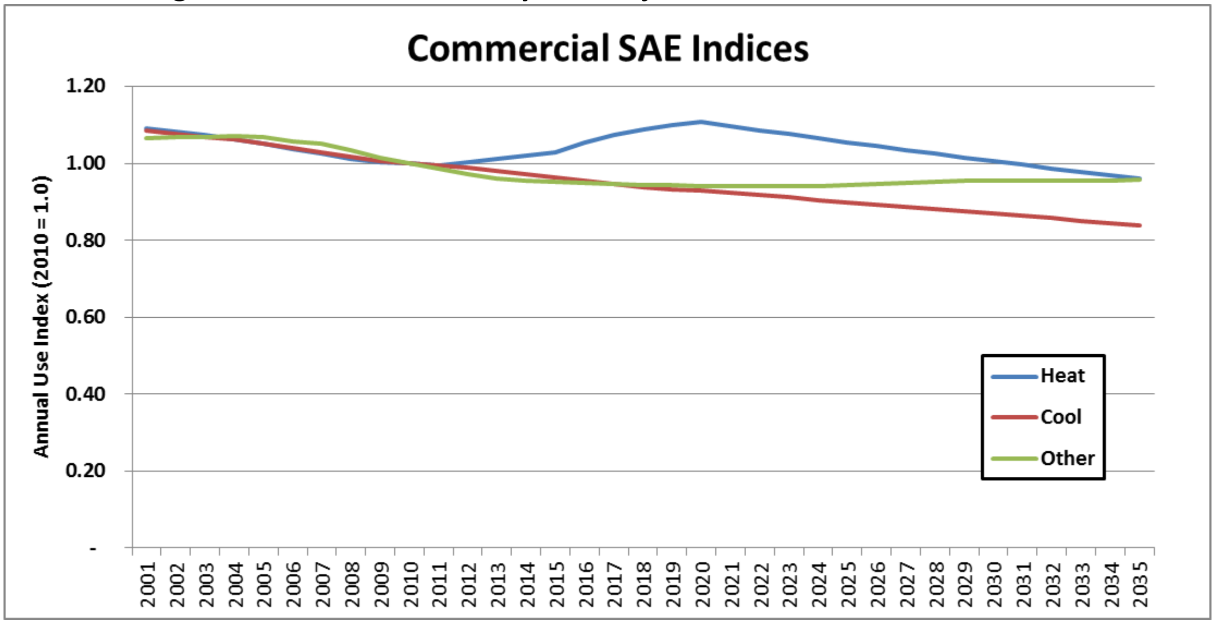


Figure 3-7 - Annual Summary of a Major Trend - Commercial SAE Indices



2.5 Adjustments to Historical Data Description and Documentation

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

The forecast uses historical sales, peak, customers, weather, economic, and end-use data in the development of 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. Estimates of historic curtailments are restored in the hourly net system loads prior to obtaining the monthly peak data.

Economic data are provided by Economy.com for Joplin and Springfield MSAs. The data are combined applying 66% weight to the Joplin MSA and 34% weight to the Springfield MSA. Weights are based on April 2014 through March 2015 residential and commercial energy consumption for counties in the Empire service territory and the two MSAs.

End-use data are provided by Itron and are adjusted to reflect Empire's 2008 Potential Study and 2015 Saturation Survey. Further adjustments of the end-use data are made to smooth the transition between known 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 were made to reflect actual DSM programs and smooth transitions between years.

Commercial adjustments include changes to heating saturations and office equipment saturations. Heating changes were made for consistency with residential heating saturations. Office equipment changes were made to reduce the impact of EIA changes.

2.6 Length of Historical Database

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

Empire retains the historical database for a minimum of 10 years

SECTION 3 ANALYSIS OF NUMBER OF UNITS

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

3.1 Identification of Explanatory Variables

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

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 Economy.com forecasts for the Joplin and Springfield MSAs.
	Average Use (SAE Model)	End Use Efficiency Trends	End-use efficiencies by technology type are based on 2015 EIA data.
		End Use Saturation Trends	End-use saturations by technology type based on EIA data and calibrated to Empire's technology saturation information.
		Housing Stock	Housing information is based on EIA data calibrated to Empire's 2008 Potential Study and 2015 Saturation survey.
		Household Size & Income	Historical and forecast household size and income are based on Economy.com 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 Empire's 2008 Potential Study and 2015 Saturation Surveys.
		HDD and CDD	Heating and cooling degree days
Commercial			
	Customer	Residential Customers	Historical and forecast residential customers are obtained from the Residential Customer modeling process.
	Average Use (SAE Model)	HDD and CDD	Heating and cooling degree days
		End Use Efficiency	End-use efficiencies by technology type are based

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Key Drivers for Forecast Models			
Major Class	**Model**	**Key Explanatory Variable**	**Description**
		Trends	on 2015 EIA data.
		End Use Saturation Trends	End-use saturations by technology type are based on 2015 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 and GDP	Historical and forecast employment and gross regional product are based on Economy.com forecasts for the Joplin and Springfield MSAs.
Industrial			
	Energy - OPP - Praxair - Other Industrial	CDD	Heating and cooling degree days
Municipals			
	Energy - Monett - Mt. Vernon - Lockwood - Chetopa	Population	Historical and forecast population is based on Economy.com forecasts for the Joplin and Springfield MSAs.
		End Use Efficiency Trends	End-use efficiencies by technology type are based on 2015 EIA data.
		End Use Saturation Trends	End-use saturations by technology type based on EIA data and calibrated to Empire's technology saturation information.
		Housing Stock	Housing information is based on EIA data, Empire's 2008 Potential Study and Empire's 2015 Saturation survey.
		Household Size & Income	Historical and forecast household size and household income are based on Economy.com 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 Empire's 2008 Potential Study and 2015 Saturation Survey findings.
		HDD and CDD	Heating and cooling degree days
Street Highway			
	Customer	Population and Non-Manufacturing Employment	The weighted index of population and non-manufacturing employment for the Joplin and Springfield MSA areas.

Key Drivers for Forecast Models			
Major Class	**Model**	**Key Explanatory Variable**	**Description**
	Average Use	Outside Lighting Efficiency	The outside lighting efficiency index is based on the 2015 SAE West North Central zone commercial dataset developed by Itron based on EIA data.
Interdepartmental			
	Average Use	HDD and CDD	Heating and cooling degree days
Public Authority			
	Customer	Government Employment	Historical and forecast government employment is based on Economy.com forecasts for the Joplin and Springfield MSAs.
	Average Use	HDD and CDD	Heating and cooling degree days

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

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.

4.1.1 End-Use Load Information

1. The utility shall consider developing information on at least the following end-use loads:

4.1.1.1 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 applies 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. These data are obtained from the 2015 EIA Annual Energy Outlook and developed by Itron for the West North Central region. End-use saturations are modified by incorporating the Empire 2008 Potential Study and 2015 Saturation Survey.

4.1.1.2 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 applies 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 2015 EIA Annual Energy Outlook and developed by Itron for the West North Central region.

4.1.1.3 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. Empire submitted a variance request specifying that end-use information was not available for the industrial class. The variance request was approved on July 2, 2015.

4.1.2 Modifications of End-Use Loads

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

4.1.2.1 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 aggregates technology information for heating, cooling, and base load end-uses. These variables are combined with economic variables that describe how customers use each end-use.

4.1.2.2 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.

4.1.2.3 Modification of End-Use Documentation

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

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

4.1.3 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.

4.1.4 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. These have been modeled with the XHeat, XCool, HDD, and CDD variables. 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;

Empire does not maintain a database of equipment stock for use in the SAE model. Instead, Empire relies upon the EIA collection of equipment stock which is included in the SAE dataset.

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 estimates are larger than seen in the historic sales, the SAE model will identify a coefficient that reduces the cooling end-use estimate to match the historic sales (i.e., calibrate).

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. As a result, calibration is included by allowing the regression model coefficients to adjust the sales trends (and end-use estimates) for base, summer, and winter loads to the historic peak values.

SECTION 5 SELECTING LOAD FORECASTING MODELS

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

5.1 Consumption Drivers and Usage Patterns

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

Empire’s load forecast uses SAE models for the residential and commercial classes and traditional 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 results of the forecast models are hourly load forecasts from 2016 through 2035.

The process is summarized below:

1. Energy Models: The energy forecast models employ Itron's SAE method for the residential and commercial classes and the traditional econometric method for the remaining classes. 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).

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

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 model and system peak model forecasts resulting in an hourly forecast for each class. The aggregation of the hourly forecasts comprises the 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.

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, Empire determined whether temperature is critical in the forecast model. Through the examination of scatter plots and statistical models, temperature is incorporated into most class energy models. When temperature is included, weather variables are constructed using multipart weather splines (HDD and CDD) and weighted to approximate billing cycle impacts. Forecasts use 30-year normal temperatures for Springfield, Missouri.

b. End-Use Variables. For residential and commercial classes, Empire uses the SAE model. End-use trends calibrated to 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 models and traditional econometric models. The 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 includes the monthly net system peaks from 2001.

b. Weather. A key driver in the peak forecast is the monthly peak producing weather. Peak weather is obtained by averaging the monthly peak producing weather from January 2001 through September 2014. 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 2014 are developed from NOAA data.

2) Replace the April average with cold weather producing peaks only (i.e. remove from the average the years where the peak is produced by hot weather).

3) Replace the October average with hot weather producing peaks only (i.e. remove from the average the years where the peak is produced by cold weather).

4) Replace the January average with the seasonal average calculated on the last ten seasonal cold peak producing events. The seasonal peak event could occur in December, January, or February.

5) Replace the August average with the seasonal average calculated based on the last ten seasonal hot peak producing events. The summer peak event may occur in July, August, or September.

6) Calculate a 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. Empire uses the energy forecast from the Energy Models 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 hourly net system load shape and to calculate coincident class peaks. The key driver in the load profile models and calibration 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 from 30-year (1984 to 2014) rank-and-average method 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 key variables included in each class model are summarized in Table 3-4. This section summarizes the modeling method 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.
2. UPC Model: This model forecasts the average use-per-customer (UPC) for a month.

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.

2. UPC Model: This model forecasts the average UPC for a month.

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 energy forecast is composed of four municipal utilities (Monett, Mt. Vernon, Lockwood, and Chetopa). The forecast for the wholesale class is developed with four energy models, one for each municipal utility. 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.

2. UPC Model: This model forecasts the average UPC for a month.

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.

2. UPC Model: This model forecasts the average UPC for a month.

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 (customer model) and changes in customer usage patterns (UPC model).

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.

2. UPC Model: This model forecasts the average UPC for a month.

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 (customer model) and annual customer usage patterns (UPC model).

Industrial Class

The industrial class is comprised 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.

2. Oil and Pipeline: The oil and pipeline segment consists of 12 customers. Two models are developed to forecast the oil and pipeline energy forecast. The customer model is designed to maintain the 12 customers in the forecast horizon. 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 forecast horizon. 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 that is designed to forecast monthly peaks for the net system load. The system peak model forecast provides the overall peak into which the class level peaks are calibrated.

Profile Model

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

6.1.1.2 Independent and Historical Explanatory Variable Difference

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

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. A summary of major changes from the variables used in the 2013 IRP forecast models is shown in Table 3-5.

Table 3-5 - Variable Differences Between the 2013 and 2016 IRP Models

Key Drivers Changes for Forecast Models			
Class	**Model**	**2013 IRP**	**2016 IRP**
Residential			
	Customer	Population (Missouri, Kansas, Arkansas, and Oklahoma)	Population (Joplin and Springfield MSAs)
	Average Use (SAE Model)	2011 SAE Data XHeatShift2005	2015 SAE Data XHeatShift2007 • Updated heating trend shift
Commercial			
	Customer	Residential Customers Employment	Residential Customers • Removed employment to improve statistical fit.
	Average Use (SAE Model)	2011 SAE Data	2015 SAE Data Additional Binary Shifts • Added shift variables to adjust trends to new data
Industrial			
	Energy - OPP - Praxair - Other		Additional Binary Shifts • Added shift variables to adjust trends to new data

Key Drivers Changes for Forecast Models			
Class	**Model**	**2013 IRP**	**2016 IRP**
Municipals			
	Energy - Monett - Mt. Vernon - Lockwood - Chetopa	2011 SAE Data Missouri Households Kansas Households	2015 SAE Data Removed Households as an independent variable. Included Population (Joplin and Springfield MSAs) into the XOther variable
Street Highway			
	Customer	Households	Population and Non-Manufacturing Employment • Updated drivers to improve statistical fit.
	Average Use		No Change
Interdepartmental	Customers		Additional Binary Shifts • Added shift variables to adjust trends to new data
	Average Use		Additional Binary Shifts • Added shift variables to adjust trends to new data
Public Authority			
	Customer	Households	Government Employment • Changed driver for a better class fit. Additional Binary Shifts • Added shift variables to adjust trends to new data
	Average Use	HDD Base 60 CDD Base 60	HDD Base 55 CDD Base 55 • Change weather response for a better statistical fit.
System Peak		CDD HDD Energy Trend Winter Energy Trend Summer Energy Trend	CDD Trend Interaction HDD Trend Interaction Other (Baseload) Trend January 2012 Plus Winter Energy Trend CDD80 Spline • Heating and cooling modeling include end-use trend interaction • Baseload trend represents non-HVAC end-uses • Additional CDD80 spline capture flatting summer response • January 2012 Plus Trend captures growing heating response
Hourly Profile Models		Individual HDD and CDD splines	Weighted Average HDD and CDD splines

Key Drivers Changes for Forecast Models			
Class	Model	2013 IRP	2016 IRP
			• Combining HDD and CDD splines into weighted average improves capturing the nonlinear weather response.

