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Empire District Electric Company
Forecast Models for 2016 IRP

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** Denotes Highly Confidential **

Table of Contents

Empire District Electric Company Forecast Models

In February 2015, Empire District Electric Company (Empire) contracted with Itron to develop the load forecast for use in Empire's 2016 Integrated Resource Plan filing. This report summaries the forecast, forecast models, and key assumptions.

The forecast contains three main modeling processes. These processes are summarized below.

- **Energy Models.** The energy forecast models employ Itron's Statistically Adjusted End-Use (SAE) method for the residential and commercial classes and the traditional econometric method for the remaining classes. The following classes are modeled.

  - Residential
  - Commercial
  - Wholesale (Monett, Mt. Vernon, Lockwood, Chetopa)
  - Street & Highway
  - Interdepartmental
  - Public Authority
  - Industrial (Oil & Pipelines, Praxair, Other)

  The energy models include the impacts of historic DSM programs, photovoltaic penetration, and electric vehicles.

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

- **Load Profile Models.** Hourly load profile forecasts are developed 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. The result of the calibration process is hourly forecasts for the net system loads and each class. From these forecasts coincident peaks information are obtained.

After the three main modeling processed are completed, the forecast models are applied to economic and weather scenarios. The scenarios are created to capture a range of possible forecast outcomes.

This report presents an overview of the forecast approach, a description of the forecast models, and forecast results. Detailed information about the forecast models, calibration method, and results may be viewed in the MetrixND and MetrixLT project files. The technical description of the SAE forecasting method is included in Appendix A and B.

1. Forecast Method

The development of the forecast and scenarios relies upon historical monthly billing data, load research data, historical weather data, and economic data. The steps to develop the forecast are described in this section.

Step 1. Energy Forecast

For each class, the monthly energy forecast is developed using an econometric or SAE model framework. For some classes (e.g. Wholesale, Industrial), multiple models are developed capturing the differences between the general class and unique customers. The forecast models for each class are described in Sections 4 through 10. At the completion of the forecast models, the system energy forecast is calculated as the sum of the class energy forecasts.

The key drivers in the energy forecast models are weather and economics. Weather data are derived from the National Oceanic and Atmospheric Administration (NOAA) data for Springfield, Missouri. Economic data are purchased from Economy.com. These drivers are described below.

Monthly Weather Forecast. A key driver in the energy forecast is monthly weather. For the energy forecast, monthly weather is calculated from a 30-year average (1985-2014) using Springfield, Missouri daily average temperatures. The monthly weather is calculated using the following steps.

1. Calculate daily average temperatures from the hourly temperatures.
2. Calculate daily heating and cooling degree days (HDD and CDD) based on the daily average temperature.
3. Calculate monthly heating and cooling degree days by summing the daily HDD and CDD over the calendar months.
4. Weight the current month and prior month HDD and CDD values to replicate billing cycle effects in the model. The current and prior month weights are 40% and 60% respectively. These weights are based on a residential class screening model using the coefficients of the current and prior month weather.

Economic Forecast. The economic forecast drives growth impacting both the customer and energy models. The economic forecast is developed by summing the Joplin MSA and Springfield MSA economic forecasts. The Joplin and Springfield MSA represent 7 out of the 21 counties or 38% of the population (based on 2010 census data) served by Empire. While a substantial portion of the population served by Empire is not included in the MSAs, their economic conditions are driven by their physical proximity to the Joplin and Springfield MSAs.

Step 2. System Peak Forecast

The monthly net system load peak forecast is developed using an econometric model based on historical monthly peak day events from 2003 forward. The peak model is described in Section 11. The peak model controls the overall system peaks and is used as the calibration target for the class coincident peaks.

The key drivers in the peak model are weather and energy growth drivers. Weather data are derived from historic weather conditions on past monthly peak days. The energy growth drivers are derived from the energy models in Step 1. These drivers are described below.

Peak Weather Forecast. Peak weather is obtained by averaging the monthly peak producing weather events from January 2001 through December 2014. The weather calculation uses the following steps.

1. Identify the peak producing weather conditions for each month from 2001 through 2014. The weather conditions include the current day average temperature and the two prior day's average temperatures.
2. Average the temperatures for the current day, prior day, and prior two-days from 2001 through 2014.
3. Replace the April averages with cold weather producing peaks only (i.e. remove from the average the years where the peak is produced by hot weather).
4. 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).
5. Replace the January average with the month's average calculated based on the last ten cold peak producing events (2005-2014). For example, when the winter peak occurs in February or December, the January weather is not used in the calculation in favor of the higher February or December value.
6. Replace the August average with the month's average calculated based on the last ten hot peak producing events (2005-2014). For example, when the summer peak occurs in July or September, the August weather is not used in the calculation in favor of the higher July or September value.

Peak Growth Drivers. Peak growth through the forecast time horizon is related to the underlying changes in end-use equipment in the customer classes. For example, the acceleration of electric space heating is currently outpacing the growth of space cooling. The effect of the growth differential in heating and cooling results in faster growth in winter peaks than summer peaks. The peak growth drivers are developed from the energy models in Step 1 by decomposing the models into the heating, cooling, and base load components. After the decomposition, the three components are aggregated into heating, cooling, and base load growth trends which are applied in the peak model.

Step 3. Hourly Load Forecast

The hourly load forecast is developed using a bottom-up approach, then calibrating the hourly load forecast to the system peak forecast. The approach begins by developing hourly revenue class models based on Empire's load research data to forecast the hourly profiles. These models are described in Section 12. The models are forecast using normal daily weather to obtain the hourly class profile. Next, the profiles are calibrated to their respective class energy forecasts from Step 1 to obtain the hourly class loads. The hourly class loads are summed to obtain the hourly system loads which are then scaled upward for losses and calibrated to the system peak forecast from Step 2.

The key components in the hourly load forecast are the hourly class models and normal daily weather. These are described below.

Hourly Class Models. For each class, hourly load profiles are forecast based on rate-class- level load-research data. Because a direct matching of load research sample data to revenue classes was not available, rate class load research sample data were averaged for each revenue class based on average customer counts in 2014. The forecast models are developed as hourly econometric models.

Normal Daily Weather. Normal daily average temperatures are derived from a 30-year period (1985-2014) using the rank-and-average method. In the forecast period, the result of the rank-and-average process is mapped to the 2003 temperature calendar which represents the average year.

Once the class hourly loads and the net system loads are developed, class coincident peaks are obtained using coincident peak factors from the hourly load forecast.

Step 4. Economic Scenarios

Three economic scenarios are created to construct reasonable planning bounds around the base forecast. The High and Low scenarios based on alternative economic scenarios constructed by increasing the base economic forecast. The High-High scenario is constructed by increasing the Base scenario results based on a negotiated solution between Empire and Missouri Commission Staff.

The subjective probabilities of each scenario occurring are shown below

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

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 1 through Figure 4 show the key economic drivers for the base, high, and low scenarios.

