COMMONWEALTH OF KENTUCKY

BEFORE THE PUBLIC SERVICE COMMISSION

In the Matter of:

ELECTRONIC JOINT APPLICATION OF KENTUCKY UTILITIES COMPANY AND LOUISVILLE GAS AND ELECTRIC COMPANY FOR CERTIFICATES OF PUBLIC CONVENIENCE AND NECESSITY AND SITE COMPATIBILITY CERTIFICATES AND APPROVAL OF A DEMAND SIDE MANAGEMENT PLAN	))))))))	**CASE NO. 2022-00402**

DIRECT TESTIMONY OF
TIM A. JONES
MANAGER, SALES ANALYSIS AND FORECASTING
KENTUCKY UTILITIES COMPANY AND
LOUISVILLE GAS AND ELECTIC COMPANY

Filed: December 15, 2022

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INTRODUCTION

Q. Please state your name, position, and business address.

A. My name is Tim Jones. I am the Manager of Sales Analysis and Forecasting for Kentucky Utilities Company ("KU") and Louisville Gas and Electric Company ("LG&E") (collectively, "Companies") and an employee of LG&E and KU Services Company, which provides services to KU and LG&E. My business address is 220 West Main Street, Louisville, Kentucky 40202. A complete statement of my education and work experience is attached to this testimony as Appendix A.

Q. Please describe your job responsibilities.

A. The primary responsibility of the Sales Analysis and Forecasting team is to support decision making within the Companies. This begins with an understanding of how the Companies' customers use electricity and gas in all hours, which we obtain through economic and statistical analysis and research into factors that could change future usage patterns. Though not a comprehensive list, this includes the following tasks:

- analyzing monthly sales and energy requirements variances;
- analyzing key factors that influence customers' energy consumption, such as the state of the economy, federal and state regulations, weather, demand-side programs, end-use appliance efficiencies and saturations, distributed generation, electrification, and rates and rate design;
- analyzing available interval data and using clustering algorithms to create hourly usage profiles by rate class;
- considering additional inputs that could aid in analysis or forecasting; and
- documenting our processes.

As Manager of the Sales Analysis and Forecasting team, each year I am responsible for producing the Companies' 30-year electric load forecast and a 10-year gas volumes forecast. In my role, I am well acquainted with all aspects of the Companies' load forecasting.

In addition, my education and prior work experience have equipped me well for my current role. I hold a bachelor's degree in mathematics from Bellarmine University, and I worked 11 years at Schneider Electric, primarily in a data analysis role, before joining the Companies more than six years ago. I have spent my entire career with the Companies in the Sales Analysis and Forecasting group as an analyst or manager.

Q. What is the purpose of your direct testimony?

A. The purpose of my testimony is to discuss the Companies' electric load forecast and the process used to create it.

Q. Are you sponsoring any exhibits to your testimony?

A. Yes. I am sponsoring the following exhibits:

- Exhibit TAJ-1: 2022 CPCN Load Forecast
- Exhibit TAJ-2: Electric Sales & Demand Forecast Process
- Exhibit TAJ-3: 2022 CPCN Load Forecast Workpapers

Note that Exhibit TAJ-3 consists of electronic workpapers concerning the load forecast and are being provided separately.

<u>OVERVIEW OF COMPANIES' LOAD FORECASTING APPROACH</u>

Q. Please describe the Companies' electric load forecast process.

A. Each year from approximately March through July, the Companies prepare a 30-year demand and energy forecast. The electric load forecast process is essentially the same for both KU and LG&E. Fundamentally, the electric load forecast process involves:

- Using historical data to develop models that relate the Companies' electricity usage, demand, sales, and number of customers by rate classes to exogenous factors such as economic activity, appliance efficiencies and adaptation, demographic trends, and weather conditions;
- Using the models in combination with forecasts of the exogenous factors to forecast the Companies' electricity usage, demand, sales, and number of customers for the various rate classes; and
- Using historical load shapes for each of KU and LG&E to convert the monthly sales forecasts into a 30-year hourly forecast that can be used for generation planning purposes, including forecasting peak demands.[1]

Q. How do the Companies ensure their electric load forecast is reasonable?

A. The Companies seek to ensure their load forecasts are prepared using sound methods by people who are qualified professionals. There are three practices that the Companies employ to help produce methodologically sound and reasonable forecasts:

1. Building and rigorously testing statistically and economically sound mathematical models of the load forecast variables;

2. Using high-quality forecasts of future macroeconomic events that influence the load forecast variables, both nationally and in the service territory; and

[1] For an extended discussion of the forecasting process, see Exhibit TAJ-2, "Electric Sales & Demand Forecast Process."

3. Thoroughly reviewing and analyzing model outputs to ensure the results are reasonable based on historical trends and the Companies' own experience and understanding of long-term trends in electricity and natural gas usage.

Notably, the Commission Staff Report in the Companies' 2021 Integrated Resource Plan ("IRP") case stated, "LG&E/KU's assumptions and methodologies for load forecasting are generally reasonable."[2]

Q. Have the Companies materially changed their approach to electric load forecasting since their 2021 IRP?

A. No. Although we try to improve our models each year, these changes are typically minor and do not depart fundamentally from methods the Companies have used for years. These methods have proven to be reasonably reliable on the whole (though unforeseeable circumstances can and do arise). The 2022 CPCN Load Forecast reflects information that has become available since the 2021 IRP, such as updated actual load and customer data, updated national and regional economic forecasts and regulations, and updated model parameters.

Q. What did the Commission Staff Report state concerning the Companies' load forecasting process used in the 2021 IRP?

A. As I noted above, the report stated that the Companies' assumptions and methodologies for load forecasting were generally reasonable.[3] It also offered five recommendations for improvement:

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[2] *Electronic 2021 Joint Integrated Resource Plan of Louisville Gas and Electric Company and Kentucky Utilities Company*, Case No. 2021-00393, Order Appx. "Commission Staff's Report on the 2021 Integrated Resource Plan of Louisville Gas and Electric Company and Kentucky Utilities Company" at 51 (Ky. PSC Sept. 16, 2022).

[3] *Electronic 2021 Joint Integrated Resource Plan of Louisville Gas and Electric Company and Kentucky Utilities Company*, Case No. 2021-00393, Order Appx. A at 51 (Ky. PSC Sept. 16, 2022) ("LG&E/KU's assumptions and methodologies for load forecasting are generally reasonable.").

- LG&E/KU should expand their discussion of the reasonableness of underlying assumptions including supporting documentation listing known facts.

- LG&E/KU should continue to monitor and incorporate anticipated changes in EE impacts in their forecasts and sensitivity analyses. In addition, the Companies should not assume that current DSM-EE programs will not be renewed. Further, in the context of a long-range planning study, it would be reasonable for the Companies to model increased participation in current programs up to their current limits.

- LG&E/KU should expand its discussion of DERs to identify resources other than distributed solar that could potentially be adopted by customers and explain how and why those resources are expected to affect load, if at all.

- LG&E/KU should expand its discussion of the projected adoption of distributed solar and its effect on load to include separate discussions of assumptions, methodology, and projections for residential, commercial, and industrial customers and separate discussions of assumptions, methodology, and projections for customers interconnected under LG&E/KU's net metering tariffs, qualifying facilities tariffs, and other similar tariffs, if any, that are adopted after this report.

- LG&E/KU should analyze and discuss whether and the extent to which customers that would have taken service under the Net Metering Service-2 tariff would continue to interconnect DERs even if they received no credit for energy sent back into the system because the one percent cap had been reached when they sought to connect.[4]

As discussed in the relevant portions of my testimony below and in Exhibits TAJ-1 (the 2022 CPCN Load Forecast) and TAJ-2 (the Electric Sales & Demand Forecast Process document), the Companies have sought to satisfy the 2021 Commission Staff Report's load forecast recommendations in the 2022 CPCN Load Forecast.

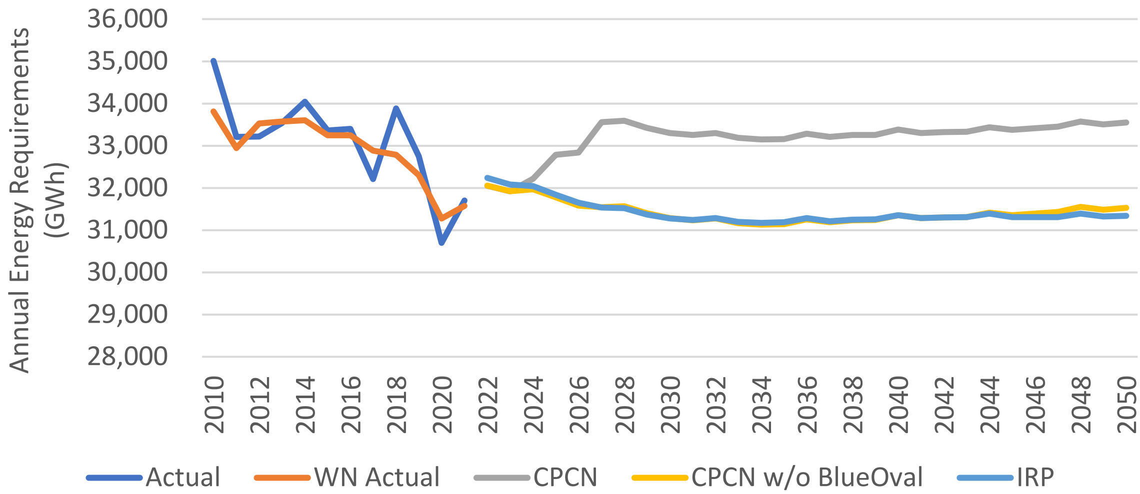
OVERVIEW OF THE 2022 CPCN LOAD FORECAST

Q. Please provide an overview of the 2022 CPCN Load Forecast.

[4] *Id.* at 67.

A. Figure 1 below provides the single most comprehensive look at the 2022 CPCN Load Forecast and how it differs from the load forecast the Companies presented in their 2021 IRP.

Figure 1: Annual Energy Requirements History and Forecast (exc. Departed Municipal Customers)



As is immediately evident from Figure 1 above, nearly all the changes the 2022 CPCN Load Forecast takes into account—including effects of the recent federal Inflation Reduction Act ("IRA") and the Companies' proposed 2024-2030 Demand-side Management and Energy Efficiency ("DSM-EE") Program Plan—have net effects that are minimal relative to the 2021 IRP load forecast.

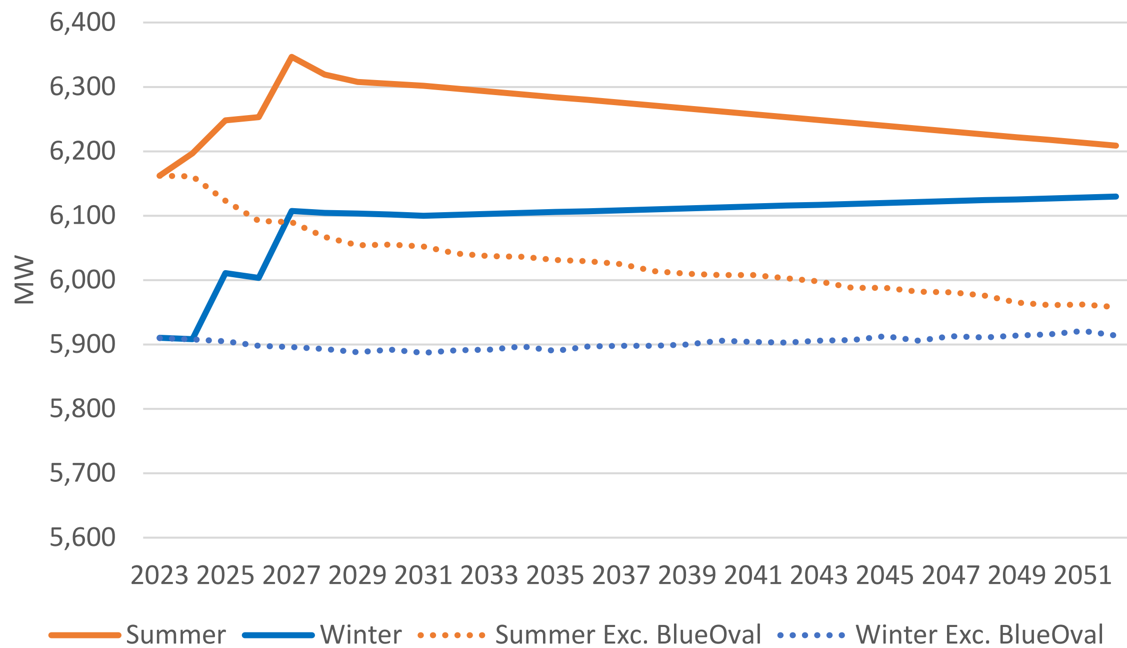
Similarly evident is that the most impactful change to the load forecast by a wide margin is the addition of Ford's planned BlueOval SK Battery Park ("BlueOval"), which has a planned summer peak load of almost 260 MW, a winter peak load around 225 MW, and a capacity factor of almost 90%.[5] Indeed, the sheer consistency and magnitude of BlueOval's energy requirements in all hours are reflected in Figure 1,

[5] The stated peak load figures represent BlueOval's non-coincident, peak hourly usage projections grossed up by a transmission loss factor of 1.02827. BlueOval's anticipated summer billing demand is 254 MW.

which shows annual energy requirements increasing rapidly as BlueOval comes fully online in 2027-2028 and remaining between 33,100 GWh and 33,600 GWh from 2028 through 2052.

BlueOval also has a pronounced effect on the Companies' projected summer and winter loads, as shown in Figure 2 below:

Figure 2: Forecasted Seasonal Peaks



As Figure 2 shows, with BlueOval load included, the Companies' peak summer load for the entire forecast period (6,347 MW) occurs in 2027, then slowly declines to 6,209 MW in 2052. Somewhat dissimilarly, the Companies' winter peak load in 2027 is 6,107 MW and gradually increases to 6,130 MW in 2052, reflecting the impacts of increasing electric heating load that are difficult to offset with increasing distributed solar generation because such peaks tend to occur in non-daylight hours.

Other highlights of the 2022 CPCN Load Forecast that I further discuss in my testimony and at greater length in Exhibit TAJ-1 are:

- The IRA and the Companies' 2024-2030 DSM-EE Program Plan significantly accelerate energy efficiency deployment, achieving the U. S. Department of Energy's Energy Information Administration's ("EIA") 2043 forecasted levels of energy efficiency by 2033.
- The IRA also drives growth in distributed generation, space heating electrification, and increased electric vehicle ("EV") adoption. The net effect of the IRA and DSM-EE is close to neutral due to the IRA's load-decreasing and load-increasing incentives and provisions (incentives for load-increasing items like EVs and heating electrification as well as load-decreasing items like energy efficiency and distributed generation).
- Distributed generation capacity (including qualifying facilities ("QFs")) increases from the current level of about 34.4 MW to almost 217 MW by 2052.
- EVs increase in the Companies' Kentucky service territory from the current level of approximately 7,000 to over 300,000 by 2052.
- By 2052, electric space heating saturation increases from 2015 levels by 7% in KU's service territory (which is already highly saturated) and by 33% in LG&E's service territory.
- Customers continue to have significant energy requirements in all hours and seasons, including in non-daylight hours, e.g., minimum hourly demand in 2028 is 2,450 MW.

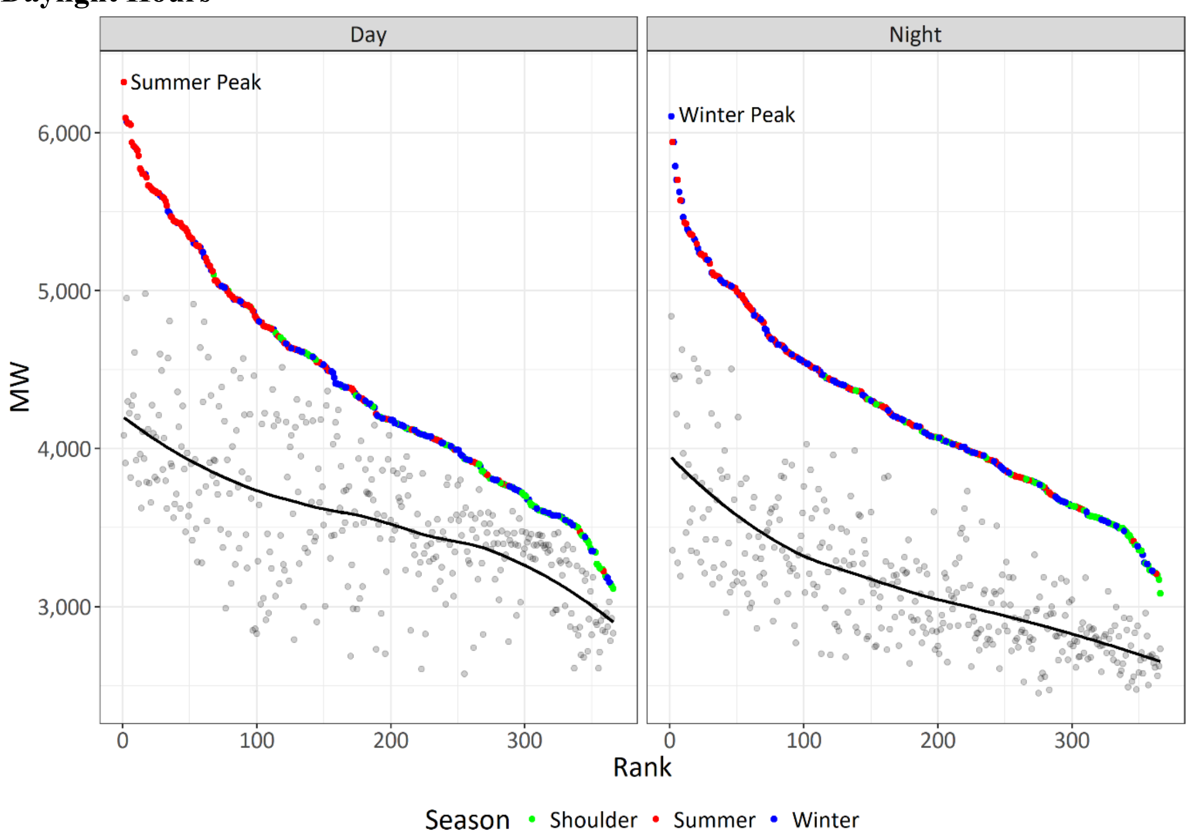
CUSTOMERS WILL CONTINUE TO REQUIRE SIGNIFICANT AMOUNTS OF ENERGY IN ALL HOURS, SEASONS, AND DAYLGHT CONDITIONS

Q. Before you provide additional detail concerning other 2022 CPCN Load Forecast highlights, please explain what you mean concerning customers' ongoing "significant energy requirements in all hours and seasons, including in non-daylight hours."

A. As David S. Sinclair and Stuart A. Wilson explain in their testimonies, because the Companies must serve customers reliably and economically in all hours, not just a handful of peak hours, it is important to understand customers' energy needs in all hours and seasons, including in daylight and non-daylight conditions. Having that understanding helps the Companies ensure they have an appropriate mix of demand- and supply-side resources available to provide reliable, low-cost service at all times.

In that vein, the figure below shows daily peak and minimum load values in both daylight and non-daylight hours for every day in calendar year 2028, ranked from highest to lowest by daily maximum (maximum values are in color; minimum values are gray):

Figure 3: 2028 Daily Maximum and Minimum Loads during Daylight and Non-Daylight Hours



Note that the values shown in this figure include the effects of IRA-enhanced distributed generation and energy efficiency, including energy efficiency incentivized by the Companies' 2024-2030 DSM-EE Program Plan. Even accounting for those effects, there are about 50 non-daylight peak hours above 5,000 MW, including a number of which occur in the summer, and more than 200 such hours above 4,000 MW, many of which occur in the winter.

The figure below highlights the amount of energy customers use during non-daylight hours, again for calendar year 2028, with approximately 35% of summer electricity usage during non-daylight hours and over 55% of winter electricity usage during non-daylight hours:

Figure 4: 2028 Proportion of Energy Consumed During Daylight and Non-Daylight Hours

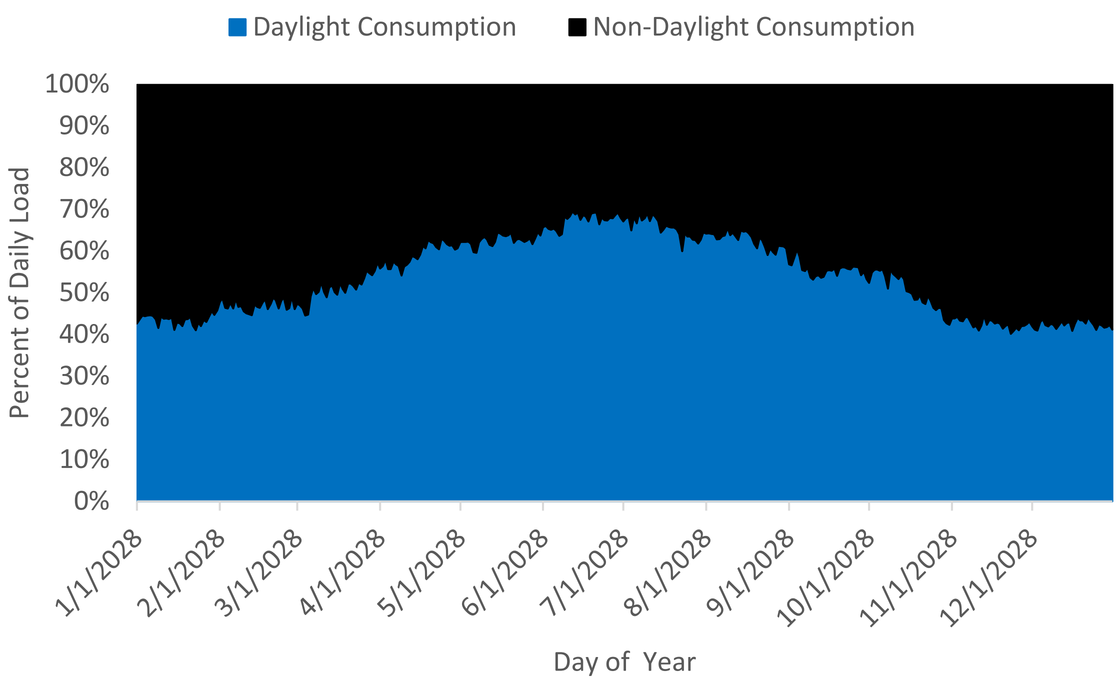


Figure 5 below shows projected hourly demand chronologically in 2028, and Figure 6 is a load duration curve of the same data. They show that the Companies' combined system hourly peak is 6,319 in 2028, minimum hourly demand is 2,452 MW, and that in 2028 there will be 20 hours with demand over 6,000 MW, 624 hours with demand over 5,000 MW, and all but 990 hours with demand over 3,000 MW.

Figure 5: LG&E and KU 2028 Hourly Load

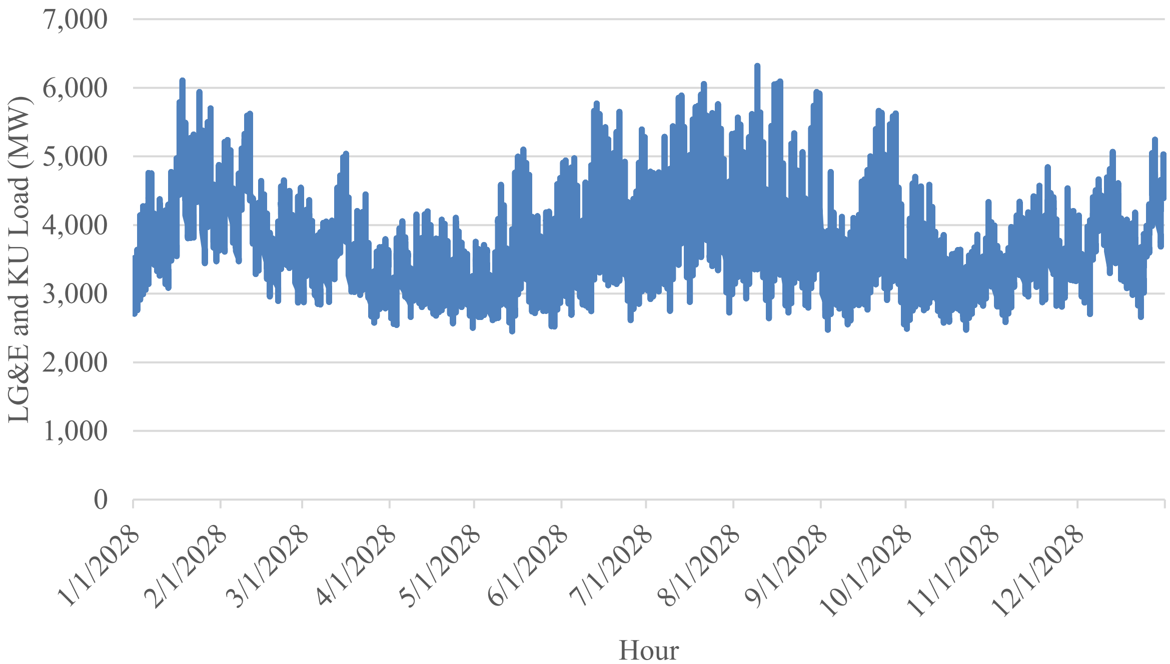
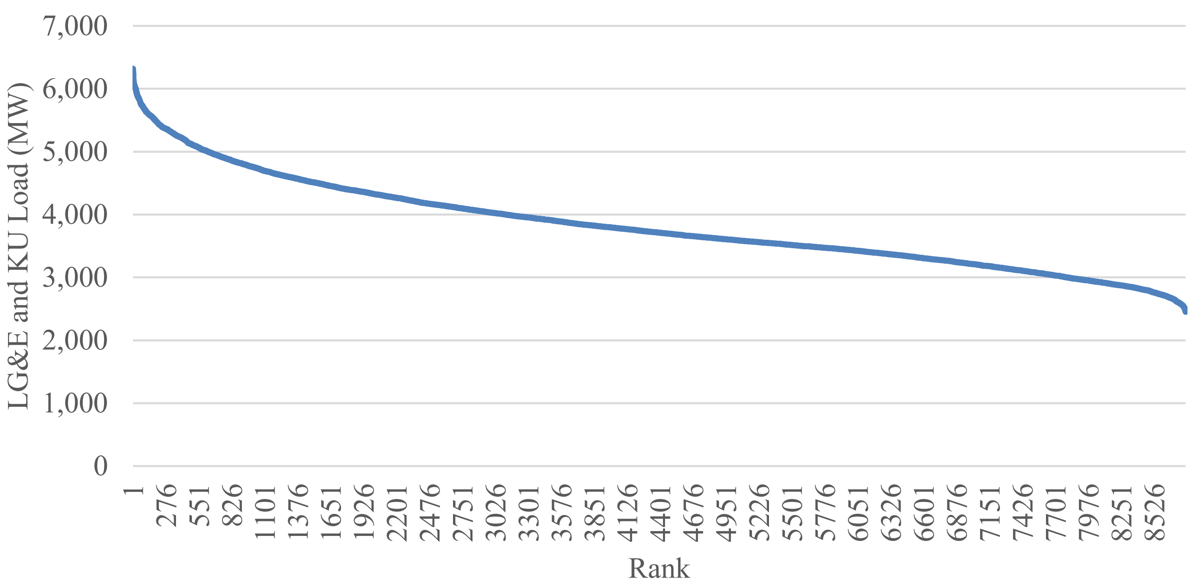


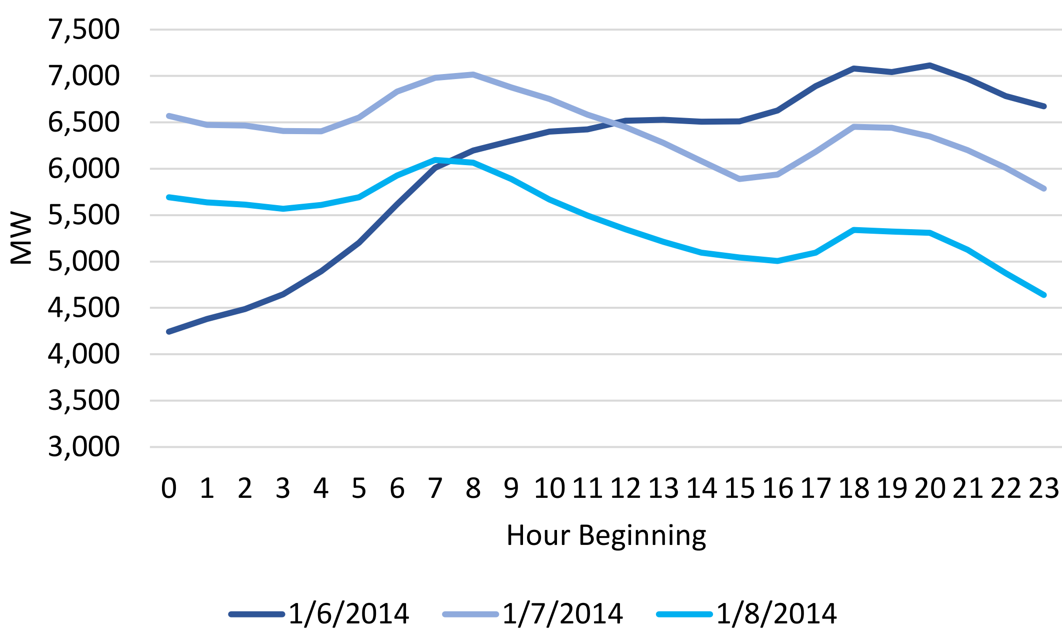
Figure 6: LG&E and KU 2028 Load Duration Curve



This data shows that customers require large amounts of energy at all times, day and night, and in all seasons and weather conditions. It further shows that system peak demands can occur in summer or winter and in daylight and non-daylight hours.

Finally, it is noteworthy that the hourly forecast and charts above assume normal weather and normal weather variability, but customers demand even greater load for a longer duration during extreme weather events. For example, Figure 7 below shows the hourly load profiles of 3 days during the Polar Vortex of January 2014.[6] During this period, hourly load remained above 6,000 MW for 32 consecutive hours and above 5,000 MW for 65 consecutive hours. The highest loads during this period were observed during non-daylight or very early morning hours.

Figure 7: Polar Vortex 2014 Hourly Load Profiles



[6] Includes load from the departed municipal customers. The addition of BlueOval load will mostly offset the loss of the departed municipal customer load. The lowest temperature recorded at the Muhammad Ali International Airport in Louisville during the Polar Vortex was -3 degrees Fahrenheit. On January 19, 1994 during a winter storm event that dumped over a foot of snow in Louisville, the recorded low temperature was -22 degrees Fahrenheit. https://www.wlky.com/article/archives-unforgettable-snow-shut-down-louisville/30562805

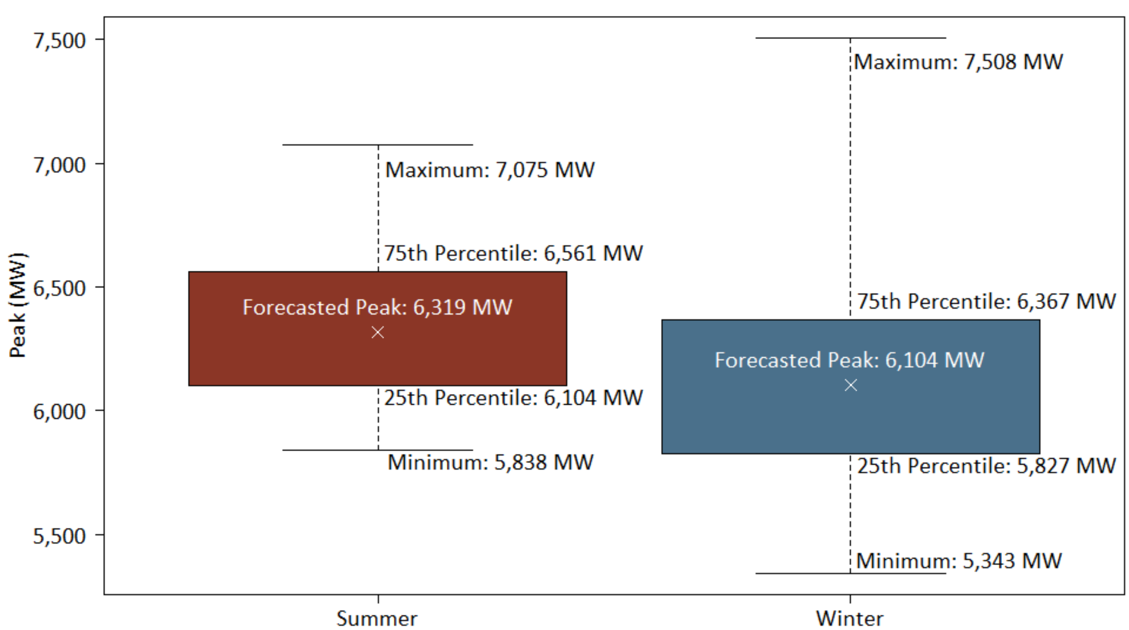
Again, this demonstrates that customers can and do have significant—and sometimes extreme—energy needs for entire days at a time, not just an hour or two.

FOUNDATIONAL LOAD FORECAST ASSUMPTIONS AND INPUTS

Q. What are the foundational weather and economic assumptions the Companies used in the 2022 CPCN Load Forecast?

A. Consistent with prior practice, the Companies used 20 years of historical weather data to develop their long-term base energy requirements forecast, which assumes average or "normal" weather in all years. To account for weather variability and support the Companies' Reserve Margin Analysis, the Companies also produced 49 hourly energy requirement forecasts for 2028 based on weather in each of the last 49 years. Figure 8 shows the resulting distribution of 2028 summer and winter peak demands, and in particular, it shows the variability of winter peak demand:

Figure 8: Distribution of 2028 Summer and Winter Peak Demands



Concerning economic assumptions, Companies used economic assumptions from a reputable forecaster, S&P Global, in forecasting their base energy requirements.[7] Regarding Kentucky's economy, S&P Global projects real economic growth of 1.4 percent during 2022. For the 2023-2027 period, the state's economy is expected to increase at an average pace of 1.8 percent, above the between-recession average of 1.4 percent. Over the longer term from 2028-2032, S&P Global projects growth to average 1.8 percent. Near-term economic risks include high inflation and a potential economic downturn resulting from attempts to curb inflation. Although there is an economic recession risk, it would likely affect only near-term growth.

BLUEOVAL SK BATTERY PARK

Q. What is the impact of BlueOval on the 2022 CPCN Load Forecast?

A. It is difficult to overstate the impact of BlueOval on this load forecast. As illustrated in Figures 1 and 2 above, without BlueOval the Companies' forecasted annual energy requirements in this forecast are similar to those in the 2021 IRP load forecast, ranging from 0.5% lower to 0.2% higher through 2030, as reductions from increased levels of energy efficiency and distributed energy resources ("DER") are essentially offset by more customers and higher consumption due to increasing penetrations of EVs and electric space heating. Similarly, without BlueOval peak demand ranges from 0.6% lower to 0.2% higher (-38 to +12 MW) in summer, and peak demand ranges from 0.6% to 2.5% higher (37 to 142 MW) in winter through 2030.

[7] All of the economic assumptions the Companies used are from S&P Global's May 2022 U.S. Economic Outlook. (S&P Global was formerly IHS Markit.) The spreadsheet containing those assumptions is included in the 2022 Load Forecast workpapers, Exhibit TAJ-3. Note that the S&P Global data contains many more assumptions than the Companies' load-forecasting models used.

But with BlueOval in full operation, annual energy requirements are approximately 6.5% higher than the 2021 IRP load forecast beginning in 2027. Summer and winter peak demand are approximately 4% and 6% higher, respectively.[8] Thus, it is not hyperbole to state that the BlueOval SK Battery Park is the single most impactful change to the Companies' load forecast since the 2021 IRP—and by a wide margin.

Q. Did the Companies assume any ancillary load associated with BlueOval?

A. No. Although it is reasonable to assume that BlueOval will drive economic and load growth in Glendale and surrounding areas, the Companies do not serve much of the area surrounding Glendale. Therefore, the Companies attempted to be conservative in projecting BlueOval's total impact by not explicitly including any ancillary load growth associated with BlueOval.

OVERVIEW OF THE INFLATION REDUCTION ACT'S EFFECTS ON THE 2022 CPCN LOAD FORECAST

Q. Please provide a short overview of the Inflation Reduction Act's ("IRA") effects on the 2022 CPCN Load Forecast.

A. On August 16, 2022, President Biden signed the IRA. Although details of the IRA's implementation remain to be addressed through guidance from various agencies, four impacts of the IRA are reasonably clear and have effects on the 2022 CPCN Load Forecast. Two of those impacts tend to increase the load forecast. First, the IRA provides incentives for electric vehicle ("EV") adoption in the form of tax credits for

[8] *See* Exhibit TAJ-1, 2022 Load Forecast, Technical Appendix 1 tables comparing annual energy requirements and seasonal peak loads for the 2021 IRP load forecast and the 2022 Load Forecast.

both new and used vehicles.[9] Second, the IRA provides incentives to promote heating electrification in the form of large rebates for energy-efficient heat pumps ($8,000 for low-income customers and $4,000 for mid-income customers that qualify) and related electrical panel upgrades ($4,000 for low-income customers).

