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2023 LONG-TERM ELECTRIC ENERGY AND DEMAND FORECAST REPORT

Prepared For:

Vermont Electric Power Company, Vermont

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1 OVERVIEW

Itron, Inc. (Itron) recently completed the long-term energy and demand forecast for 2024 Vermont Long Range Transmission Plan. The forecast provides system energy, peak demand, and hourly load forecasts for the state and for each of the Vermont Electric Power Company (VELCO) transmission planning zones. The forecast is a key input into the transmission system reliability analysis and determining future system upgrade requirements. The forecast was completed in June 2023 based on system, transmission-level load data, and class sales data (i.e., residential, commercial, and industrial) through December 2022. The forecast was developed over the January 2023 through June period with significant input and review by the Vermont Load Forecasting Sub-Committee (LFSC). The LFSC reviewed forecast assumptions, models, and results. Model inputs included state and regional economic forecasts, end-use energy intensity trends, weather trends, installed and projected solar capacity, electric heat pump recent adoptions and forecast, and electric vehicle projections – both non-fleet and fleet vehicles. LFSC discussions about new technologies and their potential load impacts contributed to a better understanding as to how these technologies work, how best to integrate these technologies into the long-term load forecast, and as a result likely impact on future electricity requirements and peak demand.

As part of the forecasting process, two forecast scenarios were developed: low and expected. The Expected Case reflects current state policy; the forecast incorporates aggressive heat pump adoption and nearly total transition to electric vehicles. The Low Case is itself relatively strong but assumes slower adoption of heat pumps and electric vehicles. In this report the Expected Case is referenced throughout unless noted otherwise.

The 20-year forecast extends through 2043. Over the next ten years (2023-2033), system energy deliveries are projected to increase 1.9% annually. Baseline energy (excluding solar, heat pumps, and electric vehicles) decline 0.1% annually over this period as continued improvements in energy efficiency from both new standards and state efficiency program activity outweigh the addition of new customers and economic growth. While solar capacity continues to increase, it's more than offset by rapidly increasing electric sales associated with cold climate heat pump market penetration and projected electric vehicle adoption. The expected growth in heat pump adoption and electric vehicles in the next decade results in strong winter-peak demand growth averaging 3.6% per year through 2033. Peak demand growth slows after 2033 with winter peak demand averaging 1.2% per year as heat pump saturation decelerates. Table-1 shows the long-term energy and demand forecast.

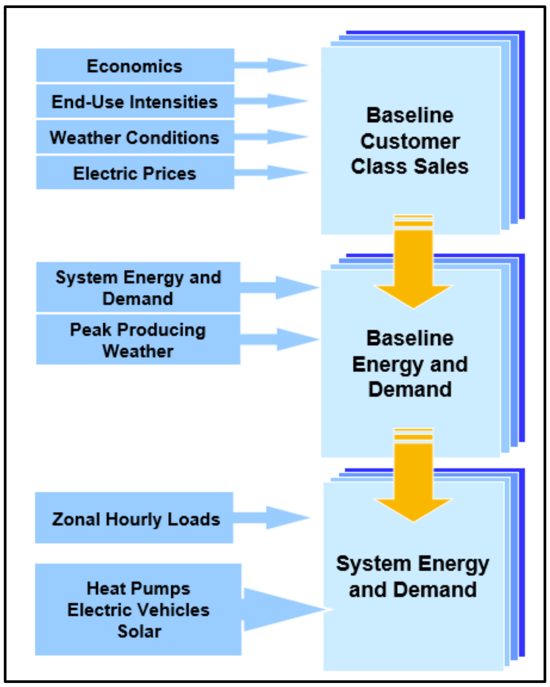
TABLE-1: SYSTEM ENERGY (MWH) AND PEAK (MW) FORECAST

Year	Energy (MWh)	Summer Peak (MW)	Winter Peak (MW)
2023	5,402,297	966.5	978.8
2024	5,434,976	975.3	1,001.7
2025	5,490,519	991.9	1,032.3
2026	5,570,913	1,014.5	1,068.8
2027	5,661,741	1,037.6	1,110.8
2028	5,794,371	1,062.0	1,154.6
2029	5,928,232	1,087.2	1,200.1
2030	6,069,464	1,115.1	1,249.1
2031	6,219,886	1,140.8	1,297.2
2032	6,375,873	1,169.7	1,342.9
2033	6,513,005	1,195.4	1,388.9
2034	6,654,594	1,223.4	1,430.2
2035	6,779,200	1,243.6	1,465.0
2036	6,889,232	1,262.4	1,491.5
2037	6,968,090	1,278.5	1,515.5
2038	7,041,559	1,289.5	1,533.1
2039	7,111,557	1,300.1	1,546.8
2040	7,183,085	1,309.4	1,551.5
2041	7,231,115	1,317.5	1,562.3
2042	7,246,592	1,322.1	1,566.2
2043	7,259,201	1,329.9	1,568.6
2023 - 33	1.9%	2.1%	3.6%
2033 - 43	1.1%	1.1%	1.2%
2023 - 43	**1.5%**	**1.6%**	**2.4%**

2 FORECAST APPROACH

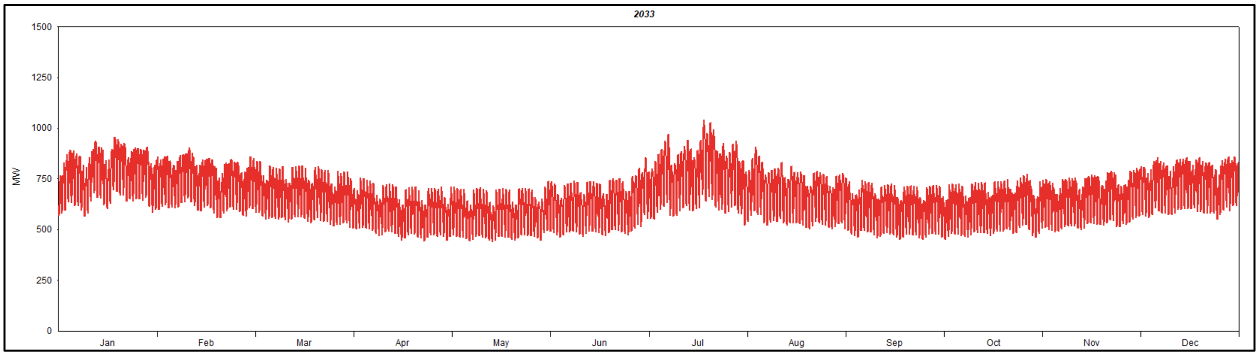
The long-term energy and demand forecast is derived using a "build-up" approach as depicted in Figure 1.

FIGURE 1: MODELING FRAMEWORK



The forecast approach starts with residential, commercial, and industrial sales and customer forecasts. End-use sales derived from the class-level sales models drive the Baseline energy and peak forecasts. As a result, the baseline energy and peak forecast capture population and economic growth, end-use saturation (before adjustments for program impacts), energy efficiency (both standards and state programs), and expected weather conditions for the system and each of the planning zones. Zonal energy projections combined with zonal hourly load profiles are aggregated to system load and calibrated to system peak. The hourly baseline forecast is generated for the period 2023 to 2043. The baseline forecast peaks in the summer as it excludes the impact of solar generation. Figure 2 shows the resulting baseline hourly load forecast for 2033.

FIGURE 2: BASELINE SYSTEM HOURLY LOAD FORECAST (2033)



Adjusting for New Technologies. Solar, cold-climate heat pumps, and electric vehicle hourly load forecasts are layered on the baseline hourly load zonal forecasts. These technologies significantly reshape system load over time. Figure 3 and Figure 4 show how these technologies reshape loads. The baseline forecast is in red and adjusted forecast is in blue.

FIGURE 3: JANUARY SYSTEM HOURLY LOAD FORECAST (4TH WEEK)

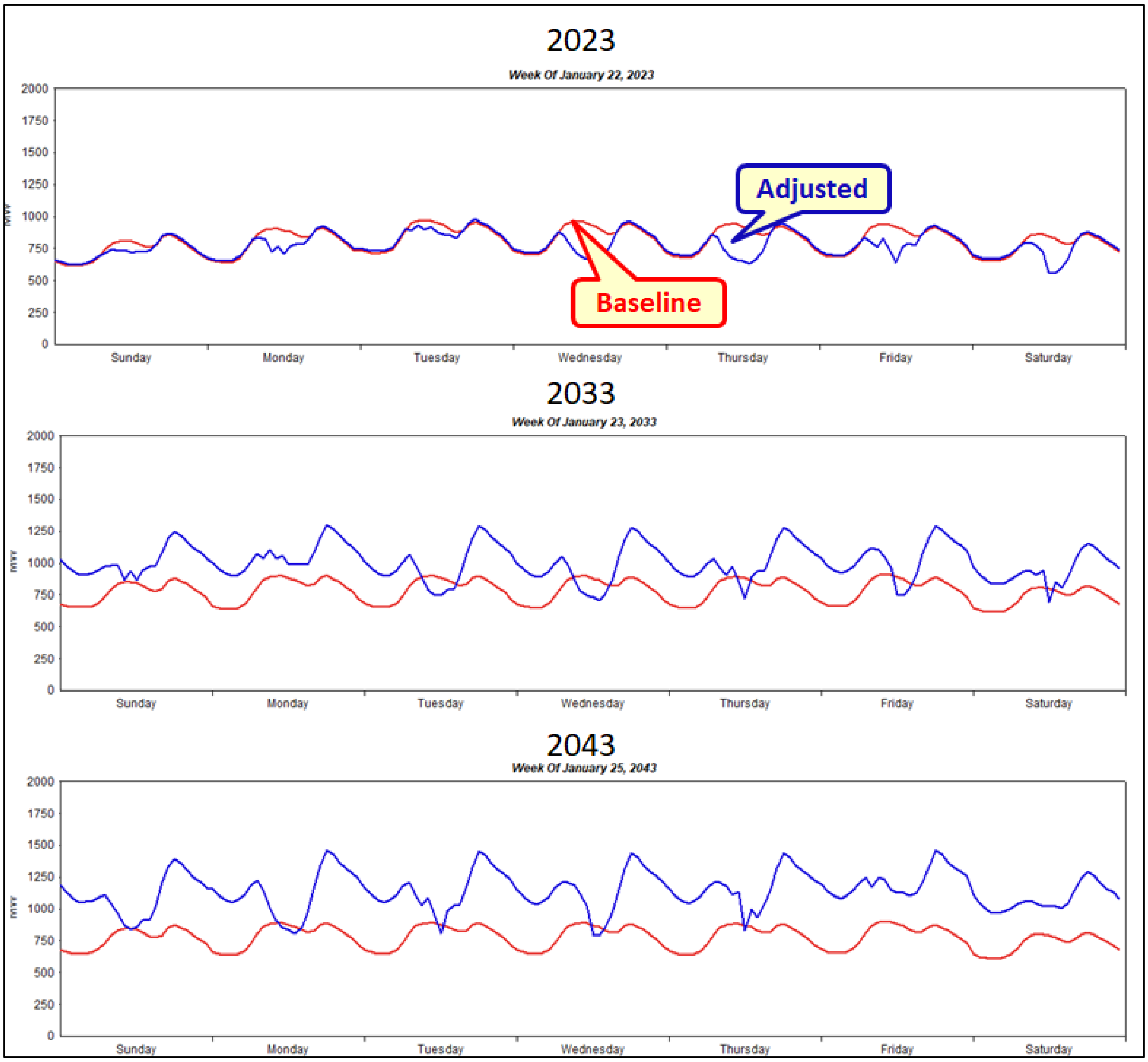
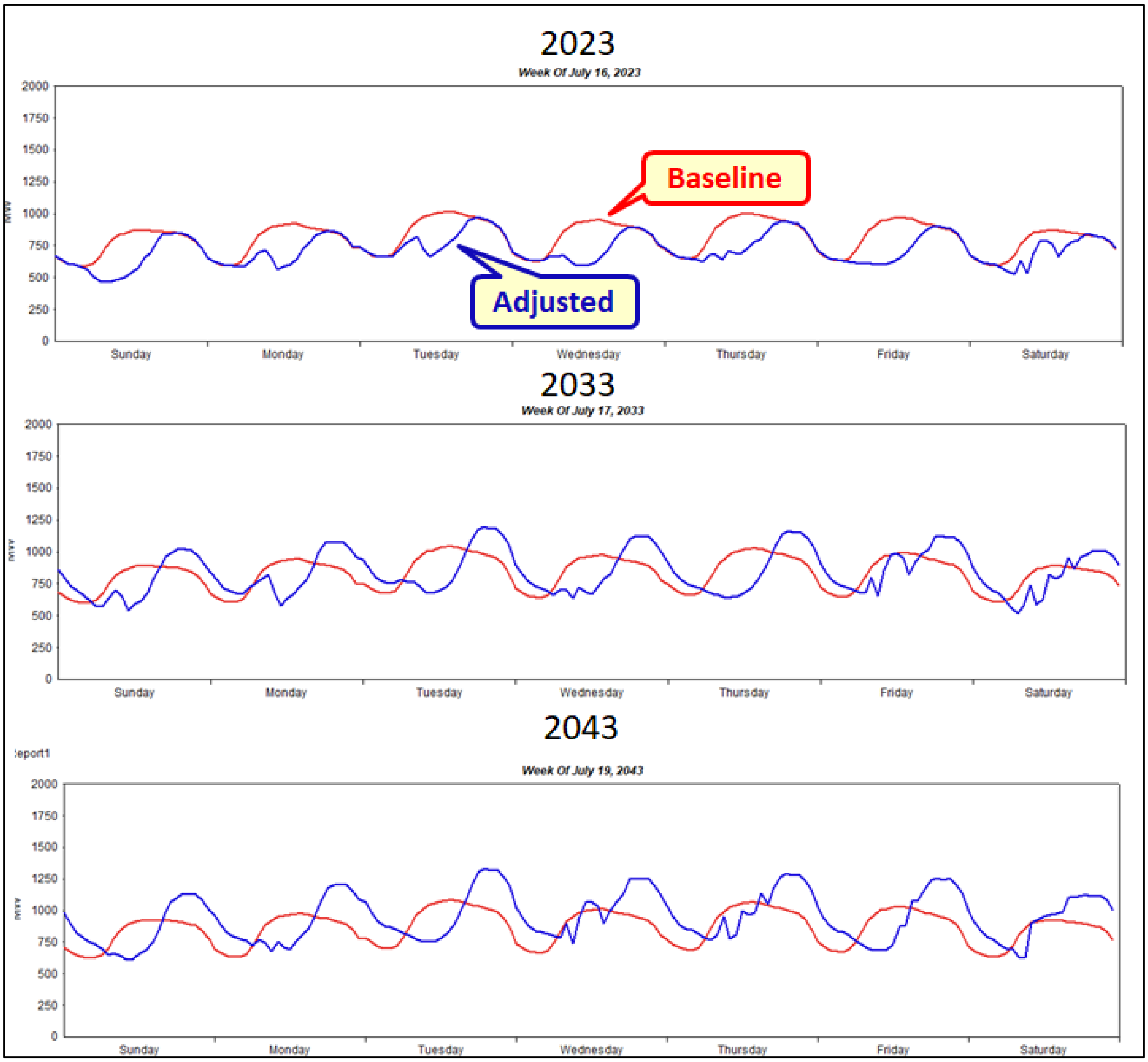


FIGURE 4: JULY SYSTEM HOURLY LOAD FORECAST (3RD WEEK)



In the early years its solar that is reshaping system load. But by 2033 heat pump adoption and EV growth totally reshape system load pushing the peak to the winter nighttime hours.

The summer and winter peaks are derived by finding the maximum hour summer and winter load. Heat pump and electric vehicle growth have a significant impact on system energy and peak demand. While solar growth continues to impact system energy requirements, it has very little impact on peak demand as the combination of the three technologies shifts the peaks into the winter evening hours. Table 2 through Table 4 shows the impact these technologies have on system energy and peak demand.

TABLE 2: ENERGY FORECAST COMPONENTS (MWH)

Year	Baseline	HP	EV	Solar	Adjusted
2023	5,954,597	23,386	21,234	-596,921	5,402,297
2028	5,961,311	176,260	402,014	-745,214	5,794,371
2033	5,877,652	339,378	1,072,632	-776,658	6,513,005
2038	5,845,997	425,620	1,573,340	-803,398	7,041,559
2043	5,852,070	465,708	1,755,413	-813,990	7,259,201
2023 - 33	-0.1%	30.7%	48.0%	2.7%	1.9%
2033 - 43	0.0%	3.2%	5.0%	0.5%	1.1%
2023 - 43	**-0.1%**	**16.1%**	**24.7%**	**1.6%**	**1.5%**

TABLE 3: COINCIDENT SUMMER PEAK FORECAST COMPONENTS (MW)

Year	Baseline	HP	EV	Solar	Adjusted
2023	972	3	3	-11	966
2028	977	20	66	-1	1,062
2033	984	38	175	-1	1,195
2038	1,000	47	243	-1	1,290
2043	1,023	52	255	-1	1,330
2023 - 33	0.1%	29.9%	48.6%	-22.2%	2.1%
2033 - 43	0.4%	3.2%	3.9%	-0.2%	1.1%
2023 - 43	**0.3%**	**15.8%**	**24.2%**	**-11.9%**	**1.6%**

TABLE 4: COINCIDENT WINTER PEAK FORECAST COMPONENTS (MW)

Year	Baseline	HP	EV	Solar	Adjusted
2023	961	13	5	0	979
2028	961	94	100	0	1,155
2033	944	183	262	0	1,389
2038	938	229	366	0	1,533
2043	934	250	384	0	1,569
2023 - 33	-0.2%	30.7%	47.8%	0.0%	3.6%
2033 - 43	-0.1%	3.2%	3.9%	0.0%	1.2%
2023 - 43	**-0.1%**	**16.1%**	**23.9%**	**0.0%**	**2.4%**

2.1 CLASS SALES FORECAST

The forecast begins at the customer-class level. Changes in economic conditions, prices, weather conditions, appliance saturation and efficiency trends, and state energy efficiency programs drive energy deliveries and demand through a set of monthly customer class sales and customer forecast models. Models are estimated from reported-state level billed sales, customers, and retail prices (derived from reported revenue) for the period January 2011 to December 2022. Monthly regression models are estimated for each of the following primary revenue classes:

- Residential
- Commercial
- Industrial
- Street Lighting

2.1.1 Residential Sales Forecast

The residential sales forecast is derived as the product of monthly average use and customer forecasts. Models are estimated from utility reported monthly sales and customers. Because a significant amount of residential energy use is self-generated through rooftop and community-based solar systems, estimated monthly self-generation is added back to the historical sales data; models are estimated for the reconstituted data series.

Model inputs include:

- Monthly weather data measured in heating degree-days (HDD) and cooling degree-days (CDD)
- Historical and projected state households, and household income data
- End-use energy intensities adjusted for state energy efficiency program impacts.
- Historical and projected state efficiency program savings (DSM).

Residential Average Use Model. The residential average use model is specified as a function of monthly cooling requirements (XCool), heating requirements (XHeat), and other use (XOther):

$$ResAvgUse_m = (B_h \times XHeat_m) + (B_c \times XCool_m) + (B_o \times XOther_m) + (B_d \times DSM_m\ ) + e_m$$

Model coefficients B_h, B_c B_o, and B_d are estimated using linear regression. The end-use variables incorporate both a structural component that captures change in end-use efficiency and saturation (and improvements in thermal shell integrity) and short-term utilization that depends on household income, number of household members, and price. The model also includes a DSM savings variable to capture state program efficiency activity that is not directly captured by the model intensity inputs. Figure 5 to Figure 7 show the constructed monthly end-use variables.