Figure 1: Scenarios: GDP

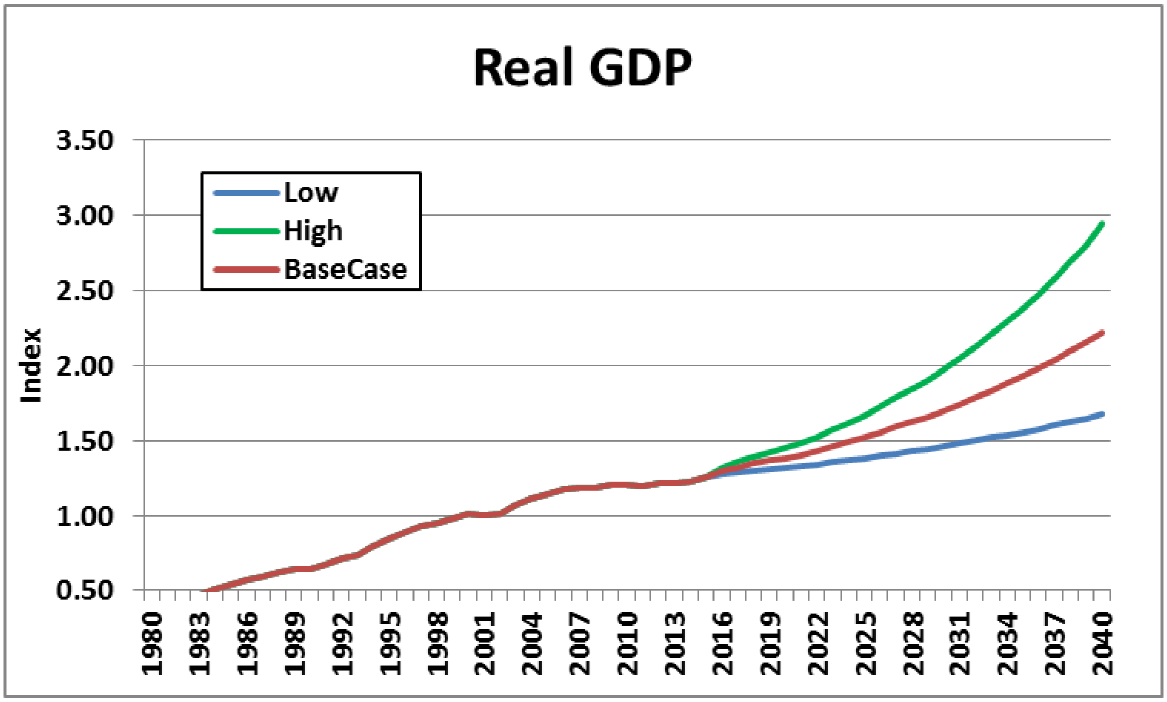


Figure 2: Scenarios: Non-Manufacturing Employment

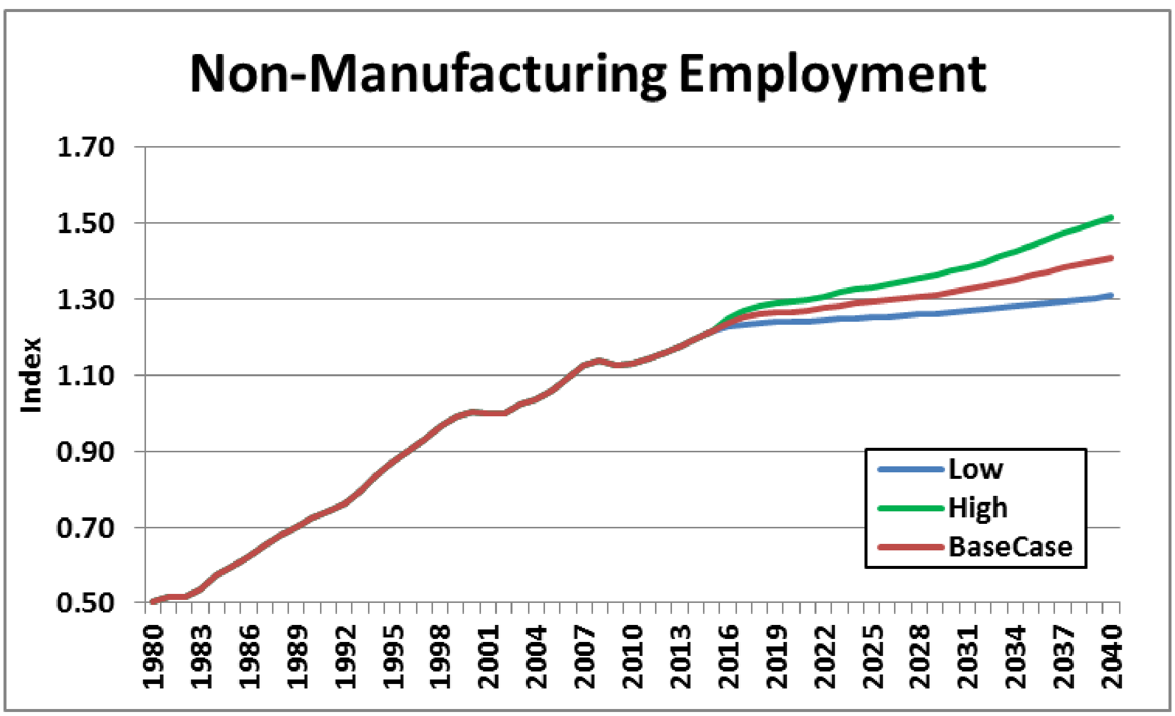


Figure 3: Scenarios: Population

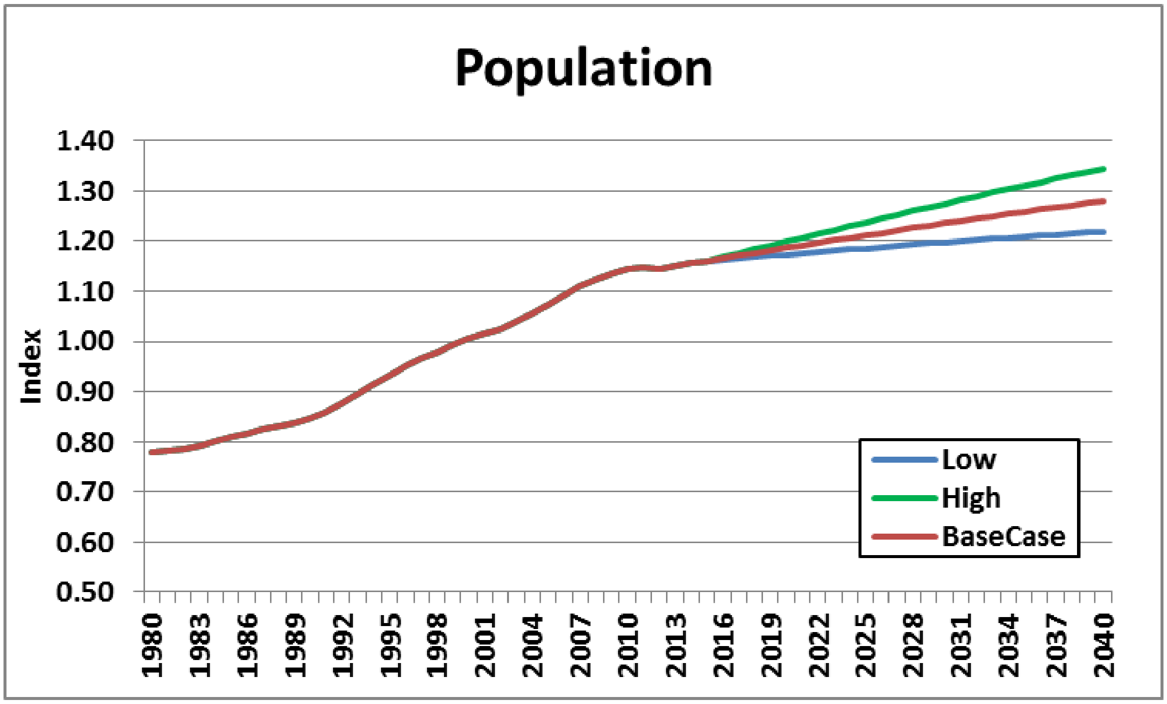
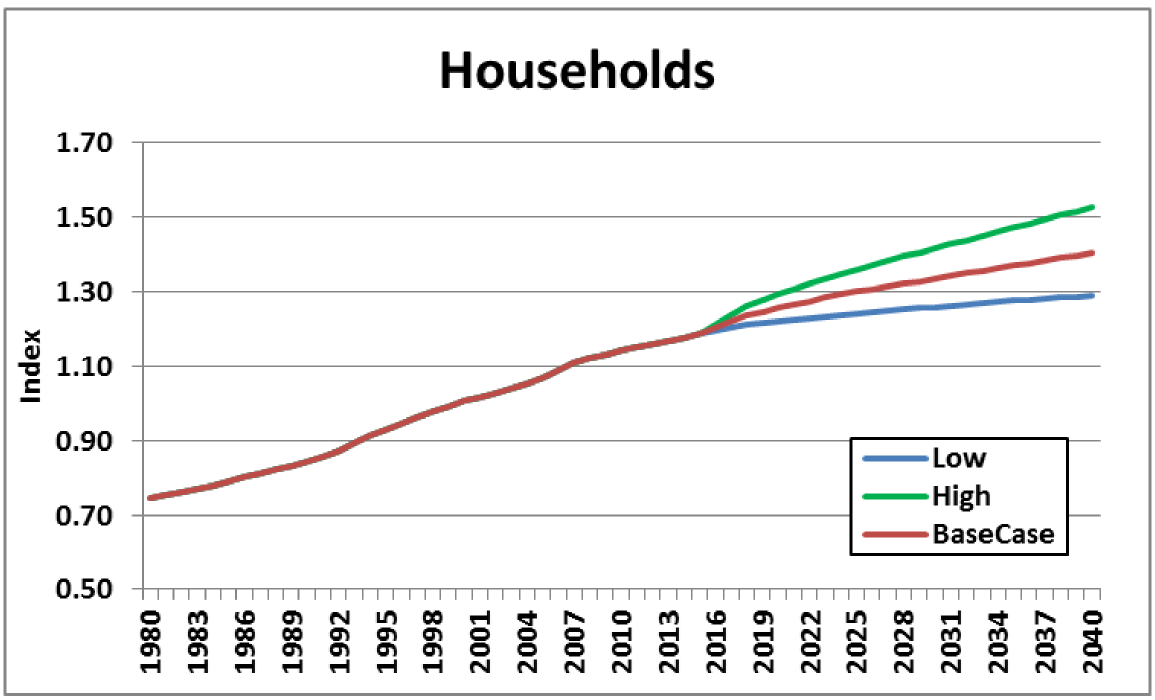


Figure 4: Scenarios: Households



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. Figure 5 shows the increased High-High scenario peaks relative to the Base, High, and Low scenarios.

Figure 5: Scenarios: High-High Case Peak Comparison

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Step 5. Weather Scenarios

The mild and extreme weather scenarios are created to capture the uncertainty associated with weather conditions. These scenarios are developed using the same historical weather data as the base case, but identify a 1-in-10 scenario above and below the base forecast normal temperatures.

Two types of weather are developed to create the mild and extreme scenarios. Monthly weather is developed and used in the energy models. Peak weather is developed and used in the peak model. The development of these scenarios is discussed below.

Monthly Weather Scenarios. Monthly HDD and CDD scenarios are created by ranking 30 years of 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 6 and Figure 7 show the ordered annual HDD and CDD with the mild and extreme scenarios. Table 1 shows the annual HDD and CDD values for the base, mild, and extreme scenarios.

