VOLUME 3

LOAD ANALYSIS AND LOAD FORECASTING

THE EMPIRE DISTRICT ELECTRIC COMPANY

4 CSR 240-22.030

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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:

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 demandside analysis as described in 4 CSR 240-22.050, and the load forecasting described in 4 CSR 240-22.030.

1.5 Selection of Revenue Class Level versus Rate Class Level

Empire has made updates to both the load forecasting methodology and the load forecast results since the last triennial compliance filing. In the September 2010 IRP filing, Empire utilized customer class forecasts using historical sales, weather, customer counts, and, at times, trend binaries and input from the Commercial Services Department. System energy and peak demands were forecast with linear regression analysis employing the "least squares" method to determine a best fit line through a set of historical observations. All of these methods fall into the category of statistical modeling, not end-use modeling. In the last IRP filing, Empire was granted variances from the IRP Rule's requirements for end-use modeling. Since the load forecast is one of the first steps in developing an IRP, the load forecast for the September 2010 IRP filing was developed around mid-2009.

Following the last IRP filing and the subsequent IRP Rule revision, Empire presented a proposal for a new load forecasting methodology to its IRP Stakeholder Advisory Group. With the help of Itron, Inc. (Itron), Empire created a preliminary demand and energy forecast utilizing the new method. This new method can be described as a Statistically Adjusted End-Use (SAE) model for the Residential and Commercial classes. The other classes rely on econometric models that include weather and econometric drivers. The SAE models rely upon technology saturations

and efficiencies developed by the U.S. Energy Information Administration (EIA). The models also utilize weather, the price of electricity and economic drivers. The Forecast Model Report prepared by Itron is included as Appendix 3A.

The base-case forecast was developed by Itron at the revenue class level using the following classes:

- 1. Residential.
- 2. Commercial.
- 3. Wholesale (Monett, Mt. Vernon, Lockwood, and Chetopa).
- 4. Street and highway.
- 5. Interdepartmental.
- 6. Public authority.
- 7. Industrial (oil and pipelines, Praxair, and other).

The revenue class approach aggregates similar customers into larger groups that offer data stability and generally align with economic drivers. These two factors are important as statistical models attempt to identify correlations between historical sales and economic drivers. Unstable data generally results in a poor model fit and difficulty in identifying the correct economic drivers. Based on Itron's experience, most utilities across North America model at the revenue class level.

In the base case, the residential and commercial revenue class models are developed using Itron's SAE models. These models describe residential and commercial sales as a function of weather and end uses that are specific to the classes. The remaining models are developed using econometric models describing sales as a function of weather and economic drivers where appropriate. Overall, the base-case models produce a strong overall fit and a reasonable forecast.

After the base forecast was developed, Empire discussed with Itron the potential to model at the rate class level. Itron's Forecast Analysis of Modeling at the rate class level is included as Appendix 3B.

Empire maintains data by the five rate classes listed below:

- 1. Residential.
- 2. Commercial (CB).
- 3. General power (GP).
- 4. Small heating (SH).
- 5. Total electric building (TEB).

As discussed above, the primary concern with modeling at the rate class level is the mix of customers included in the rate classes. A diverse mix of customers makes identifying the correct economic drivers difficult. To explore the modeling potential, Itron examined two rate classes (CB rate and GP rate) to test whether better models could be developed at the rate class level.

- 1. CB Rate:
 - a. The CB rate class includes customers in the commercial, industrial, street/highway, public authority, and interdepartmental revenue classes. Upon initial inspection, the CB rate appears visually stable on a use-per-customer (UPC) basis as shown in *Figure 3-1*.



Figure 3-1 - CB Rate Class - Use-Per-Customer

b. Because most of the CB customers are included in the commercial revenue class, the commercial revenue model specification is applied to the CB data. Using identical model estimation periods, the adjusted R-square (Adj R-Sq) for the CB model is 0.839 compared to the commercial model with a value of 0.924. Upon closer inspection, the CB class data prior to 2004 contains some data anomalies. By removing data prior to 2004 from the model estimation period, the Adj R-Sq can be improved to 0.907. The model Adj R-Sq and mean absolute percent error (MAPE) results are shown in *Table 3-1*.

Class	Adj R-Sq	MAPE
Commercial (Revenue Class)	0.924	2.72%
CB Class (Rate Class)	0.839	3.92%
CB Class (Rate Class)	0.907	3.54%
Remove Data prior to 2004		

Table 3-1 - CB Rate Class andCommercial Revenue Class Model Fit Comparison

c. The overall statistics show a weaker fit for the CB class models. This weakness is likely due to the greater diversity of customers included in the CB class. By including industrial and street/highway customers into the CB

class, the descriptive drivers capturing the saturation and efficiencies of end-use base load, heating, and cooling technologies are less correlated with historical sales than the commercial class. While the overall CB model is not bad, the commercial model still demonstrates an overall improvement.

- 2. GP Rate:
 - a. The GP rate class includes customers in the commercial, industrial, and interdepartmental revenue classes. Upon initial inspection, the GP rate appears stable on a UPC basis as shown in *Figure 3-2*.



Figure 3-2 - GP Rate Class - Use-Per-Customer

b. The difficulty in the GP class appears not in the UPC model, but in the customer count forecast. The number of customers in the GP class has grown at an annual rate of 3.68 percent per year from 2001 through 2010. This growth can be seen in the monthly customer count graph in *Figure 3-3*.



Figure 3-3 - GP Rate Class - Customer Counts

- c. When modeling customer counts, identifying the appropriate economic driver that describes the growth is essential. Among the drivers used in the forecasting process, employment, gross state product (GSP), and households were examined to determine which economic driver is correlated with customer growth.
- d. Three models were developed to identify the correct economic driver for GP customer growth. Each model was designed as a regression model estimated with data from 2001 through 2011 with employment, households, or GSP as the only independent variable. The model results are discussed briefly below:
 - 1) Employment: The employment driver model results in an R-squared of 0.470 and a forecast as shown in *Figure 3-4*. While the overall fit is poor, the greatest indication of the model problem is seen in the visual inspection of the forecast and the elasticity of the employment driver. In this case, the employment elasticity is 3.266 implying that a 1-percent increase in employment results in a 3.266-percent increase in the number of GP customers.





2) Gross State Product: The GSP driver model results in an R-squared of 0.917 and a forecast shown in *Figure 3-5*. While the overall fit is much better than employment, once again the GSP elasticity is unrealistically high at 2.055.



Figure 3-5 - GP Rate Class Customer Forecast -GSP Driver (\$ Million 05)

3) Households: The household's driver model results in an R-squared of 0.913 and a forecast shown in *Figure 3-6*. As with the GSP driver, the overall fit is similar, but the household elasticity is also unrealistically high at 3.622.





- 4) Based on the economic data options available and the time spent on exploring model fit, the overall impression is that the GP customer count growth does not fit well with any of the available economic drivers.
- 3. Rate Stability Conclusion: While an exhaustive examination of rate class modeling was not performed, the two exploratory samples for the CB and GP classes tend to identify either weaker model fits or difficulties with the economic drivers. While these problems may be overcome with additional effort, the initial findings are not convincing enough, considering that the base-case forecast contains a strong model fit and shows a reasonable forecast.

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 has historically analyzed loads according to major revenue class (i.e., Industrial, Commercial, and Residential). "Major Class" is defined in the rule [4CSR 240-22.020 (37)] as "a cost-of-service class of the utility". Empire maintains the historical database for each of the major classes in this manner. Empire maintains its customer database for additional divisions. These include energy forecasts with a database 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 for at least 10 years.

In addition, weather data and customer record databases are also maintained.

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;

Weather-normalization is the process of determining how historical usage would have differed had normal weather conditions existed. The process involves using a statistical model to adjust actual sales levels under normal weather conditions.

The technique for weather-normalization of the customer class was to substitute actual heating degree days (HDD) and cooling degree days (CDD) with normal HDD and CDD calculated from data based on the National Oceanographic and Atmospheric Administration (NOAA) at the Springfield, Missouri airport.

The data of the historical weather-normalized energy are contained in *Table 3-2*.

Weather-normalized values are based on the following equation:

Normal_C = Actual_C - (Model_a- Model_n) Where: Normal_C = Class Normal Sales Actual_C = Class Actual Sales Model_a = Model simulated with actual weather Model_n = Model simulated with normal weather Data from October 2011 to December 2012 is from the forecast models simulated with normal weather. These data are used because actual data from October 2011 to December 2012 was not available at the time of the forecast model development.

Annual Normal Sales (MWh) - Billed Sales Basis							
		Residential	Commercial	Industrial	System		
	2000	1,599,305	1,295,244	1,002,248	4,285,342		
	2001	1,680,333	1,373,634	1,005,896	4,466,279		
	2002	1,702,388	1,385,060	1,031,136	4,523,898		
	2003	1,749,672	1,398,739	1,060,740	4,616,455		
	2004	1,800,861	1,438,074	1,088,241	4,748,551		
	2005	1,839,817	1,476,992	1,101,552	4,852,151		
	2006	1,882,363	1,530,274	1,137,369	4,995,631		
	2007	1,836,043	1,549,026	1,095,987	4,931,748		
	2008	1,920,913	1,613,402 1,078,682 5,083,290				
	2009	1,935,693	1,601,617	998,393	4,998,392		
	2010	1,920,455	1,608,169	1,001,293	5,001,378		
	2011	1,863,697	1,561,461	1,016,319	4,923,998		
	2012	1,908,983	1,561,868	1,011,946	4,970,045		
Notes:							
1.	January 2000 to September 2011 are weather-normalized actual values.						
2.	October 2011 to December 2012 are forecasts using normal weather.						

 Table 3-2 - Historical Weather-normalized Energy (MWh)

The results for weather-normalized annual energy are shown in *Figure 3-7. Table 3-3* shows regression statistics from the spreadsheet modeling conducted on the course of developing the weather-normalized energy as shown in *Figure 3-7.*



Forecast Model Coefficients						
Residential Customer	Model					
Variable	Coefficient	StdErr	T-Stat	P-Value		
May2011Plus	-2437.472	261.335	261.335 -9.327			
Population	24.906	0.264 94.443		0.00%		
AR(1)	0.981	0.007	147.829	0.00%		
Residential UPC Mode	el					
Variable	Coefficient	StdErr	T-Stat	P-Value		
XHeat	1.41	0.042	33.906	0.00%		
XCool	0.815	0.02	41.109	0.00%		
XOther	0.709	0.015	47.608	0.00%		
September	92.589	21.073	4.394	0.00%		
XHeatShift2005	0.198	0.039	5.057	0.00%		
Commercial Customer	r Model					
Variable	Coefficient	StdErr	T-Stat	P-Value		
Constant	5134.428	1495.731	3.433	0.08%		
Residential	0.093	0.005	18.534	0.00%		
Customers	2.240	1.070	2 104	0.220/		
Employment	3.349	1.079	3.104	0.23%		
AR(1)	0.898	0.041	22.002	0.00%		
Commercial UPC IVIOD	ei					
Variable	Coefficient	StdErr	T-Stat	P-Value		
XHeat	0.04	0.003	13.427	0.00%		
XCool	0.121	0.004	26.901	0.00%		
XOther	0.039	0.001	53.284	0.00%		
XHeatShift2006	0.005	0.003	2.106	3.72%		
January	44.677	71.884	0.622	53.54%		
May	-113.532	66.49	-1.708	9.02%		
June	-157.676	62.75	-2.513	1.32%		
September	366.136	63.351	5.779	0.00%		
November	-36.462	67.808	-0.538	59.17%		
Year2000	-281.891	60.189	-4.683	0.00%		
Year2006	-288.807	62.175	-4.645	0.00%		
Year2007	-277.627	61.976	-4.48	0.00%		
Year2006Plus	493.459	46.945	10.511	0.00%		
Praxair Model						
Variable	Coefficient	StdErr	T-Stat	P-Value		
Constant	5350017.131	47875.889	111.748	0.00%		
Year2008Plus	320812.286	135413.463	2.369	1.94%		
Year2009Plus	-333030.167	179135.173	-1.859	6.54%		
Year2010Plus	-486356.417	179135.173	-2.715	0.76%		
Year2011Plus	305382.833	193488.101	1.578	11.71%		
Oil & Pipeline UPC Model						
Variable	Coefficient	StdErr	T-Stat	P-Value		
Constant	371130.1	28132.261	13.192	0.00%		
Year2003Plus	-209917.581	58378.248	-3.596	0.05%		
Year2004Plus	480591.097	62518.525	7.687	0.00%		
Year2005Plus	-67128.524	36534.77	-1.837	6.84%		

Forecast Model Coefficients						
Year2006Plus	-21636.226	36534.77	-0.592	55.47%		
Year2007Plus	6934.815	36534.77	0.19	84.97%		
Year2008Plus	-85154.134	36534.77	-2.331	2.13%		
Year2009Plus	-64552.154	36534.77	-1.767	7.96%		
Year2010Plus	7956.731	36534.77	0.218	82.79%		
Year2011Plus	36925.747	39708.247	0.93	35.41%		
Year2003Trend	57412.987	7804.985	7.356	0.00%		
January	64317.13	36572.118	1.759	8.10%		
February	21330.284	36462.716	0.585	55.96%		
March	55762.115	36362.898	1.533	12.76%		
April	64458.483	36272.745	1.777	7.79%		
May	100723.909	36192.327	2.783	0.62%		
June	110720.187	36121.711	3.065	0.26%		
July	157206.894	36060.954	4.359	0.00%		
August	155628.105	36010.106	4.322	0.00%		
September	123351.741	35969.209	3.429	0.08%		
October	66511.472	36557.921	1.819	7.11%		
November	49532.566	36540.559	1.356	17.76%		
Other Industrial UPC N	Nodel					
Variable	Coefficient	StdErr	T-Stat	P-Value		
Constant	204436.023	2008.197	101.801	0.00%		
January	10862.175	2600.326	4.177	0.01%		
February	2120.433	2661.372	0.797	42.72%		
March	10706.95	2650.615	4.039	0.01%		
April	2634.277	2793.99	0.943	34.77%		
May	6605.467	3725.627	1.773	7.88%		
June	7495.995	5875.075	1.276	20.45%		
July	7205.645	8196.685	0.879	38.11%		
August	8776.419	9144.685	0.96	33.92%		
September	-1958.809	7479.501	-0.262	79.39%		
October	4609	4403.539	1.047	29.74%		
November	1047.385	2965.506	0.353	72.46%		
Year2009	-12988.871	1972.563	-6.585	0.00%		
CDD55	52.836	12.681	4.166	0.01%		
Year2010Plus	-11886.449	1535.328	-7.742	0.00%		
Year2003	-7064.261	1985	-3.559	0.05%		
Year2004	-2335.951	2090.393	-1.117	26.61%		
Year2006	5515.43	1903.237	2.898	0.45%		

 Table 3-3 - Regression Analysis Results - Forecast Energy Model Coefficients

2.2.2 Historical Weather-Normalized Demands at System Peak

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

Individual regression models were not developed to weather-normalize class peaks. Instead, class peaks are derived from the system peak model and normalized system peaks. Class level weather-normalized peaks were developed by applying the class' historical share of the system peak to the normalized system peak. The method to obtain normalized residential, commercial, and industrial peaks is shown below:

- 1. Obtain class actual load research data for residential, commercial, and industrial classes and all other classes.
- 2. Scale load research data to historic monthly calendar sales.
- 3. Sum load research data to obtain estimated system loads.
- 4. Find the residential, commercial, and industrial coincident peaks with the NetSystemLoads using MetrixLT.
- 5. Calculate the residential, commercial, and industrial percent based on the ratio of the coincident peaks (e.g., ResClass Peak/Net System) multiplied by the ratio of the NetSystemLoads to the SumofClasses load (i.e., Error Correction Factor).