FIGURE 5: RESIDENTIAL XHEAT (KWH PER MONTH)

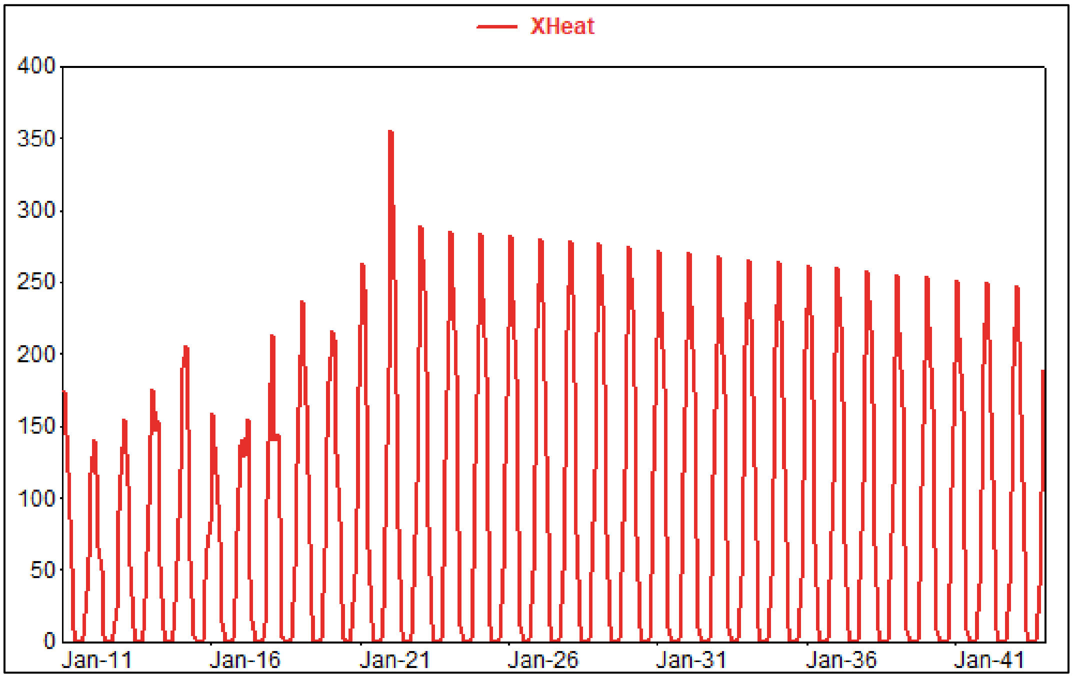


FIGURE 6: RESIDENTIAL XCOOL (KWH PER MONTH)

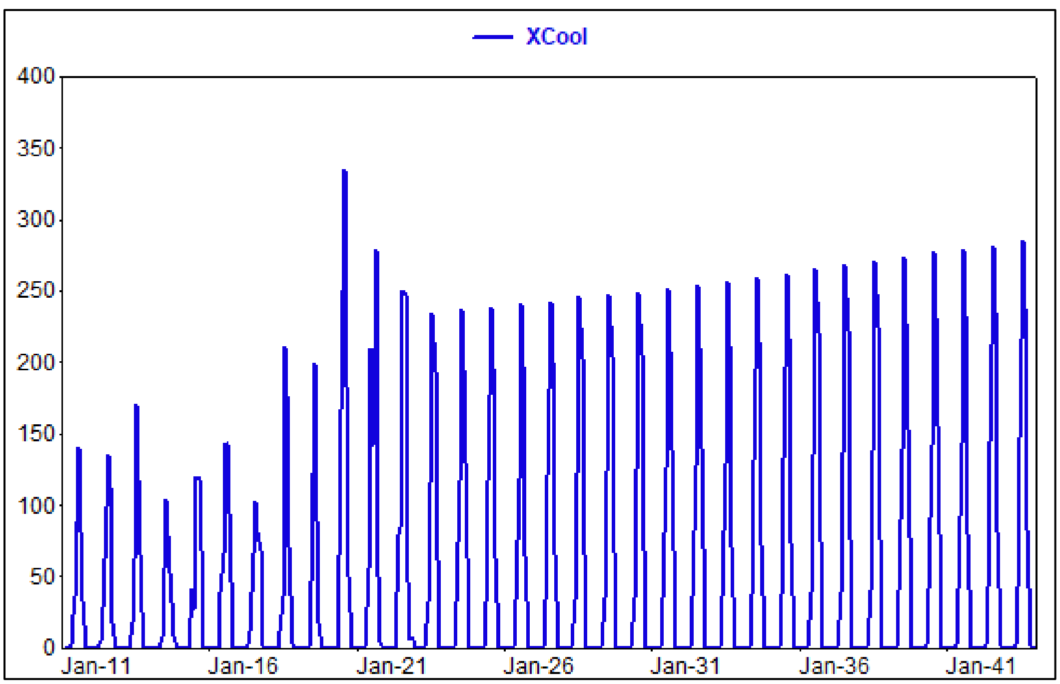
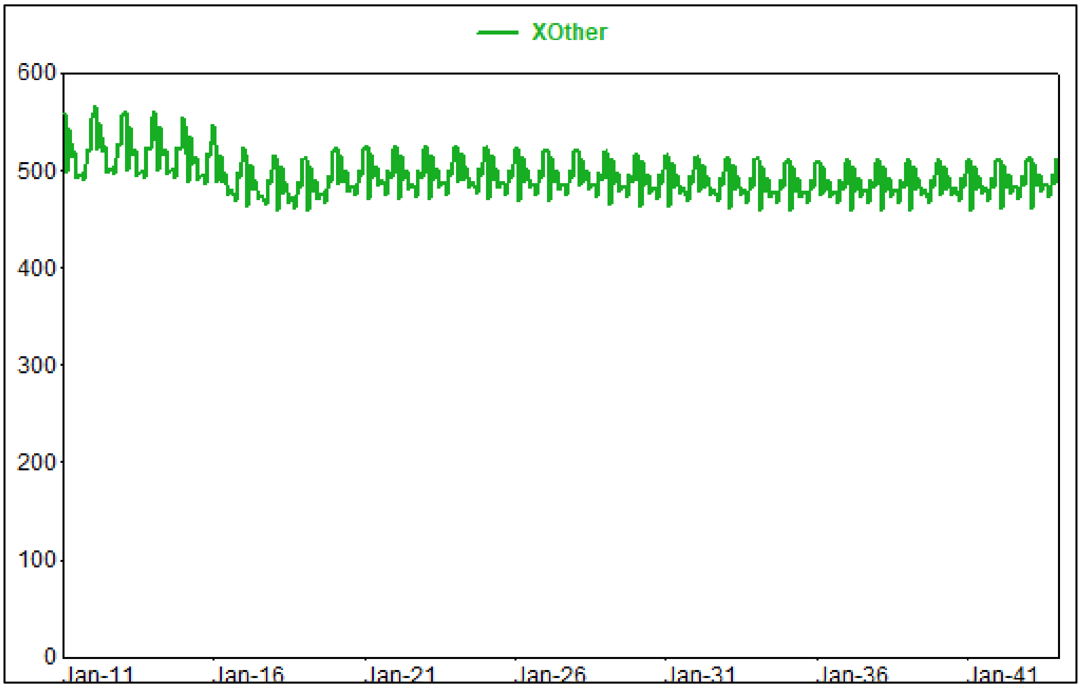


FIGURE 7: RESIDENTIAL XOTHER (KWH PER MONTH)



Heating shows strong growth through 2022. The growth in heating load through 2022 is the result of strong heat pump adoption. Roughly 50,000 heat pumps have been added since 2017. In the baseline forecast, heat pump saturations are held constant at 2022 levels with increasing temperature contributing to lower baseline heating. The expected impact from future heat pump adoptions are treated as a separate technology that is added to the baseline forecast. future impact resulting from strong heat pump adoption is treated as In the forecasting heat use declines. The primary reason is that in baseline model heat pump saturations are held constant (at 2022 levels); additional heat pump growth is treated as a separate technology adjustment that is added to the baseline forecast.

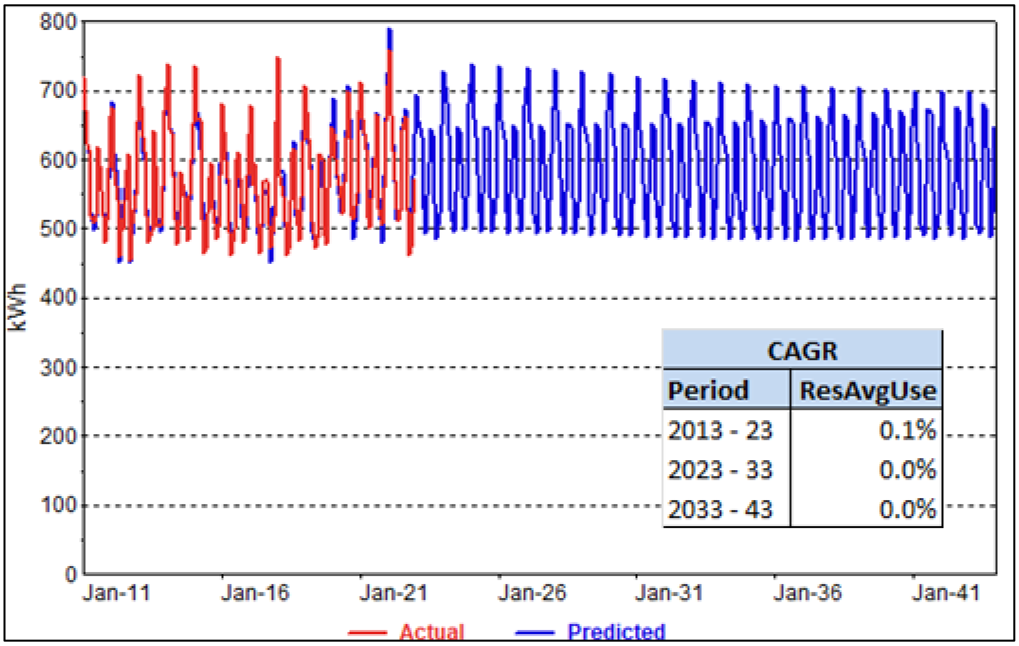
The baseline cooling intensity increases over time with expected increase in near-term room and central air conditioning saturation and increasing temperatures. Over the longer term, room and central air conditioning growth is replaced with heat pumps.

Non-weather sensitive end-use loads increased measurably after COVID changed work patterns with a significant share of the workforce working from home; Other Use has stayed elevated and is relatively flat through the forecast period as the impact of current appliance standards and state energy efficiency efforts counter increases in appliance saturation (mostly in miscellaneous end-uses) and economic growth. Total intensity (including cooling and heating) averages 0.1% decline through 2033. With DSM savings, total intensity declines 0.4%.

The average use model is estimated over the period January 2011 through December 2022. The model explains historical average use well with an Adjusted R^2 of 0.93 and in-sample mean absolute percent error (MAPE of 2.6%). The Adjusted R^2 is a measure of how much the sales variance from the mean the model can explain; 1.0 would be a perfect explanation of month-to-month sales variation. MAPE is a measure of the absolute average error over the estimation period; the smaller the MAPE, the more confidence we can have in the estimated model. Figure 8 shows actual and predicted average use.

FIGURE 8: ACTUAL AND PREDICTED RESIDENTIAL AVERAGE USE (KWH PER MONTH)

Reconstituted Sales

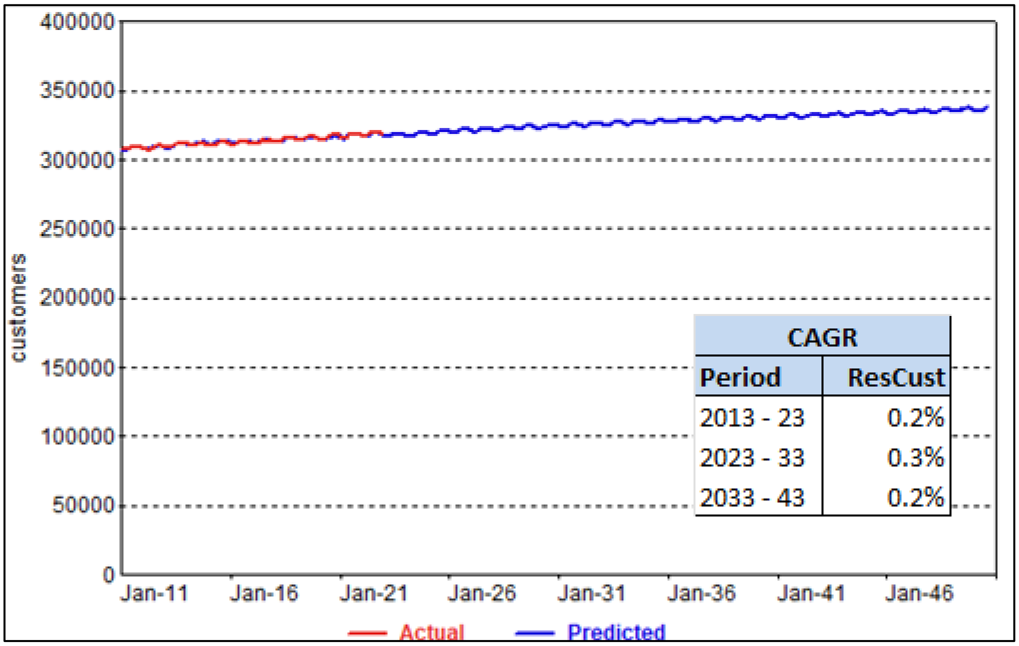


Model coefficients and statistics are provided in Appendix A.

Customer Forecast

The customer forecast is based on a simple linear regression model that relates the number of residential electric customers to historical and projected number of households. Household projections are based on Moody Analytics December 2022 Vermont forecast. Not surprisingly, the relationship between the number of customers and state number of households is statistically strong with an Adjusted R^2 of 0.94 and MAPE of 0.2%. Figure 9 below shows the residential model's actual and predicted.

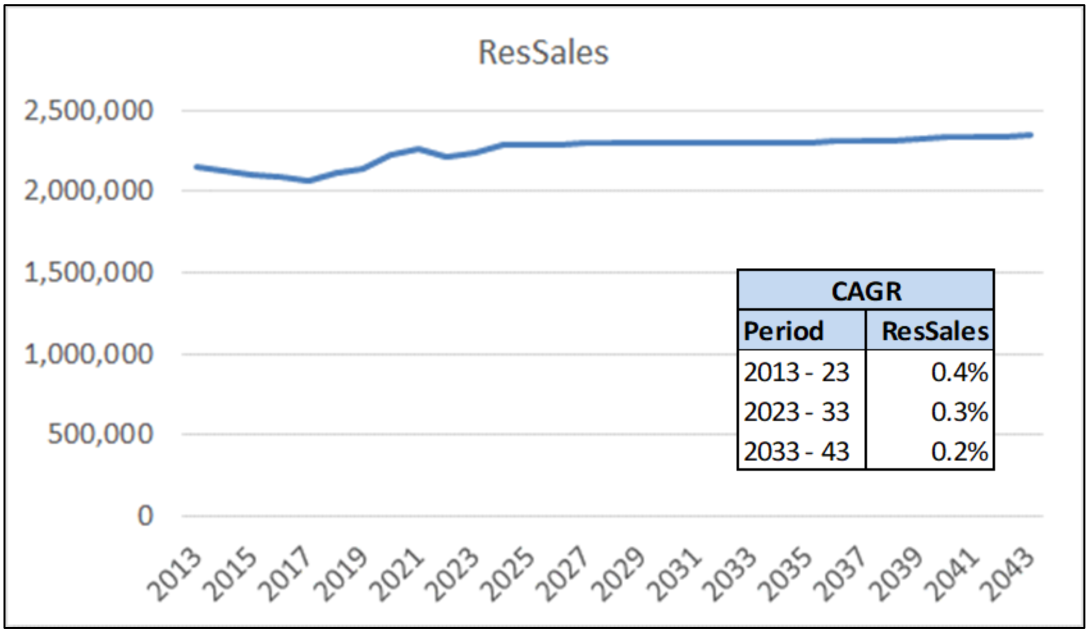
FIGURE 9: RESIDENTIAL CUSTOMERS



Residential customers are expected to increase 0.3% annually through the first ten years and 0.2% annually after 2033. While the customer growth rate is low, this still results in 7,500 new residential customers by 2033 – 2% higher than current state electric customers.

Total energy requirements are derived as the product of the average use and customer forecast. With slow customer growth and flat average use baseline electricity use averages 0.3% average annual growth over the next ten years. Figure 10 shows historical and projected reconstituted residential energy. When adjusted for solar own-use generation, delivered energy declines 0.3% per year.

FIGURE 10: RECONSTITUTED RESIDENTIAL SALES (MWH)



CAGR	
Period	ResSales
2013 - 23	0.4%
2023 - 33	0.3%
2033 - 43	0.2%

2.1.2 Commercial Sales Forecast

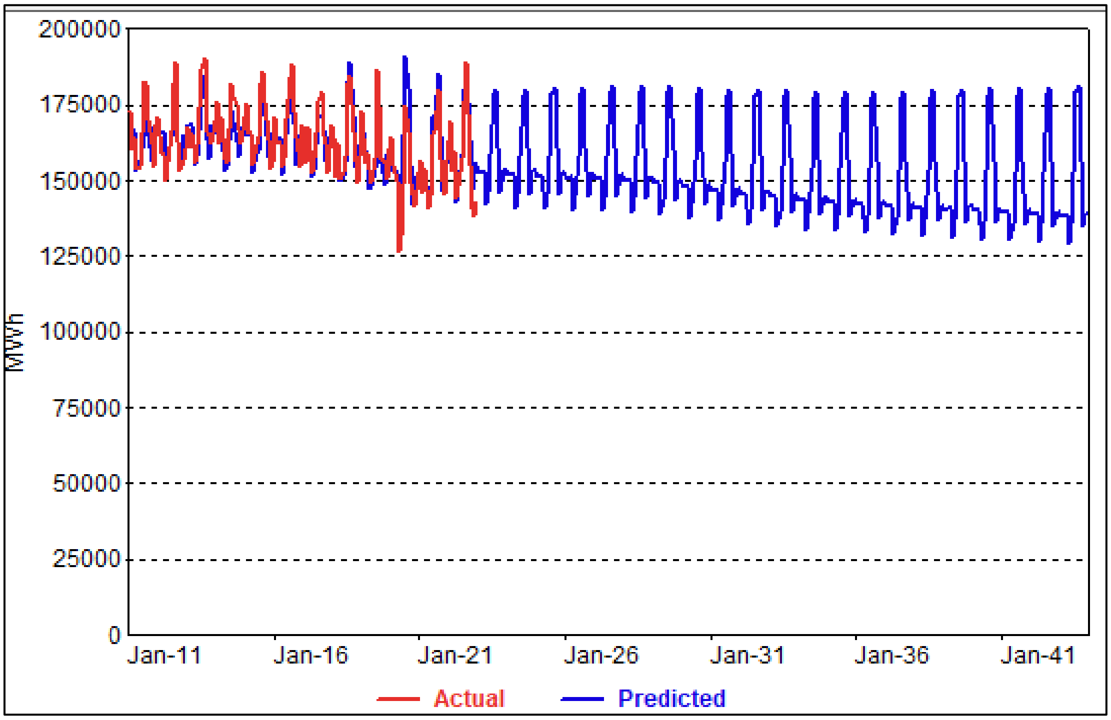
The commercial sales model is also estimated using an SAE specification; monthly sales are specified as a function of heating requirements (*XHeat*), cooling requirements (*XCool*), and other uses (*XOther*). The end-use variables are constructed by interacting annual commercial end-use intensity projections (measured in kWh per sqft) with Gross State Product, non-manufacturing employment, real price, and monthly HDD and CDD.

The commercial sales model is estimated as:

$$ComSales_m = B_0 + B_1 XHeat_m + B_2 XCool_m + B_3 XOther_m + (B_d \times DSM_m) + e_m$$

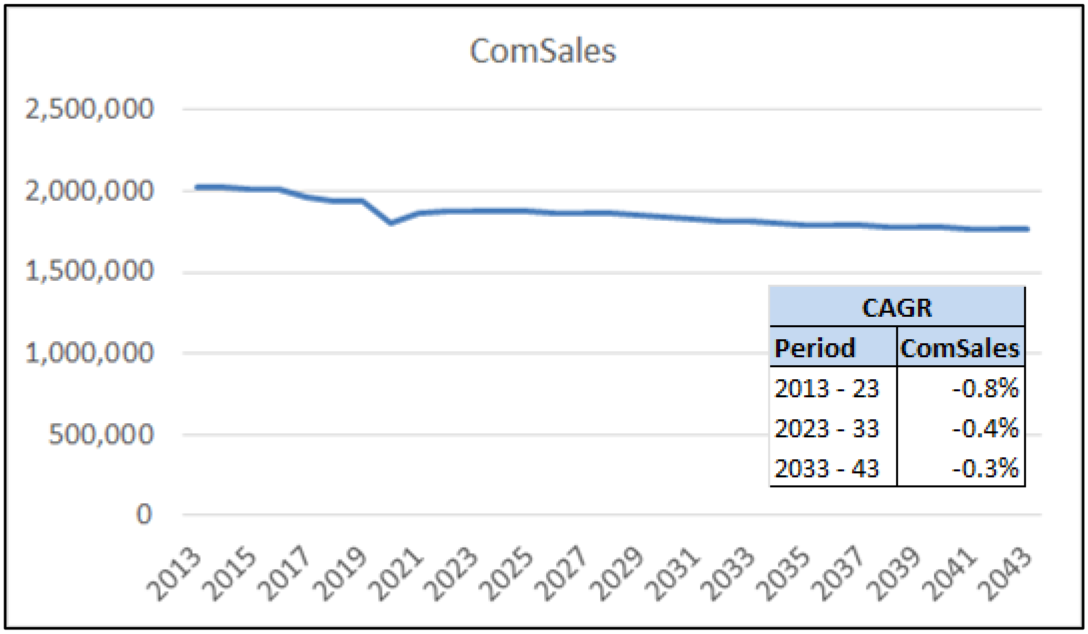
Figure 11 depicts actual and forecasted monthly commercial sales. Estimated model coefficients and model statistics are included in Appendix A.

FIGURE 11: ACTUAL AND PREDICTED COMMERCIAL SALES (MWH)



In early 2020 the commercial sector saw a sharp drop in sales as a result of the COVID mandated business closures in early 2020. While sales growth has recovered, it is still not back to pre-COVID levels. We now assume we have seen a permanent shift lower in commercial sales as a significant share of the workforce is expected to continue to work from home. Moving forward, commercial sales are expected to track their long-term decline of 0.4% per year resulting from continued business end-use efficiency improvements and further solar adoption. Figure 12 shows annual commercial sales forecast.

FIGURE 12: BASELINE COMMERCIAL SALES (MWH)



2.1.3 Industrial Sales

Industrial sales classification includes Vermont's largest customers – both industrial and large commercial. Given the large share of commercial sales that are classified as "industrial" the forecast model includes the commercial other use energy intensity variable (EI_{other}) that captures underlying efficiency improvements in the large customer segment. EI_{other} is combined with price and an industrial economic driver, *IndVar*.

