3. Load Analysis and Forecasting[1]

Highlights

- *Ameren Missouri expects energy consumption to grow 23% and peak demand to grow 18% over the next 20 years.*
- *The commercial class is expected to provide the most growth while federal efficiency standards slow residential growth compared to historical trends.*
- *The estimated range of peak demand uncertainty is 2,183 MW in 2030.*
- *Key forecast uncertainties include growth in miscellaneous plug load, the adoption of electric vehicles, and the impact of rising prices.*
- *Significant enhancements have been made throughout the forecasting process to include more end-use detail.*

Ameren Missouri has developed a range of load forecasts consistent with the scenarios outlined in Chapter 2. These load forecasts provide the basis for estimating Ameren Missouri's future resource needs and provide hourly load information used in the modeling and analysis discussed in Chapter 9. In addition, the Statistically Adjusted End-use forecasting tools and methods used to the develop the forecasts provided a solid analytical basis for testing and refining the assumptions used in the development of the potential demand-side resource portfolios discussed in Chapter 7. The energy intensity of the future economy and the inherent energy efficiency of the stock of energy using goods are explored throughout the analysis to arrive at reasonable estimates of high, base, and low load growth.

3.1 Energy Forecast

This chapter describes the forecast of Ameren Missouri's energy, peak demand, and customers that underlies the analysis of resources undertaken in this IRP. In order to account for a number of combinations of possible economic and policy outcomes, ten different forecasts were prepared. Based on the subjective probabilities of these scenarios identified by Ameren Missouri, an eleventh case was developed to represent the base, or planning case for the study. The planning case forecast projects Ameren Missouri's retail sales to grow by 1.09% annually between 2010 and 2030, and retail peak demand to grow by 0.91% per year.

[1] 4 CSR 240-22.030(8)(H)

As with any forecast of energy, there are several underlying assumptions. Expectations for economic growth underlying the load forecast are from Moody's Analytics' (formerly Economy.com) forecast of economic conditions in the Ameren Missouri service territory. Expectations about future energy market conditions, such as fuel prices and the impact on electricity prices of different environmental policy regimes are based on modeling results from Charles River Associates (CRA) and their interviews with internal Ameren subject matter experts.

Compared to Ameren Missouri's last IRP, filed in 2008, both the level and the growth rate of the forecast are lower. In the 2008 IRP, the 2010 sales were expected to be 39,623 GWh, as compared to an expectation at the time of forecast in this IRP of 38,110 GWh. The initial level of sales is lower primarily because the unusually severe recession that Missouri and the US experienced between 2007 and 2009, and the impact that has had on energy consumption. The 1.09% growth rate in retail sales for the 2010-2030 time period in this filing is also lower than the 1.48% retail sales growth rate expected for the same time period in the 2008 IRP forecast largely due to the effects of energy efficiency codes and standards, many of which were established as a part of the Energy and Information Security Act of 2007 (EISA 2007) after the 2008 IRP forecast had been prepared. Finally, expectations of higher energy prices than were contemplated in the 2008 filing also slow the rate of growth through assumed customer conservation efforts.

It should be noted that in the development of this forecast, only the underlying growth of energy efficiency due to market conditions was included. The energy efficiency impacts of Ameren Missouri's energy efficiency and demand side management (DSM) programs were calculated in a separate and parallel process and then added to forecast results. So the energy efficiency changes embedded in the energy forecasts presented in this section of the IRP are only the result of changes other than Ameren Missouri's specific programs, such as changes to Federal law, or changes in consumer behavior. The impacts of Ameren Missouri's measureable DSM and energy efficiency programs are included in the IRP and thus affect the choice of the optimal supply side plan, but were not part of the load forecast process. For that reason Ameren Missouri's DSM and energy efficiency programs are not discussed in forecasting section of the IRP documentation. They are discussed in great detail in Chapter 7.

The modeling of carbon policy and the other critical dependent uncertain factors is another key difference between this IRP and the 2008 IRP. For this IRP, ten scenario forecasts were produced based on different assumptions about the future path of load growth, natural gas prices, and carbon policy. Those scenarios and their development are discussed in more detail in section 3.1.5.

3.1.1 Historical Database

Ameren Missouri tracks its historical sales and customer counts[2] by revenue class (Residential, Commercial, and Industrial)[3], and also by rate class (Small General Service, Large General Service, Small Primary Service, and Large Primary Service). Ameren Missouri uses these rate classes as the sub-classes for forecasting, both because the data is readily accessible from the billing system and because it provides relatively homogeneous groups of customers in terms of size[4]. Historical billed sales are available for all rate and revenue classes back to January 1995[5]. At the time of the preparation of the load forecast for this IRP, historical sales were known through December of 2009. Except as noted later in this document, any data presented for 2010 or beyond is forecasted data and data from 2009 and earlier is actual metered sales data. Historical energy consumption and customer count data is available in the Appendix to Chapter 3[6].

Ameren Missouri routinely weather normalizes the observed energy consumption of its customers to remove the impact of unusual weather patterns. The process for weather normalizing sales is described in section 3.3, and weather normalized historical consumption from 1995 forward is also reported in the Appendix[7]. In Ameren Missouri's 2008 IRP, the historical sales for the wholesale class were normalized to remove the load associated with expired contacts. The load data in this IRP starts with that historical data set and reports sales from that point forward based on the mix of wholesale customers that existed at the time.

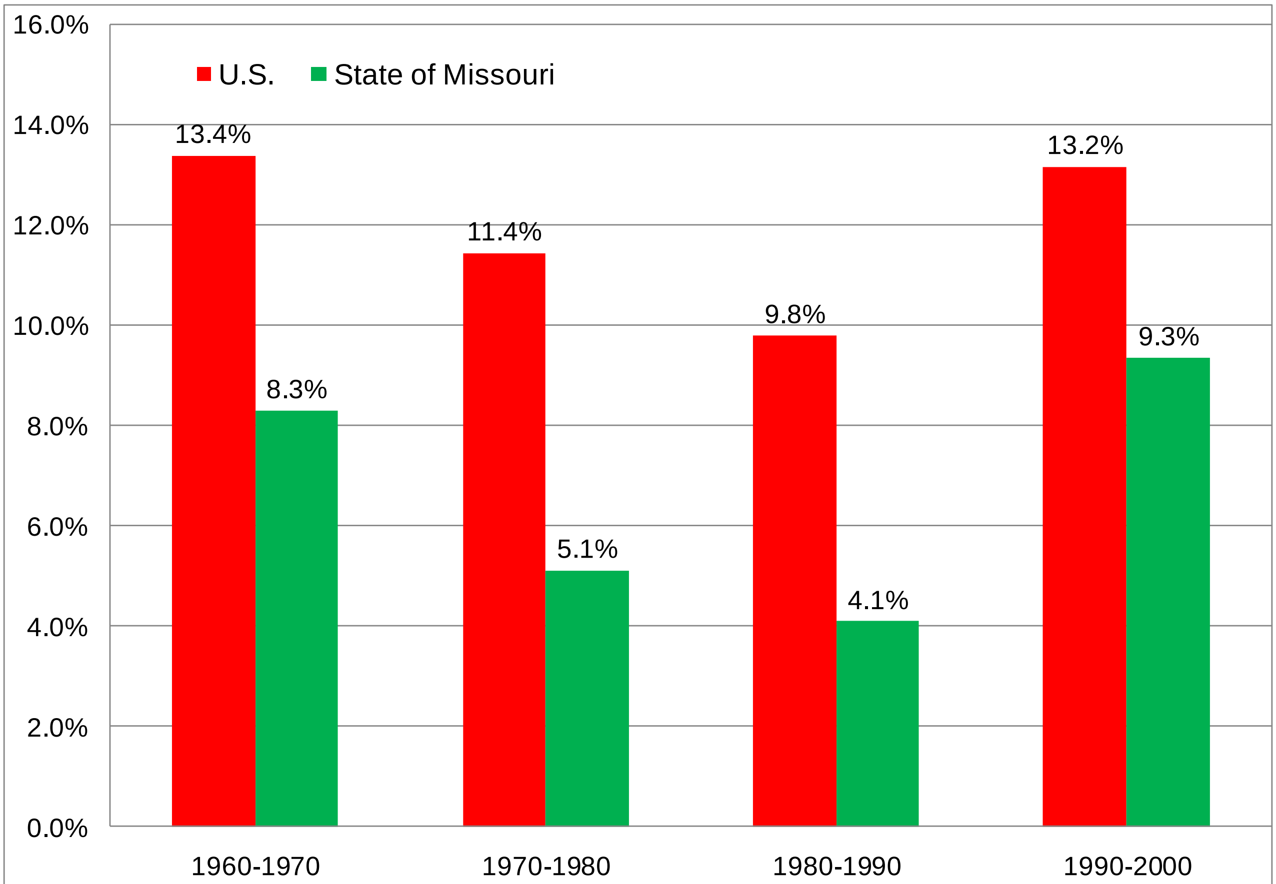
The appendix includes use per unit energy sales and demand data for all classes[8]. In each case, the unit included in the analysis is the customer count for the class. This is selected because it is a measured value for each class that is accessible and meaningful in all cases[9].

3.1.2 Service Territory Economy

The Ameren Missouri electric service territory is comprised of 59 counties in eastern and central Missouri (It should be noted, however, that although Ameren Missouri serves customers in 59 counties, it does necessarily not serve every electric customer in those counties). As would be expected, the level of sales is highly correlated with the behavior of the economy in the service territory.

[2] 4 CSR 240-22.030(1)(B)1
[3] 4 CSR 240-22.030(1)(A)
[4] 4 CSR 240-22.030(1)(A)1-2
[5] 4 CSR 240-22.030(1)(D), 4 CSR 240-22.030(1)(D)1
[6] 4 CSR 240-22.030(1)(B)1
[7] 4 CSR 240-22.030(1)(B)1
[8] 4 CSR 240-22.030(1)(C)
[9] 4 CSR 240-22.030(1)(C)1, 4 CSR 240-22.030(5)(B)2

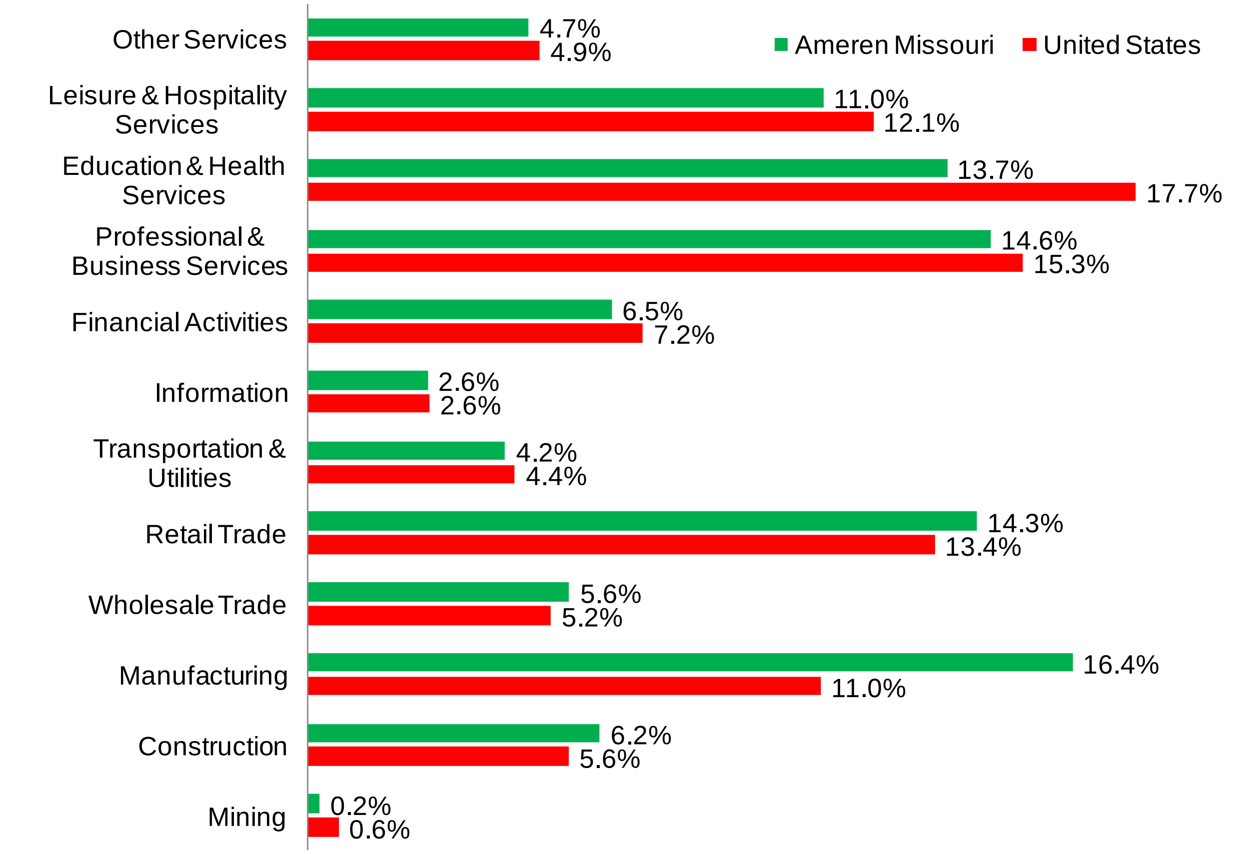
Figure 3.1: US and Missouri Population Change by Decade



Source: US Census Bureau

Historically, the Ameren Missouri service territory has been characterized by slower demographic growth than the US as a whole. In that respect, the service territory's economy is not terribly different from most other Midwestern states and metropolitan areas. Like much of the Midwest, the region's economy was based on manufacturing for many years, but over the past several decades the share of the territory's employment in manufacturing has been declining while employment in services, particularly health care, has grown. So although the service territory still has a higher than average share of employment in manufacturing, it is no longer the employment growth engine it once was. The allocation of service territory employment by NAICS sector is shown in Figure 3.2; a list of some of the largest employers in the service territory is in Table 3.1.

Figure 3.1: US and Ameren Missouri Service Territory Employment by Industry



Source: Moody's Analytics

The territory's major employers are spread across a number of different industries, but the region's single biggest employer is a hospital system, BJC Healthcare. Two other healthcare systems and three universities are among the largest employers in the territory, highlighting the importance of the health and education services to both the growth and level of employment, as well as to electricity sales.

As noted above, the service territory economy has grown at a slightly slower pace than the US as a whole because of slower demographic growth. In addition to the trend of slower demographic growth, the St. Louis region did not experience as big of a boost from the housing bubble as some other markets did.

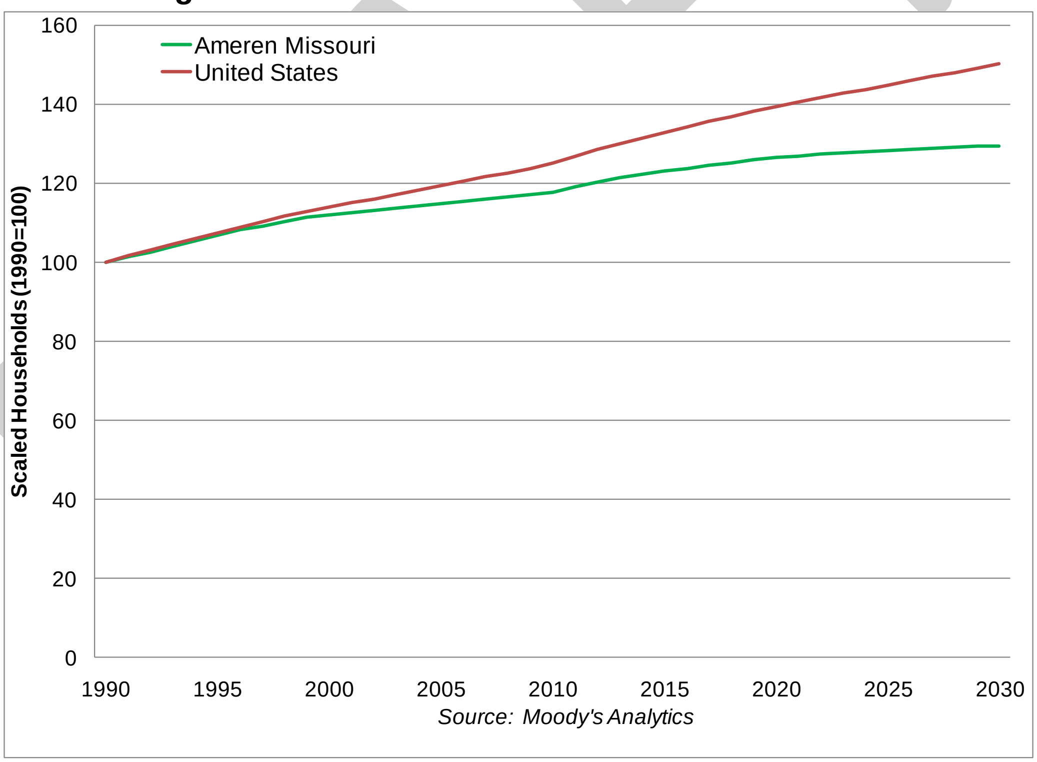
The service territory economy also contains a number of nationally know financial firms, including Stifel Financial, Scottrade, and Edward Jones. These firms, however, were not among those that garnered headlines during the financial crisis in 2008.

Table 3.1: Major Employers in the Ameren Missouri Service Territory

Employer	Industry	Number of Employees
BJC Healthcare	Education & Health	23,378
Boeing Integrated Defense Systems	Manufacturing	16,600
Wal- Mart Stores, Inc	Retail Trade	13,400
Washington University	Education & Health	12,390
SSM Health Care System	Education & Health	12,102
Schnuck's Markets	Retail Trade	11,000
AT & T Incorporated	Information	8,990
St. John's Mercy Health Care	Education & Health	8,876
University of Missouri Columbia	Education & Health	8,188
Saint Louis University	Education & Health	8,016
McDonald's	Leisure & Hospitality	8,000
AB InBev	Manufacturing	6,000
Dierberg's Markets	Retail Trade	5,000
Edward Jones	Financial Activities	4,422

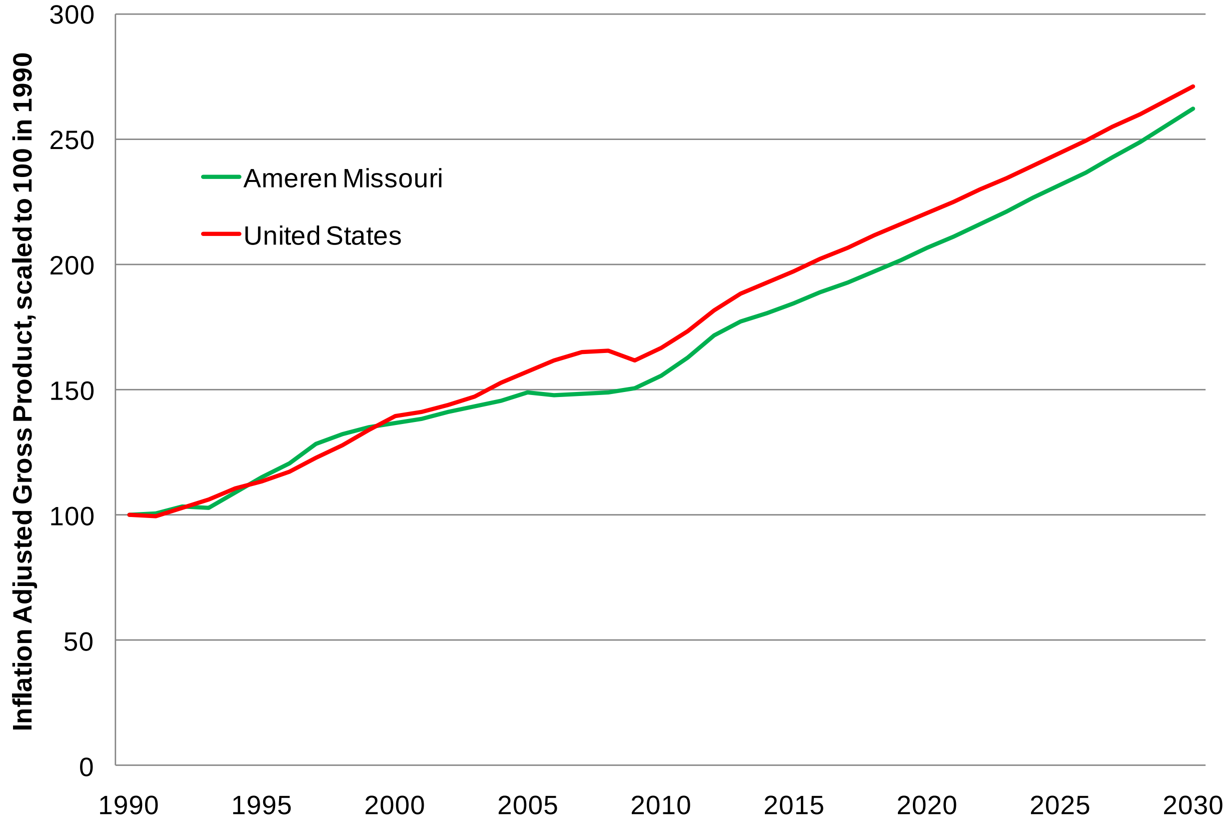
Source: Moody's Analytics

Figure 3.3: US and Ameren Missouri Households



Going forward Ameren Missouri expects that the service territory economy will recover apace with the US economy. Moody's Analytics predicts, and Ameren Missouri concurs, that the number of households will grow at an accelerating pace in 2011 and 2012 before slowing in the longer term. The acceleration in 2011 and 2012 is a rebound from 2009-2010, when weak housing and labor markets slowed household formation to a below trend rate; as labor markets recover and home prices remain low household formation should increase at an above trend rate for a time. In both the short and the longer term, however, the number of households in the Ameren Missouri service territory will likely grow at a slower rate than in the US as a whole.