The IRA also has two impacts that tend to reduce the load forecast. First, the IRA incentivizes distributed energy resources, such as providing an investment tax credit ("ITC") of 30% for distributed solar through 2032, which then decreases to 26% and 22% in 2033 and 2034, respectively, before ending entirely in 2035. Second, the IRA incentivizes energy efficient or electric end-use appliances (not just heat pumps) by providing qualifying low- and mid-income customers home energy efficiency and electrification tax incentives and rebates up to a lifetime maximum of $14,000.

As I explain below and in Exhibit TAJ-1, the Companies have attempted to estimate the impacts of these incentives in various ways in the 2022 CPCN Load Forecast.

ENERGY EFFICIENCY: THE INFLATION REDUCTION ACT AND THE COMPANIES' 2024-2030 DSM-EE PROGRAM PLAN

Q. How did the Companies account for the energy-efficiency effects of the IRA and the Companies' proposed 2024-2030 DSM-EE Program Plan in the 2022 CPCN Load Forecast?

A. To understand how the Companies accounted for the energy-efficiency effects of the IRA and the Companies' 2024-2030 DSM-EE Program Plan, it is necessary to understand how the Companies forecast energy efficiency in their load forecasts. In

[9] The IRA provides tax credits up to $7,500 for new vehicles and up to $4,000 for used vehicles that meet requirements. *See* Inflation Reduction Act of 2022, available at https://www.congress.gov/bill/117th-congress/house-bill/5376.

general terms, the Companies assume that through DSM-EE programs and customers' own adoption of more efficient end-use items (e.g., more efficient replacement appliances) customers will achieve projected levels of end-use efficiencies based on data the Companies receive from Itron, who uses data from the U.S. Department of Energy's Energy Information Administration ("EIA").

In this load forecast, because the IRA's energy-efficiency provisions and the Companies' non-dispatchable DSM-EE programs and measures all tend to have the same effect—accelerating the deployment of energy efficiency—the Companies modeled their effects together. (The dispatchable components of the Companies' proposed DSM-EE programs, i.e., the demand response programs, are addressed in Mr. Wilson's supply-side analysis and testimony.) More precisely, to model the impact of the IRA and proposed DSM-EE programs on energy consumption, the Companies assumed that the joint impact of the IRA and DSM-EE programs would be to accelerate the EIA's forecast of energy efficiency improvements for residential and small commercial customers by 10 years, i.e., customers would achieve 2043 levels of EIA forecasted energy efficiency by 2033.

Although the 10-year acceleration is an estimate, it is a reasonable assumption; by 2043, EIA's projected energy efficiency improvements begin to plateau. For example, Figure 9 below shows an indexed view of residential central air conditioning and heat pump efficiencies over time according to the EIA, as well as the impact of accelerating those curves by 10 years (i.e., original 2043 efficiencies now seen in 2033) and 15 years (i.e., original 2048 efficiencies now seen in 2033) for comparison purposes. Because the original forecast began to level off in the early 2040s, there is not a material difference between the 10 and 15 years accelerated curves.

Figure 9: Residential Central Air Conditioning and Heat Pump Efficiency Index

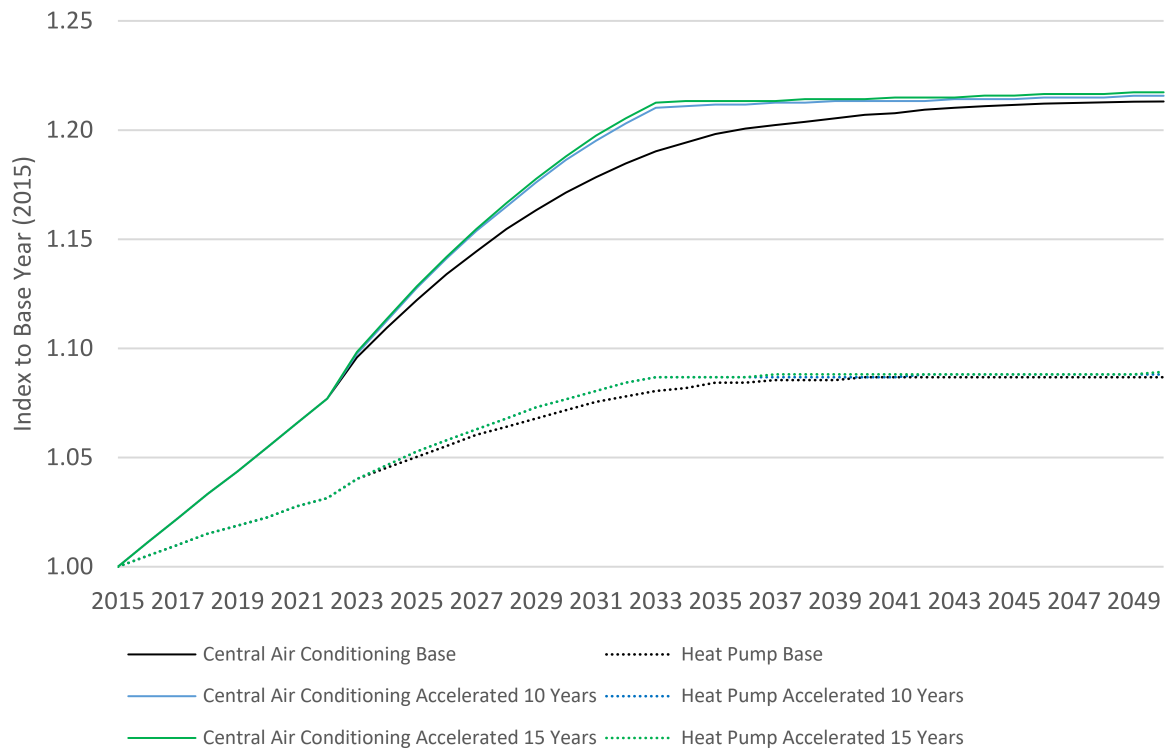
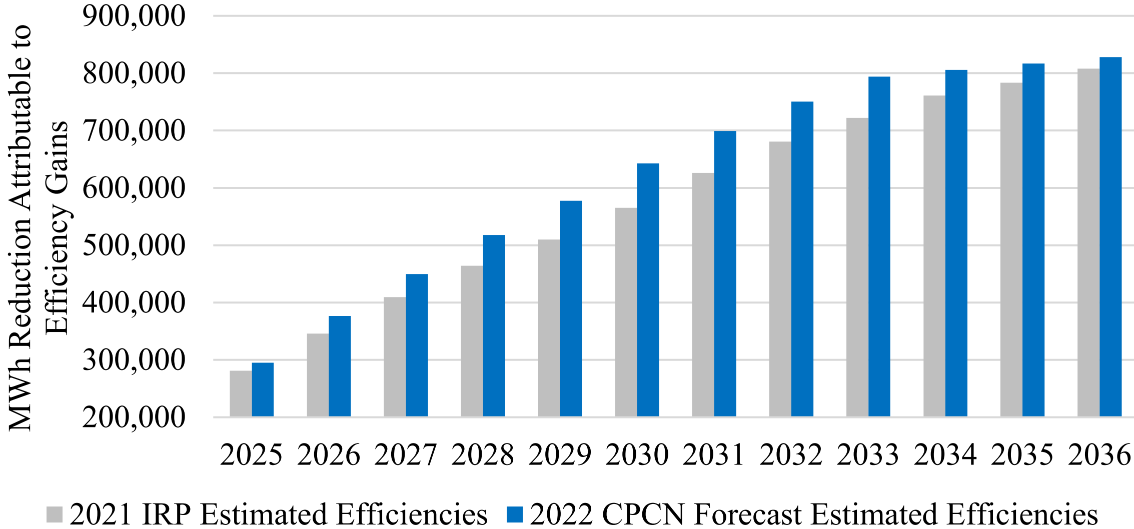


Figure 10 below shows the combined impact of DSM-EE and customer-initiated energy efficiency savings (including those incentivized by the IRA) on residential and small commercial customers in this forecast:

Figure 10: Energy Efficiency Impact – Forecast Comparison (Residential and GS)



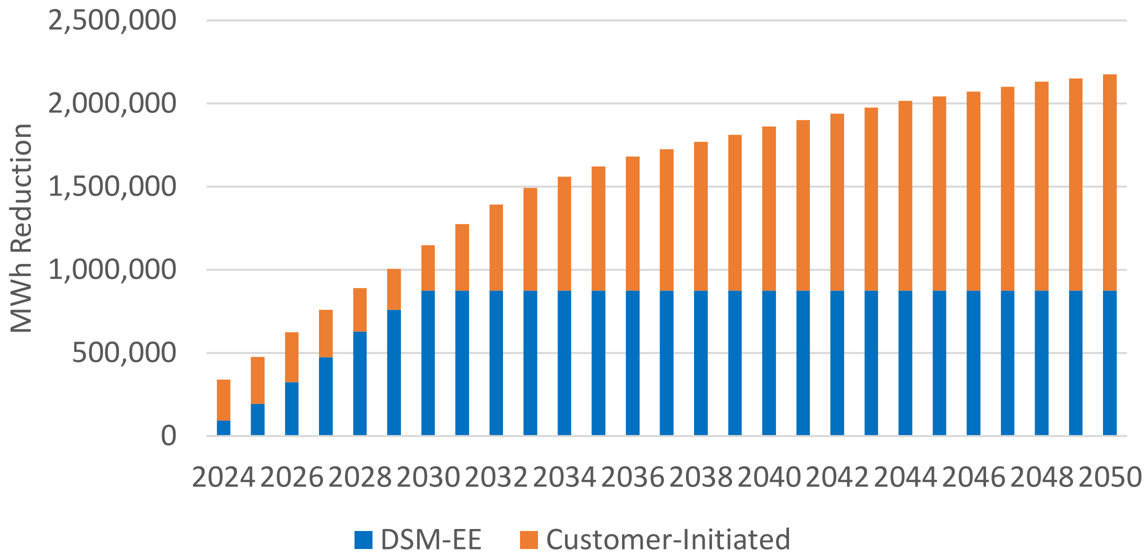
The proposed DSM-EE programs and the IRA accelerate the already substantial energy efficiency assumptions over the next decade. In total, sales to residential and small commercial customers (i.e., customers on residential or GS rates) in 2028 are 3.8% lower than they otherwise would be due to the combined impact of customer-initiated energy efficiency and proposed DSM-EE programs.[10]

Figure 11 below shows the significant forecasted annual energy impact of energy efficiency for all residential and commercial customers broken down into components for the estimated effects of the proposed DSM-EE programs versus customer-initiated energy efficiency (including IRA incentive effects).[11]

[10] *See, e.g.,* Exhibit JB-1 to the testimony of John Bevington for a list and description of the DSM-EE programs in the Companies' 2024-2023 DSM-EE Program Plan.

[11] Note that although the models used to forecast commercial sales for Secondary rates (i.e., Power Service-Secondary and Time of Day Secondary rates) are not identical to those used to forecast RS and GS sales; there is a variable used in the large commercial models to account for energy efficiency gains over time.

Figure 11: Estimate of DSM-EE vs. Customer-Initiated Energy Efficiency (Residential and Commercial)[12]



Notably, the Companies' forecasted energy savings resulting from energy efficiency compare favorably to the energy savings projected for achievable cumulative energy efficiency potential shown in Table 1 of the Cadmus 2022 Cross-Sector DSM Potential Study Projection (Exhibit LI-1 to the testimony of Lana Isaacson).

Also, the energy efficiency reflected in the figure above results in summer peak demand reductions in 2035 through 2038 ranging from 341 MW to 367 MW and winter peak demand reductions ranging from 256 MW to 279 MW. In 2043, the resulting summer peak demand reduction is 406 MW, and the winter peak demand reduction is 313 MW.[13] These values also compare favorably to the achievable (and even economic) demand reductions associated with cumulative energy efficiency potential shown in Table 2 of the Cadmus 2022 Cross-Sector DSM Potential Study Projection.

[12] The DSM-EE energy savings estimates were held constant after 2030, assuming that DSM-EE programs would continue beyond 2030. Note that although the models used to forecast commercial sales for Secondary rates (i.e., Power Service-Secondary and Time of Day Secondary rates) are not identical to those used to forecast RS and GS sales, there is a variable used in the large commercial models to account for energy efficiency gains over time.
[13] The workpaper showing these calculations is in Exhibit TAJ-3.

These comparisons show that the energy efficiency assumed to occur in the 2022 Load Forecast is reasonable, if not aggressive.

In sum, the effects of the IRA and the Companies' 2024-2030 DSM-EE Program Plan are markedly accelerated energy efficiency deployment—and therefore increased energy savings—in the 2022 CPCN Load Forecast.

EFFECT OF DISTRIBUTED ENERGY RESOURCES

Q. Does the electric load forecast reflect the impact of distributed energy resources?

A. Yes. As discussed in Exhibits TAJ-1 and TAJ-2, a significant amount of analysis and consideration goes into the distributed generation forecast.

Q. How did the Companies determine which distributed energy resources to include in their 2022 CPCN Load Forecast modeling and analysis?

A. As discussed at length in Exhibit TAJ-1, the Companies elected to analyze only distributed solar generation in the 2022 CPCN Load Forecast for two main reasons. First, about 99.7% of all of the Companies' current distributed generation installations (including qualifying facilities ("QFs")) are solar, indicating that solar has been customers' strong preference to date. Second, as the Companies show in TAJ-1, if future distributed energy resource ("DER") customers choose their DER technology on the basis of economics, they will almost certainly choose solar over wind, hydro, biomass, and battery energy storage. Indeed, the Companies' data indicate that although some customers have chosen to install distributed generation even when it has not been obviously economical, there is clear evidence that customers have been rapidly increasing their deployment of solar generation in recent years as retail energy rates have increased and the levelized cost of solar has decreased. Therefore, it is reasonable to assume that the great majority of customers who will deploy DER technology will do so economically, which in turn makes it reasonable to assume that all or nearly all DER deployments over the load forecast period will be solar (barring unforeseen technology or policy developments).

Q. What determines the economics of distributed solar generation?

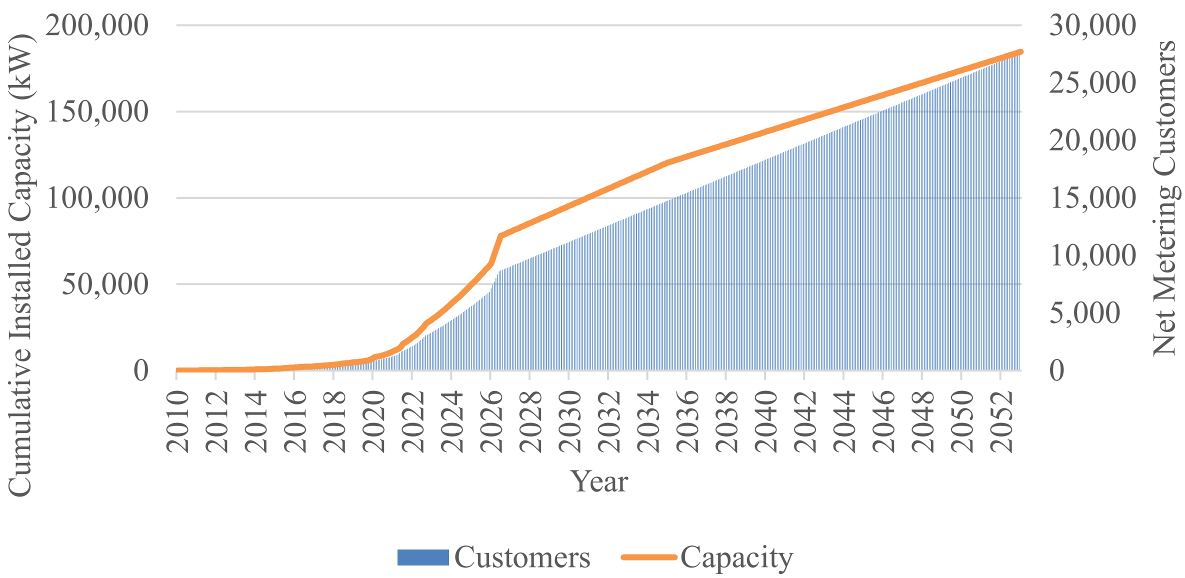
A. The economics of distributed solar generation depend on several factors: the extent to which solar generation reduces consumption from the grid versus energy exported to the grid; the levelized cost of energy ("LCOE"), which includes available financial incentives such as the federal ITC in addition to capital and annual operating costs; and retail rates for energy consumption and credits customers receive for exported energy. I discuss the Companies' distributed generation forecast assumptions for those factors in Exhibit TAJ-1.[14]

Q. What is the Companies' forecast of distributed solar installations in the 2022 CPCN Load Forecast?

A. On the basis of the inputs discussed above, Figure 12 below shows the Companies' distributed generation model's projections of customers and capacity for net metering and QF (not more than 45 kW) for this load forecast. Notably, the Companies project that by 2052 about 28,000 customers will have installed such generation with a total capacity of almost 185 MW.

[14] *See* Section 3.6.2.2.

Figure 12: Distributed Generation Customer and Capacity Forecast (customers with capacity ≤ 45 kW)



The results shown above reveal three distinct phases of distributed generation development in the load forecast. In the first phase, there is rapid growth in distributed generation customers and capacity while NMS-2 service remains available to new customers, which the model predicts will cease to be the case in mid-2026 when distributed generation capacity reaches 1% of the Companies' annual peak load. In the second phase, there is a more gradual increase in distributed generation customers and capacity from mid-2026 through 2034 while the IRA's extended federal ITC persists but compensation for exported energy falls from NMS-2 rates to the SQF rate. In the third phase, which begins when the ITC ends in 2035, the increase in the number of distributed generation customers continues relatively unchanged, but the amount of capacity added per customer decreases, which is consistent with the increase in solar cost experienced by customers after the ITC ends. Ultimately, by the end of 2052, the

Companies project there will be almost 185 MW of distributed generation capacity for customers whose per-system capacity does not exceed 45 kW.

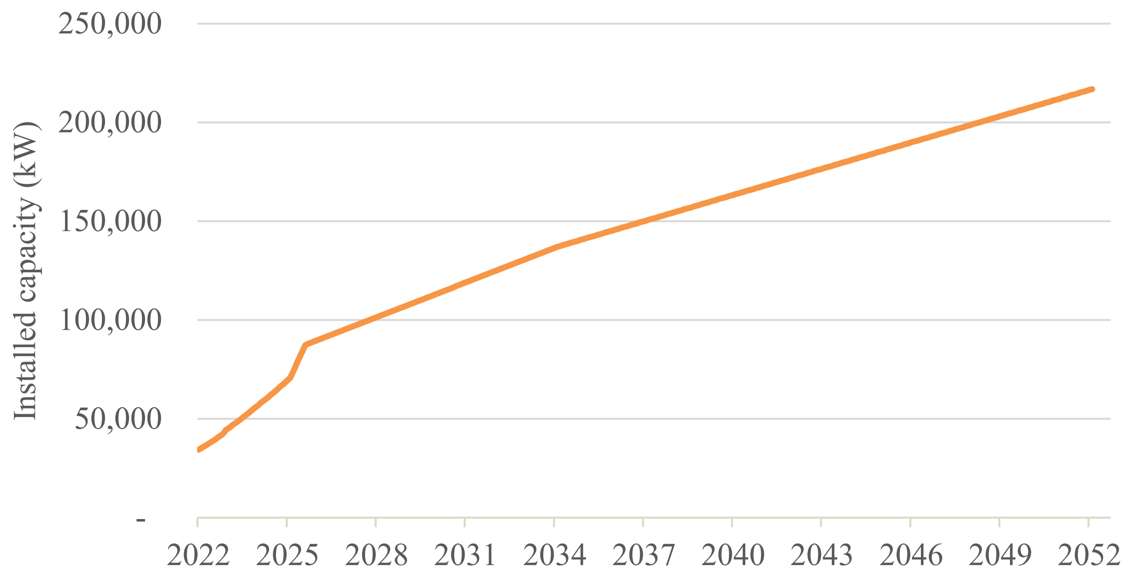
Q. Did the Companies consider a case in which customers received no compensation for exported energy?

A. The Companies did not analyze a situation in which such customers would receive *no* compensation for exported energy because it would be inconsistent with their SQF tariff provisions to provide no compensation for such energy. Instead, as noted above and consistent with the Companies' tariffs, the Companies modeled providing customers SQF compensation for exported energy after reaching the 1% capacity level in mid-2026.

Q. Did the Companies consider other QFs?

A. Yes. The Companies forecast behind-the-meter QF customers separately from net metering customers (and net-metering-sized facilities, i.e., QFs not exceeding 45 kW). This includes only those customers served by the Companies, not independent or merchant generators. Historically, the Companies have projected that future numbers of QF customers will be consistent with the historical observed linear trend for the Companies' QF customers to date. The Companies also typically assume that the forecasted capacity per new QF customer will be the average of current QF installations. But to account for IRA impacts on QFs, the Companies modeled a 15% increase in per-customer new QF capacity compared to the historical average. Total forecasted solar capacity is shown in Figure 13, which reaches almost 217 MW by 2052, indicating behind the meter QF capacity of about 32 MW in addition to 185 MW of distributed generation capacity with a per-system capacity not exceeding 45 kW.

Figure 13: Total Distributed Solar Capacity Forecast (NMS and QF)



Q. Is it reasonable to assume that the majority of solar adopters will be in the residential and general service ("GS") classes?

A. Yes. As shown in Figures 25, 26, and 27 of Exhibit TAJ-1, the rate structure of the residential and general service rates makes those rates more likely to adopt solar. Because these rates do not have demand charges (i.e., \$/kW), their energy charge (i.e., \$/kWh) is higher than other rates. The Power Service ("PS") rates and rates for larger customers, on the other hand, have an energy charge closer to the Companies' avoided cost, making distributed solar uneconomical for most large customers, who might nonetheless pursue such generation for reasons other than economics.

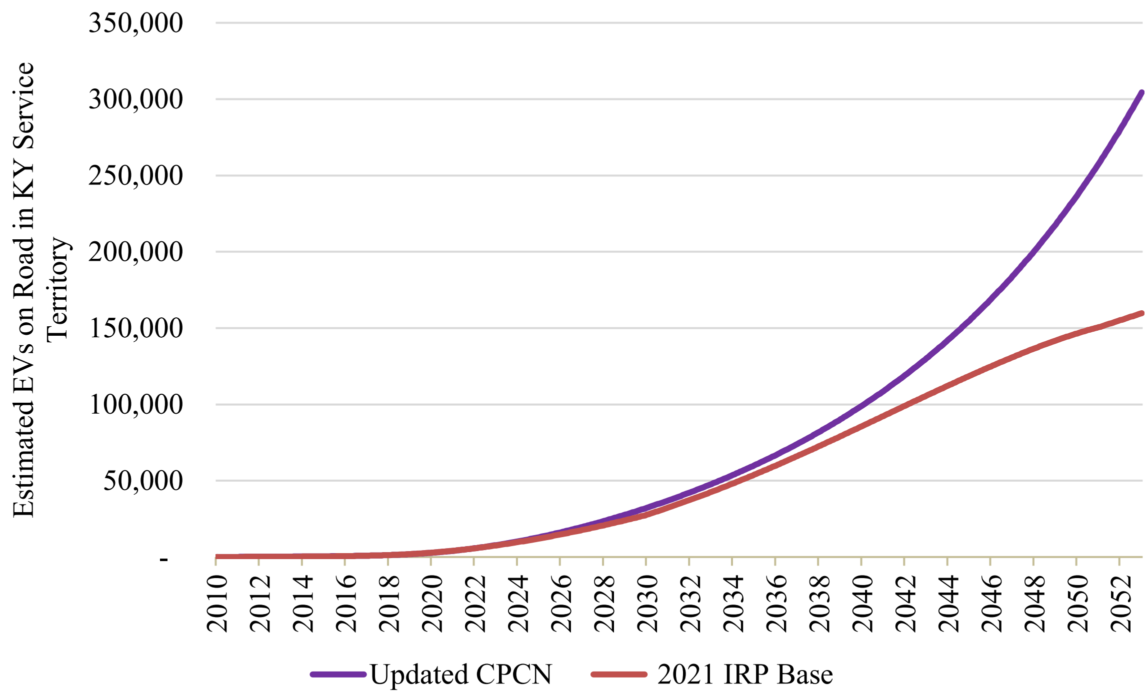
<u>EFFECT OF ELECTRIC VEHICLES</u>

Q. Does the electric load forecast reflect the impact of electric vehicles?

A. Yes. The model used to forecast EV adoption considers historical adoption of EVs, the comparison of EV to internal combustion engine car costs, IRA tax credits, and EIA's projected number of vehicles in the service territory. Beginning with data from the

Electric Power Research Institute ("EPRI"), the Companies estimate there were a total of almost 7,800 battery and plug-in hybrid EVs in their Kentucky service territories as of September 2022.[15] In this forecast, the Companies project that EVs in operation in the Companies' Kentucky service territory will increase to over 100,000 by the end of 2040 and to over 300,000 by 2052, as shown in Figure 14 below:

Figure 14: Electric Vehicle Forecast



EFFECT OF SPACE HEATING ELECTRIFICATION

Q. How did the Companies account for space heating electrification in the 2022 CPCN Load Forecast?

A. In this load forecast, the Companies assumed that new customers would have electric heating penetrations comparable to the average of such penetrations for new customers in 2015 through 2019, which is about 72% for KU and 44% for LG&E (compared to

[15] For EPRI estimates of total EVs in the service territory, see Excel workpaper: "Work Papers\Hourly_Forecast_Updates \EV\mostRecent_LG_E_KU.xlsx"

59% and 21%, respectively, for residential customers added in 2010 or earlier). This load forecast further assumes that, with the passage of the IRA, a small portion of existing premises will switch from gas to electric. Figure 15 below shows the forecasted change in electric space heating including IRA impacts as an index to 2015 as the base year. Not surprisingly, the increase in LG&E is much higher given a much smaller percentage of customers have electric heating today as compared to the KU service territory.

Figure 15: Space Heating Saturation Percentage Change by Company

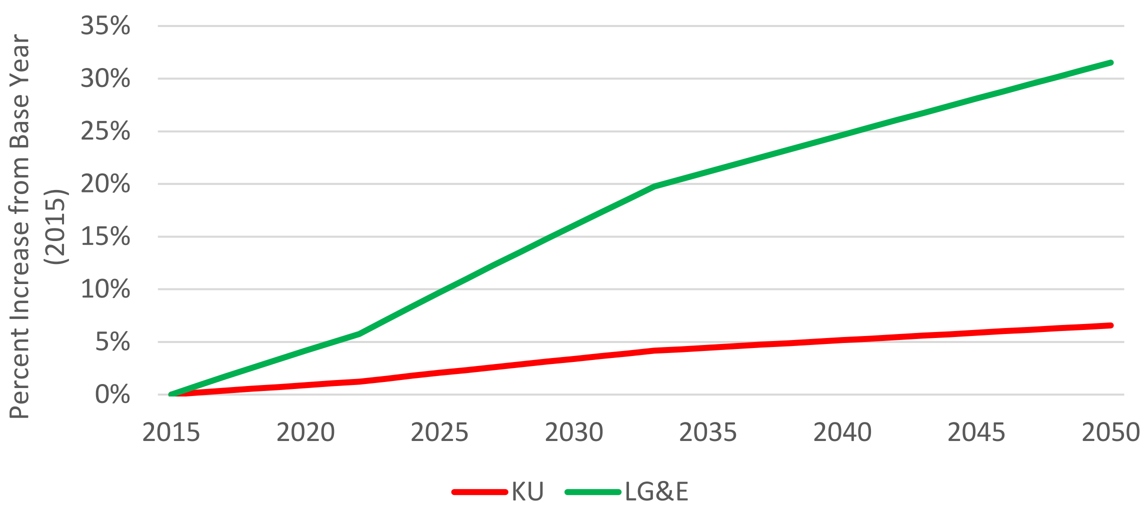
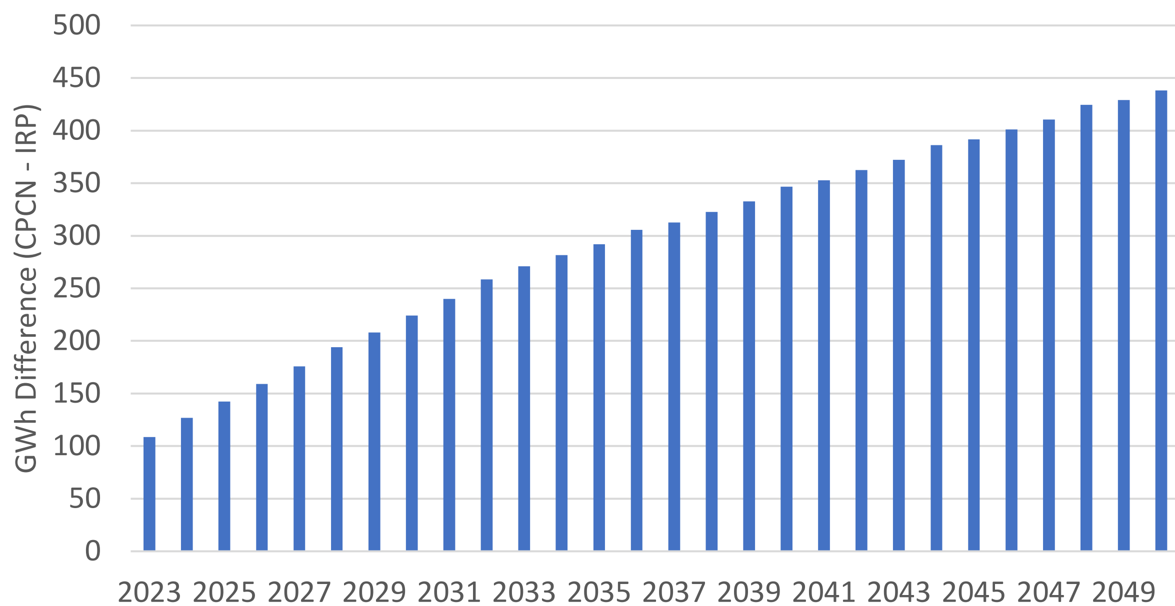


Figure 16 below shows the impact of added electric heating load on this load forecast and the 2021 IRP load forecast:

Figure 16: Space Heating Impact in Winter Months by Year (CPCN minus IRP)



The increase in the incidence of electric space heating and space heating consumption is not unique to the Companies. Nationally, space heating accounted for just 6% of residential consumption in 2010 but is up to 14% of total consumption as of 2021 – an almost 150% increase in just a decade. Therefore, the Companies projection of increased space heating penetration in the 2022 CPCN Load Forecast—particularly considering IRA incentives to invest in heat pumps—is reasonable.

OTHER MATTERS

Q. Did the Companies consider Advanced Metering Infrastructure ("AMI") benefits factored in the load forecast?

A. Yes. The forecast assumes that both Conservation Voltage Reduction ("CVR") and AMI ePortal savings will reduce the load forecast. By 2028 and 2030, CVR reduces annual sales by 123 and 205 GWh, respectively, and AMI ePortal reductions are approximately 57 GWh.

Q. Did the Companies consider the price elasticity of demand in the load forecast?

A. Yes. As Exhibit TAJ-1 addresses in greater detail, the Companies' forecast models incorporate class-specific estimates of price elasticity between -0.1 and -0.15. For this load forecast, the Companies assumed base electricity prices (rates) would not change prior to July 1, 2025, which is consistent with the Companies' 2020 base rate case commitments.[16] Thereafter, the forecast assumes prices will increase by two percent per year, consistent with long-term inflation expectations. If higher-than-expected prices materialize, the Companies anticipate a decline in sales as compared to the current forecast (all else equal) due to the negative price elasticities incorporated into the forecasting models.

CONCLUSION

Q. Do you believe the electric load forecast is reasonable?

A. Yes. The Companies' 2022 CPCN Load Forecast is a reasonable forecast of customers' hourly energy needs for the next 30 years. It builds on the time-tested models and tools that the 2021 Commission Staff Report found reasonable and addresses the recommendations raised in the report. It also fully updates the forecast from the 2021 IRP in all respects, including updating it for the impacts of the BlueOval SK Battery Park, the Inflation Reduction Act, and the Companies' proposed 2024-2030 DSM-EE Program Plan. It demonstrates that customers will continue to have robust demand and energy requirements in all hours and all seasons, day and night.

Therefore, I conclude that the 2022 CPCN Load Forecast is reliable for resource planning purposes.

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[16] Case No. 2020-00349, Order at 11-12 (Ky. PSC June 30, 2021); Case No. 2020-00350, Order at 13-15 (Ky. PSC June 30, 2021).

But as with any forecast, there are known (and of course unknown and unforeseeable) uncertainties associated with the forecast. Among the known uncertainties are those that could result in greater demand and energy requirements than forecasted here, such as greater or more rapid EV adoption, space heating electrification, or economic development, including possible additional load related to BlueOval locating in the Companies' service territories. Uncertainties that could cause lower demand and energy requirements than forecasted here include greater or more rapid adoption of distributed generation or energy efficiency, as well as slower economic development or even the loss of existing industrial or commercial load. On balance, for the reasons discussed at length in Exhibit TAJ-1, I believe the more impactful uncertainty is that demand and energy requirements could be above those forecasted in the 2022 CPCN Load Forecast.

Q. What is your recommendation for the Commission?

A. I recommend the Commission accept the 2022 CPCN Load Forecast as reasonable and a reliable for making resource decisions in this case.

Q. Does this conclude your testimony?

A. Yes.

VERIFICATION

COMMONWEALTH OF KENTUCKY)
)
COUNTY OF JEFFERSON)

The undersigned, **Tim A. Jones**, being duly sworn, deposes and says that he is Manager – Sales Analysis and Forecast for Louisville Gas and Electric Company and Kentucky Utilities Company, an employee of LG&E and KU Services Company, and that he has personal knowledge of the matters set forth in the foregoing testimony, and that the answers contained therein are true and correct to the best of his information, knowledge, and belief.

Tim A. Jones

Subscribed and sworn to before me, a Notary Public in and before said County and State, this 9th day of December 2022.

Notary Public

Notary Public ID No. KYNP53381

My Commission Expires:

July 11, 2026

APPENDIX A

Tim Jones
Manager of Sales Analysis and Forecasting
Kentucky Utilities Company
Louisville Gas and Electric Company
220 West Main Street
Louisville, Kentucky 40202
Telephone: (502) 627-2216

Previous Positions

LG&E and KU Energy	Jun 2016 – Present
Energy Analyst III, Sales Analysis & Forecasting	Jun 2016 – Jun 2019
Schneider Electric	Feb 2005 – May 2016
Manager, Data Processing	Aug 2014 – May 2016
Manager, Data Analysis	Apr 2012 – Aug 2014
Senior Data Analyst	Mar 2010 – Apr 2012
Data Analyst	Apr 2007 – Mar 2010
Sourcing Analyst	Jul 2006 – Apr 2007
Regulated Markets Analyst	Feb 2005 – Jul 2006

Education

Bachelor of Science in Mathematics
Bellarmine University, December 2004

Civic Activities

Golf Scramble Committee Member	
National Kidney Foundation	Nov 2013 – Jun 2018

2022 CPCN Load Forecast

PPL companies

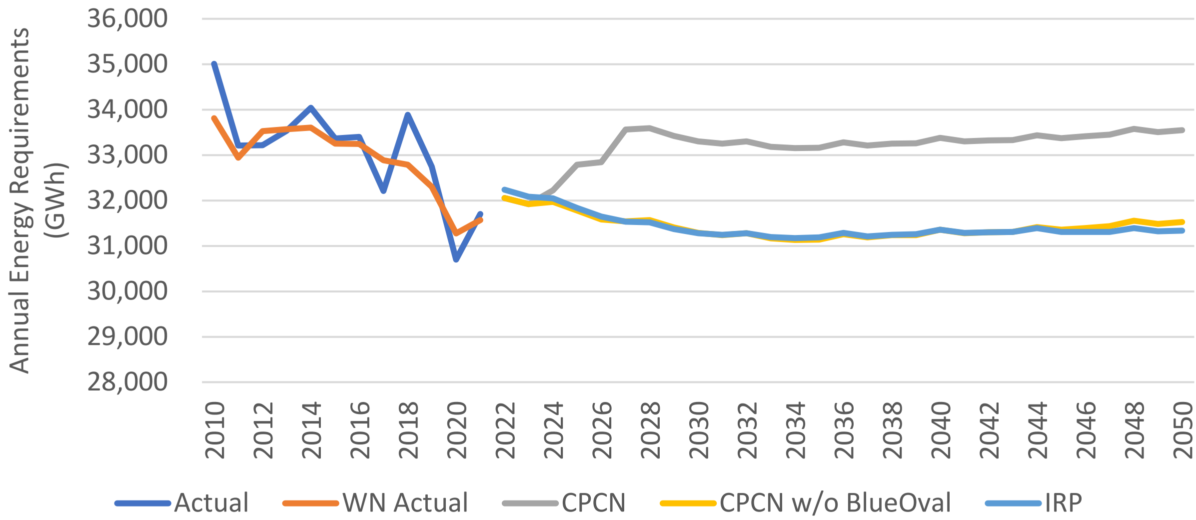
Sales Analysis & Forecasting
December 2022

Table of Contents

1 2022 CPCN Load Forecast at a Glance

The 2022 CPCN Load Forecast is a 30-year hourly load forecast (2023-2052) that accounts for the effects of Ford's BlueOval SK Battery Park, the Inflation Reduction Act ("IRA"), and the Companies' proposed 2024-2030 Demand-Side Management and Energy Efficiency ("DSM-EE") Program Plan.