Figure 6: Scenarios: Annual HDD Base 65

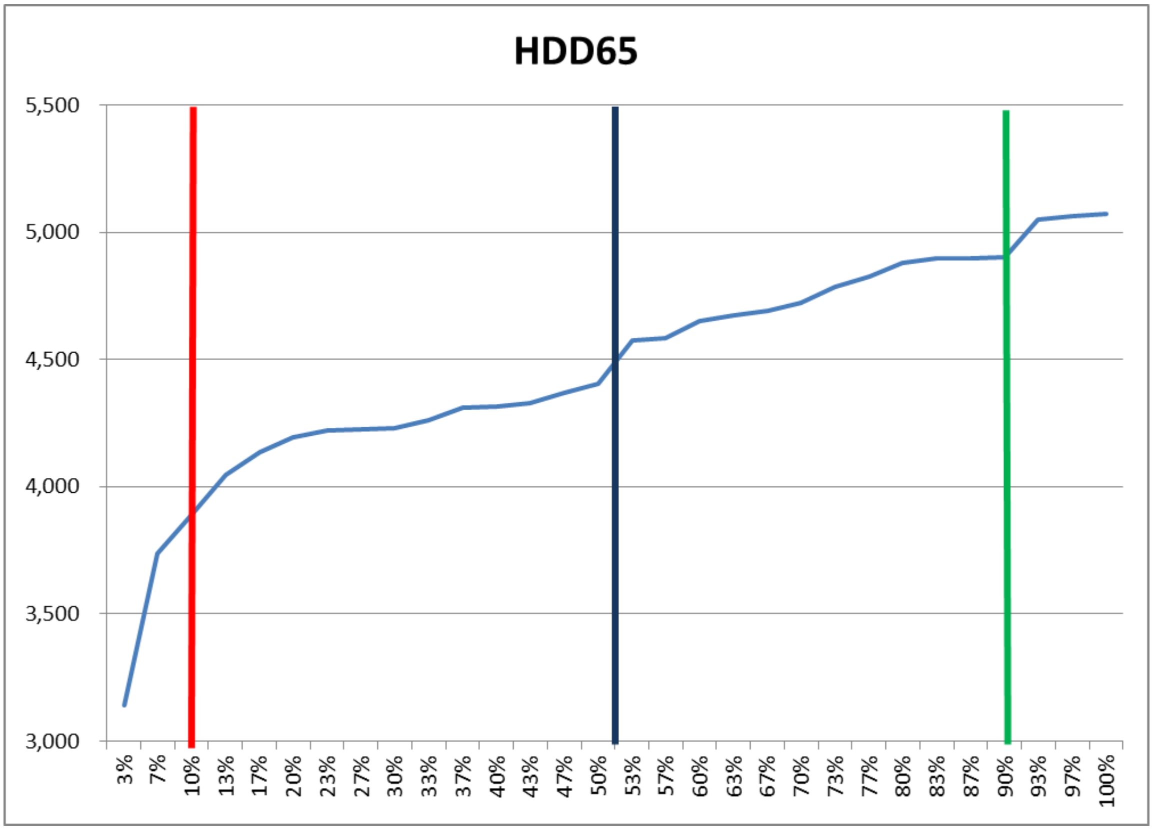


Figure 7: Scenarios: Annual CDD Base 65

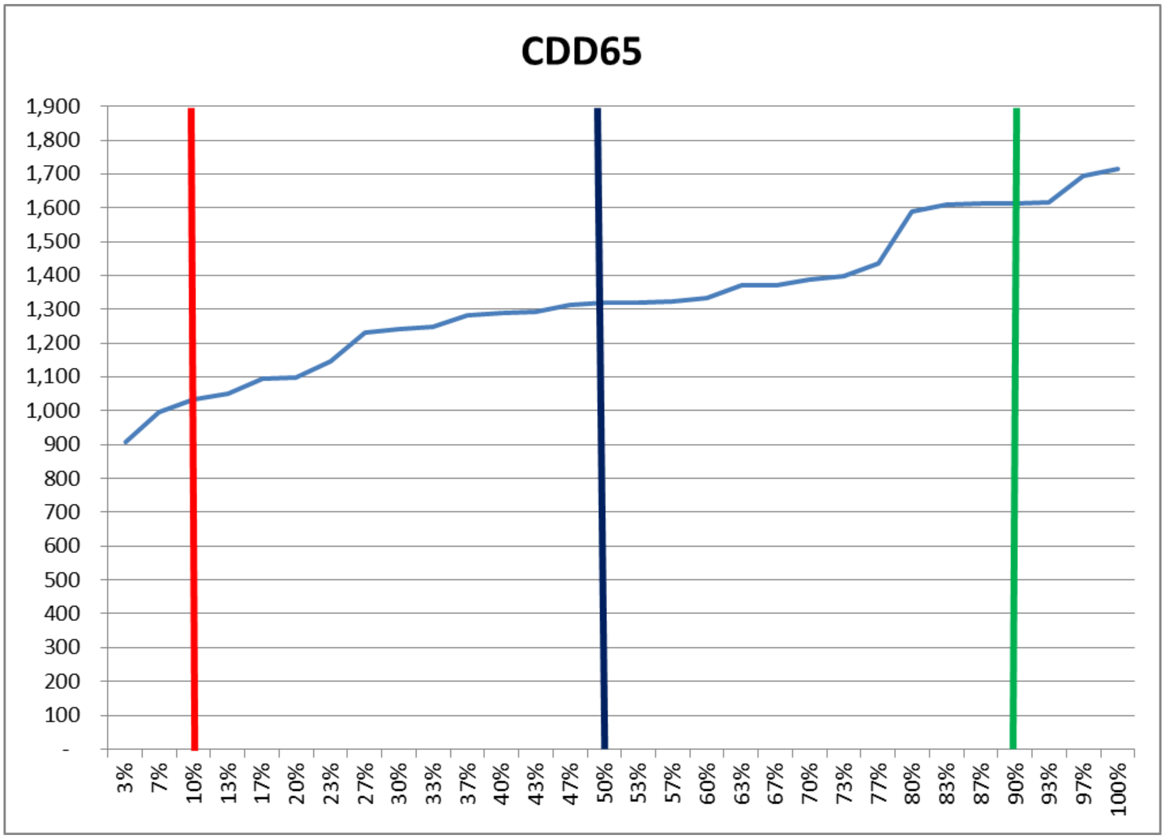


Table 1: Scenario Annual Degree Days

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

After determining the annual HDD and CDD scenario, monthly HDD and CDD values are calculated by distributing the annual HDD and CDD values based on the base case normal monthly pattern. Figure 8 and Figure 9 show the monthly HDD and CDD values for the base, mild and extreme scenarios.

Figure 8: Scenarios: Monthly HDD Base 65

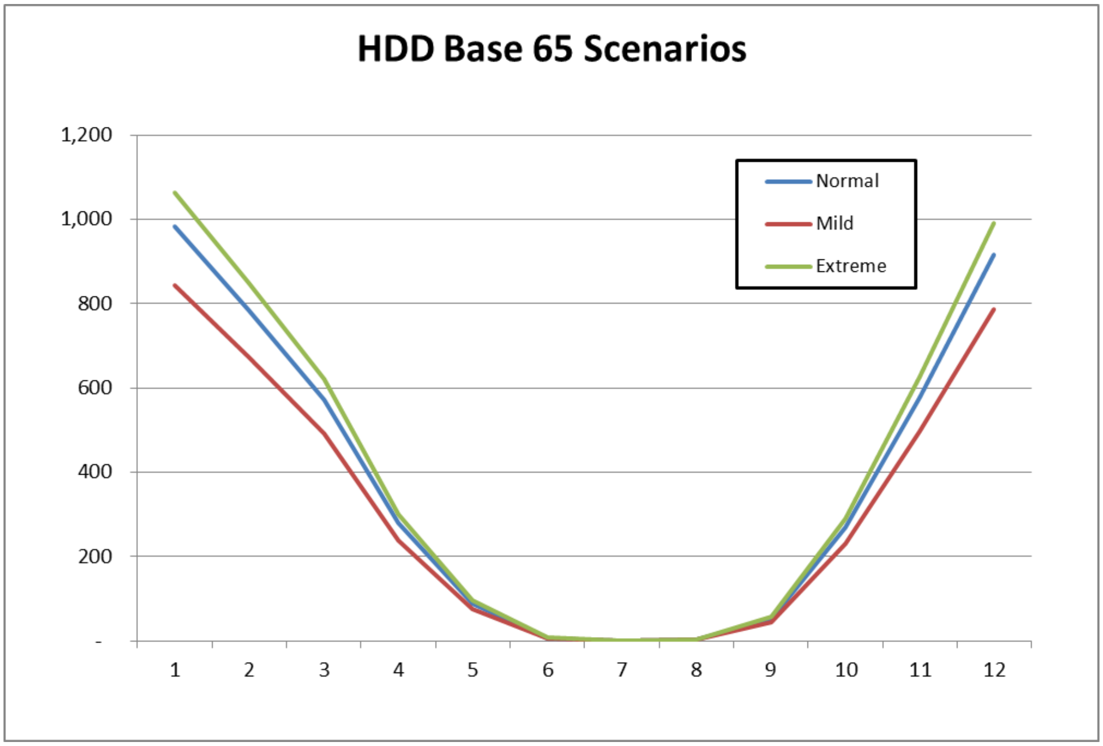
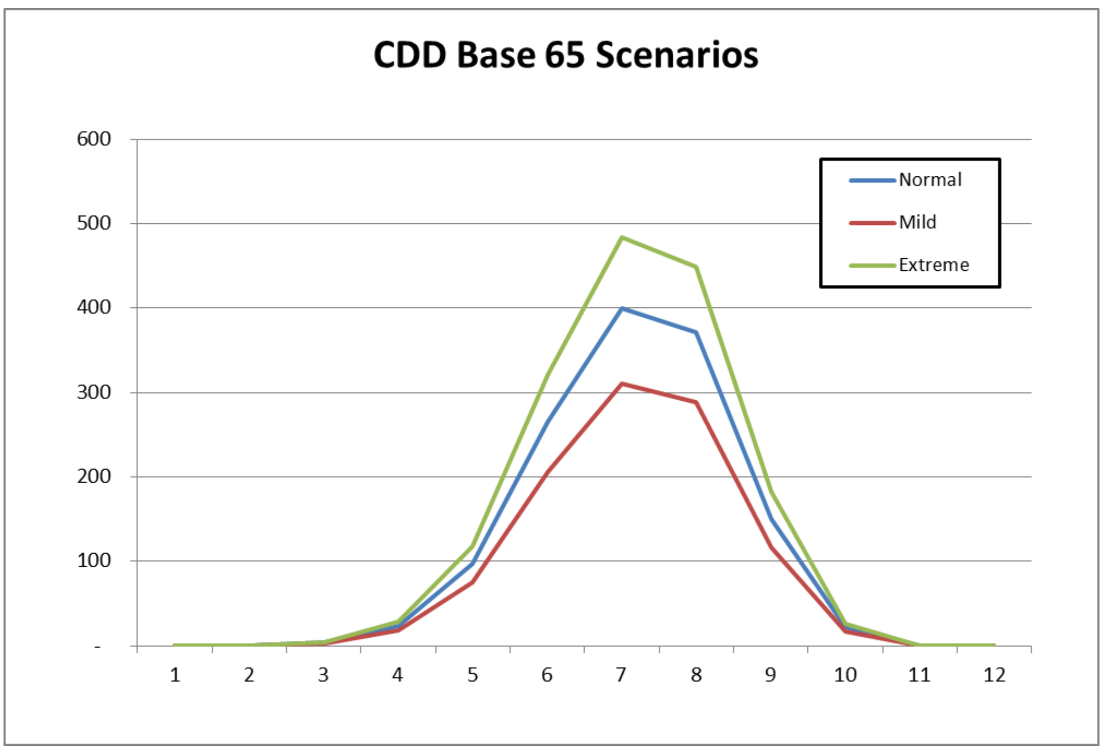


Figure 9: Scenarios: Monthly CDD Base 65



Peak Weather Scenarios. The mild and extreme 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 average temperatures in the winter months and the highest average temperatures in the summer months. The mild case is obtained by selecting the highest average temperatures in the winter month and the lowest average temperatures in the summer months.

Three exceptions were made in the mild scenario. In January, October, and November the second mildest temperatures are selected to create a smoother scenario temperature profile. Figure 10 and Table 2 show the extreme and mild peak temperature scenarios.

