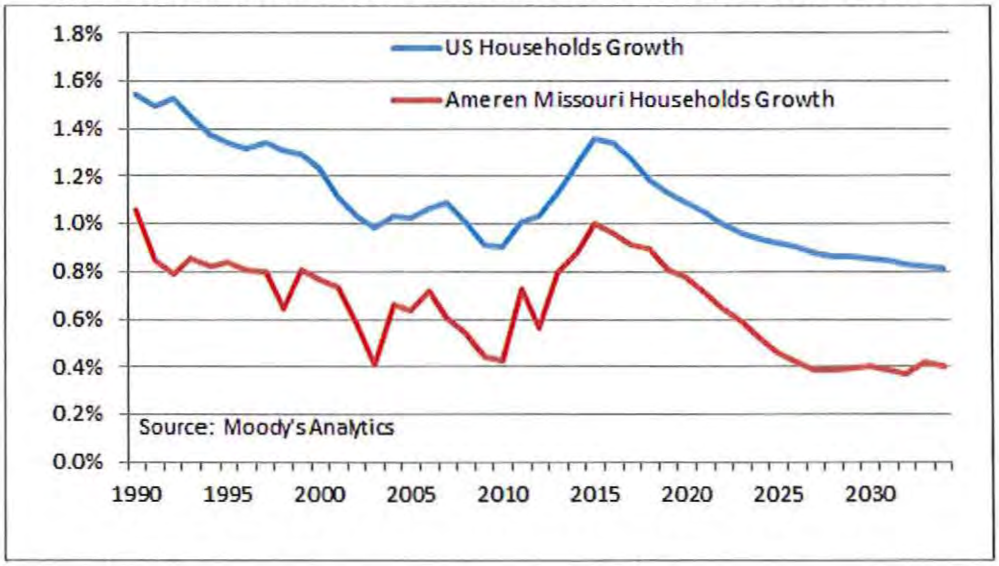
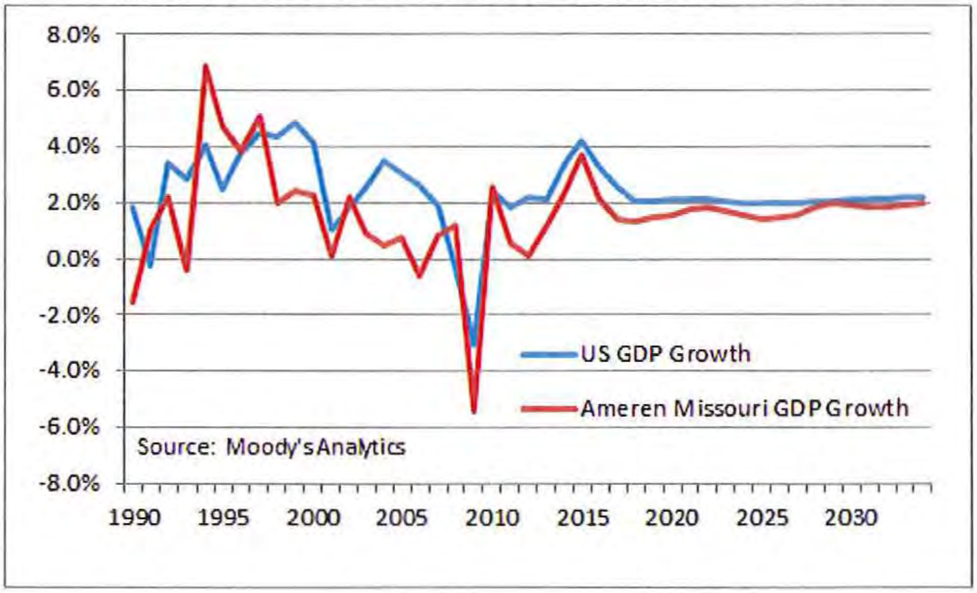
Figure 3.6: Growth in U.S. and Ameren Missouri Households[12]



Ameren Missouri expects that the service territory economy will recover similar to the U.S. economy's recovery, although at a slower pace than the pace of the U.S. recovery. This is evident from the chart of the U.S. and Service Territory GDP Growth shown in Figure 3.7, in which the red line for Ameren Missouri growth follows a pattern similar to that of the U.S., but is below the blue line for the U.S. GDP growth.[13]

Figure 3.7: U.S. and Service Territory GDP Growth[14]



[12] 4 CSR 240-22.030(2)(D)3
[13] 4 CSR 240-22.030(7)(B)3
[14] 4 CSR 240-22.030(2)(D)3

3.1.4 Economic Drivers

Several economic indicators were used as independent variables (independent variables in the forecasting models are often referred to as "drivers") in our energy forecasting process.[15]

- For the residential class, income, population, and the number of households in the service territory were used as drivers. These drivers are consistent with drivers used in all recent IRP forecasts.[16]
- For the four classes of commercial sales (small general service, large general service, small primary service, large primary service), GDP for one or more of four sectors of the economy were used as drivers. Those four sectors were Retail Trade, Information Services, Financial Services, and Education/Health Services, and these four sectors account for almost all of the non-manufacturing and non-government entries in the top employers list in Table 3.1 shown above. These drivers are consistent with drivers used in all recent past IRP forecasts except to the extent that a different sector may have been included for a particular rate class as compared with a previous forecast, only if the analysis of historical correlation of that driver to the historical loads indicated a better relationship between the two.[17]
- For the four classes of industrial sales (same classes as in commercial listed above), one or more of the following drivers were used: GDP, Manufacturing GDP, Employment, and Manufacturing Employment. These variables are consistent with past load forecast drivers for the industrial class.
- Table 3.2 illustrates these drivers and their expected growth over the IRP horizon.

Table 3.2 Growth Rates of Selected Economic Drivers

	2015-2034 Compound Growth Rate
Households	0.6%
Population	0.3%
Real Personal Income	2.2%
GDP Retail	2.8%
GDP Info	2.0%
GDP Financial	0.3%
GDP Educ/Health	-0.5%
GDP Total	1.8%
GDP Manufacturing	3.4%
Employmt Total	0.5%
Employmt Mfg	-0.7%

[15] 4 CSR 240-22.030(5)(A)
[16] 4 CSR 240-22.030(6)(A)1A
[17] 4 CSR 240-22.030(6)(A)1B

As in prior IRPs and IRP Annual Updates, the economic forecasting firm Moody's Analytics was the source for the forecasts of these economic drivers. Moody's Analytics is a highly reputable firm in the macroeconomic forecasting arena with a specialized competency in doing this work, and Ameren Missouri has extensive history using their forecasts and has consistently found them to be credible. Their forecasts are done for individual counties, and Ameren Missouri aggregates those counties that make up its service territory. The forecasting models used by Moody's are proprietary and not available to Ameren Missouri.[18]

That said, the forecast delivered by Moody's for the Manufacturing GDP variable for the Ameren Missouri service territory projected growth at a rate faster than that projected for the national economy, despite the fact that Missouri's overall economy is projected to grow more slowly than the U.S. as a whole. In recognition of this fact as well as the fact that over recent history manufacturing has grown more slowly in Ameren Missouri's service territory than in the U.S. in total, Ameren Missouri chose to use the national growth rate in Manufacturing GDP forecasted by Moody's for its service territory in place of Moody's service territory specific forecast.[19] This is consistent with the fact that Ameren Missouri's industrial customer loads have declined every year for over a decade, even during the national expansions of manufacturing observed in between the 2001-2002 and 2007-2009 recessions.

3.1.5 Energy Forecasting

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. The discussion below details the process followed for developing the models, inputs, assumptions, and parameters used in forecasting. No after the fact judgmental adjustments are utilized after the completion of the modeling.[20]

Statistically Adjusted End-Use (SAE)

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

---

[18] 4 CSR 240-22.030(7)(B)1;4 CSR 240-22.030(7)(B)2
[19] 4 CSR 240-22.030(7)(B)4
[20] 4 CSR 240-22.030(7)(A)5

end use energy consumption 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 of equipment and appliances which may be driven by policy, economics, or consumer preferences,[21] 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 against a relatively long period of time rather than calibrated to sales from a single year, and it is therefore easier to detect and correct any systematic errors or biases 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.[22] 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 load analysis and forecasting work[23] was developed by Itron, a consulting firm Ameren Missouri has worked with for many years, and implemented by Ameren Missouri forecasting personnel.[24] In it there are specific end uses for 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.[25] Furnace fans are consolidated with the space heating end use due to the fact that in the SAE regression, they are analyzed using a common driver: heating degree days. Personal computers, plug loads and other loads are also consolidated due to the availability of data from the EIA as packaged by Itron, and due to the fact that these end uses constitute many, many small devices for which gathering accurate historical appliance stock data beyond what Itron has analyzed from the EIA would be challenging.[26] No end uses were added to the analysis, although as discussed later in this chapter, self-generation resulting from solar photovoltaic systems is treated essentially as a negative end use and modeled explicitly in each class' load.[27] For the commercial class, the end uses are heating, cooling, ventilation, water heating, cooking, refrigeration, outdoor lighting, indoor lighting, office equipment, and

[21] 4 CSR 240-22.030(5)(C)
[22] 4 CSR 240-22.030(5)(B)
[23] 4 CSR 240-22.030(6)(B)
[24] 4 CSR 240-22.030(6)(A)3
[25] 4 CSR 240-22.030(4)(A)1A
[26] 4 CSR 240-22.030(4)(A)2A
[27] 4 CSR 240-22.030(4)(A)2B

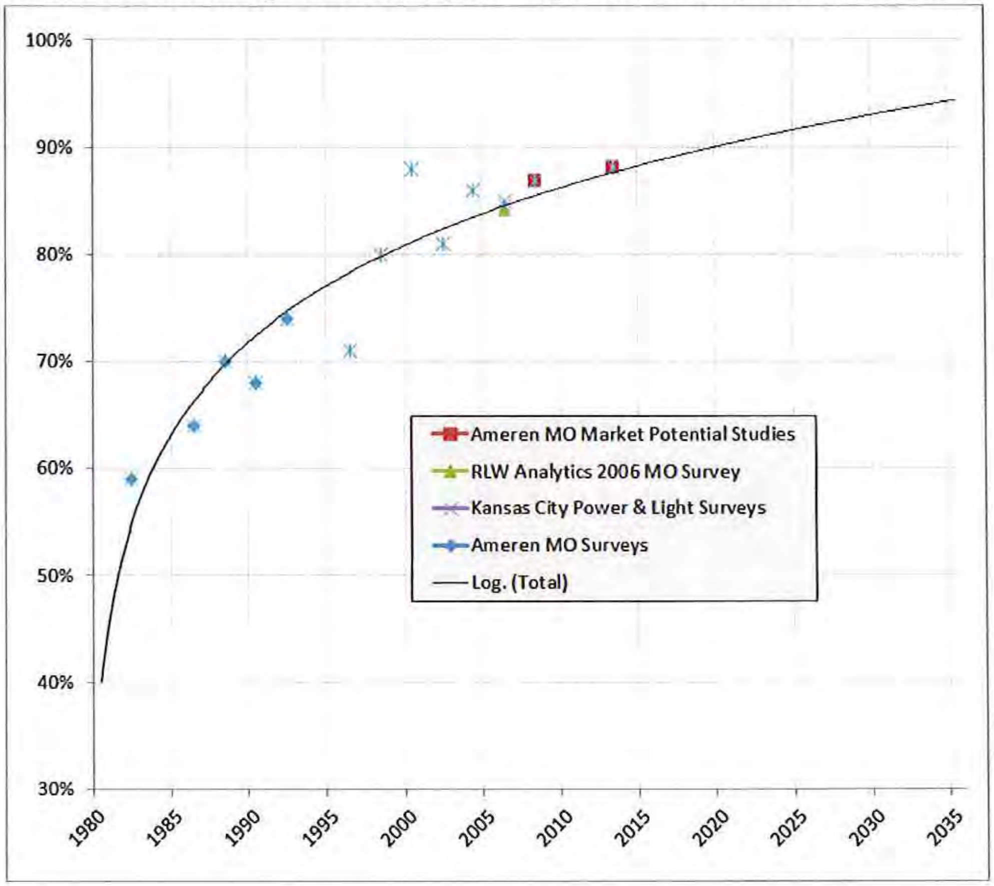
miscellaneous.[28] The combination of Itron's analysis and past and future Market Potential Studies provide a framework for maintaining the appropriate end use data for future IRPs.[29]

To predict future changes in the efficiency of the various end uses for the residential class, Ameren Missouri relied on an analysis of EIA's Annual Energy Outlook forecast performed by Itron and also on the analysis performed by Enernoc Utility Solutions (previously Global Energy Partners) as a part of Ameren Missouri's 2013 DSM Market Potential Study, discussed in Chapter 8. Both of these sources rely on stock accounting logic that projects appliance efficiency trends based on appliance life and past and future efficiency standards. These models account for the impacts of all currently effective laws and regulations regarding appliance efficiency, along with life cycle models of each appliance.[30] 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 U.S. Department of Energy's Energy Information Administration (EIA), or in the case of Enernoc's study, other primary market research data and secondary sources determined to be relevant to Ameren Missouri's service territory. The EIA estimates the efficiency of appliance stocks and the saturation of appliances at the national level and for the Census Regions while Enernoc's analysis was focused on Ameren Missouri's specific service territory.

The saturation trends for the end use appliances from EIA for 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 surveys conducted by Enernoc in 2009 and 2013.[31] These studies were conducted in order to provide primary data for Ameren Missouri's energy efficiency and demand side management programs. An historical and forecasted time series of appliance saturations are necessary for the SAE forecasting models that capture long term trends and changes in appliance and equipment ownership. The two surveys done in conjunction with the market potential studies provide a good starting point for developing these trends, however some additional information was utilized in order to fully develop them across more years.

[28] 4 CSR 240-22.030(4)(A)1B
[29] 4 CSR 240-22.030(4)(A)2C
[30] 4 CSR 240-22.030(7)(A)2
[31] 4 CSR 240-22.030(4)(B)1

Figure 3.8: Air Conditioning Saturation, Survey Data Points and Fitted Curve[32]



Three other sources of survey information were used to complement Ameren Missouri's market potential study surveys 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 and 1992. Next, a series of surveys of its households conducted by Kansas City Power and Light between 1996 and 2006 and published in their public IRP documents 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 Missouri market potential studies were conducted in 2009 and 2013, so a set of observations spanning the period between 1982 and 2013 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

[32] 4 CSR 240-22.030(2)(D)3

resulted in what is almost certainly a more accurate representation of the Ameren Missouri customer base than the regional EIA data. Figure 3.8 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 93.1% in 2030.

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 and actual observed loads are used to estimate model coefficients.

In the SAE framework, elasticities[33] 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. (Espey, 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. After determining an appropriate starting point, the elasticity parameters were then adjusted up or down by small amounts to determine 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 3.1.6) 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 -0.13. This is similar to the -0.15 value used in the 2011 and 2008 Ameren Missouri IRPs. The 2008 IRP 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

[33] 4 CSR 240-22.030(7)(A)1; 4 CSR 240-22.060(4)(D)

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 which indicates a bias in the model). So natural gas prices were excluded from final model specifications used to generate the energy forecasts used in this IRP.

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.

The functional framework of the SAE model is:[34]

$$\begin{aligned} Use\ per\ customer \\ &= B1 * ((cooling\ use) * (cooling\ index)) + B2 * ((heating\ use) \\ &* (heating\ index)) + B3 * ((other\ use) * (other\ index))^{35} \end{aligned}$$

In each term the "index" variable captures past and future trends in appliance saturation and efficiency. This variable is characterizing changes over time in the stock of end use appliances within the service territory. The "use" variable is a combination of variables that characterize the utilization of those appliances, including household income, the number of people per household, heating & cooling degree days, and the relevant elasticities. As would be expected, income has a positive correlation with consumption (i.e. as people have more money they tend to consume more), price has a negative correlation (the higher the price of electricity the less people tend to use) and heating and cooling degree days have a positive correlation with usage (as the weather gets more extreme, more energy is required to condition the space in the home to a comfortable level). The specific form of cooling use, for example, is:

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

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

[34] 4 CSR 240-22.030(6)(A)2
[35] 4 CSR 240-22.030(4)(A)4

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 49.9, 64.1, and 57.4 respectively. The adjusted r-squared for that model is 0.985.

