3. Load Analysis and Forecasting

Highlights

- *Ameren Missouri expects energy consumption to grow 0.30% annually and peak demand to grow 0.26% annually for the planning case over the next 20 years before company-sponsored energy efficiency and demand response programs.*
- *Economic growth, naturally occurring energy efficiency and customer adoption of distributed energy resources such as solar and electric vehicles are key drivers of future growth in our base case forecast before company-sponsored energy efficiency and demand response programs.*
- *Ameren Missouri has also considered the potential for electrification of heating and cooking energy use and industrial vehicles such as forklifts. The base case load forecast includes nearly one billion kilowatt-hours for such uses by 2037.*

Ameren Missouri has developed a range of load forecasts consistent with the scenarios outlined in Chapter 2. These load forecasts provide the basis for estimating Ameren Missouri's future resource needs and provide hourly load information used in the modeling and analysis discussed in Chapter 9. In addition, the Statistically Adjusted End-use forecasting tools and methods used to develop the forecasts provide a solid analytical basis for testing and refining the assumptions used in the development of the potential demand-side resource portfolios discussed in Chapter 8.[1] The energy intensity of the future economy and the inherent energy efficiency of the stock of energy using goods are explored throughout the analysis to arrive at reasonable estimates of high, base, and low load growth.

3.1 Energy Forecast

This chapter describes the forecast of Ameren Missouri's energy, peak demand, and customers that underlies the analysis of resources undertaken in this IRP. In order to account for a number of combinations of possible economic and policy outcomes, three different forecast scenarios, a high load growth scenario, low load growth scenario, and base case scenario were prepared. Based on the subjective probabilities of these scenarios identified by Ameren Missouri, a fourth case was developed to represent the

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

planning case for the study. The planning case forecast projects Ameren Missouri's retail sales to grow by 0.30% annually between 2018 and 2037, and retail peak demand to grow by 0.26% per year.

As with any forecast of energy, there are several underlying assumptions. Expectations for economic growth underlying the load forecast are based on Moody's Analytics' forecast of economic conditions in the Ameren Missouri service territory. Expectations about future energy market conditions, such as fuel prices and the impact on electricity prices of different environmental policy regimes are based on interviews with internal Ameren subject matter experts.

Compared to Ameren Missouri's last IRP, filed in 2014, both the level and the growth rate of the forecast are lower. Since the last IRP filing, Ameren Missouri has implemented significant energy efficiency programs, which has significantly reduced overall energy consumption year over year. The 0.30% growth rate in retail sales in this filing (between 2018 and 2037) is also lower than the 0.6% retail sales growth rate expected for the study period in the 2014 IRP forecast largely due to a combination of factors. First, the projections of growth for some key economic indicators such as manufacturing GDP or household formation are lower in this IRP than they were in the last IRP study. Second, the impacts of both energy efficiency standards and the programs of Ameren Missouri are expected to further reduce the energy intensity of the service territory economy. This forecast assumes significant savings from Missouri Energy Efficiency Investment Act (MEEIA) Cycle 2 programs that are already in the implementation phase. In addition, Ameren Missouri has saved more energy than originally planned at the time of 2014 IRP filing through MEEIA Cycle 1 programs. Finally, and most importantly, Ameren Missouri's point of view assumes a significant increase in customer adoption of distributed energy resources (DER) and electric vehicles (EV) during the planning horizon compared to prior IRP filings.

It should be noted that in the development of this forecast, expectations of improving energy efficiency of end use equipment and appliances is reflected only to the extent that it is due to market conditions, federal standards, or the first three year cycle of energy efficiency programs Ameren Missouri is currently implementing under the MEEIA . The second cycle of MEEIA programs is included in the load forecast because it is already planned and approved and in the process of being implemented by the company. Future energy efficiency programs are the subject of Chapter 8, and the impacts of those programs will be included according to their role in the various candidate resource plans discussed in Chapter 9.

3.1.1 Historical Database[2]

Ameren Missouri tracks its historical sales[3] and customer counts by revenue class (Residential, Commercial, and Industrial), and also by rate class (Small General Service, Large General Service, Small Primary Service, and Large Primary Service)[4]. Ameren Missouri uses these rate classes as the sub-classes for forecasting, both because the data is readily accessible from the billing system and because it provides relatively homogeneous groups of customers in terms of size. Historical billed sales are available for all rate and revenue classes back to January 1995 and calendar month sales and class demand data[5] is available beginning with July 2003. At the time of the preparation of the load forecast for this IRP, historical sales were known through June of 2016.[6] Except as noted later in this chapter, any data presented for 2017 or beyond is forecasted data and data from 2016 and earlier is actual metered or weather normalized sales data. Historical energy consumption and customer count data is available in Appendix A.

Ameren Missouri routinely weather normalizes the observed energy consumption of its customers to remove the impact of weather variations. The process for weather normalizing sales is described in section 3.3, and weather normalized historical consumption from 2004 forward is also reported in Appendix A. Appendix B includes weather normalization model statistics for various rate-revenue classes. Appendix A includes use per unit energy sales and demand data for all classes. In each case, the unit included in the analysis is the customer count for the class.[7] Customer count is selected because it is a measured value for each class that is accessible and meaningful in all cases.

3.1.2 Forecast Vintage Comparison

Independent variables[8]

Section 4 CSR 240-22.030(6)(C)3 of the Missouri IRP rules requires a comparison of prior projections of all independent variables used in the energy usage and peak load forecasts made in at least the last 10 years to actual historical values and to projected values in the current IRP filing. Actual historical values for each independent variable for a period of at least the last 20 and up to 40 or more years are acquired by Ameren

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

Missouri from Moody's Analytics, along with forecasts of each variable for the entire planning horizon.[9]

The following discusses only the independent variables used in the energy usage forecasts, since the peak load forecast comes from further processing the energy forecast. The growth rates in peak demand are driven by the energy forecasts for each class and end use as described later in this chapter, so the same economic variables used in the energy forecast are also being used to forecast the peak loads.

The prior projections involved in addressing this requirement are from the 2005 IRP, the 2008 IRP, the 2011 IRP, the 2012 Annual Update, the 2013 Annual Update, and the 2014 IRP. Besides these prior projections, projections for this 2017 IRP are included. Sales volume shown for the 2017 IRP includes the actuals for years up to 2016 and projections starting from 2018.

In some cases, the data vendor may have changed the 'base year' for the independent variables' values. In addition, between certain IRP's, Ameren Missouri has changed its methodology for weighting county level variables into a service territory indicator, so the absolute level of the values for the same year among various vintages may be significantly different. However, the key is the growth rate or trend in these values, so each table is expressed in terms of the year over year growth rate and is accompanied by a chart showing the same, which overcomes the problem of sometimes relying on different bases for some of the variables.

For the residential energy forecast, independent variables used in these forecasts were Households, Population, and Personal Income. For the commercial and industrial energy forecasts, independent variables used in these forecasts were total GDP and GDP for several sectors of the economy, including Manufacturing, Retail Trade, Information Services, Financial Services, Education/Health Services, total non-farm employment, and manufacturing employment. Service territory GDP variables from each archived forecast are shown below in Figure 3.1. The growth rates for each of the variables discussed above is shown in chart and tabular form in Appendix A.

Forecasts[10]

Section 4 CSR 240-22.030(6)(C)4 requires a comparison of prior projections of energy and peak demand made in at least the last 10 years to the actual historical energy and peak demands and to projected values in the current IRP filing.

Figures 3.2 and 3.3 below show previous forecasts of energy and peak demand, including those for the 2005 IRP, 2008 IRP, 2011 IRP, 2012 Update, 2013 Update, the 2014 IRP,

[9] 4 CSR 240-22.030(6)(C)1
[10] 4 CSR 240-22.030(6)(C)4

the 2017 IRP and actual historical values. The data from these charts are presented in tabular form in Appendix A.

Figure 3.1: Ameren Missouri Service Territory GDP Forecasts from Prior IRP Forecasts

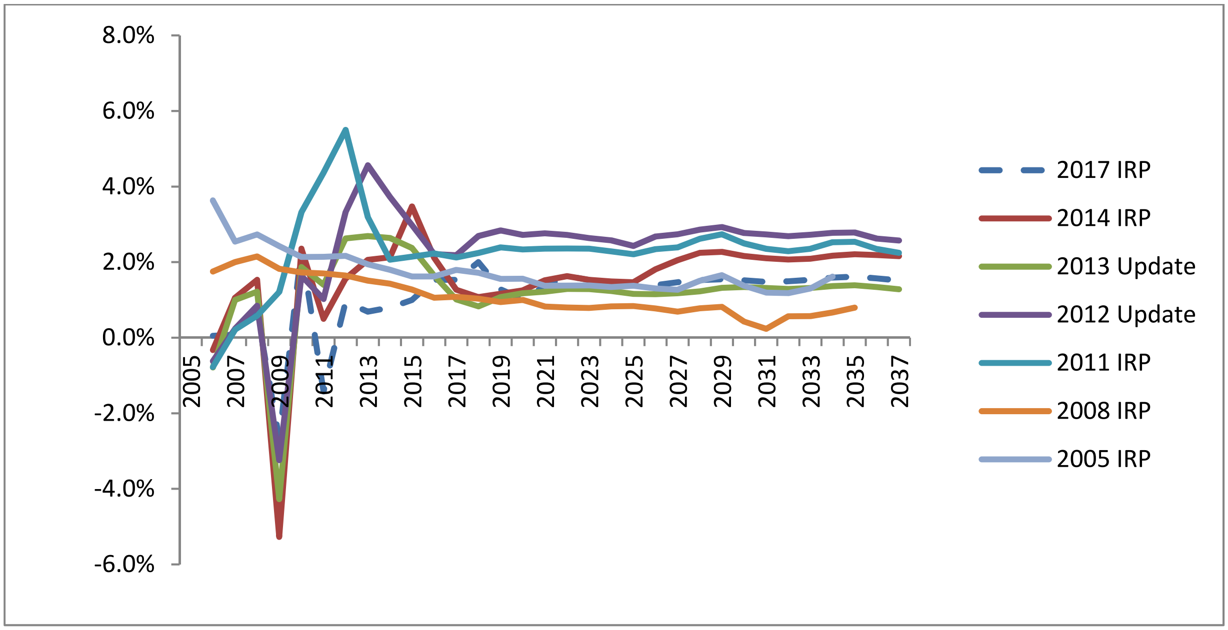


Figure 3.2: Ameren Missouri Actual Historical Energy Sales and Past IRP Energy Forecasts

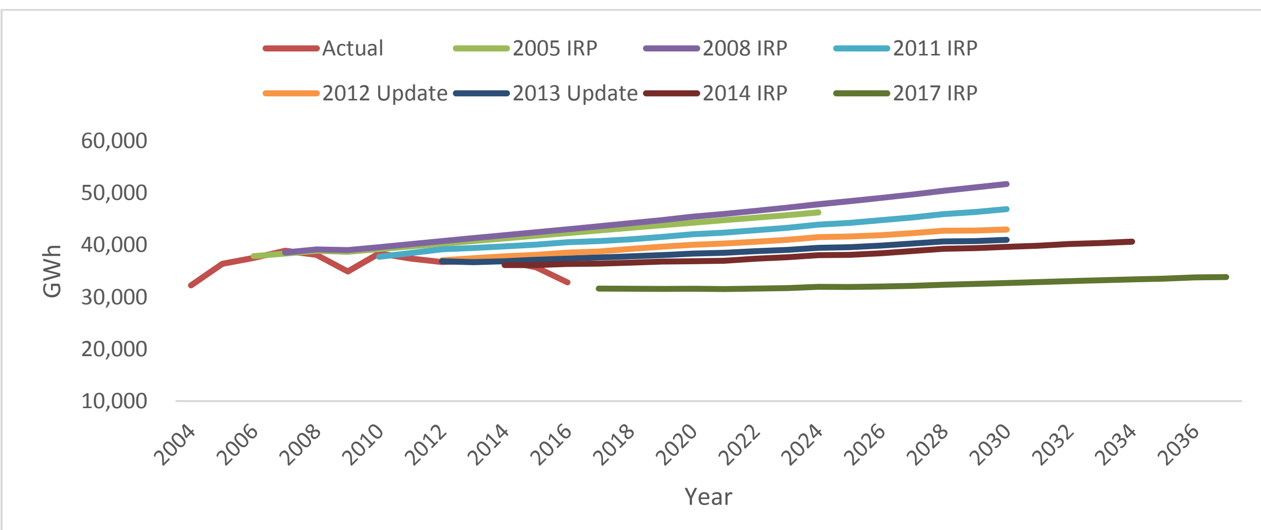
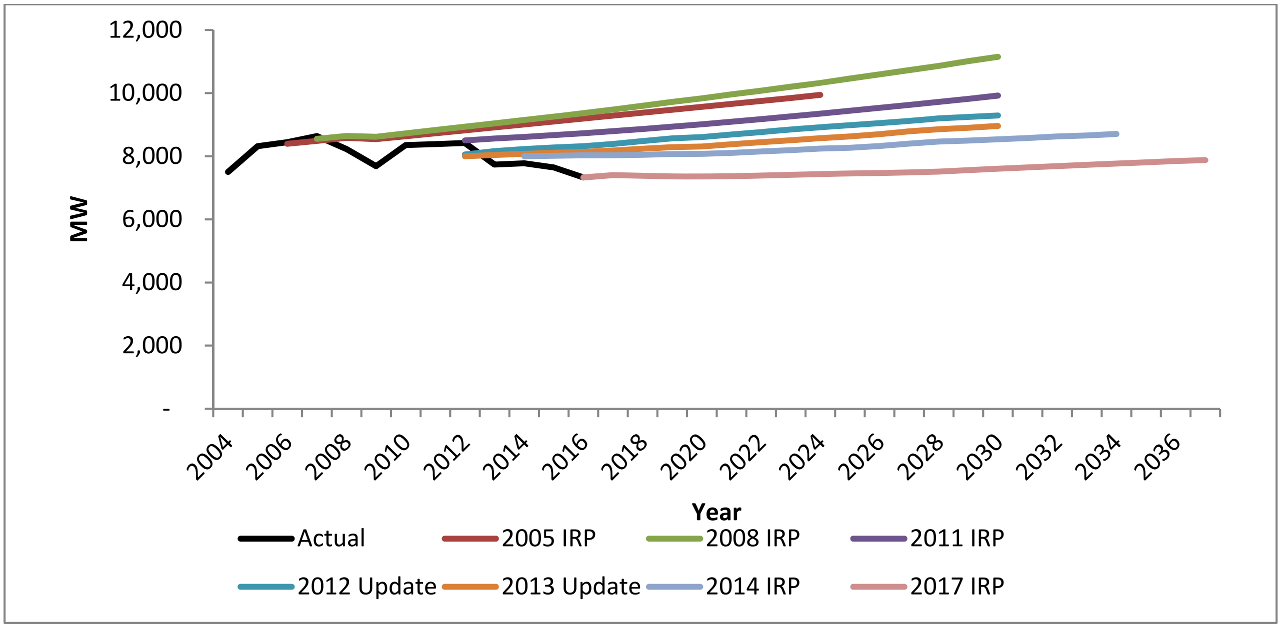


Figure 3.3: Ameren Missouri Actual Historical Peak Demand and Past IRP Peak Demand Forecasts



As is evident from the forecasts in the tables, the projections of both energy consumption and peak demand have decreased quite significantly over time. This is due to three factors. First, increases in the efficiency of end uses of electricity has reduced electric consumption relative to the earlier projections. As an example, the Energy Independence and Security Act of 2007 included an efficiency standard for light bulbs that significantly reduces the energy consumption associated with lighting. This and other standards, as well as the energy efficiency programs under the MEEIA that have already been implemented by Ameren Missouri have served to reduce the rate of growth in energy and peak demand below what they otherwise would have been. Secondly, Ameren Missouri anticipates a significant increase in customer-owned solar and other distributed sources of energy over next 20 years which negatively impacts both the energy and peak forecast. Ameren Missouri's base forecast reflects 622 MW of installed customer owned solar generation within its terrirtory by 2037. Finally, past IRP forecasts included sales to one of the largest aluminum smelting facilities in the country amounting more than 10% of annual sales when the customer operated at its full capacity. Due to the current state of operations at the smelter, Ameren Missouri did not include this customer in its forecast scenarios. The possibility of restored operations at the smelter is considered as part of a sensitivity case in Chapter 10.