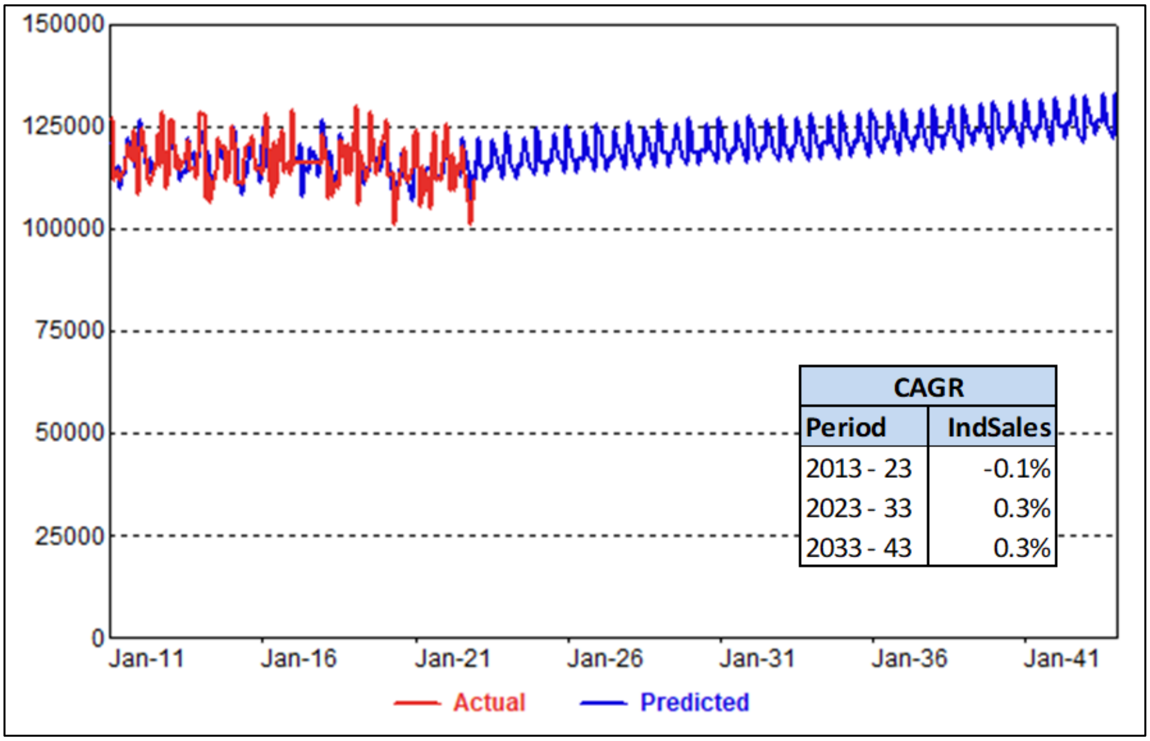
- $IndOther_m = EI_{other} \times Price_m^{-0.20} \times IndVar_m$

IndVar is a weighted combination of state GSP and manufacturing employment. *IndVar* is defined as:

$$IndVar_m = (ManEmploy_m^{0.4}) \times (Output_m^{0.6})$$

The weights are determined by evaluating the in-sample and out-of-sample model statistics for different sets of employment and output weights. The forecast model also includes monthly binaries to account for seasonal variation. Figure 13 shows the baseline sales forecast.

FIGURE 13: ACTUAL AND PREDICTED INDUSTRIAL SALES EXCLUDING GLOBAL FOUNDRIES (MWH)



Excluding the impact of future PV adoption, sales average 0.3% annual growth over the next ten years.

2.1.4 Forecast Drivers

The primary forecast drivers are:

- Moody Analytics December 2022 state economic forecast
- EIA 2022 end-use intensity projections (calibrated to Vermont)
- Expected HDD and CDD based on historical temperature trend
- Constant real price assumption
- Current Plan DSM savings projection

Economic Forecast

Customer class energy forecasts are based on *Moody's Economy.com* December 2022 economic forecast for Vermont. The economic drivers in the residential model include the number of state households (drives customer growth) and average household income and household size (average use model). Commercial sales are related to gross state product (GSP) and nonmanufacturing employment, while the industrial sales forecast is based on GSP and manufacturing employment. Table 5 shows the state economic forecast.

TABLE 5: VERMONT ECONOMIC FORECAST

Year	Households (thou)	Household Income ($ thou)	GSP ($ mil)	Non-Manufacturing Employment (thou)	Manufacturing Employment (thou)
2023	259.1	128.4	31,575	274.5	29.1
2024	260.0	129.6	32,083	276.2	29.2
2025	260.9	131.7	32,884	277.6	29.4
2026	261.7	134.0	33,726	278.2	29.4
2027	262.2	136.3	34,527	278.8	29.2
2028	262.7	138.5	35,311	279.6	29.0
2029	263.1	140.6	36,053	280.4	28.8
2030	263.5	142.5	36,708	281.0	28.6
2031	263.9	144.1	37,313	281.3	28.3
2032	264.3	145.8	37,932	281.6	28.1
2033	264.7	147.6	38,584	281.9	27.8
2034	265.1	149.4	39,234	282.2	27.6
2035	265.5	151.1	39,867	282.3	27.3
2036	265.9	152.7	40,488	282.3	27.1
2037	266.3	154.3	41,095	282.3	26.8
2038	266.7	155.9	41,686	282.2	26.6
2039	267.1	157.4	42,279	282.1	26.4
2040	267.5	158.9	42,870	282.1	26.2
2041	267.9	160.4	43,461	282.1	26.0
2042	268.3	161.9	44,060	282.1	25.8
2043	268.7	163.5	44,675	282.0	25.6
2023 - 33	0.2%	1.4%	2.0%	0.3%	-0.5%
2033 - 43	0.2%	1.0%	1.5%	0.0%	-0.8%
2023 - 43	**0.2%**	**1.2%**	**1.8%**	**0.1%**	**-0.6%**

Over the long-term Moody's Analytics projects relatively slow household growth and moderate economic growth.

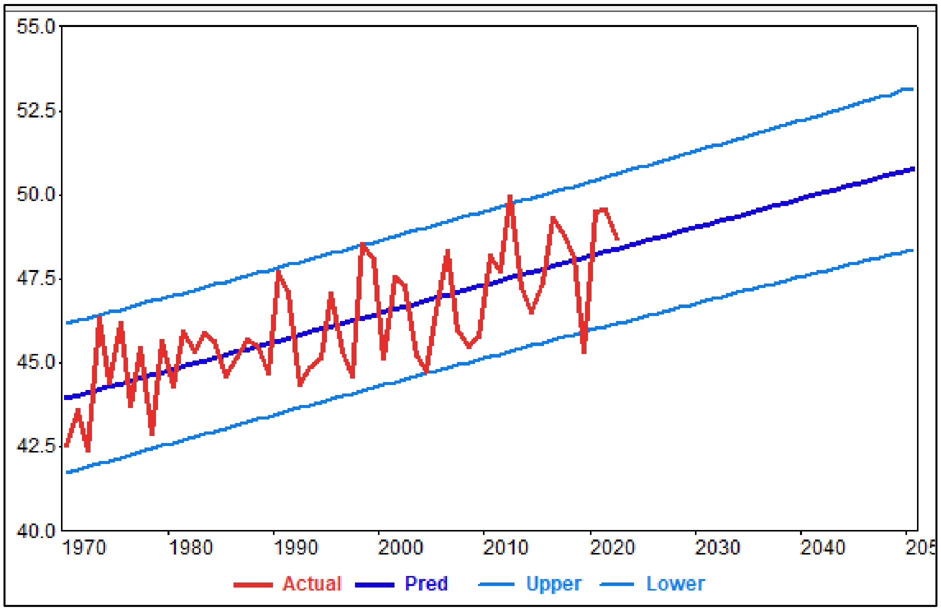
Heating and Cooling Degree-Day Projections

Heating related sales are captured by the number of heating degree-days (HDD) and summer cooling use by cooling degree days (CDD). HDDs take on a value when temperatures are below a specified temperature reference point and CDDs are defined when temperatures are above temperature reference point. Breakpoints that provided the best statistical fit are 55 degrees for HDD and 65 degrees for CDD. Historical monthly HDD and CDD are calculated from daily average temperature data from Burlington International Airport. Monthly HDD and CDD are calculated as the sum of the daily degree days:

- $HDD55_m = \sum Max(55 - Temperature_d, 0)$
- $CDD65_m = \sum Max(Tempature_d - 65, 0)$

One factor evident in historical temperature data is that on average temperatures are increasing. Figure 14 shows the long-term temperature trend for Burlington Airport.

FIGURE 14: BURLINGTON AIRPORT TEMPERATURE TREND (DEGREES F)



Using a simple regression model, we've estimated that the average annual temperature has been increasing 0.085 (0.85 degrees per decade) since 1970. In 1970 the expected average annual temperature was 43.9 degrees. Today the expected average annual temperature is 48.5; current annual average temperature is 4.6 degrees warmer than in 1970. Most climate models indicate that temperatures will continue to warm at minimum at current rates. Some modeling work suggests that temperatures will start increasing at an even faster rate in the near future. We assume that temperatures will continue to increase through the forecast period at the current trend of 0.085 per year. This translates into a 0.8% annual increase in the number of CDD (Figure 15) and 0.5% annual decline in the number of HDD (Figure 16).

FIGURE 15: ACTUAL AND PROJECTED CDD

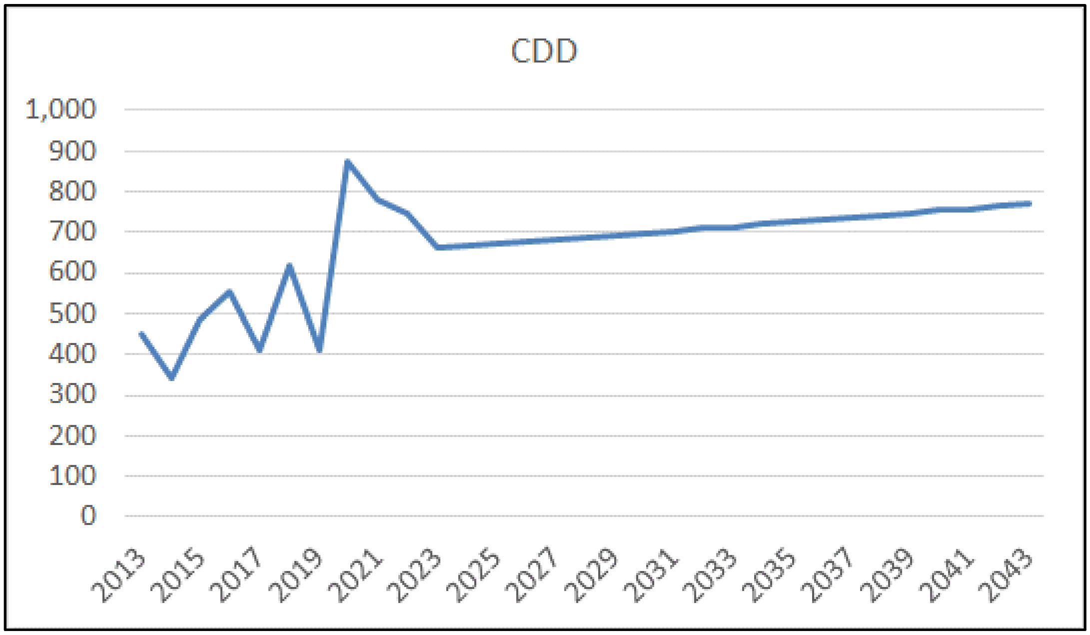
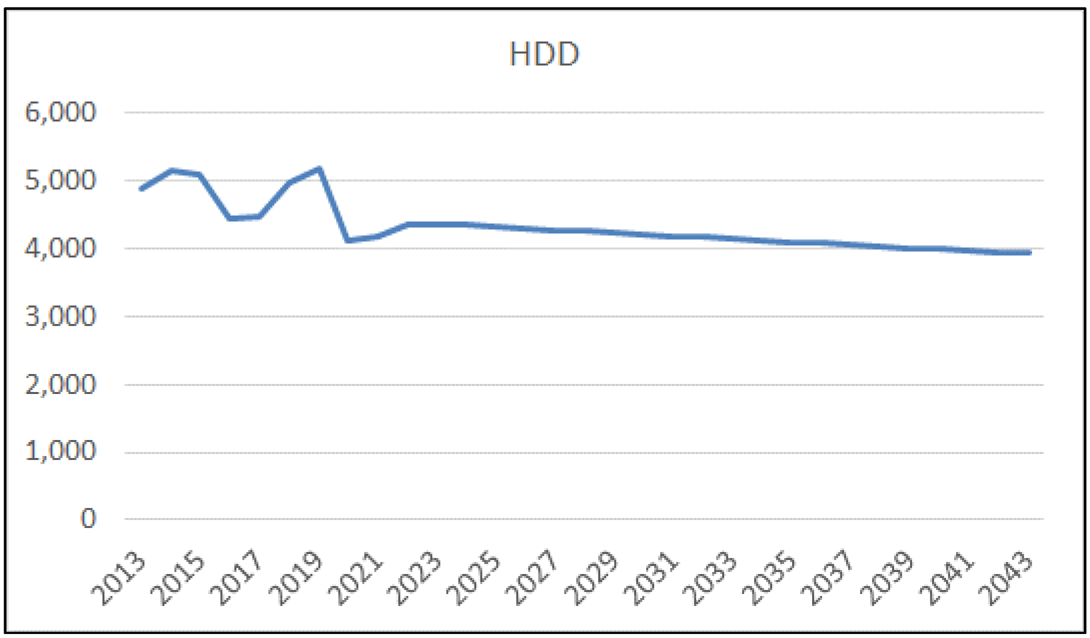


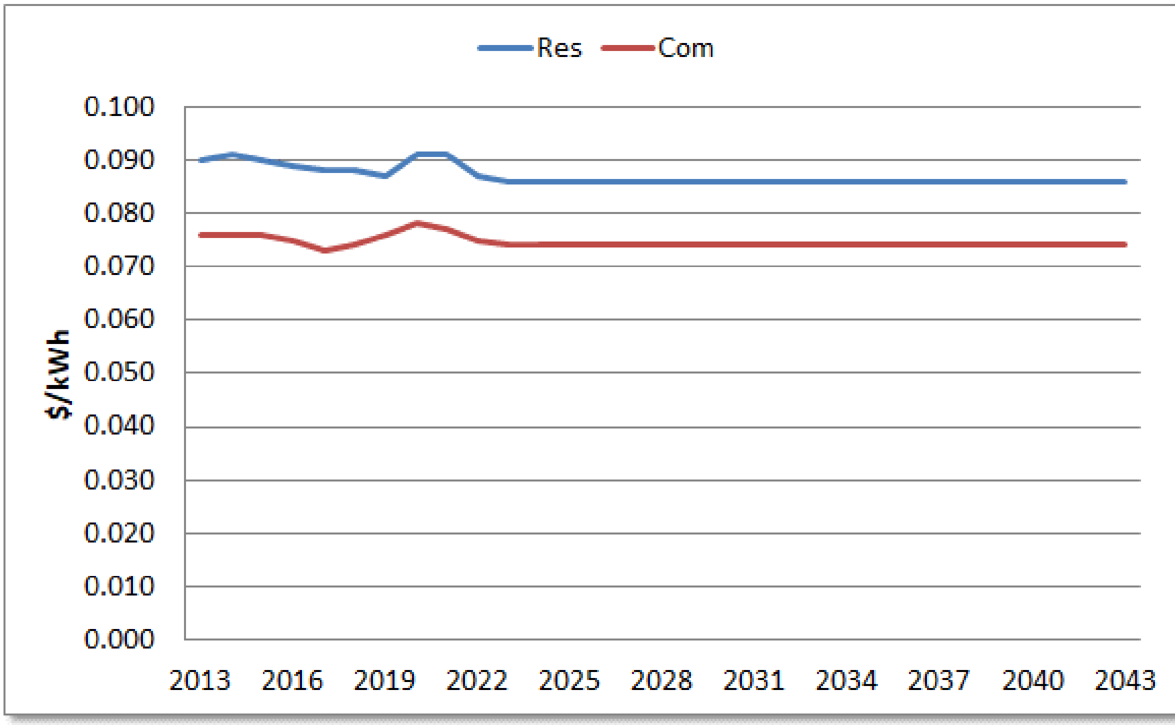
FIGURE 16: ACTUAL AND PROJECTED HDD



Retail Electricity Prices

Historical prices (real dollars) are derived from historical billed sales and revenue data. Prices impact the class sales through imposed price elasticities in the constructed model variables. As specified, prices impact the short-term utilization of the primary end-uses; the residential price elasticity is -0.15 and commercial is set to -0.2; elasticities are determined by evaluating in-sample and out-of-sample model fit for different elasticity values. The utilization elasticities are small as they only impact the use of the equipment that is in place. Long-term price impacts drive decisions to invest in more efficient appliance and end-use options, decisions on thermal shell investments such as new windows and insulation, and participation in state EE programs and purchases through state incentive programs. Long-term elasticities are captured in the end-use stock saturation and efficiency inputs. For the baseline forecast, we assume constant real prices. Figure 17 shows price forecasts by class.

FIGURE 17: HISTORICAL AND PROJECTED REAL ELECTRICITY PRICES ($ PER KWH)

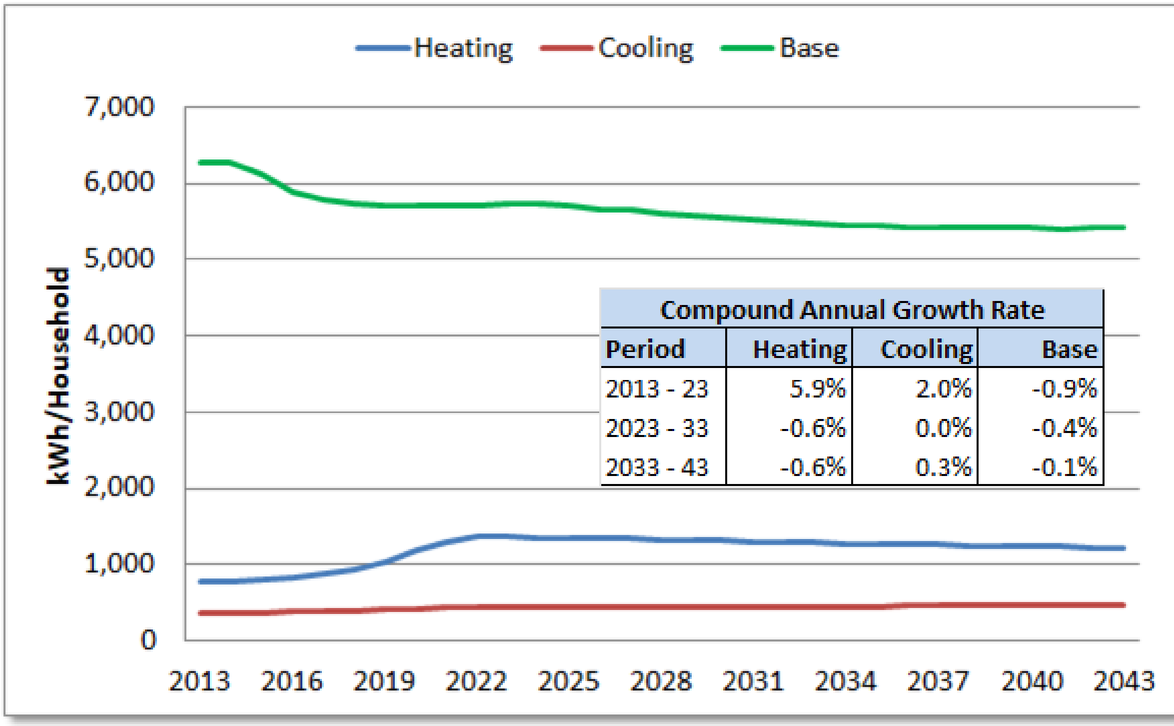


Appliance Saturation and Efficiency Trends

Over the longer-term, changes in end-use saturation and stock efficiency impact class sales, system energy, and peak demand. End-use energy intensities (expressed in kWh per household in the residential sector and kWh per square foot in the commercial sector) are the expected average annual end-use kWh use. Increase in end-use saturation (i.e., appliance ownership) push intensities higher while improvements in end-use stock efficiency drive intensities lower. The residential sector incorporates saturation and efficiency trends for seventeen end-uses while the commercial sector captures end-use intensity projections for ten end-use classifications across ten building types. Residential end-use efficiency and commercial end-use intensity projections are derived from the Energy Information Administration's (EIA) 2022 New England Census Division forecast. End-use saturations are then adjusted to better reflect Vermont based on Vermont specific end-use data. Key inputs used in calibrating end-use saturation include recent Vermont residential appliance saturation survey and National Renewable Energy Laboratory (NREL) residential and commercial building simulations for Vermont.

The residential sales forecast is derived as the product of monthly household forecast and average use forecast. For the residential average use model, end-use intensity projections (use per household) are aggregated into three generalized end-uses: heating, cooling, and other use. Figure 18 shows the resulting aggregated end-use intensity projections.

FIGURE 18: RESIDENTIAL END-USE ENERGY INTENSITIES



Period	Heating	Cooling	Base
2013 - 23	5.9%	2.0%	-0.9%
2023 - 33	-0.6%	0.0%	-0.4%
2033 - 43	-0.6%	0.3%	-0.1%

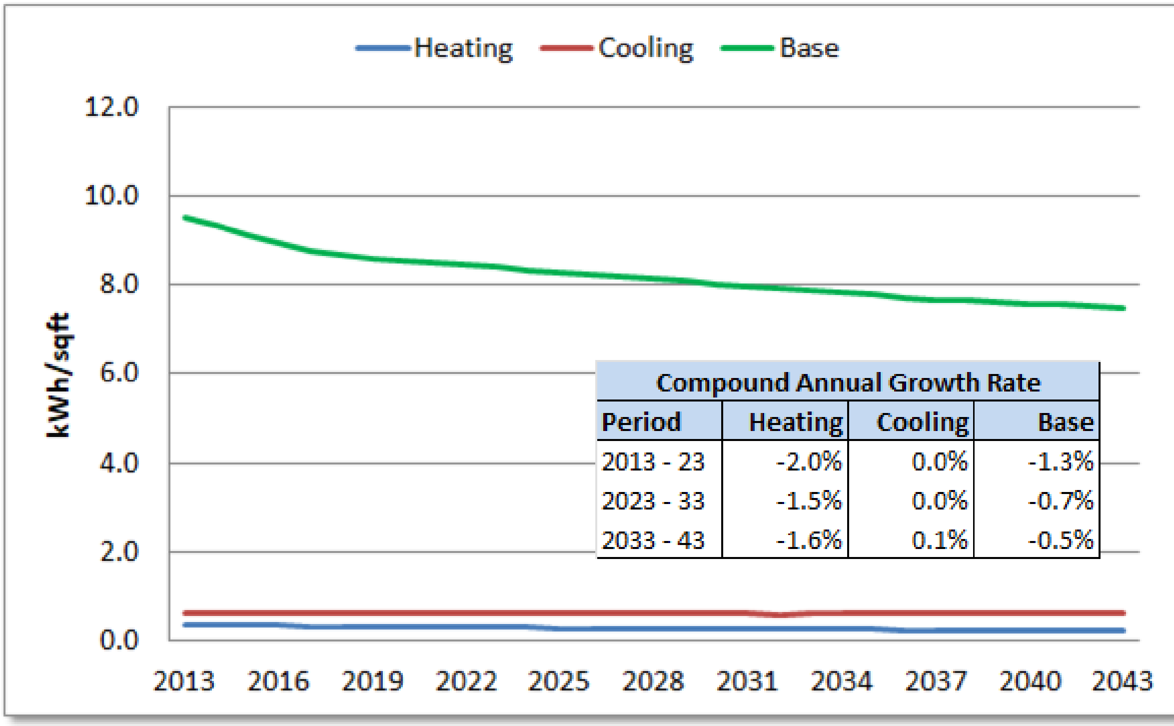
There has been a steady decrease in residential non-weather sensitive end-use intensity largely as result of new standards, building codes, and state efficiency programs. This decline is expected to slow over time with lower impacts from existing standards. In addition, there has been relatively strong growth in miscellaneous end-uses which includes everything from electric lawn mowers to laptops and game devices.

