Exhibit No.:	
Issue(s):	IRP Analysis
Witness:	Matt Michels
Type of Exhibit:	Surrebuttal Testimony
Sponsoring Party:	Union Electric Company
File No.:	ET-2025-0184
Date Testimony Prepared:	November 3, 2025

MISSOURI PUBLIC SERVICE COMMISSION

FILE NO. ET-2025-0184

SURREBUTTAL TESTIMONY

OF

MATT MICHELS

ON

BEHALF OF

UNION ELECTRIC COMPANY

D/B/A AMEREN MISSOURI

St. Louis, Missouri
November, 2025

TABLE OF CONTENTS

I. INTRODUCTION 1

II. PURPOSE OF TESTIMONY 1

SURREBUTTAL TESTIMONY

OF

MATT MICHELS

FILE NO. ET-2025-0184

I. INTRODUCTION

Q. Please state your name and business address.

A. My name is Matt Michels. My business address is One Ameren Plaza, 1901 Chouteau Ave., St. Louis, Missouri.

Q. Are you the same Matt Michels that submitted direct testimony in this case?

A. Yes, I am.

II. PURPOSE OF TESTIMONY

Q. To what testimony or issues are you responding?

A. I am responding to the Missouri Public Service Commission Staff's ("Staff") concerns and recommendation[1] regarding the Company's proposed Clean Energy Choice ("CEC") Program and Office of the Public Counsel ("OPC") witness Dr. Geoff Marke's criticism[2] of the Company's use of its Integrated Resource Plan ("IRP") analysis as the basis for assessing risks associated with tariffed service to Large Load Customers ("LLC") as described in the Direct Testimony of Company witness Steve Wills.

[1] File No. ET-2025-0184, *Staff Recommendation/Rebuttal*, p. 74-85, filed September 5, 2025.
[2] File No. ET-2025-0184, Dr. Geoff Marke Rebuttal Testimony, p. 10-14.

Q. Please summarize Staff's concerns regarding the Company's proposed CEC Program.

A. The following summarizes Staff's key concerns regarding the Company's proposed CEC program. Specifically, Staff states:

1. That Ameren Missouri differs in its expectations regarding the CEC Program from the expectations expressed by Evergy regarding its similar program. Specifically, Staff notes that Ameren Missouri's program would not involve changes to its Preferred Resource Plan ("PRP") selected through its IRP to address the resource preferences of subscribers under the CEC program, but would rather require that such resource preferences be addressed in an alternative Clean Energy PRP, whereas the similar program to be implemented by Evergy would allow for changes to its PRP to address subscriber resource preferences.[3]

2. That the Commission should wait to address the CEC Program until its new IRP rules and process pursuant to Senate Bill 4, passed earlier this year, are established due to the uncertainty regarding the nature and specifics of that process and its importance to resource decisions.[4]

3. That the cost differential to be paid by a subscribing customer should not be paid by any other customers in the event the subscriber is unable to fulfill its obligations.[5]

4. That the CEC program would introduce increased contentiousness to a new IRP process that is already expected to be contentious.[6]

---

[3] File No. ET-2025-0184, *Staff Recommendation/Rebuttal*, p. 76, ll. 18-21, filed September 5, 2025.
[4] File No. ET-2025-0184, *Staff Recommendation/Rebuttal,* p. 78, ll. 21-26, filed September 5, 2025
[5] File No. ET-2025-0184, *Staff Recommendation/Rebuttal,* p. 81, ll. 41-43, filed September 5, 2025.
[6] File No. ET-2025-0184, *Staff Recommendation/Rebuttal,* p. 83, ll. 8-13, filed September 5, 2025.

5. That net present value of revenue requirement ("NPVRR") "is not a clean tool to evaluate the costs and benefits of investment opportunities for ratepayers."[7]

Q. Please respond to Staff's first concern regarding the potential for changes to the Company's PRP to address CEC program participant preferences.

A. Ameren Missouri's CEC program is designed to allow LLCs to pay for additional clean resources that would not otherwise be included in the Company's PRP. Other programs have been proposed by the Company to provide choices to LLCs that can be supported by the Company's existing and planned portfolio under its PRP, separate and apart from the CEC. These other programs all involve assets that would exist and serve all customers irrespective of LLC loads but can produce additional revenues from LLCs that will benefit all customers. These include the Company's proposed Renewable Solutions Program for Large Load Customers ("RSP-LLC") and the proposed Nuclear Energy Credit ("NEC") Program. It is important to explicitly distinguish resources used to serve LLCs under the CEC that would not be built absent an LLC's binding commitment to appropriately contribute to the resource's cost, but which could serve to displace the need for other resources that would have been built, by explicitly assessing the cost differential to be recovered from the CEC program participant.

The Company makes no representation and takes no position regarding the program suite operated or proposed by Evergy. The Commission can make appropriate determinations regarding the programs of each utility in the context of each utility's unique circumstances and set of program offerings. Staff offers no preference regarding the approach to addressing PRP changes to address CEC program participant's preferences.

[7] File No. ET-2025-0184, *Staff Recommendation/Rebuttal*, p. 83, ll. 30-31, filed September 5, 2025

Q. Please respond to Staff's second concern regarding the uncertainty of the new IRP process to be implemented under Senate Bill 4.

A. There is always uncertainty that must be dealt with regarding decisions about the future. Such uncertainties, including those surrounding potential changes to the IRP process, should not serve to limit the tools available to customers, the Company, or the Commission to advance public interest. As Mr. Wills explained in his Direct Testimony, the Company will have full discretion as to whether to seek a CEC agreement with a customer, and the Commission will have full discretion as to whether to approve such an agreement, including pricing and other terms.

Specifically, Mr. Wills states that, "... because of the very customized nature of solutions expected to be contemplated under Rider CEC, the program tariff provides a template for engaging in the study and selection of alternative Clean Energy PRPs, while leaving the specifics of program pricing and payments to be fully detailed within the participation agreement itself. Again, all such terms and conditions, including prices, quantities, duration, termination provisions, and any other salient features of the agreement will be brought before the Commission for approval prior to implementation of any Clean Energy PRP."[8]

Staff does not describe what kinds of complications may arise in the development of new IRP rules and processes that would preclude Commission consideration of CEC agreements under the Company's proposal. If such complications do arise, it is possible they could be satisfactorily addressed in the rules. If for some reason there is an issue that

[8] File No. ET-2025-0184, Steven M. Wills Direct Testimony, p. 25, ll. 6-12.

becomes unresolvable, it may be necessary to make modifications to the program. Until such issues are known, opportunities should not be sacrificed on the altar of nebulous fears.

Q. Please respond to Staff's third concern regarding recovery of cost differentials from non-CEC program participants.

A. The Company appreciates Staff's good intentions regarding potential impacts to non-participants and seeks to ensure that non-participants are not unfairly burdened with additional costs. The appropriate time and setting for addressing such concerns will be part of the Commission's review of one or more CEC agreements, when the Commission and stakeholders have an opportunity to fully review and assess the pricing and other terms and conditions in the agreement(s), including any provisions to address the risk of cost shifting. It is also possible that in the event a participant is unable to fulfill its obligations under a CEC agreement, that this eventuality will be accompanied by a significant shift in the Company's resource needs, including the potential to defer resources that otherwise would have been implemented. It is simply not possible to prejudge all the relevant facts and circumstances that might be involved in such a situation. As noted, the Commission has full authority to take these kinds of issues into account as it considers whether it should approve a CEC agreement.

Q. Please respond to Staff's fourth concern regarding the expected contentious nature of the new IRP process.

A. As I mentioned previously in response to Staff's second concern, options to promote public interest should not be denied to customers, the Company, or the Commission for reasons of uncertainty, including speculation about the degree to which IRP proceedings will be contentious. The fact that they are expected to be contentious highlights the nature and built in safeguards of the program itself – CEC agreements will be subject to substantial scrutiny. If the Commission finds that an agreement should not be approved based on the details of an agreement brought before it, then the Commission has every right to reject such an agreement, but they should at least be given the chance to review one.

Q. Please respond to Staff's fifth concern regarding the use of NPVRR for determining cost differentials to be recovered from CEC subscribers.

A. NPVRR has long been used in making resource decisions, both in Missouri and throughout the nation. It properly addresses the time value of money from the utility perspective and accounts for the relative impacts of cost effects of resource decisions that may differ in time. The Commission's own current IRP rules require that NPVRR be used as the primary selection criterion for selecting a PRP,[9] and the exact language from the current IRP rule is included in the proposed tariff. The Commission will have discretion to approve a CEC agreement or to reject a CEC agreement if it believes it is not in the public interest, whether based on pricing, other terms and conditions, or other considerations.

Q. Staff includes an example with charts to portray a situation in which cost recoveries based on NPVRR are insufficient to cover undiscounted revenue requirement differentials over time. Do you find this analysis compelling?

A. No. As I mentioned previously, NPVRR is the appropriate measure to use for assessing cost differentials over long periods just as it is the appropriate measure for assessing the cost of alternative resource plans as part of an IRP analysis. Staff's example

[9] 20 CSR 4240-22.010(2)(B).

also reflects some flaws that, while not particularly relevant to the conceptual preference for NPVRR I have stated here in my Surrebuttal Testimony, serve to highlight the rigorous nature of a full IRP analysis that would assess the costs of a PRP and one or more alternative CEC PRPs.

Q. Please describe the flaws you referenced above.

A. The most critical flaw is one that has emerged in multiple cases in recent years – the conflation of *revenue requirements*, which is the full cost of providing service to customers, with estimated future *revenues*, which depend on rate case timing and the operation of various cost recovery and risk sharing mechanisms like the Fuel Adjustment Clause ("FAC"). Decisions regarding long-lived utility resources should not be driven by arbitrary assumptions regarding the timing of future rate cases or the idiosyncrasies of specific cost recovery mechanisms. These are subject to change and do not affect the underlying costs of the decisions themselves. Rather, decisions should be focused on those underlying costs.

The other flaws are more mechanical in nature – improper exclusion of deferred tax impacts on rate base, incorrectly calculating income taxes on equity return, and applying the same market price to the output of both gas and solar resources. These are not particularly important to the point of the example, which I have already addressed, but they do highlight that the kind of rigorous analysis used for IRP planning is necessary to ensure that such details are appropriately captured.

Q. Staff recommends that the Commission reject the Company's proposed CEC program due to the concerns you've addressed. What is your recommendation?

A. I recommend that the Commission approve the Company's proposed CEC program to provide an *opportunity* for the Company and prospective customers to come forward with a CEC agreement for the Commission to consider with the benefit of all relevant facts and circumstances at the time it is offered for approval. Staff's concerns are vague and are not supported by compelling evidence that suggests there will be any harm that results from the Commission at least considering such agreements, which will be accompanied by substantial detail regarding the basis for pricing and other terms and conditions, as previously described in the Direct Testimony of Mr. Wills.

Q. Please summarize Dr. Marke's criticisms of the Company's use of its IRP analysis to support the risk analysis presented in the Direct Testimony of Mr. Wills.

A. Dr. Marke makes the following assertions regarding the Company's IRP analysis:

1. That the IRP should be held to a high degree of skepticism for its analytical value due to the dynamic nature of the environment in which planning is performed.[10]

2. That the impacts of the Company's adjustments to its long-term demand-side resources portfolio are not credible.[11]

[10] File No. ET-2025-0184, Geoff Marke Rebuttal Testimony, p. 10, l. 12, to p. 11, l. 2.
[11] File No. ET-2025-0184, Geoff Marke Rebuttal Testimony, p. 11, ll. 12-14. Specifically, Dr. Marke states that, "According to Ameren Missouri, the Commission's rejection of its proposed MEEIA application will result in an additional 375 MW of generation in 2032 and 875 MW of generation in 2043. I believe this is an absurd conclusion,"

3. That my Direct Testimony does not explicitly address the benefits of time-of-use ("TOU") rates.[12]

4. That the Commission should also take into consideration changes to Ameren Missouri's historical planned capital investments over time.[13]

5. That the cost of gas-fired resources has risen substantially since the Company filed its 2023 IRP.[14]

Q. Please respond to Dr. Marke's first assertion regarding the general appropriateness of using the Company's IRP analysis as the basis for Mr. Wills' risk analysis.

A. The IRP process includes analysis of key uncertainties affecting the market and the cost of resources. These include natural gas prices, environmental policy and regulations, demand growth, technology costs and performance, and numerous other variables that affect long-term resource decisions. The IRP analysis underlying Mr. Wills' risk analysis further accounts for the uncertainty in the extent of LLC demand and the extent to which such demand is sustained, including its effects on resource needs and additions, as I described in detail in my Direct Testimony. While there is no avoiding the fact that there is uncertainty when planning for the future, the IRP framework provides the best basis for evaluating the potential impacts of LLC demand on resource needs and costs.

[12] File No. ET-2025-0184, Geoff Marke Rebuttal Testimony, p. 11, ll. 20-21.
[13] File No. ET-2025-0184, Geoff Marke Rebuttal Testimony, p. 11, ll. 24-25.
[14] File No. ET-2025-0184, Geoff Marke Rebuttal Testimony, p. 14, ll. 4-5.

Q. Please address Dr. Marke's second assertion regarding the Company's long-term demand-side resource portfolio.

A. I believe there may be some confusion on Dr. Marke's part as to exactly what the change in resource need described in my Direct Testimony represents. It is not the impact of the rejection of only the Company's original cycle 4 application for programs under the Missouri Energy Efficiency Investment Act ("MEEIA") that results in the increased need for resources. It is also the continuation of similar program budgets based on the Company's approved MEEIA 4 plan relative to the much higher program budgets assumed in the Company's 2023 IRP preferred plan that gives rise to the additional need for resources of 375 MW in 2032 and 875 MW in 2043. These were demand savings that the Company had assumed would be achieved under its 2023 IRP preferred plan that would not be achievable with the kind of reduced program budgets approved for the Company's current programs, and it was appropriate to remove those demand savings from the Company's PRP, as reflected in its February 2025 Notice of Change in PRP.[15]

Q. Please address Dr. Marke's third assertion regarding the Company's lack of discussion of TOU rates in its PRP.

A. Ameren Missouri included the impacts of TOU rates in its IRP load forecasts, as described in its 2023 IRP filing.[16] Those IRP load forecasts were carried over into the Company's 2025 PRP analysis and supplemented with assumptions for LLC demand at various levels, as described in my Direct Testimony. While not explicitly noted

[15] File No. ET-2025-0184, Matt Michaels Direct Testimony, Schedule MM-D1, pp. 15-16.
[16] File No. EO-2024-0020, Schedule MM-S1 – Ameren Missouri 2023 IRP Chapter 3 – Load Analysis and Forecasting, pp. 48-49.

in my Direct Testimony or in Schedule MM-D1, TOU rates are included in the Company's PRP and in the IRP analysis underlying Mr. Wills' risk analysis.

Q. Please address Dr. Marke's fourth assertion regarding changes in the Company's planned resource investments.

A. It is true that the Company's plans have changed significantly since 2020. It is also true that the planning environment has changed dramatically in that same time - evolution of MISO's resource adequacy framework to a seasonal approach, which established a basis for the Company's winter resource needs, and more rigorous assessment of the capacity value of renewables, accelerated retirement for Company's combustion turbine Generator (CTG) units located in Illinois due to the passage of the Illinois Climate and Equitable Jobs Act, diminished reliance on demand-side programs as long-term resources following the conclusion of the Company's 2024 MEEIA case, and the onset of large customers, like data centers, have all contributed to the need for more investment in generation. Circumstances will continue to change, and we must plan in an environment that is constantly changing. The IRP process provides a way to consider the effects of such changes and uncertainty, and while it is subject to limitations, it provides the best basis for considering the impact of LLCs on future resource needs and consideration of how the associated costs are recovered.

Q. Please address Dr. Marke's fifth assertion regarding the rising cost of gas-fired resources.

A. Dr. Marke correctly observes that the cost of gas-fired resources has risen. The cost of some of the other resources has risen as well, and the Company included these more recent and higher cost estimates for resources in its IRP analysis underlying Mr.

Wills' risk analysis. The Company therefore used the most recent estimates for resource costs available at the time it prepared its risk analysis.

Q. What is your conclusion regarding the Company's use of its IRP analysis to assess risks associated with the cost of serving LLCs.

A. The IRP analysis presented in my Direct Testimony is a reasonable basis for assessing the risks associated with the cost of serving LLCs as presented in Mr. Wills' Direct Testimony. While the future is always subject to uncertainty, the Company's IRP analysis assesses the impacts of such uncertainty in the context of the Company's request in this case and the potential for significant changes in LLC demand in the future.

Q. Does this conclude your surrebuttal testimony?

A. Yes, it does.

3. Load Analysis and Forecasting

Highlights

- *Ameren Missouri expects energy consumption to grow 0.9% annually and peak demand to grow 0.5% annually for the planning case over the next 20 years including potential impacts from electrification and behind the meter solar generation and including economic development additions.*
- *Economic growth, naturally occurring energy efficiency and customer adoption of distributed energy resources such as solar and efficient electrification of end-uses are key drivers of future growth in our base case forecast.*

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. Additionally, 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 planning case for the study. The planning case forecast projects Ameren Missouri's retail sales to grow by 0.8% annually between 2024 and 2043, and retail peak demand to grow by 0.4% per year.

1 20 CSR 4240-22.030(1)(A)

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.

Since the last IRP filing, Ameren Missouri has implemented significant energy efficiency programs, which has significantly reduced overall energy consumption year over year. This forecast assumes significant savings from company-sponsored energy efficiency programs under the Missouri Energy Efficiency Investment Act (MEEIA). Savings from MEEIA Cycle 2 programs and MEEIA Cycle 3 programs are forecasted through 2043. This IRP forecast assumes 2043 will cumulatively have implemented 1,966 GWh of energy savings. As mandated by SB 564, Ameren Missouri will provide $23 million in incentives between 2018 and 2024 resulting in approximately 100 MWs of customer owned renewables, if the rebates are fully subscribed. The base case scenario assumes that the customer owned renewable generation capacity would increase during the planning years, reaching 700 MWs by 2043. Customer owned renewable generation capacity is assumed to reach as high as 1,400 MWs by 2043 in the low load growth scenario and 350 MWs by 2043 in the high load growth scenario.

Compared to Ameren Missouri's last IRP, which was filed in 2020, the growth rate of the forecasts is lower in the base, low, and planning scenario, but higher in the high scenario. The growth rate in the high scenario increased due to additional adoption of Electric Vehicles by 2043. Ameren Missouri's current initiatives on efficient electrification programs are expected to increase total consumption by 285 GWh between 2022 and 2027. An efficient electrification study conducted by the Electric Power Research Institute (EPRI) shows significant potential for adoption of electric vehicles and other efficient electrification technologies by 2043 raising the overall electric consumption by approximately 4,868 GWh in the base case scenario. Forecasts for the high load growth scenario assumes approximately 8,426 GWh and forecasts for low growth scenario assumes approximately 963 GWh of additional load from efficient electrification.

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 past and current cycles of energy efficiency programs Ameren Missouri has implemented under the MEEIA program. The third cycle of MEEIA programs is included in the load forecast because it is already planned and approved and is 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 March of 2022.[6] Except as noted later in this chapter, any data presented for 2022 or beyond is forecasted data and data from 2021 and earlier is actual metered or weather normalized sales data. Historical energy consumption and customer count data are provided in the electronic workpapers.

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 will also are provided in the electronic workpapers. Appendix A includes weather normalization model statistics for various rate-revenue classes. Workpapers that include use per unit energy sales and demand data for all classes are provided in the electronic workpapers. 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 Variable [8]

Missouri IRP rule 20 CSR 4240-22.030(6)(C)3 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 Missouri from Moody's Analytics, along with forecasts of each variable for the entire planning horizon.[9]

[2] 20 CSR 4240-22.030(1)(B)
[3] 20 CSR 4240-22.030(2)(B)1
[4] 20 CSR 4240-22.030(2)(A)
[5] 20 CSR 4240-22.030(2)(B)2
[6] 20 CSR 4240-22.030(2)(F)
[7] 20 CSR 4240-22.030(2)(C)1
[8] 20 CSR 4240-22.030(6)(C)3
[9] 20 CSR 4240-22.030(6)(C)1

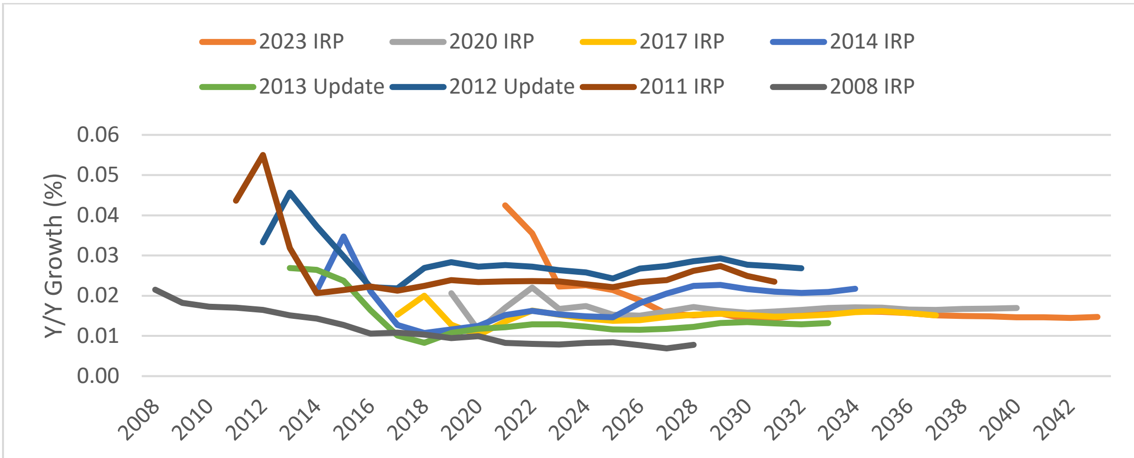
The following discusses only the independent variables used in the energy usage forecasts. The peak forecast is derived from using the output from the energy forecast and modeling historical peaks as the Y variable. The growth rates in peak demand are driven by the energy forecasts for each class and 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 2008 IRP, the 2011 IRP, the 2012 Annual Update, the 2013 Annual Update, the 2014 IRP, the 2017 IRP, and the 2020 IRP. Besides these prior projections, projections for this 2023 IRP are included. Sales volume shown for the 2023 IRP includes the actuals for years up to 2021 and projections starting from 2024.

In some cases, the data vendor may have changed the 'base year' for the independent variables' values. In addition, between certain IRPs, 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 will be shown in chart and tabular form in the final filing.

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

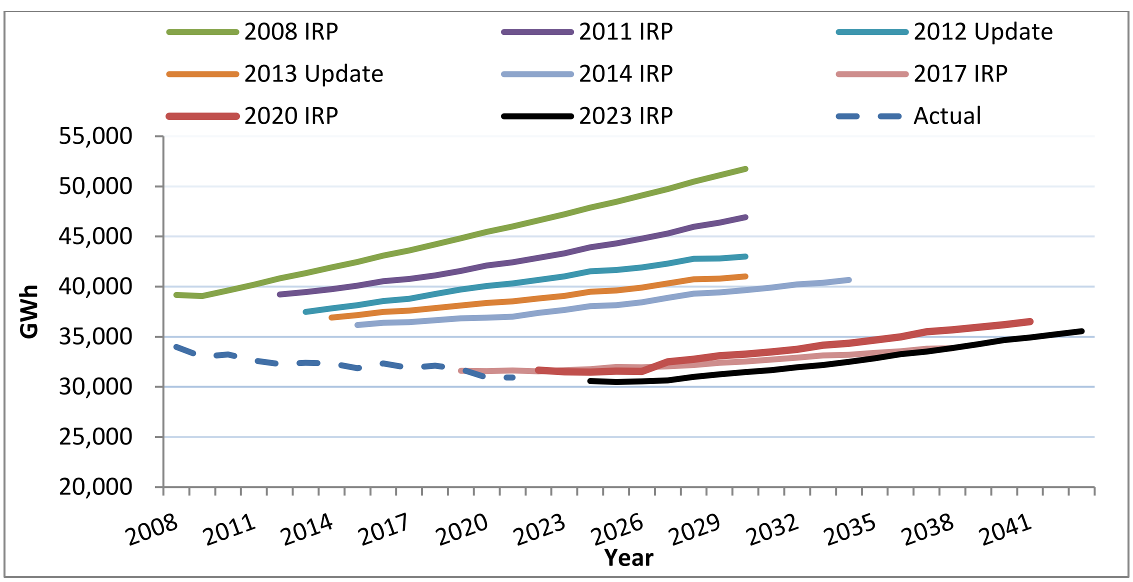


Forecasts[10]

IRP rule 20 CSR 4240-22.030(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.

