Appendices

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2020 Long-Term Electric Energy and Demand Forecast Report

Burlington Electric Department

Submitted to:

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1 Overview

Itron, Inc. recently completed a long-term sales, energy, and demand forecast for Burlington Electric Department (BED). The forecast extends through 2040.

BED serves approximately 21,100 customers – 17,200 residential customers and 3,900 commercial customers. As the state's primary commercial and education center, the commercial sector accounts for roughly 75% of BED's sales. In 2018, total system deliveries (including losses) were 341,234 MWh (a 0.7% increase over 2017) with system peak reaching 67.3 MW. The 2018 sales increase can largely be attributed to warmer weather as since 2010 sales have been declining 0.4% annually even with relatively strong customer growth of 0.6% per year. Reduction in sales can largely be attributed to strong energy efficiency (EE) program activity and new appliance standards that have been phasing in over the last five years.

Over the next twenty years, base-case system energy requirements average 0.3% annual growth with annual customer growth of 0.5%. Peak demand increases 0.2% annually over this period. In comparison, since 2010, system energy has declined on average 0.5% annually and peak demand has declined 0.1% on average. Positive forecasted energy requirements are largely the result of expected electric vehicle sales growth in the second half of the forecast period.

Table 1-1 shows BED energy and demand forecast.

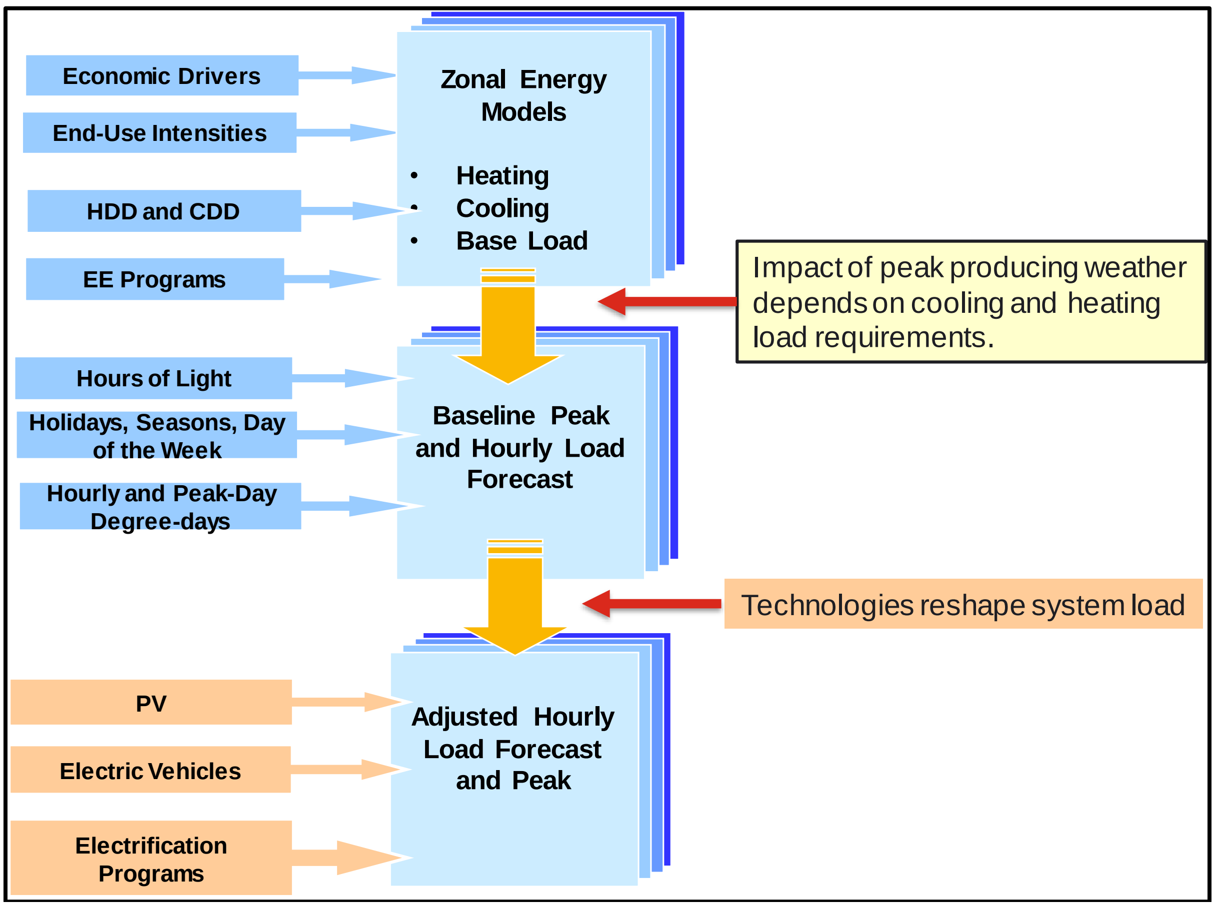
Table 1-1: BED System Energy and Demand Forecast (Base Case)

Year	Energy (MWh)	% Chg	SumPk (MW)	% Chg	WinPk (MW)	% Chg
2010	358,868		70.4		52.2	
2011	353,211	-1.6%	65.8	-6.5%	53.5	2.5%
2012	350,753	-0.7%	63.6	-3.3%	50.9	-4.9%
2013	349,150	-0.5%	67.2	5.7%	53.1	4.3%
2014	348,338	-0.2%	64.1	-4.6%	53.5	0.8%
2015	350,950	0.7%	64.7	0.9%	53.0	-0.9%
2016	347,309	-1.0%	65.2	0.8%	50.5	-4.7%
2017	338,936	-2.4%	61.7	-5.4%	49.7	-1.6%
2018	341,234	0.7%	67.3	9.1%	50.3	1.2%
2019	336,402	-1.4%	64.5	-4.1%	51.0	1.4%
2020	338,299	0.6%	64.8	0.4%	50.9	-0.2%
2021	339,933	0.5%	65.2	0.6%	51.7	1.6%
2022	342,348	0.7%	65.4	0.3%	51.6	0.0%
2023	342,126	-0.1%	65.2	-0.2%	51.8	0.3%
2024	343,500	0.4%	65.4	0.3%	51.9	0.2%
2025	343,029	-0.1%	65.4	-0.1%	51.8	-0.3%
2026	342,657	-0.1%	65.3	0.0%	51.8	0.1%
2027	342,650	0.0%	66.3	1.5%	51.8	0.1%
2028	343,789	0.3%	65.5	-1.3%	51.8	-0.1%
2029	343,693	0.0%	65.4	-0.1%	51.6	-0.5%
2030	343,418	-0.1%	65.3	-0.2%	51.5	-0.1%
2031	343,637	0.1%	65.2	-0.1%	51.5	-0.1%
2032	345,036	0.4%	65.3	0.1%	51.7	0.4%
2033	345,130	0.0%	65.2	-0.1%	51.6	-0.1%
2034	346,245	0.3%	65.3	0.0%	51.6	-0.1%
2035	347,589	0.4%	65.3	0.1%	51.6	0.0%
2036	349,961	0.7%	65.5	0.3%	51.9	0.6%
2037	350,755	0.2%	65.6	0.2%	52.2	0.7%
2038	352,314	0.4%	65.8	0.4%	52.4	0.3%
2039	353,667	0.4%	66.0	0.3%	52.3	-0.2%
2040	355,190	0.4%	66.4	0.5%	52.1	-0.3%
10-18		-0.6%		-0.4%		-0.4%
19-29		0.2%		0.1%		0.1%
19-39		0.3%		0.1%		0.1%

- Actual through 2018
- Base case includes solar and electric vehicle projections

System energy requirements and peak demand forecasts are derived using a "build-up" approach. This entails first developing residential and commercial forecast models that are then used to isolate heating, cooling, and non-weather sensitive end-use energy projections. End-use energy forecasts combined with peak-day weather conditions then drive system peak demand. Energy, peak, and hourly load profile forecasts are combined to generate a system baseline hourly load forecast. The baseline hourly load forecast is then adjusted for the impact of new technologies including solar, electric vehicles, and cold climate heat pumps. Figure 1 outlines the modeling approach.