Ameren Missouri has also assumed a significant increase in the adoption of electric vehicles and electrification of end uses in its territory over next 20 years. Adoption of electric vehicles is assumed to increase at an annual rate of approx. 17% over the planning horizon.

3.1.3 Service Territory Economy

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

Historically, the Ameren Missouri service territory has been characterized by slower population growth than the U.S. as a whole due to demographic and migration factors. In that respect, the service territory's economy is not terribly different from most other Midwestern states and metropolitan areas. Like much of the Midwest, the region's economy was based on manufacturing for many years, but over the past several decades the share of the territory's employment in manufacturing has been declining while employment in services, particularly health care, has grown. So although the service territory still has a higher than average share of employment in manufacturing, it is no longer the employment growth engine it once was. The allocation of service territory employment by NAICS sector is shown in Figure 3.5; a list of some of the largest employers in the service territory is shown in Table 3.1.

Figure 3.4: U.S. and Missouri Population Change

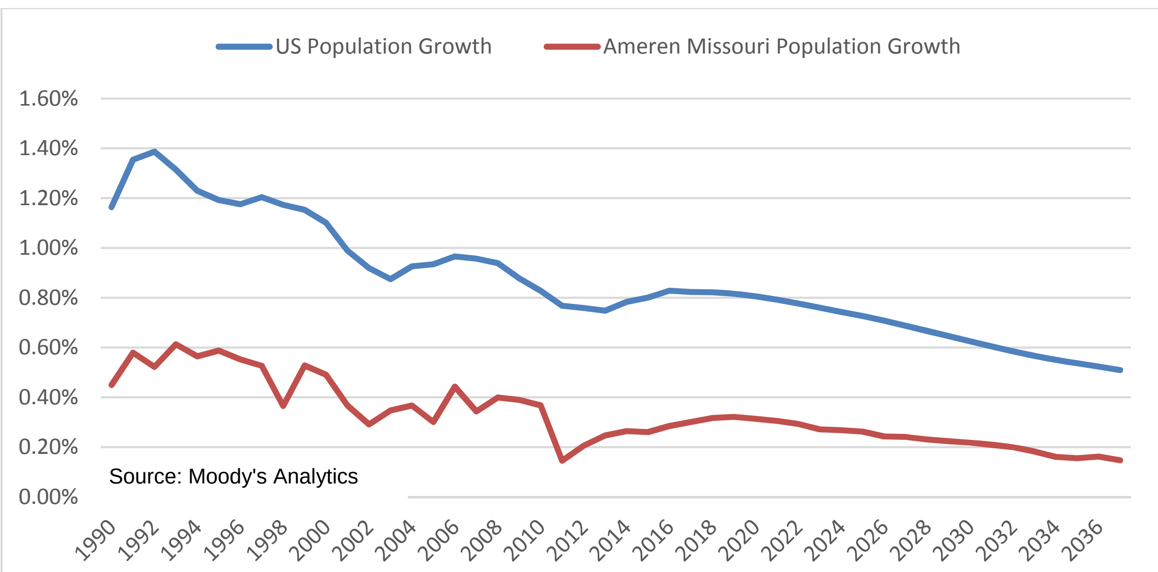
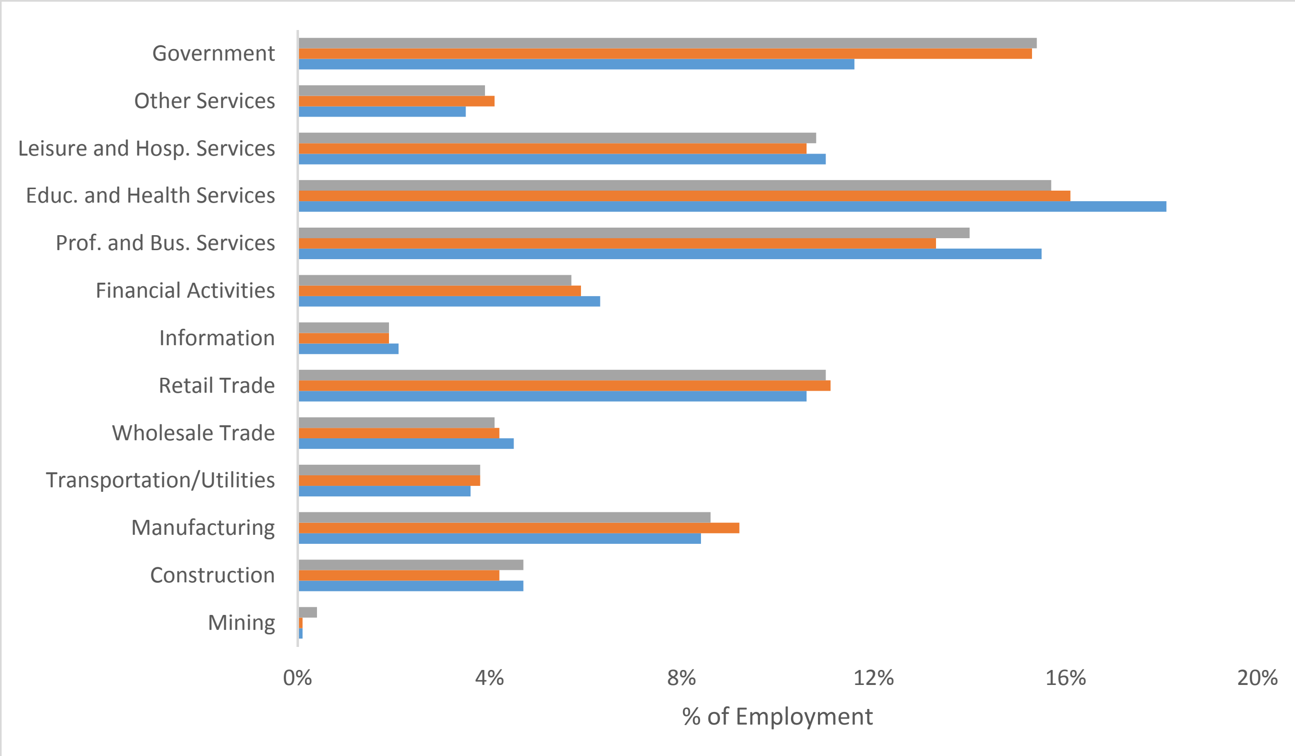


Figure 3.5: U.S. and Ameren Missouri Service Territory Employment by Industry

Source: BLS, Moody's Analytics



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

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

The service territory economy also contains a number of nationally known financial firms, including Wells Fargo and Edward Jones.

Table 3.1: Major Employers in Ameren Missouri

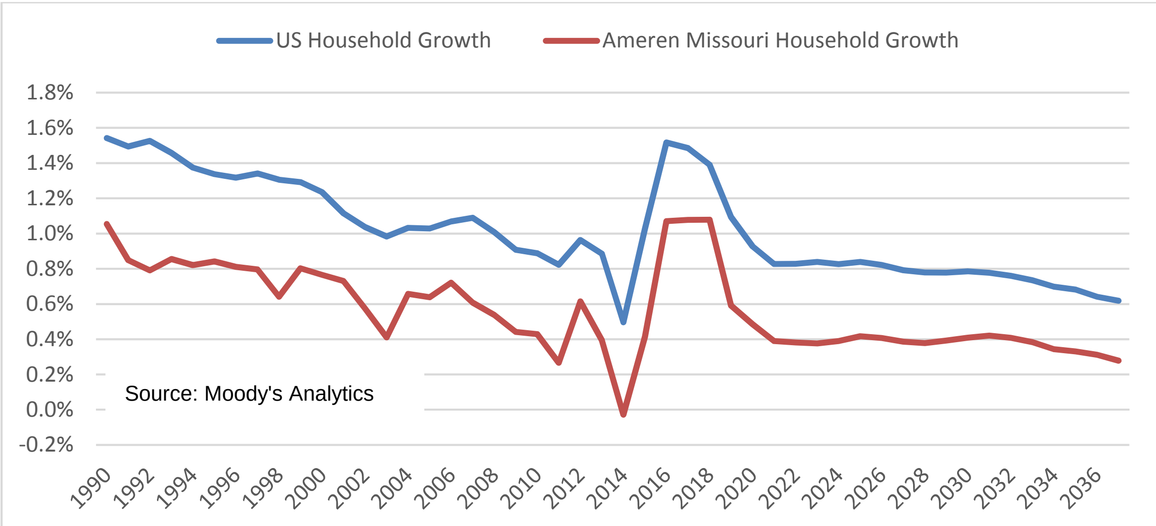
Rank	Employer	Industry	Number of Employees
1	BJC Healthcare	Education or Health Services	24,082
2	Boeing Defense, Space & Security	Manufacturing	15,000
3	Washington University in St. Louis	Education or Health Services	14,170
4	Scott Air Force Base	Federal Government	12,548
5	SSM Health Care System	Education or Health Services	13,000
6	Mercy Health Care	Education or Health Services	12,013
7	Schnuck Markets Inc.	Retail Trade	11,008
8	Wal-Mart Stores, Inc.	Retail Trade	10,550
9	McDonald's Corporation	Retail Trade	9,500
10	University of Missouri-Columbia	Education or Health Services	8,750
11	St Louis University	Education or Health Services	6,803
12	AT&T	Information	6,800
13	Enterprise Holdings	Trans./Warehouse/Utilities	6,234
14	Wells Fargo	Financial Activities	5,400
15	Imo's Pizza	Retail Trade	5,400
16	Monsanto Company	Manufacturing	5,192
17	Tenet Healthsystem Medical Inc.	Education or Health Services	5,125
18	Edward Jones	Financial Activities	4,846
19	Express Scripts Inc.	Education or Health Services	4,700
20	Ameren Corporation	Trans./Warehouse/Utilities	4,584
21	University Hospital & Clinics	Education or Health Services	4,284
22	CitiMortgage Inc.	Financial Activities	4,200
23	Dierbergs Markets	Retail Trade	4,100
24	U.S. Banks	Financial Activities	4,033
25	Archdiocese of St Louis	Other Services	4,000

Sources: Moody's Analytics

Ameren Missouri expects that the service territory economy will continue to recover in a manner similar to the U.S. economy's recovery, although at a slower pace than that 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.[11]

[11] 4 CSR 240-22.030(7)(B)3

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



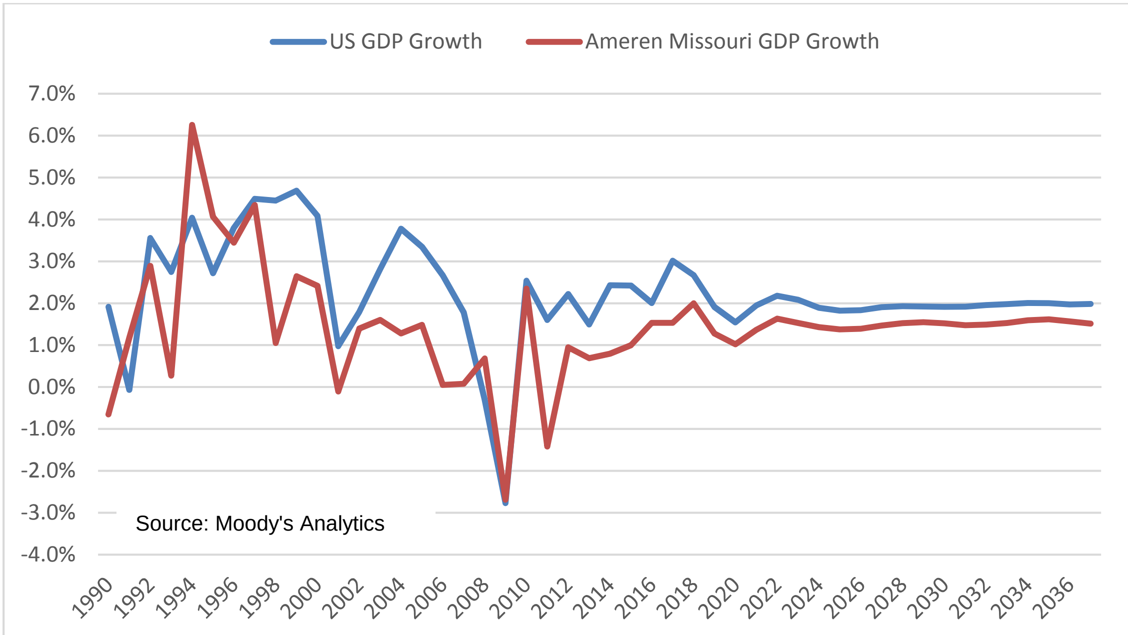
3.1.4 Economic Drivers

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.[13]

- 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.[14]
- 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 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, but only if the analysis of historical correlation of that driver to the historical loads indicated a better relationship between the two.[15]

[12] 4 CSR 240-22.030(2)(D)3
[13] 4 CSR 240-22.030(5)(A)
[14] 4 CSR 240-22.030(6)(A)1A
[15] 4 CSR 240-22.030(6)(A)1B

Figure 3.7: U.S. and Service Territory GDP Growth[16]



- 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 planning horizon.
- 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 with using its 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.[17]

[16] 4 CSR 240-22.030(2)(D)3
[17] 4 CSR 240-22.030(7)(B)1;4 CSR 240-22.030(7)(B)2

Table 3.2 Growth Rates of Selected Economic Drivers

	2017-2037 Compound Growth Rate
Households	0.43%
Population	0.24%
Real Personal Income	4.15%
GDP Retail	1.69%
GDP Info	2.13%
GDP Financial	1.12%
GDP Education /Health	1.51%
GDP Total	1.49%
GDP Manufacturing	1.58%
Employment Total	0.57%
Manufacturing Employment	-0.51%

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 replace Moody's service territory specific forecast for manufacturing GDP with the recent growth rate observed in Manufacturing GDP for its service territory.[18] 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 the recent past.

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 the company's residential general service rate class, and for all four of its commercial rate classes. The discussion below details the process followed for developing the models, inputs, assumptions, and parameters used in forecasting.