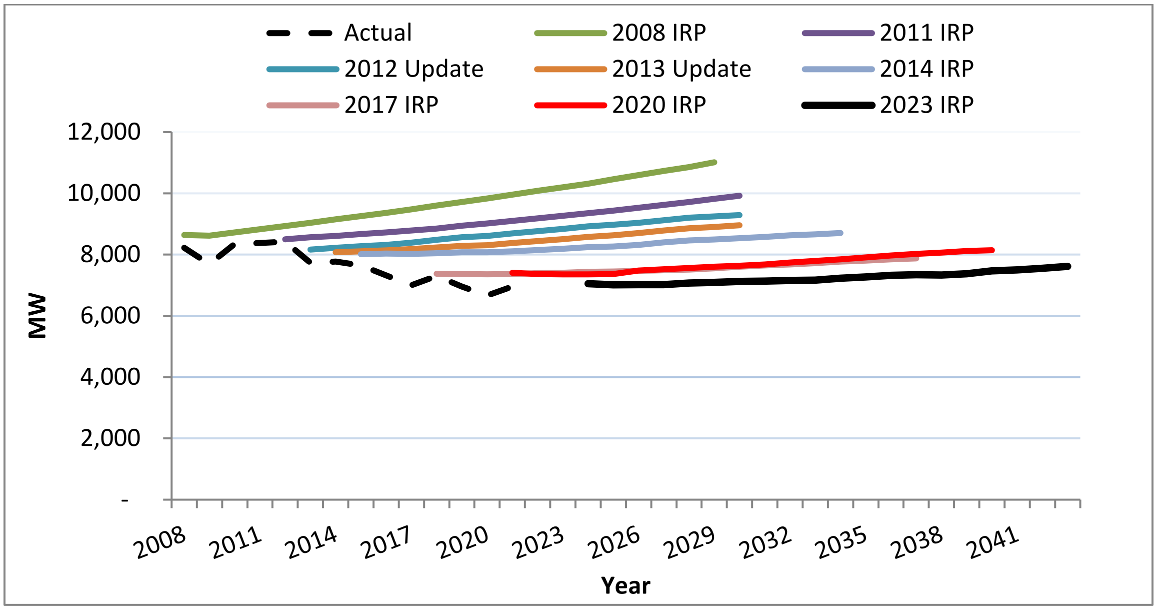
Figures 3.2 and 3.3 below show previous forecasts of energy and peak demand, including those for the 2008 IRP, 2011 IRP, 2012 Update, 2013 Update, the 2014 IRP, the 2017 IRP, the 2020 IRP, the 2023 IRP, and actual historical values. The data from these charts will be presented in tabular form in the final filing.

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



[10] 20 CSR 4240-22.030(6)(C)4

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 programs 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 reduces both the energy and peak forecast. Ameren Missouri's base case forecast reflects ~700 MW of installed customer owned solar generation capacity within its terrirtory by 2043. Finally, past IRP forecasts included sales to one of the largest aluminum smelting facilities in the country at the time amounting to more than 10% of annual sales when the customer operated at its full capacity. Ameren Missouri no longer serves this customer. This customer was the only entity in the Large Transmission Service class and hence, forecasts pertaining to Large Transmission Service class have been excluded in the forecast scenarios developed for the 2020 IRP. Sales and peak demand in the 2023 IRP also saw a decrease due to the COVID-19 pandemic. Sales in 2020 decreased by ~3% compared to 2019, and have not yet fully recovered to pre-pandemdic levels. Sales are not expected to return to 2019 levels until 2029.

Based on a state wide study conducted by EPRI, Ameren Missouri has also assumed a significant increase in the adoption of electric vehicles and efficient electrification of end uses in its territory over next 20 years. Adoption of such technologies is assumed to increase at an annual rate of approximately 22% over the planning horizon.

3.1.3 Service Territory Economy

The Ameren Missouri electric service territory is comprised of 59 counties primarily 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.

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 several nationally known financial firms, including Wells Fargo and Edward Jones.

Figure 3.4: U.S. and Missouri Population Change

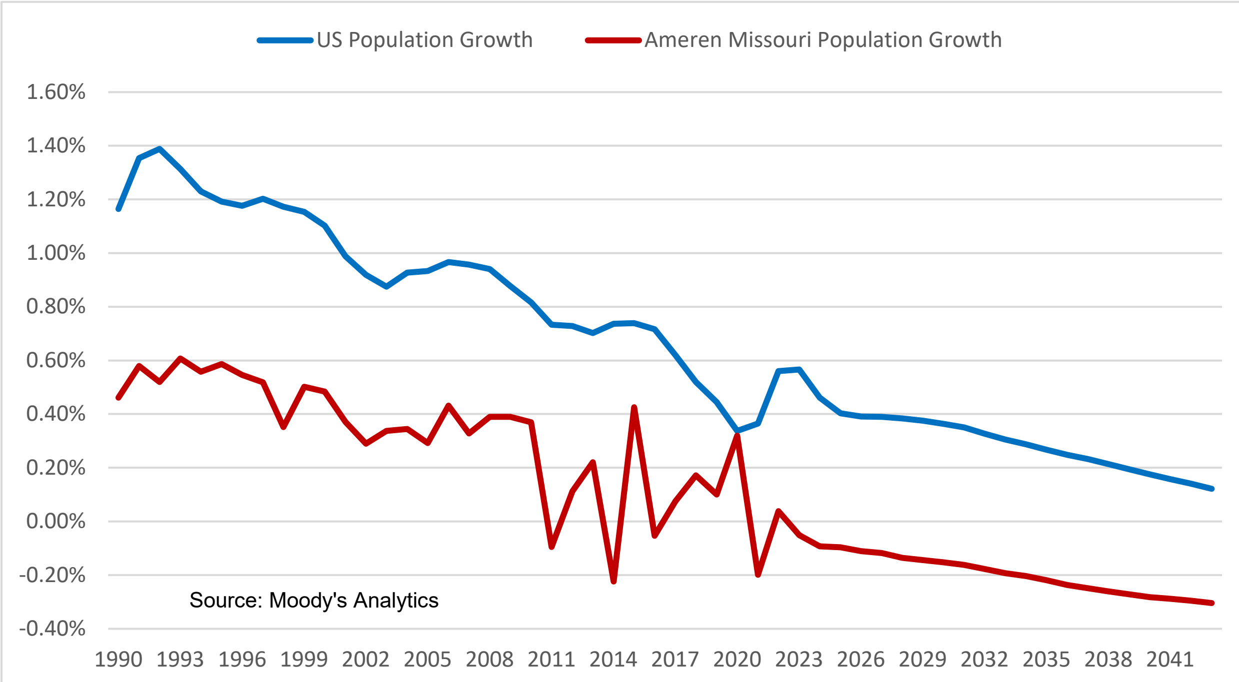


Figure 3.5: U.S. and Ameren Missouri Service Territory Employment by Industry

Source: BLS, Moody's Analytics

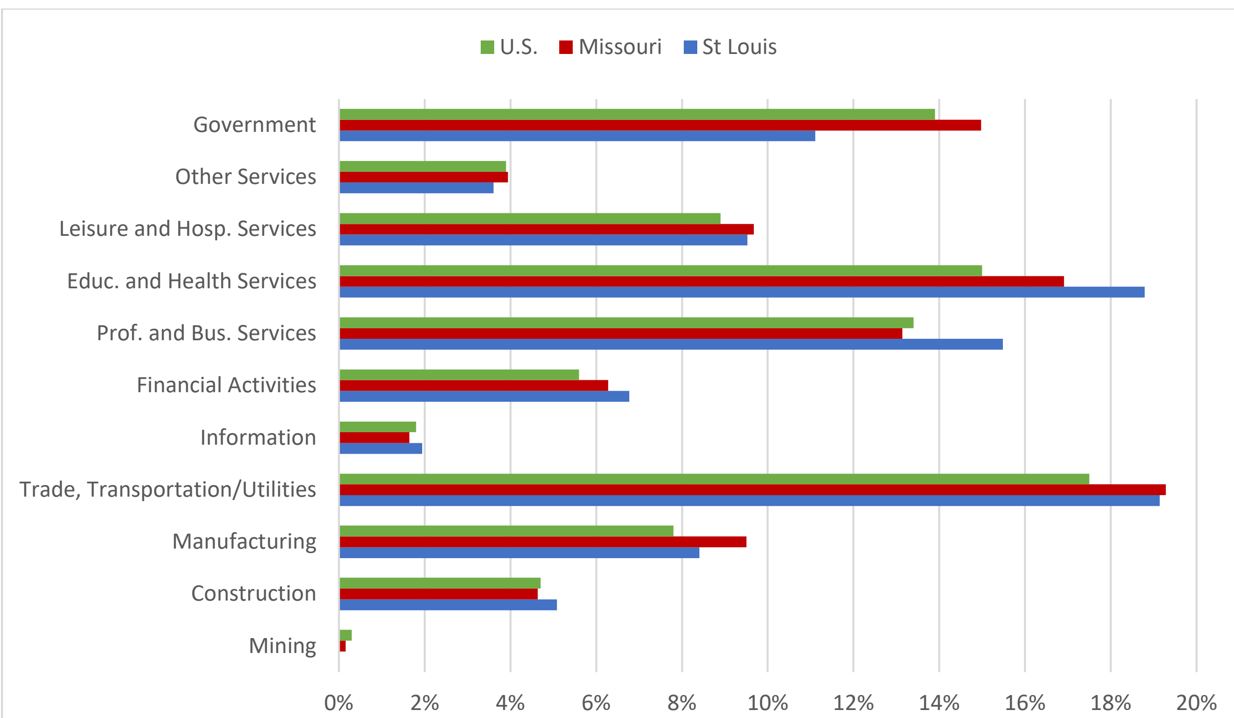


Table 3.1: Major Employers in Ameren Missouri Service Territory

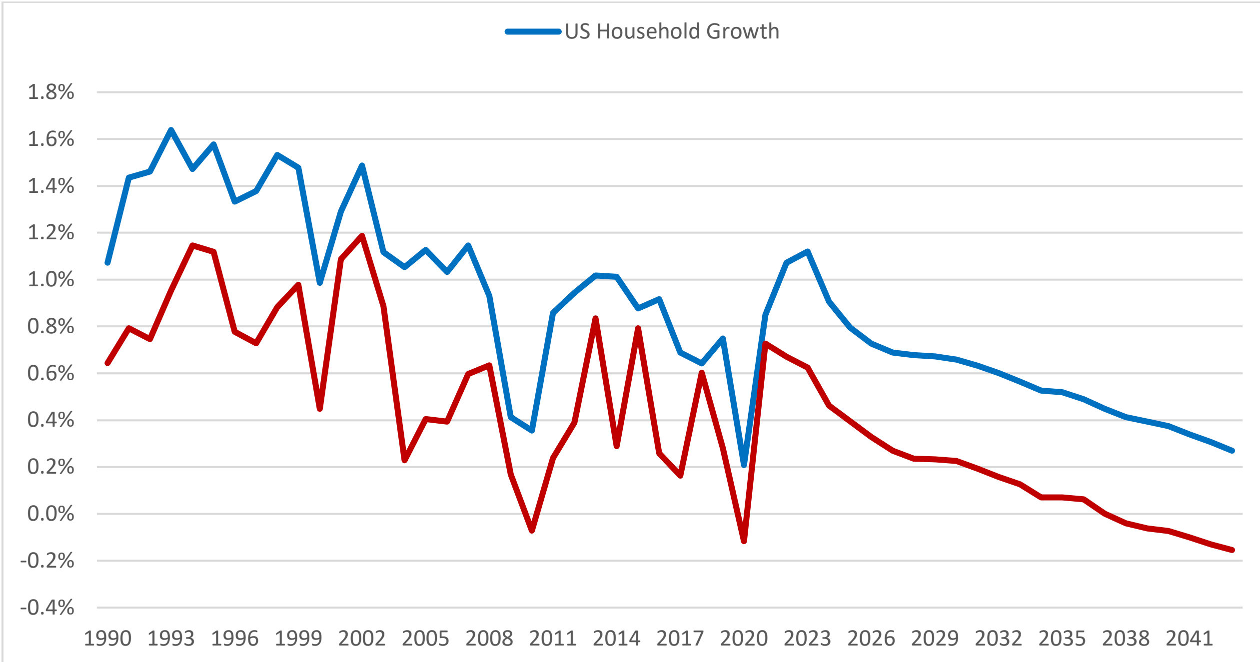
Rank	Employer	Industry	Number of Employees
1	BJC Healthcare	Education or Health Services	28,516
2	Mercy Health Care	Education or Health Services	23,011
3	Wal-Mart Stores, Inc.	Retail Trade	22,290
4	Washington University in St. Louis	Education or Health Services	17,442
5	Boeing Defense, Space & Security	Boeing Defense, Space & Security	14,566
6	SSM Health Care System	Education or Health Services	13,500
7	Scott Air Force Base	Federal Government	13,000
8	Archdiocese of St Louis	Other Services	10,460
9	Schnuck Markets Inc.	Retail Trade	9,956
10	AT&T	Information	9,000
11	McDonald's Corporation	Retail Trade	7,550
12	St Louis University	Education or Health Services	7,311
13	Washington University Physicians	Education or Health Services	7,222
14	Edward Jones	Financial Activities	6,100
15	Imo's Pizza	Retail Trade	5,515
16	Enterprise Holdings	Trans./Warehouse/Utilities	5,500
17	Express Scripts Inc.	Financial Activities	5,323
18	Wells Fargo	Financial Activities	5,000
19	Walgreens	Retail Trade	4,740
20	Target Corp.	Retail Trade	4,675

Source: Moody's Analytics

Since the great recession of the past decade, Ameren Missouri's service territory economy continued to recover in a manner like 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 like that of the U.S. but is below the blue line for the U.S. GDP growth.[11] During 2020, GDP saw a decrease due to the COVID-19 Pandemic, but GDP saw a recovery in 2021 after the government started lifting COVID-19 restrictions.

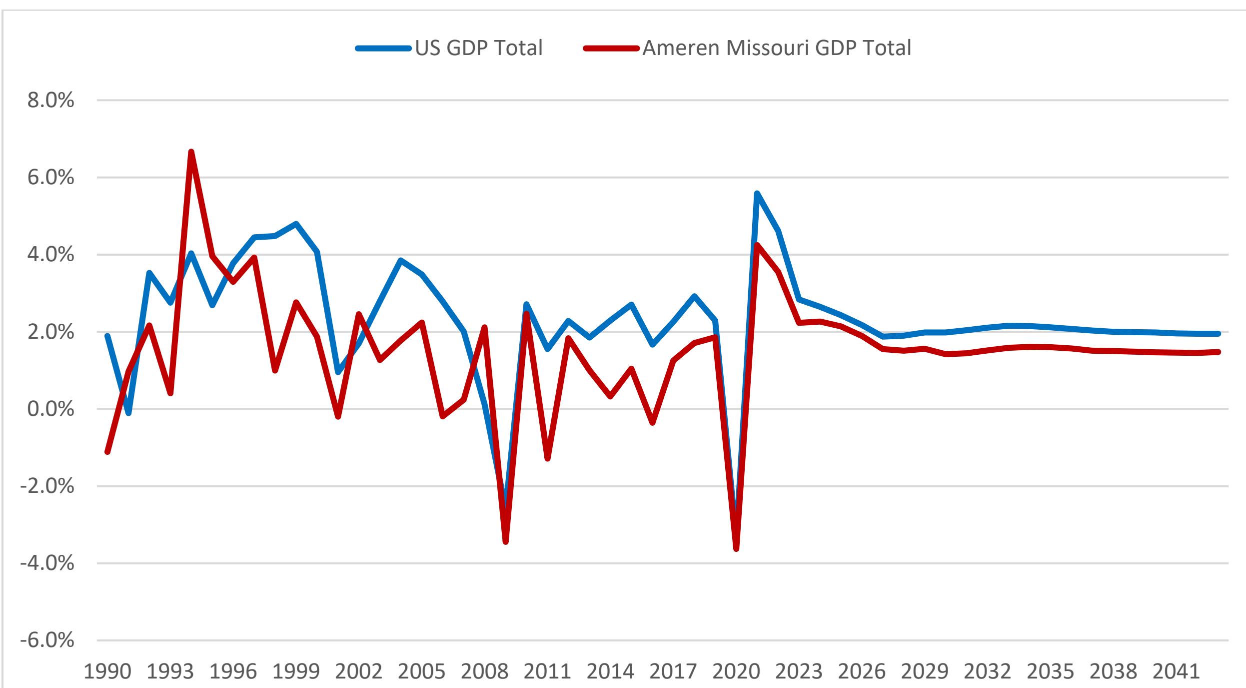
[11] 20 CSR 4240-22.030(7)(B)3

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



Source: Moody's Analytics

Figure 3.7: U.S. and Service Territory GDP Growth[13]



[12] 20 CSR 4240-22.030(2)(D)3
[13] 20 CSR 4240-22.030(2)(D)3

3.1.4 Economic Drivers

Several economic indicators were used as independent variables (independent variables in the forecasting models are often referred to as “drivers") in our energy forecasting process.[14]

- 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.[15]
- 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 six sectors of the economy were used as drivers. Those six sectors were Retail Trade, Information Services, Financial Services, Education/Health Services, Leisure, and Other Services, and these six sectors account for almost all 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.[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. Moody’s Analytics' 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]

[14] 20 CSR 4240-22.030(5)(A)
[15] 20 CSR 4240-22.030(6)(A)1A
[16] 20 CSR 4240-22.030(6)(A)1B
[17] 20 CSR 4240-22.030(7)(B)1; 20 CSR 4240-22.030(7)(B)2

Table 3.2 Growth Rates of Selected Economic Drivers

	2024-2043 Compound Growth Rate
Households	0.10%
Population	-0.21%
Real Personal Income	3.70%
GDP Retail	1.68%
GDP Info	2.60%
GDP Financial	1.22%
GDP Education /Health	1.92%
GDP Leisure	1.81%
GDP Other Services	-0.24%
GDP Total	1.56%
GDP Manufacturing	1.84%
Employment Total	0.00%
Manufacturing Employment	-1.11%

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.

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,[18] even if the changes are not present in observable history. In a traditional econometric model, it can be difficult

[18] 20 CSR 4240-22.030(5)(C)

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.[19] 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[20] was developed by Itron, a consulting firm Ameren Missouri has worked with for many years, and implemented by Ameren Missouri forecasting personnel.[21] 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's (primary and secondary), freezers, dishwashing, clothes washing, clothes drying, television, lighting, and miscellaneous.[22] 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 small devices for which gathering accurate historical appliance stock data beyond what Itron has analyzed from the EIA would be challenging at best.[23] Also, as discussed later in this chapter, self-generation resulting from solar photovoltaic systems is treated essentially as a negative end use and modeled explicitly in the load for each class.[24] Similarly, electric vehicle charging and other types of efficient electrification were considered as end use, contributing additional load. For the commercial class, the end uses are heating, cooling, ventilation, water heating, cooking, refrigeration, lighting, office equipment, and miscellaneous.[25] 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.[26]

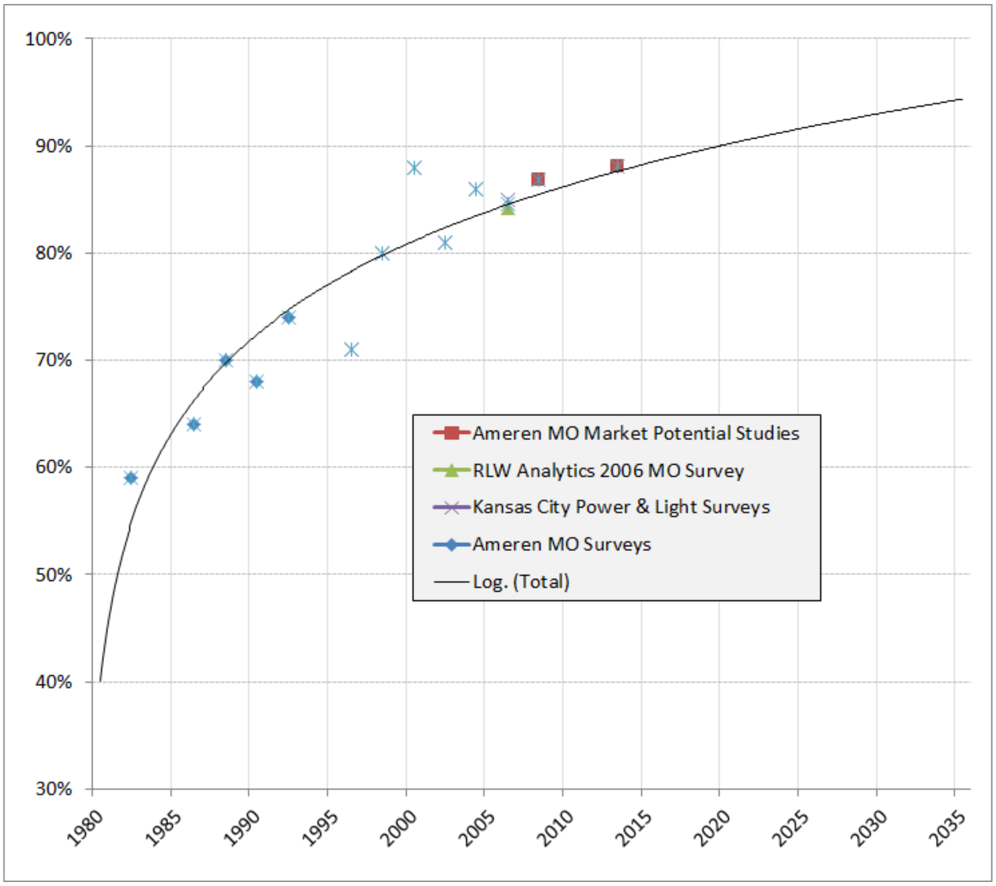
[19] 20 CSR 4240-22.030(5)(B)
[20] 20 CSR 4240-22.030(6)(B)
[21] 20 CSR 4240-22.030(6)(A)3
[22] 20 CSR 4240-22.030(4)(A)1A
[23] 20 CSR 4240-22.030(4)(A)2A
[24] 20 CSR 4240-22.030(4)(A)2B
[25] 20 CSR 4240-22.030(4)(A)1B
[26] 20 CSR 4240-22.030(4)(A)2C

To predict future changes in the efficiency of the various end uses for the residential class, Ameren Missouri relied on analysis of EIA's Annual Energy Outlook forecast performed by Itron and the past Market Potential Studies. 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.[27] 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 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 Ameren's market potential study focusses 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.[28] 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 to fully develop them across more years.

[27] 20 CSR 4240-22.030(7)(A)2
[28] 20 CSR 4240-22.030(4)(B)1

Figure 3.8: Air Conditioning Saturation, Survey Data Points and Fitted Curve[29]



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 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

[29] 20 CSR 4240-22.030(2)(D)3

of all of the best information available and resulted in what is almost certainly a more accurate representation of the Ameren Missouri customer base than the regional EIA data. Figure 3.8 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 and at least 95.5% in 2043.

At the time of this forecast work, Ameren Missouri's market potential study was being conducted. After successful implementation of energy efficiency programs under MEEIA since 2012, it is expected to have higher saturation of certain end use stocks such as air conditioners. Since the study results were not available at the time of this forecast work, this forecast partially relied on the previous market potential studies.

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 with respect to price and income are determined exogenously and included in the calculation of the independent variables.[30] 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.[31]

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.[32] The price elasticity in the base case load growth

[30] 20 CSR 4240-22.030(7)(A)1; 20 CSR 4240-22.060(4)(D)
[31] 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.
[32] Differences between the base, high, and low load growth scenarios are discussed in section 3.1.6

residential model is -0.13. This is similar to the elasticity values used in prior Ameren Missouri IRPs.

