GREAT RIVER ENERGY

APPENDIX C

Advance Forecasts

2023-2037 INTEGRATED RESOURCE PLAN

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Great River Energy 2023 IRP Forecast

Submitted to:
Great River Energy

Prepared by:

10875 Rancho Bernardo Road
Suite 200
San Diego, CA 92127
www.itron.com/forecasting

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EXECUTIVE SUMMARY

In 2023, Great River Energy (GRE) developed the demand forecast for use in its 2023 Integrated Resource Plan (IRP) filing. This report presents an overview of the forecasting approach, a description of the forecast models, and forecast results. Detailed information about the forecast models, calibration method, and results may be viewed in the MetrixND and MetrixLT project files.

The forecast is developed using the three main modeling processes summarized below.

- **All Requirements Forecast.** The forecast begins with developing the long-term sales forecast for GRE's All Requirements (AR) cooperatives. This forecast combines three modelling processes. First, the monthly class sales forecast is developed by modelling individual class sales and combining the results into the monthly AR system forecast. Second, the AR system peak forecast is developed by modelling the AR monthly peaks. Third, the AR system shape forecast is developed by modelling the AR system hourly load shape. The three forecasts are combined by calibrating the system shape forecast to the monthly sales and peak forecasts. The result of this process is the hourly forecast for AR cooperatives**.**
- **Fixed Member and Other Adjustments**. After the AR hourly forecast is complete, it is adjusted to include the hourly impacts of Fixed Members, Harvestone, Alliant, and transmission losses. For each adjustment, hourly shapes are calibrated to the monthly or annual energy forecasts to create the hourly forecasts.
- **Electric vehicles and Photovoltaics.** Finally, the forecast is adjusted for two major uncertainties - electric vehicles (EV) and behind-the-meter photovoltaics (PV). For EVs and PVs, hourly shapes are calibrated to monthly forecasts to create the hourly forecasts.

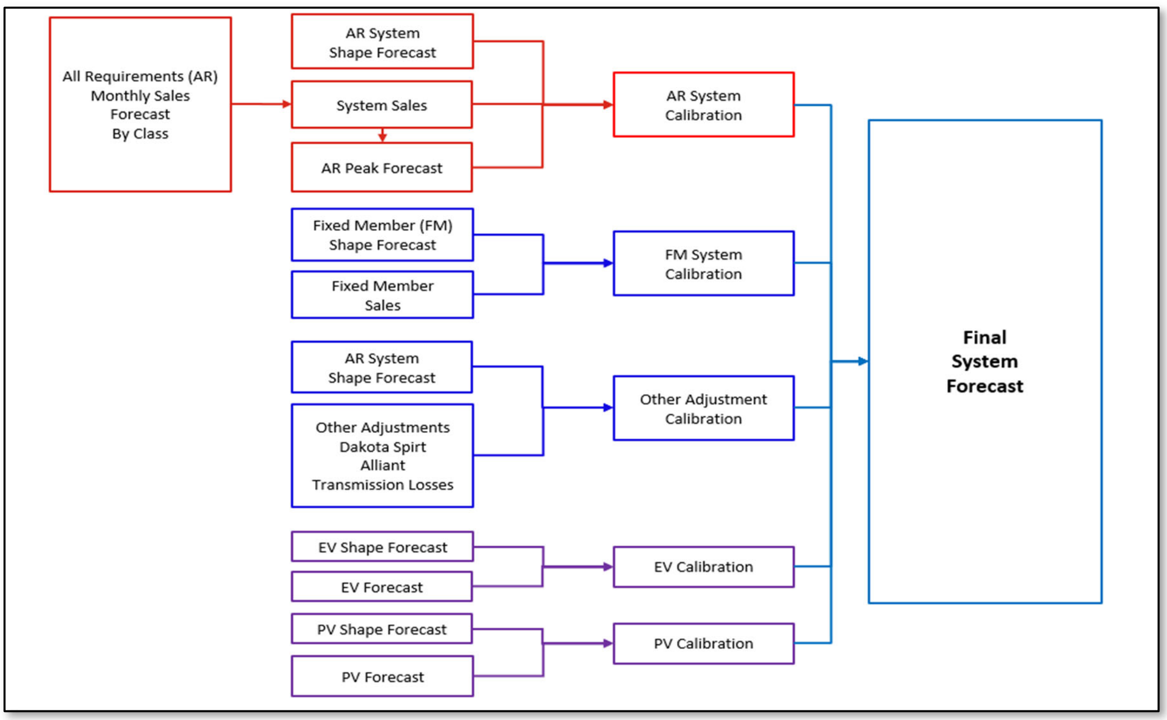
The three main modeling results are combined to create the base GRE system hourly forecast. The hourly load forecast captures the impact of economic drivers, weather, and load shapes.

After the base forecast is completed, the modeling framework is applied to high and low economic scenarios and extreme and mild weather scenarios. The scenarios create reasonable planning bound for the long-term plan.

1 FORECAST METHOD

The 2023 IRP forecast extends from January 2023 through December 2038. The forecast is developed in three phases. First, the All Requirements (AR) cooperative hourly forecast is developed based on class monthly sales and the AR system load data. Second, the Fixed Member (FM) cooperative hourly forecasts and other major adjustment forecasts are developed based on known obligations. Finally, external forecasts for electric vehicles (EV) and behind-the-meter photovoltaics (PV) are created. The hourly results from these three phases are aggregated to create the final hourly system forecast. The general forecast process is shown in Figure 1.

FIGURE 1: FORECAST OVERVIEW



This section summarizes the steps involved in each phase.

1.1 PHASE 1. ALL REQUIREMENTS FORECAST

The AR forecast is developed by combining three forecasts. First, the monthly class sales forecast is developed by modelling individual class sales and combining the results into the monthly AR system forecast. Second, the AR system peak forecast is developed by modelling the AR monthly peaks. Third, the AR system shape forecast is developed by modelling the AR hourly load shape. The three forecasts are combined by calibrating the system shape forecast to the monthly sales and peak forecasts. The AR forecasts consists of forecasts for the following cooperatives.

- Arrowhead Electric Cooperative
- Benco Electric Cooperative

- Brown County Rural Electric Association
- Connexus Energy
- Cooperative Light and Power
- Dakota Electric Association
- East Central Energy
- Goodhue County Cooperative Electric Association
- Itasca-Mantrap Cooperative Electrical Association
- Kandiyohi Power cooperative
- Lake County Power
- Lake Region Electric Cooperative
- McLeod Cooperative Power Association
- Mille Lacs Energy Cooperative
- North Itasca Electric cooperative
- Nobles Cooperative Electric
- Runestone Electric Association
- Stearns Electric Association
- Steele-Waseca Cooperative Electric
- Todd-Wadena Electric Cooperative

1.1.1 AR Monthly Class Sales Forecast

This section describes the method used for each class forecast and their key assumptions. For each class, the monthly sales forecast is developed using an econometric or a Statistically Adjusted End-Use (SAE) model. The class models are described in Sections 4.1 through 4.9 . The modelled classes are defined using the AR cooperatives' Form 7 data which divides their sales into the following classes. Form 7 data is complete for all AR cooperatives through December 2021.

- Residential
- Seasonal
- Irrigation
- Small Commercial
- Large Commercial
- Street and Highway
- Public Authority
- Resale
- Own Use

Once the class forecasts are complete, the class forecasts are summed together for the system sales forecast.

The key drivers in the monthly sales models include weather data, economic data, and SAE data. The weather data is obtained from The Weather Company (WSI). The economic data are obtained from Woods and Poole Inc. (Woods and Poole), and the SAE data are obtained from Itron Inc (Itron). The driver data and their derivations are described below.

Monthly Weather Forecast

Hourly weather for Alexandria (AXN), Hibbing (HIB), Mason City (MCW), and Minneapolis (MSP) from January 1, 1992, through December 31, 2021, are acquired from WSI by GRE. These data are converted to monthly weather and used to calculate the normal weather forecast. The following steps are used to develop the weather data for each station.

1. **Daily Average Temperature**. Calculate daily average temperatures from the original hourly temperatures. The daily average temperature is the average of the 24-hourly values.
2. **Daily HDD and CDD**. Daily heating and cooling degree days (HDD and CDD) are calculated using different temperature reference points (i.e., 50, 55, 60, 65 degrees) and the daily average temperature.
3. **Monthly HDD and CDD**. Monthly HDDs and CDDs are calculated by summing the daily HDD and CDD values over the calendar month. Monthly HDDs and CDDs are used to estimate the sales models.
4. **Normal Monthly HDD and CDD**. Normal monthly HDDs and CDDs are calculated by averaging historical monthly HDDs and CDDs from 1992 through 2021. The Normal HDDs and CDDs are 30-year normal values.

System weather is the weighted average of the 4 weather stations. The weights are determined using a screening model to identify the relative power of each weather station. The screening model is a neural network model estimated with daily data from August 2016 through December 2021. As an output, the neural network produces weather slopes for each station as first order derivatives. The weather station weights are calculated using the first order derivatives. Table 1 shows the weather stations weights.

TABLE 1: WEATHER STATION WEIGHTS

Weather Station	Weight
AXN	13%
HIB	15%
MCW	2%
MSP	70%

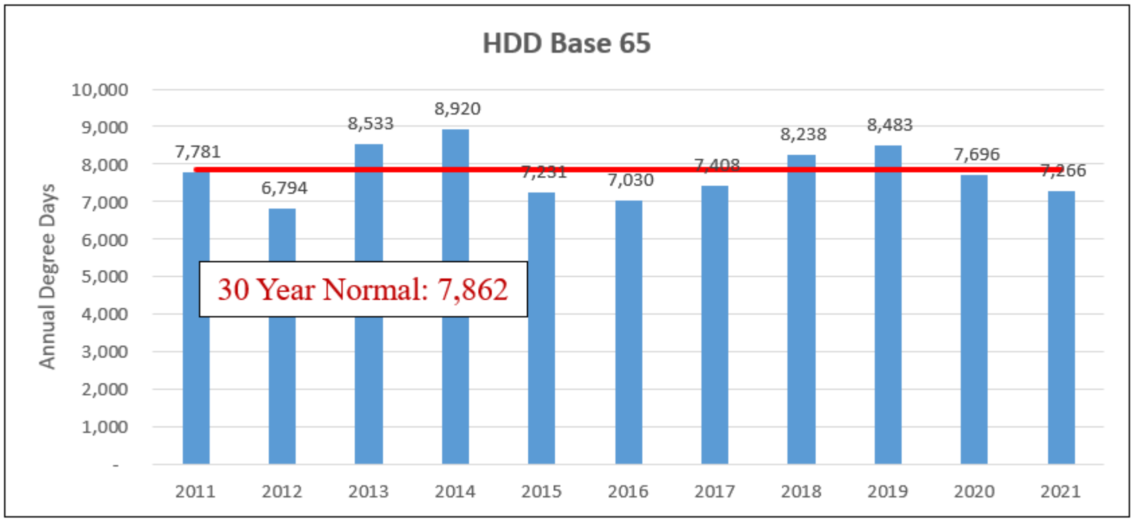
Within several models, multipart splines variables are used to model the non-linear response between sales and weather. Multipart splines variables weight together HDD and CDD variables with different temperature reference points into aggregate variables to avoid multicollinearity. The weights are developed using a system energy regression model estimated with daily data from January 2017 through December 2021. The relative sizes of the HDD and CDD coefficients are used to develop the weighting scheme. Table 2 shows the weighting scheme. These weights show that the heating slope begins at 55 degrees and accelerates at 45 degrees. Similarly, the cooling slope begins at 60 degrees and accelerates through 70 degrees. The cooling slope declines at 80 degrees capturing the cooling saturation effect.

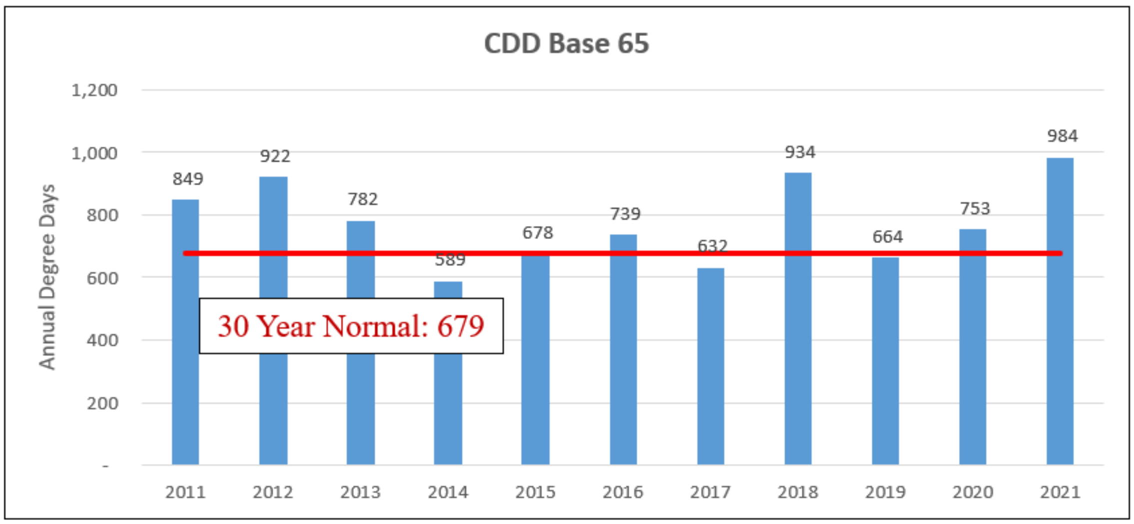
TABLE 2: WEIGHTED HDD AND CDD SPLINES

Variable	Spline	Weight
WtHDD	HDD Base 55 Degrees	78%
	HDD Base 45 Degrees	22%
WtCDD	CDD Base 60 Degrees	16%
	CDD Base 65 Degrees	49%
	CDD Base 70 Degrees	35%
	CDD Base 80 Degrees	-26%

The final system monthly weather contains both historical and normal HDD and CDD variables representing different temperature reference points and the weighted HDD and CDD results. Figure 2 compares the recent historical (2011-2021) and normal (30-year average) wether results. This figure shows the HDD and CDD data with a temperature reference point of 65 degrees aggregated to annual values.

FIGURE 2: NORMAL HDD AND CDD COMPARISON





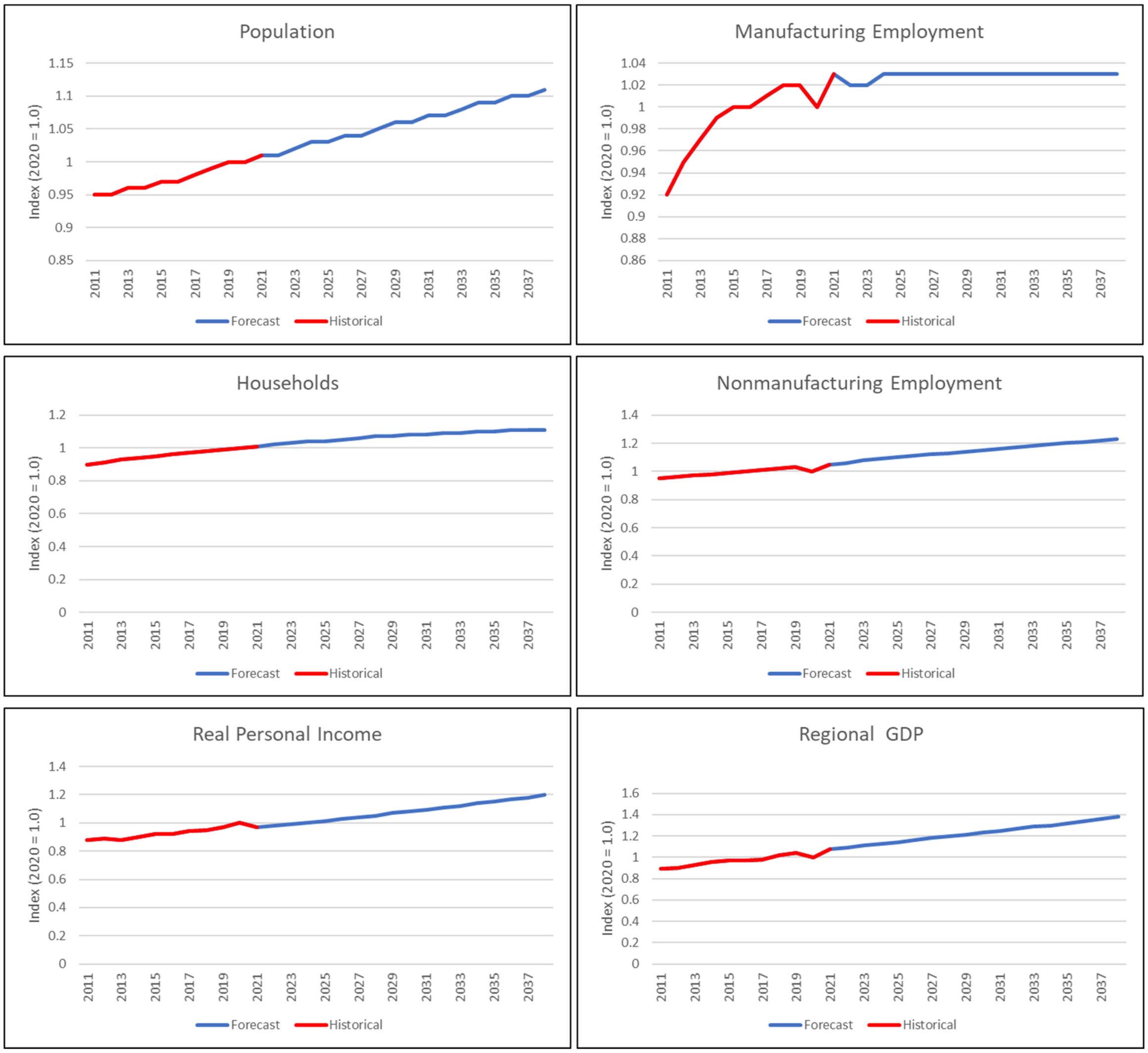
Economic Forecast

The economic forecast is a primary driver of long-term growth in the class sales forecast. The economic forecast is obtained from Woods and Poole and reflects the economic conditions as of May 2021. The economic data contains annual county-level data for multiple economic concepts. Woods and Poole largely viewed COVID to have short term impacts to the forecast and only showed minimum impacts to the long-term forecast. For the monthly sales forecast, the following economic concepts are used.

- Population
- Households
- Income
- Manufacturing Employment
- Nonmanufacturing Employment
- GDP

System economic data is developed by summing cooperative-level economic data. Cooperative economic data is developed by summing together a portion of the county data that are served by each cooperative. The portion of a county served by a cooperative is calculated using the ratio of 2021 residential customers in a county to 2021 households in the county. Figure 3 shows the historical and forecast economic data for the primary drivers used in the sales models. These data are converted to 1.0 based indices for comparative purposes.

FIGURE 3: ECONOMIC DRIVERS



End Use Data

The SAE data captures energy efficiency changes for residential and commercial end-uses. The SAE data are provided by Itron and based on the Energy Information Administration's (EIA) 2021 Annual Energy Outlook (AEO). The SAE data are applied to the residential, seasonal, small commercial, and large commercial class average use models.

The SAE data are detailed end-use data derived from the EIA forecast for the northwest central census region and used to construct end-use intensities (kWh per household or kWh per square foot) that are then integrated into monthly heating, cooling, and base load model variables. These variables are then used to forecast residential and commercial sales using linear regression models. Using the constructed model variables, the forecast captures improvements in end-use efficiency driven by new standards, declining cost of high efficiency technology options, and availability of new end-use technologies.

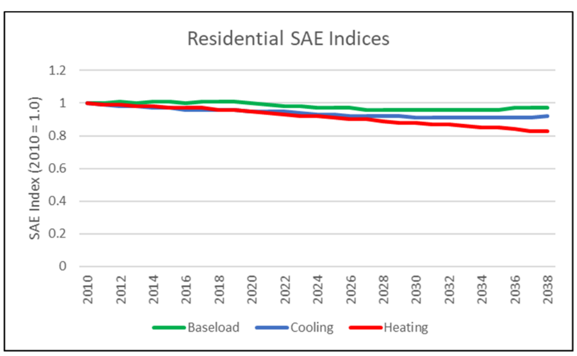
Table 3 shows the end-uses that are represented in the SAE data.

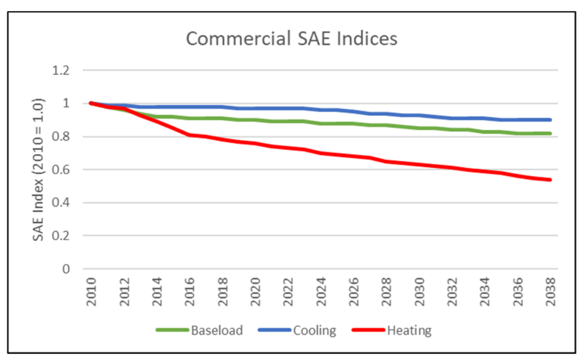
TABLE 3: SAE DATA: END USES

Residential	Commercial
• Resistance heating/furnaces • Air-source heat pumps (heating) • Ground-source heat pumps (heating) • Secondary heating • Central air conditioning • Air-source heat pumps (cooling) • Ground-source heat pumps (cooling) • Room air conditioning • Water heating • Cooking • 1st & 2nd refrigerators • Freezers • Dishwashers • Clothes washers • Clothes dryers • TVs and related equipment • Furnace fans • Lighting • Miscellaneous	• Heating • Cooling • Ventilation • Water Heating • Cooking • Refrigeration • Lighting • Office Equipment • Miscellaneous

Figure 4 shows in the SAE data derived from the EIA's 2021 AEO converted to 1.0 based indices for comparative purposes. Generally, these indices capture a downward trend representing the improving energy efficiency of end-uses through adopted codes and standards.

FIGURE 4: SAE DRIVER DATA

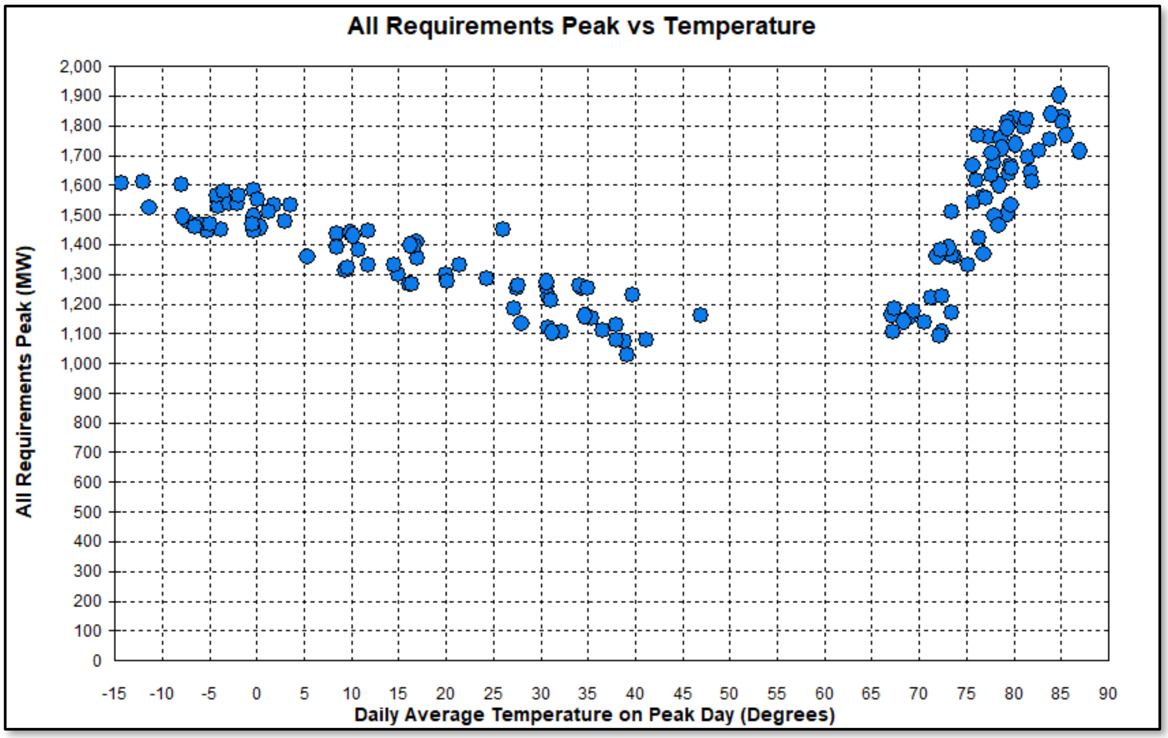




1.1.2 AR Peak Forecast

The monthly system peak forecast uses an econometric model based on historical monthly peak day events from January 2011 through December 2022. The historical dataset is obtained from the historical system weather data and the AR hourly system loads. Figure 5 shows the historical system monthly peaks plotted against the daily average temperature on the monthly peak day. This figure shows strong linear relationships between the monthly peaks and their peak producing weather.

FIGURE 5: HISTORICAL AR PEAKS AND TEMPERATURE



The peak model is described in Section 4.10 . The peak model consists of two main drivers: sales and weather. The next sections describe the main drivers of the peak model.

Sales Forecast

Historical and forecast sales drivers are obtained from the monthly class modelling process as described in Section 1.1.1 . The sales forecast is decomposed into heating, cooling, and baseload components based on the sales models' coefficients. By using the forecast sales, the peak model captures the changing impact of energy efficiency and the growth from the economic forecast.