Figure 10: Scenarios: Peak Temperatures

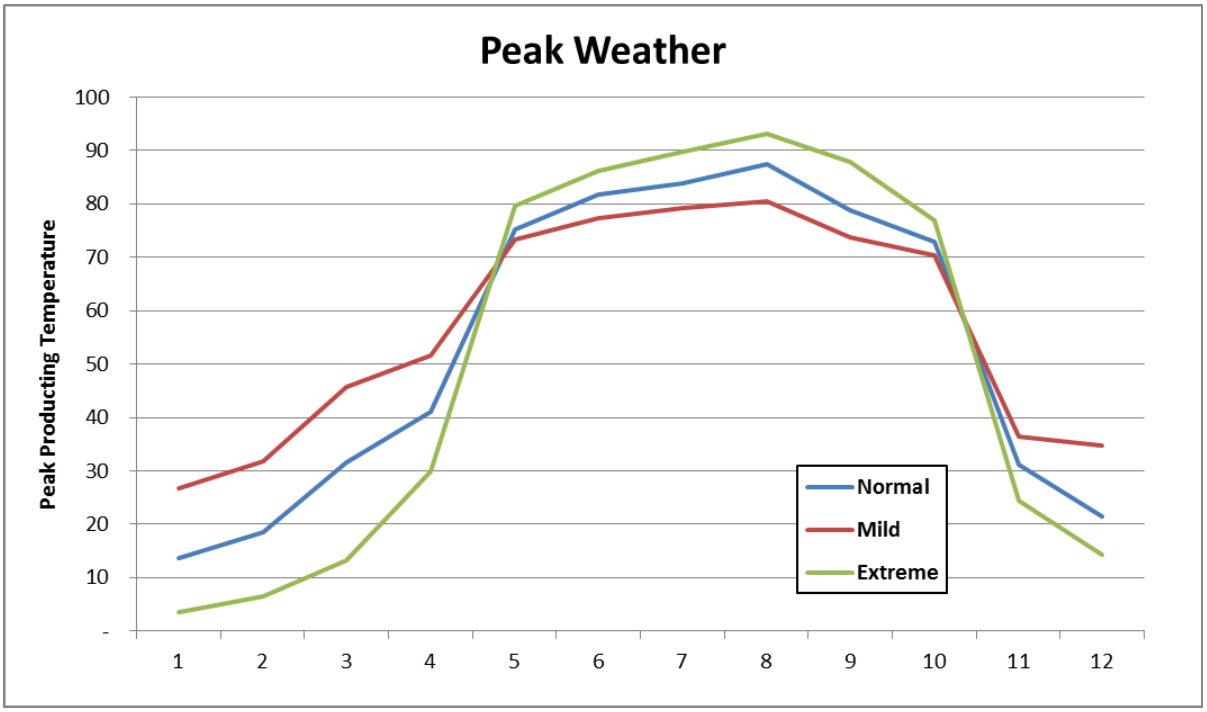


Table 2: Scenario Monthly Peak Producing Temperatures

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

Step 6. Electric Vehicle Scenario

The electric vehicle scenario is an additional scenario which adds to the Base Case forecast presenting a hypothetical case of extreme electric vehicle adoption. While the vehicle adoption in the Base Case represents 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 adoptions scenarios such as a 10%, 30%, and 50% cases were considered. However, these alternatives did not sufficiently exceed the bound of the high economic scenarios calculated in Step 4. For planning purposes, the 75% electric vehicle adoption case offers an additional sensitivity outside the high case.

The scenario is created by increasing the electric vehicle adoption rate through the forecast period to obtain a 75% adoption rate in 2035. Electric vehicles are assumed to use 15 kWh and demand 5 kW per day with a system peak coincident factor of 10%. Figure 11 shows the Electric Vehicle scenario compared to the economic scenarios based on net system energy.

Figure 11: Scenarios: Electric Vehicles

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2. Base Forecast Summary

The overall system grows from 5,025,148 MWh in 2016 to 5,279,302 MWh in 2035 (billed sales basis) with an average annual growth rate of 0.24%. The summer and winter peaks (net system peaks) move consistently with the energy forecast with average annual growth rates of 0.29% (summer peak) and 0.27% (winter peak). Beginning in 2015, the system peak is a winter peak. Annual forecast values are shown in Table 3.

Figure 12 and Figure 13 show the system-energy and system-peak forecasts.

Table 3: System Forecast Summary

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Figure 12: System Energy Forecast

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Figure 13: System Summer and Winter Peak Forecast

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3. Scenario Forecast Summary

After the development of the base forecast, the forecast models are applied to the High and Low economic scenario inputs and the Mild and Extreme weather scenario inputs. The Mild and Extreme weather scenarios and the High and Low economic scenarios are created by substituting weather and economic inputs consistent with the scenario design.

Table 4 and Table 5 compare the scenario forecasts for sales (billed basis) and peak (net system gross peaks). Figure 14 and Figure 15 show the scenarios relative to the base case.

Table 4: Scenarios: Base, Mild, Extreme, High, Low, High-High, and Electric Vehicle Billed Sales Forecast (MWh)

Year	Base	Mild	Extreme	Low	High	High-High	Electric Vehicle
2010	5,211,531						
2011	5,121,397						
2012	4,886,854						
2013	4,954,395						
2014	5,036,558						
2015	** **						
2016	** **	** **	** **	** **	** **	** **	** **
2017	** **	** **	** **	** **	** **	** **	** **
2018	** **	** **	** **	** **	** **	** **	** **
2019	** **	** **	** **	** **	** **	** **	** **
2020	** **	** **	** **	** **	** **	** **	** **
2021	** **	** **	** **	** **	** **	** **	** **
2022	** **	** **	** **	** **	** **	** **	** **
2023	** **	** **	** **	** **	** **	** **	** **
2024	** **	** **	** **	** **	** **	** **	** **
2025	** **	** **	** **	** **	** **	** **	** **
2026	** **	** **	** **	** **	** **	** **	** **
2027	** **	** **	** **	** **	** **	** **	** **
2028	** **	** **	** **	** **	** **	** **	** **
2029	** **	** **	** **	** **	** **	** **	** **

Year	Base	Mild	Extreme	Low	High	High-High	Electric Vehicle
2030	** **	** **	** **	** **	** **	** **	** **
2031	** **	** **	** **	** **	** **	** **	** **
2032	** **	** **	** **	** **	** **	** **	** **
2033	** **	** **	** **	** **	** **	** **	** **
2034	** **	** **	** **	** **	** **	** **	** **
2035	** **	** **	** **	** **	** **	** **	** **

Figure 14: Scenarios: Sales Forecast Comparison

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Table 5: Scenarios: Base, Mild, Extreme, High, Low, High-High, and Electric Vehicle Gross Peak Forecast (MW)

Year	Base	Mild	Extreme	Low	High	High-High	EV
2010	1,205						
2011	1,209						
2012	1,142						
2013	1,080						
2014	1,162						
2015	1,149						
2016	** **	** **	** **	** **	** **	** **	** **

Year	Base	Mild	Extreme	Low	High	High-High	EV
2017	** **	** **	** **	** **	** **	** **	** **
2018	** **	** **	** **	** **	** **	** **	** **
2019	** **	** **	** **	** **	** **	** **	** **
2020	** **	** **	** **	** **	** **	** **	** **
2021	** **	** **	** **	** **	** **	** **	** **
2022	** **	** **	** **	** **	** **	** **	** **
2023	** **	** **	** **	** **	** **	** **	** **
2024	** **	** **	** **	** **	** **	** **	** **
2025	** **	** **	** **	** **	** **	** **	** **
2026	** **	** **	** **	** **	** **	** **	** **
2027	** **	** **	** **	** **	** **	** **	** **
2028	** **	** **	** **	** **	** **	** **	** **
2029	** **	** **	** **	** **	** **	** **	** **
2030	** **	** **	** **	** **	** **	** **	** **
2031	** **	** **	** **	** **	** **	** **	** **
2032	** **	** **	** **	** **	** **	** **	** **
2033	** **	** **	** **	** **	** **	** **	** **
2034	** **	** **	** **	** **	** **	** **	** **
2035	** **	** **	** **	** **	** **	** **	** **

Figure 15: Scenarios: Peak Forecast Comparison

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4. Residential Energy Model

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 developed to forecast the residential electric consumption. These models are defined below.

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

The class forecast is calculated by multiplying the customer forecast by 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).

Customer Model

The Customer Model is a regression model estimated with historical data from January 2001 through March 2015. Table 6 shows the Customer Model specification and Table 7 shows the Customer Model statistics. A full description of the model is shown in the MetrixND project file. In the project file, the Customer Model is labeled **Residential_Cust**.

Table 6: Residential Customer Model

Variable	Coefficient	StdErr	T-Stat	P-Value
May2011Tornado	67208.775	47765.424	1.407	16.14%
Population	-2171.910	178.774	-12.149	0.00%
Year2012Plus	67544.244	39312.096	1.718	8.78%
March	-1890.843	255.351	-7.405	0.00%
April	-170.854	42.117	-4.057	0.01%
May	-461.418	57.192	-8.068	0.00%
June	-638.277	66.443	-9.606	0.00%
July	-732.338	71.007	-10.314	0.00%
August	-648.763	72.455	-8.954	0.00%
September	-586.642	70.977	-8.265	0.00%
October	-681.120	66.379	-10.261	0.00%
AR(1)	-591.278	57.928	-10.207	0.00%

Table 7: Residential Customer Model Statistics

Statistics	Residential Customer Model
Estimation	1/2001 – 3/2015
R^2	0.999
Adj. R^2	0.999
MAPE	0.08%
DW	2.024

Model Variables. The residential model is primarily driven by population, incorporates adjustments for the 2011 tornado, and captures seasonality.

- **Population.** This variable is derived from historical data and population forecasts for the Springfield and Joplin MSAs.

- **May2011Tornado and Year2012Plus**. The May2011Tornaodo variable takes the value of "1" from May 2011 through December 2011 and "0" at all other times. The Year2010 Plus variable takes the value of "1" in January 2012 and all subsequent months and a value of "0" in months before 2012. These variables capture the reduction in customers from the May 22, 2011 Joplin F5 tornado.

- **May through October**. The May through October binary variables capture the changing number of seasonal customers through the calendar year. Customer counts dip slightly in the summer months.

- **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.

UPC Model

The UPC Model is an SAE model estimated with historical data from January 2000 through March 2015. The SAE model is described fully in the technical paper shown in Appendix A. Table 8 shows the UPC Model specification and Table 9 shows the UPC Model statistics. A full description of the model is shown in the MetrixND project file. In the project file, the UPC Model is labeled **Residential_UPC**.

Residential SAE Model Summary. The SAE model implemented for the Residential Class contains end-use information for heating, cooling, and base load technologies from Itron's 2015 SAE West North Central region. Included in the model are the following data:

- **End-Use Efficiencies.** End-use efficiencies by technology type are based on Energy Information Administration (EIA) data.
- **End-Use Saturations and Intensities.** End-use saturations and intensities by technology type are based on EIA data calibrated to Empire's 2008 Potential

Study and 2015 Saturation Survey. End-use intensities are modified to account for Empire's historic investment in demand-side management (DSM) programs.