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

The functional framework of the SAE model is:[33]

$$Use\ per\ customer = B1 * ((cooling\ use) * (cooling\ index)) + B2 * ((heating\ use) * (heating\ index)) + B3 * ((other\ use) * (other\ index))$$[34]

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 and 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 44.01, 51.42, and 45.89 respectively. The residential model also included an additional interaction variable

[33] 20 CSR 4240-22.030(6)(A)2
[34] 20 CSR 4240-22.030(4)(A)4

between xCool and Shoulder months. T-stat for this interaction variable is ~-2.00. The adjusted R-squared for that model is 0.98 with Mean Absolute Percentage Error (MAPE) of 2.29%.

For this IRP iteration a "COVID-19" variable was added to the SAE equation for the Residential and Commercial class. This variable was multiplied to the Heat, Cool, and Other End Uses. The variable was constructed as a binary variable and ranged from 0 to 2. A unit greater than 1 represents that load increased due to COVID-19, and a unit less than 1 means load decreased due to COVID-19. Residential load had a positive impact due to increased work from home, and Commercial had a negative impact caused by lockdowns and capacity requirements. The Covid variable is only applicable for the time March 2020 to December 2028. After 2028, Ameren Missouri assumes no impact due to COVID-19.

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

The functional form of the commercial SAE model is:

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

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, SGS, LGS, SPS, and 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. However, the industrial customers are much less homogenous. 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.[35] As additional studies are done, enough history may be developed to consider an end use approach, but the heterogeneous nature of the large industrial customers may still be an overriding factor in determining that econometric forecasts are preferable.

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

In the case of Ameren Missouri’s industrial sales data, however, that approach does not always work, so a slightly different approach was used. Price in particular is problematic because real prices trended flat to down over much of the historical estimation period of the sales models, and the period of time with price increases is largely overshadowed by the significant economic disruptions of the 2007-2009 recession. The result is that models with each factor input as standalone independent variables tend to produce coefficients for the price term that are either statistically insignificant, practically insignificant (i.e., a positive sign on the price coefficient), or both. A modification was chosen that combined price, output, and their respective elasticities into one composite independent variable.

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

[35] 20 CSR 4240-22.030(4)(A)1C; 20 CSR 4240-22.030(4)(A)3

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

Price, output, and their elasticities were combined into one term. As was the case with the SAE residential and commercial models, estimating elasticity was a challenge, because estimates of elasticity in electricity consumption vary widely. Initial elasticities were chosen that reflected a mid-point of estimates from the literature. Through an iterative process elasticities were chosen that minimized the MAPE 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 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 and 2017 IRPs, Ameren Missouri's DSM programs under the MEEIA were relatively new. 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 for the 2023 IRP was to "add back" the savings from the programs to the observed loads and create time series of dependent variable in the forecast models.[36] The forecast models were then executed based on the reconstituted loads (dependent variable). The estimates of the savings associated with historical programs are deducted from the forecast model outputs to create the future load projections. This approach makes sense in that the SAE end use driver variables were based off 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.

It should also be noted that the anticipated savings of Ameren Missouri's third cycle of energy efficiency programs under the MEEIA programs 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, and therefore these savings are

[36] 20 CSR 4240-22.030(6)(C)2

considered as a given that they will occur. All future DSM impacts beyond MEEIA cycles 2 and 3 (i.e., programs approved for implementation through December 2023) are excluded from the base forecast and are the subject of the DSM chapter of this IRP study.

Other Forecasting Considerations – Weather[37]

As in the past IRP forecasts, SAE models are typically built using three explanatory variables representing cooling, heating and other loads. However, for some classes, an additional explanatory variable was added to some of the models 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 additional explanatory variable is constructed as interaction between month/season and one of the three primary variables in SAE model construction. This is especially applicable in a class where some subset of customers start cooling at one temperature, but another subset does so at a higher temperature. This additional term in the forecast equation captures these seasonal and non-linear weather effects. Additionally, the degree day break points are evaluated to ensure best model fit to the weather and load relationships. 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. For the 2023 IRP, Ameren Missouri used a normal weather definition based on the years 1992-2021.

Table 3.3 Degree Day Break Points Used in Energy Modeling

Class	HDD	CDD
Residential	60	65
ComSGS	50	60
ComLGS	50	60
ComSPS	50	50
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 especially with incentives mandated in SB 564. 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 drove a rapid increase in solar installations in recent years. The total amount paid for

[37] 20 CSR 4240-22.030(5)(A); 20 CSR 4240-22.030(2)(D)2

rebates were subsequently capped by regulatory agreement. In this forecast, we assumed that solar installations would continue at their current pace until 2024, 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 to increase at a compound annual growth rate of approximately 8.6% between 2024 and 2043 (base case scenario). In this case, the cumulative installed customer-owned solar capacity is expected to reach approximately 145 MW in 2024, if SB 564 mandated rebates are fully subscribed and 700 MW by 2043 in Ameren Missouri's territory. The high load growth scenario assumes low adoption of customer owned solar (approximately 350 MW of cumulative installed customer owned solar capacity by 2043), and the low load growth scenario assumes high adoption of customer owned solar (approximately 1,400 MW of cumulative installed customer owned solar capacity by 2043) (Figure 3.9).

Figure 3.9: Cumulative Installed Private Solar (MW)

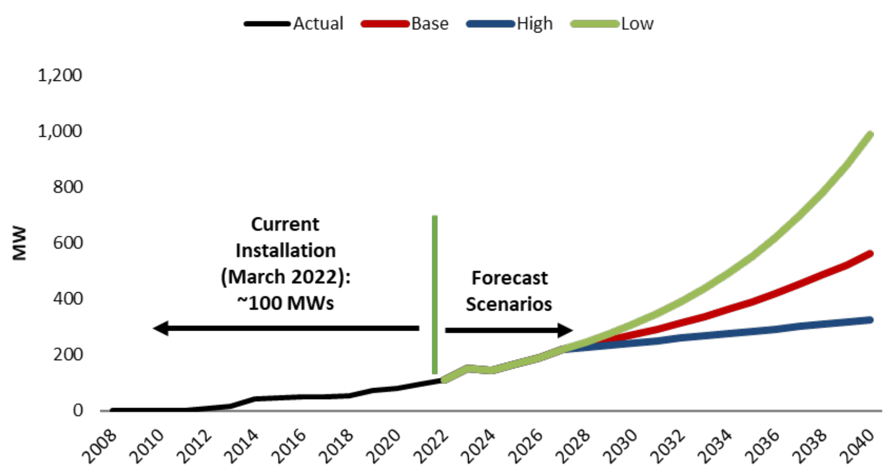
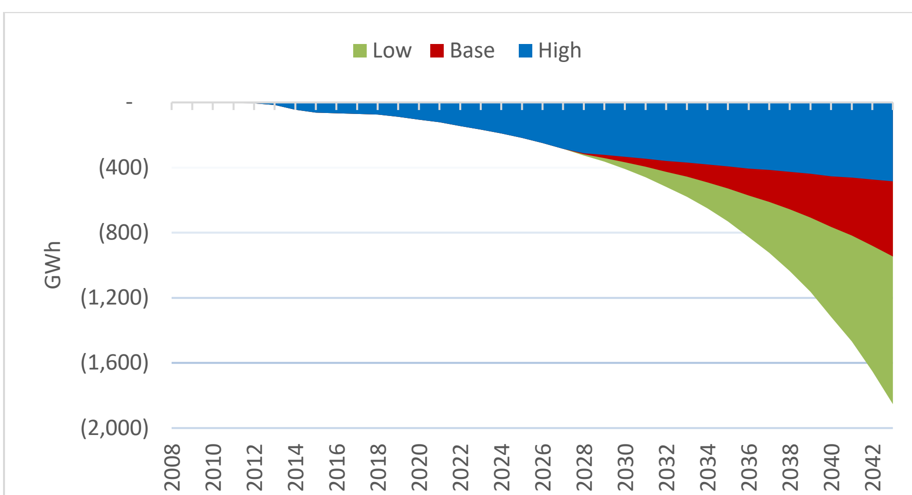


Figure 3.10: Cumulative Energy Reduction due to Solar Adoption (GWh)



Other Forecasting Considerations – Efficient Electrification[38]

At the time of the IRP 2020 publication, Ameren Missouri worked with EPRI to identify cost-effective and resilient strategies to produce and use clean energy. The two year work plan laid out research to identify efficient electrification opportunities in Missouri and specifically in Ameren Missouri's service territory. Based on this detailed statewide study, EPRI provided an initial estimation of potential impacts of efficient electrification on various end uses. This forecast includes projections of additional energy consumption from efficient electrification during the planning horizon. After discussions with internal EPRI members, it was concluded that the 2020 study was still valid for the 2023 IRP. Ameren Missouri's load forecast for the 2023 IRP incorporates the results from the 2020 study for the base and low load growth assumptions along with its current business targets for the years 2024 to 2027. For the High load Growth Scenario, the EPRI forecast was modified to include a larger EV adoption rate. The High load scenario now assumes by 2050 all 2.5 million vehicles in Ameren Missouri's service territory will be Electric. A brief description of the scope of the 2020 EPRI study has been provided below.

The EPRI study consisted of four tasks: Energy System Assessment, Environmental Assessment, High-level Transmission Assessment, and Electrification Potential and Implementation Plan. Additional details for each task are provided below.

- ***Task 1: Energy System Assessment (2020-2050)***

The U.S. Regional Economy, Greenhouse Gas, and Energy (US-REGEN) modeling system has been adapted in this task to conduct an integrated analysis of potential development paths for the energy system in Missouri.[39] US-REGEN has a national scope with flexible regional disaggregation based on state or sub-state-level data. US-REGEN combines a detailed capacity expansion and dispatch model of the electric sector with a detailed end-use model that includes a high resolution of economy-wide energy use, as well as a representation of upstream non-electric energy activities. For each scenario evaluated, the electric model is solved out to 2050, in five year time steps, to meet electric load at lowest economic costs. The end-use model is solved over the same time horizon, with iteratively updated electricity prices and hourly load shapes based on the changing end-use mix. A version of the model that evaluates Missouri as one of the 16 regions is being used to evaluate a series of Ameren-specified scenarios.

- ***Task 2: Environmental Assessment (2020-2050)***

US-REGEN outputs include projections of greenhouse gas (GHG) emissions namely carbon dioxide (CO_2) and methane (CH_4) and air pollution from the energy system. Estimated energy system CO_2 and CH_4 emissions changes include emissions associated with fossil resource energy development, extraction, distribution, and use. Changes in air

[38] 20 CSR 4240-22.030(7)(A)5
[39] US-REGEN Model documentation: http://eea.epri.com/models.html

emissions will be estimated for each scenario broken down by sector and geography to illustrate how electrification strategies could impact emissions over time and space.

Detailed air quality modeling is being conducted for the U.S. lower-48 to explore the implications of a set of high electrification and low electrification scenarios. The air quality analysis includes economy-wide emissions of air pollutants—including SO_2, NO_x, VOC, NH_3, CO and primary particulate matter—which are calculated by the US-REGEN model and examines the implications for ozone, PM2.5 and other air quality measures.

- ***Task 3: High Level Transmission Assessment (2020-2050)***

The results from Task 1, Energy System Assessment (supply side), details on the electric sector power generation mix and capacity, and demand side changes to overall energy demand and load shapes across the end-use sector of buildings, industry, and transportation form the basis of the high-level transmission assessment in Task 3. The transmission assessment will focus on enhancing the safety, reliability, and resiliency of bulk power and distribution system infrastructure consistent with the achieving the goals defined in the analysis scenarios.

The assessment in this task was conducted to understand the qualitative impacts on transmission needs in the state with particular attention to the following:

a) Assessment of potential ability of the system to incorporate increased loads based on knowledge of existing system
b) Description of operational implications of new loads and the new system resources required to meet those loads
c) Guidance for utility internal follow-up study of these issues

- ***Task 4: Electrification Potential and Implementation Plan***

Incorporate the state-level results from Tasks 1, 2, and 3 into strategic, utility-specific guidance for the implementation of electrification programs to realize the economic and environmental benefits projected in the state-level analyses. This included energy technology assessments over the industrial, commercial, residential, and transportation sectors covering both energy-efficiency achievable potentials and opportunities for electrification. The final analysis includes: a utility-specific assessment of electric technologies, location-specific and across all customer classes, and a strategic vision and assessment for near- and long-term emerging technologies and their benefits and impacts. The resulting Customer Electrification Potential Model is used to guide near term program design as well as long-term strategic planning. The model is designed to incorporate other relevant data from prior analyses conducted by Ameren Missouri.

Ameren Missouri's Customer Electrification Potential Model incorporates the best available data, organized by:

- Technology categories within the four customer classes

- Locational distribution of key technologies within the utility service territory
- Projected adoption of both current and emerging technologies from present day to 2050

The Technology Pipeline will be updated over time to include detailed analysis for technologies with high impact and high potential to deliver customer and societal benefits across the timeframe of the project, including:

- Evaluation of Electric Technology Characteristics: Changes in cost and performance over time; identification of energy and non-energy benefits
- Detailed analysis for high-impact, high-potential technologies, including:
    - Electric transportation (light, medium, and heavy-duty), material handling, airports, and rail and other transit terminals.
    - Residential and commercial space and water heating.
    - High impact industrial electrification opportunities.
    - High impact emerging technologies: Indoor agriculture, additive manufacturing, and others.
- Strategic vision and assessment for near and long-term emerging technologies and their benefits and impact.
- Detailed System Impact: Hourly load shapes developed for each technology. Assessment of customer and grid flexibility for each technology.

Implementation scenarios will be prioritized for utility specific opportunities and customer requirements, and will continue to leverage existing EPRI tools, including the Electrification Knowledge Base and the Technology Readiness Guide.

Projected increases in load from electrification for Ameren Missouri were estimated using the US Regional Economy, Greenhouse Gas, and Energy Model, an energy-economy model developed and maintained by the Electric Power Research Institute. US-REGEN analyses were the basis of the EPRI's U.S. National Electrification Assessment (USNEA), which explored the potential for efficient electrification across the U.S. for four core scenarios – two with and two without federal climate policy. Utilities in 14 states are conducting electrification assessments with the model. A central feature in the USNEA and in the runs made for Missouri is the assumption that customers have free choice to choose the technologies – electric or non-electric that make the most sense to them.

There are three cases defined for the Ameren Missouri IRP: The Low, Base and High Electrification scenarios. All use the same basic structure for the models as discussed earlier, but make changes to the input assumptions. The Low and Base case scenarios assume a low forecast of natural gas prices (developed by Ameren Missouri) and zero carbon price. In the High Electrification case, high natural gas price is used, as well as a countrywide, economy-wide carbon price. Additionally, for the Low Electrification case, the share of electric vehicle (EV) and other electrification is restricted to grow at a constant rate. In the base case, a $5,000 cost adder is added to the estimated future cost of electric vehicles, to account for the fact that battery prices may not fall as fast as EPRI projections. In addition, the study had assumed that autonomous vehicles are not developed. Finally, the High Electrification case uses the default assumptions from the EPRI NEA (except for Ameren Missouri's gas and CO_2 prices). The imposition of an economy-wide carbon tax tends to increase electrification, however, in some sectors, electrification decreases between the Base and High cases, because the much higher deployment of electric vehicles, fueled by the relative decrease in EV costs between the two scenarios as well as the economy-wide carbon price increases the cost of electricity, which reduces the incentive to electrify in other sectors. In order to ensure that the High Electrification case represents a true maximum potential for electrification, each sector's maximum load from across all the scenarios is used to construct the electric load in the High Electrification case. For the 2023 IRP, the team further increased EV adoption in the High Electrification case to show expected electrification if the region were on track to fully electrify on-road vehicles by 2050.

Other Forecasting Considerations – Electric Vehicle Adoption[40]

The IRP 2023 electrification forecast combines the current business plan and long term efficient electrification potential estimates from EPRI. All three scenarios utilize Ameren Missouri's internal five-year budget electrification projections through 2027. Beyond 2027, the low adoption scenario bypasses the economic choice mechanism in US-REGEN and assumes that the share of electric vehicles continues to increase at recent historical rates. The medium adoption scenario assumes that the purchase price of electric vehicles does not decline as rapidly as in the default assumptions, and the high electrification scenario has default assumptions and also assumes the Ameren Missouri service territory is on track to see full electrification of all 2.5 million on road vehicles by 2050. Figure 3.11 shows the projected share of electric vehicles from 2024-2043 in terms of total on road vehicles.

[40] 20 CSR 4240-22.030(7)(A)5

Figure 3.11: Shares of Electric Vehicles by Number of Vehicles

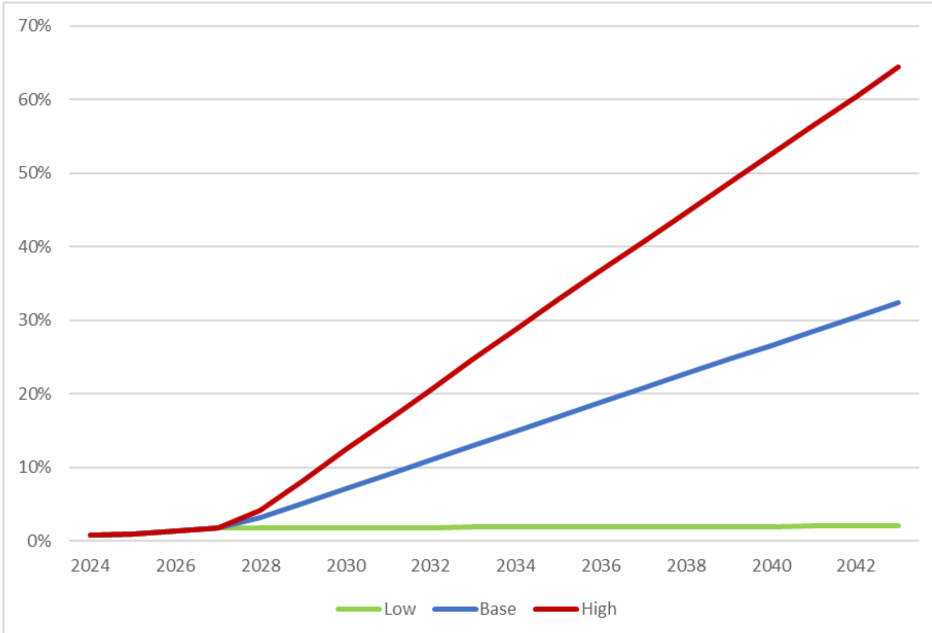


Figure 3.12 shows long term electrification projections used in different load forecasting scenarios. Figure 3.13 shows long term load growth projection from light duty electric vehicles adopted for residential and commercial classes.

Figure 3.12: Long-term electrification projection

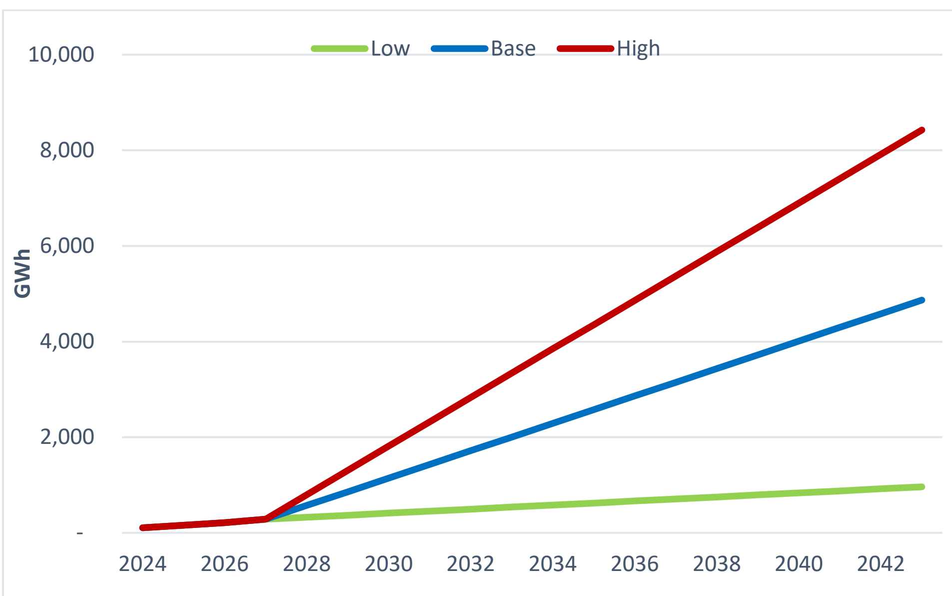
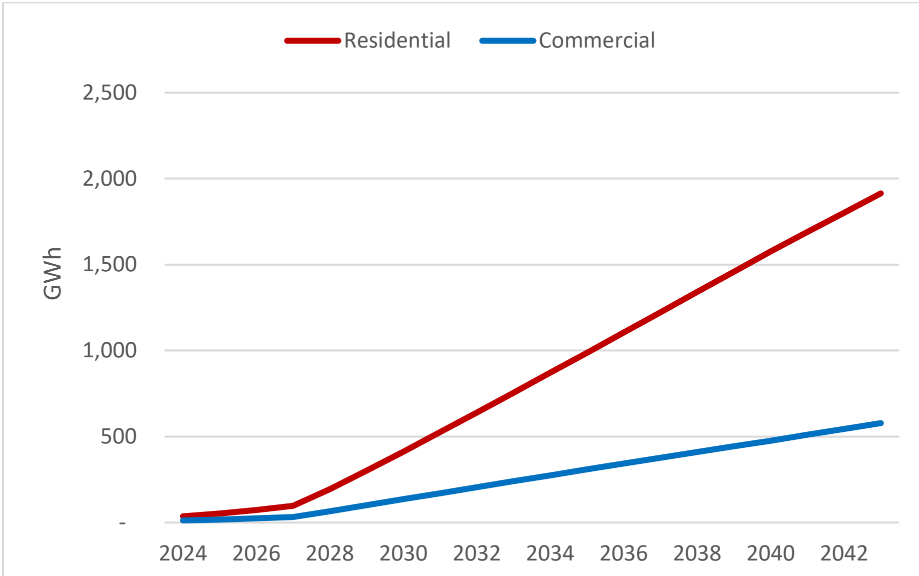


Figure 3.13: Long-Term Load Growth from Electric Vehicle Adoption in Base Case Scenario



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 such as time of the year. With the adoption of LED technologies, sales in the lighting categories are expected to decline. Hence, the projected sales in lighting categories are modeled as a function of the light bulb replacement with LED technologies along with a seasonal shape. This forecast assumes that all the streetlights will be replaced with LED by 2027.

Ameren Missouri's current business plan dictates to replace lightbulbs once they stop functioning and therefore, there is no pre-determined schedule for the LED installations. It's assumed that the annual kWh reduction due to LEDs will be similar year over year. Therefore, this forecast utilizes the kWh reduction in annual kWh sales in lighting classes from April 2021 to March 2022. After the annual reduction in lighting load was established, a monthly shape was applied to derive the monthly energy for the lighting classes.

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.[41] The customer

[41] 20 CSR 4240-22.030(3)(A)

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[42]

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. While the renewable generation forecasts were based on discussions with Ameren subject matter experts, the electrification projections were developed in consultation with EPRI. The scenario development process is discussed in Chapter 2.

In order to forecast high, base and low load growth scenarios, Ameren Missouri forecast team first developed energy forecast for various classes without including long-term projections of customer owned renewables and efficient electrification of end uses as described in previous sections.This added with various levels of customer owned renewables and efficient electrification provided base, high and low load growth forecast scenarios. Table 3.4 summarizes the key assumptions used to develop base, high and low load growth scenarios. In all the cases, the forecasts remain the same until 2027 and changes after that due to changing assumptions on solar and electrification to create different scenarios.