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 Model: The customer model is a regression model estimated with historical data from January 2000 through March 2015. 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	67208.775	47765.424	1.407	16.14%
May2011Tornado	-2171.910	178.774	-12.149	0.00%
Population	67544.244	39312.096	1.718	8.78%
Year2012Plus	-1890.843	255.351	-7.405	0.00%
March	-170.854	42.117	-4.057	0.01%
April	-461.418	57.192	-8.068	0.00%
May	-638.277	66.443	-9.606	0.00%
June	-732.338	71.007	-10.314	0.00%
July	-648.763	72.455	-8.954	0.00%
August	-586.642	70.977	-8.265	0.00%
September	-681.120	66.379	-10.261	0.00%
October	-591.278	57.928	-10.207	0.00%
November	-210.039	43.435	-4.836	0.00%
AR(1)	0.986	0.009	115.993	0.00%

Table 3-7 - Residential Customer Model Statistics

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Statistics	Residential Customer Model
Estimation	1/2001 - 3/2015
R2	0.999
Adj. R2	0.999
MAPE	0.08%
DW	2.024

a. Model Variables: The primary driver of the customer model is population. Two binary shift variables are included to capture the impact of the Joplin tornado in 2011. Monthly binary variables are included to capture the season pattern and the 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 Economy.com.

2) May2011Tornado: This variable takes the value of “0” through April 2011 and then takes the value of “1” from May 2011 through December 2011.

3) January2012Plus: This variable takes the value of “0” through December 2011 and then takes the value of “1” from January 2012 through the forecast period. .

4) 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.

5) 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 March 2015. 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 2015 SAE West North Central region modified for

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	1.254	0.041	30.901	0.00%
XCool	0.930	0.050	18.438	0.00%
XOther	0.837	0.015	57.270	0.00%
September	151.732	25.128	6.038	0.00%
January	107.821	19.386	5.562	0.00%
July	158.542	26.663	5.946	0.00%
August	111.016	32.761	3.389	0.09%
November	-93.318	17.147	-5.442	0.00%
XHeatShift2007	0.137	0.033	4.172	0.01%
Year2014Plus	-27.458	16.904	-1.624	10.61%

Table 3-9 - Residential UPC Model Statistics

Statistics	Residential Customer Model
Estimation	1/2000 – 3/2015
R2	0.955
Adj. R2	0.953
MAPE	4.11%
DW	2.195

b. Model Variables: The UPC model includes the three standard SAE variables (XHeat, XCool, and XOther) as wells as monthly binary variables and shift 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) September, January, July, August, and November: These binary variables are included to capture a patterned residual for each month.

5) 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.

6) year2014Plus: This shift variable adjusts the model to ensure that the forecast is consistent with recent history beginning in 2014.

6.1.2.2 Commercial Class

1. Customer Model: The customer model is a regression model estimated with historical data from January 2002 through March 2015.

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	4786.052	1608.159	2.976	0.34%
Residential Customers	0.134	0.009	14.303	0.00%
March	19.536	8.229	2.374	1.89%
April	54.673	11.666	4.686	0.00%
May	85.162	14.801	5.754	0.00%
June	150.735	16.345	9.222	0.00%
July	80.580	17.124	4.706	0.00%
August	77.407	16.629	4.655	0.00%
September	94.794	16.497	5.746	0.00%
October	80.224	14.958	5.363	0.00%
November	37.769	11.735	3.218	0.16%
December	21.279	8.445	2.520	1.28%
AR(1)	0.992	0.012	81.594	0.00%

Table 3-11 - Commercial Customer Model Statistics

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

a. Model Variables: The primary driver in the customer model is the number of residential customers. Monthly binary variables are included to capture the season pattern, and the AR term corrects for serial correlation.

1) Residential Customers: This variable is the historical and forecasted number of customers based on the residential customer model. Commercial customer counts are highly correlated with residential customer counts.

2) Monthly Binary Variables: Binary variables for March through December are included to capture seasonal customer effects. These variables take the value of "1" in their month and a "0" for all other months.

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

2. UPC Model: The UPC model is an SAE model estimated with historical data from January 2000 through March 2015. 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 other technologies. The data for the SAE model is from Itron's 2015 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	0.042	0.002	20.787	0.00%
XCool	0.182	0.005	34.650	0.00%
XOther	0.041	0.000	111.321	0.00%
XHeatShift2006	339.660	59.329	5.725	0.00%
September	-255.226	64.336	-3.967	0.01%
Year2000	-390.122	64.599	-6.039	0.00%
Year2006	-315.858	64.510	-4.896	0.00%
Year2007	488.168	36.578	13.346	0.00%
Year2006Plus	160.388	47.505	3.376	0.09%
Year2013Plus	0.042	0.002	20.787	0.00%

Table 3-13 - Commercial UPC Model Statistics

Statistics	Commercial UPC Model
Estimation	1/2000 – 3/2015
R2	0.911
Adj. R2	0.907
MAPE	2.96%
DW	2.152

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) XOther: This variable captures the general response for all non-heating and cooling technologies. The response includes the effects of other base load technology efficiencies, saturation by technology and

building types, price, employment, output indices, DSM programs, and photovoltaics.

4) XHeatShift2006: This variable is used to capture a general heating response shift beginning in 2006. The shift occurs near the end of the high economic growth period in the mid-2000 time.

5) September Binary: This binary variable is included to capture a patterned residual.

6) Year2000, Year2006, and Year2007: These independent binary variables are included to capture the quick growth in average use during the high economic growth period.

7) Year2006Plus: This binary variable consists of a "1" value beginning in 2006 and continues throughout the forecast period. This variable is used to capture the consistent shift in average use obtained during the high economic growth period.

8) Year2013Plus: This binary variable consists of a "1" value beginning in 2013 and continues throughout the forecast period. This variable is used to calibrate recent historical shifts into the forecast period.

6.1.2.3 Wholesale Class

1. Energy Models: The models forecast total energy and are not divided into a customer and UPC model. 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.

5) 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.

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

7) 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.

Table 3-14 - Monett Energy Model
****Highly Confidential in its Entirety****

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Table 3-15 - Monett Energy Model Statistics

Statistics	Monett Model
Estimation	1/2002 – 3/2015
R2	0.896
Adj. R2	0.890
MAPE	2.79%
DW	2.082

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

Table 3-16 - Mt. Vernon Energy Model
****Highly Confidential in its Entirety****

Table 3-17 - Mt. Vernon Energy Statistics

Statistics	Mt. Vernon Model
Estimation	1/2000 – 3/2015
R2	0.927
Adj. R2	0.926
MAPE	3.40%

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Statistics	Mt. Vernon Model
DW	2.156

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

Table 3-18 - Lockwood Energy Model
****Highly Confidential in its Entirety****

Table 3-19 - Lockwood Energy Model Statistics

Statistics	Lockwood Model
Estimation	1/2000 – 3/2015
R2	0.949
Adj. R2	0.947
MAPE	3.54%
DW	1.731

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

Table 3-20 - Chetopa Energy Model
****Highly Confidential in its Entirety****

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Table 3-21 - Chetopa Energy Model Statistics

Statistics	Chetopa Model
Estimation	1/2000 – 3/2015
R2	0.889
Adj. R2	0.885
MAPE	5.31%
DW	1.511

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 March 2015. Table 3-22 shows the customer model specification and Table 3-23 shows the customer model statistics.

Table 3-22 - Street and Highway Customer Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	195.752	22.137	8.843	195.752
Oct2007ToDec2008 Binary	-9.931	2.361	-4.206	-9.931
Population & Non-Manufacturing Employment	243.374	19.981	12.180	243.374
AR(1)	0.777	0.048	16.085	0.777

Table 3-23 - Street and Highway Customer Model Statistics

Statistics	Street and Highway Customer Model
Estimation	1/2001 – 3/2015
R2	0.951
Adj. R2	0.950
MAPE	0.53%
DW	1.882

a. Model Variables: The street and highway model includes two variables and an AR term. The primary driver of the customer model 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) AR Term: The AR term corrects the model for serial correlation and does not impact the overall relationship between the economic driver and customers.

2. UPC Model: The UPC model is a regression model estimated with historical data from January 2001 through March 2015. 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	3811.627	98.763	38.594	0.00%
January	1257.704	69.388	18.126	0.00%
February	660.792	69.391	9.523	0.00%
March	536.169	69.395	7.726	0.00%
April	90.053	70.585	1.276	20.39%
May	10.193	70.584	0.144	88.54%
July	285.912	70.435	4.059	0.01%
August	427.882	70.436	6.075	0.00%
September	500.202	70.592	7.086	0.00%
October	924.992	70.596	13.103	0.00%
November	1044.867	70.601	14.800	0.00%
December	1491.108	70.607	21.119	0.00%
OutsideLightEfficiency	-5.313	1.917	-2.772	0.62%
Sep2007ToMay2008	161.157	64.522	2.498	1.35%

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Table 3-25 - Street and Highway UPC Model Statistics

Statistics	Street and Highway UPC Model
Estimation	1/2001 – 3/2015
R2	0.875
Adj. R2	0.864
MAPE	2.63%
DW	2.602

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 using 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.

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 an end-shift binary variable to capture the value of the last actual data point and project that value through the forecast horizon.

2. UPC Model: The UPC model is a regression model estimated with historical data from January 2001 through March 2015. 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	10577.682	387.893	27.270	0.00%
Year2008Plus	-4871.585	489.595	-9.950	0.00%
Year2007Plus	-2858.430	489.966	-5.834	0.00%
Year2014Plus	3645.059	448.845	8.121	0.00%
HDD55	4.931	0.798	6.183	0.00%
CDD55	2.730	0.754	3.622	0.04%

Table 3-27 - Interdepartmental UPC Model Statistics

Statistics	Interdepartmental UPC Model
Estimation	1/2001 – 3/2015
R2	0.846
Adj. R2	0.841
MAPE	13.09%
DW	1.815

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, and Year2014Plus) capture annual shifts in the average use which continue through the forecast period. These shifts capture the rapid decline through 2008 and the sudden increase in 2014.

6.1.2.6 Public Authority Class

1. Customer Model: The customer model is a regression model designed to provide the 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	313.690	52.000	6.033	0.00%
Government Employment	973.127	42.502	22.896	0.00%
Sept2014Plus	-23.031	7.582	-3.037	0.30%
July 2012 to August 2014	156.234	4.473	34.932	0.00%

Table 3-29 - Public Authority Customer Model Statistics

Statistics	Public Authority Customer Model
Estimation	1/2000 - 3/2015
R2	0.981
Adj. R2	0.980
MAPE	0.74%
DW	0.293

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 Joplin and Springfield MSAs forecast for government employment.

   2) Annual Shift Variables: This variables (Sept2014Plus) 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 March 2015. This model is designed to capture 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	4424.877	67.540	65.514	0.00%
Year2008Plus	308.446	46.791	6.592	0.00%
Year2002Plus	-200.854	51.995	-3.863	0.02%
Year2012Plus	-569.638	53.802	-10.588	0.00%
HDD55	2.176	0.136	15.968	0.00%
CDD55	2.139	0.114	18.792	0.00%
February	-333.389	74.276	-4.489	0.00%
June	177.756	66.938	2.656	0.86%

Table 3-31 - Public Authority UPC Model Statistics

Statistics	Public Authority UPC Model
Estimation	1/1999 - 9/2011
R2	0.727
Adj. R2	0.717
MAPE	3.66%
DW	1.780

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

   1) Weather Variables: This set of variables (HDD55 and CDD55) captures the weather response of the public authority class.

   2) Annual Shift Variables: This set of variables (Year2002Plus, Year2008Plus, and year2012Plus) captures annual shifts in the average use which continue through the forecast period.

   3) Monthly Binaries: The February and June binary variables capture the patterned residuals which contribute to the seasonal shape.

6.1.2.7 Industrial Class

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1. Praxair Model: The Praxair model is a single regression model developed to forecast monthly energy. The model is created to provide a forecast based on the 2013 through 2015 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
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Table 3-33 - Praxair Model Statistics

Statistics	Praxair Model
Estimation	1/2001 – 3/2015
R2	0.191
Adj. R2	0.140
MAPE	6.50%
DW	1.376

a. Model Variables: The Praxair model consists of five annual shift variables (Year2008Plus, Year2009Plus, Year2010Plus, Year2011Plus, and Year2013Plus). These variables are designed to capture the average energy load for the year and project the 2013 through 2015 average energy load through the forecast horizon.

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

2. Oil and Pipeline Model:

a. Oil and pipeline uses two models to forecast energy. The customer model is designed to forecast the existing 12 customers throughout the forecast horizon. The UPC model is designed to capture monthly variation for these customers.

b. The UPC model is designed to capture 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	383595.727	26286.230	14.593	0.00%
Year2003Plus	-207852.205	60556.528	-3.432	0.08%
Year2004Plus	478525.721	64917.346	7.371	0.00%
Year2005Plus	-79241.070	31188.850	-2.541	1.19%
Year2008Plus	-128125.525	22053.848	-5.810	0.00%
Year2011Plus	47840.686	22053.848	2.169	3.14%
Year2014Plus	52809.933	28849.581	1.831	6.89%
Year2003Trend	57095.236	8075.304	7.070	0.00%
January	24795.637	33066.396	0.750	45.43%
February	-2117.439	32991.968	-0.064	94.89%
March	52329.412	32924.227	1.589	11.38%
April	70539.842	33326.267	2.117	3.57%
May	107482.294	33268.891	3.231	0.15%
June	110868.262	33219.086	3.337	0.10%
July	140708.587	33176.884	4.241	0.00%
August	141872.686	33142.316	4.281	0.00%
September	103368.823	33115.404	3.121	0.21%
October	45000.511	33096.168	1.360	17.57%
November	25106.746	33084.621	0.759	44.89%

Table 3-35 - Oil and Pipeline UPC Model Statistics

Statistics	Oil and Pipeline UPC Model
Estimation	1/1999 – 3/2015
R2	0.591
Adj. R2	0.549
MAPE	13.73%
DW	1.449

c. Model Variables:

1) Annual Shift Binary: These variables (Year2003Plus through Year2014Plus) are designed to capture the average energy load for the year and project the 2014 and 2015 average energy load through the forecast horizon.

2) Year2003Trend: This variable is a trend variable that applies only in 2003. The variable is designed to capture the rapid change in 2003.

3) Monthly Binary: These independent binary variables are included to capture a patterned residual through the course of the year.