Figure 3.4: US and Service Territory GDP



Source: Moody's Analytics

Commercial sales are expected to be boosted by increased household formation and the attending demand for retail services as well the fact that the region's major employers in healthcare, education, and financial services are billed in our commercial class.

Long term risks to the service territory economic outlook include further declines in manufacturing such as the closure of the GM plant in Wentzville or the end of fighter aircraft production at Boeing. Upside risks would include faster population growth due to the area's low cost of living, faster than expected growth in the life sciences and financial sectors in the region, or faster than expected growth of energy intensive commercial customers such as data centers.

3.1.3 Economic Drivers[10]

Several specific economic indicators were used as independent variables (independent variables in the forecasting models are often referred to as "drivers") in our energy forecasting process.

For the residential class income, population, and the number of households in the service territory were used as drivers. For forecasts of commercial class sales, service territory GDP disaggregated by major industry group (NAICS sector), such as financial activities, educational & health services or professional & business services depending upon which sector or combination of sectors best correlates with each rate class' sales were used[11]. For the forecast of industrial class sales, manufacturing employment and GDP were used as drivers depending upon the rate class and scenario. Table 3.2 illustrates key drivers and their expected growth over the IRP horizon[12].

Table 3.2: Growth Rates of Selected Economic Drivers

Economic Driver	CAGR, 2010-2030
Real Personal Income	1.9%
Population	0.4%
Households	0.5%
GDP	2.6%
Manufacuring GDP	3.5%
Employment	0.6%
Manufacturing Employment	0.1%

Source: Moody's Analytics

Noteworthy in the forecast is the robust growth in manufacturing GDP. Moody's Analytics forecast is for manufacturing output to grow faster than output in the other sectors of the service territory economy, but for manufacturing employment to grow slower than employment in the other sectors. This implies that service territory manufacturing will become more productive with respect to labor over the IRP forecast horizon. That implication is an important risk factor to the energy forecast. If industrial energy sales are closely correlated with manufacturing employment, then they will decline. If sales are more closely correlated with output, then they will grow more rapidly. The preferred strategy would be to let the past be the prologue in determining which variable to use, but in the past few years (specifically the time frame over which the forecasting models are estimated), manufacturing employment and output declined together. Therefore the effect of the predicted divergence is difficult to model. One could make a case for either variable as a driver, but if productivity growth is due to the

[10] 4 CSR 240-22.030(2)(A)
[11] 4 CSR 240-22.030(2)(C)
[12] 4 CSR 240-22.030(5)(B)1.A

replacement of workers with electricity consuming capital equipment, than output may be a better predictor of industrial electricity sales. As discussed below, this uncertainty was used to help shape the high, base, and low load growth scenarios.

The uncertainty about industrial sales is not the only source of uncertainty related to the economic drivers. The growth in residential sales over the next several years is dependent upon growth in households and the growth in use per household. Obviously, then, unforeseen changes in the number of households would cause changes in the amount of residential electricity demand.

3.1.4 Energy Forecasting[13]

This forecast of Ameren Missouri energy sales was developed with traditional econometric forecasting techniques, as well as a functional form called Statistically Adjusted End-Use (SAE). In the SAE framework, variables of interest related to economic growth, the price of electricity, and energy efficiency and intensity of end-use appliances, are combined into a small number of independent variables, which are used to predict the dependent variable (typically energy sales or sales per customer by class). The SAE framework was used to forecast energy sales in our residential general service rate class, and for all four of our commercial rate classes.

Statistically Adjusted End-Use (SAE)[14]

The advantage of the SAE approach is that it combines the benefits of engineering models and econometric models. Engineering models, such as REEPS, COMMEND and INFORM, modeled energy sales with a bottom up approach by building up estimates of end use by appliance type, appliance penetration, and housing unit or business type. These models are good at forecasting energy because they can be used to estimate the effects of future changes in saturations or efficiency levels, even if the changes are not present in observable history. In a traditional econometric model, it can be difficult to model precisely how the changing appliance efficiency standards will affect sales if the standards have been unchanged during the estimation period.

Econometric models, however, are estimated rather than calibrated, and it is easier to detect and correct any systematic errors in the forecasting model. For that reason, a system that combines the bottom up approach of engineering models with an econometric approach should produce more accurate forecasts. The SAE approach allows us to do that for our residential and commercial class sales. For the industrial classes, we used an econometric approach that was influenced by the SAE approach.

The SAE framework used in this forecast was developed by ITRON, a consulting firm Ameren Missouri has worked with for many years. In it there are specific end uses for

[13] 4 CSR 240-22.030(2)(B), 4 CSR 240-22.030(5)(B)2.A
[14] 4 CSR 240-22.030(3)(A)1-4

which saturation and efficiency must be estimated, as well as a miscellaneous category. The residential end uses are heating, cooling, water heating, cooking, two refrigeration (primary and secondary), freezers, dishwashing, clothes washing, clothes drying, television, lighting, and miscellaneous. For the commercial class, the end uses are heating, cooling, ventilation, water heating, cooking, refrigeration, outdoor lighting, indoor lighting, office equipment, and miscellaneous[15].

To predict future changes in the efficiency of the various end uses for the residential class[16], an excel spreadsheet model obtained from ITRON was utilized. That model contains stock accounting logic that projects appliance efficiency trends based on appliance life and past and future efficiency standards. The model embeds all currently appropriate laws and regulations regarding appliance efficiency, along with life cycle models of each appliance[17]. The life cycle models are based on the decay and replacement rates, which are necessary to estimate how fast the existing stock of any given appliance turns over and newer more efficient equipment replaces older less efficient equipment. The underlying efficiency data is based on estimates of energy efficiency from the US Department of Energy's Energy Information Administration (EIA). The EIA estimates the efficiency of appliance stocks and the saturation of appliances at the national level and for the Census Regions.

Missouri is in the West North Central Census region, so data for that Census Region is the default information provided in Itron's spreadsheet analysis. That raises some interesting issues for our forecast, however, as Missouri is at the southern end of the West North Central region, and Ameren Missouri's service territory is probably more urbanized than the bulk of the region and also has a generally warmer climate. Fortunately there were several sources of primary data and more closely related secondary data available to use to customize the analysis. The structure of the end-use analysis spreadsheets allows the utility to customize the saturation trends and efficiency trends to local data. The trends in future efficiency of the various end uses that are ultimately used in the sales forecast were based on the relationships that EIA has developed and Itron has analyzed that characterize the tradeoff between upfront capital costs and ongoing operating costs. Those relationships apply generally to the census region, but utility specific energy costs are introduced into the tradeoff equation in order to generate a forecast of the marginal efficiency mix that will be observed in the future in Ameren Missouri's service territory. The stock accounting mechanism then is used to

[15] 4 CSR 240-22.030(3)(A)1-4

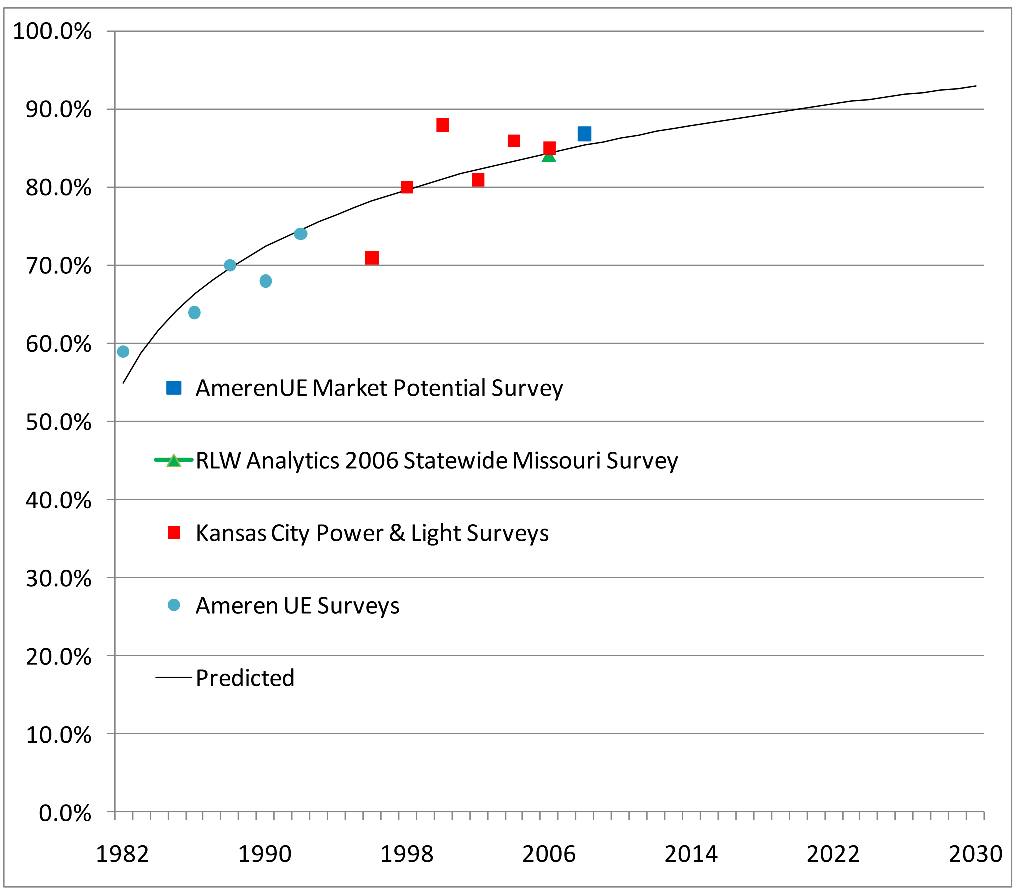
[16] For the Commercial class, the stock accounting spreadsheet has not been made available from Itron. Additionally, saturation survey data was not available from additional sources to supplement the 2009 Ameren Missouri Market Potential Study. For these reasons, the trends from the West North Central region EIA data were more heavily relied on for the Commercial classes, although that data was adjusted to match the saturations and building type mix from the Market Potential Study in 2009.

[17] EO-2007-0409 – Stipulation and Agreement #10

translate that marginal efficiency of new stock into an average efficiency forecast for the end use for the entire customer base.

The saturation trends for the end use appliances from the Census Region were generally discarded in the residential analysis in favor of more locally relevant information. The primary source for up to date saturation information was the Ameren Missouri Market Potential Study survey conducted by Global Energy Partners in 2009[18]. This study was conducted in order to provide primary data for Ameren Missouri's energy efficiency and demand side management programs. The results of the survey, however, represent only one point in time. Since a historical and forecast time series of appliance saturations are necessary for the SAE forecasting models, some additional information was utilized in order to develop the saturation trends.

Figure 3.5: Air Conditioning Saturation, Survey Data Points and Fitted Curve



Three other sources of survey information were used to complement Ameren's Market Potential Study survey and make the process of developing the saturation trend time series easier and more accurate. One was a series of surveys conducted by Ameren Missouri (then Union Electric Company) of its service territory households between 1982

[18] 4 CSR 240-22.030(3)(B)1

and 1992. Next, a series of surveys of its households conducted by Kansas City Power and Light between 1996 and 2006 and published publicly in their IRP document was used. The geographic proximity of KCP&L to Ameren Missouri is much better than the entire West North Central Census Region and the demographic make-up is more similar, and therefore it is a preferable source of secondary data to the EIA information. Finally, information from a statewide survey of Missouri households conducted by RLW Analytics in 2006 was also incorporated. The Ameren Market Potential Study was conducted in 2009, so a set of observations spanning the period between 1982 and 2009 was ultimately available. The approach used to develop the complete time series of saturation data for the historical and forecast period was to plot the points from all four survey sources and then fit a curve through the points. This methodology took advantage of all of the best information available and resulted in what is almost certainly a more accurate representation of the Ameren Missouri customer base than the regional EIA data. Figure 3.5 is a graph of this process for residential central air conditioning. In this case, one can see how this approach allows the incorporation of different survey data, and also allows us to incorporate a trend in saturation that is reasonable – in this case growth at a decreasing rate. In the example above for central air conditioning, this methodology predicted a saturation of 92.9% in 2030[19].

Appliance saturation and efficiency data is an obvious and important explanatory variable in modeling electricity sales, but there are other important variables that need to be included. Other logical predictors of electricity sales include the number of households in the service territory, income, and weather. Although this sales forecast is based on 30 year normal weather, actual historical weather is used to estimate model coefficients.

In the SAE framework, elasticities with respect to price and income are determined exogenously and included in the calculation of the independent variables. The estimation of price and income elasticities is a complicated subject, and, especially with regard to price elasticity, there is a great deal of literature on the subject. One paper that was reviewed identified 36 different studies with 123 estimates of short run residential price elasticity, and those estimates ranged from -2.01 to -0.004. (Epsey, James A. and Molly Espey. "Turning on the Lights: A Meta-Analysis of Residential Electricity Demand Elasticities." Journal of Agricultural and Applied Economics, 36, 1 (April 2004):65-81.).

Ameren Missouri's approach to estimating elasticity parameters for each model was to start with a figure that was close to a central tendency from the literature reviewed where possible, incorporating recommendations from the consultant firm Itron where necessary to supplement the available information[20]. After determining an appropriate starting point, the elasticity parameters were then adjusted up or down by small amounts to determine

[19] 4 CSR 240-22.030(5)(B)2.C
[20] EO-2007-0409 – Stipulation and Agreement #9, 4 CSR 240-22.060(6)(D)

whether model statistics improved from the change. The elasticities used in the base case load (the differences between the base, high, and low load growth scenarios are discussed in section 3.1.5) forecast models were values that minimized the model mean absolute percent error (MAPE) over the estimation period. The price elasticity in the base case load growth residential model is -0.15. This is also consistent with the value used in the 2008 Ameren Missouri IRP, which included a study of company specific data in a model that produced an estimate of -0.157 as reported in the Supplemental filing made by Ameren Missouri in that docket.

Ameren Missouri also considered the use of retail natural gas prices in the forecast as a competing fuel for certain end uses. After evaluating how the sales models performed with and without retail natural gas prices, retail natural gas prices were not included in the model as explanatory variables. When the natural gas prices were introduced to the forecasting model, a very strong trend appeared in the model residuals. Exclusion of the retail natural gas price produced slightly better model statistics and specifically an improved Durbin-Watson statistic which indicates a reduction in the correlation of the error term of the model (i.e. removal of gas prices eliminated the strong trend in the residuals).

Each model used a different economic driver, or a set of economic drivers. In the SAE model framework for residential sales, household income and the number of people per household in the service territory act as drivers for use per customer, and the number of households.

The functional framework of the SAE model is:

$$\begin{aligned}
&\mathit{Use\ per\ customer} \\
&\qquad = B1 * ((\mathit{cooling\ use}) * (\mathit{cooling\ index})\ ) + B2\ *\ ((\mathit{heating\ use}) \\
&\qquad * (\mathit{heating\ index})\ ) +\ B3 *\ ((\mathit{other\ use}) * (\mathit{other\ index})\ )
\end{aligned}$$

In each term the “index” variable captures past and future trends in appliance saturation and efficiency. The “use” variable is a combination of variables that characterize the utilization of the appliances, including household income, the number of people per household, heating & cooling degree days, and the relevant elasticities. The specific form of cooling use, for example, is:

$$\begin{aligned}
&\mathit{Cooling\ use} \\
&= \ (\mathit{persons\ per\ household}\ \text{^}\ \mathit{persons\ per\ household\ elasticity\ of\ use\ per\ customer}) \\
&* (\mathit{household\ income}\ \text{^}\ \mathit{household\ income\ elasticity\ of\ use\ per\ customer}) \\
&* (\mathit{electricity\ price}\ 1\ \mathit{year\ moving\ average}\ \text{^}\ \mathit{price\ elasticity\ of\ use\ per\ customer}) \\
&* (\mathit{index\ of\ billing\ days}) * (\mathit{index\ of\ cooling\ degree\ days})
\end{aligned}$$

The heating and other use variables are similar, except that the heating use variable includes heating degree days and the other use variable does not include a weather term.

The coefficients B1, B2, and B3 are estimated with ordinary least squares (OLS) regression. One advantage of the SAE approach is that it produces very high, relative to most econometric models, t-statistics for each variable. In the base case residential model, for example, the t-statistics for the heating, cooling, and other variables are 55.68, 67.41, and 54.79 respectively. The adjusted r-square for that model is 0.987.

The SAE framework was also used for the four classes of commercial electricity sales: small general service (SGS), large general service (LGS), small primary service (SPS), and large primary service (LPS).

The functional form of the commercial SAE model is:

$$Use = B1 * \quad cooling\ use \ * \ cooling\ index \quad + B2 * \quad heating\ use \ * \ heating\ index \\ + B3 * \quad other\ use \ * \ other\ index$$

The coefficients B1, B2, and B3 were estimated with OLS regression.

The SAE approach used to forecast sales for the commercial rate classes is very similar to that used in the residential model. As with the residential class, the “index” variable includes past and forecasted data on appliance efficiency and saturation, while the “use” variable includes an economic driver, electricity prices, weather, and the appropriate elasticities. The commercial SAE model also includes building types and electric intensity that we matched to our customer base with data from the Ameren Missouri Market Potential Study.

One difference between the commercial class SAE models and the residential SAE model is that in the residential model the SAE function is used to forecast use per customer, and separate regression model predicts customers. Total MWh sales in the residential class are the product of the result of the customer model and the SAE model. In the case of the commercial class, we are forecasting MWh sales with the SAE models rather than use per customer.

Econometric

The four industrial rate classes were forecasted without including estimates of appliance saturation or efficiency that distinguish the SAE models from more traditional econometric models. The four industrial rate classes, small general service (SGS), large general service (LGS), small primary service (SPS), and large primary service (LPS) lack the homogeneity necessary to make the SAE approach useful. Across households, appliance use and saturation is fairly homogeneous, and even within the commercial class there is some homogeneity, especially within building types. Our industrial customers are much less homogenous, however. The way that, for example, a brewery uses electricity is likely to be quite different from the way that an aircraft manufacturer uses electricity, and the way an aircraft manufacturer uses electricity is likely to be quite different from a cement factory.

In order to produce a forecast of energy that is reasonable and is able to incorporate future changes in the economic environment and electricity prices, it is necessary to include a price term, a price elasticity term, an economic driver, and some elasticity with respect to the economic driver in a sales model. The SAE framework does this very well, but as noted above that form is not appropriate for Ameren Missouri's industrial class sales. In a typical econometric model this would be done by including price and an economic driver in the model as independent variables. The regression estimated coefficients would then serve as de facto elasticities.

In the case of Ameren Missouri's industrial sales data, however, that approach does not always work, so a slightly different approach was used. Price in particular is problematic because real prices have trended flat to down over most of the estimation period of the sales models, and this tends to produce coefficients for the price term that are either statistically insignificant, practically insignificant (ie, a positive sign on the price coefficient), or both. A modification was chosen that combined price, output, and their respective elasticities into one composite independent variable.

The functional form was different from, but inspired by the SAE framework:

$$\begin{aligned} Sales = B1 &* (economic\ driver^\wedge economic\ driver\ elasticity) * (price\ ^\wedge price\ elasticity) \\ &* index\ of\ billing/calendar\ days\ in\ the\ month + B2 * (CDD\ index) + B3 \\ &* (HDD\ Index) \end{aligned}$$

Price, output, and their elasticities were combined into one term. As was the case with the SAE residential and commercial models, estimating elasticity was a challenge, because estimates of elasticity in electricity consumption vary widely. Initial elasticities were chosen that reflected a mid-point of estimates from the literature. Through an iterative process elasticities were chosen that minimized the MAPE (Mean Absolute Percentage Error) over the sample period. A measure of billing or calendar days was added to the variable, to better reflect the volume of energy used in a month.

Obviously, the composite independent variable didn't include a weather term. In each rate class, an index of CDD and HDD were added as separate independent variables. In each of the four cases, the weather terms remained in the model if they were both practically and statistically significant.