Peak Weather Forecast

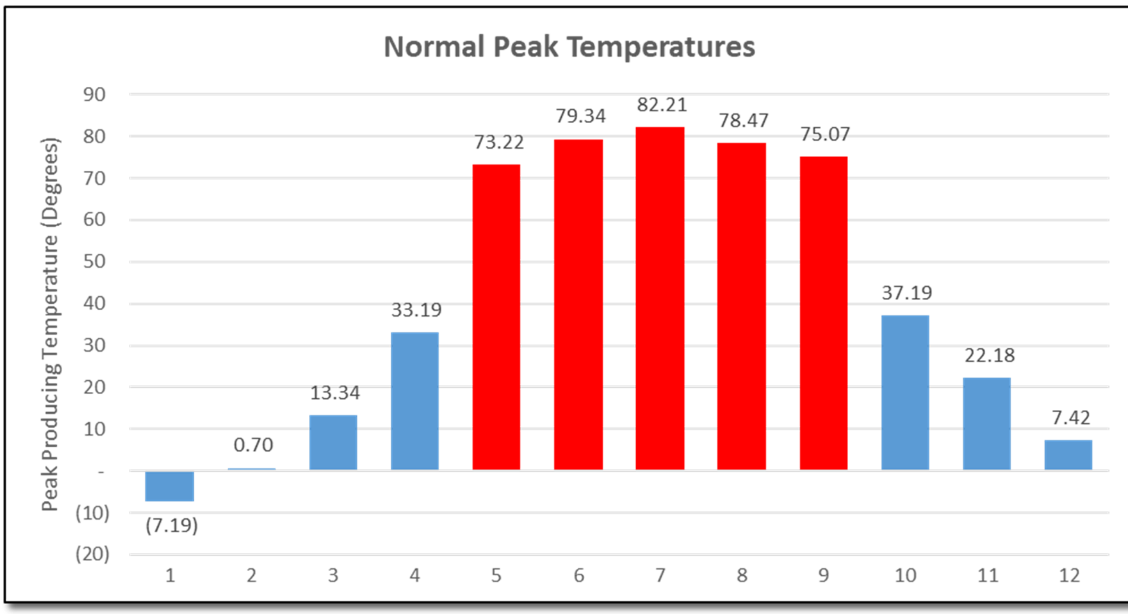
The peak weather forecast (normal peak weather) is obtained by averaging the monthly peak producing weather at the time of the monthly system peak. The following steps are used to develop the normal peak weather.

1. **Monthly Peak Weather Conditions**. Identify the daily average temperature on the monthly peaks from 2003 through 2021.

2. **Normal Monthly Peak Weather**. The normal peak weather is the average of historical peak weather conditions over the prior 19 years (2003-2021). For example, the March peak weather is the average of the 19 historical March peak producing temperatures.
3. **Correct Shoulder Month Weather**. Shoulder month peaks may be driven by hot or cold weather. For instance, April peaks are driven by hot weather in 2 of the 19 historical years. For normal peak weather in April, May and October, the normal weather is modified by removing historical years from the average that do not match the primary weather effect. In April, the predominate peak weather effect is heating. As a result, the cooling peak weather is removed from the April normal weather calculation. May is designated as a cooling month, and October is designated as a heating month.
4. **Correct Seasonal Peak**. Because January and July are considered the seasonal peaks, their normal values are replaced using the seasonal peak averages. The seasonal peaks are the historical average of the temperatures on the seasonal annual peaks.

Figure 6 shows the normal peak temperatures for each month. The summer peak temperatures are shown in red represent peaks driven by hot weather. The winter peak temperatures are shown in blue and represent peaks driven by cold weather.

FIGURE 6: NORMAL PEAK TEMPERATURES



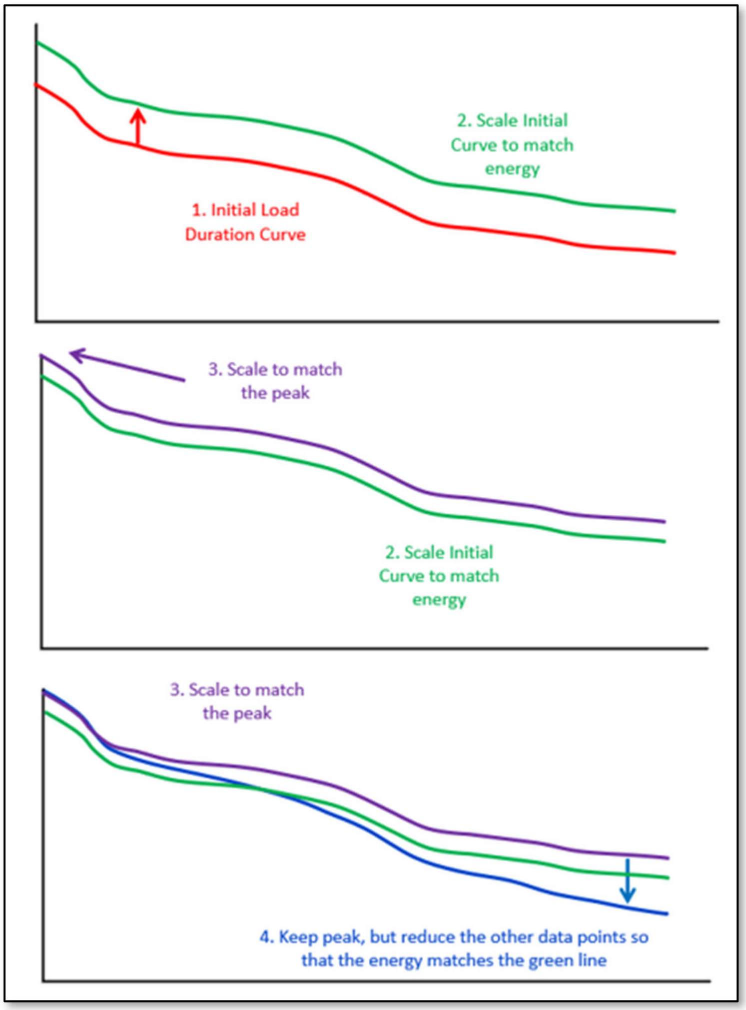
1.1.3 AR Hourly Load Forecast

The AR hourly load forecast is developed by calibrating the AR hourly load shape forecast to the AR sales forecast (Section 1.1.1) and AR peak forecast (Section 1.1.2). Section 4.11 describes the hourly shape model used to develop the hourly shape forecast. The calibration process is performed in MetrixLT and ensures that hourly load shape contains the same total monthly sales as the sales forecast and the same monthly peak as the peak forecast. This section summarizes the calibration process and the hourly shape forecast drivers.

Calibration Process

Figure 7 illustrates the calibration process steps performed in MetrixLT. In this figure, the hourly load shape forecast is converted into a monthly load duration curve (step 1). In the second step, initial load duration curve is scaled to match the monthly energy (or sales) value. In the third step, the load duration curve is again scaled to ensure that the curve's peak value matches the monthly peak value. In the last step (step 4), the curve is rotated to retain the peak value and reduce the energy back to the monthly energy value. After this process is complete, load duration curve is mapped back to the original calendar.

FIGURE 7: CALIBRATION PROCESS

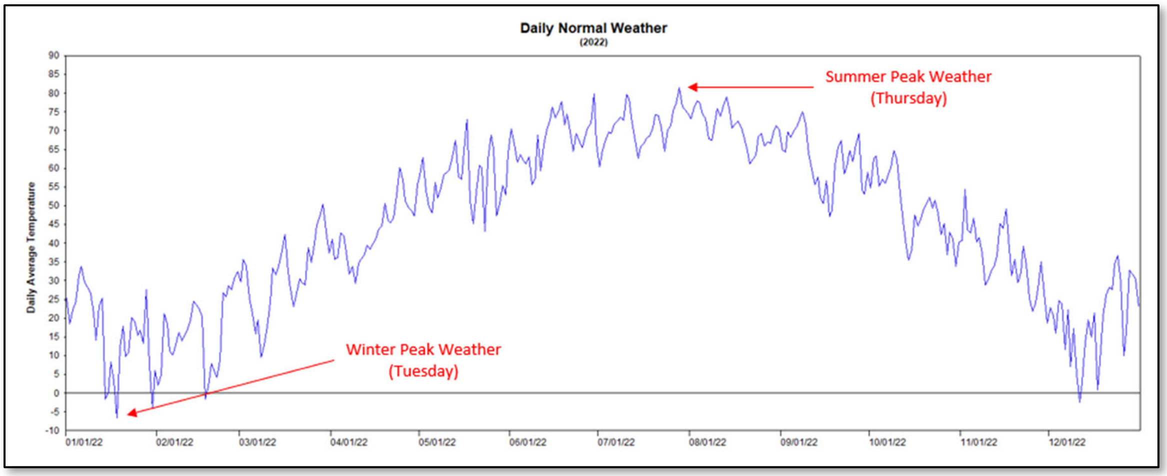


Historical Shape Model Drivers

The hourly shape model is designed to capture the recent AR hourly load shape. The AR hourly shape is based on the sum of the hourly AR cooperative data and daily weather. Historical daily weather development is described in Section 1.1.1 . Normal daily weather is developed using a rank-and-average method.

The rank-and-average method ensures that forecast normal daily weather retains a realistic weather pattern that can produce monthly peaks and still represent average energy. The normal daily weather is calculated using 30 years (1992-2021) of historical system daily average temperatures mapped to the 2007 historical weather year and rotated to ensure that January peak weather occurs on a Tuesday and July peak weather occurs on a Thursday. Figure 8 shows the daily normal weather for 2022.

FIGURE 8: DAILY NORMAL WEATHER



1.2 PHASE 2. FIXED MEMBER AND ADJUSTMENTS FORECASTS

In Phase 2, external adjustments are developed to account for fixed obligations and losses. Four adjustment forecasts are developed which are combined with the hourly AR load forecast. The four adjustments are listed below.

- Fixed Member Forecast
- Dakota Spirit Ag Forecast
- Alliant Load Southern Cooperative Forecast
- Transmission Losses

For each adjustment, an hourly load forecast is developed using an energy forecast, a peak forecast (if available), and an hourly shape forecast. The hourly forecast is created by calibrating the hourly shape forecast to the energy and peak forecasts using the calibration process described in Section 1.1.3 . By developing hourly shape forecasts, each adjustment captures the coincident peak impacts with the hourly AR load forecast. Each adjustment is described in this section.

1.2.1 Fixed Member Requirements

Eight of GRE's 28 cooperative members entered into long-term power purchase agreements that purchase a fixed amount of their energy and capacity from GRE. These cooperatives are the Fixed Member (FM) cooperatives, and they are listed below.

- Agralite Electric Cooperative
- Crow Wing Power
- Federated Rural Electric Association
- Meeker Cooperative Light & Power Association
- Minnesota Valley Electric Association
- Redwood Electric Association
- South Central Electric Association
- Wright Hennepin Cooperative Electric Association

The hourly FM forecast is developed by calibrating the FM hourly load shape forecast to the FM sales forecast. The calibration process is described in Section 1.1.3 and ensures that the FM monthly coincident peaks align with the AR hourly load forecast.

FM Sales Forecast

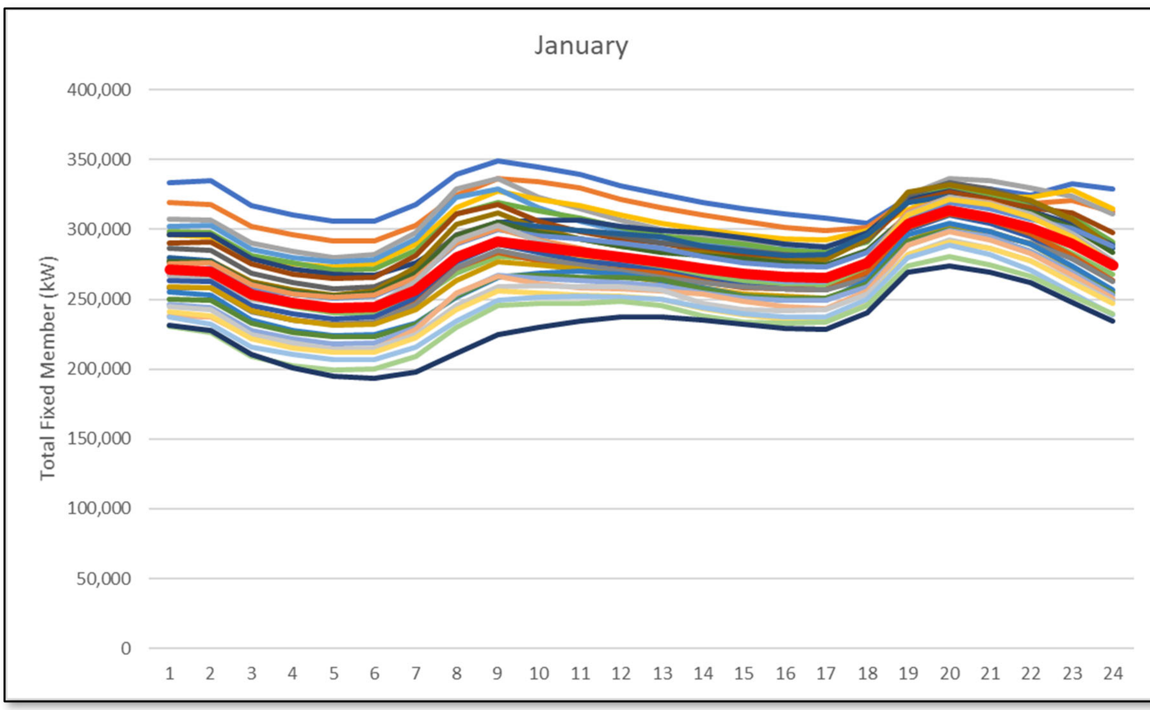
The FM sales forecast is based on GRE's contractual obligation to the FM cooperatives. GRE's total FM sales obligation is approximately 1,506 GWh per year.

FM Hourly Load Shape Forecast

The FM shape forecast is based on the hourly contractual obligations for each cooperative. Because each cooperative may schedule their hourly load profile on a daily basis, GRE finds that it is impossible to predict their daily decisions. Instead of forecasting the cooperatives' daily decisions, the forecast shape is calculated as the average monthly shape.

The average monthly shape represents the expected value of the daily decisions over a calendar month. Because most daily shapes show a similar pattern, the average shape is a reasonable approximation of the hourly impact. Figure 9 illustrates the possible daily shapes for January. In this figure, each line represents the 31 possible daily shapes in January. The bold red line is the average of the 31 daily shapes.

FIGURE 9: FM DAILY SHAPES FOR JANUARY



1.2.2 Harvestone Forecast

Harvestone (formerly Dakota Spirit AgEnergy) biorefinery began commercial operation in 2015 and produces ethanol, modified distillers' grains, corn oil, and E85. Harvestone is not forecast within the AR or FM cooperative forecasts and is included as a separate forecast item. The sales forecast is developed from historical consumption patterns with an econometric model.

The hourly Harvestone forecast is developed by calibrating the AR hourly load shape forecast to the Harvestone sales forecast. The calibration process is described in Section 1.1.3 and produces a coincident peak forecast consistent with the AR system shape. The Harvestone forecast is approximately 41 GWh per year with a coincident peak of 6 MW.

1.2.3 Alliant Load Southern Cooperative Forecast

The Alliant Load Southern Cooperative (Alliant) forecast consists of additional load that will be served by five AR cooperative members beginning in 2025. The additional load requirement results from the formation of the Southern Minnesota Electrical Cooperative (SMEC). SMEC is formed by 12 electric distribution cooperatives as the single point of contact for the purchase of electric service in southern Minnesota from Alliant Energy. Five of the 12 distribution cooperatives are AR members of GRE. At the end of 2024, a supply agreement with Alliant Energy will be terminated and five All Requirement Members in SMEC will be required to serve this load.

The hourly Alliant forecast is developed by calibrating the AR hourly load shape forecast to the Alliant sales forecast. The sales forecast is developed using historical consumption patterns and econometric modeling. The calibration process is described in Section 1.1.3 and produces a coincident peak forecast consistent with the AR system shape. The Alliant forecast is approximately 112 GWh per year with a coincident peak of 21 MW.

1.2.4 Transmission Losses

Transformation and transmission losses associated with AR members, FM members, Dakota, and Alliant are added to the final load forecast. The losses are assumed to be 4.5%. Table 4 shows the loss additions.

TABLE 4: TRANSMISSION LOSSES

Year	MWh	MW
2023	525,240	104
2024	527,872	105
2025	534,899	106
2026	536,774	107
2027	538,938	107
2028	541,699	108
2029	543,136	108
2030	544,747	109
2031	546,480	109
2032	549,015	110
2033	550,429	110
2034	552,599	111
2035	554,749	111
2036	557,627	112
2037	559,308	112
2038	561,822	112

The hourly loss forecast is developed by calibrating the AR hourly load shape forecast to the energy loss and peak loss forecast. The calibration process is described in Section 1.1.3 and produces a coincident peak forecast consistent with the AR system shape.

1.3 PHASE 3. EV AND PV FORECASTS

Currently, the electric industry is undergoing a transformation with the introduction of new technologies. Electric vehicles (EV) are likely to significantly contribute to future electric growth. Conversely, the growing adoption of behind-the-meter photovoltaics (PV) will likely reduce demand for energy. Because these technologies are nascent in the GRE service territory and cannot be reliability forecast within the existing cooperative model structure, external forecasts of EVs and PVs are incorporated into the forecast.

There are two advantages to including EV and PV forecasts externally. First, the high level of uncertainty associated with these technologies allows for creating alternative scenarios without changing the underlying system growth factors. Second, the load profiles for these technologies are substantially different than the current system. Using an external forecasting process accounts for these load shapes which may alter the time of system peak.

Phase 3 forecasts feature hourly impacts of EV and PVs. This section describes these forecasts.

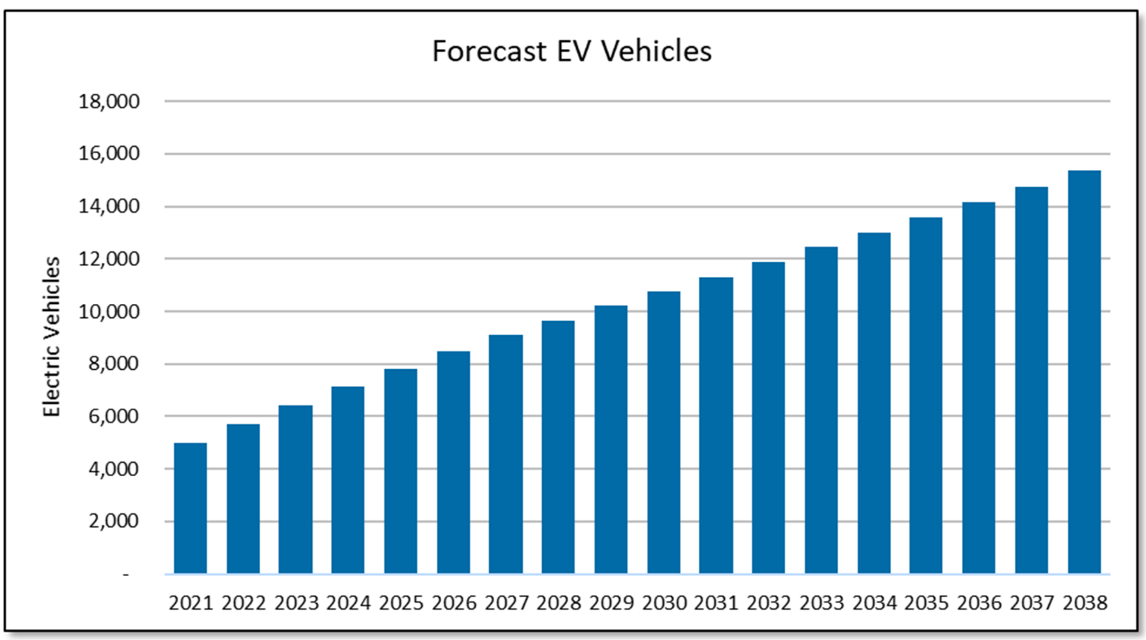
1.3.1 EV Model

The hourly EV forecast is developed based on an annual sales forecast of EV sales and an hourly charging profile. The hourly forecast is developed by calibrating the hourly charging profile to the EV sales forecast using the calibration process is described in Section 1.1.3 .

EV Sales Forecast

The EV sales forecast is based on the estimated number of electric vehicles in GRE's service territory and the EIA's EV growth rate. In 2021, GRE estimates that 9,972 EVs (i.e., battery and plug-in hybrid vehicles) exist in the service territory. The forecast increases the EV count using the EIA's 2021 AEO forecast for electric (and plug-in hybrid) light-duty vehicle stock. Figure 10 shows the number of EV forecast. In this figure, GRE expects 15,362 EVs in 2038 representing approximately 3.1% of residential customers (EV/Residential Customers).

FIGURE 10: ELECTRIC VEHICLE FORECAST

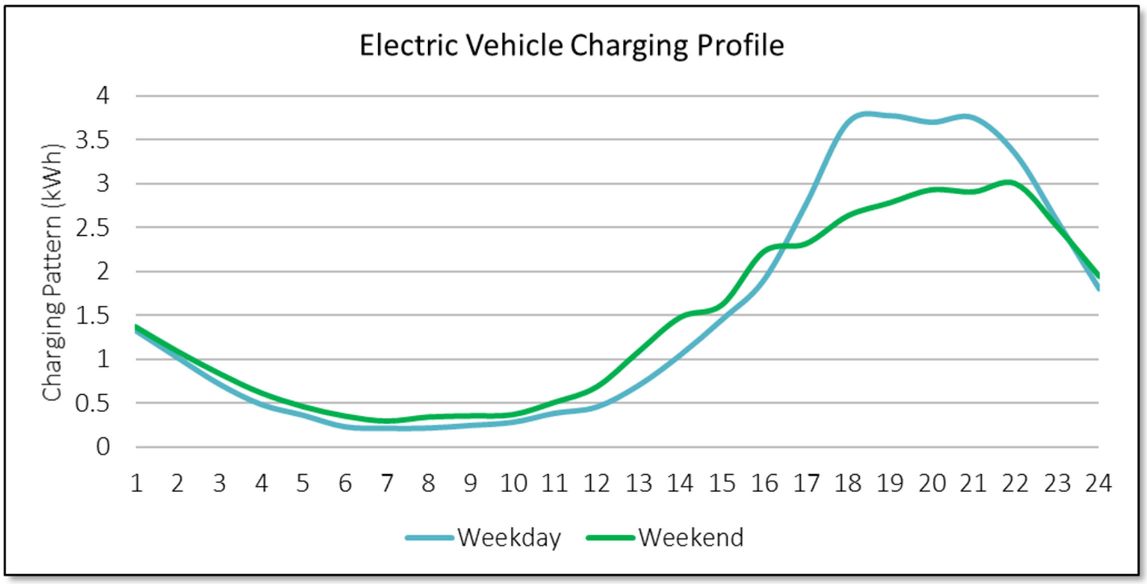


The EV electric sales forecast is calculated by converting the number of vehicles forecast to energy. The conversion assumes 35 miles driven per day with an average vehicle efficiency for SUVs and sedans.

EV Charging Profile

While charging patterns for mass market adoption of EVs are largely unknown, several studies estimate charging patterns based on early adoption, rate incentives and commuter work hours. To develop the hourly EV forecast, estimated hourly charging profiles based on the National Renewable Energy Laboratory EVI-Pro Lite tool are utilized. The load profiles are based on 2021 data, sedans and average temperatures. Figure 11 shows the charging profiles separated into weekday and weekend patterns. As expected, most EV charging is assumed to occur after commuting hours.

FIGURE 11: ELECTRIC VEHICLE CHARGING PROFILE



1.3.2 PV Model

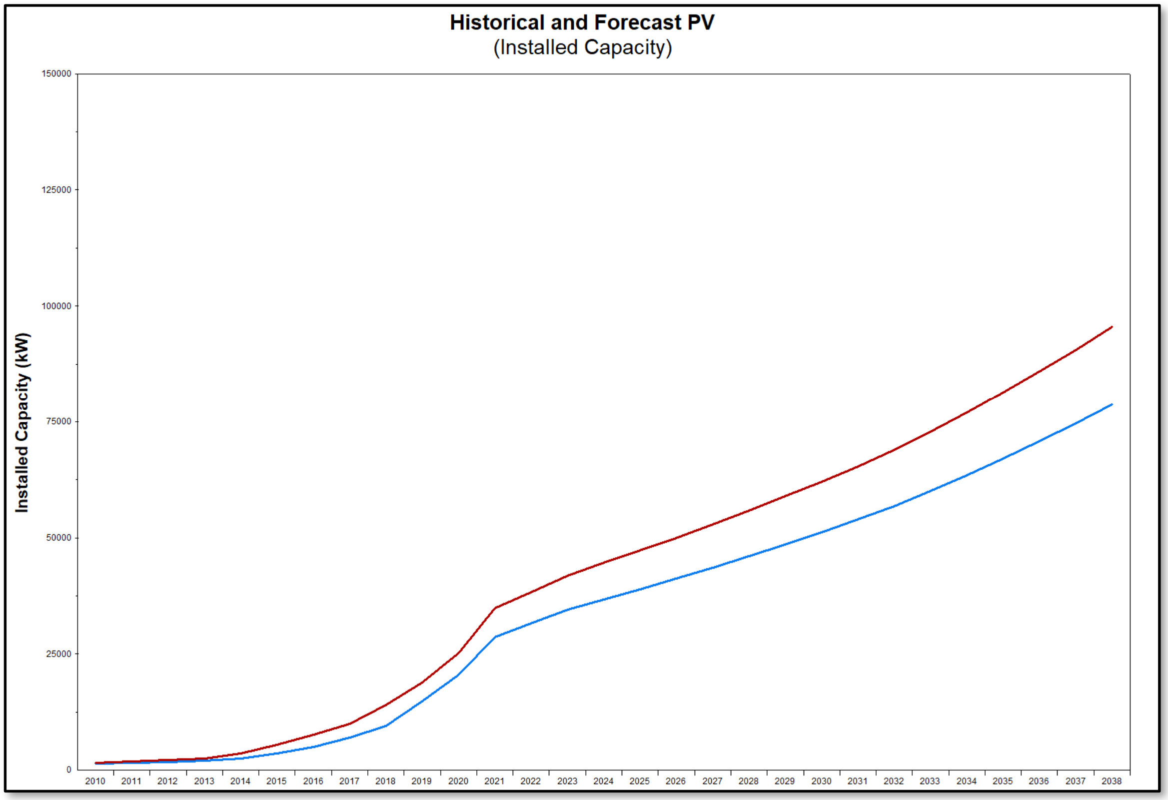
The hourly PV forecast is developed based on monthly generation forecast of behind-the-meter solar and an hourly generation profile. The hourly forecast is developed by calibrating the hourly generation profile to the monthly PV generation forecast using the calibration process as described in Section 1.1.3 .

PV Generation Forecast

The monthly PV generation forecast is developed from an annual installed PV capacity forecast converted to monthly generation.

The annual installed capacity forecast is based on the current cumulative installed capacity and the EIA's AEO national solar growth rates. In 2021, the total installed capacity for GRE cooperatives is 34,809 kW based on the Minnesota Department of Commerce Distributed Generation Interconnection Reports. Of the installed capacity, 28,700 kW are residential systems, and 6,109 kW are non-residential systems. The forecast applies the EIA's AEO solar generation growth rate forecast to the 2021 installed capacity. The residential and non-residential PV forecast applies the EIA's 2021 AEO growth rates. Figure 12 shows the installed PV capacity forecast.