3. Other Industrial Model: The remaining industrial customers ("other industrial") are modeled using two models to forecast energy. The customer model is designed to forecast the existing 338 customers throughout the forecast horizon. The UPC model is designed to capture 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	203678.839	1924.056	105.859	0.00%
January	11871.386	2552.124	4.652	0.00%
February	2512.104	2551.800	0.984	32.63%
March	10893.579	2545.741	4.279	0.00%
April	3724.034	2736.706	1.361	17.54%
May	11945.979	3693.482	3.234	0.15%
June	13996.666	5827.993	2.402	1.74%
July	16832.039	8107.280	2.076	3.94%
August	20183.733	9083.895	2.222	2.76%
September	6205.952	7620.289	0.814	41.66%
October	9134.373	4456.193	2.050	4.20%
November	3476.178	2782.296	1.249	21.33%
CDD55	37.861	12.550	3.017	0.30%
Year2003	-8862.554	2192.180	-4.043	0.01%
Year2006	6260.339	2200.934	2.844	0.50%
Year2009	-13156.871	2242.160	-5.868	0.00%
Year2010Plus	-12466.684	2198.913	-5.669	0.00%
Year2011Plus	6267.319	2275.934	2.754	0.66%

Table 3-37 - Other Industrial UPC Model Statistics

Statistics	Other Industrial Model
Estimation	1/2000 – 3/2015
R2	0.840
Adj. R2	0.824
MAPE	2.29%
DW	2.096

a. Model Variables:

1) Annual Shift Binary: The shift variables (Year2010Plus and Year2011Plus) capture the average energy load for the year and

project the 2011 to 2015 average energy load through the forecast horizon.

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 are included to capture the seasonality of the industrial class.

6.1.2.8 System Peak Model

The model is estimated with historical monthly peak and monthly peak producing weather from January 2003 through March 2015. 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	65.640	118.094	0.556	57.93%
HDD x Heating Trend	11.051	0.301	36.672	0.00%
CDD x Cooling Trend	31.797	1.003	31.694	0.00%
Other Trend Index	564.002	109.015	5.174	0.00%
January 2012 Plus x Winter Energy Trend	38.622	15.660	2.466	1.50%
Cooling Peak CDD 80	-14.789	2.264	-6.534	0.00%

Table 3-39 - System Peak Model Statistics

Statistics	Public Authority Customer Model
Estimation	1/2003 – 3/2015
R2	0.954
Adj. R2	0.952
MAPE	2.75%
DW	1.719

1. Model Variables: The system peak model is primarily driven by the energy forecast and includes 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. Other Trend Index: The Other Trend Index captures the non-HVAC growth trends of the energy models.

    d. 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 2010. This variable is designed to capture additional growth in the winter peak above the energy trend.

    e. Cooling Peak CDD80: The variable captures a flattening of the summer peak weather response when the three-day weighted average temperature exceeds 80 degrees.

6.1.2.9 Profile Model

1. Data Development: 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 2014 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% 6% 13% 4%
Wholesale	Monett, Mt. Vernon, Lockwood, Chetopa	NA
Street Highway	CB Generic Lighting Shape SH	77% 22% 1%
Interdepartmental	CB GP - Secondary	86% 14%
Industrial: Other Industrial	CB GP - Secondary LP - Primary SH TEB	26% 57% 8% 5% 4%
Industrial: Praxair	Praxair	NA
Industrial: OPP	GP - Primary LP - Primary	67% 33%

2. Profile Models: The profile models developed consist of a standard set of variables used to 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	X	X	X	X	X	
Street Highway	X	X	X	X	X	
Interdepartmental	X	X		X	X	

Class	HDD CDD	Day of Week	Month	Year	Holiday	Hours of Light
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 multipart 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: This set of binary variables is used to capture variations in the profile shape based on the day of the week.

c. Annual Binaries: This set of binary variables is used to 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: Of the eight class models, three models contain exceptions to the general modeling method. These exceptions are summarized below:

   a. Wholesale Class: The wholesale class consists of four wholesale customers. Historical interval data for these customers exist. As a result, data were not derived from load research data. Instead, the class profile is obtained by summing the hourly loads for the four wholesale customers.

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 Empire.

6.2 Deviations

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

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

6.3 Historical Database

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

6.3.1 Independent Variables

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

Empire maintains a 10 year data set of historical values for independent variables. 2015 is the first year of forecast driver values.

6.3.2 Adjustments

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

Adjustments to the historical data are described in Section 2.5.

6.3.3 Comparison of Historical Independent Variable Projections

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

Over the past 10 years, Empire has filed IRP forecasts in 2007, 2010, and 2013. The 2013 IRP filing employed a substantially different method than prior filings including the use of SAE models and a new economic vendor. As a result, relevant comparison independent variables from 2007 and 2010 are not possible.

However, the 2013 IRP is similar to the 2016 IRP. The key differences in the method are in changes to the definition of the economic variables. In the 2013 IRP, economic variables were developed based on state-level economic forecasts. In the 2016 IRP, economic variables are based on the Joplin and Springfield MSAs economic forecasts. To compare the economic data, the key drivers are indexed. The comparisons shown are for employment, households, and population in Figure 3-8 through Figure 3-10.

Figure 3-8 - Comparison 2013 and 2016 IRP Employment Index

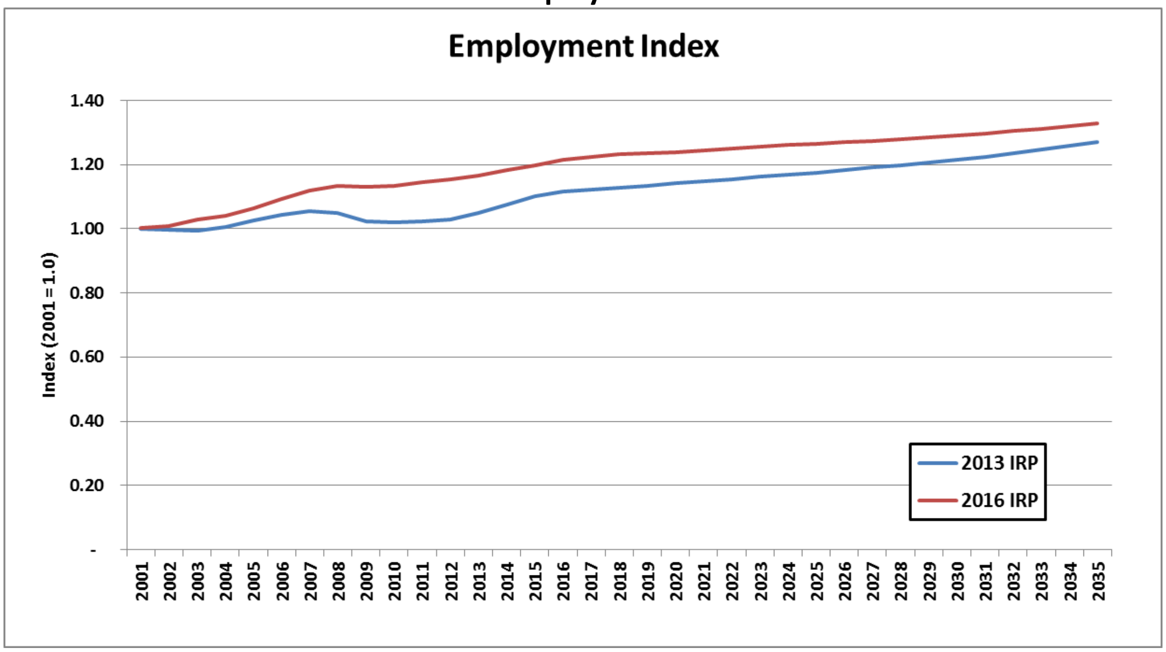

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Figure 3-9 - Comparison 2013 and 2016 IRP
Population Index

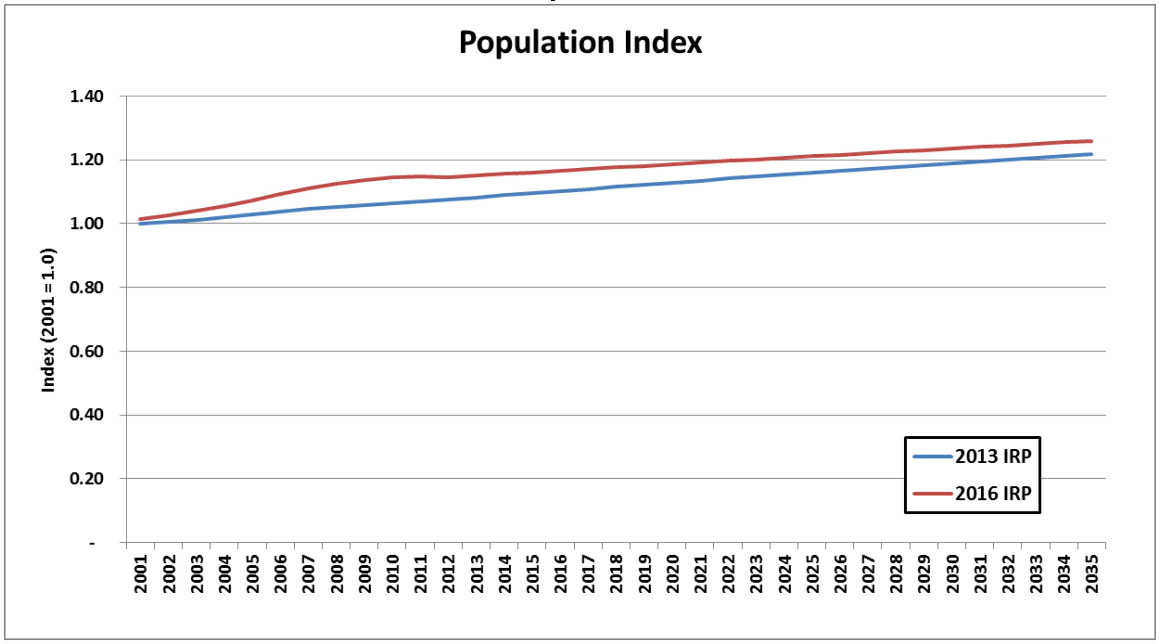
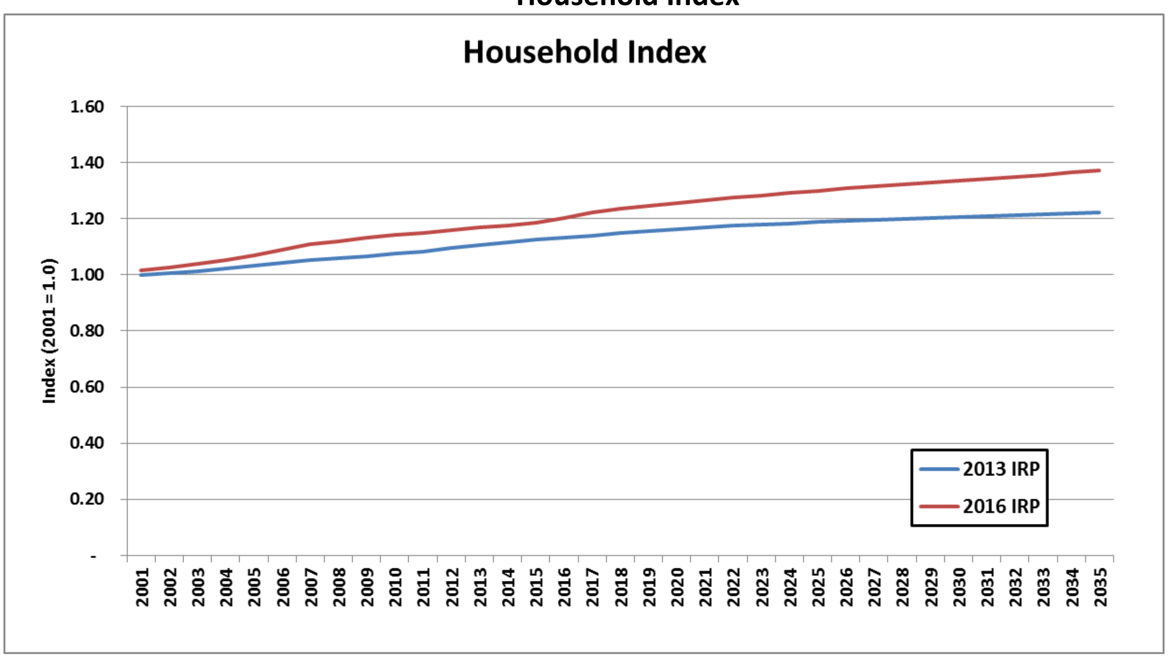


Figure 3-10 - Comparison 2013 and 2016 IRP
Household Index



The SAE data for the 2013 and 2016 IRPs are developed by Itron. The 2013 IRP SAE data was developed in 2011 using Itron's 2011 SAE Data. The 2016 IRP SAE data is developed using Itron's 2015 SAE Data. The following figures show the differences between the 2011 and 2015 data. Figure 3-11 through Figure 3-13 compare the SAE indices for residential heating, cooling, and other (baseload).

Figure 3-14 through Figure 3-16 compare SAE indices for commercial heating, cooling, and other (baseload).