[18] 4 CSR 240-22.030(7)(B)4

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, model energy sales with a bottom-up approach by building up estimates of 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,[19] 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.[20] 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[21] was developed by Itron, a consulting firm Ameren Missouri has worked with for many years, and implemented by Ameren Missouri forecasting personnel.[22] 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.[23] 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 from various forms of electrification are also consolidated due to the availability of data from the U.S. Energy Information Administration (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 at best.[24] Also, as discussed later in this chapter, self-generation resulting from solar photovoltaic systems is treated essentially as a negative end use and

[19] 4 CSR 240-22.030(5)(C)
[20] 4 CSR 240-22.030(5)(B)
[21] 4 CSR 240-22.030(6)(B)
[22] 4 CSR 240-22.030(6)(A)3
[23] 4 CSR 240-22.030(4)(A)1A
[24] 4 CSR 240-22.030(4)(A)2A

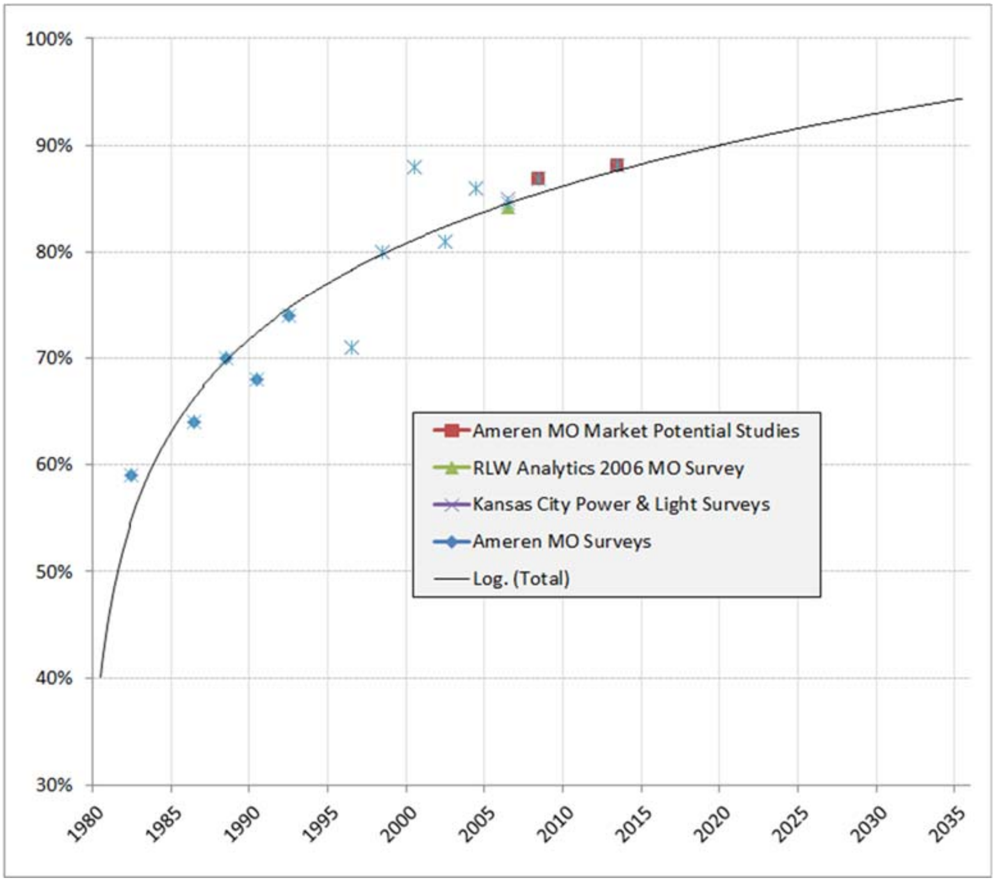
modeled explicitly in the load for each class.[25] Similarly, electric vehicle charging was considered as an end use, contributing additional load for the residential class. For the commercial class, the end uses are heating, cooling, ventilation, water heating, cooking, refrigeration, outdoor lighting, indoor lighting, office equipment, and miscellaneous.[26] 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.[27]

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.[28] 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 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 specifically on Ameren Missouri's 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.[29] 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. Additional information was utilized in order to fully develop them across more years.

[25] 4 CSR 240-22.030(4)(A)2B
[26] 4 CSR 240-22.030(4)(A)1B
[27] 4 CSR 240-22.030(4)(A)2C
[28] 4 CSR 240-22.030(7)(A)2
[29] 4 CSR 240-22.030(4)(B)1

Figure 3.8: Air Conditioning Saturation, Survey Data Points and Fitted Curve[30]



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 its public IRP documents was used. The geographic proximity of KCP&L to Ameren Missouri contributes to its greater similarity compared to the entire West North Central Census Region, and the demographic make-up has greater similarity. 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

[30] 4 CSR 240-22.030(2)(D)3

of the best information available and resulted in what is almost certainly a more accurate representation of the Ameren Missouri customer base than the regional EIA data. Figure 3.8 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[31] 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.[32]

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 forecast models were values that minimized the model mean absolute percent error (MAPE) over the estimation period.[33] The price elasticity in the base case load growth residential model is -0.19. This is similar to the elasticity values used in prior 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.

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.

[31] 4 CSR 240-22.030(7)(A)1; 4 CSR 240-22.060(4)(D)
[32] 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.
[33] Differences between the base, high, and low load growth scenarios are discussed in section 3.1.6

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

$$Use\ per\ customer = B1*((cooling\ use)*(cooling\ index)) + B2 * ((heating\ use)*(heating\ index)) + B3*((other\ use)*(other\ index))$$[35]

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:

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

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.

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 t-statistics for each variable relative to most econometric models. In the base case residential model, for example, the t-statistics for the heating, cooling, and other variables are 60.96, 67.43, and 64.65 respectively. The adjusted r-squared for that model is 0.987.

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

The functional form of the commercial SAE model is:

---

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

$$Use = B1 * \big((cooling\ use) * (cooling\ index)\big) + B2 * \big((heating\ use) * (heating\ index)\big) + B3 * \big((other\ use) * (other\ index)\big)$$

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 the number of 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 a brewery, for example, 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 the 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

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

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:

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

Price, output, and their elasticities were combined into one term. As was the case with the SAE residential and commercial models, estimating elasticity was a challenge, because estimates of elasticity in electricity consumption vary widely. Initial elasticities were chosen that reflected a mid-point of estimates from the literature. Through an iterative process elasticities were chosen that minimized the Mean Absolute Percentage Error (MAPE) 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 2014 and 2017 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 2014 IRP, Ameren Missouri's DSM programs under the MEEIA were very new and their cumulative impacts were still relatively small. 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 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, with several years of implementation behind us, impacts of our programs would now potentially be reflected in the driver variables, so it may no longer be necessary to go through the process of separately accounting for program impacts outside of the base energy models.

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 MEEIA are also subtracted from the load forecast projections. These programs are already being implemented and are not the subject of any decision making resulting from this IRP, so it is taken as a given that they will occur. All future DSM impacts beyond the first two 3-year MEEIA cycles (i.e., programs approved for implementation through March 2019) are excluded from the base forecast and are the subject of the DSM chapter of this IRP.

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

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 operating 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 generally good indicator of the need for heating and cooling, as 65 degrees is a moderate temperature that requires little heating or cooling.

However, each customer class in reality has a bit of difference in the way they respond to temperatures. So, rather than just generically using a 65 degree 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 of daily residential load research data plotted against daily temperatures. It is apparent from the slopes indicated by the data that residential customers begin cooling at about 65 degrees. But there is a little break before heating equipment is widely utilized, which occurs at about 60 degrees.

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 that 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 subset 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.

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

Figure 3.9: Residential Load/Temperature Relationship

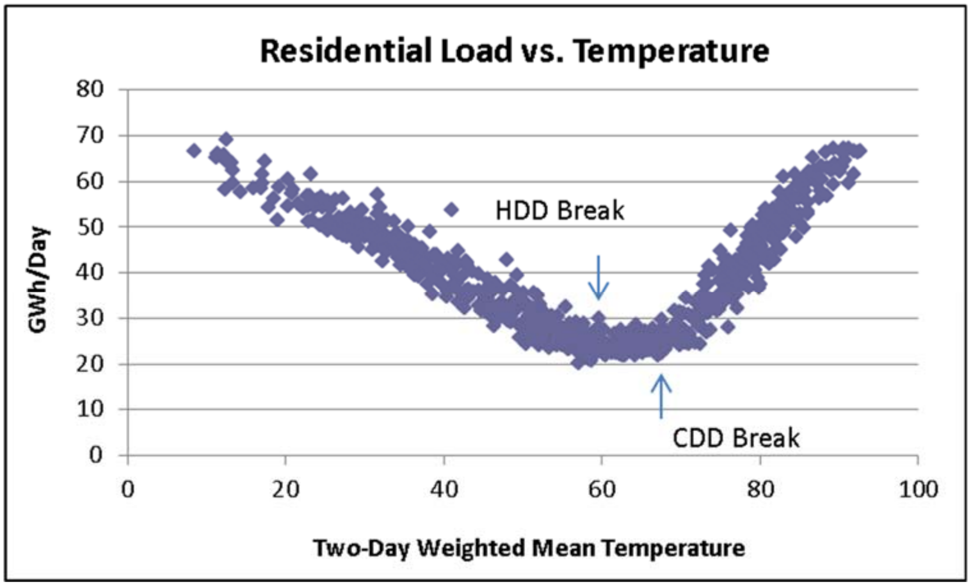


Table 3.3 Degree Day Break Points Used in Energy Modeling

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 electricity. To capture the impact on demand for power supplied by the utility, we have incorporated an offset of load by using 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 drove a rapid increase in solar installations in recent years. The total amount paid for rebates were subsequently capped by regulatory agreement. In this forecast, we assumed that solar installations would continue at their current pace until the early- to mid-2020's, during which time distributed solar is expected to begin to reach parity with utility rates, beginning with larger customers. Ameren Missouri expects the customer-owned solar would increase at a compound annual growth rate of 12.5% between 2018 and 2037 (base case scenario). In this case, we expect that the cumulative installed customer-owned solar capacity would reach approximately 622 MW by 2037 in Ameren Missouri's territory. The high load growth scenario assumes low adoption of customer owned solar (approximately 114 MW of cumulative installed customer owned solar capacity by 2037), and the low load growth scenario assumes high adoption of customer owned solar (approximately 930 MW of cumulative installed customer owned solar capacity by 2037).

Other Forecasting Considerations – Electric Vehicles[39]

Although the market share of EVs in the USA is around 0.7% (as of 2016), the EIA projects Battery EV (BEV) sales to increase to 6% of total light-duty vehicles sold in the United States between 2016 and 2040, while plug-in hybrid electric vehicle (PEV) sales are projected to increase to 4% over the same period41. EV sales in the USA have soared in the recent past, with a compound annual growth rate (CAGR) of 32% between 2012 and 2016. Supportive EV policies, such as the federal tax credit, state-level incentives, and supportive utility tariffs, have been strong drivers for EV adoption within the USA. In comparison, EV adoption in Ameren Missouri's footprint has been rather slow, with approximately 400 PEVs sold every year in the footprint. The primary reasons for such slow growth include range anxiety and the purchase price of PEVs. As of 2016, approx. 2,100 PEVs are in use in Ameren Missouri's footprint. As the battery technology improves and the cost of batteries decreases, Ameren Missouri believes that the PEV adoption in its territory has the potential to significantly increase over the next 20 years. Supportive tariff design and regulatory policies and favorable tax policies will foster such growth. Ameren Missouri has started taking proactive measures, such as proposing highway-charging corridor in the recently concluded rate review (ER-2016-0179), to promote PEVs in its footprint, and is continuing to explore options to stimulate investment in PEV charging infrastructure that will provide more access to charging for customers.

Ameren Missouri's analysis shows that future adoption can follow one of three scenarios. The base case scenario assumes approximately 75,000 PEVs will be in use by 2037 in the footprint. The minimum adoption scenario assumes that there will be approximately 20,000 PEVs on the road by 2037, whereas the maximum adoption scenario assumes approximately 300,000 PEVs on the road under the assumption that ~30% of new car sales are PEVs in the future. PEVs can be a growth vehicle for Ameren Missouri, representing approximately 335 GWh in annual energy usage by 2037 under the base case scenario. The maximum adoption scenario estimates approximately 1,400 GWh and the minimum adoption scenario estimates approximately 290 GWh in energy usage by

[39] EO-2017-0073 1.F; EO-2017-0073 1.K; 4 CSR 240-22.030(7)(A)5

2037. The base case CAGR assumption of 17.2% over the planning horizon is a conservative estimation compared to the US and global growth potential of PEVs.

The 2016 Ameren Missouri DSM Market Potential Study indicates that in the near-term and mid-term there is not significant penetration of PEVs. Ameren Missouri load forecasts include three scenarios of PEV adoption (See Other Forecasting Considerations in Chapter 3). While continuing to explore options to stimulate investment in PEV charging infrastructure and reduce the barrier to PEV adoption by customers, Ameren Missouri is very aware that there will be opportunities to educate customers and, potentially, to offer cost-effective programs to affect customer charging behavior in a way that increases system operational flexibility and utilization efficiency. However, the 2016 potential study does not identify any cost-effective program options at this time but Ameren Missouri will continue to seek viable program options as PEV penetration increases and technology changes increase available options to deploy cost-effective programs.

Ameren Missouri currently does not have any formal PEV programs but is providing basic PEV education to customers via website and key account outreach, occasional business presentations, utilizing PEVs in the Ameren Missouri fleet, and encouraging coworkers to drive PEVs through incentives, education and making workplace charging available.

Other Forecasting Considerations – Electrification of End-uses[40]

With the goal of reducing greenhouse gas (GHG) emissions and addressing other environmental concerns, research publications[41] show that electrification of end uses could help in achieving such goals. Electrification of end uses such as space heating, water heating, and transportation, which conventionally use natural gas, propane, gasoline, diesel, or fuel oil, will help achieve emission reduction goals for carbon dioxide and GHG. Advancements in solar and battery storage technologies make it increasingly easier for the end use customers to actively participate in their energy consumption and contribute to a greener and cleaner environment. Analysis published by The Brattle Group shows that coupling electrification of heating and transport with significant decarbonization of the power sector (e.g., through the adoption of clean power generation sources such as renewables, nuclear, or carbon capture) and modest reductions in other energy sectors could lead to more than a 70 percent reduction in U.S. energy-related GHG emissions relative to 2015 levels, and thus represent an important step towards overall economy-wide emissions reductions targets[42]. While the Brattle study identified what could be termed technical potential and did not evaluate the economics of such an

[40] 4 CSR 240-22.030(7)(A)5
[41] Dennis, K. 2015. “Environmentally Beneficial Electrification: Electricity as the End Use Option.” Electricity Journal 28(9): 100–112
[42] Electrification: Emerging Opportunities for Utility Growth, Brattle Group Report, January 2017

electrification scenario, it does highlight that there is significant potential worth considering in the context of future resource needs Ameren Missouri worked with Electric Power Research Institute (EPRI) to quantify the potential of electrification of various end uses across its customer bases which has been included in the final forecast.

Other Customer Class Forecasts

There are two other classes of energy sales which fell into neither the SAE nor econometric form of forecasting. Those two were Street Lighting and Public Authority (SLPA), and Dusk to Dawn lighting (DTD). SLPA and 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.

Customer History and Forecasts

Forecasts of customer counts were produced at the rate class level; however, those forecasts were aggregated to revenue class for documentation purpose. 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.[43] The customer models may include 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 to incorporate unusual effects of economic recession in 2008-2009 into the customer count growth. The models may also include auto-regressive and moving average terms as well as combinations of multiple of the aforementioned modeling approaches to smooth out the customer forecast in some cases.

3.1.6 Sensitivities and Scenarios[44]

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, three different scenarios were modeled that stemmed from the combinations of assumptions about load growth, economic factors, customer owned renewable generation, electric vehicles and electrification of end uses. These forecasts were based

[43] 4 CSR 240-22.030(3)(A)
[44] 4 CSR 240-22.030(8); 4 CSR 240-22.030(8)(A)

on ranges of variables resulting from discussions with Ameren subject matter experts. The scenario development process is discussed in Chapter 2.

In order to forecast high, base and low load growth scenarios, Ameren Missouri developed different levels of selected independent variables and elasticity parameters. The variables and parameters that were selected to be varied in the scenario forecasts differed by class. In each case, it was important to consider not only which variables or parameters 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 among 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 using miscellaneous growth as a primary variable through which to capture uncertainty is its inherent unpredictability. It is impossible to know with any degree of confidence 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. Uncertainties also arise from the timing and amount of solar and other renewable energy adoption by Ameren Missouri’s customer base, which could significantly impact the overall energy consumption as well as peak demand. Forecasting the timing and amount of such demand without detailed market research injects uncertainty in the load forecasting scenarios. 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 range 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.