Other

There are four other classes of energy sales which fell into neither the SAE nor econometric form of forecasting. Those four were Noranda, Street Lighting and Public Authority (SLPA), Dusk to Dawn lighting (DTD), and wholesale sales to cities and partial requirements customers. For Noranda sales (Noranda is an aluminum smelter which is its own rate class) the assumption is that they will operate at constant level, and require a constant amount of energy, for the foreseeable future. Noranda is part of a vertically integrated aluminum company, with its inputs coming from and outputs going to other parts of a common corporate parent. Load at Noranda would decline if the facility closed, and load could only expand if the facility were to add more production lines. The most likely case is that Noranda will continue to operate at its present capacity; if that assumption is correct then the only factor that will explain variation in monthly sales is the number of days in the month. Therefore Noranda sales are modeled as a function of the number of calendar days in the month.

Street lighting and public authority (SLPA) and dusk to dawn lighting (DTD) sales are both functions of the light in a day and other seasonal factors. We do not anticipate meaningful growth of sales in the DTD category; while we anticipate some very slight growth associated with population growth in the SLPA class. So the DTD classes are modeled such that monthly energy sales are functions of seasonal factors (specifically dummy variable for months) and the number of calendar days in the month. The SLPA class is similar, except that service territory population is included as an independent variable because we expect some slight growth dependent upon population growth.

Ameren Missouri served two types of wholesale customers at the time the IRP forecast was developed, full requirements municipal customers and partial requirements customers. The contracts for both types of customers expire during the IRP horizon.

The partial requirements customers are AEP, an investor owned utility, and Wabash Valley Power Authority. For the partial requirements customers the forecasting process was straightforward; electricity sales were the product of the amount of capacity and energy called for by the contract.

For four municipal utilities, the cities of Perry, Kahoka, Marceline, and California, Ameren Missouri is the full provider of required electricity, as opposed to partially meeting their energy needs. For a fifth, the city of Kirkwood, Ameren Missouri is contracted as full provider for the term of one contract and then transitions to a partial provider under a second contract for an additional term. Sales to these five customers were modeled econometrically, but the process was not the same as that used for Ameren Missouri’s retail sales. This was partially because the cities include a mix of customer types, rather than being strictly residential or commercial, although a majority of the load is residential. The independent variables in those sales models were GDP and persons per household.

Since an exact tabulation of GDP and persons per household was not available for those five, relatively small cities, the corresponding value for Ameren Missouri's service territory was used. This is defensible as the five cities are within Ameren Missouri's service territory, and we have no reason to expect a systematic and sustained difference between the economic performance of those five cities and the Ameren Missouri service territory.

Customer History and Forecasts

Forecasts of customer counts were produced at the rate class level, although in charts and tables they are aggregated to revenue class[21]. In each case, an econometric approach was used with customers modeled as a function of an appropriate driver, such as households, employment, or GDP[22]. Normally this would be a straight forward process, but it was complicated by the fact that GDP and employment both contracted rather severely in 2008 and 2009, and to a greater extent than the number of customers did. There was a similar, but opposite problem in the residential class, as the growth in households under-predicted the rate of residential customer growth between 2003 and 2008 (the period now recognized as a housing bubble). The customer models therefore included dummy variables to capture the fact that customer growth and driver growth diverged over the last few years, and also included auto-regressive and moving average terms to smooth out the customer forecast.

3.1.5 Sensitivities and Scenarios[23]

The nature of the forecasting models used in this IRP forecast is such that the dependent variable (energy sales) is sensitive to changes in the independent variables as well as to the parameter estimates used to represent elasticity. This is a feature of econometric and SAE models, but it is worth mentioning here because it means that the forecast of energy sales is highly sensitive to changes in any one of the driver variables. The forecast of residential sales is sensitive to changes in households, electricity prices, income, population, and changes in appliance saturation and efficiency. Commercial and industrial sales are sensitive to changes in service territory GDP, employment, electricity prices.

In this IRP, ten different scenarios were modeled that stemmed from the permutations of independent assumptions about load growth (low, medium, high[24]), natural gas prices (high, base, or low), and carbon prices (no carbon policy, energy bill mandates, EPA regulation, or a cap and trade system). Charles River Associates (CRA) produced different forecasts of retail electricity prices to match each permutation. They also produced forecasts of national and regional economic conditions associated with those scenarios that were used to adjust the Ameren Missouri service territory specific

[21] 4 CSR 240-22.030(5)(B)1
[22] 4 CSR 240-22.030(2)
[23] 4 CSR 240-22.030(6), 4 CSR 240-22.030(7), 4 CSR 240-22.030(8)(C)
[24] EO-2007-0409 – Stipulation and Agreement #13

assumptions used in the modeling. CRA developed these forecasts based on interviews with Ameren subject matter experts, and results of the interviews were translated in to quantitative forecasts. The overall scenario development process is discussed fully in Chapter 2.

The different carbon policy and natural gas price scenarios affected the forecasts of energy sales through the retail price term and economic drivers, as changes in wholesale natural gas prices and regulatory regimes flowed through CRA's model to set different levels and growth rates of retail electricity prices and different national and regional economic conditions. Since the retail price of electricity and economic drivers are inputs into the sales models (both SAE and econometric), the different carbon and natural gas scenarios result in different forecasts of energy sales[25]. Additionally, the energy bill mandates cases included some assumptions regarding new future federal energy efficiency standards that were implemented in the SAE framework.

In order to forecast high, base and low load growth consistent with the scenarios envisioned by the load growth subject matter experts, Ameren Missouri developed different levels of selected independent variables and elasticity parameters. The variables and parameters that were selected to be varied in the scenario forecasts differed by class. In each case, it was important to consider not only which variable or parameter had the biggest impact on load, but also which ones had the greatest inherent uncertainty over the planning horizon.

For example, in the residential model the forecast of miscellaneous end use energy was modified to produce high and low load growth scenarios. Miscellaneous load is generally considered to be one of the most challenging categories to forecast amongst industry forecasters. Since miscellaneous load makes up a significant share of total residential energy consumption (approximately 20% in 2010), changes in the growth rate of this end use grouping will certainly have a material impact on the load forecast. Implied in the EIA information is a historical trend in miscellaneous growth that in individual years is over 5% and for a sustained period of time exceeded 3%. However, over the forecast period, EIA's forecast implies reductions in miscellaneous load growth such that it remains in only the 1-1.5% range. The difference between the historical and forecast EIA trends alone make meaningful differences in the total residential load forecast. Part of the appeal of miscellaneous growth as the variable through which to capture uncertainty is its inherent unpredictability. It is impossible to know what new devices might be invented in the future that will consume more or less electricity than what is currently anticipated. A forecast of 2010 energy sales prepared in 1990 for example, might have underestimated the number of mobile phone chargers, not have predicted the adoption of technologies like digital video recording devices, or not have expected that some households would have a

[25] 4 CSR 240-22.060(4)(C), 4 CSR 240-22.060(6)(D)

device called a wireless router. It is also conceivable that technologies could converge in the future and multiple plug devices are replaced by more efficient and fewer devices.

Electric vehicles (EVs) are another example of a category of miscellaneous sales growth that could affect the forecast of energy sales. It is also a category of sales about which there is a great deal of uncertainty. Ameren Missouri has and continues to research the potential of plug in EVs as a source of load growth, but at present the state of technology leads to a wide spectrum of possible outcomes. Currently Ameren Missouri does not see the likelihood of electric vehicle sales reaching levels high enough to meaningfully affect electricity sales in the near to medium term, as a survey of Ameren Missouri customers showed that 65% of respondents described themselves as “not very likely” to buy an electric or hybrid electric car. Only 8% of respondents characterized themselves as “very likely” to purchase such a vehicle.

Under an aggressive scenario envisioned where electric vehicle production ramped up significantly such that the market penetration of EVs reached 15% as fast as 2015 and 25% by 2020, the total estimated impact to residential load would only be about 4%. That means that if EVs take off immediately, load growth from 2010 to 2020 would only be 0.4% per year higher. However, over the entire IRP planning horizon, it is easily conceivable that EVs could provide much of the growth envisioned in the high load growth case.

For the commercial class, the output and price elasticity parameter estimates were identified as the largest source of uncertainty for the forecast period. As mentioned in Section 3.1.4, the academic literature and even the opinions of the forecasting community present a wide spread of supportable estimates of elasticity. However, much of the literature that does cover elasticity actually focuses on the residential class. Therefore the evidence for a single parameter estimate for Commercial price or output elasticity is scarce. The impact of these estimates is, however, significant. Since we are in a time period during which retail electric prices have been and are forecasted to continue rising, the price elasticity term has a pronounced effect.

Additionally, economic growth in the commercial sector is not uniformly energy intensive. So the addition of load like data centers and medical facilities could use more energy per unit of economic output than retail space or offices. Therefore using the output elasticity to model sensitivity accurately captures one of the larger uncertainties in this sector.

The industrial class had three different variables/parameters that were affected in the load growth scenario modeling. First, similar to the commercial class, different output and price elasticity parameters were introduced across the cases for reasons similar to those described for the commercial class. Second, the handling of the recovery from the severe recession in 2007-2009 was handled differently across scenarios. In the high and base growth cases, a modeling technique was used that produced more of a "V" recovery. This is how many past recessions have occurred, with economic decline being followed by a period of above trend growth that quickly brings the economy close to where it was pre-recession. In the low load growth scenario, the recession variable in the model did not indicate a rapid recovery, and a permanent loss in load was the ultimate effect.

The final mechanism used to differentiate the load growth cases in the industrial class models was the choice of economic driver variables. As discussed earlier, both manufacturing output and manufacturing employment correlate with electricity sales. The key difference between the two in this forecast, however, is that Moody's Analytics' forecast of Ameren Missouri's service territory activity predicts growth in manufacturing output but declining manufacturing employment. This is not an illogical outcome; it merely implies manufacturing productivity growth at a rate greater than the growth of output. That logic non-withstanding, the choice of employment as opposed to output as a driver has big implications for electricity sales in the future. If industrial sales are driven by output then Ameren Missouri's industrial energy sales will grow over the IRP horizon, but if they are instead driven by manufacturing employment they will decline.

For our base case, we essentially split the difference by creating an industrial output index that was the average of indexed levels of manufacturing employment and output. The rationale for this combination is that in some instances electricity consumption will be a complement to employment, but in others it will be a substitute for employment. Some industries will cut their employment and electricity use as their output grows, while others will cut employment but increase use. For the high load growth case the assumption is that manufacturers in the region become more efficient by replacing labor with electricity intensive capital, while for the low load case the assumption is that manufacturers become more efficient users of both labor and electricity, so their use of both declines as output grows.

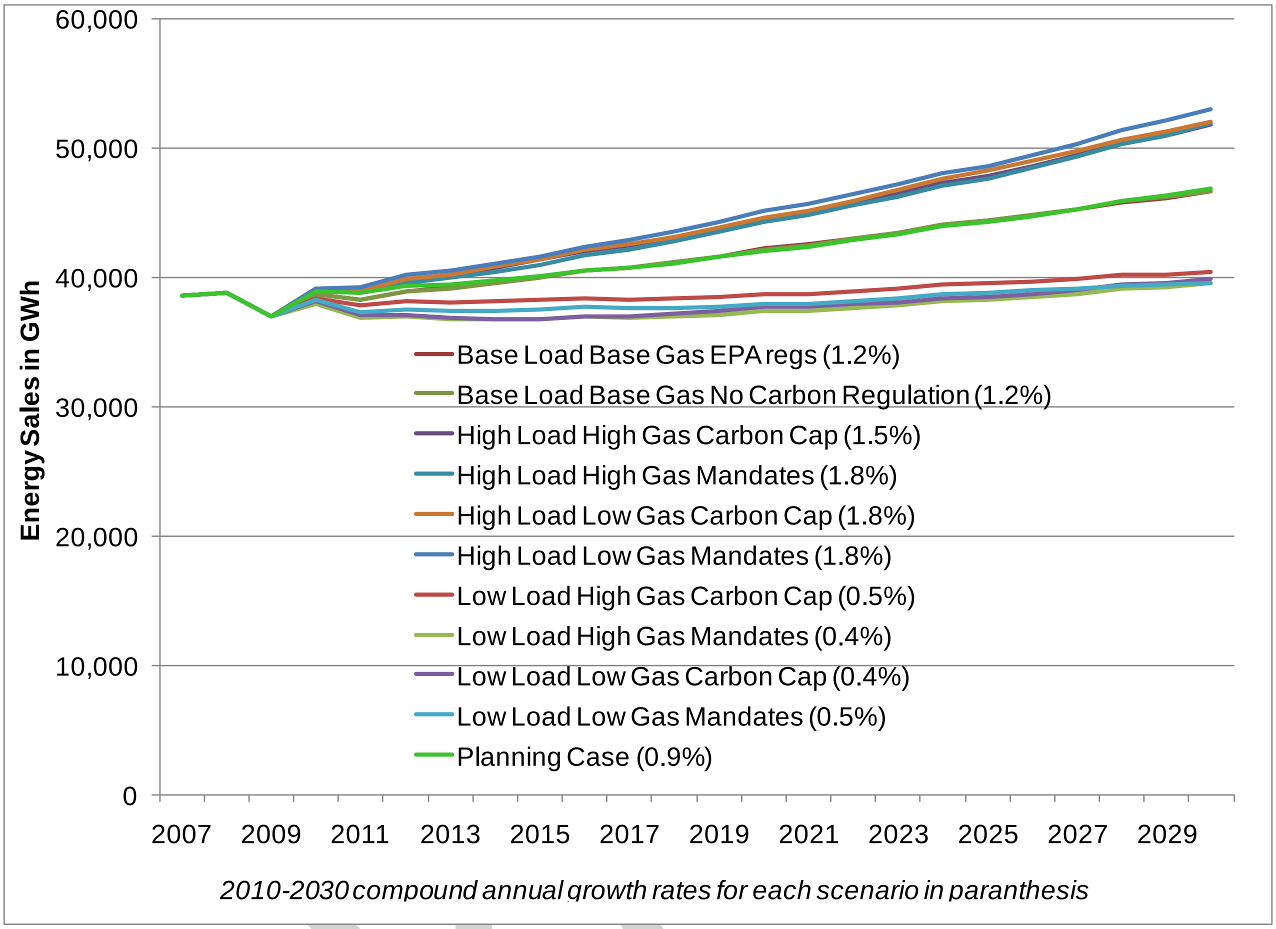
As described in the paragraphs above, careful consideration was given to the factors in the forecast of each class that would drive the differences between the high, base, and low load forecast scenarios. In each case, an assessment was made that not only considered the model's sensitivity to a given variable, but also the inherent uncertainty in that variable. By using this approach, Ameren Missouri developed a range of load growth outcomes that realistically reflects the uncertainty that is truly present in the details underlying the load forecasting process. The results of this modeling served to reinforce the results of the surveys that CRA conducted with the subject matter experts.

A summary detailing all of the changes between high, base, and low load forecast scenarios can be found in Table 3.3.

Table 3. 3: Scenario Driver and Parameter Differences

Class	High Load Growth Assumption	Base Load Growth Assumption	Low Load Growth Assumption
Residential	Miscellaneous load continues robust growth of 3.1% per year following inferred historical trend	Miscellaneous load slows somewhat from inferred historical trend to 1.5% annually (similar to EIA assumption)	Miscellaneous load growth flattens off significantly to only 0.2% per year
Commercial	Elasticity - SGS Output - (20%), Price - (-5%) Elasticity - LGS Output - (60%), Price - (-10%) Elasticity - SPS Output - (25%), Price - (-5%) Elasticity - LPS Output - (85%), Price - (-5%)	Elasticity - SGS Output - (15%), Price - (-10%) Elasticity - LGS Output - (50%), Price - (-15%) Elasticity - SPS Output - (20%), Price - (-10%) Elasticity - LPS Output - (75%), Price - (-10%)	Elasticity - SGS Output - (10%), Price - (-15%) Elasticity - LGS Output - (40%), Price - (-20%) Elasticity - SPS Output - (15%), Price - (-15%) Elasticity - LPS Output - (65%), Price - (-15%)
Industrial	Recession dummy - industrial class sales rebound from recession losses Driver - manufacturing GDP Price elasticity - (-10%) Output elasticity - (80%)	Recession dummy - industrial class sales rebound from recession losses Driver - blended employment and GDP Price elasticity - (-20%) Output elasticity - (100%, 80% for LPS)	Recession end shift - i.e. there is permanent loss of load from recession Driver - manufacturing employment Price elasticity - (-25%) Output elasticity - (90%, 70% for LPS)

Figure 3.6: Total Energy Sales by Scenario



3.1.6 Planning Case Forecast[26]

The ten scenarios described in section 3.1.5 describe the range of likely outcomes for load growth over the planning horizon. The single forecast that represents the expected value of load growth over the planning horizon is referred to as the planning case. This forecast is needed in order to have a base expectation against which the candidate resource plans can be developed. The integration modeling is actually run against each scenario forecast, but the plans were created in order to maintain an appropriate amount of capacity given expectations in the planning case.

The initial calculation of the planning case forecast was a fairly simple exercise. The subjective probabilities of each scenario, as determined by the subject matter experts for the various uncertain factors, were used to weight together the different scenarios. The planning case did not have its own set of forecast models with case specific drivers, but instead was derived from the modeling results for all other scenarios.

[26] 4 CSR 240-22.030(5), 4 CSR 240-22.030(5)(A)

Following completion of the original planning case calculation as described above, but before integration analysis had begun in earnest, a review was undertaken to determine how well the forecast was performing against first quarter 2010 observed weather normalized loads. Because there is a very long lead time required to prepare all of the load analysis and forecasting work, the forecast assumptions are a few months old before the forecast is even used. There was a short window of opportunity to get updated information into the forecast, and Ameren Missouri chose to take one last look at it before proceeding with integration analysis.

It turns out that the forecast for the first quarter was significantly lower than the observed loads were coming in. Specifically, total weather normalized load was 2.7% higher than the forecast. This was most pronounced in the residential class which was 5.7% above the original planning case forecast.

Ameren Missouri determined that, although it was very confident in the subjective probabilities over the duration of the planning horizon, due primarily to the observed deviation of the actual load to the forecast, the high case load growth was more likely in the very near term. To reflect this reality, an additional model was executed that included the base load and base gas assumptions, but that incorporated for the most part the high load growth assumptions[27]. This additional model also incorporated 2010 loads through May in the estimation and weather normalized observed first quarter 2010 loads through April in the results.

The results of the new model described above were utilized for the planning case for the first two years (recall the near term expectation for high load growth described above). After 2011, the annual growth rates from the original planning case were applied to the level of sales in 2011 produced by these new models on a class by class basis.

3.1.7 Forecast Results[28]

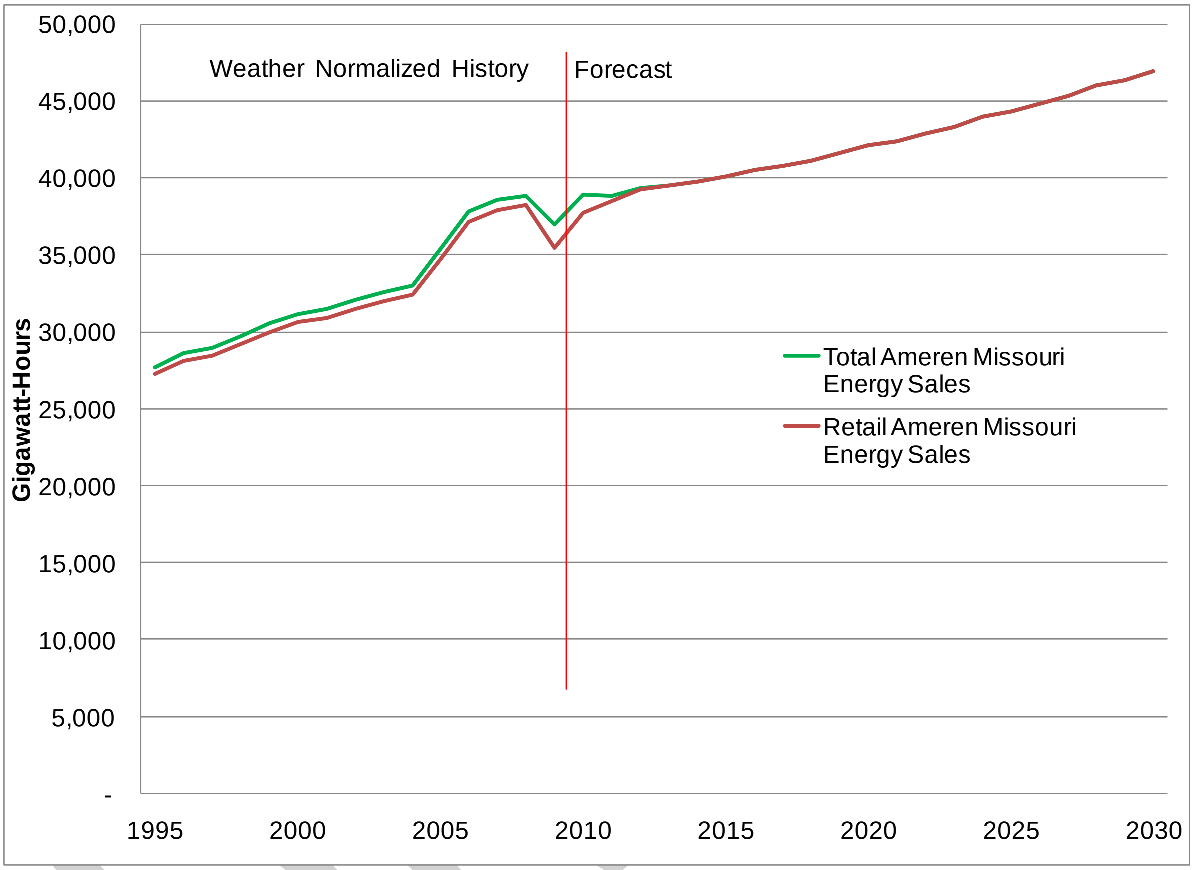
For the planning case, total retail energy sales are forecast to grow at 1.09% compound annual rate between 2010 and 2030. Between 1996 and 2009, total retail sales grew at a compound annual rate of 2.2%. Sales dipped sharply in 2009, but are expected to recover in 2010 and 2011 and then grow at a relatively stable and slow rate through 2030. Because of expiring wholesale contracts that cause and artificial decline in load, Ameren Missouri's total load obligation is expected to grow by only 0.94% per year from 2010 to 2030.