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:

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

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 end use index variables in the commercial SAE model also include consideration of the mix of building types in the rate class and associated estimates of 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 a 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 without having a robust history of primary customer information. 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. Additionally, the SAE framework which has been utilized for residential and commercial classes requires a significant history of end use information to identify end use trends, and such history is not readily available from any internal studies or external sources that have been identified. Ameren Missouri has collected a significant amount of primary data on these customers as a part of DSM market potential studies in 2009 and 2013, but has not used that data to perform end use forecasting for the reasons described above.[36] As additional studies are done, enough history may be developed to consider an end use approach, but the heterogeneous nature of the large industrial customers may still be an overriding factor in determining that econometric forecasts are preferable.

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 parameter, 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 currently 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 trended flat to down over much of the historical estimation period of the sales models, and the period of time with price increases is largely overshadowed by the significant economic disruptions of the 2007-2009 recession. The result is that models with each factor input as standalone independent variables tend to produce coefficients for the price term that are either statistically insignificant, practically insignificant (i.e., 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

[36] 4 CSR 240-22.030(4)(A)1C; 4 CSR 240-22.030(4)(A)3

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 changes in the volume of energy used in a month driven simply by the varying number of days of consumption that each month includes.

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 Forecasting Considerations – Historical DSM Impacts

There are a few minor changes in methodology that occurred between the 2011 and 2014 IRPs that bear noting. First is the treatment of historical DSM program impacts on the load. At the time that the forecast work was executed for the 2011 IRP, Ameren Missouri's DSM programs were very new and the cumulative impacts of them were still small. At that time the historical program impacts were not a significant concern in the energy modeling process.

Since that time, Ameren Missouri has implemented programs that have achieved significant energy savings across almost all customer classes. Care must be taken not to "double-count" energy efficiency program impacts when using a methodology like SAE that accounts for efficiency trends on its own. Ameren Missouri's approach to this problem prior to this forecast (in the annual updates between the 2011 IRP and now) has been to "add back" the savings from the programs to the observed loads based on evaluated results.[37] We then executed the forecast model based on the reconstituted loads. When we projected energy into the future, we then deducted the estimates of savings associated with historical programs from the future load projections. This made sense in that the SAE end use driver variables were based off of regional and secondary data about the stock of end using equipment in the service territory that would not have accounted for the specific impacts of our own programs.

Now, however, we have the benefit of a Market Potential Study performed by Enernoc which collected primary market data on the appliances in our service territory since the broad implementation of energy efficiency programs. Where possible, Ameren Missouri has reflected the results of this primary market research in its forecast already. Since the impact of our programs would now potentially be reflected the driver variables, it may no longer be necessary to go through the process of separately accounting for program impacts outside of the base energy models.

[37] 4 CSR 240-22.030(6)(C)2

So for this forecast, Ameren Missouri made an evaluation on a class by class basis of how well the driver variables were accounting for the impacts of the DSM programs it has run. This was accomplished by running estimates of the model coefficients with the DSM "add-back" methodology and without it. We then evaluated the model residuals (the difference between observed loads and the model's predictions of loads at the same time period) to determine which model was the most appropriate for that class.

It should also be noted that the anticipated savings of Ameren Missouri's first cycle of energy efficiency programs under the Missouri Energy Efficiency Investment Act (MEEIA) are also subtracted from the load forecast projections. These programs are already being implemented and are not the subject of any decision making from this IRP, so they are taken as a given that they will occur. All future DSM impacts beyond the first 3 year MEEIA cycle are excluded from the base forecast and are the subject of the DSM chapter of this IRP.

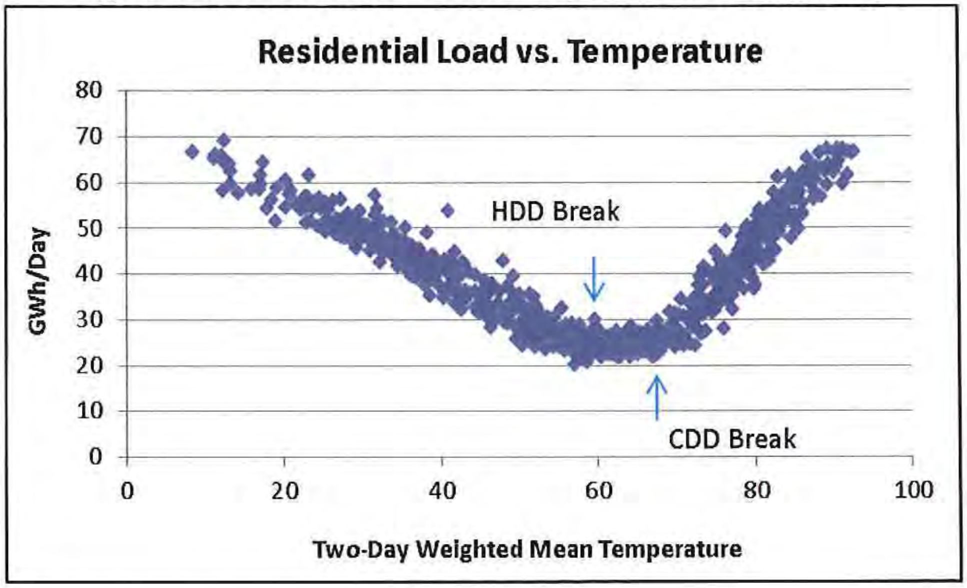
Other Forecasting Considerations – Weather[38]

Another change or enhancement to the forecasting process was the use of heating degree day and cooling degree day variables customized for each class with different break points. Degree days are a statistic that measures weather over a time period as an indicator of how much need for heating and cooling equipment there was during that time period. Generically, heating degree days are usually calculated as the difference between the average temperature and 65 degrees when the temperatures are colder than 65, and the difference between the average temperature and 65 degrees when temperatures are warmer than 65 are cooling degree days. This is a pretty good indicator of the need for heating and cooling, as 65 degrees is a moderate temperature that requires little heating or cooling. So either side of 65 you start to see an increasing need for either air conditioners or space heaters.

However, each customer class in reality has a bit of difference in the way they respond to temperatures. So, rather than just generically use a 65 break point between heating and cooling, we analyzed class specific load research data to find the most appropriate degree day breakpoints for each class. Below in Figure 3.9 is an example to of daily residential load research data plotted against daily temperatures. It is apparent from the slopes of the data that residential customers begin cooling at right about 65 degrees. But there is a little break before heating equipment is widely utilized, which occurs at about 60 degrees.

[38] 4 CSR 240-22.030(5)(A); 4 CSR 240-22.030(2)(D)2

Figure 3.9: Residential Load/Temperature Relationship



For the residential class we utilized Cooling Degree Days calculated with a 65 degree base, but Heating Degree Days with a 60 degree base. Similarly, for each class we customized the degree day calculations based on a review of the load data from that class. Additionally, for some classes, we added an additional term to the model to reflect the fact the customers in that class either use their heating or cooling equipment differently during different times of the year, or that there is a non-linearity in their weather response (this could happen in a class because some subset of customers start cooling at one temperature, but another does so at a higher temperature). This will show up as an extra term in the estimated forecasting equation. Its effect is to capture these seasonal and non-linear weather effects. Table 3.3 below shows the degree day breakpoints used for heating and cooling for each class. To the extent that there are two values in the table, a non-linear response was detected and there will be an extra term in the forecasting equation.

Table 3.3 Degree Day Break Points Used in Energy Modeling

Class	HDD	CDD
Residential	60	65
ComSGS	55	60/70
ComLGS	55	55/70
ComSPS	N/A	65
ComLPS	N/A	50

Other Forecasting Considerations – Customer Owned Solar PV

Over the past couple of years, there has been an increasing penetration of customer owned solar photovoltaic generating systems in Ameren Missouri's service territory. Generation from these systems appears to the utility as a reduction in demand for its product. To capture the impact on ultimate demand of power supplied by the utility, we have incorporated an offset of load by a projection of customer owned generation in this forecast.

The rebate that Ameren Missouri offered to customers pursuant to applicable Missouri law of up to $2/watt of installed solar generating capacity is seen as largely driving the rapid increase in solar installations. That rebate is capped by law and regulatory agreement. So in this forecast, we assumed that solar installations would continue their current pace until the rebate funds were exhausted. After that time, there is a tremendous amount of uncertainty about how much solar will be installed. However, there are still federal tax incentives involved and it is also clear that the costs of solar have continued to decline. In recognition of the likelihood that solar will continue to be installed at some uncertain level after the rebates expire, Ameren Missouri assumed that installations would slow from their current pace to 5 MW per year going forward.

The forecast of energy generated from the PV systems that are installed was calculated based on a tool developed by the National Renewable Energy Laboratory (NREL) called PV Watts. The estimated energy of existing and projected new systems was deducted from the modeled energy sales in the future for purposes of the final forecast of customer demand served by Ameren Missouri.

In recognition of the uncertainty around the future pace of solar installations, Ameren Missouri is also testing the sensitivity of its plan to a high penetration of distributed generation like solar PV. For purposes of that analysis, we utilized projections of installed capacity from the U.S. Department of Energy's (DOE) Sunshot Initiative. The Sunshot Initiative is an effort of the DOE to advance the development of solar technology to a point where the costs reach $1/kW installed by 2020. Under that future scenario, the DOE projects gross solar PV capacity installations at various future years by state. We adopted those penetration estimates for Missouri, interpolating to fill in all years of the forecast horizon, and used the same NREL PV Watts assumptions to estimate the output of those PV resources. By subtracting the estimated distributed generation from the base load forecast, we came up with a new load forecast net of the expanded solar PV generation. The results of that sensitivity analysis will be described in Chapter 10 of this report.

Other Customer Class Forecasts

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 with their own municipal electric systems. 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 capacity or new processes. 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 lighting categories so the projected lighting sales are modeled as a function of seasonal factors and the number of calendar days in the month.

Ameren Missouri also serves the energy requirements of two municipal electric systems under full requirements contracts. The contracts for these customers expire during the first few years of the IRP horizon. Sales to these 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 a reasonable approach as the two 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 two 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 in this document they are aggregated to revenue class. In each case, an econometric approach was used with customers modeled as a function of an appropriate driver for that customer class, such as households, employment, or GDP.[39] Normally this

[39] 4 CSR 240-22.030(3)(A)

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, end shift variables, or trends to capture the fact that customer growth and driver growth diverged over that part of the historical model estimation period, and also included auto-regressive and moving average terms as well as combinations of multiple of the above modeling approaches to smooth out the customer forecast in some cases.

3.1.6 Sensitivities and Scenarios[40]

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 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, and electricity prices.

In this IRP, fifteen different scenarios were modeled that stemmed from the combinations of assumptions about load growth, natural gas prices, and environmental regulations and carbon prices discussed in Chapter 2. Ameren Missouri produced different forecasts of retail electricity prices to match each permutation. These forecasts were based on ranges of variables resulting from interviews with Ameren subject matter experts. The scenario development process is discussed in Chapter 2.

The different environmental policy and natural gas price scenarios affected the forecasts of energy sales through the retail price term. Changes in wholesale natural gas prices and regulatory regimes flowed through the model of power markets to set different levels and growth rates of retail electricity prices. Since the retail price of electricity is an input into the sales models (both SAE and econometric) and is impacted by the price elasticity assumption described earlier in this chapter, the different scenarios result in different forecasts of energy sales.

In order to forecast high, base and low load growth consistent with the scenarios established, 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

[40] 4 CSR 240-22.030(8); 4 CSR 240-22.030(8)(A)

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 forecasts of miscellaneous, heating and cooling end use energies were modified along with the elasticity parameters applied to the price and income variables 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, changes in the growth rate of this end use grouping will certainly have a material impact on the 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, would in all likelihood not have contemplated 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 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. Additionally, heating and cooling loads were impacted for the scenarios because they are the most significant drivers of peak load conditions, so uncertainty in those end uses is important to consider in order to reflect a full range of potential future capacity needs. The heating end use had particular appeal as an uncertainty, as the observed load growth in recent years for Ameren Missouri's residential class has been clearly strongest in the winter season. Whether that be due to more homes with electric heat as their primary heat source, or due to a proliferation of secondary space heating units, it is important to understand the dynamics of increasing winter loads on the system.

For the commercial and industrial classes, the output and price elasticity parameter estimates were identified as the largest source of uncertainty for the forecast period. As mentioned in Section 3.1.5, 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 or industrial 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 these sectors is not uniformly energy intensive. So the addition of load like data centers and medical facilities in the commercial class could use more energy per unit of economic output than retail space or offices. Similarly, a manufacturing load that serves an assembly plant may have dramatically different energy intensity than a smelter or chemical manufacturing facility. Therefore using the output elasticity to model sensitivity accurately captures one of the larger uncertainties in the commercial and industrial sectors.

In the description of the process of setting the base modeling elasticity parameters, it was noted that we varied the parameters to optimize the model statistics. While performing that process, however, it becomes apparent that there is a range of elasticity estimates within which the model performs well and produces reasonable fits. All of the subjective adjustments to elasticity parameters as a part of the high and low scenario development kept the elasticity parameters within the range where the models were deemed to perform well.

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 present in the details underlying the load forecasting process. The results of this modeling served to reinforce the results of the surveys conducted with the subject matter experts.

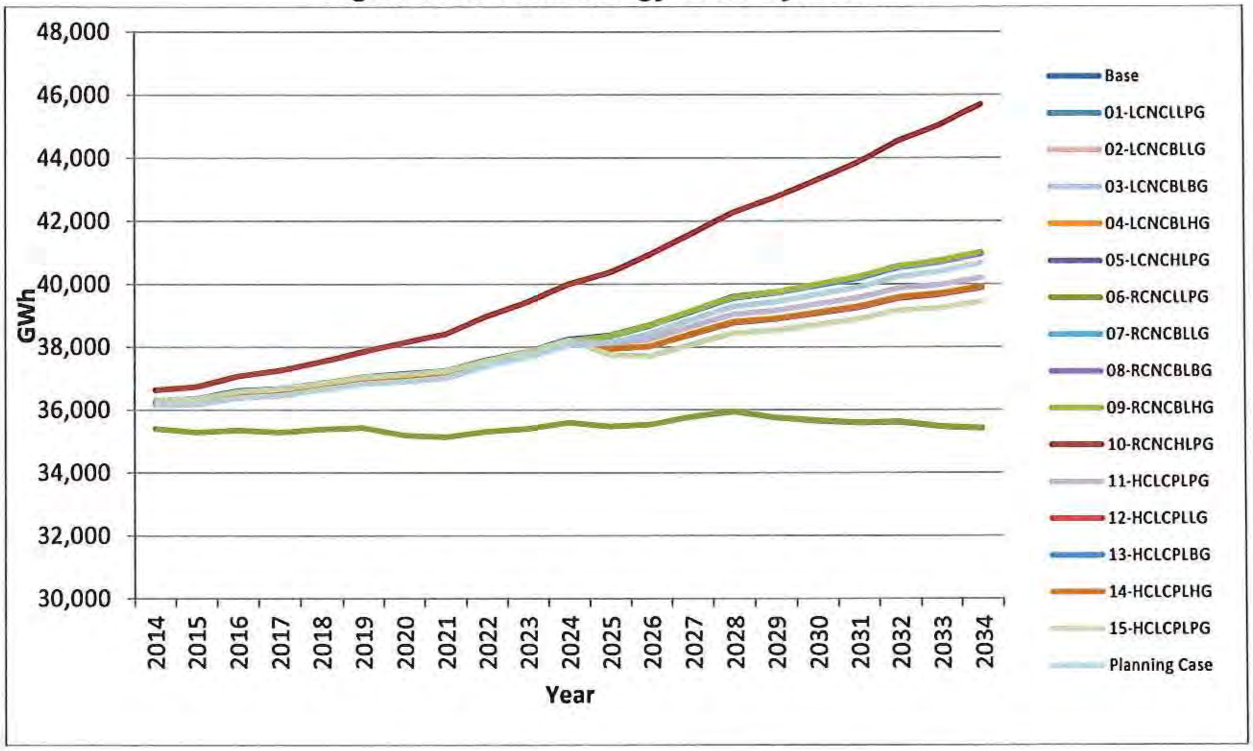
A summary detailing all of the changes between high, base, and low load forecast scenarios can be found in Table 3.4.