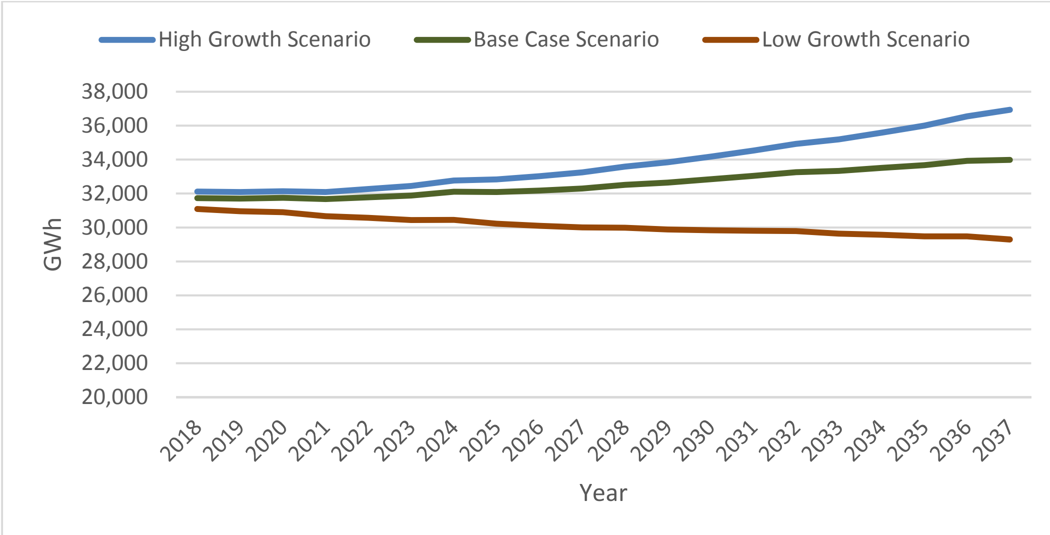
As described in the paragraphs above, careful consideration was given to the factors in the forecast of each class that would drive the differences between the high, base, and low load forecast scenarios. In each case, an assessment was made that not only considered the model's sensitivity to a given 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.

As earlier noted, given the uncertainty around the former Noranda aluminum smelter, Ameren Missouri did not include this load in the forecast.

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

Statistical models built with aforementioned assumptions provide us with energy forecasts for the corresponding scenarios. System energy forecasts are obtained by adding all individual class level energy forecasts. Comparisons of annual system energy forecasts associated with three scenarios are shown below in Figure 3.10.

Figure 3.10: Total Energy Sales Forecast by Scenario



3.1.7 Planning Case Forecast

The three 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, as discussed in Chapter 9. The integration modeling is actually performed using each forecast scenario, 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 the different scenarios and thus determine a probability weighted average load. 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 the three independently generated scenarios.

3.1.8 Forecast Results

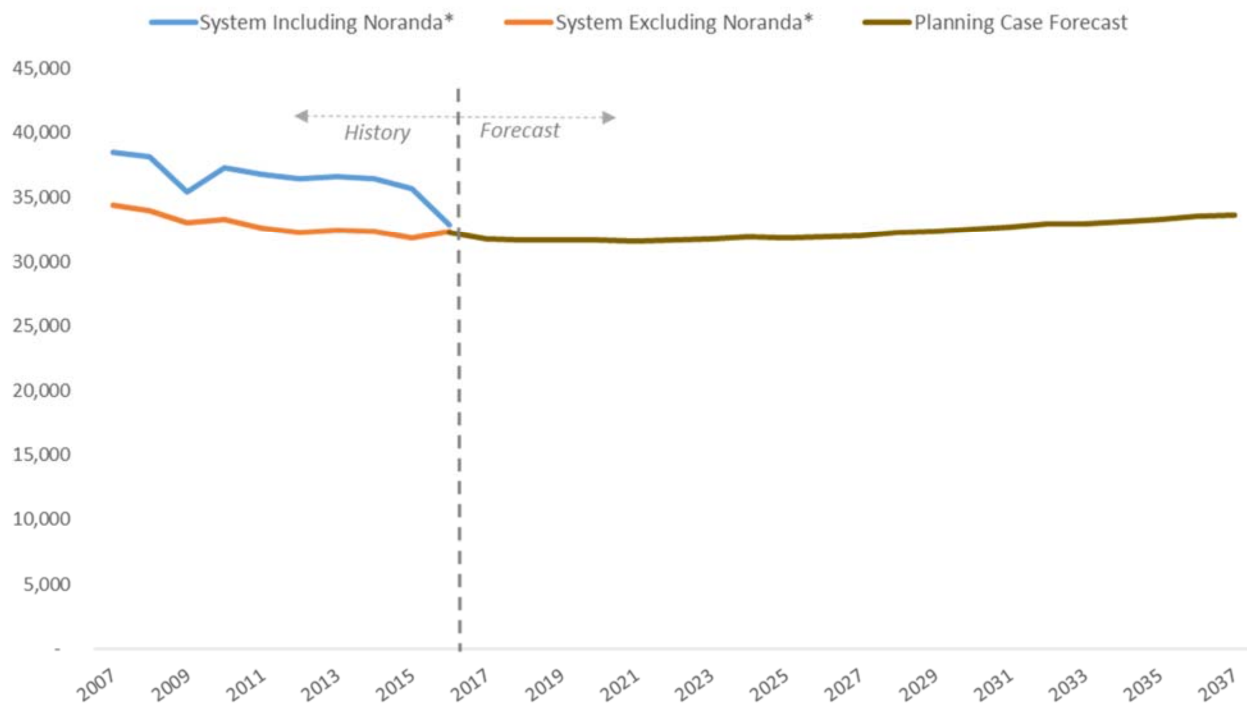
For the planning case, total retail energy sales are expected to grow at 0.3% compound annual rate between 2018 and 2037. Between 2006 and 2016, total retail sales declined at a compound annual rate of 1.2% primarily due to the naturally occurring and company sponsored energy efficiency programs and a decline in consumption by the aluminum smelter Excluding the load for the aluminum smelter, Ameren Missouri's system energy declined at a compound annual rate of 0.2% between 2006 and 2016. Sales dipped sharply in 2009, and went through an uneven period of recovery following the recession. Post-recession recovery was also offset by naturally occurring and company sponsored energy efficiency programs. Despite projecting steady economic growth over the near term period, loads are forecast to remain essentially flat because of the impact of efficiency standards and programs. As mentioned earlier, the load forecast scenarios only incorporate savings from MEEIA programs through the 3-year cycle ending in March 2019. After those programs end in the base forecast, load growth resumes at a slow, but fairly stable pace.[45]

[45] 4 CSR 240-22.030(7)(A)3

Table 3.4: Scenario Driver and Parameter Differences

	High Load Growth Assumptions	Base Load Growth Assumptions	Low Load Growth Assumptions
Res	• Price elasticity: -0.11 • Household size elasticity: 0.5 • Income elasticity: 0.16 • 20 year CAGR for Cooling intensity: 0.03% • 20 year CAGR for Households growth: 0.53% • Solar adoption (20 year CAGR): 3.6% • EV adoption (20 year CAGR):21.5%	• Price elasticity: -0.19 • Household size elasticity: 0.5 • Income elasticity: 0.1 • 20 year CAGR for Cooling intensity: 0.03% • 20 year CAGR for Households growth: 0.4% • Solar adoption (20 year CAGR): 12.8% • EV adoption (20 year CAGR): 17.2%	• Price elasticity: -0.29 • Household size elasticity: 0.5 • Income elasticity: 0.05 • 20 year CAGR for Cooling intensity: - 0.41% • 20 year CAGR for Households growth: 0.25% • Solar adoption (20 year CAGR): 15.1% • EV adoption (20 year CAGR):10.5%
Com	**Lower price elasticity parameter and output elasticity increasing trend until 2038** • SGS Output 0.86, Price -0.04 • LGS Output 0.60, Price -0.05 • SPS Output 0.90, Price -0.07 • LPS Output 0.56, Price -0.05	**Base price and output elasticity assumptions** • SGS Output 0.71, Price -0.19 • LGS Output 0.5, Price -0.05 • SPS Output 0.65, Price -0.05 • LPS Output 0.47, Price -0.05	**Higher price elasticity parameter and output elasticity decreasing trend until 20378** • SGS Output 0.47, Price -0.11 • LGS Output 0.56, Price -0.04 • SPS Output 0.20, Price -0.38 • LPS Output 0.2, Price -0.29
Ind	**Lower price and higher output elasticity assumptions** • SGS Output 0.9, Price -0.05, Output Weight 0.90 • LGS Output 0.9, Price -0.05, Output Weight 0.92 • SPS Output 0.9, Price -0.15, Output Weight 0.5 • LPS Output 0.9, Price -0.05, Output Weight 0.2 • 20 year CAGR for Manufacturing GDP: 1.2%	**Base price and output elasticity assumptions** • SGS Output 0.65, Price -0.29, Output Weight 0.9 • LGS Output 0.65, Price -0.29, Output Weight 0.8 • SPS Output 0.65, Price -0.2, Output Weight 0.5 • LPS Output 0.65, Price -0.11, Output Weight 0.2 • 20 year CAGR for Manufacturing GDP: 1.0%	**Higher price and lower output elasticity assumptions** • SGS Output 0.3, Price -0.38, Output Weight 0.9 • LGS Output 0.4, Price -0.38, Output Weight 0.9 • SPS Output 0.7, Price -0.38, Output Weight 0.5 • LPS Output 0.5, Price -0.22, Output Weight 0.2 20 year CAGR for Manufacturing GDP: -1%

Figure 3.11: Planning case energy sales forecast



**Noranda is currently registered as Magnitude 7 Aluminum*

Ameren Missouri's overall sales increased noticeably in 2005 when it began serving the Noranda aluminum smelting facility in New Madrid area. In 2009, an ice storm caused the transmission system (not owned by Ameren Missouri) that served the plant to fail in part, and the resulting power outage damaged the plant. It did not return to operating at full capacity until mid-2010. Noranda, due to economic and other business factors, reduced production capacity in 2014, which resulted in a 3.3% reduction in sales to Noranda. In 2015, sales to Noranda further declined by 5% and in 2016, energy sales to Noranda reduced by approx. 87%. Since April 2017, the smelter (now owned by Magnitude 7 Metals, LLC) has been served under the Small Primary Service tariff class.

The outage at Noranda is not the only reason sales slumped in recent years. 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 13.6%. Energy efficiency programs under MEEIA Cycle 1 have incrementally reduced sales by ~1% in each of its program years. As the economy recovered from the severe recession, Ameren Missouri's residential and commercial customer count began growing at a historically slow, yet steady pace. However, the savings from energy efficiency programs have diminished any sales growth achieved as a result of this customer growth. The planning case forecast reflects slow growth due to these factors (Figure 3.11).

Table 3.5: Historical (2006-2016) and Forecast Planning Case (2018-2037) Annual Sales Growth by Class

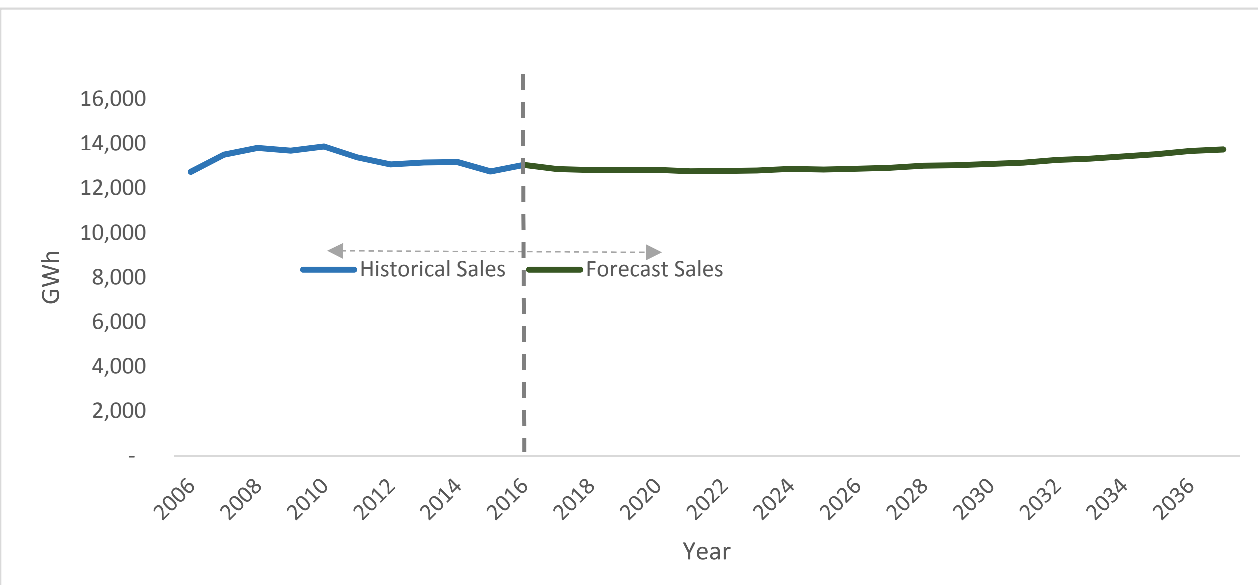
Year	Residential	Commercial	Industrial	Lighting	Total
2006	-0.1%	3.5%	-1.3%	-2.5%	1.2%
2007	6.1%	3.9%	2.8%	0.3%	4.5%
2008	2.2%	-1.6%	-7.8%	-0.7%	-1.1%
2009	-0.9%	-1.0%	-13.6%	-1.1%	-2.9%
2010	1.4%	0.5%	-0.3%	-0.4%	0.7%
2011	-3.5%	-0.3%	-1.6%	-2.6%	-1.8%
2012	-2.3%	-0.2%	-0.3%	-0.4%	-1.1%
2013	0.7%	0.5%	-0.4%	-0.8%	0.5%
2014	0.1%	-0.7%	0.7%	-0.7%	-0.2%
2015	-3.2%	-0.5%	-0.2%	0.1%	-1.5%
2016	2.3%	1.1%	0.6%	1.0%	1.5%
2017	-1.4%	-2.1%	-1.7%	-1.5%	-1.8%
2018	-0.4%	-0.2%	0.1%	-0.1%	-0.2%
2019	0.0%	-0.5%	0.3%	-0.1%	-0.2%
2020	0.0%	0.1%	0.4%	-0.1%	0.1%
2021	-0.5%	-0.2%	-0.1%	-0.1%	-0.3%
2022	0.1%	0.3%	0.4%	-0.1%	0.2%
2023	0.2%	0.3%	0.3%	-0.1%	0.2%
2024	0.5%	0.6%	0.9%	-0.1%	0.6%
2025	-0.2%	-0.1%	0.0%	-0.1%	-0.1%
2026	0.2%	0.2%	0.2%	-0.1%	0.2%
2027	0.3%	0.2%	0.4%	-0.1%	0.3%
2028	0.7%	0.6%	0.3%	-0.1%	0.6%
2029	0.2%	0.4%	0.5%	-0.1%	0.3%
2030	0.4%	0.6%	0.8%	-0.1%	0.5%
2031	0.5%	0.5%	1.0%	-0.1%	0.6%
2032	1.0%	0.4%	0.4%	-0.1%	0.6%
2033	0.4%	0.0%	0.2%	-0.1%	0.2%
2034	0.8%	0.4%	0.4%	-0.1%	0.5%
2035	0.7%	0.3%	0.3%	-0.1%	0.5%
2036	1.1%	0.7%	0.4%	-0.1%	0.8%
2037	0.5%	0.0%	0.1%	-0.1%	0.2%

One seemingly trivial feature of our sales modeling does affect 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 impact 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 detailed modeling used in the forecasting process.

Residential

Between 2006 and 2016, residential class weather normalized sales grew at a compound annual rate of 0.24%. This period was characterized by three distinctly different trends, however. From 2006 through 2008, residential load grew at a robust pace of around 4.1%. Beginning around the time of the 2007-2009 recession but also around the time Ameren Missouri's energy efficiency program spending ramped up, the trajectory of residential load flattened considerably. The economic impacts of the recession and post-recession recovery coincided with increasing energy efficiency program impacts during this time period. The result is load characterized by years that have been either close to flat in terms of load growth or even declining in some years. Residential load between 2004 and 2012 changed at a compound annual rate of -0.69%. The period beginning with 2013 exhibited slow, yet steady year over year customer growth. However, Ameren Missouri also started the first cycle of MEEIA programs in 2013, which had incrementally reduced energy sales by approximately 1% during each of its program years. Sales growth due to customer growth between 2013 and 2016 was diminished by naturally occurring and company sponsored energy efficiency programs. This trend is similar to the trends seen in other utilities and nationwide.