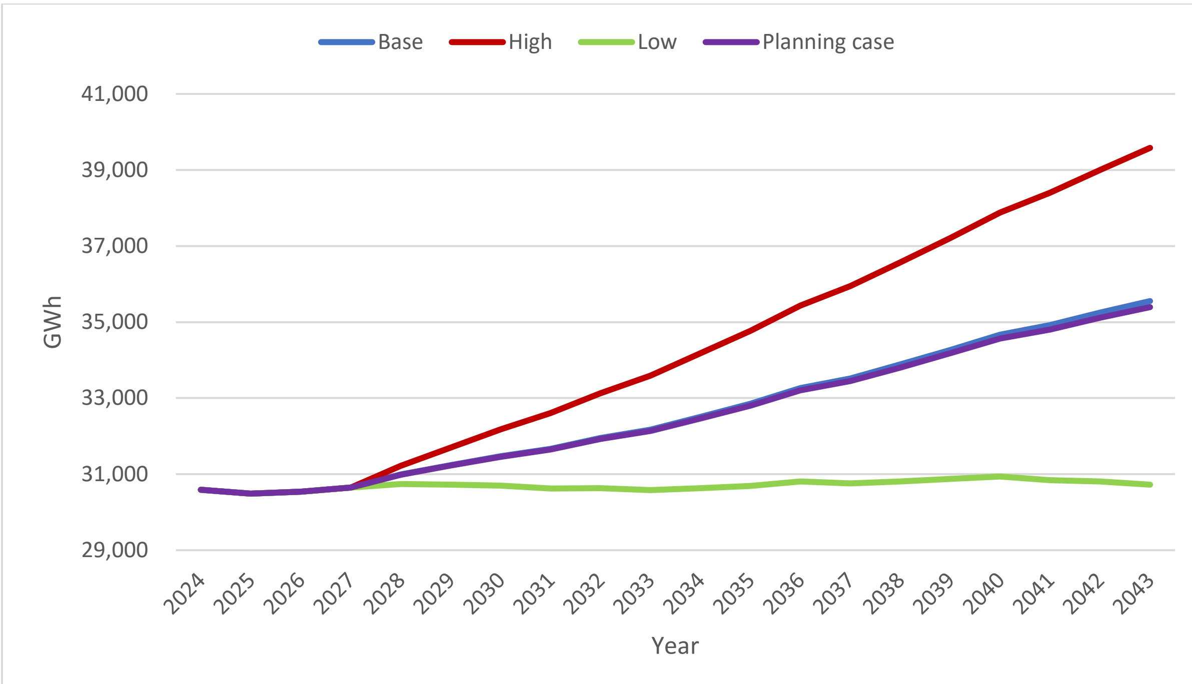
[42] 20 CSR 4240-22.030(8); 20 CSR 4240-22.030(8)(A)

Table 3.4: Scenario Driver and Parameter Differences

	High Load Growth Assumptions (Low Solar and High Electrification)	Base Load Growth Assumptions	Low Load Growth Assumptions (High Solar and Low Electrification)
Res	• Solar adoption (20 year CAGR): 5.7% • EV adoption (20 year CAGR): 28.2%	• Price elasticity: -0.13 • Household size elasticity: 0.20 • Income elasticity: 0.40 • Solar adoption (20 year CAGR): 9.5% • Electrification (20 year CAGR): 23.2%	• Solar adoption (20 year CAGR): 13.4% • EV adoption (20 year CAGR):13.1%
Com	• Solar adoption (20 year CAGR): 4.1% • Electrification (20 year CAGR): 26.0%	• SGS Output 0.30, Price -0.17 • LGS Output 0.06, Price -0.11 • SPS Output 0.19, Price -0.06 • LPS Output 0.40, Price -0.06 • Solar adoption (20 year CAGR): 7.8% • Electrification (20 year CAGR): 22.4%	• Solar adoption (20 year CAGR): 11.7% • Electrification (20 year CAGR): 12.4%
Ind	• Solar adoption (20 year CAGR): 4.9% • Electrification (20 year CAGR): 21.0%	• SGS Output 0.75, Price -0.22, Output Weight 0.15 • LGS Output 0.60, Price -0.10, Output Weight 0.70 • SPS Output 0.25, Price -0.10, Output Weight 0.30 • LPS Output 0.05, Price -0.04, Output Weight 0.90 • Solar adoption (20 year CAGR): 8.7% • Electrification (20 year CAGR): 20.8%	• Solar adoption (20 year CAGR): 12.6% • Electrification trend (20 year CAGR): 11.0%

Statistical models built with 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 3.14.

Figure 3.14: 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 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.

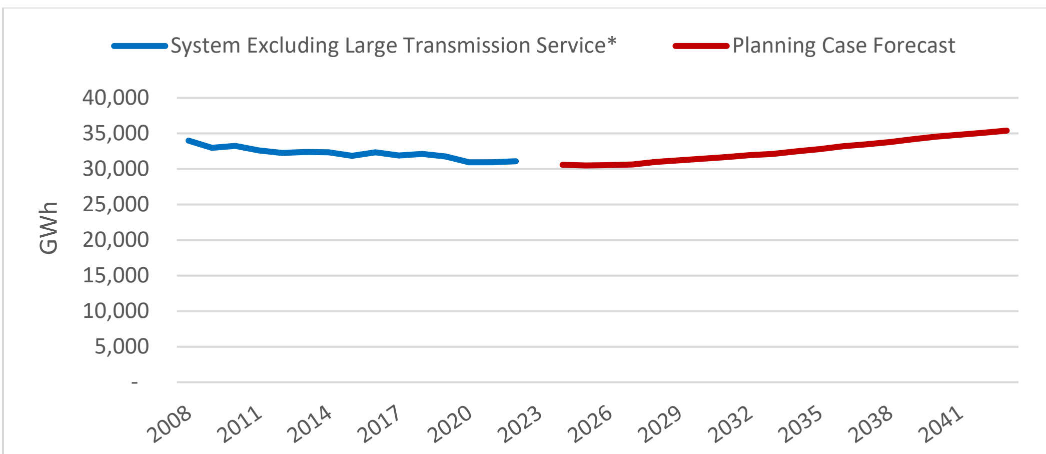
The calculation of the planning case forecast is a fairly simple exercise. The subjective probabilities of each scenario, as determined by the subject matter experts for the various uncertain factors, were used to weight the different scenarios and thus determine a probability weighted average load. 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.

For this IRP analysis, 60% probability was assigned to base case scenario and 20% probability was assigned to each of high and low growth scenarios. Planning case forecast was developed using these probability weights.

3.1.8 Forecast Results

For the planning case, total retail energy sales are expected to grow at 0.8% compound annual rate between 2024 and 2043. In the last decade, total retail sales declined primarily due to the naturally occurring and company sponsored energy efficiency programs and a decline in consumption by the aluminum smelter. 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 3 cycles through the program year ending in December 2023.[43]

Figure 3.15: Planning Case Energy Sales Forecast



**Historical sales have been adjusted to reflect that Ameren Missouri does not serve any customer in Large Transmission rate class at this time.*

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 large smelter customer, fell by 13.6%. Energy efficiency programs under MEEIA (Cycle 1, 2 and 3) 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. Over the past three years, Ameren Missouri's customer counts in residential and commercial classes have grown steadily between 0.5 and 1% year over year. However, the savings

[43] 20 CSR 4240-22.030(7)(A)3

from energy efficiency programs have diminished any sales growth achieved as a result of this customer growth. Also, after experiencing significant economic growth for past several years, Ameren Missouri's economic projections expect a slowdown in the economy in the near term. Additionally, the implementation of LED technologies in the lighting classes reduces sales to the lighting categories significantly over four years. (Figure 3.15).

Table 3.5: Planning Case (2024-2043) Annual Sales Growth by Class

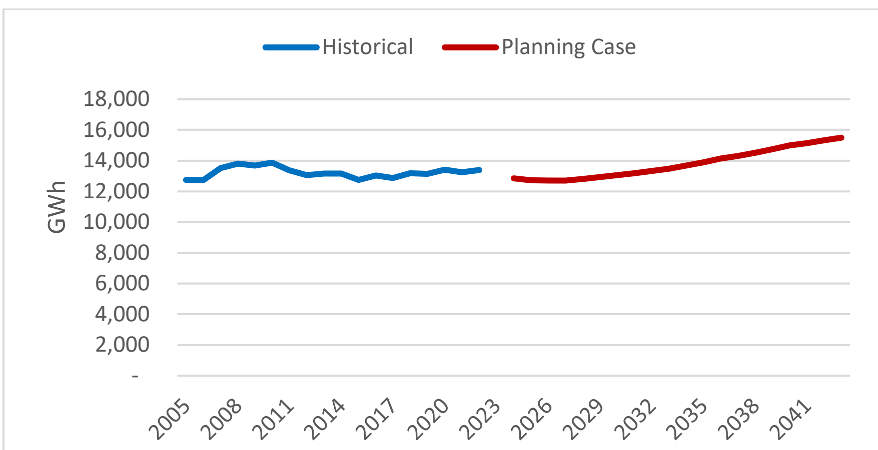
Year	Residential	Commercial	Industrial	Lighting	Total
2024	-0.6%	0.4%	0.5%	-1.8%	0.0%
2025	-1.0%	0.0%	0.7%	-1.8%	-0.3%
2026	-0.1%	0.2%	0.8%	-1.9%	0.2%
2027	0.0%	0.6%	0.9%	-1.9%	0.4%
2028	0.9%	1.0%	2.3%	0.0%	1.1%
2029	0.9%	0.3%	1.9%	0.0%	0.8%
2030	0.9%	0.2%	1.8%	0.0%	0.7%
2031	0.9%	0.0%	1.5%	0.0%	0.6%
2032	1.3%	0.3%	1.5%	0.0%	0.9%
2033	1.0%	0.1%	1.4%	0.0%	0.7%
2034	1.5%	0.5%	1.3%	0.0%	1.0%
2035	1.5%	0.5%	1.3%	0.0%	1.0%
2036	1.8%	0.6%	1.3%	0.0%	1.2%
2037	1.2%	0.1%	1.2%	0.0%	0.7%
2038	1.5%	0.6%	1.2%	0.0%	1.1%
2039	1.5%	0.6%	1.2%	0.0%	1.1%
2040	1.7%	0.6%	1.2%	0.0%	1.1%
2041	1.0%	0.1%	1.2%	0.0%	0.7%
2042	1.2%	0.4%	1.3%	0.0%	0.9%
2043	1.1%	0.3%	1.2%	0.0%	0.8%

One seemingly trivial feature of our sales modeling affecting sales growth is leap day. 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 3.15, 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, followed by the years when Ameren Missouri's energy efficiency program spending ramped up, 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 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 2005 and 2012 changed at a compound annual rate of 0.36%. 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. Customer count in residential class has been growing modestly in the past three years. Sales growth due to customer growth between 2013 and 2022 was diminished by naturally occurring and company sponsored energy efficiency programs. Residential Sales grew in 2020 by 2.0% due to the COVID-19 pandemic and an increase in telework. This trend is like the trends seen in other utilities and nationwide.

Figure 3.16: Planning Case Forecast of Residential Energy Sales



In the planning case forecast, residential load is anticipated to grow at a compound annual rate of 1.0% between 2024 and 2043.

The number of residential customers is expected to grow at a compound average rate of 0.08% between 2024 and 2043. Compared to historical standards, customer growth has been rather modest since the recovery from the recession years of 2008-2009. Ameren Missouri's residential customer count grew at a compound annual rate of 0.3% between 2009 and 2022. The forecast assumes that the residential customer count will continue the slow, yet steady growth over the planning horizon at an annual compound growth rate of 0.1%.

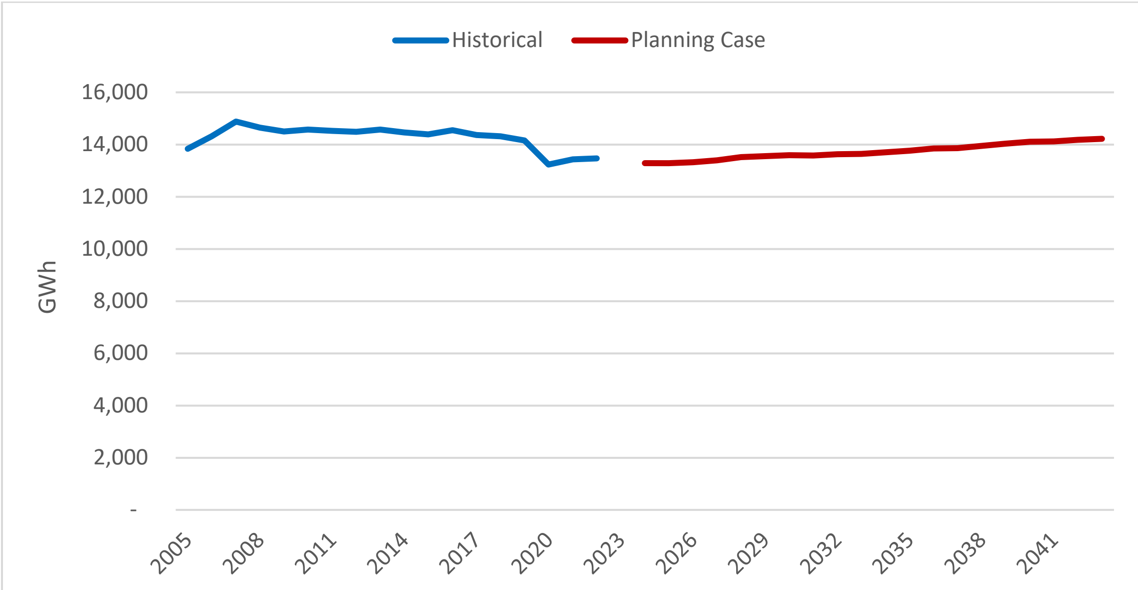
Use per customer growth in the residential class is expected to remain modestly declining for the first few years of the forecast horizon. Again, customer owned distributed energy resources, efficiency standards of appliances and MEEIA programs hold average customer consumption down during this time. 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

Prior to the COVID-19 pandemic, 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. During 2020, Ameren Missouri Commercial Sales decreased 6.6% due to remote work, government lockdowns, and capacity restrictions on businesses. Since 2020, Commercial sales have seen a recovery, but are still below 2019 levels.

Three different factors contributed to the load growth prior to 2020. 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% 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 0.4% in the planning scenario over next 20 years.

Figure 3.17: Planning Case Forecast of Commercial Class Energy Sales



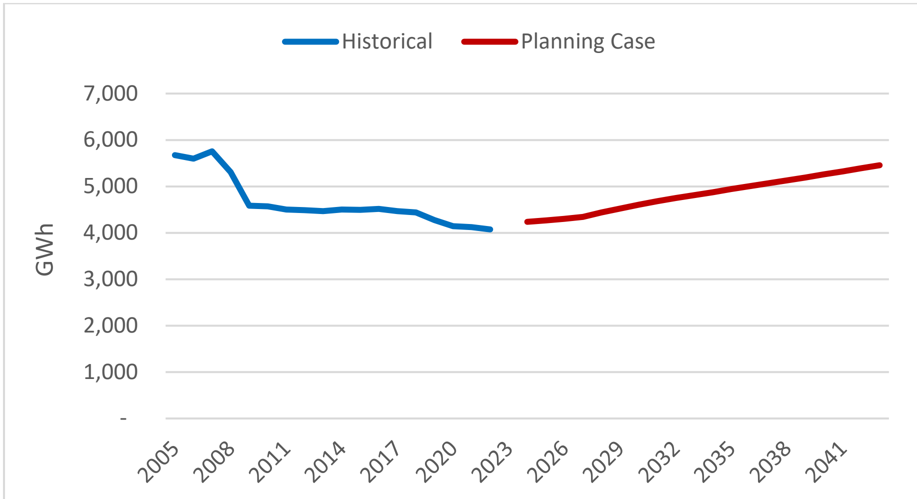
Industrial

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

Casualties of this decline in the service territory manufacturing base include the Ford Assembly plant in Hazelwood, Missouri, which closed in 2003, and the Chrysler plant in Fenton Missouri, which closed in 2010. Between 2009 and 2022, Ameren Missouri's industrial sales declined at a compound annual rate of 0.9%. Note that Ameren Missouri's largest single customer by far in the past decade, the aluminum smelter in New Madrid, Missouri, is not included in these industrial load statistics, as this customer is no longer an Ameren Missouri customer.

The planning case forecast calls for industrial sales growth at a compound annual rate of 1.3% between 2024 and 2043, primarily driven by significant potential from efficient electrification. While the overall industrial forecast is directionally positive after the long-term industrial sales decline that has been experienced in the recent years, expected growth without electrification is still flat. In fact, the forecast does not anticipate that the industrial sales will reach pre-recession levels at all during the planning horizon without efficient electrification.

Figure 3.18: Planning Case Forecast of Industrial Class Energy Sales



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 slow the growth in customer counts.

Table 3.6: Customer Growth Rates

Year	Residential	Commercial	Industrial
2009-2022	0.3%	0.7%	-1.8%
2024-2043	0.1%	0.7%	-0.2%

Lighting and Other

We anticipate reduction in energy consumption in the Dusk-to-Dawn lighting classes due to expected conversion to LED technologies. Once all the light bulbs are converted into LEDs by 2027, there is no anticipated change in the consumption level during the planning horizon. Overall compound annual growth rate (CAGR) is -0.3% in lighting classes during the planning horizon.

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.

3.2.1 Historical Peak and System Load

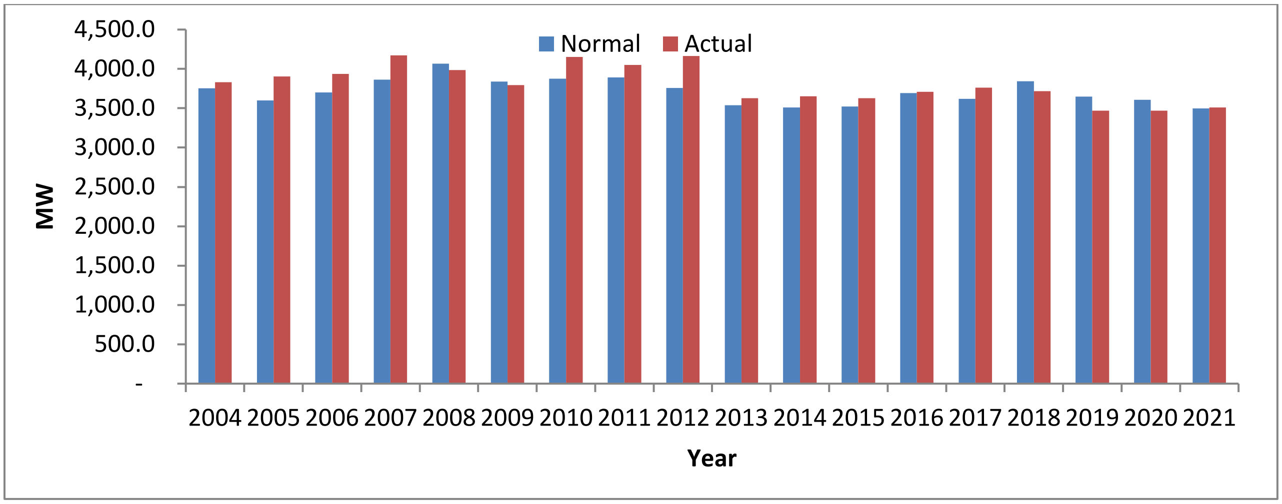
Ameren Missouri's historical database of actual and weather normalized class and system demands is maintained back to July 2003.[44] Actual hourly system data is available back to the beginning of January 2001. Earlier data for both class demands and system loads does exist, but is not applicable to 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.

[44] 20 CSR 4240-22.030(2)(B)3

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 2008 and 2021, residential class demand declined at a compound annual rate of 1.2%. The class load dropped from a weather normalized 4,065 MW in 2008 to 3,497 MW in 2021 (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 3.19: Residential Coincident Peak Demand (MW)



For the commercial class, the annual coincident peak demand declined at 0.6% per year, from a weather normalized 2,983 MW in 2008 to 2,748 MW in 2021 (at generation, i.e., inclusive of transmission and distribution losses). On an actual basis, the commercial class load reached its highest level in 2011, with an hourly integrated demand of 3,127 MW.

The industrial class annual coincident peak demand declined on a weather normalized basis from the year 2008 to 2021 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 nine years with a 2021 normalized peak load of 626 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 3.20: Commercial Coincident Peak Demand (in MW)

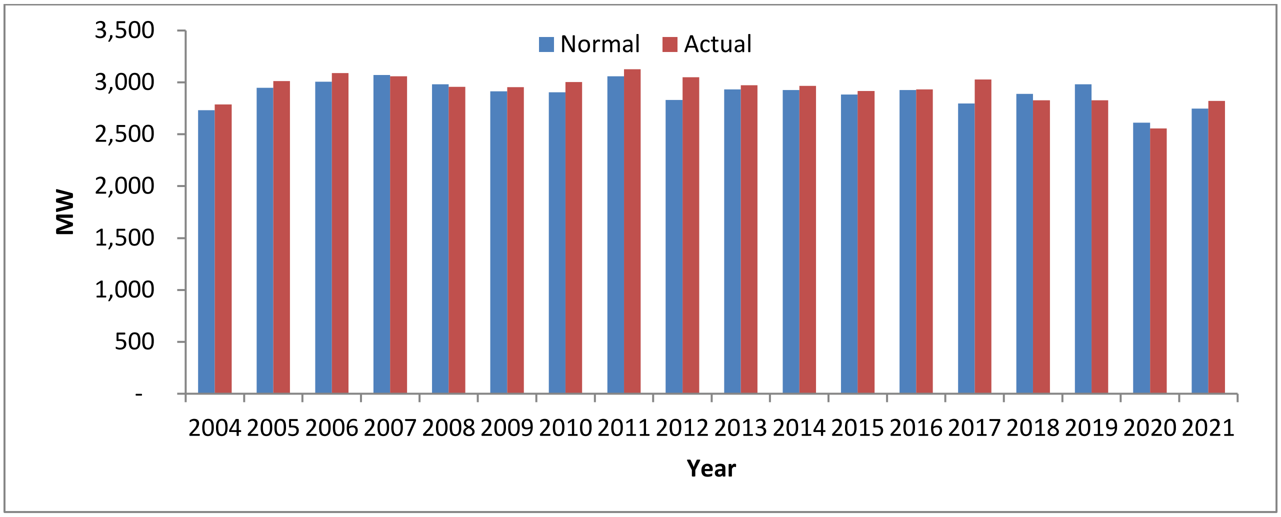
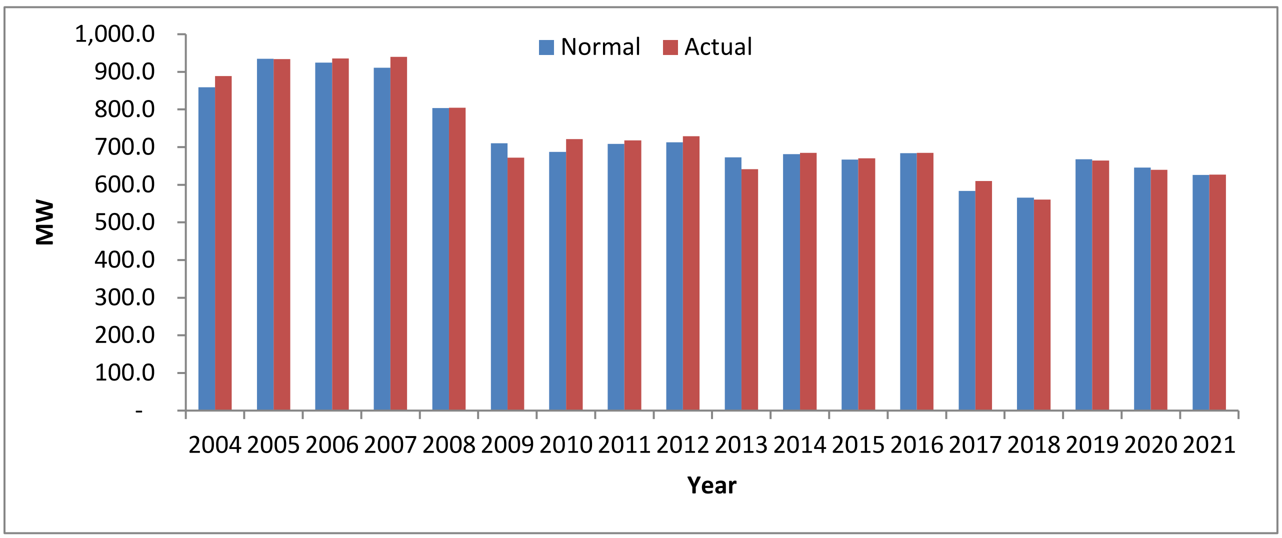


Figure 3.21: Industrial Coincident Peak Demand (MW)



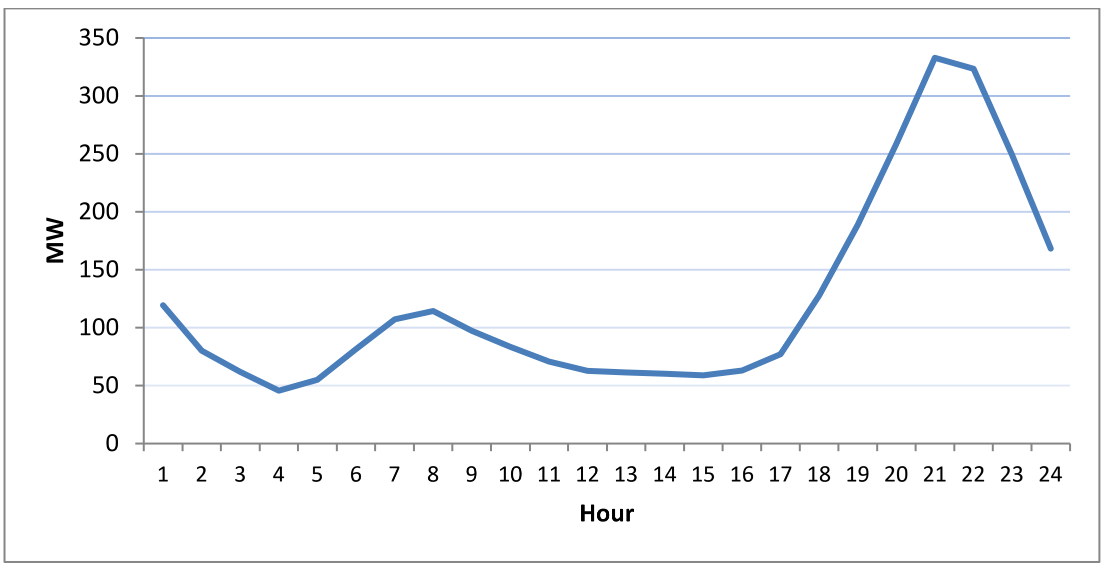
3.2.2 Profile Shapes

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 3.22, 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 3.22: Lighting Load Shape



Because the Energy Indpendence and Security Act (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 it 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[45]

Because the data in Itron's eShapes database is secondary data and probably more than a decade old, and more recent and geographically similar data is nearly impossible to come by, Ameren Missouri worked with this data to ensure that it was as applicable to the Ameren Missouri load as possible. For a 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

[45] 20 CSR 4240-22.030(4)(B)2; 20 CSR 4240-22.030(1)(C); 20 CSR 4240-22.030(1)(D)

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

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

The synthetic class load shapes were plotted on graphs against the load research data to allow for visual inspection of the loads side by side. Also an hourly error series was developed by subtracting the load research from the synthetic class load. This error series was examined by averaging it across several time dimensions (hour of the day, day of the week, month) to determine whether there were systematic ways in which the synthetic load profile was varying from the load research data. It quickly became apparent that the average hourly class load shape that had been generated from the end-use data was not consistent with the load shape observed from the load research data. This is not surprising, as again, the end-use load research is secondary data and is removed from its original source in both time and geography. Figure 3.23 shows the average hourly error pattern that was generated in this process for the residential class.