Figure 1: BED Long-Term Build-up Model



In the long-term, both economic growth and structural changes drive energy and demand requirements. Structural changes are captured in the residential and commercial sales forecast models through SAE (Statistically Adjusted End-Use) specifications. The SAE model variables explicitly incorporate end-use saturation and efficiency projections, as well as changes in population, economic conditions, price, and weather. End-use efficiency projections include the expected impact of new end-use standards, naturally occurring efficiency gains and BED energy efficiency (EE) programs. Streetlight sales are forecasted using a simple trend and seasonal model. Table 1-2 shows customer class sales forecast. The forecast includes solar impacts and electric vehicles.

Table 1-2: Customer Class Sales Forecast (MWh)

Year	Residential	Chg	Commercial	Chg	Other	Chg	Total	chg
2010	85,311		260,165		3,053		348,528	
2011	84,817	-0.6%	255,031	-2.0%	3,031	-0.7%	342,879	-1.6%
2012	83,579	-1.5%	254,374	-0.3%	2,956	-2.5%	340,910	-0.6%
2013	85,320	2.1%	251,896	-1.0%	2,744	-7.2%	339,960	-0.3%
2014	83,404	-2.2%	253,290	0.6%	2,597	-5.4%	339,291	-0.2%
2015	83,177	-0.3%	257,480	1.7%	2,525	-2.8%	343,181	1.1%
2016	81,981	-1.4%	255,173	-0.9%	2,412	-4.5%	339,565	-1.1%
2017	79,795	-2.7%	249,217	-2.3%	2,245	-6.9%	331,258	-2.4%
2018	84,130	5.4%	247,479	-0.7%	2,155	-4.0%	333,764	0.8%
2019	81,171	-3.5%	246,572	-0.4%	2,160	0.2%	329,903	-1.2%
2020	81,164	0.0%	248,466	0.8%	2,123	-1.7%	331,752	0.6%
2021	81,189	0.0%	250,076	0.6%	2,086	-1.7%	333,351	0.5%
2022	81,323	0.2%	252,330	0.9%	2,049	-1.8%	335,702	0.7%
2023	81,665	0.4%	251,796	-0.2%	2,013	-1.8%	335,474	-0.1%
2024	82,702	1.3%	252,147	0.1%	1,976	-1.8%	336,825	0.4%
2025	83,298	0.7%	251,132	-0.4%	1,939	-1.9%	336,369	-0.1%
2026	83,916	0.7%	250,194	-0.4%	1,902	-1.9%	336,012	-0.1%
2027	84,811	1.1%	249,341	-0.3%	1,865	-1.9%	336,017	0.0%
2028	86,008	1.4%	249,310	0.0%	1,829	-2.0%	337,147	0.3%
2029	87,053	1.2%	248,226	-0.4%	1,792	-2.0%	337,071	0.0%
2030	88,419	1.6%	246,652	-0.6%	1,755	-2.1%	336,826	-0.1%
2031	90,018	1.8%	245,333	-0.5%	1,718	-2.1%	337,069	0.1%
2032	92,010	2.2%	244,780	-0.2%	1,681	-2.1%	338,471	0.4%
2033	93,793	1.9%	243,161	-0.7%	1,645	-2.2%	338,599	0.0%
2034	95,864	2.2%	242,255	-0.4%	1,608	-2.2%	339,727	0.3%
2035	98,203	2.4%	241,310	-0.4%	1,571	-2.3%	341,083	0.4%
2036	100,877	2.7%	241,038	-0.1%	1,534	-2.3%	343,449	0.7%
2037	102,969	2.1%	239,799	-0.5%	1,497	-2.4%	344,266	0.2%
2038	105,263	2.2%	239,109	-0.3%	1,461	-2.5%	345,832	0.5%
2039	107,315	1.9%	238,453	-0.3%	1,424	-2.5%	347,192	0.4%
2040	109,462	2.0%	237,870	-0.2%	1,387	-2.6%	348,718	0.4%
2010 - 18		-0.1%		-0.6%		-4.2%		-0.5%
2019 - 29		0.7%		0.1%		-1.9%		0.2%
2019 - 39		1.4%		-0.2%		-2.1%		0.3%

After adjusting for expected efficiency savings, total sales projections are flat; improvements in end-use efficiency balance customer and economic growth. There is a near-term increase in residential sales as a result of several multi-family construction projects. Commercial sales are flat to declining through the period as a result of strong energy efficiency improvements.

2 Forecast Data and Assumptions

2.1 Historical Class Sales and Energy Data

Sales forecasts are based on linear regression models estimated for residential, commercial, and street lighting customer classes. Models are estimated using historical monthly billing data that includes sales, customers, and revenue. Sales loss as a result of solar adoption are added back to residential and commercial sales. The estimation period includes January 2010 to December 2018.

System monthly energy and monthly peak demands are derived from historical system hourly load data with solar load added back in. Models are estimated over the period January 1, 2010 to December 31, 2018. System energy is forecast is derived by applying average monthly loss factors to the sales forecasts. Monthly system peak demand is estimated using linear regression model.

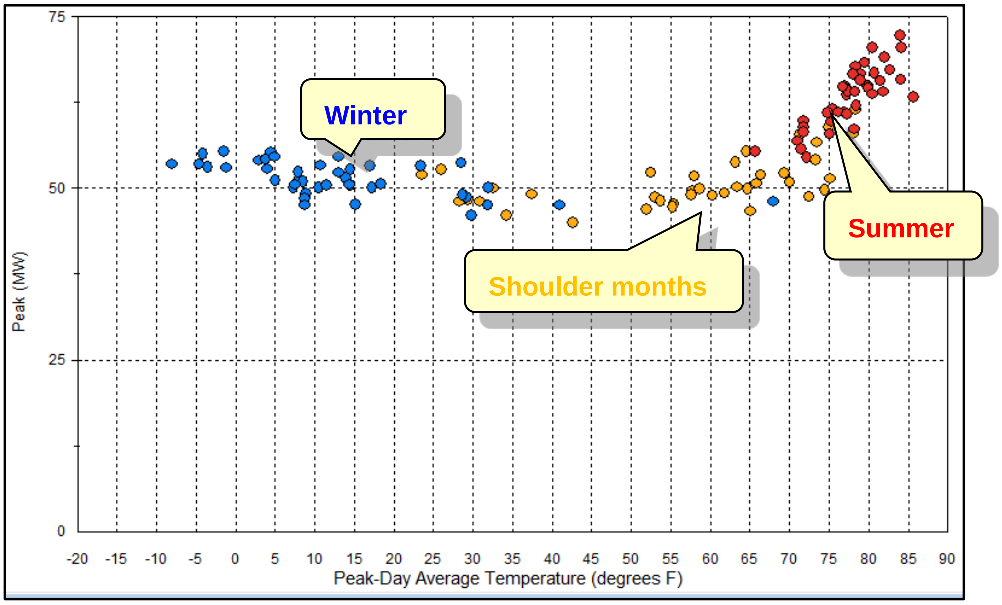
2.2 Weather Data

Historical and normal monthly HDD and CDD were provided by BED. Normal degree days are based on the 20-year period 1999 to 2018.