[27] The industrial class forecast for the revised planning case did not fully incorporate the high load growth assumptions. Specifically, it was modeled with a "fuzzy" recession variable. This in effect produced neither a "V" recovery in industrial load nor a permanent load loss, but a slower recovery of load to pre-recession levels.

[28] 4 CSR 240-22.030(5)(B), 4 CSR 240-22.030(5)(A)

Sales increased noticeably in 2005 when Ameren Missouri began serving the Noranda aluminum smelting facility. In 2009 an ice storm caused the failure of some transmission lines (not owned by Ameren Missouri) that served the plant, and the resulting power outage damaged the plant. It did not return until full capacity until mid 2010.

Figure 3.7: Planning case energy sales forecast



The outage at Noranda is not the only reason why sales slumped in 2009, however, as the severe recession that the US experienced depressed service territory electricity sales. Residential sales fell by 1.3% in 2009, commercial sales fell by 1.5%, and Industrial sales, exclusive of Noranda, fell by a staggering 14.5%. The planning case assumes that recovery from those declines takes several years, as can be seen in Figure 3.7.

Table 3.4: Planning Case Annual Sales Growth by Class

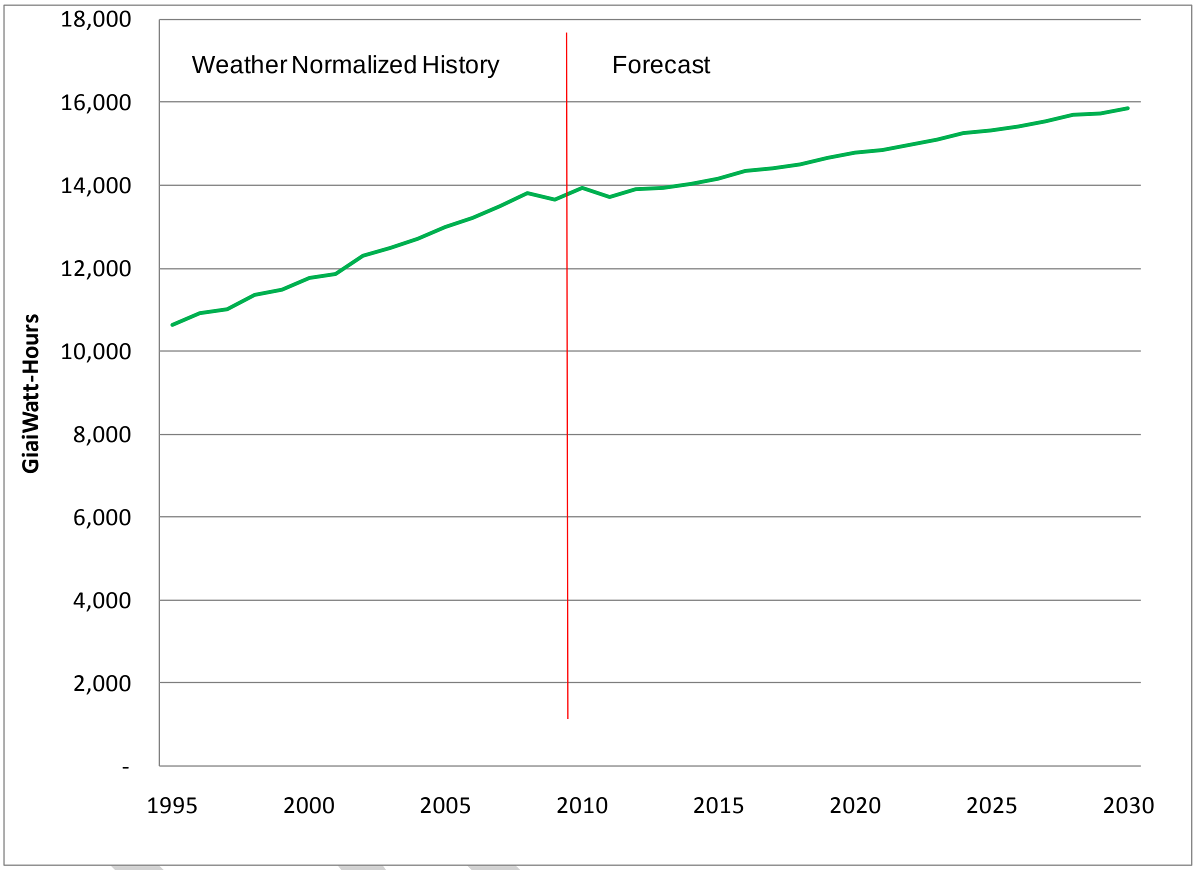
Year	Residential	Commercial	Industrial	Noranda	Dusk-to-Dawn Lighting, Street Lighting, & Public Authority	Wholesale	Total
2000	2.3%	2.7%	0.8%	n.a.	-5.2%	4.0%	2.2%
2001	0.9%	1.1%	1.2%	n.a.	-3.0%	-2.4%	0.9%
2002	3.7%	2.1%	-2.5%	n.a.	33.7%	0.9%	1.9%
2003	1.5%	2.7%	-1.6%	n.a.	2.0%	4.7%	1.5%
2004	2.0%	1.7%	-0.7%	n.a.	1.0%	1.8%	1.4%
2005	2.0%	1.8%	-1.6%	n.a.	0.6%	4.8%	7.4%
2006	1.7%	2.0%	-3.8%	104.2%	0.3%	-2.0%	6.6%
2007	2.3%	3.3%	-0.2%	0.3%	-1.7%	3.3%	2.1%
2008	2.4%	0.9%	-3.1%	0.8%	0.9%	-2.2%	0.8%
2009	-1.3%	-1.5%	-14.5%	-39.4%	-0.7%	149.2%	-4.9%
2010	2.1%	3.2%	2.6%	58.8%	1.5%	-23.4%	5.4%
2011	-1.5%	1.9%	10.8%	3.1%	0.2%	-73.2%	-0.4%
2012	1.5%	2.1%	4.0%	0.3%	0.4%	-61.4%	1.4%
2013	0.1%	0.9%	1.9%	-0.3%	0.0%	-87.8%	0.3%
2014	0.8%	0.9%	0.9%	0.0%	0.2%	-100.0%	0.7%
2015	0.9%	1.2%	0.5%	0.0%	0.2%	…	0.9%
2016	1.2%	1.5%	0.6%	0.3%	0.4%	…	1.1%
2017	0.4%	1.0%	0.0%	-0.3%	0.0%	…	0.5%
2018	0.8%	1.4%	0.4%	0.0%	0.2%	…	0.9%
2019	1.0%	1.6%	0.5%	0.0%	0.2%	…	1.1%
2020	1.0%	1.9%	0.9%	0.3%	0.4%	…	1.3%
2021	0.4%	1.4%	0.4%	-0.3%	0.0%	…	0.8%
2022	0.8%	1.7%	0.6%	0.0%	0.2%	…	1.1%
2023	0.8%	1.8%	0.7%	0.0%	0.2%	…	1.1%
2024	1.1%	2.0%	1.0%	0.3%	0.4%	…	1.4%
2025	0.4%	1.5%	0.5%	-0.3%	0.0%	…	0.8%
2026	0.7%	1.8%	0.9%	0.0%	0.2%	…	1.1%
2027	0.7%	1.8%	0.9%	0.0%	0.2%	…	1.2%
2028	1.0%	2.2%	1.1%	0.3%	0.4%	…	1.5%
2029	0.3%	1.7%	0.4%	-0.3%	0.0%	…	0.9%
2030	0.6%	2.0%	0.8%	0.0%	0.2%	…	1.2%
CAGR, 2010-2030	0.6%	1.6%	1.4%	0.2%	0.2%	n.a.	0.9%

One seemingly trivial feature of our sales modeling does impact sales growth. In each of our models, the number of calendar days in the month is included as an explanatory variable; either on its own or combined with another. Each leap year is one day, or 0.27% longer than normal, and that extra day is in a month when we typically experience meaningful heating load. That causes sales growth in every leap year to be slightly higher than it otherwise would be, and growth in each year that follows a leap year to be slightly lower. This isn't noticeable in Figure 3.6, but is noticeable in Table 3.4. The effect of leap years on sales is in one sense trivial, and doesn't meaningfully affect capacity planning, which is of course the central goal of the IRP. It is, however, a logical and observable result of the forecasting process.

Residential[29]

Between 1996 and 2009, residential class weather normalized sales grew at a compound annual rate of 1.8%. Total US residential sales, according to the EIA, also grew by 1.8% (although it is important to note that EIA numbers are not weather normalized), so Ameren Missouri's residential electricity consumption growth was similar to the US as a whole.

Figure 3.8: Planning Case Forecast of Residential Energy Sales



In the planning case forecast, that growth slows to a compound annual rate of 0.6% between 2010 and 2030 because of higher electric rates, slower growth in households, and increasing adoption of energy efficient technologies. According to the EIA, US residential electricity sales are expected to grow at a compound annual rate of 0.8% over the same time period. The slightly lower growth of Ameren Missouri electricity sales is consistent with the idea that the Ameren Missouri service territory will experience slightly slower demographic growth than the US in the long term.

In the near term, sales will decline in 2011. This is due to the inclusion of the weather normalized observed results for the first quarter of 2010 in the updated planning case. As

[29] 4 CSR 240-22.030(5)(A)

mentioned above, particularly high load growth was observed in this period (which led to the decision to update the planning case). Although these months were also included in the estimation of the planning case forecast model, the three additional months of strong load were not enough to force the model to repeat this level of load in 2011. Therefore returning to a more "normal" winter sales level in 2011 actually caused a reduction in load compared with 2010. Additionally, a significant rate increase in June 2010 drives conservation impacts in 2011 through the 1 year moving average of price treatment in the model described just below. The surge in growth in 2012 is due to an expected rebound in household formation. In 2013 the effects of efficiency standards partially offset favorable economic trends. Growth is robust, again due to higher rates of household formation and income growth, through 2016, but then decelerates over time. The effect of higher prices also depresses sales growth. Prices were relatively flat in real terms between 1995 and 2008, but began to rise in 2009. The forecasting models use a 1-year moving average of prices because we believe that although prices rise immediately after a rate case, our customers respond more slowly. That means that the demand reducing effects of higher prices show up over the year following the rate increase.

The number of residential customers is expected to grow at a compound average rate of 0.8% between 2010 and 2030. Customers grow more rapidly, at a rate of 1.5%, between 2010 and 2015 as a recovery from the 2007-2009 recessions spurs an above trend rate of household formation. Between 2015 and 2030 growth slows to 0.5% as slow demographic growth leads to low rates of household formation.

Use per customer growth in the residential class is expected to slow relative to historical trends. Over the 1995-2009 time period, user per customer grew at approximately 1.1%. Over the forecast horizon, use per customer is expected to be very close to flat, with all usage growth coming from a modestly increasing customer base[30].

Commercial[31]

Ameren Missouri commercial class sales are the fastest growing segment of sales, partially reflecting the shift away from manufacturing toward health and education in the service territory economy, and partially because of the growth of new types of commercial load such as data centers. Between 1996 and 2009, weather normalized sales grew at a compound annual rate of 2.0%. According to the EIA, total US commercial sales grew at a compound annual rate of 3.1% between 1996 and 2001, so Ameren Missouri's growth was slower than the US average.

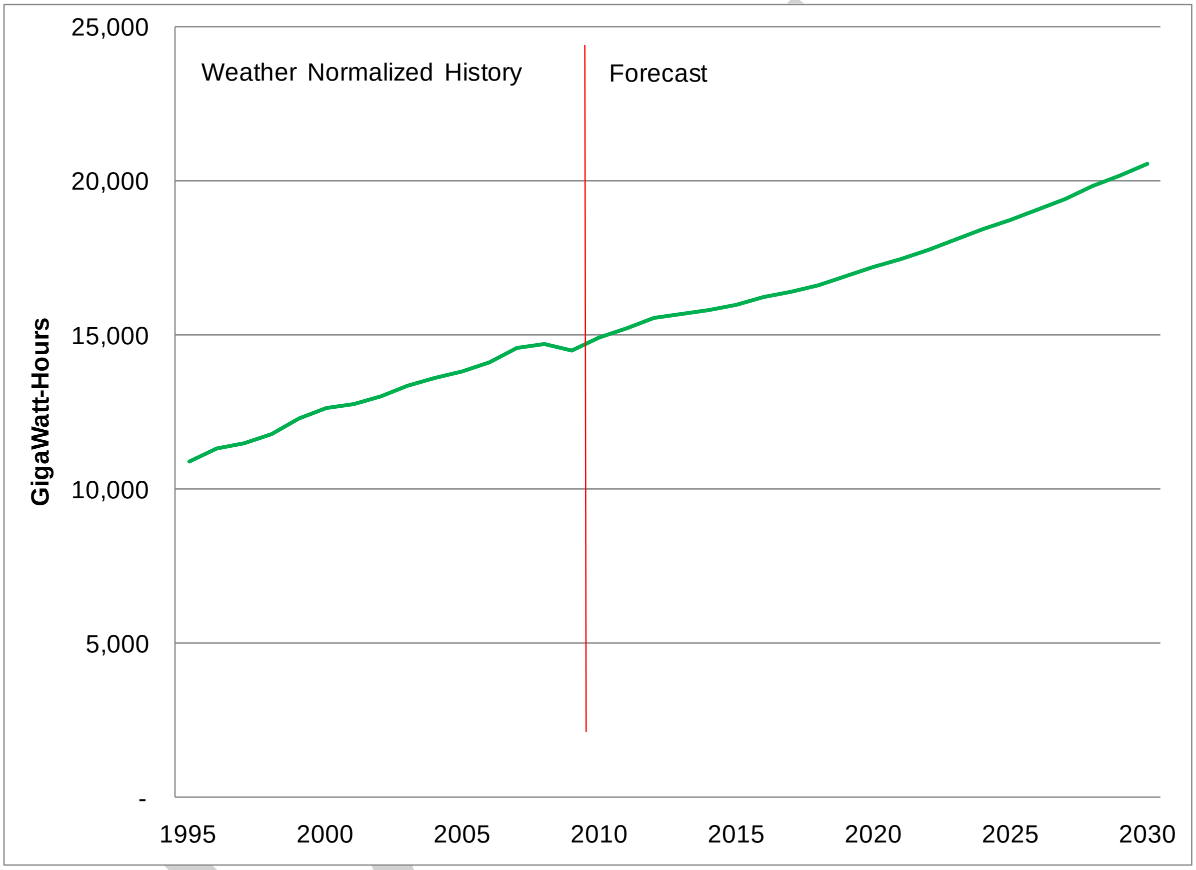
Sales are expected to grow at a compound annual rate of 1.6% between 2010 and 2030. The EIA's estimate of commercial electricity sales growth over that same period is 1.8%,

[30] 4 CSR 240-22.030(5)(B)2.D
[31] 4 CSR 240-22.030(5)(A)

so the planning case for Ameren Missouri anticipates slightly slower growth that the US average.

Use per customer growth in the commercial class has been negligible over the historical period of 1995-2009 with growth being driven by an increasing customer base. This trend is expected to continue, with essentially flat commercial use per customer over the forecast horizon[32].

Figure 3.9: Planning Case Forecast of Commercial Class Energy Sales



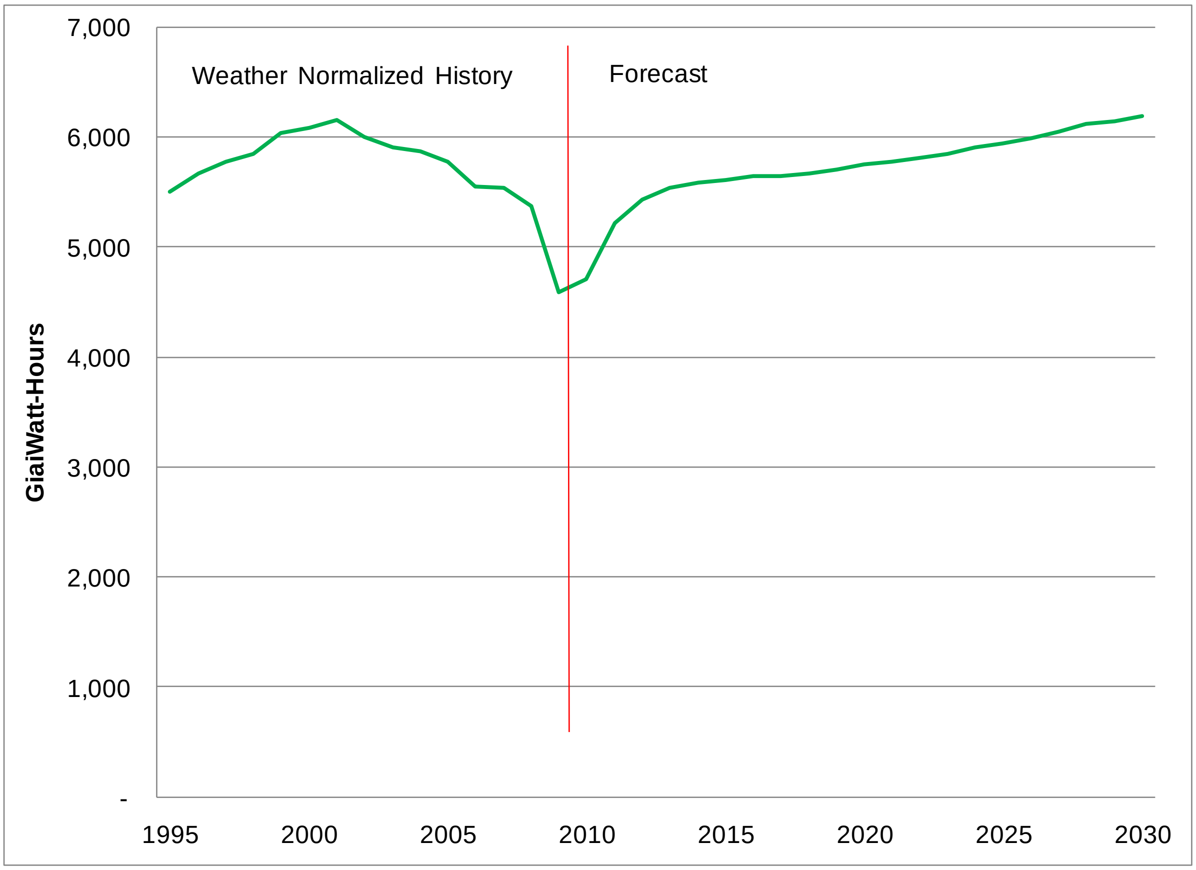
Industrial[33]

Ameren Missouri Industrial class sales grew at a compound annual average rate of 2.0% between 1995 and 2001, before a structural decline in service territory manufacturing output began to depress sales. The decline in manufacturing activity was not one confined to the Ameren Missouri service territory; between 2001 and 2009, manufacturing employment fall by 27.7% nationwide, 31.7% in the State of Missouri, and by 25.9% in the St. Louis metropolitan area.

[32] 4 CSR 240-22.030(5)(B)2.D
[33] 4 CSR 240-22.030(5)(A)

Casualties of this secular decline in the service territory include the Ford Assembly plant in Hazelwood, MO, which closed in 2003, and the Chrysler plant in Fenton MO, which closed in 2010. Between 2001 and 2009, Ameren Missouri's Industrial sales declined at a compound annual rate of 3.6%; according to the Energy Information Administration US industrial electricity sales fell by a compound annual rate of 1.5% between 2001 and 2009. The fact that Ameren Missouri's sales declines are larger than the US is partly due to the complete loss of the large customers mentioned above.