As is apparent in Figure 3.23, 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 3.23: Average Hourly Difference-End Use Build Up vs. Load Research

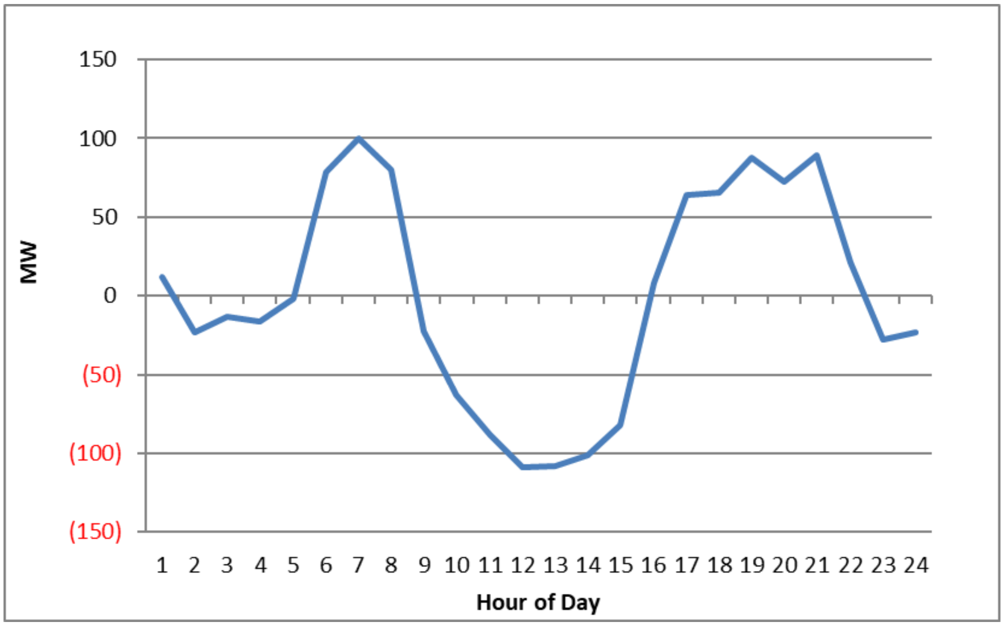
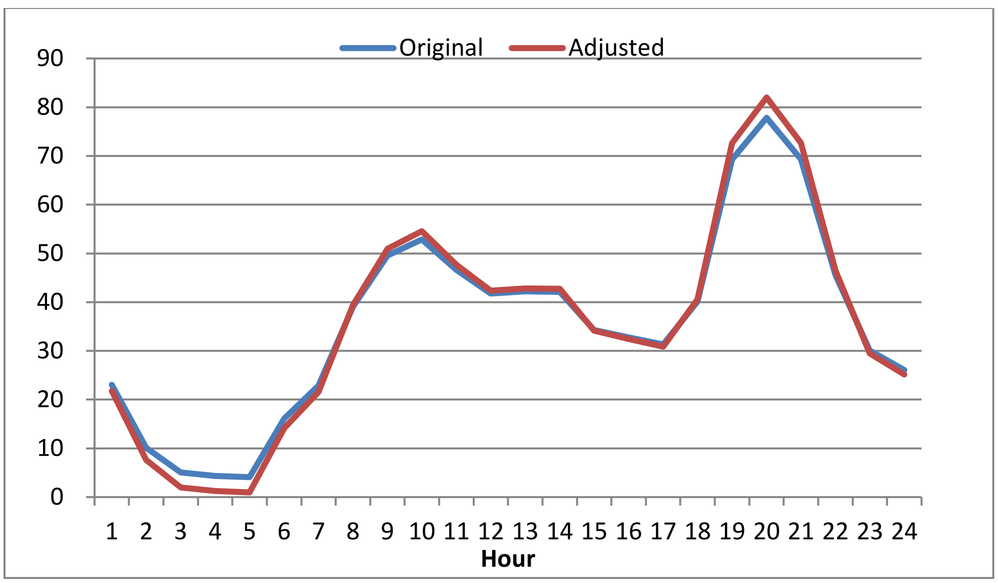


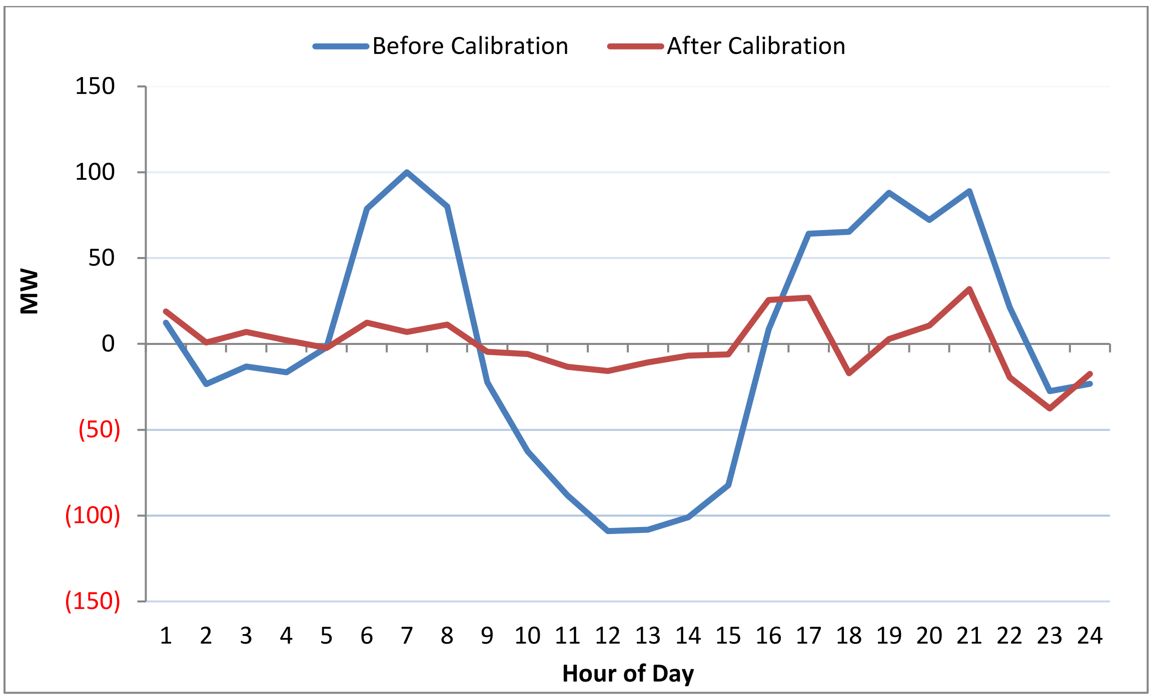
Figure 3.24: Dishwasher Load Shapes



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 will be included in a chart in the final filing. The pattern of the hourly differences before and after adjustment is shown in Figure 3.25.

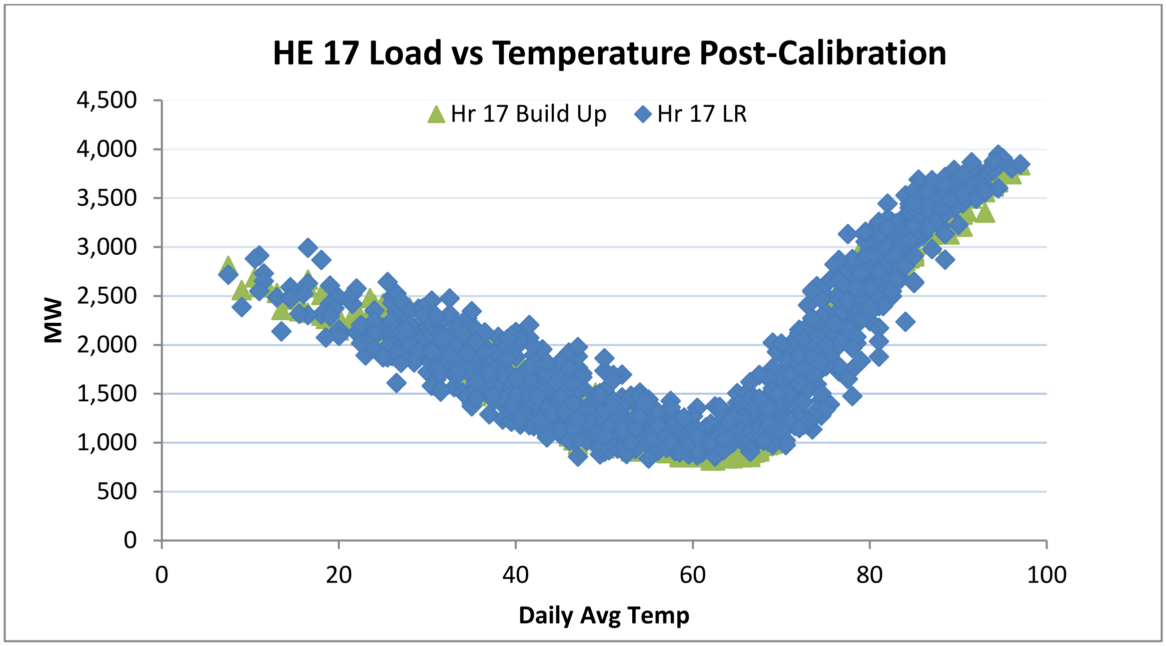
While the adjusted load shape still exhibits some differences from the class actual load shape, the magnitude of the differences is clearly reduced by a substantial amount. It would be impossible to make the synthetic load shape have a perfect fit with the load research data while respecting the characteristic 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 3.25. 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 3.25: 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 3.26: 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 4:00 pm to 5:00 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 3.26 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 temperatures 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. The 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.

Monthly System Peak Model Development

For this 2023 IRP update, Ameren Missouri developed an end use-based model to forecast the monthly system peak. Ameren Missouri's peak demand forecast methodology adopted for this work captures the underlying end use trends and economic trends. The peak demand forecast model was built based on the historical relationship between the system peak load and end use energy for peak weather conditions. The methodology is a derivation of the SAE energy forecasting techniques where the monthly class level energy forecasts are decomposed into three primary components for most customer classes: heating, cooling, and base load. The basis for the heating, cooling and base load variables extended to the forecast year are derived from the energy forecast models as discussed in section 3.1.5. The cooling and heating variables for peak load were constructed using the weather conditions on the peak day. The base load contribution to the peak demand, which is not influenced by weather conditions, was derived using the share of each end use in the base load at the time of system peak. The system peak model variables, coefficients, and other model statistics are shown in appendix A. The peak forecasting methodology also incorporates impacts of solar and projected electrification described in the respective sections in 3.1.5.

The monthly peak forecast from this process is then combined with the hourly load profiles in the previous section to come up with a class level peak forecast and hourly load forecast.

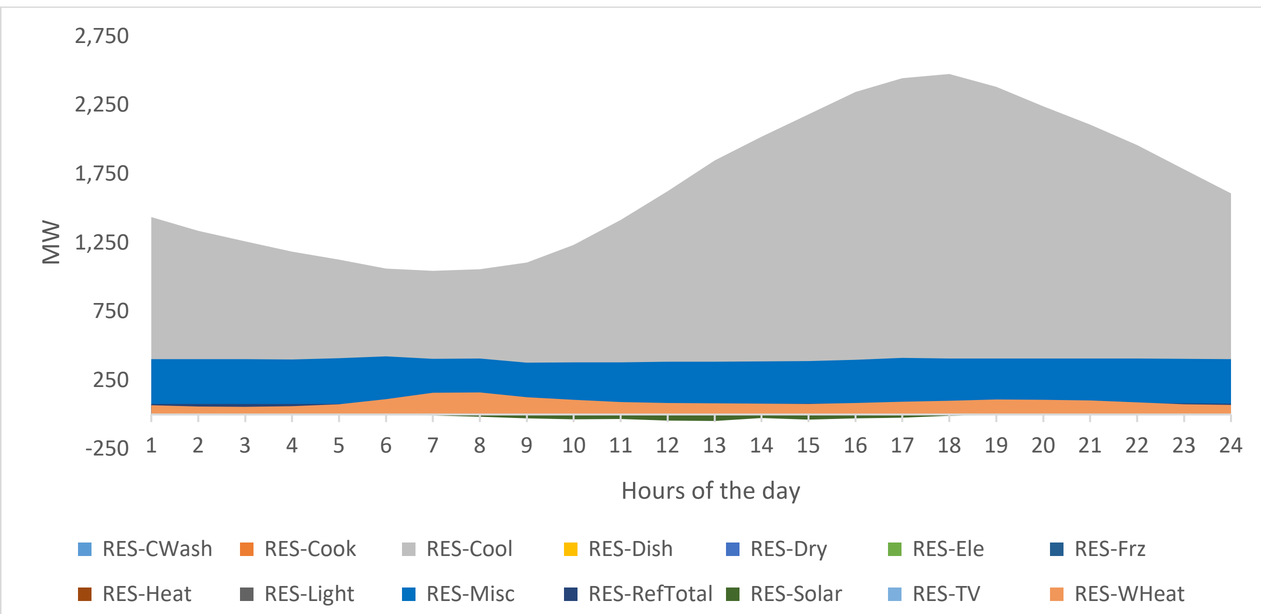
In order account for reductions in load due to Time of Use (TOU) rate programs, adjustments were made to the hourly load based upon the methodology from Dr. Ahmad Faruqui, of the Brattle Group prior to his recent retirement, as reflected in his workpapers from the Company's previous rate cases. These TOU options include Evening/Morning

Savers, Overnight Savers, Smart Savers and Ultimate Savers. Definitions of the hours reduced, reduction rate, and participation rate can be found in the TOU section in Appendix A.

Bottom-Up Forecasting

From earlier steps in the forecast process, we have developed class level or end-use energy forecasts, profile models that will generate load shapes for each class and end use, and a monthly system peak forecast from a model. Developing the final peak and hourly forecast is a relatively simple process of bringing these three inputs together. The profile shape for each class and end-use is scaled to the monthly energy from the energy forecast and the monthly system peak 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 3.27 shows an example of the buildup of the residential load for a summer day from the end use components.

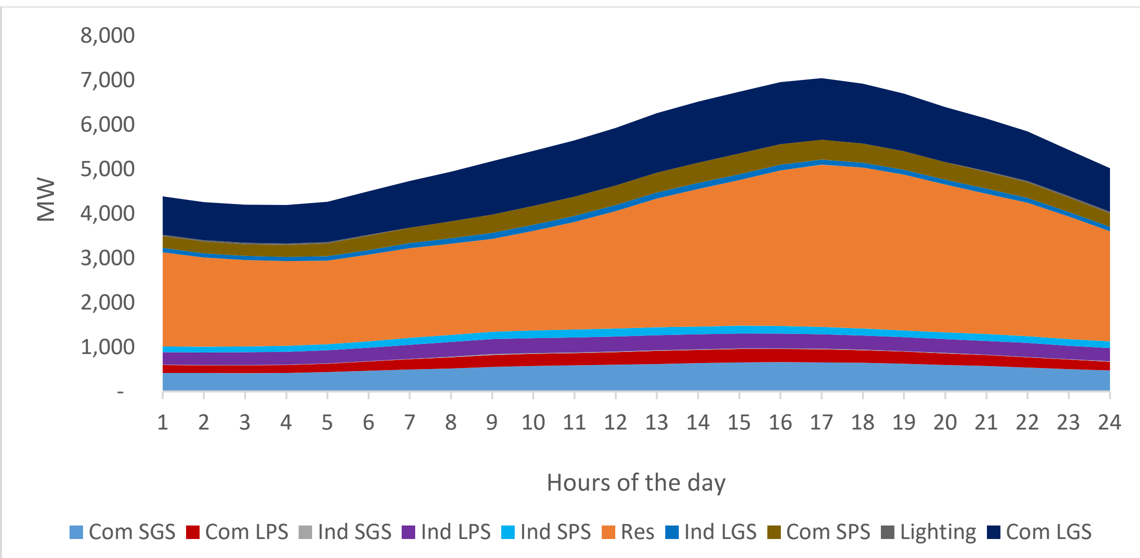
Figure 3.27: Residential Summer Day Usage Built-Up by End Use



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 2018 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. Like 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 3.28.

Figure 3.28: 2024 Summer System Peak Day Usages Built-Up by Class



3.2.4 Hourly System Load Forecast[46]

After the bottom-up forecast has been generated using the planning calendar, demand loss rate, and the system level peak model that was used to determine the class level peak load forecast, the same process is replicated using the actual calendar information described

[46] 20 CSR 4240-22.030(7)(C)

above and energy loss rates. This hourly system load data is what is actually passed on to the integration analysis.

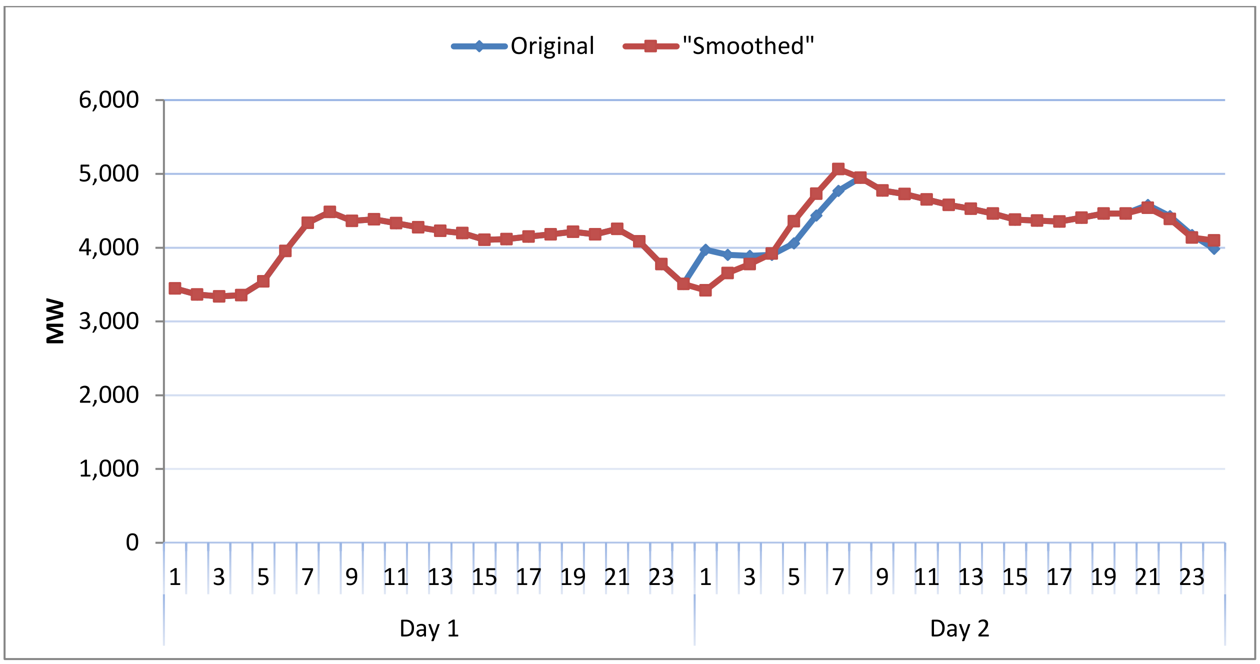
The actual calendar data as described above is used to make the hourly load forecast apply correctly to dates in the future. Since the energy for the forecast horizon is an input to this process and not determined by this process, and since we will use the peak forecast from the planning calendar run, 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 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 2018 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) 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 3.29.

Figure 3.29: 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 2024 through 2043 of 0.4%. For the planning case, the peak load in 2024 is projected to be 7,049 MW, growing to 7,618 MW by 2043. The compound annual growth rates in the various scenarios range from a low of -0.1% (low growth scenario), to 0.8% (high growth scenario).