The heating intensity saw a sharp increase starting around 2020 largely as a result of heat pump adoption. For the baseline forecast, heat pump intensities are held constant; new heat pump loads are treated as a separate load adjustment that is layered on the baseline load forecast. Efficiency gains in furnace fans, motors, and decreasing resistant heat saturation drive the baseline heating intensity lower.

Baseline cooling intensities are flat through the forecast period as cooling saturation slows while efficiency continues to improve. Like heating, baseline cooling intensities do not reflect expected cooling loads due to future heat pump adoption.

The commercial sector has seen a strong decline in average use largely as a result of significant efficiency improvements. Figure 19 shows commercial end-use energy intensity forecasts for heating, cooling, and non-weather sensitive use (base).

FIGURE 19: COMMERCIAL END-USE ENERGY INTENSITY



Compound Annual Growth Rate			
Period	Heating	Cooling	Base
2013 - 23	-2.0%	0.0%	-1.3%
2023 - 33	-1.5%	0.0%	-0.7%
2033 - 43	-1.6%	0.1%	-0.5%

Given temperate summers and low saturation of electric heat, commercial heating and cooling intensities are relatively small. It's largely the decline in the non-weather sensitive end-uses (Base) that is driving commercial sales lower. The end-uses showing the strongest decline are commercial lighting and ventilation. The decline in non-HVAC intensities is the result of improving commercial equipment efficiency and EE program impacts.

Adjusting for EE Program Impacts

End-use intensity projections are adjusted for the impact of future EE program impacts. Adjusted residential end-use intensities include heating, cooling, water heating, refrigeration, kitchen and laundry, and lighting, and miscellaneous use. To avoid double counting EE impacts, EE savings forecasts are to account for future EE savings that are embedded in the end-use intensity forecasts. An EE adjustment factor is estimated by including historical EE savings as a model variable. The estimated coefficient in the residential model is -0.27 and the commercial model -0.34 indicating that roughly 70% of EE program savings is captured by the end-use model intensites. The forecasted end-use intensities are adjusted lower to reflect the additional 30% of future EE savings not captured by the initial intensity projections. With adjustments for future EE program impacts, average residential intensity declines 0.4% annually and commercial building intensity declines 2.0% per year.

2.1.5 Baseline Sales Forecasts

Table 6 summarizes the baseline sales forecast by customer class. The baseline forecast includes solar generation for own use.

TABLE 6: CUSTOMER CLASS RECONSTITUTED SALES FORECAST (MWH)

Year	Residential	Commercial	Industrial	Other	Total
2023	2,237,515	1,878,461	1,398,516	35,678	5,550,170
2028	2,307,428	1,858,501	1,424,503	35,678	5,626,111
2033	2,298,015	1,810,019	1,437,754	35,678	5,581,467
2038	2,314,091	1,780,626	1,459,151	35,678	5,589,545
2043	2,352,688	1,764,002	1,485,748	35,678	5,638,117
2023 - 33	0.3%	-0.4%	0.3%	0.0%	0.1%
2033 - 43	0.2%	-0.3%	0.3%	0.0%	0.1%
2023 - 43	**0.3%**	**-0.3%**	**0.3%**	**0.0%**	**0.1%**

Total baseline sales average 0.1% annual growth through the forecast period, in line with growth over the prior ten years. Increases in customer growth and business activity are balanced out by improvements in end-use and thermal shell efficiency gains. Billed sales which exclude solar generation are negative.

3 ZONAL AND SYSTEM LOAD FORECAST

In past years, the baseline hourly load forecast was developed at the system level and allocated to zones. The allocation process sometimes distorted the zone load shapes. To avoid this problem, the current approach is to build out the zone-level hourly load forecast and to then add-up the zone load forecasts to the system.

3.1 ZONAL BASELINE ENERGY AND HOURLY LOAD FORECASTS

Monthly energy forecasts are estimated for each planning area. There are 16 zone planning areas including a defined zone for Global Foundries. Monthly zonal energy models are estimated with linear regression. The estimation period is from 2013 through 2022. The zonal energy models are specified as a function of heating, cooling, and base use energy requirements:

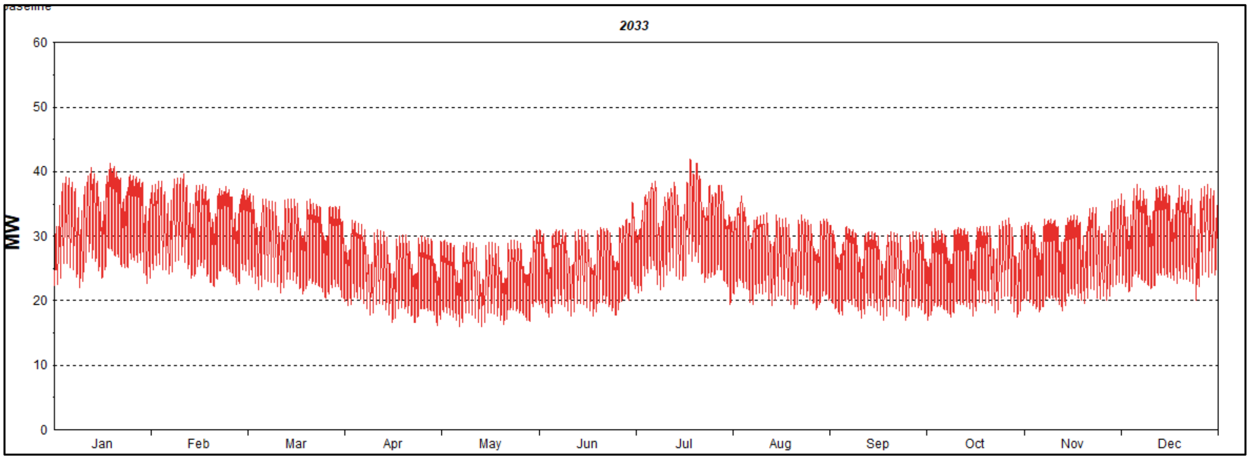
$$Energy_m = B_0 + (B_1 \times HeatVar_m) + (B_2 \times CoolVar_m) + (B_3 \times BaseVar_m) + e_m$$

Heating (HeatVar), cooling (CoolVar) and base-use (BaseVar) are derived from the customer class sales forecasts. The model variables capture the relative mix of residential and nonresidential customers served within each zone. Heating and cooling variables are a weighted combination of residential and commercial heating and cooling requirements. The base variable (BaseVar) combines base load components of the residential and commercial classes and industrial and street lighting sales.

The estimated models explain zonal sales relatively well with model adjusted R^2 that vary from 0.80 to 0.95 and Mean Absolute Percent Errors (MAPE) that vary from 1.0% to 3.0%.

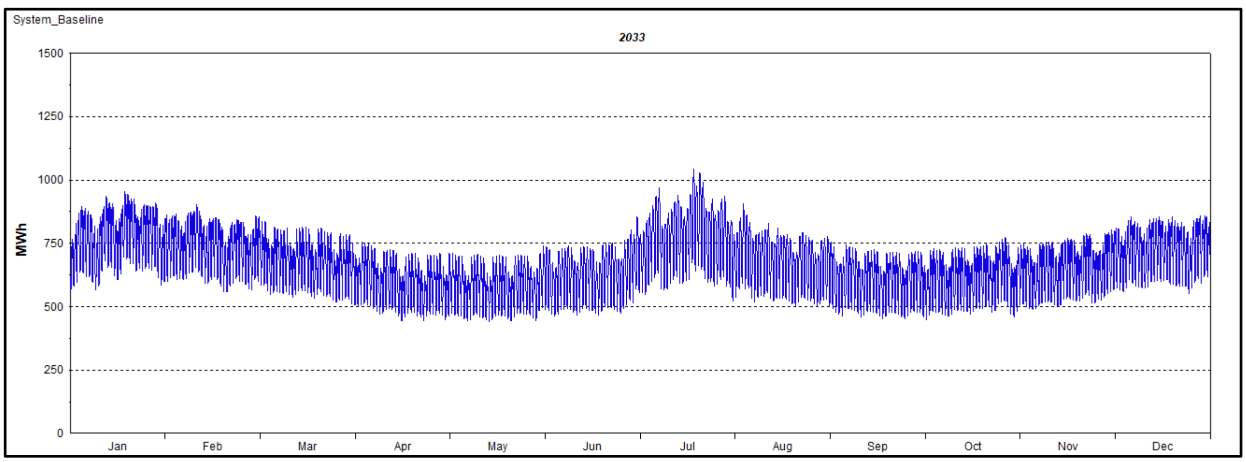
The zone baseline hourly load forecast is derived by combining the zone energy forecast with the zone hourly load profile. The zone hourly load profile is derived as a function of day of the week, holidays, seasons, hours of light and daily HDD and CDD. Figure 20 shows Newport 2023 baseline load forecast. The baseline zone-level models exclude solar load impacts.

FIGURE 20: BASELINE ZONAL LOAD (MWH) – NEWPORT



The system baseline forecast is generated by aggregating the zone level forecast and calibrating to the system baseline summer and winter peak demand. Figure 21 shows the resulting baseline system load forecast.

FIGURE 21: 2033 BASELINE SYSTEM LOAD FORECAST



Zonal and system load forecast are adjusted for expected solar load (both what's been added back in and new solar generation), CCHP, and EVs. Solar load forecasts are generated for each zone based on zone-specific installed solar capacity, System CCHP energy is allocated to zones based on the zone's share of system energy, and EV charging load is allocated to zones based on the share of registered vehicles within the planning zone.

Hourly solar, CCHP, and EV forecasts are derived for each zone by combining zonal-level solar, CCHP, and EV energy projections with technology hourly profiles. These technology forecasts are then added to zonal baseline hourly load forecasts. Figure 22 to Figure 24 show Newport solar, CCHP, and EV forecasts for 2033. Because the impacts are additive, solar loads are expressed as a negative load.

FIGURE 22: SOLAR LOAD (MW) – NEWPORT

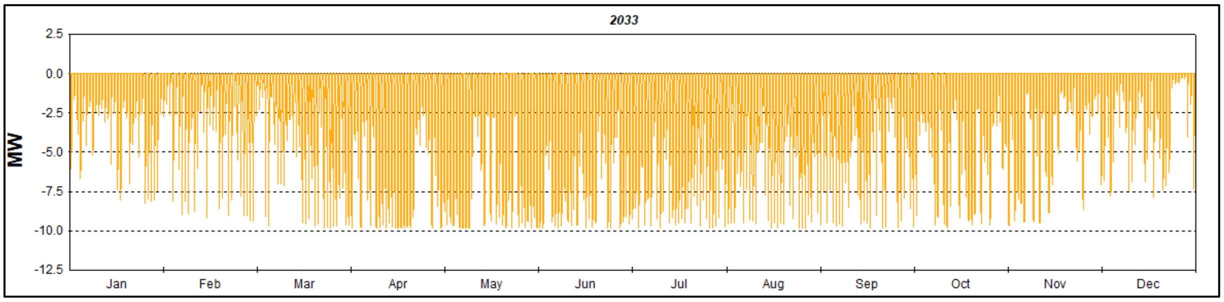


FIGURE 23: CCHP LOAD (MW) – NEWPORT

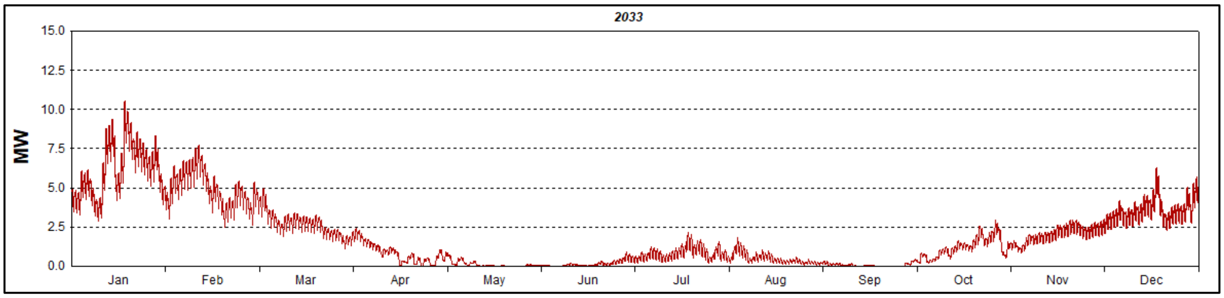


FIGURE 24: ELECTRIC VEHICLE LOAD (MW) – NEWPORT

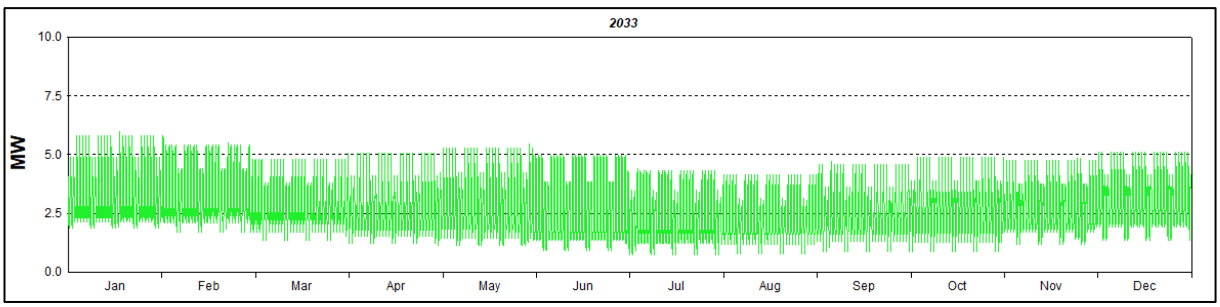


Figure 25 shows the 2033 baseline and adjusted July hourly load forecast for Newport. Figure 26 shows January 2033 load forecast.

FIGURE 25: NEWPORT 2033 SUMMER LOAD (MWH)

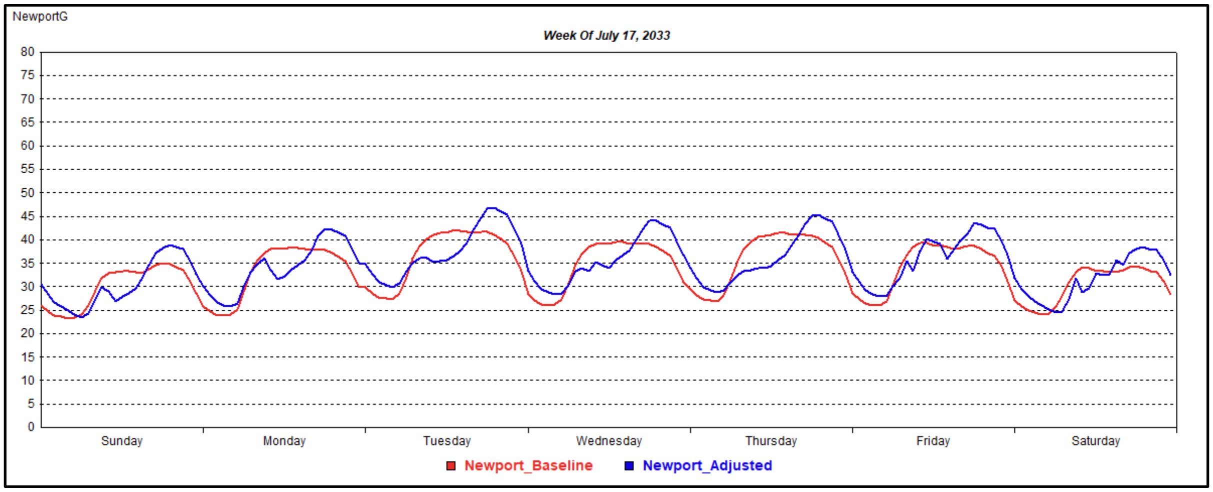
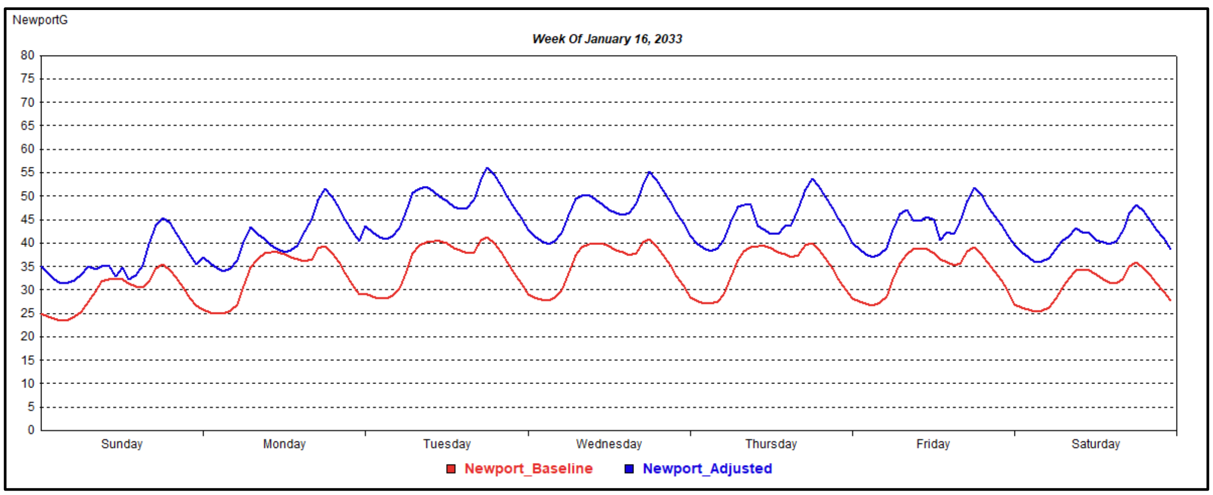


FIGURE 26: NEWPORT 2033 WINTER LOAD (MWH)



Similar hourly load forecasts are generated for each planning zone that are then aggregated to the system level. Adjusted zonal coincident peaks are derived by finding the hourly zonal load that coincides with the system peak. Table 27 and Table 28 show zonal coincident peaks.