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 0.35% between 2018 and 2037. 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 continue to be slow as the energy savings from the MEEIA energy efficiency programs (Cycle 1 and 2) and customer-owned distributed energy resources (DER) offset increases in energy usage from electrification of various end uses along with wider adoption of electric vehicles over the planning horizon. The MEEIA savings are sufficient to offset virtually all residential growth during the program years. Load during this time period would otherwise be growing slowly, 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 is realized and further incremental savings associated with them become smaller, the incremental energy savings from existing MEEIA programs diminishes. At that time, customer owned DER in the residential class begins to offset observable growth. Longer term, electrification of end uses and wider adoption of electric vehicles help to maintain a modest level of growth in residential class sales.

The number of residential customers is expected to grow at a compound average rate of 0.24% between 2018 and 2037. Compared to historical standards, customer growth has been very slow since the 2007-2009 recession. Ameren Missouri's residential customer count grew at a compound annual rate of 0.2% between 2006 and 2016. The forecast assumes that the residential customer count will continue the slow, yet steady growth over the planning horizon. While the customer count growth in the near term (between 2016 and 2020) will be approx. 0.5% (compound annual rate), it will slow down over the rest of the planning horizon to a compound annual rate of 0.25%.

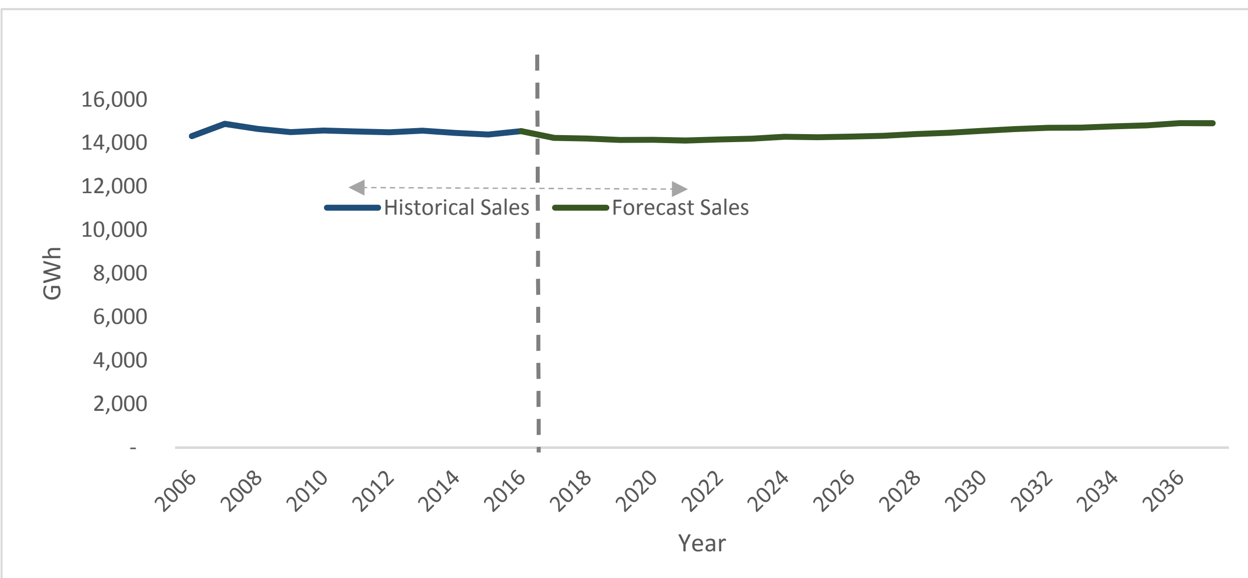
Use per customer growth in the residential class is expected to remain modestly declining for the first half of the forecast horizon. Again, customer owned distributed energy resources, efficiency standards of appliances and MEEIA programs hold average customer consumption down during this time. Use per customer increases slowly as already approved standards transform the stock of end use appliances and equipment and more electrification takes hold at the end use level.

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 services 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 due to naturally occurring and company sponsored energy efficiency programs.

Three different factors contributed to the load growth in the recent past. From 2006 through 2008, commercial load grew at a robust pace of around 1.1%. The recession between 2007 and 2009 combined with Ameren Missouri's energy efficiency programs flattened the trajectory of commercial load considerably. The economic impacts of the recession and post-recession recovery coincided with increases in energy efficiency savings during this time period. Customer count has been growing at a year over year rate slightly below 1% since 2012. However, Ameren Missouri also started the first cycle of MEEIA programs in 2013, which had incrementally reduced energy sales by little less than 1% on each of its program years. MEEIA Cycle 2 programs are expected to incrementally reduce sales by approx. 0.6% in each of its program years. As savings from MEEIA programs are fully realized, Ameren Missouri expects customer owned distributed energy resources will increase which will further impact the growth in sales to commercial customers. However, positive impacts from electrification of end uses may stabilize the decline in the sales. Ameren Missouri anticipates commercial sales to grow at a compound annual rate of 0.24% over the planning horizon.

Figure 3.13: Planning Case Forecast of Commercial Class Energy Sales

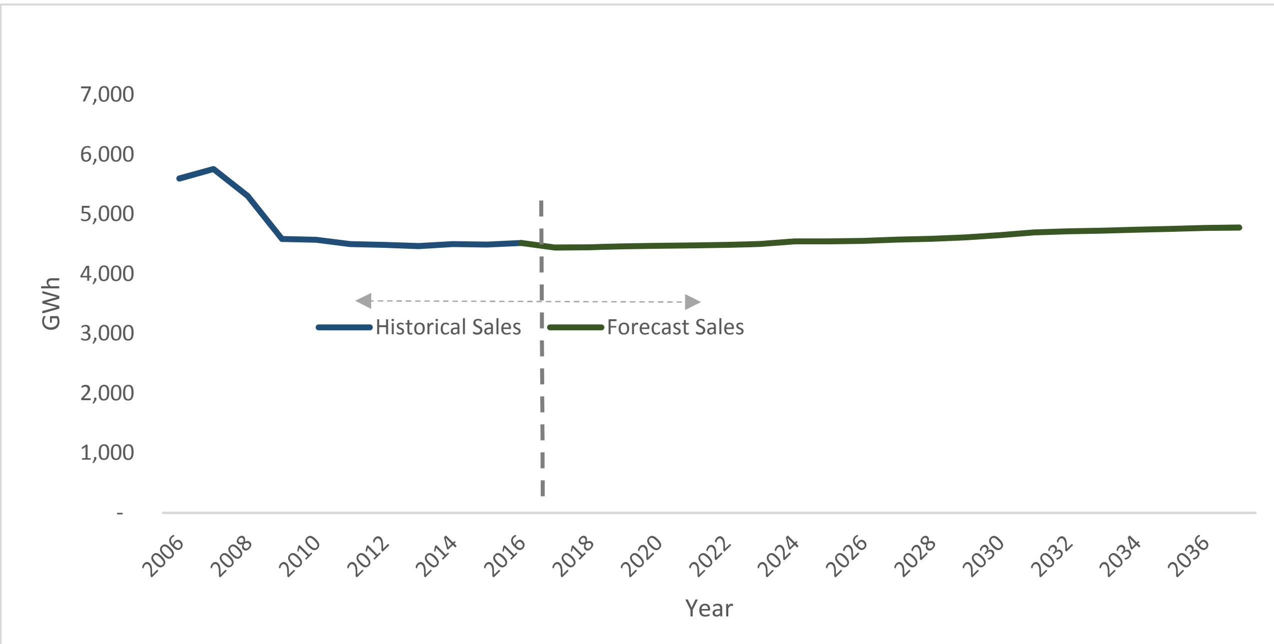


Industrial

Ameren Missouri industrial class sales have been experiencing a structural decline for more than 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 2006 and 2016, Ameren Missouri's industrial sales declined at a compound annual rate of 2.1%; according to the EIA U.S. industrial electricity sales fell by a compound annual rate of 0.8% during those the same years. Note that Ameren Missouri's largest single customer by far in recent years, the aluminum smelter in New Madrid, MO, is not included in these industrial load statistics, as it has historically been reflected in a separate class.

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 0.36% between 2018 and 2037. While the overall industrial forecast is directionally positive after the long-term sales industrial sales decline that has been experienced, expected growth is still slow. In fact, the forecast does not anticipate that the industrial sales will reach pre-recession levels at all during the planning horizon.

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
2006-2016	0.27%	0.70%	-1.40%
2018-2037	0.24%	0.42%	-0.23%

Magnitude 7 Metals (new owner of the smelter formerly owned by Noranda)

The New Madrid aluminum smelter, Ameren Missouri's largest customer in the last decade, accounting for approximately 10% of Ameren Missouri's annual sales, reduced production capacity in 2014 due to economic and other business reasons followed by further reduction in production capacity in 2015-2016. Noranda eventually filed for Chapter 11 bankruptcy protection in 2017 and sold the New Madrid smelting facility to Magnitude 7 Metals, LLC (Magnitude 7). The smelter is currently not operating and its limited use (offices, etc.) is now served as part of the Small Primary Service tariff class. Given the current state of operations of the smelter, Ameren Missouri chose not to separately forecast sales to this customer.

Lighting and Other

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

3.2 Peak and Hourly System Load Forecast

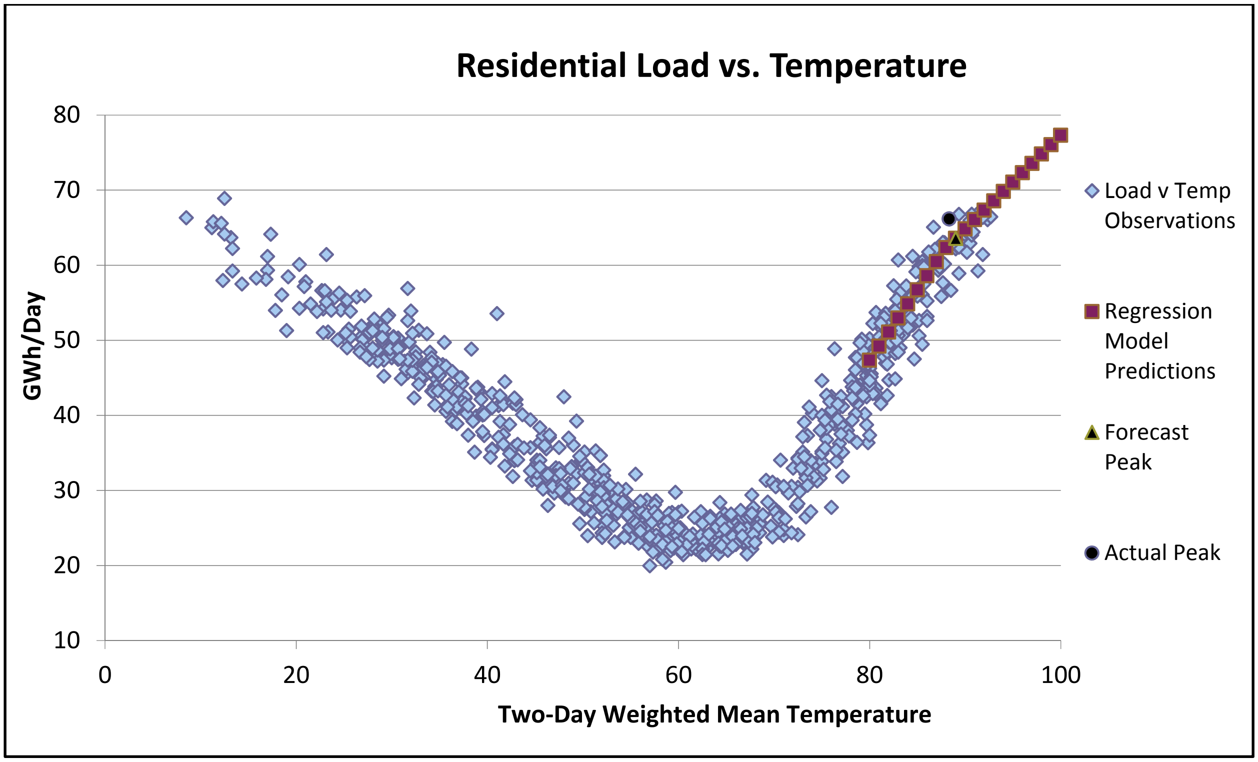
The peak demand forecast is of critical importance to the IRP. The demand on the system at the hour of peak drives the need for generating capacity. While the need for energy influences the optimal mix of generation resources, the timing and amount of capacity additions are most directly tied to peak 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 prior IRP forecasts, 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 prepared on an end use basis for the residential and commercial classes as described previously. 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 forecast peak load.

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 an 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 this line goes through the center of the points in the scatter plot. The result of that is that there are a number of days with high temperatures that 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.[46] 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.

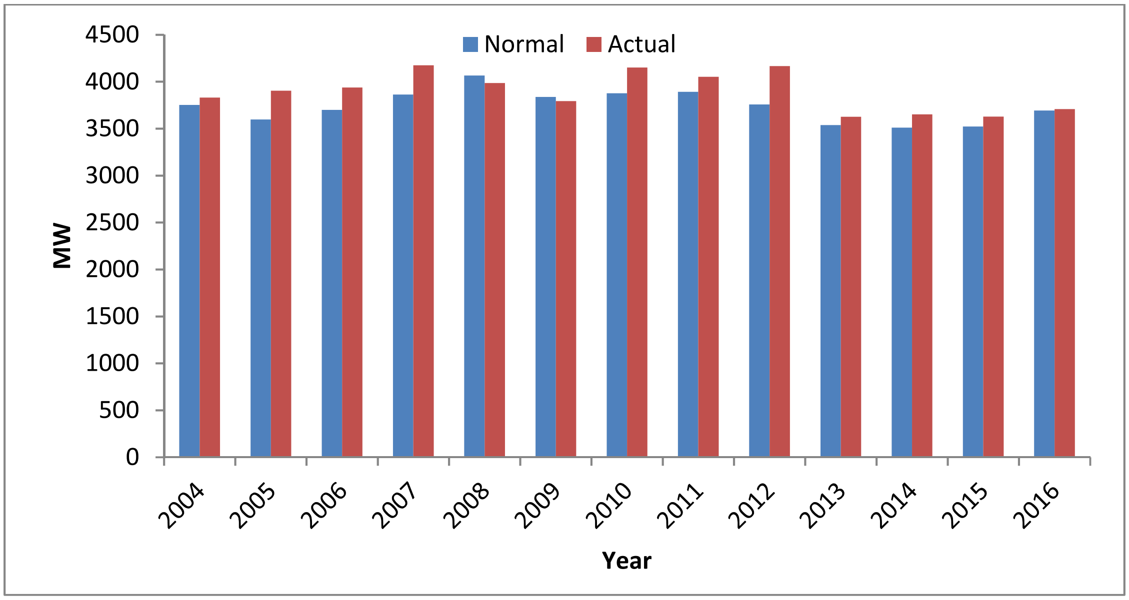
All class demand data is based on Ameren Missouri's load research program. As a part of the load research process, hourly class demands are calibrated to the observed system load to ensure that all energy consumed on the system is attributed to classes appropriately.