Peak-Day Weather Variables

The peak forecast is generated from a monthly peak regression model. Peak-day CDD and HDD are derived from historical daily average weather data for Burlington. Peak-day HDD and CDD are calculated by first finding the peak in each month (the maximum hourly demand), identifying the day, and finding the average temperature for that day. The average peak-day temperature is then used to construct peak-day HDD and CDD variables. The appropriate breakpoints for the HDD and CDD variables are determined by evaluating the relationship between monthly peak and the peak-day average temperature, shown in Figure 2.

Figure 2: Monthly Peak Demand /Temperature Relationship



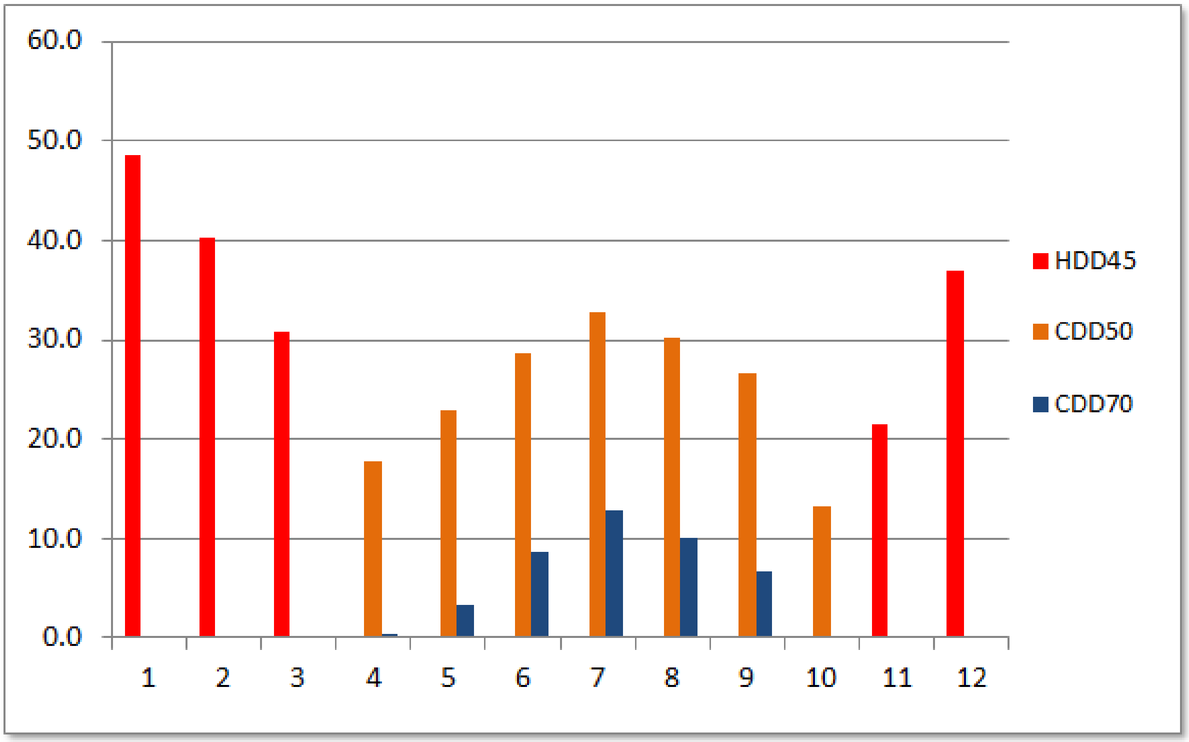
Winter peaks occur when average daily temperature is below 45 degrees and summer peaks occur when average daily temperature exceeds 70 degrees. Peak-day degree-days are defined for these breakpoints and used in estimating the monthly peak regression model. Shoulder month peaks generally are cooling-driven with average day temperature between 50 and 70 degrees; a second peak-day CDD with a 50-degree temperature breakpoint captures the weather impact for these days.

Normal peak-day CDD and HDD are calculated from daily HDD (base 45 degrees) and CDD (bases 50 and 70 degrees) for Burlington. Normal peak-day HDD and CDD are calculated using twenty years of historical weather data (1999to 2018). The calculation process entails using a *rank and average* approach as described below:

1. Calculate daily HDD and CDD over the twenty-year period.
2. Find the highest HDD and CDD that occur in each month. This results in twelve monthly HDD and twelve monthly CDD for each year.
3. *Rank* the monthly HDD and CDD in each year from the highest value to the lowest value.
4. *Average* across the annual rankings – average the highest HDD values in each year, average the second highest in each year, the third highest …., average the lowest HDD values in each year. This results in twelve HDD values and twelve CDD values.
5. Assign the HDD and CDD values to specific months based on past weather patterns. The highest HDD is assigned to January and the highest CDD value is assigned to

August. Figure 3 shows the calculated peak-day normal HDD (base 45 degrees) and CDD (bases 50 and 70 degrees).

Figure 3: Peak-Day Normal HDD and CDD



2.3 Economic Data

The class sales forecasts are based on *Moody's Economy.com* January 2019 economic forecast for the Burlington MSA. The primary economic drivers in the residential model include household income and the number of new households. Commercial sales are driven by regional output and employment.

Table 2-1 summarizes the primary economic drivers.

Table 2-1: Economic Forecast (Burlington MSA)