The data for the class weather-normalized peaks at the time of the system peak are contained in *Table 3-4*.

Weather-Normalized System Peaks (MW) Net Summer Winter Normal Res Com Ind System Normal Normal Peak Peak Normal Normal Normal 2001 1,001 1,184 891 1,184 549 353 185 2002 987 1,113 940 1,113 559 288 180 2003 1,041 1,124 967 1,124 574 286 178 2004 1,014 1,152 986 1,152 549 319 194 2005 1,087 1,020 1,019 1,020 503 276 158 2006 1,159 1,034 1,056 1,034 500 278 169 2007 1,173 1,168 1,086 1,168 569 324 175 2008 1,153 1,191 1,094 1,191 608 324 169 <t< th=""><th colspan="8"></th></t<>									
Net Summer Winter Normal Peak Res Com Ind System Normal Peak Peak Peak Normal 185 185 185 185 180 178 178 178 178 178 178 194 </td <td colspan="8">Weather-Normalized System Peaks (MW)</td>	Weather-Normalized System Peaks (MW)								
System Normal Normal Peak Normal Normal <td></td> <td>Net</td> <td>Summer</td> <td>Winter</td> <td>Normal</td> <td></td> <td>Res</td> <td>Com</td> <td>Ind</td>		Net	Summer	Winter	Normal		Res	Com	Ind
PeakPeakPeakImage: Margin and Marg		System	Normal	Normal	Peak		Normal	Normal	Normal
20011,0011,1848911,18454935318520029871,1139401,11355928818020031,0411,1249671,12457428617820041,0141,1529861,15254931919420051,0871,0201,0191,02050327615820061,1591,0341,0561,03450027816920071,1731,1681,0861,16856932417520081,1531,1911,0941,19160832416920091,0851,0301,0961,03045230916820101,1991,1681,1411,14162330913020111,1861,0601,186594321177Notes:2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010.2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010.		Peak	Peak	Peak					
20029871,1139401,11355928818020031,0411,1249671,12457428617820041,0141,1529861,15254931919420051,0871,0201,0191,02050327615820061,1591,0341,0561,03450027816920071,1731,1681,0861,16856932417520081,1531,1911,0941,19160832416920091,0851,0301,0961,03045230916820101,1991,1681,1411,14162330913020111,1861,0601,186594321177Notes:2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010.2012 system normal peaks are forecasted peak (assuming normal weather), split is based	2001	1,001	1,184	891	1,184		549	353	185
20031,0411,1249671,12457428617820041,0141,1529861,15254931919420051,0871,0201,0191,02050327615820061,1591,0341,0561,03450027816920071,1731,1681,0861,16856932417520081,1531,1911,0941,19160832416920091,0851,0301,0961,03045230916820101,1991,1681,1411,14162330913020111,1861,0601,186594321177Notes:2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010.2012 system normal peaks are forecasted peak (assuming normal weather), split is based on bistorical summer average normal.	2002	987	1,113	940	1,113		559	288	180
20041,0141,1529861,15254931919420051,0871,0201,0191,02050327615820061,1591,0341,0561,03450027816920071,1731,1681,0861,16856932417520081,1531,1911,0941,19160832416920091,0851,0301,0961,03045230916820101,1991,1681,1411,14162330913020111,1861,0601,186594321177Notes:2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010.2012 system normal peaks are for casted peak (assuming normal weather), split is baseda paint of starting normal peak as an operate.	2003	1,041	1,124	967	1,124		574	286	178
20051,0871,0201,0191,02050327615820061,1591,0341,0561,03450027816920071,1731,1681,0861,16856932417520081,1531,1911,0941,19160832416920091,0851,0301,0961,03045230916820101,1991,1681,1411,14162330913020111,1861,0601,186594321177Notes:2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010.2012 system normal peaks are forecasted peak (assuming normal weather), split is basedop historical summer average percenter.	2004	1,014	1,152	986	1,152		549	319	194
20061,1591,0341,0561,03450027816920071,1731,1681,0861,16856932417520081,1531,1911,0941,19160832416920091,0851,0301,0961,03045230916820101,1991,1681,1411,14162330913020111,1981,0951,0451,09558428113720121,1861,1861,0601,186594321177Notes:2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010.2012 system normal peaks are for casted peak (assuming normal weather), split is based on bit orical summer average part	2005	1,087	1,020	1,019	1,020		503	276	158
20071,1731,1681,0861,16856932417520081,1531,1911,0941,19160832416920091,0851,0301,0961,03045230916820101,1991,1681,1411,14162330913020111,1981,0951,0451,09558428113720121,1861,1861,0601,186594321177Notes:2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010.2012 system normal peaks are forecasted peak (assuming normal weather), split is basedon historical summer average percente	2006	1,159	1,034	1,056	1,034		500	278	169
2008 1,153 1,191 1,094 1,191 608 324 169 2009 1,085 1,030 1,096 1,030 452 309 168 2010 1,199 1,168 1,141 1,141 623 309 130 2011 1,198 1,095 1,045 1,095 584 281 137 2012 1,186 1,186 1,060 1,186 594 321 177 Notes: 2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010. 2012 system normal peaks are forecasted peak (assuming normal weather), split is based on hist arised summer average parter	2007	1,173	1,168	1,086	1,168		569	324	175
2009 1,085 1,030 1,096 1,030 452 309 168 2010 1,199 1,168 1,141 1,141 623 309 130 2011 1,198 1,095 1,045 1,095 584 281 137 2012 1,186 1,186 1,060 1,186 594 321 177 Notes: 2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010. 2012 system normal peaks are forecasted peak (assuming normal weather), split is based on bit orical summer average parameter	2008	1,153	1,191	1,094	1,191		608	324	169
2010 1,199 1,168 1,141 1,141 623 309 130 2011 1,198 1,095 1,095 584 281 137 2012 1,186 1,186 1,060 1,186 594 321 177 Notes: 2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010. 2012 system normal peaks are forecasted peak (assuming normal weather), split is based on bictorical summer average parameter.	2009	1,085	1,030	1,096	1,030		452	309	168
2011 1,198 1,095 1,095 584 281 137 2012 1,186 1,186 1,060 1,186 594 321 177 Notes: 2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010. 2012 system normal peaks are forecasted peak (assuming normal weather), split is based on historical summer average percente.	2010	1,199	1,168	1,141	1,141		623	309	130
20121,1861,0601,186594321177Notes:2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010.2012 system normal peaks are forecasted peak (assuming normal weather), split is basedop historical summer average percents	2011	1,198	1,095	1,045	1,095		584	281	137
Notes: 2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010. 2012 system normal peaks are forecasted peak (assuming normal weather), split is based on historical summer average percents	2012	1,186	1,186	1,060	1,186		594	321	177
2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010. 2012 system normal peaks are forecasted peak (assuming normal weather), split is based on historical summer average percents	Notes:								
2012 system normal peaks are forecasted peak (assuming normal weather), split is based	2010 actual peak is a winter peak. Use winter normal peak as the system peak for 2010.								
on historical summer average percents	2012 system normal peaks are forecasted peak (assuming normal weather), split is based								

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

2.2.3 Historical Weather-Normalized System Peak

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

The data for the historical weather-normalized system peaks are also contained in *Table 3-4*. System peaks are obtained using the same method as used in the weather-normalized energy section, but applying normal peak instead of normal HDD and CDD values to the system peak model

The results for weather-normalized system peak are shown in *Figure 3-8*. System peaks for summer and winter are shown in *Figure 3-9*. *Table 3-5* shows regression statistics from the model used to develop the weather-normalized system peaks as shown in *Figures 3-8 and 3-9*.







Peak Forecast Model Coefficients						
System Peak Model						
Variable	Coefficient	StdErr	T-Stat	P-Value		
CONST	-323.775	99.324	-3.26	0.15%		
CoolingPeakCDD	24.472	1.469	16.663	0.00%		
HeatingPeakHDD	9.868	0.661	14.932	0.00%		
EnergyTrend	935.553	91.919	10.178	0.00%		
WinterEnergyTrend	18.613	14.315	1.3	19.60%		
SummerEnergyTrend	35.97	16.279	2.21	2.90%		

Table 3-5 - Regression Analysis Results -Forecast Weather-Normalized System Peak Model Coefficients

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 demandside 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. Customer classes include residential, commercial, industrial, and total. This applies to both actual and weather-normalized loads.

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 non linear response of loads to daily weather and seasonal variations in loads.

Empire's load forecast is revised annually and close attention is paid to the levels of peak demand during the summer and winter months. Scheduled reviews on the load forecast are held with senior management. Each month, Empire prepares a variance report related to the demand and energy forecast and the actual results.

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 workpapers supplied at the time the compliance report is filed;

Weather-normalization is described above in Section 2.2.1 - Actual and Weather-Normalized Energy, and Number of Customers.

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;

End-use drivers are obtained from EIA and used in the SAE model. These data capture changing end-use saturation and energy efficiency trends for each census region. *Figures 3-12* and *3-14* show the historic and forecast trends for end-use drivers used in the forecast models.

2.4.2 Weather Sensitivity of Energy and Peak Demand

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

Each forecast model is developed using a regression model framework. Within these models, independent weather variables are used to capture weather sensitivity. The coefficient of weather variables indicates the sensitivity of energy and peak demand to weather for the customer classes.

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. *Figures 3-10 through 3-14* contain annual summaries of all these major trends used in the forecast models.





Figure 3-11 - Annual Summary of a Major Trend - Electric Prices



Figure 3-12 - Annual Summary of a Major Trend - Residential SAE Indices



Figure 3-13 - Annual Summary of a Major Trend - Heating and Cooling Degree Days



Figure 3-14 - 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 load forecast uses historical sales, 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. Economic data was provided by Economy.com and were not modified prior to use.

End-use data were provided by Itron and were adjusted to reflect the Empire 2008 Potential Study saturation values. The adjustments of the end-use data are recommended by Itron to better align regional end-use technology information to known levels in the Empire service territory.

Adjustments were made to the residential saturation of heating, cooling, water heating, refrigeration, dishwashing, clothes washing, and clothes drying technologies. Associated end-use intensities for these technologies were also modified to accompany the saturation 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 has developed and retains the historical database for 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

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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 explanatory variables which are key drivers for each forecast model are listed and documented in *Table 3-6*.

Key Drivers for Forecast Models			
Major Class	Model	Key Explanatory Variable	Description
Residential			
	Customer	Population	This variable is derived from the historical and forecast projection of the Missouri, Kansas, Oklahoma, and Arkansas populations. Population is calculated as the weighted average of the four state population forecasts based on twelve months of energy ending in September 2011 (10/10-9/11). The quarterly data provided by Economy.com is smoothed using a three period moving average.
	Average Use (SAE Model)	End-Use Efficiency Trends	End-use efficiencies by technology type are based on EIA data.
		End-Use Saturation Trends Housing Stock	End-use saturations by technology type based on EIA data and calibrated to Empire's 2008 Potential Study technology saturation findings. Housing information is based on EIA data and modified based on Empire's 2008 Potential Study housing stock
		Household Size	Historical and forecast household size and household
		& Income Price	income based on Economy.com forecasts. Class energy prices are based on historical revenues and kWh consumption. Energy price forecasts are created
		End-Use Intensities	End-use intensities are derived based on an average of the SAE West North Central and West South Central zones and adjusted to reflect Empire's 2008 potential study saturations.
		HDD and CDD	Heating and cooling degree days
Commercial			
	Customer	Employment	This variable is derived from the historical and forecast projection of the Missouri, Kansas, Oklahoma, and Arkansas populations. Population is calculated as the weighted average of the four state employment forecasts based on twelve months of energy ending in September 2011 (10/10-9/11). The quarterly data provided by Economy.com is smoothed using a three period moving average. The employment variable provides additional model flexibility that captures changes based on economic conditions.
		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.
	Average Use (SAE Model)	HDD and CDD	Heating and cooling degree days
		End-Use Efficiency Trends End-Use	End-use efficiencies by technology type are based on EIA data. End-use saturations by technology type based on EIA
		Saturation Trends Price	data. Class energy prices are based on historical revenues and
			kWh consumption. Energy price forecasts are created by applying a 2% annual growth rate.