Figure 3.30: IRP Annual Peak Forecast—Planning Case and Scenarios

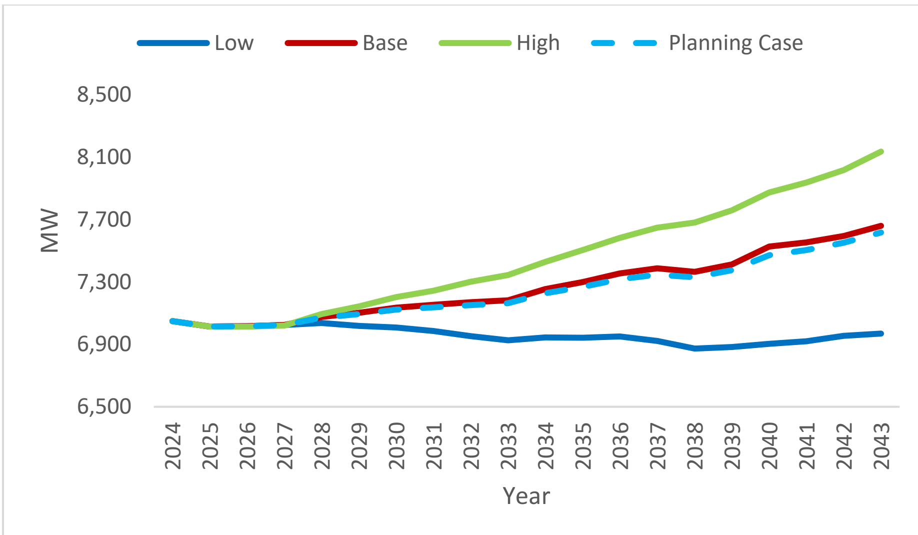
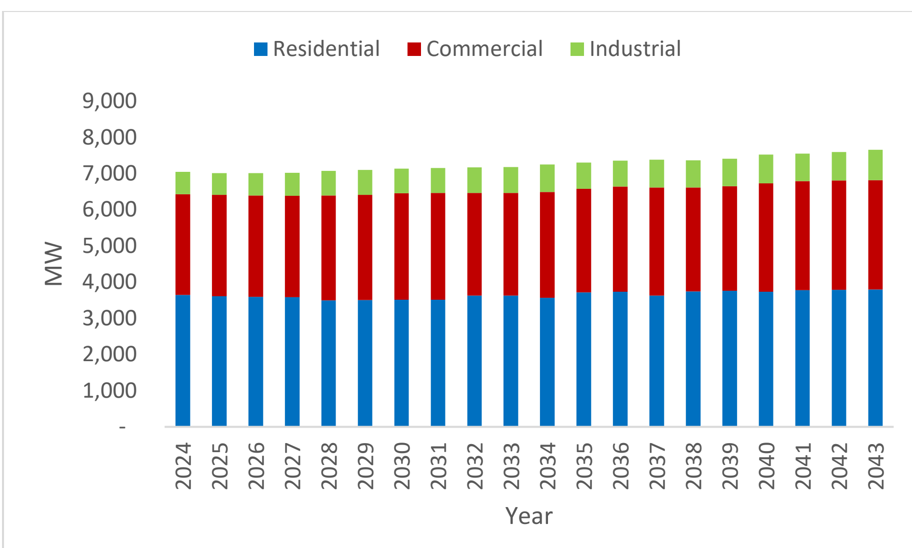


Figure 3.31: Class Contribution to Annual Peak Forecast



3.2.6 Base Case Peak Demand Forecast

Class and End-Use Peak Demands

The peak contribution of the residential class grows at 0.2% per year from 2024 to 2043, while the commercial class and industrial class peaks are forecasted to grow at a compound annual rate of 0.4% and 1.6% respectively. Although the energy consumption in industrial classes are declining since last decade, it is expected to increase due to efficient electrification.

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 22.4% per year. Tables 3.7-3.8 and Figures 3.32-3.36 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 (2024) and the last year of the forecast (2043).

Table 3.7: Residential End-Use Contribution to Peak

	2024 Peak Contribution (MW)	% of Peak Load (2024)	2043 Peak Contribution (MW)	% of Peak Load (2043)	CAGR
Cooking	38	1.0%	38	1.0%	0%
Cooling	2,793	76.6%	2,662	70.1%	0%
Clothes Washer	13	0.4%	15	0.4%	1%
Dish Washer	6	0.2%	7	0.2%	1%
Electric Dryer	87	2.4%	98	2.6%	1%
Electrification	4	0.1%	196	5.2%	22%
Freezer	40	1.1%	38	1.0%	0%
Heating	-	0.0%	-	0.0%	NA
Lighting	10	0.3%	7	0.2%	-2%
Misc	429	11.8%	487	12.8%	1%
Refrigerator	84	2.3%	82	2.2%	0%
Solar	(27)	-0.7%	(20)	-0.5%	-2%
TV	64	1.8%	82	2.2%	1%
Water Heater	103	2.8%	102	2.7%	0%

Figure 3.32: Residential Peak Load Composition 2024

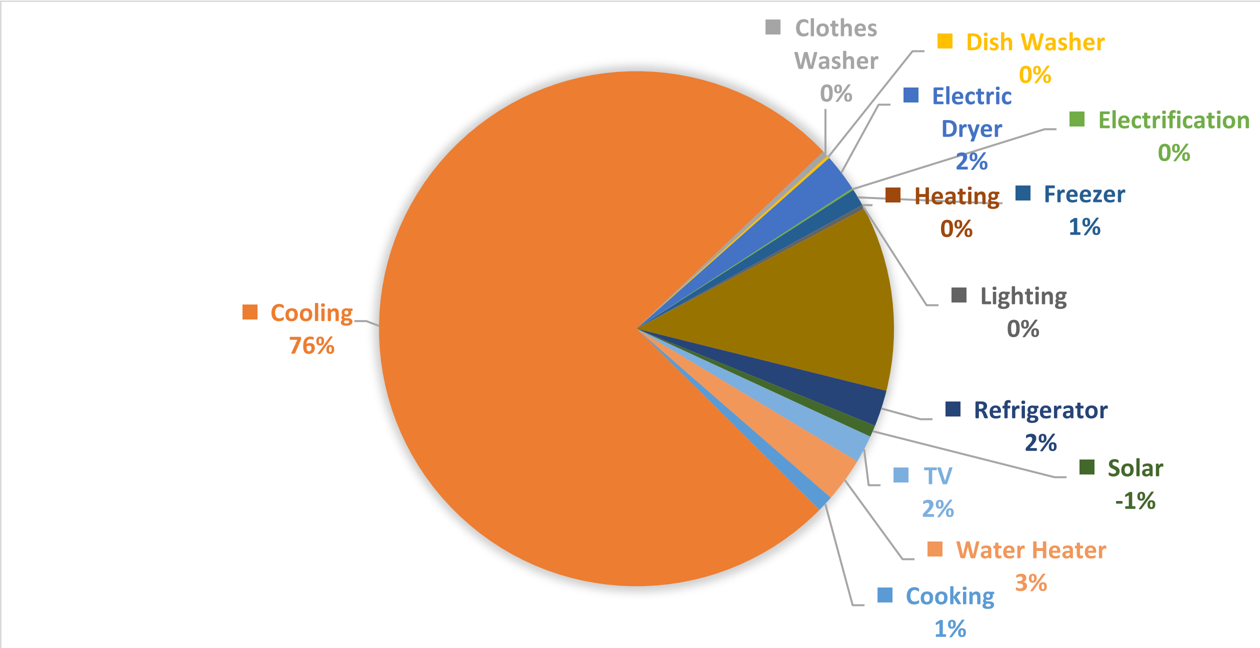
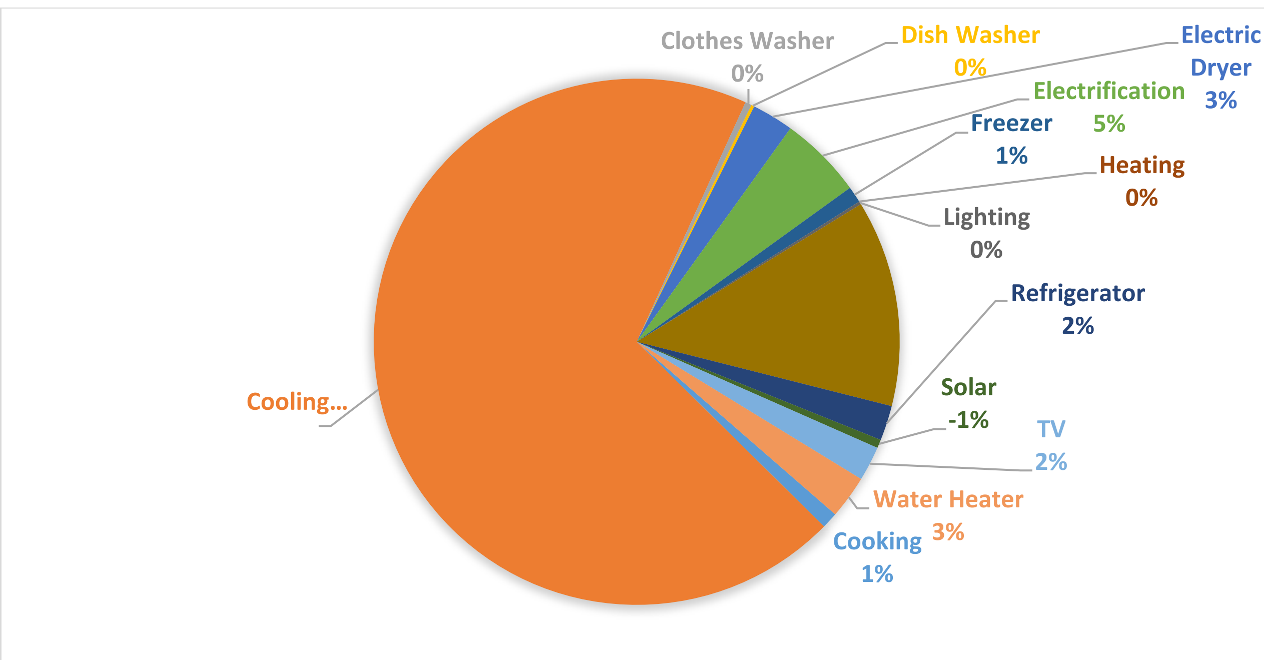


Figure 3.33: Residential Peak Load Composition 2043

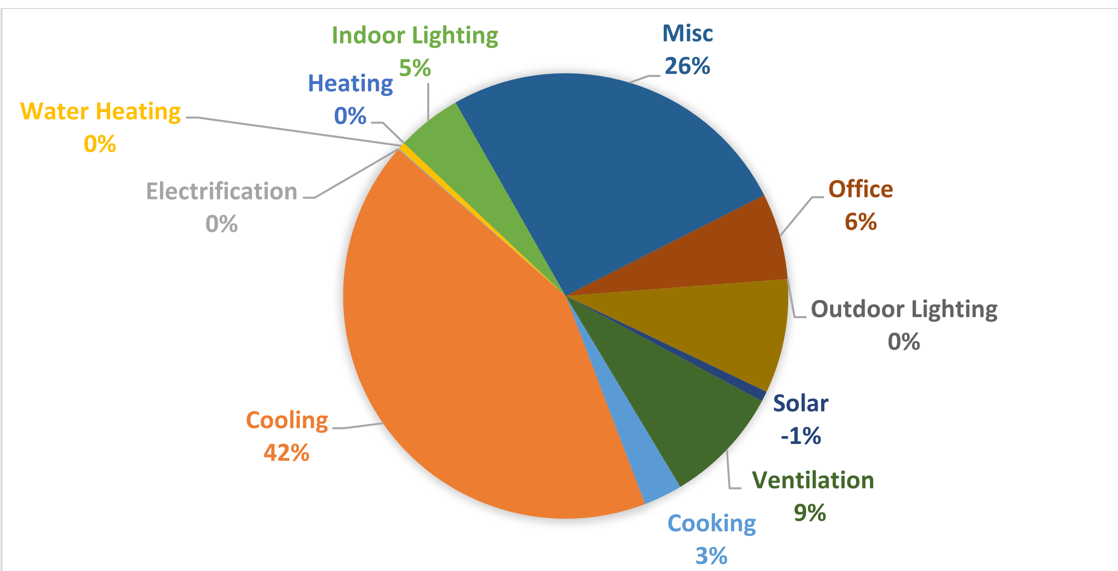


Schedule MM-S1 (Part 1)

Table 3.8: Commercial End-Use Contribution to Peak

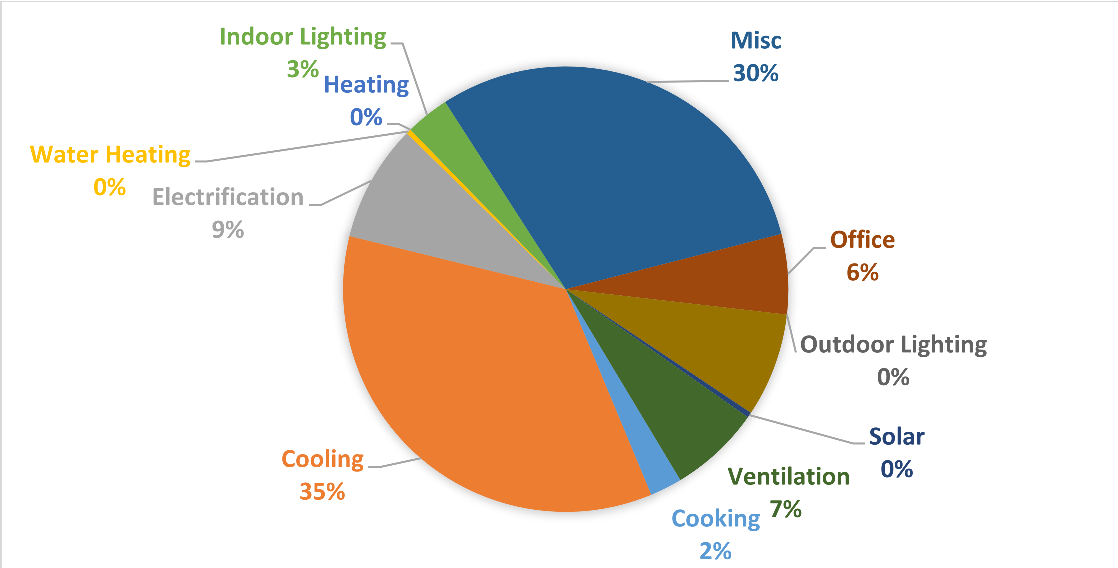
	2024 Peak Contribution (MW)	% of Peak Load	2043 Peak Contribution (MW)	% of Peak Load	CAGR
Cooking	79	3%	71	2%	-0.6%
Cooling	1,194	43%	1,070	35%	-0.6%
Electrification	2	0%	259	9%	27.9%
Water Heating	15	1%	11	0%	-1.4%
Heating	-	0%	-	0%	NA
Indoor Lighting	133	5%	97	3%	-1.7%
Miscellaneous	728	26%	917	30%	1.2%
Office	177	6%	177	6%	0.0%
Outdoor Lighting	0	0%	0	0%	NA
Refrigeration	234	8%	230	8%	-0.1%
Solar	(21)	-1%	(12)	0%	-3.1%
Ventilation	242	9%	202	7%	-0.9%

Figure 3.34: Commercial Peak Load Composition 2024



Schedule MM-S1 (Part 1)

Figure 3.35: Commercial Peak Load Composition 2043



3.2.7 Peak Demand – Extreme Weather Sensitivity[47]

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. An analysis was undertaken to determine the range of effect on peak demand due to extreme weather events as they have been observed historically.

In this process, Ameren Missouri identified the highest 10 weekday peak load projections from the month in which the annual peak is forecasted to occur (July) for 2022. 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 146.5 MW of increased system demand per degree.

This estimate was tested using 2024 summer peak data. The 2024 summer peak forecast (from the base case modeling) called for a normal weather (at a two-day weighted average temperature of 89.36 degrees) load of 7,049 MW. Next, Ameren Missouri calculated the expected peak load given two day weighted average temperatures equaling the 90th percentile of summer peak temperatures from 1992-2021 and at the absolute maximum temperature observed in that time frame. Additionally, Ameren Missouri tested against a temperature that occurred outside of the 1992-2021 period. Outside this period, the maximum (two day weighted) temperature was 92.17 degrees, occurred in 2022. The peak load corresponding to this temperature was forecasted to reach 7,460 MW, or 5.8% higher

[47] 20 CSR 4240-22.030(8)(B); 20 CSR 4240-22.070(1)(D)

than the normal weather forecast. At the 90th percentile temperature, i.e., 92.11 degrees, the load was estimated to reach 7,451 MW, or 5.7% higher than the normal weather peak. In 2012, when Ameren Missouri's service territory experienced historically record high temperature (two day weighted average temperature of 96.67), the corresponding peak load is estimated to be 8,200 MW, 15.2% higher than the normal weather forecast.[48]

Weather Normalization[49]

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. Historical data for 2021 and 2022 has been normalized with the same normal weather used for Ameren Missouri's rate review case (ER-2022-0337). Historical data for 2020 has been normalized with the same normal weather used to settle Ameren Missouri's rate review case (ER-2021-0240). For historical periods covered by Ameren Missouri's 2020 IRP and earlier, the weather normalized information prepared for and reported in that filing is utilized in this filing as is.

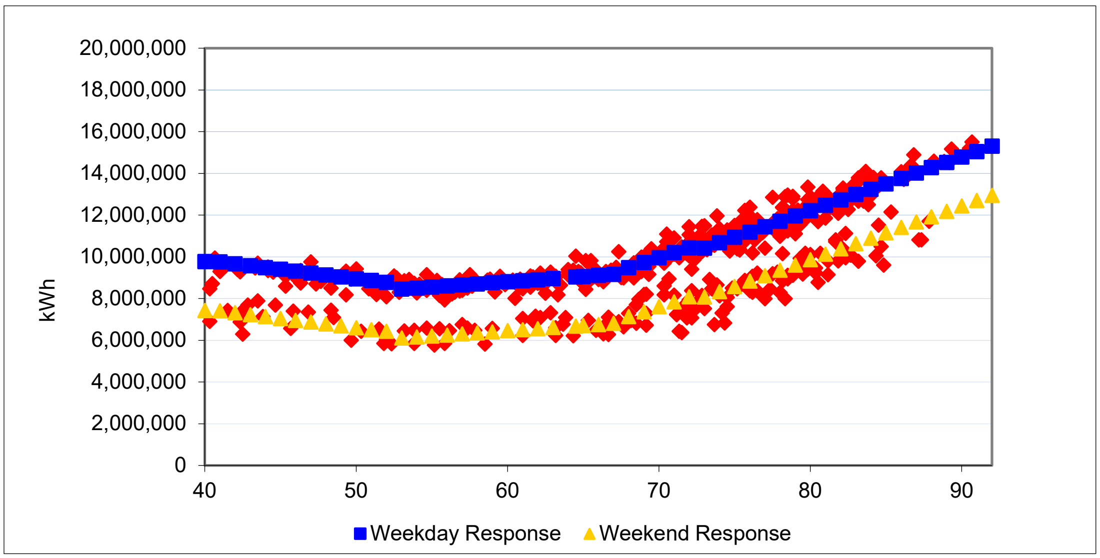
The weather normalization process starts with defining normal weather. As referenced above, Ameren Missouri currently uses actual temperature readings for St. Louis Lambert Airport from the period 1992-2021 to develop its normal weather conditions, as adjusted for certain changes in the recording equipment 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

[48] Please see additional discussion on extreme weather in Chapter 10.
[49] 20 CSR 4240-22.030(2)(C)2

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.[50] A graphical representation of this modeling approach can be seen in Figure 3.36.

Figure 3.36: 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 A.[51] The weather normalized sales results will also be provided in the final filing. 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.

[50] 20 CSR 4240-22.030(2)(D)2
[51] 20 CSR 4240-22.030(2)(C)3

3.3 Future Research Projects[52]

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

Much of this effort is focused on increasing the ways we can segment our data. Whether it be analyzing our commercial class by segmenting the business types, or analyzing our residential and commercial classes by the end use appliances and equipment they operate, our analysis is continually increasing in its 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 evaluation, measurement, and verification 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's load research sample was designed in the early 2000s. Although the existing sample has continued to perform well in all measurable ways, it will benefit from a refresh as the sample has been in place for a number of years. Ameren Missouri, as of this writing, is in the process of implementing smart meter infrastructure, which will collect interval reading for every customer in the system unless opted out. Once smart meter infrastructure is in place and interval data is collected for every customers in the system, Ameren Missouri will conduct load research based on the data collected from every

[52] 20 CSR 4240-22.070(6)(A)

customer in the smart metering system. This will eliminate much of statistical errors rising from load research process and provide a better in depth understanding of true load profile of Ameren Missouri customers.

3.4 Supplemental Economic Development Load Estimates

Following the completion of the Company's load forecasting process, Ameren Missouri evaluated further potential for economic development and included incremental loads for use in its modeling. The estimated incremental load is based on recently emerging trends with respect to potential large customer additions in Ameren Missouri's service territory. Such potential customers include data centers and manufacturing facilities. Ameren Missouri typically does not include new customer additions in its load forecasts until a firm commitment has been made. However, because of the size, volume and nature of recently identified potential customers, Ameren Missouri management determined that it was appropriate to include some level of estimated customer and load additions to ensure sufficient resources should a portion of such potential additions materialize. Based on joint assessment by Ameren Missouri's Economic Development, Risk Management, Load Forecasting, and Resource Planning teams, the incremental annual loads shown below were added to all three levels of load forecast and included in the development of capacity positions and the modeling of alternative resource plans described in Chapter 9. For purposes of modeling, the incremental load additions were assumed to have a load factor of 80% with 30% of incremental peak demand being interruptible. These incremental additions are not reflected in the numerous charts reflected in Appendix A to this chapter but are included in the load summary information presented in Chapter 1 Appendix A.