The annual coincident peak demand, on a weather normalized basis, for the residential class from the year 2004 to 2016 declined at a compound annual rate of 0.1%. Between 2006 and 2016, residential class demand declined at a compound annual rate of 0.02%,

[46] 4 CSR 240-22.030(2)(B)3

essentially remaining flat over this period. The class load dropped from a weather normalized 3,752 MW in 2004 to 3,692 MW in 2016 (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 on 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)



For the commercial class, the annual coincident peak demand grew at 0.6% per year, from a weather normalized 2,733 MW in 2004 to 2,929 MW in 2016 (at generation, i.e. inclusive of transmission and distribution losses). However, the commercial peak load actually declined at a compound annual rate of 0.3% between 2006 and 2016. On an actual basis, the commercial class load reached its highest level in 2011, with an hourly integrated demand of 3,127 MW.

The industrial class annual coincident peak demand declined on a weather normalized basis from the year 2004 to 2016 by approximately 1.9% 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. Industrial peak further declined over the next four years with a 2016 normalized peak load of 684 MW. There was broad based weakness across this class, but a couple of specific large customer closures coupled with energy efficiency programs had a significant impact on such reduction over last decade. For the industrial class, 2007 saw the highest actual coincident peak demand at 940 MW.

Figure 3.17: Commercial Coincident Peak Demand (in MWs)

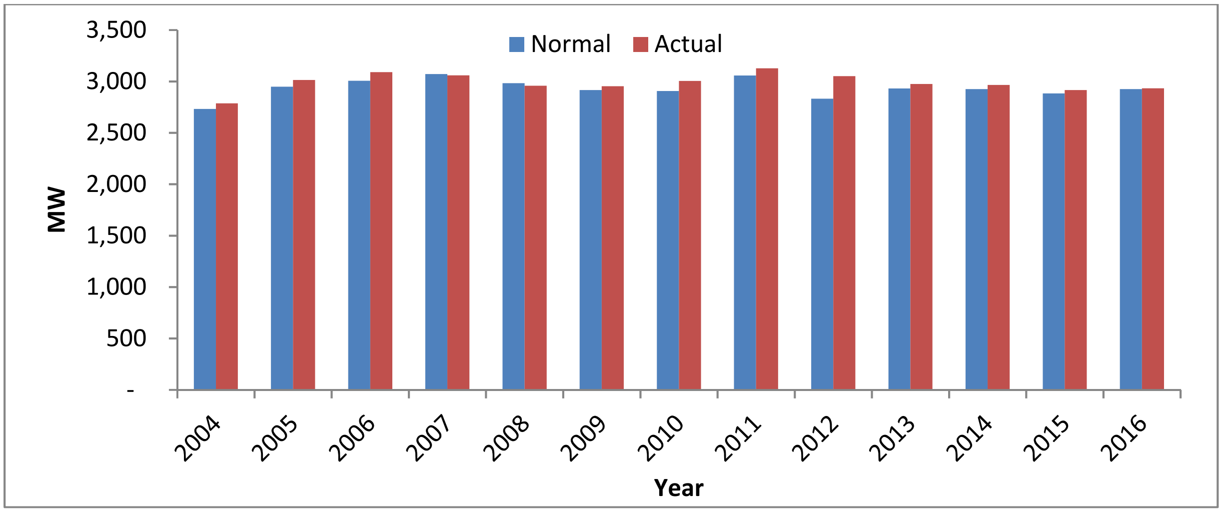
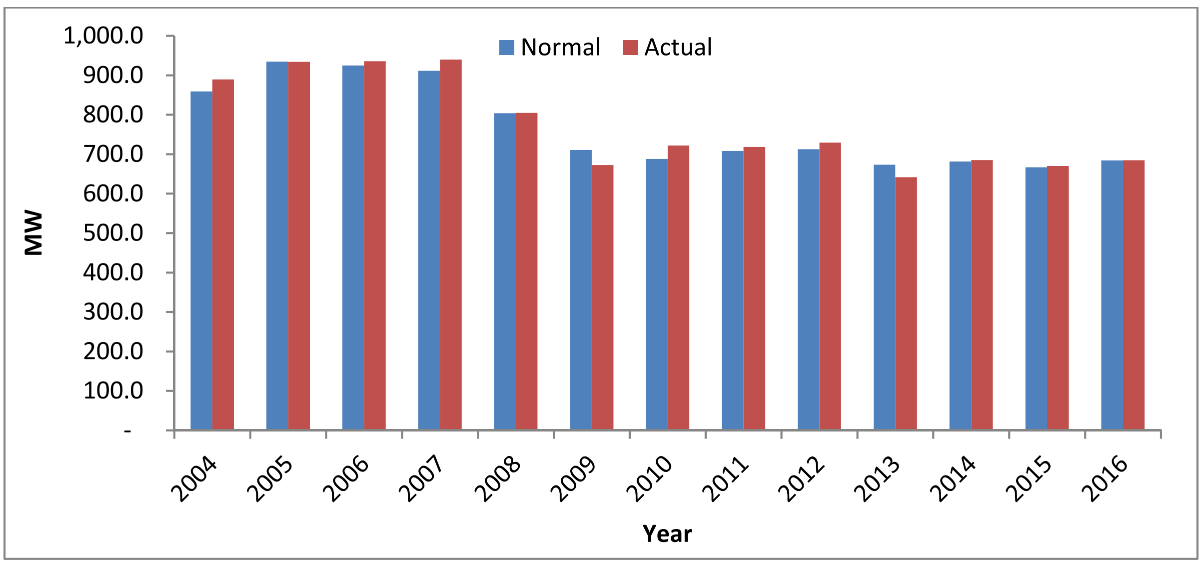


Figure 3.18: Industrial Coincident Peak Demand (MWs)



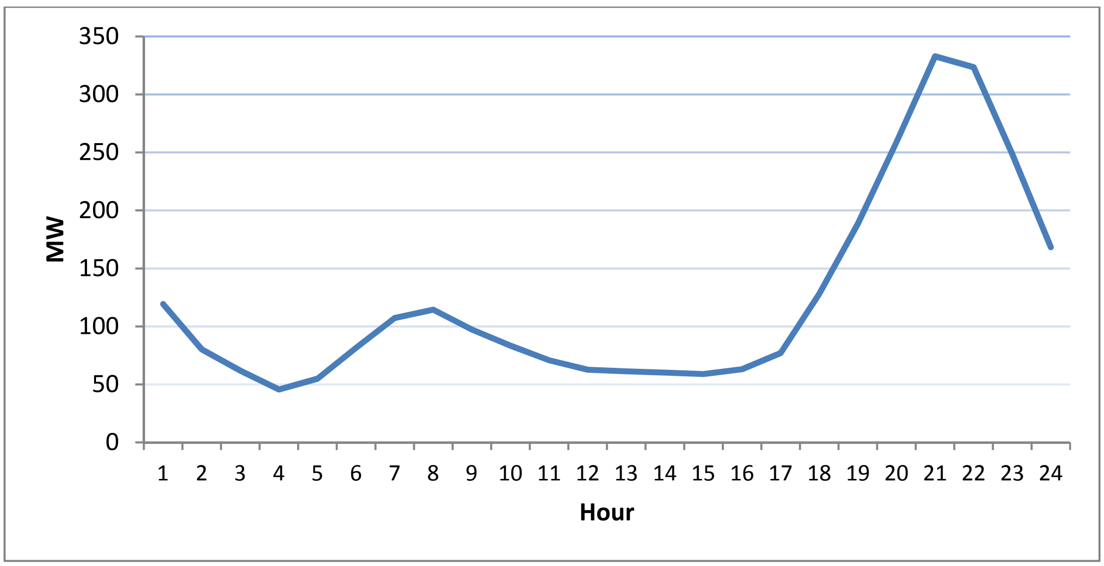
3.2.2 Profile Shapes

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. For the industrial classes that were forecasted using econometric models (no end-use detail), Ameren Missouri specific load research data is used to determine that pattern of usage.

For the residential and commercial classes, the energy forecast from the SAE 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 EISA (issued in 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, but 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 of which we are aware, 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 can be a very costly activity. 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 premises of the customer and develop a new infrastructure for collecting this data. The cost of is generally prohibitive, and end-use load research programs are not common today as a result. However, in the 1990's a number of utilities did engage in end-use load research, and the data collected was shared through EPRI.

Itron, an industry leading forecasting and load analysis consulting company, has a product called eShapes, 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 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 its peak and hourly load forecasting process.

Load Shape Calibration[47]

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

[47] 4 CSR 240-22.030(4)(B)2; 4 CSR 240-22.030(1)(C); 4 CSR 240-22.030(1)(D)

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.

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

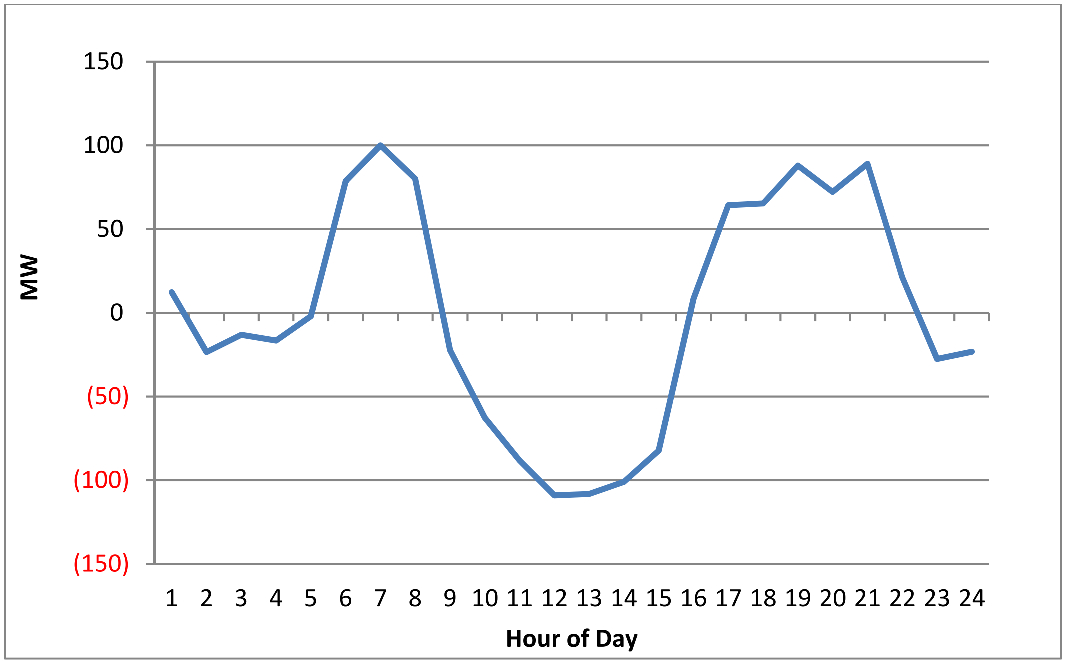
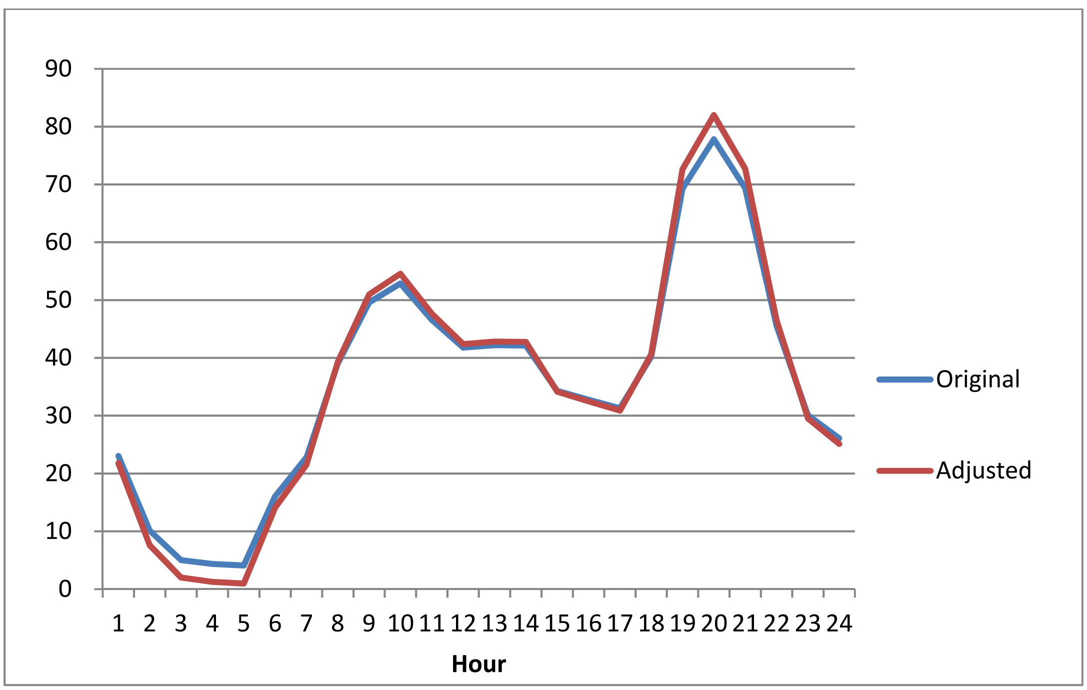


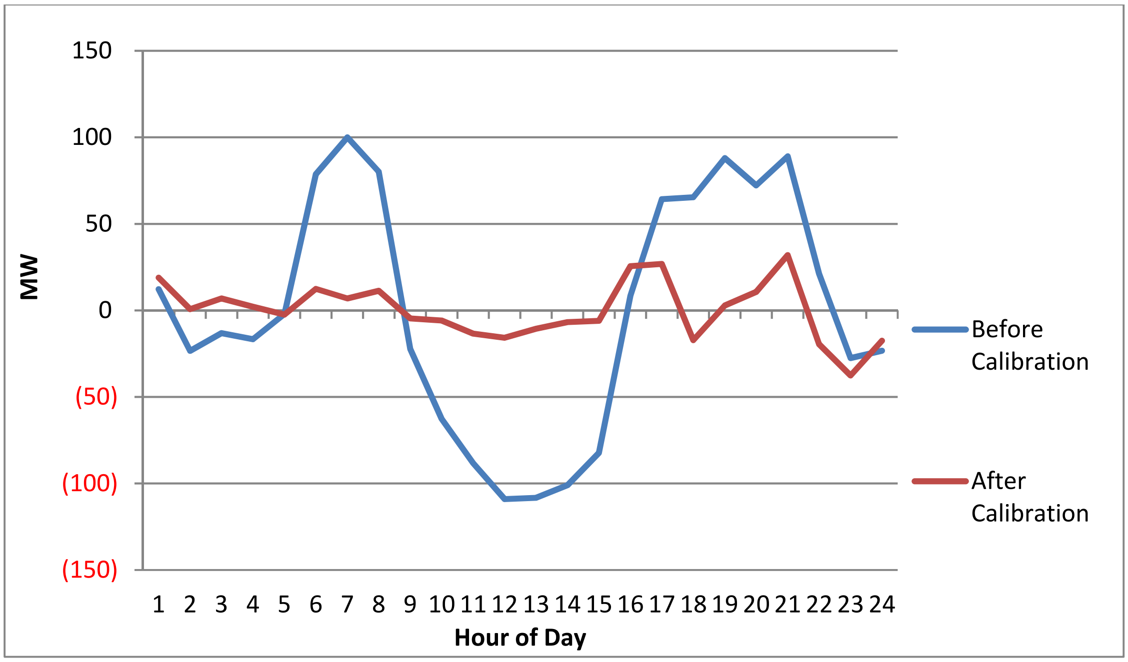
Figure 3.21: Dishwasher Load Shapes



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 was reviewed and a similar adjustment process applied until the error pattern in the difference series was minimized. The final load shapes for each end use are included in a chart in Appendix A. The pattern of the hourly differences before and after adjustment is shown in Figure 3.22.