Table 3.4: Scenario Driver and Parameter Differences

Class	High Load Growth Assumption	Base Load Growth Assumption	Low Load Growth Assumption
Residential	Price Elasticity -0.05	Price Elasticity -0.13	Price Elasticity -0.23
	Income Elasticity 0.19	Income Elasticity 0.15	Income Elasticity 0.15
	Misc Index CAGR 3.1%	Misc Index CAGR 1.5%	Misc Index CAGR -0.1%
	Heating Index CAGR 0.8%	Heating Index CAGR 0.4%	Heating Index CAGR 0.0%
	Cooling Index CAGR 0.3%	Cooling Index CAGR -0.1%	Cooling Index CAGR -0.4%
Commercial	Lower price elasticity parameter and output elasticity increasing trend until 2035	Base price and output elasticity assumptions	Higher price elasticity parameter and output elasticity decreasing trend until 2035
	SGS Output 0.8, Price -0.05	SGS Output 0.55, Price -0.15	SGS Output 0.3, Price -0.35
	LGS Output 1.0, Price -0.05	LGS Output 0.9, Price -0.11	LGS Output 0.8, Price -0.35
	SPS Output 0.6, Price -0.05	SPS Output 0.35, Price -0.10	SPS Output 0.1, Price -0.35
	LPS Output 1.0, Price -0.05	LPS Output 0.9, Price -0.05	LPS Output 0.8, Price -0.25
Industrial	Lower price and higher output elasticity assumptions	Base price and output elasticity assumptions	Higher price and lower output elasticity assumptions
	SGS Output 1.0, Price -0.05	SGS Output 1.0, Price -0.20	SGS Output 0.9, Price -0.45
	LGS Output 0.9, Price -0.05	LGS Output 0.7, Price -0.20	LGS Output 0.4, Price -0.45
	SPS Output 0.95, Price -0.05	SPS Output 0.9, Price -0.15	SPS Output 0.75, Price -0.35
	LPS Output 0.5, Price -0.05	LPS Output 0.3, Price -0.05	LPS Output 0.1, Price -0.05

After application of the assumptions from the 15 scenarios to the models with the parameters described above, each scenario's model output represents the energy forecast for that scenario. The total energy associated with the 15 scenario forecasts are shown below in Figure 3.10.

Figure 3.10: Total Energy Sales by Scenario



3.1.7 Planning Case Forecast

The fifteen scenarios described in section 3.1.6 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.

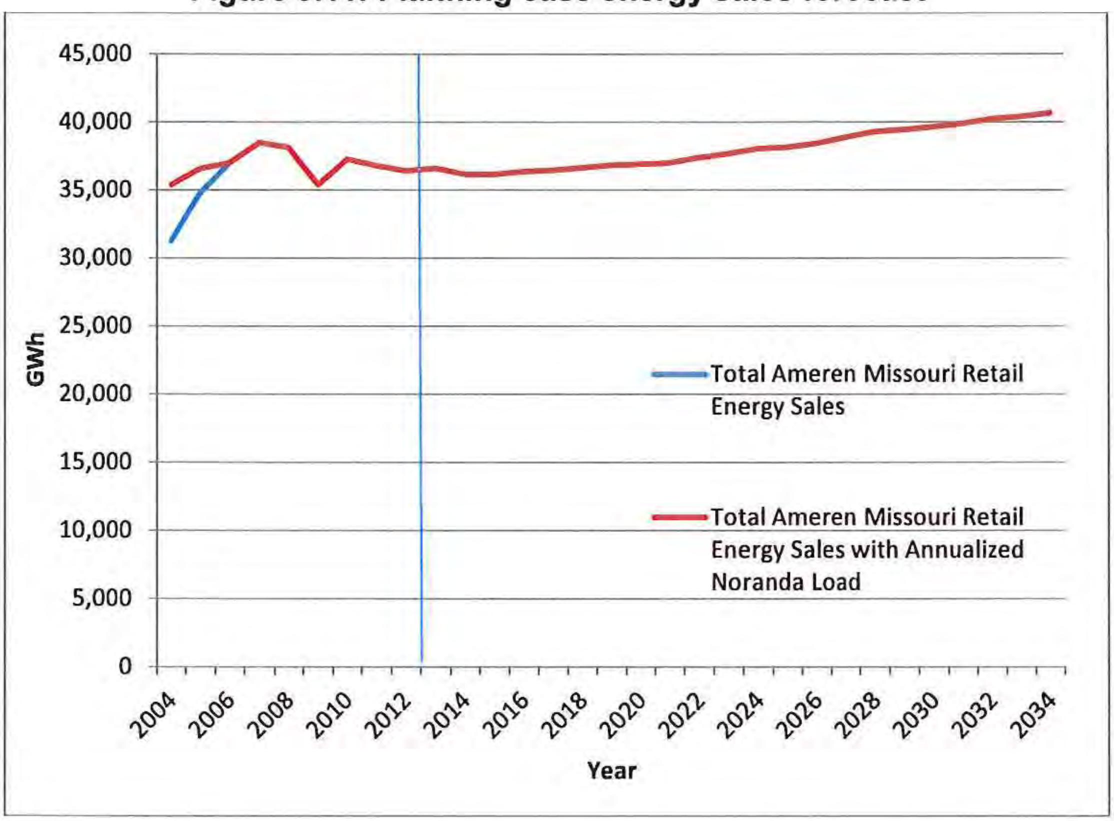
The calculation of the planning case forecast is a fairly simple exercise. The subjective probabilities of each scenario, as determined by the subject matter experts for the various uncertain factors, were used to weight together the different scenarios. The planning case does not have its own set of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

3.1.8 Forecast Results

For the planning case, total retail energy sales are forecast to grow at 0.62% compound annual rate between 2015 and 2034. Between 2004 and 2012, total retail sales grew at a compound annual rate of 0.4% (excluding the impact of the addition of the Noranda aluminum smelting load, 1.9% including the Noranda addition). Sales dipped sharply in 2009, and went through an uneven period of recovery following the recession. Because of the impact of efficiency standards and programs, loads over the near term forecast are projected to stay fairly close to flat. As mentioned earlier, the load forecast only incorporates savings from MEEIA programs for the first 3 year cycle (2013-2015). After those programs stop impacting the base forecast, load growth resumes at a historically slow, but fairly stable pace.[41]

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 3.11: Planning case energy sales forecast



[41] 4 CSR 240-22.030(7)(A)3

The outage at Noranda is not the only reason why sales slumped in 2009, however, as the severe recession that the U.S. experienced depressed service territory electricity sales. Residential sales fell by 0.9% in 2009, commercial sales fell by 1.0%, and Industrial sales, exclusive of Noranda, fell by a staggering 13.6%. The planning case assumes that recovery from those declines takes several years, as can be seen in Figure 3.11.

Table 3.5: Historical and Forecast Planning Case Annual Sales Growth by Class

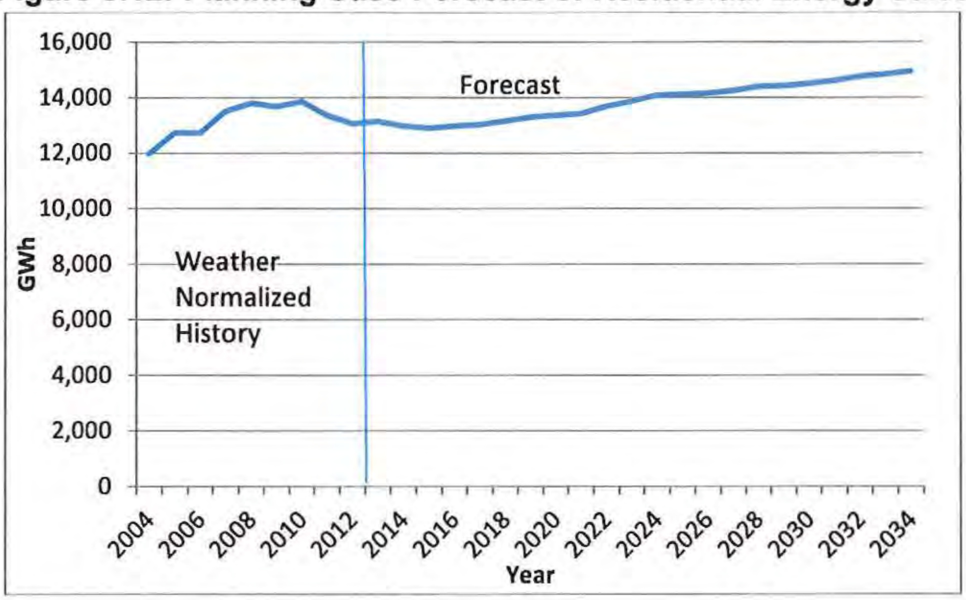
Year	Residential	Commercial	Industrial	Noranda	Lighting	Total
2005	6.3%	3.3%	-0.1%	N/A	3.2%	11.4%
2006	-0.1%	3.5%	-1.3%	74.4%	-2.5%	6.2%
2007	6.1%	3.9%	2.8%	-0.6%	0.3%	4.0%
2008	2.2%	-1.6%	-7.8%	0.8%	-0.7%	-0.9%
2009	-0.9%	-1.0%	-13.6%	-41.8%	-1.1%	-7.1%
2010	1.4%	0.5%	-0.3%	67.9%	-0.4%	5.3%
2011	-3.5%	-0.3%	-1.6%	3.2%	-2.6%	-1.3%
2012	-2.3%	-0.2%	-0.3%	-0.5%	-0.4%	-1.1%
2013	0.7%	0.5%	-0.4%	1.2%	-0.8%	0.5%
2014	-1.3%	-1.0%	0.3%	-1.2%	0.0%	-1.2%
2015	-0.6%	0.7%	-0.6%	0.0%	0.0%	0.0%
2016	0.5%	0.9%	0.3%	0.3%	0.3%	0.6%
2017	0.5%	0.0%	0.6%	-0.3%	-0.3%	0.2%
2018	1.0%	0.3%	0.2%	0.0%	0.0%	0.5%
2019	1.1%	0.3%	0.2%	0.0%	0.0%	0.5%
2020	0.5%	-0.1%	0.1%	0.3%	0.3%	0.2%
2021	0.4%	0.4%	0.3%	-0.3%	-0.3%	0.3%
2022	2.0%	0.6%	0.7%	0.0%	0.0%	1.0%
2023	1.4%	0.5%	0.3%	0.0%	0.0%	0.7%
2024	1.6%	0.9%	0.5%	0.3%	0.3%	1.0%
2025	0.2%	0.3%	0.6%	-0.3%	-0.3%	0.2%
2026	0.3%	1.4%	0.9%	0.0%	0.0%	0.8%
2027	0.7%	1.9%	1.2%	0.0%	0.0%	1.2%
2028	1.0%	1.5%	0.4%	0.3%	0.3%	1.1%
2029	0.2%	0.8%	0.2%	-0.3%	-0.3%	0.4%
2030	0.6%	0.8%	0.2%	0.0%	0.0%	0.6%
2031	0.7%	0.8%	0.2%	0.0%	0.0%	0.6%
2032	1.1%	1.0%	0.2%	0.3%	0.3%	0.9%
2033	0.5%	0.5%	0.2%	-0.3%	-0.3%	0.4%
2034	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

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 3.11, but is noticeable in Table 3.5. 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

Between 2004 and 2012, residential class weather normalized sales grew at a compound annual rate of 1.1%. This period was characterized by two distinctly different trends, however. From 2004 through 2008, residential load grew at a robust pace of around 3.6%. Beginning around the time of the 2007-2009 recession, but also, perhaps not coincidentally, around the time Ameren Missouri's energy efficiency program spending ramped up, the trajectory of residential load flattened considerably. Most likely the economic impacts of the recession are mixing with program impacts during this time period. The result, however is load characterized by years that have been either close to flat in terms of load growth or even declining in some years. Total US residential sales, according to the EIA, grew by 0.8% over the years from 2004-2012 (although it is important to note that EIA numbers are not weather normalized). Similar to the pattern of Ameren Missouri's sales, national consumption grew early in this time period, but have declined (again on a non-weather normalized basis) since 2010.

Figure 3.12: Planning Case Forecast of Residential Energy Sales



In the planning case forecast, residential load is anticipated to grow at a compound annual rate of 0.7% between 2014 and 2034. According to the EIA, US residential electricity sales are also expected to grow at a compound annual rate of 0.7% over the same time period.

Growth is expected to be slow, in fact basically flat over the time period in which the savings from the MEEIA energy efficiency programs are incorporated in the forecast. The MEEIA savings are sufficient to offset virtually all residential growth during these years. This time period would be otherwise growing fairly slowly anyway, as the full effect of the 2007 EISA lighting standard take effect, and the 2006 air conditioner efficiency standard continues to roll through the appliance stock. As the impact of those standards becomes realized and incremental savings associated with them are small, the impact of MEEIA programs also fades from the forecast (and is picked up in the DSM analysis). At that time observable growth is projected to resume in the residential class.

The number of residential customers is expected to grow at a compound average rate of 0.5% between 2014 and 2034. Customer growth has been very slow since the housing crisis that accompanied the 2007-2009 recession, but has resumed at a slow pace in the last couple of years. The forecast assumes that the recovery in housing will continue to produce an increase in customer growth for the next few years, with growth peaking around 0.8% per year in 2020. After that, customer counts are still projected to grow, but at a slowing pace as the demographics of the population change to reduce growth in household formation. By the end of the forecast horizon, customer growth is projected to average approximately 0.4% per year.

Use per customer growth in the residential class is expected to also stay relatively flat to modestly declining for the first half of the forecast horizon. Again, efficiency standards and the three years of MEEIA programs hold average customer consumption down during this time. As already approved standards transform the stock of end using appliances and equipment, modest use per customer growth is projected to resume in the 2020s. The final phase of the 2007 EISA lighting standard takes effect in 2020, so after that there are few new energy efficiency standards that are in place to impact future consumption growth.