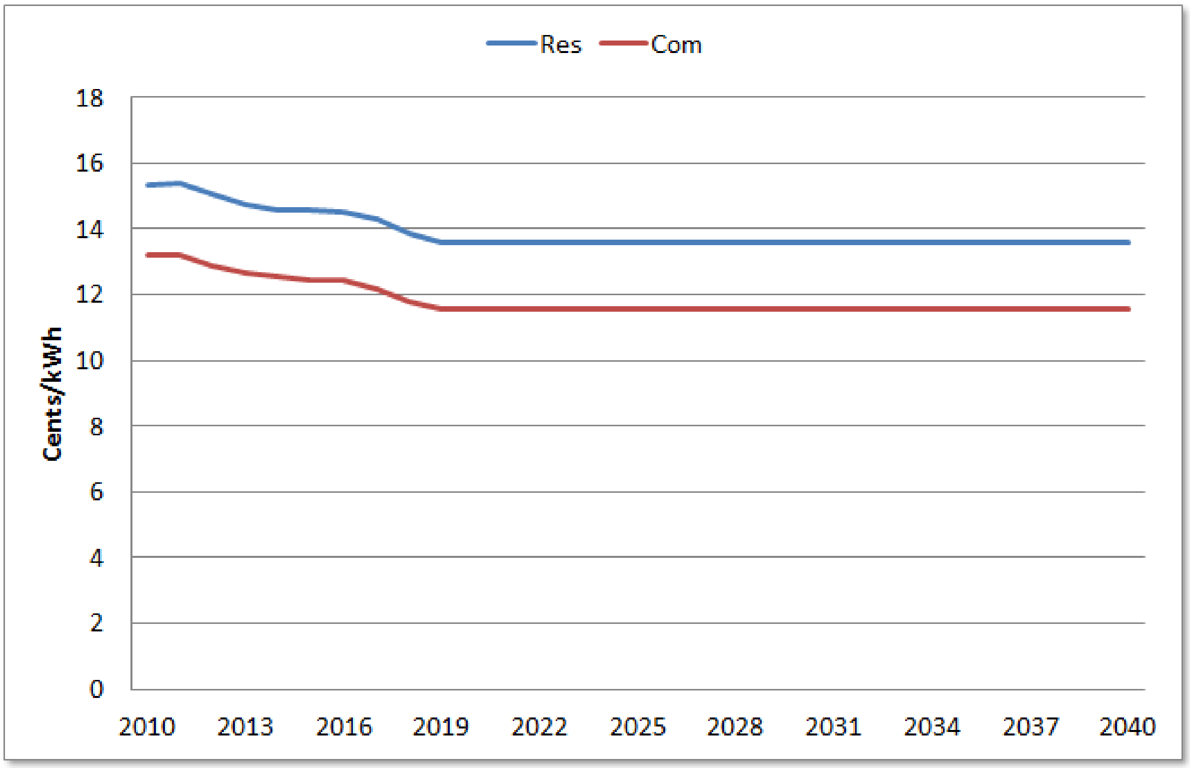
Year	HHs (thou)	% Chg	HHInc ($ thou)	% Chg	GDP ($ mil)	% Chg	Emp (thou)	% Chg
2010	80.8		107.1		9,959		116.0	
2011	81.5	0.8%	108.8	1.6%	9,900	-0.6%	116.8	0.7%
2012	82.2	0.9%	109.5	0.7%	10,127	2.3%	117.0	0.2%
2013	82.9	0.9%	106.5	-2.7%	10,009	-1.2%	114.5	-2.1%
2014	83.6	0.8%	106.3	-0.1%	10,513	5.0%	115.7	1.0%
2015	84.2	0.7%	111.8	5.1%	10,948	4.1%	117.8	1.8%
2016	84.8	0.7%	113.3	1.4%	11,210	2.4%	119.6	1.5%
2017	85.3	0.6%	112.7	-0.5%	11,015	-1.7%	120.5	0.8%
2018	85.4	0.2%	114.8	1.9%	11,125	1.0%	121.0	0.4%
2019	85.5	0.1%	117.5	2.4%	11,304	1.6%	123.5	2.1%
2020	86.0	0.5%	120.1	2.2%	11,633	2.9%	124.3	0.6%
2021	86.5	0.5%	121.9	1.4%	11,924	2.5%	125.6	1.0%
2022	86.9	0.6%	122.9	0.8%	12,126	1.7%	126.8	1.0%
2023	87.4	0.5%	123.5	0.5%	12,285	1.3%	127.7	0.7%
2024	87.8	0.4%	124.0	0.4%	12,412	1.0%	128.1	0.3%
2025	88.1	0.4%	124.7	0.6%	12,562	1.2%	128.5	0.3%
2026	88.5	0.4%	125.5	0.7%	12,731	1.3%	129.1	0.5%
2027	88.8	0.4%	126.4	0.7%	12,903	1.3%	129.7	0.5%
2028	89.2	0.4%	127.2	0.7%	13,076	1.3%	130.3	0.5%
2029	89.5	0.4%	128.1	0.7%	13,251	1.3%	130.9	0.5%
2030	89.9	0.4%	129.0	0.7%	13,435	1.4%	131.5	0.5%
2031	90.3	0.4%	130.0	0.8%	13,633	1.5%	132.2	0.5%
2032	90.6	0.4%	131.0	0.8%	13,839	1.5%	133.0	0.6%
2033	91.0	0.4%	132.1	0.8%	14,048	1.5%	133.8	0.6%
2034	91.4	0.4%	133.1	0.8%	14,264	1.5%	134.6	0.6%
2035	91.7	0.4%	134.2	0.8%	14,482	1.5%	135.5	0.7%
2036	92.1	0.4%	135.4	0.9%	14,708	1.6%	136.4	0.7%
2037	92.4	0.4%	136.6	0.9%	14,943	1.6%	137.3	0.7%
2038	92.8	0.4%	137.9	0.9%	15,185	1.6%	138.2	0.7%
2039	93.1	0.4%	139.2	1.0%	15,441	1.7%	139.2	0.7%
2040	93.4	0.4%	140.6	1.0%	15,707	1.7%	140.2	0.7%
10-18		0.7%		0.9%		1.4%		0.5%
19-29		0.5%		0.9%		1.6%		0.6%
19-39		0.4%		0.9%		1.6%		0.6%

Burlington MSA is expected to see stronger economic growth than the state overall, with the region adding 300 to 400 new households per year with moderate GDP growth averaging 1.6% over the forecast period.

2.4 Price Data

Historical prices (real dollars) are provided by BED. Prices impact the class sales through imposed price elasticities. The residential and commercial price elasticities are set at -0.10. Over the long-term, we assume constant real prices. Figure 4 shows price forecasts by customer class.

Figure 4: Historical and projected real electricity prices (cents per kWh)



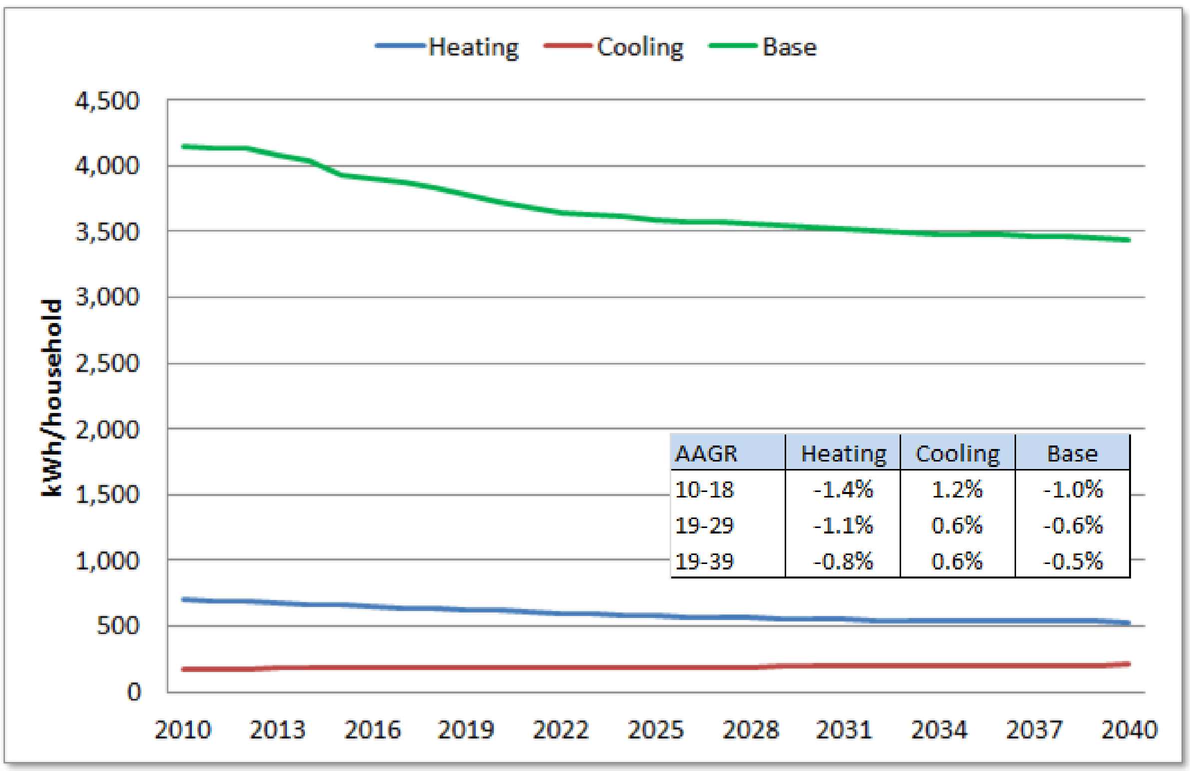
2.5 Appliance Saturation and Efficiency Trends

Average use in both residential and commercial sector have been declining over the last ten years. The primary contributor has been significant efficiency improvements in residential appliances, thermal shell, and business end-uses. Efficiency improvements are a result of appliance standards, building codes, and BED energy efficiency programs. Efficiency impacts are captured through historical and projected end-use intensities. In the residential sector intensities are measured in kWh per household and in the commercial sector intensities are in kWh per square foot. Starting end-use intensities are derived from the Energy

Information Administration's (EIA) 2018 New England Census Division forecast. These saturation projections are adjusted to reflect BED residential appliance saturation surveys and mix of multi-family and single-family homes. Efficiency projections are adjusted to account for additional program efficiency savings that are not reflected in the EIA's regional forecast. The residential sector includes saturation and efficiency trends for seventeen end-uses, and the commercial sector has end-use intensity projections for ten end-uses across ten building types.