Figure 3-11 - Comparison 2013 and 2016 IRP
Residential Heating Index

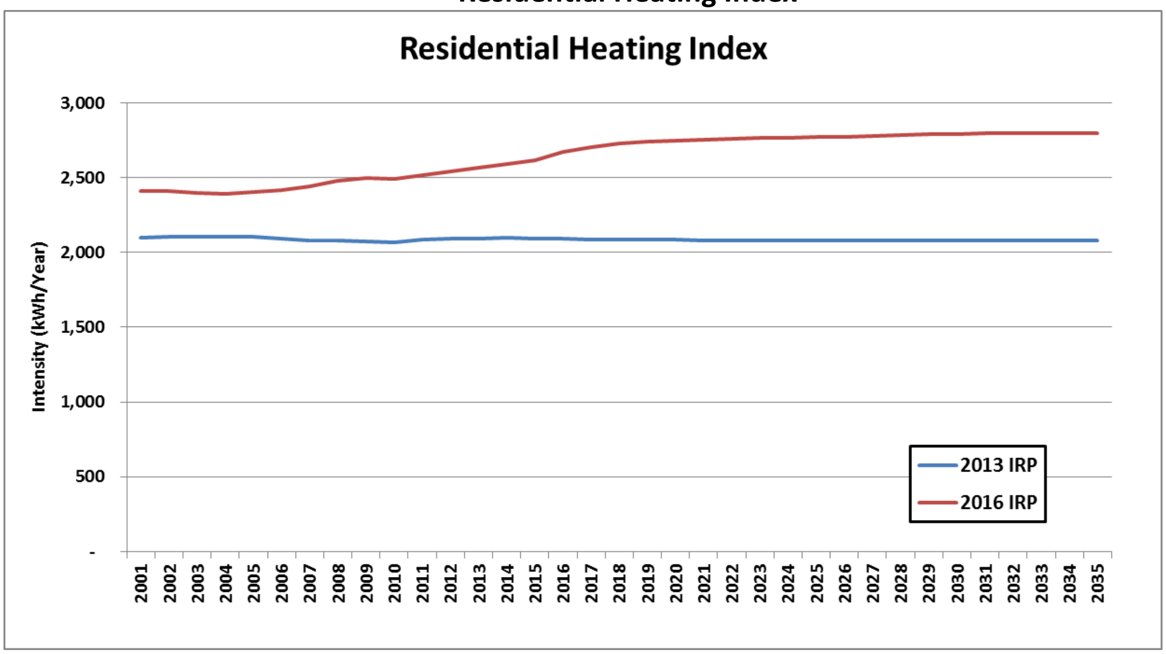


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Figure 3-12 - Comparison 2013 and 2016 IRP
Residential Cooling Index

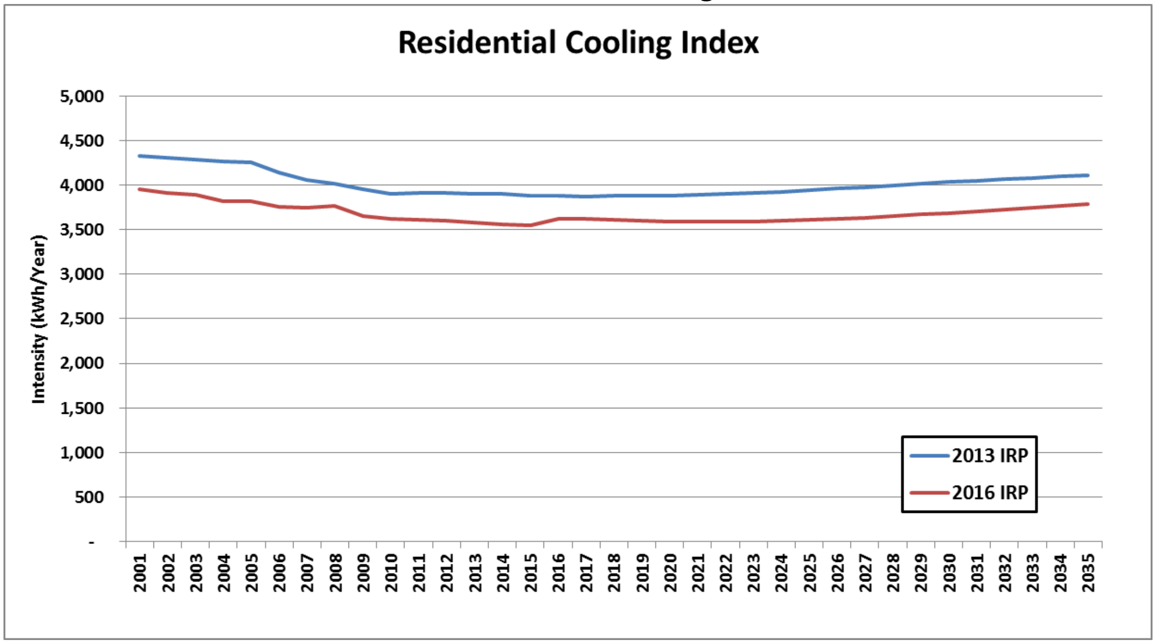

Figure 3-13 - Comparison 2013 and 2016 IRP
Residential Other Index

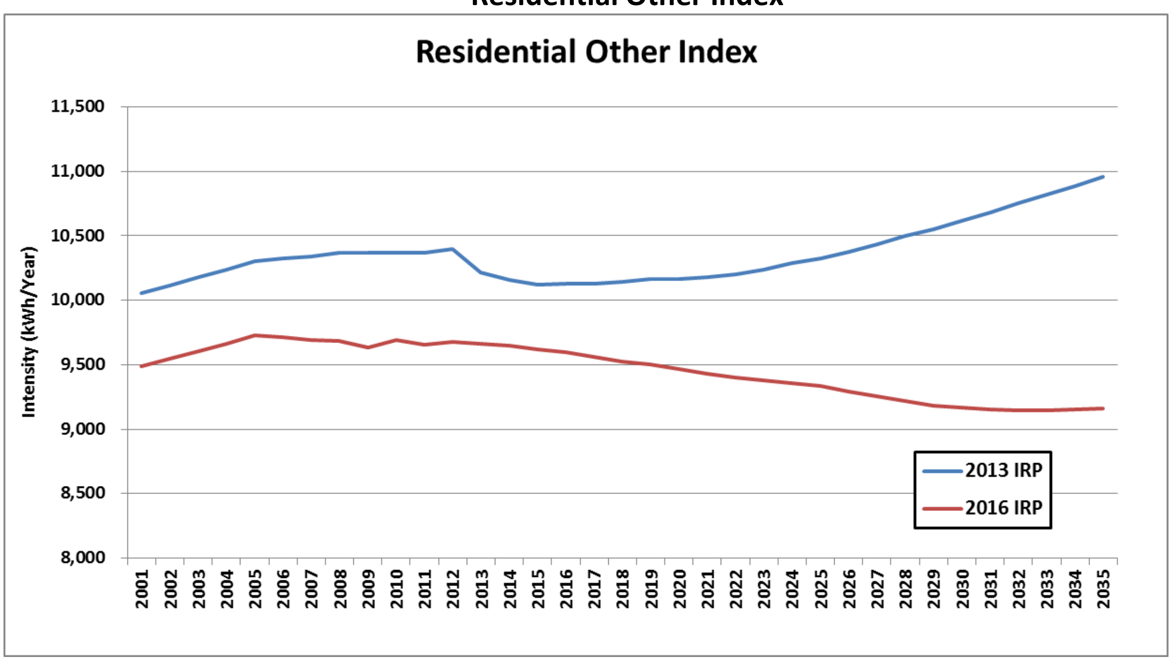

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Figure 3-14 - Comparison 2013 and 2016 IRP
Commercial Heating Index

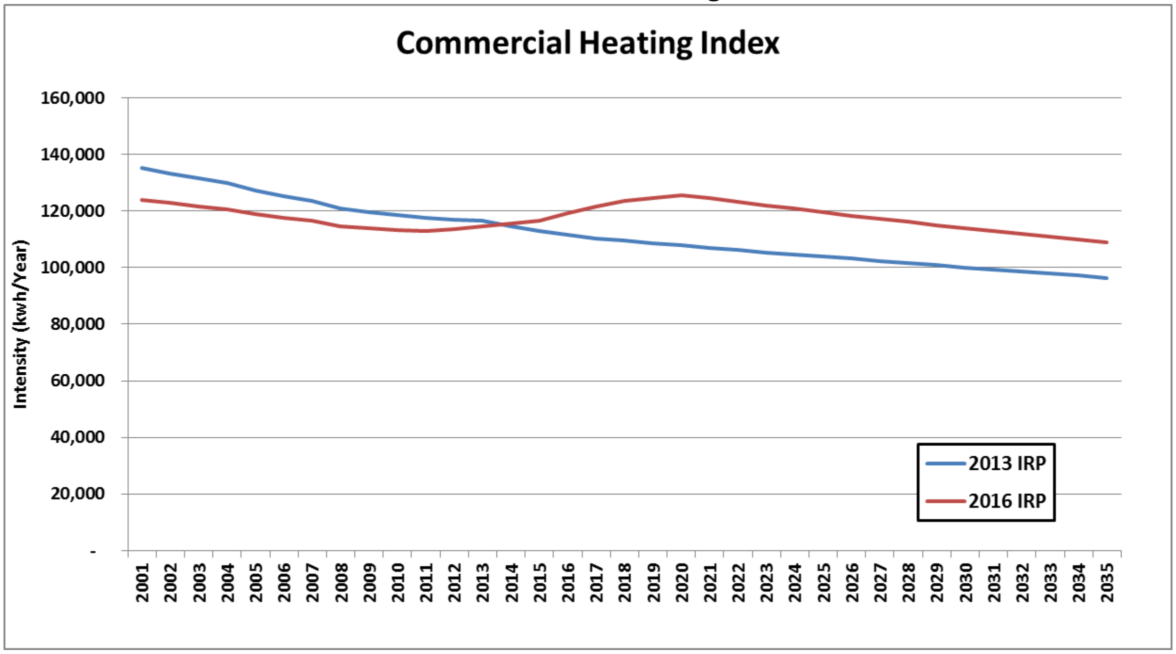


Figure 3-15 - Comparison 2013 and 2016 IRP
Commercial Cooling Index

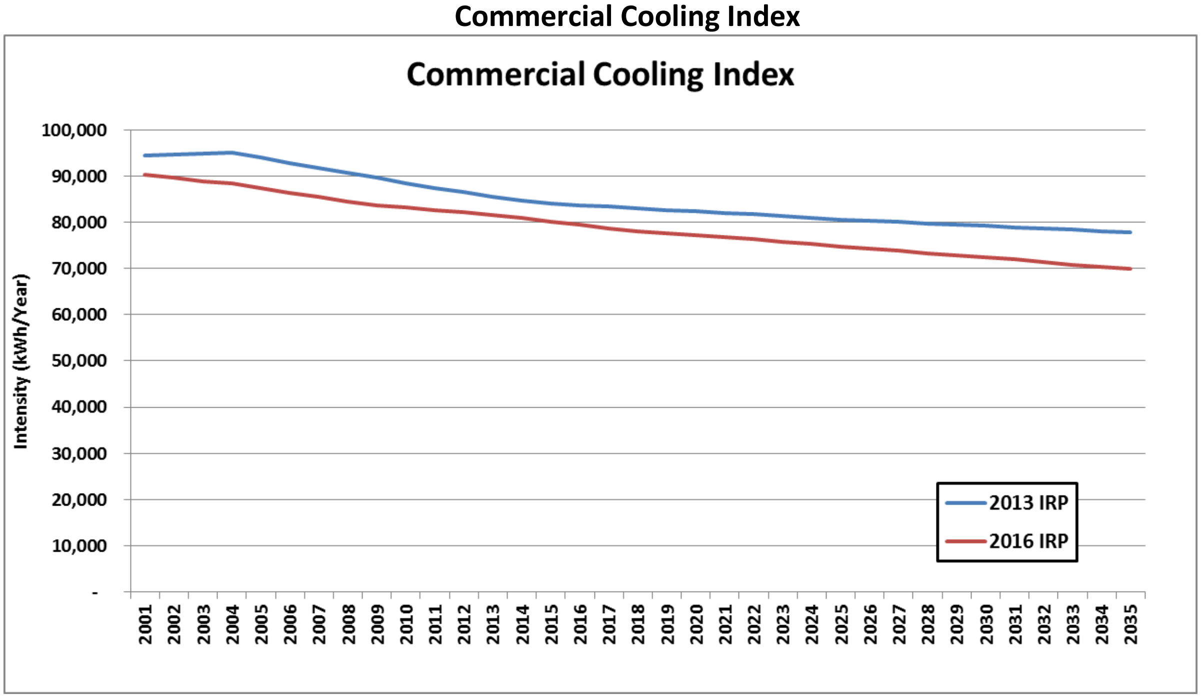
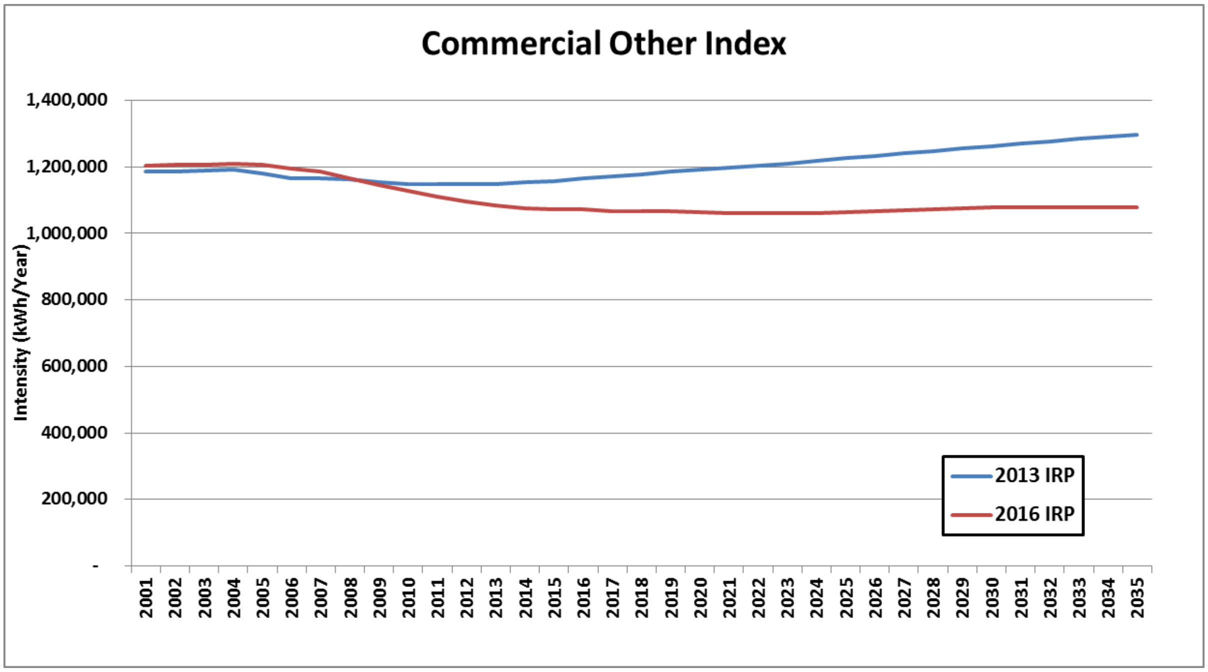


Figure 3-16 - Comparison 2013 and 2016 IRP
Commercial Other Index



The weather assumption between the 2013 IRP and 2016 IRP is updated to reflect a new historical period for normal weather. Table 3-42 shows historic heating and cooling degree days per year with the 2013 and 2016 IRP assumptions for normal. 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	Heating Degree Days Base 65	Cooling Degree Days Base 65
1990	4,136	1,335
1991	4,309	1,436
1992	4,193	907
1993	5,063	1,289
1994	4,262	1,282
1995	4,584	1,319
1996	5,050	1,100
1997	4,900	1,051
1998	4,226	1,590
1999	4,048	1,249
2000	4,722	1,371

Year	Heating Degree Days Base 65	Cooling Degree Days 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
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, 2010, 2013, and 2016 IRPs are shown in Table 3-43 through Table 3-45. In these tables actual values are not weather normalized. Figure 3-17 through Figure 3-19 illustrate the comparison of the four IRP forecasts.