2025-2028	40 MW per year
2029	30 MW
2030	20 MW
2031	10 MW

3.5 Compliance References

20 CSR 4240-22.030(1)(A) 1
20 CSR 4240-22.030(1)(B) 3
20 CSR 4240-22.030(1)(C) 42
20 CSR 4240-22.030(1)(D) 42
20 CSR 4240-22.030(2)(A) 3
20 CSR 4240-22.030(2)(B)1 3
20 CSR 4240-22.030(2)(B)2 3
20 CSR 4240-22.030(2)(B)3 38
20 CSR 4240-22.030(2)(C)1 3
20 CSR 4240-22.030(2)(C)2 58
20 CSR 4240-22.030(2)(C)3 59
20 CSR 4240-22.030(2)(D)2 .... 21, 59
20 CSR 4240-22.030(2)(D)3 .... 10, 15
20 CSR 4240-22.030(2)(F) 3
20 CSR 4240-22.030(3)(A) 28
20 CSR 4240-22.030(4)(A)1A 13
20 CSR 4240-22.030(4)(A)1B 13
20 CSR 4240-22.030(4)(A)1C 19
20 CSR 4240-22.030(4)(A)2A 13
20 CSR 4240-22.030(4)(A)2B 13
20 CSR 4240-22.030(4)(A)2C 13
20 CSR 4240-22.030(4)(A)3 19
20 CSR 4240-22.030(4)(A)4 17
20 CSR 4240-22.030(4)(B)1 14
20 CSR 4240-22.030(4)(B)2 42
20 CSR 4240-22.030(5)(A) 11, 21
20 CSR 4240-22.030(5)(B) 13
20 CSR 4240-22.030(5)(C) 12
20 CSR 4240-22.030(6)(A)1A 11
20 CSR 4240-22.030(6)(A)1B 11
20 CSR 4240-22.030(6)(A)2 17
20 CSR 4240-22.030(6)(A)3 13
20 CSR 4240-22.030(6)(B) 13
20 CSR 4240-22.030(6)(C)1 3
20 CSR 4240-22.030(6)(C)2 20
20 CSR 4240-22.030(6)(C)3 3
20 CSR 4240-22.030(6)(C)4 5
20 CSR 4240-22.030(7)(A)1 16
20 CSR 4240-22.030(7)(A)2 14
20 CSR 4240-22.030(7)(A)3 32
20 CSR 4240-22.030(7)(A)5 .... 23, 26
20 CSR 4240-22.030(7)(B)1 11
20 CSR 4240-22.030(7)(B)2 11

20 CSR 4240-22.030(7)(B)3 9
20 CSR 4240-22.030(7)(C) 50
20 CSR 4240-22.030(8) 29
20 CSR 4240-22.030(8)(A) 29
20 CSR 4240-22.030(8)(B) 57
20 CSR 4240-22.060(4)(D) 16
20 CSR 4240-22.070(1)(D) 57
20 CSR 4240-22.070(6)(A) 60

Chapter 3 – Appendix A

Weather Normalized Energy Models[1]

Residential Weather Normalization Energy Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	81,884,501	2,029,560	40.35	0.00%
DOWBinary.Monday	-1,903,214	233,954	-8.14	0.00%
DOWBinary.Tuesday	-2,048,085	232,467	-8.81	0.00%
DOWBinary.Wednesday	-1,808,305	228,732	-7.91	0.00%
DOWBinary.Thursday	-1,797,965	234,403	-7.67	0.00%
DOWBinary.Friday	-1,760,050	230,841	-7.63	0.00%
DOWBinary.Saturday	-867,956	225,654	-3.85	0.01%
MonthBinary.Jan	4,160,028	316,031	13.16	0.00%
MonthBinary.Feb	3,996,584	323,862	12.34	0.00%
MonthBinary.Mar	1,096,129	277,190	3.95	0.01%
MonthBinary.Apr	-2,335,049	297,999	-7.84	0.00%
MonthBinary.May	-2,978,956	269,815	-11.04	0.00%
MonthBinary.Jul	876,265	294,030	2.98	0.30%
MonthBinary.Aug	636,910	281,343	2.26	2.38%
MonthBinary.Sep	-1,777,380	275,079	-6.46	0.00%
MonthBinary.Oct	-2,132,275	270,313	-7.89	0.00%
MonthBinary.Dec	3,154,991	298,514	10.57	0.00%
ResSplines.AvgT	-2,148,540	233,279	-9.21	0.00%
ResSplines.XColdAvgT	1,342,900	238,164	5.64	0.00%
ResSplines.CoolAvgT	238,371	31,836	7.49	0.00%
ResSplines.MILDAvgT	533,553	69,551	7.67	0.00%
ResSplines.WarmAvgT	959,194	97,208	9.87	0.00%
ResSplines.HotAvgT	564,120	69,253	8.15	0.00%
ResSplines.ShoulderWarm	-360,625	114,931	-3.14	0.18%
US_Holidays.RES_HolidaysX	1,711,395	338,321	5.06	0.00%
GMI_Transform.MO_Residential	140,532	14,587	9.63	0.00%

[1] 20 CSR 4240-22.030(2)(C)3

Residential Weather Normalization Energy Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	1096
Deg. of Freedom for Error	1070
R-Squared	0.96
Adjusted R-Squared	0.96
F-Statistic	1062.88
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	4.14%
Durbin-Watson Statistic	1.13

Commercial SGS Weather Normalization Energy Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	13,683,219	156,480	87.44	0.00%
DOWBinary.MonFri	960,971	114,698	8.38	0.00%
DOWBinary.TWT	1,129,287	115,704	9.76	0.00%
MonthBinary.Feb	271,633	70,145	3.87	0.01%
MonthBinary.Mar	130,671	67,098	1.95	5.19%
MonthBinary.May	-315,476	72,892	-4.33	0.00%
MonthBinary.Jun	-360,685	62,212	-5.80	0.00%
MonthBinary.Oct	-271,245	65,581	-4.14	0.00%
MonthBinary.Nov	137,405	81,998	1.68	9.42%
COMSGSSplines.AvgT	-139,999	3,492	-40.09	0.00%
COMSGSSplines.CoolAvgT	31,896	9,420	3.39	0.08%
COMSGSSplines.MildAvgT	114,858	15,205	7.55	0.00%
COMSGSSplines.WarmAvgT	114,993	20,497	5.61	0.00%
COMSGSSplines.HotAvgT	119,810	16,744	7.16	0.00%
COMSGSSplines.WkndAvgT	-6,178	1,821	-3.39	0.07%
COMSGSSplines.ShoulderAvgT	-6,132	1,341	-4.57	0.00%
US_Holidays.ComSGS_HolidayX	-596,732	121,284	-4.92	0.00%
GMI_Transform.MO_Workspaces	11,508	2,163	5.32	0.00%
MonthBinary.COVID_April_May2020	-557,561	84,421	-6.61	0.00%

Note: Some of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

ComSGS Weather Normalization Energy Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	711
R-Squared	0.94
Adjusted R-Squared	0.94
F-Statistic	613.29
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	3.87%
Durbin-Watson Statistic	1.01

ComLGS Weather Normalization Energy Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	22,719,487	221,548	102.55	0.00%
DOWBinary.Monday	3,159,894	93,125	33.93	0.00%
DOWBinary.TWT	3,204,393	81,147	39.49	0.00%
DOWBinary.Friday	2,584,051	85,725	30.14	0.00%
DOWBinary.Saturday	622,492	75,228	8.28	0.00%
MonthBinary.May	526,856	91,534	5.76	0.00%
MonthBinary.Jun	-953,001	80,997	-11.77	0.00%
MonthBinary.Oct	839,881	85,731	9.80	0.00%
COMLGSSplines.AvgT	-189,682	6,262	-30.29	0.00%
COMLGSSplines.CoolAvgT	31,889	9,009	3.54	0.04%
COMLGSSplines.WarmAvgT	193,423	9,222	20.98	0.00%
COMLGSSplines.HotAvgT	202,991	11,324	17.93	0.00%
COMLGSSplines.SummerAvgT	31,712	1,454	21.81	0.00%
COMLGSSplines.WkdayWarmAvgT	51,377	4,148	12.39	0.00%
GMI_Transform.MO_Workspaces	33,020	2,561	12.90	0.00%
US_Holidays.July4thHol	-1,302,451	397,110	-3.28	0.11%
US_Holidays.MemorialDay	-2,096,004	407,515	-5.14	0.00%
US_Holidays.LaborDay	-2,328,396	403,637	-5.77	0.00%
US_Holidays.Thanksgiving	-1,333,772	410,505	-3.25	0.12%
MonthBinary.Yr2021_Shift	523,006	47,745	10.95	0.00%

ComLGS Weather Normalization Energy Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	710
R-Squared	0.96
Adjusted R-Squared	0.96
F-Statistic	826.67
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	2.41%
Durbin-Watson Statistic	1.01

ComSPS Weather Normalization Energy Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	7,936,270	85,453	92.87	0.00%
DOWBinary.Friday	-136,196	23,470	-5.80	0.00%
DOWBinary.Saturday	-652,842	27,591	-23.66	0.00%
DOWBinary.Sunday	-729,559	26,591	-27.44	0.00%
COMSPSSplines.AvgT	-34,755	1,954	-17.79	0.00%
COMSPSSplines.CooLAvgT	40,156	2,866	14.01	0.00%
COMSPSSplines.MildAvgT	37,349	10,003	3.73	0.02%
COMSPSSplines.WarmAvgT	26,530	10,591	2.51	1.25%
COMSPSSplines.SummerAvgT	1,099	619	1.78	7.63%
US_Holidays.ComSPS_HolidayX	-137,494	36,659	-3.75	0.02%
GMI_Transform.MO_Workspaces	7,763	959	8.10	0.00%
MonthBinary.Jan	175,829	34,950	5.03	0.00%
MonthBinary.Feb	394,181	37,687	10.46	0.00%
MonthBinary.Apr	-84,959	32,633	-2.60	0.94%
MonthBinary.May	-130,863	33,862	-3.87	0.01%
MonthBinary.Jul	377,206	36,809	10.25	0.00%
MonthBinary.Aug	219,561	36,202	6.07	0.00%
MonthBinary.Sep	157,569	38,303	4.11	0.00%
MonthBinary.Nov	96,575	30,189	3.20	0.15%

Note: One of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

Com SPS Weather Normalization Energy Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	711
R-Squared	0.92
Adjusted R-Squared	0.91
F-Statistic	424.03
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	2.35%
Durbin-Watson Statistic	0.79

Com LPS Weather Normalization Energy Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	3,412,149	40,091	85.11	0.00%
DOWBinary.Saturday	-122,467	17,742	-6.90	0.00%
DOWBinary.Sunday	-160,788	17,781	-9.04	0.00%
MonthBinary.Jan	-332,997	25,846	-12.88	0.00%
MonthBinary.Jul	65,261	27,302	2.39	1.71%
MonthBinary.Aug	120,892	26,378	4.58	0.00%
MonthBinary.Oct	65,689	23,069	2.85	0.45%
MonthBinary.Dec	35,992	23,796	1.51	13.09%
MonthBinary.apr2020	-137,003	31,862	-4.30	0.00%
COMLPSSplines.AvgT	3,849	881	4.37	0.00%
COMLPSSplines.HotAvgT	20,570	3,280	6.27	0.00%
COMLPSSplines.WarmAvgT	18,941	2,145	8.83	0.00%
US_Holidays.ComLPS_HolidayX	-73,241	30,663	-2.39	1.72%
MonthBinary.Customer_Com_Outage	-397,869	39,291	-10.13	0.00%

Note: One of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

Com LPS Weather Normalization Energy Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	716
R-Squared	0.88
Adjusted R-Squared	0.88
F-Statistic	417.978
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	3.31%
Durbin-Watson Statistic	0.58

Ind SGS Weather Normalization Energy Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	322,533	6,257	51.55	0.00%
DOWBinary.Monday	75,369	3,093	24.37	0.00%
DOWBinary.Tuesday	77,520	3,093	25.06	0.00%
DOWBinary.Wednesday	75,696	3,094	24.47	0.00%
DOWBinary.Thursday	75,090	3,093	24.28	0.00%
DOWBinary.Friday	65,726	3,105	21.17	0.00%
DOWBinary.Sunday	-12,561	3,086	-4.07	0.01%
MonthBinary.Feb	7,406	3,767	1.97	4.97%
MonthBinary.May	-10,941	3,457	-3.17	0.16%
MonthBinary.Oct	38,730	3,213	12.06	0.00%
MonthBinary.Nov	69,488	3,361	20.68	0.00%
MonthBinary.Dec	28,347	3,328	8.52	0.00%
INDSGSSplines.AvgT	-3,657	140	-26.08	0.00%
INDSGSSplines.MILDAvgT	2,639	269	9.80	0.00%
INDSGSSplines.WarmAvgT	6,700	401	16.70	0.00%
US_Holidays.IndSGS_HolidayX	-43,287	4,861	-8.91	0.00%
US_Holidays.July4thHol	-55,840	16,607	-3.36	0.08%
MonthBinary.Jul_2020	12,502	4,488	2.79	0.55%
MonthBinary.COVID_IndSGS	-8,280	3,476	-2.38	1.74%

Ind SGS Weather Normalization Energy Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	711
R-Squared	0.85
Adjusted R-Squared	0.85
F-Statistic	227.84
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	8.33%
Durbin-Watson Statistic	1.25

Ind LGS Weather Normalization Energy Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	1,510,923	17,611	85.79	0.00%
DOWBinary.TWT	805,038	21,106	38.14	0.00%
DOWBinary.MonFri	689,700	20,350	33.89	0.00%
MonthBinary.Jan	147,625	25,615	5.76	0.00%
MonthBinary.Feb	95,073	26,588	3.58	0.04%
MonthBinary.May	46,972	26,146	1.80	7.28%
MonthBinary.Jun	139,444	30,760	4.53	0.00%
MonthBinary.Jul	345,825	34,650	9.98	0.00%
MonthBinary.Aug	272,775	31,322	8.71	0.00%
MonthBinary.Sep	207,351	26,781	7.74	0.00%
MonthBinary.Nov	136,368	27,403	4.98	0.00%
INDLGSSplines.HotAvgT	9,778	3,219	3.04	0.25%
GMI_Transform.MO_Workspaces	3,935	821	4.79	0.00%
US_Holidays.NYHol	-639,364	132,869	-4.81	0.00%
US_Holidays.GoodFridays	-933,956	127,458	-7.33	0.00%
US_Holidays.MemorialDay	-1,031,656	134,139	-7.69	0.00%
US_Holidays.LaborDay	-928,377	135,757	-6.84	0.00%
US_Holidays.WedB4Thanks	-397,861	128,922	-3.09	0.21%
US_Holidays.Thanksgiving	-1,169,310	137,451	-8.51	0.00%
US_Holidays.FriAftThanks	-1,080,303	131,934	-8.19	0.00%
US_Holidays.SatAftThanks	-414,986	128,826	-3.22	0.13%
US_Holidays.XMasEve	-755,682	128,174	-5.90	0.00%
US_Holidays.XMasHol	-890,474	133,529	-6.67	0.00%
US_Holidays.XMASAft	-285,207	54,875	-5.20	0.00%
US_Holidays.July4Total	-831,551	93,866	-8.86	0.00%

Note: One of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

Ind LGS Weather Normalization Energy Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	705
R-Squared	0.83
Adjusted R-Squared	0.82
F-Statistic	141.10
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	7.48%
Durbin-Watson Statistic	1.34

Ind SPS Weather Normalization Energy Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	3,305,208	35,233	93.81	0.00%
DOWBinary.Tuesday	155,332	18,949	8.20	0.00%
DOWBinary.Wednesday	166,713	18,904	8.82	0.00%
DOWBinary.Thursday	109,051	18,890	5.77	0.00%
DOWBinary.Saturday	-481,993	18,942	-25.45	0.00%
DOWBinary.Sunday	-665,778	18,970	-35.10	0.00%
MonthBinary.Feb	84,728	25,700	3.30	0.10%
MonthBinary.May	80,096	25,398	3.15	0.17%
MonthBinary.Jun	77,580	33,540	2.31	2.10%
MonthBinary.Jul	85,670	35,940	2.38	1.74%
MonthBinary.Aug	244,663	34,021	7.19	0.00%
MonthBinary.Sep	63,986	27,966	2.29	2.24%
INDSPSSplines.AvgT	-2,709	698	-3.88	0.01%
INDSPSSplines.WarmAvgT	13,637	1,906	7.16	0.00%
MonthBinary.COVIDSPS2	-105,897	24,230	-4.37	0.00%
US_Holidays.IndSPS_HolidayX	-513,906	24,381	-21.08	0.00%

Ind SPS Weather Normalization Energy Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	714
R-Squared	0.84
Adjusted R-Squared	0.84
F-Statistic	254.71
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	3.94%
Durbin-Watson Statistic	0.83

Ind LPS Weather Normalization Energy Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	6,105,449	81,896	74.55	0.00%
DOWBinary.WeekEnd	-335,412	54,689	-6.13	0.00%
DOWBinary.Monday	-175,816	22,845	-7.70	0.00%
MonthBinary.Jan	-140,971	40,570	-3.48	0.06%
MonthBinary.Feb	-354,742	41,863	-8.47	0.00%
MonthBinary.Mar	-157,151	34,263	-4.59	0.00%
MonthBinary.Apr	201,318	42,797	4.70	0.00%
MonthBinary.Jun	102,336	46,936	2.18	2.96%
MonthBinary.Jul	299,325	47,368	6.32	0.00%
MonthBinary.Aug	296,471	42,946	6.90	0.00%
MonthBinary.Sep	95,909	54,880	1.75	8.10%
MonthBinary.Oct	159,989	34,224	4.68	0.00%
MonthBinary.Nov	174,482	36,244	4.81	0.00%
MonthBinary.apr2020	-727,157	59,390	-12.24	0.00%
INDLPSSplines.AvgT	-6,201	1,822	-3.40	0.07%
INDLPSSplines.MildAvgT	14,696	2,949	4.98	0.00%
INDLPSSplines.WarmAvgT	26,669	3,605	7.40	0.00%
INDLPSSplines.WkndAvgT	-3,291	884	-3.72	0.02%
MonthBinary.Customer_Idle	-231,170	39,721	-5.82	0.00%
MonthBinary.LPS_Winter_Storm	-484,652	101,790	-4.76	0.00%
MonthBinary.Sept2020	-143,707	61,810	-2.33	2.04%
MonthBinary.COVIDLPS	-99,322	29,456	-3.37	0.08%

Note: One of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

Ind LPS Weather Normalization Energy Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	691
Deg. of Freedom for Error	669
R-Squared	0.85
Adjusted R-Squared	0.85
F-Statistic	182.20
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	2.65%
Durbin-Watson Statistic	0.90

Weather Normalized Peak Demand Models[2]

Residential Weather Normalization Peak Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	3,816,626	165,239	23.10	0.00%
DOWBinary.Sunday	49,334	16,818	2.93	0.34%
MonthBinary.Jan	45,107	26,563	1.70	8.98%
MonthBinary.Feb	60,850	27,310	2.23	2.61%
MonthBinary.Mar	-83,093	24,676	-3.37	0.08%
MonthBinary.Apr	-244,218	24,881	-9.82	0.00%
MonthBinary.May	-252,464	22,885	-11.03	0.00%
MonthBinary.Sep	-104,729	21,836	-4.80	0.00%
MonthBinary.Oct	-223,983	23,640	-9.48	0.00%
MonthBinary.Nov	-138,720	24,136	-5.75	0.00%
ResSplines.AvgT	-84,281	16,710	-5.04	0.00%
ResSplines.MildAvgT	42,961	4,594	9.35	0.00%
ResSplines.xColdAvgT	50,919	16,937	3.01	0.27%
ResSplines.WarmAvgT	37,189	20,573	1.81	7.09%
ResSplines.WkndMildAvgT	2,423	960	2.52	1.18%
ResSplines.HotAvgT	36,248	18,302	1.98	4.79%
MonthBinary.June2019	-80,901	34,183	-2.37	1.81%
GMI_Transform.MO_Residential	4,510	1,235	3.65	0.03%
US_Holidays.RES_HolidaysX	100,129	28,377	3.53	0.05%

Note: One of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

[2] 20 CSR 4240-22.030(2)(C)3

Residential Weather Normalization Peak Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	1096
Deg. of Freedom for Error	1077
R-Squared	0.92
Adjusted R-Squared	0.91
F-Statistic	640.99
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	6.37%
Durbin-Watson Statistic	1.48

Com SGS Weather Normalization Peak Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	621,877	8,909	69.80	0.00%
DOWBinary.TWT	127,894	4,345	29.44	0.00%
DOWBinary.MonFri	110,701	4,211	26.29	0.00%
MonthBinary.Feb	11,743	5,191	2.26	2.40%
MonthBinary.Mar	14,840	4,591	3.23	0.13%
MonthBinary.May	-39,064	4,679	-8.35	0.00%
MonthBinary.Jun	-35,031	4,988	-7.02	0.00%
MonthBinary.Jul	-16,120	5,227	-3.08	0.21%
COMSGSSplines.AvgT	-5,965	186	-31.99	0.00%
COMSGSSplines.MildAvgT	5,902	1,044	5.66	0.00%
COMSGSSplines.WarmAvgT	8,667	1,361	6.37	0.00%
COMSGSSplines.HotAvgT	7,949	854	9.31	0.00%
COMSGSSplines.WkndMildAvgT	-2,101	226	-9.29	0.00%
COMSGSSplines.ShoulderMildAvgT	-2,119	580	-3.65	0.03%
US_Holidays.ComSGS_HolidayX	-38,175	9,059	-4.21	0.00%
MonthBinary.April2020	-43,286	7,161	-6.05	0.00%
GMI_Transform.MO_Workspaces	1,443	159	9.07	0.00%

Com SGS Weather Normalization Peak Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	713
R-Squared	0.92
Adjusted R-Squared	0.92
F-Statistic	508.33
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	5.71%
Durbin-Watson Statistic	1.25

Com LGS Weather Normalization Peak Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	1,076,950	16,216	66.41	0.00%
DOWBinary.MonFri	183,798	5,683	32.34	0.00%
DOWBinary.TWT	205,744	5,891	34.92	0.00%
DOWBinary.Saturday	36,501	5,272	6.92	0.00%
MonthBinary.Jan	-67,948	8,382	-8.11	0.00%
MonthBinary.Feb	-59,882	8,786	-6.82	0.00%
MonthBinary.Mar	-38,488	6,391	-6.02	0.00%
MonthBinary.May	-19,730	5,745	-3.43	0.06%
MonthBinary.Jul	41,390	6,524	6.35	0.00%
MonthBinary.Aug	65,542	6,169	10.62	0.00%
MonthBinary.Sep	73,032	5,965	12.24	0.00%
MonthBinary.Nov	-12,364	6,544	-1.89	5.93%
MonthBinary.Dec	-33,535	7,738	-4.33	0.00%
COMLGSSplines.AvgT	-8,527	273	-31.28	0.00%
COMLGSSplines.MildAvgT	15,336	592	25.91	0.00%
COMLGSSplines.HotAvgT	12,114	852	14.22	0.00%
COMLGSSplines.ShoulderMildAvgT	-4,189	750	-5.59	0.00%
COMLGSSplines.WkndMildAvgT	-3,906	281	-13.91	0.00%
GMI_Transform.MO_Workspaces	2,247	214	10.48	0.00%
MonthBinary.March_10_2021	-106,211	37,338	-2.85	0.46%
MonthBinary.Yr2021_Shift	44,917	3,644	12.33	0.00%

Note: One of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

Com LGS Weather Normalization Peak Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	682
Deg. of Freedom for Error	661
R-Squared	0.95
Adjusted R-Squared	0.95
F-Statistic	600.52
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	3.22%
Durbin-Watson Statistic	1.47

Com SPS Weather Normalization Peak Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	314,539	5,249	59.93	0.00%
DOWBinary.Monday	41,754	1,542	27.08	0.00%
DOWBinary.TWT	42,564	1,254	33.95	0.00%
DOWBinary.Friday	37,160	1,536	24.20	0.00%
DOWBinary.Saturday	5,370	1,532	3.51	0.05%
MonthBinary.Feb	7,001	1,784	3.92	0.01%
MonthBinary.May	-12,268	2,121	-5.78	0.00%
MonthBinary.Jun	-9,379	1,770	-5.30	0.00%
MonthBinary.Sep	-5,677	1,915	-2.96	0.31%
MonthBinary.Oct	-9,897	2,294	-4.31	0.00%
COMSPSSplines.ColdAvgT	906	211	4.30	0.00%
COMSPSSplines.AvgT	-1,270	178	-7.16	0.00%
COMSPSSplines.HotAvgT	1,648	273	6.05	0.00%
COMSPSSplines.WarmAvgT	2,687	226	11.89	0.00%
COMSPSSplines.WinterAvgT	-240	45	-5.39	0.00%
COMSPSSplines.ShoulderAvgT	-211	40	-5.29	0.00%
MonthBinary.COVIDSPS	-19,971	1,261	-15.84	0.00%
US_Holidays.ComSPS_HolidayX	-21,247	1,667	-12.75	0.00%

Com SPS Weather Normalization Peak Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	1096
Deg. of Freedom for Error	1078
R-Squared	0.87
Adjusted R-Squared	0.87
F-Statistic	439.01
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	3.29%
Durbin-Watson Statistic	0.86

Com LPS Weather Normalization Peak Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	141,365	996	141.98	0.00%
MonthBinary.Feb	14,912	1,499	9.95	0.00%
MonthBinary.Mar	17,528	1,387	12.63	0.00%
MonthBinary.May	16,283	1,535	10.61	0.00%
MonthBinary.Jun	15,705	2,068	7.60	0.00%
MonthBinary.Jul	19,409	2,167	8.96	0.00%
MonthBinary.Aug	19,843	2,090	9.50	0.00%
MonthBinary.Sep	17,636	1,809	9.75	0.00%
MonthBinary.Oct	20,467	1,465	13.97	0.00%
MonthBinary.Dec	19,367	1,692	11.45	0.00%
DOWBinary.WeekEnd	-10,058	637	-15.78	0.00%
COMLPSSplines.WarmAvgT	1,597	65	24.67	0.00%
COMLPSSplines.ShoulderAvgT	289	23	12.73	0.00%
MonthBinary.Dec15_Jan1	-4,066	1,902	-2.14	3.28%
US_Holidays.ComLPS_HolidayX	-3,537	1,479	-2.39	1.71%
MonthBinary.Customer_Com_Outage	-21,387	2,703	-7.91	0.00%

Com LPS Weather Normalization Peak Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	714
R-Squared	0.88
Adjusted R-Squared	0.88
F-Statistic	346.92
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	3.51%
Durbin-Watson Statistic	0.78

Ind SGS Weather Normalization Peak Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	19,301	609	31.67	0.00%
DOWBinary.Monday	7,204	321	22.46	0.00%
DOWBinary.Tuesday	7,118	319	22.28	0.00%
DOWBinary.Wednesday	7,003	318	22.01	0.00%
DOWBinary.Thursday	7,039	321	21.90	0.00%
DOWBinary.Friday	6,259	324	19.32	0.00%
DOWBinary.Sunday	-1,522	316	-4.82	0.00%
MonthBinary.Feb	1,196	379	3.16	0.17%
MonthBinary.Mar	2,026	358	5.66	0.00%
MonthBinary.Jun	970	541	1.79	7.32%
MonthBinary.Jul	2,586	569	4.55	0.00%
MonthBinary.Aug	1,629	542	3.01	0.28%
MonthBinary.Sep	806	486	1.66	9.78%
MonthBinary.Oct	3,315	433	7.65	0.00%
MonthBinary.Nov	2,702	380	7.11	0.00%
INDSGSSplines.AvgT	-217	14	-15.81	0.00%
INDSGSSplines.MildAvgT	87	50	1.72	8.54%
INDSGSSplines.WarmAvgT	418	60	6.95	0.00%
INDSGSSplines.SummerAltAvgT	-11	8	-1.48	14.00%
INDSGSSplines.mild_shoulder	174	57	3.06	0.23%
MonthBinary.COVIDpeak_IndSGS	-1,625	376	-4.32	0.00%