Key Drivers for Forecast Models				
Major Class	Model	Key Explanatory Variable	Description	
		Employment	Historical and forecast employment and gross state	
Industrial		and GDP	product are based on Economy.com forecasts.	
muustriai	Epergy	HDD and CDD	Heating and cooling degree days	
	- OPP		Treating and cooling degree days	
	- Praxair			
	- Other Industrial			
Municipals				
	Energy	Households	This variable is used to capture long-term growth of	
	- Monett		energy caused by population changes in the municipal	
	- IVIT. Vernon		areas. Household forecasts are provided by Economy com and reflect the household history and	
	- Chetpoa		forecast for the state in which the municipal resides.	
	energed			
		End- Use	End-use efficiencies by technology type are based on EIA	
		Efficiency Trends	data.	
		End-Use Saturation	end-use saturations by technology type based on EIA	
		Trends	technology saturation findings.	
		Housing Stock	Housing information is based on EIA data and modified	
		0	based on Empire's 2008 Potential Study housing stock	
			findings.	
		Household Size	Historical and forecast household size and household	
		& Income	income based on Economy.com forecasts.	
		Price	class energy prices are based on historical revenues and kWb concumption. Energy price forecasts are created	
			hy applying a 2% applied growth rate	
		End-Use	End-use intensities are derived based on an average of	
		Intensities	the SAE West North Central and West South Central	
			zones and adjusted to reflect Empire's 2008 potential	
			study saturations.	
		HDD and CDD	Heating and cooling degree days	
Street Highway				
	Customer	Households	This variable is derived from the historical and forecast	
			projection of the households in Missouri, Kansas,	
			Oklahoma, and Arkansas. Household is calculated as the	
			hased twelve months of energy ending in Sentember	
			2011 (10/10-9/11). The quarterly data provided by	
			Economy.com is smoothed using a three period moving	
			average.	
	Average Use (SAE	Outside Lighting	This variable captures the increasing energy efficiency of	
	iviodel)	Efficiency	outside lighting technology. The variable is derived from	
			index provided by the FIA. The increasing value of the	
			index implies that lighting technologies are becoming	
			more efficient and using less energy over time.	
Interdepartmental				
	Average Use	HDD and CDD	This set of variables (HDD55 and CDD55) capture the	
			weather response of the interdepartmental class.	

Key Drivers for Forecast Models				
Major Class	Model	Key Explanatory	Description	
		Variable		
Public Authority				
	Customer	Households	This variable is derived from the historical and forecast projection of the households in Missouri, Kansas, Oklahoma, and Arkansas. Household is calculated as the weighted average of the four state household forecasts based twelve months of energy ending in September 2011 (10/10-9/11). The quarterly data provided by Economy.com is smoothed using a three period moving average.	
	Average Use	HDD and CDD	This set of variables (HDD55 and CDD55) capture the weather response of the Public Authority class	

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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 2.2.1 -Actual and Weather-Normalized Energy, and Number of Customers and 2.2.3 - Historical Weather-Normalized System Peak.

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.

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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 considers end-use information as follows:

- 1. End-Use Efficiencies: End-use efficiencies by technology type are based on EIA.
- 2. End-Use Saturations: End-use saturations by technology type based on EIA data and calibrated to Empire's 2008 Potential Study technology saturation findings.
- 3. Housing Stock: Housing information is based on EIA data and modified based on Empire's 2008 Potential Study housing stock findings.
- 4. Economic Data: Historical and forecast household size and household income based on Economy.com forecasts.
- 5. Energy Prices: Class energy prices are based on historical revenues and kWh consumption. Energy price forecasts are created by applying a 2-percent annual growth rate.
- 6. End-Use Intensities: End-use intensities are derived based on an average of the SAE West North Central and West South Central zones and adjusted to reflect Empire's 2008 Potential Study saturations.

A complete description of the end-use model is provided in Appendix 3C.

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 considers end-use information as follows:

- 1. End-Use Efficiencies: End-use efficiencies by technology type are based on EIA data.
- 2. End-Use Saturations: End-use saturations by technology type based on EIA data.
- 3. Economic Data: Historical and forecast employment and GSP are based on Economy.com forecasts.
- 4. Energy Prices: Class energy prices are based on historical revenues and kWh consumption. Energy price forecasts are created by applying a 2-percent annual growth rate.

A complete description of the commercial end-use model is provided in Appendix 3D.

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 had three models: Praxair, Oil and Pipeline, and Other Industrial. The Other Industrial UPC model was designed to capture monthly variation in cooling weather response and seasonality.

A complete description of the commercial end-use model is provided in Appendix 3A.

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 models consolidated end-use loads using the variable "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. A full description of the variable and its construction is included in Appendix 3C.

For the commercial energy forecast, this variable captures the general response for all nonheating 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. A full description of the variable and its construction is included in Appendix 3D.

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. Consideration was given to electric vehicles. Electric vehicles, and their associated battery technology, have been under development for several decades. Today's hybrid electric vehicles, available for purchase by the mass market and part of the rental car fleets, have significantly advanced the likelihood that such cars can be a commercial success and not just an oddity. The hybrid electric vehicles recharge themselves as they are still fueled by gasoline or similar fuel. The next step in the evolution of personal transportation appears to be plug-in hybrid electric vehicles (PHEV) and

plug-in electric vehicles, which are dependent on advances in battery technology. This evolutionary step could have significant impacts on the electric utility industry.

PHEVs will require charging, presumably daily. Without a smart grid, or a smart plug, the PHEVs could recharge during on-peak periods, thus increasing an electric utility's load and potentially causing the need for new generating capacity. A smart plus would know not to begin charging until a utility's off-peak hours.

In addition, PHEVs represent what transmission planners call "mobile loads". This means that the car might be charged at home, at the office, at the mall, or at other locations. Such flexibility for the customer will require accommodation through the design or redesign of the transmission and distribution systems which have yet to occur on any utility system in the country including Empire. No changes to the load forecast or modifications to the transmission and distribution plans are contained in this IRP as would be necessary to accommodate widespread adoption of PHEVs in Empire's service territory.

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.

The consolidation of end-use loads in the residential and commercial energy model through use of the variable "XOther" is documented in Sections 7.3.1 and 7.3.2, and further explained in Appendix 3C (residential) and 3D (commercial).

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.

Cooling and heating components have been found to have a significant portion of the total load for the residential and commercial classes. These have been accounted for with the variables "XHeat" and "XCool" as explained in Sections 7.3.1 and 7.3.2 and further documented in Appendix 3C (residential) and Appendix 3D (commercial).

4.2 End-Use Development

(B) The database and historical analysis required for each end use shall be developed from a utilityspecific 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;

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, as discussed in Sections 7.3.1, 7.3.2, and 7.3.3, respectively. 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 including the sales trends into the peak model. Because the calibrated end-use data are included in the sales trends, the enduse 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.

Figure 3-15 shows an example of the residential model variables which includes end-use data and the peak model which includes the residential forecast.

Residential UPC Model						
Variable	Coefficient	StdErr	T-Stat	P-Value		
XHeat	1.41	0.042	33.906	0.00%		
XCool	0.815	0.02	41.109	0.00%		
XOther	0.709	0.015	47.608	0.00%		
September	92.589	21.073	4.394	0.00%		
XHeatShift2005	0.198	0.039	5.057	0.00%		
Note: Xheat, Xcool, and Xother inclu						

System Peak Model				
Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	-323.775	99.324	-3.26	0.15%
CoolingPeakCDD	24.472	1.469	16.663	0.00%
HeatingPeakHDD	9.868	0.661	14.932	0.00%
EnergyTrend	935.553	91.919	10.178	0.00%
WinterEnergyTrend	18.613	14.315	1.3	19.60%
SummerEnergyTrend	35.97	16.279	2.21	2.90%

Note: Residential Use-Per-Customer Model from July 2012 Report. EnergyTrend, WinterEnergyTrend, SummerEnergyTrend include the forecast for all classes (including the residential SAE models)

Figure 3-15 - How End-Use Information is used in the Forecast Model

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:

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5.1 Consumption Drivers and Usage Patterns

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

Consumption drivers and customer usage patterns were incorporated into the load forecast through the use of the SAE method for residential and commercial classes and the traditional econometric method for the remaining classes. The use of these drivers are included in the Base Load Forecast (Section 7). The SAE method is technically described in Appendices 3C and 3D.

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 fore-casting 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) calibrate class level hourly profiles to the monthly sales and peak. The results of the forecast models are hourly load forecasts from 2012 through 2032.

These processes are 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. The following classes are modeled:
 - 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 model is an econometric model that uses the energy forecast as a primary driver.
- 3. 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 each class. From these forecasts, coincident peaks are obtained.

The technical description of the SAE forecasting method is included in Appendix 3C and 3D.

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.

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.

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

- 1. Step 1 Energy Forecast:
 - a. 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 recognizing the differences between the general class and unique customers. The system energy forecast is calculated as the sum of the class energy forecasts.
 - A key driver in the energy forecast is monthly weather. For the energy forecast, monthly weather is calculated from a 30-year average (1981 to 2010) 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 based on the daily average temperature.
 - 3) Calculate monthly heating and cooling degree days by summing the daily heating and cooling degree days over the calendar months.
 - 4) Apply current month and prior month weather to replicate billing cycle effects in the model. The current and prior month weights are 45 percent and 55 percent, respectively. These weights are based on the average number of billing days in the current and prior months.
- 2. Step 2 System Peak Forecast:
 - a. The monthly net system load peak forecast is developed using an econometric model based on historical peak day events from 2001. The

peak model controls the overall forecast peaks and is used as the calibration target for the class coincident peaks.

- b. A key driver in the peak forecast is the monthly peak producing weather. Peak weather is obtained by averaging the monthly peak producing weather events from January 2001 through September 2011. The weather calculation uses the following steps:
 - 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.
 - 2) Average the TDWT for the monthly peak days from 2001 through 2011.
 - 3) 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).
 - 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 average calculated based on the last five cold peak producing events. In some years, the winter peak event is in February or December. For these years, the January peak producing weather is not used in the calculation in favor of the February or December value.
 - 6) Replace the August average with the average calculated based on the last five hot peak producing events. In some years, the summer peak event is in July or September. For these years, the August peak producing weather is not used in the calculation in favor of the July or September value.
- 3. Step 3 Energy Load Shapes:
 - a. For each class, hourly load shapes are forecast based on class level load research data. Because a direct matching of load research sample data to classes was not available, load research sample data were averaged for each class based on customer counts in December 2011. The forecast models are developed as hourly econometric models.

- b. The key driver in the load shape forecast is the daily average temperatures. For the load shape forecast, daily temperatures are calculated from a 30-year (1981 to 2010) rank and average method. In the forecast period, the result of the rank and average process is mapped to the 2001 temperature calendar which represents the average year.
- 4. Step 4 Class Peak Forecast: The class level coincident peak forecast is obtained by calibrating the energy load shapes (Step 3) to the class energy forecast (Step 1) and summing the class to obtain a system hourly forecast. The system hourly forecast is then calibrated to the monthly peak forecast (Step 2). Finally, the hourly class forecasts are adjusted to sum to the calibrated monthly peak forecast.

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.

6.1.1.1.1 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 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).

6.1.1.1.2 Commercial Class

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:

- 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).

6.1.1.1.3 Wholesale Class

The wholesale energy forecast is composed of four municipal utilities (Monett, Mt. Vernon, Lockwood, and Chetopa). Each municipal utility is small and consists of a large 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:

- 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.

6.1.1.1.4 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).

6.1.1.1.5 Interdepartmental Class

The interdepartmental class is modeled with two models:

- 1. Customer Model: This model forecasts the number of interdepartmental 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 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).

6.1.1.1.6 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).

6.1.1.1.7 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 its energy.
- 2. Oil and Pipeline: The oil and pipeline segment consists of 13 customers. Two models are developed to forecast the oil and pipeline energy forecast. The customer model is designed to maintain the 13 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.

6.1.1.1.9 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.

The model is estimated with historical monthly peak and monthly peak producing weather from January 2001 through September 2011.

6.1.1.1.10 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;

The forecasting methods have been much different in each of the 2007, 2010, and 2013 IRPs. Economic variables for the 2007 IRP 2007 came from Woods & Poole Economics and Empire has not continued to purchase this data. 2013 economic variables were supplied by Economy.com and Empire did not purchase this data prior to this forecast. 2007 IRP economic variables were retail sales, population, gross regional product, employment, households, income, and wealth. The models differed by class. 2010 IRP regression models mainly used customers and weather. The models differ by class. 2013 IRP used SAE modeling for residential and commercial appliance efficiency data, economic variables such as population, households, employment, and the price of electricity. Load research data also utilized the models differ by class. Weather from the Springfield-Branson Regional Airport was used in all IRP forecasts.

6.1.3 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

6.1.3.1 Residential Class

1. Customer Model: The customer model is a regression model estimated with historical data from January 2000 through September 2011. *Table 3-7* shows the customer model specification and *Table 3-8* shows the customer model statistics.

Variable	Coefficient	StdErr	T-Stat	P-Value
May2011Plus	-2,437.472	261.335	-9.327	0.00%
Population	24.906	0.264	94.443	0.00%
AR(1)	0.981	0.007	147.829	0.00%

Table 3-7 -	Residential	Customer	Model
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Statistics	Residential
	Customer Model
Estimation	1/2000 - 9/2011
R2	0.998
Adj. R2	0.998
MAPE	0.14%
DW	1.772

Table 3-8 - Residential Customer Model Statistics

- a. Model Variables: The residential model includes two variables and an AR term. The primary driver of the customer model is population.
 - 1) Population: This variable is derived from the historical and forecast projection of the Missouri, Kansas, Oklahoma, and Arkansas populations. Population is calculated as the weighted average of the four-state population forecasts based on 12 months of energy ending in September 2011 (October 2010 to September 2011). The quarterly data provided by Economy.com is smoothed using a three-period moving average.