The residential sales forecast is derived as the product of monthly customer forecast and average use forecast. For the residential average use model, end-use intensity projections are aggregated into three generalized end-uses: heating, cooling, and other use. Figure 5 shows the primary end-use intensity projections.

Figure 5: Residential End-Use Energy Intensities

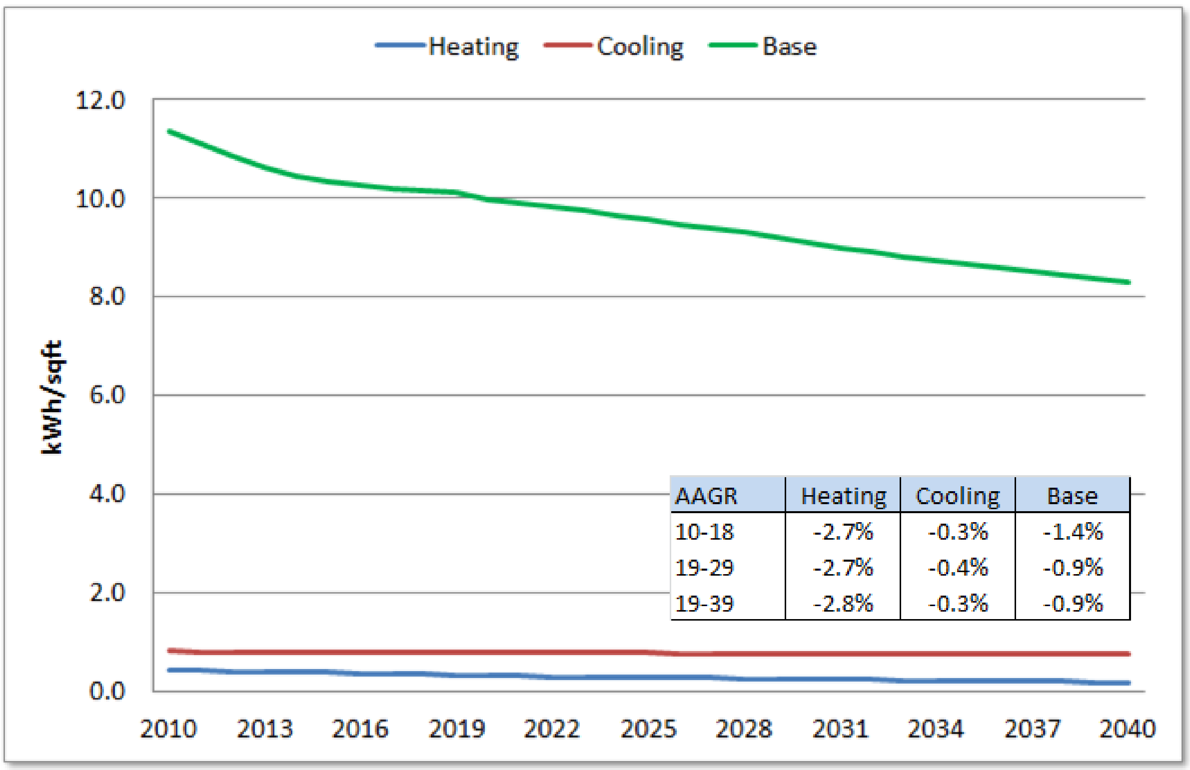


* Incorporates impact of BED Funded EE Programs

Heating intensity declines 0.8% annually through the forecast period reflecting continuing improvements in heating technology (improvements in heat pump and furnace fan efficiency), substitution of resistance heat for heat pumps, and declining overall heating saturation. Average heating intensity is relatively low as majority of households' heat with natural gas. Though small, cooling intensity is expected to increase. Through 2018, BED experienced strong growth in cooling intensity averaging 1.2% annual growth. This increase was largely driven by room air conditioning saturation growth. Cooling intensity flattens-out over the forecast period as room air conditioning saturation growth slows. Non-weather sensitive end-use intensity continues to decline over the forecast period as a result of new appliance standards and natural replacement of existing equipment stock, and EE program activity.

Commercial end-use intensities (expressed in kWh per square foot) are adjusted to reflect BED commercial building-mix. As in the residential sector, there have been significant improvements in end-use intensities as a result of new standards and EE programs. Figure 6 shows commercial end-use energy intensity forecasts for the aggregated end-use categories.

Figure 6: Commercial End-Use Energy Intensity



Given temperate summers and low saturation of electric heat, commercial heating and cooling intensities are relatively small. The decline in non-HVAC intensities is the result of improving commercial equipment efficiency and EE program impacts. Strong declines in lighting and ventilation intensities have the largest impact on non-weather sensitive use.

Adjusting for EE Program Impacts

EIA's New England intensity projections reflect expected impacts of regional EE program activity. EIA uses an end-use modeling approach where the more efficient technology options are "rebated" which in turn lowers the technology costs and results in selection of the more efficient technology options. A given utility may do more or less EE than what is assumed for the region. End-use intensities are adjusted to reflect any difference in EE program impacts. An EE adjustment factor is estimated by incorporating historical cumulative EE savings as a model variable. For BED, the residential EE savings variable is statistically significant with a coefficient of approximately -0.2. This implies that the regional intensity projections are capturing 80% (1.0 - 0.2) of BED's program activities. The end-use intensities (other than lighting) are adjusted down an additional 20% of projected program savings. With adjustments for EE programs total residential intensity averages 0.5% annual decline over the forecast period, and commercial intensity declines 0.9% annually.

3 Forecast Methodology

3.1 Class Sales Forecast

Changes in economic conditions, prices, weather conditions, as well as appliance saturation and efficiency trends drive energy deliveries and demand through a set of monthly customer class sales forecast models. Monthly regression models are estimated for each of the following primary revenue classes:

- Residential
- Commercial
- Street Lighting

3.1.1 Residential Model

Residential average use and customers are modeled separately. The residential sales forecast is then generated as the product of the average use and customer forecasts. As the objective is to model what is actually consumed, solar load for "own-use" is added back to historical billed sales.

The residential average use model is specified using an SAE model structure. Average use is defined as a function of the three primary end-uses - cooling (XCool), heating (XHeat) and other use (XOther):

$$ResAvgUse_m = B_0 + (B_1 \times XHeat_m) + (B_2 \times XCool_m) + (B_3 \times XOther_m) + e_m$$

The end-use variables incorporate both a variable that captures short-term utilization (Use) and a variable that captures changes in end-use efficiency and saturation trends (Index). The heating variable is calculated as:

$$XHeat = HeatUse \times HeatIndex$$

Where

$$HeatUse = f(HDD, Household\ Income, Household\ Size, Price)$$

$$HeatIndex = g(Heating\ Saturation, Efficiency, Shell\ Integrity, Square\ Footage)$$

The cooling variable is defined as:

$$XCool = CoolUse \times CoolIndex$$

Where

$$CoolUse = f(CDD, Household\ Income, Household\ Size, Price)$$
$$CoolIndex = g(Cooling\ Saturation, Efficiency, Shell\ Integrity, Square\ Footage)$$

XOther captures non-weather sensitive end-uses:

$$XOther = OtherUse \times OtherIndex$$

Where

$$OtherUse = f(Seasonal\ Use\ Pattern, Household\ Income, Household\ Size, Price)$$
$$OtherIndex = g(Other\ Appliance\ Saturation\ and\ Efficiency\ Trends)$$

The specific calculations of the end-use variables are presented in Appendix B.