Figure 1: Annual Energy Requirements History and Forecast (exc. Departed Municipal Customers)



Highlights of the 2022 CPCN Load Forecast are:

- Peak summer load of 6,347 MW occurs in 2027; summer peak load declines to 6,209 MW in 2052
- Winter peak load in 2027 is 6,107 MW; winter peak load increases to 6,130 MW in 2052
- Annual energy requirements increase rapidly as BlueOval SK Battery Park comes online and remain between 33,100 GWh and 33,600 GWh from 2028 through 2052; BlueOval alone will use over 2,000 GWh annually
- BlueOval SK Battery Park is the major driver of change from the 2021 IRP load forecast, with almost 260 MW summer peak load,[1] about 225 MW winter peak load, and a load factor of almost 90%
- The IRA and the Companies' 2024-2030 DSM-EE Program Plan significantly accelerate energy efficiency deployment, achieving the U. S. Department of Energy's Energy Information Administration's ("EIA") 2043 forecasted levels of energy efficiency by 2033[2]
- The IRA also drives growth in distributed generation, space heating electrification, and increased electric vehicle ("EV") adoption; net effect of IRA and DSM-EE is close to neutral due to IRA's load decreasing and increasing incentives and provisions
- Distributed generation capacity (including qualifying facilities ("QFs")) increases from the current level of about 34.4 MW to almost 217 MW by 2052

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[1] The stated peak load figures represent BlueOval's non-coincident, peak hourly usage projections grossed up by a transmission loss factor of 1.02827. BlueOval's anticipated summer billing demand is 254 MW.

[2] EIA forecasted levels of energy efficiency for the East South Central region are obtained by the Companies through information provided by Itron on an annual subscription basis.

- EVs increase in the Companies' Kentucky service territory from the current level of approximately 7,000 to over 300,000 by 2052
- By 2052, electric space heating saturation increases from 2015 levels by 7% in KU's service territory (already highly saturated) and by 33% in LG&E's service territory
- Customers continue to have significant energy requirements in all hours and seasons, including in non-daylight hours, e.g., minimum hourly demand in 2028 is 2,450 MW

2 Load Forecast Summary and Key Results and Observations

2.1 Impetus for 2022 CPCN Load Forecast

The Companies' Sales Analysis and Forecasting group performed an updated 30-year hourly load forecast (2023-2052) to inform the Companies' decisions regarding the possible retirement and replacement of certain generating units through 2028 while maintaining reliable service at the lowest reasonable cost.

2.2 2022 CPCN Load Forecast Methodology and Process

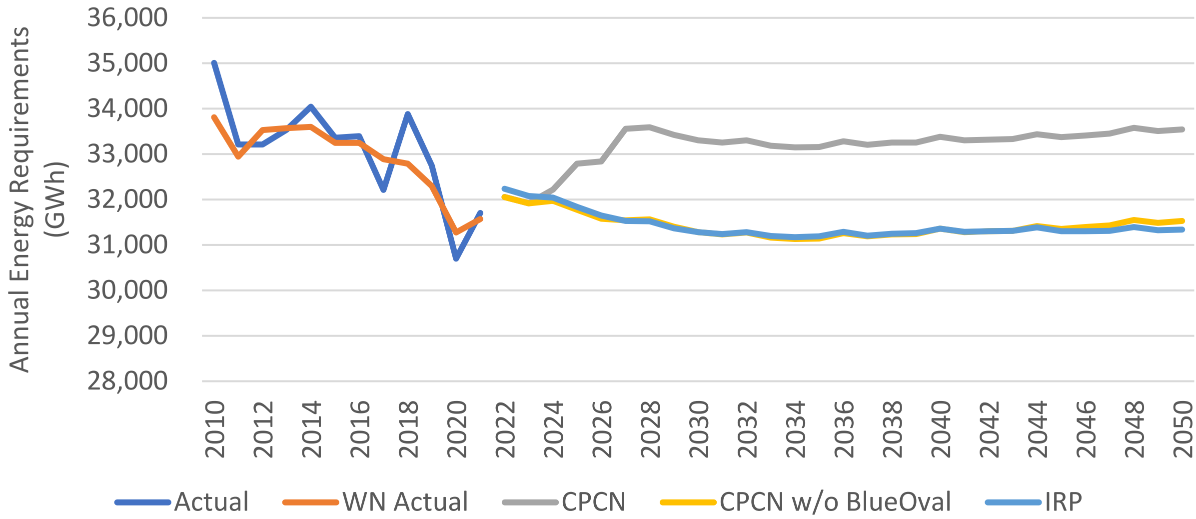
The Companies performed the 2022 CPCN Load Forecast using the same models, modeling tools, and procedures used in the 2021 IRP load forecast, which the Commission Staff's Report on the 2021 IRP found to be generally reasonable.[3] The Companies have updated their entire load forecast, including updates to address three significant changes: (1) the most current BlueOval SK Battery Park load forecast; (2) the Inflation Reduction Act ("IRA"); and (3) the effects of the Companies' proposed 2024-2030 Demand-Side Management and Energy Efficiency ("DSM-EE") Program Plan. This load forecast also explicitly addresses the recommendations made in the 2021 IRP Commission Staff's Report issued on September 16, 2022.

2.3 2022 CPCN Load Forecast Key Results

The 2022 CPCN Load Forecast projects annual energy requirements that rise from the current levels of about 32,000 GWh to a peak of almost 33,600 GWh in 2028 and remain in a range of 33,100 GWh and 33,600 GWh for the remaining forecast period, as shown in Figure 2 below:

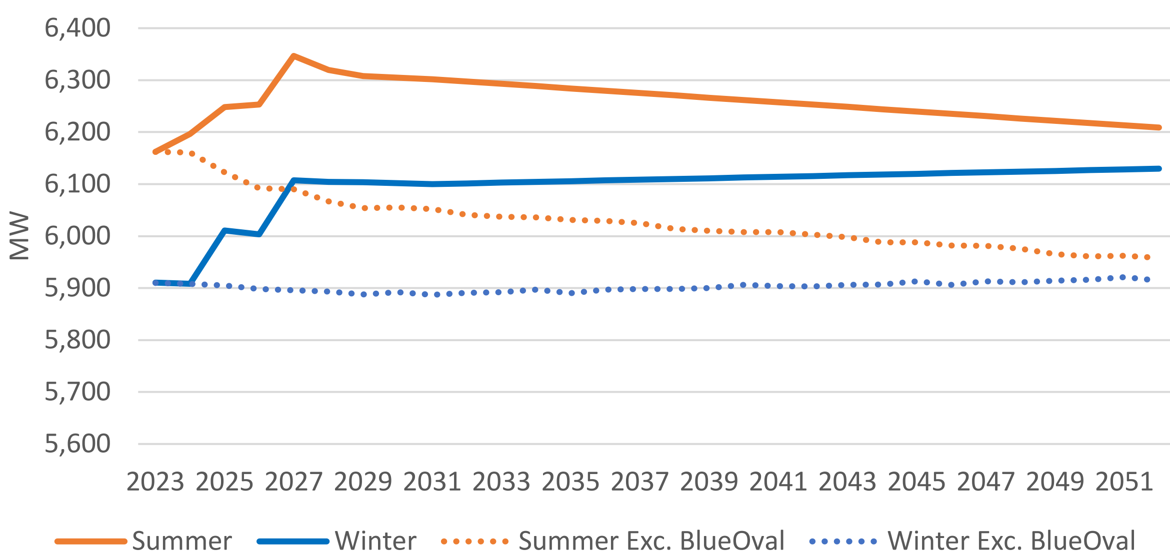
[3] *See* Case No. 2021-00393, Order Appx. "Commission Staff's Report on the 2021 Integrated Resource Plan of Louisville Gas and Electric Company and Kentucky Utilities Company" at 51 (Ky. PSC Sept. 16, 2022) ("LG&E/KU's assumptions and methodologies for load forecasting are generally reasonable."). Details of the Companies' load forecasting models, modeling tools, and procedures are set out in detail in the Electric Sales & Demand Forecast Process document dated December 2022 (Exhibit TAJ-2).

Figure 2: Annual Energy Requirements History and Forecast (exc. Departed Municipal Customers)



The 2022 CPCN Load Forecast projects the highest summer peak hourly load for the forecast period (6,347 MW) will occur in 2027 and then decrease over the forecast period to an hourly summer peak of 6,209 MW in 2052. Dissimilarly, the 2022 CPCN Load Forecast projects the winter peak hourly load will increase to 6,107 MW in 2027 and then generally trend slowly upward across the remaining forecast period to an hourly winter peak of 6,130 MW in 2052, as shown in Figure 3 below:

Figure 3: Forecasted Seasonal Peaks



The Companies are providing electronically the full hourly load forecast for all 30 years, as well as all supporting workpapers.[4]

[4] The Companies' workpapers are Exhibit TAJ-3. A guide to the workpapers is Technical Appendix 2 to this document.

2.4 2022 CPCN Load Forecast Key Observations

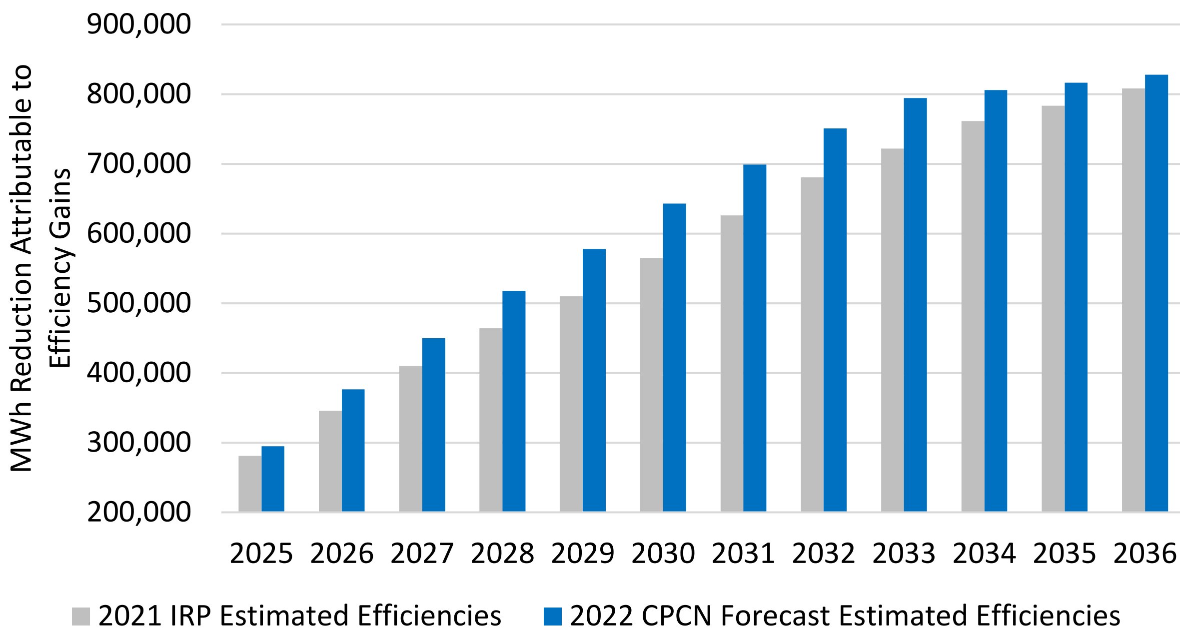
2.4.1 BlueOval SK Battery Park Is the Primary Driver of Changes from the 2021 IRP Load Forecast

The Companies forecast that BlueOval SK Battery Park will add over 2,000 GWh per year at full production. They are estimated to use almost 260 MW at their summer peak and about 225 MW at their winter peak and will have a load factor of almost 90%.[5] As shown in Figure 1 and Figure 3 above, the addition of this load is by far the most significant driver of changes from the 2021 IRP Load Forecast.

2.4.2 The IRA and the Companies' 2024-2030 DSM-EE Program Plan Reduce Annual Energy Requirements in Nearly All Years of the Load Forecast

The IRA and the Companies' 2024-2030 DSM-EE Program Plan accelerate the pace of energy efficiency deployment. Figure 4 below shows the impacts of customer-initiated and DSM-EE-driven energy efficiency in the IRP load forecast and this load forecast, including IRA energy efficiency impacts.

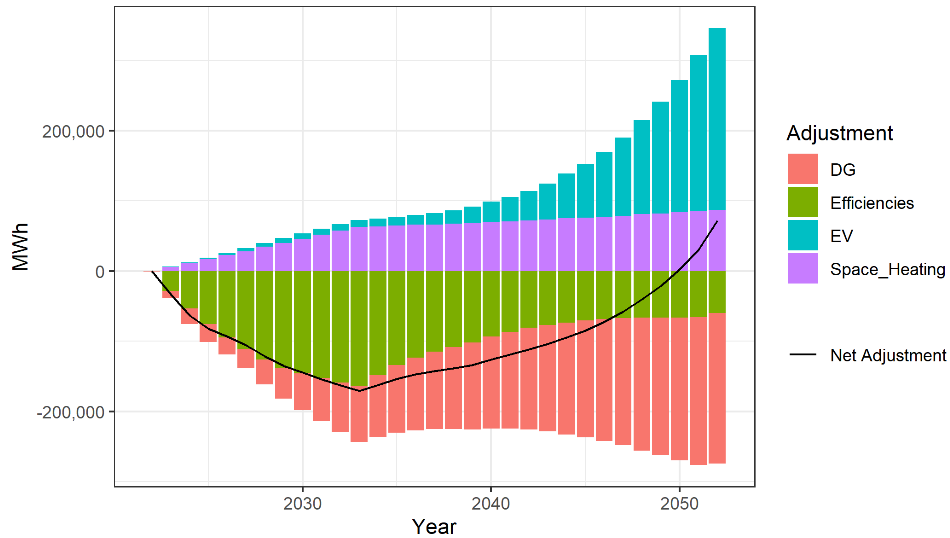
Figure 4: Absolute Impacts of Energy Efficiency (including IRA and DSM-EE)



In addition to the energy-efficiency impacts of the IRA and DSM-EE, the IRA has provisions regarding three other key inputs to this load forecast, two of which tend increase load (space heating electrification and electric vehicles) and one of which decreases load (distributed generation). Figure 5 below shows the annual energy requirements forecast impacts of these four components:

[5] The stated peak load figures represent BlueOval's non-coincident, peak hourly usage projections grossed up by a transmission loss factor of 1.02827. BlueOval's anticipated summer billing demand is 254 MW.

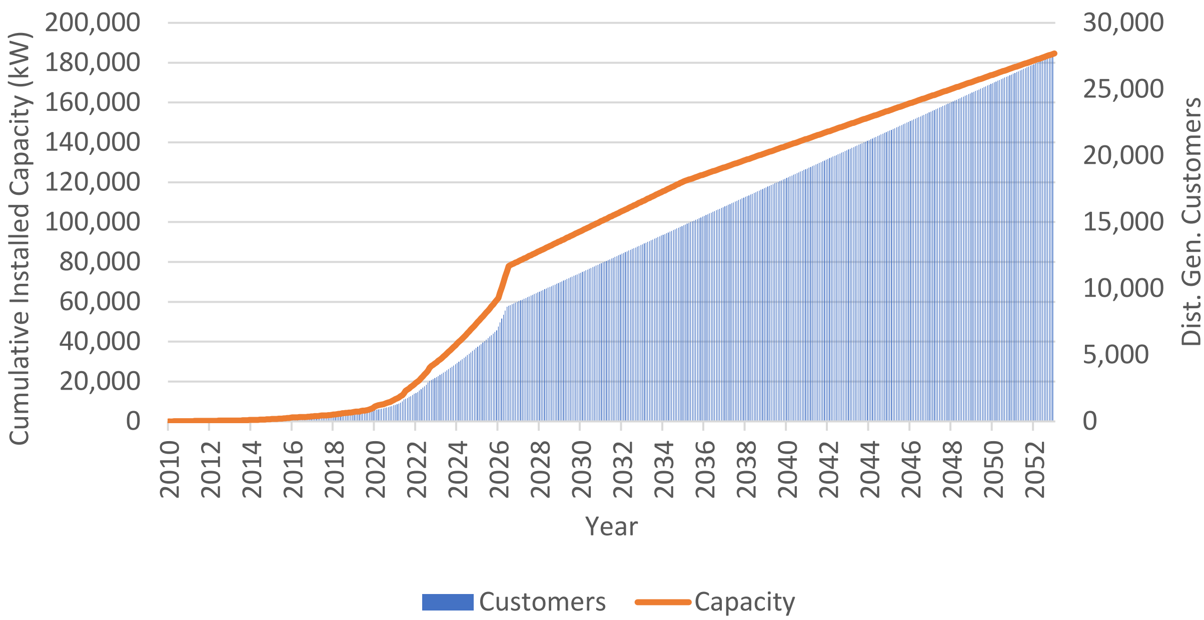
Figure 5: Incremental Annual Energy Requirements Impacts of IRA and DSM-EE-Affected Items



2.4.3 Distributed Generation Continues to Expand throughout the Load Forecast Period

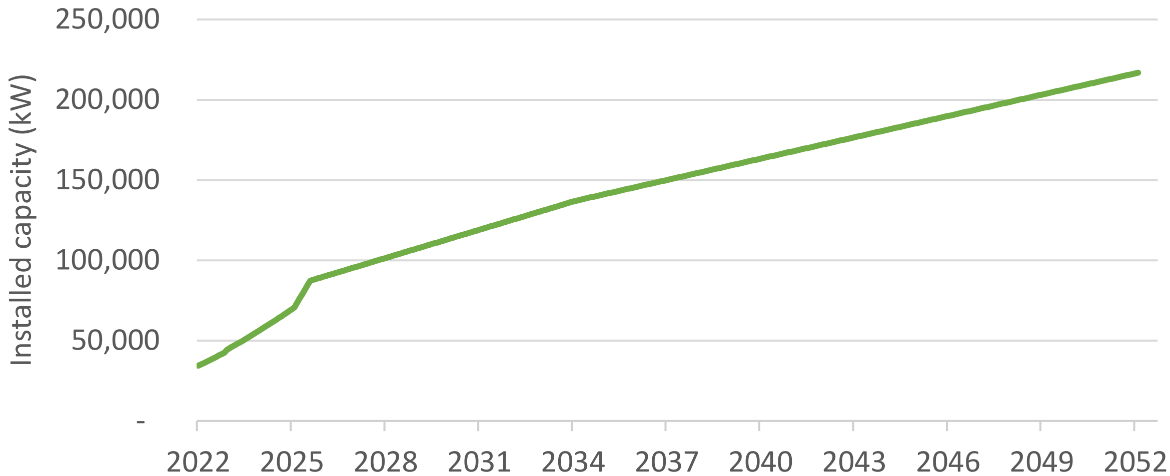
As Figure 6 below shows, distributed generation capacity and customers grow rapidly through mid-2026 when net metering-eligible capacity reaches 1% of the Companies' peak load. Growth continues at a more moderate pace thereafter, reaching 87 MW by 2028 and almost 185 MW by 2052.

Figure 6: Distributed Generation Customer and Capacity Forecast (customers with capacity ≤ 45 kW)



As shown in Figure 7 below, including the impact of all qualifying facilities ("QFs") raises the total of all forecasted distributed generation to about 100 MW by 2028 and over 200 MW by 2052.

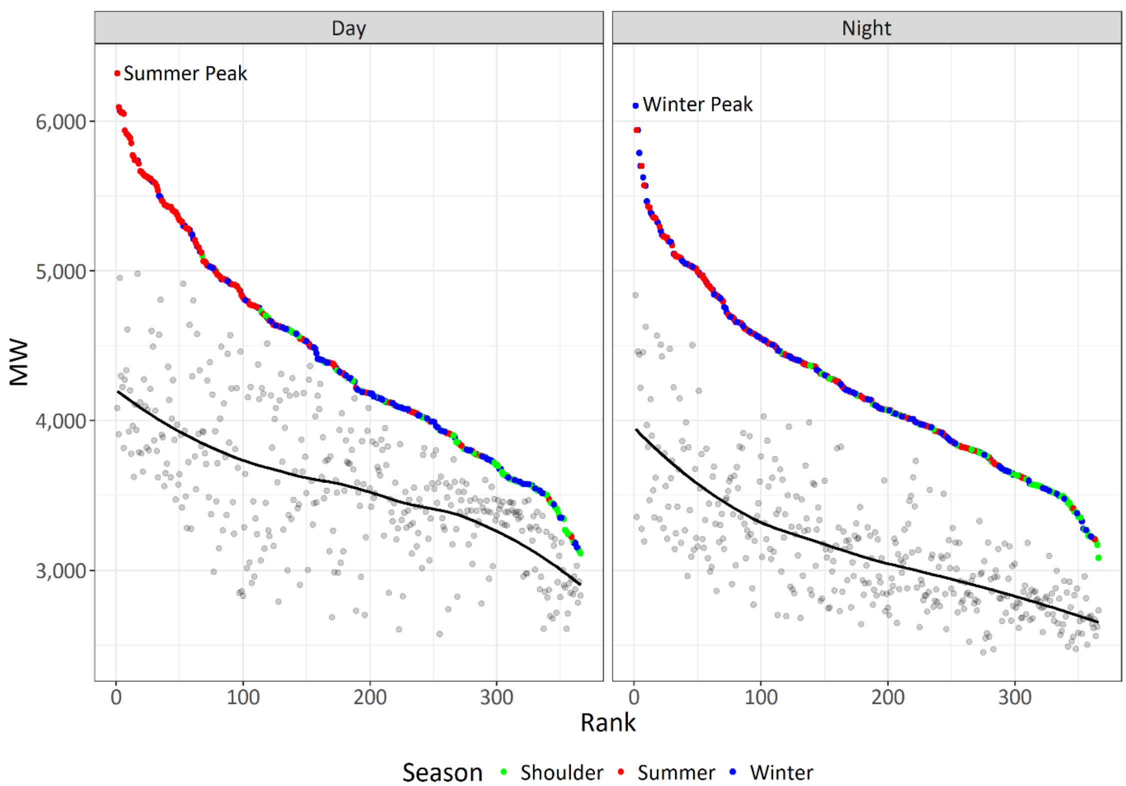
Figure 7: Total Distributed Generation Capacity Forecast



2.4.4 Customers Continue to Have Significant Energy Requirements in All Hours

As Figure 8 below illustrates for just one year, the Companies project that customers will have significant demand in all hours and all seasons, including in non-daylight hours.

Figure 8: 2028 Daily Maximum and Minimum Loads during Daylight and Non-Daylight Hours[6]

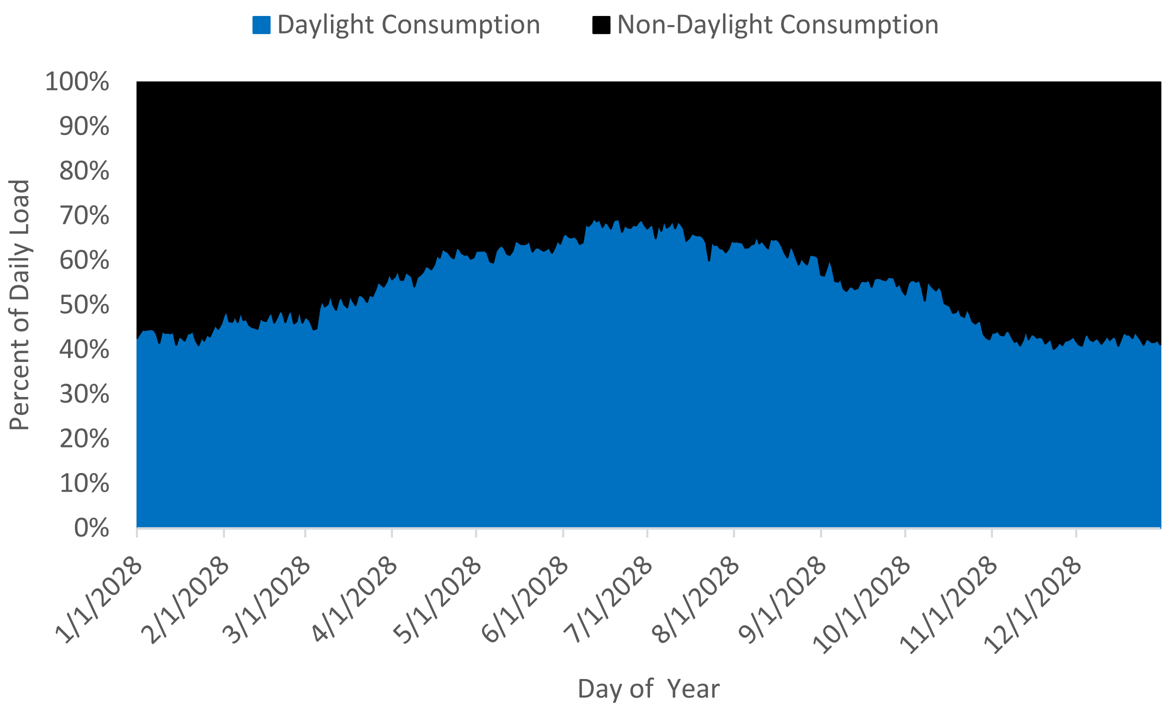


[6] Data points in color represent daily maximum values; those in light grey represent daily minimums. The solid black line is a smoothed curve fit through the daily minimums.

Figure 8 further demonstrates that: (1) the Companies' forecasted winter peak (6,104 MW in 2028), which occurs during non-daylight hours, is comparable to the Companies' summer peak (6,319 in 2028); (2) a number of non-daylight summer peaks exceed 5,000 MW; and (3) the curve for daylight daily peak loads is fairly close to the curve for non-daylight daily peak loads.

Figure 9 below shows projected daily electricity consumption divided into daylight and non-daylight daily usage for 2028, showing approximately 35% of summer electricity usage during non-daylight hours and over 55% of winter electricity usage during non-daylight hours.

Figure 9: 2028 Proportion of Energy Consumed During Daylight and Non-Daylight Hours



As shown in Figure 10 below, projected 2028 peak demand across LG&E and KU's combined system is 6,319 in 2028, with peak demand in both summer and winter topping 6,100 MW. Projected minimum demand is at least 2,452 MW in each hour of the year, including non-daylight hours. Additionally, the load duration curve in Figure 11 below shows that the Companies forecast that in 2028 there will be 20 hours with demand over 6,000 MW, 624 hours with demand over 5,000 MW, and all but 990 hours with demand over 3,000 MW.

This data shows that customers require large amounts of energy at all times, day or night, and in all seasons and weather conditions. It further shows that system peak demands can occur in summer or winter and in daylight and non-daylight hours.

Figure 10: LG&E and KU 2028 Hourly Load

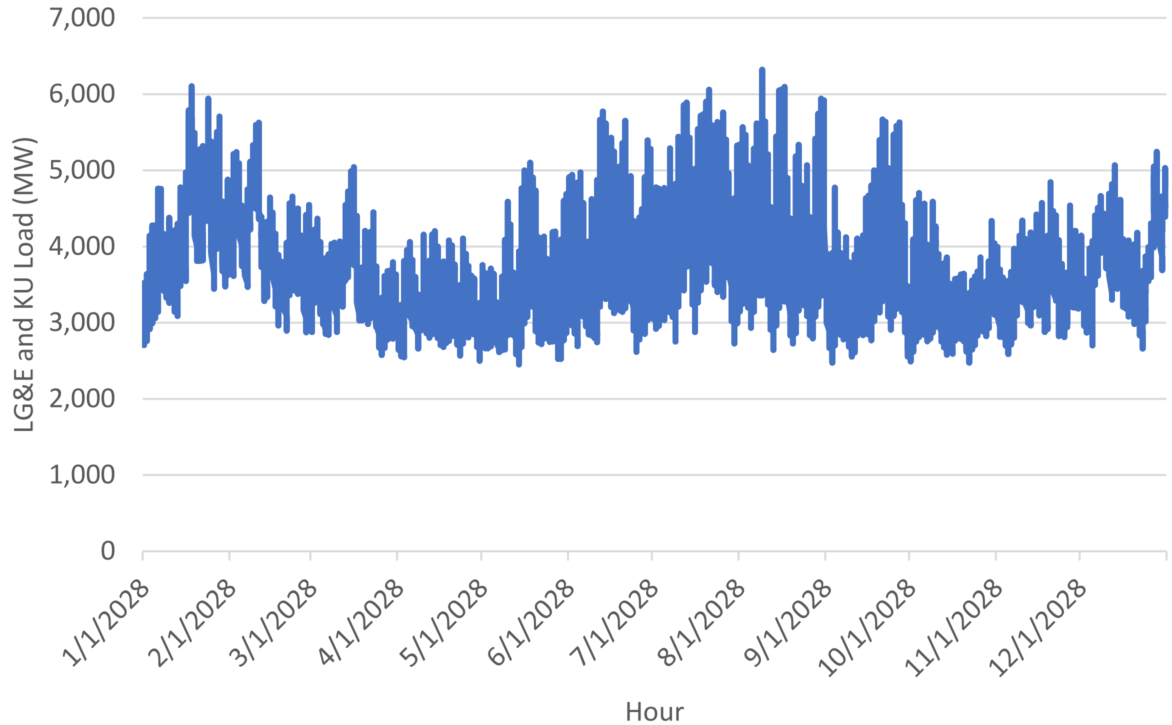
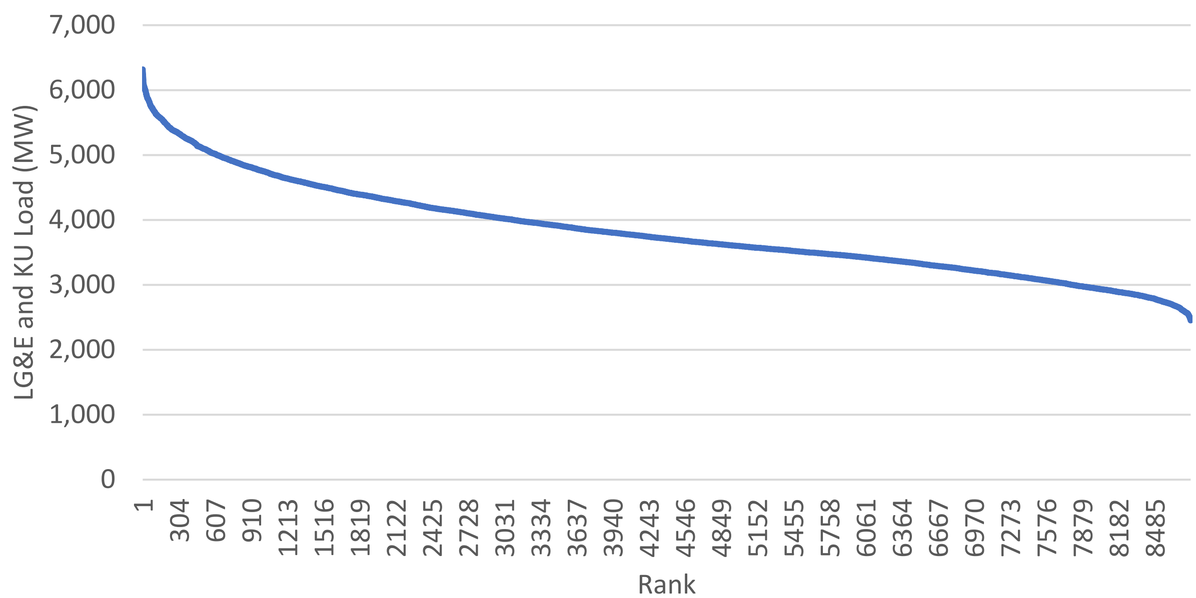
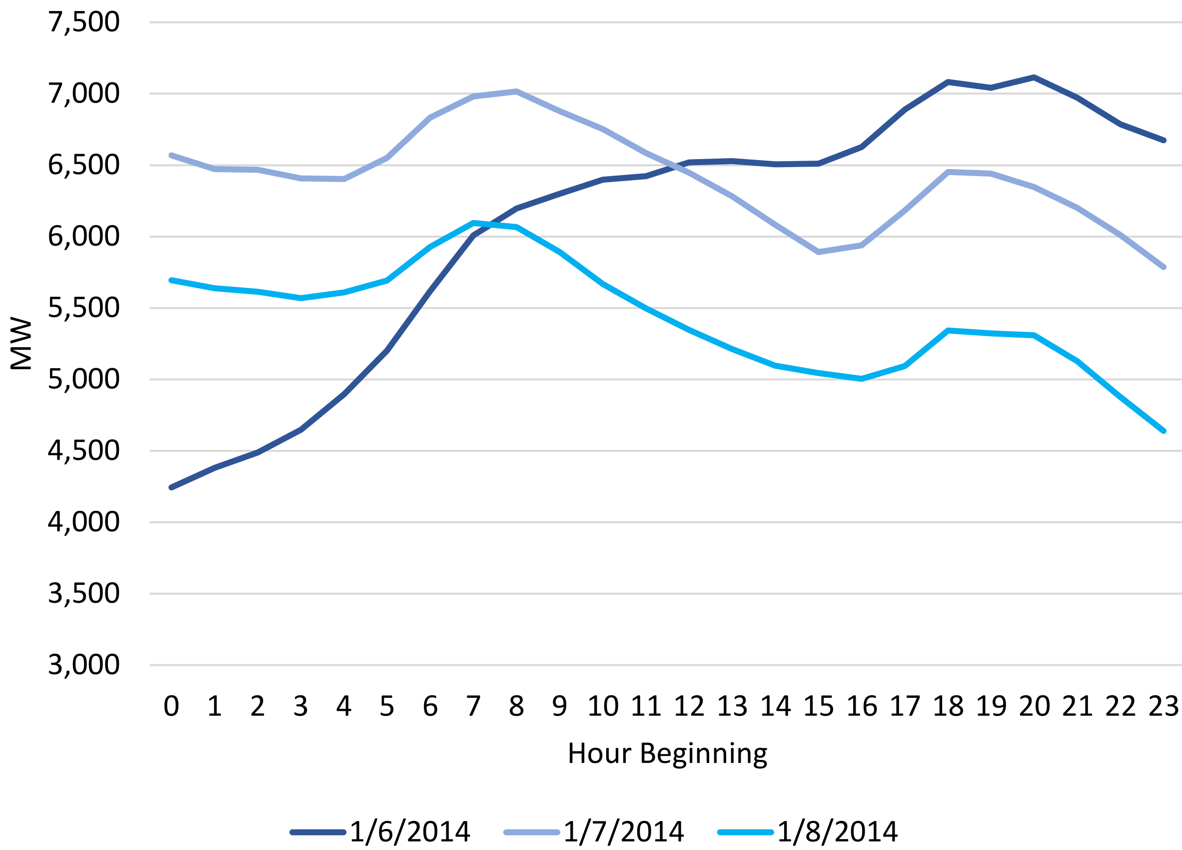


Figure 11: LG&E and KU 2028 Hourly Load Duration Curve



The hourly forecast and charts above assume normal weather, but customers demand even greater load for a longer duration during extreme weather events. Figure 12 shows the hourly load profiles of 3 days during the Polar Vortex of January 2014.[7] During this period, hourly load remained above 6,000 MW for 32 consecutive hours and above 5,000 MW for 65 consecutive hours. The highest loads during this period were observed during non-daylight or very early morning hours.

Figure 12: Polar Vortex 2014 Hourly Load Profiles



3 Key Forecast Assumptions and Uncertainties

One recommendation in the 2021 IRP Commission Staff Report is, "LG&E/KU should expand their discussion of the reasonableness of underlying assumptions including supporting documentation listing known facts."[8] The discussion in this section is responsive to that recommendation. Please note that additional documentation of the Companies' load forecasting process is available in Exhibit TAJ-2, "Electric Sales & Demand Forecast Process." Also, a guide to the electronic workpapers being provided with this load forecast is available in Technical Appendix 2 at the end of this document.