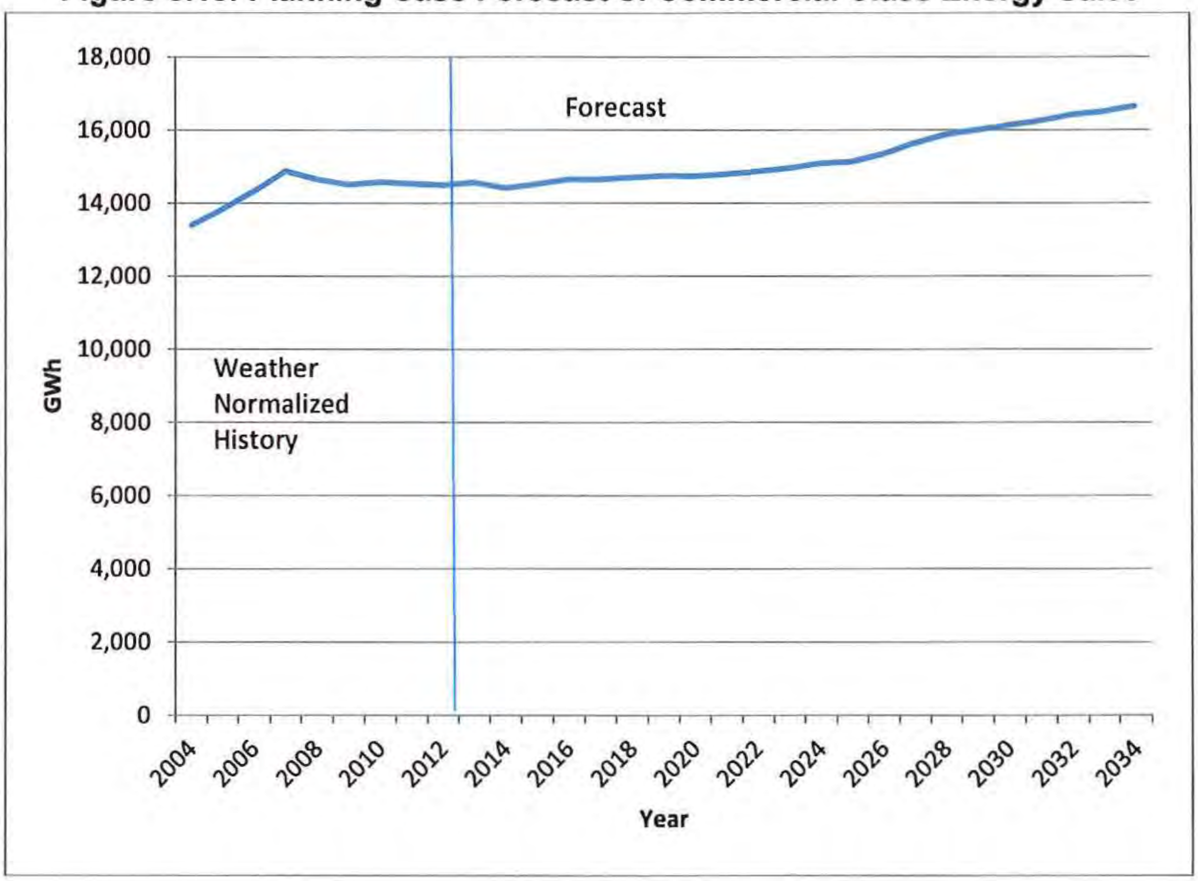
Commercial

Ameren Missouri commercial class sales have been the fastest growing segment of sales over the period of historical review for this IRP, 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 2004 and 2012, weather normalized sales grew at a compound annual rate of 1.0%. Like residential sales, commercial sales were impacted by the recession and have grown more slowly than the previous historical trend since 2009. According to the EIA, total US commercial sales grew at a compound annual rate of 0.95% between 2004 and 2012, but have been essentially flat since the 2007 onset of the recession.

Sales are expected in the planning case to grow at a compound annual rate of 0.7% between 2014 and 2034. The EIA's estimate of commercial electricity sales growth over that same period is 0.9%, so the planning case for Ameren Missouri anticipates slightly slower growth that the U.S. average. This is consistent with the point of view that Ameren Missouri's service territory economy is growing more slowly than the national economy.

Use per customer growth is projected to be negligible in the commercial class over the first decade of the forecast horizon with growth being driven by an increasing customer base. In the latter half of the forecast, use per customer is projected to resume, with the impacts of energy efficiency standards and trends already largely realized. Over the full forecast horizon, growth is expected to be driven in pretty much equal parts by use per customer increases and an increasing customer base.

Figure 3.13: Planning Case Forecast of Commercial Class Energy Sales

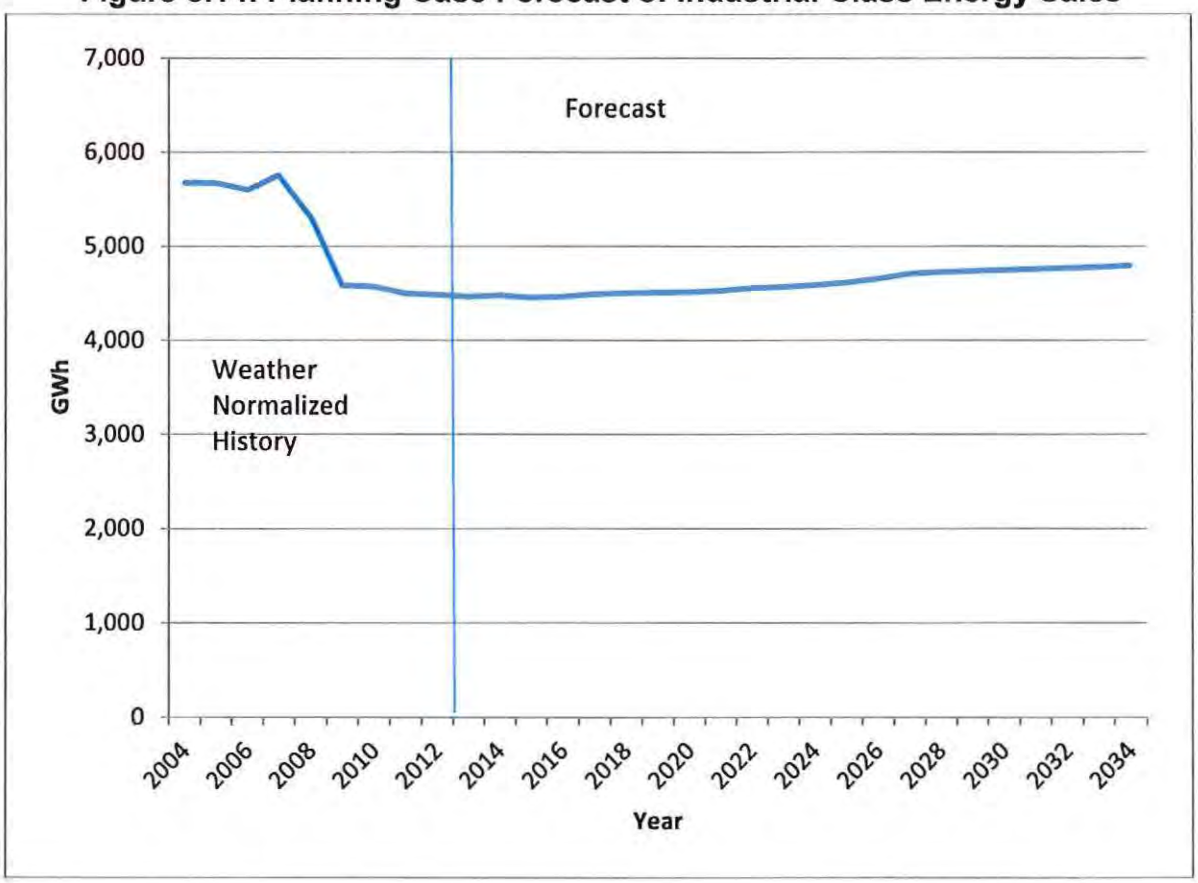


Industrial

Ameren Missouri industrial class sales have been experiencing a structural decline for over a decade. Compounding this decline was the significant toll the 2007-2009 recession took on the service territory manufacturing base. The decline in manufacturing activity was not one confined to the Ameren Missouri service territory; national manufacturing severely contracted during the recession as well. However, industrial loads elsewhere recovered at least a significant portion of their losses in the years of slow recovery since the recession. Ameren Missouri's industrial load remained relatively flat to modestly declining in those years.

Casualties of this decline in the service territory manufacturing base include the Ford Assembly plant in Hazelwood, MO, which closed in 2003, and the Chrysler plant in Fenton MO, which closed in 2010. Between 2004 and 2012, Ameren Missouri's industrial sales declined at a compound annual rate of 2.9%; according to the Energy Information Administration US industrial electricity sales fell by a compound annual rate of 0.4% between the same years. Note that Ameren Missouri's largest single customer by far, the Noranda aluminum smelter, is not included in these industrial load statistics, as it is so large as to be treated as a class by itself.

Figure 3.14: Planning Case Forecast of Industrial Class Energy Sales



The planning case forecast calls for industrial sales growth at a compound annual rate of 0.3% between 2014 and 2034. The forecast also contemplates the expected closure of one of Ameren Missouri's largest industrial customers, a lead smelting plant that is closing due to an environmental judgment. While the overall industrial forecast is directionally positive after the long term sales industrial sales decline that has been experienced, it is still quite slow growth that is anticipated. In fact the forecast does not anticipate that industrial sales will reach pre-recession levels at all during the planning horizon. By contrast, the EIA's forecast for US industrial sales anticipates compound annual growth of 1.1%. This forecast represents a significant upward revision to recent national forecasts of industrial sales. It may be influenced by increasing manufacturing activity in the chemical and fertilizer industries driven by recent low natural gas prices and increases in domestic production of shale gas and oil. However, such load increases to date have not located in or near the Ameren Missouri service territory and at this time we do not anticipate a significant concentration of those customers here due to the geographical location of the gas and oil resources and the refining and processing plants for those commodities.

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. The historical growth rates shown in Table 3.6 below are impacted by the 2007-2009 recession, which caused declines or at least a significant slowing of growth for all classes. Going forward, we expect the modest growth that has developed since the recession ended to continue to accelerate for a few years, before the forces associated with demographic and economic trends begin to again slow the growth in customer counts.

Table 3.6: Customer Growth Rates

Year	Residential	Commercial	Industrial
2004-2012	0.43%	1.06%	-1.63%
2014-2034	0.54%	0.44%	-0.54%

Wholesale

Ameren Missouri currently sells electricity to two small municipal electric systems as full requirements wholesale customers. At the time of the forecast, Ameren Missouri anticipated, because of existing contracts, sales to one of these cities to continue through December of 2014 and sales to the other to extend through May of 2017. These are relatively small loads and do not represent a significant long-term planning obligation by Ameren Missouri. There is an estimated load in the forecast for the duration of the existing contracts, but the load falls to zero by the summer of 2017. It is possible that Ameren Missouri may choose to enter into new wholesale sales contracts subject to future market conditions and resource availability.

Noranda

Noranda sales are expected to be essentially flat over the forecast horizon. As was noted in the methodology section, Noranda is a 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

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

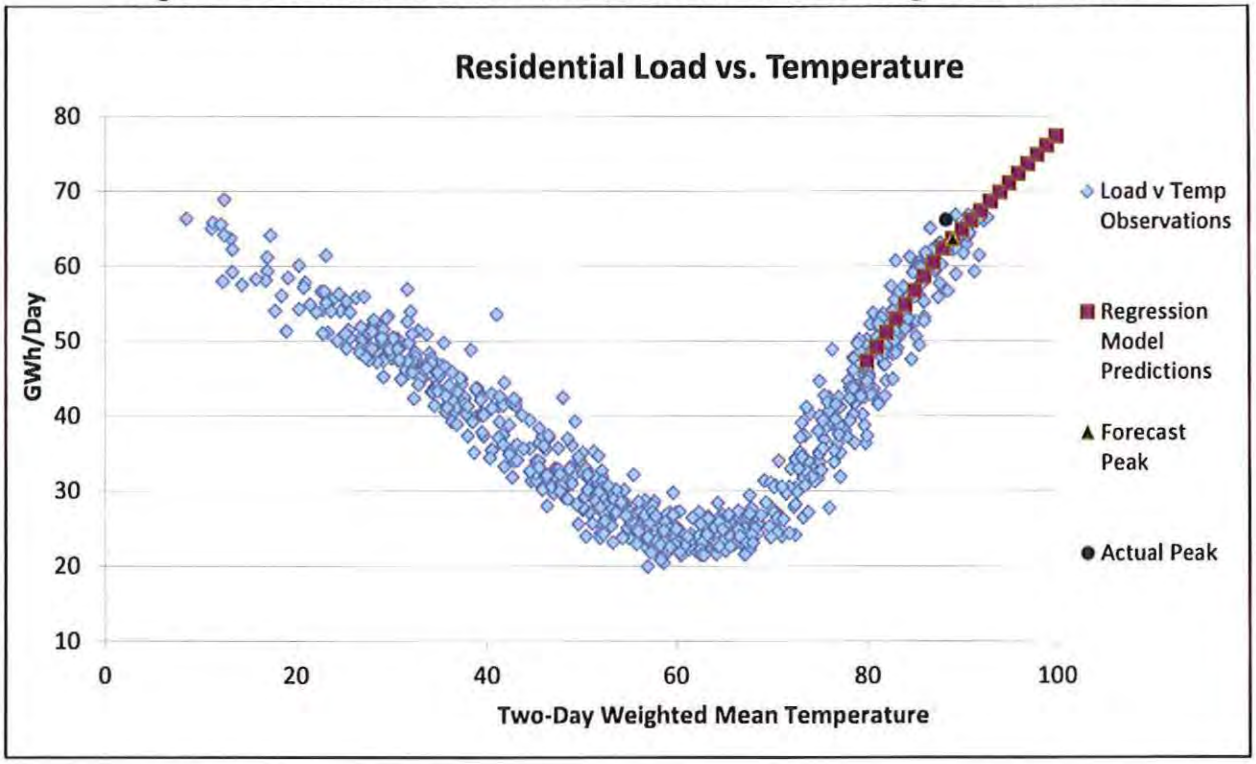
The peak demand forecast is of critical importance to the Integrated Resource Plan. The demand on the system at the hour of peak drives the need for generating capacity. While the need for energy influences the optimal mix of generation resources, the timing and amount of capacity additions are most directly tied to peak demand.

The 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. As in the 2011 IRP forecast, there is an additional level of granularity in this forecast stemming 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 chapter. 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 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 1.4% (measured as actual load minus modeled load) over a period of historical years from 2007-2012. 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.

A positive error as described above is actually expected based on the forecast methodology used. Profiling loads into an hourly shape as we are doing here is a useful forecasting technique, but is specifically designed to produce a forecast of average load for any given weather condition. By definition, the peak load is an hour where we observe and extreme load condition. So the bias identified above is the difference between an average load during extreme weather, and an extreme load during extreme weather. To further illustrate, consider the scatter plot in Figure 3.15 below. The observed loads are plotted vs. temperature in blue dots. The dark red dots represent the load forecast at various temperatures. Notice that, as it should this line goes through the center of the points in the scatter plot. But of course the result of that is that there are a number of days with high temperatures fall above this line. Those are extreme observations. By making the adjustment described above, we are able to predict a true peak load, rather than just the expected value of the load at an extreme temperature.

Figure 3.15: Illustration of Bias in Profile Forecasting of Peak Loads



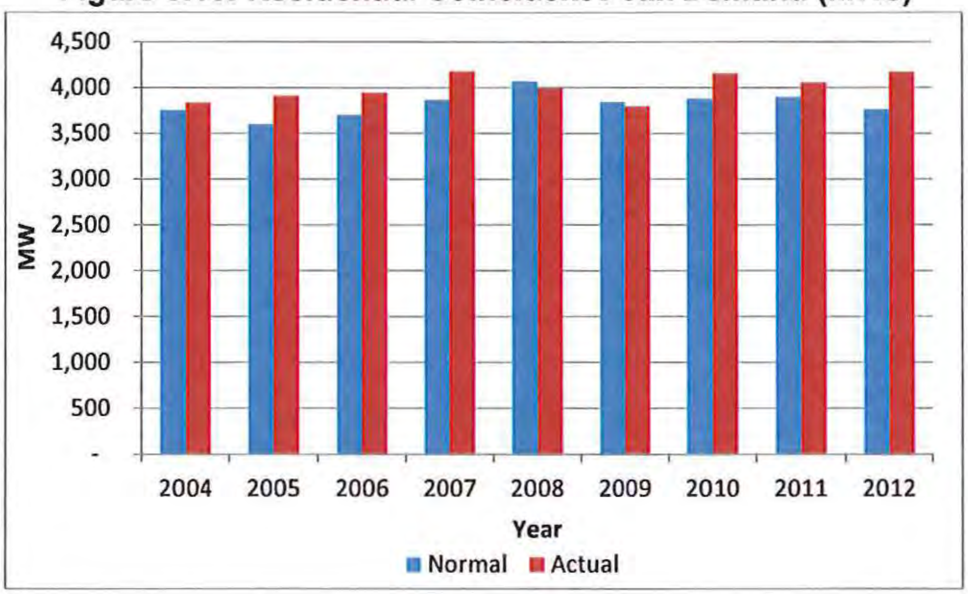
3.2.1 Historical Peak and System Load

Ameren Missouri's historical database of actual and weather normalized class and system demands is maintained back to July 2003.[42] Actual hourly system data is available back to the beginning of January 2001. 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.