FIGURE 12: PV FORECAST

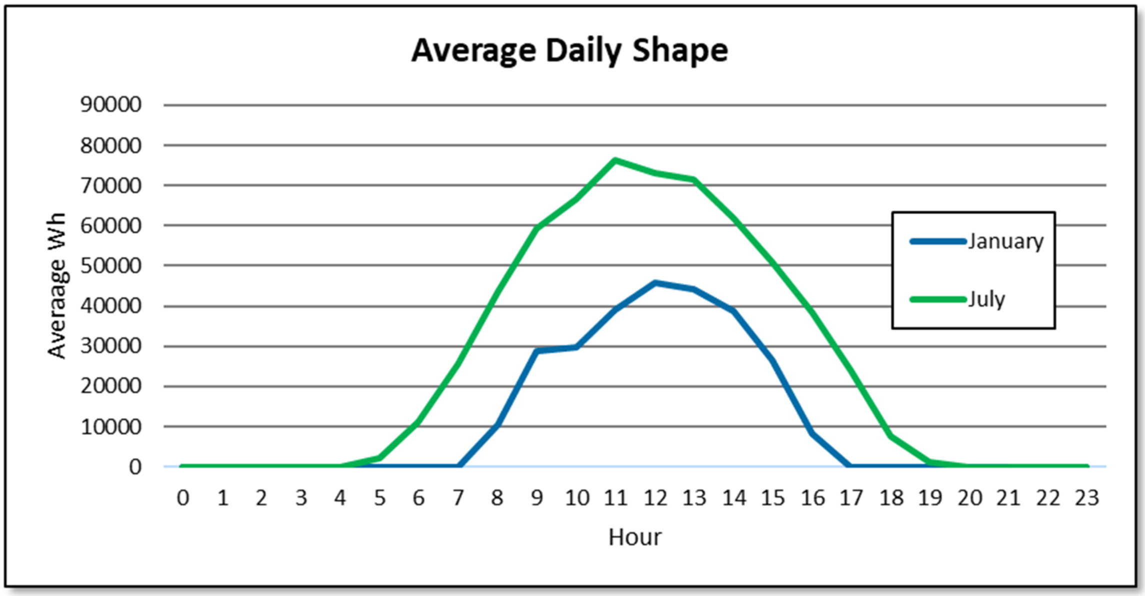


The annual installed capacity is converted to monthly generation using the hourly profile estimated from National Renewable Energy Laboratory's (NREL) PVWatts Calculator. The NREL data calculates hypothetical monthly generation for a 4 kWh system in St. Cloud, MN with an annual capacity factor of 14.9%.

PV Generation Profile

For long-term forecasting hourly solar generation profiles are predictable based on the sunrise and sunset times of the year. Using the NREL data, average monthly generation profiles are used to capture the expected value of generation in each month. The monthly profiles allow the generation pattern to change through the year without trying to predict nuanced impact of cloud cover changes. Figure 13 illustrates the average generation pattern for January and July. By showing the extreme months, this figure illustrates the range of hourly generation across the year.

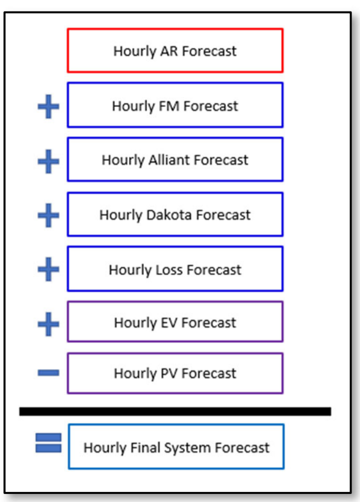
FIGURE 13: PV SHAPE FORECAST



1.4 SCENARIOS

Once the three forecast Phases are complete, the hourly base scenario forecast is calculated as the aggregation of all hourly load forecasts. Figure 14 simplifies Figure 1 and shows the hourly components as they contribute to the hourly base system forecast.

FIGURE 14: FORECAST AGGREGATION



Once the hourly base forecast is complete, alternative scenarios are generated by applying the forecast models and framework to alternative input assumptions. These scenarios are intended to provide reasonable planning bound that capture both economic and weather uncertainty. This section summarizes the alternative input assumptions used to create the economic and weather scenarios.

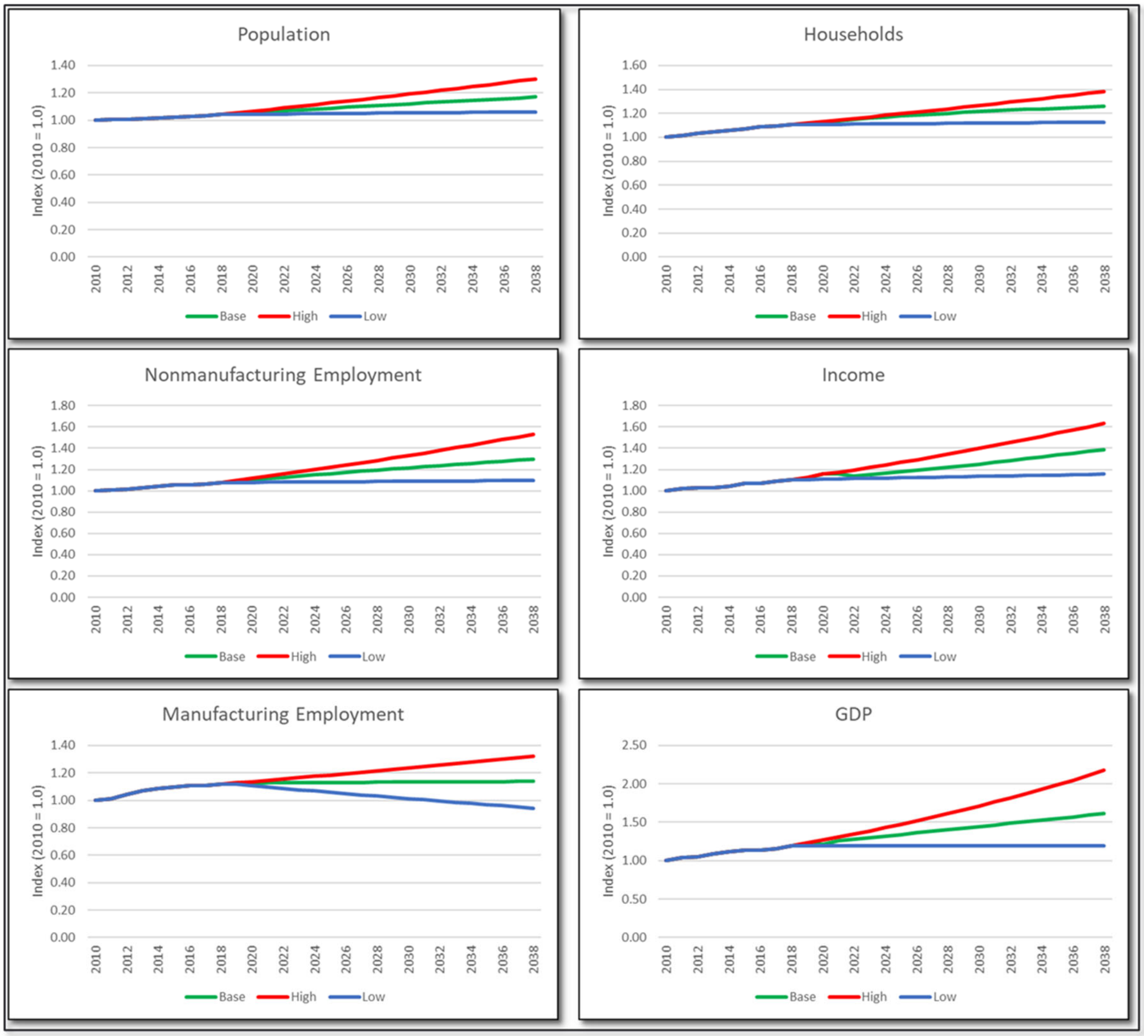
1.4.1 Economic Scenarios

The two economic scenarios are created to construct reasonable planning bounds around the base forecast based on high and low economic conditions. The High and Low scenarios are constructed by increasing or decreasing the base economic forecast in the AR forecast. Table 5 and Figure 15 show economic scenarios compared with recent history. The figure shows the scenarios using a 1.0 based index for comparison purposes.

TABLE 5: ECONOMIC SCENARIO GROWTH RATES

Year	2010-2021 Annual Avg Growth Rate	2023-2038 Annual Avg Growth Rate	Difference From Base Scenario
Population			
Base	0.53%	0.58%	
High		1.12%	0.54%
Low		0.09%	0.49%
Households			
Base	1.22%	0.59%	
High		1.12%	0.53%
Low		0.09%	0.50%
Income			
Base	1.12%	1.23%	
High		1.98%	0.75%
Low		0.23%	1.00%
Manufacturing Employment			
Base	1.58%	0.04%	
High		0.84%	0.80%
Low		-0.88%	0.92%
Nonmanufacturing Employment			
Base	1.06%	0.90%	
High		1.78%	0.87%
Low		0.09%	0.81%
Regional GDP			
Base	2.24%	1.46%	
High		3.03%	1.57%
Low		0.00%	1.46%

FIGURE 15: ECONOMIC SCENARIOS



The high case scenarios are constructed based on the historical annual average growth rates from 1992 through 2021. In the past (1992 through 2021), all economic concepts increase faster than the current base scenario forecast.

The low case scenarios are constructed to reduce the base scenario growth rates based on the difference between the high case scenario and the base case scenario. For example, if the base case scenario growth rate is 5% and the high scenario growth rate is 7%, then the low scenario growth rate is 3% (5% minus the difference between the base and high growth rates). The low case scenario includes three exceptions to the construction rules. First, the household low case uses the same growth rates as the population low case to ensure consistency between the economic concepts. Second, the GDP low case is capped at 0% growth to prevent long-term negative GDP from occurring. Finally, nonmanufacturing employment is developed as the difference between total employment and manufacturing employment. Like GDP, total employment is capped at 0% for to prevent long-term negative employment growth.

1.4.2 Weather Scenarios

The mild and extreme weather scenarios are created to capture the uncertainty associated with weather conditions. These scenarios are developed using the historical weather data as the base case but identify a 1-in-10 scenario above and below the base forecast normal temperatures.

Monthly HDD and CDD scenarios are created by ranking 30 years of historical annual HDD and CDD values (base 65 degrees) from lowest to highest values. The mild case is determined by using the 3rd lowest year in the ranked list (i.e., 1 in 10 occurrences). The extreme case is determined by using the 3rd highest year in the ranked list. Figure 16 and Figure 17 show the ordered annual HDD and CDD with the mild and extreme scenarios in red. Table 6 shows the annual HDD and CDD values for the base, mild, and extreme scenarios.

FIGURE 16: SCENARIOS: ANNUAL HDD BASE 65

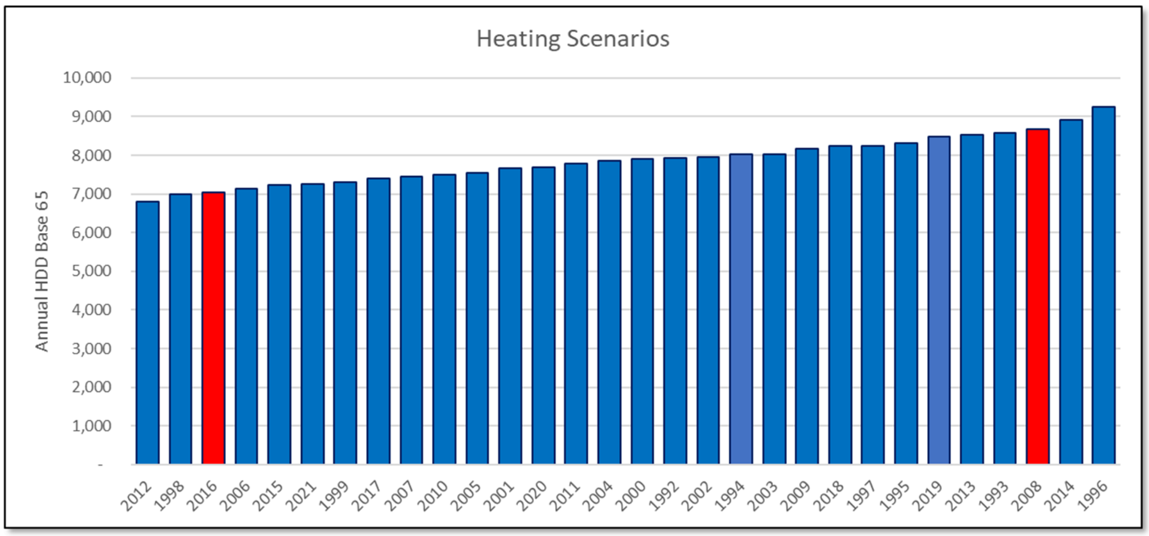


FIGURE 17: SCENARIOS: ANNUAL CDD BASE 65

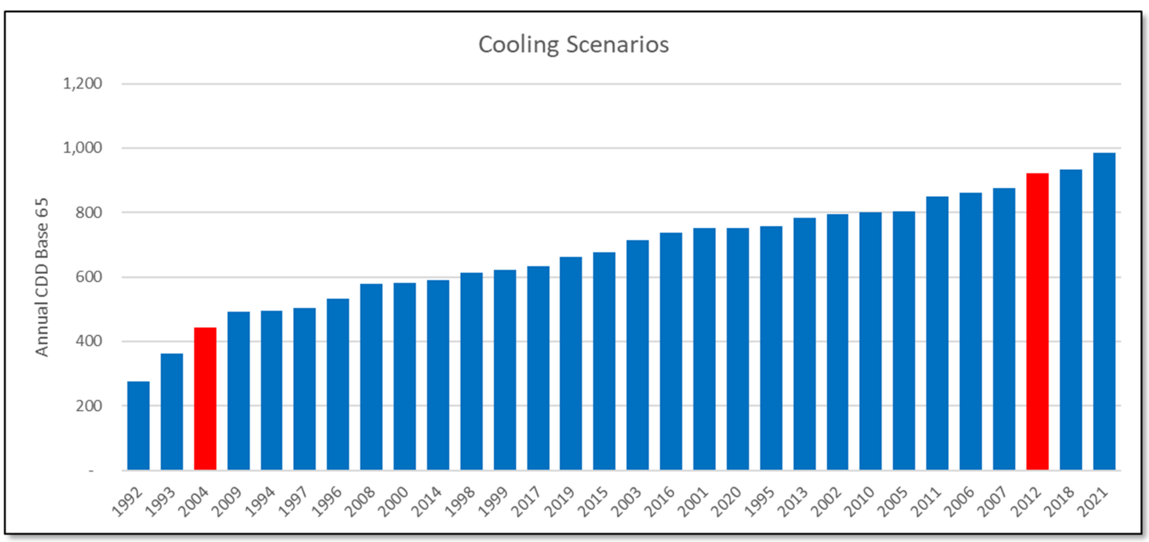


TABLE 6: SCENARIO ANNUAL DEGREE DAYS

Scenario	HDD65	CDD65
Base	7,862	679
Mild	8,665	922
Extreme	7,030	443

After determining the annual HDD and CDD scenario, monthly HDD and CDD values are calculated by distributing the annual HDD and CDD values based on the base case normal monthly pattern.

2 BASE SCENARIO FORECAST SUMMARY

The Base Scenario system forecast consists of the all the components forecasted in Phases 1 through 3. The components include the hourly forecasts for the following items.

- AR
- FM
- Dakota
- Alliant
- Losses
- EV
- PV

While the full hourly forecast from 2023 through 2038 is contained in the MetrixLT file (***System_Calibration.LTM***) and associated workpapers, this section summarizes the hourly forecast at the annual level.

The total system grows from 11,225,803 MWh in 2023 to 12,099,344 MWh in 2038 with an average annual growth rate (2023-2038) of 0.53%. The system peaks move consistently with the energy forecast with average annual growth rate (2023-2038) of 0.40% (summer peak). Annual forecast values are shown in Table 7 and Table 8.

TABLE 7: SYSTEM FORECAST SUMMARY (MWH)

Year	AR	FM	Harvestone	Alliant	Losses	EV	PV	Total Energy
2023	9,140,512	1,506,103	41,936	-	525,240	19,074	(7,061)	11,225,803
2024	9,211,394	1,506,103	41,936	-	527,872	28,710	(11,108)	11,304,907
2025	9,240,111	1,506,103	41,936	112,706	534,899	37,546	(14,569)	11,458,731
2026	9,279,658	1,506,103	41,936	112,706	536,774	46,073	(18,082)	11,505,168
2027	9,325,320	1,506,103	41,936	112,706	538,938	54,090	(21,734)	11,557,359
2028	9,383,811	1,506,103	41,936	112,706	541,699	61,735	(25,536)	11,622,453
2029	9,414,261	1,506,103	41,936	112,706	543,136	68,695	(29,491)	11,657,345
2030	9,449,204	1,506,103	41,936	112,706	544,747	75,847	(33,560)	11,696,983
2031	9,486,533	1,506,103	41,936	112,706	546,480	83,174	(37,826)	11,739,107
2032	9,540,794	1,506,103	41,936	112,706	549,015	90,844	(42,318)	11,799,080
2033	9,571,504	1,506,103	41,936	112,706	550,429	98,084	(47,153)	11,833,609
2034	9,618,327	1,506,103	41,936	112,706	552,599	105,598	(52,455)	11,884,814
2035	9,664,675	1,506,103	41,936	112,706	554,749	113,104	(58,012)	11,935,260
2036	9,726,423	1,506,103	41,936	112,706	557,627	121,012	(63,776)	12,002,030
2037	9,762,686	1,506,103	41,936	112,706	559,308	128,443	(69,858)	12,041,325
2038	9,816,437	1,506,103	41,936	112,706	561,822	136,486	(76,146)	12,099,344
5 Yr CAGR (2023-2028)	**0.53%**	**0.00%**	**0.00%**	**0.00%**	**0.62%**	**26.48%**	**29.32%**	**0.70%**
10 Yr CAGR (2023-2033)	**0.46%**	**0.00%**	**0.00%**	**0.00%**	**0.47%**	**17.79%**	**20.91%**	**0.53%**
15 Yr CAGR (2023-2038)	**0.48%**	**0.00%**	**0.00%**	**0.00%**	**0.45%**	**14.02%**	**17.18%**	**0.50%**

TABLE 8: SYSTEM PEAK SUMMARY (MW)

Year	AR	FM	Harvestone	Alliant	Losses	EV	PV	Total Peak
2023	1,877	220	6	-	104	4	(1)	2,210
2024	1,875	220	6	-	105	6	(2)	2,210
2025	1,881	220	6	21	106	8	(3)	2,239
2026	1,886	220	6	21	107	10	(1)	2,248
2027	1,892	220	6	21	107	11	(2)	2,255
2028	1,899	220	6	21	108	13	(5)	2,261
2029	1,905	220	6	21	108	14	(5)	2,269
2030	1,911	220	6	21	109	16	(6)	2,276
2031	1,917	220	6	21	109	18	(6)	2,284
2032	1,924	220	6	21	110	19	(7)	2,291
2033	1,930	220	6	21	110	21	(5)	2,302
2034	1,937	220	6	21	111	22	(9)	2,307
2035	1,945	220	6	21	111	24	(10)	2,317
2036	1,954	220	6	21	112	25	(11)	2,326
2037	1,962	220	6	21	112	27	(3)	2,344
2038	1,954	219	6	20	112	38	(3)	2,346
5 Yr CAGR (2023-2028)	**0.23%**	**0.00%**	**0.00%**	**0.00%**	**0.64%**	**26.42%**	**31.27%**	**0.46%**
10 Yr CAGR (2023-2033)	**0.28%**	**0.00%**	**0.00%**	**0.00%**	**0.53%**	**17.80%**	**15.83%**	**0.41%**
15 Yr CAGR (2023-2038)	**0.27%**	**-0.03%**	**-0.01%**	**0.00%**	**0.47%**	**16.24%**	**7.16%**	**0.40%**

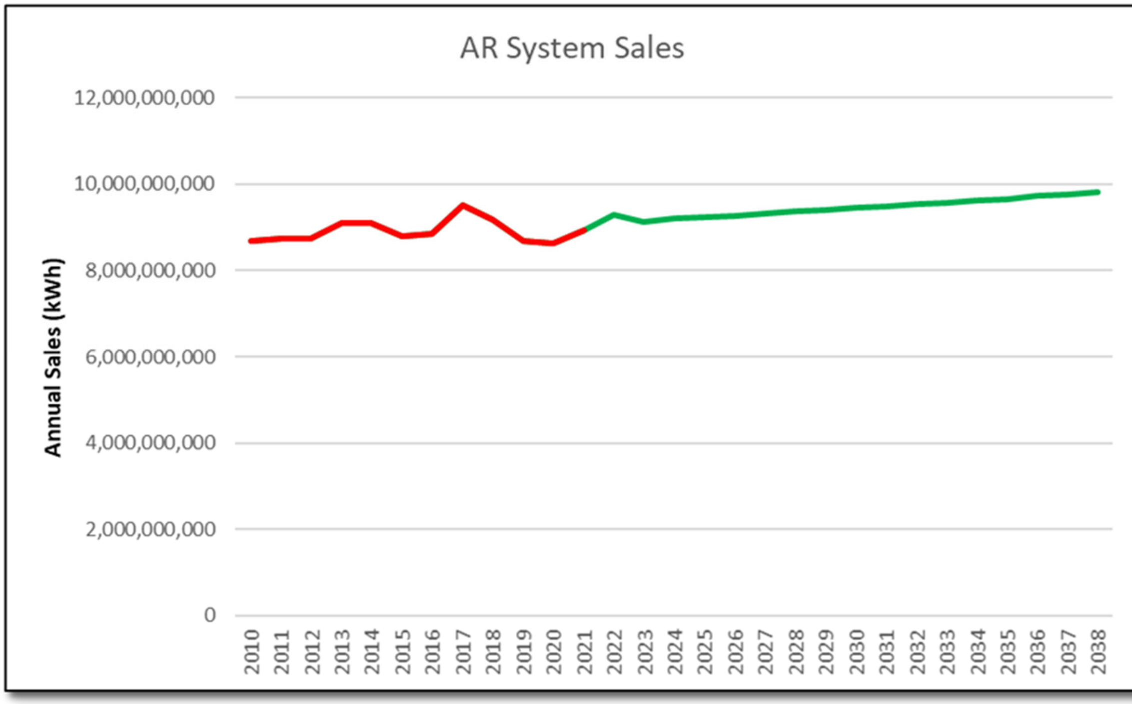
Of the seven forecast components listed in this section, the AR, EV, and PV forecasts contribute to most of the GRE system. These components have a forecasted energy annual average growth rate (2023-2038) of 0.51% which is slightly higher than the recent historical growth rate (2010-2021) of 0.28%.

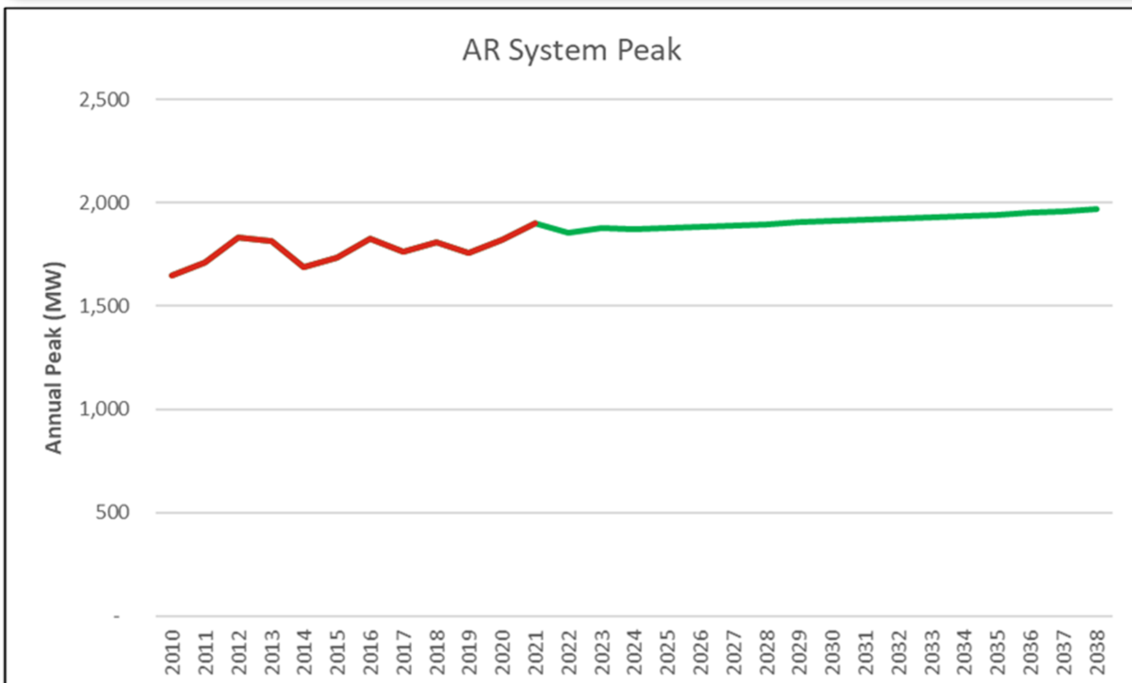
Table 9 and Figure 18 show the All Requirements forecast including historical data from 2010-2021.

TABLE 9: ANNUAL SALES AND PEAK (ALL REQUIREMENTS)

Year	AR Sales (MWh)	AR Coincident Peak (MW)
2010	8,675,887,102	1,651
2011	8,730,971,044	1,714
2012	8,739,097,682	1,830
2013	9,088,721,005	1,814
2014	9,098,428,127	1,692
2015	8,799,847,661	1,737
2016	8,847,024,237	1,826
2017	9,504,098,286	1,766
2018	9,170,797,438	1,811
2019	8,694,645,391	1,756
2020	8,631,351,578	1,824
2021	8,948,846,394	1,902
2022	9,304,956,764	1,857
2023	9,140,511,568	1,877
2024	9,211,394,037	1,875
2025	9,240,111,209	1,881
2026	9,279,658,062	1,886
2027	9,325,319,890	1,892
2028	9,383,810,526	1,899
2029	9,414,261,189	1,905
2030	9,449,203,669	1,911
2031	9,486,533,323	1,917
2032	9,540,793,913	1,923
2033	9,571,504,480	1,930
2034	9,618,326,695	1,937
2035	9,664,675,207	1,945
2036	9,726,423,186	1,953
2037	9,762,685,873	1,961
2038	9,816,437,357	1,970
5 Yr CAGR (2023-2028)	**0.53%**	**0.23%**
10 Yr CAGR (2023-2033)	**0.46%**	**0.28%**
15 Yr CAGR (2023-2038)	**0.48%**	**0.32%**

FIGURE 18: SCENARIOS: ANNUAL SALES AND PEAK (ALL REQUIREMENTS)





3 SCENARIO FORECAST SUMMARY

Four alternative scenarios provide reasonable planning bounds that capture both economic and weather uncertainty. The scenario assumptions are described in Section 1.4 and hourly scenario results are included in the workpapers.