TABLE 27: SUMMER ADJUSTED ZONAL COINCIDENT PEAK DEMANDS (MW)

Year	Newport	Highgate	StAlbans	Johnson	Morrisville	Montpelier	StJohnsbury	BED	IBM
2023	40.2	40.9	72.7	11.4	32.4	91.8	26.4	63.9	53.1
2028	42.9	44.6	79.6	13.0	35.4	102.7	28.3	70.8	52.6
2033	46.8	47.9	86.5	14.4	38.5	120.3	30.3	83.0	52.8
2038	49.6	50.7	92.1	15.3	40.7	132.1	31.7	91.6	52.8
2043	51.2	53.0	96.2	15.7	41.7	135.9	32.6	94.8	52.8
2023 - 33	1.5%	1.6%	1.7%	2.3%	1.7%	2.7%	1.4%	2.7%	-0.1%
2033 - 43	0.9%	1.0%	1.1%	0.8%	0.8%	1.2%	0.7%	1.3%	0.0%
2023 - 43	**1.2%**	**1.3%**	**1.4%**	**1.6%**	**1.3%**	**2.0%**	**1.1%**	**2.0%**	**0.0%**

Year	Burlington	Middlebury	Central	Florence	Rutland	Ascutney	Southern	System
2023	156.3	35.1	56.6	18.7	91.4	67.8	107.8	966.5
2028	183.6	37.5	62.5	18.6	99.0	74.1	116.8	1,062.0
2033	225.2	40.3	68.9	18.7	107.1	82.9	131.8	1,195.4
2038	253.9	42.5	73.4	18.7	113.1	89.2	142.1	1,289.5
2043	264.7	43.8	76.2	18.7	115.7	91.6	145.4	1,329.9
2023 - 33	3.7%	1.4%	2.0%	0.0%	1.6%	2.0%	2.0%	2.1%
2033 - 43	1.6%	0.8%	1.0%	0.0%	0.8%	1.0%	1.0%	1.1%
2023 - 43	**2.7%**	**1.1%**	**1.5%**	**0.0%**	**1.2%**	**1.5%**	**1.5%**	**1.6%**

TABLE 28: WINTER ADJUSTED ZONAL COINCIDENT PEAK DEMAND (MW)

Year	Newport	Highgate	StAlbans	Johnson	Morrisville	Montpelier	StJohnsbury	BED	IBM
2023	42.4	36.5	63.4	15.0	33.6	105.9	29.7	52.2	42.0
2028	48.7	41.6	73.2	17.3	38.5	127.7	33.7	66.9	41.9
2033	56.1	47.3	84.9	20.2	44.5	158.2	38.0	88.4	42.0
2038	60.5	51.1	92.5	21.9	48.0	176.6	40.4	101.9	42.0
2043	61.9	52.7	95.6	22.2	48.7	180.0	41.0	105.7	42.0
2023 - 33	2.9%	2.6%	3.0%	3.0%	2.8%	4.1%	2.5%	5.4%	0.0%
2033 - 43	1.0%	1.1%	1.2%	0.9%	0.9%	1.3%	0.8%	1.8%	0.0%
2023 - 43	**1.9%**	**1.9%**	**2.1%**	**2.0%**	**1.9%**	**2.7%**	**1.6%**	**3.6%**	**0.0%**

Year	Burlington	Middlebury	Central	Florence	Rutland	Ascutney	Southern	System
2023	132.4	33.9	67.0	19.6	105.0	64.4	135.8	978.8
2028	180.3	38.3	78.4	19.6	118.4	74.2	155.8	1,154.6
2033	249.7	43.6	91.3	19.6	134.6	88.0	182.5	1,388.9
2038	293.9	46.8	99.0	19.6	144.0	96.6	198.3	1,533.1
2043	305.9	47.6	101.8	19.6	145.5	98.0	200.5	1,568.6
2023 - 33	6.6%	2.5%	3.1%	0.0%	2.5%	3.2%	3.0%	3.6%
2033 - 43	2.0%	0.9%	1.1%	0.0%	0.8%	1.1%	0.9%	1.2%
2023 - 43	**4.3%**	**1.7%**	**2.1%**	**0.0%**	**1.6%**	**2.1%**	**2.0%**	**2.4%**

4 TECHNOLOGY FORECASTS

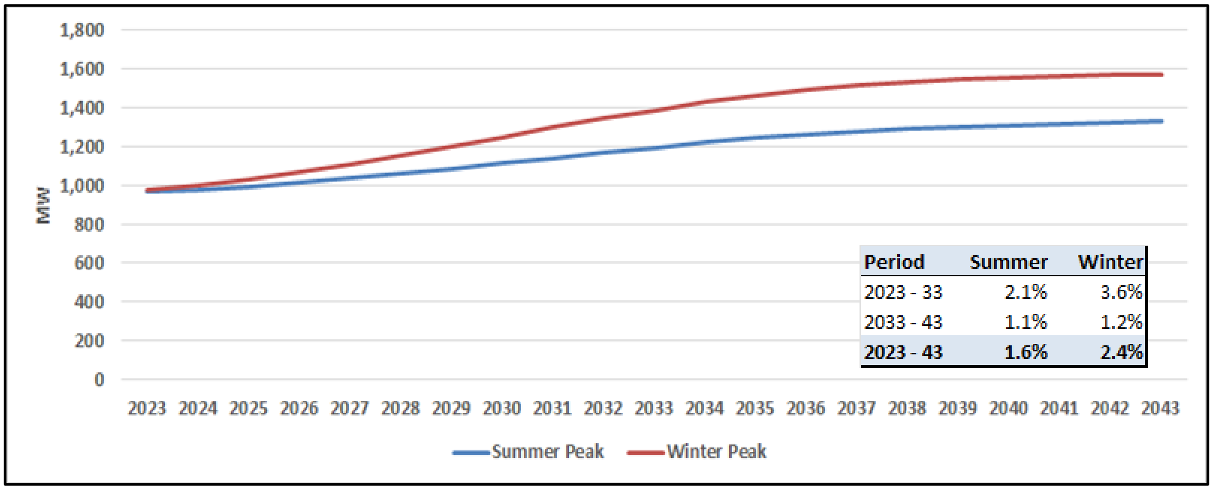
The baseline peak demand is flat, increasing just 0.1% annually over the forecast period. It is the expected impact of electrification that drives future demand – specifically, cold climate heat pumps (CCHP) and electric vehicles (EV). While behind the meter solar (PV) continues to expand it has little impact on system peak; largely because of past solar adoption the peak has shifted into the summer evenings and winter nighttime hours. Solar continues to have a significant impact on hourly loads where in some zones, expected solar growth results in negative load hours in the high generation spring months. Technologies that are incorporated into the forecast include:

- BTM Solar Generation
- Cold Climate Heat Pumps through the state heat pump incentive program
- Electric Vehicles

Two scenarios are developed for evaluating transmission capacity. Both scenarios include the baseline system load forecast and same solar load forecast. Scenarios focused on two technologies with the greatest uncertainty and load impact - CCHP and EVs. The expected case incorporates Vermont Efficiency Investment Corporation (VEIC) most recent mid-case CCHP forecast and high EV adoption projection, and ISO New England high case fleet EV adoption forecast. The low case assumes heat pumps continue to expand at the current heat pump adoption rate and incorporates lower (mid-case) electric vehicle adoption scenario reflecting the possibility of slower long-term penetration path.

Hourly load forecasts are developed for BTM solar, the state heat pump incentive program, and fleet and nonfleet electric vehicle projections. These forecasts are then layered (added) onto the baseline hourly load forecasts to generate the adjusted system hourly load forecast. Solar load growth reduces system hourly load across the daytime hours; this has a significant impact on baseline summer peak demand, but no impact on winter peak demand as winter peaks are late in the evening. Cold-climate heat pumps add significant heating loads and a small amount of cooling loads, while electric vehicles add loads primarily in the evening hours across the year with higher charging loads on the winter months; for this forecast we assume that EV loads are not controlled. The expected case energy and demand forecasts are derived from the 8,760 adjusted system hourly load forecast. The energy forecast is calculated by summing the adjusted hourly load forecast and the seasonal peak forecasts are derived by finding the maximum monthly hourly demand in summer and winter months. Figure 29 shows the expected case demand forecast.

FIGURE 29: EXPECTED CASE PEAK DEMAND FORECAST (AVERAGE ANNUAL GROWTH)



Forecasted summer peak shifts out to the evening hours largely driven by expected EV charging loads; summer peak averages 2.1% growth through 2033 and increases at 1.1% per year after 2033. Winter peak increases at an even faster rate driven by not only EV charging, but by additional heat pump related electric load. Expected system energy averages 1.5% annual growth; continued solar market penetration partly counters CCHP and EV electricity sales.

4.1 SOLAR FORECAST

4.1.1 Overview

Vermont has one of the largest per capita solar capacities in the country. There is over 450 MW of installed solar capacity on a system with a 1,000 MW peak demand. A combination of federal, state, and utility incentives, along with higher-than-average electric rates has made solar an attractive investment. The recent growth in Group, or Community-Based Solar provides a viable alternative to on-premises installations, broadening the market for residential and nonresidential participation.

The behind the meter (BTM) solar capacity forecast is based on a demand model that relates customer adoption to customer investment return; adoption is modeled as a function of simple investment payback; customers will adopt a solar system if the benefits in the form of lower electricity costs outweigh the initial system cost. Environmental concerns also play a role in adoption as customers have installed solar systems even with long investment paybacks.

Leased and group systems are also influenced by customer economics. The difference is that the solar leasing company or solar developer invests the initial upfront capital costs with the customer paying the lessor for generated solar power. The customer savings is the utility bill savings less the cost of payment to the lessor. Whether customer-owned or leased, there is a strong correlation between simple payback and solar adoption rates. Simple payback is a measure of the number of years required to recover the solar system cost. Across the country, we have seen the highest level of solar system adoption where the simple payback is the lowest or investment returns are the highest.

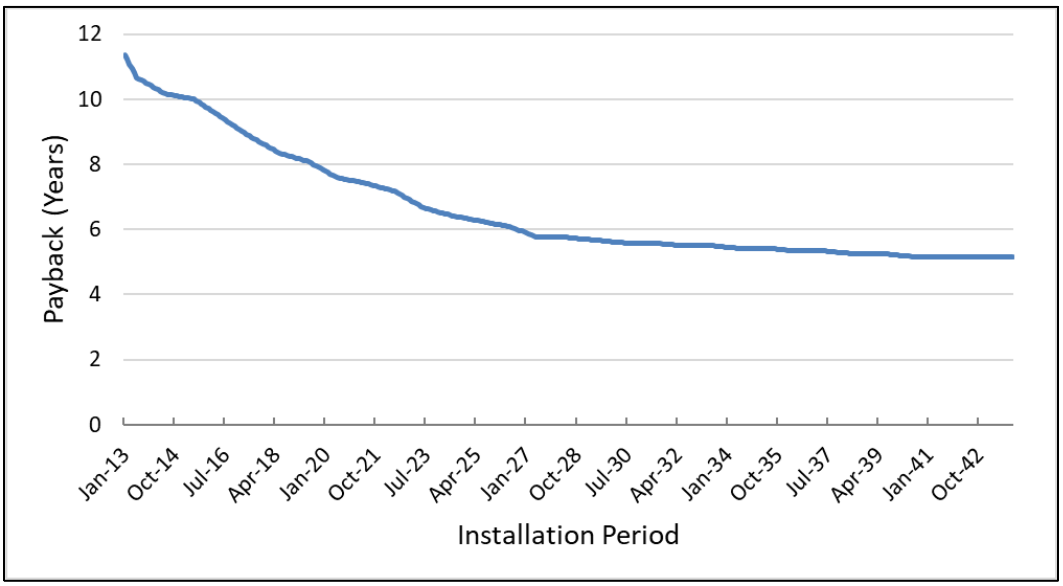
4.1.2 Modeling Approach

Installed solar capacity forms the basis for the estimated solar adoption model. Historical capacity data is available by town; this data is aggregated to VELCO transmission planning zones. A separate capacity adoption model is estimated for each zone. Monthly solar capacity, excluding standard offer solar, is modeled as a function of simple payback. An annual payback is calculated for each historical and forecasted year based on system costs, incentives, and projected electricity prices. Inputs into system payback calculations include:

- System cost
- System size
- Tax credits and incentives (includes Inflation Reduction Act changes)
- Solar Generation profile (used in calculating monthly load factors)
- Electricity rates (variable component)

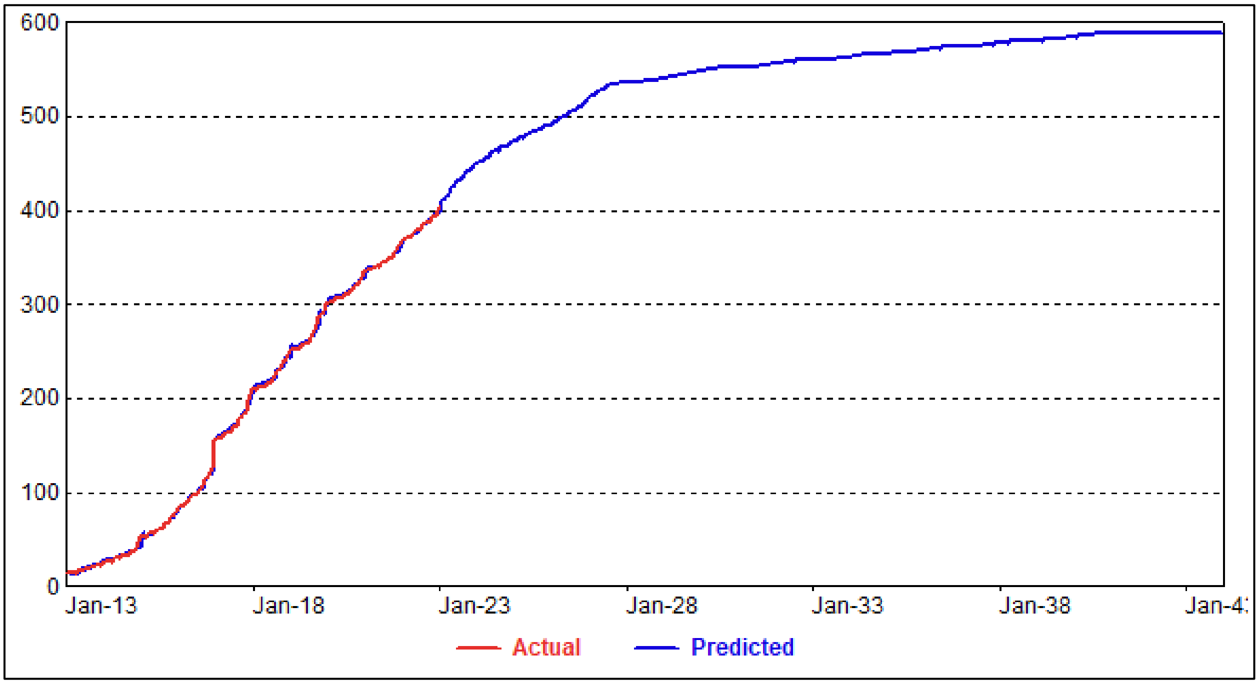
Figure 30 shows the resulting Vermont payback curve.

FIGURE 30: SOLAR PAYBACK



Currently the average system payback is a little over 6 years. While solar payback continues to decline, it declines at a significantly slower rate as solar system costs stabilize. Solar capacity is modeled using a cubic specification and an auto-regressive term to capture the influence of on-going solar market activity. The cubic specification fits the historical data well and imposes an S-shaped adoption path. Models are estimated for each zone as well as VELCO total solar. The VELCO total system model has an Adjusted R^2 of 0.99 and an in-sample MAPE of 1.8%. Figure 31 shows actual and predicted state solar capacity.

FIGURE 31: ACTUAL AND PREDICTED SOLAR CAPACITY (MW)



Zone-level models allow us to capture differences in solar capacity growth across planning zones. While solar growth is widespread across the state, certain zones have higher rates of adoption than others.

The capacity forecast is translated into a total monthly generation forecast by applying monthly solar load factors to the capacity forecast. The monthly load factors are derived from engineering-based solar hourly load profile for 1 MW solar system load. The load shape is a weighted profile, which assumes 33% of systems are roof-mounted, 57% are fixed-tilt, and 10% are axis trackers. The system hourly load profile was developed by Green Mountain Power (GMP) and has proven to work well when compared with measured solar generation loads. The following equation shows an example of how 1 MW of capacity is translated into June generation:

$$1MW_{june} \times 0.23LdFct_{june} \times 720hrs_{june} = 151\ MWh_{june}$$

The solar hourly load forecast is calculated by combining the solar generation forecast with the solar load profile. The solar hourly load forecast is then subtracted from the VELCO system load. BTM solar has been growing at a relatively strong rate for a number of years. As a result, the adjusted system summer peak has already been pushed out into the early evening hours; additional solar load growth has little impact on system peak demand. As peaks transition to winter with the adoption of heat pumps and electric vehicles, solar will have no impact on peak demand. Table 7 shows the BTM solar average annual capacity and annual generation forecast.

TABLE 7: SOLAR CAPACITY & GENERATION

Year	Capacity (MW)	Generation (MWh)
2023	431	596,921
2024	463	642,369
2025	484	669,467
2026	505	698,411
2027	531	735,514
2028	538	745,214
2029	544	753,575
2030	551	762,897
2031	554	766,118
2032	559	774,702
2033	561	776,658
2034	566	783,840
2035	569	786,861
2036	573	794,998
2037	576	796,714
2038	580	803,398
2039	583	806,201
2040	587	813,849
2041	588	813,990
2042	588	813,990
2043	588	813,990

4.2 COLD CLIMATE HEAT PUMP FORECAST

As part of state efforts to reduce CO2 emissions, the state has launched an aggressive program to promote CCHP adoption with significant financial incentives. The primary objective is to reduce heating oil and propane consumption – a primary contributor to greenhouse gases. So far, the program has been very effective with roughly 50,000 heat pumps installed over the last five years. This has had a measurable impact on electric sales and load. One of the most interesting outcomes is when system load is adjusted to account for solar generation, the 2021 and 2022 system peak occurred in November with an average daily temperature around 30 degrees. The forecast is based on VEIC and DPS recent expected case scenario. The forecast is relatively aggressive assuming that the number of annual heat pump units increases from roughly 10,500 units per year today to 18,000 annual units by 2029 before beginning to decline. Figure 32 and Figure 33 show expected annual net adoptions and resulting saturation (assuming 1.7 units per customer).

FIGURE 32: EXPECTED HEAT PUMP SALES

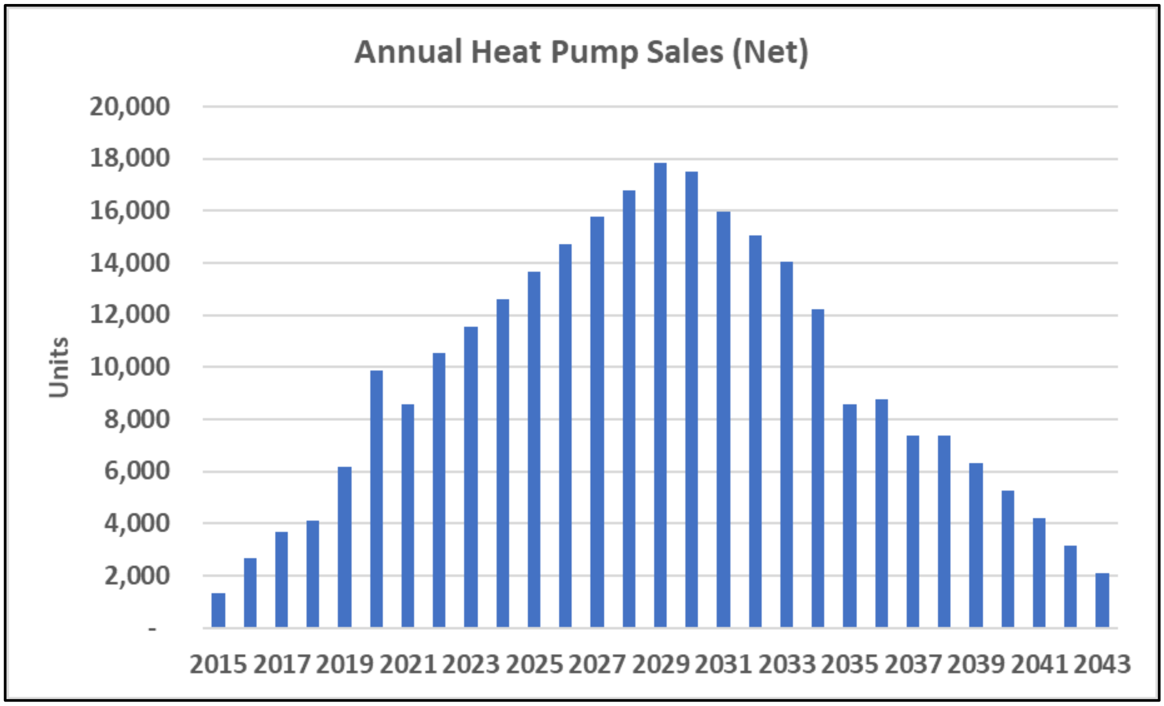
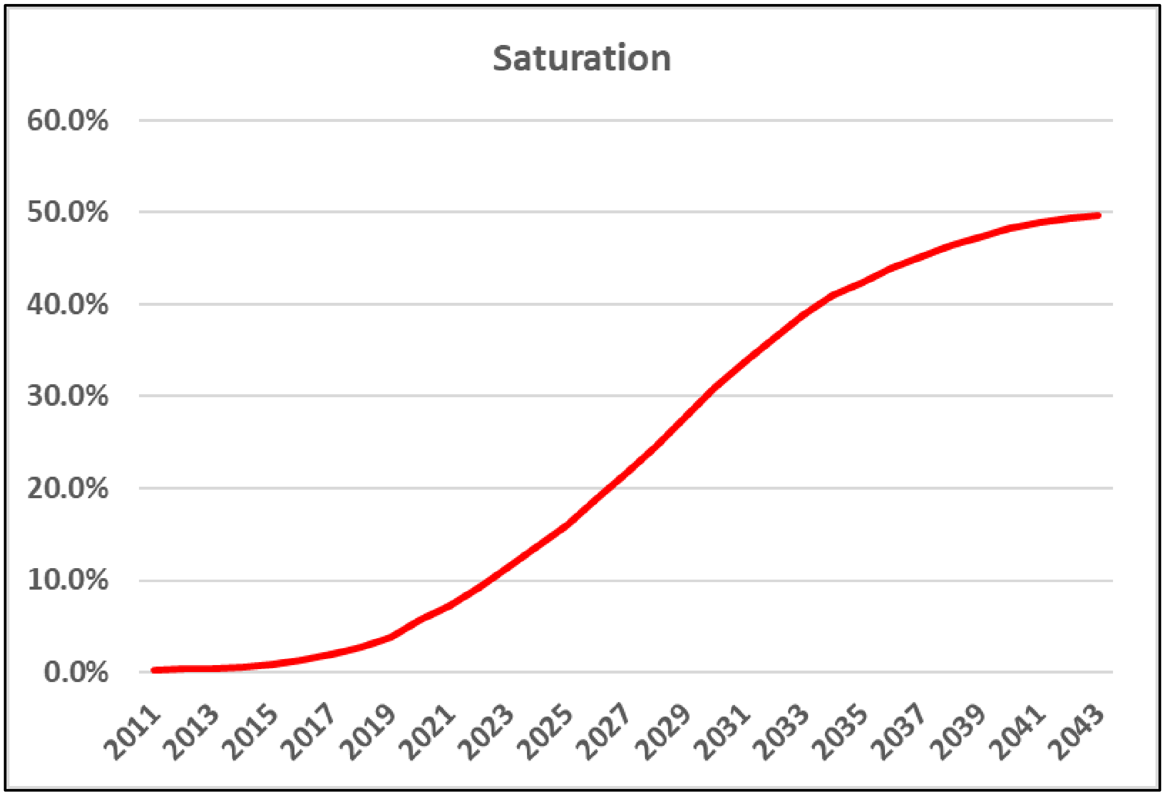


FIGURE 33: HEAT PUMP SATURATION



*Assume on average 1.7 units installed per customer.

By 2043, half the homes in the state have heat pump heating and cooling systems. In the low case we assume heat pumps are installed at the current rate of 10,500 units through 2034 and then track the declining adoption path after that. The number of units is translated to energy consumption based on unit energy estimates derived from an earlier Cadmus study for Vermont. Table 8 shows resulting MWh forecast.