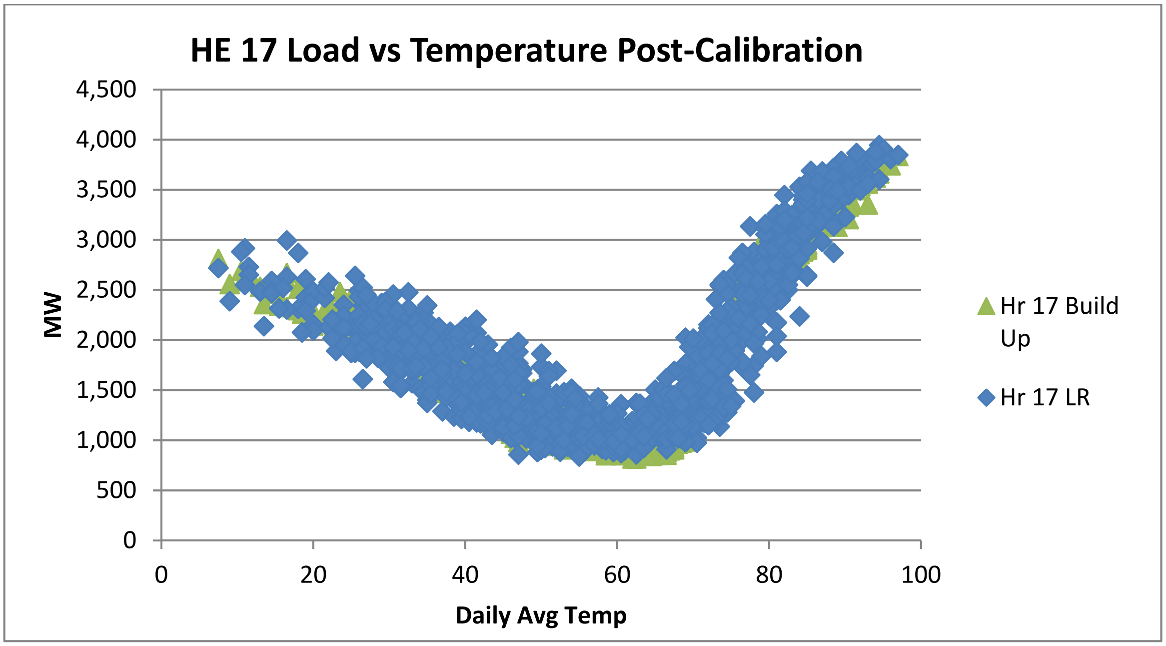
While the adjusted load shape still exhibits some differences from the class actual load shape, the magnitude of the differences is clearly reduced by a substantial amount. It would be impossible to make the synthetic load shape have a perfect fit with the load research data while respecting the characteristic 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 the adjusted load shape for each individual end use to confirm that it was reasonable.

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



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.

Figure 3.23: Cooling End Use Shape Calibration



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 peak typically occurs 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, a high level of agreement between the observed loads and the calculated loads was achieved. The chart shown in Figure 3.23 shows a comparison of the two scatter plots.

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 straightforward. 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, for future years we cannot know the actual pattern in which the weather will occur. So a reference historical year is selected for forecasting purposes. For this forecast, 2011 was used as 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' weekly 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 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 previously) 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 previously. In the case of both 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.

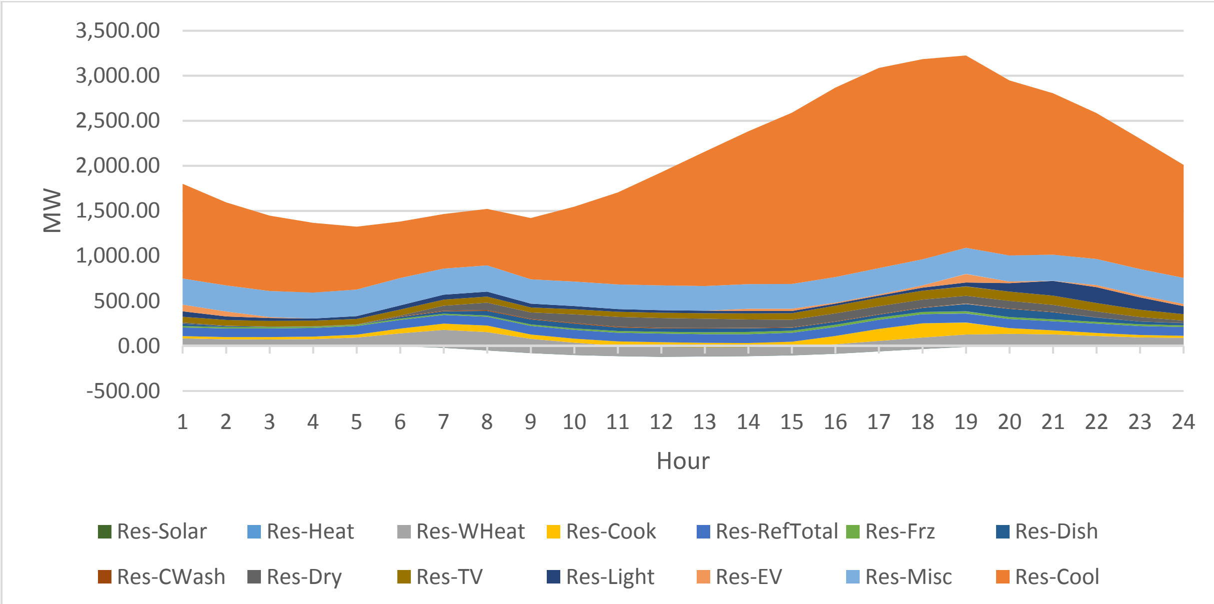
Actual Calendar Profile Development

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. This way the final hourly loads are realistic relative to that actual calendar that will be used in the forecast. To ensure consistent peaks that do not vary due to changes in the day of the week on which they fall, 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.

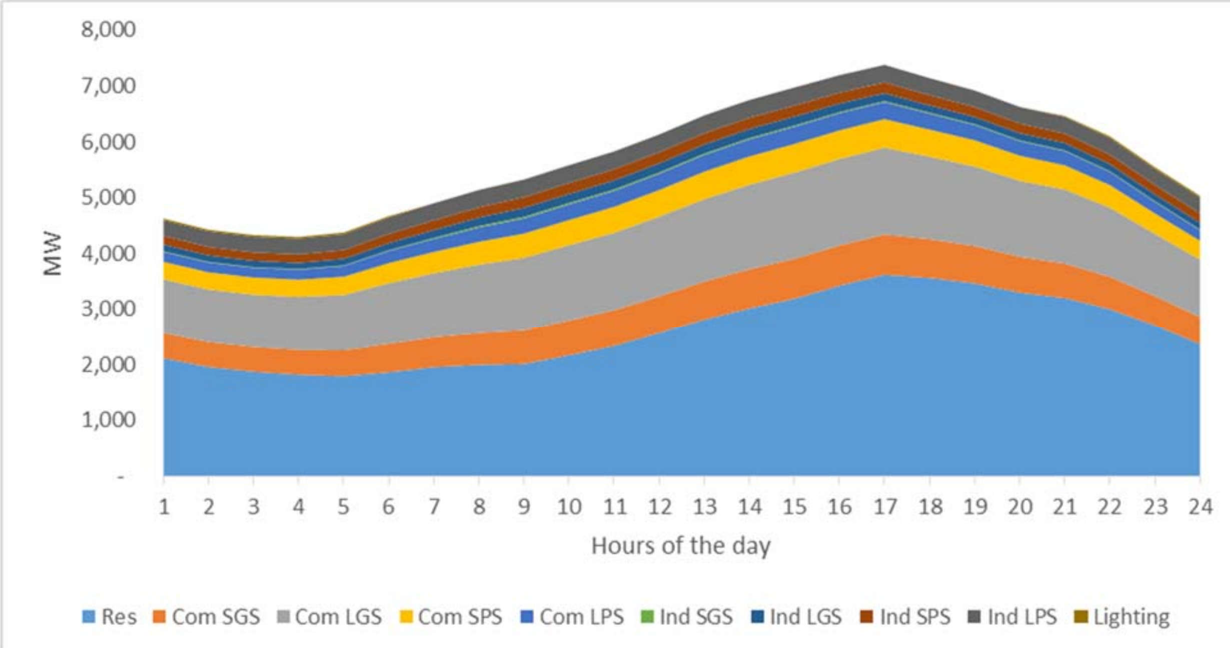
Figure 3.24: Residential Summer Day Usage Built-Up by End Use



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 2015 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: 2018 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.

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 represent.

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%**

3.2.4 Hourly System Load Forecast[48]

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 since we will use the peak forecast from the planning calendar runs, it is no longer necessary to force the days of the week to fall in the same order each year for the sake of consistency. 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

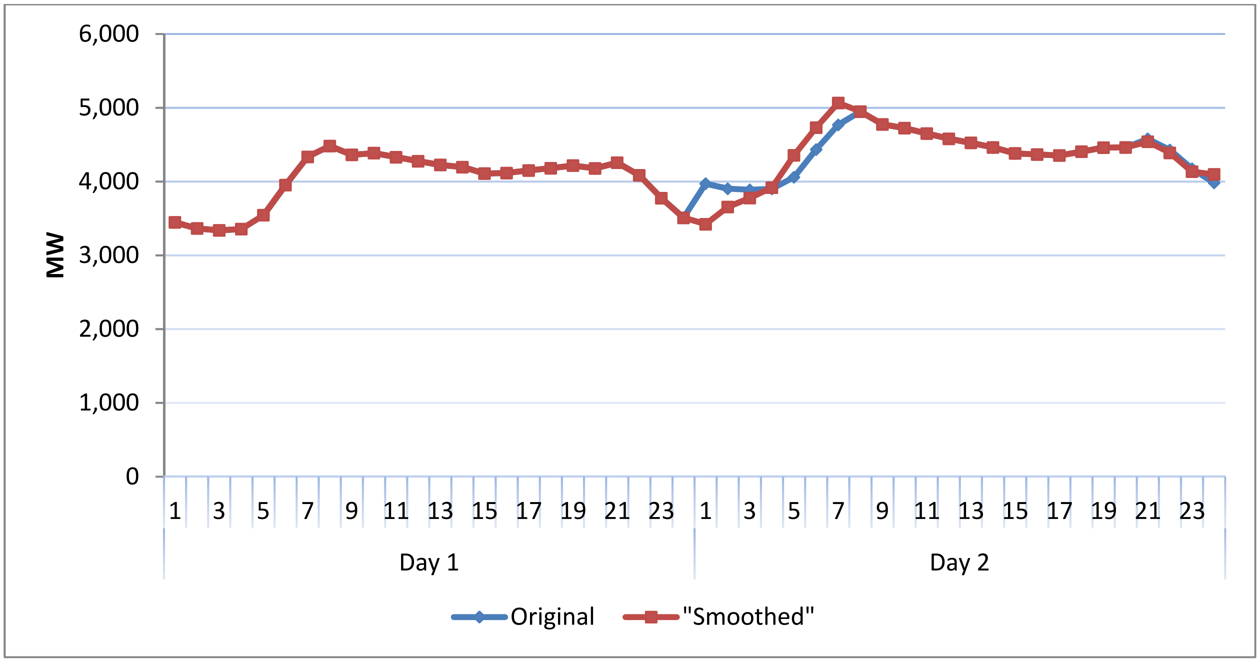
[48] 4 CSR 240-22.030(7)(C)

were created to determine the level of losses that are occurring on the system at the time of peak. Energy loss rates determine the losses that are incurred across the entire year. These are used to gross up meter level sales to reflect the level of energy that will actually need to be generated in order to meet the demand of Ameren Missouri's customers. The energy loss factors were based on the 2015 loss study mentioned previously.

The process of generating the hourly system forecast begins in exactly the same way as the bottom-up forecasting of the peak does, with the exception of the use of the actual calendar and the energy loss rates. The profile shape 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 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 power and energy to serve 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.

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 exhibits a significant "jump." In the cases where this issue is detected, Ameren Missouri has corrected the situation with a smoothing algorithm. 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 three different scenarios. Each of these scenarios was based on a certain combination of the critical uncertain factors identified in this IRP. 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 2018 through 2037 of 0.3%. For the planning case, the peak load in 2018 is projected to be 7,365 MW, growing to 7,760 MW by 2037. The compound annual growth rates in the various scenarios range from a low of -0.4% (low growth scenario), to 0.7% (high growth scenario).

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

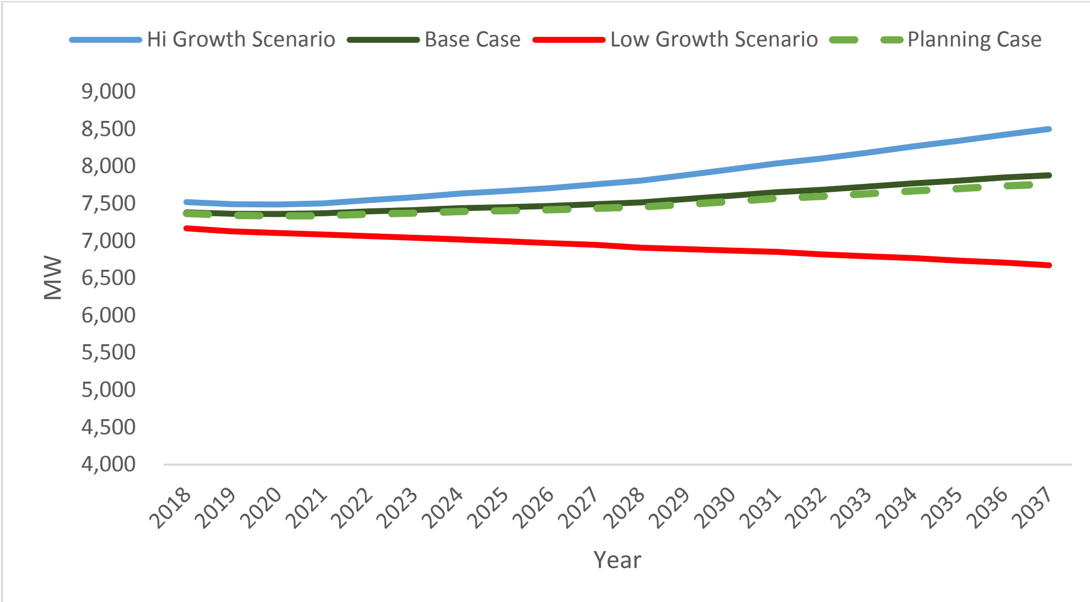


Figure 3.28: Class Contribution to Annual Peak Forecast

3.2.6 Base Case Peak Demand Forecast

Class and End-Use Peak Demands

The peak contribution of the residential class grows at 0.40% per year from 2018 to 2037, while the commercial class and industrial class peaks are forecasted to grow at a compound annual rate of 0.01% and 0.07% respectively, essentially remaining flat over the planning horizon.

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 electric vehicle load. This end use is projected to grow at 17.2% 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 shown for both the first full year of the forecast (2018) and the last year of the forecast (2037).