Note: Some of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

Ind SGS Weather Normalization Peak Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	705
Deg. of Freedom for Error	684
R-Squared	0.79
Adjusted R-Squared	0.78
F-Statistic	127.92
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	13.24%
Durbin-Watson Statistic	1.36

Ind LGS Weather Normalization Peak Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	74,531	1,197	62.25	0.00%
DOWBinary.Monday	36,385	1,380	26.37	0.00%
DOWBinary.TWT	38,233	1,052	36.33	0.00%
DOWBinary.Friday	28,089	1,377	20.40	0.00%
MonthBinary.Jan	5,388	1,642	3.28	0.11%
MonthBinary.Apr	-4,320	1,689	-2.56	1.07%
MonthBinary.May	-4,870	1,959	-2.49	1.31%
MonthBinary.Jun	-4,367	1,630	-2.68	0.76%
MonthBinary.Oct	-4,712	1,797	-2.62	0.89%
US_Holidays.IndLGS_HolidayX	-29,840	1,697	-17.58	0.00%
INDLGSSplines.SummerAvgT	61	30	2.01	4.49%
INDLGSSplines.WkdayWarmAvgT	2,476	642	3.86	0.01%
INDLGSSplines.SummerWkdayWarmAvgT	-2,056	646	-3.18	0.15%
INDLGSSplines.MildAvgT	108	65	1.66	9.66%

Note: One of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

Ind LGS Weather Normalization Peak Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	716
R-Squared	0.76
Adjusted R-Squared	0.76
F-Statistic	178.77
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	9.57%
Durbin-Watson Statistic	1.22

Ind SPS Weather Normalization Peak Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	119,591	2,120	56.41	0.00%
DOWBinary.Monday	45,830	1,233	37.16	0.00%
DOWBinary.Tuesday	50,250	1,211	41.48	0.00%
DOWBinary.Wednesday	49,749	1,185	41.98	0.00%
DOWBinary.Thursday	47,035	1,225	38.39	0.00%
DOWBinary.Friday	40,601	1,097	37.02	0.00%
DOWBinary.Saturday	9,151	1,064	8.60	0.00%
MonthBinary.Feb	3,521	1,319	2.67	0.78%
MonthBinary.Mar	-4,119	1,193	-3.45	0.06%
MonthBinary.Apr	-3,010	1,191	-2.53	1.17%
MonthBinary.Aug	10,179	1,117	9.11	0.00%
MonthBinary.Nov	-2,966	1,182	-2.51	1.23%
MonthBinary.Dec	-3,405	1,260	-2.70	0.70%
INDSPSSplines.AvgT	-131	44	-3.01	0.27%
INDSPSSplines.WarmAvgT	519	186	2.79	0.53%
INDSPSSplines.MildAvgT	287	164	1.75	8.09%
US_Holidays.INDSPS_Holidays2	-17,701	1,515	-11.69	0.00%
GMI_Transform.MO_Workspaces	313	36	8.80	0.00%

Note: One of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

Ind SPS Weather Normalization Peak Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	712
R-Squared	0.87
Adjusted R-Squared	0.87
F-Statistic	287.22
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	4.30%
Durbin-Watson Statistic	0.96

Ind LPS Weather Normalization Peak Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	262,453	1,611	162.87	0.00%
DOWBinary.Monday	-4,636	964	-4.81	0.00%
DOWBinary.WeekEnd	-17,596	2,340	-7.52	0.00%
MonthBinary.Feb	-10,547	1,416	-7.45	0.00%
MonthBinary.Mar	-5,373	1,368	-3.93	0.01%
MonthBinary.Apr	9,643	1,749	5.51	0.00%
MonthBinary.Jul	13,390	1,474	9.08	0.00%
MonthBinary.Aug	13,093	1,479	8.85	0.00%
MonthBinary.Oct	7,573	1,333	5.68	0.00%
MonthBinary.Nov	7,919	1,359	5.83	0.00%
MonthBinary.Apr2020	-25,465	2,386	-10.68	0.00%
MonthBinary.Sept2020	-4,898	1,785	-2.74	0.62%
INDLPSSplines.ColdAvgT	-171	68	-2.50	1.26%
INDLPSSplines.MildAvgT	1,229	110	11.19	0.00%
INDLPSSplines.WarmAvgT	629	191	3.30	0.10%
INDLPSSplines.WkndAvgT	-221	38	-5.87	0.00%
MonthBinary.Customer_Idle	-6,039	1,222	-4.94	0.00%
US_Holidays.XMASAft	-20,755	2,656	-7.81	0.00%
US_Holidays.XMasHol	-25,661	6,404	-4.01	0.01%
US_Holidays.July4thHol	-20,582	6,339	-3.25	0.12%
US_Holidays.DAJuly4th	-17,666	6,249	-2.83	0.48%
GMI_Transform.MO_Workspaces	491	37	13.31	0.00%

Ind LPS Weather Normalization Peak Models Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	730
Deg. of Freedom for Error	708
R-Squared	0.87
Adjusted R-Squared	0.86
F-Statistic	218.66
Prob (F-Statistic)	0
Mean Abs. % Err. (MAPE)	2.71%
Durbin-Watson Statistic	1.07

Energy Sales and Customer Forecast Models[3]

Note: The F-Statistic and associated probability cannot be computed in a regression model, such as the usual SAE specification, that does not include an intercept. Therefore, F-Statistic and associated probability were not reported whenever an SAE model was developed for forecasting purpose, or an intercept was not included in the model.

Residential Energy Sales Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
ResidentialVars_Billed.XHeat	1.34	0.03	44.01	0.00%
ResidentialVars_Billed.XCool	2.01	0.04	51.42	0.00%
ResidentialVars_Billed.XOther	0.75	0.02	45.88	0.00%
ResidentialVars_Billed.xCool_shoulder	-0.16	0.08	-2.00	4.98%

[3] 20 CSR 4240-22.030(3)(B)

Residential Energy Sales Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	75
Deg. of Freedom for Error	71
R-Squared	0.98
Adjusted R-Squared	0.98
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	2.29%
Durbin-Watson Statistic	1.67

Residential Customer Count Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
UtilityData.Households	1,108	7	163.75	0.00%
BinaryVars.Apr	-1,191	298	-3.99	0.01%
BinaryVars.May	-1,959	398	-4.92	0.00%
BinaryVars.Jun	-1,976	456	-4.34	0.00%
BinaryVars.Jul	-2,244	487	-4.61	0.00%
BinaryVars.Aug	-2,494	497	-5.02	0.00%
BinaryVars.Sep	-2,833	487	-5.81	0.00%
BinaryVars.Oct	-3,374	456	-7.40	0.00%
BinaryVars.Nov	-3,053	398	-7.67	0.00%
BinaryVars.Dec	-762	298	-2.55	1.22%
AR(1)	0.99	0.02	55.90	0.00%

Residential Customer Count Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	110
Deg. of Freedom for Error	99
R-Squared	1.00
Adjusted R-Squared	1.00
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	0.06%
Durbin-Watson Statistic	1.42

Commercial SGS Energy Sales Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CommercialVars_Billing.SGS_XHeat	29,106	1,169	24.90	0.00%
CommercialVars_Billing.SGS_XCool	17,055	638	26.74	0.00%
CommercialVars_Billing.SGS_XOther	879	10.6	82.75	0.00%

Commercial SGS Energy Sales Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	75
Deg. of Freedom for Error	72
R-Squared	0.93
Adjusted R-Squared	0.93
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	2.41%
Durbin-Watson Statistic	1.51

Commercial SGS Customer Count Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
BinaryVars.Jan	12,496	1,443	8.66	0.00%
BinaryVars.Feb	12,460	1,444	8.63	0.00%
BinaryVars.Mar	12,439	1,445	8.61	0.00%
BinaryVars.Apr	12,372	1,441	8.59	0.00%
BinaryVars.May	12,399	1,442	8.60	0.00%
BinaryVars.Jun	12,465	1,443	8.64	0.00%
BinaryVars.Jul	12,523	1,444	8.68	0.00%
BinaryVars.Aug	12,465	1,445	8.63	0.00%
BinaryVars.Sep	12,430	1,446	8.60	0.00%
BinaryVars.Oct	12,386	1,447	8.56	0.00%
BinaryVars.Nov	12,374	1,448	8.55	0.00%
BinaryVars.Dec	12,454	1,449	8.60	0.00%
BinaryVars.TimeTrend	3.11	0.03	93.50	0.00%

Commercial SGS Customer Count Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	87
Deg. of Freedom for Error	74
R-Squared	0.99
Adjusted R-Squared	0.99
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	0.12%
Durbin-Watson Statistic	0.12

Commercial LGS Energy Sales Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CommercialVars_Billing.LGS_XCool	17,123	374	45.75	0.00%
CommercialVars_Billing.LGS_XHeat	36,520	1,748	20.89	0.00%
CommercialVars_Billing.LGS_XOther	975.15	6.3	155.78	0.00%

Commercial LGS Energy Sales Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	60
Deg. of Freedom for Error	57
R-Squared	0.97
Adjusted R-Squared	0.97
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	1.28%
Durbin-Watson Statistic	1.52

Commercial LGS Customer Count Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
BinaryVars.Jan	9,852	128	76.98	0.00%
BinaryVars.Feb	9,851	128	77.06	0.00%
BinaryVars.Mar	9,843	128	77.09	0.00%
BinaryVars.Apr	9,836	128	77.02	0.00%
BinaryVars.May	9,835	128	76.91	0.00%
BinaryVars.Jun	9,854	128	76.98	0.00%
BinaryVars.Jul	9,864	128	76.99	0.00%
BinaryVars.Aug	9,874	128	77.03	0.00%
BinaryVars.Sep	9,882	128	77.08	0.00%
BinaryVars.Oct	9,868	128	76.97	0.00%
BinaryVars.Nov	9,862	128	76.95	0.00%
BinaryVars.Dec	9,855	128	76.94	0.00%
AR(1)	0.98	0.01	138.76	0.00%

Commercial LGS Customer Count Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	107
Deg. of Freedom for Error	94
R-Squared	1.00
Adjusted R-Squared	1.00
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	0.09%
Durbin-Watson Statistic	1.90

Commercial SPS Energy Sales Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CommercialVars_Billing.SPS_XHeat	21,478	3,674	5.85	0.00%
CommercialVars_Billing.SPS_XCool	5,433	343.49	15.82	0.00%
CommercialVars_Billing.SPS_XOther	1,142	14.96	76.39	0.00%

Commercial SPS Energy Sales Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	51
Deg. of Freedom for Error	48
R-Squared	0.88
Adjusted R-Squared	0.87
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	2.11%
Durbin-Watson Statistic	1.13

Commercial SPS Customer Count Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
BinaryVars.Jan	480	1.69	284.19	0.00%
BinaryVars.Feb	480	1.59	302.47	0.00%
BinaryVars.Mar	480	1.55	310.28	0.00%
BinaryVars.Apr	480	1.64	292.21	0.00%
BinaryVars.May	481	1.68	287.17	0.00%
BinaryVars.Jun	478	1.69	283.82	0.00%
BinaryVars.Jul	479	1.69	283.76	0.00%
BinaryVars.Aug	482	1.69	285.70	0.00%
BinaryVars.Sep	480	1.69	284.48	0.00%
BinaryVars.Oct	479	1.69	283.89	0.00%
BinaryVars.Nov	479	1.69	283.45	0.00%
BinaryVars.Dec	479	1.69	283.74	0.00%
AR(1)	0.61	0.12	5.02	0.00%

Commercial SPS Customer Count Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	50
Deg. of Freedom for Error	37
R-Squared	0.47
Adjusted R-Squared	0.29
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	0.36%
Durbin-Watson Statistic	2.09

Commercial LPS Energy Sales Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CommercialVars_Billing.LPS_XCool	14,076	666.71	21.11	0.00%
CommercialVars_Billing.LPS_XOther	877	8.29	105.87	0.00%

Commercial LPS Energy Sales Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	75
Deg. of Freedom for Error	73
R-Squared	0.83
Adjusted R-Squared	0.83
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	3.88%
Durbin-Watson Statistic	1.97

Commercial LPS Customer Count Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
Simple Smoothing	0.71	0.13	5.60	0

Commercial LPS Customer Count Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	63
Deg. of Freedom for Error	62
R-Squared	0.45
Adjusted R-Squared	0.45
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	0.65%
Durbin-Watson Statistic	1.87

Industrial SGS Energy Sales Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	10,410	2,269	4.59	0.00%
Weather_Trans.Billed_HDD	4	0.23	15.34	0.00%
Weather_Trans.Billed_CDD	6.85	0.43	16.13	0.00%
Binary_Vars.January	1,332	314.42	4.24	0.01%
Binary_Vars.October	1,116	158.74	7.03	0.00%
Binary_Vars.November	1,869	160.26	11.67	0.00%
Binary_Vars.December	2,082	231.41	9.00	0.00%
Econ_Trans.SGS_Index	-176.50	81.63	-2.16	3.63%
Binary_Vars.Pandemic_Shift	-739.97	80.17	-9.23	0.00%

Industrial SGS Energy Sales Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	51
Deg. of Freedom for Error	42
R-Squared	0.95
Adjusted R-Squared	0.94
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	2.43%
Durbin-Watson Statistic	1.76

Industrial SGS Customer Count Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
Binary_Vars.January	2,311	104.96	22.02	0.00%
Binary_Vars.February	2,312	104.99	22.02	0.00%
Binary_Vars.March	2,313	104.98	22.03	0.00%
Binary_Vars.April	2,304	105.15	21.91	0.00%
Binary_Vars.May	2,303	105.27	21.87	0.00%
Binary_Vars.June	2,303	105.36	21.86	0.00%
Binary_Vars.July	2,301	105.41	21.83	0.00%
Binary_Vars.August	2,298	105.42	21.80	0.00%
Binary_Vars.September	2,296	105.39	21.79	0.00%
Binary_Vars.October	2,300	105.33	21.84	0.00%
Binary_Vars.November	2,302	105.24	21.87	0.00%
Binary_Vars.December	2,305	105.12	21.92	0.00%
AR(1)	0.98	0.01	196.71	0.00%

Industrial SGS Customer Count Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	62
Deg. of Freedom for Error	49
R-Squared	1.00
Adjusted R-Squared	1.00
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	0.13%
Durbin-Watson Statistic	2.02

Industrial LGS Energy Sales Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	46,950	6,584	7.13	0.00%
Weather_Trans.Billed_CDD	19	1	14.25	0.00%
Binary_Vars.February	2,336	804	2.91	0.53%
Binary_Vars.April	-2,398	822	-2.92	0.51%
Binary_Vars.May	-2,371	808	-2.94	0.49%
Binary_Vars.June	-2,997	768	-3.90	0.03%
Econ_Trans.LGS_Index	808	223	3.62	0.07%
Binary_Vars.Pandemic_Shift	-3,729	527	-7.08	0.00%
Binary_Vars.End_shift_2018	-4,205	545	-7.71	0.00%

Industrial LGS Energy Sales Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	63
Deg. of Freedom for Error	54
R-Squared	0.92
Adjusted R-Squared	0.91
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	1.77%
Durbin-Watson Statistic	1.30

Industrial LGS Customer Count Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
Binary_Vars.January	881	89.42	9.85	0.00%
Binary_Vars.February	880	89.42	9.84	0.00%
Binary_Vars.March	880	89.41	9.84	0.00%
Binary_Vars.April	878	89.44	9.82	0.00%
Binary_Vars.May	877	89.46	9.80	0.00%
Binary_Vars.June	879	89.48	9.83	0.00%
Binary_Vars.July	879	89.49	9.82	0.00%
Binary_Vars.August	881	89.49	9.85	0.00%
Binary_Vars.September	883	89.49	9.87	0.00%
Binary_Vars.October	881	89.48	9.85	0.00%
Binary_Vars.November	881	89.46	9.85	0.00%
Binary_Vars.December	880	89.44	9.84	0.00%
AR(1)	0.99	0.01	118.47	0.00%

Industrial LGS Customer Count Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	134
Deg. of Freedom for Error	121
R-Squared	0.99
Adjusted R-Squared	0.99
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	0.21%
Durbin-Watson Statistic	2.60

Industrial SPS Energy Sales Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
Econ_Trans.SPS_Index	-4,266	1,525	-2.80	0.84%
Weather_Trans.Billed_CDD	26	13	1.93	6.15%
Binary_Vars.January	240,814	49,775	4.84	0.00%
Binary_Vars.February	222,071	44,472	4.99	0.00%
Binary_Vars.March	223,482	44,481	5.02	0.00%
Binary_Vars.April	223,536	45,163	4.95	0.00%
Binary_Vars.May	220,969	44,731	4.94	0.00%
Binary_Vars.June	226,483	46,979	4.82	0.00%
Binary_Vars.July	226,270	47,428	4.77	0.00%
Binary_Vars.August	223,949	46,006	4.87	0.00%
Binary_Vars.September	224,816	47,016	4.78	0.00%
Binary_Vars.October	222,614	45,375	4.91	0.00%
Binary_Vars.November	223,149	45,476	4.91	0.00%
Binary_Vars.December	233,663	47,955	4.87	0.00%
Binary_Vars.COVID_Lockdowns_SPS	-4,741	1,410	-3.36	0.19%
Binary_Vars.Flooding_SPS	7,895	3,573	2.21	3.40%

Note: One of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

Industrial SPS Energy Sales Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	50
Deg. of Freedom for Error	34
R-Squared	0.83
Adjusted R-Squared	0.75
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	1.61%
Durbin-Watson Statistic	0.91

Industrial SPS Customer Count Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
Binary_Vars.January	185	0.58	320	0.00%
Binary_Vars.February	185	0.56	329	0.00%
Binary_Vars.March	185	0.56	332	0.00%
Binary_Vars.April	184	0.57	322	0.00%
Binary_Vars.May	185	0.58	320	0.00%
Binary_Vars.June	184	0.58	318	0.00%
Binary_Vars.July	185	0.58	320	0.00%
Binary_Vars.August	185	0.58	320	0.00%
Binary_Vars.September	184	0.58	318	0.00%
Binary_Vars.October	184	0.58	317	0.00%
Binary_Vars.November	184	0.58	318	0.00%
Binary_Vars.December	185	0.58	319	0.00%
AR(1)	0.56	0.08	7.20	0.00%

Industrial SPS Customer Count Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	122
Deg. of Freedom for Error	109
R-Squared	0.36
Adjusted R-Squared	0.29
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	0.59%
Durbin-Watson Statistic	2.19

Industrial LPS Energy Sales Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
Econ_Trans.LPS_Index	5,278	29	179.8	0.00%
Binary_Vars.March	11,947	1,777	6.73	0.00%
Binary_Vars.April	19,016	2,009	9.47	0.00%
Binary_Vars.May	33,659	2,399	14.03	0.00%
Binary_Vars.June	27,962	2,019	13.85	0.00%
Binary_Vars.July	41,672	1,921	21.70	0.00%
Binary_Vars.August	44,060	1,909	23.08	0.00%
Binary_Vars.September	24,758	1,920	12.90	0.00%
Binary_Vars.October	27,516	1,910	14.41	0.00%
Binary_Vars.November	16,242	1,916	8.48	0.00%
Binary_Vars.Flooding	-13,658	3,094	-4.41	0.01%
Binary_Vars.COVID_Lockdowns	-21,928	3,094	-7.09	0.00%
Binary_Vars.Customer_Outage_May21	-14,530	4,411	-3.29	0.18%

Industrial LPS Energy Sales Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	63
Deg. of Freedom for Error	50
R-Squared	0.94
Adjusted R-Squared	0.93
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err. (MAPE)	1.58%
Durbin-Watson Statistic	2.13

Industrial LPS Customer Count Forecast Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
Binary_Vars.January	34	0.32	107	0.00%
Binary_Vars.February	34	0.31	108	0.00%
Binary_Vars.March	34	0.31	108	0.00%
Binary_Vars.April	34	0.32	107	0.00%
Binary_Vars.May	34	0.32	107	0.00%
Binary_Vars.June	34	0.32	106	0.00%
Binary_Vars.July	34	0.32	106	0.00%
Binary_Vars.August	34	0.32	106	0.00%
Binary_Vars.September	34	0.32	105	0.00%
Binary_Vars.October	34	0.32	105	0.00%
Binary_Vars.November	34	0.32	106	0.00%
Binary_Vars.December	34	0.32	106	0.00%
AR(1)	0.85	0.05	19	0.00%

Industrial LPS Customer Count Forecast Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	86
Deg. of Freedom for Error	73
R-Squared	0.84
Adjusted R-Squared	0.81
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err (MAPE)	0.65%
Durbin-Watson Statistic	2.29

Non-Coincident System Peak Model Coefficients

Variable	Coefficient	StdErr	T-Stat	P-Value
Heating Variable	32	3.09	10	0.00%
Cooling Variable	84	9.83	9	0.00%
Base Variable	1	0.04	29	0.00%
January	799	172.70	5	0.00%
February	868	160.54	5	0.00%
March	457	137.58	3	0.15%
May	584	162.27	4	0.06%
June	1026	220.41	5	0.00%
July	1083	230.10	5	0.00%
August	1157	209.10	6	0.00%
September	820	200.20	4	0.01%
October	318	164.54	2	5.81%
November	536	137.51	4	0.02%
December	511.32	157.93	3	0.20%

Note: One of the explanatory variables were retained in the model despite being only marginally statistically significant (p-value>.05). The direction and magnitude of the coefficient are reasonable, the standard error is consistent with other variables, and the interpretation of all the weather variables is cleaner with the inclusion of this variable.

Non-Coincident System Peak Model Statistics

Model Statistic	Value of the Statistic
Adjusted Observations	75
Deg. of Freedom for Error	61
R-Squared	0.94
Adjusted R-Squared	0.93
F-Statistic	#NA
Prob (F-Statistic)	#NA
Mean Abs. % Err (MAPE)	3.06%
Durbin-Watson Statistic	2.04

Time of Use Adjustments

	Hours Reduced	Summer Reduction (Jun - Sept)	Winter Reduction (Oct - May)	Estimated Customer Participation Rate																				
				2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040	2041	2042	2043
Evening/Morning Savers	Between 9 am and 9 pm, everyday for all seasons	0.3%	0.3%	40.10%	47.15%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%	54.19%
Overnight Savers	6 am to 10pm everyday for all seasons	6.8%	3.5%	0.06%	0.07%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%
Smart Savers	3 pm to 7 pm on summer (June – September) non-holiday weekdays, and 6 to 8 am and pm (both morning and evening) on non-summer (all other months) non-holiday weekdays	11.8%	9.0%	0.04%	0.05%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%
Ultimate Savers	3 pm to 7 pm on summer (June – September) non-holiday weekdays, and 6 to 8 am and pm (both morning and evening) on non-summer (all other months) non-holiday weekdays	12.9%	9.3%	0.03%	0.04%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%

Abbreviations

Res: Residential
Com: Commercial
Ind: Industrial
SGS: Small General Service
LGS: Large General Service
SPS: Small Primary Service
LPS: Large Primary Service
WN: Weather Normalized
LTS: Large Transmission Service

Compliance References

20 CSR 4240-22.030(2)(C)3 .... 1, 12
20 CSR 4240-22.030(3)(B) 21

BEFORE THE PUBLIC SERVICE COMMISSION
OF THE STATE OF MISSOURI

In the Matter of the Application of Union	)	
Electric Company d/b/a Ameren Missouri	)	File No. ET-2025-0184
for Approval of New or Modified Tariffs	)	
for Service to Large Load Customers.	)	

AFFIDAVIT OF MATT MICHELS

STATE OF MISSOURI)
) ss
CITY OF ST. LOUIS)

Matt Michels, being first duly sworn states:

My name is Matt Michels and on my oath declare that I am of sound mind and lawful age; that I have prepared the foregoing *Surrebuttal Testimony*; and further, under the penalty of perjury, that the same is true and correct to the best of my knowledge and belief.

/s/ Matt Michels
Matt Michels

Sworn to me this 3rd day of November, 2025.