- **Housing Stock.** Housing information is based on EIA data modified for Empire's 2008 Potential Study and 2015 Saturation Survey housing stock findings.
- **Economic data.** Historic and forecasted household size and household income are based on Economy.com forecasts for the Springfield and Joplin MSAs.
- **Energy Prices.** Class energy prices are based on historical revenues and energy consumption. The energy price forecast is held flat in real dollars.
- **Photovoltaic Forecast.** Penetration of rooftop solar in Empire's service area in included based on an Empire forecast of saturation and EIA growth rates.
- **Electric Vehicle Forecast**. Penetration of electric vehicle is based on EIA projected growth rates for the West North Central Region.

A full description of the model is shown in the MetrixND project file. In this project file, the UPC Model is labeled **Residential_UPC**. SAE assumptions are contained in the Excel file database, **WestNorthCentral15.xls**.

Table 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%
XHeatShift2007	-93.318	17.147	-5.442	0.00%
Year2014Plus	0.137	0.033	4.172	0.01%

Table 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

Model Variables. The UPC Model includes the three standard SAE variables (XHeat, XCool, and XOther), as wells as monthly binary variables and shift variables.

- **XHeat.** This variable captures the general heating response for a typical residential customer. The response includes the effects of heating technology efficiencies, saturations, thermal shell, weather, price, income, and household size. Heating intensities are adjusted for historic DSM programs. A full description of the variable and its construction is included in Appendix A.

- **XCool.** This variable captures the general cooling response for a typical residential customer. The response includes the effects of cooling technology efficiencies, saturations, thermal shell, weather, price, income, and household size. Cooling intensities are adjusted for historic DSM programs. A full description of the variable and its construction is included in Appendix A.

- **XOther.** This variable captures the general response for all non-heating and non-cooling technologies including electric vehicles and photovoltaics. The response includes the effects of hours of light, price, income, billing cycles, and household size. Intensities are adjusted for historic DSM programs. A full description of the variable and its construction is included in Appendix A.

- **Monthly Binaries.** Selected monthly binary variables are included to capture additional baseload shift not represented in the Xheat, Xcool, or Xother variables.

- **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 accounts for the rapid growth in new electric heated homes.

- **Year2014Plus**. This binary variable begins in 2014 and continues through the forecast horizon. The shift calibrates the forecast to recent history, smoothing the transition for historic to forecasted data.

Demand Side Management Programs. Empire's residential DSM programs began in 2007 and impact heating, cooling, and lighting intensities. Estimated incremental DSM savings (annual savings from the new incremental participation) are converted to cumulative DSM savings over the expected life of the technology. The cumulative savings are used to modify the heating, cooling, and lighting intensities in the SAE model variables. As an example, Figure 16 shows the intensity reduction (kWh/Household/Year) for the SAE heating variable resulting from the DSM programs.

Figure 16: Residential DSM Heating Intensity Modification

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Photovoltaic Forecast. The penetration of rooftop solar (photovoltaics) installations in Empire's service territory is a recent event. The photovoltaic forecast is included in the SAE model in the XOther variable. The forecast is developed using Empire's short-term forecast which projects a total of 707 installations by 2020. After 2020, solar projections are developed using the EIA's 2015 AEO forecasted growth rates.

Electric Vehicle Forecast. The electric vehicle forecast is included in the SAE model in the XOther variable. The forecast is developed based on EIA's 2015 AEO forecast of EVs and plug-in EVs. The percent of EVs relative to the total population in the EIA's West North Central region is applied to an estimate of Empire's projected residential customers to obtain the forecasted number of EVs in Empire's service territory.

Residential Base Energy Forecast

The residential energy forecast is developed as the product of the customer and use-per-customer (UPC) forecasts.

The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 17, Figure 18, and Figure 19. Both the energy and use-per-customer figures show normalized and historic energy and use-per-customer for comparative purposes.

Table 10 and Table 11 summarize the energy, customer, and use-per-customer forecasts with annual energy for selected years and average annual growth rates. Because population is a primary driver in the residential forecast, Table 11 includes the average annual growth rate for population.

Figure 17: Residential Energy Forecast (Actual, Normalized, Forecast)

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Figure 18: Residential Customer Forecast (Actual, Forecast)

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Figure 19: Residential UPC Forecast (Actual, Normalized, Forecast)

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Table 10: Residential Energy Forecast Summary

Year	Energy (MWh)	Customers	Use-Per-Customer (MWh)	Normalized Energy (MWh)	Normalized Use-Per-Customer (MWh)
2005	1,893,691	134,724	14.06	1,861,643	13.82
2010	2,069,460	141,693	14.60	1,940,320	13.69
2014	1,957,659	141,838	13.80	1,867,906	13.17
2016	** **	** **	** **		
2020	** **	** **	** **		
2025	** **	** **	** **		
2030	** **	** **	** **		
2035	** **	** **	** **		

Table 11: Residential Energy Forecast - Average Annual Growth Rates

Time Period	Energy	Customers	Use-Per-Customer	Population
2003-2014 (Historical)	1.2%	0.8%	0.4%	1.34%
2009-2014 (Historical)	1.2%	0.1%	1.1%	0.70%
2016-2020 (5 Yr Forecast)	** **	** **	** **	0.71%

2016-2025 (10 Yr Forecast)	** **	** **	** **	0.56%
2016-2030 (15 Yr Forecast)	** **	** **	** **	0.51%
2016-2035 (20 Yr Forecast)	** **	** **	** **	0.52%

5. Commercial Energy Model

As with the Residential class, Commercial energy is modeled using two models. These models capture both the growth in the sector based on the number of customers and the changing usage of the average customer based on end-use information. These models are defined below.

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

The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total energy in each month. Using two models to develop the commercial class forecast captures class growth based a changing number of customers (Customer Model) as well as changes in customer usage patterns (UPC Model).

Customer Model

The Customer Model is a regression model estimated with historical data from January 2002 through March 2015. Table 12 shows the Customer Model specification and Table 13 shows the Customer Model statistics. A full description of the model is shown in the MetrixND project file. In the project file, the Customer Model is labeled **Commercial_Cust**.

Table 12: 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 13: Commercial Customer Model Statistics

Statistics	Commercial Customer Model
Estimation	1/2002 – 3/2015
R^2	0.997
Adj. R^2	0.996
MAPE	0.10%
DW	2.037

Model Variables. The customer model is primarily driven by the residential customer forecast and accounts for seasonality.

- **Residential Customers**. This variable is the historical and forecast number of customers based on the Residential Customer model. Commercial customers are highly correlated with residential customers.

- **Monthly Binaries.** The March through December binary variables capture the changing number of seasonal customers through the calendar year. Customer counts increase slightly through the summer months

- **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.

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 (Appendix A), but modified for commercial end-use information. The SAE framework for the Commercial model is described in Appendix B. Table 14 shows the UPC Model specification and Table 15 shows the UPC Model statistics. A full description of the model is shown in the MetrixND project file. In the project file, the UPC Model is labeled **Commercial_UPC**.

Commercial SAE Model Summary. The SAE model implemented for the Commercial Class contains end-use information for heating, cooling, and base load technologies from Itron's 2015SAE West North Central region. Included in the model are the following data.

- **End-use Saturations and Efficiencies.** End-use saturations and efficiencies by technology type are based on Energy Information Administration (EIA) data and adjusted for historic DSM programs.
- **Economic data.** Historic and forecast employment levels and gross regional product are based on Economy.com forecasts for the Springfield and Joplin MSAs
- **Energy Prices.** Price is based on historical revenues and energy consumption. The energy prices are held flat in real dollars through the forecast period.
- **Photovoltaic Forecast.** Penetration of rooftop solar in Empire's service area in included based on an Empire forecast of saturation and EIA growth rates.

A full description of the model is shown in the MetrixND project file. In this project file, the UPC Model is labeled **Commercial_UPC**. SAE assumptions are contained in the Excel file database, **WestNorthCentral15.xls**.

Table 14: 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%
September	339.660	59.329	5.725	0.00%
Year2000	-255.226	64.336	-3.967	0.01%
Year2006	-390.122	64.599	-6.039	0.00%
Year2007	-315.858	64.510	-4.896	0.00%
Year2006Plus	488.168	36.578	13.346	0.00%
Year2013Plus	160.388	47.505	3.376	0.09%

Table 15: 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

Model Variables. The UPC Model includes the three standard SAE variables (XHeat, XCool, and XOther) as wells as a monthly binary variable and shift variables.

- **XHeat.** This variable captures the general heating response for a typical commercial customer. The response includes the effects of heating technology efficiencies, saturation by technology and building types, weather, price, employment and output indices. Heating intensities are adjusted for historic

DSM programs. A full description of the variable and its construction is included in Appendix B.

- **XCool.** This variable captures the general cooling response for a typical commercial customer. The response includes the effects of cooling technology efficiencies, saturation by technology and building types, weather, price, employment and output indices. Cooling intensities are adjusted for historic DSM programs. A full description of the variable and its construction is included in Appendix B.

- **XOther.** This variable captures the general response for all non-heating and cooling technologies. The response includes the effects of other base load technology efficiencies, saturation by technology and building types, price, employment and output indices. Baseload intensities are adjusted for historic DSM programs in lighting and motors. A full description of the variable and its construction is included in Appendix B.

- **Monthly Binaries.** Selected monthly binary variables are included to capture a patterned residual through the course of the year.

- **Year2000, Year2006, and Year2007.** These independent binary variables are included to capture the quick growth in average use during high economic growth periods.

- **Year2006Plus and Year2013Plus.** These binary variables consist of a "1" value beginning in 2006 and 2013 which continues throughout the forecast period. These variables are used to capture the consist shift in average use experienced during high economic growth periods and calibrate the forecast to the most recent data.

Demand Side Management Programs. Empire's commercial DSM programs began in 2007 and impact heating, cooling, miscellaneous, and lighting intensities. Estimated incremental DSM savings (annual savings from the new incremental participation) are converted to cumulative DSM savings over the expected life of the technology. The cumulative savings are used to modify the heating, cooling, lighting, and miscellaneous intensities in the SAE model variables.

Photovoltaic Forecast. The penetration of rooftop solar (photovoltaic) installations in Empire's service territory is a recent event. The photovoltaic forecast is included in the SAE model in the XOther variable. The forecast is developed using Empire's short-term forecast of a total of 254 total installations by 2020. After 2020, solar projections are developed using the EIA's 2015 AEO forecasted growth rates.