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.

The annual coincident peak demand, on a weather normalized basis, for the residential class from the year 2004 to 2012 grew at a compound annual rate of less than 0.1%, essentially remaining flat. The class load grew from a weather normalized 3,752 MW in 2004 to 3,757 MW in 2012 (at generation, i.e. inclusive of transmission and distribution losses). On an actual basis (not weather normalized), 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.

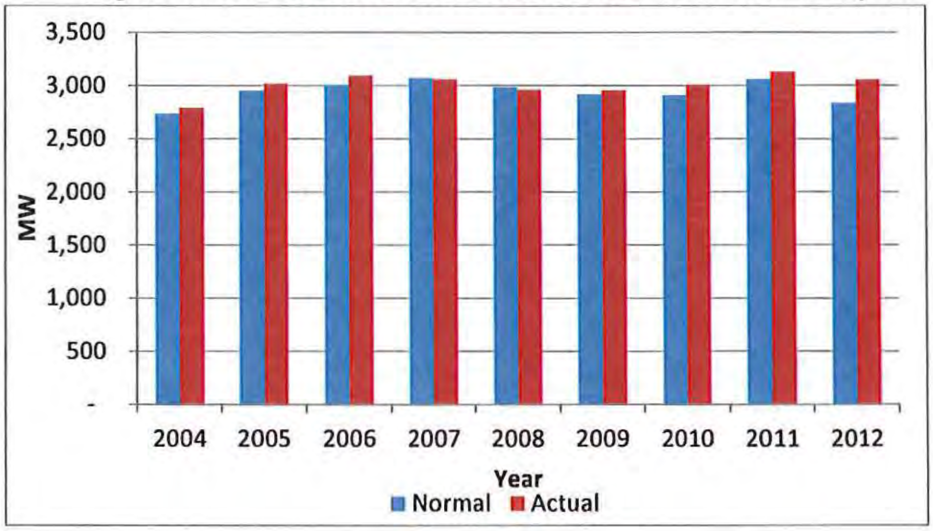
Figure 3.16: Residential Coincident Peak Demand (MWs)



[42] 4 CSR 240-22.030(2)(B)3

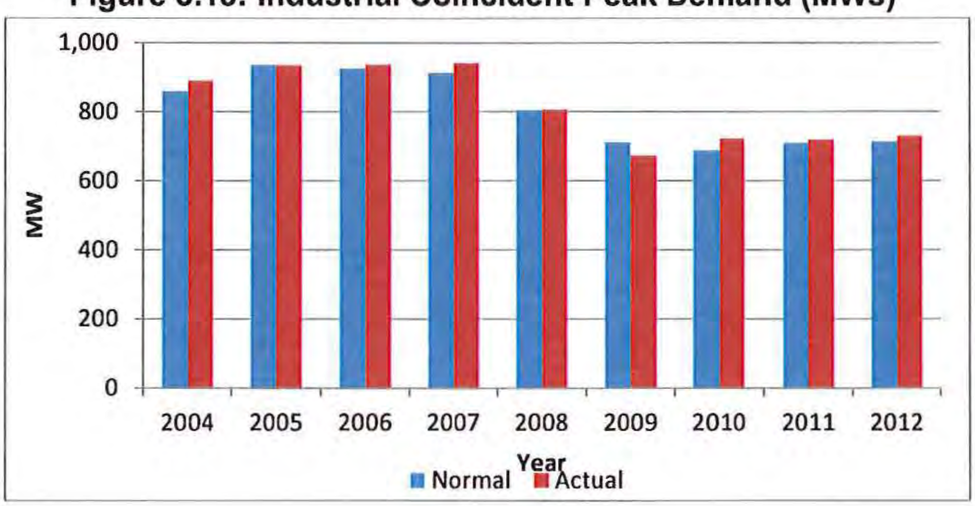
For the commercial class, the annual coincident peak demand grew at 0.4% per year, from a weather normalized 2,733 MW in 2004 to 2,832 MW in 2012 (at generation, i.e. inclusive of transmission and distribution losses). On an actual basis, the commercial class load reached its highest level in 2011, with an hourly integrated demand of 3,127 MW.

Figure 3.17: Commercial Coincident Peak Demand (in MWs)



The industrial class annual coincident peak demand declined on a weather normalized basis from the year 2004 to 2012 by approximately 2.3% per year. The normalized class demand increased modestly between 2004 (859 MW) and 2005 (934 MW), but fell rapidly through the recession of 2007-2009 and ended 2012 at 713 MW. There was broad based weakness across this class, but a couple of specific large customer closures had a significant impact. For the industrial class, 2007 saw the highest actual coincident peak demand at 940 MW.

Figure 3.18: Industrial Coincident Peak Demand (MWs)



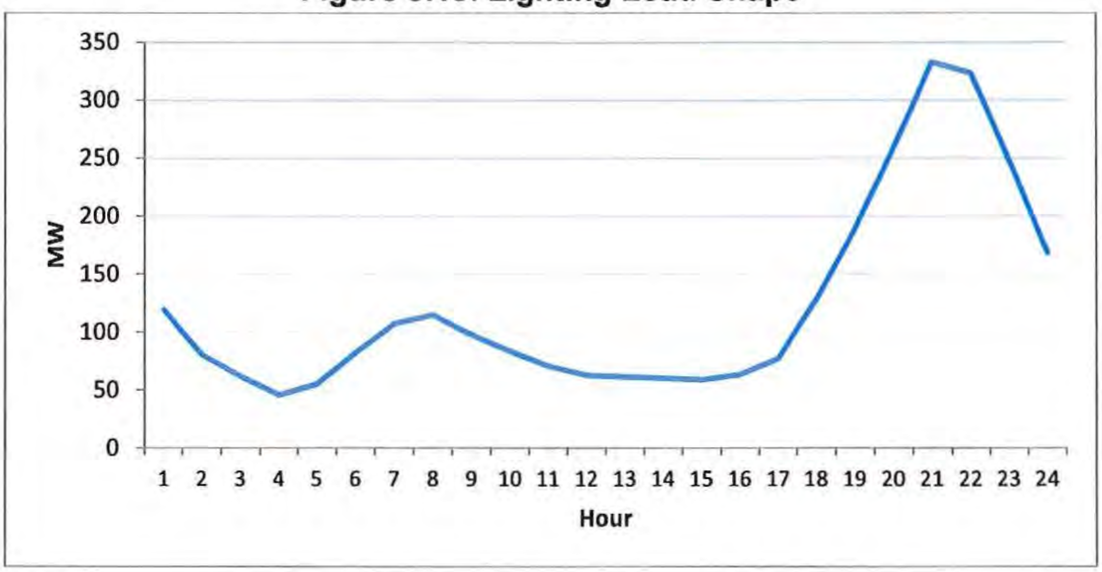
3.2.2 Profile Shapes

The energy forecast provides a view of how much energy is expected to 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.

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 3.19, note the peak at hour 21 and the fact that hour 17 (likely the summer system peak hour) energy is only 23% of the peak.

Figure 3.19: 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

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[43]

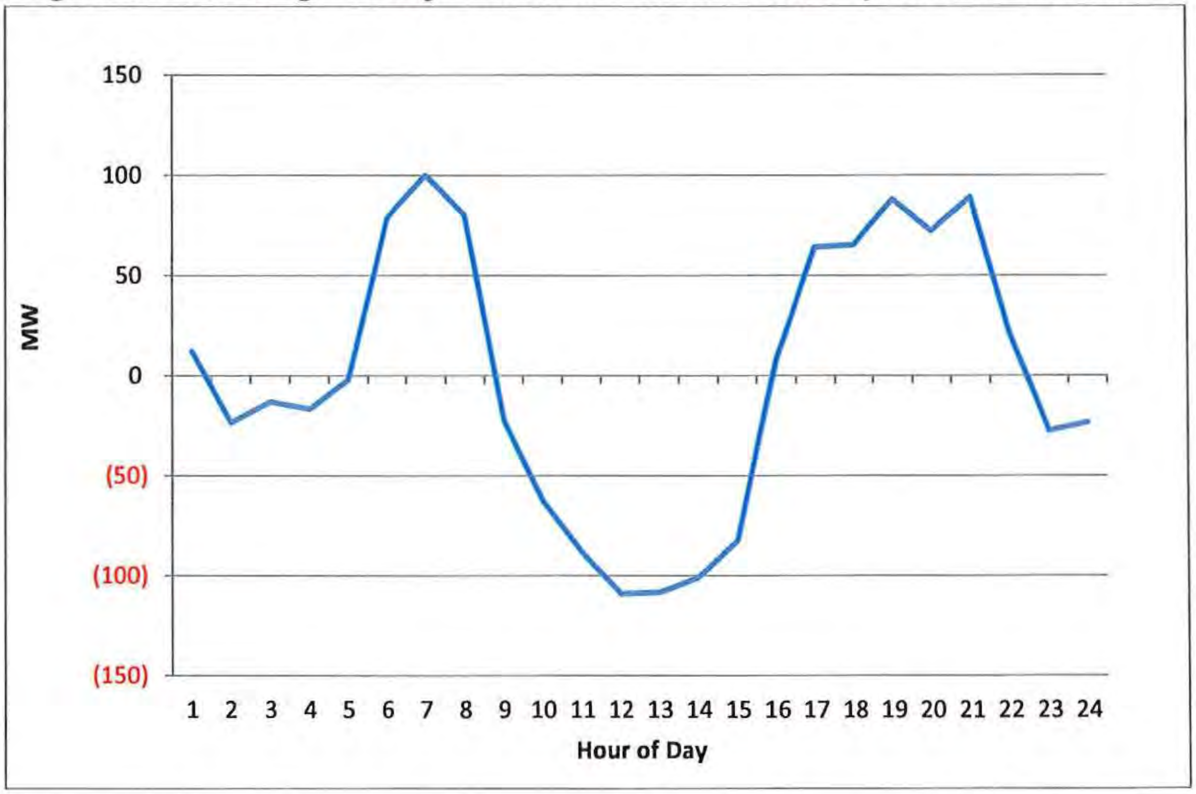
Because the data in Itron's eShapes database is secondary data and probably more than a decade old, and more recent and geographically similar data is nearly impossible to come by, Ameren Missouri worked with this data to ensure that it was as applicable to the Ameren Missouri load as possible. For a three year period (2010-2012), the Itron data was utilized to construct Ameren Missouri class level data from the bottom-up. Historical energy sales for 2010-2012 were divided into end uses based on information from the SAE forecasting models. The eShapes profiles for each end use were then scaled so that they represented the estimated energy from those years. The scaled end-use shapes were then aggregated to create a "synthetic" class level load shape. That synthetic load shape was 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 the study years 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 on graphs 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 load research from the synthetic class load. 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 3.20 shows the average hourly error pattern that was generated in this process for the residential class.

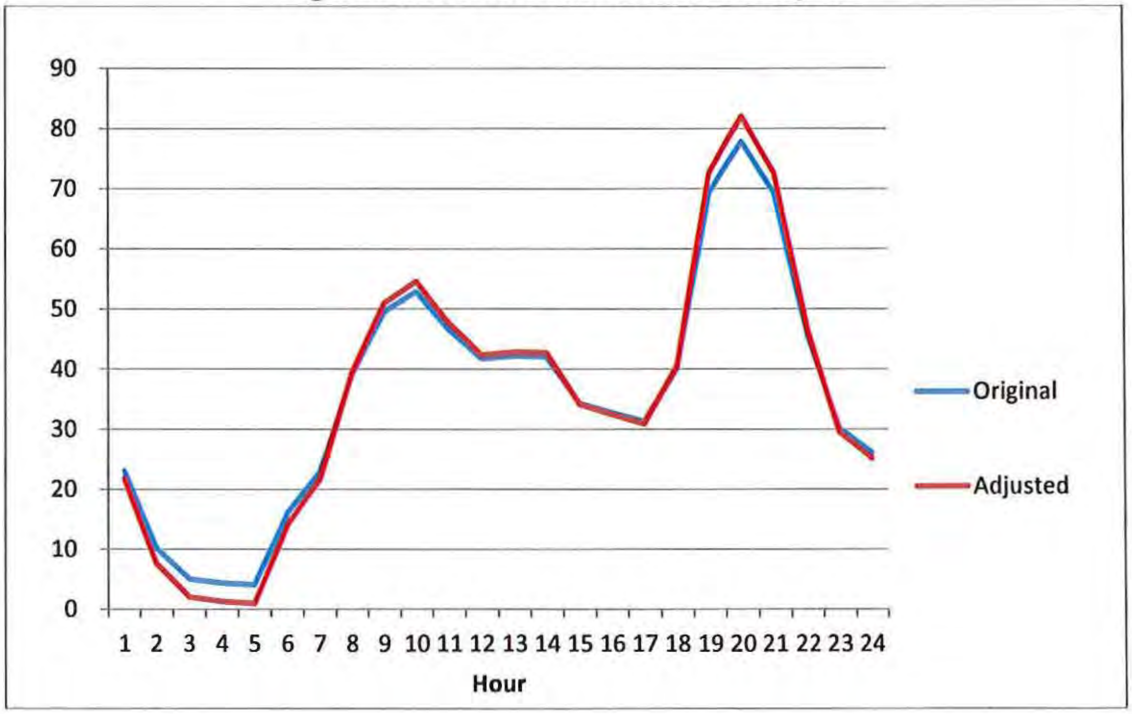
[43] 4 CSR 240-22.030(4)(B)2

Figure 3.20: Average Hourly Difference-End Use Build Up vs. Load Research



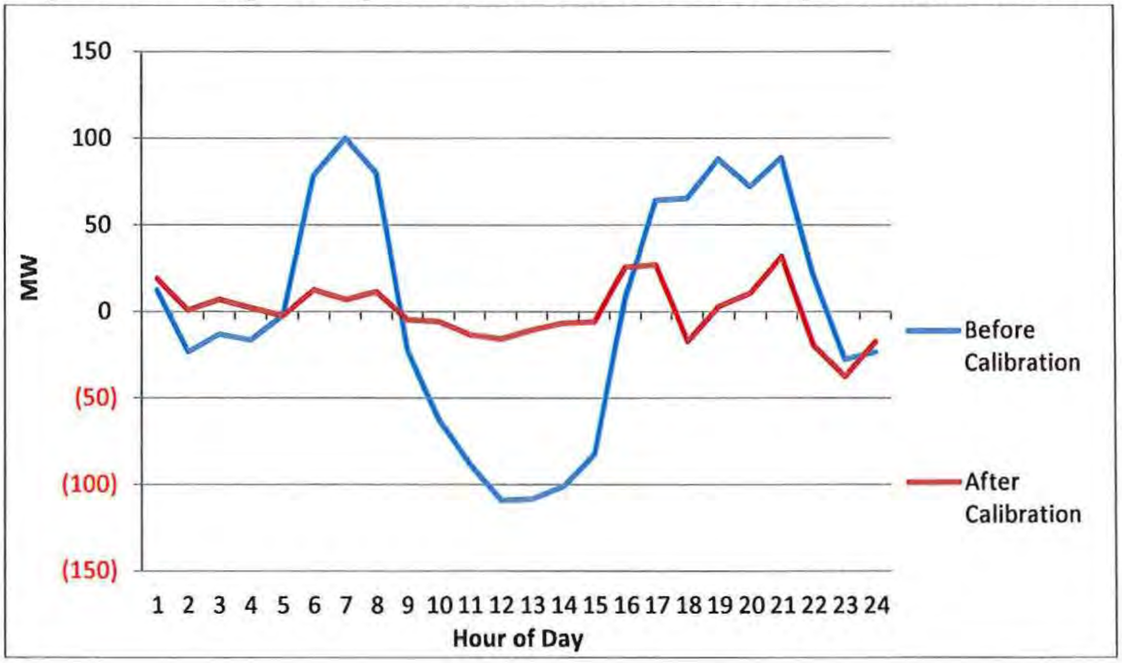
As is apparent in Figure 3.20, the synthetic class load shape was too high during the late morning and evening hours (generating a positive error pattern) and too low in the mid-afternoon hours (generating a negative error pattern). In order to improve the fit of the build-up load, the individual end-use load shapes were adjusted slightly. The overall characteristic of the shape was respected, as the eShapes 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. 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 3.21: Dishwasher Load Shapes



As is visible in the chart of the dishwasher shape, the basic characteristic is retained, but the load factor is reduced in this instance (the peak of the adjusted shape is higher relative to the total energy). Each end use went through review and a similar adjustment process until the error pattern in the difference series was minimized. The final load shapes for each end use is included in a chart in Appendix A to this chapter. The pattern of the hourly differences before and after adjustment is shown in Figure 3.22.