Figure 7 to Figure 9 show the constructed monthly end-use variables.

Figure 7: Residential XHeat (kWh per month)

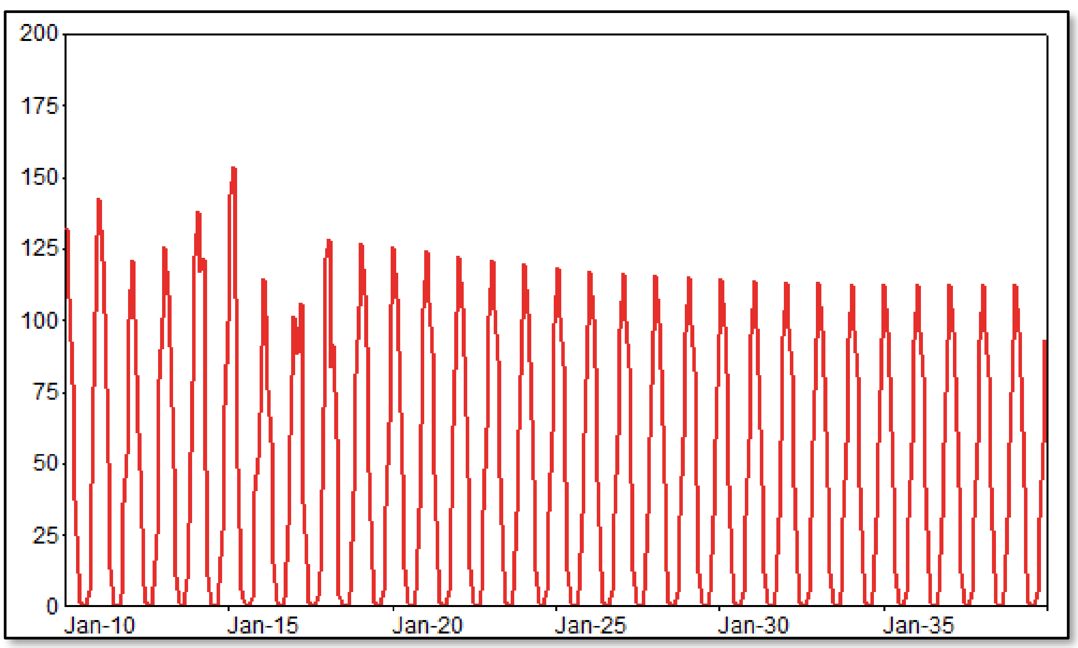


Figure 8: Residential XCool (kWh per month)

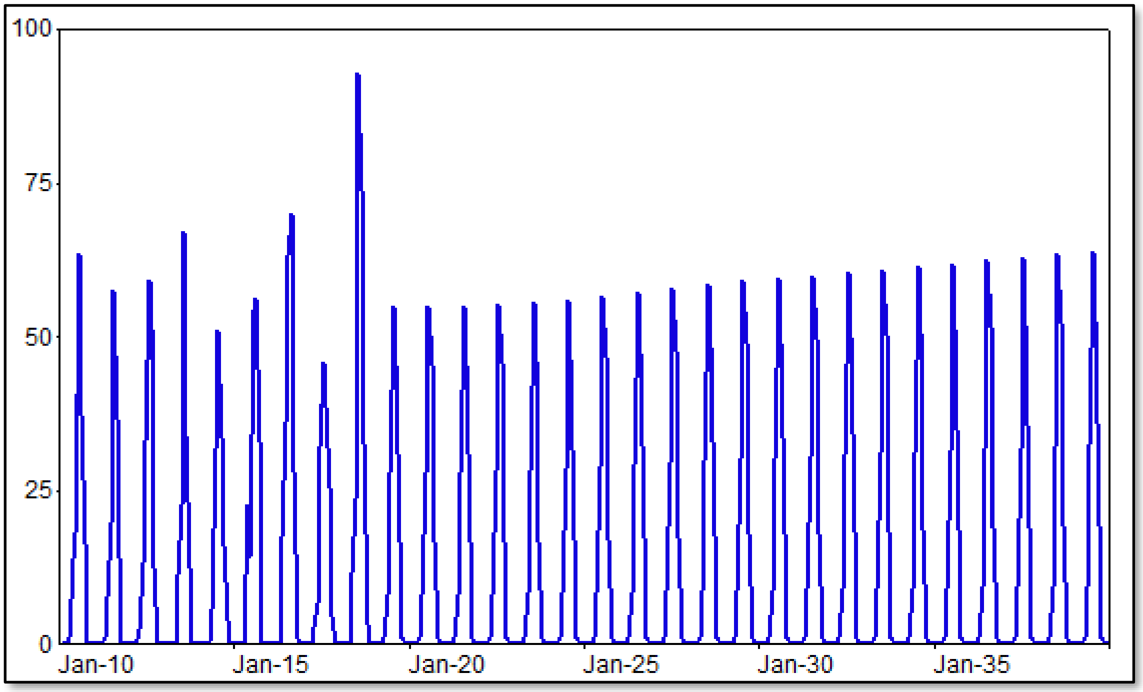
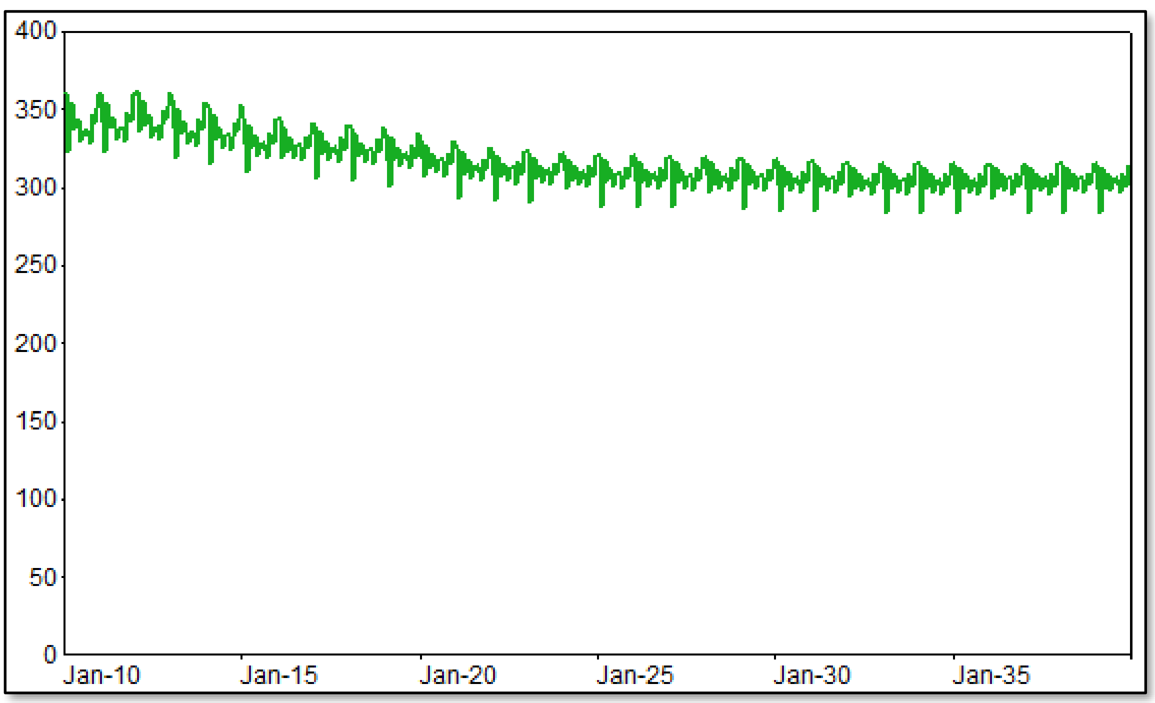
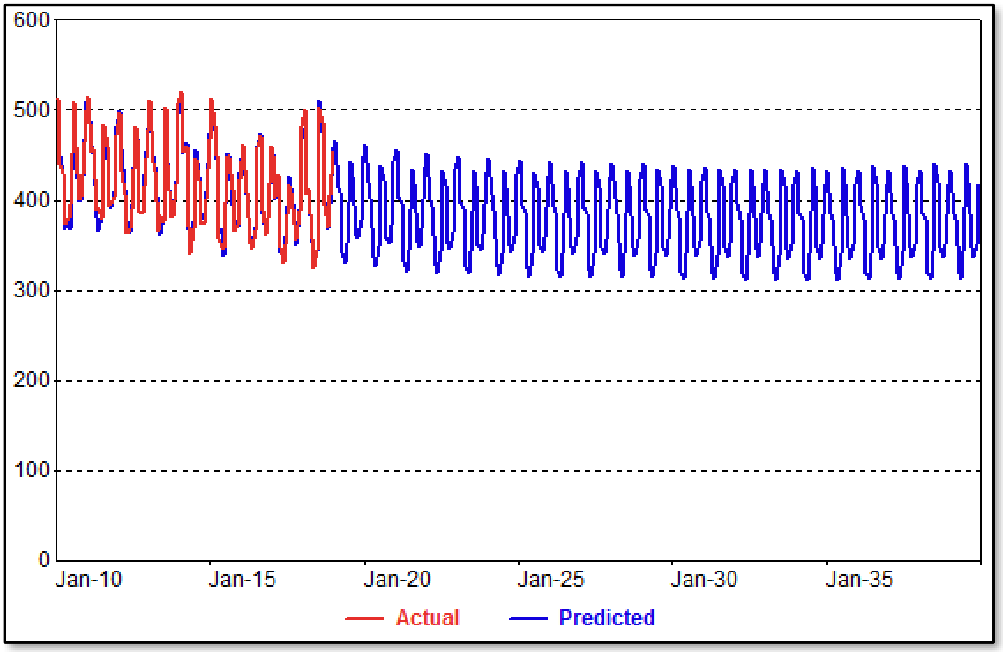