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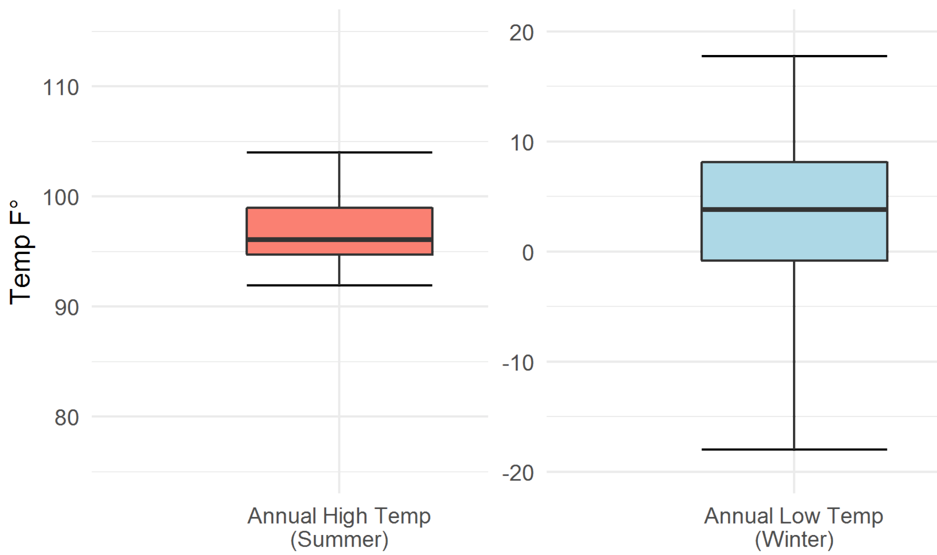
[7] Includes load from the departed municipal customers. The addition of BlueOval load will mostly offset the loss of the departed municipal customer load. Additionally, the lowest temperature recorded at the Muhammad Ali International Airport in Louisville during the Polar Vortex was -3 degrees Fahrenheit. On January 19, 1994 during a winter storm event that resulted in over a foot of snow in Louisville, the recorded low temperature was -22 degrees Fahrenheit. https://www.wlky.com/article/archives-unforgettable-snow-shut-down-louisville/30562805

[8] Case No. 2021-00393, Order Appx. "Commission Staff's Report on the 2021 Integrated Resource Plan of Louisville Gas and Electric Company and Kentucky Utilities Company" at 67 (Ky. PSC Sept. 16, 2022).

3.1 Weather

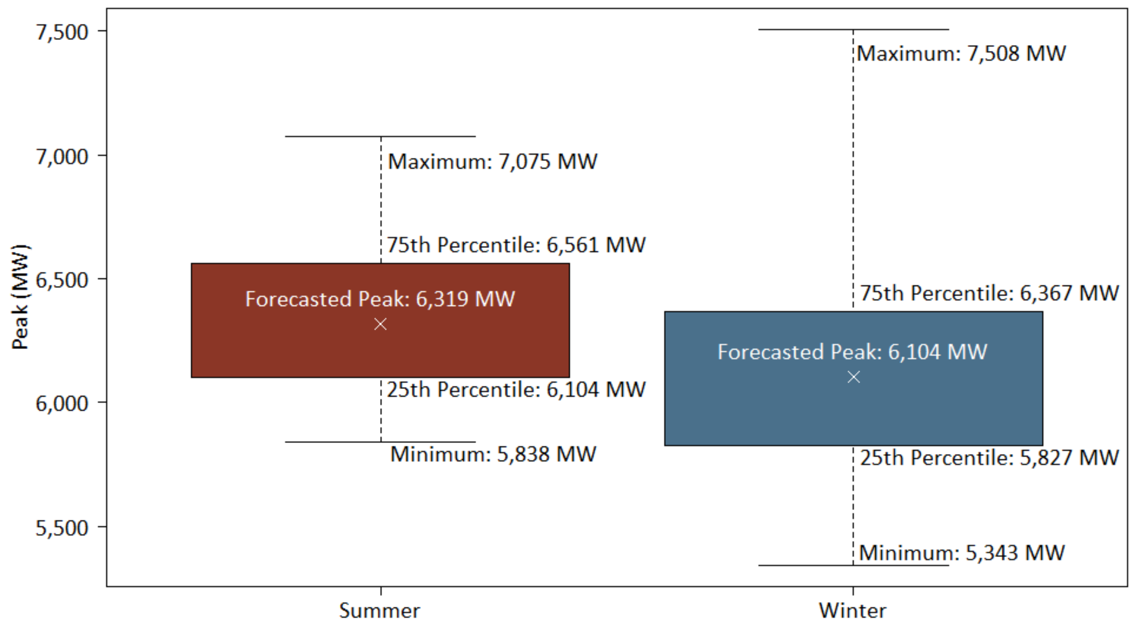
Weather is a foundational driver of energy consumption, and variations in energy requirements due to weather are a key consideration in resource planning. Therefore, consistent with their prior practice, the Companies used 20 years of historical weather data to develop their long-term base energy requirements forecast, which assumes weather will be average or "normal" in all years. To account for weather variability and support the Companies' Reserve Margin Analysis, the Companies also produced 49 hourly energy requirement forecasts for 2028 based on weather in each of the last 49 years. Figure 13 and Figure 14 below show greater variation in winter peak demands than summer peak demands, which results from greater winter temperature variability, including extreme low temperatures that can drive significant demand from electric heating systems of all kinds. Thus, if a higher percentage of customers adopt electric heating than projected in this forecast, winter peak and non-daylight energy requirements could be markedly higher than forecasted here.

Figure 13: Louisville Annual High and Low Temperature Distributions (1973-2021)[9]



[9] The limits of the box in the boxplots reflect the 25th and 75th percentiles while the "whiskers" represent the maximum and minimum.

Figure 14: Distribution of 2028 Summer and Winter Peak Demands



3.2 Economic Assumptions

As with weather, macroeconomic assumptions are foundational to the Companies' load forecast. Therefore, Companies used economic assumptions from a reputable forecaster, S&P Global, in forecasting their base energy requirements.[10]

For the U.S. overall, S&P Global projects real economic growth of 2.4 percent during 2022. For the 2023-2027 timeframe, real GDP is forecasted to increase at an average annual rate of 2.4 percent, above the 2010-2019 between-recession (Great Recession and the COVID-19 pandemic) average of 2.3 percent. Over the longer term from 2028-2032, S&P Global projects growth to average 2.1 percent.

In Kentucky, S&P Global projects real economic growth of 1.4 percent during 2022. For the 2023-2027 period, the state's economy is expected to increase at an average pace of 1.8 percent, above the between-recession average of 1.4 percent. Over the longer term from 2028-2032, S&P Global projects growth to average 1.8 percent.

Key near-term uncertainties to the U.S. economy and Kentucky's economy include high inflation and a potential economic downturn due to the Federal Reserve's attempts to curb inflation. Although there is a real risk of an economic recession, it would likely affect only near-term growth.

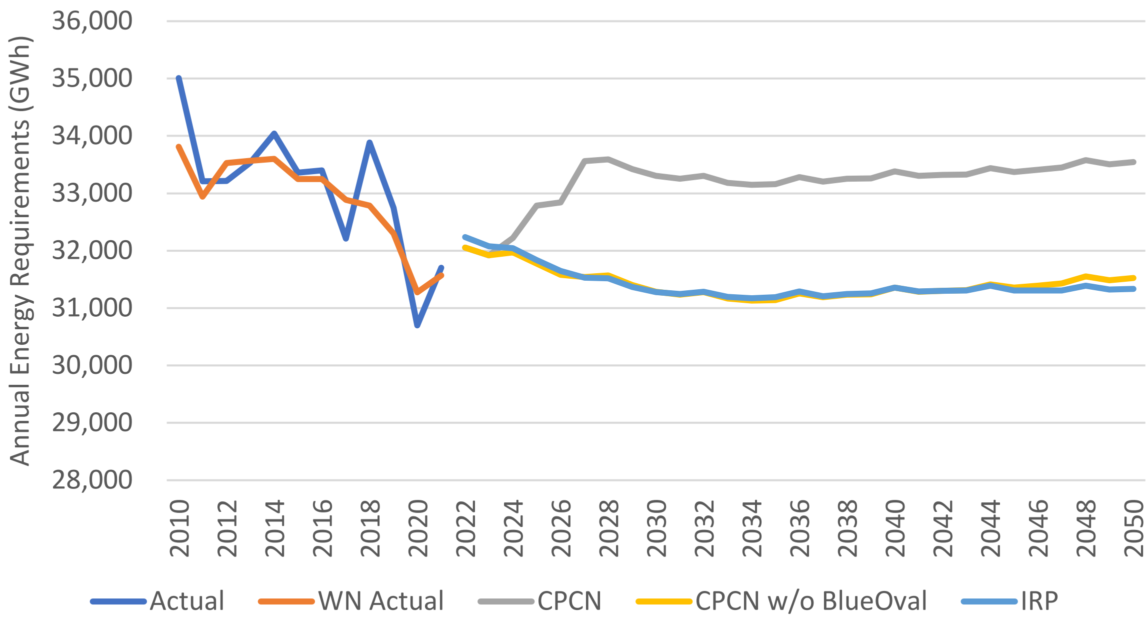
[10] All of the economic assumptions the Companies used are from S&P Global's May 2022 U.S. Economic Outlook. (S&P Global was formerly IHS Markit.) The spreadsheet containing those assumptions is in the Companies' workpapers, Exhibit TAJ-3. Technical Appendix 2 to this document is a guide to the Companies' workpapers. Note that the S&P Global data contains many more variables than the Companies' load-forecasting models used.

3.3 BlueOval SK Battery Park

Governor Beshear recently described Kentucky as the EV battery production capital of the United States.[11] A primary reason for that is Ford's planned BlueOval SK Battery Park in Glendale, Kentucky, which the Companies will serve. Ford announced its plans to construct the battery park after the Companies completed their 2021 IRP load forecast, so it is a new and impactful addition to this load forecast.

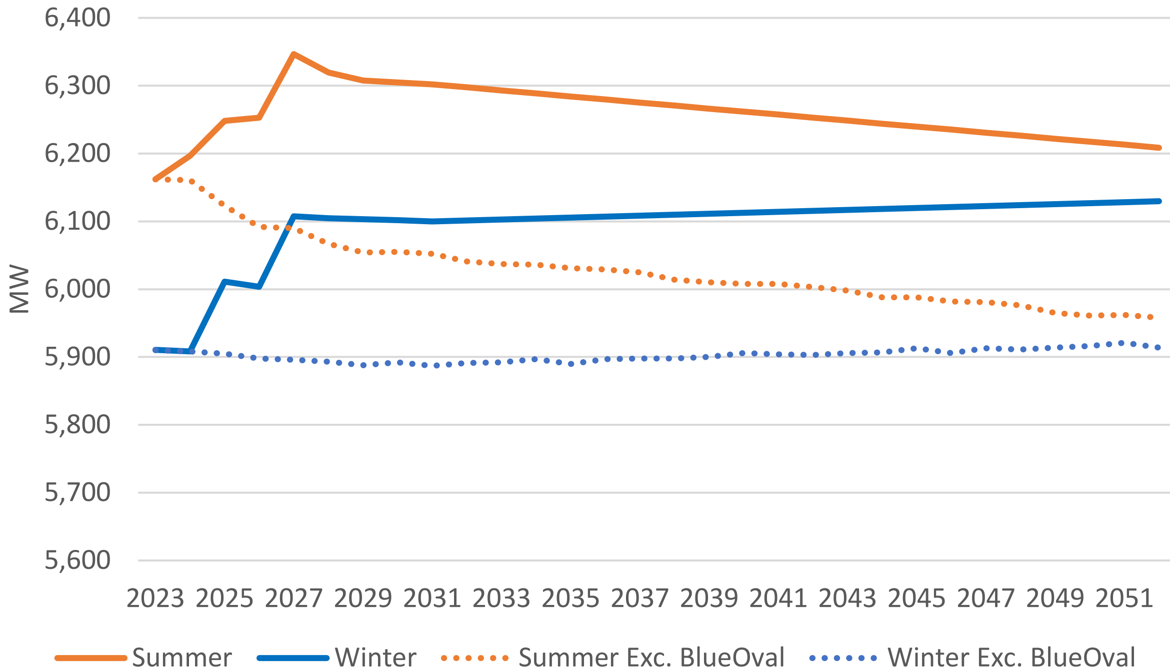
Indeed, it is difficult to overstate the impact of BlueOval on this load forecast compared to the 2021 IRP load forecast. Figure 15 and Figure 16 below show the magnitude of BlueOval's effects on projected annual energy requirements and seasonal peak demands, respectively:

Figure 15: Annual Energy Requirements History and Forecast (exc. departed KU municipal customers)



[11] *See, e.g.*, "Electric battery company plans $2 billion factory in Bowling Green," (Apr. 13, 2022) ("[Gov.] Beshear said Kentucky is the 'undisputed electric battery capital of the United States of America.'"), available at https://www.wdrb.com/in-depth/electric-battery-company-plans-2-billion-factory-in-bowling-green/article_eaa8df74-bb3c-11ec-959d-67c45528113c.html.

Figure 16: Forecasted Seasonal Peaks



These figures reflect the addition of BlueOval's large new load (almost 260 MW summer peak; about 225 MW winter peak) and high, consistent, day-and-night energy requirements (load factor almost 90%), resulting in projected annual energy requirements of more than 2,000 GWh if Ford fully constructs the battery park as planned.[12]

By way of comparison and as illustrated in the figures above, without the battery park the Companies' forecasted annual energy requirements in this forecast are similar to those in the 2021 IRP load forecast, ranging from 0.5% lower to 0.2% higher through 2030, as reductions from increased levels of energy efficiency and distributed energy resources ("DER") are essentially offset by more customers and higher consumption due to increasing penetrations of EVs and electric space heating. Similarly, without BlueOval peak demand ranges from 0.6% lower to 0.2% higher (-38 to +12 MW) in summer, and peak demand ranges from 0.6% to 2.5% higher (37 to 142 MW) in winter through 2030.

But with BlueOval in full operation, annual energy requirements are approximately 6.5% higher than the 2021 IRP load forecast beginning in 2027. Summer and winter peak demand are approximately 4% and 6% higher, respectively.[13] Thus, it is not hyperbole to state that BlueOval is the single most impactful change to the Companies' load forecast since the 2021 IRP—and by a wide margin.

Note that although is reasonable to assume that BlueOval will drive economic and load growth in Glendale and surrounding areas, because the Companies do not serve much of the area surrounding Glendale, this load forecast does not include any load growth associated with BlueOval other than the park itself.

[12] The stated peak load figures represent BlueOval's non-coincident, peak hourly usage projections grossed up by a transmission loss factor of 1.02827. BlueOval's anticipated summer billing demand is 254 MW.
[13] See Technical Appendix 1 at the end of this document for two tables comparing annual energy requirements and seasonal peak loads for the 2021 IRP load forecast and this load forecast.

Therefore, other possible load growth associated with BlueOval, which the Companies did not attempt to forecast, is a significant upside uncertainty to this load forecast.

3.4 Inflation Reduction Act

On August 16, 2022, President Biden signed the Inflation Reduction Act. The IRA supports the Biden administration's economy-wide GHG reduction target (50-52% vs. 2005 levels by 2030) through various means, including tax credits, grants, loans, and rebates for clean technologies. Details regarding the IRA's implementation remain to be addressed through guidance from various agencies, including the Department of Energy, Department of Treasury, Internal Revenue Service, and the Environmental Protection Agency.

The IRA is expected to impact load both positively and negatively through a variety of programs designed to incentivize either reduced consumption through distributed solar and more energy efficient appliances, or electrification (and therefore increased consumption) through EVs and heat pumps. Most programs are targeted toward residential and small commercial customers.

Incentives for EVs are in the form of tax credits for both new and used vehicles.[14] Model results including these incentives are discussed in Section 3.7. There is also an investment tax credit ("ITC") for distributed solar and even residential battery storage. The ITC has been raised to 30% and extended through 2032. Then, it decreases to 26% and 22% in 2033 and 2034, respectively, before ending entirely in 2035. Given that over 99% of current distributed generation installations in the service territory are in the form of solar today, the forecast assumption is that this will be solar in the future as well. Model results including these incentives are discussed in Section 3.6. Over the past decade, both EVs and distributed solar have been primarily adopted by those with relatively high incomes,[15] but it is reasonable to assume that customers with a broader range of incomes will adopt these technologies as they become more affordable.

The IRA also provides significant incentives around energy efficient or electric end-use appliances, particularly for low-income customers. Although high income customers do not qualify, low- and mid-income customers qualify for many of the home energy efficiency and electrification tax incentives and rebates up to a lifetime maximum of $14,000. It is uncertain at this point how these programs will be implemented and whether energy efficiency or electrification incentives will be more appealing to customers. But it is noteworthy that electric (and possibly dual fuel) heat pumps are eligible for the highest rebate of all appliances at $8,000 for low-income customers and half of that for qualifying middle-

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[14] The IRA provides tax credits up to $7,500 for new vehicles and up to $4,000 for used vehicles that meet requirements. *See* Inflation Reduction Act of 2022, available at https://www.congress.gov/bill/117th-congress/house-bill/5376.

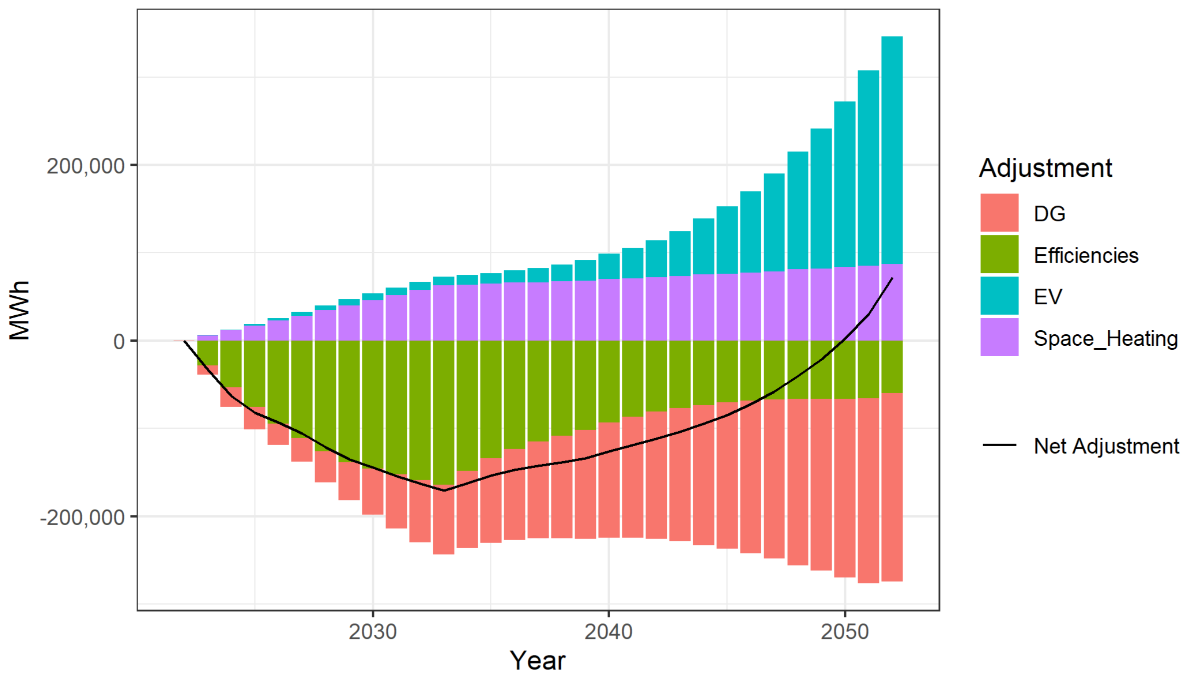
[15] According to the U.S. Department of Energy's Lawrence Berkeley National Laboratory, the median income of 2021 solar adopters was $110,000 nationwide. Residential Solar-Adopter Income and Demographic Trends: November 2022 Update at 5, available at https://eta-publications.lbl.gov/sites/default/files/solar-adopter_income_trends_nov_2022.pdf. According to the U.S. Census Bureau, the median household income in Kentucky for 2016-2020 was $52,238 in 2020 dollars. *See* https://www.census.gov/quickfacts/fact/table/KY/INC110220. Also, according to Berkeley Lab, nearly 80% of Kentucky solar adopters had household incomes at or above $50,000. Residential Solar-Adopter Income and Demographic Trends: November 2022 Update at 17.

income customers. Customers choosing the electrification option may require an electrical panel upgrade, which is also covered by the IRA with a rebate of $4,000 for low-income customers.

To account for these IRA effects, the Companies accelerated pre-IRA EIA inputs for both end-use efficiencies and electric space heating by 10 years, i.e., the Companies' load forecast assumes the IRA will cause efficiencies and electric space heating to escalate more quickly from now until 2033, reaching previously forecasted 2043 levels by 2033. For distributed generation, the Companies included the effects of the IRA's extended ITC in their projections (see Section 3.6). For EVs, the Companies used the IRA's tax credits in their EV modeling (see Section 3.7).

Figure 17 below shows the annual energy requirements effects of all four load forecast components the IRA affects: energy efficiency, electric vehicles, distributed generation, and space heating. (Note that the "Efficiencies" adjustments include the effects of the Companies' proposed 2024-2030 DSM-EE Program Plan, as well.)

Figure 17: Incremental Annual Energy Requirements Impacts of IRA and DSM-EE-Affected Items



At first glance, the incremental energy efficiency savings may appear strangely skewed in the figure above. Though it might appear odd, it is entirely consistent with the Companies' projection that the combined energy-efficiency effect of the IRA and 2024-2030 DSM-EE Program Plan will be to accelerate energy-efficiency implementation such that the aggregate level of energy efficiency in 2033 reaches the level that would have been achieved by 2043 absent the acceleration. A necessary result of this acceleration is that years following 2033 show lower levels of incremental energy-efficiency gains than would have obtained absent the ten-year acceleration. Note that this acceleration results in net energy savings for the forecast period compared to not accelerating energy-efficiency deployment.

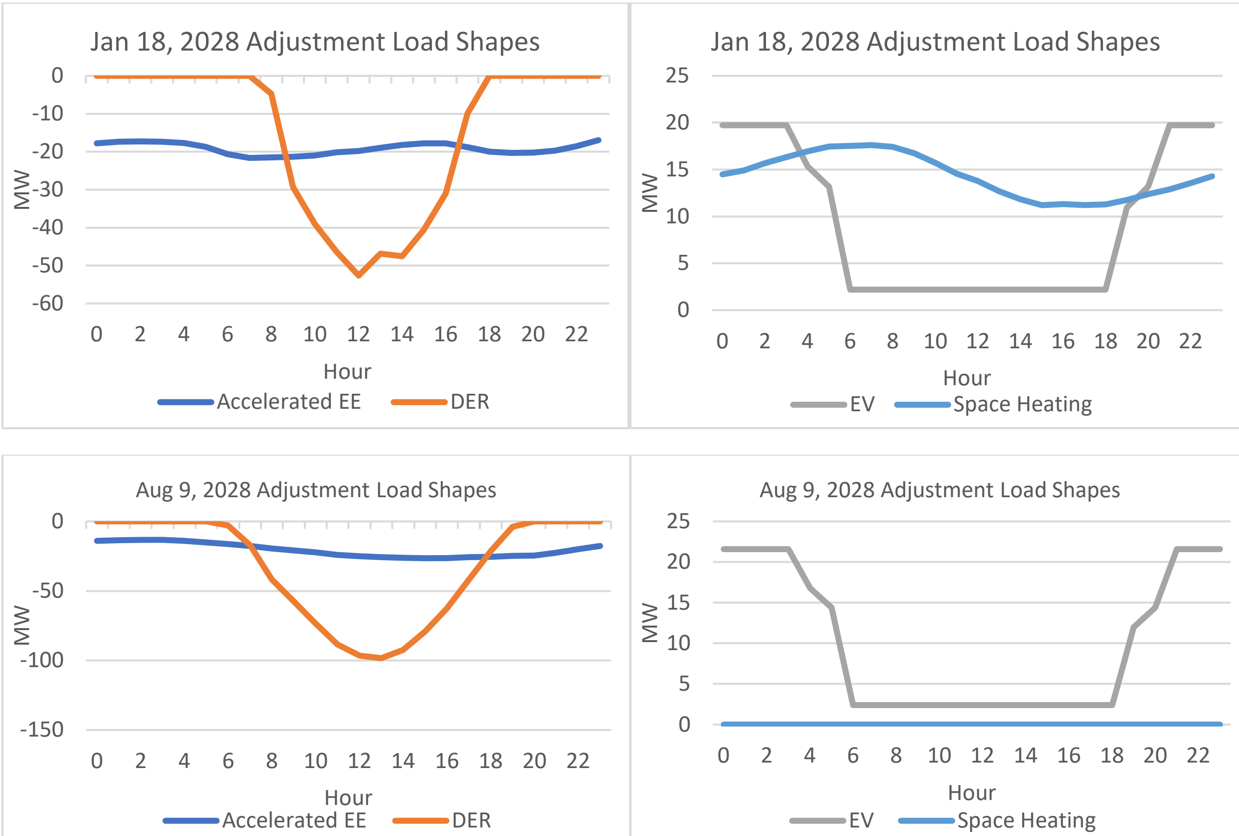
Taking the four IRA and DSM-EE-affected items together, although the positive and negative energy impacts may nearly offset each other in terms of their total annual impact, they have differing load profiles that affect the hourly load forecast differently:

- Positive Load Impacts
    - Because heat pumps have the highest rebate of any appliance discussed in the IRA, space heating electrification is anticipated to increase as a result. This will especially increase morning, evening, and overnight load during the winter months, but will have little to no impact on summer peaks.[16]
    - As was assumed in the 2021 IRP, electric vehicles are assumed to primarily charge at homes and overnight. This should have little impact on the summer peak and minimal impact on the winter peak in the morning. Identical to the IRP, the Companies assumed overnight charging would occur, so EVs also have less impact on winter evening load than they would under an unmanaged charging scenario.
- Negative Load Impacts
    - Distributed generation will primarily be in the form of solar, similar to today. The hourly impacts will only occur during the daylight hours, and the actual impacts on specific days will vary by cloud cover and day length.
    - Accelerated energy efficiencies resulting from the IRA and proposed DSM-EE programs are assumed to impact load in all hours by a monthly percentage difference as a variety of appliances are affected.

Figure 18 below provides a sample of the daily load profiles in summer and winter 2028 for the items discussed above. They illustrate that the four IRA and DSM-EE-affected items can have different aggregate hourly, daily, and seasonal impacts.

[16] A new heat pump will likely also have a high efficiency rating, so the summer peak should decline marginally as a result assuming the heat pump is used to both heat and cool the home. However, this higher efficiency is captured within the accelerated energy efficiencies adjustment.

Figure 18: Load Shapes of IRA and DSM-EE Adjustments



3.5 DSM and Energy Efficiency

Over the past decade, customers in all classes have taken significant action to use electricity more efficiently. The base energy requirements forecast assumes similar energy efficiency trends, although leveling off in the out years of the forecast, will continue throughout the forecast period. Forecasted end-use efficiency improvements are explicitly incorporated in residential and small commercial through the statistically adjusted end-use modeling approach described in Exhibit TAJ-2. Although the model structures differ, the Power Service-Secondary and Time of Day Secondary rate forecasts also include a variable to measure the impact of end-use efficiencies over time.

From 2010 to 2021, residential and small commercial use-per-customer has decreased by 7% and 18%, respectively, primarily due to customer-initiated energy efficiency and the Companies' DSM-EE programs. Including impacts of IRA and the Companies' proposed DSM-EE programs, the load forecast assumes residential and small commercial use-per-customer will decrease by an additional 4% and 9% from 2021 levels, respectively, by 2028. The number of residential and small commercial customers is forecasted to grow by approximately 0.4% and 0.5%, respectively, per year, consistent with historical trends and population forecast from S&P Global. Despite this growth in customers, total residential and small commercial sales are 3% and 9% lower, respectively, than they otherwise would be due to customer-initiated energy efficiency and DSM-EE.

A portion of improved energy efficiency occurs naturally as appliances fail and require replacement. Because of advances in technology and updates to federal standards, appliance replacement options with even the lowest efficiency ratings are more efficient than most options were 15 or more years ago. For those that need to replace appliances anyway, particularly related to HVAC or water heating, incentives such as those offered in the IRA or the Companies' proposed DSM-EE programs may allow them to purchase a more efficient model than they otherwise would have. Thus, like IRA energy-efficiency efforts and incentives, DSM-EE can drive a more rapid increase in average appliance efficiency in the service territory.

Because the IRA's energy-efficiency provisions and the Companies' non-dispatchable DSM-EE programs and measures all tend to have the same effect—accelerating the deployment of energy-efficiency—the Companies modeled their effects together. More precisely, to model the impact of the IRA and proposed DSM-EE programs on energy consumption, the Companies assumed that the joint impact of the IRA and DSM-EE programs would be to accelerate the EIA's forecast of energy efficiency improvements by 10 years for residential and small commercial customers, i.e., those customers would achieve 2043 levels of EIA forecasted energy efficiency by 2033.

Although the 10-year acceleration is an estimate, it is a reasonable assumption; by 2043, EIA's projected energy efficiency improvements begin to plateau. For example, Figure 19 below shows an indexed view of residential central air conditioning and heat pump efficiencies over time according to the EIA, as well as the impact of accelerating those curves by 10 years (i.e., original 2043 efficiencies now seen in 2033) and 15 years (i.e., original 2048 efficiencies now seen in 2033) for comparison purposes. Because the original forecast began to level off in the early 2040s, there is not a material difference between the 10 and 15 years accelerated curves.

Figure 19: Residential Central Air Conditioning and Heat Pump Efficiency Index

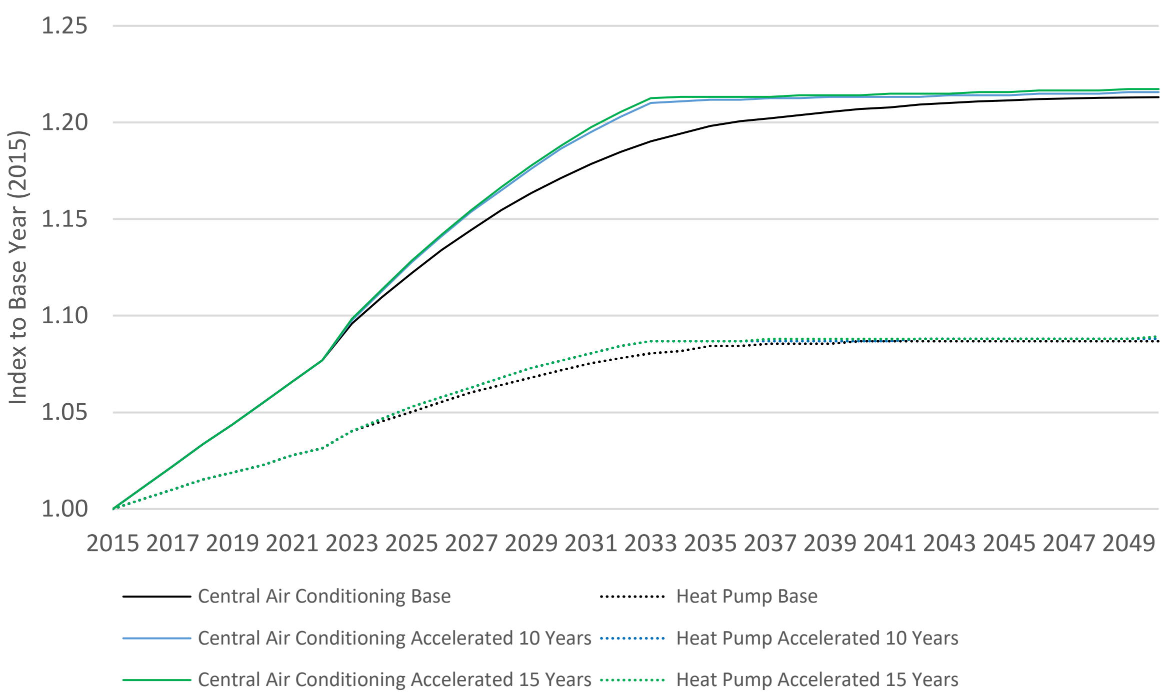


Figure 20 shows the combined impact of DSM-EE and customer-initiated energy efficiency savings for residential and small commercial customers (including savings incentivized by the IRA) in this forecast. The proposed DSM-EE programs and IRA accelerate the already aggressive energy efficiency assumptions over the next decade. In total, sales to residential and small commercial customers (i.e., customers on residential or GS rates) in 2028 are 3.8% lower than they otherwise would be due to the combined impact of customer-initiated energy efficiency and proposed DSM-EE programs.[17]

Figure 20: Energy Efficiency Impact – Forecast Comparison (Residential and GS)

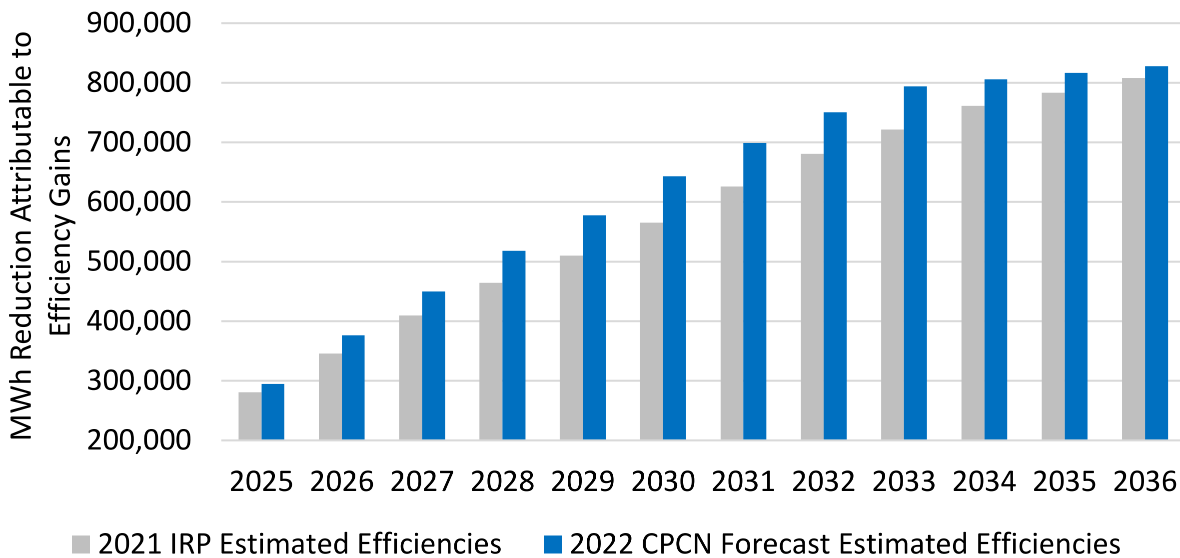
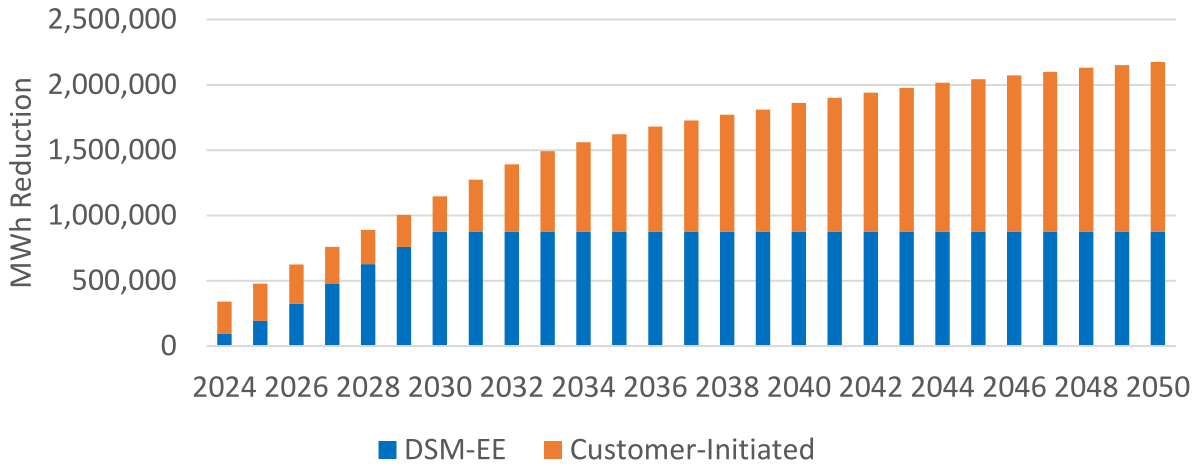


Figure 21 shows the forecasted annual energy impact of energy efficiency for all residential and commercial customers broken down into components for the estimated effects of the proposed DSM-EE programs versus customer-initiated energy efficiency (including IRA incentive effects).[18] The figure shows there is a significant amount of energy efficiency load reduction in the forecast.