Commercial Base Energy Forecast

The commercial energy forecast is developed as the product of the customer and UPC forecasts. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 20, Figure 21, and Figure 22. Both the energy and use-per-customer figures show historic and normalized energy and use-per-customer for comparative purposes.

Table 16 and Table 17 summarize the energy, customer, and use-per-customer forecasts with annual energy for selected years and average annual growth rates. Because employment is a key driver in the commercial forecast, Table 17 includes the average annual growth rate for non-manufacturing employment.

Figure 20: Commercial Energy Forecast (Actual, Normalized, and Forecast)

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Figure 21: Commercial Customer Forecast (Actual, Forecast)

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Figure 22: Commercial UPC Forecast (Actual, Normalized, and Forecast)

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Table 16: Commercial Energy Forecast Summary

Year	Energy (MWh)	Customers	Use-Per-Customer (MWh)	Normalized Energy (MWh)	Normalized Use-Per-Customer (MWh)
2005	1,495,868	23,684	63.14	1,474,686	62.25

2010	1,652,292	24,505	67.43	1,603,016	65.42
2014	1,583,796	24,146	65.60	1,558,779	64.56
2016	** **	** **	** **		
2020	** **	** **	** **		
2025	** **	** **	** **		
2030	** **	** **	** **		
2035	** **	** **	** **		

Table 17: Commercial Energy Forecast - Average Annual Growth Rates

Time Period	Energy	Customers	Use-Per-Customer	Employment
2003-2014 (Historical)	1.2%	0.4%	0.7%	1.47%
2009-2014 (Historical)	0.2%	-0.2%	0.4%	0.72%
2016-2020 (5 Yr Forecast)	** **	** **	** **	0.98%
2016-2025 (10 Yr Forecast)	** **	** **	** **	0.64%
2016-2030 (15 Yr Forecast)	** **	** **	** **	0.58%
2016-2035 (20 Yr Forecast)	** **	** **	** **	0.59%

6. Wholesale Energy Models

The Wholesale energy forecast is composed of models for four municipal utilities: Monett, Mt. Vernon, and Lockwood, Missouri, and Chetopa, Kansas. Empire sells electricity to each municipality, which in turn provides service to their respective customers. Each municipal utility is small and serves a largely residential population. The forecast for the wholesale class is developed with four energy models, one for each municipal utility. The models used in this class forecast are defined below.

- **Monett Energy Model**. This model forecasts the total kWh for Monett in a month.
- **Mt. Vernon Energy Model**. This model forecasts the total kWh for Mt. Vernon in a month.
- **Lockwood Energy Model**. This model forecasts the total kWh for Lockwood in a month.
- **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 for each month.

Energy Models

The models forecast total energy and are not divided into customer and use-per-customer models. The energy models use the SAE model framework, including an economic variable to capture customer growth, and forecast total energy provided to each municipality. The SAE model variable construction is identical to the construction used in the residential class with the exception of changing the temperature variable to reflect a stronger current month weather relationship.

Model Variables. The energy models include the three standard SAE variables (XHeat, XCool, and XOther) with a modification to XOther variable to capture economic growth. The general definitions of the variables are listed below.

- **XHeat.** This variable captures the general heating response for a typical residential customer. The response includes the effects of heating technology efficiencies, saturation, and efficiencies, thermal shell, weather, price, income, and household size. A full description of the variable and its construction is included in Appendix A.

- **XCool.** This variable captures the general cooling response for a typical residential customer. The response includes the effects of cooling technology efficiencies, saturation, and efficiencies, thermal shell, weather, price, income, and household size. A full description of the variable and its construction is included in Appendix A.

- **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. The modification to the standard XOther calculation is adding population. The XOther variable is constructed as defined below where OtherIndex and OtherUse are standard SAE construction and Population is the weighted average population index for the Springfield and Joplin MSAs.

$$XOther_{y,m} = OtherIndex_{y,m} \times OtherUse_{y,m} \times Population\,Index_{y,m}$$

  A full description of the variable and its construction is included in Appendix A.

- **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 or household variables.

- **Plus Binaries.** The binary plus variables (e.g. Year2009Plus, Year2011Plus, JanDec2007Plus) capture an ongoing shift in base load which is expected to continue into the future.

Monett Energy Model

The Monett energy model is summarized in Table 18 and Table 19. A full description of the model is shown in the MetrixND project file. In this project file, the energy Model is labeled **Monett**.

Table 18: Monett Energy Model

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Table 19: 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

Mt. Vernon Energy Model

The Mt. Vernon energy model is summarized in Table 20 and Table 21. A full description of the model is shown in the MetrixND project file. In this project file, the energy Model is labeled **MtVernon**.

Table 20: Mt. Vernon Energy Model

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Table 21: Mt. Vernon Energy Model Statistics

Statistics	Mt. Vernon Model
Estimation	1/2000 – 3/2015
R2	0.927
Adj. R2	0.926
MAPE	3.40%
DW	2.156

Lockwood Energy Model

The Lockwood energy model is summarized in Table 22 and Table 23. A full description of the model is shown in the MetrixND project file. In this project file, the energy Model is labeled **Lockwood**.

Table 22: Lockwood Energy Model

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Table 23: Lockwood Energy Model Statistics

Statistics	Lockwood Model
Estimation	1/2000 – 3/2015
R2	0.949
Adj. R2	0.947
MAPE	3.45%
DW	1.731

Chetopa Energy Model

The Chetopa energy model is summarized in Table 24 and Table 25. A full description of the model is shown in the MetrixND project file. In this project file, the energy Model is labeled **Chetopa**.

Table 24: Chetopa Energy Model

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Table 25: 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

Wholesale Base Energy Forecast

The wholesale energy forecast is the sum of the forecasts generated by the four municipal utility energy models.

The wholesale energy forecast is primarily driven by the forecasts for Monett and Mt. Vernon, which are the largest of the four municipalities. Figure 23 shows the total energy forecast. Table 26 and Table 27 summarize the wholesale energy forecast and show the forecasts for each municipal utility for comparative purposes.

Figure 23: Wholesale Energy Forecast (Actual, Forecast)

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Table 26: Wholesale Energy Forecast Summary

Year	Monett (MWh)	Mt. Vernon (MWh)	Lockwood (MWh)	Chetopa (MWh)
2005	229,262	74,975	10,854	13,712
2010	250,546	79,214	11,053	14,993
2012	235,497	74,904	11,534	14,379
2015	** **	** **	** **	** **
2020	** **	** **	** **	** **
2025	** **	** **	** **	** **
2030	** **	** **	** **	** **
2035	** **	** **	** **	** **

Table 27: Wholesale Energy Forecast Average Annual Growth Rates

Time Period	Monett	Mt. Vernon	Lockwood	Chetopa
2003-2014 (Historical)	1.2%	0.7%	1.2%	0.9%
2009-2014 (Historical)	0.2%	0.4%	2.5%	0.3%
2016-2020 (5 Yr Forecast)	** **	** **	** **	** **
2016-2025 (10 Yr Forecast)	** **	** **	** **	** **
2016-2030 (15 Yr Forecast)	** **	** **	** **	** **
2016-2035 (20 Yr Forecast)	** **	** **	** **	** **

7. Street & Highway Energy Model

Street & Highway class consists primarily of outside lighting accounts. Two models are used to forecast this class as defined below.

- **Customer Model**. This model forecasts the number of Street & Highway customers in each month.
- **UPC Model**. This model forecasts the average use-per-customer (UPC) for a month.

The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total monthly energy. Using two models to develop the Street & Highway class forecast captures class growth based on a changing number of customers (Customer Model) and changes in customer usage patterns (UPC Model).

Customer Model

The Customer Model is a regression model estimated with historical data from January 2001 through March 2015. Table 28 shows the Customer Model specification and Table 29 shows the Customer Model statistics. A full description of the model is shown in the MetrixND project file. In the project file, the Customer Model is labeled **SH_Cust**.

Table 28: Street & Highway Customer Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	195.752	22.137	8.843	0.00%
Oct2007ToDec2008 Binary	-9.931	2.361	-4.206	0.00%
PopNonManEmp	243.374	19.981	12.180	0.00%
AR(1)	0.777	0.048	16.085	0.00%

Table 29: Street & Highway Customer Model Statistics

Statistics	Street & Highway Customer Model
Estimation	1/2001 – 3/2015
R^2	0.951
Adj. R^2	0.950
MAPE	0.53%
DW	1.882

Model Variables. The Street & Highway model includes two variables and an AR term. The primary driver the Customer model is the weighted average of population and non-manufacturing employment.

PopNonManEmp. This variable is derived from the historical and forecasted population and non-manufacturing employment for the Springfield and Joplin MSAs. The index is created as a weighted average of the population and non-manufacturing employment indices using 1/3 and 2/3 weights respectively.

- **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 2007-2008 timeframe.

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

UPC Model

The UPC Model is a regression model estimated with historical data from January 2001 through March 2015. Table 30 shows the UPC Model specification and Table 31 shows the UPC Model statistics. A full description of the model is shown in the MetrixND project file. In the project file, the Customer Model is labeled **SH_UPC**.

Table 30: Street & 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%

Table 31: Street & Highway UPC Model Statistics

Statistics	Street & Highway UPC Model
Estimation	1/2001 – 9/2011
R2	0.875
Adj. R2	0.864
MAPE	2.63%
DW	2.602

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

- **Monthly Binaries.** This set of binary variables capture the general seasonal response due to the changing sunrise and sunset times.

- **Outside Light Efficiency.** This variable captures the increasing energy efficiency of outside lighting technology. The variable is derived from the Commercial SAE model's outside lighting efficiency index provided by the EIA. The increasing value of the index indicates that lighting technologies are becoming more efficient and using less energy over time.

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

Street & Highway Base Energy Forecast

The Street & Highway energy forecast is the product of the customer model and use-per-customer (UPC) forecast.

The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 24, Figure 25, and Figure 26.

Table 32 and Table 33 summarize the energy, customer, and use-per-customer forecasts with annual energy for selected years and average annual growth rates. Because the PopNonManEmp index and outside lighting efficiency index are key drivers in the Street & Highway forecast, Table 33 includes the average annual growth rates for both indices.