The economic scenarios show that annual average system energy growth ranges between 0.14% and 0.64% (Low and High Scenarios). The weather scenarios show that the base forecast energy may increase 2.82% (Extreme Scenario) or decrease 2.86% (Mild Scenario) in 2023. Table 10 shows the scenario growth rates and the scenario differences from the base scenario.

TABLE 10: SCENARIO GROWTH RATES AND DIFFERENCES

Year	2023-2038 Annual Average Growth Rate	2023 Difference From Base	2038 Difference From Base
System Energy			
Base Scenario	0.38%		
High Scenario	0.64%	.15%	4.26%
Low Scenario	0.14%	-0.54%	-4.04%
Extreme Scenario	0.54%	2.82%	2.76%
Mild Scenario	0.22%	-2.86%	-2.79%
System Peak			
Base Scenario	0.44%		
High Scenario	0.62%	0.08%	2.92%
Low Scenario	0.25%	-0.29%	-2.88%
Extreme Scenario	0.79%	4.80%	5.64%
Mild Scenario	0.00%	-6.08%	-6.90%

Table 11 and Figure 19 show the scenario annual energy forecasts.

Table 12 and Figure 20 show the scenario annual peak forecasts. Hourly results are located in the associated workpapers.

TABLE 11: SCENARIOS: BASE, EXTREME, MILD, HIGH, AND LOW ENERGY FORECAST (MWH)

Year	Base	Extreme	Mild	High	Low
2023	11,225,803	11,542,395	10,904,510	11,242,992	11,164,802
2024	11,304,907	11,622,731	10,982,340	11,340,315	11,209,708
2025	11,458,731	11,776,558	11,136,247	11,515,989	11,332,269
2026	11,505,168	11,823,811	11,181,902	11,585,893	11,347,697
2027	11,557,359	11,876,935	11,233,193	11,662,186	11,368,158
2028	11,622,453	11,943,670	11,296,616	11,753,760	11,401,936
2029	11,657,345	11,979,008	11,331,156	11,817,309	11,407,658
2030	11,696,983	12,019,601	11,369,871	11,887,934	11,418,799
2031	11,739,107	12,062,923	11,410,832	11,963,025	11,432,970
2032	11,799,080	12,124,785	11,468,893	12,058,412	11,464,774
2033	11,833,609	12,160,087	11,502,749	12,129,761	11,473,018
2034	11,884,814	12,212,683	11,552,619	12,220,516	11,497,791
2035	11,935,260	12,264,488	11,601,768	12,312,609	11,522,320
2036	12,002,030	12,333,302	11,666,497	12,423,800	11,562,604
2037	12,041,325	12,373,550	11,704,965	12,508,316	11,577,381
2038	12,099,344	12,433,244	11,761,382	12,614,649	11,610,258
5 Yr CAGR (2023-2028)	**0.70%**	**0.69%**	**0.71%**	**0.89%**	**0.42%**
10 Yr CAGR (2023-2033)	**0.53%**	**0.52%**	**0.54%**	**0.76%**	**0.27%**
15 Yr CAGR (2023-2038)	**0.50%**	**0.50%**	**0.51%**	**0.77%**	**0.26%**

FIGURE 19: SCENARIOS: ENERGY FORECAST COMPARISON

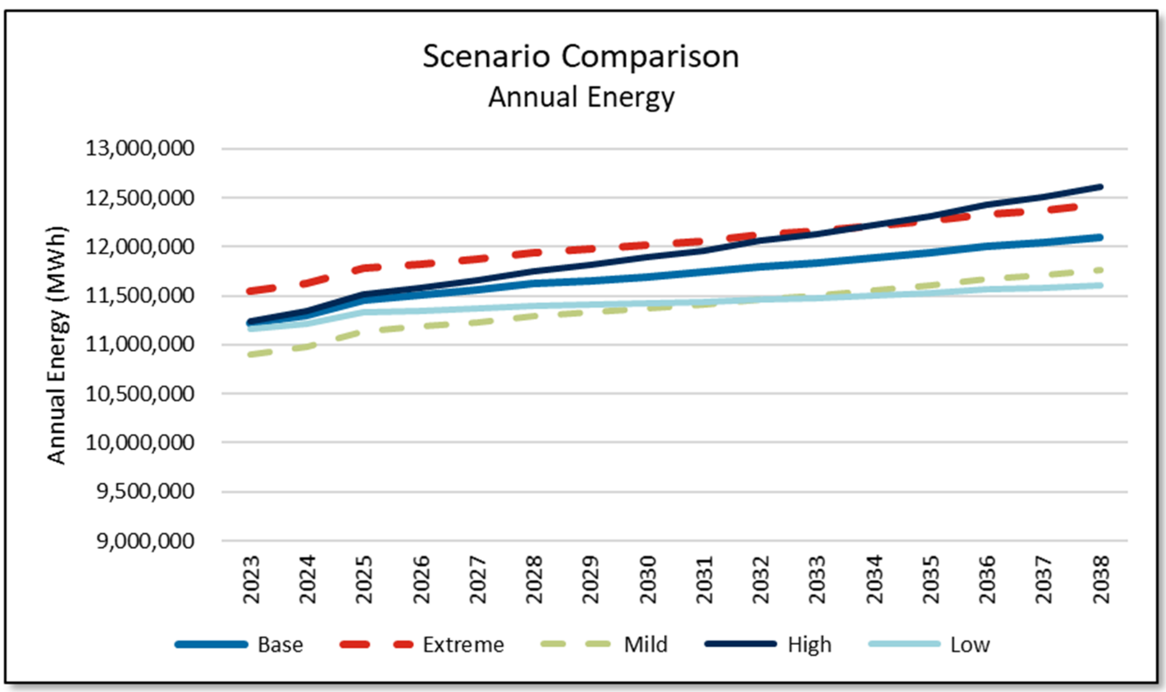
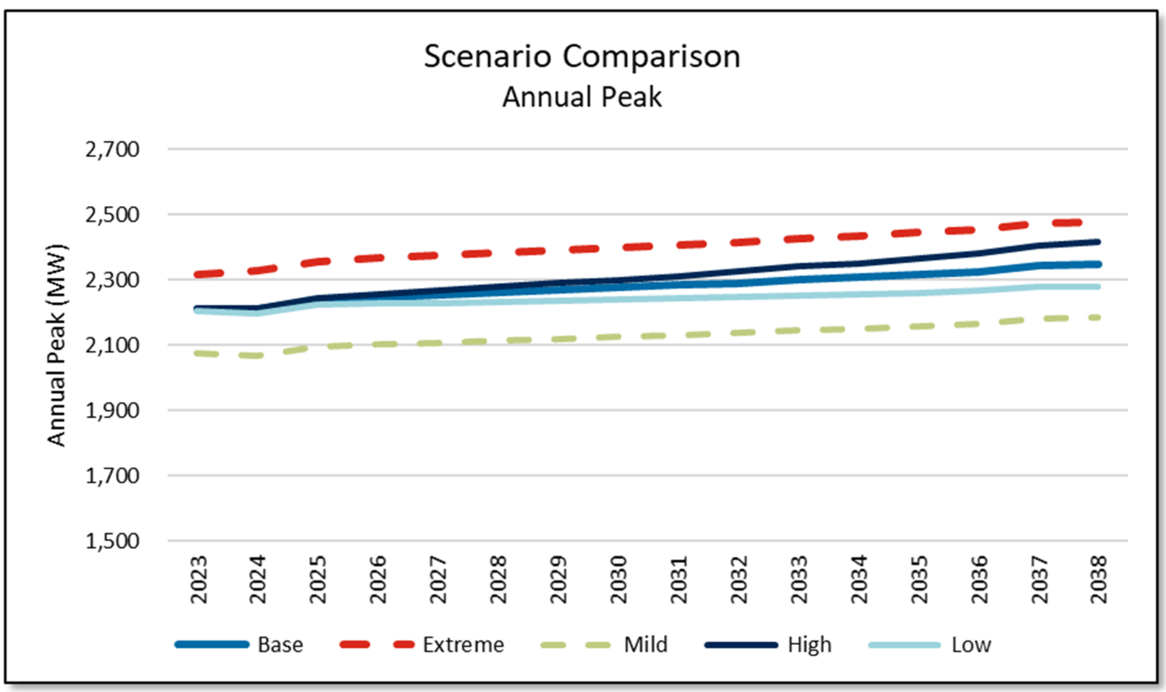


TABLE 12: SCENARIOS: BASE, EXTREME, MILD, HIGH, AND LOW PEAK FORECAST (MW)

Year	Base	Extreme	Mild	High	Low
2023	2,210	2,315	2,077	2,212	2,203
2024	2,210	2,327	2,066	2,214	2,198
2025	2,239	2,357	2,094	2,245	2,223
2026	2,248	2,367	2,102	2,258	2,228
2027	2,255	2,375	2,108	2,268	2,230
2028	2,261	2,382	2,113	2,278	2,232
2029	2,269	2,391	2,120	2,290	2,236
2030	2,276	2,399	2,126	2,300	2,239
2031	2,284	2,407	2,132	2,312	2,243
2032	2,291	2,416	2,138	2,324	2,246
2033	2,302	2,428	2,148	2,340	2,253
2034	2,307	2,434	2,151	2,351	2,254
2035	2,317	2,445	2,159	2,366	2,260
2036	2,326	2,455	2,167	2,381	2,266
2037	2,344	2,475	2,183	2,406	2,280
2038	2,346	2,478	2,184	2,415	2,279
5 Yr CAGR (2023-2028)	**0.46%**	**0.58%**	**0.35%**	**0.59%**	**0.26%**
10 Yr CAGR (2023-2033)	**0.41%**	**0.48%**	**0.34%**	**0.57%**	**0.22%**
15 Yr CAGR (2023-2038)	**0.40%**	**0.46%**	**0.34%**	**0.59%**	**0.22%**

FIGURE 20: SCENARIOS: PEAK FORECAST COMPARISON



4 AR MODELS

In Phase 1, the AR forecast is developed using statistical model for each class (e.g., residential, seasonal). The statistical models are regression models and are developed in MetrixND. This section describes the statistical models and their results.

4.1 RESIDENTIAL SALES FORECAST AND MODELS

The Residential class consists of all AR cooperative Residential sales. The AR cooperatives provided historical sales and customer counts from their Form 7 data reports. Data is complete for all AR cooperatives through December 2021. The Residential sales forecast is modelled with two models - a customer model and an average use (i.e., Use-Per Customer, or UPC) model. The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total sales in each month. Using two models captures both the class growth based on a changing number of customers (Customer Model) and usage changes based on end-use information (UPC Model).

4.1.1 Residential Customer Model

The Customer Model is a regression model estimated with monthly historical data from January 2012 through December 2021. Table 13 shows the Customer Model specification and

Table 14 shows the Customer Model statistics.

TABLE 13: RESIDENTIAL CUSTOMER MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	99953.824	5938.303	16.832
Household Index	312084.373	5495.553	56.789
Year2013	-49.114	433.018	-0.113
Year2016	-2863.011	461.648	-6.202
Year2017	-2484.953	472.403	-5.26
Year2018	-1374.613	455.349	-3.019
Year2021Plus	4104.244	534.122	7.684
MA(1)	0.93	0.081	11.551
MA(2)	0.586	0.079	7.429

TABLE 14: RESIDENTIAL CUSTOMER MODEL STATISTICS

Statistics	Residential Customer Model
Estimation	1/2012 – 12/2021
R^2	0.996
Adj. R^2	0.996
MAPE	0.12%
DW	1.251

The residential model is driven by households and incorporates five binary adjustments. Additionally, the moving average (MA1, MA2) terms correct for serial correlation. The variables included in the model are described below.

- **Household Index.** This variable is the household forecasts.
- **Binary Adjustments**. The binary adjustments variables are **Year2013**, **Year2016**, **Year2017**, **Year2018**, and **Year2021Plus**. The **Year2021Plus** is a binary shift variable that captures positive level shift during 2021. Binary shift variables assume that the level impact continues through the forecast period. The **Year2013**, **Year2016**, **Year2017** and **Year2018** binary variables capture short term level shifts in 2013,2016, 2017 and 2018.
- **MA1 and MA2.** The MA1 and MA2 are moving average terms that correct for serial correlation in the model.

4.1.2 Residential UPC Model

The UPC Model is an SAE model estimated with historical data from January 2010 through December 2021.

Table 15 shows the UPC Model specification and Table 16 shows the UPC Model statistics.

The SAE model contains end-use information for heating, cooling, and base load technologies from Itron's 2021 SAE West North Central region. The following data are included in the model.

- **End-Use Efficiencies.** End-use efficiencies by technology type are based on Energy Information Administration (EIA) data.
- **End-Use Saturations and Intensities.** End-use saturations and intensities by technology type are based on EIA data.
- **Economic data.** Historical and forecasted population and household income data are based on Woods and Poole's 2021 forecasts.
- **Energy Prices.** Class energy prices are based on historical revenues and energy consumption. The energy price forecast is held constant in real dollars.

TABLE 15: RESIDENTIAL UPC MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	249.388	76.991	3.239
XHeat	1.028	0.023	45.463
XCool	0.843	0.023	37.139
XOther	0.752	0.125	6.030
Year2010	31.179	9.524	3.274
May	-38.733	10.286	-3.766

TABLE 16: RESIDENTIAL UPC MODEL STATISTICS

Statistics	Residential UPC Model
Estimation	1/2010 – 12/2021
R2	0.964
Adj. R2	0.963
MAPE	2.52%
DW	1.661

The UPC Model includes the SAE variables (XHeat, XCool, and XOther) and two binary adjustments.

- **SAE Variables.** The SAE variables are **XHeat**, **XCool**, and **XOther**. **XHeat** captures the heating response and includes the effects of heating technology efficiencies, saturations, thermal shell, weather, price, income, and household size. **XCool** captures the cooling response and captures the effects of cooling technology efficiencies, saturations, thermal shell, weather, price, income, and household size. **XOther** captures the baseload response for all non-heating and non-cooling technologies.
- **Binary Adjustments**. Two binary adjustments variables, **Year2010** and **May**, capture shifts in the underlying data. Year2010 captures the recovery from the 2008-2009 recession. May captures a recurring decline in May usage.

4.1.3 Residential Base Sales Forecast

The Residential sales forecast is the product of the customer and UPC forecasts. The annual sales forecast, customer forecast, and use-per-customer forecast are shown in Figure 21, Figure 22, and Figure 23.

Table 17 shows the annual sales, customer, and average use forecast with average growth rates.

FIGURE 21: RESIDENTIAL SALES FORECAST (ACTUAL AND FORECAST)

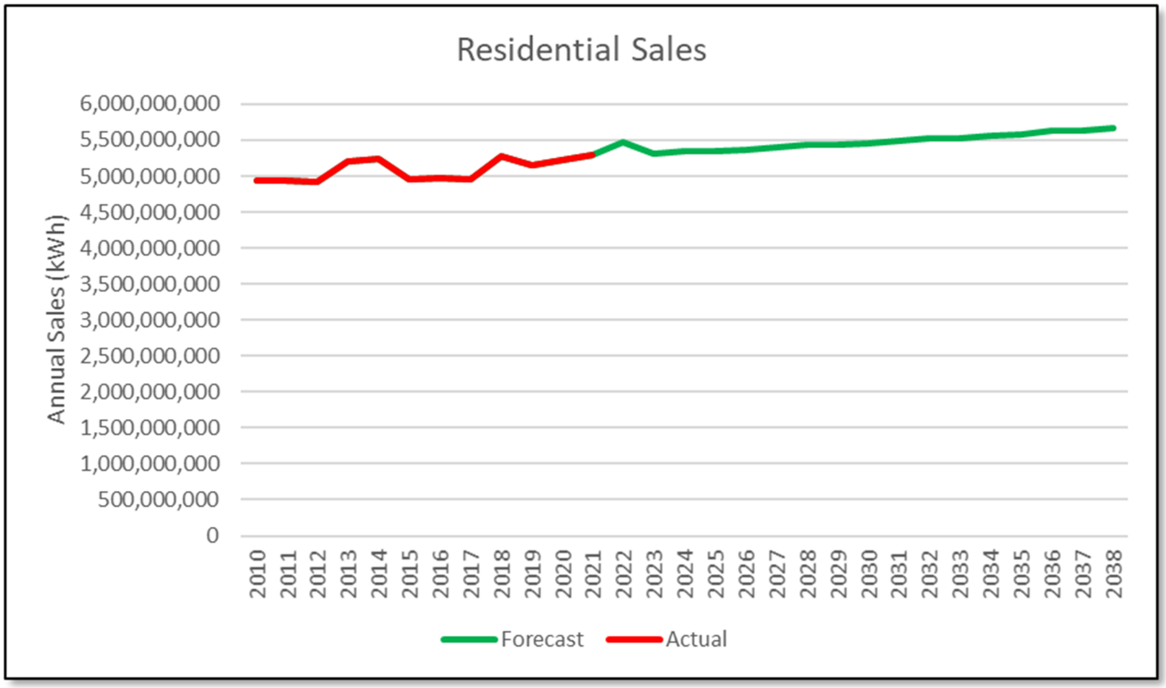


FIGURE 22: RESIDENTIAL CUSTOMER FORECAST (ACTUAL AND FORECAST)

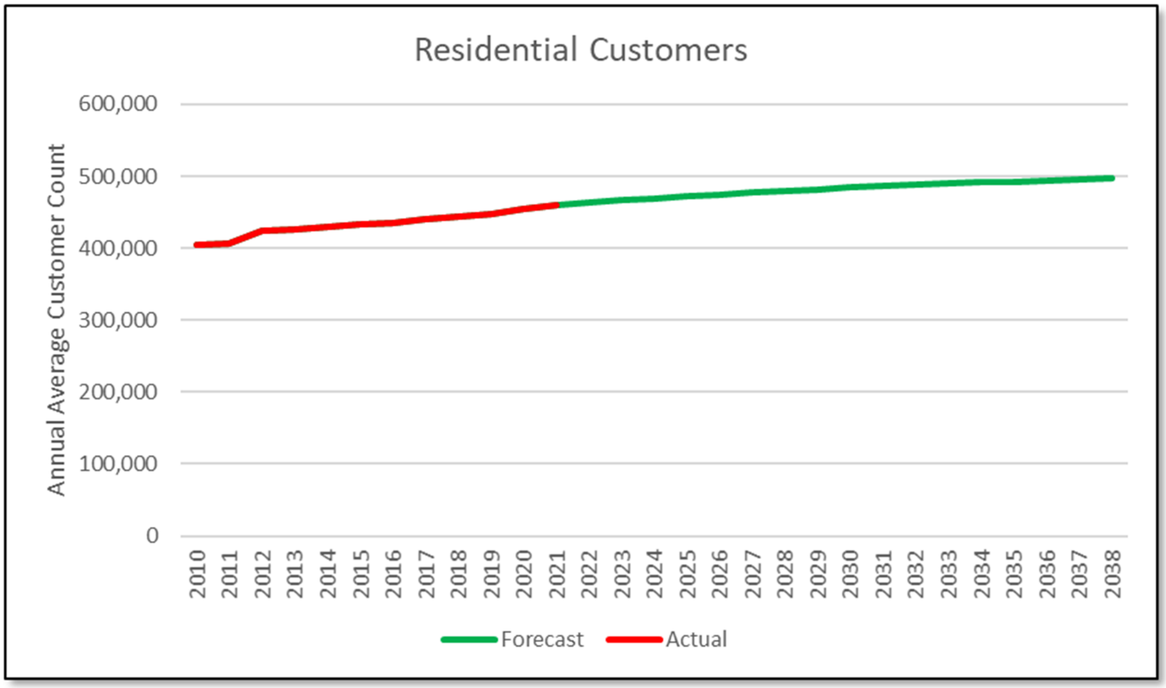


FIGURE 23: RESIDENTIAL UPC FORECAST (ACTUAL AND FORECAST)

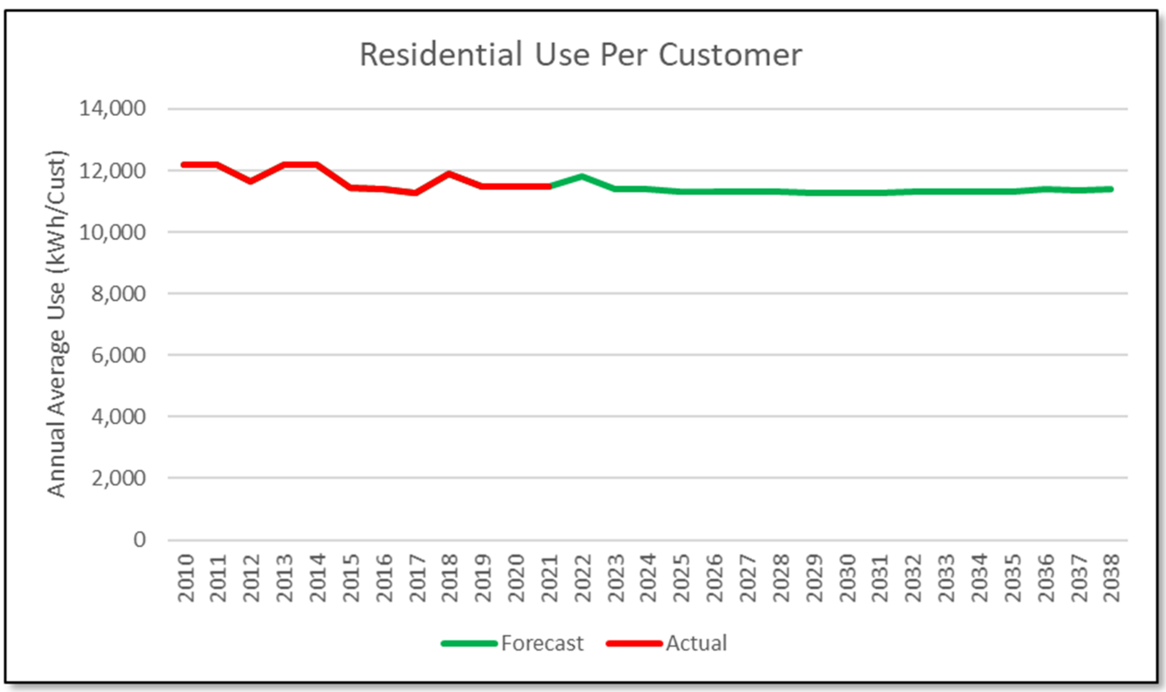


TABLE 17: RESIDENTIAL SALES FORECAST SUMMARY

Year	Sales (kWh)	Sales Growth	Customers	Customer Growth	AvgUse (kWh)	AvgUse Growth
2023	5,318,112,287		466,545		11,400	
2024	5,347,152,998	0.55%	469,472	0.63%	11,346	-0.47%
2025	5,351,552,548	0.08%	472,220	0.59%	11,335	-0.10%
2026	5,370,573,486	0.36%	474,817	0.55%	11,264	-0.62%
2027	5,392,054,506	0.40%	477,288	0.52%	11,240	-0.22%
2028	5,428,230,639	0.67%	479,642	0.49%	11,227	-0.11%
2029	5,437,878,134	0.18%	481,861	0.46%	11,258	0.27%
2030	5,459,895,851	0.40%	483,940	0.43%	11,222	-0.32%
2031	5,482,308,054	0.41%	485,902	0.41%	11,223	0.01%
2032	5,519,165,903	0.67%	487,754	0.38%	11,229	0.05%
2033	5,531,006,172	0.21%	489,502	0.36%	11,277	0.43%
2034	5,557,630,336	0.48%	491,166	0.34%	11,263	-0.12%
2035	5,583,560,633	0.47%	492,756	0.32%	11,291	0.25%
2036	5,623,735,614	0.72%	494,285	0.31%	11,320	0.25%
2037	5,637,331,091	0.24%	495,768	0.30%	11,387	0.59%
2038	5,665,645,420	0.50%	497,204	0.29%	11,386	-0.01%
2011-2021		**0.69%**		**1.20%**		**-0.49%**
2023-2038		**0.21%**		**0.44%**		**-0.22%**
5 Yr CAGR (2023-2028)		**0.41%**		**0.56%**		**-0.14%**
10 Yr CAGR (2023-2033)		**0.39%**		**0.48%**		**-0.09%**
15 Yr CAGR (2023-2038)		**0.42%**		**0.43%**		**0.00%**

4.2 SEASONAL SALES MODEL

The Seasonal class consists of all AR cooperative Seasonal sales. The Seasonal class is composed of seasonal residential customers. The AR cooperatives provided historical sales and customer counts from their Form 7 data reports. The seasonal sales forecast is modelled with two models, a Customer Model and a UPC Model. The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total sales in each month. Using two models captures both the class growth based on a changing number of customers (Customer Model) and usage changes based on end-use information (UPC Model).

4.2.1 Seasonal Customer Model

The Customer Model is a regression model estimated with monthly historical data from January 2013 through December 2021. Table 18 shows the Customer Model specification and Table 21 shows the Customer Model statistics.

TABLE 18: SEASONAL CUSTOMER MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	2645.056	3351.062	0.789
Population Index	32602.628	3212.083	10.150
JanToMar2013	418.807	132.712	3.156
Apr2013	-3799.836	86.509	-43.924
AR1	0.848	0.045	19.036

TABLE 19: SEASONAL CUSTOMER MODEL STATISTICS

Statistics	Seasonal Customer Model
Estimation	1/2013 – 12/2021
R^2	0.986
Adj. R^2	0.985
MAPE	0.13%
DW	1.789

The Seasonal model is driven by population and incorporates binary adjustments in 2013. Additionally, the autoregressive (AR1) term corrects for serial correlation. The variables included in the model are described below.