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- 2) May2011Plus: This variable takes the value of "0" through April 2011 and then takes the value of "1" from May 2011 through the forecast period. This binary variable captures the dramatic reduction in customer counts based on the 2011 Joplin tornado. Based on the model results, roughly 2,400 customers were lost due to the 2011 tornado.
- 3) 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 September 2011. The SAE model is described fully in the technical paper shown in Appendix 3C. *Table 3-9* shows the UPC model specification and *Table 3-10* shows the UPC model statistics.
 - a. Residential SAE Model Summary: The SAE model implemented for the residential class contains end-use information for heating, cooling, and other technologies. The data for the SAE model is from Itron's 2011 SAE West North Central region. Included in the model are the following data:
 - 1) End-Use Efficiencies: End-use efficiencies by technology type are based on EIA data.
 - End-Use Saturations: End-use saturations by technology type based on EIA data and calibrated to Empire's 2008 Potential Study technology saturation findings.
 - 3) Housing Stock: Housing information is based on EIA data and modified based on Empire's 2008 Potential Study housing stock findings.
 - 4) Economic Data: Historical and forecast household size and household income based on Economy.com forecasts.
 - 5) Energy Prices: Class energy prices are based on historical revenues and kWh consumption. Energy price forecasts are created by applying a 2-percent annual growth rate.
 - 6) End-Use Intensities: End-use intensities are derived based on an average of the SAE West North Central and West South Central zones and adjusted to reflect Empire's 2008 Potential Study saturations.

Variable	Coefficient	StdErr	T-Stat	P-Value
XHeat	1.410	0.042	33.906	0.00%
XCool	0.815	0.020	41.109	0.00%
XOther	0.709	0.015	47.608	0.00%
September	92.589	21.073	4.394	0.00%
XHeatShift2005	0.198	0.039	5.057	0.00%

Table 3-9 - Residential UPC Model

Statistics	Residential	
	Customer Model	
Estimation	1/2000 - 9/2011	
R2	0.945	
Adj. R2	0.943	
MAPE	4.23%	
DW	2.335	

Гable 3-10 -	Residential	UPC Model	Statistics
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- b. Model Variables: The UPC model includes the three standard SAE variables (XHeat, XCool, and XOther) as wells as a monthly binary variable and shift variable:
 - 1) XHeat: This variable captures the general heating response for a typical residential customer. The response includes the effects of heating technology efficiencies, saturation, and efficiencies, thermal shell, weather, price, income, and household size. A full description of the variable and its construction is included in Appendix 3C.
 - 2) 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 3A.
 - 3) XOther: This variable captures the general response for all nonheating and cooling technologies. The response includes the effects of hours of light, price, income, billing cycles, and household size. A full description of the variable and its construction is included in Appendix 3A.
 - 4) September: This binary variable is included to capture a patterned residual for the month of September.

5) XHeatShift2005: This variable is used to capture a general heating response shift beginning in 2005. 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.

6.1.3.2 Commercial Class

1. Customer Model: The customer model is a regression model estimated with historical data from January 1999 through September 2011. *Table 3-11* shows the customer model specification and *Table 3-12* shows the customer model statistics.

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	5,134.428	1,495.731	3.433	0.08%
Residential Customers	0.093	0.005	18.534	0.00%
Employment	3.349	1.079	3.104	0.23%
AR(1)	0.898	0.041	22.002	0.00%

Statistics	Commercial	
	Customer Model	
Estimation	1/1999 - 9/2011	
R2	0.997	
Adj. R2	0.997	
MAPE	0.14%	
DW	1.885	

Table 3-12 - Commercial Customer Model Statistics

- a. Model Variables: The commercial model includes two variables and an AR term. The primary drivers in the customer model are the number of residential customers and area employment.
 - 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.
 - 2) Employment: This variable is derived from the historical and forecast projection of the Missouri, Kansas, Oklahoma, and Arkansas populations. Population is calculated as the weighted average of the four-state employment forecasts based on 12 months of energy

ending in September 2011 (October 2010 to September 2011). The quarterly data provided by Economy.com is smoothed using a three-period moving average. The employment variable provides additional model flexibility that captures changes based on economic conditions.

- 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 or employment drivers.
- 2. UPC Model: The UPC model is an SAE model estimated with historical data from January 2000 through September 2011. The SAE model is based on the same theoretical foundation as the residential SAE model (Appendix 3C) but is modified for commercial end-use information. The SAE framework for the commercial model is described in Appendix 3D. *Table 3-13* shows the UPC model specification and *Table 3-14* shows the UPC model statistics.
 - a. Commercial SAE Model Summary: The SAE model implemented for the commercial class contains end-use information for heating, cooling, and other technologies. The data for the SAE model is from Itron's 2011 SAE West North Central region. Included in the model are the following data:
 - 1) End-Use Efficiencies: End-use efficiencies by technology type are based on EIA data.
 - 2) End-Use Saturations: End-use saturations by technology type based on EIA data.
 - 3) Economic Data: Historical and forecast employment and GSP are based on Economy.com forecasts.
 - 4) Energy Prices: Class energy prices are based on historical revenues and kWh consumption. Energy price forecasts are created by applying a 2-percent annual growth rate.

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Variable	Coefficient	StdErr	T-Stat	P-Value
XHeat	0.040	0.003	13.427	0.00%
XCool	0.121	0.004	26.901	0.00%
XOther	0.039	0.001	53.284	0.00%
XHeatShift2006	0.005	0.003	2.106	3.72%
January	44.677	71.884	0.622	53.54%
May	-113.532	66.490	-1.708	9.02%
June	-157.676	62.750	-2.513	1.32%
September	366.136	63.351	5.779	0.00%
November	-36.462	67.808	-0.538	59.17%
Year2000	-281.891	60.189	-4.683	0.00%
Year2006	-288.807	62.175	-4.645	0.00%
Year2007	-277.627	61.976	-4.480	0.00%
Year2006Plus	493.459	46.945	10.511	0.00%

Statistics	Commercial	
	UPC Model	
Estimation	1/2000 - 9/2011	
R2	0.931	
Adj. R2	0.924	
MAPE	2.72%	
DW	2.137	

Table 3-14 - Comm	ercial UPC Mode	Statistics
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- b. Model Variables: The UPC model includes the three standard SAE variables (XHeat, XCool, and XOther) as well as a monthly binary variable and shift variable:
 - 1) XHeat: This variable captures the general heating response for a typical commercial customer. The response includes the effects of heating technology efficiencies, saturation by technology and building types, weather, price, employment, and output indices. A full description of the variable and its construction is included in Appendix 3D.
 - 2) XCool: This variable captures the general cooling response for a typical commercial customer. The response includes the effects of cooling technology efficiencies, saturation by technology and building types, weather, price, employment, and output indices. A full description of the variable and its construction is included in Appendix 3D.

- 3) XOther: This variable captures the general response for all non-heating and cooling technologies. The response includes the effects of other base load technology efficiencies, saturation by technology and building types, price, employment, and output indices. A full description of the variable and its construction is included in Appendix 3D.
- 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) January, May, June, September, and November: These independent binary variables are included to capture a patterned residual through the course of the year.
- 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.

6.1.3.3 Wholesale Class

- 1. Energy Models: The models forecast total energy and are not divided into a customer and UPC model. However, the energy models use the SAE model framework, include an economic variable to capture customer growth, and forecast total energy instead of UPC. 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.
 - a. Model Variables. The energy models include the three standard SAE variables (XHeat, XCool, and XOther) and an economic driver (households) 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, and efficiencies, thermal shell, weather, price, income, and household size. A full description of the variable and its construction is included in Appendix 3C.
- 2) XCool: This variable captures the general cooling response for a typical wholesale 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 3C.
- 3) XOther: This variable captures the general response for all nonheating and cooling technologies. The response includes the effects of hours of light, price, income, billing cycles, and household size. A full description of the variable and its construction is included in Appendix 3C.
- 4) Households: This variable is used to capture long-term growth of energy caused by population changes in the municipal areas. Household forecasts are provided by Economy.com and reflect the household history and forecast for the state in which the municipal resides.
- 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 or household variables.
- 6) Annual Plus Binaries: The annual binary plus variables (e.g. Year2009Plus, Year2011Plus) capture an ongoing shift in base load which is expected to continue into the future.
- b. Monett Energy Model: The Monett energy model is summarized in *Tables 3-15* and *3-16*.

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Variable	Coefficient	StdErr	T-Stat	P-Value
XHeat	3,259.417	494.041	6.597	0.00%
XCool	5,810.358	211.046	27.531	0.00%
XOther	2,410.639	3,612.742	0.667	50.60%
Households	6,666.709	1,300.623	5.126	0.00%
Year2011Plus	868,141.411	245,218.517	3.540	0.06%
Year2002	-1,657,506.502	218,878.889	-7.573	0.00%
Year2003	-1,898,950.547	218,324.651	-8.698	0.00%
Year2004	-1,439,632.543	220,015.923	-6.543	0.00%
Year2005	-901,871.634	215,860.960	-4.178	0.01%

Table 3-15 - Monett Energy Model

Statistics	Monett Model
Estimation	1/2002 - 9/2011
R2	0.938
Adj. R2	0.934
MAPE	2.49%
DW	2.275

Table 3-16 - Monett Energy Model Statistics

c. Mt. Vernon Energy Model: The Mt. Vernon energy model is summarized in *Tables 3-17* and *3-18*.

Variable	Coefficient	StdErr	T-Stat	P-Value
XHeat	1,943.848	149.473	13.005	0.00%
XCool	2,717.762	69.473	39.120	0.00%
XOther	-378.541	1,046.034	-0.362	71.80%
Households	2,363.829	377.557	6.261	0.00%
Year2000	-537,110.011	780,78.850	-6.879	0.00%
Year2001	-409,782.641	786,73.761	-5.209	0.00%
Year2002	-409,204.179	761,23.374	-5.376	0.00%
Year2003	-302,979.877	760,03.862	-3.986	0.01%
Year2004	-239,996.832	764,29.151	-3.140	0.21%

Table 3-17 - Mt. Vernon Energy Model

Statistics	Mt. Vernon Model		
Estimation	1/2000 - 9/2011		
R2	0.949		
Adj. R2	0.946		
MAPE	2.89%		
DW	2.233		

Table 3-18 - Mt	. Vernon E	Energy Model	Statistics
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d. Lockwood Energy Model: The Lockwood energy model is summarized in *Tables 3-19* and *3-20*.

Variable	Coefficient	StdErr	T-Stat	P-Value
XHeat	466.358	27.522	16.945	0.00%
XCool	555.439	13.135	42.288	0.00%
XOther	263.789	173.938	1.517	13.17%
Households	178.108	63.670	2.797	0.59%
AR(1)	0.276	0.086	3.201	0.17%

Table 3-19 - Lockwood Energy Model

Statistics	Lockwood Model
Estimation	1/2000 - 9/2011
R2	0.951
Adj. R2	0.949
MAPE	3.69%
DW	2.097

Table 3-20 - Lockwood Energy Model Statistics

e. Chetopa Energy Model: The Chetopa energy model is summarized in *Tables 3-21* and *3-22*.

Variable	Coefficient	StdErr	T-Stat	P-Value
XHeat	926.608	52.843	17.535	0.00%
XCool	651.878	23.245	28.044	0.00%
XOther	454.688	433.574	1.049	29.62%
Households	328.452	345.089	0.952	34.29%
Year2000	-104,476.415	21,394.845	-4.883	0.00%
Year2001	-65,121.580	21,442.385	-3.037	0.29%
Year2008	91,909.951	23,291.608	3.946	0.01%
Year2009Plus	109,827.787	23,848.366	4.605	0.00%

Chetopa Model
1/2000 - 9/2011
0.914
0.909
4.94%
1.777

Table 3-21 - Chetopa Energy Model

Table 3-22 - Chetopa Energy Model Statistics

6.1.3.4 Street and Highway Class

1. Customer Model: The customer model is a regression model estimated with historical data from January 2001 through September 2011. *Table 3-23* shows the customer model specification and *Table 3-24* shows the customer model statistics.

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	-3.033	34.765	-0.087	93.06%
Households	0.204	0.015	13.274	0.00%
Oct2007ToDec2008 Binary	-9.250	1.947	-4.750	0.00%
AR(1)	0.701	0.058	12.161	0.00%

Statistics	Street and Highway
	Customer Model
Estimation	1/2001 - 9/2011
R2	0.937
Adj. R2	0.936
MAPE	0.50%
DW	1.705

Table 3-23 -	Street	and Highway	Customer	Model
	30,000	and monthly	Castonici	model

Table 3-24 - Street and Highway Customer Model Statistics

- a. Model Variables: The street and highway model includes two variables and an AR term. The primary driver of the customer model is households.
 - 1) Households: This variable is derived from the historical and forecast projection of the households in Missouri, Kansas, Oklahoma, and Arkansas. Household is calculated as the weighted average of the four-state household forecasts based on 12 months of energy ending

in September 2011 (October 2010 to September 2011). The quarterly data provided by Economy.com is smoothed using a three-period moving average.

- 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.
- 2. UPC Model: The UPC model is a regression model estimated with historical data from January 2001 through September 2011. *Tables 3-25* shows the UPC model specification and *Table 3-26* shows the UPC model statistics.

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	4,241.426	107.285	39.534	0.00%
January	1,284.024	44.991	28.539	0.00%
February	631.839	46.309	13.644	0.00%
March	488.664	43.880	11.136	0.00%
April	63.082	46.318	1.362	17.61%
May	46.026	44.968	1.024	30.84%
July	293.999	43.743	6.721	0.00%
August	440.521	43.744	10.070	0.00%
September	504.945	43.866	11.511	0.00%
October	894.807	44.984	19.892	0.00%
November	1,127.038	47.884	23.537	0.00%
December	1,389.693	46.286	30.024	0.00%
OutsideLightEfficiency	-15.333	2.413	-6.354	0.00%
Sep2007ToMay2008	195.216	36.546	5.342	0.00%

Table 3-25 - Street and Highway UPC Model

Statistics	Street and Highway
	UPC Model
Estimation	1/2001 - 9/2011
R2	0.958
Adj. R2	0.953
MAPE	1.83%
DW	1.750

Table 3-26 - Street and Highway UPC Model Statistics

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- 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.