Figure 3.10: Planning Case Forecast of Industrial Class Energy Sales



The planning case forecast calls for industrial sales growth at a compound annual rate of 1.4% between 2010 and 2030. That may seem aggressive given the decline in sales since 2001, but it is also the case that the forecast does not anticipate that industrial sales will reach 2001 levels until after 2030. The EIA's forecast for US industrial sales anticipates compound annual growth of 0.8%, slower than the planning case forecast. The difference between the planning case forecast for Ameren Missouri and the EIA's is primarily due to Moody's Analytics' fairly robust forecast of manufacturing activity in the service territory, which calls for manufacturing GDP to grow at a compound annual rate of 3.4% between 2010 and 2030. The EIA, on the other hand, sees shipments of manufactured goods (an analogous but not identical measure to manufacturing GDP) to grow at a compound annual rate of 2.3%.

The earlier discussion of forecast drivers detailed the difference that the use of manufacturing output as opposed to employment as a forecast driver has on manufacturing sales. The base load growth case forecast essentially splits that difference, using an equally weighted blend of the growth of manufacturing employment and GDP.

While total sales declined over the historical period from 1995-2009, this was driven primarily by a declining customer base. Use per customer actually grew at 0.6% per year over the same years. Over the forecast horizon, that is expected to continue and actually accelerate. Use per customer is forecast to grow by 1.8% per year as output expands despite declining employment in the sector[34].

Customer Forecast

The forecasts of customers for the residential, commercial and industrial classes are reasonable given the performance of customer growth over the prior decade and a half[35]. For the residential class, forecasted growth rates are very close to the rate of the past fifteen years. For the commercial class, we expect growth to decelerate slightly. The commercial class does remain the fastest growing retail class, however.

Table 3.5: Customer Growth Rates

Year	Residential	Commercial	Industrial
1995-2009	0.73%	2.21%	-1.83%
2010-2030	0.77%	1.50%	-0.38%

The number of industrial customers decline at a slower rate over the forecast horizon than it is over the last fifteen years by a significant margin, over 140 basis points. This is primarily because the Ameren Missouri service territory has experienced a secular decline in manufacturing over the last several decades, but we believe that decline is slowing. This is partially because the sustained declines in industrial customers are leaving a customer base that is more concentrated with competitive firms that are more likely to survive.

Wholesale[36]

Ameren Missouri sells electricity to five full requirements wholesale customers; the cities of California, Kahoka, Kirkwood, Marceline, and Perry, and two partial requirements wholesale customers; AEP and Wabash Valley. At the time of the forecast, Ameren Missouri anticipated, because of existing contracts, sales to Kahoka and Marceline to continue through December of 2011, sales to Kirkwood to extend through August of 2012, sales to California through May of 2013, and sales to Perry to continue through 2013.

[34] 4 CSR 240-22.030(5)(B)2.D
[35] 4 CSR 240-22.030(5)(B)1.B, EO-2007-0409 – Stipulation and Agreement #12
[36] 4 CSR 240-22.030(5)(A)

Both the AEP and Wabash Valley contracts end within 2010, the first year of the forecast. It is possible that Ameren Missouri may choose to enter into new wholesale sales contracts subject to future market conditions and resource availability[37]. As of this writing, however, there are no contracts for wholesale sales after 2013. Because of the expiring contracts and uncertainty about their renewal, we expect wholesale sales to decline by 73% in 2011, 61% in 2012, 88% in 2013, and fall to zero in 2014.

Noranda[38]

Noranda sales are expected to be essentially flat over the forecast horizon. As was noted in the methodology section, Noranda is a single three shift manufacturing facility that is part of a vertically integrated aluminum producer. Load is not expected to grow, as that would entail additional capacity installation at the plant, or decline, since its output is used by firm with which it shares a common corporate parent. There is of course the possibility that the plant could close, but that is not seen as a likely outcome at this point.

Lighting and Other[39]

We do not anticipate growth in the DTD lighting classes, and expect only minimal growth from our street lighting and public authority class.

3.2 Peak and Hourly System Load Forecast

The peak demand forecast is of critical importance to the Integrated Resource Plan. The demand on the system at the hour of peak drives the need for generating capacity. While the need for energy influences the optimal mix of generation resources, the timing and amount of capacity additions are most directly tied to peak demand. The peak forecast for the 2011 Ameren Missouri IRP has been done at a more detailed and granular level than past forecasts, incorporating additional information and new techniques in an attempt to refine this important piece of the IRP.

The system load forecast, as in years past, is done on a bottom up basis. This means that the load is forecasted by aggregating customer class loads and their associated transmission and distribution losses in order to represent all energy consumed on the system. In fact, the additional level of granularity in this forecast comes from the fact that the bottom up forecast is being built from the level of the end-use load when possible rather than just the customer class load. The energy forecast is done on an end use basis for the residential and commercial classes as described in previous sections of this document. Each end use that has an energy forecast also has an accompanying load profile to shape it into an hourly forecast. These individual end use forecasts are aggregated to the class level. Where end-use energy forecasts are not available, particularly in the industrial class, class level profile models based off of load research

[37] EO-2007-0409 – Stipulation and Agreement #7
[38] 4 CSR 240-22.030(5)(A)
[39] 4 CSR 240-22.030(5)(A)

data are used to shape the hourly forecast. Class level forecasts based on the aggregated end uses or class level models have appropriate loss factors applied to them and are then added to create the system level forecast. The maximum load hour from the system load forecast for each year becomes the annual peak load forecast.

This methodology is validated and enhanced through a process of back testing and calibration. Historical observed monthly energy is shaped using end-use and class level profiles. The hourly profiled data is adjusted for losses and aggregated and compared to observed system loads at the time of the annual peak. The difference between the bottom up aggregation and the observed load represents the modeling error. The average of the modeling error in the analysis is 0.52% (measured as actual load minus modeled load) over a period of historical years from 2003-2008. This can be seen as the inherent bias in the estimation methodology. Therefore the future peak values in the forecast horizon are adjusted for this bias to produce a reliable estimate of future system peak demand

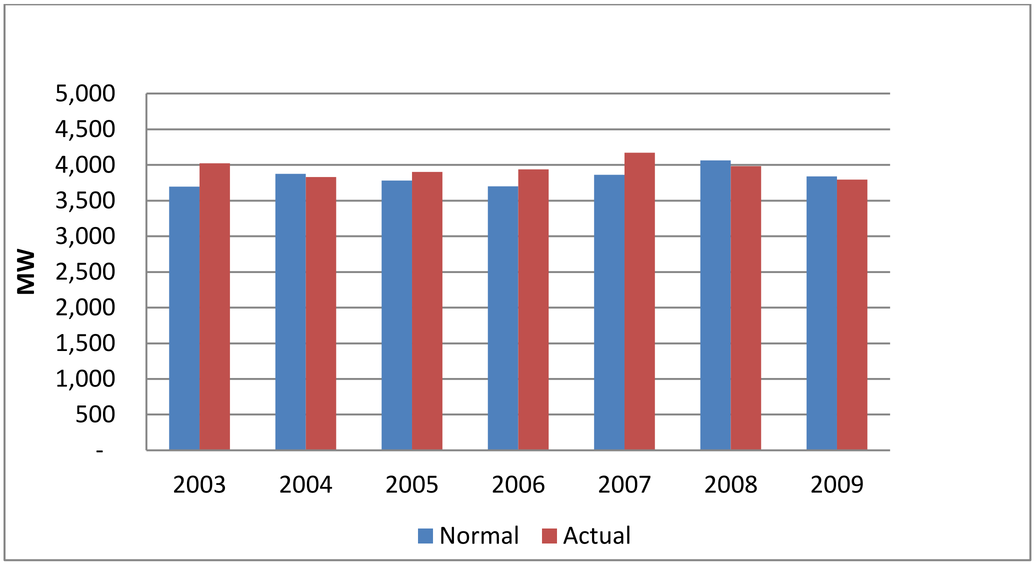
3.2.1 Historical Peak and System Load

Ameren Missouri's historical database of actual and weather normalized class and system demands is maintained back to July 2003[40]. Actual hourly system data is available back to the beginning of January 2001[41]. Earlier data for both class demands and system loads does exist, but is not applicable to the Missouri jurisdiction only. Prior to 2005, Ameren Missouri served the Metro East load in Illinois. For the periods described above, the data was able to be disaggregated into its Missouri and Illinois components. For earlier data, the detail needed to perform this disaggregation was no longer available at the time of the Metro East transfer. Ameren Missouri filed a waiver request indicating that the length of its historical databases would be consistent with what is described in this paragraph.

All class demand data is based on Ameren Missouri's load research program. As a part of the load research process, hourly class demands are calibrated to the observed system load to ensure that all energy consumed on the system is attributed to classes' appropriately[42].

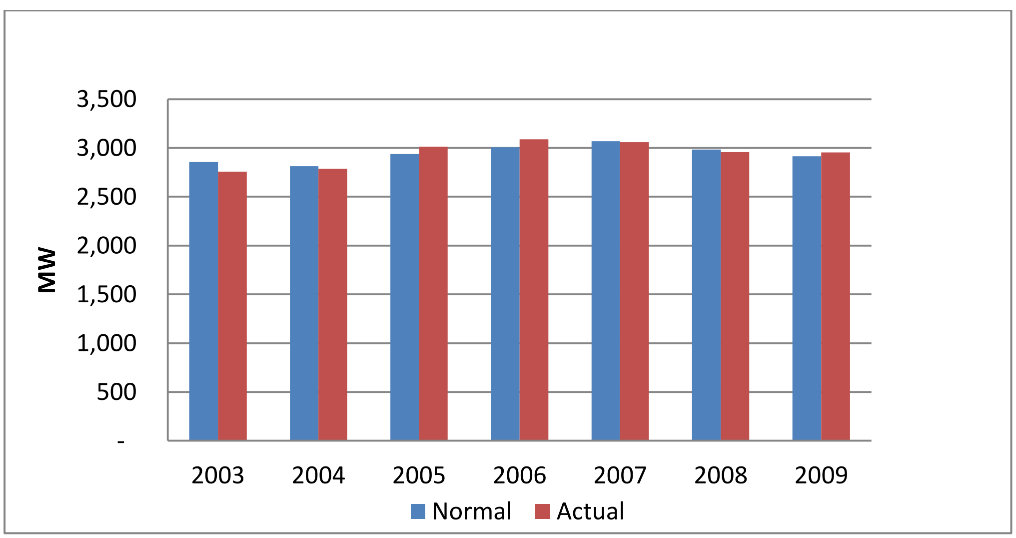
[40] 4 CSR 240-22.030(1)(B)2, 4 CSR 240-22.030(1)(D)2
[41] 4 CSR 240-22.030(1)(B)3
[42] 4 CSR 240-22.030(4)(B)

Figure 3.11: Residential Coincident Peak Demand (MWs)



The annual coincident peak demand, on a weather normalized basis, for the residential class from the year 2003 to 2009 grew at a compound annual rate of 0.62%. The class load grew from a weather normalized 3,697 MW in 2003 to 3,838 MW in 2009 (at generation, i.e. inclusive of transmission and distribution losses). On an actual basis, the residential class load reached its highest level August 15, 2007, when the temperature in St. Louis reached 105 degrees Fahrenheit. On that day, the highest hourly integrated residential demand at the time of system peak was 4,174 MW.

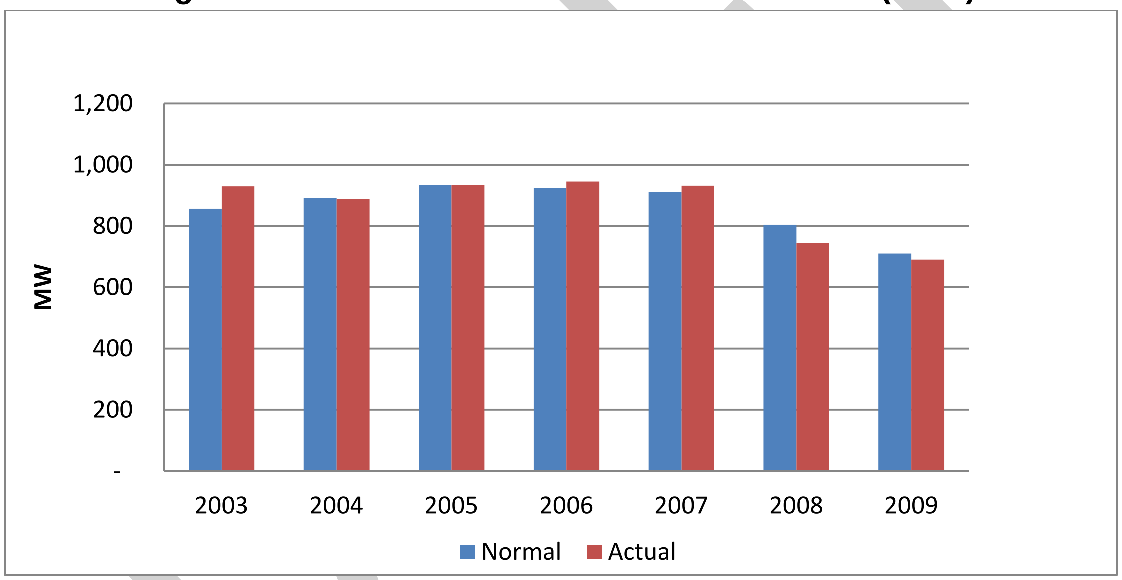
Figure 3.12: Commercial Coincident Peak Demand (in MWs)



For the commercial class, the annual coincident peak demand was essentially flat on a weather normalized basis from the year 2003 and 2009. The class load grew from a weather normalized 2,857 MW in 2003 to 3,071 MW in 2007, but declined in subsequent years, likely due in large part to the 2008/09 recession, to a level of 2,915 MW in 2009 (at generation, i.e. inclusive of transmission and distribution losses). On an actual basis, the commercial class load also reached its highest level in 2006, with an hourly integrated demand of 3,090 MW.

The industrial annual coincident peak demand declined on a weather normalized basis from the year 2003 and 2009 by approximately 3.1% per year. The normalized class demand increased modestly between 2003 (856 MW) and 2005 (934 MW), but fell rapidly to 710 MW during the 2008/09 recession. There was broad weakness across this class, but a couple of specific large customer closures had a significant impact. For this class, 2006 saw the highest actual coincident peak demand at 945 MW.

Figure 3.13: Industrial Coincident Peak Demand (MWs)



3.2.2 Profile Shapes[43]

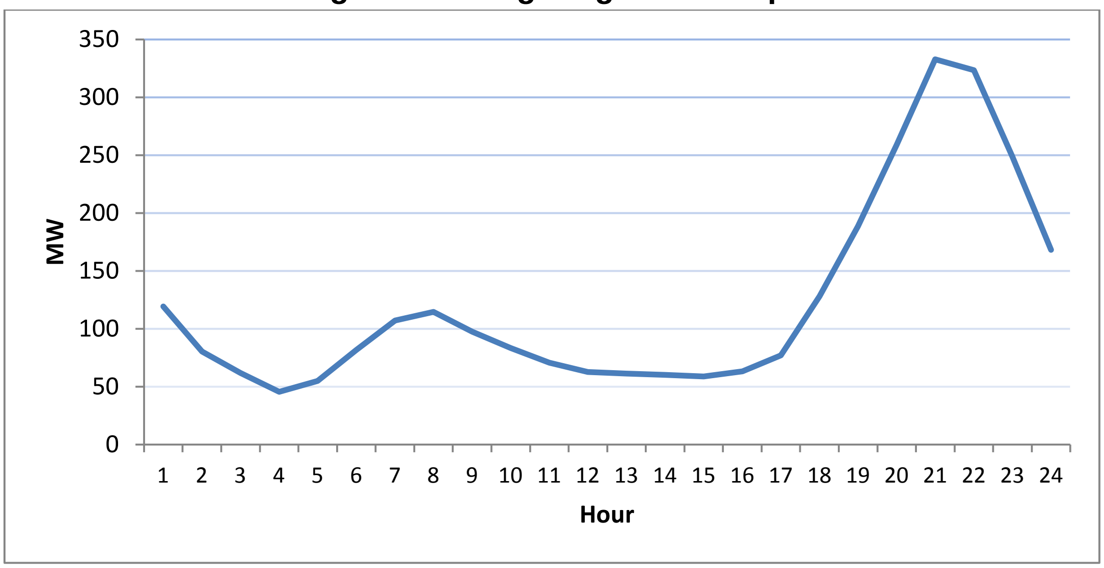
The energy forecast provides a view of how much energy will be used by each category of end use for each customer class where applicable and for each total class where end uses are not contemplated in the energy forecast. The challenge of developing a system peak and hourly forecast comes down to determining when that usage will occur. This problem is well-suited to the application of load research data. And for the industrial classes that were forecasted using econometric models (no end-use detail), Ameren Missouri specific load research data is exactly what is used to determine that pattern of usage.

[43] 4 CSR 240-22.030(4), 4 CSR 240-22.030(4)(A)

For the residential and commercial classes, the energy forecast from the Statistically Adjusted End-Use models can be disaggregated into its end-use components relatively easily. Because of various changes in energy efficiency standards for different end uses as well as differences in the natural growth of the stock of each end-use appliance in the service territory, it was hypothesized that a more accurate peak and hourly forecast could be generated by applying specific end-use shapes to this end-use energy forecast.

To illustrate the point, consider the lighting end use. Lighting is most prominently used by residential customers after sunset to illuminate homes in the evening. The summer peak load, which is arguably the most critical component of this forecast, will almost certainly occur late in the afternoon on a summer weekday. At this time, the sun is shining brightly and lighting use is relatively low for residential customers compared to the evening. A typical lighting load shape is shown in Figure 3.14, note the peak at hour 21 and the fact that hour 17 (likely the summer peak hour) energy is only 23% of the peak.

Figure 3.14: **Lighting Load Shape**



Because the Energy and Information Security Act of 2007 (EISA 2007) included standards to increase the efficiency of most light bulbs used by residential customers, the energy forecast associated with lighting is actually declining fairly significantly relative to other end uses over the planning horizon. If a class level model was used to forecast the residential summer peak, the decline in lighting load would produce a 1 for 1 decline in the summer peak. In other words, if lighting load hypothetically represented 10% of the residential energy usage, and the forecast included a 10% decrease in lighting energy, then the peak load forecast would be 1% lower (10% lighting share * 10% decline in lighting load = 1% decline in total load). However, under the end-use profile framework, lighting may still hypothetically represent 10% of the residential energy consumption, and it may still decline by 10% in a forecast year. However, because the lighting profile is at a relatively lower level during the summer peak hours (23% of the peak lighting usage and 63% of the average lighting usage), the lighting contribution to peak will cause something less than a 1% decline in peak load. More of the decline induced by the lighting efficiency gains will be associated with energy usage that occurs later in the evening, not affecting the peak. As this example highlights, by assigning specific end-use profiles to the end-use energy forecast, more realistic load impacts on the peak should result.

Unfortunately, neither Ameren Missouri, nor any other utility we are aware of, currently collects load research data at the end use level. So for developing load shapes that are applicable to the end use energy forecast, secondary data must be acquired.

Itron's EShapes Database[44]

End-use load research is a very costly activity for an electric utility to engage in. Whereas traditional load research utilizes the existing meter and meter reading infrastructure, end-use load research typically requires the utility to install additional equipment within the premise of the customer and develop a new infrastructure for collecting this data. The cost of this for nearly all utilities is prohibitive, and therefore end-use load research programs are not common today, if they exist at all. However, in the 1990's a number of utilities did engage in end-use load research, and the data collected was shared through the Electric Power Research Institute (EPRI).

Itron, an industry leading forecasting and load analysis consulting company, has a product called eShapes. EShapes is a database of load shapes that apply to loads from various combinations of end use, customer class, and geographic location. The data underlying Itron's eShapes database is proprietary, but it is likely based in large part on the end-use load research data collected by EPRI. Itron's eShapes data has been publicly available for years and is relied upon widely as a high quality set of end-use load shapes. Ameren Missouri has acquired the Itron eShapes database and utilized its load shapes in the peak and hourly load forecasting process.