Figure 24: Street & Highway Energy Forecast (Actual, Forecast)

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Figure 25: Street & Highway Customer Forecast (Actual, Forecast)

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Figure 26: Street & Highway UPC Forecast (Actual, Forecast)

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Table 32: Street & Highway Energy Forecast Summary

Year	Energy (MWh)	Customer	Use-Per-Customer (MWh)
2005	23,560	455	51.78
2010	23,472	475	49.38
2012	24,257	487	49.88
2015	** **	** **	** **
2020	** **	** **	** **
2025	** **	** **	** **
2030	** **	** **	** **
2035	** **	** **	** **

Table 33: Street & Highway Energy Forecast Average Annual Growth Rates

Time Period	Energy	Customer	Use-Per-Customer	Efficiency Gains Index	Weighted Pop and Non-Man Employment
2003-2014 (Historical)	0.6%	0.8%	-0.2%	3.83%	1.34%
2009-2014 (Historical)	1.0%	0.5%	0.4%	4.32%	0.70%
2016-2020 (5 Yr Forecast)	** **	** **	** **	1.67%	0.71%
2016-2025 (10 Yr Forecast)	** **	** **	** **	1.65%	0.56%
2016-2030 (15 Yr Forecast)	** **	** **	** **	1.52%	0.51%
2016-2035 (20 Yr Forecast)	** **	** **	** **	1.52%	0.52%

8. Interdepartmental Energy Model

The Interdepartmental class is forecast using two models.

- **Customer Model**. This model forecasts the number of Interdepartmental customers in each month.
- **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. The developed models capture the number of customers (Customer Model) and usage patterns (UPC Model).

Customer Model

The Customer Model is a regression model that is designed to provide a flat forecast based on the last actual value. This produces a forecast of 41 customers.

The model uses an end-shift binary variable to identify the last actual data point and project that value throughout the forecast horizon. The model is shown in the MetrixND project file. In the project file, the Customer Model is labeled **IntDep_Cust**.

UPC Model

The UPC Model is a regression model estimated with historical data from January 2001 through March 2015. This model captures seasonal fluctuations based on weather response and forecasts loads based historical usage from 2008 forward. Table 34 shows the UPC Model specification and Table 35 shows the UPC Model statistics. A full description of the model is shown in the MetrixND project file. In the project file, the Customer Model is labeled **IntDep_UPC**.

Table 34: 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 35: 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

Model Variables. The UPC Model is designed to capture seasonal variations in usage. The variables included in the model are described below.

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

- **Annual Shift Variables.** Annual shift variables (Year2007Plus, Year2008Plus, and Year2014Plus) capture rapid changes in average use beginning in 2007 and 2008. The Year2014Plus shift captures average use levels in 2014 and 2105 and projects this average usage forward.

Interdepartmental Base Energy Forecast

The Interdepartmental energy forecast is the product of the customer and use-per-customer (UPC) forecast. The forecast is designed to be flat with no expected addition of customers or changes in annual use-per-customer.

The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 27, Figure 28, and Figure 29. Table 36 and Table 37 summarize the energy, customer, and use-per-customer forecasts with annual energy for selected years and average annual growth rates.

Figure 27: Interdepartmental Energy Forecast (Actual, Forecast)

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Figure 28: Interdepartmental Customer Forecast (Actual, Forecast)

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Figure 29: Interdepartmental UPC Forecast (Actual, Forecast)

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Table 36: Interdepartmental Energy Forecast Summary

Year	Energy (MWh)	Customer	Use-Per-Customer (MWh)
2005	1,675	11	155.74
2010	1,900	33	57.58
2012	3,733	40	94.66
2015	** **	** **	** **
2020	** **	** **	** **
2025	** **	** **	** **
2030	** **	** **	** **
2035	** **	** **	** **

Table 37: Interdepartmental Energy Forecast Average Annual Growth Rates

Time Period	Energy	Customer	Use-Per-Customer
2003-2014 (Historical)	10.4%	13.8%	0.2%
2009-2014 (Historical)	22.0%	6.0%	15.8%
2016-2020 (5 Yr Forecast)	** **	** **	** **
2016-2025 (10 Yr Forecast)	** **	** **	** **
2016-2030 (15 Yr Forecast)	** **	** **	** **
2016-2035 (20 Yr Forecast)	** **	** **	** **

9. Public Authority Energy Model

The Public Authority class is forecasted with the following two models:

- **Customer Model**. This model forecasts the number of Public Authority customers in each month.
- **UPC Model**. This model forecasts the average use-per-customer (UPC) for a month.

The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total energy in each month. Using two models to develop the Public Authority class forecast captures class growth based a changing number of customers (Customer Model) and annual customer usage patterns (UPC Model).

Customer Model

The Customer Model is a regression model that is designed to forecast growth for the class. 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. The model is shown in the MetrixND project file. In the project file, the Customer Model is labeled **PublicAuthority_Cust**.

Table 38: 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%
July12toAugust14	156.234	4.473	34.932	0.00%

Table 39: Public Authority Customer Model Statistics

Statistics	Public Authority Customer Model
Estimation	1/2006 – 3/2015
R2	0.981
Adj. R2	0.980
MAPE	0.74%
DW	0.293

Model Variables. The Customer Model is primarily driven by the household forecast and calibrated to the last actual number of customers. The variables are discussed below.

- **Government Employment.** This variable is derived from historical data and the forecasted projection of government employment for the Springfield and Joplin MSAs.

- **Sept2014Plus.** This variable calibrates the forecast to the historical values from September 2015 through March 2015.

- **July12toAugust14.** This binary variable captures a large shift in the number of customers between July 2012 and August 2014.

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 customer average use. Table 40 shows the UPC Model specification and Table 41 shows the UPC Model statistics. A full description of the model is shown in the MetrixND project file. In the project file, the Customer Model is labeled **IntDep_UPC**.

Table 40: 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 41: Public Authority UPC Model Statistics

Statistics	Public Authority UPC Model
Estimation	1/1999 – 3/2015
R2	0.727
Adj. R2	0.717
MAPE	3.66%
DW	1.780

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

- **Weather Variables.** This set of variables (HDD55 and CDD55) capture the weather response of the Public Authority class.

- **Monthly Binaries.** The February and June binary variables capture bias in specific months which are not captured in the weather variables.

- **Annual Shift Variables.** This set of variables (Year2002Plus and Year2008Plus, Year2012Plus) capture annual shifts in average use which continue throughout the forecast period.

Public Authority Base Energy Forecast

The Public Authority energy forecast is the product of the customer model and use-per-customer (UPC) forecast. The forecast is designed to provide growth based on an increasing number of customers driven by government employment growth, but with flat average usage.

The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 30, Figure 31, and Figure 32. Table 42 and Table 43 summarize the energy, customer, and use-per-customer forecasts with annual energy for selected years and average annual growth rates.

Figure 30: Public Authority Energy Forecast (Actual, Forecast)

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Figure 31: Public Authority Customer Forecast (Actual, Forecast)

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Figure 32: Public Authority UPC Forecast (Actual, Forecast)

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Table 42: Public Authority Energy Forecast Summary

Year	Energy (MWh)	Customer	Use-Per-Customer (MWh)
2005	87,685	1,382	63.40
2010	101,082	1,528	66.15
2012	100,029	1,688	59.25
2015	** **	** **	** **
2020	** **	** **	** **
2025	** **	** **	** **
2030	** **	** **	** **
2035	** **	** **	** **

Table 43: Public Authority Energy Forecast Average Annual Growth Rates

Time Period	Energy	Customer	Use-Per-Customer	Government Employment
2003-2014 (Historical)	2.2%	2.7%	-0.4%	1.80%
2009-2014 (Historical)	0.3%	2.2%	-1.7%	1.40%
2016-2020 (5 Yr Forecast)	** **	** **	** **	-0.09%
2016-2025 (10 Yr Forecast)	** **	** **	** **	0.05%
2016-2030 (15 Yr Forecast)	** **	** **	** **	0.08%
2016-2035 (20 Yr Forecast)	** **	** **	** **	0.08%

10. Industrial Energy Models

The Industrial class is comprised large customers. The forecast for this class is developed with three separate models as described below.

- **Praxair**. Praxair is a large individual customer. A single energy model is developed to forecast its energy.

- **Oil & 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 use-per-customer model is created to capture the seasonal variations of the class.

- **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 use-per-customer model is created to capture the monthly variations of the segment.

The class forecast is calculated by summing the Praxair, Oil & Pipeline, and Other Industrial energy forecasts. An additional adjustment is made to the industrial class that increases the number of customers and energy based on known customer expansion plans.

Praxair Model

The Praxair Model is a single regression model developed to forecast monthly energy. The model is created to provide a flat forecast based on the 2013 through 2015 average annual energy usage. The model results are shown in Table 44 and Table 45. The full model is shown in the MetrixND project file. In the project file, the model is labeled **Praxair_UPC**.

Table 44: Praxair Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	5440209.085	55716.059	97.642	0.00%
Year2008Plus	320812.286	135560.088	2.367	1.91%
Year2009Plus	-333030.167	179329.140	-1.857	6.51%
Year2010Plus	-486356.417	179329.140	-2.712	0.74%
Year2011Plus	326005.417	155303.591	2.099	3.74%
February	-339865.151	121682.844	-2.793	0.59%
April	-131093.235	125357.241	-1.046	29.72%
June	-204959.521	125357.241	-1.635	10.40%
September	-247829.593	125357.241	-1.977	4.98%
November	-158555.950	125357.241	-1.265	20.78%
Year2013Plus	21673.761	123292.375	0.176	86.07%

Table 45: Praxair Model Statistics

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

Model Variables. The Praxair model is designed to forecast the average energy based on historic usage in 2013 through 2015. The model consists of the following variables.

- **Monthly Binaries.** The monthly binaries capture seasonal variables associated with the number of days in each month.

- **Annual Shift Variables.** This set of variables (Year2008Plus, Year2009Plus, Year2010Plus, Year2011Plus, year2013Plus) capture annual shifts in the average use. The final shift (Year2013Plus) captures the average load from 2013 through 2015 and forecasts this energy through the forecast time horizon. The effect of these variables can be seen in Figure 20.

Figure 33: Praxair Energy Model Actual Versus Predicted Plot

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Oil & Pipeline Model

Oil & Pipeline uses two models to forecast energy. The customer model is designed to forecast the existing 12 customers throughout the forecast horizon. The use-per-customer (UPC) model is designed to capture monthly variation for these customers. The model results are shown in Table 46 and Table 47. The full model is shown in the MetrixND project file. In the project file, the model is labeled **OPP_UPC**.

Table 46: Oil & Pipeline UPC 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 47: Oil & Pipeline UPC Model Statistics

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

Model Variables

- **Annual Shift Binary.** These variables (e.g. Year2003Plus, Year 2011Plus, Year2014Plus) are designed to capture the average energy load for the year and project the 2014 average energy load through the forecast horizon.