Figure 3.22: Avg. Hourly Difference-End Use Build Up vs. Load Research



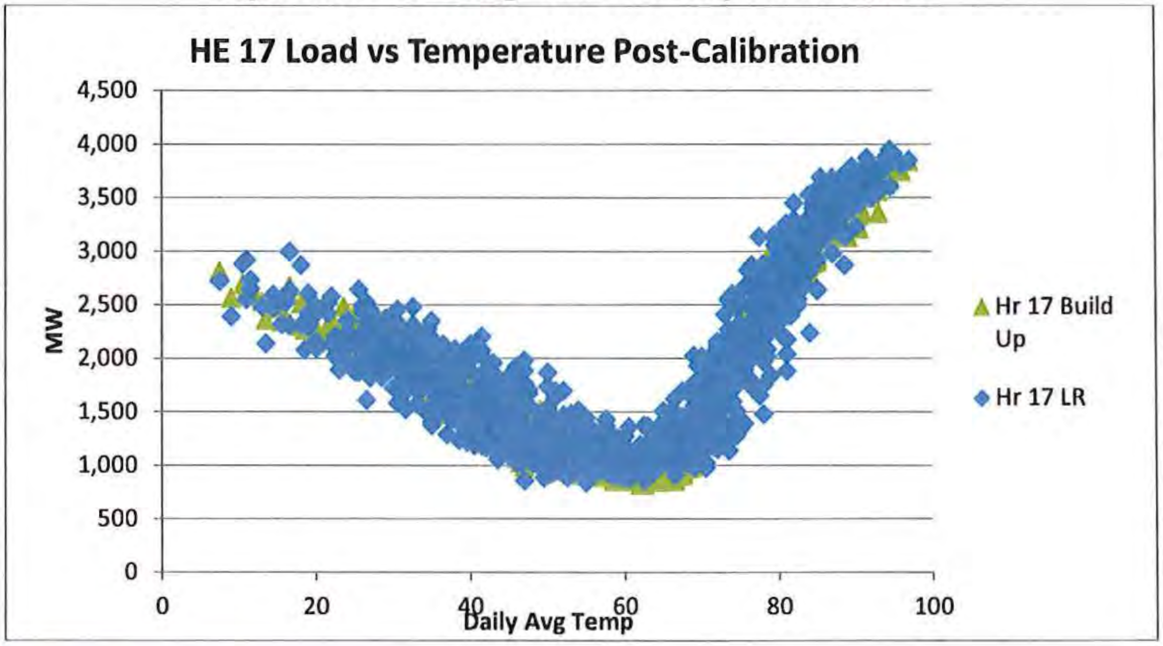
While the adjusted load shape still has some differences from the class actual load shape, the magnitude of the differences is clearly reduced by a substantial amount. It would be impossible to make the synthetic load shape have a perfect fit with the load research data while respecting the characteristic 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 at times, now no hour's difference exceeds 35 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.

For the 2014 IRP, an additional level of scrutiny was given to the heating and cooling end use loads, as these are significant contributors to the peak load hours and hence the peak forecast to which Ameren Missouri will plan its capacity needs. Since the system typically peaks at hour ended 17 (the hour from 4 to 5 pm) in the summer, we created a scatter plot of HE 17 loads vs temperature using both the load research data and the synthetic load data. After further adjustment of the cooling load shape, still respecting its basic shape, very good agreement between the observed loads and the calculated loads was achieved. The chart shown in Figure 3.23 below shows a comparison of the two scatter plots.

Figure 3.23: Cooling End Use Shape Calibration



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, 2011 was the reference year. This historical year (2011) 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 2011. So for example, the hottest day of August 2011 fell on the 2nd. In our planning calendar case, the hottest weather of August will also fall on the 2nd. 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 2nd (2011) was a Tuesday. So for the planning calendar (which will be applied to forecast all future years), August 2nd will remain a Tuesday 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.

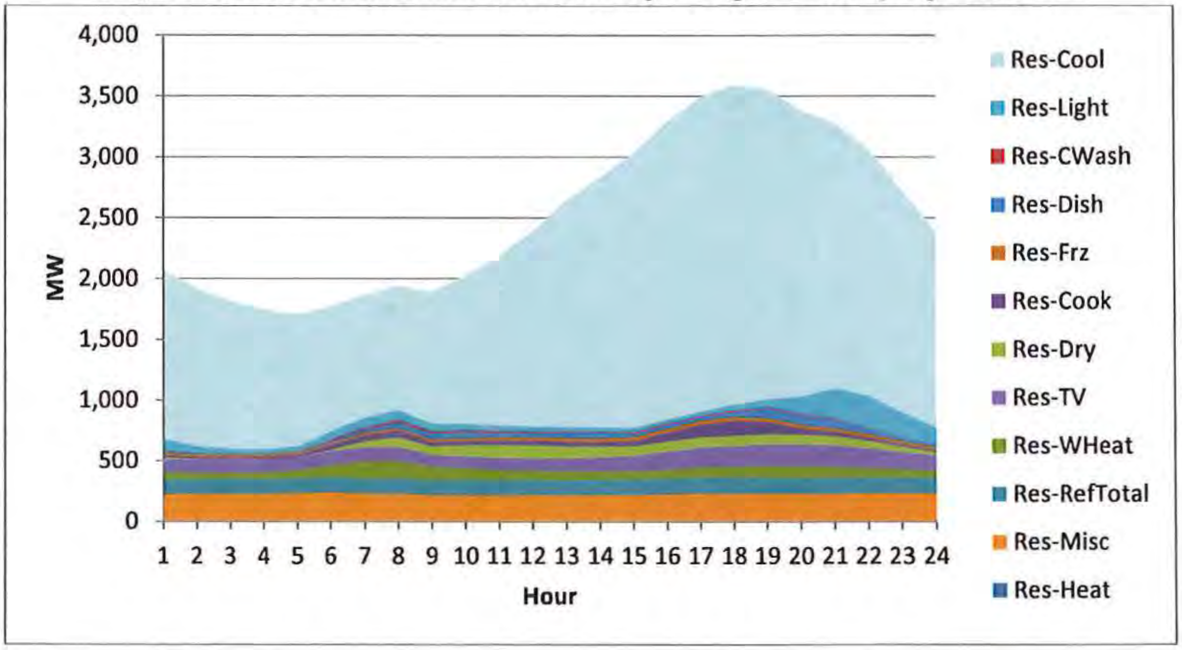
Actual Calendar Profile Development

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 (2011). 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 2nd of every year being a Tuesday, in, for example, 2017, August 2nd will be a Wednesday. 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 an Excel model developed by Ameren Missouri, 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 3.24 shows an example of the buildup of the residential load for a summer day from the end use components.

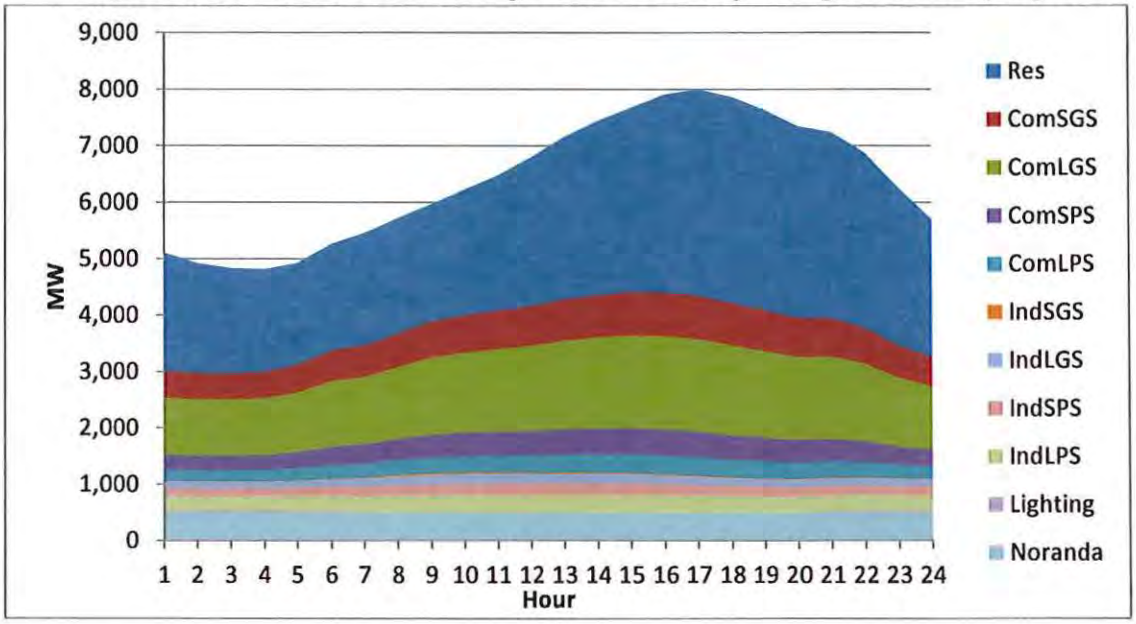
Figure 3.24: Residential Summer Day Usage Built-Up by End Use



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 2011 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 3.25.

Figure 3.25: 2014 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 2007 through 2012. Historical calendar month actual sales were disaggregated into end uses where necessary by application of information from the Statistically Adjusted End Use models. The end use and class level profiles were updated with actual historical weather and calendar information to produce historical shapes to represent actual conditions. 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 3.7.

Table 3.7: Actual vs. Model Peak

Year	Modeled Peak (MW)	Actual Peak (MW)	Difference	% Diff
2007	8,458	8,784	326	3.7%
2008	8,254	8,367	113	1.3%
2009	7,750	7,761	11	0.1%
2010	8,248	8,444	196	2.3%
2011	8,037	8,413	376	4.5%
2012	8,744	8,439	-305	-3.6%
Avg.	**8,249**	**8,368**	**120**	**1.4%**

While the results of the back testing exercise indicate good performance of the model in that no year's modeled result was more than 4.5% off from the observed value, on average the model has slightly under predicted the historical peak loads by 1.4%.

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[44]

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

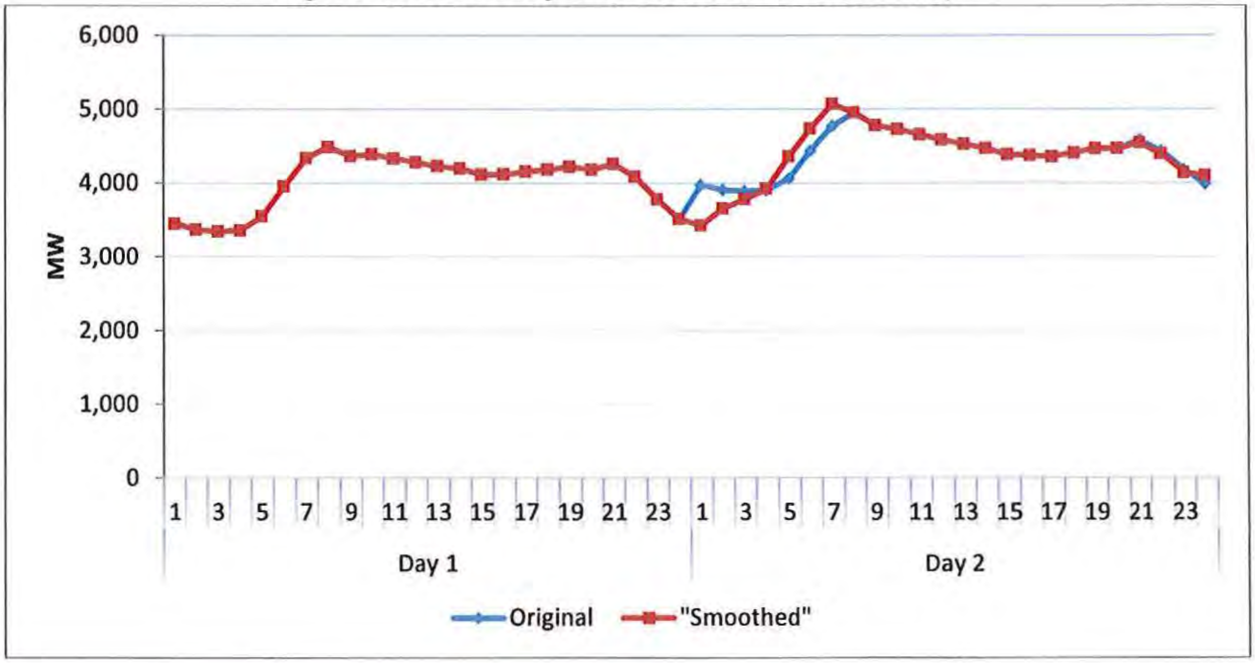
[44] 4 CSR 240-22.030(7)(C)

actually need to be generated in order to meet the demand of Ameren Missouri's customers. The energy loss factors were also based on the 2011 loss study. An additional 3.5% loss beyond the value in the study 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.

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 aggregated 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 Midcontinent 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 2009 through 2011.

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 3.26.