Load Shape Calibration[45]

Because the data in Itron's eShapes database is secondary data and probably more than a decade old, and more recent and geographically similar data is nearly impossible to come by, Ameren Missouri worked with this data to ensure that it was as applicable to the Ameren Missouri load as possible. For a one year period (2008), the Itron data was utilized to construct Ameren Missouri class level data from the bottom-up. Historical energy sales for 2008 were divided into end uses based on information from the SAE forecasting models. The eShape profiles for each end use were then scaled so that they represented the estimated energy from 2008. The scaled end-use shapes were then aggregated to create a "synthetic" class level load shape. That synthetic load shape was

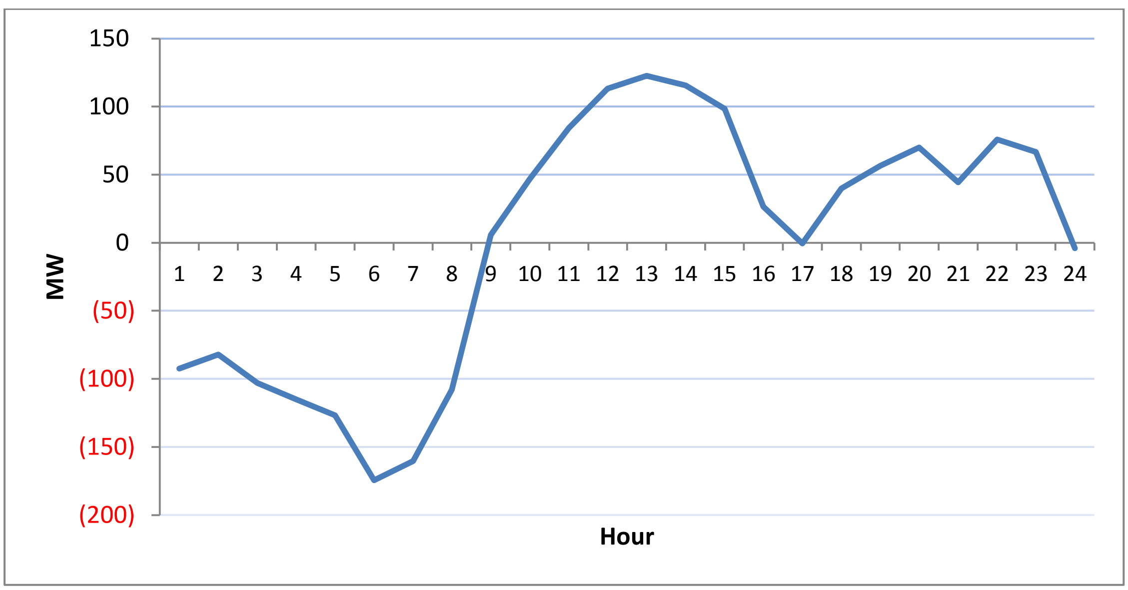
[44] 4 CSR 240-22.030(3)(A)
[45] 4 CSR 240-22.030(4)(B)

then compared to the Ameren Missouri load research data for the same class to determine whether the resultant bottom-up shape was an accurate representation of the relevant load. The eShapes profiles were then calibrated to ensure that the load shapes utilized in the final forecast were a good representation of the load for the class.

For the weather sensitive end uses (heating and cooling), it was necessary to build a regression model of the load temperature relationship of the end use in order to make the load shapes applicable to the historical period in question given the weather that occurred. The data used in the model in the case of these end uses did not come directly from the eShapes database, but instead was based on the end-use data simulated for Ameren Missouri by Itron for its 2008 IRP filing. The actual weather from 2008 was applied to the model coefficients to produce weather sensitive heating and cooling shapes that are based off of the weather experienced in that year.

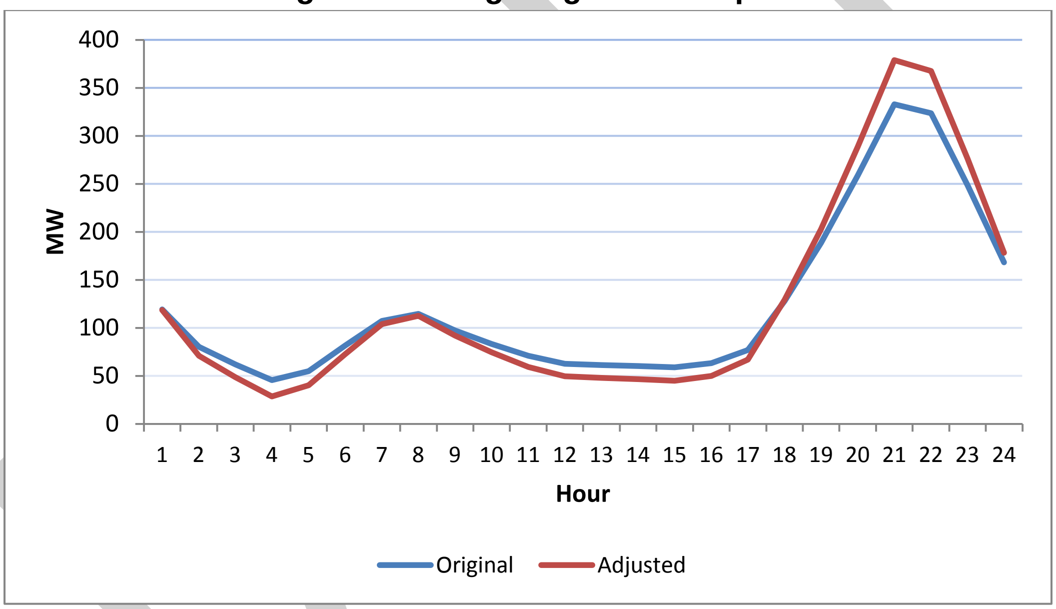
The synthetic class load shapes were plotted against the load research data to allow for visual inspection of the loads side by side. Also an hourly error series was developed by subtracting the synthetic class load from the actual load research. This error series was examined by averaging it across several time dimensions (hour of the day, day of the week, month) to determine whether there were systematic ways in which the synthetic load profile was varying from the load research data. It quickly became apparent that the average hourly class load shape that had been generated from the end-use data was not consistent with the load shape observed from the load research data. This is not surprising, as again, the end-use load research is secondary data and is removed from its original source in both time and geography. Figure 3.15 shows the average hourly error pattern that was generated in this process for the residential class:

Figure 3.15: Average Hourly Difference-End Use Build Up vs. Load Research



As is apparent in Figure 3.15, the synthetic class load shape was too high in the overnight and early morning hours (generating a negative error pattern), too low in the mid-afternoon hours, and again too low in the evening lighting hours (generating a positive error pattern). In order to improve the fit of the build-up load, the individual end-use load shapes were adjusted slightly. The overall characteristic of the shape was respected, as the eShape data is the best information available to discern the usage patterns of these end uses. However the load factor of each shape was adjusted up or down using the unitized load calculation[46]. An algorithm was set up to vary each end-use load shape within certain parameters judged by the forecasting staff to be reasonable, with the goal of minimizing the sum of the hourly absolute errors in the calculation represented by the chart above. Through this process, using the adjusted end-use load shapes, the hourly pattern in the error was reduced significantly. Below is an example of an end-use load shape both before and after load factor adjustment.

Figure 3.16: Lighting Load Shapes



---

46 **Unitized hourly load calculation:**

1) From the actual hourly load data, estimate the daily peak $PK_t(0)$, daily average $AVG_t(0)$
2) Calculate 'unitized hourly load' using the equation:

$$D_{ht}(0) = \frac{MW_{ht}(0) - AVG_t(0)}{PK_t(0) - AVG_t(0)} \qquad (1)$$

3) Simulate the constructed models using normal weather as the input. Obtain the weather normalized daily peak $PK_t(0)'$ and daily average $AVG_t(0)'$
4) Get the 'normalized load curve' using the equation:

$$MW_{ht}(0)' = AVG_t(0)' + D_{ht}(0)(PK_t(0)' - AVG_t(0)')$$

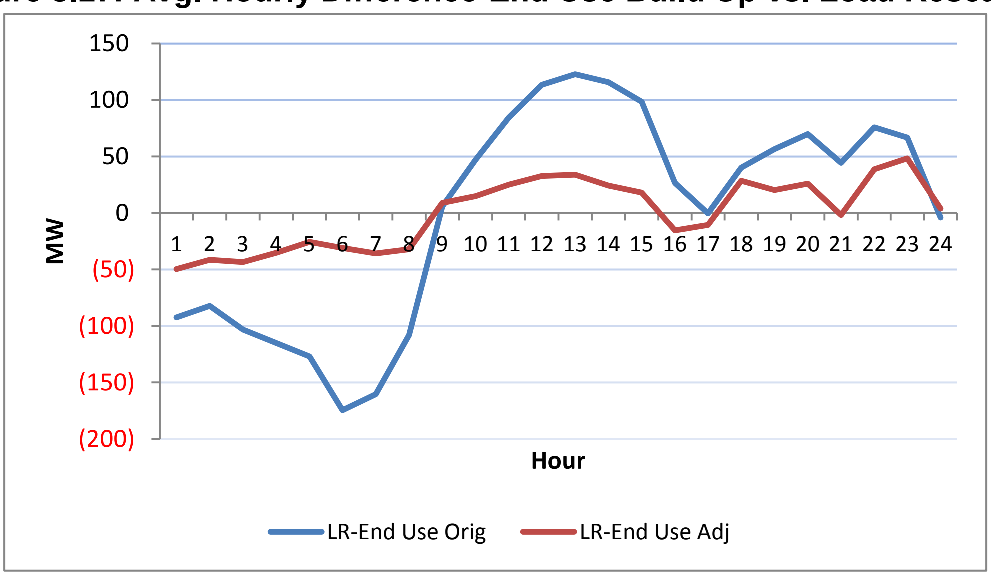
As is visible in the chart of the lighting shape, the basic characteristic is retained, but the load factor is reduced in this instance (the pea k of the adjusted shape is higher relative to the total energy). By reducing the lighting load factor, the observed characteristic of the synthetic load shape being too low in the evening is improved. As mentioned before, each end-use profile shape went through a similar adjustment process simultaneously with the objective of minimizing the hourly differences between the synthetic bottom-up load shape and the actual class load shape from load research. The pattern of the hourly differences before and after adjustment is shown in Figure 3.16.

While the adjusted load shape still has some differences from the class actual load shape, the magnitude of the differences is clearly reduced by a substantial amount. It would be impossible to make the synthetic load shape have a perfect fit with the load research data while respecting the characteristic shape of each end use. But with reasonable adjustments, the fit was dramatically improved. Where the original load shape had absolute differences that exceeded 100 MW and reached as high as 170 MW, now no hour's difference exceeds 50 MW as shown in Figure 3.17. This innovative process helped bring the secondary data much more in line with the specific characteristics of the Ameren Missouri service territory loads. The forecasting staff reviewed each individual end-uses' adjusted load shape to confirm that it was reasonable.

The process described above was replicated for the four commercial rate classes to provide end-use load shapes for all classes for which the energy forecast contemplated this level of detail.

All of the adjusted end use load shapes were provided to Ameren Missouri's DSM team in order to develop the hourly load reductions associated with planned energy efficiency programs.

Figure 3.17: Avg. Hourly Difference-End Use Build Up vs. Load Research



3.2.3 Peak Load Forecast

Once the load shapes, both end-use and class level, have been developed, the process of forecasting the peak system loads is fairly straight forward. The most complicated part is developing a planning calendar to base the forecast period profile shapes on and later substituting the actual calendar for this.

Planning Calendar Profile Development

While the forecast is based on normal weather, in future years, we do not yet know the pattern in which the weather will occur. So a reference historical year is selected for forecasting purposes. For this forecast, 2008 was the reference year. This historical year (2008) becomes the base for the ordering of the daily normal temperatures across the calendar. So the normal weather will follow the pattern that the actual weather followed within each month of 2008. So for example, the hottest day of August 2008 fell on the 4th. In our planning calendar case, the hottest weather of August will also fall on the 4th. However, when applying normal weather to the planning calendar, if the most extreme weather in the historical year fell on a weekend day, the most extreme normal temperature will be shifted down to the next most extreme day, until it lands on a weekday. Weekdays tend to have the highest loads to begin with due to the business cycles of the commercial and industrial customers. It is therefore important to have peak temperatures on a weekday so that the peak is not under-forecasted by matching the highest residential load with lower levels of commercial and industrial load.

In the planning calendar forecast run, both the weather and the days of the week are forced to follow the pattern of the reference year. For example, August 4th (2008) was a Monday. So for the planning calendar (which will be applied to forecast all future years), August 4th will remain a Monday for modeling purposes in all years. This prevents the peak load from changing simply due to changing combinations of weather and weekday over the forecast horizon. If our peak temperature were allowed to float to different weekdays over the forecast horizon, the load forecast would change from year to year based on nothing more than the assumed day of the week on which the peak fell. Again, as industrial and commercial load patterns follow those customers' business cycles, it is important to reflect a consistent match between the point in the weekly business cycle and the peak load.

The profile shapes must then be extended over the forecast horizon using the planning calendar assumptions. For the non-weather sensitive end-uses, this is a very easy exercise. These shapes from the eShapes are generally comprised of just a weekday and weekend shape for each month of the year. To extend the shapes to the forecast horizon, the weekday shapes and the weekend shapes (as adjusted per the calibration process described above) are applied to the appropriate days given the month and day of week in the planning calendar.

For the weather sensitive end-uses and classes, the statistical profile models and the reference year weather and calendar patterns are used to project the planning case load shape. For classes that are not modeled with end use detail, the models are based on Ameren Missouri load research data for the class consistent with the weather normalization modeling. For the weather sensitive end-uses, the models are based on the Itron simulated heating and cooling shapes consistent with the load shape calibration process mentioned above. In both cases of the end use and class level profiles, the daily peak load and daily energy are modeled as a function of temperature and calendar (day of week, month, and season) variables. The models are then simulated using the planning calendar normal temperatures and weekdays

Once both the end-use and class level profiles have been simulated for the planning calendar year, that year is replicated exactly in order to represent the load shape for each year in the forecast horizon for peak modeling purposes.

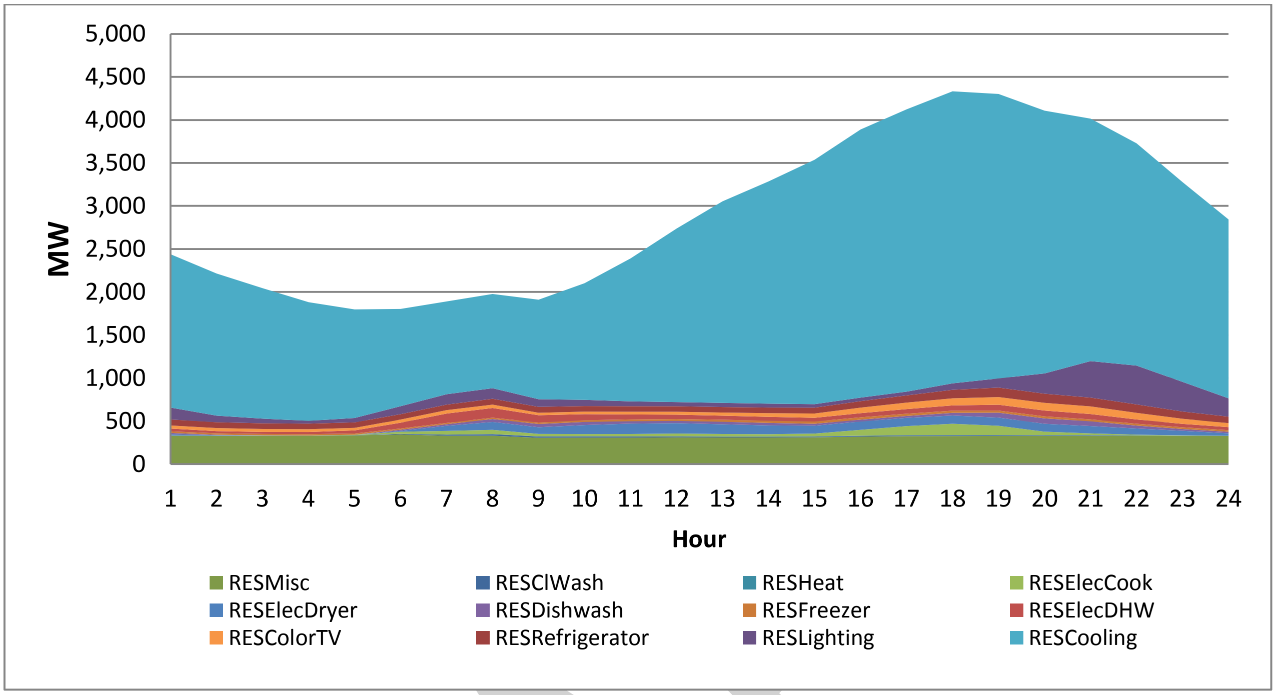
Actual Calendar Profile Development

While the planning calendar shapes are utilized, as will be discussed further below, to generate a consistent peak forecast from year to year, the final net system hourly load shape will be developed by load shapes based on the actual calendar. In the actual calendar, the temperatures are still mapped to the historical reference year (2008). But in this case, the days of the week are allowed to fall as they actually will in the years in question. So now instead of August 4th of every year being a Monday, in, for example, 2017, August 4th will be a Friday. Care is taken to still ensure that the extreme temperature falls on a weekday. But otherwise the temperatures fall onto different days of the week in each year. This way the final hourly loads are realistic relative to that actual calendar that will be used in the years. To ensure consistent peaks that do not vary relative due to changes in the day of the week on which it falls, the peak hour's load for each month is calibrated to the peak forecast from the planning calendar case.

Bottom-Up Forecasting

From earlier steps in the forecast process, we have developed class level or end-use energy forecasts, and profile models that will generate load shapes for each class and end-use. Developing the final peak and hourly forecast is a relatively simple process of bringing these two inputs together. Using Itron's MetrixLT software, the profile shape for each class and end-use is scaled to the monthly energy from the energy forecast. This is a simple mathematical exercise, where a ratio is developed between the energy forecast for each class or end-use and the sum of the hourly profile for that class or end-use within each month of the forecast horizon. That ratio is applied to each hour in the profile so that the hourly load retains the profile shape, but sums across the hours of the month to the forecasted energy level. Figure 3.18 shows an example of the buildup of the residential load for a summer day from the end use components.

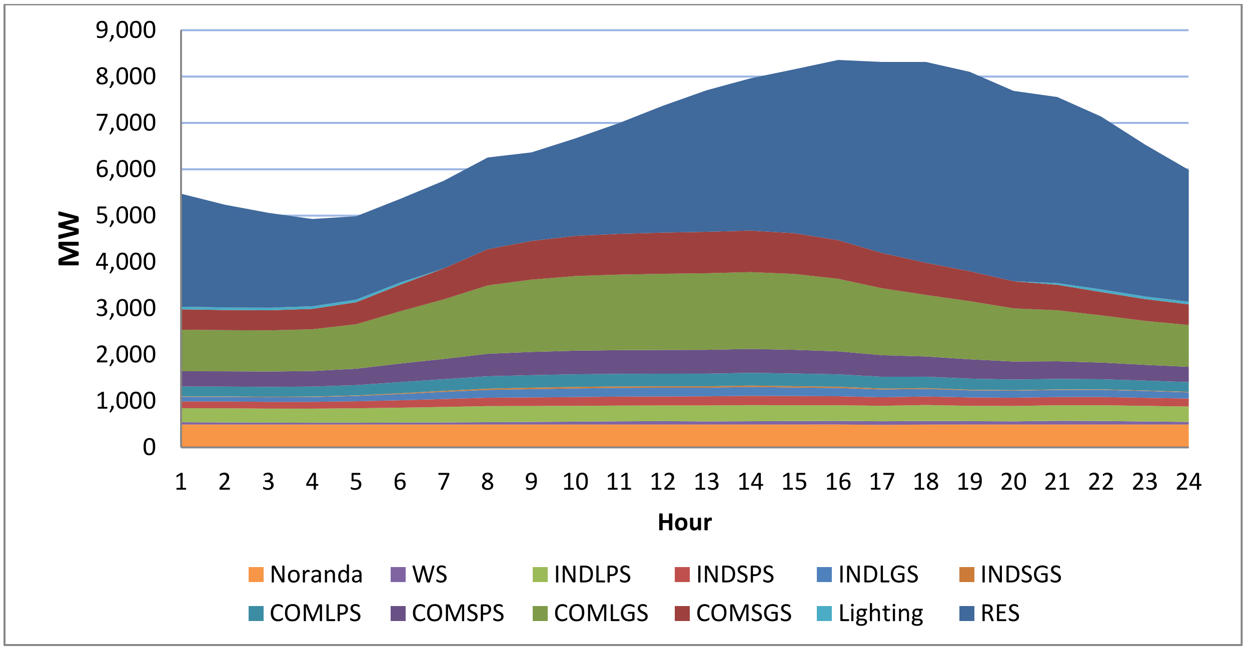
Figure 3.18: Residential Summer Day Usage Built-Up by End Use



Once each class load has been constructed on an hourly basis (either through direct application of the class profile to the class energy forecast or through the aggregation of the end-use scaled load shapes), transmission and distribution losses are applied. The transmission and distribution losses are based on the Ameren Missouri 2008 loss study performed by its distribution engineers. For purposes of calculating the load for the peak forecast, demand loss rates are utilized. Demand loss rates are the loss rates determined by the study to apply to loads at times of peak demand. Typically this loss rate is higher than average or energy loss rates due to the properties of the system that cause losses to increase both under high load conditions and high temperatures.

The demand loss rates are applied to the profiled loads based on the planning calendar. This is done because the planning calendar was created specifically to develop a consistent peak forecast across time and the demand loss rates are designed specifically for application to peak periods. Each class has the applicable loss rate applied to it based on the voltage level at which its customers are served. When each class' hourly load has been grossed up to represent the amount of energy that must be generated to serve them inclusive of applicable losses, the class loads are summed for each hour. This results in a forecast of the hourly load from which the maximum value for each month can be isolated as the forecasted peak load for that month. Similar to the build-up of the residential class from end-use data, a graphical representation of the build-up of the system load by class can be seen in Figure 3.19.