6.1.3.5 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 September 2011. This model is designed to capture seasonal fluctuations based on weather response and forecast loads based the recent history from 2008 forward. *Table 3-27* shows the UPC model specification and *Table 3-28* shows the UPC model statistics.

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	11,010.877	280.561	39.246	0.00%
Year2008Plus	-7,008.588	780.984	-8.974	0.00%
Year2006Plus	-587.628	314.023	-1.871	6.40%
Year2007Plus	195.340	820.072	0.238	81.22%
Year2007Trend	-489.702	108.879	-4.498	0.00%
HDD55	2.682	0.595	4.510	0.00%
CDD55	2.307	0.550	4.198	0.01%

Table 3-27 - Interdepartmental	UPC Model
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Statistics	Interdepartmental UPC Model
Estimation	1/2001 - 9/2011
R2	0.930
Adj. R2	0.926
MAPE	8.38%
DW	1.423

Table 3-28 - Interdepartmental UPC Model Statistics

- 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 (Year2006Plus, Year2007Plus, and Year2008Plus) capture annual shifts in the average use which continue through the forecast period. These shifts capture the rapid decline in average use over the three-year period.
 - 3) Year2007 Trend: This is a trend variable only active during 2007. This variable captures the rapid decline in average usage over 2007.

6.1.3.6 Public Authority Class

1. Customer Model: The customer model is a regression model that is designed to provide the growth for the class. *Table 3-29* shows the customer model specification and *Table 3-30* shows the customer model statistics. The model is primarily driven by the household forecast and includes an end-shift binary variable to calibrate the forecast to the last actual data point.

Variable	Coefficient	StdErr	T-Stat	P-Value
Households	0.567	0.007	82.461	0.00%
End Shift Sep 2011	3.262	7.191	0.454	65.09%
Year2003To2006Trend	0.134	0.013	10.195	0.00%
Year2003Plus	-5,049.719	496.824	-10.164	0.00%
Year2007Plus	5,244.498	512.475	10.234	0.00%
AR(1)	0.915	0.031	29.076	0.00%

Table 3-29 - Public Authority Customer Model

Statistics	Public Authority Customer Model		
Estimation	1/2000 - 9/2011		
R2	0.997		
Adj. R2	0.997		
MAPE	0.39%		
DW	2.199		

Table 3-30 - Public Authority Customer Model Statistics

- a. 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:
 - 1) Households: This set of variables (HDD55 and CDD55) capture the weather response of the public authority class.
 - 2) End Shift Sep 2011: This variable calibrates the forecast to the last actual value of the model estimation period.
 - 3) Year2003To2006Trend: This is a trend variable only active from 2003 through 2007. This variable captures the higher than average growth through the 2003 through 2007 time frame.
 - 4) Annual Shift Variables: This set of variables (Year2003Plus and Year2007Plus) capture annual shifts in the average use which continue through the forecast period.
- 2. UPC Model: The UPC model is a regression model estimated with historical data from January 1999 through September 2011. 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 3-31* shows the UPC model specification and *Table 3-32* shows the UPC model statistics.

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	4,616.465	69.187	66.725	0.00%
HDD60	1.169	0.113	10.348	0.00%
CDD60	2.463	0.160	15.407	0.00%
Year2008Plus	372.852	48.982	7.612	0.00%
Year2002Plus	-175.152	53.065	-3.301	0.12%

Table 3-31 - Public Authority UPC Model
Statistics	Public Authority UPC Model
Estimation	1/1999 - 9/2011
R2	0.696
Adj. R2	0.687
MAPE	3.63%
DW	2.049

Table 3-32 - Public Authority UPC Model Statistics

- 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 (HDD60 and CDD60) captures the weather response of the public authority class.
 - 2) Lag Weather Variables: This set of variables (LagHDD60 and LagCDD60) captures the prior month weather response of the public authority class due to the characteristics of billing cycle energy reads.
 - 3) Annual Shift Variables: This set of variables (Year2002Plus and Year2008Plus) captures annual shifts in the average use which continue through the forecast period.

6.1.3.7 Industrial Class

1. 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 2011 average annual energy usage. The model results are shown in *Tables 3-33* and *3-34*.



Table 3-33 - Praxair Model

Statistics	Praxair		
	Model		
Estimation	1/2001 - 9/2011		
R2	0.157		
Adj. R2	0.129		
MAPE	6.63%		
DW	1.260		

Table 3-34 - Praxair Model Statistics

a. Model Variables: The Praxair model consists of four annual shift variables (Year2008Plus, Year2009Plus, Year2010Plus, and Year2011Plus). These variables are designed to capture the average energy load for the year and project the 2001 average energy load through the forecast horizon. The effect of these variables can be seen in *Figure 3-16*.



Highly Confidential in its Entirety Figure 3-16 - Praxair Energy Model Actual Versus Predicted Plot

- 2. Oil and Pipeline Model:
 - a. Oil and pipeline uses two models to forecast energy. The customer model is designed to forecast the existing 13 customers throughout the forecast

b. The model results are shown in *Tables 3-35* and *3-36*. The full model is shown in the MetrixND project file.

Variable	Coefficient	StdErr	T-Stat	P-Value
Constant	371,130.100	28,132.261	13.192	0.00%
Year2003Plus	-209,917.581	58,378.248	-3.596	0.05%
Year2004Plus	480,591.097	62,518.525	7.687	0.00%
Year2005Plus	-67,128.524	36,534.770	-1.837	6.84%
Year2006Plus	-21,636.226	36,534.770	-0.592	55.47%
Year2007Plus	6,934.815	36,534.770	0.190	84.97%
Year2008Plus	-85,154.134	36,534.770	-2.331	2.13%
Year2009Plus	-64,552.154	36,534.770	-1.767	7.96%
Year2010Plus	7,956.731	36,534.770	0.218	82.79%
Year2011Plus	36,925.747	39,708.247	0.930	35.41%
Year2003Trend	57,412.987	7,804.985	7.356	0.00%
January	64,317.130	36,572.118	1.759	8.10%
February	21,330.284	36,462.716	0.585	55.96%
March	55,762.115	36,362.898	1.533	12.76%
April	64,458.483	36,272.745	1.777	7.79%
May	100,723.909	36,192.327	2.783	0.62%
June	110,720.187	36,121.711	3.065	0.26%
July	157,206.894	36,060.954	4.359	0.00%
August	155,628.105	36,010.106	4.322	0.00%
September	123,351.741	35,969.209	3.429	0.08%
October	66,511.472	36,557.921	1.819	7.11%
November	49,532.566	36,540.559	1.356	17.76%

Table 3-35 - Oil and Pipeline Model

Statistics	Oil and Pipeline UPC Model
Estimation	1/2001 - 9/2011
R2	0.665
Adj. R2	0.611
MAPE	12.90%
DW	1.571

Table 3-36 - Oil and Pipeline UPC Model Statistics

c. Model Variables:

- 1) Annual Shift Binary: These variables (Year2003Plus through Year2011Plus) are designed to capture the average energy load for the year and project the 2001 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. The effect of these variables can be seen in *Figure 3-17*.



Highly Confidential in its Entirety Figure 3-17 - Oil and Pipeline UPC Model Actual Versus Predicted Plot

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 342 customers throughout the forecast horizon. The UPC model is designed to capture monthly variation for these customers. The model results are shown in *Tables 3-37* and *3-38*.

Variable Coefficient StdErr T-Stat **P-Value** Constant 204,436.023 2,008.197 101.801 0.00% January 10,862.175 2,600.326 4.177 0.01% February 2,120.433 2,661.372 0.797 42.72% March 10,706.950 2,650.615 4.039 0.01% April 2,634.277 2,793.990 0.943 34.77% May 6,605.467 3,725.627 1.773 7.88% 7,495.995 5,875.075 1.276 June 20.45% July 8,196.685 0.879 38.11% 7,205.645 8,776.419 9,144.685 0.960 33.92% August September -1,958.8097,479.501 -0.262 79.39% 4,403.539 October 4,609.000 29.74% 1.047 November 1,047.385 2,965.506 0.353 72.46% Year2009 1,972.563 -12,988.871 -6.585 0.00% CDD55 52.836 12.681 4.166 0.01% Year2010Plus -11,886.449 1,535.328 -7.742 0.00% Year2003 -7,064.261 1,985.000 -3.559 0.05% Year2004 -2,335.951 2,090.393 -1.117 26.61% Year2006 5,515.430 1,903.237 2.898 0.45%

Table 3-37 - Other Industrial UPC Model

Statistics	Other Industrial Model
Estimation	1/2001 - 9/2011
R2	0.886
Adj. R2	0.870
MAPE	2.02%
DW	1.783

- a. Model Variables:
 - 1) Annual Shift Binary: This variable (Year2010Plus) is designed to capture the average energy load for the year and project the 2010 average energy load through the forecast horizon.
 - 2) Weather Variables: This variable (CDD55) captures the cooling weather response of the industrial customers.

- Annual Binaries: These binary variables (Year2003, Year2004, 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.

6.1.3.8 System Peak Model

The model is estimated with historical monthly peak and monthly peak producing weather from January 2001 through September 2011. The model is summarized in *Tables 3-39* and *3-40*.

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	-323.775	99.324	-3.260	0.15%
CoolingPeakCDD	24.472	1.469	16.663	0.00%
HeatingPeakHDD	9.868	0.661	14.932	0.00%
EnergyTrend	935.553	91.919	10.178	0.00%
WinterEnergyTrend	18.613	14.315	1.300	19.60%
SummerEnergyTrend	35.970	16.279	2.210	2.90%

Table 3-39 -	System	Peak Model
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Statistics	Public Authority		
	Customer Model		
Estimation	1/2000 - 9/2011		
R2	0.905		
Adj. R2	0.901		
MAPE	4.11%		
DW	1.628		

Table 3-40 -	System	Peak Mode	Statistics
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- 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. Cooling Peak CDD: This variable is calculated based on the three-day weighted average temperature for degrees above 70 degrees. The cooling peak temperatures are applied only from May through October in the forecast period.

- b. Heating Peak HDD: This variable is calculated based on the three-day weighted average temperature for degrees below 45 degrees. The cooling peak temperatures are applied only from November through April in the forecast period.
- c. Energy Trend: The energy trend variable is created based on the annual historical sales and forecast sales. Historical sales are normalized. The annual sales are then converted to a "1" based index and smoothed to obtain the monthly trend series. This variable is designed to capture the base load growth of the system.
- d. Winter Energy Trend: The winter energy trend variable is created by the interaction of the energy trend with a binary variable that is active only from November through February. This variable is designed to capture additional growth in the winter peak above the energy trend.
- e. Summer Energy Trend: The summer energy trend variable is created by the interaction of the energy trend with a binary variable that is active only from June through August. This variable is designed to capture additional growth in the summer peak above the energy trend.

6.1.3.9 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 December 2011 customer counts associated with each rate in the class. *Table 3-41* shows the class and the weights used for each load research profile.

Class	Load Research	Weight
Residential	Residential	100.00%
Commercial	СВ	76.17%
	GP - Secondary	6.53%
	LP-Primary	0.03%
	LP-Secondary	0.02%
	SH	13.09%
	TEB	4.16%
Wholesale	Monett, Mt. Vernon,	NA
	Lockwood, Chetopa	
Street Highway	СВ	76%
	Generic Lighting Shape	24%
Interdepartmental	СВ	85%
	GP - Secondary	15%
Industrial:	СВ	21.60%
Other Industrial	GP - Secondary	49.90%
	GP - Primary	7.60%
	LP - Primary	8.60%
	LP - Secondary	2.00%
	LP - Transmission	0.30%
	PFM	2.00%
	SH	4.00%
	TEB	4.00%
Industrial: Praxair	Praxair	NA
Industrial: OPP	GP - Primary	62%
	GP - Secondary	8%
	LP - Primary	30%

Table 3-41 - Load Research to Class Profile Mapping

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 3-42* identifies the sets of variables used in each profile model. Definitions of the variables are summarized below:

Class	HDD CDD	Day of Week	Month	Year	Holiday	Hours of Light
Residential	Х	Х	Х	Х	Х	Х
Commercial	Х	Х		Х	Х	Х
Wholesale	Х	Х	Х	Х	Х	
Street Highway	Х	Х	Х	Х	Х	
Interdepartmental	Х	Х		Х	Х	
Industrial: Other Industrial	Х	Х		Х	Х	
Industrial: Praxair						
Industrial: OPP	Х	Х		Х	Х	

Table	3-42 -	Model	Variable	Classes
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- a. Heating and Cooling Splines: HDD and CDD spline variables are 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.
- 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 developed 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 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.

6.1.4 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. 2012 is the first year of economic end-use drivers.

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;

The load forecast uses historical sales, 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. Economic data was provided by Economy.com and were not modified prior to use.

End-use data were provided by Itron and were adjusted to reflect the Empire 2008 Potential Study saturation values. The adjustments of the end-use data are recommended by Itron to better align regional end-use technology information to known levels in the Empire service territory.

Adjustments were made to the residential saturation of heating, cooling, water heating, refrigeration, dishwashing, clothes washing, and clothes drying technologies. Associated end-use intensities for these technologies were also modified to accompany the saturation changes.

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

A comparison of historical number of customers and UPC to forecasts in the 2007, 2010, and 2013 IRPs are shown in Tables 3-43 and 3-44. Historical and IRP normal heating degree days and cooling degree days are shown in Table 3-45.

Figure 3-18 shows a comparison of total actual historical electric customers to the 2007, 2010, and 2013 IRP Base Forecasts. *Figure 3-19* shows a comparison of actual historical heating degree and cooling degree days to the Normal IRP.