- **Population Index.** This variable is the population forecasts. Because seasonal customers are primarily seasonal residential customers, population growth captures customer count growth.
- **Binary Adjustments**. The binary adjustments variables are **JanToMar2013** and **Apr2013**. The **JanToMar2013** and **Apr2013** binary variables correct for anomalous data in the early part of 2013.
- **AR1.** The AR1 term corrects serial correlation.

4.2.2 Seasonal UPC Model

The UPC Model is an SAE model estimated with historical data from January 2009 through December 2021. Table 20 shows the UPC Model specification and Table 21 shows the UPC Model statistics.

TABLE 20: SEASONAL UPC MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	2645.056	3351.062	0.789
XHeat	0.525	0.024	22.169
XCool	0.280	0.020	14.021
XOther	0.047	0.093	0.502
FebMar2016Trinary	145.981	15.722	9.285
Jul	45.258	8.639	5.239
Winter	37.440	7.195	5.203
Year2017Plus	26.878	4.787	5.615
Year2020Plus	29.130	5.793	5.028

TABLE 21: SEASONAL MODEL STATISTICS

Statistics	Seasonal UPC Model
Estimation	1/2009 – 12/2021
R2	0.954
Adj. R2	0.951
MAPE	4.50%
DW	1.515

Like the Residential UPC model, the Seasonal UPC Model includes the SAE variables (XHeat, XCool, and XOther). In addition to the SAE variables, the model includes variables to correct for anomalous data, seasonal patterns, and data shifts.

- **SAE Variables.** The SAE variables are **XHeat**, **XCool**, and **XOther**. **XHeat** captures the heating response and includes the effects of heating technology efficiencies, saturations, thermal shell, weather, price, income, and household size. **XCool** captures the cooling response and captures the effects of cooling technology efficiencies, saturations, thermal shell, weather, price, income, and household size. **XOther** captures the baseload response for all non-heating and non-cooling technologies.
- **Trinary Variable**. One trinary variable, **FebMar2016Trinary,** captures opposing data shifts in the underlying data. This variable captures the February 2016 increase in usage which is offset by the March 2016 decrease in usage.
- **Seasonal Variables**. Two seasonal variables (**Jul** and **Winter**) capture recurring monthly patterns in the usage. **Jul** captures a regular increase in usage in the month of July. **Winter** captures a regular increase in usage from November through February.
- **Data Shift Variable**. Data shift variables, **Year2017Plus and Year2020Plus**, captures a sustained increase in usage beginning in 2017 and again in 2020 continuing through the forecast period.

4.2.3 Seasonal Base Sales Forecast

The Seasonal sales forecast is developed as the product of the customer and UPC forecasts. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 24, Figure 25, and Figure 26. Table 22 shows the annual sales, customer, and average use forecast with average growth rates.

FIGURE 24: SEASONAL SALES FORECAST (ACTUAL AND FORECAST)

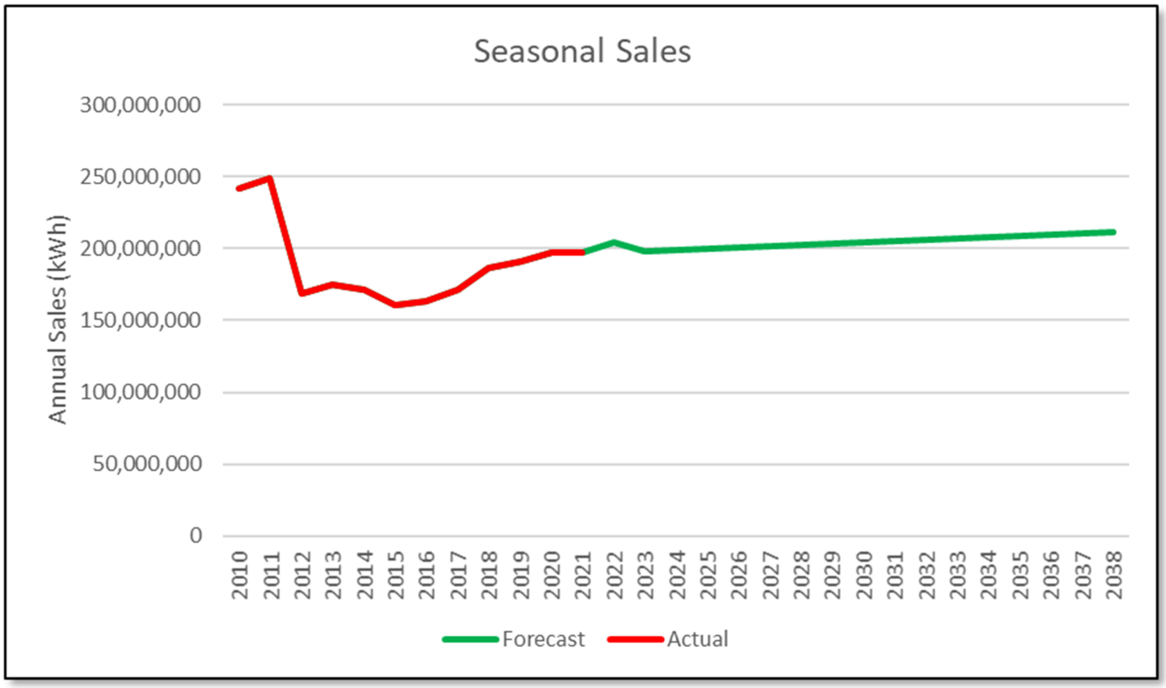


FIGURE 25: SEASONAL CUSTOMER FORECAST (ACTUAL AND FORECAST)

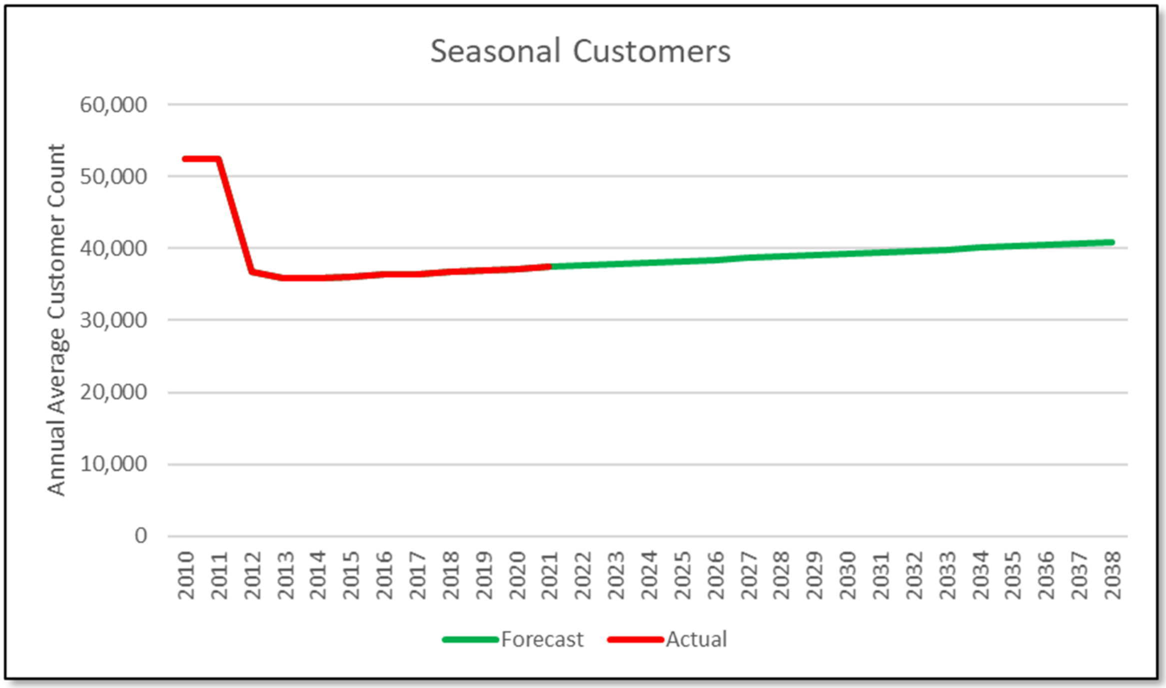


FIGURE 26: SEASONAL UPC FORECAST (ACTUAL AND FORECAST)

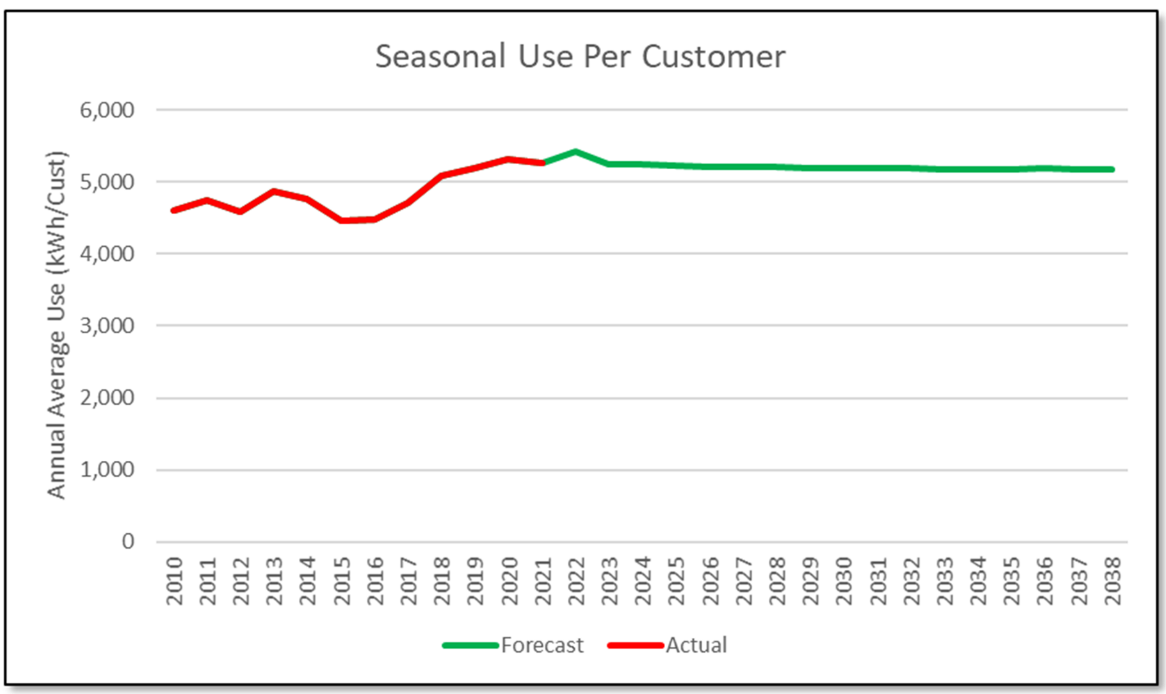


TABLE 22: SEASONAL SALES FORECAST

Year	Sales (kWh)	Sales Growth	Customers	Customer Growth	AvgUse (kWh)	AvgUse Growth
2023	198,117,156		37,793		5,242	
2024	199,104,645	0.50%	37,999	0.54%	5,240	-0.05%
2025	199,600,215	0.25%	38,213	0.56%	5,223	-0.31%
2026	200,398,950	0.40%	38,426	0.56%	5,215	-0.16%
2027	201,243,793	0.42%	38,639	0.55%	5,208	-0.13%
2028	202,397,151	0.57%	38,850	0.55%	5,210	0.03%
2029	203,006,932	0.30%	39,059	0.54%	5,197	-0.24%
2030	203,894,481	0.44%	39,267	0.53%	5,193	-0.09%
2031	204,807,857	0.45%	39,473	0.53%	5,189	-0.08%
2032	206,018,215	0.59%	39,678	0.52%	5,192	0.07%
2033	206,672,673	0.32%	39,880	0.51%	5,182	-0.19%
2034	207,614,082	0.46%	40,080	0.50%	5,180	-0.05%
2035	208,549,265	0.45%	40,278	0.49%	5,178	-0.04%
2036	209,772,795	0.59%	40,472	0.48%	5,183	0.10%
2037	210,425,094	0.31%	40,663	0.47%	5,175	-0.16%
2038	211,351,883	0.44%	40,851	0.46%	5,174	-0.02%
2011-2021		**-1.15%**		**-2.55%**		**1.33%**
2023-2038		**0.23%**		**0.51%**		**-0.29%**
5 Yr CAGR (2023-2028)		**0.43%**		**0.55%**		**-0.12%**
10 Yr CAGR (2023-2033)		**0.42%**		**0.54%**		**-0.11%**
15 Yr CAGR (2023-2038)		**0.43%**		**0.52%**		**-0.09%**

4.3 IRRIGATION SALES MODEL

The Irrigation class consists of all AR cooperative Irrigation sales. The Irrigation class is composed of agriculture customers who use electricity through the summer season. The AR cooperatives provided historical sales and customer counts from their Form 7 data reports. The irrigation sales forecast is modelled with two models - a Customer Model and a UPC Model. The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total sales in each month. Using two models captures both the class growth based on a changing number of customers (Customer Model) and usage changes based on seasonal patterns (UPC Model).

4.3.1 Irrigation Customer Model

The Customer Model is a regression model estimated with monthly historical data from January 2015 through December 2021. Table 23 shows the Customer Model specification and Table 24 shows the Customer Model statistics.

TABLE 23: IRRIGATION CUSTOMER MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	184.756	116.127	1.591
May	483.814	9.181	52.698
Jun	485.694	9.180	52.908
Jul	489.548	9.181	53.324
Aug	487.445	9.186	53.064
Sep	486.006	9.188	52.894
Oct	482.701	9.196	52.490
Residential Customers	0.006	0.000	22.864

TABLE 24: IRRIGATION CUSTOMER MODEL STATISTICS

Statistics	Irrigation Customer Model
Estimation	1/2015 – 12/2021
R^2	0.993
Adj. R^2	0.992
MAPE	0.55%
DW	0.313

The Irrigation model is driven by residential customers, incorporates season adjustments, and includes binary adjustments. The variables included in the model are described below.

- **Residential Customers.** This variable is the residential customer count forecast using the residential customer model described in Section 4.1.1 .
- **Seasonal Adjustments**. Six binary adjustments variables (**May**, **Jun**, **Jul**, **Aug**, **Sep**, and **Oct**) capture the seasonal increase in customers. During the summers, the customer count increases by almost 500 customers.

4.3.2 Irrigation UPC Model

The UPC Model is regression model estimated with historical data from January 2014 through December 2021. Table 25 shows the UPC Model specification and Table 26 shows the UPC Model statistics.

TABLE 25: IRRIGATION UPC MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	-34.084	109.306	-0.312
Jul	1446.747	488.233	2.963
Aug	2371.636	406.827	5.830
CDD65	21.694	1.572	13.804

TABLE 26: IRRIGATION UPC MODEL STATISTICS

Statistics	Irrigation UPC Model
Estimation	1/2014 – 12/2021
R2	0.900
Adj. R2	0.897
MAPE	150.21%
DW	1.090

The UPC Model captures the summer energy usage pattern and forecasts a constant average use through the forecast period. While model shows a strong correlation between average use and the model variables (i.e., R^2=0.900), the high errors result from the highly uncertain beginning and ending of the irrigation season and the level of irrigation necessary for the season. The following variables are used in the model.

- **CDD65.** The class's weather response is modelled using the CDD variable with a temperature reference point of 65 degrees.
- **Seasonal Variables.** Two seasonal adjustment variables (**Jul** and **Aug**) capture the increased electric use above the **CDD65** variable impact.

4.3.3 Irrigation Base Sales Forecast

The Irrigation sales forecast is developed as the product of the customer and UPC forecasts. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 27, Figure 28, and Figure 29.

Table 27 shows the annual sales, customer, and average use forecast with average growth rates.

FIGURE 27: IRRIGATION SALES FORECAST (ACTUAL AND FORECAST)

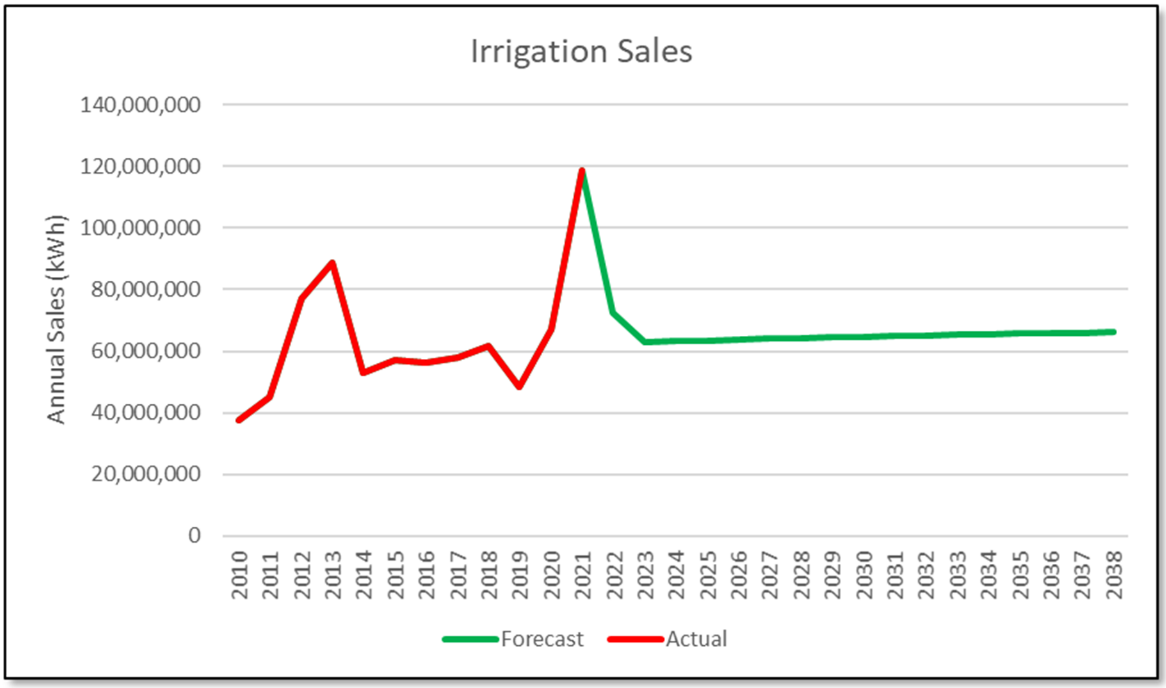


FIGURE 28: IRRIGATION CUSTOMER FORECAST (ACTUAL AND FORECAST)

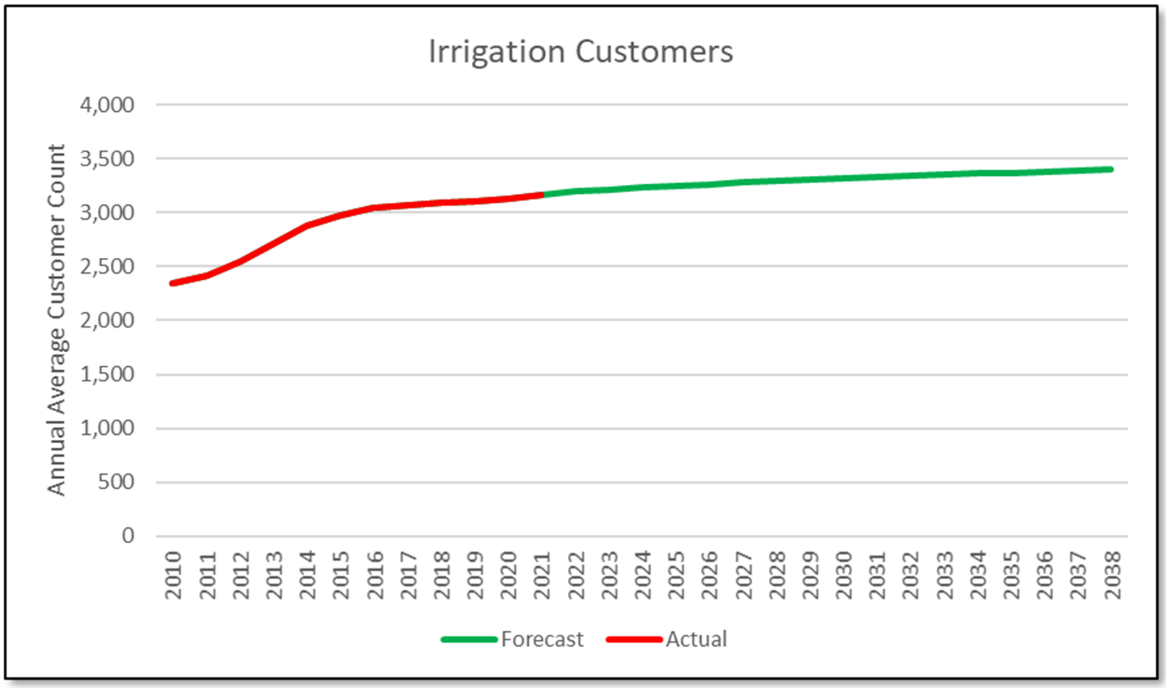


FIGURE 29: IRRIGATION UPC FORECAST (ACTUAL AND FORECAST)

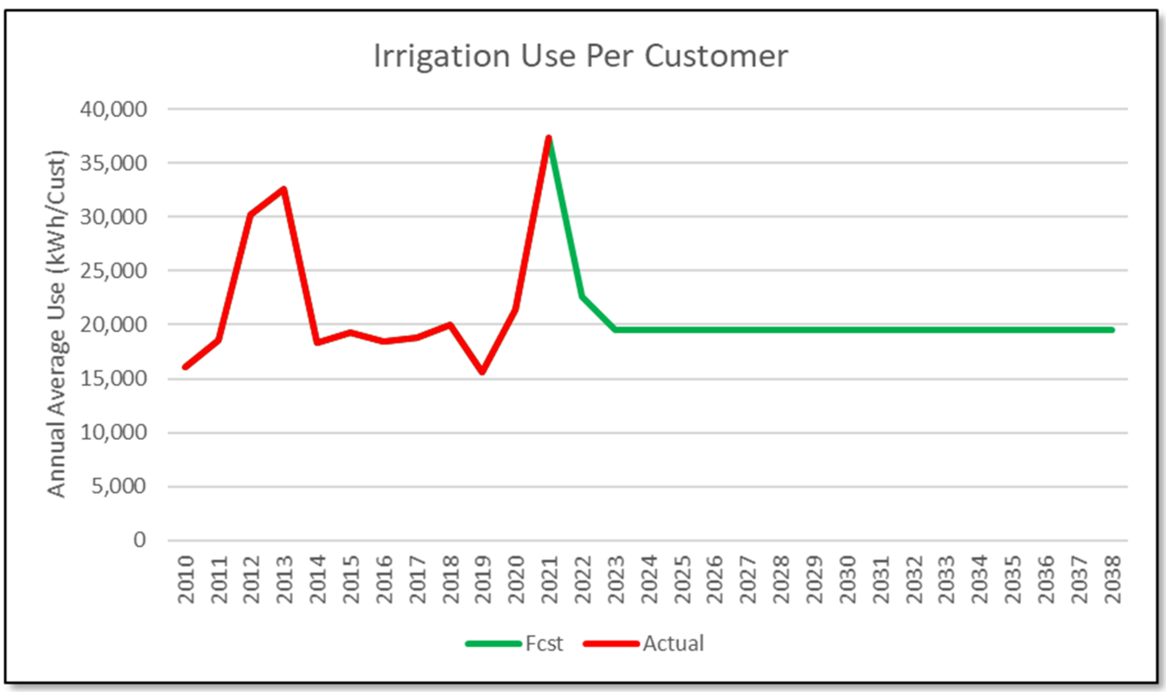


TABLE 27: IRRIGATION SALES FORECAST

Year	Sales (kWh)	Sales Growth	Customers	Customer Growth	AvgUse (kWh)	AvgUse Growth
2023	62,861,652		3,214		19,560	
2024	63,177,549	0.50%	3,231	0.54%	19,552	-0.04%
2025	63,474,240	0.47%	3,248	0.51%	19,545	-0.04%
2026	63,754,753	0.44%	3,263	0.48%	19,538	-0.04%
2027	64,021,737	0.42%	3,278	0.45%	19,531	-0.03%
2028	64,276,097	0.40%	3,292	0.43%	19,525	-0.03%
2029	64,515,517	0.37%	3,305	0.40%	19,519	-0.03%
2030	64,739,958	0.35%	3,318	0.38%	19,514	-0.03%
2031	64,951,877	0.33%	3,329	0.35%	19,509	-0.03%
2032	65,151,775	0.31%	3,340	0.33%	19,504	-0.02%
2033	65,340,647	0.29%	3,351	0.31%	19,500	-0.02%
2034	65,520,401	0.28%	3,361	0.30%	19,495	-0.02%
2035	65,692,202	0.26%	3,370	0.28%	19,491	-0.02%
2036	65,857,595	0.25%	3,379	0.27%	19,488	-0.02%
2037	66,018,092	0.24%	3,388	0.26%	19,484	-0.02%
2038	66,173,302	0.24%	3,397	0.25%	19,481	-0.02%
2011-2021		**15.96%**		**2.83%**		**12.87%**
2023-2038		**-0.50%**		**0.38%**		**-0.88%**
5 Yr CAGR (2023-2028)		**0.45%**		**0.48%**		**-0.04%**
10 Yr CAGR (2023-2033)		**0.39%**		**0.42%**		**-0.03%**
15 Yr CAGR (2023-2038)		**0.34%**		**0.37%**		**-0.03%**

4.4 SMALL COMMERCIAL SALES MODEL

The Small Commercial class consists of all AR cooperative Small Commercial sales. The AR cooperatives provided historical sales and customer counts from their Form 7 data reports. The Small Commercial sales forecast is modelled with two models, a Customer Model and a UPC Model. The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total sales in each month. Using two models capture both the class growth based on a changing number of customers (Customer Model) and usage changes based on end-use information (UPC Model).

4.4.1 Small Commercial Customer Model

The Customer Model is a regression model estimated with historical data from January 2011 through December 2021. Table 28 shows the Customer Model specification and Table 29 shows the Customer Model statistics.

TABLE 28: SMALL COMMERCIAL CUSTOMER MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	8376119.797	10233360688.394	0.001
Nonmanufacturing Employment Index	-3176.959	6662.622	-0.477
Year2021	45.039	119.683	0.376
AR(1)	1.000	0.007	152.905

TABLE 29: SMALL COMMERCIAL CUSTOMER MODEL STATISTICS

Statistics	Small Commercial Customer Model
Estimation	1/2011 – 12/2021
R^2	0.994
Adj. R^2	0.994
MAPE	0.16%
DW	2.203

The customer model is driven by nonmanufacturing employment, incorporates a binary adjustment in 2021. Additionally, the autoregressive (AR1) term corrects for serial correlation. The variables included in the model are described below.