Figure 3.19: 2010 Summer System Peak Day Usages Built-Up by Class



Back Testing and Calibration of Peaks

In order to ensure that the bottom-up forecast is producing a peak load estimate that is reliable, Ameren Missouri used the same methodology to backcast historical peaks for the period from 2003 through 2009. Historical calendar month actual sales were disaggregated into end uses where necessary by application of information from the Statistically Adjusted End Use models[47]. The end use and class level profiles were updated with actual historical weather and calendar information to produce historical shapes to represent actual conditions[48]. The historical sales were shaped using the profiles, grossed up for line losses, and aggregated. The peak values from those historical calculations for each year were compared to the actual peak loads observed in those years. The results are shown in the Table 3.6.

Table 3.6: Actual vs. Model Peak

Year	Modeled System Peak (MW)	Actual Peak (MW)	Difference
2003	7,648	7,856	2.65%
2004	7,802	7,634	-2.20%
2005	8,503	8,463	-0.47%
2006	8,400	8,596	2.28%
2007	8,623	8,780	1.79%
2008	8,463	8,384	-0.94%
		AVG	***0.52%***

While the results of the back testing exercise indicate good performance of the model in that no year's modeled result was more than 2.65% off from the observed value, on average the model has slightly under predicted the historical peak loads by 0.52%.

[47] 4 CSR 240-22.030(3), 4 CSR 240-22.030(1)(C)2.B
[48] 4 CSR 240-22.030(3)(B)2

This information was used to adjust the forecast values for future years. In effect, the historical bias evident in the modeling has been used to calibrate the forecast so that it is reflecting the level of peak load that should be expected based on the historical performance of the model. It should be pointed out that the historical trend of forecasting slightly under the peak is not at all unexpected. The bottom-up methodology employed in this forecast is really designed to forecast the expected value of the load when peak temperatures are present. However there is still some uncertainty regarding the variability of the load that is unexplained by the model. In years with multiple very hot days that could produce peak load conditions, it is likely that the unexplained variability in the load will be positive on one of those days. In other words, all forecasts have error in them. Sometimes the forecast is too high and sometimes it is too low. But given several observations of actual vs. forecast comparisons, we expect to have both positive and negative errors. The peak load will most likely occur on a hot day that also has a positive error (i.e. the actual load came in above forecast). The adjustment factor applied takes the forecast from being a prediction of the expected value of load given peak temperatures to being the expected value of peak load. This is exactly what the peak forecast should be doing.

3.2.4 Hourly System Load Forecast[49]

After the bottom-up forecast has been generated using the planning calendar and demand loss rates in order to determine the peak load forecast, the same process is replicated using the actual calendar information described above and energy loss rates. This hourly system load data is what is actually passed on to the integration analysis.

The actual calendar data as described above is used to make the hourly load forecast apply correctly to dates in the future. Since the energy for the forecast horizon is an input to this process and not determined by this process and we will use the peak forecast from the planning calendar runs, it is no longer necessary to force the days of the week fall in the same order each year for consistency sake. The days can now fall as they will when the years actually occur so that the modeling results are calendar correct.

Also because the peak forecast has been determined in the previous step, energy loss rates can now be utilized instead of demand loss rates. Recall that the demand loss rates were created to determine the level of losses that are occurring on the system at the time of peak. Energy loss rates determine the losses that are incurred across the entire year. These are used to gross up meter level sales to reflect the level of energy that will actually need to be generated in order to meet the demand of Ameren Missouri's customers. The energy loss factors in Table 3.7 were utilized in the forecast process and the Class and System weighted loss factors (weighted by 2008 loads) were also provided to the DSM and integration teams such that consistent loss rates were used across the

[49] 4 CSR 240-22.030(5)(C)

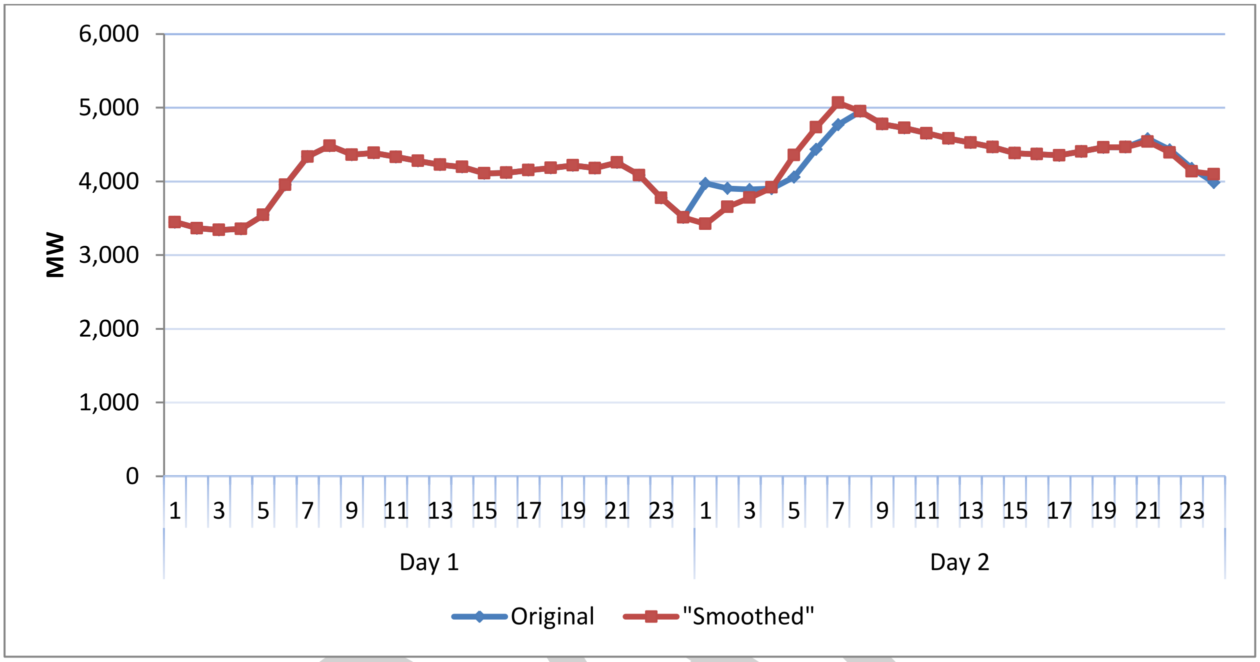
entire analysis. An additional 3.5% loss beyond the value in the table is applied to the Noranda load to represent the contractual obligation of Ameren Missouri to provide for 3.5% losses while crossing the AECI transmission system.

Table 3.7: Energy Loss Rates

	@ Meter (KWh)	@ Transmission (KWh)	@ Generation (KWh)	Distr. Losses	Total Losses	Ameren Trans. Losses	Losses to MISO Transmission
Res	13,817,108	14,745,746	14,929,153	1.0672	1.0805	1.0124	1.0572
Com SGS	3,518,470	3,754,933	3,801,636	1.0672	1.0805	1.0124	1.0572
Ind SGS	130,691	139,475	141,209	1.0672	1.0805	1.0124	1.0572
Com LGS	7,236,083	7,722,380	7,818,431	1.0672	1.0805	1.0124	1.0572
Ind LGS	1,088,971	1,162,152	1,176,607	1.0672	1.0805	1.0124	1.0572
Com SPS	2,533,332	2,619,113	2,651,689	1.0339	1.0467	1.0124	1.0242
Ind SPS	1,360,968	1,407,051	1,424,552	1.0339	1.0467	1.0124	1.0242
Com LPS	1,353,805	1,398,801	1,416,199	1.0332	1.0461	1.0124	1.0236
Ind LPS	2,719,290	2,790,605	2,825,314	1.0262	1.0390	1.0124	1.0166
Wholesale	624,773	631,067	638,917	1.0101	1.0226	1.0124	1.0006
Lighting	232,270	247,877	250,960	1.0672	1.0805	1.0124	1.0572
Noranda	4,130,376	4,158,645	4,210,370	1.0068	1.0194	1.0124	0.9974
Com Avg	***14,641,691***	***15,495,227***	***15,687,955***	***1.0583***	***1.0715***	***1.0124***	***1.0484***
Ind Avg	***5,299,920***	***5,499,283***	***5,567,682***	***1.0376***	***1.0505***	***1.0124***	***1.0279***
System Avg	***38,746,139***	***40,777,845***	***41,285,036***	***1.0524***	***1.0655***	***1.0124***	***1.0426***

The process of generating the hourly system forecast begins in exactly the same way as the bottom-up forecasting of the peak was done, with the exception of the use of the actual calendar and the energy loss rates. The profile shapes for each class and end-use where applicable is scaled to the energy forecast, grossed up for losses, and aggregate to the system level. After that has been completed, there are only a couple of more steps involved in the creation of the hourly system forecast. First, the annual peak load is calibrated to the peak forecast developed in the planning case (as adjusted per the back-calibration routine). Next, transmission losses are deducted from the forecasted loads. Remember that energy loss rates were used to gross the sales up to the level of load that will have to be generated. The transmission losses are then deducted because of the way that the company interacts with the Midwest Independent System Operator's (MISO's) energy markets. Ameren Missouri sells its generation to MISO, and buys its load from MISO. The difference between generation and load is the volume of off-system sales (net of power purchases) made by the company. However, the load that is purchased from MISO does not include transmission losses. In MISO's market, there is a financial charge for transmission losses, but the physical energy is not purchased by the load serving entity. To reflect this reality, a loss rate is used to back the energy forecast down from the level of energy required to meet customer demand at the generation level to the level of energy needed at the interface between the transmission and distribution system. A loss rate of 2.2% was used to perform this calculation. This rate was based on the actual rate of losses observed on the Ameren Missouri control area based on MISO settlements for the years of 2008 and 2009.

Figure 3.20: Example of Smoothed Load Shape



The final step in the process of developing the hourly system loads involves checking for, and if necessary correcting, discontinuities in the load pattern during the overnight hours. Because each day is modeled independently, there are occasions when the transition from hour 24 of one day to hour 1 of the next day has a significant jump. In the cases where this issue is detected, Ameren Missouri has corrected the situation with a smoothing algorithm that it developed. This algorithm maintains the total energy for each day from the original forecast, but reorganizes certain hours so that the load pattern is more realistic. This is important so that the dispatch algorithms in the integration analysis will not be forced to commit units overnight for an artificial jump in load. An example of before and after "smoothed" load can be seen in Figure 3.20.

Scenarios and Planning Case Forecasts

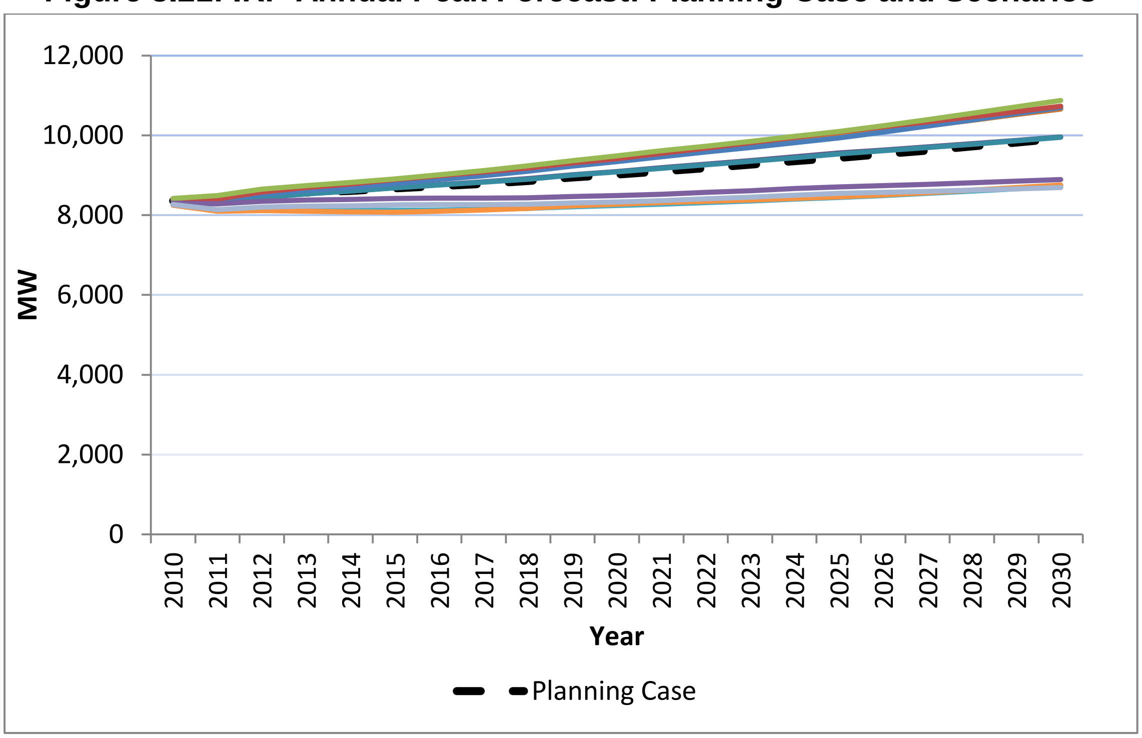
The energy forecast described in Section 3.1 was modeled under ten different scenarios. Each of these scenarios was based on a certain combination of the three critical uncertain factors identified in this IRP (gas prices, load growth, and carbon policy). The peak and hourly system forecast was also run for each of these scenarios. This was simply a matter of running the class and end-use level energy forecast results from each scenario through the process detailed above. When this process was complete, again similar to the energy forecast, a planning case peak forecast was developed. This forecast was calculated by taking the subjective probabilities assigned to each scenario and using those as weighting factors to average the scenario load forecasts. Again this mirrors the process for the planning case energy forecast. The planning case energy forecast was passed to integration analysis to develop the capacity position for the IRP. The scenario based load forecasts were also passed to integration so that the candidate resource plans could be tested under all scenarios identified in the IRP.

3.2.5 Forecast Results

The planning case forecast results indicate a forecasted annual peak load growth rate from 2010 through 2030 of 0.86%. The peak load in 2010 is projected to be 8,359 MW, growing to 9,923 MW by 2030. The growth rates in the various scenarios range from a low of 0.25% annually, to 1.29% per year.

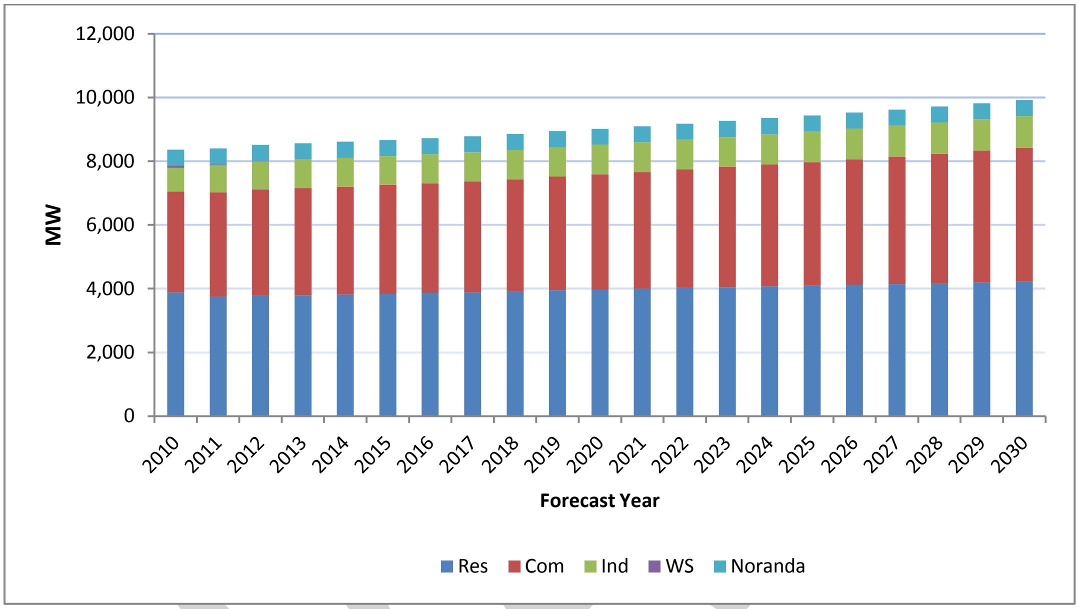
The forecast for the same 20 year period from Ameren Missouri's 2008 IRP was 1.23%. The starting point of this IRP's forecast is also almost 400 MW lower than the 2010 peak that was forecasted three years ago. The lower starting point is primarily attributable to the severe recession and significant load loss that was incurred that had not been anticipated as of the February 2008 filing. The lower growth going forward is due partly to lower overall energy growth rates in this IRP, but also a change in the relative contribution of each class to the growth. The overall growth rates in this IRP are slower than the previous filing due to both efficiency standards that were passed as a part of EISA 2007, as well as larger assumed price increases in this forecast, that result in more customer conservation efforts as modeled by the elasticity component of the forecast.

Figure 3.21: IRP Annual Peak Forecast: Planning Case and Scenarios



The fact that the residential class is now forecasted to be the slowest growing class (due largely to efficiency standards impacting residential lighting and air conditioning) also contributes to the lower level of peak growth in this IRP. Because the residential class has the lowest load factor, when this class grows more slowly, it has the effect of improving the forecasted system load factor over the longer term. A lower load factor necessarily produces less growth in peak demand.

Figure 3.22: Class Contribution to Annual Peak Forecast



Class and End-Use Peak Demands[50]

The peak contribution of the residential class grows at 0.40% per year from 2010 to 2030, while the commercial class peak grows at a forecasted 1.44%, and the industrial class peak is expected to grow by 1.50% per year.

The end use contributions to the peak load growth within each class varied fairly significantly. For the residential class, the fastest growing end use in the forecast in percentage terms is television load. This end use is projected to grow at 2.6% per year. The most growth on an absolute megawatt basis comes from air conditioning. Despite the fact that air conditioning is growing slower than the class as a whole, due to efficiency gains and slowing of new stock additions as the appliance nears full saturation, the sheer size of the air conditioning load during peak periods dictates that any growth in this end use will add a significant number of megawatts. The tables and charts below indicate the end-uses that contribute to the peak load for both the residential and commercial classes. The end-use make-up of the peak load is displayed for both the first year of the forecast (2010) and the last year of the forecast (2030).