The actual data shown is not weather-normalized. 2013 IRP forecast data is lower than the 2007 and 2010 IRP data due to a "new normal" following the recent unprecedented economic downturn and energy efficiency and conservation. More independent variables have been utilized in all forecasts, but the forecasting methods have been much different in each of the 2007, 2010, and 2013 IRPs. All independent variables are not listed. In some cases no actuals to compare against or no similar data in other forecasts to compare against are available. 2007 economic variables came from Woods & Poole Economics and Empire has not continued to purchase this data. 2013 economic variables were supplied by Economy.com and Empire did not purchase this data prior to this forecast. 2007 IRP economic variables were retail sales, population, gross regional product, employment, households, income, and wealth. The models differed by class. 2010 IRP regression models mainly used customers and weather. The models differ by class. 2013 IRP used SAE modeling for residential and commercial appliance efficiency data, economic variables such as population, households, employment, and the price of electricity. Load research data also utilized the models differ by class. The independent variables Empire is supplying are customers and weather data. These variables have been relevant to all forecasts and actuals are available to compare. While UPC (NSI/average

customers) may not technically be an independent variable, it is provided for informational purposes. Note that the downturn in 2011 customers is due to the May 22, 2011 Joplin tornado. The 2010 forecast was completed in the third quarter of 2009 and was about one year old when the 2010 IRP was filed and missed some of the recent downward trend. IRP forecasts also include the impacts of existing DSM programs. This is another reason for the lowering of the forecasts over time. In 2007, the DSM was just getting started and by 2013, DSM programs have been in place for several years. The 30-year weather-normal degree days are the most recent 30-year averages from the Springfield-Branson Regional Airport and represent a close approximation of normal degree days used in the IRP forecasts.

Year	Actual ¹	2007 IRP	2010 IRP	2013 IRP	
1990	117,032				
1991	118,890				
1992	121,480				
1993	125,333				
1994	130,090				
1995	134,686				
1996	137,923				
1997	140,667				
1998	143,139				
1999	145,845				
2000	148,148				
2001	150,655				
2002	152,585				
2003	155,038				
2004	157,555				
2005	160,625				
2006	164,015				
2007	166,477	168,292			
2008	167,647	172,073			
2009	168,002	175,873			
2010	168,597	179,710	169,682		
2011	166,210	183,592	171,803		
2012	167,156	187,528	174,294		
2013		191,490	176,909	167,300	
2014		195,481	179,562	168,585	
2015		199,522	182,256	170,000	
2016		203,595	184,989	171,405	
2017		207,706	187,764	172,709	
2018		211,833	190,581	173,946	
2019		215,995	193,440	175,165	
2020		220,215	196,341	176,235	
2021		224,494	199,286	177,288	
2022		228,845	202,276	178,304	
2023		233,247	205,310	179,300	
2024		237,690	208,389	180,283	
2025		242,176	211,515	181,226	
2026		246,706	214,688	182,156	
2027			217,908	183,083	
2028			221,177	184,007	
2029			224,494	184,936	
2030				185,872	
2031				186,810	
2032				187,753	
¹ Actual data not weather-normalized.					

Table 3-43 - Historical and Base Forecasts for 2007, 2010,

and 2013 IRPs - Total Customers

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	Heating Degree Days		Cooling Degree Days		
Year	Actual ¹	IRP Normals ²	Actual ¹	IRP Normals ²	
1990	3,981	4,578	1,439	1,389	
1991	4,197	4,578	1,580	1,389	
1992	4,108	4,578	1,032	1,389	
1993	4,925	4,578	1,371	1,389	
1994	4,151	4,578	1,381	1,389	
1995	4,521	4,578	1,438	1,389	
1996	4,967	4,578	1,181	1,389	
1997	4,864	4,578	1,129	1,389	
1998	4,164	4,578	1,692	1,389	
1999	3,945	4,578	1,336	1,389	
2000	4,684	4,578	1,448	1,389	
2001	4,337	4,578	1,395	1,389	
2002	4,588	4,578	1,507	1,389	
2003	4,541	4,578	1,313	1,389	
2004	4,135	4,578	1,199	1,389	
2005	4,270	4,578	1,759	1,389	
2006	3,813	4,578	1,697	1,389	
2007	4,103	4,578	1,752	1,389	
2008	4,767	4,578	1,265	1,389	
2009	4,577	4,578	1,110	1,389	
2010	4,710	4,578	1,737	1,389	
2011	4,587	4,578	1,817	1,389	
2012	3,650	4,578	1,766	1,389	
2013		4,578		1,389	
2014		4,578		1,389	
2015		4,578		1,389	
2016		4,578		1,389	
2017		4,578		1,389	
2018		4,578		1,389	
2019		4,578		1,389	
2020		4,578		1,389	
2021		4,578		1,389	
2022		4,578		1,389	
2023		4,578		1,389	
2024		4,578		1,389	
2025		4,578		1,389	
2026		4,578		1,389	
2027		4,578		1,389	
2028		4,578		1,389	
2029		4,578		1,389	
2030		4,578		1,389	
2031		4,578		1,389	
2032		4,578		1,389	
¹ Degree day data from the Springfield-Branson Regional Airport.					
² IRP normal degree days used for all years in the forecast. The 30-year					
Regional Airport and represent a close approximation of normal degree					
days used in the IRP forecast.					

Total Electric Customers: Actual and IRP Base Forecasts 300,000 250,000 200,000 Actual 150,000 2007 IRP 2010 IRP 100,000 - 2013 IRP 50,000 2006 2010 2014 2018 2026 2030 2002 2022 199⁸ 1995 1991

Table 3-45 - Historical and IRP Normal Heating Degree Days and Cooling Degree Days

Figure 3-18 - Comparison of Total Electric Customers Actual Historical and 2007, 2010, and 2103 IRP Base Forecasts



Figure 3-19 - Comparison of Heating and Cooling Degrees Actual Historical and 2007, 2010, and 2013 IRP Normal Normals

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 energy net system input (MWh) and system peak (MW) to forecasts in the 2007, 2010, and 2013 IRPs are shown in Table 3-46 and 3-47. Figure 3-20 shows a comparison of the actual historical net system input to the 2007, 2010, and 2013 IRP base forecasts. Figure 3-21 shows a comparison of actual historical system peak to the 2007, 2010, and 2013 IRP base forecasts.



Highly Confidential in its Entirety Table 3-46 - Historical and Base Forecasts for 2007, 2010, and 2013 IRPs - Energy Net System Input (MWh)



Highly Confidential in its Entirety Table 3-47 - Historical and Base Forecasts for 2007, 2010, and 2013 IRPs - Net Peak (MW)

Highly Confidential in its Entirety Figure 3-20 - Comparison of Energy Net System Input (MWh) Actual Historical and 2007, 2010, and 2013 Base Forecasts

Highly Confidential in its Entirety Figure 3-21 - Comparison of Net Peak (MW) Actual Historical 2007, 2010, and 2013 IRP Base Forecasts

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.

6.4 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.

6.4.1 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 prices of electricity and competitive energy sources, real incomes, and other economic and demographic factors in their models for forecasts. End-use efficiencies, end-use saturations, and housing stock are from the EIA data. Historical and forecast household size and income was based on Economy.com. Class energy prices are based on historical revenues and kWh consumption. Energy price forecasts are created by applying a 2-percent annual growth rate. End-use intensities are derived based on an average of the SAE West North Central and west South Central zones and adjusted to reflect Empire's 2008 potential saturations.

6.4.2 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.

The forecast of energy sales (kWh) for residential, commercial, and wholesale energy sales utilized SAE methodologies. This methodology accounts for appliance efficiency standards and building codes.

6.4.3 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 forecasts incorporate the following to be consistent with historical trends:

- 1. EIA data on end-use saturations have been calibrated to Empire's 2008 Potential Study technology saturation findings.
- 2. EIA data on housing information have been modified based on Empire's 2008 Potential Study housing stock findings.
- 3. A general heating response shift beginning in 2005 has been included. This 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.

6.4.4 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 model 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).

Monthly heating and cooling for the residential, commercial, and industrial classes were calculated.

Table 3-48 below summarizes the heating, cooling, and base load components of the major classes at the annual level.



Highly Confidential in its Entirety Table 3-48 - Annual Heating, Cooling, and Base Load Components of the R, C, and I Classes MWh (Billed Year Basis)

Describe and Document Modification of Modules

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

The final residential energy forecast was adjusted upward in 2012 through 2015 to reflect a slower than modeled adoption of end-use technologies resulting in slightly higher use per customer. After 2015, no further adjustments are used reflecting the belief that customers' end-use technologies are consistent with the EIA regional forecast.

The final commercial energy forecast was adjusted downward by reducing the overall number of customers in the customer forecast. The reduction considers the current number of customers and reduces the forecast model's results by 50 customers per year through 2015. After 2015, the 300 customer reduction is sustained through the forecast time horizon.

6.4.5 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.

This section presents the annual and peak month energy forecasts (billed year basis) by class first (Section 7.1.6.1), then summer/winter system, and coincident peak demand (gross peak basis) by class (Section 7.1.6.2).

6.4.5.1 Energy Forecasts

6.4.5.1.1 Residential Annual

The residential energy forecast is developed as the product of the customer model and UPC forecast. The final forecast is adjusted upward in 2012 through 2015 to reflect a slower than modeled adoption of end-use technologies resulting in slightly higher use per customer. After 2015, no further adjustments are used reflecting the belief that customers' end-use technologies are consistent with the EIA regional forecast. The adjustments used between 2012 and 2015 are shown in *Table 3-49*.

Year	Energy Increase Per Month (MWh)
2012	4,000
2013	3,000
2014	2,000
2015	1,000

Table 3-49 - Post Forecast Adjustments

The annual energy forecast, customer forecast, and UPC forecast are shown in *Figures 3-22*, *3-23*, and *3-24*. Both the energy and UPC figures show normalized energy and UPC for comparative purposes.

Tables 3-50 and *3-51* summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates. Because population is a primary driver in the residential forecast, *Table 3-51* includes the average annual growth rate for population for comparison purposes.



Highly Confidential in its Entirety Figure 3-22 - Residential Energy Annual Forecast (Actual, Normalized, Forecast)







Highly Confidential in its Entirety Figure 3-24 - Residential UPC Forecast (Actual, Normalized, Forecast)



Highly Confidential in its Entirety Table 3-50 - Residential Energy Forecast Summary

Time Period	Energy	Customer	Use-Per-	Population
			Customer	
2003-2012 (Historical)	1.1%	0.9%	0.2%	0.7%
2008-2012 (Historical)	0.2%	-0.1%	0.3%	0.6%
2013-2017 (5 Yr Forecast)	0.1%	0.8%	-0.7%	0.6%
2013-2022 (10 Yr Forecast)	0.5%	0.7%	-0.2%	0.6%
2013-2027 (15 Yr Forecast)	0.7%	0.7%	0.0%	0.6%
2013-2032 (20 Yr Forecast)	0.8%	0.6%	0.2%	0.5%

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

6.4.5.1.2 Commercial Annual

The commercial energy forecast is developed as the product of the customer model and UPC forecast. The final forecast is adjusted downward by reducing the overall number of customers in the customer forecast. The reduction considers the current number of customers and reduces the forecast model's result by 50 customers per year through 2015. After 2015, the 300-customer reduction is sustained through the forecast time horizon. The adjustments used between 2012 and 2015 are shown in *Table 3-52*.

Year	Reduced Number of Customers Per Month		
2012	50		
2013	150		
2014	250		
2015 and Beyond	300		

Table 3-52 - Commercial Post Forecast Adjustments

The annual energy forecast, customer forecast, and UPC forecast are shown in *Figures 3-25*, *3-26*, and *3-27*. Both the energy and UPC figures show normalized energy and UPC for comparative purposes.

Tables 3-53 and *3-54* summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates. Because employment is a primary driver in the commercial forecast, *Table 3-54* includes the average annual growth rate for employment for comparison purposes.



Highly Confidential in its Entirety Figure 3-25 - Commercial Energy Forecast (Actual, Normalized, Forecast)







Highly Confidential in its Entirety Figure 3-27 - Commercial UPC Forecast (Actual, Normalized, Forecast)



Highly Confidential in its Entirety Table 3-53 - Commercial Energy Forecast Summary

Time Period	Energy Customer		Use-Per- Customer	Employment	
2003-2012 (Historical)	1.2%	0.5%	0.7%	0.5%	
2008-2012 (Historical)	-0.3%	-0.2%	-0.1%	0.0%	
2013-2017 (5 Yr Forecast)	1.8%	0.7%	1.1%	1.5%	
2013-2022 (10 Yr Forecast)	1.6%	0.6%	0.9%	1.0%	
2013-2027 (15 Yr Forecast)	1.5%	0.6%	0.9%	0.9%	
2013-2032 (20 Yr Forecast)	1.5%	0.5%	1.0%	0.9%	

Table 3-54 - Commercial Energy Forecast Average Annual Growth Rates

6.4.5.1.3 Wholesale Annual

The wholesale energy forecast is developed as the sum of the four municipal utility energy models. No post model adjustments have been made to the energy forecast. However, two data points were removed from the Chetopa model. These data points are August and September 2010 as shown in *Figure 3-28*.

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Highly Confidential in its Entirety Figure 3-28 - Chetopa Bad Data

The total energy forecast is shown in *Figure 3-29*. *Tables 3-55* and *3-56* summarize the annual energy forecast and show the forecasts for each municipal utility for comparative purposes.



Highly Confidential in its Entirety Figure 3-29 - Wholesale Energy Forecast (Actual, Forecast)



Highly Confidential in its Entirety Table 3-55 - Wholesale Energy Forecast Summary

Time Period	Monett	Mt. Vernon	Lockwood	Chetopa	
2003-2012 (Historical)	1.9%	1.3%	0.1%	1.1%	
2008-2012 (Historical)	1.3%	0.0%	-0.3%	1.5%	
2013-2017 (5 Yr Forecast)	0.6%	0.8%	0.3%	0.1%	
2013-2022 (10 Yr Forecast)	0.6%	0.7%	0.4%	0.2%	
2013-2027 (15 Yr Forecast)	0.5%	0.6%	0.4%	0.3%	
2013-2032 (20 Yr Forecast)	0.5%	0.5%	0.4%	0.3%	

Table 3-56 - Wholesale Energy Forecast Average Annual Growth Rates

6.4.5.1.4 Street and Highway Annual

The street and highway energy forecast is developed as the product of the customer model and UPC forecast. No post model adjustments have been made to the energy forecast. However, nine data points were removed from the street and highway UPC model. These data point presented as large residuals and are listed below:

- 1. November 2001.
- 2. April 2004.
- 3. May 2004.
- 4. November 2005.
- 5. December 2005.
- 6. January 2006.