- **Year2003Trend.** This variable is a trend variable that applies only in 2003. The variable is designed to capture the rapid change in 2003.

- **Monthly Binary.** These independent binary variables are included to capture a patterned residual through the course of the year.

The effect of these variables can be seen in Figure 34.

Figure 34: Oil & Pipeline UPC Model Actual Versus Predicted Plot

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Other Industrial Model

The remaining industrial customers (Other Industrial) are forecast using two models. The customer model is designed to forecast the existing 338 customers throughout the forecast horizon. The use-per-customer (UPC) model is designed to capture monthly usage variations for these customers. The model results are shown in Table 48 and Table 49. The full model is shown in the MetrixND project file. In the project file, the model is labeled **OtherIndustrial_UPC**.

Table 48: 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 49: 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

Model Variables

- **Annual Shift Binary.** These variables (e.g. Year2010Plus, Year2011Plus) are designed to capture the average energy load for the year and project the average energy load through the forecast horizon.
- **Weather Variables.** This variable (CDD55) captures the cooling response.
- **Annual Binaries.** These binary variables (Year2003, Year2006, and Year2009) capture underlying shifts in the average use for industrial customers.

- **Monthly Binary.** These independent binary variables are included to capture seasonality in the industrial class.

Industrial Base Energy Forecast

The Industrial energy forecast is the sum of the Praxair, Oil & Pipeline, and Other Industrial forecasts adjusted for known customer expansions. For all three segments, the forecast models are designed to hold the number of customers in the industrial class constant through the forecast time horizon. The energy models are designed to provide seasonal shape to the energy forecast.

Known customer expansions include new customers, expanded operations by existing customers, and reductions or closures by existing customers. Overall, the industrial class includes three new customers with estimated annual consumption of up to 63,844,750 kWh during the forecast horizon. The adjustment to the industrial forecast is shown in Table 50.

Table 50: Industrial Customer Expansions

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The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 35, Figure 36, and Figure 37. Table 51 and Table 52 summarize the energy, customer, and use-per-customer forecasts with annual energy for selected years and average annual growth rates.

Figure 35: Industrial Energy Forecast (Actual, Forecast)

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Figure 36: Industrial Customer Forecast (Actual, Forecast)

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Figure 37: Industrial UPC Forecast (Actual, Forecast)

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Table 51: Industrial Energy Forecast Summary

Year	Energy (MWh)	Custom ers	Use-Per-Customer (MWh)
2005	1,108,069	365	3,036

2010	1,007,518	358	2,814
2012	1,030,770	346	2,979
2015	** **	** **	** **
2020	** **	** **	** **
2025	** **	** **	** **
2030	** **	** **	** **
2035	** **	** **	** **

Table 52: Industrial Energy Forecast Average Annual Growth Rates

Time Period	Energy	Customer	Use-Per-Customer
2003-2014 (Historical)	-0.2%	-0.4%	0.2%
2009-2014 (Historical)	0.8%	-0.5%	1.3%
2016-2020 (5 Yr Forecast)	** **	** **	** **
2016-2025 (10 Yr Forecast)	** **	** **	** **
2016-2030 (15 Yr Forecast)	** **	** **	** **
2016-2035 (20 Yr Forecast)	** **	** **	** **

11. System Peak Model

The System Peak Model is a regression model that is designed to forecast monthly peaks for the Net System Load (Gross Peaks). Historic Net System Loads are adjusted to restore estimated curtailment. The model is estimated with historical monthly peaks and monthly peak producing weather from January 2003 through March 2015. The model is shown in the **SystemMonthyPeaks.NDM** project file and summarized in Table 53.

Table 53: System Peak Model

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	65.640	118.094	0.556	57.93%
HeatTrendxHDD	11.051	0.301	36.672	0.00%
CoolTrendxCDD	31.797	1.003	31.694	0.00%
OtherTrendIndexSmooth	564.002	109.015	5.174	0.00%
January2010Plus_WinterEnergyTrend	38.622	15.660	2.466	1.50%
CoolingPeakCDD80	-14.789	2.264	-6.534	0.00%

Table 54: 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

Model Variables. The System Peak Model is primarily driven by the energy forecast and peak producing weather. The variables are discussed below.

- **HeatTrendxHDD.** This variable is calculated as the interaction between the three-day weighted average temperature for degrees below 60 degrees and the heating components of the energy models. The heating components are derived by multiplying the heating variable coefficients from the class energy models by normal heating degree days. The results are smoothed using a 12-month moving average. This variable is designed to capture the heating contribution to peak growth.

- **CoolTrendxCDD.** This variable is calculated as the interaction between the three-day weighted average temperature for degrees above 60 degrees and the cooling components of the energy models. The cooling components are derived by multiplying the cooling variable coefficients from the class energy models by normal cooling degree days. The results are smoothed using a 12-month moving average. This variable is designed to capture the cooling contribution to peak growth.

- **OtherTrendIndexSmooth.** This variable is derived using the non-heating and non-cooling energy from class energy models. The energy results are smoothed using a 12-month moving average. This variable is designed to capture the base load contribution to peak growth.

- **January2010Plus_WinterEnergyTrend.** This variable applies the winter energy trend in January beginning in 2010 and continuing through the forecast horizon. The Winter Energy Trend Variable is created by the interaction of the total energy sales with a binary variable that is active only from November through February. This variable is designed to capture additional growth in the winter peak in January based on system sales growth.

- **CoolingPeakCDD80.** This variable is a temperature spline impacting the change in cooing response when the peak is driven by three-day weighted average temperature for degrees above 80 degrees. Above 80 degrees, the temperature response slows.

Peak Base Forecast Results.

The summer and winter peak forecast compared against actual and normalized data is shown in Figure 38 and Figure 39. Numerical values for the peaks are shown in Table 3 above.

The peak forecast results capture Empire's transition from a traditional summer peaking utility to a dual peaking utility. The transition results from an increasing saturation of electric heating technologies and improved efficiencies in cooling technologies. The heating and cooling trends are expected to continue in the forecast period resulting in higher winter than summer peaks.

Figure 38: System Summer Peak Forecast

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Figure 39: System Winter Peak Forecast

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12. Hourly Load Forecast

Nine 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.

Data Development

Empire maintains an active load research program. Unfortunately, the program is not designed to forecast load shapes by the revenue 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 2014 customer counts associated with each rate in the class. Table 55 shows the class and the weights used for each load research profile.

Table 55: Load Research to Class Profile Mapping

Class	Load Research	Weight
Residential	Residential	100%
Commercial	CB	77%
	LP-Secondary	6%
	SH	13%
	TEB	4%
Wholesale	Monett, Mt. Vernon, Lockwood, Chetopa	NA
Street Highway	CB	77%
	SH	1%
	Generic Lighting Shape	22%
Interdepartmental	CB	86%
	GP – Secondary	14%
Industrial: Other Industrial	CB	26%
	GP – Secondary	57%
	LP – Primary	8%
	SH	5%
	TEB	4%
Industrial: Praxair	Praxair	NA
Industrial: OPP	GP – Primary	67%
	LP – Primary	33%
Public Authority	CB	80%
	GP – Secondary	11%
	SH	8%
	TEB	1%

Hourly 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 developed in MetrixND and estimated with data from 2012 through 2014. A full description of the models can be found in the MetrixND project files. Table 56 identifies the sets of variables used in each profile model. Definitions of the variables are summarized below.

Table 56: Model Variables by Class

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	X
Wholesale	X	X	X	X	X	
Street Highway	X	X	X	X	X	
Interdepartmental	X	X	X	X	X	
Industrial: Other Industrial	X	X	X	X	X	
Industrial: Praxair						
Industrial: OPP	X	X	X	X	X	
Public Authority	X	X	X	X	X	

- **Heating and Cooling Splines.** HDD and CDD spline variables are 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. The final HDD and CDD variables are determined based on statistical fit.
- **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.
- **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.
- **Holidays**. Key holidays are identified using this set of binary variables. These holidays capture the unique shape for specific holidays.
- **Monthly Binaries.** Monthly binary variables are used to capture the underlying load shape variation through the seasons of the year.
- **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.

Model Exceptions

Of the nine class models, three models contain exceptions to the general modeling method. These exceptions are summarized below.

- **Wholesale Class.** The wholesale class consists of four wholesale customers. The class profile is obtained by summing the hourly loads for the four wholesale customers.

- **Street Highway Class.** The Street & Highway class includes a large percentage of outdoor 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.

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

System Load Calibration

The hourly system loads are calculated by calibrating the class hourly load profiles to the class monthly energy and the system peak forecast. The calibration process ensures consistency with the monthly energy and peak forecasts and converts the billed sales forecast to the Net System hourly forecast. The calibration process consists of the following steps.

1. Forecast class hourly profiles throughout the forecast time horizon.
2. Calibrate each class's hourly profile to the class's monthly energy forecast to obtain hourly class loads.
3. Sum hourly class loads to obtain hourly system loads.
4. Scale the hourly system loads by an average loss factor of 6.8% based on the average difference between sales and the net system loads from 1999 through 2014.
5. Calibrate the hourly system loads to the monthly system peak forecast.

The result of the calibration process are hourly system (Net System loads) and class loads consistent with the monthly peak forecast and class monthly sales.

Coincident Peaks

Class-level coincident peaks are calculated by using the ratio of the hourly class loads and system loads at the time of the system peak. The results for the major classes (Residential, Commercial, and Industrial) are shown in Table 57 and Table 58.

Table 57: Summer Coincident Peak By Class (MW)

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Table 58: Winter Coincident Peak By Class (MW)

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13. Conclusion

The 2016 IRP forecast and scenarios are based on historic growth patterns in Empire's service territory and reflect future changes in electric consumption. As with most of North America, average use continues to flatten with a weak economy and increasing energy efficiency. The overall system grows at an average annual growth rate of 0.24% from 2016 through 2035 with winter peaks growing at 0.27% and summer peaks growing at 0.29%. While Empire is a dual peaking system, the acceleration of electric space heating results in the system peak forecast as a winter peak.

While the overall growth presents a plausible view of the future, the strength of the forecast is in its theoretical basis. First, the forecast contains key elements of end-use information using the SAE model framework. Increasing energy efficiency and changing saturation of end-uses drive the residential and commercial classes. The framework includes DSM programs, rooftop solar penetration, and electric vehicles. Second, the economic drivers represent economic activity in the Joplin and Springfield area which encompasses most of Empire's customers. Finally, the statistical models demonstrate strong model fit and variable statistics.

While this report summarized the forecast models and results, full results are available in the MetrixND and MetrixLT project files as well as in the associated analysis workbooks.