Figure 3.26: Example of Smoothed Load Shape



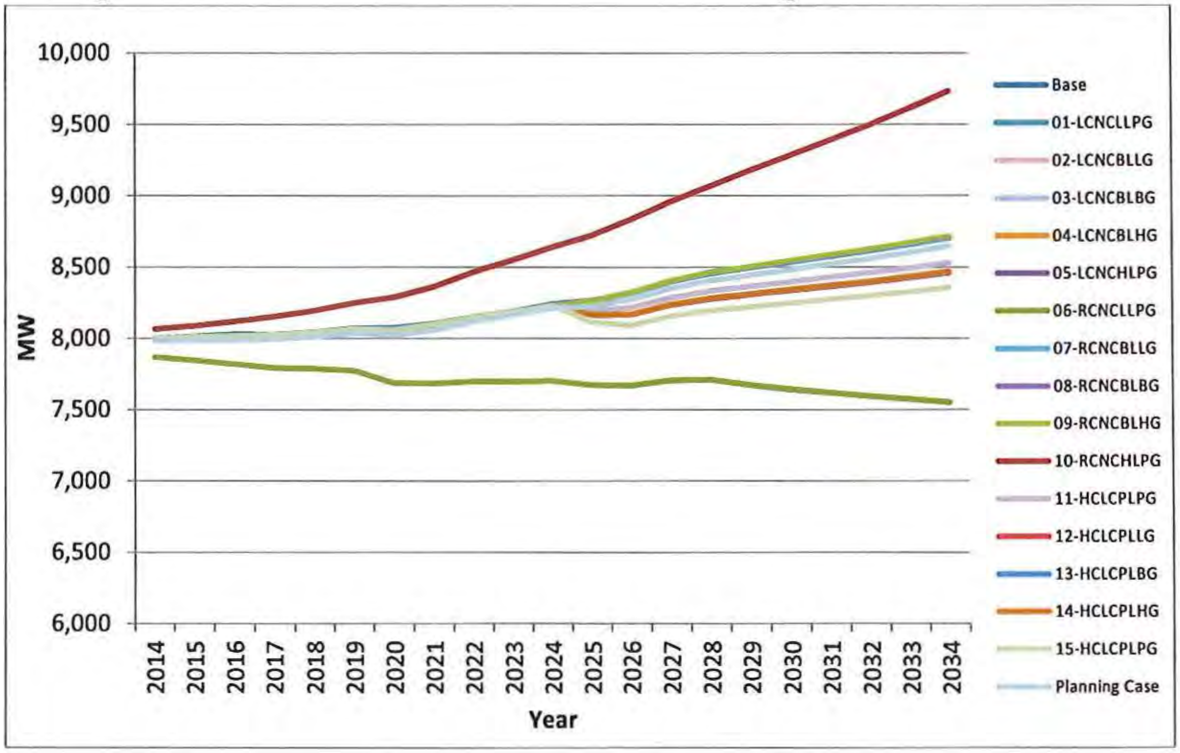
Scenarios and Planning Case Forecasts

The energy forecast described in Section 3.1 was modeled under fifteen different scenarios. Each of these scenarios was based on a certain combination of the critical uncertain factors identified in this IRP (gas prices, load growth, and coal retirements/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 peak 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

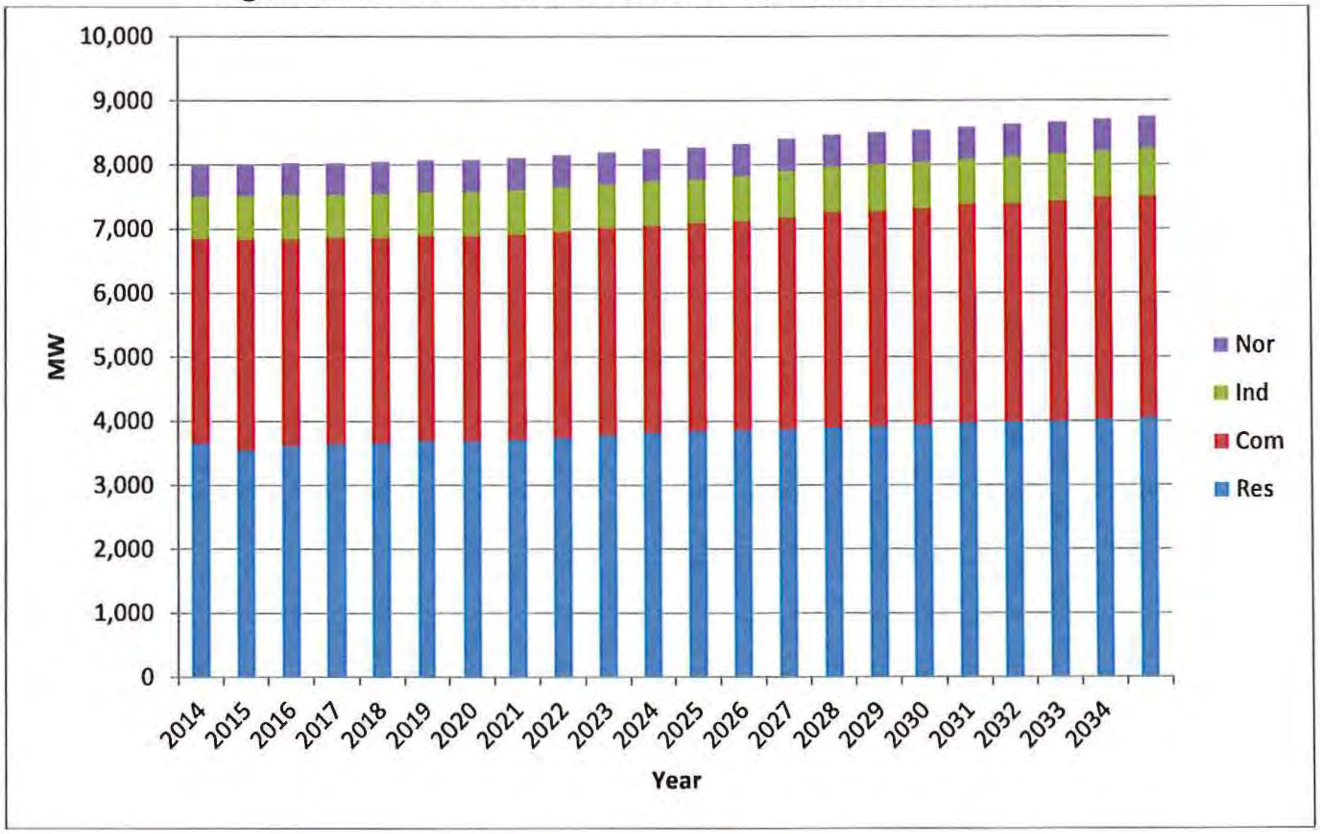
The planning case results indicate a forecasted annual peak load growth rate from 2014 through 2034 of 0.4%. The peak load in 2014 is projected to be 7,983 MW, growing to 8,648 MW by 2034. The growth rates in the various scenarios range from a low of -0.21% annually, to 0.94% per year.

Figure 3.27: IRP Annual Peak Forecast: Planning Case and Scenarios



One conclusion evident from observing the results of the energy and peak forecasts is that the peak is growing more slowly than energy. This is due to a couple of factors. First, the commercial class is the fastest growing class. The Commercial class has a higher load factor than the residential class and higher than system average. This growth drives an improving load factor overall. Secondly, while the residential class has the poorest load factor of any class, it is improving over time with the increase in efficiency of central air conditioning units. Air conditioning is the largest end use contributor to peak load, so the efficiency improvements have a pronounced impact on peak load conditions.

Figure 3.28: Class Contribution to Annual Peak Forecast



3.2.6 Planning Case Peak Demand Forecast

Class and End-Use Peak Demands

The peak contribution of the residential class grows at 0.51% per year from 2014 to 2034, while the commercial class peak grows at a forecasted 0.41%, and the industrial class peak is expected to grow by 0.59% 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 miscellaneous load. This end use is projected to grow at 2.0% 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 full year of the forecast (2014) and the last year of the forecast (2034).

Table 3.8: Residential End-Use Contribution to Peak

	2014 Peak Contribution (MW)	% of Peak Load	2034 Peak Contribution (MW)	% of Peak Load	CAGR
Clothes Washer	10	0%	7	0%	-1.5%
Refrigerator	132	4%	112	3%	-0.8%
Miscellaneous	237	6%	350	8%	2.0%
Lighting	35	1%	25	1%	-1.7%
Heating	0	0%	0	0%	0.0%
Freezer	33	1%	27	1%	-1.0%
Electric Dryer	87	2%	87	2%	0.0%
Electric DHW	82	2%	87	2%	0.3%
Electric Cook	105	3%	122	3%	0.7%
Dish Washer	30	1%	29	1%	-0.1%
Cooling	2743	75%	2963	70%	0.4%
Color TV	163	4%	223	5%	1.6%
Total	***3,657***	***100%***	***4,210***	***100%***	***0.7%***

Figure 3.29: Residential Peak Load Composition 2014

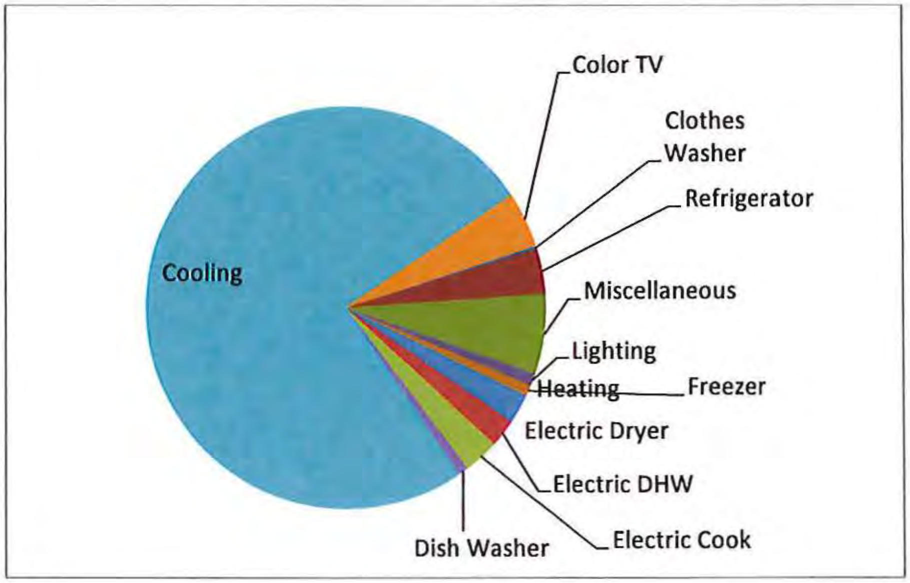


Figure 3.30: Residential Peak Load Composition 2034

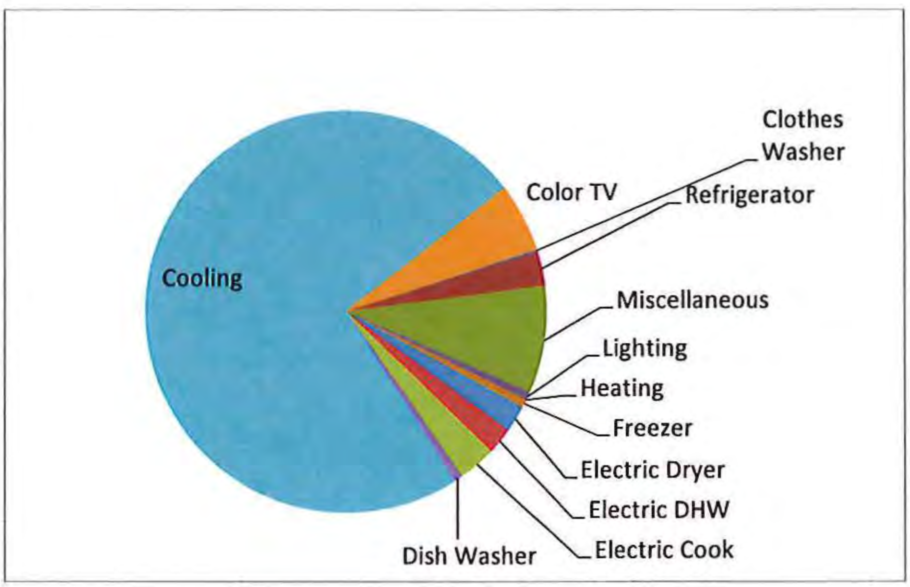


Table 3.9: Commercial End-Use Contribution to Peak

	2014 Peak Contribution (MW)	% of Peak Load	2034 Peak Contribution (MW)	% of Peak Load	CAGR
Cooling	1,426	45%	1,316	38%	-0.4%
Cooking	65	2%	66	2%	0.1%
Water Heating	69	2%	66	2%	-0.3%
Lighting	632	20%	555	16%	-0.6%
Miscellaneous	469	15%	844	24%	3.0%
Office Equip.	163	5%	228	7%	1.7%
Refrigeration	139	4%	155	4%	0.5%
Ventilation	228	7%	238	7%	0.2%
Total	***3,192***	***100%***	***3,468***	***100%***	***0.4%***

Figure 3.31: Commercial Peak Load Composition 2014

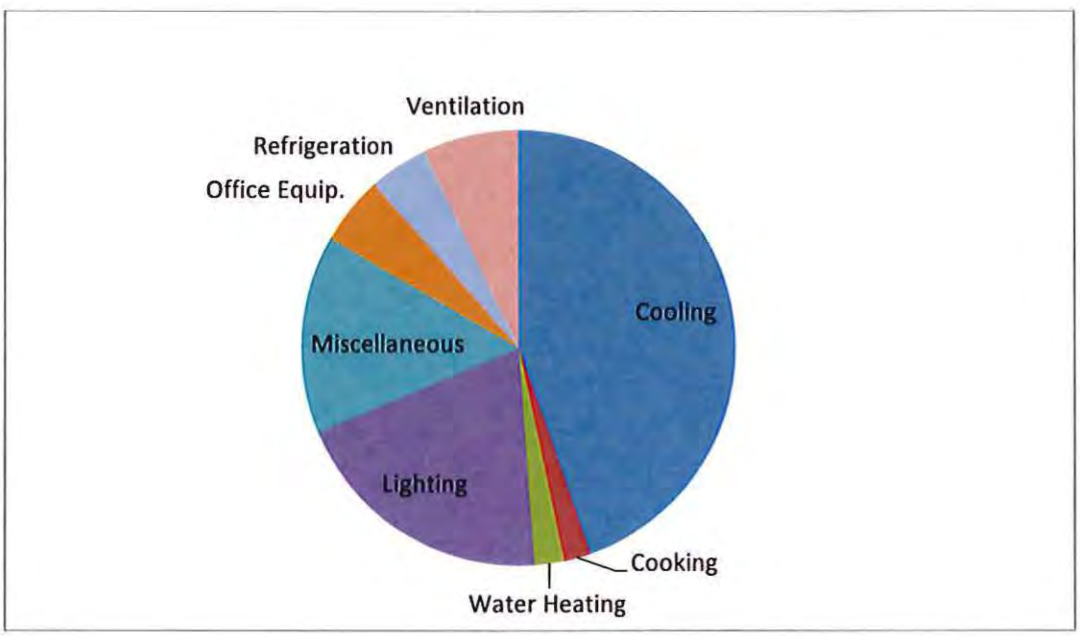
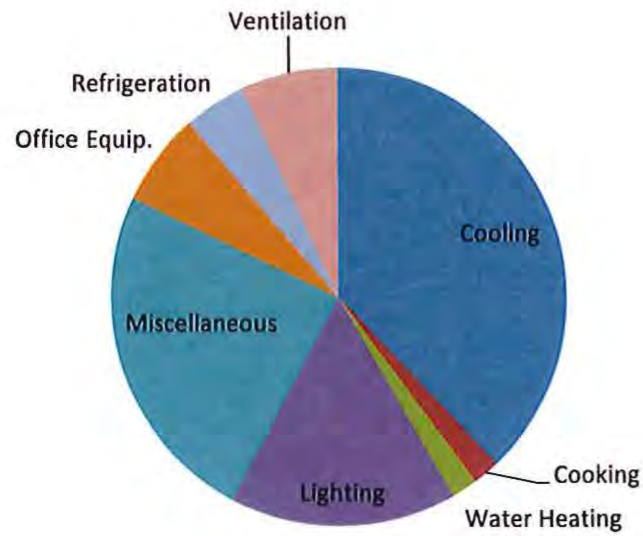


Figure 3.32: Commercial Peak Load Composition 2034



3.2.7 Peak Demand – Extreme Weather Sensitivity[45]

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 17.3%. So in the capacity position, 17.3% is added to the load 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 2014. 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 125.6 MW of increased system demand per degree.