TABLE 8: CUMULATIVE CCHP ENERGY USE (MWH)

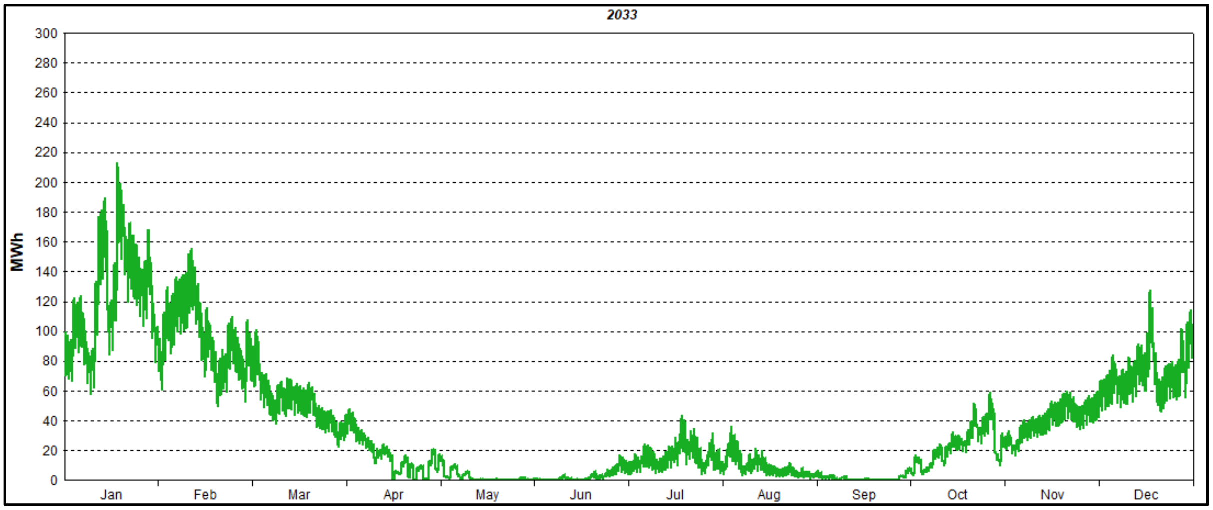
Year	Low	Expected
2023	21,172	23,386
2024	43,207	49,891
2025	65,049	78,420
2026	86,730	108,975
2027	108,308	141,596
2028	129,781	176,260
2029	151,148	212,947
2030	172,419	248,739
2031	193,579	281,088
2032	214,657	311,312
2033	235,659	339,378
2034	256,609	363,562
2035	273,464	380,125
2036	290,721	397,126
2037	305,205	411,393
2038	319,629	425,620
2039	331,940	437,761
2040	342,159	447,836
2041	350,289	455,845
2042	356,341	461,799
2043	360,324	465,708

4.2.1 CCHP Program Load Impacts

A large part of the reason we believe heat pumps peaked in November is that the primary heating system turned on when the average temperature fell below 30 degrees reducing the heat pump output. We assume that over time, that heat pump and primary system thermostat setting are coordinated, and heat pump loads follow typical heating and cooling load patterns.

Expected heating and cooling load profiles are derived from GMP residential AMI load data. A residential hourly load model is estimated that relates loads to day-of-the-week, holidays, hours of daylight, monthly and seasonal binaries, and daily HDD and CDD. Once estimated, the model is used to simulate hourly heating and cooling loads for normal daily weather conditions, the CCHP heating and cooling load forecasts are then derived by combining the CCHP energy forecast with the heating and cooling hourly profiles. Figure 34 shows the 2033 heat pump hourly load forecast.

FIGURE 34: CCHP 2033 EXPECTED CASE LOAD FORECAST



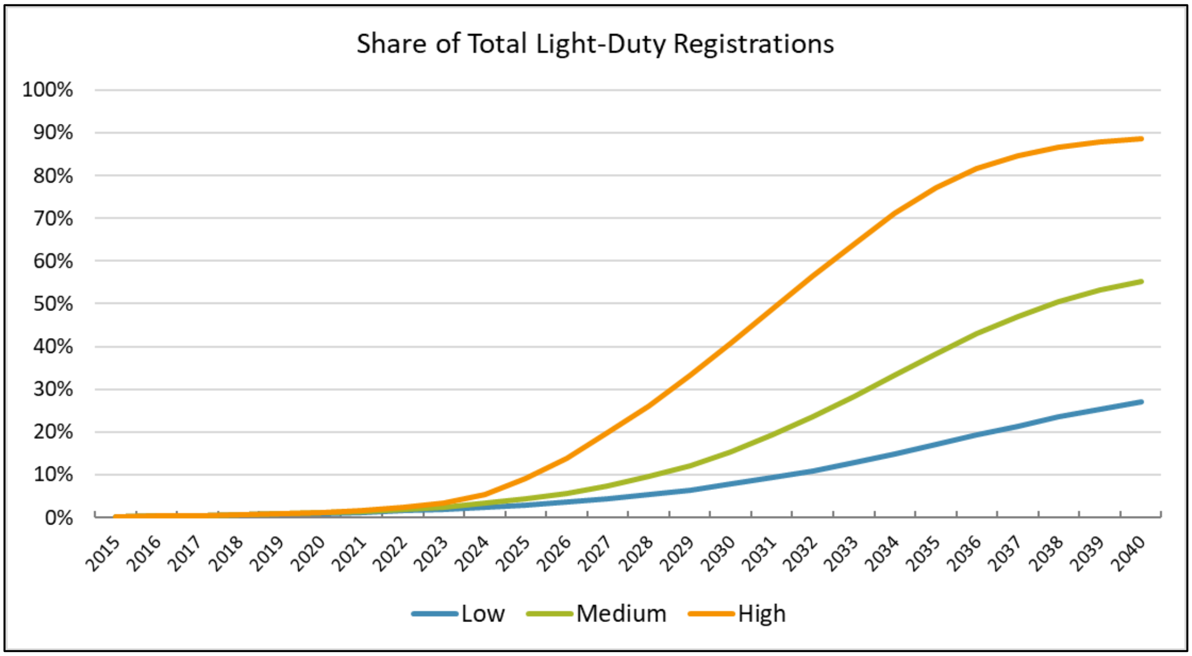
By 2033, heat pumps are expected to add over 200 MW of load at 7:00 AM; this increases to nearly 300 MW by 2043.

4.3 ELECTRIC VEHICLE FORECAST

The electric vehicle forecast includes the impact of non-fleet light-duty vehicles (primarily residential) and fleet electric vehicles. The non-fleet and fleet forecast electricity requirements and impact on demand are driven by assumptions of number of vehicles, number of miles driven, kWh per mile, and charging load patterns.

The non-fleet EV forecast is based on work done by VEIC in the prior IRP to developed three forecast paths (low, medium, and high) based on saturation targets for light-duty registered vehicles. Figure 35 shows the three saturation paths through the end of the forecast period.

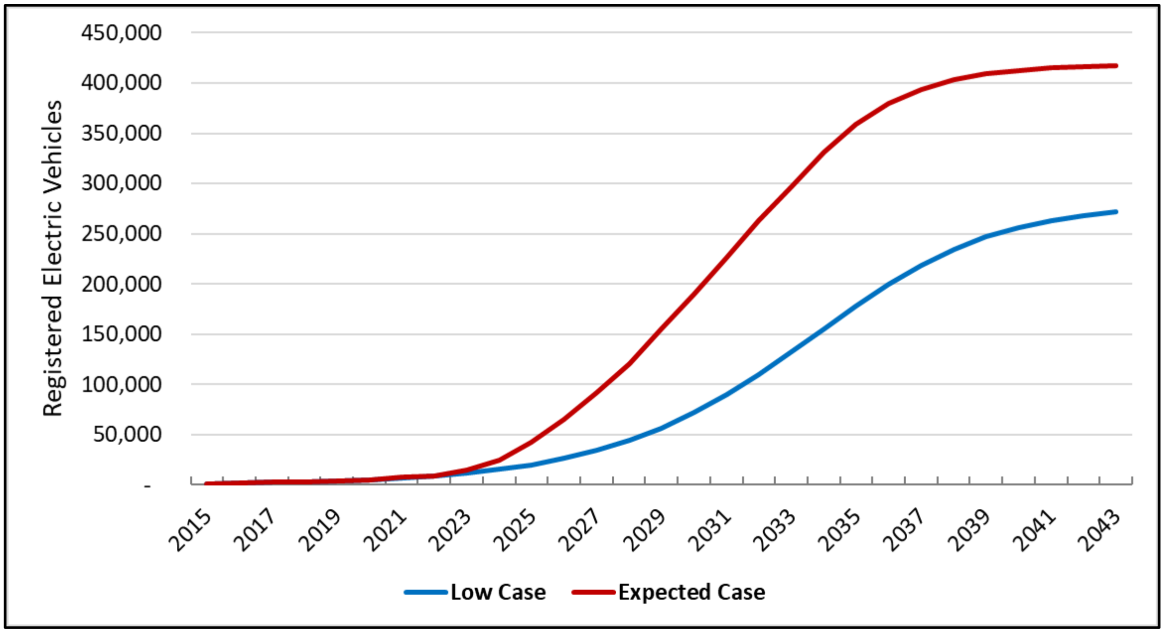
FIGURE 35: SATURATION OF NON-FLEET ELECTRIC VEHICLES



The expected case is based on the high adoption path. Vermont, like eleven other states, has adopted the California Advance Clean Cars II rule. This requires that 35% of new car sales are zero-emission in 2026, 68% by 2030, and 100% by 2035. While the VEIC EV forecast is based on the percentage of total registered vehicles and the Advanced Clean Cars II rule applies to new vehicle sale, the VEIC high case saturation level is possible only if 100% of new vehicles sales are electric as soon as 2025.

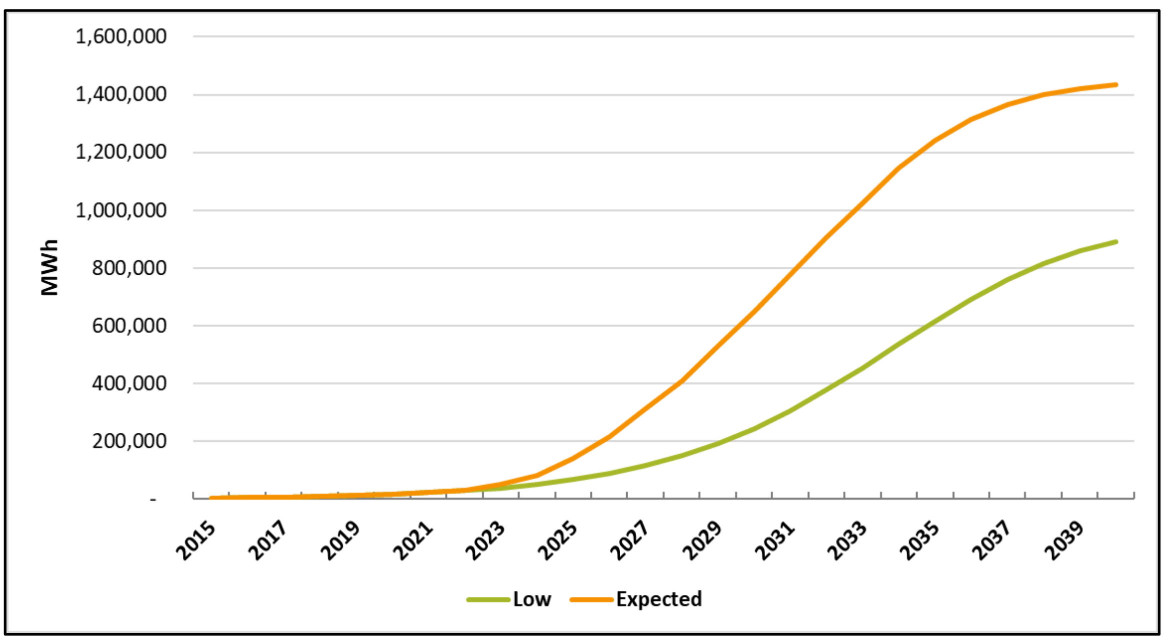
The EV vehicle forecast is derived by applying saturation projections to forecasted number light-duty vehicles where the number of vehicles is derived from state household projection and expected number of vehicles per household. In January 2023, there were approximately 8,900 registered electric vehicles. In the expected case, this increases to nearly 300,000 electric vehicles by 2033 and 420,000 vehicles by 2040. In the low case we assume a slower adoption rate (medium case) as a result of potentially slower infrastructure buildout; the EV saturation rate is close to 60% by 2043, representing 272,000 electric vehicles. Figure 36 shows the EV forecast.

FIGURE 36: NUMBER OF NON-FLEET EVS



EV energy requirements are derived as the product of number of EVs and average annual kwh per vehicle. The average charging load is based on 12,000 annual miles traveled per vehicle. EV usage projection accounts for the changing mix of "all electric" and "plug-in hybrid" electric vehicles as well as improvement to EV efficiency over time. Figure 37 show resulting electricity sales for the low and expected case.

FIGURE 37: NON-FLEET EV CHARGING ENERGY REQUIREMENTS



The fleet electric vehicle forecast is based on ISO New England's Draft 2023 Transportation Electrification Forecast for Vermont. The ISO New England forecast provides vehicle count forecasts and average kWh per day for light-duty fleet, medium-duty fleet, school bus, and transit bus vehicle types through 2032. Figure 38 to Figure 41 show the fleet electric vehicle forecast by vehicle type.

FIGURE 38: LIGHT DUTY FLEET VEHICLES

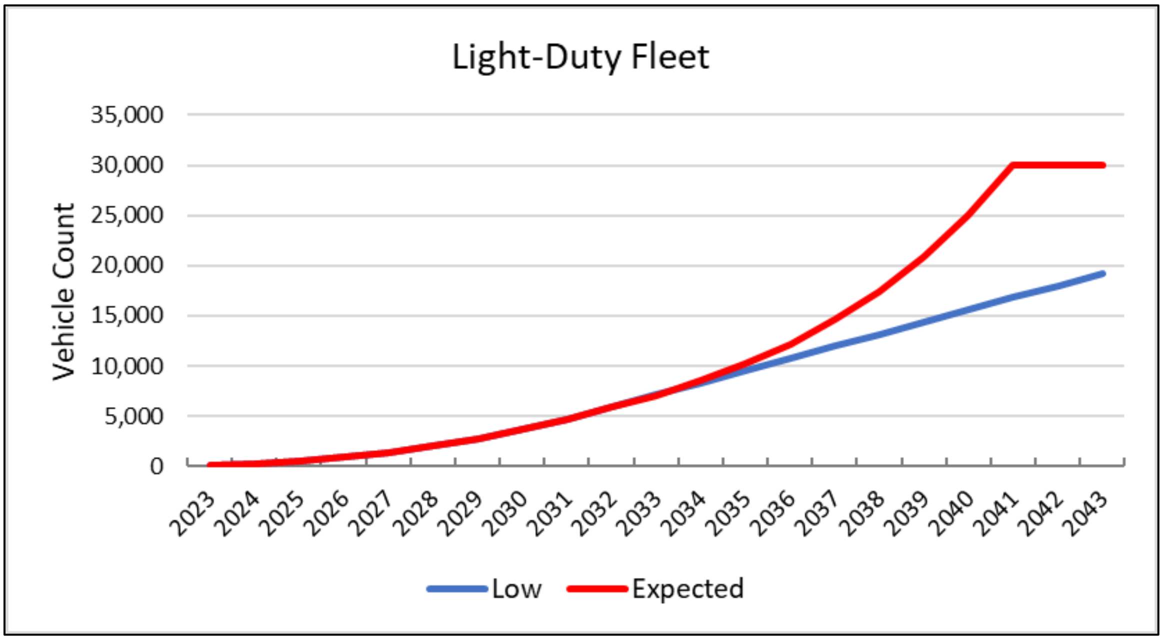


FIGURE 39: MEDIUM-DUTY FLEET VEHICLES

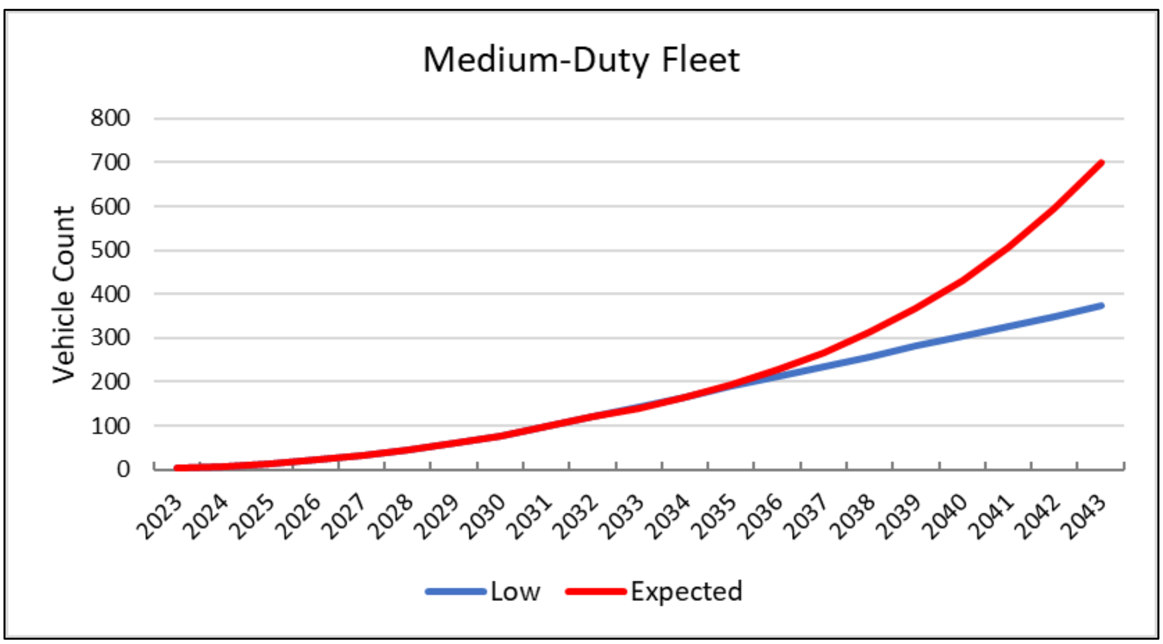


FIGURE 40: SCHOOL BUS VEHICLES

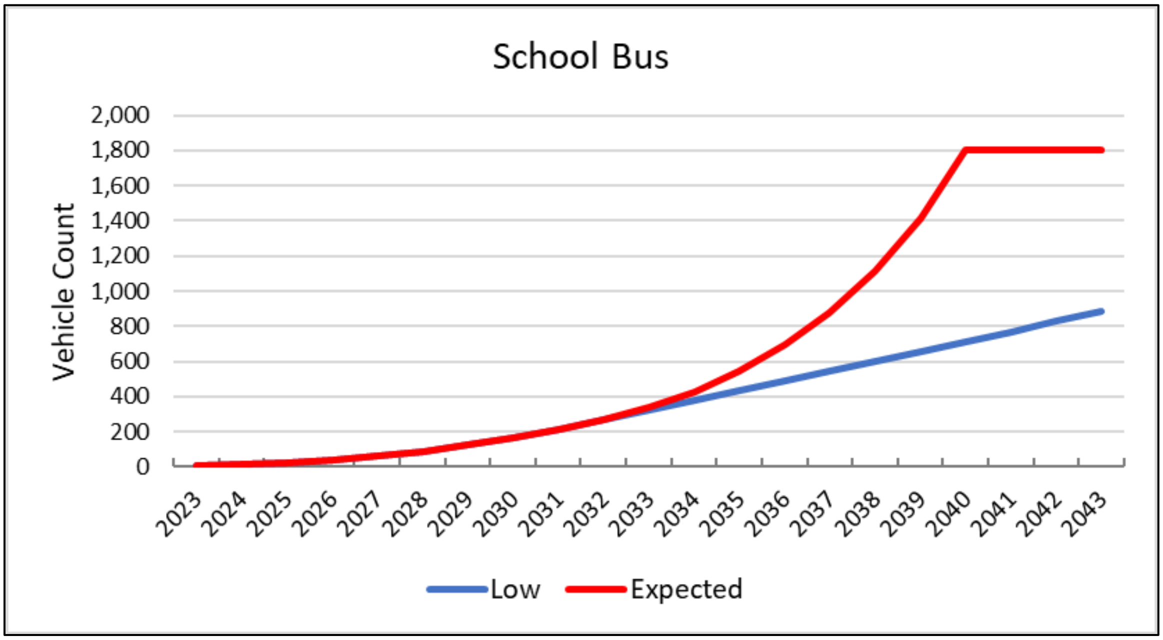
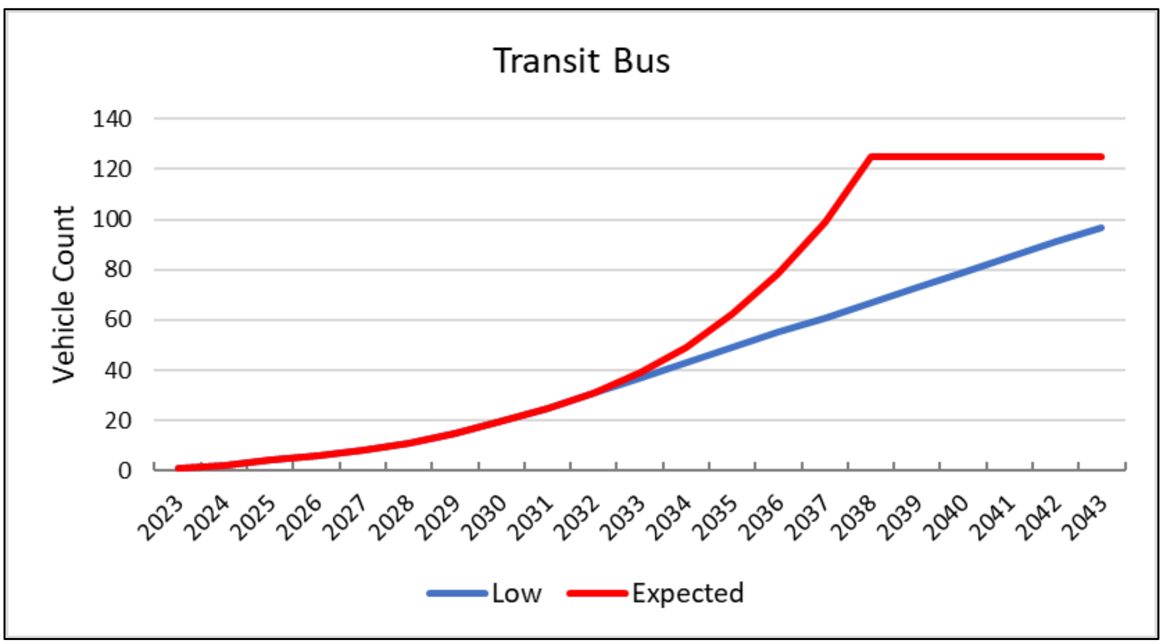


FIGURE 41: TRANSIT BUS VEHICLES



The fleet vehicle count forecast is translated into fleet vehicle MWh charging based on assumptions of annual kWh per vehicle type. Annual kWh per vehicle ranges from approximately 132,000 kWh for transits buses to 8,000 kWh for light-duty fleet vehicles.