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Table 3-43 - Historical and Base Forecasts for 2007, 2010, 2013, and 2016 IRPs - Total Customers

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Figure 3-17 - Comparison of Total Electric Customers Actual Historical and 2007, 2010, 2103, and 2016 IRP Base Forecasts
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Table 3-44 - Historical and Base Forecasts for 2007, 2010, 2013 and 2016 IRPs - Energy Net System Input (MWh)
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Figure 3-18 - Comparison of Energy Net System Input (MWh)
Actual Historical and 2007, 2010, 2013, and 2016 Base Forecasts
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Table 3-45 - Historical and Base Forecasts for 2007, 2010, 2013 and 2016 IRPs - Net Peak (MW)

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Figure 3-19 - Comparison of System Peak (MW) Actual Historical 2007, 2010, and 2013 IRP Base Forecasts
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SECTION 7 BASE-CASE LOAD FORECAST

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

7.1 Major Class and Total Load Detail

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

7.1.1 Describe and Document Relevant Economic and Demographics

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

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

7.1.2 Describe and Document Effects of Legal Mandates

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

Empire uses the SAE model for the residential and commercial classes. The SAE model uses the EIA Annual Energy Outlook (AEO) for 2015 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 show in 6.1.2.

7.1.4 Describe and Document Weather-Normalized Class Loads

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

Weather sensitive components of the residential, 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.

Table 3-46 - Annual Heating, Cooling, and Base Load Components of the R, C, and I Classes MWh (Billed Year Basis)
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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.

Because the model for Other Industrial customers projects a flat number of customers through the forecast horizon (Section 6.1.2.7), the final industrial forecast is increased to account for known project and customer expansions. The industrial customer count increases in 2015 by 3 customers and represents 63,844,750 kWh per year of energy when the full expansions are completed. The increase is shown in Table 3-47.

Table 3-47 - Industrial Forecast Adjustment
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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

7.1.6.1.1 Residential Annual

The residential energy forecast is developed as the product of the customer model and UPC forecast. The annual energy forecast, customer forecast, and UPC forecast are shown in Figure 3-20 through Figure 3-22. 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, 2014 is the last full year of actual data, and 2016 is the first full year of forecast data. When shown, 2015 values are actual values through March and forecast values from April through December.

Figure 3-20 - Residential Energy Annual Forecast
(Actual, Normalized, Forecast)
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Figure 3-21 - Residential Customer Forecast
(Actual, Forecast)
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Figure 3-22 - Residential UPC Forecast
(Actual, Normalized, and Forecast)
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Table 3-48 - Residential Energy Forecast Summary
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Table 3-49 - Residential Energy Forecast Average Annual Growth Rates
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7.1.6.1.2 Commercial Energy Annual

The commercial energy forecast is developed as the product of the customer model and UPC forecast. The annual energy forecast, customer forecast, and UPC forecast are shown in Figure 3-23 through Figure 3-25. 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, 2014 is the last full year of actual data, and 2016 is the first full year of forecast data. When shown, 2015 values are actual values through March and forecast values from April through December.

Figure 3-23 - Commercial Energy Forecast
(Actual, Normalized, and Forecast)
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Figure 3-24 - Commercial Customer Forecast
(Actual, Forecast)

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Figure 3-25 - Commercial UPC Forecast
(Actual, Normalized, and Forecast)
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Table 3-50 - Commercial Energy Forecast Summary
****Highly Confidential in its Entirety****

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

The wholesale energy forecast is developed as the sum of the four municipal utility energy models. The total energy forecast is shown in Figure 3-26. Table 3-52 and Table 3-53 summarize the annual energy forecast and show the forecasts for each municipal utility for comparative purposes.

Figure 3-26 - Wholesale Energy Forecast (Actual, Forecast)
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Table 3-52 - Wholesale Energy Forecast Summary
****Highly Confidential in its Entirety****

Table 3-53 - Wholesale Energy Forecast Average Annual Growth Rates
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7.1.6.1.4 Street and Highway Annual

The street and highway energy forecast is developed as the product of the customer model and UPC forecast. The annual energy forecast, customer forecast, and UPC forecast are shown in Figure 3-32 through Figure 3-34.

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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.

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Figure 3-27 - Street and Highway Annual Energy Forecast (Actual, Forecast)
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Figure 3-28 - Street and Highway Customer Forecast (Actual, Forecast)
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Figure 3-29 - Street and Highway UPC Forecast (Actual, Forecast)
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Table 3-54 - Street and Highway
Energy Forecast Summary
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Table 3-55 - Street and Highway Energy Forecast
Average Annual Growth Rates
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7.1.6.1.5 Interdepartmental Annual

The interdepartmental energy forecast is developed as the product of the customer model and UPC forecast. The forecast is designed to be flat with no expected addition of customers or change in annual UPC.

The annual energy forecast, customer forecast, and UPC forecast are shown in Figures 3-33, 3-34, and 3-35. Tables 3-58 and 3-59 summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates.

Figure 3-30 - Interdepartmental Annual Energy Forecast (Actual, Forecast)
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Figure 3-31 - Interdepartmental Customer Forecast (Actual, Forecast)
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Figure 3-32 - Interdepartmental UPC Forecast (Actual, Forecast)
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Table 3-56 - Interdepartmental
Energy Forecast Summary
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Table 3-57 - Interdepartmental Energy Forecast
Average Annual Growth Rates
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7.1.6.1.6 Public Authority Annual

The public authority energy forecast is developed as the product of the customer model and UPC forecast. The forecast is designed to provide growth based on an increasing government employment, but flat for average usage.

The annual energy forecast, customer forecast, and UPC forecast are shown in Figure 3-33 through Figure 3-35. 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.

Figure 3-33 - Public Authority Annual Energy Forecast (Actual, Forecast)
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Figure 3-34 - Public Authority Customer Forecast (Actual, Forecast)
****Highly Confidential in its Entirety****

Figure 3-35 - Public Authority UPC Forecast (Actual, Forecast)
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Table 3-58 - Public Authority
Energy Forecast Summary
****Highly Confidential in its Entirety****

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

7.1.6.1.7 Industrial Energy Forecast

The industrial energy forecast is developed as sum of the Praxair, oil and pipeline, 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 forecast time horizon. However, the other industrial segment forecast is increased by 3 customers totaling over 63,844 MWh/year for known industrial projects.

The annual energy forecast, customer forecast, and UPC forecast are shown in Figure 3-36 through Figure 3-38. 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.

Figure 3-36 - Industrial Energy Annual Forecast (Actual, Forecast)
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Figure 3-37 - Industrial Customer Forecast (Actual, Forecast)
****Highly Confidential in its Entirety****

Figure 3-38 - Industrial UPC Forecast (Actual, Forecast)
****Highly Confidential in its Entirety****

Table 3-60 - Industrial Energy Forecast Summary
****Highly Confidential in its Entirety****

Table 3-61 - Industrial Energy Forecast Average Annual Growth Rates
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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, and industrial class are shown in Figure 3-44 and Figure 3-45, respectively.

Figure 3-39 - Peak Summer Calendar Month Energy, MWh
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Figure 3-40 - Peak Winter Calendar Month Energy, MWh
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7.1.6.2 Class Level Coincident Peak Forecasts

7.1.6.2.1 System Level Peak

System level peaks are shown in Figure 3-41 and Figure 3-42 for each season.

Figure 3-41 - System Summer Peak Forecast
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Figure 3-42 - System Winter Peak Forecast
****Highly Confidential in its Entirety****

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 3-43 through Figure 3-48 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 3-43 - Residential Coincident Summer Peak Forecast
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Figure 3-44 - Residential Coincident Winter Peak Forecast
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Figure 3-45 - Commercial Coincident Summer Peak Forecast
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Figure 3-46 - Commercial Coincident Winter Peak Forecast
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Figure 3-47 - Industrial Coincident Summer Peak Forecast
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Figure 3-48 - Industrial Coincident Winter Peak Forecast

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Table 3-62 - Summer Coincident Peak by Class

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Table 3-63 - Winter Coincident Peak by Class

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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, 5, 10, and 20 years broken out by summer and winter peak days for each major class and system level are shown in Figure 3-49 through Figure 3-56.

Figure 3-49 - Forecasted Residential Summer Peak Day Profiles
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Figure 3-50 - Forecasted Residential Winter Peak Day Profiles
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Figure 3-51 - Forecasted Commercial Summer Peak Day Profiles
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Figure 3-52 - Forecasted Commercial Winter Peak Day Profiles

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Figure 3-53 - Forecasted Industrial Summer Peak Day Profiles

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Figure 3-54 - Forecasted Industrial Winter Peak Day Profiles

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Figure 3-55 - Forecasted System Summer Peak Day Profiles
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Figure 3-56 - Forecasted System Winter Peak Day Profiles

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7.2 Describe and Document Forecasts of Independent Variables

(B) Forecasts of Independent Variables.

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

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

7.2.1 Documentation of Mathematical Models

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

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

7.2.2 Documentation of Adopted Forecasts Developed by Another Entity

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

The forecast is developed by Itron on behalf of Empire.

7.2.3 Comparison of Forecast from Independent Variables to Historical Trends

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

The forecasts are compared to historical trends are shown in the figures contained in Section 2.4.3.

7.2.4 Applied to Modify Results

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

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Post forecast adjustments are made to the industrial class. Because the industrial class models are constructed to show no growth in customer counts or average use, additions are made to the industrial class for 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
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7.3 Net System Load Forecast

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

The net system load forecast is constructed by calibrating hourly load profiles with monthly peaks and energy. The 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).

Empire created six scenarios. The high and low scenarios capture changes to the economic assumptions, but use normal weather. The extreme and mild scenarios capture changes to weather, but use baseline economics. An additional scenario, the high-high case, is included to capture broader deviations from the high and low scenario responding to comments from stakeholders provided during the November 20, 2015 stakeholder meeting. In addition, Empire developed an aggressive electric vehicle adoption case. The high-high and aggressive electric vehicle cases use normal weather.

The results of the scenarios and analysis are presented in this section.

8.1 Normal Weather Load Forecast Scenarios

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

Four 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 to create two additional normal weather load forecasts. These two forecasts are created by adjusting the economic inputs in the forecast model capturing economic uncertainty. The high-high scenario is created as an extreme high scenario in response to stakeholder comments provided in the November 20, 2015 Stakeholder meeting. The Aggressive Electric Vehicle scenario is created as a hypothetical case of extreme electric vehicle adoption. The subjective probabilities of these economic scenarios occurring are shown below.

- High-High Case 5%
- High Case 20%
- Base Case 50%
- Low Case 25%

The Aggressive Electric Vehicle case is developed as an alternative plan and is not given a probability.

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, the 2016 population base population growth is 0.411%. Increasing or decreasing the growth rate by 50% creates the high and low scenario population growth of 0.616% and 0.205%, respectively. Figure 3-57 through Figure 3-60 show the high and low scenario for key economic drivers.