This estimate was tested using 2014 summer peak data. The 2014 summer peak forecast (from the base case modeling) called for a normal weather (at a two-day weighted average temperature of 88.63 degrees) load of 8,003 MW. Next, Ameren Missouri calculated the expected peak load given two day weighted average

[45] 4 CSR 240-22.030(8)(B); 4 CSR 240-22.070(1)(D)

temperatures equaling the 90th percentile of summer peak temperatures from 1981-2010 and at the absolute maximum temperature observed in that time frame. Additionally, Ameren Missouri tested against a temperature that occurred outside of the 1981-2010 time period, because since then the historically hot summer of 2012 gave an extreme observation that far exceeded what came in the 1981-2010 years. The result was that at the 90th percentile two day weighted average temperature (91.18 degrees), the peak load was forecasted to reach 8,324 MW, or 4.0% higher than the normal weather forecast. At the absolute maximum two day weighted average temperature reached during the 1981-2010 years (91.83 degrees), the load was estimated to reach 8,406 MW, or 5.0% higher than the normal weather peak. Even under the extreme conditions of 2012, when the two day weighted average temperature reached 96.67 degrees, the peak forecast reached 9,014 MW, or 12.6% above the original forecast.

In each case, the extreme weather produced an effect that was lower than the 17% reserve margin, leaving room for additional contingencies, such as a unit outage. For the 90th percentile temperature and the hottest temperature from 1981-2010, the weather uncertainty used well under half of the reserve margin available. The heat in 2012 was well beyond the 1 in 10 planning threshold typically used for reliability planning, and even at that level the load increased against the normal weather forecast by less than the 17.3% reserve margin by several percent.

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 Midcontinent Independent System Operator (MISO) in its Loss of Load Expectation (LOLE) study for 2014. On page 34 of the 2014 LOLE study, MISO provides a chart which indicates the Load Forecast Uncertainty (LFU), which includes weather related uncertainty that is embedded in the reserve margin estimates. MISO's chart shows the reserve margin needed given various levels of LFU. The reserve margin of 16.5% on that chart (very close to the long-term planning assumption of 17.3%) is associated with LFU of 9%. That 9% LFU value is significantly higher than the 5% weather sensitivity exhibited by Ameren Missouri's load based on the most extreme weather experienced over the 1981-2010 time period. It is just slightly eclipsed by the weather sensitivity associated with the record setting conditions of the 2012 summer. All in all, the amount of uncertainty associated with extreme weather conditions, is in line with both the LOLE study and the principle that the 17.3% planning reserve margin should account for extreme weather and additional generation contingencies with loss of load expected no more than once in ten years.

3.3 Weather Normalization[46]

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-2012-0166. For historical periods covered by Ameren Missouri's 2011 IRP and earlier, the weather normalized information prepared for and reported in that filing is utilized in this filing, as adjusted for the updated definition of normal weather used in this IRP.

This adjustment was necessary because at the time of the preparation of the 2011 IRP filing, Ameren Missouri was using normal weather calculations based on the time period of 1971-2000. Every decade, the National Oceanic and Atmospheric Administration (NOAA) recomputes weather normals using the most recent 30 years of data. Consistent with this practice, Ameren Missouri has since updated its weather normal calculations to be based on the years 1981-2010. In order to maintain consistency between weather normalized sales being reported, Ameren Missouri is restating its historical normalized sales with the new normal. The process for calculating the adjustment was basically to take an historical year and calculate weather normalized sales using the "old" normal (1971-2000) and the "new" normal (1981-2010) temperatures and following the process as described further below. For each month a ratio was computed between the new and old normalized sales. That ratio was applied to the same month's sales from each of the years of historical sales in the database.

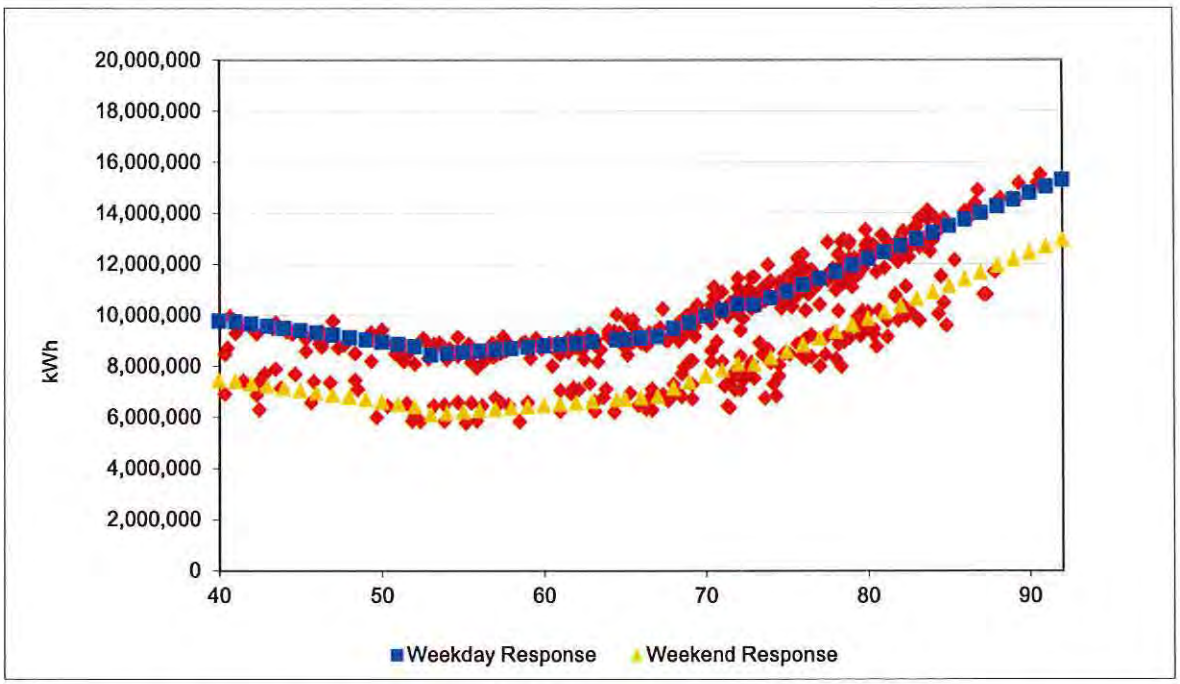
The weather normalization process starts with defining normal weather. As referenced above, Ameren Missouri currently uses actual temperature readings for St. Louis Lambert Airport from the period 1981-2010 to develop its normal weather conditions, as adjusted for certain changes in the recording equipment 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 and peak demand later in the process. Essentially it is used to ensure that

[46] 4 CSR 240-22.030(2)(C)2

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 if needed as explanatory variables to create a piecewise linear temperature response function.[47] A graphical representation of this modeling approach can be seen in Figure 3.33.

Figure 3.33: MetrixND COMSGS Non-Winter Weather Response



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

[47] 4 CSR 240-22.030(2)(D)2

the load in question. The actual model variables and corresponding coefficients are presented in the appendix.[48] 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[49]

Ameren Missouri continually works to improve its load analysis processes to produce more accurate forecasts that provide an increasing depth to our analytical capabilities. The load analysis function is of increasing importance in this era of increasing energy efficiency, both through company sponsored programs and non-utility efforts. To that end we continue to explore additional data sources, and enhanced forecasting and analytical techniques.

Much of this effort is focused on increasing the ways we can segment our data. Whether it be analyzing our commercial class by segmenting the business types, or analyzing our residential and commercial classes by the end use appliances and equipment they operate, our analysis is continually increasing in its detail.

NAICS Codes

To facilitate that increasingly detailed analysis, Ameren Missouri recently worked with a vendor to append North American Industrial Classification System (NAICS) codes to its commercial and industrial accounts. Going forward, this data will help us to monitor trends in usage by different types of businesses, and therefore give insights into the causes of changes in the energy intensity of our service territory economy.

End-Use Load Research

Ameren Missouri has been monitoring industry efforts to develop new end use load shape data. We have participated in workshops and discussions within the industry evaluating the ability of Non-Intrusive Load Monitoring devices to disaggregate whole premise load data into its end use components, and will continue to monitor efforts to increase data availability from industry sources in this area. Additionally, the Ameren Missouri load analysis function is working to make sure we are able to leverage any end use metering data collected by its EM&V contractors for purposes of energy efficiency program impact evaluation. This data can be a valuable tool to further enhance the processes described in this chapter for assessing and improving the applicability of end use load shape data to our customers' loads.

Load Research Sample Design

[48] 4 CSR 240-22.030(2)(C)3
[49] 4 CSR 240-22.070(6)(A)

Ameren Missouri, as of this writing, is in the process of developing and implementing a new sample for its load research program. Although the existing sample has continued to perform well in all measurable ways, it has been in place for a number of years and will benefit from being refreshed. New customers added to the system since the last sample design in the early 2000s will now be represented in the load research process. Also, the new sample customers in the commercial class will be segmented by business type based on the NAICS code designations discussed above. A benefit of this segmentation will be the ability to develop load shapes and perform other types of load analysis by business and building type. As the demands on load analysis grow due to increasing need to understand demand side management program impacts, more granular data will be particularly valuable. Going forward, the new sample should help maintain the high quality of analysis by making sure the sample accurately represents our evolving customer base and should add new intelligence into the analysis that supports our DSM efforts.

End-Use Surveys

Ameren Missouri, as described in this chapter, worked with Enernoc Utility Solutions in 2009 and 2013 to perform extensive primary market research on the stock of end using appliances and equipment in its service territory. In addition to the role the data collected in these potential studies play in the development and evaluation[50] of demand side programs, this data is very valuable to the forecasting and load analysis area. As more surveys are conducted, the value of the data increases, as a time series of market data can help to track changes in saturations of appliances over time.[51] 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 anticipates continuing to do periodic collection of primary data to further enhance its understanding of the mix of end using goods in its service territory.

[50] 4 CSR 240-22.030(1)(C)
[51] 4 CSR 240-22.030(1)(D)

3.5 Compliance References

4. Existing Supply Side Resources

Highlights

- *Ameren Missouri currently owns and operates 10,280 MW of supply side resources: 5,364 MW of coal, 1,190 MW of nuclear, 2,896 MW of peaking natural gas, and 830 MW of renewables and storage.*
- *Ameren Missouri is scheduled to complete two unit upgrades at Keokuk Energy Center (Units 5 and 6) in 2016. In addition, upgrades of Units 14 and 15 at Keokuk Energy Center are scheduled to be complete in 2018.*
- *Ameren Missouri is considering options for Meramec Energy Center including combinations of unit retirements and gas conversion, with all units retired by the end of 2022*
- *Ameren Missouri is planning for additional retirements of fossil-fueled generating units during the planning horizon:*
    - *Sioux Energy Center is assumed to be retired in 2033.*
    - *Assumed retirement by 2020 of 367 MW (summer net capacity) of older, less efficient gas and oil fired CTGs.*
    - *Ameren Missouri has developed assumptions for an evaluation of retirements of Labadie and Rush Island Energy Centers.*

Ameren Missouri owns and operates thermal, nuclear, hydroelectric and storage energy centers to serve the energy needs of its customers. About 92% of generation comes from its coal-fired, nuclear, and oil/natural gas-fired energy centers. Ameren Missouri continuously evaluates energy center performance and upgrades that are necessary to operate its plants in an efficient, safe, cost-effective and environmentally-friendly manner.

During the 20-year planning horizon, Ameren Missouri is considering four Keokuk Energy Center Units for upgrades, adding a new CTG unit at the Maryland Heights Renewable Energy Center (MHREC), adding the largest investor-owned utility solar center in Missouri with approximately 5.7 MW [direct current (DC)] capacity, and the potential retirement of eight CTG units.

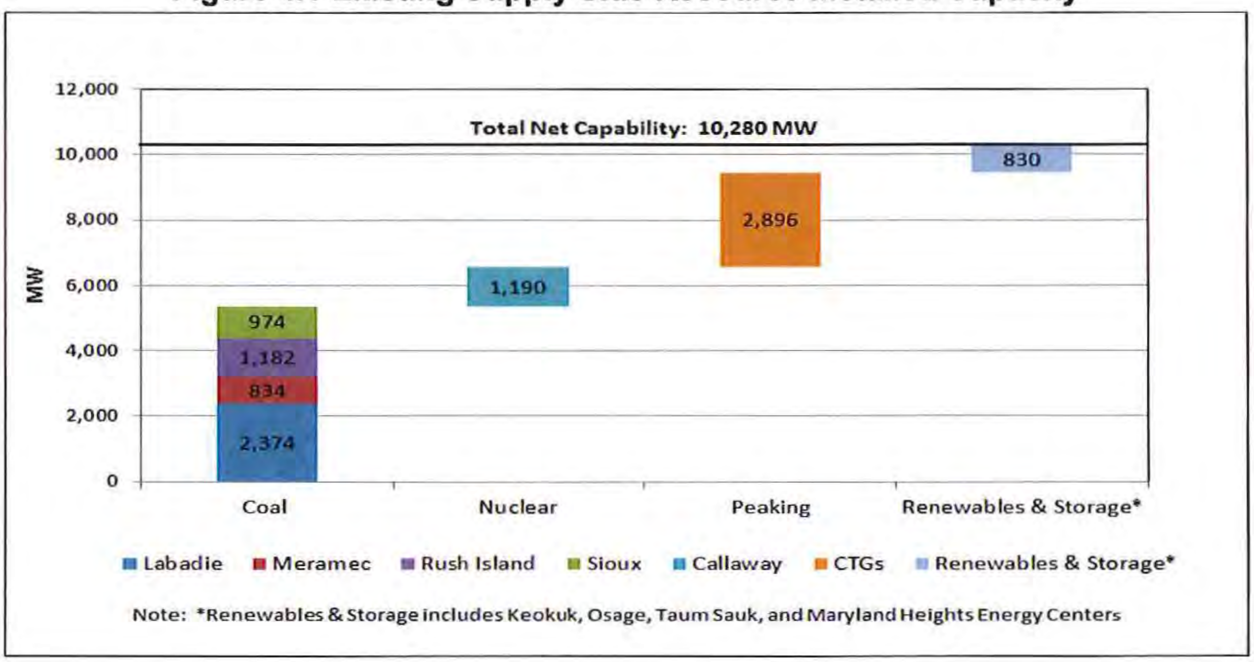
Ameren Missouri retained the services of Burns & McDonnell to complete a Condition Assessment of the Meramec Energy Center to determine ongoing costs necessary to keep the plant operating safely and reliably through the planning horizon. Ameren Missouri is considering options for Meramec Energy Center including combinations of unit retirements and gas conversion, with all units retired by the end of 2022.

Ameren Missouri has implemented various initiatives to improve efficiency and reduce greenhouse gas (GHG) emissions at its existing facilities. In addition, Ameren Missouri has evaluated a range of generation efficiency options as part of the End-to-End Efficiency Study performed with the assistance of the EPRI. As of 2012, the successful implementation of several projects identified in the End-to-End Efficiency Study, as well as other efforts, helped Ameren Missouri reduce heat rate by over 0.8% from a 2009 baseline. Ameren Missouri has also been proactively monitoring the status of light–emitting diode (LED) technology and engaged the Electric Power Research Institute (EPRI) to conduct a pilot program testing LED street lights. The overall conclusion is that while LEDs appear to be a viable technology, current economics and associated uncertainty do not support near-term adoption. Ameren Missouri will continue assessing and implementing projects that prove to be feasible on an ongoing basis.

4.1 Existing Generation Portfolio[1]

Ameren Missouri owns and operates thermal, nuclear, hydroelectric and storage energy centers to serve the energy needs of its customers. Figure 4.1 reflects the 2014 summer net capability of Ameren Missouri's existing supply side resources. Appendix A includes a unit rating summary table. Appendix B includes the existing capacity position table for 2014-2034.[2]

Figure 4.1 Existing Supply Side Resource Installed Capacity



[1] 4 CSR 240-22.040(1); 4 CSR 240-22.040(2)
[2] 4 CSR 240-22.060(4)(B)9