Table 9 shows the forecast of non-fleet and fleet charging requirements for the low and expected case scenarios. The fleet figure is the aggregation of light-duty and medium duty fleet, transit bus and school bus.

TABLE 9: EV ENERGY USE MWH

Year	Low			Expected		
	Non-Fleet	Fleet	Total	Non-Fleet	Fleet	Total
2023	8,928	1,145	10,073	20,089	1,145	21,234
2024	21,428	2,604	24,033	53,997	2,990	56,988
2025	37,780	4,464	42,243	111,206	5,954	117,160
2026	58,992	6,960	65,952	188,119	9,944	198,063
2027	86,220	10,078	96,298	281,486	15,108	296,594
2028	120,696	13,943	134,638	380,257	21,757	402,014
2029	163,592	18,805	182,397	498,932	29,897	528,829
2030	215,794	24,620	240,414	620,982	39,630	660,612
2031	277,582	31,546	309,128	747,652	50,901	798,553
2032	348,262	44,464	392,726	874,984	63,951	938,935
2033	425,867	57,381	483,248	995,224	77,407	1,072,632
2034	507,094	70,298	577,392	1,116,551	93,749	1,210,300
2035	587,661	83,216	670,877	1,213,963	113,608	1,327,572
2036	663,080	96,133	759,213	1,286,398	137,759	1,424,156
2037	729,618	109,051	838,668	1,336,912	167,147	1,504,060
2038	785,041	121,968	907,009	1,370,404	202,937	1,573,340
2039	828,826	134,885	963,711	1,391,732	242,228	1,633,960
2040	861,834	147,803	1,009,636	1,404,814	289,966	1,694,781
2041	885,720	160,720	1,046,440	1,412,463	332,050	1,744,513
2042	902,374	173,637	1,076,012	1,416,558	334,375	1,750,933
2043	913,554	186,555	1,100,109	1,418,308	337,105	1,755,413

4.3.1 EV System Load Impact

Electric vehicles' impact on system demand depends not only on the charging energy requirements but also on the timing of the charging activity. Approximately 80% of residential EV charging is expected to occur at home with 20% at the workplace or public charging stations; "at home" and "away" charging profiles have very different charging loads across the day and hours. The residential at home charging profile is based on measured EV charging data from GMP for non-controlled days. The profile is highest in the early evening hours. The away charging profile is derived from the Department of Energy's Electric Vehicle Infrastructure Projection Tool (EVI-Pro) Lite. This is a publicly available online tool used to generate typical EV charging profiles by charging type. The tool generates a typical 15-minute weekday and weekend charging profile for the following charging types:

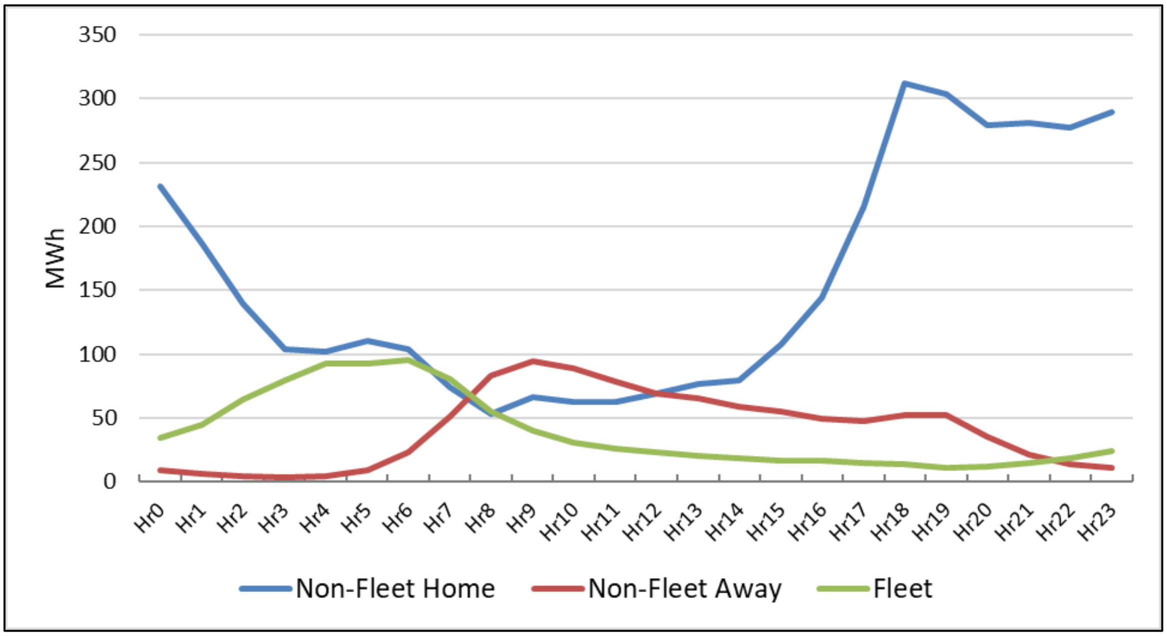
- Home Level 1
- Home Level 2
- Work Level 1
- Work Level 2

- Public Level 2
- Public DC Fast Level 3

The away from home charging profile is a summation of the work and public charging profiles. The profile has a seasonal component to account for increased charging needs in winter months.

The fleet charging profile is derived by altering EVI-Pro charging strategies; the resulting profile which is consistent with that presented by ISO New England in their Draft 2023 Transportation Electrification Forecast. Figure 42 shows a January weekday hourly charging profile for non-fleet, home and away, and fleet charging for 2040.

FIGURE 42: CHARGING PROFILES



The EV hourly load forecast is calculated by combining the annual EV energy forecast with the EV charging profile, by EV type.

4.4 ADJUSTED SYSTEM LOAD FORECAST

The adjusted system load forecast is derived by subtracting the solar hourly load forecast from the baseline hourly load forecast and adding the electric vehicle and heat-pump hourly load forecasts.

Figure 43 and Figure 44 compare the 2023, 2033, and 2043 summer and winter peak-day hourly load profiles.

FIGURE 43: SUMMER PEAK-DAY PROFILE (MW)

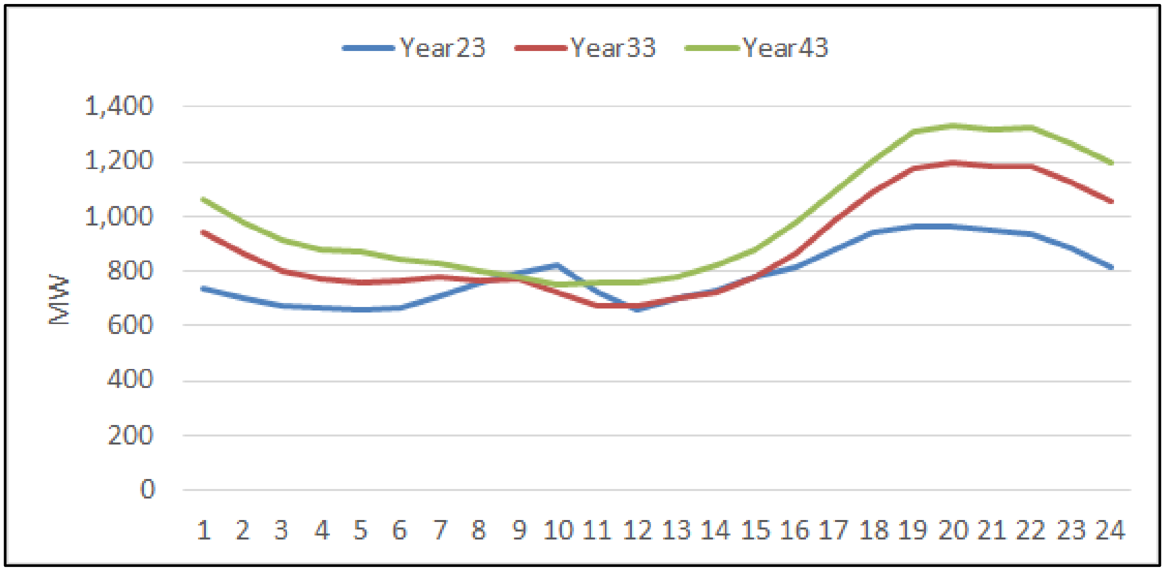
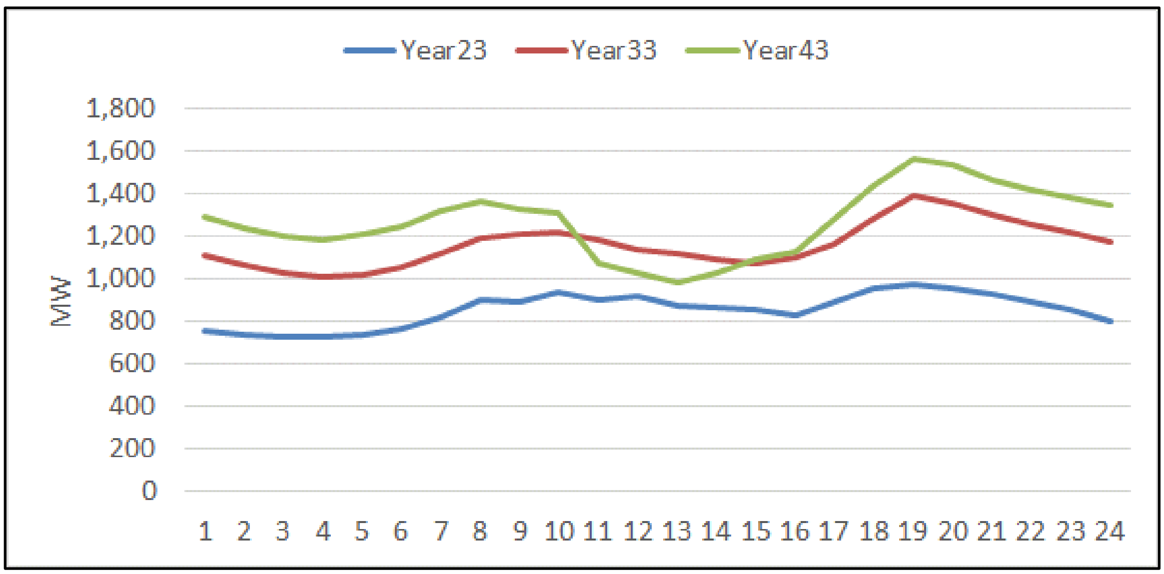


FIGURE 44: WINTER PEAK-DAY PROFILE (MW)



As illustrated, PV, CCHP, and EVs reshape system load over time. In aggregate, these technologies drive system energy and peak demand growth and push loads significantly higher in the winter months.

The expected energy requirements are derived by summing across the adjusted system hourly load forecast. Summer and winter peaks are the maximum hourly load that occurs in the summer and winter periods.

A low case scenario was also developed. The baseline forecast is the same for both the expected and low case. The low case assumes that number of new heat pumps continues at the current rate of 10,500 heat pumps per year and that EV adoption takes longer than the expected case following the middle EV penetration curve. The primary difference is in terms of system and zonal growth over the first ten years as the expected case assumes much faster EV and CCHP adoption. Table 10 and Table 11 compare the expected and low case energy and peak forecasts.

TABLE 10: FORECAST SCENARIOS – ENERGY (MWH)

Year	Low Case	Expected Case
2023	5,388,921	5,402,297
2028	5,480,517	5,794,371
2033	5,819,902	6,513,005
2038	6,269,237	7,041,559
2043	6,498,513	7,259,201
2023 - 33	0.8%	1.9%
2033 - 43	1.1%	1.1%
2023 - 43	**0.9%**	**1.5%**

TABLE 11: FORECAST SCENARIOS – SUMMER PEAKS (MW)

Year	Low Case	Expected Case
2023	964.4	966.5
2028	1,011.7	1,062.0
2033	1,084.5	1,195.4
2038	1,173.8	1,289.5
2043	1,226.3	1,329.9
2023 - 33	1.2%	2.1%
2033 - 43	1.2%	1.1%
2023 - 43	**1.2%**	**1.6%**

TABLE 12: FORECAST SCENARIOS – WINTER PEAKS (MW)

Year	Low Case	Expected Case
2023	974.7	978.8
2028	1,062.1	1,154.6
2033	1,184.2	1,388.9
2038	1,320.1	1,533.1
2043	1,373.8	1,568.6
2023 - 33	2.0%	3.6%
2033 - 43	1.5%	1.2%
2023 - 43	**1.7%**	**2.4%**

4.5 THE ONE-IN-TEN DEMAND FORECASTS

VELCO plans for system demand that can meet one-in-ten year (10% probability of occurring) weather conditions. The 10% probability weather is identified by evaluating actual peak-day weather conditions over the last 30 years. Summer peak-day weather is defined for the maximum weighted temperature/humidity index (THI) that occurred in each month over the last twenty years. Figure 45 shows the results when ranked from the hottest to the coolest peak-day THI. Figure 46 shows the same for peak-day HDD.

FIGURE 45: SUMMER PEAK-DAY THI RANKING

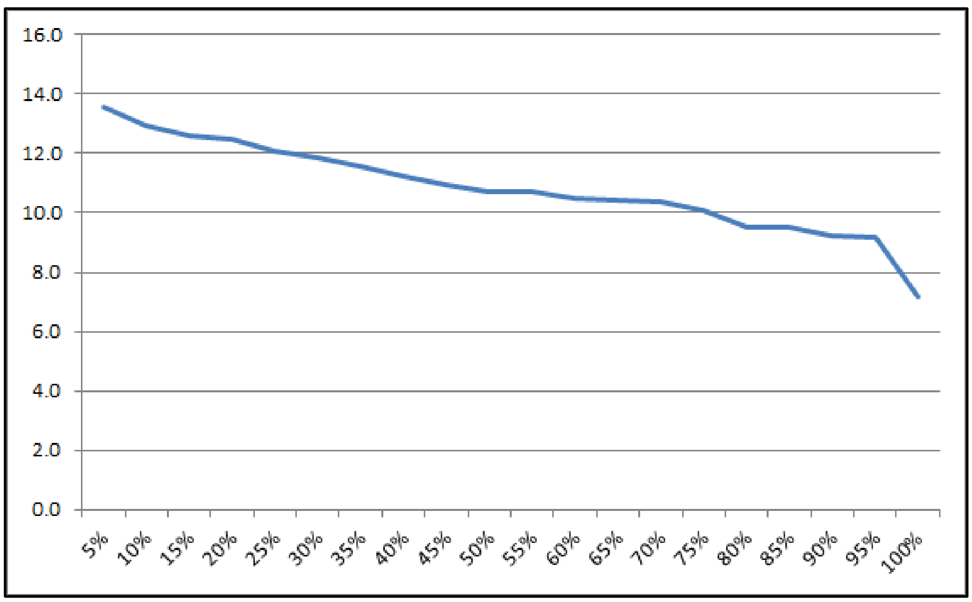
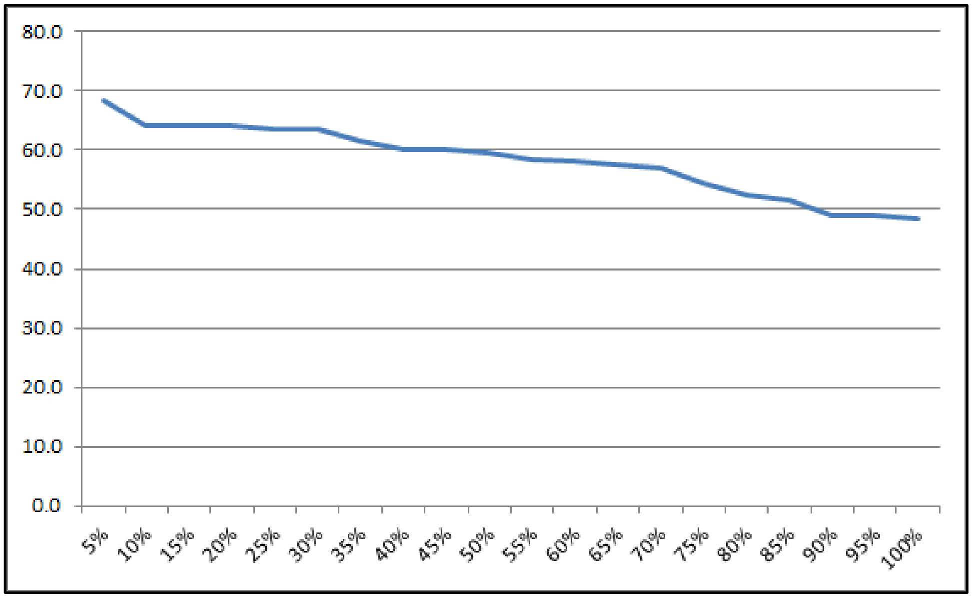


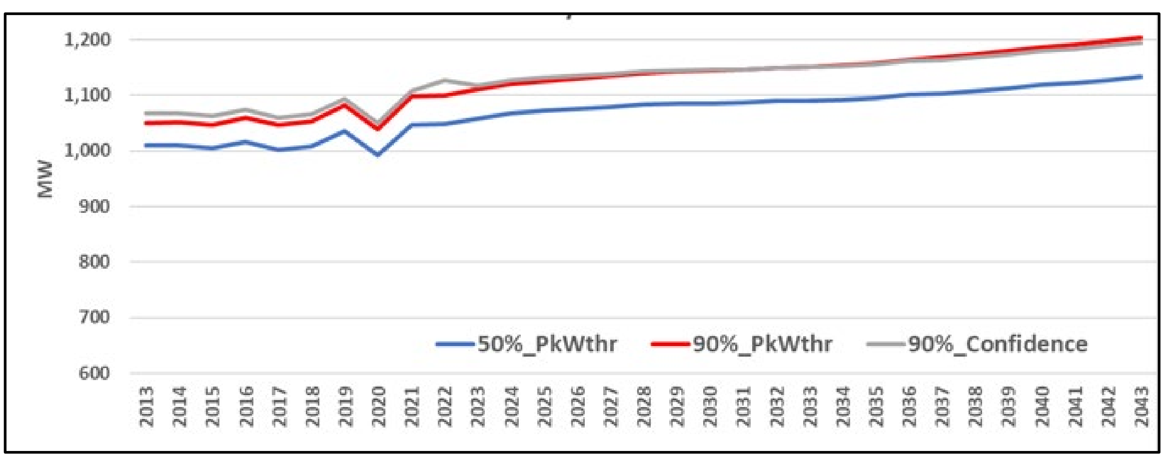
FIGURE 46: WINTER PEAK-DAY HDD RANKING



The 10% and 50% probability peak-day weather conditions are found from the peak-day weather distributions. Estimated system and zonal peak models are used to simulate demand with the 10% and 50% probability weather conditions. The difference between 10% and 50% probability simulations are used to calculate extreme weather adjustment factors that are applied to the adjusted system and zonal peak demand forecasts. The summer 90% peak-day THI is 26% higher than expected peak-day summer THI. For winter peak, the 90% peak-day HDD is just 13% higher than the 50% peak-day HDD; the winter peak-day HDD profile is much flatter. While the 90% summer peak THI results in a reasonable bound for evaluating hot weather impacts, the winter peak adjustment is too low in light of expected growth in heat pumps that in turn will result in winter peak demands that are much more sensitive to winter peak weather conditions. As an alternative, we elected to bound the peak forecasts with a 90% confidence interval derived from the system peak model.

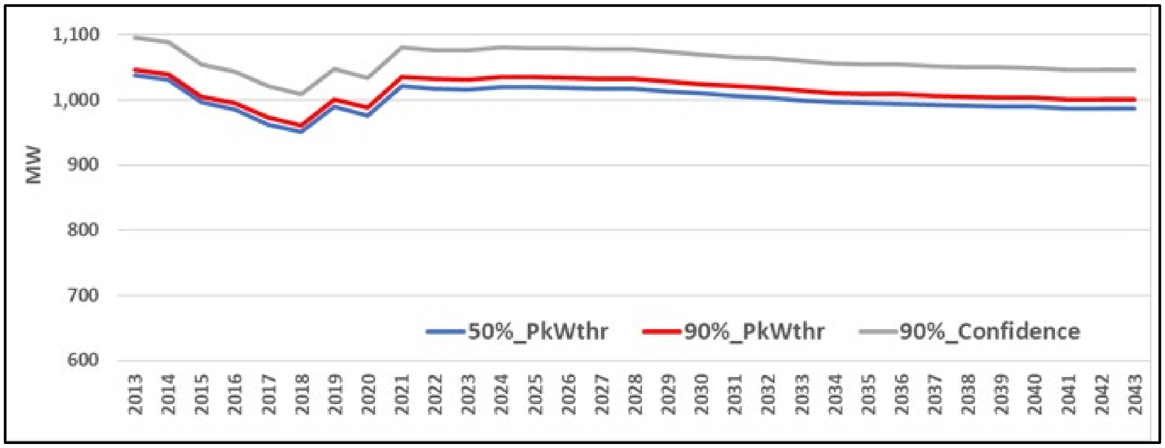
For the summer peak, there is little difference between 90% peak weather and 90% confidence interval; both add roughly 100 MW of load to summer peak. This is shown in Figure 47.

FIGURE 47: 90% SUMMER PEAK BASELINE FORECAST



As winter 90% peak weather has a relatively small impact, the 90% confidence adjustment is much higher as illustrated in Figure 48.