Figure 9: Residential XOther (kWh per month)



The average use model is estimated over the period January 2010 through December 2018. The model explains historical average use well with an Adjusted R^2 of 0.97 and in-sample MAPE of 1.6%. Figure 10 shows actual and predicted average use.

Figure 10: Actual and Predicted Residential Average Use (kWh per month)



Model coefficients and statistics are provided in Appendix A.

Residential use per customer has been declining at 0.6% per year over the last ten years. It is projected to decline further in the forecast period but at a slightly slower rate as decline in lighting intensity slows and current standards work through the appliance base. In the out years average use level off as end-use intensity projections only includes standards that are currently law.

Customer Forecast

The customer forecast is based on a monthly regression model that relates the number of customers to Burlington MSA (Metropolitan Statistical Area) household projections. There is a strong correlation between the number of customers and households - customer growth generally tracks household projections. Slightly stronger average customer growth rate in the period 2019-29 is explained largely by the completion of construction projects that are expected to add almost a thousand new customers over 2019-22.

With 0.5% decrease in average use and 0.9% increase in customer growth, residential sales average 0.3% growth between 2019 and 2039. Table 3-1 shows the residential forecast excluding the impact of PV and EV adoption; historical sales includes solar energy savings that are added back.

Table 3-1: Residential Forecast

Year	Sales (MWh)	% Chg	Customers	% Chg	AvgUse (kWh)	% Chg
2010	85,358		16,308		5,234	
2011	84,876	-0.6%	16,350	0.3%	5,191	-0.8%
2012	83,671	-1.4%	16,502	0.9%	5,070	-2.3%
2013	85,481	2.2%	16,634	0.8%	5,139	1.4%
2014	83,628	-2.2%	16,741	0.6%	4,995	-2.8%
2015	83,479	-0.2%	16,810	0.4%	4,966	-0.6%
2016	82,422	-1.3%	16,876	0.4%	4,884	-1.6%
2017	80,590	-2.2%	17,032	0.9%	4,732	-3.1%
2018	85,334	5.9%	17,208	1.0%	4,959	4.8%
2019	82,057	-3.8%	17,353	0.8%	4,729	-4.6%
2020	82,452	0.5%	17,622	1.6%	4,679	-1.1%
2021	82,554	0.1%	17,902	1.6%	4,612	-1.4%
2022	83,128	0.7%	18,150	1.4%	4,580	-0.7%
2023	83,679	0.7%	18,354	1.1%	4,559	-0.5%
2024	84,512	1.0%	18,559	1.1%	4,554	-0.1%
2025	84,685	0.2%	18,702	0.8%	4,528	-0.6%
2026	84,859	0.2%	18,786	0.4%	4,517	-0.2%
2027	85,080	0.3%	18,860	0.4%	4,511	-0.1%
2028	85,555	0.6%	18,928	0.4%	4,520	0.2%
2029	85,613	0.1%	18,992	0.3%	4,508	-0.3%
2030	85,578	0.0%	19,058	0.3%	4,490	-0.4%
2031	85,632	0.1%	19,118	0.3%	4,479	-0.3%
2032	85,957	0.4%	19,173	0.3%	4,483	0.1%
2033	85,902	-0.1%	19,223	0.3%	4,469	-0.3%
2034	86,118	0.3%	19,268	0.2%	4,469	0.0%
2035	86,366	0.3%	19,315	0.2%	4,471	0.0%
2036	86,861	0.6%	19,363	0.2%	4,486	0.3%
2037	86,911	0.1%	19,407	0.2%	4,478	-0.2%
2038	87,152	0.3%	19,447	0.2%	4,482	0.1%
2039	87,346	0.2%	19,484	0.2%	4,483	0.0%
2040	87,627	0.3%	19,520	0.2%	4,489	0.1%
10-18		0.0%		0.7%		-0.6%
19-29		0.4%		0.9%		-0.5%
19-39		0.3%		0.6%		-0.3%

3.1.2 Commercial Model

Like the residential model, the commercial SAE sales model expresses monthly sales as a function of XHeat, XCool, and XOther. The end-use variables are constructed by interacting annual end-use intensity projections (EI) that capture end-use efficiency improvements, with non-manufacturing GDP and employment ($ComVar_m$), real price ($Price_m$), and monthly HDD and CDD:

- $XHeat_m = EI_{heat} \times Price_m^{-0.10} \times ComVar_m \times HDD_m$
- $XCool_m = EI_{cool} \times Price_m^{-0.10} \times ComVar_m \times CDD_m$
- $XOther_m = EI_{other} \times Price_m^{-0.10} \times ComVar_m$