Figure 3-57 - High and Low Scenario – GDP Scenarios

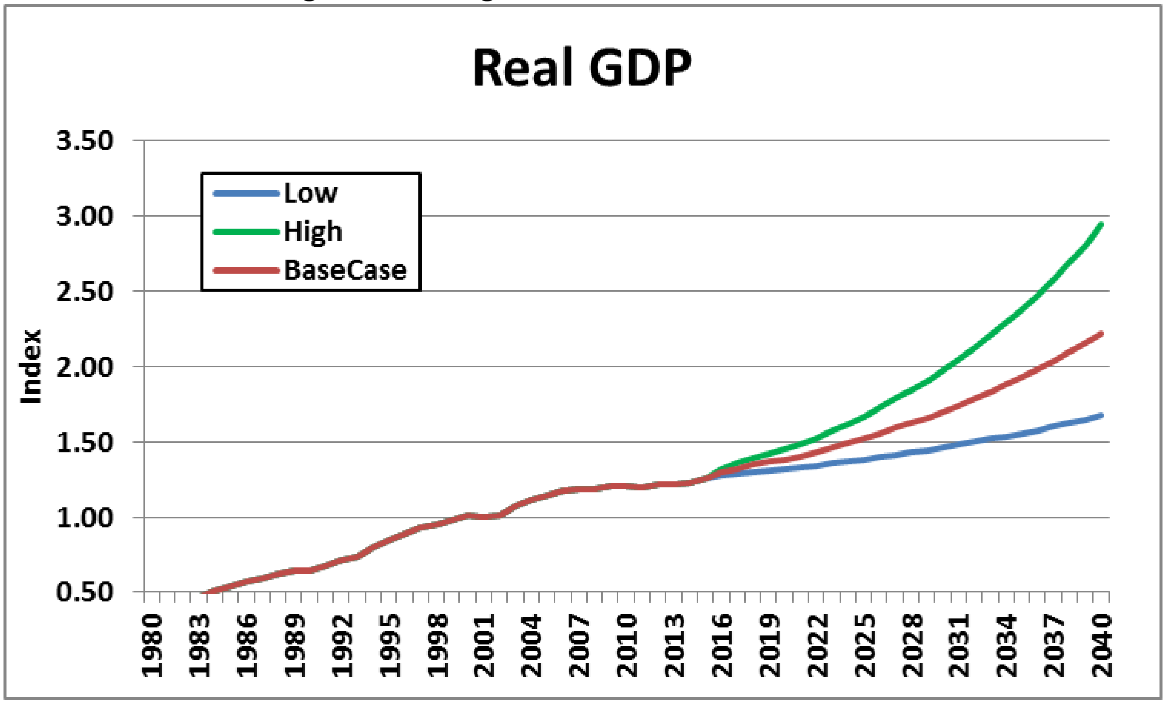


Figure 3-58 - High and Low Scenario – Non-Manufacturing Employment

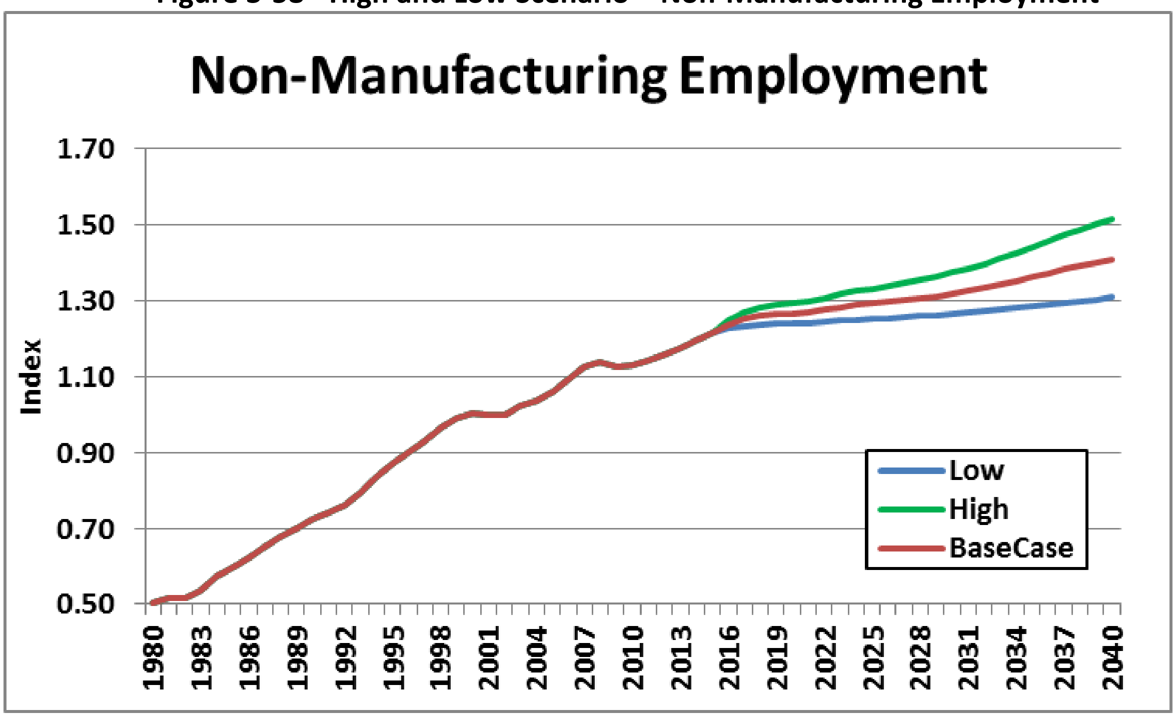


Figure 3-59 - High and Low Scenario – Population

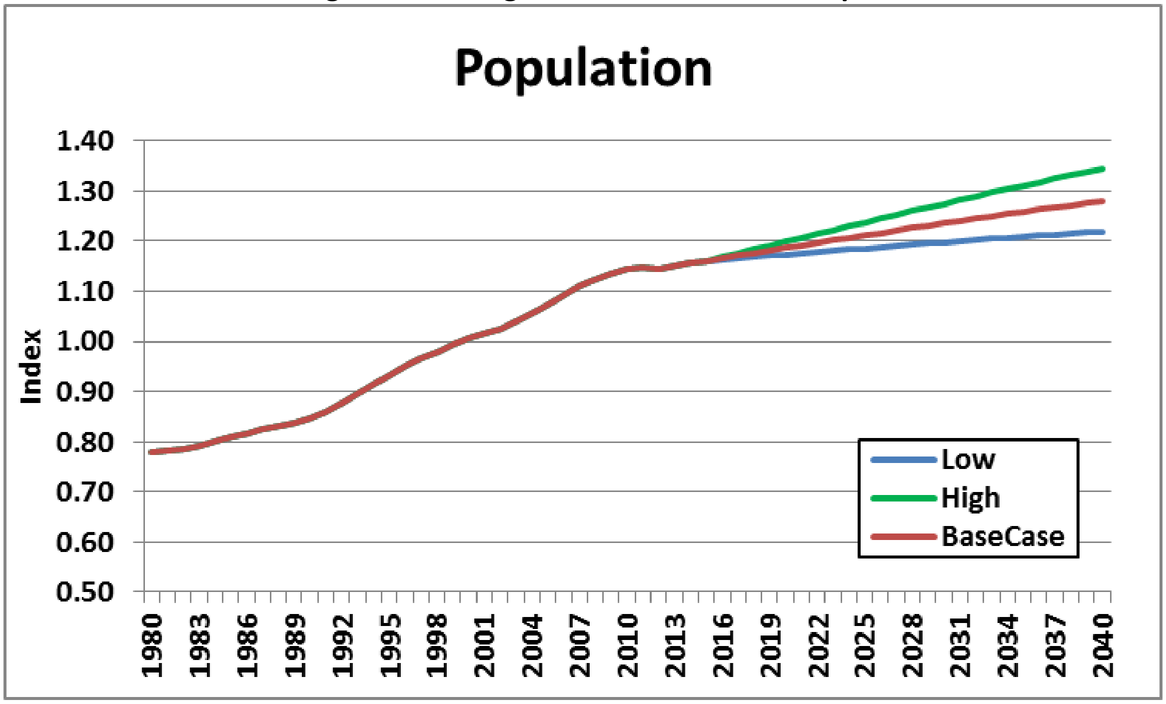
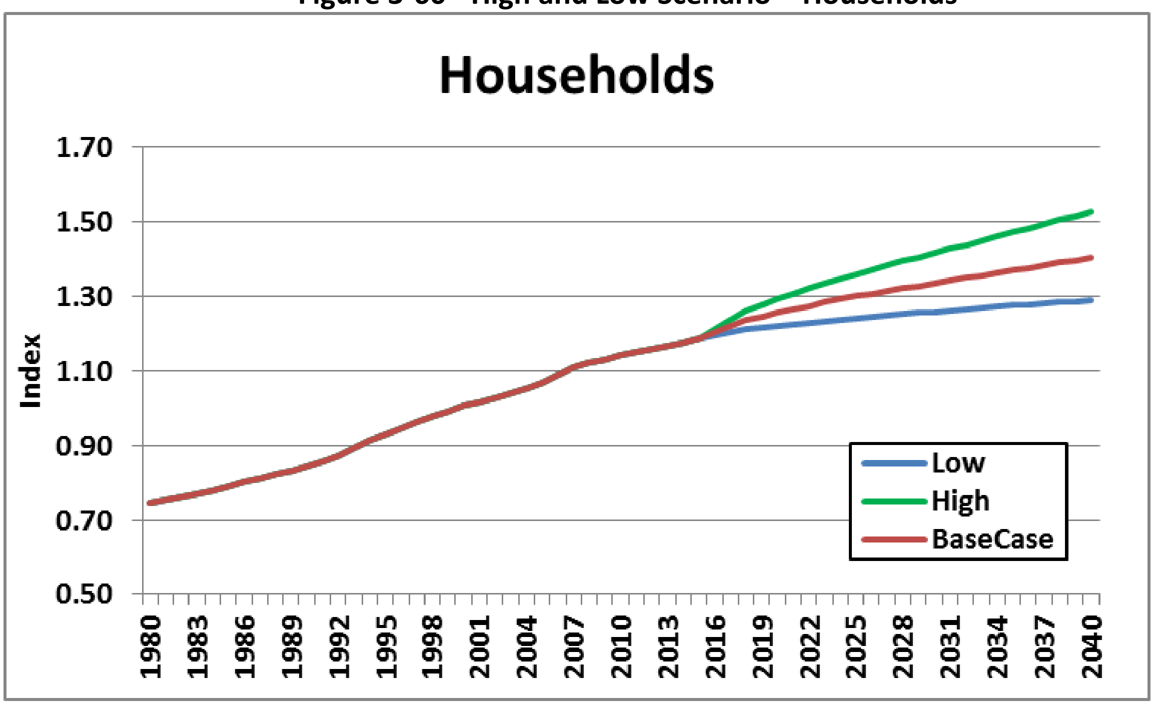


Figure 3-60 - High and Low Scenario – Households



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8.1.2 High-High Case

The High-High scenario is created by increasing the System Peak forecast and back calculating net system loads based on the average load factor across the Base, High, and Low scenarios. The scenario increases the compound annual growth rate of the peak to be approximately ** **. Figure 3-61 shows the increased High-High scenario peaks relative to the Base, High, and Low scenarios.

Figure 3-61 – High-High Case Comparison
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8.1.3 Aggressive Electric Vehicle Case

The aggressive electric vehicle scenario is an additional scenario which increases the Base Case forecast by including a hypothetical level of electric vehicle adoption. While the electric vehicle adoption in the Base Case is based on EIA projected growth rates for the West North Central

Region and assumes less than 0.5% adoption in 2035, this scenario represents 75% adoption by the end of 2035.

Alternative electric vehicle adoption scenarios were considered for inclusion. These scenarios include 10%, 30%, and 50% adoption cases. These alternatives were dismissed because they did not sufficiently exceed the bounds of the high economic scenario. The 75% adoption case exceeds the high scenario case and is useful as an additional sensitivity.

The forecast assumes an increasing level of replacement vehicle adoption per year until number of customers using electric vehicles is 75% of the residential customer base. In this scenario, electric vehicles are assumed to consume 15 kWh per day with a demand of 5 kW per day and a system peak coincident factor of 10%. Figure 3-62 shows the Electric Vehicle scenario compared to the high, low, and high-high scenarios based on net system energy.

Figure 3-62 – Aggressive Electric Vehicle Case Comparison
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8.1.4 Normal Weather Scenario Results

Scenario results are for billed sales (energy) are shown in Figure 3-63 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 Figure 3-64 and Table 3-67. Because the system forecast peaks are winter peaks beginning in 2016, Table 3-68 shows the forecast system summer peaks for comparative purposes.

Figure 3-63 - Base, High, Low, High-High, and Aggressive EV Scenario System Annual Billed Sales
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Table 3-65 - Base, High, Low, High-High, and Aggressive EV Scenario Annual Billed Sales (MWh)

Year	Base	Low	High	High-High	Aggressive EV
2005	4,939,350				
2006	5,006,800				
2007	5,052,907				
2008	5,093,341				
2009	4,886,508				
2010	5,211,531				
2011	5,121,397				
2012	4,886,854				
2013	4,954,395				
2014	5,036,558				
2015	5,034,969				
2016	** **	** **	** **	** **	** **
2017	** **	** **	** **	** **	** **
2018	** **	** **	** **	** **	** **
2019	** **	** **	** **	** **	** **
2020	** **	** **	** **	** **	** **
2021	** **	** **	** **	** **	** **
2022	** **	** **	** **	** **	** **
2023	** **	** **	** **	** **	** **
2024	** **	** **	** **	** **	** **
2025	** **	** **	** **	** **	** **
2026	** **	** **	** **	** **	** **
2027	** **	** **	** **	** **	** **
2028	** **	** **	** **	** **	** **
2029	** **	** **	** **	** **	** **
2030	** **	** **	** **	** **	** **
2031	** **	** **	** **	** **	** **
2032	** **	** **	** **	** **	** **
2033	** **	** **	** **	** **	** **
2034	** **	** **	** **	** **	** **
2035	** **	** **	** **	** **	** **

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

Year	Base	Low	High	High-High	Aggressive EV
2012	5,279,934				
2013	5,318,904				
2014	5,379,732				
2015	5,343,708				
2016	** **	** **	** **	** **	** **
2017	** **	** **	** **	** **	** **
2018	** **	** **	** **	** **	** **
2019	** **	** **	** **	** **	** **
2020	** **	** **	** **	** **	** **
2021	** **	** **	** **	** **	** **
2022	** **	** **	** **	** **	** **
2023	** **	** **	** **	** **	** **
2024	** **	** **	** **	** **	** **
2025	** **	** **	** **	** **	** **
2026	** **	** **	** **	** **	** **
2027	** **	** **	** **	** **	** **
2028	** **	** **	** **	** **	** **
2029	** **	** **	** **	** **	** **
2030	** **	** **	** **	** **	** **
2031	** **	** **	** **	** **	** **
2032	** **	** **	** **	** **	** **
2033	** **	** **	** **	** **	** **
2034	** **	** **	** **	** **	** **
2035	** **	** **	** **	** **	** **

Figure 3-64 - Base, High, Low, High-High, and Aggressive EV Scenario System Annual Peak

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Table 3-67 - Base, High, Low, High-High, and Aggressive EV Scenario Annual Peak (MW)

Year	Base	Low	High	High-High	Aggressive EV
2005	1,095				
2006	1,167				
2007	1,181				
2008	1,161				
2009	1,093				
2010	1,205				
2011	1,209				
2012	1,142				
2013	1,080				
2014	1,162				
2015	1,149				
2016	** **	** **	** **	** **	** **
2017	** **	** **	** **	** **	** **
2018	** **	** **	** **	** **	** **
2019	** **	** **	** **	** **	** **
2020	** **	** **	** **	** **	** **
2021	** **	** **	** **	** **	** **
2022	** **	** **	** **	** **	** **
2023	** **	** **	** **	** **	** **
2024	** **	** **	** **	** **	** **
2025	** **	** **	** **	** **	** **
2026	** **	** **	** **	** **	** **
2027	** **	** **	** **	** **	** **
2028	** **	** **	** **	** **	** **
2029	** **	** **	** **	** **	** **
2030	** **	** **	** **	** **	** **
2031	** **	** **	** **	** **	** **
2032	** **	** **	** **	** **	** **