[50] 4 CSR 240-22.030(5)(B)2.B

Table 3.8: Residential End-Use Contribution to Peak

	2010 Peak Contribution (MW)	% of Peak Load	2030 Peak Contribution (MW)	% of Peak Load	CAGR
Clothes Washer	9.6	0%	8.4	0%	-0.7%
Refrigerator	74.8	2%	79.8	2%	0.3%
Miscellaneous	320.7	8%	519.2	12%	2.4%
Lighting	41.4	1%	27.0	1%	-2.1%
Heating	1.7	0%	1.8	0%	0.5%
Freezer	27.0	1%	27.7	1%	0.1%
Electric Dryer	96.6	2%	104.3	2%	0.4%
Electric DHW	48.0	1%	63.8	2%	1.4%
Electric Cook	67.4	2%	77.4	2%	0.7%
Dish Washer	22.1	1%	23.6	1%	0.3%
Cooling	3,114.9	80%	3,168.4	75%	0.1%
Color TV	64.6	2%	108.9	3%	2.6%
Total	***3,889***	***100%***	***4,210***	***100%***	***0.4%***

Figure 3.23: Residential Peak Load Composition 2010

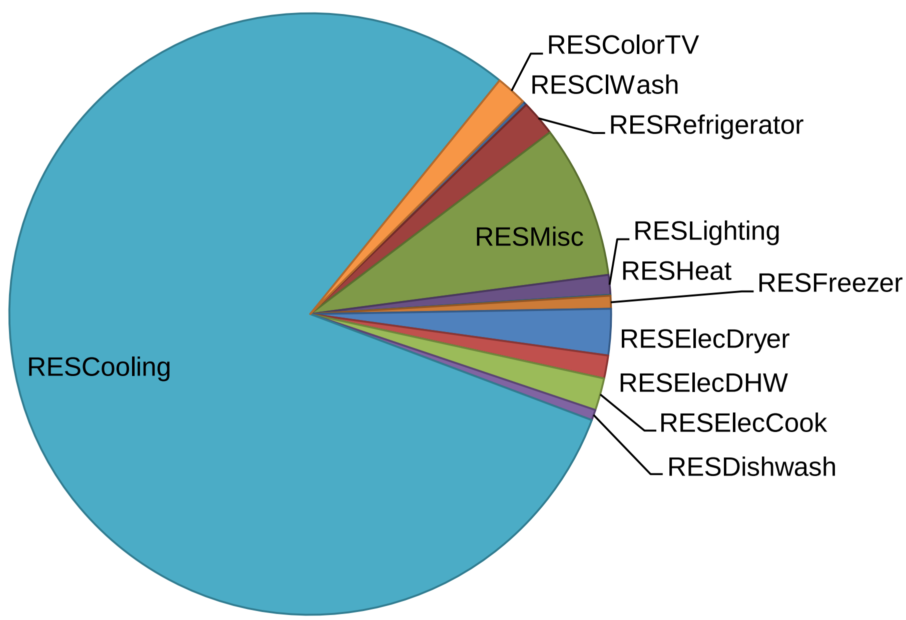


Figure 3.24: Residential Peak Load Composition 2030

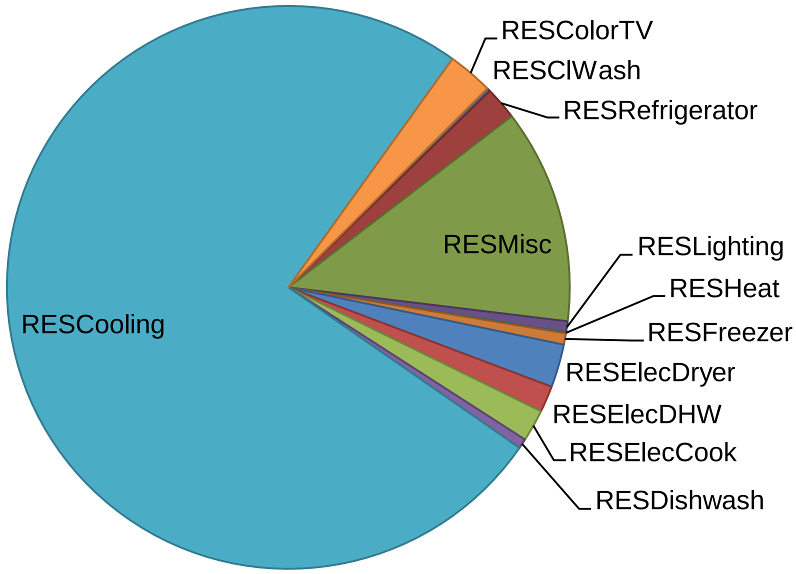
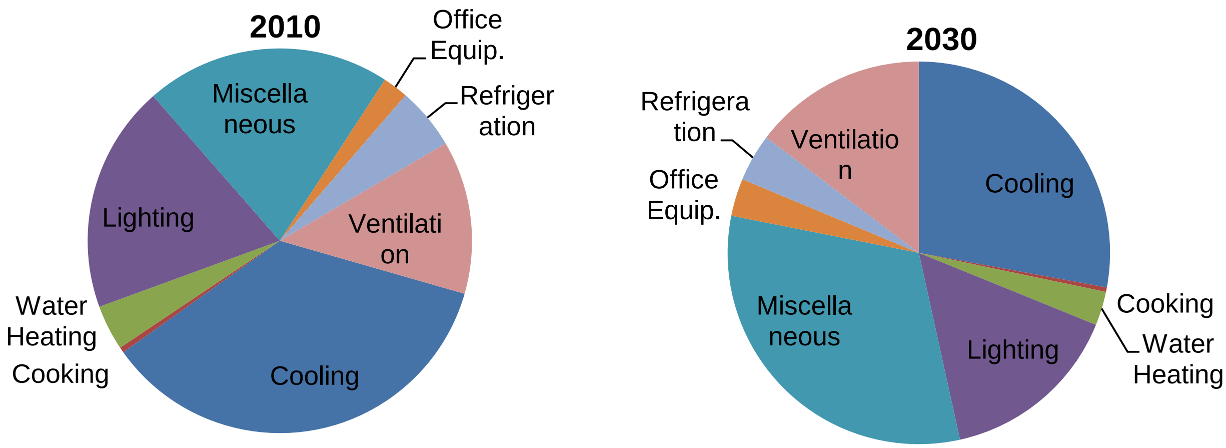


Table 3.9: Commercial End-Use Contribution to Peak

	2010 Peak Contribution (MW)	% of Peak Load	2030 Peak Contribution (MW)	% of Peak Load	CAGR
Cooling	1,129.52	36%	1,175.21	28%	0.20%
Cooking	14.35	0%	15.82	0%	0.49%
Water Heating	120.54	4%	120.83	3%	0.01%
Lighting	604.85	19%	648.82	15%	0.35%
Miscellaneous	653.14	21%	1,329.64	32%	3.62%
Office Equip.	67.68	2%	133.75	3%	3.46%
Refrigeration	164.83	5%	169.61	4%	0.14%
Ventilation	407.47	13%	618.78	15%	2.11%
Total	***3,162***	***100%***	***4,212***	***100%***	***1.44%***

Figure 3.25: Comparison of Commercial Peak Load Composition (2010 and 2030)



3.2.6 End Use Methodology Impact

The added level of end-use detail in Ameren Missouri's 2011 IRP was hypothesized to bring improved accuracy to the peak forecast. After the forecast was completed, an analysis was undertaken of the residential contribution to the system peak to see exactly what impact the end-use detail had on the resulting forecast. The study was abbreviated relative to what would be possible to do, but it is sufficient to understand the types of impacts of the new forecasting process on the future peak load estimates. In the interest of time and efficient use of resources, the forecast was not re-run in its entirety using only class level profiles in order to compare the results. Instead, some relatively simple, yet telling calculations were done to demonstrate the value of the added information. The calculations were performed using one of the scenario forecasts (Base Load Growth, Base Gas Prices, EPA Regulations of Carbon), rather than the planning case, so the peak load forecasts referenced in this section will not tie directly to the planning case peak load forecast reported elsewhere in this document.

First, it was assumed for purposes of this study, that the base year of the forecast (2010) would be the same given either methodology. While it is certainly not the case that the values would have been identical, the back-testing employed should ensure a reasonably comparable starting point for the forecast given the use of either methodology. From that point it is fairly simple to calculate the differences in the forecast in future years that arise from end-use forecast as compared with class level forecasting. We can simply take the annual growth rates in July energy for the class and apply them to the peak load. This essentially replicates what a class level forecasting methodology would produce, again given the starting value in 2010. Essentially this holds the load factor for the class constant across time. If we did not know anything about the changing contributions of the end uses to the peak load, there would be no basis for the load factor to change. By comparing the results of this type of class level forecast, we can see what refinement is brought to the forecast by the information provided for each end use.

The calculation described above was done for the year up through 2016. Air conditioning, being the dominant end use at the time of peak, is a good place to start the discussion. While the class energy in the month of July was growing by 0.78% per year between 2010 and 2016, air conditioning load was only growing by 0.29% per year. The fastest growing end use over this time period was miscellaneous load. Because air conditioning has a relatively poor load factor (it is used much more at peak times relative to its average level of use), the fact that this end use is growing more slowly than the rest of the load actually serves to improve the class load factor. Table 3.10 demonstrates the impact by end use. The first column shows the peak contribution of each end use to the 2010 forecast (check scenario and comparability with end use pie charts above). The second column shows the peak contribution of each end use to the 2016 forecast. The third column shows what the peak contribution of each end use would be to the forecast in 2016 if class level profiles had been used, per the analysis described above. It is evident that in this case, the peak forecast would have been if the forecast had employed only class average profiles instead of end-use profiles. The final column shows the impact on the forecast of the end-use profiles.

Table 3.10: Comparison of Peak Growth Using End-Use Profiles vs. Class Profiles

	Peak Contribution in 2010	Peak Contribution in 2016	Peak Contribution in 2016 with Class Average Growth	Difference
Clothes washer	9	8	10	-2
TV	78	95	82	13
Cooling	3,134	3,189	3,283	-95
Dishwasher	29	29	31	-1
Cooking	124	132	130	1
Water Heating	58	65	60	5
Dryer	90	91	95	-3
Heating	1	1	1	0
Miscellaneous	303	378	317	61
Freezer	24	24	25	-2
Lighting	71	55	74	-19
Refrigerator	93	95	98	-3
Total	4,015	4,163	4,207	-44

Because air conditioning is growing slower than the average, it contributes 95 fewer MW to peak in 2016 than it would under class level profiling. There are other end uses that grow faster than average, such as miscellaneous, and therefore contribute more to the 2016 peak than they otherwise would. But because these end uses do not have the poor load factor of air conditioning, they do not fully make up for the peak impact of the slower air conditioning load. In all, higher coincident load factor end uses are clearly growing faster than low load factor ones, causing the forecast to be lower than it would if the load factor were held constant through the years by applying only class level profiles.

While a difference of 44 MW does not create a radical change in the final analysis of the IRP, this methodology clearly represents an incremental improvement over what has been done in the past. We no longer are left to speculate whether, for example, the EISA 2007 lighting efficiency standard's impact on lighting load should really be impacting the peak less than it is the energy. This is already accounted for in the forecast through the application of the end-use profile methodology.

3.2.7 Peak Demand Weather Sensitivity

The peak demand forecast described above is based on the expectation of normal weather conditions. However, Ameren Missouri must plan its system to provide reliability even under more extreme weather conditions. In order to do this, a reserve margin is maintained. That is to say that Ameren Missouri maintains more generating capacity than is required to meet the forecasted demand in order to account for contingencies including extreme weather conditions. The long-term reserve margin utilized in this IRP is 17%. So in the capacity position, 17% is added to the forecast in order to determine annual resource requirements. An analysis was undertaken to determine whether this reserve margin is sufficient to cover extreme weather events as they have been observed historically.

In this process, Ameren Missouri identified the highest 11 weekday peak load projections from the month in which the annual peak is forecasted to occur (July) for 2010. From these days, a MW per degree statistic was calculated, that indicates the incremental demand on the system for each degree increase in the daily temperature. This process resulted in an estimate of 160 MW of increased system demand per degree.

This estimate was tested using 2010 summer peak data. The 2010 summer peak forecast called for a normal weather (at a two-day weighted average temperature of 87.58 degrees) load of 8,353 MW. The actual two-day weighted average temperature on the day of the 2010 summer peak was 88.33. So it was 0.75 degrees hotter than normal. Applying the 160 MW per degree to the 0.75 degree 2010 temperature variance produced an estimated peak load of 8,474 MW. The actual peak load for the day was 8,459. So this methodology produced a prediction that was within 0.2% of the observed load.

With this confirmation of the validity of the methodology, Ameren Missouri then calculated the expected peak load given two day weighted average temperatures equaling the 90th percentile of summer peak temperatures from 1971-2010 and at the absolute maximum temperature observed in that time frame. The result was that at the 90th percentile two day weighted average temperature (91.18 degrees), the peak load was forecasted to reach 8,929 MW, or 6.9% higher than the normal weather forecast. At the absolute maximum two day weighted average temperature reached during these years (92.26 degrees), the load was estimated to reach 9,103 MW, or 9.0% higher than the normal weather peak.

In each case, the extreme weather produced an effect that was considerably lower than the 17% reserve margin, leaving room for additional contingencies, such as a unit outage. In order to validate that sufficient reserves were left to account for an anticipated level of unit outages, Ameren Missouri also reviewed the reserve margin calculations performed by the Midwest Independent System Operator (MISO) in its Loss of Load Expectation Study for 2011. The MISO's reserve margin study explicitly accounts for generating outages through a forced outage rate calculation. Comparing the MW that are held for generating outage contingencies to those held to account for load uncertainty, it is apparent that MISO's reserve margin can be attributed evenly to the load and generation uncertainties. Said another way, half of the reserves are held to cover load uncertainty and half are covering generation contingencies. So applying this information to the analysis above indicates that, if half of the 17% reserves held by Ameren Missouri in the IRP are attributable to load uncertainty, then there are 8.5% reserves dedicated to load. Since the 90th percentile case in the extreme weather analysis only increased load projections by 6.9%, the reserve margin will adequately cover a 1 in 10 year weather event. Even considering the hottest weather experienced in 40 years, the 8.5% load related reserve margin is extremely close to matching the expected load impact of such an extreme situation. Based on these observations, Ameren Missouri concludes that the reserve margin of 17% is sufficient to account for the weather conditions that can be reasonably prepared for.

3.3 Weather Normalization[51]

Weather normalization is an important aspect of load analysis that allows the utility to determine the level of sales that it should be expected to make on an ongoing basis under normal weather conditions. It also allows the utility to quantify the impact of unusual weather on actual sales. Ameren Missouri has developed weather normalization models for various business reasons including to support rate case filings.

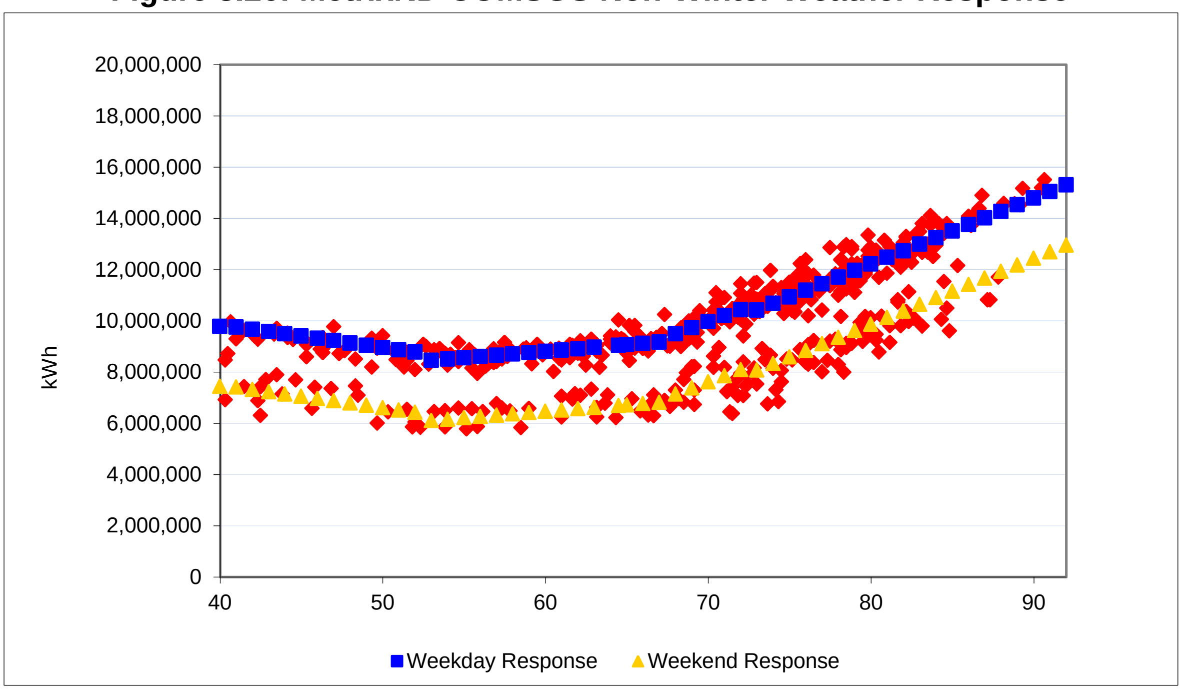
The weather normalization process involves the normalization of monthly sales, as well as hourly class level load research. The normalized class level load research also becomes the basis of a "bottom up" approach in weather normalizing its net system output. The models used in the current IRP filing are consistent with the models supporting rate case filings that are relevant to the historical period in question. The latest data has been normalized with the models developed to support case number ER-2011-0028. For historical periods covered by Ameren Missouri's 2008 IRP, the weather normalized information prepared for and reported in that filing is utilized in this filing.

[51] 4 CSR 240-22.030(1)(C)2

Weather normalization starts with defining "normal weather". Ameren Missouri currently uses actual temperature readings for St. Louis Lambert Airport from the period 1971-2000 to develop its normal weather conditions, as adjusted for certain changes in the recording equipment at Lambert. Ameren Missouri creates normal temperatures by applying the "rank and average" methodology to temperatures from these decades to accommodate unique nature of the problem of normalizing energy usage. Application of this procedure is necessary in order to produce realistic levels of normal energy later in the process. Essentially it is used to ensure that normal temperatures also exhibit a normal amount of variability that would be expected to occur within a year. This method has been utilized routinely in electric rate cases by the Missouri Public Service Commission Staff ("Staff"), and was used by both the Ameren Missouri and Staff in the Company's most recent rate cases.

The next step in the weather normalization process is to develop load-temperature relationships. Using a software package called MetrixND, daily peak and average loads at the rate and revenue class level are both modeled statistically as a function of calendar and weather variables. These statistical relationships are the basis for the weather adjustments which produce the normalized sales and hourly load research for a given period. These models are developed using various statistically significant weather variables along with various time and economic trend variables as explanatory variables to create a piecewise linear temperature response function[52]. A graphical representation of this modeling approach can be seen in Figure 3.26.

Figure 3.26: MetrixND COMSGS Non-Winter Weather Response



[52] 4 CSR 240-22.030(1)(C)2.A

The models are first built using actual weather variables along with other explanatory variables. Then the model coefficients are applied to the normal weather variable to generate a normalized version loads. The difference between the model's estimate of actual and normal loads is the weather impact for the time period in question. This weather impact is applied to the original load value to generate a normalized version of the load in question. The actual model variables and corresponding coefficients are presented in the appendix[53]. The weather normalized sales results are also provided in the appendix. For the purposes of normalization of hourly load research, the peak and average energy for each day are normalized as described above. The hourly normal values are then derived using the unitized load calculation described in Section 3.2.2.

3.4 Future Research Projects[54]

During the time period since Ameren Missouri's 2008 IRP filing, there have been several initiatives undertaken to improve the quality of load forecasting and load analysis at the utility. Some of the efforts have been described in detail throughout the body of the chapter. Those include the detailed end-use primary information gathered about the Ameren Missouri customer base as a part of the 2009 Market Potential Study conducted by Global Energy Partners and the analysis and application of end-use load shapes in the forecasting process. Beyond these analyses, there are a couple of other efforts that have been undertaken that are worth noting.

Ameren Missouri explored various options to update and validate the North American Industry Classification System (NAICS) codes in its customer database. Ameren Missouri ultimately engaged Dunn and Bradstreet to review the NAICS codes of its customer database and append the database with corrected data and fill in missing codes. This project was completed in 2009. Due to the maintenance fee required by the vendor, the data is not currently being maintained on an ongoing basis. However, the work was used to enhance the Market Potential Study mentioned above as well as the load analysis and forecasting for this IRP.

Ameren Missouri has also made several improvements to its load research process. Notably, we have changed from using billing month sales ratio analysis to calendar month sales ratio analysis. This enhancement greatly improved the results of the load research process. As evidence of this, the adjustment needed to reconcile aggregated and loss adjusted load research data to the observed system load became significantly smaller. An additional enhancement was the implementation of census analysis of the Large Primary Service Class. Instead of maintaining a sample of customers from this class, interval data for all customers in the class is obtained and aggregated to eliminate the need for any statistical estimation of the class load. Finally, some process improvements

[53] 4 CSR 240-22.030(1)(C)2.C
[54] 4 CSR 240-22.070(9)(A)

have also been made to more efficiently process load data. After evaluation of the performance of the load research sample given the improvements noted above, it was not necessary to redesign the sample at this time. The precisions of the load estimates as well as the good fit of the load research data in the process of calibrating to the net system load indicate a sample that is still performing well.

Going forward, Ameren Missouri has identified the following areas of continued analysis that we believe will allow us to continue to maintain and even improve upon the high level of analysis we has been doing.

End-Use Load Research

Ameren Missouri took a step forward in its analytical approach in this IRP by acquiring end use load shapes and using load research data to calibrate those shapes to more accurately represent the Ameren Missouri customer base's load characteristics. As noted in the discussion of the end use analysis in this chapter, obtaining new end use load shapes can be a very expensive proposition. End use load research has historically been intrusive in the customer home and required large amounts of expensive equipment, installation, meter reading, and other costs. However, with advances in metering technology, other options are being explored by the industry to obtain end use load data. As an example of the interest in the industry in this area, in October 2010, EPRI conducted a workshop entitled "End-Use Load Research in a Smart Grid World." Ameren Missouri will monitor developments in this area and assess the feasibility of utilizing new technologies to obtain improved data in this area. Ameren Missouri will also monitor the actions of other utilities and industry organization to determine if there are improved secondary data sources or collaborative initiatives to participate in.

Load Research Sample Design

Although the existing load research sample continues to perform well, it is still necessary to continue to monitor the sample performance. It is critical to maintaining a good understanding of customer usage patterns to have a sample that is representative of the class. While it appears that the current sample is still representing the customer base well, things can change over time. Ameren Missouri will monitor the load research statistics on a monthly basis and annually determine whether a new sample is required. There may be opportunities for new analysis that could result from a new sample design. Segmenting the classes in more granular ways may allow innovative analyses at, for example, the building type level for energy efficiency programs. Any new sample being implemented will be designed with additional potential uses in mind.

End-Use Surveys

Ameren Missouri, as described in this chapter, executed a very detailed survey of its customer base in 2009. This data is very valuable to the forecasting and load analysis area. Even more valuable, though, than a single survey, is a time series that helps to track changes in saturations of appliances over time. This can be useful for explaining trends in the load and for doing more detailed modeling of historical sales. This information can both improve forecasting models and lead to inferences about appliance stock that impact assumptions going forward. Ameren Missouri will weigh the potential benefits of running regular surveys to accumulate and track this type of data on an ongoing basis

3.5 Compliance References