[17] *See, e.g.,* Exhibit JB-1 to the testimony of John Bevington for a list and description of the DSM-EE programs in the Companies' 2024-2023 DSM-EE Program Plan.

[18] Note that although the models used to forecast large commercial sales (i.e., Power Service and Time-of-Day Secondary rates) are not identical to those used to forecast RS and GS sales and do not include the 2043 to 2033 acceleration assumed for residential and small commercial customers, there is a variable used in the large commercial models to account for energy efficiency gains over time.

Figure 21: Estimate of Residential and Commercial DSM-EE vs. Customer-Initiated Energy Efficiency [19]



Notably, the Companies' forecasted energy savings resulting from energy efficiency compare favorably to the energy savings projected for achievable cumulative energy efficiency potential shown in Table 1 of the Cadmus 2022 Cross-Sector DSM Potential Study Projection (Exhibit LI-1 to the testimony of Lana Isaacson).

Also, the energy efficiency reflected in the figure above results in summer peak demand reductions in 2035 through 2038 ranging from 341 MW to 367 MW and winter peak demand reductions ranging from 256 MW to 279 MW. In 2043, the resulting summer peak demand reduction is 406 MW, and the winter peak demand reduction is 313 MW.[20] These values also compare favorably to the achievable (and even economic) demand reductions associated with cumulative energy efficiency potential shown in Table 2 of the Cadmus 2022 Cross-Sector DSM Potential Study Projection. These comparisons show that the energy efficiency assumed to occur in the 2022 Load Forecast is reasonable, if not aggressive.

Finally, the Companies have not explicitly forecasted energy requirements reductions resulting from energy efficiency for industrial customers, and the DSM-EE programs were assumed to reduce only residential and commercial loads. Nonetheless, although the number of industrial customers remains flat during the forecast period and despite assumed economic growth, the compound annual growth rate for industrial sales for the forecast period (2023-2050) is around -0.2%.[21]

3.6 Distributed Energy Resources

3.6.1 Types of Distributed Energy Resources Considered

One recommendation of the Commission Staff's report on the Companies' 2021 IRP was, "LG&E/KU should expand its discussion of DERs to identify resources other than distributed solar that could

[19] DSM-EE estimates were held constant after 2030, assuming that DSM-EE programs would continue beyond 2030.
[20] The workpaper showing these calculations is in Exhibit TAJ-3.
[21] Excluding BlueOval.

potentially be adopted by customers and explain how and why those resources are expected to affect load, if at all."[22] The discussion in this section is responsive to that recommendation.

3.6.1.1 Current Makeup of Distribution-Connected Distributed Energy Resources

Currently, about 99.7% of all distributed generation installations connected to the Companies' facilities in their service territory is solar. Of the Companies' more than 3,100 distributed generation customers, there are only 11 non-solar distributed generation installations; 1 is hydro and the remainder are wind. The 10 wind installations average 2.5 kW per customer. Only 1 non-solar installation (wind) has been installed in the last 7 years, and even that one was installed 4 years ago. Table 1 lists the non-solar distributed generation facilities currently in the service territory.

Table 1: Non-Solar Distributed Generation

Company	Rider	Rate	Source	Connected KW	Date Installed
KU	NMS	RS	Wind	2.4	December 2008
KU	NMS	GS	Wind	2.4	June 2009
KU	NMS	RS	Wind	2.4	October 2009
KU	NMS	RS	Wind	2.5	November 2009
KU	NMS	GS	Hydro	50	August 2012
KU	NMS	RS	Wind	1.6	August 2015
LG&E	NMS	PS-Sec	Wind	1.9	November 2009
LG&E	NMS	RS	Wind	2.5	April 2014
LG&E	NMS	GS	Wind	3.7	October 2014
LG&E	NMS	RS	Wind	1	January 2015
LG&E	NMS	RS	Wind	4.8	December 2018

As the following discussion shows, solar is likely to remain the dominant, if not nearly exclusive, form of distributed generation customers will choose to serve their needs and to connect to the Companies' distribution system over the forecast period.

3.6.1.2 Analytical Framework for Considering Distributed Energy Resources

The Companies' analysis and forecast of distributed energy resources assumes customers are economically rational and will choose the most economically advantageous form of distributed generation. It further assumes that customers will invest in energy storage (battery energy storage systems) only if it is economically advantageous for them.

This analysis assumes that customers will determine what is most economically favorable based on a distributed energy resource's levelized cost of energy ("LCOE"). The basis of this assumption is that the vast majority of current and anticipated distributed energy resource-installing customers take service under rate schedules with energy rates that do not vary by time of day. In addition, the Companies' current net metering rider for new net metering customers (NMS-2) and qualifying facility riders (SQF and LQF) do not vary credit for exported energy based on season or time of day. Therefore, an economically

[22] Case No. 2021-00393, Order Appx. "Commission Staff's Report on the 2021 Integrated Resource Plan of Louisville Gas and Electric Company and Kentucky Utilities Company" at 67 (Ky. PSC Sept. 16, 2022).

rational customer would seek to install a distributed energy resource only if the resource's LCOE was lower than the expected benefit of avoided energy consumption and credit for any exported energy.

3.6.1.3 Consideration of Distributed Wind Generation

After solar, the most economically plausible form of distributed generation is wind generation. Some evidence for this is the handful of the Companies' customers who have installed small, distributed wind facilities, as shown above.

But two factors suggest that distributed wind is unlikely to become more than a tiny fraction of installed distributed generation capacity in Kentucky during the study period: Kentucky's low average wind speeds and the levelized cost of wind energy.

Kentucky's poor wind conditions are well documented in data assembled by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy.[23] For example, that data shows the entire Commonwealth as a "poor" wind energy resource, with annual average wind speeds at 50 meters between zero and 5.7 meters per second.[24] At 100 meters, the great majority of Kentucky has annual average wind speeds between 4.5 and 7.5 m/s, with a few locations in the far southeast of the state with wind speeds of 8.0 m/s or more.[25]

Applying that level of wind resource to data available in the 2022 NREL ATB cost projections shows that distributed wind generation has a consistently higher LCOE than distributed solar generation for Kentucky customers through 2050 (the end date of the NREL ATB data set).[26]

The conclusion that wind power is uneconomical in Kentucky finds further support in data from the United States Wind Turbine Database maintained by the U.S. Geological Survey, Lawrence Berkeley National Laboratory, and the American Clean Power Association.[27] That data shows that of more than 72,000 wind turbines in their database, none are in Kentucky.

Therefore, the Companies did not include distributed wind resources in forecasting distributed energy resource additions.

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[23] *See, e.g.,* U.S. Dept. of Energy, Office of Energy Efficiency and Renewable Energy, Kentucky Annual Average Wind Speed at 30 m, available at https://windexchange.energy.gov/maps-data/274; U.S. Dept. of Energy, Office of Energy Efficiency and Renewable Energy, Kentucky 50-Meter Community-Scale Wind Resource Map, available at https://windexchange.energy.gov/maps-data/47; U.S. Dept. of Energy, Office of Energy Efficiency and Renewable Energy, Kentucky Land-Based Wind Speed at 100 Meters, available at https://windexchange.energy.gov/maps-data/359.

[24] U.S. Dept. of Energy, Office of Energy Efficiency and Renewable Energy, Kentucky 50-Meter Community-Scale Wind Resource Map, available at https://windexchange.energy.gov/maps-data/47.

[25] U.S. Dept. of Energy, Office of Energy Efficiency and Renewable Energy, Kentucky Land-Based Wind Speed at 100 Meters, available at https://windexchange.energy.gov/maps-data/359.

[26] *See* 2022 v2 Annual Technology Baseline Workbook Corrected 7-21-2022.xlsx, available at https://data.openei.org/files/5716/2022%20v2%20Annual%20Technology%20Baseline%20Workbook%20Corrected%207-21-2022.xlsx. Comparison is of Moderate data for Class 8 Wind and Class 4 Solar for both Residential and Commercial cases.

[27] The United States Wind Turbine Database, Tabular Data, available at: https://eerscmap.usgs.gov/uswtdb/assets/data/uswtdbCSV.zip.

3.6.1.4 Consideration of Distributed Hydro and Biomass Generation

There is only one distributed hydro facility in the Companies' Kentucky service territory. There are no distributed biomass generation facilities connected to the Companies' distribution system.

The economics of such generating resources explain their nearly complete absence from the Companies' service territory. The 2022 NREL ATB cost projections show that hydro and biomass generation all have a consistently higher LCOE than distributed solar generation for Kentucky customers through 2050 (the end date of the NREL ATB data set).[28]

Therefore, the Companies did not include distributed hydro or biomass in forecasting distributed energy resource additions.

3.6.1.5 Consideration of Distributed Battery Energy Storage Systems

The Companies are currently aware of their distributed generation customers having a total of 1,615 kW of distributed battery energy storage system capacity across 244 installations, which is less than 8% of the Companies' total 3,116 distributed generation customers and less than 0.05% of all the Companies' Kentucky electric customers. The small fraction of customers who have installed such battery systems suggests that customers have not found the economics of distributed battery storage to be attractive thus far.

In addition to the small fraction of the Companies' customers who have implemented distributed battery storage, there is other evidence that the economics of distributed energy storage are not yet favorable. For example, a recent analysis published in the American Journal of Industrial and Business Management found that the economics of battery storage were not favorable for residential solar customers in southern California, which has excellent solar irradiance and time of use rates that strongly incentivize consumption during prime daylight hours (e.g., one TOU structure has a $0.27/kWh rate during prime daylight hours and a $0.43/kWh during all other hours).[29] Indeed, the southern California analysis found that on nearly all sets of assumptions the payback period for a Tesla Powerwall 2 (including applicable tax incentives) was longer than the ten-year warranty period of the battery. For the median household, the payback period ranged from 17 to almost 150 years depending on rate schedule and use profile.

It is reasonable to assume that if distributed battery energy storage is not economical for distributed solar customers in southern California, it is unlikely to be economical for distributed solar customers in the Companies' service territory, at least in the near term, due to solar irradiance and rate differences. This, along with the Companies' current low saturation of distributed battery storage, resulted in the Companies not including distributed battery energy storage systems in forecasting distributed energy resource additions.

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[28] *See* 2022 v2 Annual Technology Baseline Workbook Corrected 7-21-2022.xlsx, available at https://data.openei.org/files/5716/2022%20v2%20Annual%20Technology%20Baseline%20Workbook%20Corrected%207-21-2022.xlsx. Comparison is of Moderate data for Class 8 Wind and Class 4 Solar for both Residential and Commercial cases.

[29] Broughton, J. B., Nyer, P. U., & Ybarra, C. E. (2021). The Economics of Battery Storage for Residential Solar Customers in Southern California. American Journal of Industrial and Business Management, 11, 924-932. Available at: https://www.scirp.org/journal/paperinformation.aspx?paperid=111481.

3.6.1.6 Conclusion: Solar Generation Is the Most Economical Distributed Energy Resource

As shown above, solar generation is the most economically rational distributed energy resource for customers to deploy over the forecast period (barring unforeseen technological improvements, financial incentives, or other economically relevant developments). As noted before, solar generation makes up about 99.7% of currently deployed distributed generation installations in the Companies' service territory. Therefore, the Companies' load forecast assumes all distributed generation additions will be solar for the forecast period.

3.6.2 Adoption and Effect of Distributed Solar Generation

Regarding distributed solar generation, the Commission Staff's report on the Companies' 2021 IRP recommended:

> LG&E/KU should expand its discussion of the projected adoption of distributed solar and its effect on load to include separate discussions of assumptions, methodology, and projections for residential, commercial, and industrial customers and separate discussions of assumptions, methodology, and projections for customers interconnected under LG&E/KU's net metering tariffs, qualifying facilities tariffs, and other similar tariffs, if any, that are adopted after this report.
>
> LG&E/KU should analyze and discuss whether and the extent to which customers that would have taken service under the Net Metering Service-2 tariff would continue to interconnect DERs even if they received no credit for energy sent back into the system because the one percent cap had been reached when they sought to connect.[30]

The following discussion is responsive to those recommendations.

3.6.2.1 Historical Trends in Distributed Solar Generation in the Companies' Service Territory

The Companies' experience with their customers' adoption of distributed solar generation shows that customers generally become more inclined to adopt it as its economics improve, but also that some customers adopted solar even when it was not clearly economical.

Figure 22 and Figure 23 show annual incremental net metering customers and capacity added for the Companies since 2009:

[30] Case No. 2021-00393, Order Appx. "Commission Staff's Report on the 2021 Integrated Resource Plan of Louisville Gas and Electric Company and Kentucky Utilities Company" at 67 (Ky. PSC Sept. 16, 2022).

Figure 22: Incremental Net Metering Customer Adoption

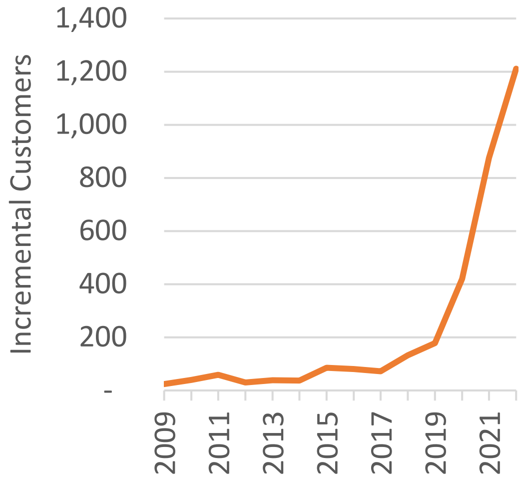
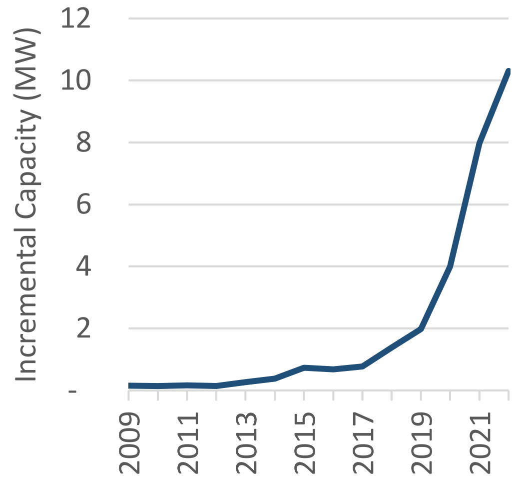


Figure 23: Incremental Net Metering Capacity Growth



Notably, both figures above show that incremental annual net metering customer and capacity additions were on a general and gentle upward trend through 2017, but then took a marked upward turn beginning in 2018 and an even more pronounced upward turn in 2020. As shown in Table 2 below, those inflection points correlate with a narrowing gap between: (1) the Companies' base energy rates;[31] and (2) one set of NREL data for the levelized cost of energy for small solar generation systems:[32]

Table 2: Retail Rates vs. LCOE

Difference between KU Energy Rate and NREL Solar LCOE per kWh (red unfavorable to PV)

Rate	2013	2014	2015	2016	2017	2018	2019	2020
RS	($0.1047)	($0.0757)	($0.0449)	($0.0349)	($0.0222)	($0.0142)	($0.0032)	($0.0022)
GS	($0.0913)	($0.0623)	($0.0313)	($0.0213)	($0.0086)	($0.0006)	$0.0193	$0.0203
PS-Sec	($0.1436)	($0.1146)	($0.0943)	($0.0843)	($0.0775)	($0.0695)	($0.0599)	($0.0589)

Difference between LG&E Energy Rate and NREL Solar LCOE per kWh (red unfavorable to PV)

Rate	2013	2014	2015	2016	2017	2018	2019	2020
RS	($0.1026)	($0.0736)	($0.0492)	($0.0392)	($0.0214)	($0.0134)	($0.0015)	($0.0005)
GS	($0.0923)	($0.0633)	($0.0405)	($0.0305)	($0.0136)	($0.0056)	$0.0112	$0.0122
PS-Sec	($0.1415)	($0.1125)	($0.0893)	($0.0793)	($0.0725)	($0.0645)	($0.0596)	($0.0586)

[31] Rates are those approved in Case Nos. 2012-00221 and 2012-00222 for 2013-2014, Case Nos. 2014-00371 and 2014-00372 for 2015-2016, Case Nos. 2016-00370 and 2016-00371 for 2017-2018, and Case Nos. 2018-00294 and 2018-00295 for 2019-2020.

[32] NREL U.S. Solar Photovoltaic System and Energy Storage Cost Benchmark: Q1 2020 at 102, Appx. B, "PV System LCOE Benchmarks in 2019 USD," available at https://www.nrel.gov/docs/fy21osti/77324.pdf. Note that the NREL data used to generate the tables is for a 6.9 kW PV system with a 16.4% capacity factor. That capacity factor is likely high for a solar facility of that size. Thus, it is an assumption favorable to solar.

Generally speaking, the economics of distributed solar generation depend on several factors: electricity usage patterns and their correlation to solar irradiance (i.e., the extent to which solar generation reduces consumption from the grid or results in excess energy exported to the grid), available financial incentives such as federal investment tax credits ("ITC"), capital and annual operating costs, retail rates for energy consumption, and credits customers receive for exported energy. But particularly for customers who became net metering customers prior to September 24, 2021, and therefore were NMS-1 (one-to-one kWh credit) customers who were indifferent to when their systems produced energy relative to their own consumption, a simple comparison of the levelized cost of energy of solar to their applicable retail energy rate (including riders and adjustment clauses, which the tables above do not include) is likely an adequate financial analysis. And it suggests that although some customers, particularly the very early adopters, were willing to invest in solar when it was not clearly economical, many more customers became willing to do so as it became more plausibly economical.

Further evidence that most net metering customers are interested in the economics of the systems they install is what has occurred since Rider NMS-2 became effective on September 24, 2021. Unlike Rider NMS-1, Rider NMS-2 provides dollar-denominated bill credits for exported energy at Commission-prescribed rates. Rider NMS-2 bill credit rates are lower than retail RS and GS rates, providing an economic incentive for customers installing distributed solar to size their systems to minimize energy exports while serving as much of their own load as possible. This could help explain why, for example, the average net metering installation prior to 2021 had a capacity of just over 9.1 kW, whereas the average net metering installation in 2021 had a capacity of just under 8.3 kW.

That observation of NMS-2 customers is also consistent with the tables below, which show the effective compensation an NMS-2 customer would receive in the form of avoided retail energy rates and NMS-2 bill credits at different percentages of energy exports, which would receive NMS-2 bill credits (all rates and credits are currently tariffed amounts). Table 3 demonstrates that for customer classes with energy rates above the NMS-2 credit (i.e., RS and GS), it is economically beneficial to minimize the amount of energy exported to the grid and compensated at the NMS-2 rate:

Table 3: Effective Solar Compensation ($/kWh)

	Percent of Solar Production Receiving NMS-2 Credit						
KU Rate	**0%**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**
RS	$ 0.09699	$ 0.09466	$ 0.09232	$ 0.08999	$ 0.08766	$ 0.08533	$ 0.08299
GS	$ 0.11869	$ 0.11419	$ 0.10968	$ 0.10518	$ 0.10068	$ 0.09618	$ 0.09167
PS-Sec	$ 0.03191	$ 0.03609	$ 0.04026	$ 0.04444	$ 0.04861	$ 0.05279	$ 0.05696

	Percent of Solar Production Receiving NMS-2 Credit						
LG&E Rate	**0%**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**
RS	$ 0.10092	$ 0.09775	$ 0.09458	$ 0.09142	$ 0.08825	$ 0.08508	$ 0.08191
GS	$ 0.11855	$ 0.11362	$ 0.10869	$ 0.10376	$ 0.09883	$ 0.09390	$ 0.08896
PS-Sec	$ 0.03362	$ 0.03718	$ 0.04074	$ 0.04431	$ 0.04787	$ 0.05143	$ 0.05499

This table also demonstrates that for customers that have demand charges (such as PS Secondary customers) and therefore have much lower energy rates, it is more challenging to cost-justify net metering investments. Again, this supports the inference that a likely reason that net metering facility sizes have decreased since NMS-2 supplanted NMS-1 for new net metering service is that customers are paying attention to these kinds of economic considerations and are decreasing the sizes of new facilities to reduce the amount of exported energy.

In sum, data from the Companies' customers' distributed solar generation adoption indicates that, on the whole, customers are more inclined to install such generation when it appears more economical to do so.

3.6.2.2 Adoption and Effect of Distributed Solar Generation (≤ 45 kW) in the Load Forecast

Because the Companies' customers have demonstrated a tendency to adopt distributed solar generation when it appears economical to do so, the Companies' distributed generation model assumes that customers would indeed adopt such generation when it is economical, but it is also accounts for the historical trend for some customers to adopt it even when it is not clearly economical.

As noted in the previous section, the economics of distributed solar generation depend on several factors: the extent to which solar generation reduces consumption from the grid versus energy exported to the grid, LCOE (including available financial incentives such as the federal ITC in addition to capital and annual operating costs), and retail rates for energy consumption and credits customers receive for exported energy. The Companies' distributed generation forecast assumes the following for those factors:

- **Reduced Consumption vs. Exported to Grid:** Average array size is assumed to be 9 kW at the beginning of the forecast period, consistent with recent installations. As array size decreases, the percentage exported to grid also decreases consistent with a recent study.[33]
- **LCOE**
    - **Federal ITC:** The Companies assumed the IRA's solar ITC provisions will apply unchanged, i.e., a 30% ITC for 2022-2032, a 26% ITC for 2033, a 22% ITC for 2034, and no ITC for all later years.
    - **Capital and operating costs:** The Companies used data from the 2022 NREL ATB for capital and operating costs for distributed solar and adjusted that data to reflect recent changes in the costs of solar.[34] The 2022 NREL ATB projects consistently decreasing solar capital costs, whereas the Companies' recent experience with solar PPAs and RFP responses indicates that solar costs are rising from recent lows, which appears to be a nationwide phenomenon.[35]
- **Retail rates:** The Companies assumed their current base retail rates would remain unchanged until July 1, 2025 and that rates would increase 2% per year thereafter.
- **Credits for exported energy:** The Companies assumed NMS-2 credits would continue at their current levels until net metering capacity reached 1% of annual peak load, at which time the

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[33] Carroll, M. (2018). Demand rate impacts on residential rooftop solar customers. The Electricity Journal, 31(8), 44-51. https://www.sciencedirect.com/science/article/pii/S1040619018302197

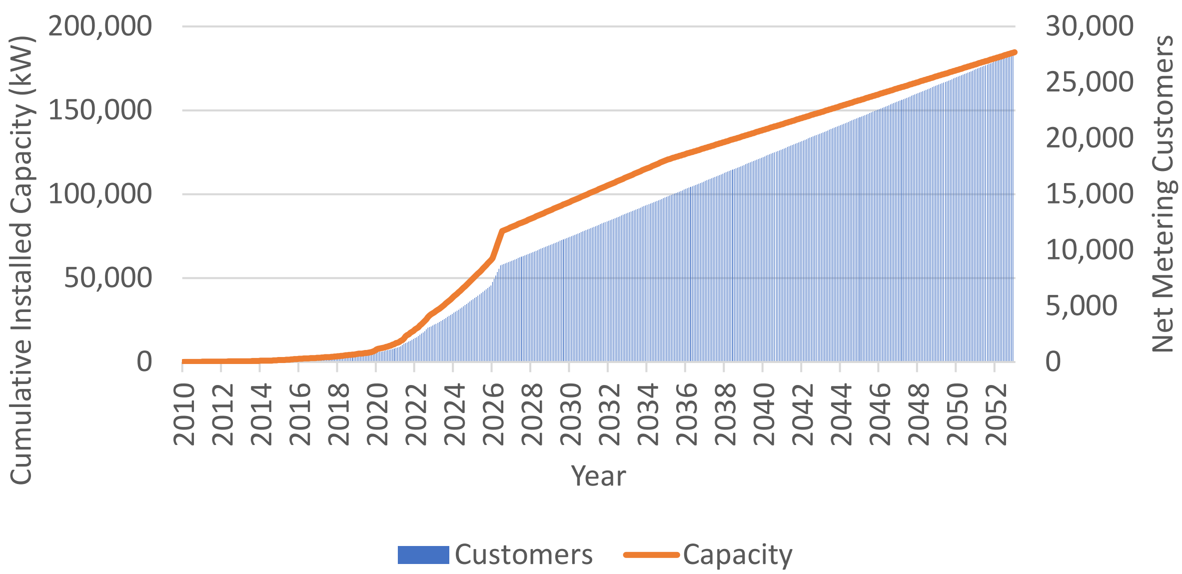
[34] See 2022 v2 Annual Technology Baseline Workbook Corrected 7-21-2022.xlsx, available at https://data.openei.org/files/5716/2022%20v2%20Annual%20Technology%20Baseline%20Workbook%20Corrected%207-21-2022.xlsx. The Excel workpaper with the adjusted nominal LCOE calculations is found in "Work Papers\Hourly_Forecast_Updates\PV\Price Needed to Meet Total Project Costs\Price Needed for Energy Exported to Grid to Meet Total Project Costs_SAW.xlsx"

[35] *See, e.g.,* LevelTen Energy Q3 2022 PPA Price Index Executive Summary (North America) at 7-9, available at https://www.leveltenenergy.com/ppa.

Companies assumed a 2-year contract energy rate (average of KU and LG&E's rates) for fixed-tilt solar SQF credit rates would apply. The Companies' model indicates distributed generation capacity would reach the 1% aggregate capacity level in mid-2026. Due to the timing of reaching the 1% capacity threshold, the Companies did not assume NMS-2 credits would change, but they did assume SQF compensation would increase 2% annually beginning in 2028.

Based on these inputs, Figure 24 below shows the Companies' distributed generation model's projections of customers and capacity for net metering and QF (not more than 45 kW) for this load forecast. Notably, the Companies project that by 2052 about 28,000 customers will have installed such generation with a total capacity of almost 185 MW.

Figure 24: Distributed Generation Customer and Capacity Forecast (customers with capacity ≤ 45 kW)



The results shown above reveal three distinct phases of distributed generation development in the load forecast. In the first phase, there is rapid growth in distributed generation customers and capacity while NMS-2 service remains available to new customers, which the model predicts will cease to be the case in mid-2026 when distributed generation capacity reaches 1% of the Companies' annual peak load. In the second phase, there is a more gradual increase in distributed generation customers and capacity from mid-2026 through 2034 while the IRA's extended federal ITC persists but compensation for exported energy falls from NMS-2 rates to the SQF rate. In the third phase, which begins when the ITC ends in 2035, the increase in the number of distributed generation customers continues relatively unchanged, but the amount of capacity added per customer decreases, which is consistent with the increase in solar cost experienced by customers after the ITC ends. Ultimately, by the end of 2052, the Companies project there will be almost 185 MW of aggregate distributed generation capacity for customers with a per-system capacity not exceeding 45 kW.

These results are consistent with the assumptions that base energy rates will increase steadily while, according to the Companies' adjusted NREL's projections, solar costs will generally continue to decrease (after recent solar market price increases abate). To illustrate, the figures below show the projected levelized cost of solar across the forecast period and the blended compensation a customer would receive at 20%, 40%, and 60% exported energy levels.[36] Whenever a blended compensation line (a solid line) is above the levelized cost of solar line (the dotted line), adding solar is financially beneficial to the customer on these assumptions:

Figure 25: RS Blended Solar Compensation Compared to Adjusted NREL LCOE

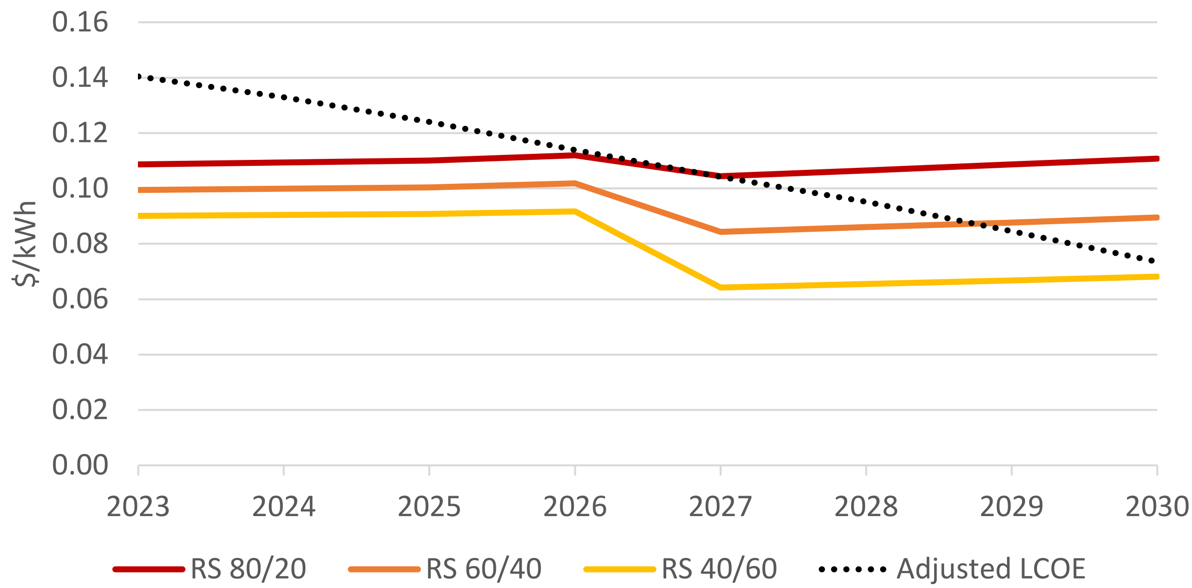
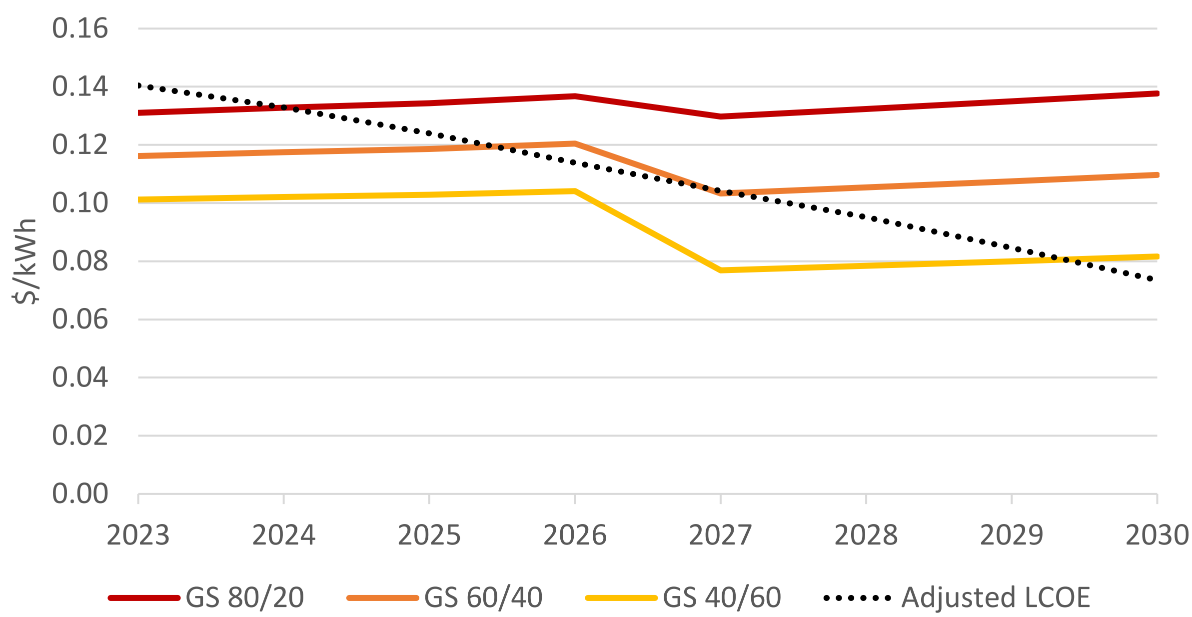
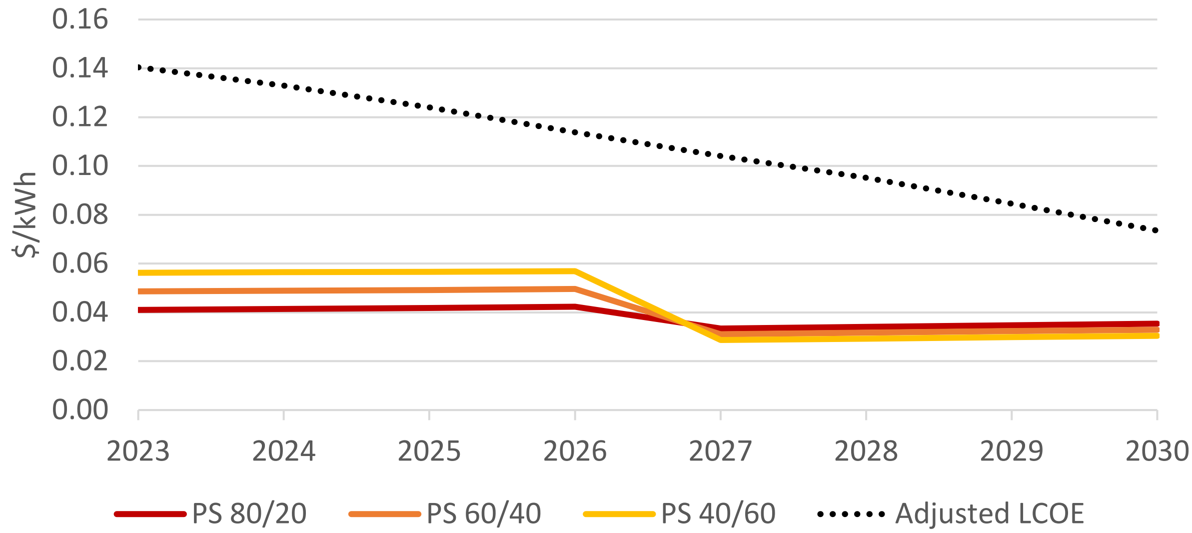


Figure 26: GS Blended Solar Compensation Compared to Adjusted NREL LCOE



[36] Blended compensation = (applicable retail energy rate * percent of energy consumed by customer) + (energy export compensation rate * percent of energy exported by customer)

Figure 27: PS-Sec Blended Solar Compensation Compared to Adjusted NREL LCOE



3.6.2.3 Analyzing a Case with No Compensation for Exported Energy

The Companies acknowledge that the Commission Staff's Report in the 2021 IRP recommended that the Companies "should analyze and discuss whether and the extent to which customers that would have taken service under the Net Metering Service-2 tariff would continue to interconnect DERs even if they received no credit for energy sent back into the system because the one percent cap had been reached when they sought to connect."[37] The Companies did not analyze a situation in which such customers would receive no compensation for exported energy because it would be inconsistent with their SQF tariff provisions to provide no compensation for such energy. Instead, as noted above and consistent with the Companies' tariffs, the Companies modeled providing customers SQF compensation for exported energy after reaching the 1% capacity level in mid-2026.

3.6.2.4 Adoption and Effect of Other QF Generation

The Companies forecast behind-the-meter QF customers separately from net metering customers (and net-metering-sized facilities, i.e., QFs not exceeding 45 kW). This includes only those customers served by the Companies, not independent or merchant generators. Historically, the Companies have projected that future numbers of QF customers will be consistent with the historically observed linear trend for the Companies' QF customers to date. The Companies also typically assume that the forecasted capacity per new QF customer will be the average of current QF installations. But to account for the IRA's potential impact on QFs, the Companies modeled a 15% increase in per-customer new QF capacity compared to the historical average. Total forecasted distributed solar capacity is shown in Figure 28.

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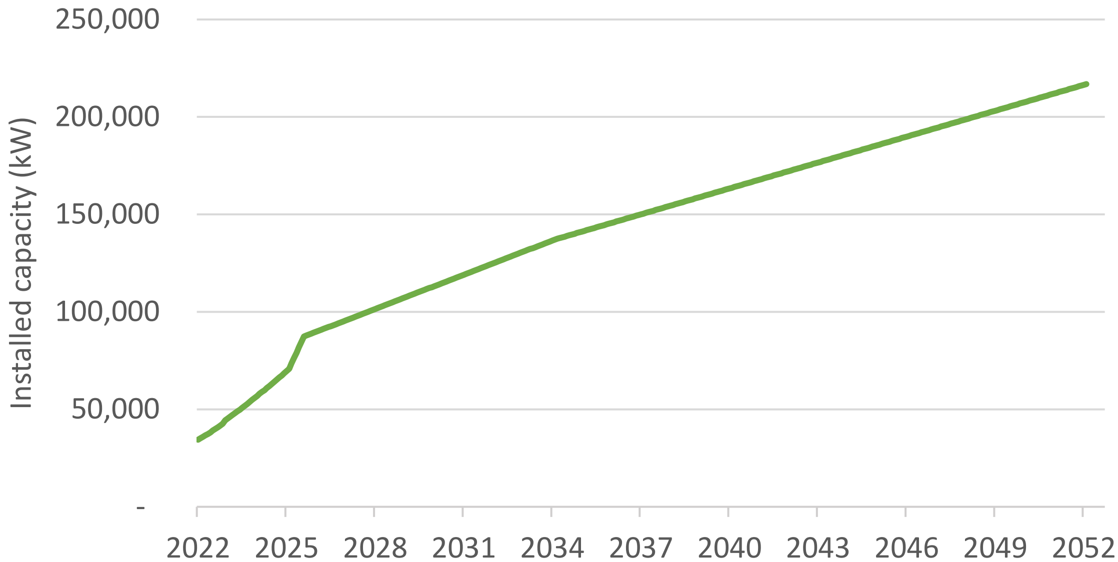
[37] Case No. 2021-00393, Order Appx. "Commission Staff's Report on the 2021 Integrated Resource Plan of Louisville Gas and Electric Company and Kentucky Utilities Company" at 67 (Ky. PSC Sept. 16, 2022).