- **Nonmanufacturing Employment Index.** The nonmanufacturing employment index is the historical and forecast nonmanufacturing employment for GRE service territory.
- **Binary Adjustments.** Three binary shifts are capture accelerating customer counts from 2017 through 2019. These binary shift variables are **Year2017Plus**, **Year2018Plus**, and **December2018Plus**.
- **AR1.** The AR1 term corrects serial correlation.

4.4.2 Small Commercial UPC Model

The UPC Model is an SAE model estimated with historical data from January 2008 through December 2021. The SAE model applies the same theoretical foundation as the Residential SAE model but modified for commercial end-use information. Table 30 shows the UPC Model specification and shows the UPC Model statistics.

The Small Commercial SAE model contains end-use information for heating, cooling, and base load technologies from Itron's 2021 SAE West North Central region. The model includes the following data.

- **End-use Saturations and Efficiencies.** End-use saturations and efficiencies by technology type are based on Energy Information. Administration (EIA) data.
- **Economic data.** Historical and forecast nonmanufacturing employment trends are based on Woods and Poole's forecast.
- **Energy Prices.** Price is based on historical revenue and energy consumption. The energy prices are held constant in real dollars through the forecast period.

TABLE 30: SMALL COMMERCIAL UPC MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	2361.511	276.303	8.547
XHeat	0.380	0.037	10.299
XCool	0.260	0.018	14.779
XOther	0.018	0.003	5.696
Year2009	-235.018	46.302	-5.076
Year2010	-248.473	43.175	-5.755
Year2011	-305.379	41.516	-7.356
Year2019Plus	-506.620	32.261	-15.704
Year2021_2022	-81.309	47.144	-1.725
Jan	-85.376	49.935	-1.710
Feb	-141.524	45.818	-3.089
Mar	-214.435	40.499	-5.295
Apr	-231.957	40.759	-5.691
May	-162.196	41.058	-3.950

TABLE 31: SMALL COMMERCIAL UPC MODEL STATISTICS

Statistics	Small Commercial UPC Model
Estimation	1/2008 – 12/2021
R2	0.875
Adj. R2	0.865
MAPE	2.37%
DW	1.245

The UPC Model includes SAE variables (XHeat, XCool, and XOther), annual binary variables, seasonal binary variables, and a binary shift. These variables are described below.

- **SAE Variables.** The SAE variables are **XHeat**, **XCool**, and **XOther**. **XHeat** captures the heating response and includes the effects of heating technology efficiencies, saturations, price, and nonmanufacturing employment. **XCool** captures the cooling response and captures the effects of cooling technology efficiencies, saturations, price, and nonmanufacturing employment. **XOther** captures the baseload response for all non-heating and non-cooling technologies.
- **Annual Binary Variables.** Three annual binary variables (**Year2009**, **Year2010**, and **Year 2011**) adjust the model for the 2008 recession and recovery. Binary variable **Year2021_2022** adjusts the model for impacts of COVID.
- **Seasonal Binary Variables.** Five seasonal binary variables (**Jan** through **May**) capture additional seasonal usages not included in the SAE variables.

- **Binary Shift**. One binary shift variable, **Year2019Plus,** captures a sustained decrease in usage beginning in January 2019 and continuing through the forecast period.

4.4.3 Small Commercial Base Sales Forecast

The Small Commercial sales forecast is developed as the product of the customer and UPC forecasts. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 30, Figure 31, and Figure 32. Table 32 shows the annual sales, customer, and average use forecast with average growth rates.

FIGURE 30: SMALL COMMERCIAL SALES FORECAST (ACTUAL AND FORECAST)

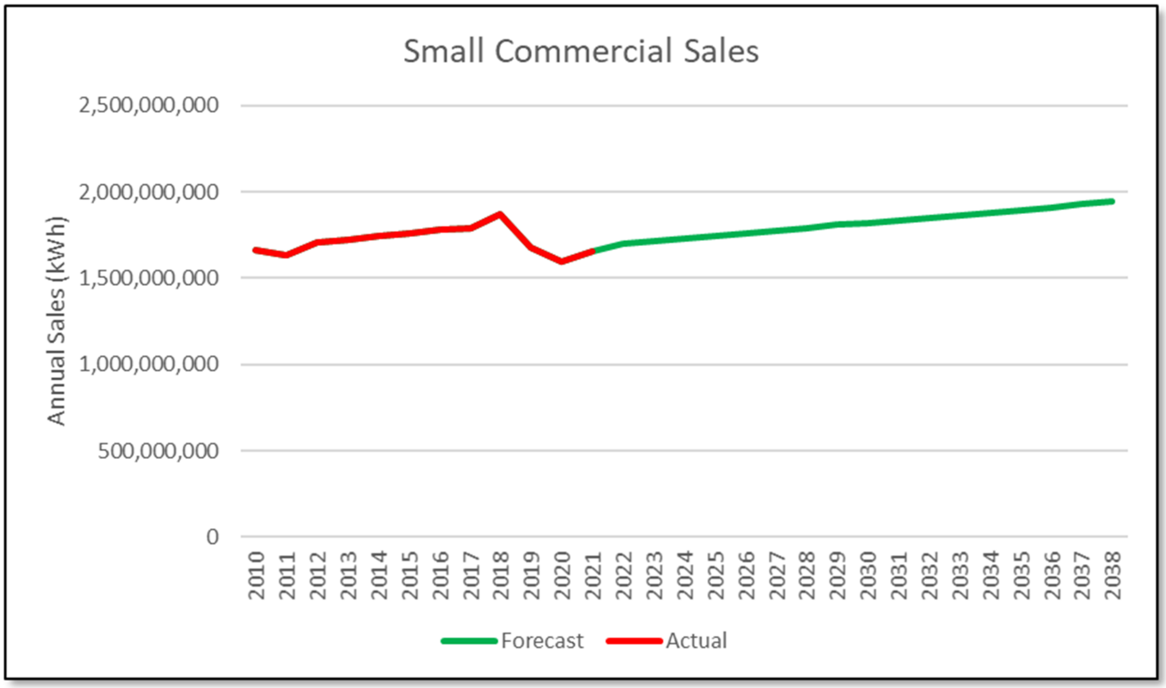


FIGURE 31: SMALL COMMERCIAL CUSTOMER FORECAST (ACTUAL AND FORECAST)

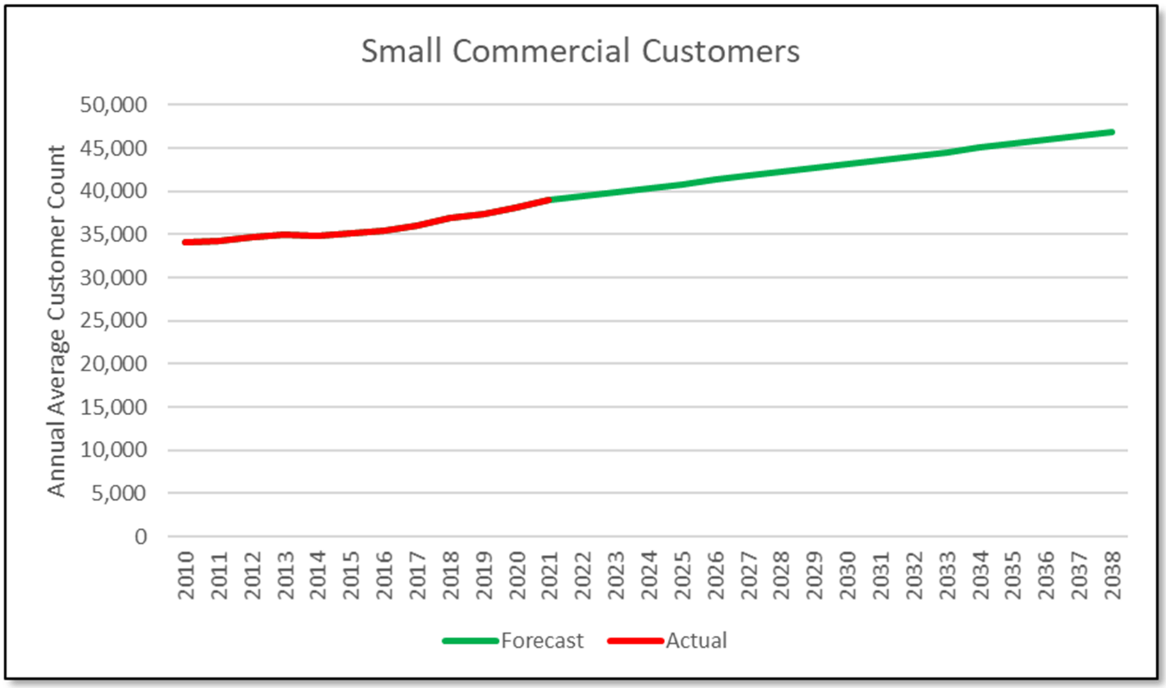


FIGURE 32: SMALL COMMERCIAL UPC FORECAST (ACTUAL AND FORECAST)

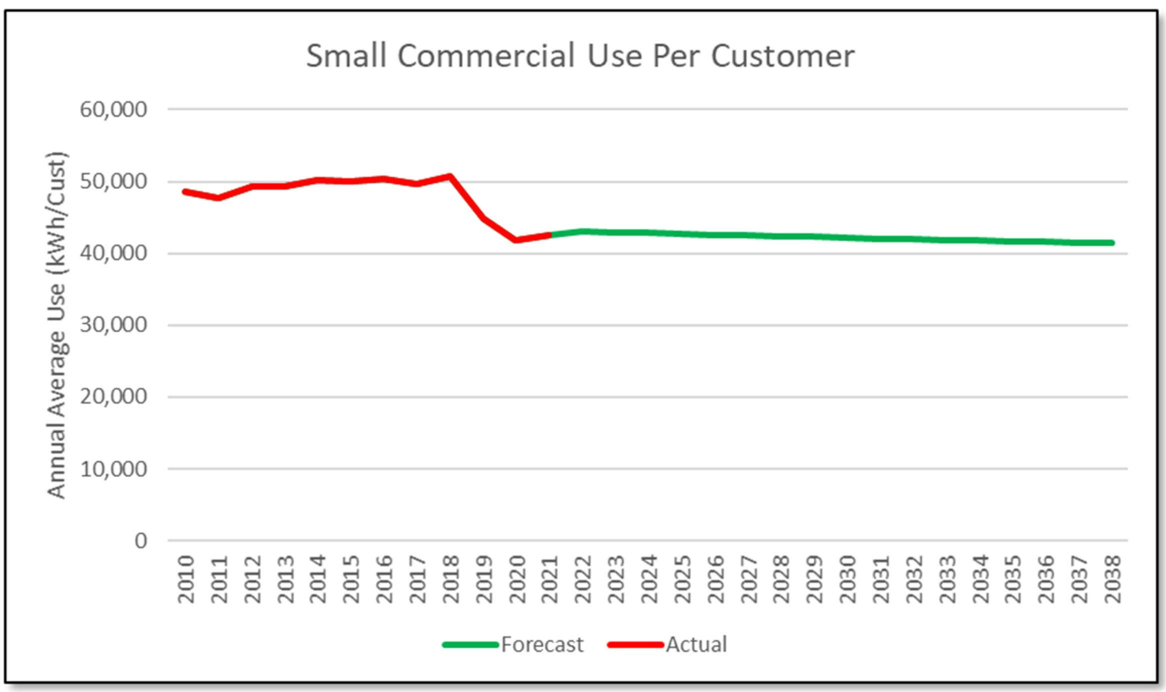


TABLE 32: SMALL COMMERCIAL SALES FORECAST

Year	Sales (kWh)	Sales Growth	Customers	Customer Growth	AvgUse (kWh)	AvgUse Growth
2023	1,713,391,390		39,935		42,905	
2024	1,729,114,068	0.92%	40,395	1.15%	42,805	-0.23%
2025	1,745,318,458	0.94%	40,856	1.14%	42,718	-0.20%
2026	1,760,462,494	0.87%	41,318	1.13%	42,608	-0.26%
2027	1,776,504,862	0.91%	41,779	1.12%	42,521	-0.20%
2028	1,792,107,482	0.88%	42,241	1.11%	42,426	-0.22%
2029	1,807,693,048	0.87%	42,703	1.09%	42,331	-0.22%
2030	1,820,866,235	0.73%	43,166	1.08%	42,183	-0.35%
2031	1,834,859,003	0.77%	43,629	1.07%	42,056	-0.30%
2032	1,849,494,340	0.80%	44,093	1.06%	41,946	-0.26%
2033	1,865,032,775	0.84%	44,557	1.05%	41,857	-0.21%
2034	1,880,161,302	0.81%	45,021	1.04%	41,762	-0.23%
2035	1,895,102,637	0.79%	45,486	1.03%	41,663	-0.24%
2036	1,910,213,232	0.80%	45,952	1.02%	41,570	-0.22%
2037	1,925,874,145	0.82%	46,418	1.01%	41,490	-0.19%
2038	1,942,443,808	0.86%	46,884	1.00%	41,431	-0.14%
2011-2021		**0.07%**		**1.20%**		**-1.12%**
2023-2038		**0.84%**		**1.08%**		**-0.24%**
5 Yr CAGR (2023-2028)		**0.90%**		**1.13%**		**-0.22%**
10 Yr CAGR (2023-2033)		**0.85%**		**1.10%**		**-0.25%**
15 Yr CAGR (2023-2038)		**0.84%**		**1.08%**		**-0.23%**

4.5 LARGE COMMERCIAL SALES MODEL

The Large Commercial class consists of all AR cooperative Large Commercial sales. The AR cooperatives provided historical sales and customer counts from their Form 7 data reports. The Large Commercial sales forecast is modelled with two models, a Customer Model and a UPC Model. The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total sales in each month. Using two models captures both the class growth based on a changing number of customers (Customer Model) and usage changes based on end-use information (UPC Model).

4.5.1 Large Commercial Customer Model

The Customer Model is a regression model estimated with historical data from January 2013 through December 2021.

Table 33 shows the Customer Model specification and Table 34 shows the Customer Model statistics.

TABLE 33: LARGE COMMERCIAL CUSTOMER MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	6425.868	1650.848	3.892
Manufacturing Employment Index	-4793.527	2542.351	-1.885
Regional GDP Index	1398.929	768.703	1.820
Jan2019	33.470	5.665	5.909
Feb2020Plus	25.178	8.171	3.081
AR1	0.982	0.007	145.618

TABLE 34: LARGE COMMERCIAL CUSTOMER MODEL STATISTICS

Statistics	Large Commercial Customer Model
Estimation	1/2013 – 12/2021
R^2	0.998
Adj. R^2	0.998
MAPE	0.19%
DW	1.247

The Customer Model growth is driven by the two economic variable, manufacturing employment and regional GDP. The additional variables capture data shifts in the historical data series. The variables are described below.

- **Economic Variables.** The **Manufacturing Employment Index** and Regional **GDP Index** capture the manufacturing and production output for the GRE service territory.
- **Binary Shifts.** Two binary shifts variables (**Jan2019**, and **Feb2020Plus)** capture the January 2019 outlier data point and the increase in customer counts beginning in February 2020.
- **AR1.** The AR1 term corrects serial correlation.

4.5.2 Large Commercial UPC Model

The UPC Model is an SAE model estimated with historical data from January 2008 through December 2021. The SAE model uses the same SAE inputs as the Small Commercial SAE model. Table 35 shows the UPC Model specification and Table 36 shows the UPC Model statistics.

The Large Commercial SAE model contains end-use information for heating, cooling, and base load technologies from Itron's 2021 SAE West North Central region. Included in the model are the following data.

- **End-use Saturations and Efficiencies.** End-use saturations and efficiencies by technology type are based on Energy Information. Administration (EIA) data.
- **Economic data.** Historical and forecast manufacturing employment trends are based on Woods and Poole's forecast.

- **Energy Prices.** Price is based on historical revenue and energy consumption. The energy prices are held constant in real dollars through the forecast period.

TABLE 35: LARGE COMMERCIAL UPC MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	157.150	3056.545	0.051
XHeat	0.413	0.339	1.219
XCool	3.484	0.200	17.454
XOther	0.488	0.034	14.199
Feb	-2473.667	497.262	-4.975
Apr	-2137.676	479.771	-4.456
Jan2017	219919.335	1650.983	133.205
Year2017Plus	-3463.345	324.498	-10.673
Oct2021Plus	5869.171	969.874	6.051

TABLE 36: LARGE COMMERCIAL UPC MODEL STATISTICS

Statistics	Large Commercial UPC Model
Estimation	1/2008 – 12/2021
R2	0.992
Adj. R2	0.991
MAPE	3.04%
DW	1.016

The UPC Model includes SAE variables (XHeat, XCool, and XOther), annual binary variables, dummy variables, seasonal variables, and shift variables. These variables are described below.

- **SAE Variables.** The SAE variables are **XHeat**, **XCool**, and **XOther**. **XHeat** captures the heating response and includes the effects of heating technology efficiencies, saturations, price, and manufacturing employment. **XCool** captures the cooling response and captures the effects of cooling technology efficiencies, saturations, price, and manufacturing employment. **XOther** captures the baseload response for all non-heating and non-cooling technologies.
- **Dummy Variables.** The dummy variable, **Jan2017**, removes an outlier data point.
- **Seasonal Binary Variables.** Two seasonal binary variables (**Feb** and **Apr**) capture additional seasonal usage not included in the SAE variables.
- **Binary Shift**. Two binary shift variables, **Year2017Plus** and **Oct2021Plus** capture sustained decreases beyond the SAE energy efficiency variables. These capture the usage decreases beginning in 2017 and the increase beginning in October 2021.

4.5.3 Large Commercial Base Sales Forecast

The Large Commercial sales forecast is developed as the product of the customer and UPC forecasts. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 33, Figure 34, and Figure 35. Table 37 shows the annual sales, customer, and average use forecast with average growth rates.

FIGURE 33: LARGE COMMERCIAL SALES FORECAST (ACTUAL AND FORECAST)

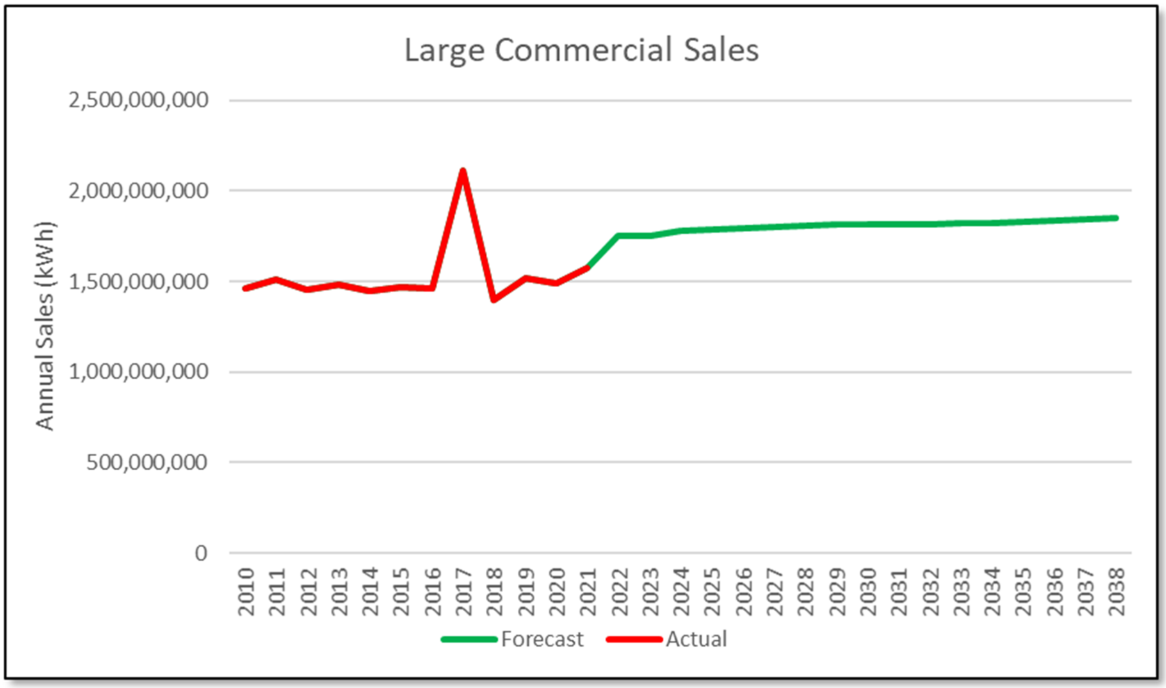


FIGURE 34: LARGE COMMERCIAL CUSTOMER FORECAST (ACTUAL AND FORECAST)

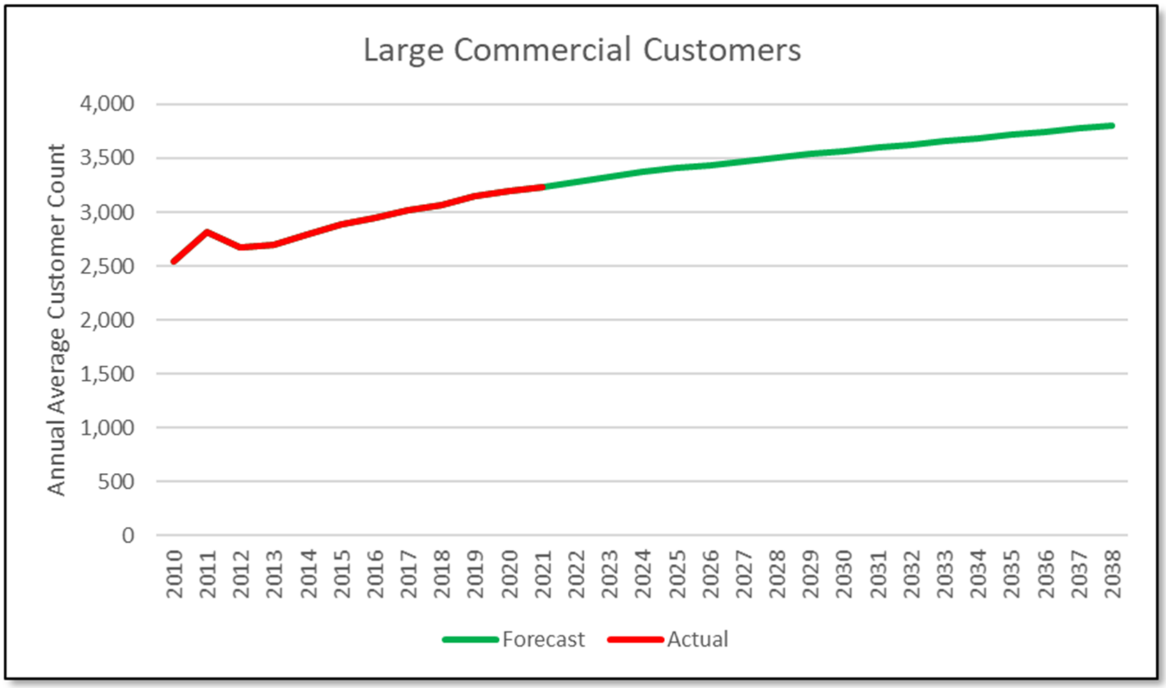


FIGURE 35: LARGE COMMERCIAL UPC FORECAST (ACTUAL AND FORECAST)

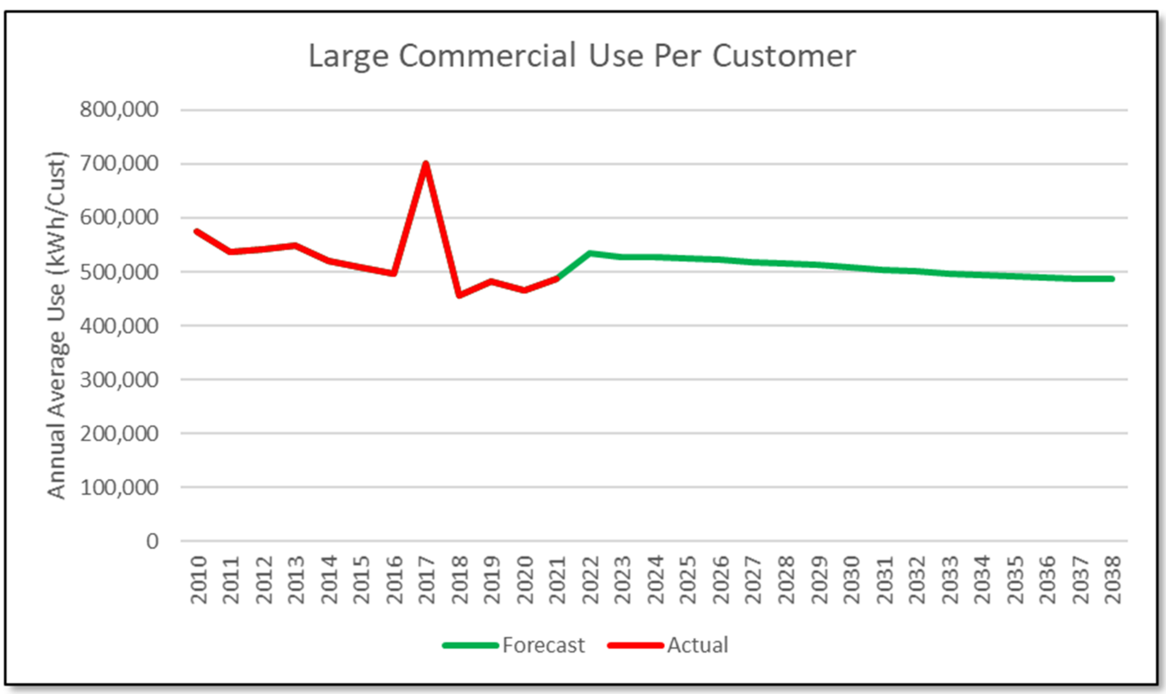


TABLE 37: LARGE COMMERCIAL SALES FORECAST

Year	Sales (kWh)	Sales Growth	Customers	Customer Growth	AvgUse (kWh)	AvgUse Growth
2023	1,753,083,714		3,328		526,799	
2024	1,779,154,615	1.49%	3,370	1.26%	527,992	0.23%
2025	1,787,765,385	0.48%	3,404	1.03%	525,139	-0.54%
2026	1,793,229,767	0.31%	3,438	0.99%	521,589	-0.68%
2027	1,801,302,156	0.45%	3,473	1.02%	518,635	-0.57%
2028	1,807,636,438	0.35%	3,507	0.97%	515,475	-0.61%
2029	1,813,033,606	0.30%	3,538	0.90%	512,416	-0.59%
2030	1,812,887,459	-0.01%	3,569	0.86%	507,997	-0.86%
2031	1,814,013,419	0.06%	3,599	0.85%	504,046	-0.78%
2032	1,816,575,411	0.14%	3,629	0.84%	500,560	-0.69%
2033	1,819,915,173	0.18%	3,659	0.82%	497,399	-0.63%
2034	1,824,521,877	0.25%	3,688	0.80%	494,686	-0.55%
2035	1,829,469,937	0.27%	3,717	0.79%	492,126	-0.52%
2036	1,835,050,723	0.31%	3,747	0.79%	489,763	-0.48%
2037	1,841,691,429	0.36%	3,776	0.78%	487,714	-0.42%
2038	1,849,872,796	0.44%	3,805	0.77%	486,118	-0.33%
2011-2021		**2.15%**		**2.27%**		**-0.08%**
2023-2038		**0.34%**		**0.94%**		**-0.59%**
5 Yr CAGR (2023-2028)		**0.61%**		**1.05%**		**-0.43%**
10 Yr CAGR (2023-2033)		**0.37%**		**0.95%**		**-0.57%**
15 Yr CAGR (2023-2038)		**0.36%**		**0.90%**		**-0.53%**

4.6 STREET AND HIGHWAY SALES MODEL

The Street and Highway class consists of all AR cooperative Street and Highway sales. The AR cooperatives provided historical sales and customer counts from their Form 7 data reports. The Street and Highway sales forecast is modelled with two models, a Customer Model and a UPC model. The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total sales in each month. Using two models captures both the class growth based on a changing number of customers (Customer Model) and usage changes based on end-use information (UPC Model).