Table 3.8: Residential End-Use Contribution to Peak

	2018 Peak Contribution (MW)	% of Peak Load (2018)	2037 Peak Contribution (MW)	% of Peak Load (2037)	CAGR
Heating	-	0.0%	-	0%	
Cooling	2,765	76.4%	3,049	78%	0.5%
Water Heating	82	2.3%	116	3%	1.8%
Cooking	105	2.9%	152	4%	1.9%
Refrigerator	116	3.2%	105	3%	-0.5%
Freezer	32	0.9%	26	1%	-1.1%
Dish Washer	29	0.8%	35	1%	1.0%
Clothes Washer	9	0.2%	5	0%	-2.5%
Electric Dryer	86	2.4%	95	2%	0.5%
Television	95	2.6%	102	3%	0.3%
Lighting	32	0.9%	19	0%	-2.5%
Solar	(10)	-0.3%	(108)	-3%	12.5%
Miscellaneous	276	7.6%	317	8%	0.7%
Electric Vehicle	1	0.0%	17	0%	17.2%

Figure 3.29: Residential Peak Load Composition 2018

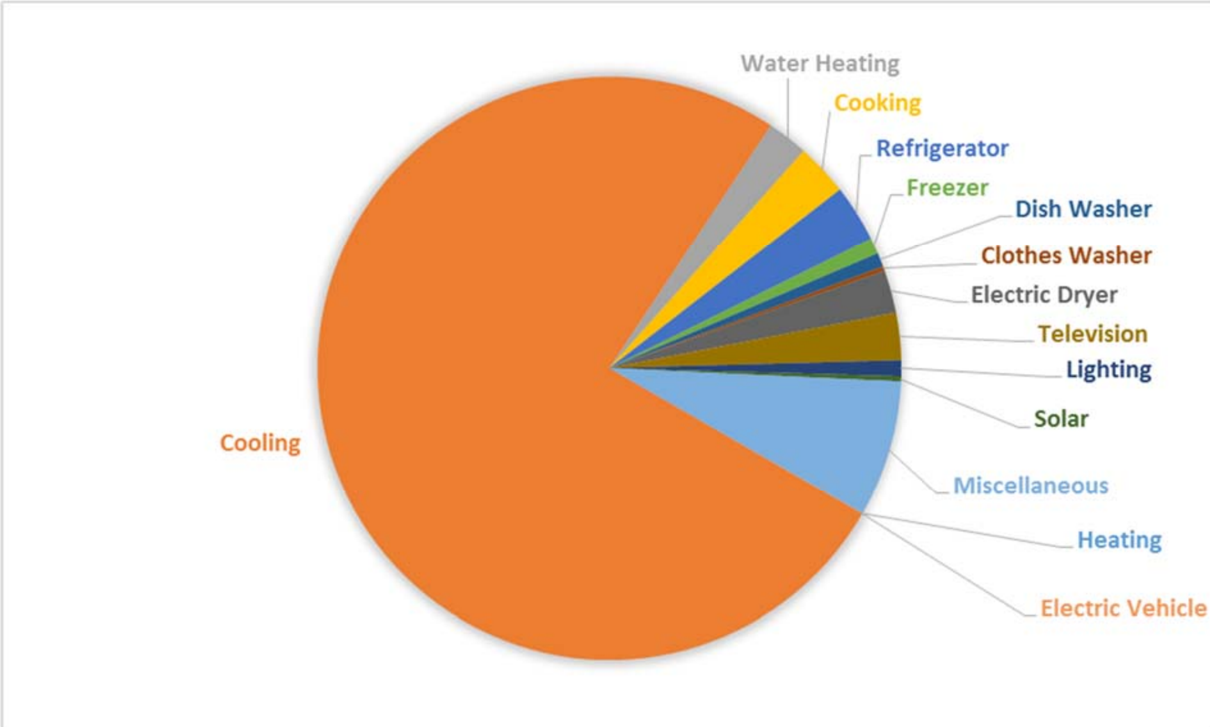


Figure 3.30: Residential Peak Load Composition 2037

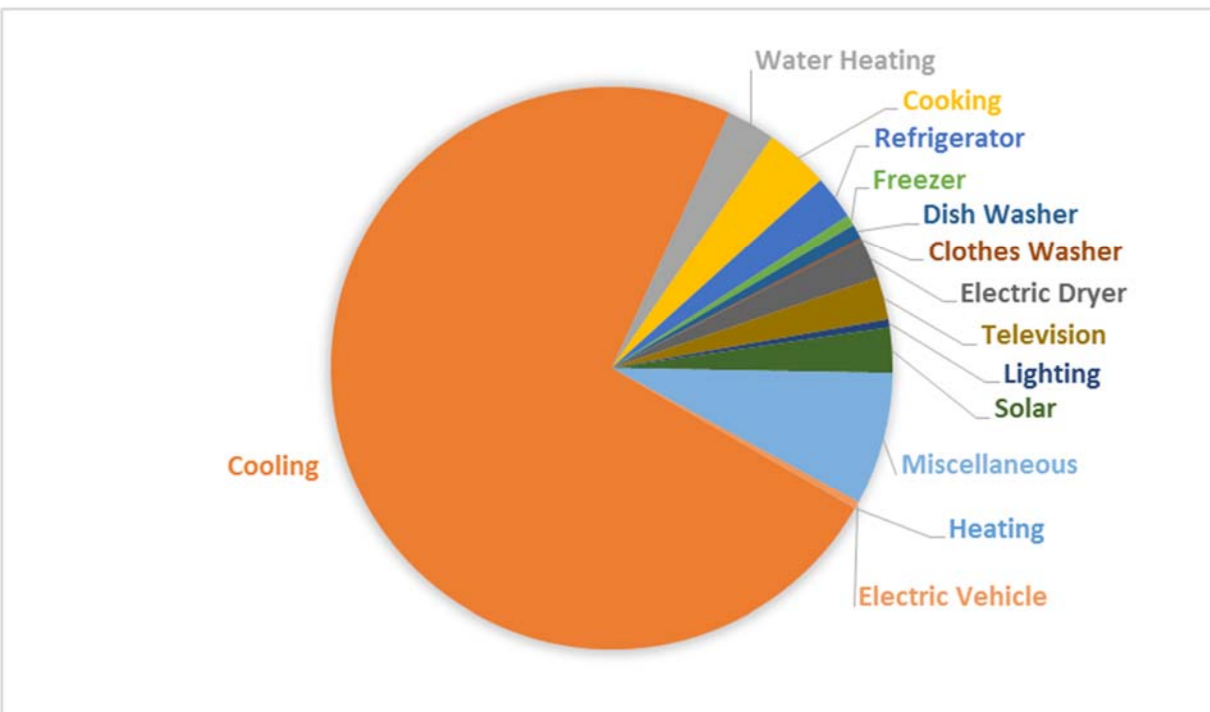


Table 3.9: Commercial End-Use Contribution to Peak

	2018 Peak Contribution (MW)	% of Peak Load	2037 Peak Contribution (MW)	% of Peak Load	CAGR
Heating	-	0.0%	-	0.0%	
Cooling	1,328	42.9%	1,391	43.2%	0.2%
Water Heating	69	2.2%	96	3.0%	1.7%
Ventilation	262	8.5%	294	9.1%	0.6%
Cooking	12	0.4%	14	0.4%	0.9%
Refrigerator	196	6.3%	180	5.6%	-0.4%
Outdoor Lighting	2	0.1%	2	0.1%	0.5%
Indoor Lighting	478	15.4%	516	16.1%	0.4%
Office	37	1.2%	14	0.4%	-4.6%
Solar	(14)	-0.4%	(143)	-4.5%	12.5%
Miscellaneous	727	23.5%	853	26.5%	0.8%

Figure 3.31: Commercial Peak Load Composition 2018

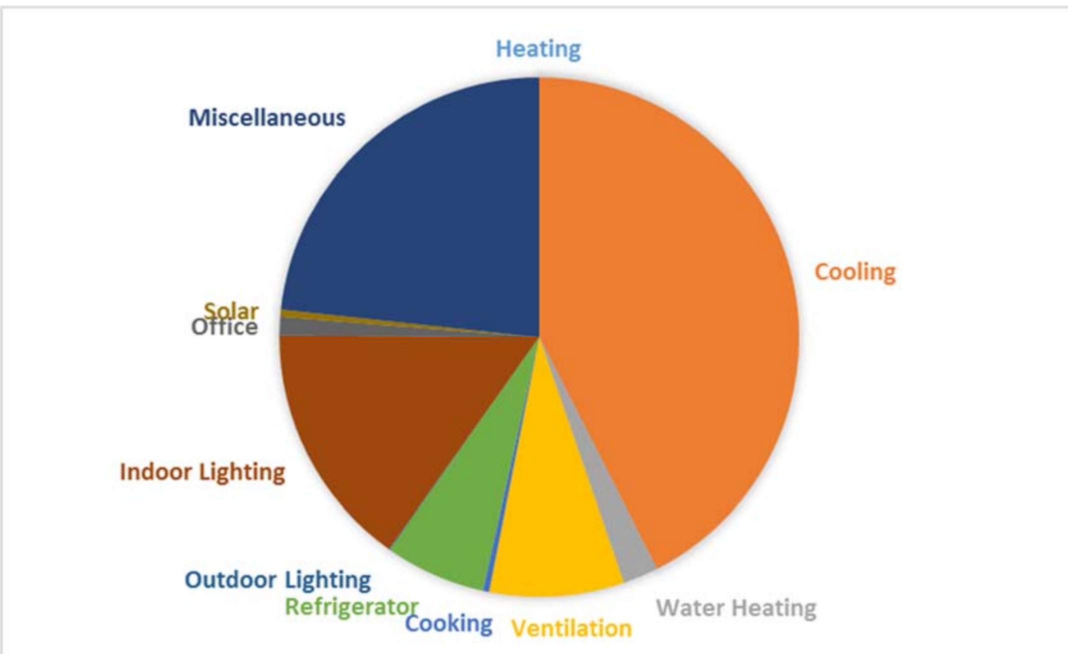
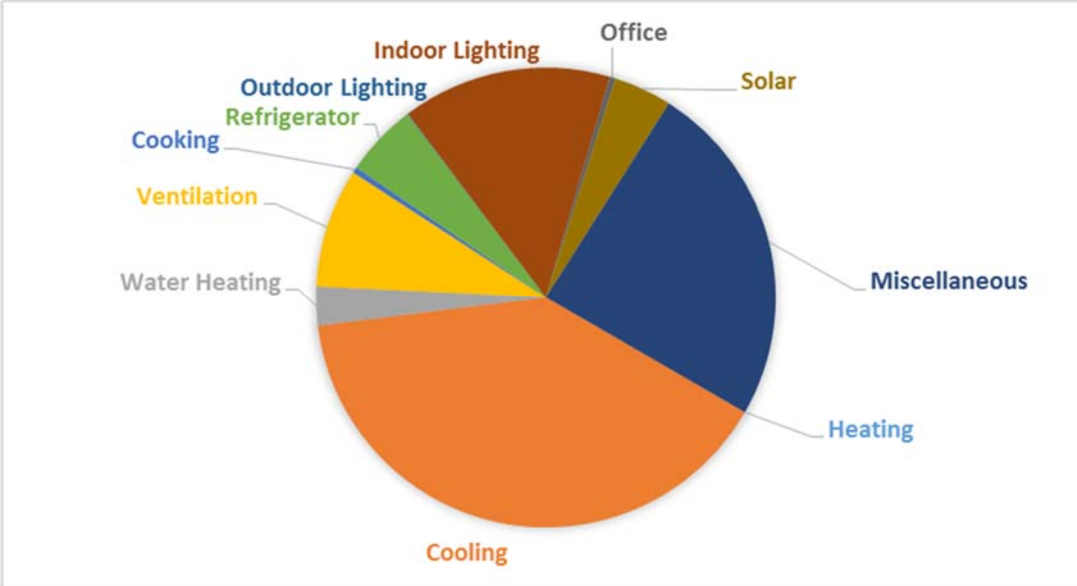


Figure 3.32: Commercial Peak Load Composition 2037



3.2.7 Peak Demand – Extreme Weather Sensitivity[49]

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 15.7%. So in the capacity position, 15.7% is added to the peak load forecast in order to determine annual capacity 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 12 weekday peak load projections from the month in which the annual peak is forecasted to occur (July) for 2018. 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 122.97 MW of increased system demand per degree.

This estimate was tested using 2018 summer peak data. The 2018 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 7,381 MW. Next, Ameren Missouri calculated the expected peak load given two day weighted average

[49] 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 was observed in the 1981-2010 time period. The result was that at the 90th percentile two day weighted average temperature (91.18 degrees), the peak load was forecasted to reach 7,694 MW, or 4.2% 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 7,775 MW, or 5.3% 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 8,370 MW, or 13.4% above the original forecast.

In each case, the extreme weather produced an effect that was lower than the 15.7% 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 15.7% reserve margin by several percent.

3.3 Weather Normalization[50]

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 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 used to support Ameren Missouri's most recent rate case (ER-2016-0179). For historical periods covered by Ameren Missouri’s 2014 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.

[50] 4 CSR 240-22.030(2)(C)2

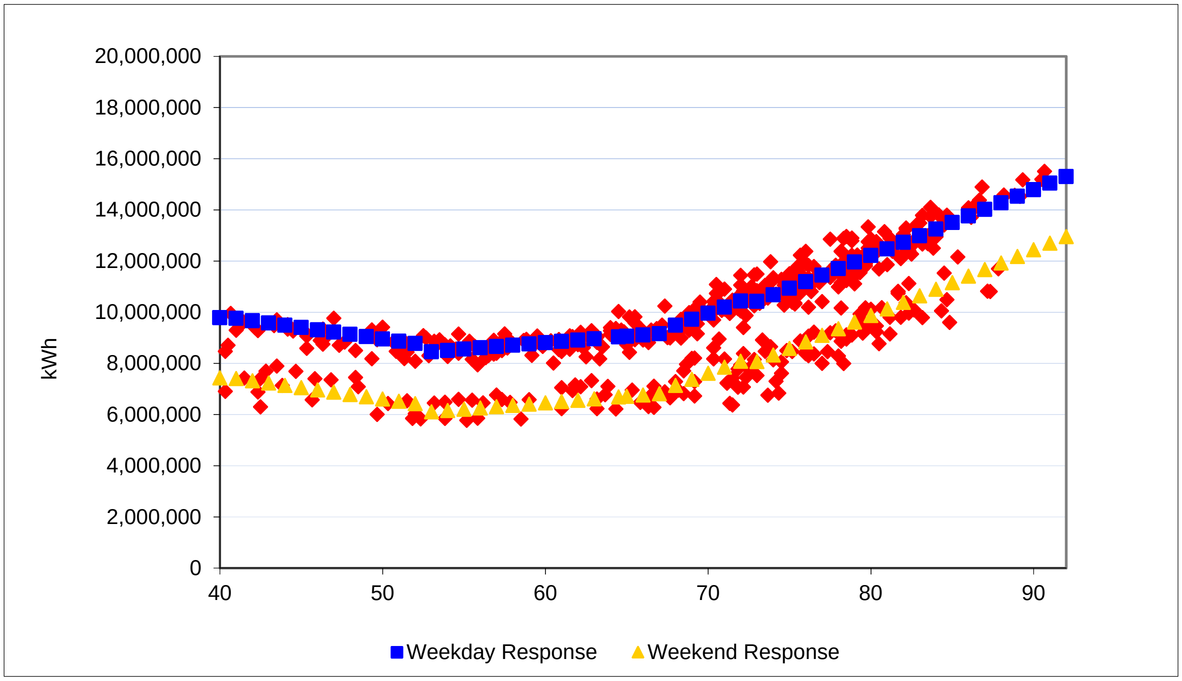
This adjustment was necessary because at the time of the preparation of the 2011 or prior IRP filings, Ameren Missouri was using normal weather calculations based on the time period of 1971-2000. Every decade, the National Oceanic and Atmospheric Administration (NOAA) recomputes weather normals using 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 weather definition. 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 this time period to accommodate the 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. It is used to ensure that normal temperatures also exhibit a normal amount of variability that would be expected to occur within a year. This method has been utilized routinely in electric rate cases by the Missouri Public Service Commission Staff (“Staff”), and was used by both 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.[51] A graphical representation of this modeling approach can be seen in Figure 3.33.

[51] 4 CSR 240-22.030(2)(D)2

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 of loads. The difference between the model's estimate of actual and normal loads is the weather impact for the time period in question. This weather impact is applied to the original load value to generate a normalized version of the load in question. The actual model variables and corresponding coefficients are presented in Appendix B.[52] The weather normalized sales results are also provided in Appendix A. 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[53]

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.

[52] 4 CSR 240-22.030(2)(C)3
[53] 4 CSR 240-22.070(6)(A)

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 level of 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 focused on 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 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

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 a refresh. 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.

3.5 Compliance References