- 7. February 2006.
- 8. February 2007.
- 9. April 2011.

The annual energy forecast, customer forecast, and UPC forecast are shown in *Figures 3-30*, *3-31*, and *3-32*.

Tables 3-57 and *3-58* summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates. Because households and outside lighting efficiency are primary drivers in the street and highway forecast, *Table 3-58* includes the average annual growth rate for households and the lighting efficiency gains.



Highly Confidential in its Entirety Figure 3-30 - Street and Highway Annual Energy Forecast (Actual, Forecast)



Figure 3-31 - Street and Highway Customer Forecast (Actual, Forecast)



Highly Confidential in its Entirety Figure 3-32 - Street and Highway UPC Forecast (Actual, Forecast)


Highly Confidential in its Entirety Table 3-57 - Street and Highway Energy Forecast Summary

Time Period	Energy	Customer	Use-Per- Customer	Efficiency Gains Index	Households
2003-2012 (Historical)	0.4%	0.8%	-0.4%	2.8%	0.9%
2008-2012 (Historical)	0.1%	1.0%	-0.9%	2.3%	0.8%
2013-2017 (5 Yr Forecast)	0.6%	0.8%	-0.2%	0.8%	0.8%
2013-2022 (10 Yr Forecast)	0.5%	0.7%	-0.2%	0.7%	0.6%
2013-2027 (15 Yr Forecast)	0.5%	0.6%	-0.1%	0.5%	0.5%
2013-2032 (20 Yr Forecast)	0.4%	0.5%	-0.1%	0.5%	0.5%

Table 3-58 - Street and Highway Energy Forecast Average Annual Growth Rates

6.4.5.1.5 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 3-59* and *3-60* summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates.



Highly Confidential in its Entirety Figure 3-33 - Interdepartmental Annual Energy Forecast (Actual, Forecast)



Figure 3-34 - Interdepartmental Customer Forecast (Actual, Forecast)



Highly Confidential in its Entirety Figure 3-35 - Interdepartmental UPC Forecast (Actual, Forecast)



Time Period	Energy	Customer	Use-Per-
			Customer
2003-2012 (Historical)	2.3%	13.4%	-7.5%
2008-2012 (Historical)	4.0%	19.6%	-10.5%
2013-2017 (5 Yr Forecast)	0.0%	0.0%	0.0%
2013-2022 (10 Yr Forecast)	0.0%	0.0%	0.0%
2013-2027 (15 Yr Forecast)	0.0%	0.0%	0.0%
2013-2032 (20 Yr Forecast)	0.0%	0.0%	0.0%

Table 3-60 - Interdepartmental Energy ForecastAverage Annual Growth Rates

6.4.5.1.6 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 number of customers driven by household growth, but flat for average usage.

The annual energy forecast, customer forecast, and UPC forecast are shown in *Figures 3-36*, *3-37*, and *3-38*. *Tables 3-61* and *3-62* summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates.



Highly Confidential in its Entirety Figure 3-36 - Public Authority Annual Energy Forecast (Actual, Forecast)



Figure 3-37 - Public Authority Customer Forecast (Actual, Forecast)



Highly Confidential in its Entirety Figure 3-38 - Public Authority UPC Forecast (Actual, Forecast)



Energy Forecast Summary

Time Period	Energy	Customer	Use-Per-	Households
			Customer	
2003-2012 (Historical)	2.9%	2.2%	0.7%	0.9%
2008-2012 (Historical)	2.6%	1.2%	1.5%	0.8%
2013-2017 (5 Yr Forecast)	0.6%	0.6%	0.0%	0.8%
2013-2022 (10 Yr Forecast)	0.5%	0.5%	0.0%	0.6%
2013-2027 (15 Yr Forecast)	0.5%	0.5%	0.0%	0.5%
2013-2032 (20 Yr Forecast)	0.4%	0.4%	0.0%	0.5%

Table 3-62 - Public Authority Energy ForecastAnnual Growth Rates

6.4.5.1.7 Industrial Forecast

The industrial energy forecast is developed as sum of the Praxair, oil and pipeline, and other industrial forecasts. For all three segments, the forecast is designed to hold the number of customers in the industrial class constant through the forecast time horizon. However, the energy modeling is designed to provide seasonal shape to the energy forecast.

The annual energy forecast, customer forecast, and UPC forecast are shown in *Figures 3-39*, *3-40*, and *3-41*. *Tables 3-63* and *3-64* summarize the energy, customer, and UPC forecasts with annual energy for selected years and average annual growth rates.



Highly Confidential in its Entirety Figure 3-39 - Industrial Energy Annual Forecast (Actual, Forecast)



Figure 3-40 - Industrial Customer Forecast (Actual, Forecast)



Highly Confidential in its Entirety Figure 3-41 - Industrial UPC Forecast (Actual, Forecast)



Highly Confidential in its Entirety Table 3-63 - Industrial Energy Forecast Summary

Time Period	Energy	Customer	Use-Per- Customer
2003-2012 (Historical)	-0.1%	0.2%	-0.4%
2008-2012 (Historical)	-1.7%	-0.3%	-1.4%
2013-2017 (5 Yr Forecast)	0.0%	0.0%	0.0%
2013-2022 (10 Yr Forecast)	0.0%	0.0%	0.0%
2013-2027 (15 Yr Forecast)	0.0%	0.0%	0.0%
2013-2032 (20 Yr Forecast)	0.0%	0.0%	0.0%

Table 3-64 - Industrial Energy Forecast Average Annual Growth Rates

7.1.6.1.8 Peak Summer/Winter Month Energy

The peak summer and winter month energy forecast by residential, commercial, and industrial class are shown in *Figures 3-42* and *3-43*, respectively.

Highly Confidential in its Entirety Figure 3-42 - Peak Summer Calendar Month Energy, MWh

Highly Confidential in its Entirety Figure 3-43 - Peak Winter Calendar Month Energy, MWh

6.4.5.2 Class Level Coincident Peak Forecasts

6.4.5.2.1 System Level Peak

System level peaks are shown in Figures 3-44 and 3-45 for each season.

Highly Confidential in its Entirety Figure 3-44 - System Summer Gross Peak Forecast



Highly Confidential in its Entirety Figure 3-45 - System Winter Gross Peak Forecast

6.4.5.2.2 Class Level Coincident Peaks

The profile model results are used to obtain the class level coincident peaks. To obtain the peaks, the profile models are first calibrated to the energy forecast developed based on the energy models described in Section 7.1. Next, the system forecast is calibrated to the peak forecast developed. The final step in the forecast process is to identify the coincident peaks based on the profile models after they have been calibrated. The results are listed in *Tables 3-65* and *3-66* and shown in Figures 3-46 through 3-51 for the residential, commercial, and industrial classes.

Class level weather-normalized peaks for this historical period were developed by applying the class's historical share of the system peak to the normalized system peak. The method to obtain normalized residential, commercial, and industrial peaks is shown below:

1. Obtain class actual load research data for residential, commercial, and industrial classes and all other classes.

- 3. Sum load research data to obtain an estimated system loads (SumofClasses)
- 4. Find the RCI coincident peaks with the NetSystemLoads
- 5. Calculate the residential, commercial, and industrial percent based on the ratio of the coincident peaks (e.g. ResClass Peak/Net System) multiplied by the ratio of the NetSystemLoads to the SumofClasses load (i.e. Error Correction Factor).



Highly Confidential in its Entirety Figure 3-46 - Residential Coincident Summer Peak Forecast



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



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



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



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



Highly Confidential in its Entirety Figure 3-51 - Industrial Coincident Winter Peak Forecast





6.4.6 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 workpapers 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 Figures 3-52 through 3-59.



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



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



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

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



Highly Confidential in its Entirety Figure 3-56 - Forecasted Industrial Summer Peak Day Profiles



Highly Confidential in its Entirety Figure 3-57 - Forecasted Industrial Winter Peak Day Profiles



Highly Confidential in its Entirety Figure 3-58 - Forecasted System Summer Peak Day Profiles



Highly Confidential in its Entirety Figure 3-59 - Forecasted System Winter Peak Day Profiles

6.5 Describe and Document Forecasts of Independent Variables

(B) Forecasts of Independent Variables.

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

Historical and forecasts for independent variables utilized in the load forecast models are provided. Various economic indices are plotted in Figure 3-60. Electric prices, residential SAE indices, heating and cooling degree days, and commercial SE indices are plotted in Figures 3-61 through 3-64.





Figure 3-61 - Historical and Forecasted Electric Prices



Figure 3-62 - Historical and Forecasted Residential SAE Indices



Figure 3-63 - Historical and Forecasted IRP Normal Heating and Cooling Degree Days



6.5.1 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.

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Major independent variables are identified and plotted in Section 7.2 above. Economic variables are obtained from Economy.Com and end-use variables are from Itron's Energy Forecasting Group which processes data from the EIA.

6.5.2 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.

Forecasts were developed by Itron as described above.

6.5.3 Comparison of Forecast from Independent Variables to Historical Trends

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

The forecasts are compared to historical trends in the figures presented in Section 7.2 above.

In addition to the historical trends depicted above, longer historical (back to 1990) and IRP normal heating degree days and cooling degree days are listed in *Table 3-67* and depicted in *Figure 3-65* in comparison to actual historical values.

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пеа	ating Degree D	ays (HDD)
Year	Actual ¹	IRP Normals ²
1990	3,981	4,578
1991	4,197	4,578
1992	4,108	4,578
1993	4,925	4,578
1994	4,151	4,578
1995	4,521	4,578
1996	4,967	4,578
1997	4,864	4,578
1998	4,164	4,578
1999	3,945	4,578
2000	4,684	4,578
2001	4,337	4,578
2002	4,588	4,578
2003	4,541	4,578
2004	4,135	4,578
2005	4,270	4,578
2006	3,813	4,578
2007	4,103	4,578
2008	4,767	4,578
2009	4,577	4,578
2010	4,710	4,578
2011	4,587	4,578
2012	3,650	4,578
2013	,	4,578
2014		4,578
2015		4,578
2016		4,578
2017		4,578
2018		4.578
2019		4.578
2020		4,578
2021		4.578
2022		4.578
2023		4.578
2024		4.578
2025		4.578
2026		4.578
2027		4.578
2028		4 578
2029		4,578 4 578
2030		4,578
2031		4,578
2032		4,578 4 578
		-,-,-

approximation of normal degree days used in IRP forecasts

Table 3-67 - Historical and IRP Normal HDD and CDD



Figure 3-65 - Comparison of Heating and Cooling Degrees Actual Historical and 2007, 2010, and 2013 IRP Normal Normals

6.5.4 Judgment Applied to Modify Results

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

Post forecast adjustments were made to the residential and commercial forecast based on judgment.

The residential forecast was adjusted upward in 2012 through 2015 to reflect a slower than modeled adoption of end-use technologies resulting in slightly higher use per customer. After 2015, no further adjustments are used reflecting the belief that customers' end-use technologies are consistent with the EIA regional forecast. The adjustments used between 2012 and 2015 are shown below.

Year	Energy Increase per Month
	MWh
2012	4,000
2013	3,000
2014	2,000
2015	1,000

Table 3-68 - Residential Post Forecast Adjustments

The commercial forecast was adjusted downward by reducing the overall number of customers in the customer forecast based on judgment. The reduction considers the current number of customers and reduces the forecast model's result by 50 customers per year through 2015. After 2015, the 300 customer reduction is sustained through the forecast time horizon. The adjustments used between 2012 and 2015 are shown below

Year	Reduced Number of	
	Customer per Month	
2012	50	
2013	150	
2014	250	
2015 and Beyond	300	

Table 3-69 - Commercial Post Forecast Adjustments

6.6 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.

Empire produced an hourly forecast of each major class and the sum of these forecasts is the hourly forecast of Net System Input (NSI).

SECTION 7 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).

The high and low scenarios and the mild and extreme weather scenarios were created by Itron to address two key modeling assumptions (economics and weather). The results of the scenarios and analysis are presented in this section.

7.1 Two Additional Normal Weather Load Forecasts

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

The high and low scenarios were created to construct reasonable planning bounds around the base forecast. These bounds were created to capture economic and model uncertainty. The method relies upon alternative economic forecasts and increasing model error bounds through the forecast horizon. The results show a peak scenario difference of 198 MW between the high and low scenarios in 2030.

The base-case forecast uses an economic forecast developed by Economy.com in 2011. Of the data provided by Economy.com, the following five economic concepts are used throughout the sales forecast models:

- 1. Real personal income.
- 2. Population.

- 3. Households.
- 4. Employment.
- 5. Gross state product (GSP).

In this section, high and low cases are developed by changing the economic forecast and incorporating model error. The probabilities associated with the forecasts are estimated to be 50 percent for the base case and 25 percent for the high and low cases.

- 1. Economic Scenarios: High and low economic scenarios are used in creating the high and low case forecasts. In this section, the development of the economic scenarios used is discussed:
 - a. Low Economic Scenario: Economy.com provided a low economic scenario labeled "Below-Trend Long-Term Growth Scenario". Associated with this scenario were forecasts for real personal income, population, households, and employment. The low GSP series is developed by calculating the percent difference between the base and low employment series and applying the percent difference to the base GSP series. For example, if the difference between the base and low employment series is 1 percent, then the GSP low series is calculated as 1 percent below the GSP base series.
 - b. High Economic Scenario:
 - Economy.com did not provide a viable high economic scenario. Instead, Itron created a high economic scenario that mirrored the low economic scenario. The high scenario was created in three steps. First, the annual growth rates for each economic series were calculated for the base and low scenarios (e.g. base growth rate is 2 percent and low growth rate is 1.5 percent). Second, the difference between the base and low scenario growth rates was calculated (e.g. difference is 0.5 percent). Finally, the high scenario was created by summing the base growth rate with the calculated difference (e.g. high growth rate is 2 percent + 0.5 percent = 2.5 percent) and extrapolating the series through the forecast horizon.
 - 2) *Figure 3-66* shows the base, high, and low economic scenarios for the employment series. For all economic series, the average annual growth rates from 2013 through 2030 are shown in *Table 3-70*.