Figure 28: Total Distributed Solar Capacity Forecast (NM and QF)



3.6.2.5 Projected Distributed Generation Is Consistent with Kentucky's Solar Resource and Rates

Currently, about 0.4% of the Companies' residential customers are solar net metering customers. This might seem small compared to certain other states, such as California (about 9% residential solar) and Arizona (about 7% residential solar).[38] Putting aside state-level policy directives and incentives that might explain a large part of the difference, as well as wealth and income differences that could affect solar adoption, two significant factors that affect solar adoption and that the Companies reflect in their modeling are the solar resource (which directly affects capacity factor) and electric rates.

According to NREL data, nearly all of Kentucky's geography has an annual average daily solar irradiance between 4 and 4.5 kWh/m^2.[39] The vast majority of Arizona's and most of California's geography has an annual average daily solar irradiance greater than 5.25 kWh/m^2, with large portions at or above 5.75 kWh/m^2.[40] These translate into capacity factor ranges of 16.1% to 19.6% for Arizona and California compared to Kentucky's 14.5% to 15.2%.[41]

Rates also matter. According to EIA, the average retail price of electricity in Arizona in 2021 was 10.73 cents per kWh and California's was 19.65; Kentucky's was 9.12.[42]

With such dramatic differences in solar resources and rates, it is unsurprising that Arizona and California have much higher rates of residential solar deployment. States with solar irradiance and rates more

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[38] Calculated using data from https://www.census.gov/quickfacts/fact/table/CA/RHI725221, https://www.census.gov/quickfacts/AZ, https://www.nbcnews.com/data-graphics/map-western-states-lead-nation-home-solar-installations-rcna28358, and https://ktla.com/news/california/california-may-cut-rooftop-solar-panel-incentives-as-market-booms/

[39] *See* https://www.nrel.gov/gis/assets/images/solar-annual-ghi-2018-usa-scale-01.jpg.

[40] *Id.*

[41] Capacity factor ranges from NREL ATB 2022 https://atb.nrel.gov/electricity/2022/residential_pv

[42] US Electricity Profile 2021, available at https://www.eia.gov/electricity/state/.

comparable to Kentucky, absent state policies to require or highly incentivize customers to deploy solar, tend to have solar deployment closer to those seen in the Companies' Kentucky service territories.[43]

For these reasons, it is unlikely that Kentucky solar will reach California's or Arizona's levels of solar penetration, and this load forecast's projection that about 3% of customers in the Companies' service territory will install solar by 2052 is reasonable.

3.7 Electric Vehicles

Based on data from the Electric Power Research Institute ("EPRI"), the Companies estimate that from 2017 to 2020 the number of EVs in operation in the Companies' Kentucky service territories increased 164% from 1,415 to 3,737.[44] Also based on EPRI data, the Companies estimate there were a total of 7,769 battery and plug-in hybrid EVs in their Kentucky service territories as of September 2022.[45]

In this forecast, the Companies project that EVs in operation in the Companies' Kentucky service territory will increase to over 100,000 by the end of 2040 and to over 300,000 by 2052. The model used to forecast EV adoption considers historical adoption of EVs, the comparison of EV to internal combustion engine ("ICE") car costs, IRA tax credits, and EIA's projected number of vehicles in the service territory. By 2050 the Companies' EV forecast is approximately double what the EIA's projection in terms of the percentage of the nationwide fleet composed of EVs and double what was projected in the base case of the 2021 IRP. The future penetration of EVs is a key forecast uncertainty as it has the potential to increase energy requirements, particularly in the evening and non-daylight hours.

Figure 29 below shows the Companies' EV forecast.

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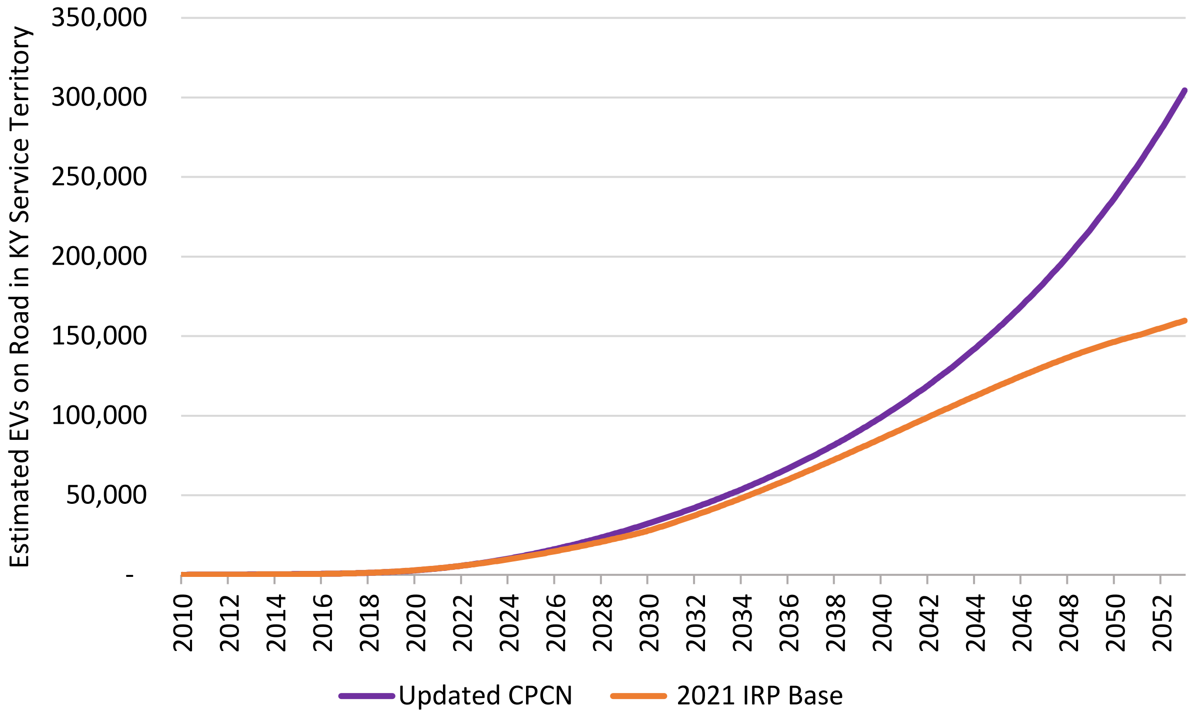
[43] For example, according to SEIA, West Virginia has a total of 23 MW of solar capacity installed across 1,267 installations (https://www.seia.org/states-map). According to the same data, Kentucky has a total of 78 MW across 4,409 installations. West Virginia's 2021 average electric rate was 8.87 cents/kWh (https://www.eia.gov/electricity/state/), and its solar irradiance is predominantly 4 to 4.25 kWh/m^2 (https://www.nrel.gov/gis/assets/images/solar-annual-ghi-2018-usa-scale-01.jpg).

Also comparable is Nebraska, which has a total of 78 MW of solar capacity installed across 2,131 installations (https://www.seia.org/states-map). Its 2021 average electric rate was 8.84 cents/kWh (https://www.eia.gov/electricity/state/), and its solar irradiance is predominantly 4.25 to 4.75 kWh/m^2 (https://www.nrel.gov/gis/assets/images/solar-annual-ghi-2018-usa-scale-01.jpg).

[44] EPRI provides EV sales data for the state of KY. See Excel workpaper located at "Work Papers\Hourly_Forecast_Updates \EV\EV data work input files\LG_E_KU_2023BP_forR.xlsx"

[45] See Excel workpaper: " Work Papers\Hourly_Forecast_Updates \EV\mostRecent_LG_E_KU.xlsx"

Figure 29: Electric Vehicle Forecast



For obvious reasons, the EV forecast cannot account for sudden, unforeseeable technological innovation that could cause a dramatic shift from historical adoption patterns. The EV forecast also does not account for potential supply chain issues stemming from electricity laws and incentives passed or in the process of being passed in other states. For example, all sales of new, light-duty passenger vehicles in California must be BEVs or PHEVs by 2035[46] and New York has recently followed suit.[47] If more states pass similar bans on gas-powered vehicles, then the increased demand for EVs in those states may limit their availability for purchase in Kentucky.

Finally, the 2021 IRP Commission Staff Report stated regarding EVs and load forecasting:

> Similarly, it would have been useful to explore the effects of having residential households being able to apply solar facility energy offsets to EV charging stations in addition to the household usage. A step further would be to apply net metering to EV charging as well as household usage could spur both the growth in EV charging and in residential distributed solar. Even if the one percent cap were to be reached, using residential solar to offset EV charging could spur additional growth.[48]

Note that any load behind a residential meter, including a residential EV charger, would be included in the energy usage that could be offset by customers' solar facilities production directly, and such charging stations' energy usage served by the Companies would appear on customers' bills that could be offset by

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[46] US Dept. of Energy AFDC, California Laws and Incentives

[47] US Dept. of Energy AFDC, New York Laws and Incentives

[48] Case No. 2021-00393, Order Appx. "Commission Staff's Report on the 2021 Integrated Resource Plan of Louisville Gas and Electric Company and Kentucky Utilities Company" at 52-53 (Ky. PSC Sept. 16, 2022).

the customers' NMS-2 credits for exported energy. This would continue to be true for customers who adopt solar generation after reaching the 1% level to which the text refers, only the compensation to customers for energy exports would be at the SQF rate rather than the NMS-2 rate.

3.8 Space Heating Electrification

Compared to residential customers added through 2010, a greater percentage of residential customers added since 2010 have electric space heating (see Table 4 and Table 5). In the KU service territory, about 60% of all residential premises added through 2010 have electric space heating, but more than 70% of new premises added since 2010 have electric space heating. This increase is even more pronounced in the LG&E service territory, in which 35% to 50% of premises added since 2010 have electric space heating versus only 21% of premises added through 2010.

Table 4: KU Electric Heating Penetration

Cohort	Estimated Electric Heating Penetration	Average Billed kWh in 2020	Premises
<= 2010	59%	13,583	390,288
2011	76%	14,212	4,169
2012	77%	13,826	3,973
2013	77%	13,649	4,314
2014	75%	13,733	3,547
2015	74%	13,300	3,570
2016	74%	12,600	4,264
2017	71%	12,004	4,839
2018	72%	12,027	4,073
2019	69%	11,608	4,034

Table 5: LG&E Electric Heating Penetration

Cohort	Estimated Electric Heating Penetration	Average Billed kWh in 2020	Premises
<= 2010	21%	11,138	332,675
2011	34%	11,819	2,488
2012	35%	13,206	2,135
2013	39%	12,987	2,552
2014	42%	11,858	3,242
2015	44%	11,789	3,284
2016	45%	11,739	3,210
2017	44%	10,865	3,823
2018	42%	10,843	3,630
2019	47%	10,108	3,598

All other things being equal, premises with a higher electric heating penetration would be expected to consume more electricity annually, but this has not been the case for premises added in recent years. For example, as seen in Table 4 and Table 5, despite a higher electric heating penetration, the average consumption in 2020 for customers added in 2019 (11,608 kWh for KU and 10,108 kWh for LG&E) is lower than that for customers added through 2010. This result reflects the previously mentioned gains in lighting and cooling end-use efficiencies as well as the fact that recent customer growth has been concentrated in urban areas where homes are smaller on average than in rural areas.

Figure 30 compares the monthly use-per-customer in 2019 for three customer cohorts. Compared to customers added through 2010, newer customers have significantly lower usage in the summer months and more similar usage in the winter months.

Figure 30: Monthly Average Use-Per-Customer by Estimated Housing Vintage

In this load forecast, the Companies assumed that new customers would have electric heating penetrations comparable to the average of such penetrations for new customers in 2015 through 2019. This load forecast further assumes that, with the passage of the IRA, a small portion (approximately 0.1% per year for the next decade) of existing premises will switch from gas to electric. Figure 31 below shows the forecasted change in electric space heating including IRA impacts as an index to 2015 as the base year. Unsurprisingly, the increase in LG&E is much higher given a much smaller percentage of customers have electric heating today as compared to the KU service territory.

Figure 31: Electric Space Heating Saturation Percentage Change by Company

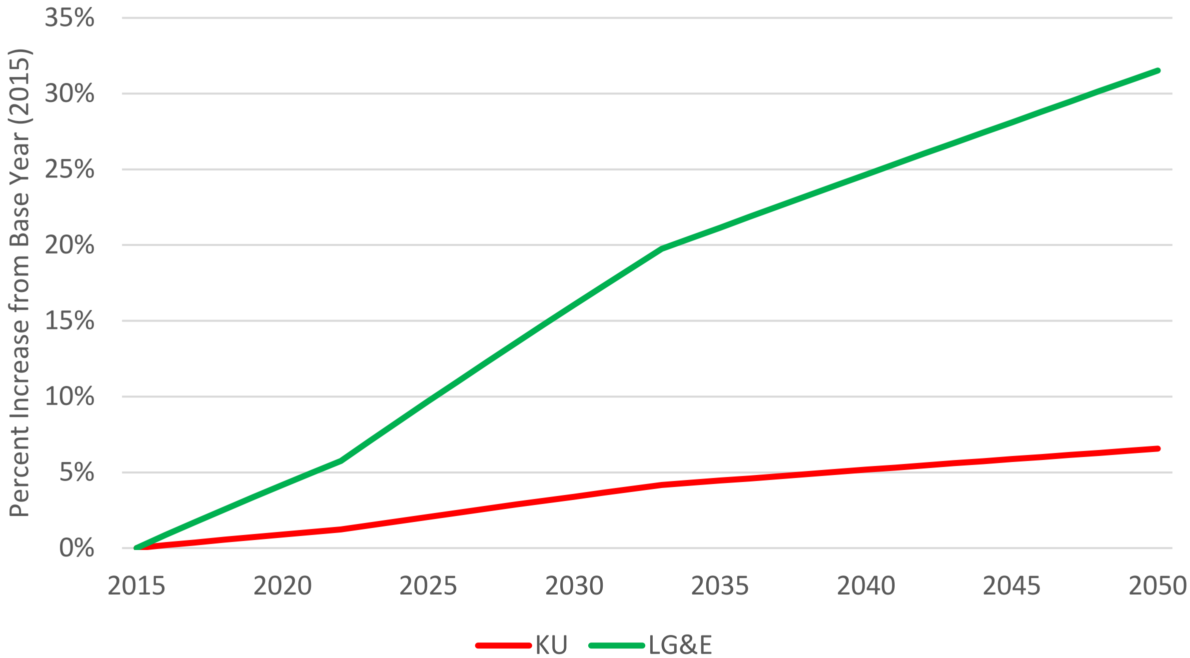

Figure 32 below shows the impact of added electric heating load on this load forecast versus what was assumed in the 2021 IRP load forecast.

Figure 32: Space Heating Impact in Winter Months by Year (CPCN minus IRP)

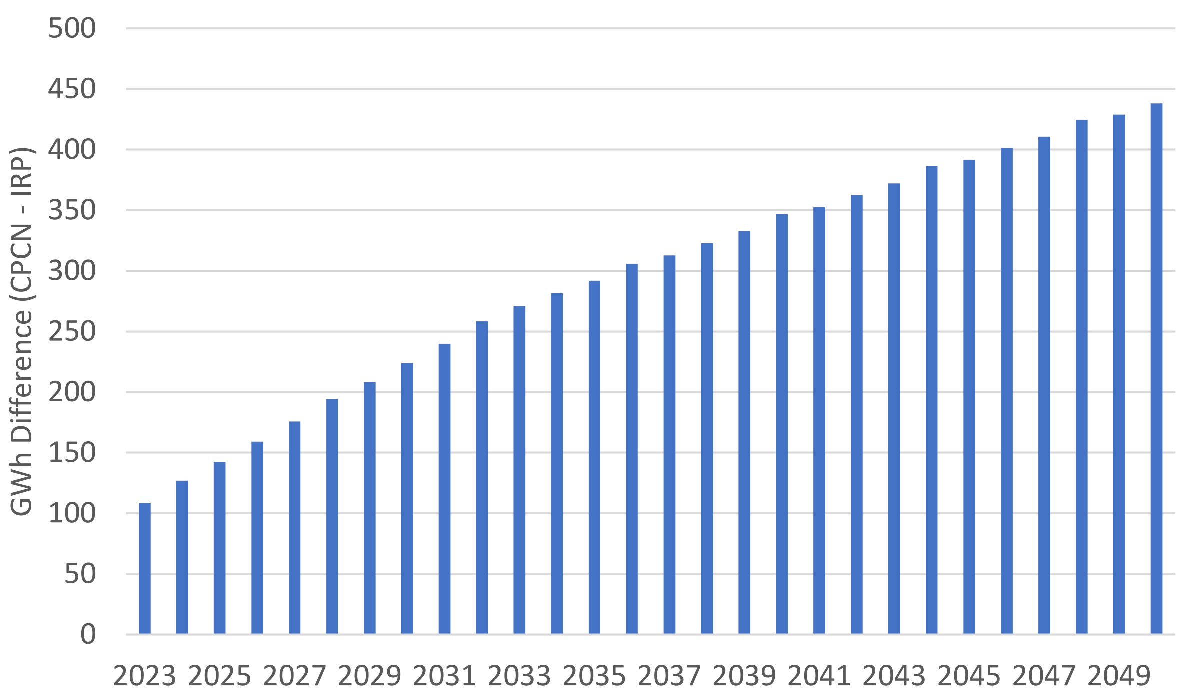

Table 6 shows the increase in the incidence of electric space heating and space heating consumption is not unique to LG&E/KU; the same trend is happening nationally. Space heating accounted for just 6% of residential consumption in 2010 but is up to 14% of total consumption as of 2021 – an almost 150% increase in just a decade. The table also shows the significant decline that lighting consumption has seen over the past decade.

Table 6: Residential Consumption of Electricity by End Use[49]

	2010		2021	
End Use	**Billion kWh**	**Share of Total**	**Billion kWh**	**Share of Total**
Space Cooling	325	22%	235	15%
Lighting	208	14%	59	4%
Water Heating	128	9%	176	12%
Refrigeration	105	7%	87	6%
Color TV and Set Top Boxes	99	7%	56	4%
Space Heating	84	6%	207	14%
Clothes Dryers	55	4%	64	4%
Computers & Related Equipment	52	4%	36	2%
Furnace Fans & Boiler Pump Circulation	41	3%	24	2%
Cooking	32	2%	16	1%
Dishwashers	26	2%	8	1%
Freezers	23	2%	20	1%
Clothes Washers	8	1%	11	1%
Other Uses	263	18%	520	34%
Total Consumption	**1,449**	**100%**	**1,519**	**100%**

3.9 Conservation Voltage Reduction and AMI ePortal Savings

As the Companies deploy advanced metering infrastructure ("AMI"), they will be able to control voltage more precisely across circuits to reliably accommodate continued growth in distributed generation and electric vehicles. In addition, AMI-provided voltage data will enable the Companies to implement Conservation Voltage Reduction ("CVR"). CVR is a technology that can reduce energy consumption with no change in customer behavior or the customer experience. CVR uses AMI data and more precise voltage controls to incrementally reduce grid voltage such that energy requirements are lowered. Lower energy requirements result in avoided generation costs thus reducing revenue requirements for rate payers. With no action from customers, CVR is assumed in the load forecast to reduce residential and small commercial energy requirements by about 1% in 2028. These CVR adjustments are phased in over time as AMI meters are deployed and the necessary distribution infrastructure is installed.

Also related to AMI deployment, this load forecast assumes AMI ePortal savings resulting from behavioral changes some customers are assumed to make as a result of obtaining access to more granular usage data. These adjustments are also phased in over time as AMI meters are deployed.

[49] 2010: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=4-AEO2011&cases=ref2011&sourcekey=0;
2021: https://www.eia.gov/tools/faqs/faq.php?id=96&t=3

3.10 Effect of Electricity Prices on Consumption (Price Elasticity of Demand)

Electricity prices are a consideration in the electric load forecast. Forecast models incorporate class-specific estimates of price elasticity between -0.1 and -0.15. These numbers are similar to those from a 2010 survey conducted by energy consultant Itron. In a review of other utility IRPs, a figure of -0.1 to -0.2 was commonly used with the EIA and the Electric Power Research Institute ("EPRI") being among the most commonly cited sources.

The Companies consistently evaluate the robustness of elasticity assumptions and sensitivity to changes in both price and elasticity. The changing economics of distributed generation and electric vehicles are of particular interest as declining prices of these technologies are driving increased adoption in both cases. However, their effects on the demand curve could offset as distributed generation decreases the quantity demanded while electric vehicles increase the quantity demanded at a given price. Other factors increasing the price of electricity would accelerate the payback on distributed generation. EV adoption could be hindered by increasing electricity prices as the total cost of EV ownership increases.

The load forecasting process explicitly contemplates short-run price elasticity of demand via statistically adjusted end-use models. The Companies continue to incorporate private solar and electric vehicle forecasts into the base load forecast. Thus, major potential drivers of change in long-run price elasticity of demand are incorporated into the load forecast directly as opposed to via the price elasticity of demand proxy. The Companies continue to view this delineation as appropriate and necessary given the hourly load profiles of these technologies. The base case load forecast represents the Companies' view of the most likely development in prices, end-use saturations and efficiencies, electric vehicle adoption, distributed energy resources, demographics, and economic conditions in the service territory.

For this load forecast, the Companies assumed base electricity prices (rates) would not change prior to July 1, 2025, which is consistent with the Companies' 2020 base rate case commitments.[50] Thereafter, the forecast assumes prices will increase by two percent per year, consistent with long-term inflation expectations. If higher-than-expected prices materialize, the Companies anticipate a decline in sales as compared to the current forecast (all else equal) due to the negative price elasticities incorporated into the forecasting models. The means in which residential or commercial customers would make such changes to reduce their consumption in the long-run would most likely be through more efficient end-uses and installation of distributed generation. Customer growth would likely weaken as compared to what the service territory has experienced over the past decade. Large customers in highly competitive industries would be more likely to move their business elsewhere or find ways to significantly reduce their demand.

4 Conclusion and Summary of Forecast Uncertainties

The Companies' 2022 CPCN Load Forecast is a reasonable forecast of customers' hourly energy needs for the next 30 years. It builds on the time-tested models and tools that the 2021 Commission Staff Report found reasonable and addresses the recommendations raised in the report. It also fully updates the

[50] Case No. 2020-00349, Order at 11-12 (Ky. PSC June 30, 2021); Case No. 2020-00350, Order at 13-15 (Ky. PSC June 30, 2021).

forecast from the 2021 IRP in all respects, including updating it for the impacts of the BlueOval SK Battery Park, the Inflation Reduction Act, and the Companies' proposed 2024-2030 DSM-EE Program Plan. It demonstrates that customers will continue to have robust demand and energy requirements in all hours and all seasons, day and night.

Therefore, the Companies conclude it is a load forecast that is reliable for supply-side planning purposes.

But as with any forecast, it is not a perfect prediction of what will occur in the future. There are known (and unknown and unforeseeable) uncertainties associated with the forecast. Among the known uncertainties are those that could result in greater demand and energy requirements than forecasted here, such as greater or more rapid EV adoption (and the charging patterns of those EVs), space heating electrification, or economic development, including possible additional load related to BlueOval locating in the Companies' service territories. Uncertainties that could cause lower demand and energy requirements than forecasted here include greater or more rapid adoption of distributed generation or energy efficiency, as well as slower economic development or even the loss of existing industrial or commercial load.

On balance, the Companies believe the more impactful uncertainty is that demand and energy requirements will be above those forecasted here. The Companies have attempted to predict aggressive energy efficiency and distributed generation adoption; barring significant federal or state policy changes, it does not appear plausible that increases in either of those beyond the current projections is likely or that they would have an impact that would affect supply-side planning. For example, more rapid deployment of distributed solar capacity might affect some summer peak hours, but it would have little to no effect on winter peaks, which tend to be in non-daylight hours. In addition, as shown in this load forecast, the Companies have already aggressively advanced energy efficiency deployment to account for the effects of the IRA and the Companies' proposed 2024-2030 DSM-EE Program Plan; there is simply not much additional available energy efficiency to deploy according to EIA projections, and the effect of advancing that deployment is negligible. Thus, barring major technological innovations—which can and do occur, such as LED lighting in the last decade—the uncertainty of significantly lower energy or demand requirements due to increased energy efficiency beyond what the Companies have projected appears low.

On the other hand, given the increasing interest in and movement toward electrification in the U.S., there is clear potential for even greater adoption of EVs and electric heating than the Companies have projected.[51] For example, it is plausible that as Kentucky increasingly becomes, as Gov. Beshear has described it, the EV battery production capital of the United States,[52] more Kentuckians will want to purchase EVs, just as any number of Kentuckians may be partial to Ford and Toyota due to their manufacturing presence in the Commonwealth. It is also possible that more customers will choose electric heating for their residences, both new and as replacements. The effects of increases in either or

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[51] Evidence of this is in Table 6 above, the IRA's electrification incentives, and the recent White House Electrification Summit (https://www.whitehouse.gov/ostp/events-webinars/electrification-summit/).

[52] *See, e.g.*, "Electric battery company plans $2 billion factory in Bowling Green," (Apr. 13, 2022) ("[Gov.] Beshear said Kentucky is the 'undisputed electric battery capital of the United States of America.'"), available at https://www.wdrb.com/in-depth/electric-battery-company-plans-2-billion-factory-in-bowling-green/article_eaa8df74-bb3c-11ec-959d-67c45528113c.html.

both of those categories beyond what the Companies have projected could result in pronounced increases to both total energy consumption and demand, particularly winter peak demand, which often occurs in non-daylight hours.

Despite the unavoidable uncertainties inherent in any such prediction, the Companies believe their 2022 CPCN Load Forecast is reasonable and reliable for resource planning. Although the Companies have presented what they believe is the most reasonable forecast at this time, the net effect of known uncertainties suggests that this load forecast is, if anything, conservative, and possibly understates energy requirements and demand over the next 30 years, barring major federal or state policy changes.

5 Technical Appendices

5.1 Technical Appendix 1: Annual Energy and Seasonal Peak Load Comparison (2021 IRP LF and 2022 CPCN LF)

Table 7: Comparison of IRP and CPCN Energy Requirements (MWh)

Year	CPCN	IRP	CPCN - IRP	% Difference
2023	31,918,683	32,079,289	(160,607)	-0.5%
2024	32,220,551	32,044,532	176,019	0.5%
2025	32,787,613	31,838,787	948,825	3.0%
2026	32,841,327	31,647,991	1,193,336	3.8%
2027	33,559,824	31,532,217	2,027,607	6.4%
2028	33,591,913	31,519,019	2,072,893	6.6%
2029	33,422,591	31,369,729	2,052,862	6.5%
2030	33,302,996	31,279,396	2,023,600	6.5%

Table 8: Comparison of IRP and CPCN Peak Demands (MW)

Year	Season	CPCN	IRP	CPCN - IRP	% Difference
2023	Summer	6,162	6,201	(38)	-0.6%
2024	Summer	6,197	6,179	17	0.3%
2025	Summer	6,248	6,150	98	1.6%
2026	Summer	6,253	6,113	140	2.3%
2027	Summer	6,347	6,088	259	4.2%
2028	Summer	6,319	6,067	252	4.2%
2029	Summer	6,308	6,055	253	4.2%
2030	Summer	6,305	6,056	248	4.1%
2023	Winter	5,910	5,874	37	0.6%
2024	Winter	5,908	5,859	49	0.8%
2025	Winter	6,011	5,831	180	3.1%
2026	Winter	6,003	5,806	198	3.4%
2027	Winter	6,107	5,790	318	5.5%
2028	Winter	6,104	5,777	327	5.7%
2029	Winter	6,103	5,758	346	6.0%
2030	Winter	6,102	5,750	352	6.1%

5.2 Technical Appendix 2: Guide to Load Forecast Electronic Workpapers

- CPCN Hourly Forecast File
  - The CPCN hourly forecast file can be found at "Work Papers\Hourly_Forecast_Updates \CPCN_Hourly_Forecast_20221026"
- Weather
  - Weather data is located in "Work Papers\July2022_Forecast \Electric \1_Inputs\DDandBillingDayFcsts"
- Economic Assumptions
  - Economic data is located in "Work Papers\July2022_Forecast \Electric\1_Inputs\ Economic"
- BlueOval SK Battery Park
  - Data and analysis on BlueOval SK Battery Park are located in "Work Papers \Hourly_Forecast_Updates\MA"
- Inflation Reduction Act
  - DSM and Energy Efficiency
    - Commercial scenarios are located in "Work Papers\July2022_Forecast\ Electric\2_Forecasts\Commercial\Analysis"
  - Distributed Energy Resources
    - Solar inputs, models, and final outputs are located in "Work Papers\Hourly_Forecast_Updates\PV"
    - LCOE calculations and price needed for exported energy to meet total project cost calculations are located in "Work Papers\Hourly_Forecast_Updates\PV\Price Needed to Meet Total Project Costs"
  - Electric Vehicles
    - EV models and final outputs are located in "Work Papers\Hourly_Forecast_Updates\ EV"
    - Input files to the EV post-processing code are located in "Work Papers\Hourly_Forecast_Updates\EV\EV processing input files"
    - Input files to the EV forecast model are located in "Work Papers\Hourly_Forecast_Updates\ EV\EV data work input files"
  - Space Heating Electrification
    - End use shapes are located in "Work Papers\Hourly_Forecast_Updates\ End_Use_Analysis"
    - Monthly model outputs are located in "Work Papers\ Hourly_Forecast_Updates\Heating_Electrification_AdjustmentsD02.xlsx
- Conservation Voltage Reduction and AMI ePortal Savings
  - CVR and AMI load reduction details are located in "Work Papers\July2022_Forecast \Electric\2_Forecasts\Summary_of_Billed_Forecasts\Work"
- Billed Forecasts
  - Forecasts are located in "Work Papers\July2022_Forecast\ Electric\2_Forecasts"
- Weather Years
  - The weather years process is located in "Work Papers\Hourly_Forecast_Updates\ WY"

- Hourly Forecast
    - The July 2022 hourly load forecast files are located in "Work Papers \July2022_Forecast\Electric\4_Demand_Forecasts\1_Hourly_Demand\LDC"
    - The Hourly Forecast update files are located in "Work Papers\Hourly_Forecast_Updates"
- Peak
    - Peak forecast and analysis are located in "Work Papers\July2022_Forecast \Electric\4_Demand_Forecasts\1_Hourly_Demand\JDL_Peak_Analysis"

Exhibit TAJ-2

Electric Sales & Demand Forecast Process

PPL companies

Sales Analysis & Forecasting
December 2022

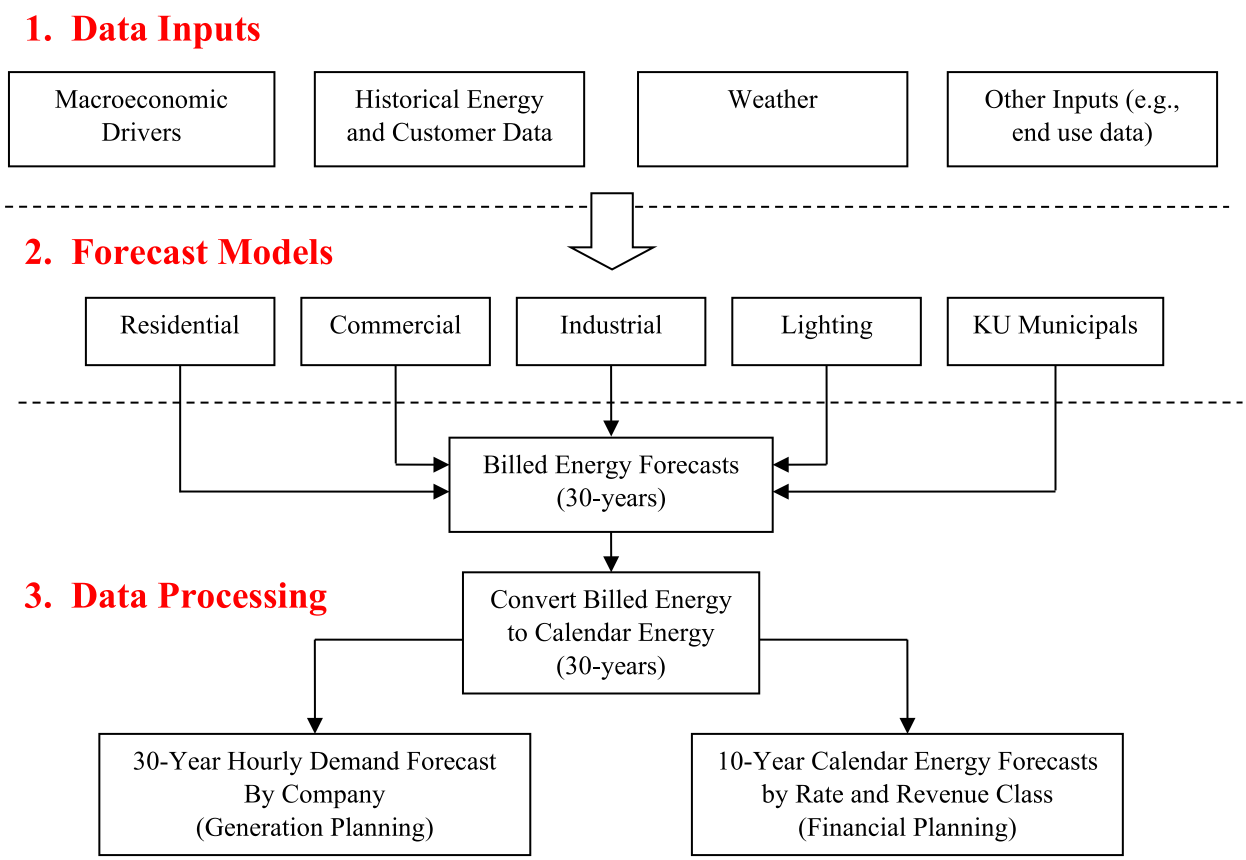
Table of Contents

1 Introduction

The Sales Analysis & Forecasting group develops the sales and demand forecasts for Louisville Gas and Electric Company ("LG&E") and Kentucky Utilities Company ("KU") (collectively, "the Companies"). This document summarizes the processes used to produce the sales and demand forecasts.

The forecast process can be divided into three parts (see Figure 1). The first part of the forecast process involves gathering and processing input data. Key inputs to the forecast process include macroeconomic, historical energy, customer, weather, residential appliance shares, and efficiencies data.

Figure 1 – Load Forecasting Process Diagram



In the second part of the forecast process, input data is used to specify several forecast models for each company. Generally, each model is used to forecast energy sales for a group of customers with homogeneous energy-use patterns within the same, or similar, tariff rates.

Most of the forecast models produce monthly energy forecasts on a billed basis.[1] In the third part of the forecast process, the billed energy forecasts are allocated to calendar months and then to rate and revenue classes for the Financial Planning department.[2] In addition, a forecast of hourly energy requirements is developed for the Generation Planning department.[3]

Throughout the forecast process, the results are reviewed to ensure they are reasonable. For example, the new forecast is compared to (i) the previous forecast and (ii) weather-normalized actual sales for the comparable period in prior years. Each of these parts and the software tools used to produce the forecast are discussed in more detail in the following sections.

2 Software Tools

The following software packages are used in the forecast process:

1. SAS
2. R
3. Metrix ND (Itron)
4. Microsoft Office: Excel, PowerPoint

SAS, R, and Metrix ND are used to specify forecast models. The Microsoft Office tools are primarily used for analysis and presentations.

[1] Customers are assigned to one of 20 billing portions. This is discussed further in Section 5.
[2] Rate class defines the tariff assigned to each customer meter while Revenue class is a higher-level grouping; a Revenue class consists of one or more rate classes.
[3] Energy requirements are equal to sales plus transmission and distribution losses.

3 Input Data

Table 1 provides a summary of data inputs. The sections that follow describe key processes used to prepare the data for use in the forecast process.