4.6.1 Street and Highway Customer Model

The Customer Model is a regression model estimated with historical data from January 2014 through December 2021 and designed to forecast a constant number of customers. Table 38 shows the Customer Model specification and Table 39 shows the Customer Model statistics.

TABLE 38: STREET AND HIGHWY CUSTOMER MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	1164.896	0.982	1186.129
Year2016	10.104	2.196	4.601
Year2017	45.938	2.196	20.918
Year2020Plus	38.800	1.726	22.486
Dec2021Plus	14.304	6.951	2.058

TABLE 39: STREET AND HIGHWAY CUSTOMER MODEL STATISTICS

Statistics	Street & Highway Customer Model
Estimation	1/2014 – 12/2021
R^2	0.897
Adj. R^2	0.893
MAPE	0.41%
DW	0.835

The Street and Highway customer model is designed to forecast a constant number of customers based on the 2021 number of customers. The primary variable in this model is Dec**Year2021Plus**. This variable captures the number of customers at the end of 2021 and forecasts these customers through the forecast time horizon. The **Year2016** and **Year2017** binary variables capture short-term shifts in customer counts while **Year2020Plus** captures a shift that increases customers in 2020 that last throughout the forecast period.

4.6.2 Street and Highway UPC Model

The UPC Model is a regression model estimated with historical data from January 2014 through December 2021. Table 40 shows the UPC Model specification and Table 41 shows the UPC Model statistics.

TABLE 40: STREET AND HIGHWAY UPC MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	-240.305	256.359	-0.937
Commercial SAE Lighting	0.149	0.017	8.850
Jan	112.107	37.063	3.025
Feb	8.135	36.976	0.220
Mar	128.144	36.903	3.472
Apr	11.616	36.842	0.315
May	70.440	36.795	1.914
Jun	65.641	36.762	1.786
Jul	59.696	36.742	1.625
Sep	63.477	36.742	1.728
Oct	73.369	36.762	1.996
Nov	144.585	36.795	3.929
Dec	225.800	36.842	6.129
Year2018Plus	174.430	30.673	5.687
Year2021Plus	63.979	31.227	2.049

TABLE 41: STREET AND HIGHWAY UPC MODEL STATISTICS

Statistics	Street & Highway UPC Model
Estimation	1/2014 – 12/2021
R2	0.695
Adj. R2	0.643
MAPE	2.49%
DW	1.952

The UPC Model captures both the historical declining average usage and seasonal pattern. The following variables are used in the model.

- **Commercial SAE Lighting.** This variable is the commercial SAE lighting intensity component used in the commercial (small and large commercial) SAE models. The lighting intensity captures the improving energy efficiency of commercial lighting technologies.
- **Seasonal Pattern**. The monthly binary variables (**Jan** through **Dec**) model the seasonal usage pattern.
- **Binary Shifts**. Two binary shift variables, **Year2018Plus** and **Year2021Plus** capture sustained shifts beyond the SAE energy efficiency variables.

4.6.3 Street and Highway Base Sales Forecast

The Street and Highway sales forecast is developed as the product of the customer and UPC forecasts. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 36, Figure 37, and Figure 38. Table 42 shows the annual sales, customer, and average use forecast with average growth rates.

FIGURE 36: STREET AND HIGHWAY SALES FORECAST (ACTUAL AND FORECAST)

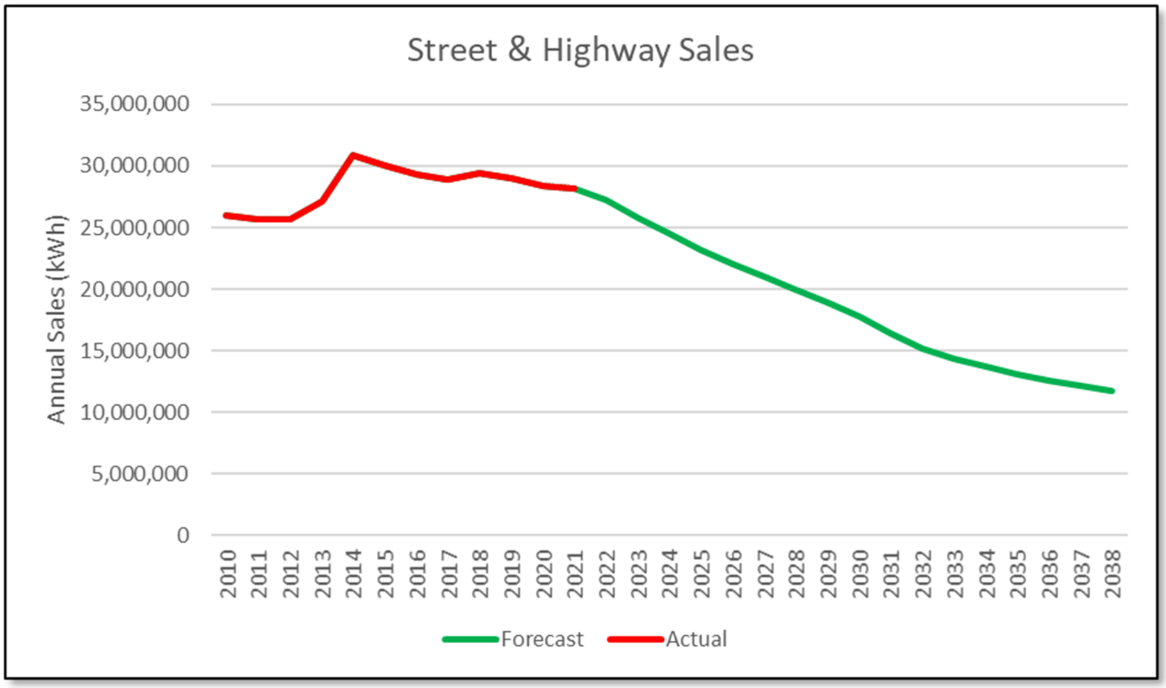


FIGURE 37: STREET AND HIGHWAY CUSTOMER FORECAST (ACTUAL AND FORECAST)

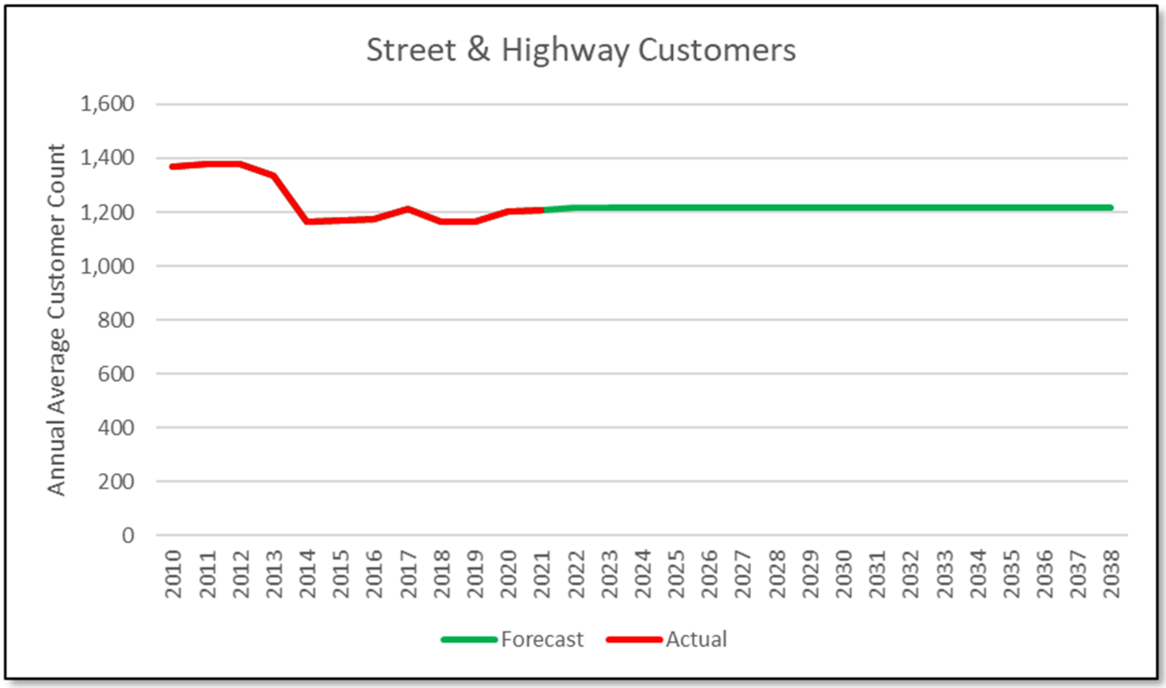


FIGURE 38: STREET AND HIGHWAY UPC FORECAST (ACTUAL AND FORECAST)

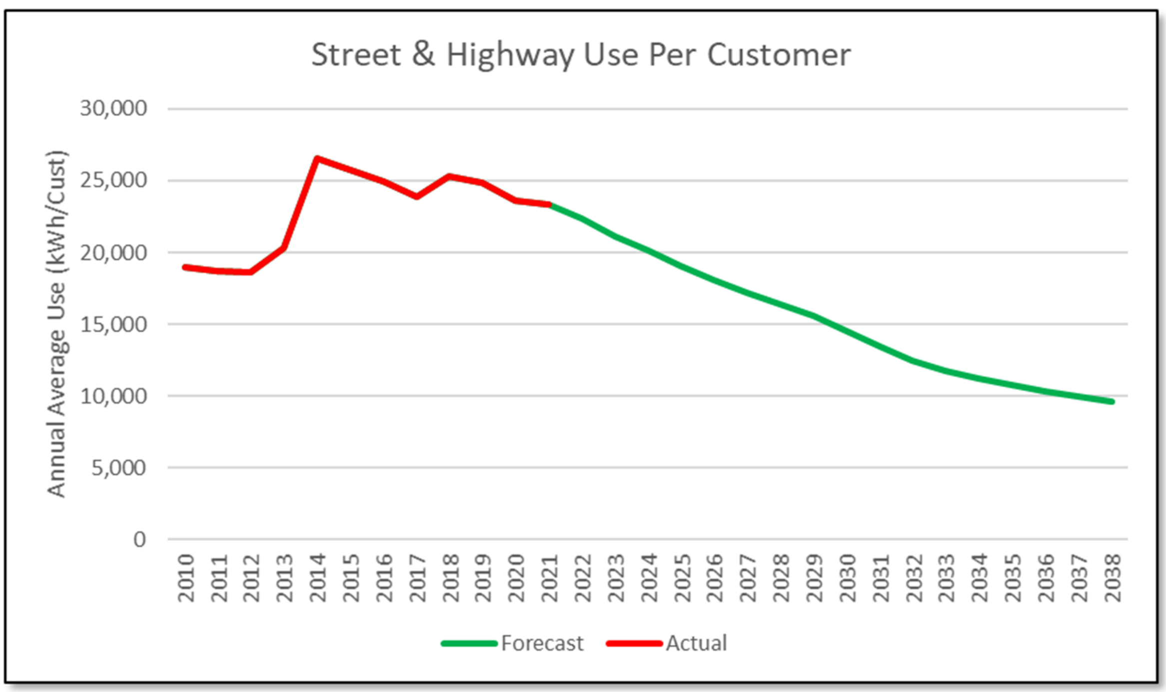


TABLE 42: STREET AND HIGHWAY SALES FORECAST

Year	Sales (kWh)	Sales Growth	Customers	Customer Growth	AvgUse (kWh)	AvgUse Growth
2023	25,745,321		1,218		21,137	
2024	24,490,114	-4.88%	1,218	0.00%	20,107	-4.88%
2025	23,200,317	-5.27%	1,218	0.00%	19,048	-5.27%
2026	22,038,565	-5.01%	1,218	0.00%	18,094	-5.01%
2027	20,992,789	-4.75%	1,218	0.00%	17,235	-4.75%
2028	19,962,672	-4.91%	1,218	0.00%	16,390	-4.91%
2029	18,933,905	-5.15%	1,218	0.00%	15,545	-5.15%
2030	17,719,638	-6.41%	1,218	0.00%	14,548	-6.41%
2031	16,393,065	-7.49%	1,218	0.00%	13,459	-7.49%
2032	15,188,222	-7.35%	1,218	0.00%	12,470	-7.35%
2033	14,336,993	-5.60%	1,218	0.00%	11,771	-5.60%
2034	13,678,650	-4.59%	1,218	0.00%	11,230	-4.59%
2035	13,100,486	-4.23%	1,218	0.00%	10,756	-4.23%
2036	12,593,179	-3.87%	1,218	0.00%	10,339	-3.87%
2037	12,145,975	-3.55%	1,218	0.00%	9,972	-3.55%
2038	11,750,100	-3.26%	1,218	0.00%	9,647	-3.26%
2011-2021		**0.83%**		**0.05%**		**2.28%**
2023-2038		**-5.12%**		**0.00%**		**-5.12%**
5 Yr CAGR (2023-2028)		**-4.96%**		**0.00%**		**-4.96%**
10 Yr CAGR (2023-2033)		**-5.69%**		**0.00%**		**-5.69%**
15 Yr CAGR (2023-2038)		**-5.09%**		**0.00%**		**-5.09%**

4.7 PUBLIC AUTHORITY SALES MODEL

The Public Authority class consists of all AR cooperative Public Authority sales. The AR cooperatives provided historical sales and customer counts from their Form 7 data reports. The Public Authority sales forecast is modelled with two models, a Customer Model and a UPC model. The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total sales in each month.

4.7.1 Public Authority Customer Model

The Public Authority customer model is an exponential smoothing model designed to forecast a constant number of customers through the forecast period. Since 2014, the number of customers remained consistent with 816 customers in January 2014 and 798 customers in December 2021. The forecast assumes the number of customers remains at 799 through the forecast period.

4.7.2 Public Authority UPC Model

The UPC Model is regression model estimated with historical data from January 2015 through December 2021. Table 43 shows the UPC Model specification and Table 44 shows the UPC Model statistics.

TABLE 43: PUBLIC AUTHORITY UPC MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	2359.816	154.022	15.321
WtHDD	0.222	0.207	1.073
WtCDD	4.900	1.023	4.792
Year2019Plus	4254.661	153.851	27.654
Year2020	-4373.260	217.182	-20.136

TABLE 44: PUBLIC AUTHORITY UPC MODEL STATISTICS

Statistics	Public Authority UPC Model
Estimation	1/2015 – 12/2021
R2	0.917
Adj. R2	0.913
MAPE	8.47%
DW	2.036

The UPC Model captures the class weather response and corrects for serial correlation. The following variables are used in the model.

- **WtCDD.** The class's weather response is modelled using the multipart spline CDD variable based on the average weather of the 4 weather stations.
- **WtHDD.** The class's weather response is modelled using the multipart spline HDD variable based on the average weather of the 4 weather stations.

4.7.3 Public Authority Base Sales Forecast

The Public Authority sales forecast is developed as the product of the customer and UPC forecasts. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 39, Figure 40, and Figure 41. Table 45 shows the annual sales, customer, and average use forecast with average growth rates.

FIGURE 39: PUBLIC AUTHORITY SALES FORECAST (ACTUAL AND FORECAST)

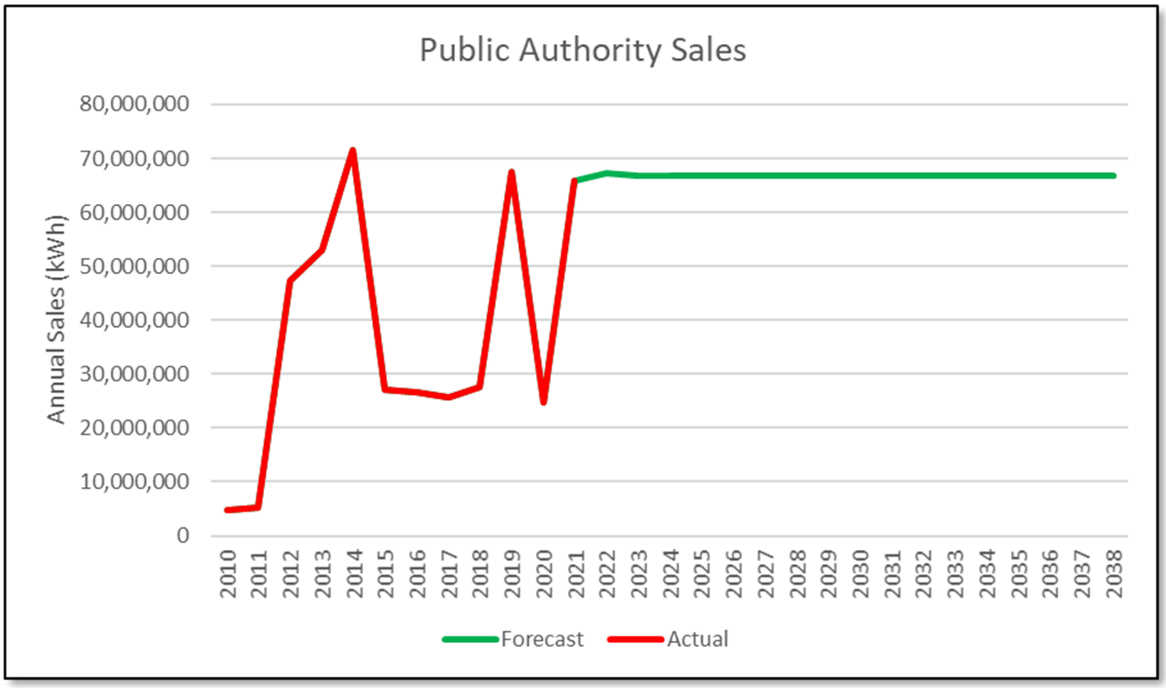


FIGURE 40: PUBLIC AUTHORITY CUSTOMER FORECAST (ACTUAL AND FORECAST)

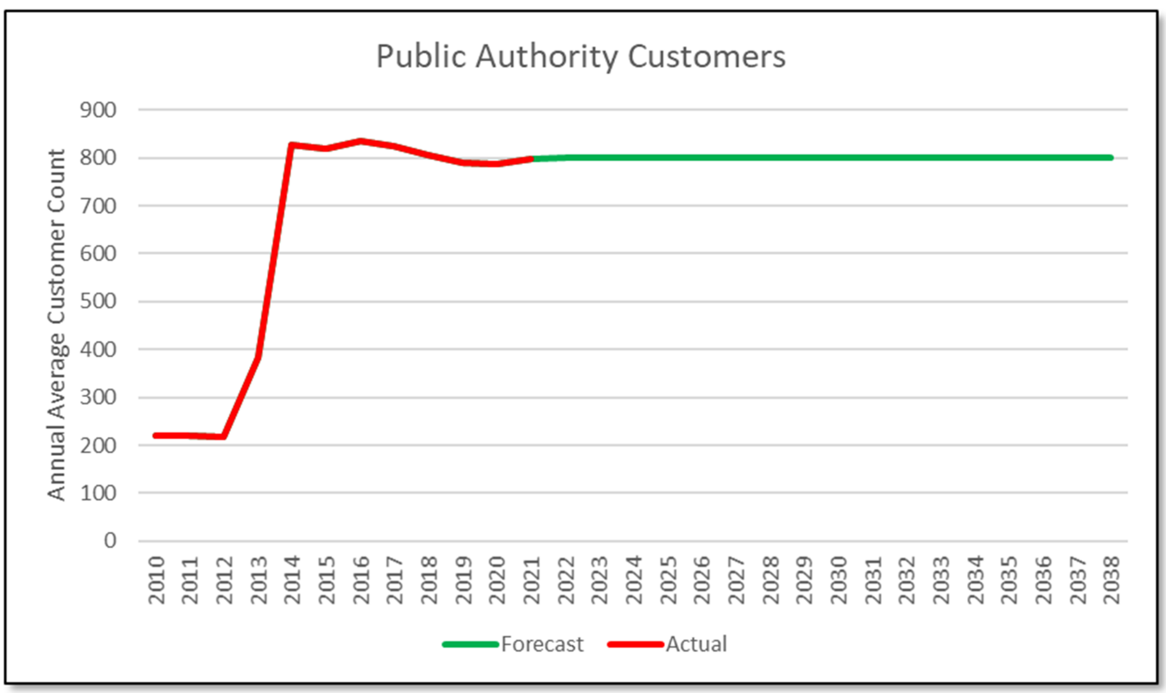


FIGURE 41: PUBLIC AUTHORITY UPC FORECAST (ACTUAL AND FORECAST)

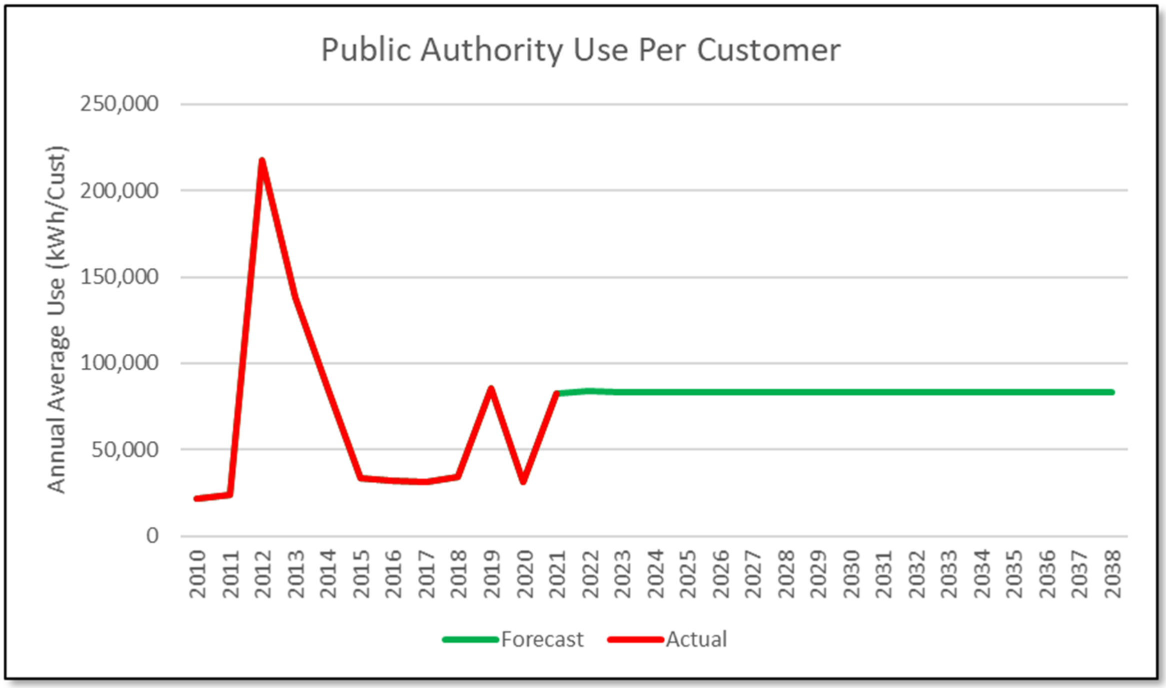


TABLE 45: PUBLIC AUTHORITY SALES FORECAST

Year	Sales (kWh)	Sales Growth	Customers	Customer Growth	AvgUse (kWh)	AvgUse Growth
2023	66,712,541		799		83,494	
2024	66,712,541	0.00%	799	0.00%	83,494	0.00%
2025	66,712,541	0.00%	799	0.00%	83,494	0.00%
2026	66,712,541	0.00%	799	0.00%	83,494	0.00%
2027	66,712,541	0.00%	799	0.00%	83,494	0.00%
2028	66,712,541	0.00%	799	0.00%	83,494	0.00%
2029	66,712,541	0.00%	799	0.00%	83,494	0.00%
2030	66,712,541	0.00%	799	0.00%	83,494	0.00%
2031	66,712,541	0.00%	799	0.00%	83,494	0.00%
2032	66,712,541	0.00%	799	0.00%	83,494	0.00%
2033	66,712,541	0.00%	799	0.00%	83,494	0.00%
2034	66,712,541	0.00%	799	0.00%	83,494	0.00%
2035	66,712,541	0.00%	799	0.00%	83,494	0.00%
2036	66,712,541	0.00%	799	0.00%	83,494	0.00%
2037	66,712,541	0.00%	799	0.00%	83,494	0.00%
2038	66,712,541	0.00%	799	0.00%	83,494	0.00%
2011-2021		**95.14%**		**16.97%**		**85.58%**
2023-2038		**-0.05%**		**0.00%**		**-0.05%**
5 Yr CAGR (2023-2028)		**0.00%**		**0.00%**		**0.00%**
10 Yr CAGR (2023-2033)		**0.00%**		**0.00%**		**0.00%**
15 Yr CAGR (2023-2038)		**0.00%**		**0.00%**		**0.00%**

4.8 RESALE SALES MODEL

The Resale class consists of all AR cooperative Resale sales. The AR cooperatives provided historical sales and customer counts from their Form 7 data reports. The Resale sales forecast is modelled with two models, a Customer Model and a UPC model. The class forecast is calculated by multiplying the customer forecast by the UPC forecast to obtain the total sales in each month.