Figure 3-66 - High and Low Case Employment Scenarios

Economic Driver	Base	High	Low
Real Personal Income	2.11%	2.54%	1.76%
Households	0.53%	0.58%	0.48%
Population	0.56%	0.56%	0.56%
Employment	0.93%	1.07%	0.79%
Gross State Product	2.64%	2.78%	2.49%

Table 3-70 - 2013 to 2030 Average Annual Growth Rates

- 2. Model Error: In addition to economic variance, each forecast model contains model error which contributes to the overall high and low cases. By capturing the model error, the scenario bands are widened to account for a greater level of uncertainty.
 - a. Joint Model Confidence: Because multiple models are used in the sales forecast process, the model error is calculated by examining a model backcast. The following steps are used in determining the joint sales model error:
 - 1) Backcast: Each model is backcast to 2000 or to the start of the model estimation period.

- 2) Errors: Annual model errors (annual energy) are calculated by comparing the backcast with the actual sales.
- 3) Standard Deviation (Std Error): Based on the model errors, the standard deviation of the errors for each class is calculated.
- 4) Confidence Level (CL): For each class, the Std Error is multiplied by a critical value that translates the standard error to a confidence level. Two confidence levels are calculated. First, the critical value of 0.31 is used to represent a 25-percent confidence level. Second, the critical value of 1.645 is used to represent a 90-percent confidence level. For the 25-percent and 90-percent levels, a joint confidence (Joint CL) is approximated by combining the confidence levels for each class. The joint confidence is calculated as:

Jo int
$$CL = \sqrt{\sum_{Class} Class}$$

a) The results of the calculation are shown in *Table 3-71*. Using a 25-percent confidence level, the annual sales to be added or subtracted from the forecast is 10,811 MWh per year. Using a 90-percent confidence level, the annual sales to be added or subtracted from the forecast is 57,368 MWh per year.

Dendel	Standard Error	25% Confidence	90% Confidence
Model	(ivivn)	Interval (IVIWh)	Interval (IVIWh)
Residential	29,740	9,219	48,923
Commercial	13,398	4,153	22,040
Street/Highway	278	86	458
Interdepartmental	64	20	106
Public Authority	1,353	419	2,226
Other Industrial	11,203	3,473	18,429
Oil/Pipeline	2,177	675	3,581
Praxair	2,744	851	4,514
Monett	3,327	1,031	5,473
Mt. Vernon	1,186	368	1,950
Lockwood	107	33	176
Chepota	157	49	258
Annual Total		10,811	57,368

Table 3-71 -	Joint	Confidence	Results
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- b. Applying Confidence Levels to the Sales Scenarios:
 - Traditionally, statistical confidence bands are determined by adding or subtracting the confidence level to the forecast to create fixed bands through the forecast horizon. For example, the 90-percent confidence level would be captured by adding or subtracting 57,368 MWh from the base-case forecast in all years resulting in fixed width bands.
 - 2) In discussions with Empire staff, Itron and Empire chose to deviate from this method to create bands that broadened to the 90-percent confidence level through the forecasting horizon. To achieve broadening this band, 10,811 MWh is added and subtracted in 2013 to the high and low economic sales forecasts. The 10,811 MWh is linearly increased to 57,368 MWh in 2030 and held constant after 2030. This band is show in *Figure 3-67*. This method results in a broadening of scenarios through time and is designed to represent growing uncertainty.



Figure 3-67 - Broadening Error Band

c. Applying Confidence Levels to the Peak Scenarios: Similar to the sales model scenarios, the peak scenarios are developed to be consistent with the sales model scenarios. Because the peak model uses the sales forecast as an independent variable, the peak forecast inherently contains the updated economic and sales error assumptions. In addition to these

drivers, the peak models include the peak model standard error (46 MW) developed with the same 25-percent and 90-percent critical values used in the sales model.

- 3. Scenario Results: The high and low cases are designed to reasonably capture the forecast variance due to changing economic conditions and model uncertainty. The overall modeling framework includes both the economic and model uncertainty. The framework is summarized below:
 - a. Sales Forecast Alternative Economics: The sales models were run using the alternative economic scenarios.
 - b. Sales Forecast Apply Broadening Confidence Levels: Once the sales forecasts are calculated with the alternative economic scenarios, the broadening sales confidence band (10,811 MWh to 57,368 MWh) is applied to the high and low sales forecasts.
 - c. Peak Forecast: The peak forecast model is run with the high and low sales forecast (Step 2) to obtain the initial high and low peak forecasts.
 - d. Peak Forecast Apply Broadening Confidence Levels: Once the peak forecasts are calculated (Step 3), the broadening peak band based on the standard error of the peak model is applied to the peak forecast. The high and low case sales forecast results are shown in *Figure 3-68* with annual results shown in *Table 3-72*.

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Highly Confidential in its Entirety Figure 3-68 - High and Low Case Sales Forecast (MWh)



Annual Billed Sales (MWh)

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e) The high and low case peak forecast results are shown in *Figure 3-69* with annual results shown in *Table 3-73*.



Highly Confidential in its Entirety Figure 3-69 - High and Low Case Peak Forecast (MW)



Table 3-74 and *Figure 3-70* show the 2013 IRP base, high, and low managed peak (demand) forecast for the IRP planning horizon. This includes the impacts of Empire's existing DSM. Also presented is Empire's base forecast less estimated future DSM based on the realistically achievable potential (RAP) case from Empire's preferred resource plan. The actual values in the graph are not weather normalized.

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Highly Confidential in its Entirety Figure 3-70 - Managed Peak Demand Forecast

Similarly, *Table 3-75* and *Figure 3-71* show the 2013 IRP base, high, and low net system input (NSI) or energy forecast for the study horizon. This includes the impacts of Empire's existing DSM. Also presented is the base forecast less estimated future DSM based on the realistically achievable potential (RAP) case from the preferred resource plan. The actual values in the graph are not weather normalized.



Highly Confidential in its Entirety Table 3-75 - Net System Input Energy Forecast



Highly Confidential in its Entirety Figure 3-71 - Net System Input Energy Forecast

7.2 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 were created to capture the uncertainty associated with weather conditions. The weather scenarios were based on a 1 in 10 occurrence. The results show a peak scenario difference of 292 MW between the mild and extreme scenario in 2030.

The base case is driven by normal monthly HDDs and CDDs based on a 30-year average (1981 to 2010) 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.

1. Weather Scenarios Definitions: Three types of weather are used in the forecasting process. Monthly HDD and CDD values are used in the sales model

to develop the long-term monthly sales forecast. Monthly peak producing temperatures are used in the peak model to develop the long-term monthly peak forecast. These two forecasts are combined together with hourly load shapes to produce the hourly forecast. The hourly load shapes use a daily normal weather pattern. In this section, the weather modifications to create the mild and extreme weather scenarios are described:

- a. Monthly HDD and CDD Scenarios: The mild and extreme monthly HDD and CDD scenarios are derived based on 30 years of annual historical HDD and CDD values with a temperature reference point of 65 degrees. The process of identifying and developing the monthly scenarios includes three steps:
 - Step 1 Annual Base Scenario: From the base scenario, the annual HDD and CDD values using a temperature reference point of 65 degrees were identified.
 - 2) Step 2 Identify 1 in 10 Scenarios: Using 30 years of historic weather data, annual HDD and CDD values were created and sorted from low to high as shown in *Figures 3-72* and *3-73*. Based on the ranking of the data, the 1 in 10 high and low cases were identified as the third warmest or coolest years. HDD scenario values use 1990 for the mild case and 2006 for the extreme case. CDD scenario values use 2009 for the mild case and 2006 for the extreme case. The annual degree day values for these scenarios are shown in *Table 3-76*.





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

Figure 3-73 - Mild and Extreme Annual CCD Base 65 Scenarios

Scenario	HDD65	CDD65
Base	4,510	1,305
Mild	4,136	1,036

Scenario	HDD65	CDD65
Extreme	4,892	1,609

 Table 3-76 - Scenario Annual Degree Days

3) Step 3 - Monthly HDD and CDD Values: While Step 2 provides the annual HDD and CDD values for the scenarios, the models require monthly HDD and CDD values. Two steps are used to obtain these values. First, the ratio between the scenario and base case annual degree days is calculated. For example, the ratio between the annual base and mild HDD value is 0.917 (i.e. 4,136/4,510). Second, the ratio is applied to the monthly base degree days are used. For example, if the monthly base HDD value is 100-degree days, then the mild HDD value for the same month would be 91.7-degree days. This results in monthly HDD and CDD patterns that are consistent with the base scenario, but higher or lower depending on the mild or extreme ratios. Results are shown in *Figures 3-74* and *3-75*.



Figure 3-74 - Mild and Extreme Monthly HDD Base 65 Scenarios



Figure 3-75 - Mild and Extreme Monthly CDD Base 65 Scenarios

- b. Peak Producing Temperatures: The mild and extreme monthly peak scenarios are derived based on 10 years of historical (2001 to 2011) peak producing weather. The process of identifying and developing the peak scenarios are discussed in the following two steps:
 - 1) Step 1 Identify Scenario: Monthly historical peak producing weather is sorted from high to low in each month. To obtain the 1 in 10 scenario, the high or low temperatures are identified for each month. Based on 10 years, the high or low temperatures are either the warmest or coldest year in the 10-year span. The mild scenario is driven by the warmest weather in the winter and the coolest weather in the summer. The extreme scenario is driven by the coldest weather in the winter and the warmest weather in the summer. April is considered a winter month and October is considered a summer month.
 - 2) Step 2 Manual Adjustment: January 2006 contained a mild winter where the peak producing temperature was 42 degrees. Because this temperature was milder than all other mild scenario in December, February, and March, the data point was removed in favor of the next mildest temperature point. No other manual adjustments were made to obtain a consistent monthly profile. The results are shown in *Figure 3-76* and *Table 3-77*.





Month	Base	Extreme	Mild
Jan	11.25	3.58	17.29
Feb	18.52	6.54	31.88
Mar	32.6	21.97	45.71
Apr	40.69	29.83	51.54
May	75.22	79.58	73.33
Jun	80.93	84.25	77.26
Jul	83.99	89.42	79.23
Aug	87.64	93.04	80.46
Sep	77.9	87.79	73.79
Oct	72.31	76.83	74.96
Nov	30.02	25.00	36.38
Dec	19.88	14.38	34.75

Table 3-77 - Scenario Monthly Peak Producing Temperatures

- c. Daily Temperature Profile: Daily temperature profiles are used to obtain the hourly profiles for each class. These profiles are calibrated to the monthly energy and peak forecast values. Through the calibration process, the final hourly results will contain the mild and extreme scenario weather. As a result, no daily temperature scenarios had to be created.
- 2. Scenario Results:
 - a. The scenarios are created by using the base-case forecast models and replacing the base-case weather with the mild and extreme weather scenarios. To the extent that a model includes weather variables (e.g residential UPC), these models produced alternative forecasts. Models that do not use weather variables (e.g. residential customer counts) result in an unchanged forecast.
 - b. The mild and extreme case sales forecast results are shown in *Figure 3-77* with annual results shown in *Table 3-78*. In this view, forecasts are close to symmetrical due to the similarities of the mild and extreme monthly HDD and CDD values. For example, the HDD values in the extreme case are 8.5-percent higher than the base and the mild case is 8.3-percent lower than the base.



Highly Confidential in its Entirety Figure 3-77 - Mild and Extreme Weather Scenario: Sales Forecast Comparison (MWh)





c. The mild and extreme case peak forecast results are shown in *Figure 3-78* with annual results shown in *Table 3-79*. In this view, forecasts appear asymmetrical due to the difference in mild and extreme scenarios. The asymmetry is caused by the summer peak temperature in the extreme case being 6.2-percent higher than the base, while the mild case is 8.2-percent lower than the base.

Highly Confidential in its Entirety Figure 3-78 - Mild and Extreme Weather Scenario -Peak Forecast Comparison (MW)





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7.3 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.

7.3.1 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 3-80* and shown in *Figures 3-79* and *3-80*. The historical and forecast summer and winter peak demands are listed in *Table 3-81* and shown in *Figure 3-81*.

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Highly Confidential in its Entirety Table 3-80 - Historical and Forecast Summer, Winter, and Total Billed Energy Use (MWh)





Highly Confidential in its Entirety Figure 3-79 - Historical and Forecast Summer and Winter Billed Energy Use (MWh)



Highly Confidential in its Entirety Figure 3-80 - Historical and Forecast Total Billed Energy Use (MWh)



Highly Confidential in its Entirety Figure 3-81 - Historical and Forecast Summer and Winter Gross Peaks (MW)

7.3.2 Base, Low, and High Forecast

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 low, base, and high, mild, and extreme scenarios are shown in *Figures 3-82* through *3-84*, respectively. The extreme and mild cases are weather scenarios using the base case economic forecast. The high and low cases are economic scenarios using the base case weather forecast. The data are revenue year sales. The historical and forecast for the summer, winter, and annual, respectively weather peak demands under the low, base, and high scenarios are shown in *Figures 3-85* through *3-87*.



for Base, Low, High, Mild, and Extreme Scenarios (MWh)

****Highly Confidential in its Entirety**** Figure 3-83 - Historical and Forecast Winter Billed Energy for Base, Low, High, Mild, and Extreme Scenarios (MWh)



for Base, Low, High, Mild, and Extreme Scenarios (MWh)

Highly Confidential in its Entirety Figure 3-85 - Historical and Forecast Summer Gross Peak for Base, Low, High, Mild, and Extreme Scenarios (MW)





Highly Confidential in its Entirety Figure 3-87 - Historical and Forecast Annual Gross Peak for Base, Low, High, Mild, and Extreme Scenarios (MW)