Table 1 – Summary of Forecast Data Inputs

Data	***Source***	***Format***
State Macroeconomic and Demographic Drivers (e.g., Employment, Wages, Households, Population)	S&P Global[4]	Annual or Quarterly by County – History and Forecast
National Macroeconomic Drivers	S&P Global	Annual or Quarterly – History and Forecast
Personal Income	S&P Global	Annual by County
Weather	National Oceanic and Atmospheric Administration ("NOAA")	Daily HDD/CDD Data and Hourly Solar Irradiance by Weather Station – History
Billing Portion Schedule	Revenue Accounting	Monthly Collection Dates – History and Forecast
Appliance Saturations/Efficiencies	Energy Information Administration ("EIA"), ITRON	Annual – History and Forecast
Structural Variables (e.g., dwelling size, age, and type)	EIA, ITRON	Annual – History and Forecast
Elasticities of Demand	EIA / Historical Trend	Annual – History
Billed Sales History	CCS Billing System	Monthly by Service Territory and Rate Group
Number of Customers History	CCS Billing System	Monthly by Service Territory and Rate Group
Energy Requirements History	Energy Management System ("EMS")	Hourly Energy Requirements by Company
Annual Loss Factors	2012 Loss Factor Study (by Management Applications Consulting, Inc.)	Annual Average Loss Factors by Company
Solar Installations	CCS Billing System, National Renewable Energy Laboratory ("NREL")	Monthly Net Metering/Qualifying Facility Customers, Private Solar Costs
Electric Vehicles	S&P Global, Bloomberg New Energy Finance ("BNEF"), NREL, Electric Power Research Institute ("EPRI"), EIA	Monthly Cars on Road (historical), Monthly Cars on Road (forecast), Hourly EV Charging Shapes

[4] Formerly IHS Markit.

3.1 Processing of Weather Data

Weather is a key explanatory variable in the electric forecast models. The weather dataset from NOAA's National Climatic Data Center ("NCDC") contains temperature (maximum, minimum, and average), heating degree days ("HDD"), and cooling degree days ("CDD") for each day and weather station over the past 20+ years. This data is used to create (a) a historical weather series by billing period, (b) a forecast of "normal" weather by billing period.[5] Each of these processes is summarized below.

3.1.1 Historical Weather by Billing Period

The process used to create the historical weather series by billing period consists of the following steps:

1. Using historical daily weather data from the NCDC, sum the HDD and CDD values by billing portion.[6] Each historical billing period consists of 20 portions. The Companies' historical meter reading schedule contains the beginning and ending date for each billing portion.
2. Average the billing portion total HDDs and CDDs by billing period.

3.1.2 Normal Weather by Billing Period

The process used to produce the forecast of normal weather by billing period includes the production of a daily forecast of normal weather. The process used to develop the daily forecast (summarized below in Steps 2-5) is consistent with the process used by the NCDC to create its daily normal weather forecast.[7] The following steps are used to create the forecast of normal weather by billing period:

1. Compute the forecast of normal monthly weather by *calendar* month by averaging monthly degree-day values over the period of history upon which the normal forecast is based. The normal weather forecast is based on the most recent 20-year historical period. Therefore, the normal HDD value for January is the average of the 20 January HDD values in this period.
2. Compute "unsmoothed" daily normal weather values by averaging temperature, HDDs, and CDDs by calendar day. The unsmoothed normal temperature for January 1st, for example, is computed as the average of the 20 January 1st temperatures in the historical period. This process excludes February 29.
3. Smooth the daily values using a 30-day moving average centered on the desired day. The "smoothed" normal temperature for January 1st, for example, is computed as the average of the unsmoothed daily normal temperatures between December 16th and January 15th.
4. Manually adjust the values in Step 3 so that the following criteria are met:

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[5] "Normal" weather is defined as the average weather over a 20-year historical period. The Companies do not attempt to forecast any trends in weather.

[6] Weather data in the electric forecast is taken from the weather stations at the Bowman Field Airport in Louisville, Bluegrass Field Airport in Lexington, and Tri-Cities Airport in Tennessee.

[7] The NCDC derives daily normal values by applying a cubic spline to a specially prepared series of the monthly normal values.

1. The sum of the daily HDDs and CDDs by month should match the normal monthly HDDs and CDDs in Step 1.
2. The daily temperatures and CDDs should be monotonically increasing from winter to summer and monotonically decreasing from summer to winter. The daily HDD series should follow a reverse trend.

These criteria ensure the daily normal series is consistent with the monthly normal series.

5. Sum the HDD and CDD values by billing portion. The Companies' forecasted meter reading schedule contains the beginning and ending date for each billing portion through the end of the forecast period. Use the February 28th weather data as a proxy for February 29th when billing portions include leap days.
6. Average the billing portion totals by billing period.

4 Forecast Models

LG&E and KU's electricity sales forecasts are developed primarily through econometric modeling of energy sales by rate class, but also incorporate specific intelligence on the prospective energy requirements of the utilities' largest customers. Econometric modeling captures the (observed) statistical relationship between energy consumption – the dependent variable – and one or more independent explanatory variables such as the number of households or the level of economic activity in the service territory. Forecasts of electricity sales are then derived from a projection of the independent variable(s).

This widely accepted approach can readily accommodate the influences of national, regional, and local (service territory) drivers of electricity sales. This approach may be applied to forecast the number of customers, energy sales, or use-per-customer. The statistical relationships will vary depending upon the jurisdiction being modeled and the class of service.

The LG&E sales forecast comprises one jurisdiction: Kentucky-retail. The KU sales forecast comprises three jurisdictions: Kentucky-retail, Virginia-retail, and FERC-wholesale.[8] Within the retail jurisdictions, the forecast typically distinguishes several classes of customers including residential, commercial, public authority, and industrial.

The econometric models used to produce the forecast must pass two critical tests. First, the explanatory variables of the models must be theoretically appropriate and widely used in electricity sales forecasting. Second, the inclusion of these explanatory variables must produce statistically significant results that lead to an intuitively reasonable forecast. In other words, the models must be theoretically and empirically robust to explain the historical behavior of the Companies' customers. These forecast models are discussed in detail in the following sections.

[8] For the purposes of this document, the KU service territory comprises KU's Kentucky-retail and FERC-wholesale jurisdictions. The ODP service territory comprises the Virginia-retail jurisdiction.

4.1 Residential Forecasts

The Companies develop a residential forecast for each service territory. For the KU and LG&E (also referred to herein as "LE") service territories, the residential forecast includes all customers on the Residential Service ("RS"), Residential Time of Day ("RTOD"), and Volunteer Fire Department ("VFD") rate schedules. The ODP (also referred to herein as "OD") Residential forecast includes all customers on the RS rate schedule.[9] Residential sales are forecasted for each service territory as the product of a customer and a use-per-customer forecast. See Table 2 for a summary:

Table 2: Residential Forecast Models and Rates

Forecast Model	Rate	Billing Determinants
KU_RS	KU Residential Service KU Residential Time-of-Day Energy Service KU Residential Time-of-Day Demand Service KU Volunteer Fire Department	Customers, Energy, Billed Demand
LE_RS	LE Residential Service LE Residential Time-of-Day Energy Service LE Residential Time-of-Day Demand Service LE Volunteer Fire Department	Customers, Energy, Billed Demand
OD_RS	OD Residential Service	Customers, Energy

4.1.1 Residential Customer Forecasts

The number of residential customers is forecasted by service territory as a function of the number of forecasted households or population in the service territory. Household and population data by county and Metropolitan Statistical Area ("MSA") is available from S&P Global.

4.1.2 Residential Use-per-Customer Forecasts

Average use-per-customer is forecast using a Statistically-Adjusted End-Use ("SAE") Model. The SAE model combines econometric modeling with traditional end-use modeling. The SAE approach defines energy use as a function of energy used by heating, cooling, and other equipment.

$$\text{Use-per-Customer} = a1*XHeat + a2*XCool + a3*XOther$$

Inputs for developing the heating, cooling, and other variables include weather (HDDs and CDDs), appliance saturations, efficiencies, and economic and demographic variables such as income, population, members per household, and electricity prices. Once the historical profile of these explanatory variables has been established, a regression model is specified to identify the statistical relationship between changes in these variables and changes in the dependent variable, use-per-customer. A more detailed discussion of each of these components and the methodology used to develop them is contained in Appendix B.

[9] KU's Virginia-retail jurisdiction does not have RTOD or VFD rate schedules.

The 2022 CPCN Load Forecast used EIA/Itron inputs that are projections of end-use efficiencies and adjusted electric space heating saturations over time. Historical data used in the residential and general service models is not adjusted for previous or current non-dispatchable demand side management and energy efficiency ("DSM-EE") programs, so the forecasts incorporate both customer-initiated energy efficiency in addition to impacts of utility DSM programs moving forward. It is very difficult to determine exactly which reductions in the history occurred because of DSM programs and which occurred because of customer-initiated efficiency gains.

Through rebates, tax incentives, or credits, the Inflation Reduction Act ("IRA") is another mechanism to accelerate energy efficiency. Given the duration of the legislation and the DSM-EE programs included in the Companies' 2024-2030 DSM-EE Program Plan, the end-use efficiency and electric space heating saturation projections have been accelerated by 10 years in the 2022 CPCN Load Forecast for residential and small commercial customers.[10] Specifically, end-use efficiency and electric space heating saturation inputs from the year 2043 were accelerated to occur in 2033 for residential and small commercial customers in the 2022 CPCN Load Forecast. Therefore, efficiencies must escalate more quickly from now until 2033 to reach those levels, which is the main goal of the IRA rebates and tax incentives, as well as the non-dispatchable DSM-EE programs proposed in the 2024-2030 DSM-EE Program Plan.

4.2 Commercial and Industrial Forecasts

Table 3 and Table 4 list the rate schedules included in the commercial and industrial forecasts. A relatively small number of the Companies' largest industrial customers account for a significant portion of total industrial sales, and any expansion or reduction in operations by these customers can significantly impact the Companies' load forecast. Because of this, sales are forecast based on information obtained through direct discussions with these customers. During these discussions, the customers are given the opportunity to review and comment on the usage and billed demand forecasts that the Companies create for them. This first-hand knowledge of the utilization outlook for these companies allows the Companies to directly adjust sales expectations. The following sections summarize the Companies' commercial and industrial forecasts.

[10] Space heating adjustments were not made for the ODP residential customers given most customers in that service territory today do not use natural gas for space heating.

Table 3: Commercial Forecast Models and Rates

Forecast Model	Rate	Billing Determinants
KU_GS	KU General Service single-phase service KU General Service three-phase service	Customers, Energy
LE_GS	LE General Service single-phase service LE General Service three-phase service	Customers, Energy
OD_Com	OD General Service single-phase service OD General Service three-phase service OD Power Service Secondary OD Time-of-Day Secondary Service	Customers, Energy, Billed Demand
KU_AES	KU All Electric School single-phase service KU All Electric School three-phase service	Customers, Energy
OD_AES	OD School Service	Energy
KU_Sec	KU Power Service Secondary KU Time-of-Day Secondary Service	Customers, Energy, Billed Demand
LE_Sec	LE Power Service Secondary LE Time-of-Day Secondary Service	Customers, Energy, Billed Demand

Table 4: Industrial Forecast Models and Rates

Forecast Model	Rate	Billing Determinants
KU_Pri	KU Power Service Primary KU Time-of-Day Primary Service	Customers, Energy, Billed Demand
LE_Pri	LE Power Service Primary LE Time-of-Day Primary Service	Customers, Energy, Billed Demand
OD_Ind	OD Retail Transmission Service OD Time-of-Day Primary Service	Customers, Energy, Billed Demand
KU_RTS	KU Retail Transmission Service	Customers, Energy, Billed Demand
LE_RTS	LE Retail Transmission Service	Customers, Energy, Billed Demand
KU_FLS	KU Fluctuating Load Service	Customers, Energy, Billed Demand
OD_FWP	OD Water Pumping Service	Customers, Energy

4.2.1 General Service Forecasts

The general service forecasts include all customers on the GS rate schedule. For each service territory, GS forecasts employ an SAE model like the model used to forecast residential use-per-customer. The main difference between the GS and RS forecast is that the GS model forecasts total sales (rather than use-per-customer) as a function of energy used by heating, cooling, and other equipment, as well as binary variables to account for anomalies in the historical data. A more detailed discussion of this model is included in Appendix A.

As discussed in the Residential UPC forecast (Section 4.1.2), commercial end-use efficiency inputs were accelerated in the same fashion. There were no space heating adjustments for commercial customers.

4.2.2 KU Secondary Forecast

The KU Secondary forecast includes all customers who receive secondary service on the PS rate schedule and all customers on the TODS rate schedule. Sales to these customers are modeled as a function of weather, economic variables, end-use intensity projections, cooling efficiencies, and binary variables which account for anomalies in the historical data.

4.2.3 KU All-Electric School Forecast

The KU All-Electric School forecast includes all customers on the AES rate schedule. Sales to these customers are modeled as a function of the number of KU AES customers (which is modeled based upon the historical trend in customer counts), weather, and monthly binaries in addition to binary variables to account for anomalies in the historical data.

4.2.4 ODP School Service Forecast

The ODP School Service forecast includes all customers on the SS rate schedule. Sales to these customers are modeled as a function of the number of ODP SS customers (which is modeled using S&P Global projections of households for Wise and Lee counties in VA as an input), weather, and monthly binaries in addition to binary variables to account for anomalies in the historical data.

4.2.5 LG&E Secondary Forecast

The LG&E Secondary forecast includes all customers who receive secondary service on the PS rate schedule and all customers on the TODS rate schedule. Sales to these customers are modeled as a function of weather, economic variables, end-use intensity projections, and other binary variables to account for anomalies in the historical data.

4.2.6 LG&E Special Contract Forecast

LG&E has one customer that is served under a special contract. This customer's consumption is forecasted separately based on information obtained through direct discussions with the customer.

4.2.7 ODP Commercial Forecast

The ODP Commercial forecast includes all customers who receive secondary service on the GS rate schedule, PS rate schedule, and all customers on the TODS rate schedule. Sales to these customers are modeled as a function of energy used by heating equipment, cooling equipment, and other equipment as well as economic variables and other binary variables to account for anomalies in the historical data.

4.2.8 ODP Municipal Pumping Forecast

The ODP municipal pumping forecast consists of customers on the Water Pumping Service rate schedule. Sales to these customers are modeled using a trend based on recent sales.

4.2.9 KU Primary Forecast

The KU Primary forecast includes all customers who receive primary service on the PS rate schedule and all customers on the TODP rate schedule. Sales to these customers are modeled as a function of an economic variable, monthly binaries, and a binary variable to capture Covid-related usage changes. If necessary, the forecast is adjusted to reflect significant expansions or reductions for large customers in these rate classes that are forecast individually based on information obtained through direct discussions with these customers.

4.2.10 KU Retail Transmission Service Forecast

The KU Retail Transmission Service forecast includes customers who receive service on the RTS rate schedule. Sales for several large KU RTS customers are forecast individually based on information obtained through direct discussions with these customers. The majority of the remaining RTS customers are mining customers. Sales to these customers are modeled as a function of a mining index, an economic variable, and a binary variable to capture Covid-related usage changes.

4.2.11 KU Fluctuating Load Service Forecast

The KU Fluctuating Load Service forecast includes the one customer on the FLS rate schedule and is developed based on information obtained through direct discussions with this customer.

4.2.12 LG&E Primary Forecast

The LG&E Primary forecast includes all customers who receive primary service on the PS rate schedule and all customers on the TODP rate schedule. Sales to these customers are modeled as a function of an economic variable and monthly binaries. If necessary, the forecast is adjusted to reflect significant expansions or reductions for large customers on these rate schedules that are forecast individually based on information obtained through direct discussions with these customers.

4.2.13 LG&E Retail Transmission Service Forecast

The LG&E Retail Transmission Service forecast includes customers who receive service on the RTS rate schedule. Sales for several large LG&E RTS customers are forecast individually based on information obtained through direct discussions with these customers. Sales to the remaining customers are modeled as a function of historical monthly usage.

4.2.14 ODP Industrial Forecast

The ODP industrial forecast includes all customers receiving primary service on the PS rate schedule as well as customers receiving service on the TODP or RTS rate schedules. ODP industrial sales are modeled as a function of mining production forecasts, number of customers, and binaries to account for rate switching.

4.3 KU Municipal Forecasts

KU's municipal customers develop their own sales forecasts. These forecasts are reviewed by KU for consistency and compared to historical sales trends. KU directs questions, concerns, and potential revisions to the municipal customers. See Table 5 for a summary:

Table 5: KU Municipal Forecast Models and Rates

Forecast Model	Rate	Billing Determinants
KU_MuniPri	KU Wholesale (Bardstown)	Energy, Billed Demand
KU_MuniTran	KU Wholesale (Nicholasville)	Energy, Billed Demand

4.4 Lighting and EV Charging Forecasts

The Lighting and EV Charging forecasts include customers receiving service on the following rate schedules in Table 6:

Table 6: Lighting and EV Charging Forecast Models and Rates

Forecast Model	Rate	Billing Determinants
KU_EV Fast Charging	KU Electric Vehicle Fast Charging Service	Energy
KU_EV Charging	KU Electric Vehicle Charging Service	Energy
KU_LES	KU Lighting Energy Service	Energy
KU_OSL	KU Outdoor Sports Lighting Service	Customers, Energy, Billed Demand
KU_TES	KU Traffic Energy Service	Customers, Energy
KU_UM	KU Unmetered Lighting Service	Customers
LE_EV Fast Charging	LE Electric Vehicle Fast Charging Service	Energy
LE_EV Charging	LE Electric Vehicle Charging Service	Energy
LE_LES	LE Lighting Energy Service	Energy
LE_OSL	LE Outdoor Sports Lighting Service	Customers, Energy, Billed Demand
LE_TES	LE Traffic Energy Service	Customers, Energy
LE_UM	LE Unmetered Lighting Service	Customers
OD_UM	OD Unmetered Lighting Service	Customers

All Lighting and EV Charging energy is modeled using a trend based on recent sales.

4.5 Distributed Solar Generation Forecast

The net metering distributed solar generation forecast is based upon a consumer choice model. The consumer choice model is driven by various economic and financial inputs, including the retail price for electricity, the levelized cost of energy ("LCOE") for solar installations, disposable personal income, and the price paid for energy exported to the grid. The changes to the timing of the solar investment tax credit ("ITC") phase-out discussed in the IRA is included in the LCOE variable in this model. Two models are specified using the above variables to create both a near-term and a long-term model. This forecast is a blend of the output of these two models.

In addition to net metering, there is also a forecast of behind-the-meter ("BTM") qualifying facilities ("QF") customers. This forecast contemplates only BTM QF and not independent or merchant generators that may locate to the area. This model is based upon the historical trend in BTM QF adoptions as well as current capacity-per-installation levels. The behind-the-meter QF capacity forecast projects an additional 15% increase in capacity over the historical average.

For purposes of revenue forecasting, the reduced sales attributable to distributed generation are allocated by rate as a reduction to the respective rate forecasts. The hourly distributed generation forecast, which is represented as negative load, is added on top of the base load forecast hourly shape discussed in Section 5.2.

4.6 Electric Vehicle Forecast

The electric vehicle forecast is based on a consumer choice model. The consumer choice model is driven by the declines in the price of electric vehicles due to projected declines in battery pack costs as well as the cost of internal combustion engine vehicles. The forecast assumes the tax credits discussed in the IRA. Consistent with previous filings, efficiency and miles driven assumptions are used to translate the vehicles-in-operation into an energy impact and that impact is allocated entirely to the Residential class.

For purposes of revenue forecasting, the EV sales forecast is allocated as an increase to the RS forecasts. The EV hourly profile, which assumes managed charging, is added on top of the base load forecast hourly profile discussed in Section 5.2.

An additional, positive adjustment was made to account for National Electric Vehicle Infrastructure ("NEVI") funds that were discussed in the Infrastructure Investment and Jobs Act ("IIJA"). The forecast assumes EV fast chargers will locate in the service territory beginning in 2023 because of this legislation and grow over time. The TODS rates for LG&E and KU receive the adjustments. By 2028, these chargers are only forecasted to add 2 GWh of load annually.

4.7 Advanced Metering Infrastructure ("AMI") Benefits

The forecast has two adjustments to account for the benefits AMI is anticipated to provide in terms of load reduction. These adjustments reduce load.

4.7.1 Conservation Voltage Reduction ("CVR")

CVR adjustments are phased in over time as AMI meters are deployed and the necessary distribution controls are installed. Beginning in 2030, the combined CVR adjustments reduce annual load by 205 GWh annually. Specifically, CVR reduces RS and GS sales. The adjustments are consistent with what was discussed in Exhibit LEB-3 in Case Nos. 2020-00349 and 2020-00350.

4.7.2 AMI ePortal Savings

AMI ePortal savings are allocated to customers on rates that do not currently have access to interval data. This primarily includes RS, GS, AES/SS, and PS rates. These are phased in as AMI meters are deployed and represent 0.35% of monthly sales reductions for the applicable rates upon full deployment. The adjustments are consistent with what was discussed in Exhibit LEB-3 in Case Nos. 2020-00349 and 2020-00350.

4.8 Billed Demand Forecasts

For most rates, regression models are developed to forecast billed demands primarily as a function of energy. For some rates, billed demand forecasts are developed by applying historical ratios of billed demand and energy to the energy forecast. For a given customer and month, tariff provisions can impact the relationship between billed demands and energy. For example, the base demand for a TODP customer is computed as the greater of several factors including the customer's contract capacity and highest measured demand for the preceding 11 billing periods. The Companies' forecasting process considers the potential impact of these factors on the overall forecasts. Base, peak, and intermediate demands for the Companies' largest customers are developed with input from the customer.

5 Data Processing

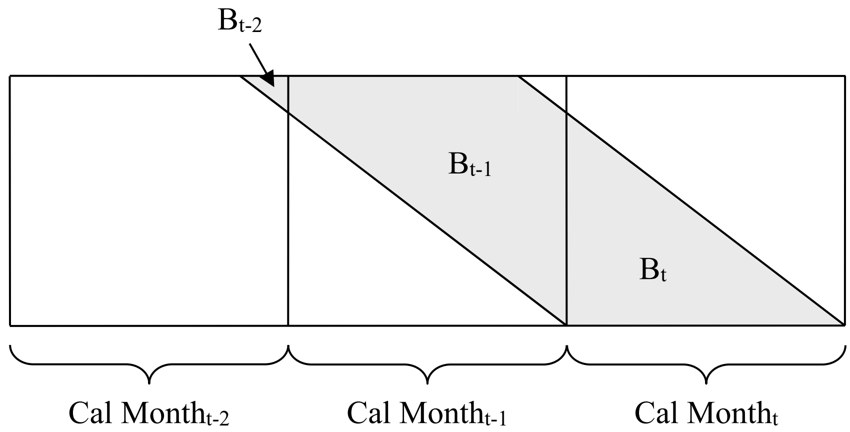
All customers are assigned to one of 20 billing portions. A billing portion determines what day of the month, generally, a customer's meter is read. Most customers' monthly bills include energy that was consumed in portions of more than one calendar month. This energy is referred to as "billed" energy and the majority of the Companies' forecast models are initially specified to forecast "billed" sales. The following processes are completed to prepare the forecasts for use as inputs to the Companies' revenue and generation forecasts:

- Billed-to-Calendar Energy Conversion
- Hourly Energy Requirements Forecast

5.1 Billed-to-Calendar Energy Conversion

Most forecast volumes must be converted from a billed to calendar basis to meet the needs of the Financial Planning department. The shaded area in Figure 2 represents a typical billing period (B). Area B_t represents the portion of billed energy consumed in the current calendar month (Cal $Month_t$). Area B_{t-1} represents the portion of billed energy consumed in the previous calendar month (Cal $Month_{t-1}$). Area B_{t-2} represents the portion of billed energy consumed in the calendar month two months prior to the current month (Cal $Month_{t-2}$). Not all billing periods include volumes that were consumed in the calendar month two months prior to the current month.

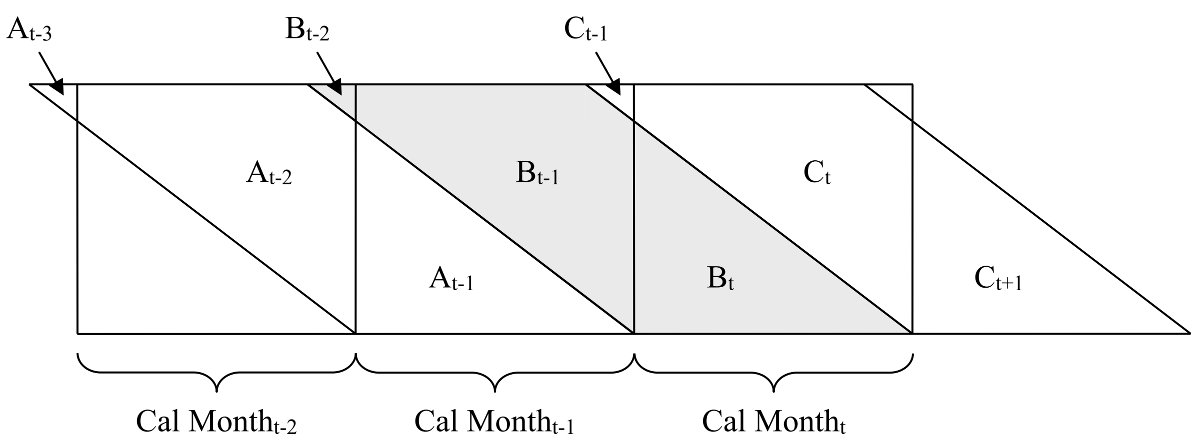
Figure 2 – Billed and Calendar Energy



In this process, billed energy is allocated to calendar months based on when the energy is consumed. Furthermore, the weather-sensitive portion of the billed energy forecast is allocated to calendar months based on degree days (HDDs and CDDs) and the non-weather-sensitive portion is allocated based on billing days.[11] For example, the June billing period includes portions of June, May, and possibly April. Under normal weather conditions, June will have more CDDs than May. Therefore, a greater portion of the weather-sensitive energy in the June billing period will be allocated to the calendar month of June.

Figure 3 contains two additional billing periods (A & C). Calendar sales for Cal Month$_{t-1}$ is equal to the sum of energy in in billing period segments A_{t-1}, B_{t-1}, and C_{t-1}.

Figure 3 – Billed and Calendar Energy



[11] For a given billing period, the number of degree days and billing days in each calendar month is computed as an average over the 20 billing portions.

5.2 Hourly Energy Requirements Forecast

5.2.1 Normal Hourly Energy Requirements Forecast

The Generation Planning department uses the hourly energy requirements forecast to develop resource expansion plans and a forecast of generation production costs. An hourly energy requirements forecast is developed for each company by adding losses to calendar-month sales and allocating the sum to hours in each month. The result reflects customers' hourly energy requirements under normal weather conditions. The following process is used to develop this forecast:

1. Sum calendar-month forecast volumes independent of distributed generation and incremental EV load by company. Then, add transmission and distribution losses as well as incremental company uses to compute monthly energy requirements. The sum of calendar-month forecast volumes for KU includes forecast volumes for the KU and ODP service territories.
2. Develop normalized load duration curves for each company and month based on 10 years of historical hourly energy requirements. For KU, to model the impact of the municipal departure, this process is completed based on historical energy requirements where the impact of the departing municipals has been removed.
3. Compute the ratio of hourly energy requirements and monthly energy requirements for each hour and company. Rank the ratios in each month from highest to lowest. The normalized load duration curves are computed by averaging the ratios by month, rank, and company.
    1. The winter and summer peak can occur in multiple months, and the predicted peak for a season (meaning winter or summer) is higher than the predicted peak for any individual month within the season. For this reason, the normalized load duration curves for January and August are adjusted to match peaks produced in separate seasonal and annual models. This process produces seasonal peak demand forecasts that are placed within January (winter) and August (annual).
4. Allocate total forecasted monthly energy requirements by company to hours using the normalized load duration curves. For KU, the normalized load durations curves reflect the municipal departure.
5. Assign hourly energy requirements to specific hours in each month based on the ordering of days and weekends in the month. Historical reference years and months having matching calendar profiles as the forecasted month (e.g., a historical August that begins on a Tuesday) are selected to be used for ordering purposes only.
6. Adjust the hourly energy requirements forecast to reflect the hourly forecasted impact of distributed solar generation and electric vehicle load. Said differently, the profiles attributable to solar and electric vehicles are layered in separately. The solar profiles are developed to ensure that the underlying weather and solar irradiance align.

5.2.2 Weather-Year Forecasts

The Companies develop their hourly energy requirements forecast with the assumption that weather will be average or "normal" in every year (see discussion above in Section 5.2.1). While this is a reasonable assumption for long-term resource planning, weather from one year to the next is never the same. For this reason, to support the Companies' Reserve Margin Analysis and other studies focused on generation reliability, the Companies produce 49 hourly energy requirement forecasts for each year of the forecast based on actual weather in each of the last 49 years (1973 through 2021).

To create these "weather year" forecasts, the Companies develop a model to forecast hourly energy requirements as a function of temperature and calendar variables such as day of week and holidays. This model is used to forecast hourly energy requirements in each year of the forecast period based on hourly temperatures from the prior 49 calendar years but using calendar variables from the forecast period. To ensure consistency with the Companies' energy forecast, all hours of the weather year forecast are adjusted so that the mean of monthly energy requirements from the weather year forecasts equals monthly energy requirements in the base energy forecast. Additionally, the mean of the seasonal peaks of the weather years are adjusted to match the peaks forecasted using normal weather as discussed in Section 5.2.1. Finally, the hourly distributed generation and EV profiles are layered in according to each weather year. For historical years for which we have solar irradiance data (since 1998), the distributed generation profile matches that year's weather profile. For prior years, the distributed generation profile represents an average of the years that are available.

6 Inflation Reduction Act and DSM-EE Programs

As mentioned in previous sections, the 2022 CPCN load forecast incorporates specific end-use changes resulting from the IRA and proposed 2024-2030 DSM-EE Program Plan. Each end-use has a distinct hourly profile that has been incorporated into the final 2022 CPCN hourly load forecast. Hourly adjustments for the following end-uses have been included:

Table 7: Summary of IRA and DSM-EE Adjustments

Adjustment	Effect on Load	Effect on Hourly Profile
Accelerated end-use efficiency gains	Decreases load in all hours	Percentage increase proportional to historical load profile
Accelerated electric space heating saturation	Increases load in winter months (particularly at night)	Winter heating profile from NREL[12]
Faster EV adoption	Increases load[13]	Same hourly profile shape, but at a higher level
Faster Distributed Generation adoption	Decreases load during the day	Same hourly profile shape, but at a higher level

7 Review

In addition to assessing the reasonableness of models (discussed in introduction to Section 4), forecast results are visually inspected versus recent history to ensure reasonableness of results. Because of the obligation to serve load in every hour, the Companies spend a lot of time ensuring monthly and hourly profiles are reasonable. To accomplish this, the new forecast is compared to (i) the previous forecast, (ii) weather-normalized actual sales for the comparable period in prior years, (iii) a range of historical actual sales and energy requirements, and (iv) the end-use projections assumed in the forecast models. This process ensures that the forecast is consistent with recent trends in the way customers are using electricity and how the way the Companies' customers use energy is projected to change in the future.

[12] https://www.nrel.gov/buildings/end-use-load-profiles.html; https://data.openei.org/s3_viewer?bucket=oedi-data-lake&prefix=nrel-pds-building-stock%2Fend-use-load-profiles-for-us-building-stock%2F2021%2Fresstock_amy2018_release_1%2Ftimeseries_aggregates%2Fby_county%2Fstate%3DKY%2F

[13] As in recent forecasts, managed charging for EVs is assumed.

Appendix A:
Commercial Statistically Adjusted End-Use Model

The traditional approach to forecasting monthly sales for a customer class is to develop an econometric model that relates monthly sales to weather, seasonal variables, and economic conditions. From a forecasting perspective, econometric models are well suited to identifying historical trends and to projecting these trends into the future. In contrast, end-use models can incorporate the end-use factors driving energy use. By including end-use structure in an econometric model, the statistically adjusted end-use (SAE) modeling framework exploits the strengths of both approaches.

There are several advantages to the SAE approach.

- The equipment efficiency trends and saturation changes embodied in the long-run end-use forecasts are introduced explicitly into the short-term monthly sales forecast, thereby providing a strong bridge between the two forecasts.
- By explicitly introducing trends in equipment saturations and efficiency levels, SAE models can explain changes in usage levels and weather-sensitivity over time.
- Data for short-term models are often not sufficiently robust to support estimation of a full set of price, economic, and demographic effects. By bundling these factors with equipment-oriented drivers, a rich set of elasticities can be built into the final model.

This section describes this approach, the associated supporting Commercial SAE spreadsheets, and MetrixND project files that are used in the implementation. The source for the commercial SAE spreadsheets is the 2020 Annual Energy Outlook (AEO) database provided by the Energy Information Administration (EIA).

Statistically Adjusted End-Use Model Framework

The statistically adjusted end-use modeling framework begins by defining energy use ($USE_{y,m}$) in year (y) and month (m) as the sum of energy used by heating equipment ($Heat_{y,m}$), cooling equipment ($Cool_{y,m}$), and other equipment ($Other_{y,m}$). Formally,

$$USE_{y,m} = Heat_{y,m} + Cool_{y,m} + \mathrm{Other}_{y,m} \tag{1}$$

Although monthly sales are measured for individual customers, the end-use components are not. Substituting estimates for the end-use elements gives the following econometric equation.

$$USE_m = a + b_1 \times XHeat_m + b_2 \times XCool_m + b_3 \times XOther_m + \varepsilon_m \tag{2}$$

$XHeat_m$, $XCool_m$, and $XOther_m$ are explanatory variables constructed from end-use information, dwelling data, weather data, and market data. As will be shown below, the equations used to construct these X-variables are simplified end-use models, and the X-variables are the estimated usage levels for each of the major end uses based on these models. The estimated model can then be thought of as a statistically adjusted end-use model, where the estimated slopes are the adjustment factors.

Constructing XHeat

As represented in the Commercial SAE spreadsheets, energy use by space heating systems depends on the following types of variables.

- Heating degree days,
- Heating intensity,
- Commercial output and energy price.

The heating variable is represented as the product of an annual equipment index and a monthly usage multiplier. That is,

$$XHeat_{y,m} = HeatIndex_{y,m} \times HeatUse_{y,m} \tag{3}$$

Where:

- $XHeat_{y,m}$ is estimated heating energy use in year (*y*) and month (*m*)
- $HeatIndex_{y,m}$ is the annual index of heating equipment
- $HeatUse_{y,m}$ is the monthly usage multiplier

The heating equipment index is composed of electric space heating intensity. The index will change over time with changes in heating intensity. Formally, the equipment index is defined as:

$$HeatIndex_y = HeatSales_{13} \times \frac{(HeatIntensity_y)}{(HeatIntensity_{13})} \tag{4}$$

In this expression, 2013 is used as a base year for normalizing the index. The ratio on the right is equal to 1.0 in 2013. In other years, it will be greater than 1.0 if intensity levels are above their 2013 level.

$$HeatSales_{13} = \left(\frac{kWh}{Sqft}\right)_{Heating} \times \left(\frac{CommercialSales_{13}}{\sum_e {}^{kWh}/_{Sqft_e}}\right) \tag{5}$$

Here, base-year sales for space heating is the product of the average space heating intensity value and the ratio of total commercial sales in the base year over the sum of the end-use intensity values. In the Commercial SAE Spreadsheets, the space heating sales value is defined on the *BaseYrInput* tab. The resulting $HeatIndex_y$ value in 2013 will be equal to the estimated annual heating sales in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

Heating system usage levels are impacted on a monthly basis by several factors, including weather, commercial level economic activity, and prices. Using the COMMEND default elasticity parameters, the estimates for space heating equipment usage levels are computed as follows:

$$HeatUse_{y,m} = \left(\frac{WgtHDD_{y,m}}{HDD_{13}}\right) \times \left(\frac{Output_y}{Output_{13}}\right) \quad \times \left(\frac{Price_{y,m}}{Price_{13}}\right)^{-0.18} \tag{6}$$

Where

- *WgtHDD* is the weighted number of heating degree days in year *y* and month *m*. This is constructed as the weighted sum of the current month's HDD and the prior month's HDD. The weights are 75% on the current month and 25% on the prior month
- *HDD* is the annual heating degree days for 2013,
- *Output* is a real commercial output driver in year *y*,
- *Price* is the average real price of electricity in month *m* and year *y*,

By construction, the $HeatUse_{y,m}$ variable has an annual sum that is close to 1.0 in the base year (2013). The first terms, which involve heating degree days, serves to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will reflect changes in commercial output and prices, as transformed through the end-use elasticity parameters. For example, if the real price of electricity goes up 10% relative to the base year value, the price term will contribute a multiplier of about .98 (computed as 1.10 to the -0.18 power).