4.8.1 Resale Customer Model

The Customer Model is a regression model designed to forecast a constant number of customers. Since 2010, the number of customers has ranged between 2 and 5. Beginning in 2019, only 2 customers are reported. The regression model is a constant model designed to produce a forecast of 2 customers.

4.8.2 Resale UPC Model

Like the Customer Model, the UPC model is designed to forecast average use based on the most recent use of the 2 resale customers. In 2019, the annual average historical UPC is 1,230 MWh. The model captures the 2019 to 2021 average use. Table 46 shows the UPC Model specification and Table 47 shows the UPC Model statistics.

TABLE 46: RESALE UPC MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	5696918.767	143170.849	39.791
Year2019Plus	-5593272.656	233797.018	-23.924

TABLE 47: RESALE MODEL STATISTICS

Statistics	Resale UPC Model
Estimation	1/2014 – 12/2021
R2	0.859
Adj. R2	0.857
MAPE	23.93%
DW	0.727

4.8.3 Resale Base Sales Forecast

The Resale sales forecast is developed as the product of the customer and UPC forecasts. The annual energy forecast, customer forecast, and use-per-customer forecast are shown in Figure 42, Figure 43, and Figure 44. Table 48 shows the annual sales, customer, and average use forecast with average growth rates.

FIGURE 42: RESALE SALES FORECAST (ACTUAL AND FORECAST)

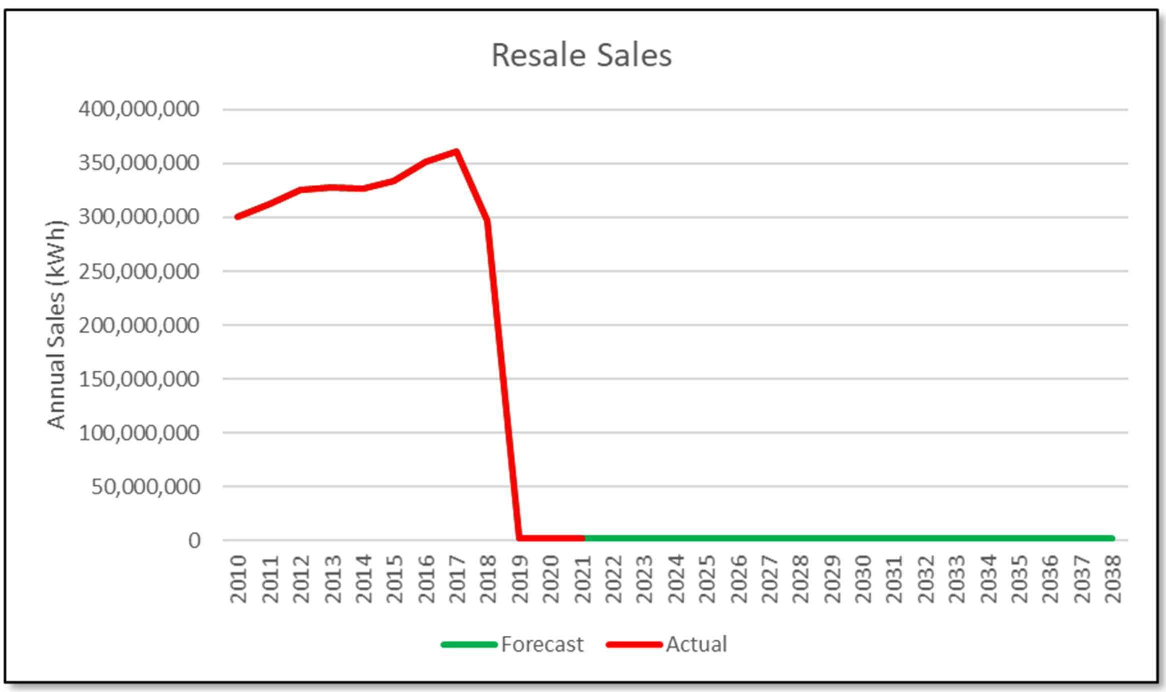


FIGURE 43: RESALE CUSTOMER FORECAST (ACTUAL AND FORECAST)

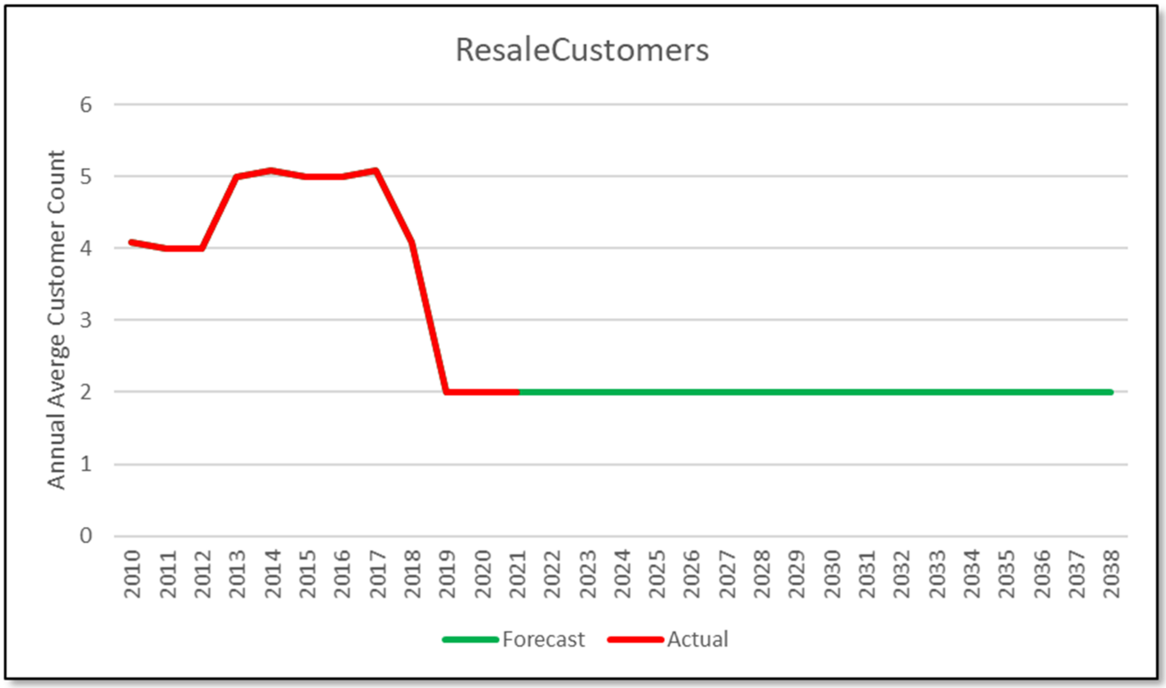


FIGURE 44: RESALE UPC FORECAST (ACTUAL AND FORECAST)

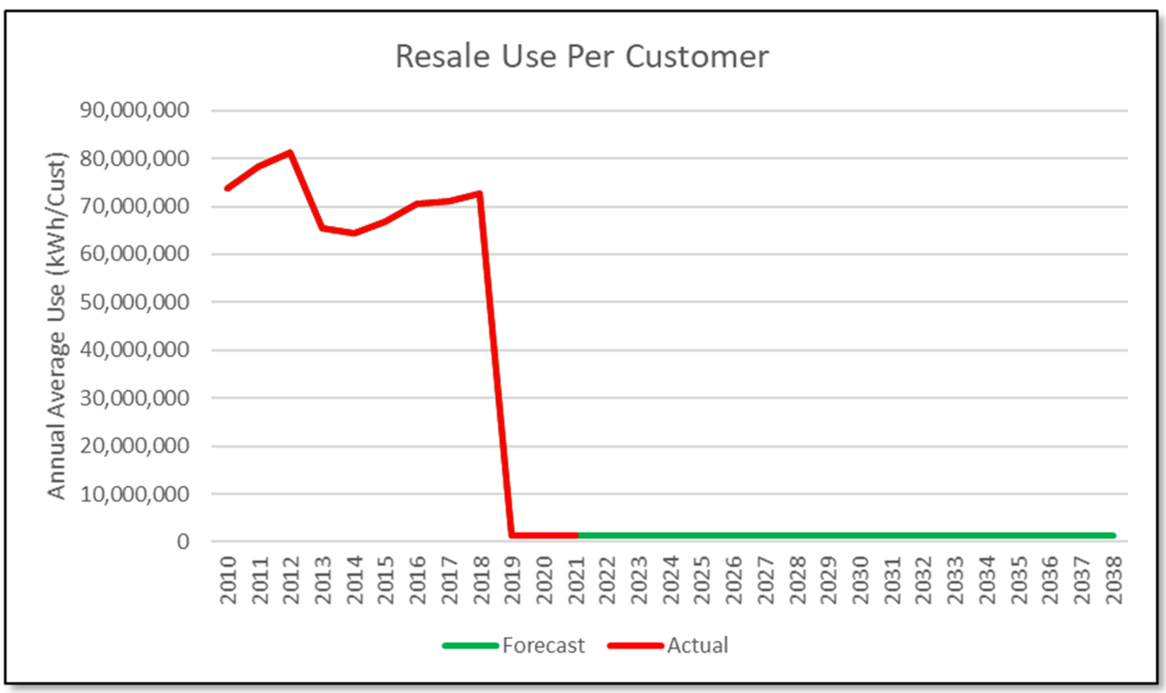


TABLE 48: RESALE SALES FORECAST

Year	Sales (kWh)	Sales Growth	Customers	Customer Growth	AvgUse (kWh)	AvgUse Growth
2023	2,487,507		2		1,243,753	
2024	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2025	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2026	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2027	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2028	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2029	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2030	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2031	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2032	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2033	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2034	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2035	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2036	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2037	2,487,507	0.00%	2	0.00%	1,243,753	0.00%
2038	2,487,507	-1.72%	2	0.00%	1,243,753	-1.72%
2011-2021		**-8.70%**		**-4.19%**		**-8.57%**
2023-2038		**0.00%**		**0.00%**		**0.00%**
5 Yr CAGR (2023-2028)		**0.00%**		**0.00%**		**0.00%**
10 Yr CAGR (2023-2033)		**0.00%**		**0.00%**		**0.00%**
15 Yr CAGR (2023-2038)		**0.00%**		**0.00%**		**0.00%**

4.9 OWN USE SALES MODEL

The Own Use class consists of all AR cooperative Own Use sales. The AR cooperatives provided historical sales and customer counts from their Form 7 data reports. The Own Use sales forecast is modelled with a single sales model. Table 49 shows the Sales Model specification and Table 50 shows the Sales Model statistics.

TABLE 49: OWN USE SALES MODEL

Variable	Coefficient	StdErr	T-Stat
Constant	577049.492	18976.595	30.408
WtHDD	1017.851	22.287	45.669
WtCDD	196.023	114.796	1.708
Year2012	-99137.738	26261.237	-3.775
Year2016	-274040.721	26215.300	-10.453
MaytoSepYear2017Plus	-127246.980	26341.037	-4.831
Year2017Plus	77014.390	19555.825	3.938

TABLE 50: MUNICIPAL MODEL STATISTICS

Statistics	Own Use Model
Estimation	1/2012 – 12/2021
R2	0.975
Adj. R2	0.973
MAPE	6.76%
DW	1.358

The sales model is designed to create a constant forecast over the forecast period. The model includes weather response variables, binary shifts variables, and binary variables. The variables are described below.

- **WtCDD.** The class's weather response is modelled using the multipart spline CDD variable based on the average weather of the 4 weather stations.
- **WtHDD.** The class's weather response is modelled using the multipart spline HDD variable based on the average weather of the 4 weather stations.
- **Shift Binary Variables.** Two binary shift variables capture the seasonal level changes beginning in 2017. The **Year2017Plus** variable increases the usage beginning in January 2017. The **MaytoSepYear2017Plus** variable decreases summer usage beginning in May 2017.
- **Binary Variables.** Two annual binary variables (**Year2016** and **Year2012**) adjust historical years (216 and 2012) for short-term data shifts.

4.9.1 Own Use Sales Forecast

Figure 45 shows the Own Use annual energy forecast and Table 51 shows the Own Use annual sales forecast with average growth rates.

FIGURE 45: OWN USE SALES FORECAST (ACTUAL AND FORECAST)

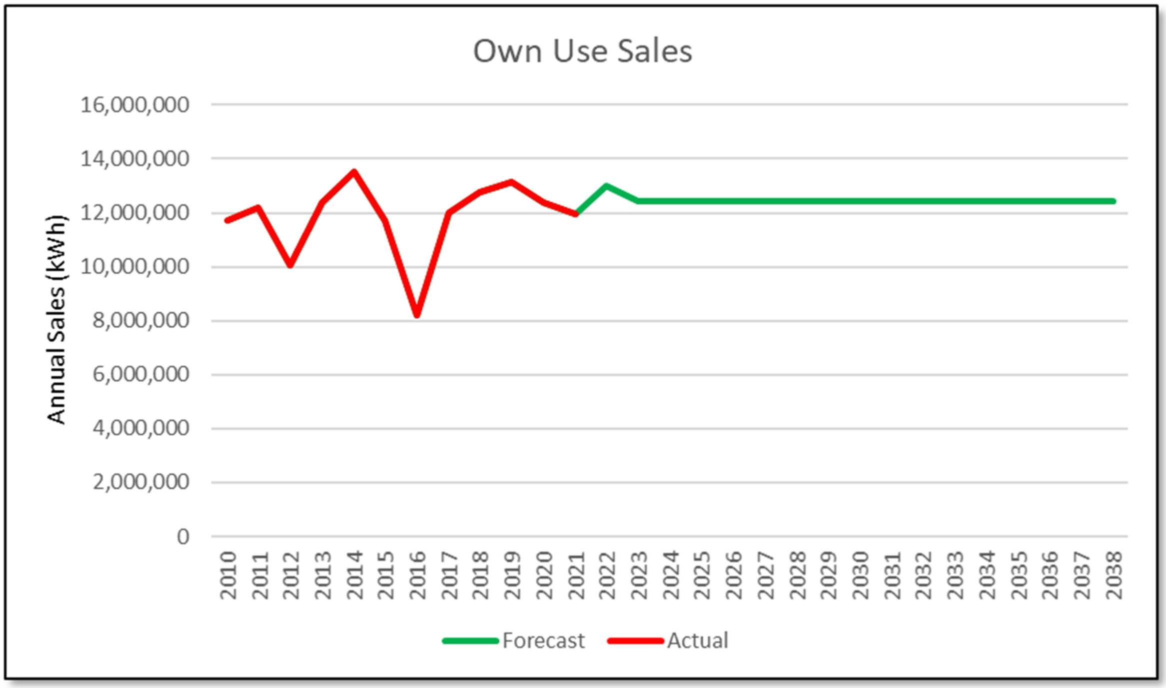


TABLE 51: OWN USE SALES FORECAST

Year	Sales (kWh)	Sales Growth
2023	12,428,144	
2024	12,428,144	0.00%
2025	12,428,144	0.00%
2026	12,428,144	0.00%
2027	12,428,144	0.00%
2028	12,428,144	0.00%
2029	12,428,144	0.00%
2030	12,428,144	0.00%
2031	12,428,144	0.00%
2032	12,428,144	0.00%
2033	12,428,144	0.00%
2034	12,428,144	0.00%
2035	12,428,144	0.00%
2036	12,428,144	0.00%
2037	12,428,144	0.00%
2038	12,428,144	0.00%
2011-2021		**2.03%**
2023-2038		**-0.28%**
5 Yr CAGR (2023-2028)		**0.00%**
10 Yr CAGR (2023-2033)		**0.00%**
15 Yr CAGR (2023-2038)		**0.00%**

4.10 AR PEAK MODEL

The AR Peak Model is a regression model that is designed to forecast the monthly AR peaks. The AR peaks are defined as the maximum monthly values for the aggregated AR cooperatives. The maximum values are restored for peak day curtailments. The model is estimated with data from January 2011 through December 2021. The model is shown in Table 52 and the model statistics are shown in Table 53.

TABLE 52: SYSTEM PEAK MODEL

Variable	Coefficient	StdErr	T-Stat
HDD50_HeatIndex	672.581	180.100	3.734
CDD65_CoolIndex	8.472	0.447	18.958
Base_Index	26.707	1.936	13.796
JunBaseTrend	117.685	56.453	2.085
JulAugBaseTrend	44.746	9.124	4.904
SepBaseTrend	82.757	9.712	8.521
Year2017	31.542	8.732	3.612
MA1	-13.822	29.643	-0.466

TABLE 53: SYSTEM PEAK MODEL STATISTICS

Statistics	Peak Model
Estimation	1/2011 – 12/2021
R2	0.911
Adj. R2	0.905
MAPE	3.75%
DW	1.965

The System Peak Model is driven by the sales forecast and peak producing weather. An additional seasonal adjustment is included to differentiate the summer baseload trend from the winter baseload trend. The variables are discussed below.

- **HDD50_HeatIndex.** This variable is an interaction between the average temperature on the monthly peak day for temperatures below 50 degrees and the heating components of the sales models. The heating components are derived by multiplying the heating variable coefficients from the class sales models by normal heating degree days. The results are smoothed using a 12-month moving average. This variable captures the heating contribution to peak growth.
- **CDD65_CoolIndex.** This variable is an interaction between average temperature on the monthly peak day for temperatures above 65 degrees and the cooling components of the energy models. The cooling components are derived by multiplying the cooling variable coefficients from the class sales models by normal cooling degree days. The results are smoothed using a 12-month moving average. This variable captures the cooling contribution to peak growth.
- **Base_Index. Base_Index** is the non-heating and non-cooling sales from class sales models. The sales results are smoothed using a 12-month moving average. This variable captures the base load contribution to peak growth.
- **Summer Baseload Trend Adjustment.** Three variables are used to differentiate the summer baseload trend from the winter baseload trend. These variables are **JunBaseTrend**, **JulAugBaseTrend**, and **SepBaseTrend**. These variables are constructed by interacting the monthly binary (e.g., Jun) with the **Base_Index** variable. The significant coefficients increase the summer month trends.

4.10.1 Peak Base Forecast Results

Figure 46 shows the annual summer and winter peaks for the AR system. The AR system is summer peaking system with stronger long-term growth in the summer than winter. Table 54 shows the summer and winter peaks and their annual growth rates.

FIGURE 46: SYSTEM SUMMER PEAK FORECAST

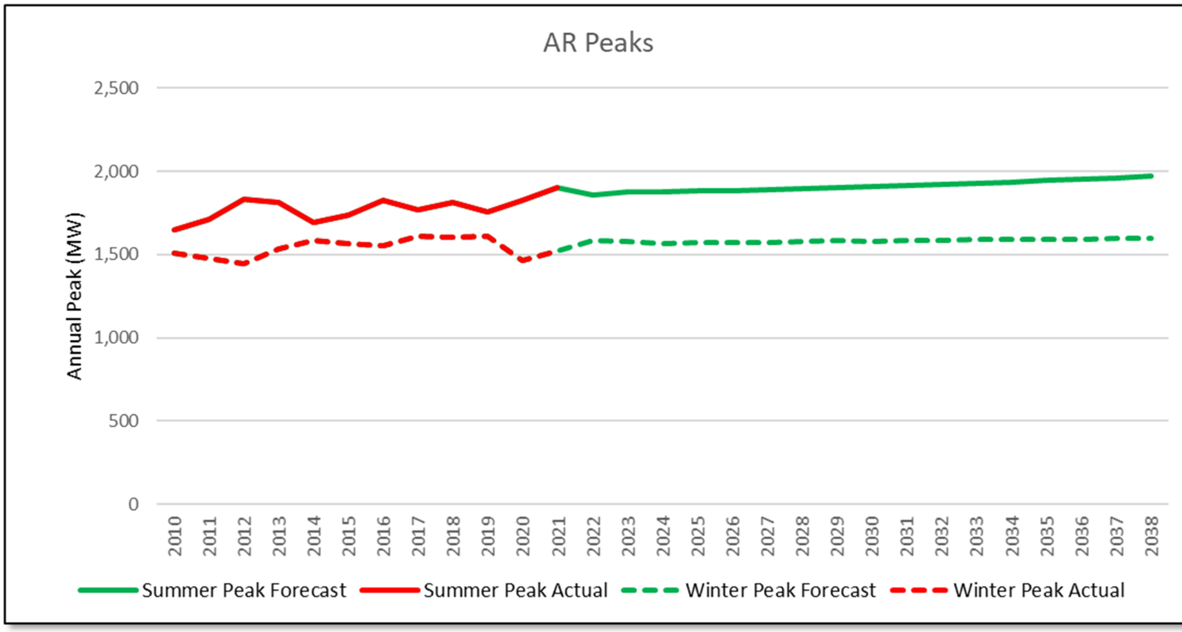


TABLE 54: AR PEAK FORECAST

Year	Summer Peak (MW)	Summer Peak Growth	Winter Peak (MW)	Winter Peak Growth
2023	1,877		1,577	
2024	1,875	-0.10%	1,569	-0.53%
2025	1,881	0.31%	1,574	0.35%
2026	1,886	0.28%	1,573	-0.07%
2027	1,892	0.32%	1,575	0.10%
2028	1,899	0.36%	1,577	0.15%
2029	1,905	0.33%	1,582	0.31%
2030	1,911	0.29%	1,581	-0.06%
2031	1,917	0.30%	1,582	0.10%
2032	1,923	0.35%	1,584	0.13%
2033	1,930	0.35%	1,589	0.29%
2034	1,937	0.37%	1,588	-0.05%
2035	1,945	0.40%	1,590	0.10%
2036	1,953	0.43%	1,592	0.11%
2037	1,961	0.42%	1,596	0.27%
2038	1,970	0.44%	1,594	-0.09%
2011-2021		**1.37%**		**0.15%**
2023-2038		**0.37%**		**0.03%**
5 Yr CAGR (2023-2028)		**0.23%**		**0.00%**
10 Yr CAGR (2023-2033)		**0.28%**		**0.08%**
15 Yr CAGR (2023-2038)		**0.32%**		**0.07%**

4.11 HOURLY SHAPE FORECAST

The AR hourly load forecast is developed by calibrating the AR hourly shape forecast to monthly AR sales forecasts and monthly AR peak forecasts. Sections 4.1 through 4.10 document the sales and peak models. This section documents the AR hourly shape model.

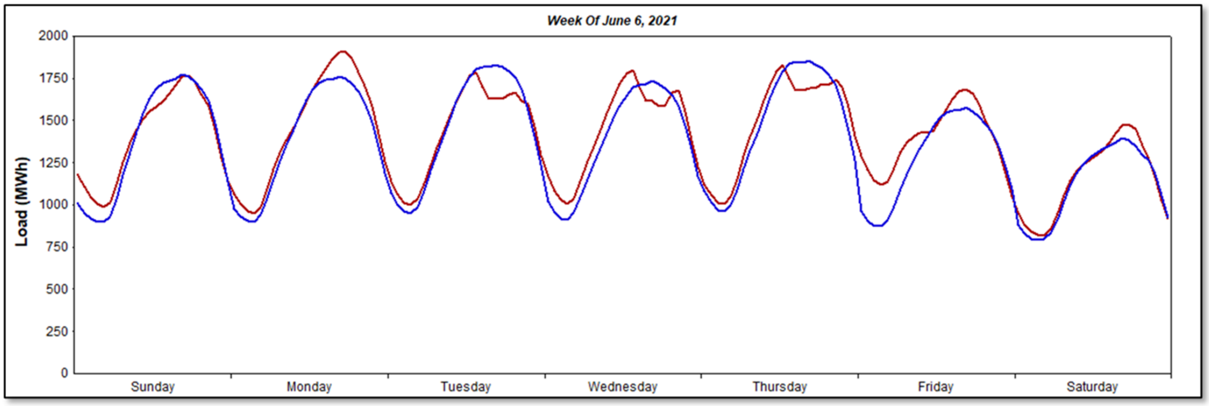
4.11.1 Hourly Profile Model

The hourly profile model is developed as a set of 24 independent hourly regression models, one regression for each hour. The models are estimated with data from 2017 through 2021 and designed to forecast the most recent load shape. The variable used in the profile model are defined below.

- **HDD and CDD.** HDD and CDD spline variables are used to capture the nonlinear load-weather response. The splines are created using multiple HDD and CDD variables (e.g., HDD35, HDD45, HDD55, CDD 60, CDD65, and CDD70) that use different temperature reference points. Using multiple weather breakpoints allows the hourly load shape's weather response to change in each hour.
- **Day of Week.** Day of week binary variables (e.g., Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, and Saturday) capture variations in the profile shape based on the day of the week.
- **Year.** Annual binary variables (e.g., Year2016, Year2017) capture load growth changes. When modeling load shape over the long-term horizon, the profile models assume no changes in the profile shape.
- **Holiday**. Key holidays are identified using this set of binary variables. These holidays capture the unique shape for specific holidays.
  - New Year Holiday
  - Memorial Day
  - July 4th Holiday
  - Labor Day
  - Thanksgiving
  - Friday After Thanksgiving
  - Christmas Holiday

The individual hourly models have MAPEs ranging between 2.6% and 5.0% and adjusted R2 vales ranging between 0.890 and 0.930. While model statistically accuracy is important, the intention of these models is to create consistent average shapes that may be used in the forecast. Figure 47 illustrates the average shapes compared to actual values for the peak in 2021. In this figure, modeled values (shown in blue) generally capture the summer shape relative to the actual values (shown in red).

FIGURE 47: HOURLY MODEL- 2021 PEAK WEEK



5 CONCLUSION

The 2023 IRP forecast and scenarios are based on GRE's AR class sales adjusted for fixed obligations, EVs, and PVs. From 2023 through 2038, system energy grows at 0.50% per year, with summer peaks growing at 0.40% per year. Growth is slightly slower than population (0.56% per year) and nonmanufacturing employment (0.88% per year), which is consistent with improving technology efficiencies over time.

The strength of the forecast is its theoretical basis. First, by using the SAE modelling approach for the residential, seasonal, small commercial, and large commercial classes, the forecast captures the improving efficiencies of end-use technologies. Second, the economic drivers represent economic activity in the GRE service territory. And finally, key uncertainties in behind-the-meter solar and electric vehicle adoption are separated from the statistical models allowing the system shape to change based on technology load profiles.

While this report summarizes the forecast models and results from 2023 through 2038, full results are available in the MetrixND and MetrixLT project files, as well as in the associated workpapers.