FIGURE 48: WINTER 90% BASELINE PEAK FORECAST



On average baseline summer peak demand is adjusted up to 5.6% and winter peak demand 5.8%. The higher baseline forecasts are then adjusted for PV, EV, and CCHP. Table 13 shows the 10% probability summer peaks and Table 14 shows 10% probability winter peaks.

TABLE 13: 10% PROBABILITY SUMMER PEAK DEMAND (MW)

Year	Newport	Highgate	StAlbans	Johnson	Morrisville	Montpelier	StJohnsbury	BED	IBM
2023	42.6	43.4	77.2	12.1	34.3	97.3	28.1	67.5	53.1
2028	45.4	47.2	84.1	13.7	37.4	108.2	29.9	74.1	52.6
2033	49.2	50.6	91.2	15.1	40.5	125.8	31.9	86.4	52.8
2038	52.1	53.5	96.9	16.1	42.7	137.7	33.4	95.0	52.8
2043	53.8	55.8	101.2	16.4	43.7	141.5	34.3	98.4	52.8
2023 - 33	1.5%	1.5%	1.7%	2.2%	1.7%	2.6%	1.3%	2.5%	-0.1%
2033 - 43	0.9%	1.0%	1.0%	0.8%	0.8%	1.2%	0.7%	1.3%	0.0%
2023 - 43	**1.2%**	**1.3%**	**1.4%**	**1.5%**	**1.2%**	**1.9%**	**1.0%**	**1.9%**	**0.0%**

Year	Burlington	Middlebury	Central	Florence	Rutland	Ascutney	Southern	System
2023	165.8	37.2	60.0	18.7	97.0	71.9	114.3	1,020.4
2028	193.1	39.6	66.0	18.6	104.5	78.2	123.2	1,116.0
2033	234.8	42.5	72.4	18.7	112.7	87.0	138.1	1,249.8
2038	263.7	44.7	77.0	18.7	118.7	93.3	148.4	1,344.7
2043	274.8	46.1	79.9	18.7	121.4	95.8	151.8	1,386.4
2023 - 33	3.5%	1.3%	1.9%	0.0%	1.5%	1.9%	1.9%	2.0%
2033 - 43	1.6%	0.8%	1.0%	0.0%	0.7%	1.0%	0.9%	1.0%
2023 - 43	**2.6%**	**1.1%**	**1.4%**	**0.0%**	**1.1%**	**1.5%**	**1.4%**	**1.5%**

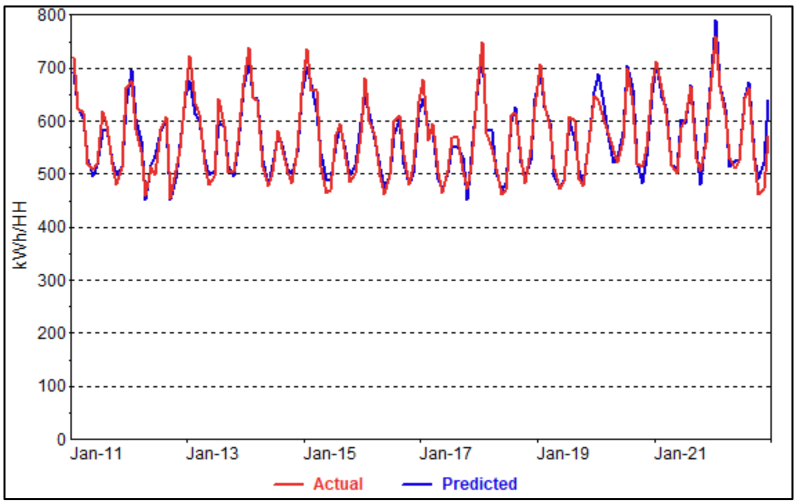
TABLE 14: 10% WINTER PEAK DEMAND (MW)

Year	Newport	Highgate	StAlbans	Johnson	Morrisville	Montpelier	StJohnsbury	BED	IBM
2023	45.0	38.8	67.4	16.0	35.7	112.5	31.6	55.0	42.0
2028	51.3	43.9	77.3	18.3	40.6	134.3	35.5	69.7	41.9
2033	58.8	49.7	89.0	21.1	46.6	164.6	39.8	91.1	42.0
2038	63.2	53.4	96.6	22.8	50.0	182.9	42.2	104.6	42.0
2043	64.5	55.1	99.7	23.0	50.7	186.3	42.8	108.4	42.0
2023 - 33	2.7%	2.5%	2.8%	2.8%	2.7%	3.9%	2.3%	5.2%	0.0%
2033 - 43	0.9%	1.0%	1.1%	0.9%	0.9%	1.2%	0.7%	1.7%	0.0%
2023 - 43	**1.8%**	**1.8%**	**2.0%**	**1.8%**	**1.8%**	**2.6%**	**1.5%**	**3.4%**	**0.0%**

Year	Burlington	Middlebury	Central	Florence	Rutland	Ascutney	Southern	System
2023	140.6	36.0	71.2	19.6	111.6	68.4	144.4	1,035.9
2028	188.7	40.5	82.6	19.6	125.0	78.2	164.3	1,211.7
2033	258.0	45.7	95.5	19.6	141.0	91.9	190.6	1,445.1
2038	302.2	48.9	103.2	19.6	150.3	100.5	206.4	1,588.9
2043	314.2	49.7	105.9	19.6	151.7	101.9	208.5	1,624.2
2023 - 33	6.3%	2.4%	3.0%	0.0%	2.4%	3.0%	2.8%	3.4%
2033 - 43	2.0%	0.9%	1.0%	0.0%	0.7%	1.0%	0.9%	1.2%
2023 - 43	**4.1%**	**1.6%**	**2.0%**	**0.0%**	**1.5%**	**2.0%**	**1.9%**	**2.3%**

5 APPENDIX A: MODEL STATISTICS

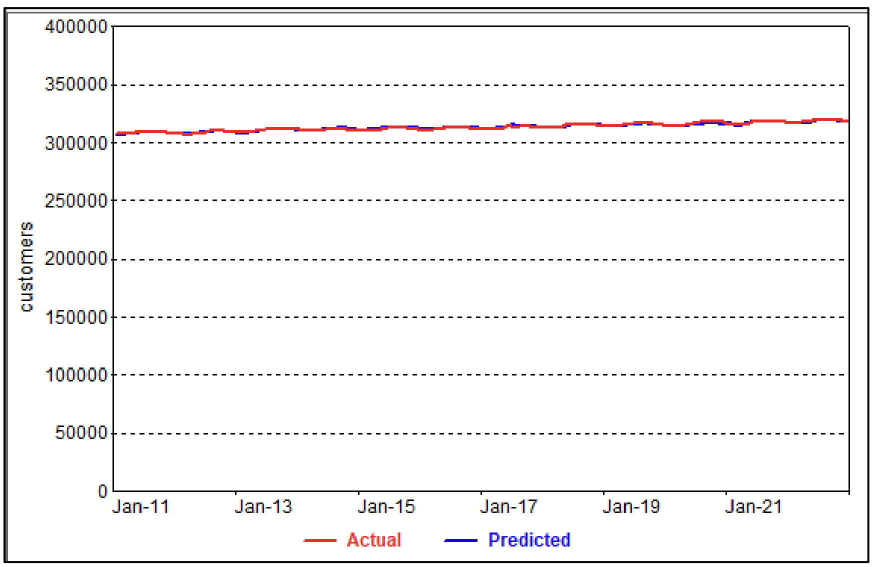
Residential Average Use Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mStructRes.WtXHeat	0.83	0.051	16.214	0.00%
mStructRes.WtXCool	0.815	0.056	14.652	0.00%
mStructRes.XOther	0.981	0.014	70.375	0.00%
CovidVar.ResIndex	-3.857	7.976	-0.484	62.95%
mBin.Mar	-27.056	8.459	-3.198	0.17%
mBin.Apr	-30.168	10.057	-3	0.32%
mBin.May	-32.941	8.537	-3.858	0.02%
mBin.Oct	-42.275	8.65	-4.887	0.00%
mBin.Nov	-33.359	8.241	-4.048	0.01%
mBin.Apr12	-60.826	16.416	-3.705	0.03%
mBin.Sep12	-75.357	16.081	-4.686	0.00%
mBin.Jan18	35.686	16.485	2.165	3.22%
MA(1)	0.52	0.08	6.488	0.00%
SMA(1)	0.353	0.093	3.818	0.02%

Model Statistics	
Iterations	22
Adjusted Observations	144
Deg. of Freedom for Error	130
R-Squared	0.935
Adjusted R-Squared	0.928
AIC	6.081
BIC	6.37
Log-Likelihood	-628.15
Model Sum of Squares	743,936.52
Sum of Squared Errors	51,860.21
Mean Squared Error	398.92
Std. Error of Regression	19.97
Mean Abs. Dev. (MAD)	14.88
Mean Abs. % Err. (MAPE)	2.61%
Durbin-Watson Statistic	1.74

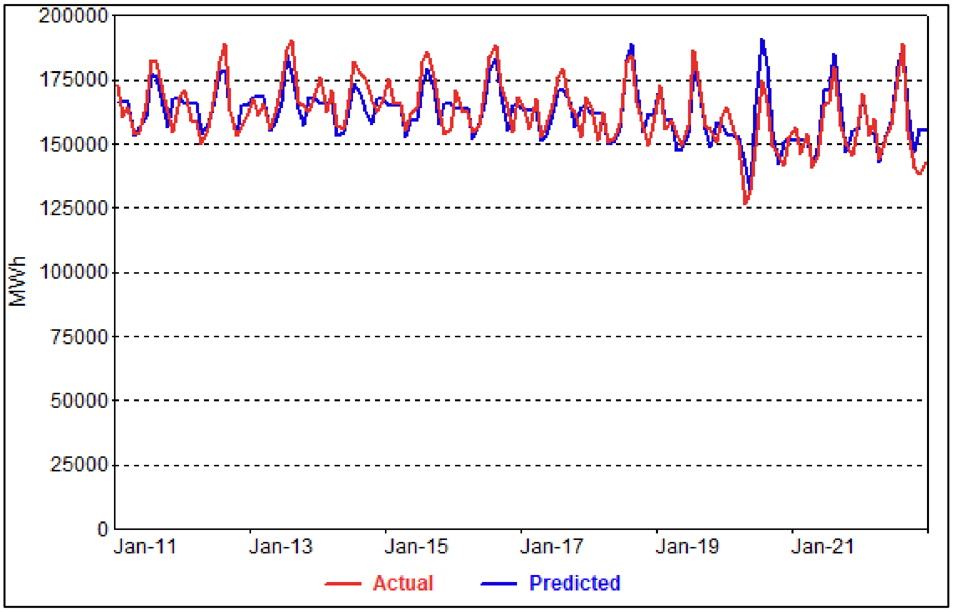
Residential Customer Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mEcon.Cust_Var	181365.81	10692	16.963	0.00%
mBin.Jan	130614.366	10651	12.264	0.00%
mBin.Feb	130425.383	10659	12.236	0.00%
mBin.Mar	130644.714	10670	12.245	0.00%
mBin.Apr	130762.022	10673	12.252	0.00%
mBin.May	131518.744	10676	12.319	0.00%
mBin.Jun	132964.627	10679	12.451	0.00%
mBin.Jul	132317.77	10682	12.387	0.00%
mBin.Aug	132658.937	10685	12.416	0.00%
mBin.Sep	132517.419	10687	12.4	0.00%
mBin.Oct	132421.261	10689	12.388	0.00%
mBin.Nov	131855.827	10681	12.345	0.00%
mBin.Dec	131630.184	10673	12.333	0.00%
mBin.Aft21	3626.588	358.3	10.121	0.00%
MA(1)	0.518	0.077	6.755	0.00%
MA(2)	0.515	0.077	6.704	0.00%

Model Statistics	
Iterations	26
Adjusted Observations	144
Deg. of Freedom for Error	128
R-Squared	0.95
Adjusted R-Squared	0.944
AIC	13.488
BIC	13.818
Log-Likelihood	-1,159.44
Model Sum of Squares	1,578,818,142.52
Sum of Squared Errors	83,071,924.07
Mean Squared Error	648,999.41
Std. Error of Regression	805.6
Mean Abs. Dev. (MAD)	598.03
Mean Abs. % Err. (MAPE)	0.19%
Durbin-Watson Statistic	1.541

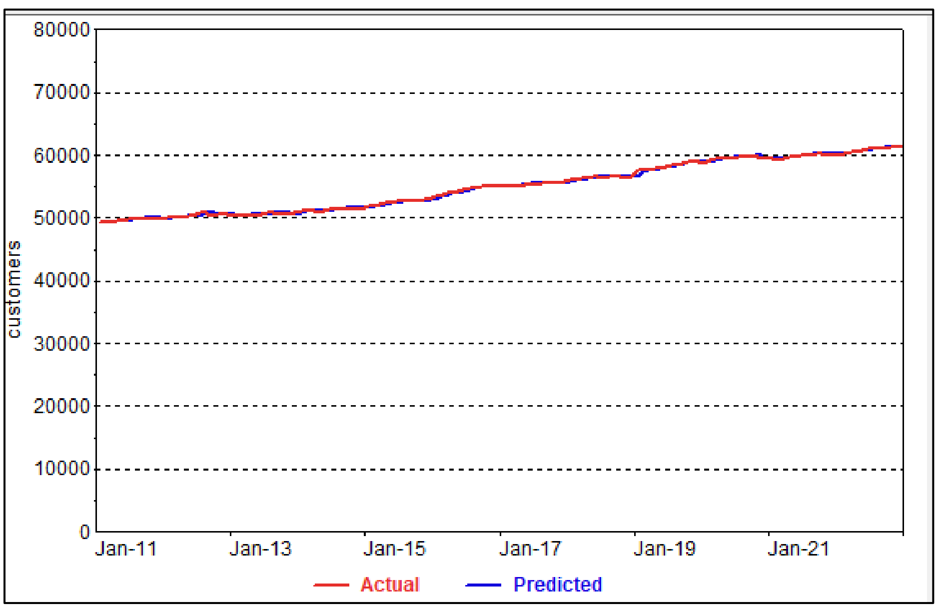
Commercial Sales Model



Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	53662.984	8880.221	6.043	0.00%
mStructNRes.XOther	106311.25	9116.444	11.661	0.00%
mStructNRes.WtXCool	85799.355	4815.707	17.817	0.00%
mBin.Bef13	-5545.335	1684.798	-3.291	0.13%
mBin.Jan19	13193.75	6613.859	1.995	4.80%
mBin.Jan22	16111.002	6616.569	2.435	1.62%
mBin.May20	-17428.061	6691.026	-2.605	1.02%

Model Statistics	
Iterations	1
Adjusted Observations	144
Deg. of Freedom for Error	137
R-Squared	0.72
Adjusted R-Squared	0.708
AIC	17.628
BIC	17.773
F-Statistic	58.739
Prob (F-Statistic)	0
Log-Likelihood	-1,466.55
Model Sum of Squares	15,216,301,265.35
Sum of Squared Errors	5,914,972,284.85
Mean Squared Error	43,174,980.18
Std. Error of Regression	6,570.77
Mean Abs. Dev. (MAD)	5,009.27
Mean Abs. % Err. (MAPE)	3.10%
Durbin-Watson Statistic	1.435

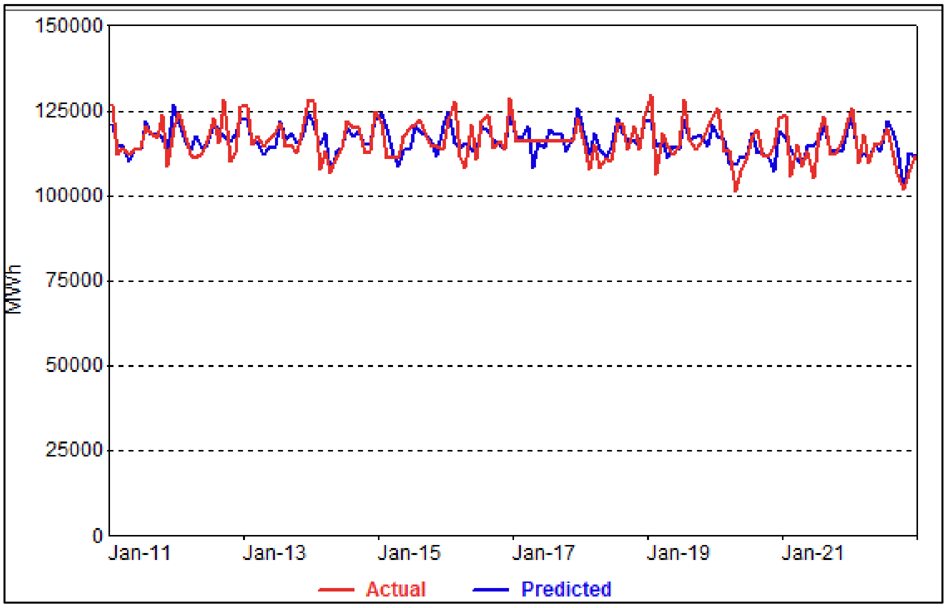
Commercial Customer Model



Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	7102972.925	1.9E+09	0.004	99.71%
Economics.NManEmp	-7.535	13.78	-0.547	58.54%
AR(1)	1	0.003	287.39	0.00%
MA(1)	-0.22	0.083	-2.657	0.88%

Model Statistics	
Iterations	99
Adjusted Observations	143
Deg. of Freedom for Error	139
R-Squared	0.997
Adjusted R-Squared	0.997
AIC	10.642
BIC	10.725
F-Statistic	17635.252
Prob (F-Statistic)	0
Log-Likelihood	-959.8
Model Sum of Squares	2,153,883,357.28
Sum of Squared Errors	5,658,926.59
Mean Squared Error	40,711.70
Std. Error of Regression	201.77
Mean Abs. Dev. (MAD)	144.99
Mean Abs. % Err. (MAPE)	0.26%
Durbin-Watson Statistic	2.029

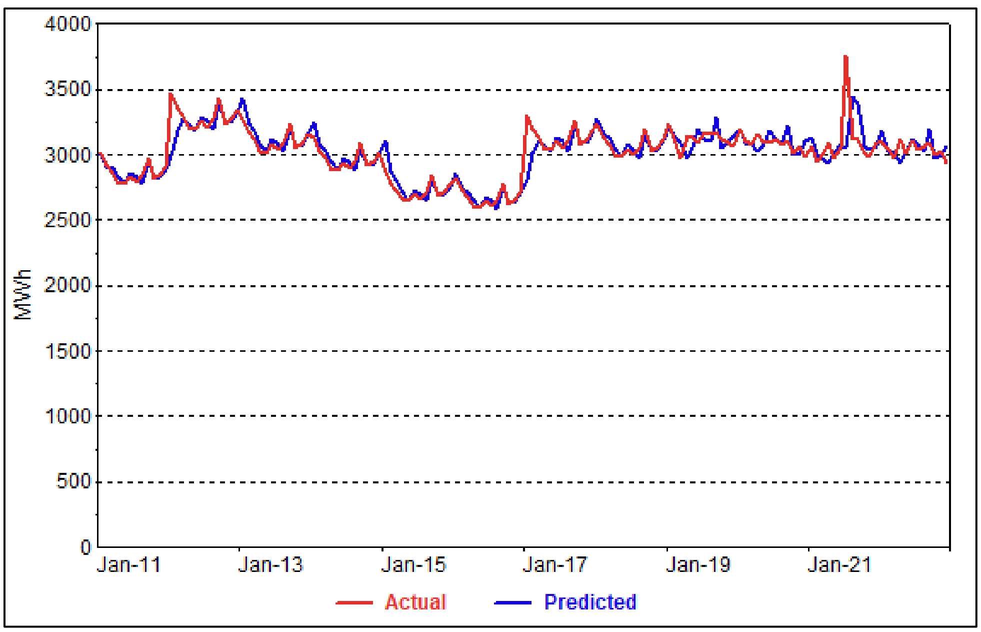
Industrial Sales Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mStructNRes.XHeat	153934.487	17078.802	9.013	0.00%
mStructNRes.LagXHeat	-151107.812	20464.789	-7.384	0.00%
mStructNRes.XCool	10931.672	3629.43	3.012	0.31%
mStructNRes.LagXCool	-8330.614	3605.239	-2.311	2.24%
mStructNRes.IndOther	3262.209	424.733	7.681	0.00%
mBin.TrendVar	1.897	0.12	15.745	0.00%
CovidVar.NResIndex	-2465.241	1164.26	-2.117	3.61%
mBin.Jun	-4303.61	1469.868	-2.928	0.40%
mBin.Oct	-4900.499	1662.782	-2.947	0.38%
mBin.Nov	-9239.561	1657.498	-5.574	0.00%
mBin.Oct22	-12340.917	4501.738	-2.741	0.70%
mBin.Dec22	-11162.935	4415.835	-2.528	1.26%

Model Statistics	
Iterations	1
Adjusted Observations	144
Deg. of Freedom for Error	132
R-Squared	0.499
Adjusted R-Squared	0.457
AIC	16.804
BIC	17.051
Log-Likelihood	-1,402.18
Model Sum of Squares	2,405,986,698.12
Sum of Squared Errors	2,419,095,389.84
Mean Squared Error	18,326,480.23
Std. Error of Regression	4,280.94
Mean Abs. Dev. (MAD)	3,251.54
Mean Abs. % Err. (MAPE)	2.80%
Durbin-Watson Statistic	2.15

Other Sales Model



Variable	Coefficient	StdErr	T-Stat	P-Value
Simple	0.617	0.081	7.626	0
Seasonal	-0.038	0.095	-0.404	0.687

Model Statistics	
Iterations	29
Adjusted Observations	144
Deg. of Freedom for Error	142
R-Squared	0.681
Adjusted R-Squared	0.678
AIC	9.418
BIC	9.459
Log-Likelihood	-880.43
Model Sum of Squares	3,673,483
Sum of Squared Errors	1,724,034
Mean Squared Error	12,141.09
Std. Error of Regression	110.19
Mean Abs. Dev. (MAD)	61.13
Mean Abs. % Err. (MAPE)	1.96%
Durbin-Watson Statistic	1.908