Constructing XCool

The explanatory variable for cooling loads is constructed in a similar manner. The amount of energy used by cooling systems depends on the following types of variables.

- Cooling degree days,
- Cooling intensity,
- Commercial output and energy price.

The cooling variable is represented as the product of an equipment-based index and monthly usage multiplier. That is,

$$XCool_{y,m} = CoolIndex_y \times CoolUse_{y,m} \tag{7}$$

Where:

- $XCool_{y,m}$ is estimated cooling energy use in year y and month m,
- $CoolIndex_y$ is an index of cooling equipment, and
- $CoolUse_{y,m}$ is the monthly usage multiplier.

As with heating, the cooling equipment index depends on equipment saturation levels (*CoolShare*) normalized by operating efficiency levels (Eff). Formally, the cooling equipment index is defined as:

$$CoolIndex_y = CoolSales_{13} \times \frac{\left(CoolShare_y / Eff_y\right)}{\left(CoolShare_{13} / Eff_{13}\right)} \tag{8}$$

Data values in 2013 are used as a base year for normalizing the index, and the ratio on the right is equal to 1.0 in 2013. In other years, it will be greater than 1.0 if equipment saturation levels are above their 2013 level. This will be counteracted by higher efficiency levels, which will drive the index downward. Estimates of base year cooling sales are defined as follows.

$$CoolSales_{13} = \left(\frac{kWh}{Sqft}\right)_{Cooling} \times \left(\frac{CommercialSales_{13}}{\sum_e {kWh}/{Sqft_e}}\right) \tag{9}$$

Here, base-year sales for space cooling is the product of the average space cooling intensity value and the ratio of total commercial sales in the base year over the sum of the end-use intensity values. In the Commercial SAE Spreadsheets, the space cooling sales value is defined on the *BaseYrInput* tab. The resulting *CoolIndex* value in 2013 will be equal to the estimated annual cooling sales in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

Cooling system usage levels are impacted on a monthly basis by several factors, including weather, economic activity levels and prices. Using the COMMEND default parameters, the estimates of cooling equipment usage levels are computed as follows:

$$CoolUse_{y,m} = \left(\frac{WgtCDD_{y,m}}{CDD_{13}}\right) \times \left(\frac{Output_y}{Output_{13}}\right) \times \left(\frac{Price_{y,m}}{Price_{13}}\right)^{-0.18} \tag{10}$$

Where:

- *WgtCDD* is the weighted number of cooling degree days in year (*y*) and month (*m*). This is constructed as the weighted sum of the current month's CDD and the prior month's CDD. The weights are 75% on the current month and 25% on the prior month.
- *CDD* is the annual cooling degree days for 2013.

By construction, the *CoolUse* variable has an annual sum that is close to 1.0 in the base year (2013). The first two terms, which involve billing days and cooling degree days, serve to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will change to reflect changes in commercial output and prices.

Constructing XOther

Monthly estimates of non-weather sensitive sales can be derived in a similar fashion to space heating and cooling. Based on end-use concepts, other sales are driven by:

- Equipment intensities,
- Average number of days in the billing cycle for each month, and
- Real commercial output and real prices.

The explanatory variable for other uses is defined as follows:

$$XOther_{y,m} = OtherIndex_{y,m} \times OtherUse_{y,m} \tag{11}$$

The second term on the right-hand side of this expression embodies information about equipment saturation levels and efficiency levels. The equipment index for other uses is defined as follows:

$$OtherIndex_{y,m} = \sum_{Type} Weight_{13}^{Type} \times \left(\frac{Share_y^{Type} \big/ Eff_y^{Type}}{Share_{13}^{Type} \big/ Eff_{13}^{Type}} \right) \tag{12}$$

Where:

- Weight is the weight for each equipment type,
- Share represents the fraction of floor stock with an equipment type, and
- Eff is the average operating efficiency.

This index combines information about trends in saturation levels and efficiency levels for the main equipment categories. The weights are defined as follows:

$$Weight_{13}^{Type} = \left(\frac{kWh}{Sqft}\right)_{Type} \times \left(\frac{CommercialSales_{13}}{\sum_e kWh \big/ Sqft_e} \right) \tag{13}$$

Further monthly variation is introduced by multiplying by usage factors that cut across all end-uses, constructed as follows:

$$OtherUse_{y,m} = \left(\frac{BDays_{y,m}}{30.44}\right) \times \left(\frac{Output_y}{Output_{13}}\right) \times \left(\frac{Price_{y.m}}{Price_{13}}\right)^{-0.18} \tag{14}$$

In this expression, the elasticities on output and real price are computed from the COMMEND default values.

Supporting Spreadsheets and MetrixND Project Files

The SAE approach described above has been implemented for each of the nine census divisions. A mapping of states to census divisions is presented in Figure 1. This section describes the contents of each file and a procedure for customizing the files for specific utility data. A total of 18 files are provided. These files are listed in Table 1.

Figure 1: Mapping of States to Census Divisions

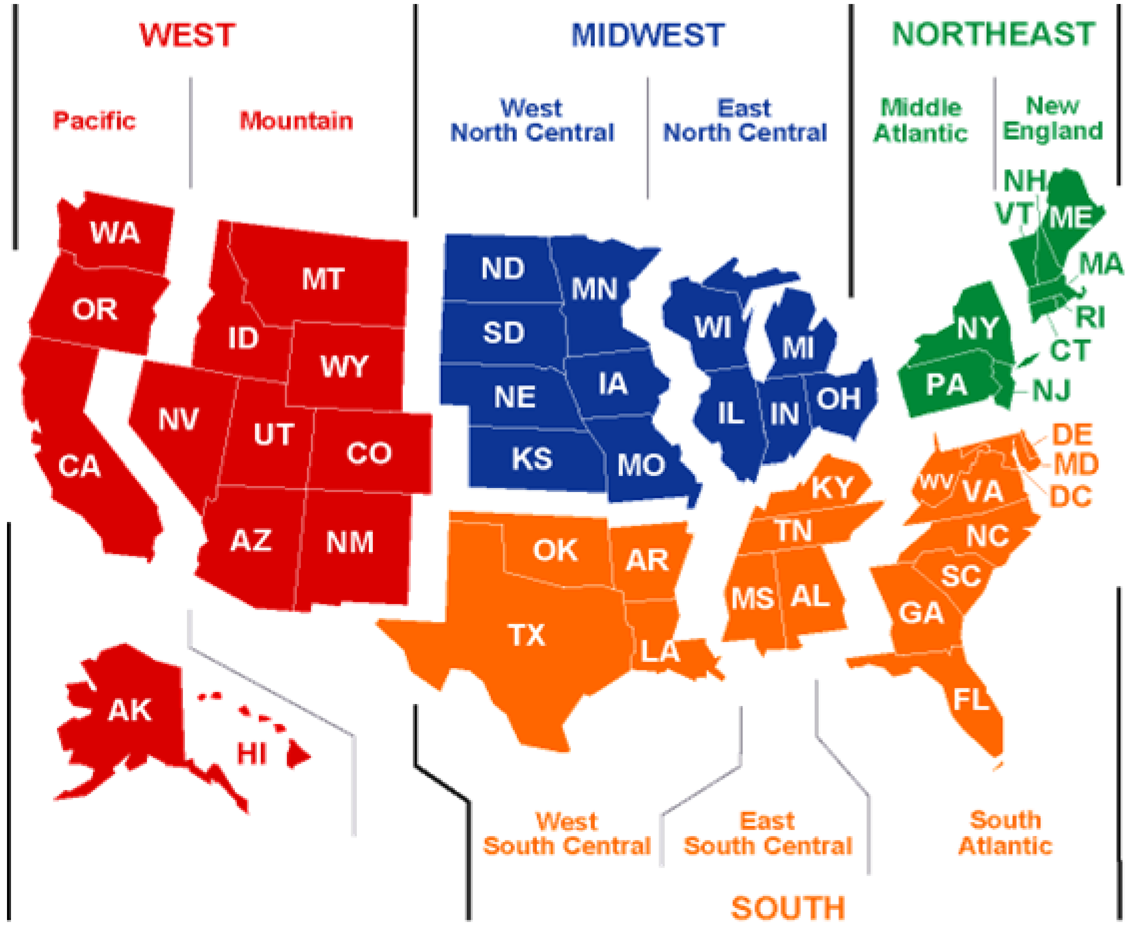


Table 1: List of SAE Electric Files

Spreadsheets	***MetrixND* Project Files**
NewEnglandCom20.xlsx	NewEnglandCom20.ndm
MiddleAtlanticCom20.xlsx	MiddleAtlanticCom20.ndm
EastNorthCentralCom20.xlsx	EastNorthCentralCom20.ndm
WestNorthCentralCom20.xlsx	WestNorthCentralCom20.ndm
SouthAtlanticCom20.xlsx	SouthAltanticCom20.ndm
EastSouthCentralCom20.xlsx	EastSouthCentralCom20.ndm
WestSouthCentralCom20.xlsx	WestSouthCentralCom20.ndm
MountainCom20.xlsx	MountainCom20.ndm
PacificCom20.xlsx	PacificCom20.ndm

As defaults, the SAE spreadsheets include regional data, but utility data can be entered to generate the *Heat*, *Cool*, and *Other* equipment indices used in the SAE approach. The data from these spreadsheets are linked to the MetrixND project files. In these project files, the end-use *Usage* variables (Equations 6, 10, and 14 above) are constructed and the SAE model is estimated.

The nine spreadsheets contain the following tabs.

- **EIAData** contains the raw forecasted data provided by the EIA.
- **BaseYrInput** contains base year Census Division intensities by end-use and building type as well as default building type weights. It also contains functionality for changing the weights to reflect utility service territory.
- **Efficiency** contains historical and forecasted end-use equipment efficiency trends. The forecasted values are based on projections provided by the EIA.
- **Shares** contains historical and forecasted end-use saturations.
- **Intensity** contains the annual intensity (kWh/sqft) projections by end use.
- **AnnualIndices** contains the annual *Heat*, *Cool* and *Other* equipment indices.
- **FloorSpace** contains the annual floor space (sqft) projections by end use.
- **PV** incorporates the impact of photovoltaic batteries into the forecast.
- **Graphs** contains graphs of Efficiency and Intensities, which can be updating by selecting from the list in cell B2.

The MetrixND project files contain the following objects.

Parameter Tables

- **Parameters.** This parameter table includes the values of the annual HDD and CDD in 2013 used to calculate the Usage variables for each end-use.
- **Elas.** This parameter table includes the values of the elasticities used to calculate the Usage variables for each end-use.

Data Tables

- **AnnualIndices.** This data table is linked to the *AnnualIndices* tab in the Commercial SAE spreadsheet and contains sales-adjusted commercial SAE indices.
- **Intensity.** This data table is linked to the *Intensity* tab in the Commercial SAE spreadsheet.
- **FloorSpace.** This data table links to *FloorSpace* tab in the Commercial SAE spreadsheet.
- **UtilityData.** This linkless data table contains Census Division level data. It can be populated with utility-specific data.

Transformation Tables

- **EconTrans.** This transformation table is used to compute the output and price indices used in the usage equations.
- **WeatherTrans.** This transformation table is used to compute the HDD and CDD indices used in the usage equations.
- **CommercialVars.** This transformation table is used to compute the *Heat*, *Cool* and *Other* Usage variables, as well as the *XHeat*, *XCool* and *XOther* variables that are used in the regression model. Structural variables based on the intensity/floor space combination are also calculated here.
- **BinaryVars.** This transformation table is used to compute the calendar binary variables that could be required in the regression model.

- **AnnualFcst.** This transformation table is used to compute the annual historical and forecast sales and annual change in sales.
- **EndUseFcst.** This transformation table breaks the forecast down into its heating, cooling, and other components.

Models

- **ComSAE.** The commercial SAE model (energy forecast driven by end-use indices, price, and output projections).
- **ComStruct.** Simple stock model (energy forecast driven by end-use energy intensities, and square footage).

Appendix B:
Residential SAE Modeling Framework

The traditional approach to forecasting monthly sales for a customer class is to develop an econometric model that relates monthly sales to weather, seasonal variables, and economic conditions. From a forecasting perspective, econometric models are well suited to identifying historical trends and to projecting these trends into the future. In contrast, end-use models can incorporate the end-use factors driving energy use. By including end-use structure in an econometric model, the statistically adjusted end-use (SAE) modeling framework exploits the strengths of both approaches.

There are several advantages to this approach.

- The equipment efficiency and saturation trends, dwelling square footage, and thermal integrity changes embodied in the long-run end-use forecasts are introduced explicitly into the short-term monthly sales forecast. This provides a strong bridge between the two forecasts.
- By explicitly incorporating trends in equipment saturations, equipment efficiency, dwelling square footage, and thermal integrity levels, it is easier to explain changes in usage levels and changes in weather-sensitivity over time.
- Data for short-term models are often not sufficiently robust to support estimation of a full set of price, economic, and demographic effects. By bundling these factors with equipment-oriented drivers, a rich set of elasticities can be incorporated into the final model.

This section describes this approach, the associated supporting SAE spreadsheets, and the MetrixND project files that are used in the implementation. The main source of the residential SAE spreadsheets is the 2020 Annual Energy Outlook (AEO) database provided by the Energy Information Administration (EIA).

Statistically Adjusted End-Use Modeling Framework

The statistically adjusted end-use modeling framework begins by defining energy use ($USE_{y,m}$) in year (y) and month (m) as the sum of energy used by heating equipment ($Heat_{y,m}$), cooling equipment ($Cool_{y,m}$), and other equipment ($Other_{y,m}$). Formally,

$$USE_{y,m} = Heat_{y,m} + Cool_{y,m} + \mathrm{Other}_{y,m} \qquad (1)$$

Although monthly sales are measured for individual customers, the end-use components are not. Substituting estimates for the end-use elements gives the following econometric equation.

$$USE_m = a + b_1 \times XHeat_m + b_2 \times XCool_m + b_3 \times XOther_m + \varepsilon_m \qquad (2)$$

$XHeat_m$, $XCool_m$, and $XOther_m$ are explanatory variables constructed from end-use information, dwelling data, weather data, and market data. As will be shown below, the equations used to construct these X-variables are simplified end-use models, and the X-variables are the estimated usage levels for each of the major end uses based on these models. The estimated model can then be thought of as a statistically adjusted end-use model, where the estimated slopes are the adjustment factors.

Constructing XHeat

As represented in the SAE spreadsheets, energy use by space heating systems depends on the following types of variables.

- Heating degree days
- Heating equipment saturation levels
- Heating equipment operating efficiencies
- Average number of days in the billing cycle for each month
- Thermal integrity and footage of homes
- Average household size, household income, and energy prices

The heating variable is represented as the product of an annual equipment index and a monthly usage multiplier. That is:

$$XHeat_{y,m} = HeatIndex_{y,m} \times HeatUse_{y,m} \tag{3}$$

Where:

- $XHeat_{y,m}$ is estimated heating energy use in year (*y*) and month (*m*)
- $HeatIndex_{y,m}$ is the monthly index of heating equipment
- $HeatUse_{y,m}$ is the monthly usage multiplier

The heating equipment index is defined as a weighted average across equipment types of equipment saturation levels normalized by operating efficiency levels. Given a set of fixed weights, the index will change over time with changes in equipment saturations (*Sat*), operating efficiencies (*Eff*), building structural index ($StructuralIndex$), and energy prices. Formally, the equipment index is defined as:

$$HeatIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \middle/ Eff_y^{Type} \right)}{\left(Sat_{15}^{Type} \middle/ Eff_{15}^{Type} \right)} \tag{4}$$

The $StructuralIndex$ is constructed by combining the EIA's building shell efficiency index trends with surface area estimates, and then it is indexed to the 2015 value:

$$StructuralIndex_y = \frac{BuildingShellEfficiencyIndex_y \times SurfaceArea_y}{BuildingShellEfficiencyIndex_{15} \times SurfaceArea_{15}} \tag{5}$$

The $StructuralIndex$ is defined on the *StructuralVars* tab of the SAE spreadsheets. Surface area is derived to account for roof and wall area of a standard dwelling based on the regional average square footage data obtained from EIA. The relationship between the square footage and surface area is constructed assuming an aspect ratio of 0.75 and an average of 25% two-story and 75% single-story. Given these assumptions, the approximate linear relationship for surface area is:

$$SurfaceArea_y = 892 + 1.44 \times Footage_y \tag{6}$$

In Equation 4, 2015 is used as a base year for normalizing the index. As a result, the ratio on the right is equal to 1.0 in 2015. In other years, it will be greater than 1.0 if equipment saturation levels are above their 2015 level. This will be counteracted by higher efficiency levels, which will drive the index downward. The weights are defined as follows.

$$Weight^{Type} = \frac{Energy_{15}^{Type}}{HH_{15}} \times HeatShare_{15}^{Type} \tag{7}$$

In the SAE spreadsheets, these weights are referred to as Intensities and are defined on the *EIAData* tab. With these weights, the $HeatIndex$ value in 2015 will be equal to estimated annual heating intensity per household in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

For electric heating equipment, the SAE spreadsheets contain two equipment types: electric resistance furnaces/room units and electric space heating heat pumps. Examples of weights for these two equipment types for the U.S. are given in Table 1.

Table 1: Electric Space Heating Equipment Weights

Equipment Type	Weight (kWh)
Electric Resistance Furnace/Room units	916
Electric Space Heating Heat Pump	346

Data for the equipment saturation and efficiency trends are presented on the *Shares* and *Efficiencies* tabs of the SAE spreadsheets. The efficiency for electric space heating heat pumps are given in terms of Heating Seasonal Performance Factor [BTU/Wh], and the efficiencies for electric furnaces and room units are estimated as 100%, which is equivalent to 3.41 BTU/Wh.

Price Impacts. In the 2007 version of the SAE models and thereafter, the Heat Index has been extended to account for the long-run impact of electric and natural gas prices. Since the Heat Index represents changes in the stock of space heating equipment, the price impacts are modeled to play themselves out over a 10-year horizon. To introduce price effects, the Heat Index as defined by Equation 4 above is multiplied by a 10-year moving-average of electric and gas prices. The level of the price impact is guided by the long-term price elasticities:

$$HeatIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \middle/ Eff_y^{Type} \right)}{\left(Sat_{15}^{Type} \middle/ Eff_{15}^{Type} \right)} \times$$
$$\left(TenYearMovingAverageElectric\,\mathrm{Pr}\,i\,ce_{y,m}\right)^{\varphi} \times \left(TenYearMovingAverageGas\,\mathrm{Pr}\,i\,ce_{y,m}\right)^{\gamma} \tag{8}$$

Since the trends in the Structural index (the equipment saturations and efficiency levels) are provided exogenously by the EIA, the price impacts are introduced in a multiplicative form. As a result, the long-run change in the Heat Index represents a combination of adjustments to the structural integrity of new homes, saturations in equipment and efficiency levels relative to what was contained in the base EIA long-term forecast.

Heating system usage levels are impacted on a monthly basis by several factors, including weather, household size, income levels, prices, and billing days. The estimates for space heating equipment usage levels are computed as follows:

$$HeatUse_{y,m} = \left(\frac{WgtHDD_{y,m}}{HDD_{15}}\right) \times \left(\frac{HHSize_y}{HHSize_{15}}\right)^{0.25} \times \left(\frac{Income_y}{Income_{15}}\right)^{0.20} \times \left(\frac{Elec\,Price_{y,m}}{Elec\,Price_{15,7}}\right)^{\lambda} \times \left(\frac{Gas\,Price_{y,m}}{Gas\,Price_{15,7}}\right)^{\kappa} \quad (9)$$

Where:

- *WgtHDD* is the weighted number of heating degree days in year (*y*) and month (*m*). This is constructed as the weighted sum of the current month's HDD and the prior month's HDD. The weights are 75% on the current month and 25% on the prior month.
- *HDD* is the annual heating degree days for 2015
- *HHSize* is average household size in a year (*y*)
- *Income* is average real income per household in year (*y*)
- *ElecPrice* is the average real price of electricity in month (*m*) and year (*y*)
- *GasPrice* is the average real price of natural gas in month (*m*) and year (*y*)

By construction, the $HeatUse_{y,m}$ variable has an annual sum that is close to 1.0 in the base year (2015). The first two terms, which involve billing days and heating degree days, serve to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will reflect changes in the economic drivers, as transformed through the end-use elasticity parameters. The price impacts captured by the Usage equation represent short-term price response.

Constructing XCool

The explanatory variable for cooling loads is constructed in a similar manner. The amount of energy used by cooling systems depends on the following types of variables.

- Cooling degree days
- Cooling equipment saturation levels
- Cooling equipment operating efficiencies
- Average number of days in the billing cycle for each month
- Thermal integrity and footage of homes
- Average household size, household income, and energy prices

The cooling variable is represented as the product of an equipment-based index and monthly usage multiplier. That is,

$$XCool_{y,m} = CoolIndex_y \times CoolUse_{y,m} \quad (10)$$

Where

- $XCool_{y,m}$ is estimated cooling energy use in year (y) and month (m)
- $CoolIndex_y$ is an index of cooling equipment
- $CoolUse_{y,m}$ is the monthly usage multiplier

As with heating, the cooling equipment index is defined as a weighted average across equipment types of equipment saturation levels normalized by operating efficiency levels. Formally, the cooling equipment index is defined as:

$$CoolIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \big/ Eff_y^{Type} \right)}{\left(Sat_{15}^{Type} \big/ Eff_{15}^{Type} \right)} \quad (11)$$

Data values in 2015 are used as a base year for normalizing the index, and the ratio on the right is equal to 1.0 in 2015. In other years, it will be greater than 1.0 if equipment saturation levels are above their 2015 level. This will be counteracted by higher efficiency levels, which will drive the index downward. The weights are defined as follows.

$$Weight^{Type} = \frac{Energy_{15}^{Type}}{HH_{15}} \times CoolShare_{15}^{Type} \quad (12)$$

In the SAE spreadsheets, these weights are referred to as Intensities and are defined on the *EIAData* tab. With these weights, the $CoolIndex$ value in 2015 will be equal to estimated annual cooling intensity per household in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

For cooling equipment, the SAE spreadsheets contain three equipment types: central air conditioning, space cooling heat pump, and room air conditioning. Examples of weights for these three equipment types for the U.S. are given in Table 2.

Table 2: Space Cooling Equipment Weights

Equipment Type	Weight (kWh)
Central Air Conditioning	1,012
Space Cooling Heat Pump	306
Room Air Conditioning	277

The equipment saturation and efficiency trends data are presented on the *Shares* and *Efficiencies* tabs of the SAE spreadsheets. The efficiency for space cooling heat pumps and central air conditioning (A/C) units are given in terms of Seasonal Energy Efficiency Ratio [BTU/Wh], and room A/C units efficiencies are given in terms of Energy Efficiency Ratio [BTU/Wh].

Price Impacts. In the 2007 SAE models and thereafter, the Cool Index has been extended to account for changes in electric and natural gas prices. Since the Cool Index represents changes in the stock of space heating equipment, it is anticipated that the impact of prices will be long-term in nature. The Cool Index as defined Equation 11 above is then multiplied by a 10-year moving average of electric and gas prices. The level of the price impact is guided by the long-term price elasticities.

$$CoolIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \middle/ Eff_y^{Type}\right)}{\left(Sat_{15}^{Type} \middle/ Eff_{15}^{Type}\right)} \times$$
$$\left(TenYearMovingAverageElectric\,Price_{y,m}\right)^{\varphi} \times \left(TenYearMovingAverageGas\,Price_{y,m}\right)^{\gamma} \quad (13)$$

Since the trends in the Structural index, equipment saturations and efficiency levels are provided exogenously by the EIA, price impacts are introduced in a multiplicative form. The long-run change in the Cool Index represents a combination of adjustments to the structural integrity of new homes, saturations in equipment and efficiency levels. Without a detailed end-use model, it is not possible to isolate the price impact on any one of these concepts.

Cooling system usage levels are impacted on a monthly basis by several factors, including weather, household size, income levels, and prices. The estimates of cooling equipment usage levels are computed as follows:

$$CoolUse_{y,m} = \left(\frac{WgtCDD_{y,m}}{CDD_{15}}\right) \times \left(\frac{HHSize_y}{HHSize_{15}}\right)^{0.25} \times \left(\frac{Income_y}{Income_{15}}\right)^{0.20} \times \left(\frac{Elec\,Price_{y,m}}{Elec\,Price_{15}}\right)^{\lambda} \times \left(\frac{Gas\,Price_{y,m}}{Gas\,Price_{15}}\right)^{\kappa} \quad (14)$$

Where:

- $WgtCDD$ is the weighted number of cooling degree days in year (y) and month (m). This is constructed as the weighted sum of the current month's CDD and the prior month's CDD. The weights are 75% on the current month and 25% on the prior month.
- CDD is the annual cooling degree days for 2015.

By construction, the $CoolUse$ variable has an annual sum that is close to 1.0 in the base year (2015). The first two terms, which involve billing days and cooling degree days, serve to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will change to reflect changes in the economic driver changes.

Constructing XOther

Monthly estimates of non-weather sensitive sales can be derived in a similar fashion to space heating and cooling. Based on end-use concepts, other sales are driven by:

- Appliance and equipment saturation levels
- Appliance efficiency levels
- Average number of days in the billing cycle for each month
- Average household size, real income, and real prices

The explanatory variable for other uses is defined as follows:

$$XOther_{y,m} = OtherEqpIndex_{y,m} \times OtherUse_{y,m} \qquad (15)$$

The first term on the right-hand side of this expression ($OtherEqpIndex_y$) embodies information about appliance saturation and efficiency levels and monthly usage multipliers. The second term ($OtherUse$) captures the impact of changes in prices, income, household size, and number of billing-days on appliance utilization.

End-use indices are constructed in the SAE models. A separate end-use index is constructed for each end-use equipment type using the following function form.

$$ApplianceIndex_{y,m} = Weight^{Type} \times \frac{\left(Sat_y^{Type} \Big/ \frac{1}{UEC_y^{Type}} \right)}{\left(Sat_{15}^{Type} \Big/ \frac{1}{UEC_{15}^{Type}} \right)} \times MoMult_m^{Type} \times$$
$$(TenYearMovingAverageElectric\,Price)^{\lambda} \times$$
$$(TenYearMovingAverageGas\,Price)^{\kappa} \qquad (16)$$

Where:

- $Weight$ is the weight for each appliance type
- Sat represents the fraction of households, who own an appliance type
- $MoMult_m$ is a monthly multiplier for the appliance type in month (m)
- Eff is the average operating efficiency the appliance
- UEC is the unit energy consumption for appliances

This index combines information about trends in saturation levels and efficiency levels for the main appliance categories with monthly multipliers for lighting, water heating, and refrigeration.

The appliance saturation and efficiency trends data are presented on the Shares and Efficiencies tabs of the SAE spreadsheets.

Further monthly variation is introduced by multiplying by usage factors that cut across all end uses, constructed as follows:

$$ApplianceUse_{y,m} = \left(\frac{BDays_{y,m}}{30.44}\right) \times \left(\frac{HHSize_y}{HHSize_{15}}\right)^{0.46} \times \left(\frac{Income_y}{Income_{15}}\right)^{0.10} \times$$
$$\left(\frac{Elec\,Price_{y,m}}{Elec\,Price_{15}}\right)^{\varphi} \times \left(\frac{Gas\,Price_{y,m}}{Gas\,Price_{15}}\right)^{\lambda} \qquad (17)$$

The index for other uses is derived then by summing across the appliances:

$$OtherEqpIndex_{y,m} = \sum_k ApplianceIndex_{y,m} \times ApplianceUse_{y,m} \quad (18)$$

Supporting Spreadsheets and MetrixND Project Files

The SAE approach described above has been implemented for each of the nine Census Divisions. A mapping of states to Census Divisions is presented in Figure 17. This section describes the contents of each file and a procedure for customizing the files for specific utility data. A total of 18 files are provided. These files are listed in Table 3 and are now in xlsx Excel file format.

Figure 17: Mapping of States to Census Divisions

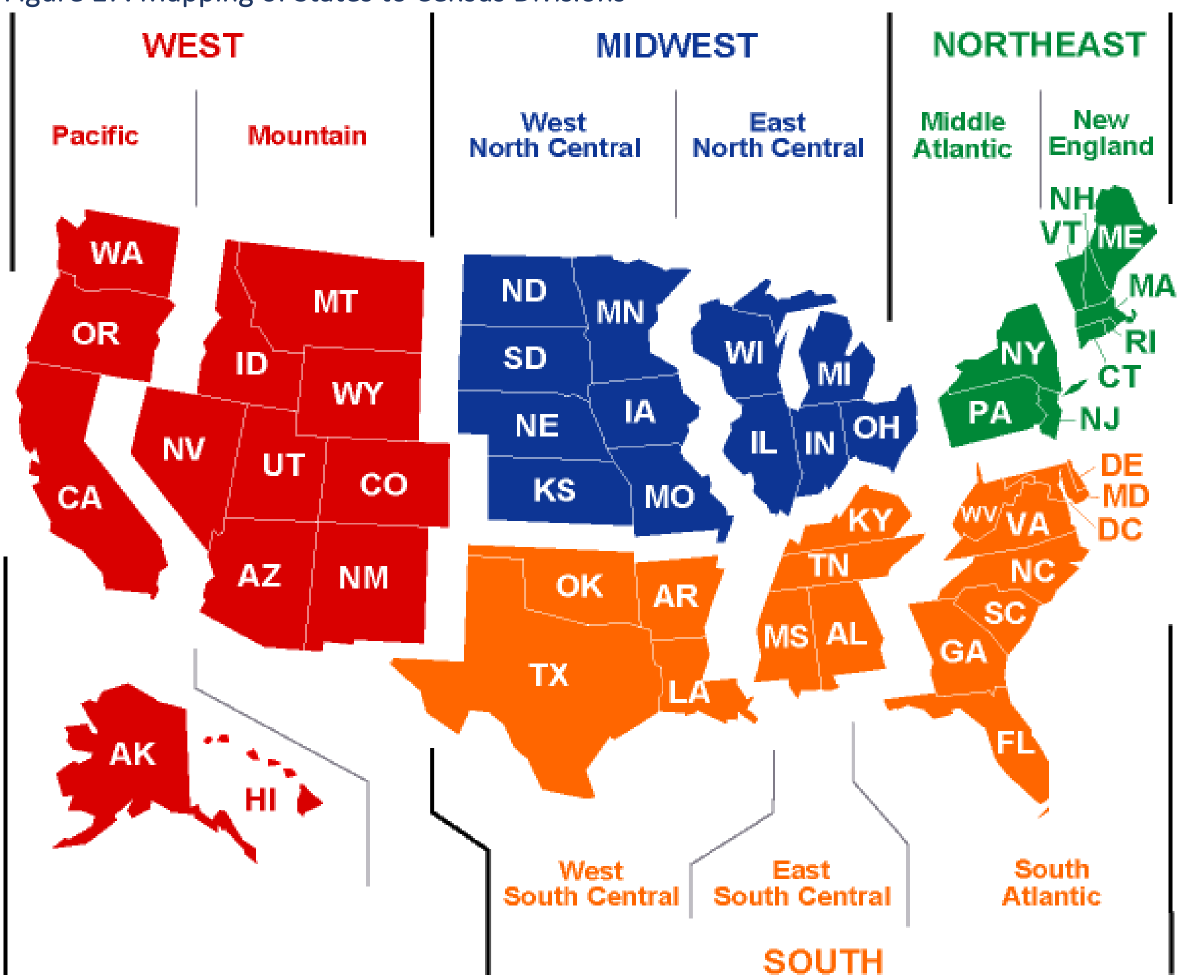


Table 3: List of SAE Files

Spreadsheet	MetrixND Project File
NewEngland.xlsx	SAE_NewEngland.ndm
MiddleAtlantic.xlsx	SAE_MiddleAtlantic.ndm
EastNorthCentral.xlsx	SAE_EastNorthCentral.ndm
WestNorthCentral.xlsx	SAE_WestNorthCentral.ndm
SouthAtlantic.xlsx	SAE_SouthAltantic.ndm
EastSouthCentral.xlsx	SAE_EastSouthCentral.ndm
WestSouthCentral.xlsx	SAE_WestSouthCentral.ndm
Mountain.xlsx	SAE_Mountain.ndm
Pacific.xlsx	SAE_Pacific.ndm

As defaults, the SAE spreadsheets include regional data, but utility data can be entered to generate the *Heat*, *Cool*, and *Other* equipment indices used in the SAE approach. The MetrixND project files link to the data in these spreadsheets. These project files calculate the end-use Usage variables are constructed and the estimated SAE models.

Each of the nine SAE spreadsheets contains the following tabs:

- **Definitions** contains equipment, end use, worksheet, and Census Division definitions.
- **Intensities** calculates the annual equipment indices.
- **Shares** contains historical and forecasted equipment shares. The default forecasted values are provided by the EIA. The raw EIA projections are provided on the *EIAData* tab.
- **Efficiencies** contains historical and forecasted equipment efficiency trends. The forecasted values are based on projections provided by the EIA. The raw EIA projections are provided on the *EIAData* tab.
- **StructuralVars** contains historical and forecasted square footage, number of households, building shell efficiency index, and calculation of structural variable. The forecasted values are based on projections provided by the EIA.
- **Calibration** contains calculations of the base year Intensity values used to weight the equipment indices.
- **EIAData** contains the raw forecasted data provided by the EIA.
- **MonthlyMults** contains monthly multipliers that are used to spread the annual equipment indices across the months.
- **EV** contains a worksheet for incorporating electric vehicle (EV) impacts.
- **PV** contains a worksheet for incorporating photovoltaic battery (PV) impacts.

The MetrixND Project files are linked to the A*nnualIndices*, *ShareUEC*, and *MonthlyMults* tabs in the spreadsheets. Sales, economic, price and weather information for the Census Division is provided in the linkless data table *UtilityData*. In this way, utility specific data and the equipment indices are brought into the project file. The MetrixND project files contain the objects described below.

Parameter Tables

- **Elas.** This parameter table includes the values of the elasticities used to calculate the Usage variables for each end-use. There are five types of elasticities included on this table.
  - Economic variable elasticities
  - Short-term own price elasticities
  - Short-term cross price elasticities
  - Long-term own price elasticities
  - Long-term cross price elasticities

The short-term price elasticities drive the end-use usage equations. The long-term price elasticities drive the Heat, Cool and other appliance indices. The combined price impact is an aggregation of the short and long-term price elasticities. As such, the long-term price elasticities are input as incremental price impact. That is, the long-term price elasticity is the difference between the overall price impact and the short-term price elasticity.

Data Tables

- **AnnualEquipmentIndices** links to the *AnnualIndices* tab for heating and cooling indices, and *ShareUEC* tab for water heating, lighting, and appliances in the SAE spreadsheet.
- **UtilityData** is a linkless data table that contains sales, price, economic and weather data specific to a given Census Division.
- **MonthlyMults** links to the corresponding tab in the SAE spreadsheet.

Transformation Tables

- **EconTrans** computes the average usage, and household size, household income, and price indices used in the usage equations.
- **WeatherTrans** computes the HDD and CDD indices used in the usage equations.
- **ResidentialVars** computes the *Heat*, *Cool* and *Other Usage* variables, as well as the *XHeat*, *XCool* and *XOther* variables that are used in the regression model.
- **BinaryVars** computes the calendar binary variables that could be required in the regression model.
- **AnnualFcst** computes the annual historical and forecast sales and annual change in sales.
- **EndUseFcst** computes the monthly sales forecasts by end uses.

Models

- **ResModel** is the Statistically Adjusted End-Use Model.

Steps to Customize the Files for Your Service Territory

The files that are distributed along with this document contain regional data. If you have more accurate data for your service territory, you are encouraged to tailor the spreadsheets with that information. This section describes the steps needed to customize the files.

Minimum Customization

- Save the MetrixND project file and the spreadsheet into the same folder
- Select the spreadsheet and MetrixND project file from the appropriate Census Division
- Open the spreadsheet and navigate to the *Calibration* tab
- In cell "B9", replace base year Census Division use-per-customer with observed use-per-customer for your service territory
- Save the spreadsheet and open the MetrixND project file
- Click on the *Update All Links* button on the *Menu* bar
- Review the model results

Further Customization of Starting Usage Levels

In addition to the minimum steps listed above, you can also utilize model-based calibration process described previously to further fine-tune starting year usage estimates to your service territory.

Customizing the End-use Share Paths

You can also install your own share history and forecasts. To do this, navigate to the *Share* tab in the spreadsheet and paste in the values for your region. Make sure that base year shares on the *Calibration* tab reflect changes on the *Shares* tab.

Customizing the End-use Efficiency Paths

Finally, you can override the end-use efficiency paths that are contained on the *Efficiencies* tab of the spreadsheet.

Exhibit TAJ-3

Information in the exhibit is confidential and proprietary and is provided under seal pursuant to a petition for confidential protection. In addition, portions of the exhibit are voluminous and are provided pursuant to a motion to deviate.