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Year	Base	Low	High	High-High	Aggressive EV
2033	** **	** **	** **	** **	** **
2034	** **	** **	** **	** **	** **
2035	** **	** **	** **	** **	** **

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

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

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

The mild and extreme weather scenarios are created to 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 (1985 to 2014) 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 3-65 and Figure 3-66 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 3-65 - Mild and Extreme Annual HDD Base 65 Scenarios

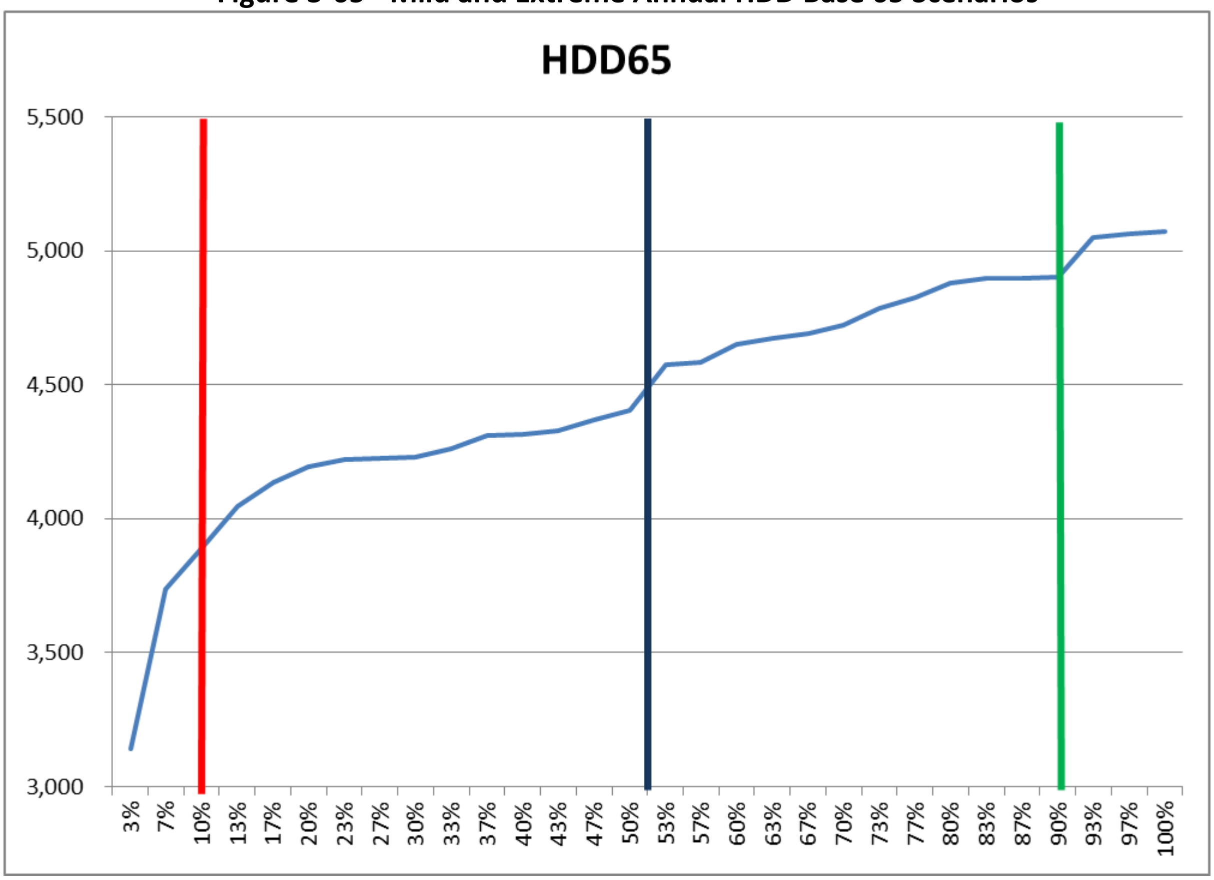

Figure 3-66 - Mild and Extreme Annual CDD Base 65 Scenarios

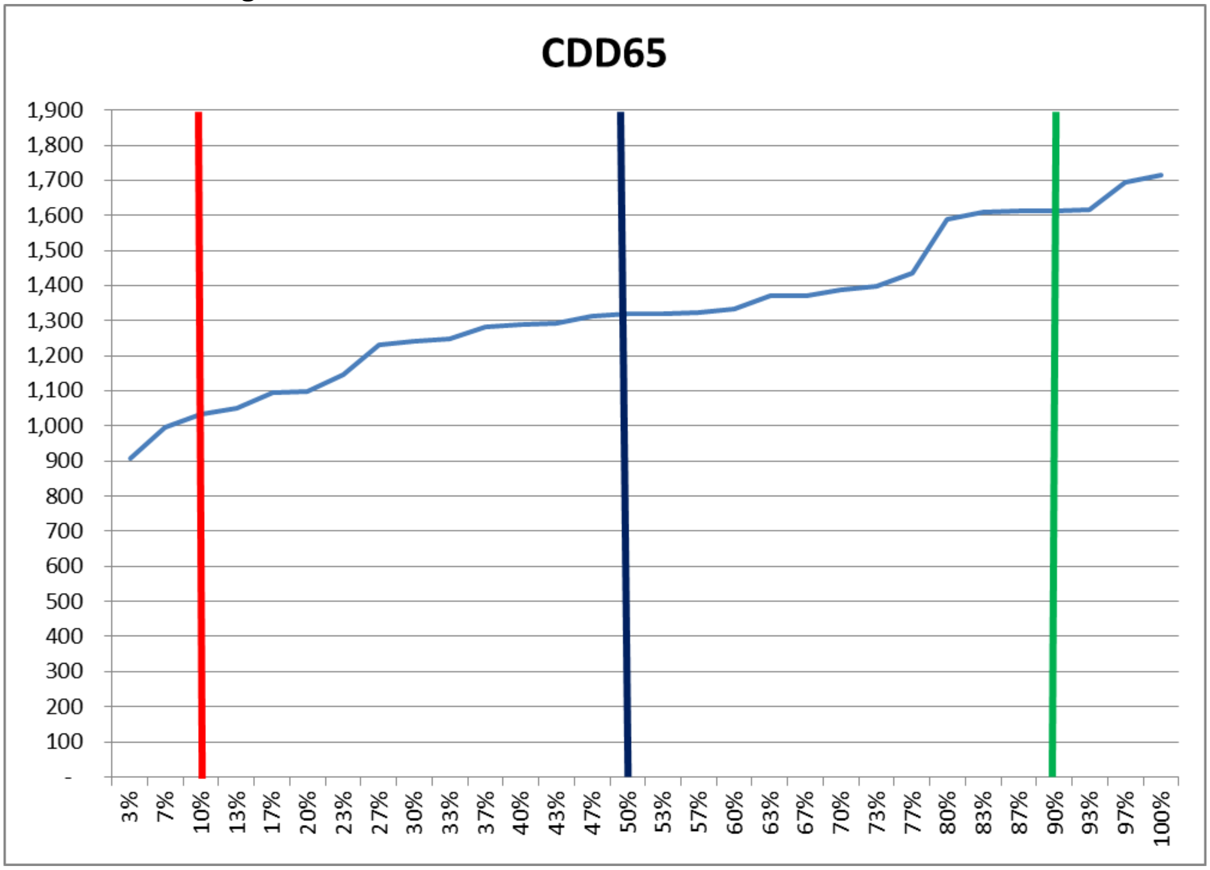

Table 3-69 - Scenario Annual Degree Days

Scenario	HDD65	CDD65
Base	4,528	1,333
Mild	3,889	1,035
Extreme	4,901	1,612

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 3-67 and Figure 3-68 show the monthly HDD and CDD scenarios.

Figure 3-67 - Mild and Extreme Monthly HDD Base 65 Scenarios

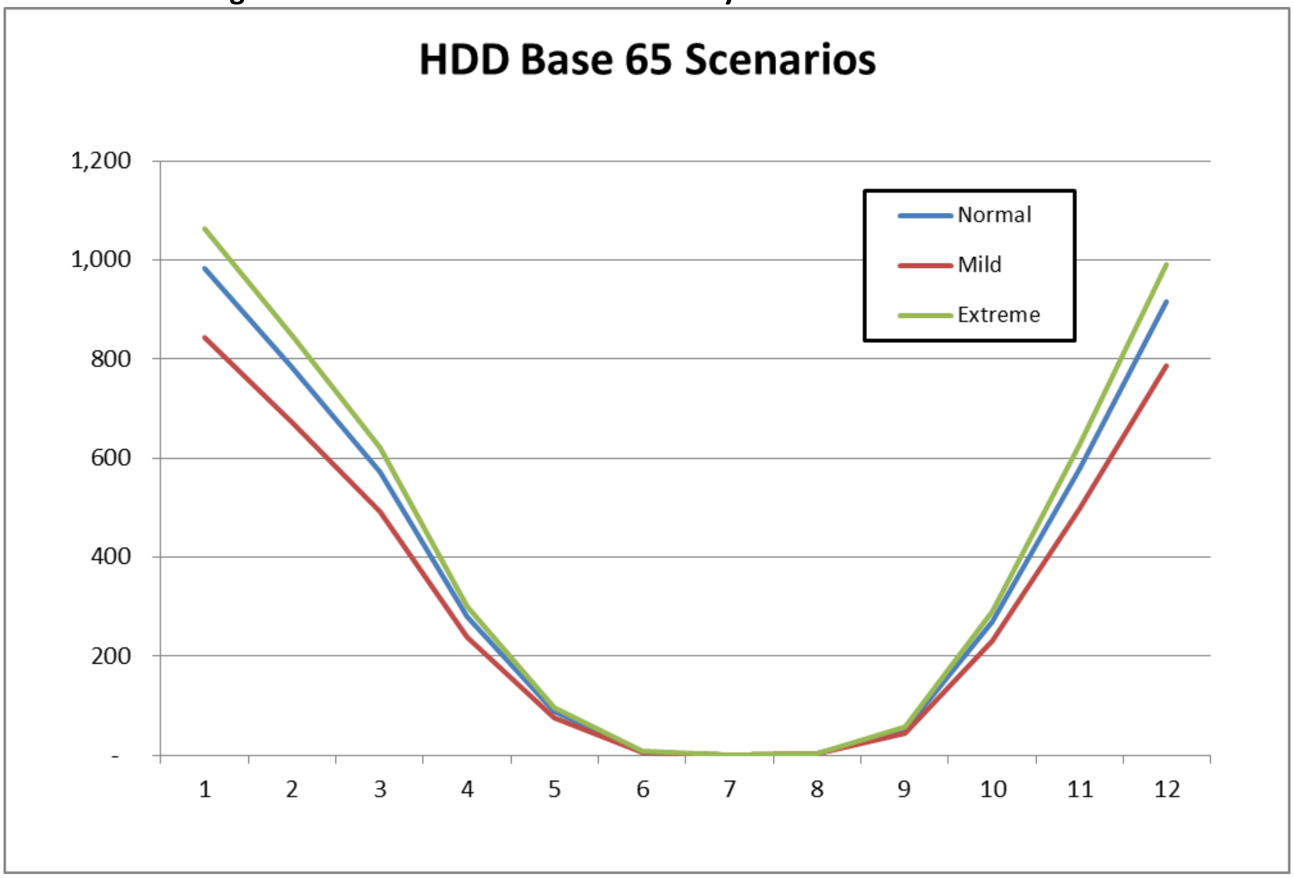

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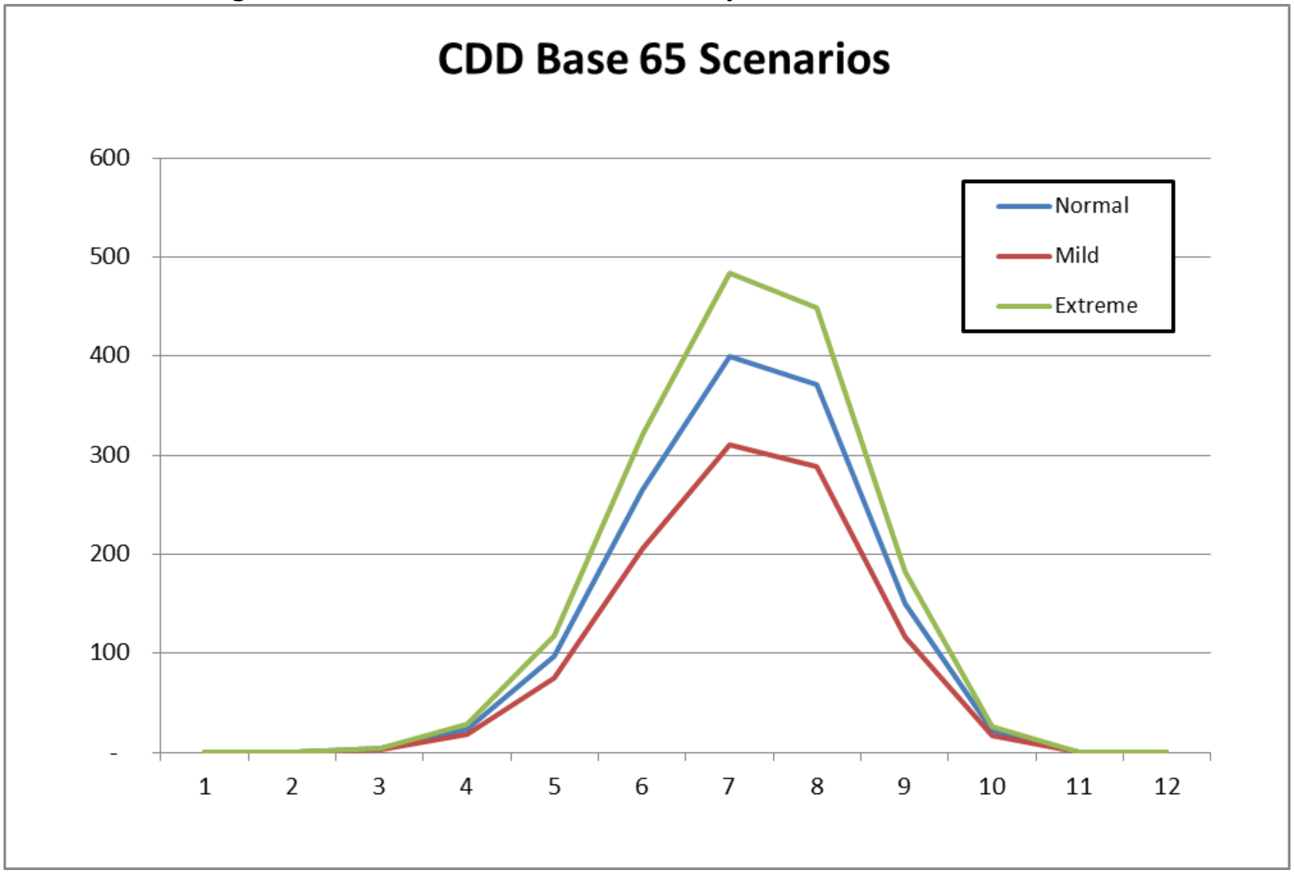
Figure 3-68 - Mild and Extreme Monthly CDD Base 65 Scenarios



Peak Producing Temperatures: The mild and extreme monthly peak scenarios are derived based on 14 years of historical (2001 to 2014) peak producing weather. 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. Three exceptions were made in the mild scenario. In January, October, and November the second mildest temperatures were selected instead of the mildest to create a smoother scenario profile. Figure 3-69 and Table 3-70 show the extreme and mild peak temperature scenarios.

Figure 3-69 - Mild and Extreme Peak Temperature Scenarios

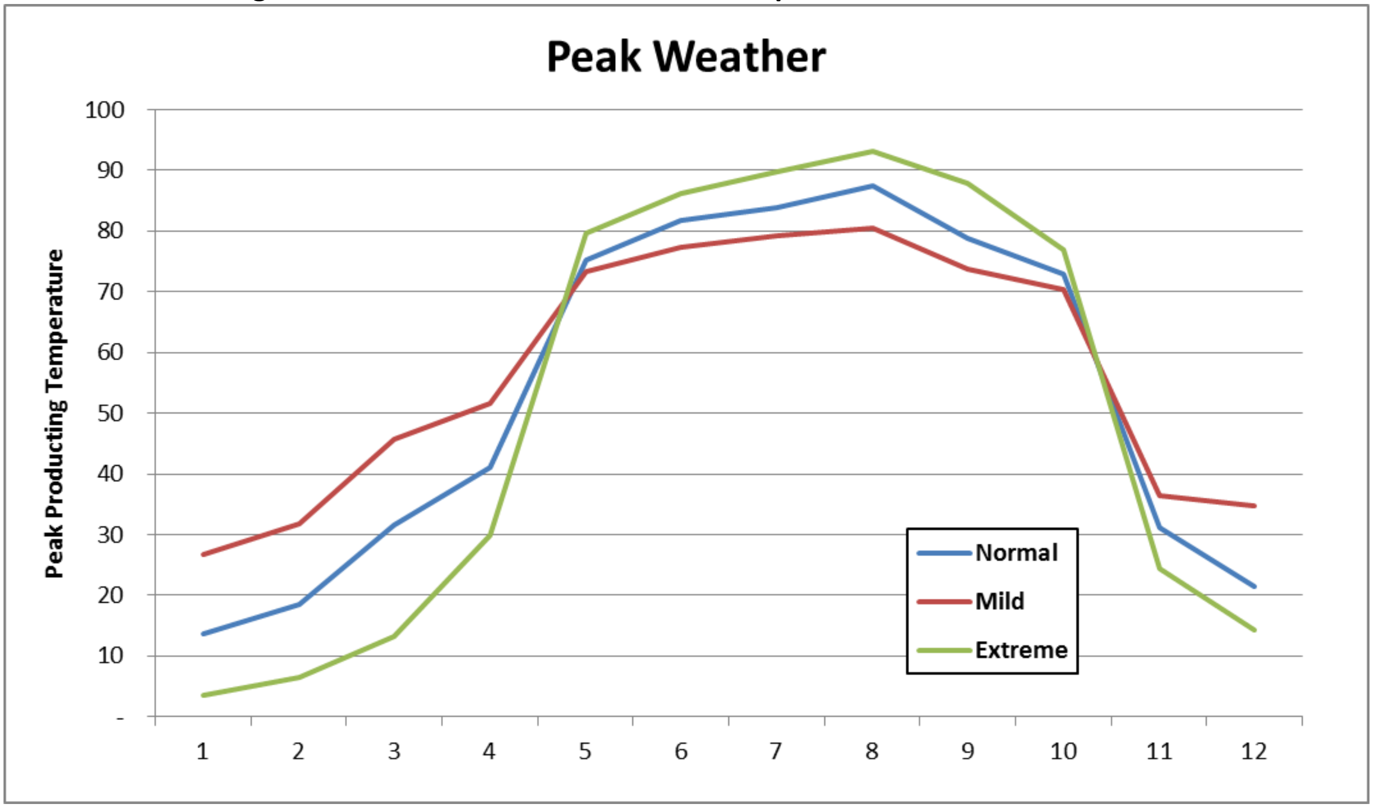


Table 3-70 - Scenario Monthly Peak Producing Temperatures

Month	Base	Extreme	Mild
Jan	13.57	3.58	26.75
Feb	18.53	6.54	31.88
Mar	31.57	13.25	45.71
Apr	41.02	29.83	51.54
May	75.18	79.58	73.33
Jun	81.69	86.13	77.26
Jul	83.90	89.71	79.23
Aug	87.40	93.04	80.46
Sep	78.70	87.79	73.79
Oct	72.91	76.83	70.38
Nov	31.19	24.46	36.38
Dec	21.38	14.38	34.75

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Scenario results are for billed sales (energy) are shown in Figure 3-70 and Table 3-71. Scenario results for Net System Input (NSI) are shown in Figure 3-73. NSI energy is calculated as class-level billed sales multiplied by an annual average loss factor. Scenario results for peaks are shown in Figure 3-71 and Table 3-73. Because the forecasted system peaks are winter peaks, Figure 3-74 shows the scenario summer peaks for comparative purposes.

Figure 3-70 - Base, Mild and Extreme Weather Scenario:
System Annual Billed Sales
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Table 3-71 - Base. Mild and Extreme Weather Scenario - Annual Billed Sales (MWh)

Year	Base	Mild	Extreme
2005	4,939,350		
2006	5,006,800		
2007	5,052,907		
2008	5,093,341		
2009	4,886,508		
2010	5,211,531		
2011	5,121,397		
2012	4,886,854		
2013	4,954,395		
2014	5,036,558		
2015	5,034,969		
2016	** **	** **	** **
2017	** **	** **	** **
2018	** **	** **	** **
2019	** **	** **	** **
2020	** **	** **	** **
2021	** **	** **	** **
2022	** **	** **	** **

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Year	Base		Mild		Extreme	
2023	**	**	**	**	**	**
2024	**	**	**	**	**	**
2025	**	**	**	**	**	**
2026	**	**	**	**	**	**
2027	**	**	**	**	**	**
2028	**	**	**	**	**	**
2029	**	**	**	**	**	**
2030	**	**	**	**	**	**
2031	**	**	**	**	**	**
2032	**	**	**	**	**	**

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Year	Base		Mild		Extreme	
2033	**	**	**	**	**	**
2034	**	**	**	**	**	**
2035	**	**	**	**	**	**

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

Year	Base	Mild	Extreme
2012	5,279,934		
2013	5,318,904		
2014	5,379,732		
2015	5,343,708		
2016	** **	** **	** **
2017	** **	** **	** **
2018	** **	** **	** **
2019	** **	** **	** **
2020	** **	** **	** **
2021	** **	** **	** **
2022	** **	** **	** **
2023	** **	** **	** **
2024	** **	** **	** **
2025	** **	** **	** **
2026	** **	** **	** **
2027	** **	** **	** **
2028	** **	** **	** **
2029	** **	** **	** **
2030	** **	** **	** **
2031	** **	** **	** **
2032	** **	** **	** **
2033	** **	** **	** **
2034	** **	** **	** **
2035	** **	** **	** **

Figure 3-71 - Base, Mild and Extreme Weather Scenario -
System Annual Peak
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Table 3-73 - Base, Mild and Extreme Weather Scenario - Annual Peak (MW)

Year	Base	Mild	Extreme

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Year	Base	Mild	Extreme
2005	1,095		
2006	1,167		
2007	1,181		
2008	1,161		
2009	1,093		
2010	1,205		
2011	1,209		
2012	1,142		
2013	1,080		
2014	1,162		
2015	1,149		
2016	** **	** **	** **
2017	** **	** **	** **
2018	** **	** **	** **
2019	** **	** **	** **
2020	** **	** **	** **
2021	** **	** **	** **
2022	** **	** **	** **

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Year	Base		Mild		Extreme	
2023	**	**	**	**	**	**
2024	**	**	**	**	**	**
2025	**	**	**	**	**	**
2026	**	**	**	**	**	**
2027	**	**	**	**	**	**
2028	**	**	**	**	**	**
2029	**	**	**	**	**	**
2030	**	**	**	**	**	**
2031	**	**	**	**	**	**
2032	**	**	**	**	**	**

Year	Base	Mild	Extreme
2033	** **	** **	** **
2034	** **	** **	** **
2035	** **	** **	** **

Table 3-74 - Base, Mild and Extreme Weather Scenario - Summer Peak (MW)
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8.3 Energy Usage and Peak Demand Plots

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

8.3.1 Energy and Peak Plots

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

The historical and forecast summer, winter, and total energy use (sales) are listed in Table 3-75 and Table 3-76 and shown in Figure 3-72 and Figure 3-73. Figure 3-74 shows the historical and forecast summer and winter peak demands.

Table 3-75 - Historical and Forecast Summer, Winter, and Total Billed Energy Use

Year	Winter	Summer	Total
2002	3,323,752	1,231,333	4,555,085
2003	3,367,826	1,240,367	4,608,193
2004	3,388,968	1,232,156	4,621,123
2005	3,581,957	1,357,393	4,939,350
2006	3,560,744	1,446,056	5,006,800
2007	3,679,861	1,373,047	5,052,907
2008	3,728,983	1,364,357	5,093,341
2009	3,575,853	1,310,655	4,886,508
2010	3,759,802	1,451,729	5,211,531
2011	3,664,076	1,457,321	5,121,397
2012	3,444,132	1,442,723	4,886,854
2013	3,684,327	1,270,069	4,954,395
2014	3,765,625	1,270,933	5,036,558
2015	3,710,953	1,324,015	5,034,969
2016	** **	** **	** **
2017	** **	** **	** **
2018	** **	** **	** **
2019	** **	** **	** **
2020	** **	** **	** **
2021	** **	** **	** **
2022	** **	** **	** **
2023	** **	** **	** **
2024	** **	** **	** **

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Year	Winter		Summer		Total	
2025	**	**	**	**	**	**
2026	**	**	**	**	**	**
2027	**	**	**	**	**	**
2028	**	**	**	**	**	**
2029	**	**	**	**	**	**
2030	**	**	**	**	**	**
2031	**	**	**	**	**	**
2032	**	**	**	**	**	**
2033	**	**	**	**	**	**
2034	**	**	**	**	**	**
2035	**	**	**	**	**	**

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

Year	Winter Peak	Summer Peak
2003	987	1,049
2004	937	1,014
2005	1,032	1,095
2006	1,031	1,167
2007	1,059	1,181
2008	1,043	1,161
2009	1,090	1,093
2010	1,205	1,156
2011	1,153	1,209
2012	955	1,142
2013	997	1,080
2014	1,162	1,083
2015	1,149	1,120
2016	** **	** **
2017	** **	** **
2018	** **	** **
2019	** **	** **
2020	** **	** **
2021	** **	** **
2022	** **	** **
2023	** **	** **
2024	** **	** **
2025	** **	** **
2026	** **	** **
2027	** **	** **
2028	** **	** **
2029	** **	** **
2030	** **	** **
2031	** **	** **
2032	** **	** **
2033	** **	** **
2034	** **	** **
2035	** **	** **

Figure 3-72 - Historical and Forecast Summer and Winter Billed Energy Use

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Figure 3-73 - Historical and Forecast Total Billed Energy Use

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Figure 3-74 - Historical and Forecast Summer and Winter Peaks
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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 six scenarios are shown in Figure 3-75 through Figure 3-77. 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. The high-high and aggressive electric vehicle cases are deviations from the base case using normal weather. Data are revenue year sales. The historical and forecast for the summer, winter, and system peak demands for all six scenarios are shown in Figure 3-78 through Figure 3-80.

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Figure 3-75 - Historical and Forecast Summer Billed Energy for Base, Low, High, High-High, Aggressive EV, Mild, and Extreme Scenarios

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Figure 3-76 - Historical and Forecast Winter Billed Energy for Base, Low, High, High-High, Aggressive EV, Mild, and Extreme Scenarios

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Figure 3-77 - Historical and Forecast Annual Billed Energy for Base, Low, High, High-High, Aggressive EV, Mild, and Extreme Scenarios

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Figure 3-78 - Historical and Forecast Summer Peak for Base, Low, High, High-High, Aggressive EV, Mild, and Extreme Scenarios

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Figure 3-79 - Historical and Forecast Winter Peak for Base, Low, High, High-High, Aggressive EV, Mild, and Extreme Scenarios

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Figure 3-80 - Historical and Forecast Annual Peak
for Base, Low, High, High-High, Aggressive EV, Mild, and Extreme Scenarios
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