The coefficients on price are imposed short-term price elasticities. A monthly forecast sales model is then estimated as:

$$ComSales_m = B_0 + B_1 XHeat_m + B_2 XCool_m + B_3 XOther_m + e_m$$

Commercial Economic Driver

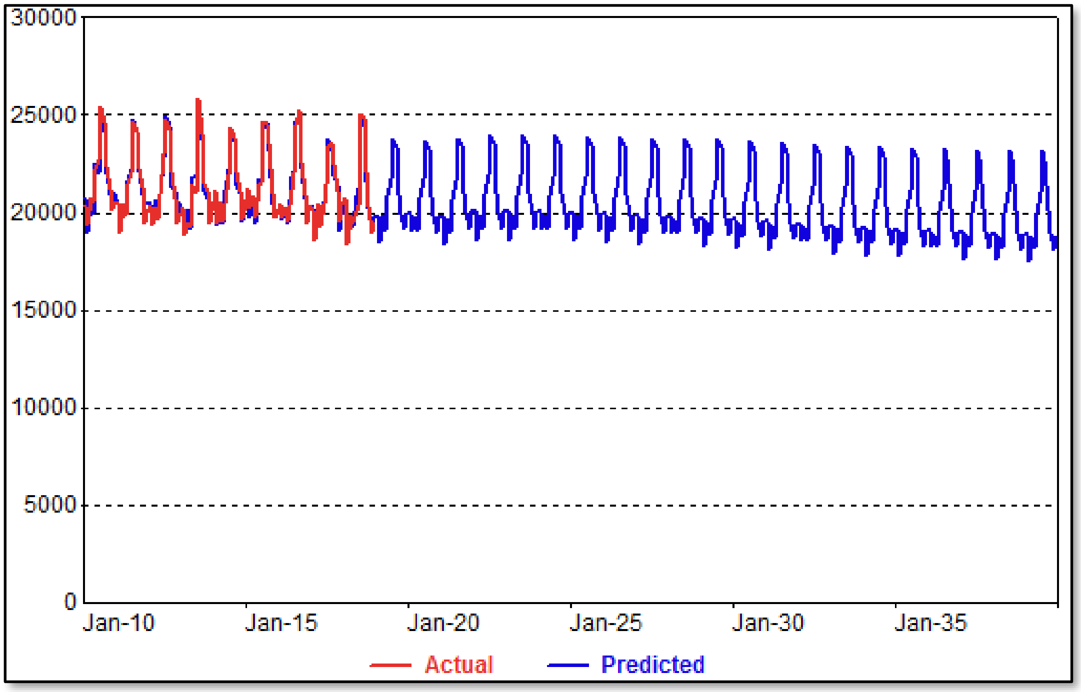
Output and employment are combined through a weighted economic variable where ComVar is defined as:

$$ComVar_m = (ComEmploy_m^{0.8}) \times (ComOutput_m^{0.2})$$

The weights were determined by evaluating the in-sample and out-of-sample model statistics for different sets of employment and output weights.

The resulting commercial sales model performs well with an Adjusted R^2 of 0.95 and an in-sample MAPE of 1.5%. Figure 11 shows actual and predicted monthly commercial energy.

Figure 11: Actual and Predicted Commercial Sales (kWh)



Commercial sales are overall flat through the forecast period; improvements in end-use and building efficiency offset the impact of customer and economic growth. The estimated model coefficients and model statistics are included in Appendix A.

A separate model is estimated for commercial customers; customer projections are based on a monthly regression model that relates the number of customers to employment in the Burlington MSA. Table 3-2 shows the commercial forecast excluding solar adjustments; historical commercial solar generation for own-use is added back to billed sales.

Table 3-2: Commercial Forecast

Year	Sales (MWh)	% Chg	Customers	% Chg	AvgUse (kWh)	% Chg
2010	260,236		3,742		69,549	
2011	255,266	-1.9%	3,737	-0.1%	68,302	-1.8%
2012	254,867	-0.2%	3,814	2.0%	66,833	-2.2%
2013	252,547	-0.9%	3,780	-0.9%	66,804	0.0%
2014	254,165	0.6%	3,821	1.1%	66,512	-0.4%
2015	258,489	1.7%	3,843	0.6%	67,268	1.1%
2016	256,346	-0.8%	3,898	1.5%	65,757	-2.2%
2017	250,821	-2.2%	3,945	1.2%	63,577	-3.3%
2018	249,734	-0.4%	3,878	-1.7%	64,392	1.3%
2019	249,064	-0.3%	3,893	0.4%	63,985	-0.6%
2020	251,154	0.8%	3,888	-0.1%	64,601	1.0%
2021	252,894	0.7%	3,880	-0.2%	65,173	0.9%
2022	255,635	1.1%	3,893	0.3%	65,667	0.8%
2023	255,422	-0.1%	3,905	0.3%	65,404	-0.4%
2024	255,834	0.2%	3,916	0.3%	65,336	-0.1%
2025	254,911	-0.4%	3,925	0.2%	64,942	-0.6%
2026	253,993	-0.4%	3,934	0.2%	64,556	-0.6%
2027	253,162	-0.3%	3,943	0.2%	64,206	-0.5%
2028	253,243	0.0%	3,951	0.2%	64,089	-0.2%
2029	252,183	-0.4%	3,960	0.2%	63,678	-0.6%
2030	250,716	-0.6%	3,969	0.2%	63,171	-0.8%
2031	249,432	-0.5%	3,977	0.2%	62,720	-0.7%
2032	248,998	-0.2%	3,984	0.2%	62,499	-0.4%
2033	247,389	-0.6%	3,991	0.2%	61,992	-0.8%
2034	246,504	-0.4%	3,997	0.2%	61,670	-0.5%
2035	245,687	-0.3%	4,004	0.2%	61,364	-0.5%
2036	245,556	-0.1%	4,011	0.2%	61,223	-0.2%
2037	244,343	-0.5%	4,018	0.2%	60,809	-0.7%
2038	243,790	-0.2%	4,026	0.2%	60,561	-0.4%
2039	243,290	-0.2%	4,033	0.2%	60,326	-0.4%
2040	242,879	-0.2%	4,041	0.2%	60,109	-0.4%
10-18		-0.5%		0.5%		-0.9%
19-29		0.1%		0.2%		0.0%
19-39		-0.1%		0.2%		-0.3%

3.1.3 Street Lighting Sales

Streetlight sales are projected using a simple regression model driven by outdoor lighting energy intensity and seasonal variables. Street lighting sales have been declining and are expected to continue to decline through the forecast period as increasing lamp efficiency outpaces installation of new streetlights.

3.2 Solar Forecast

The BED energy and peak forecast incorporates the impact of expected behind the meter photovoltaic adoption. Although relatively small in magnitude compared to the rest of Vermont, BED has experienced an uptick growth in the number and size of photovoltaic systems over the past two years. Part of the jump was due to customers racing to beat changes in net metering laws that reduced system incentives. While some of the recent adoption is incentive-driven, continuing system cost declines will drive future long-term adoption.

3.2.1 Market Share Model

We assume that the primary factor driving PV adoption is the favorable economics from the customers' perspective – system savings outweigh initial upfront cost and related financing. Simple payback is used as a proxy for customer's return on investment. Simple payback reflects the length of time needed for a customer to recover the cost of installing a solar system - the shorter the payback, the higher the system adoption rate. There is a strong correlation between adoption and simple payback. The payback calculation is based on total installed cost, annual savings from reduced energy bills, and incentive payment for excess and own-use generation.

Simple payback declines over the forecast period largely as a result of declining system cost. System costs have been declining rapidly over the last five years. In 2010, the average residential solar system cost $6.24 per watt; by 2017 costs have dropped to $3.30 per watt. For the forecast we assume that system costs continue to decline 7% annually through 2022, at which point costs continue to decline at 1% a year.

The PV adoption model relates the share of customers that have adopted solar systems to simple payback through a cubic model specification. A cubic model specification results in an S-shaped adoption curve. Figure 12 and Figure 13 show the resulting market share forecast for the residential class and commercial classes

Figure 12: Residential Solar Share Forecast

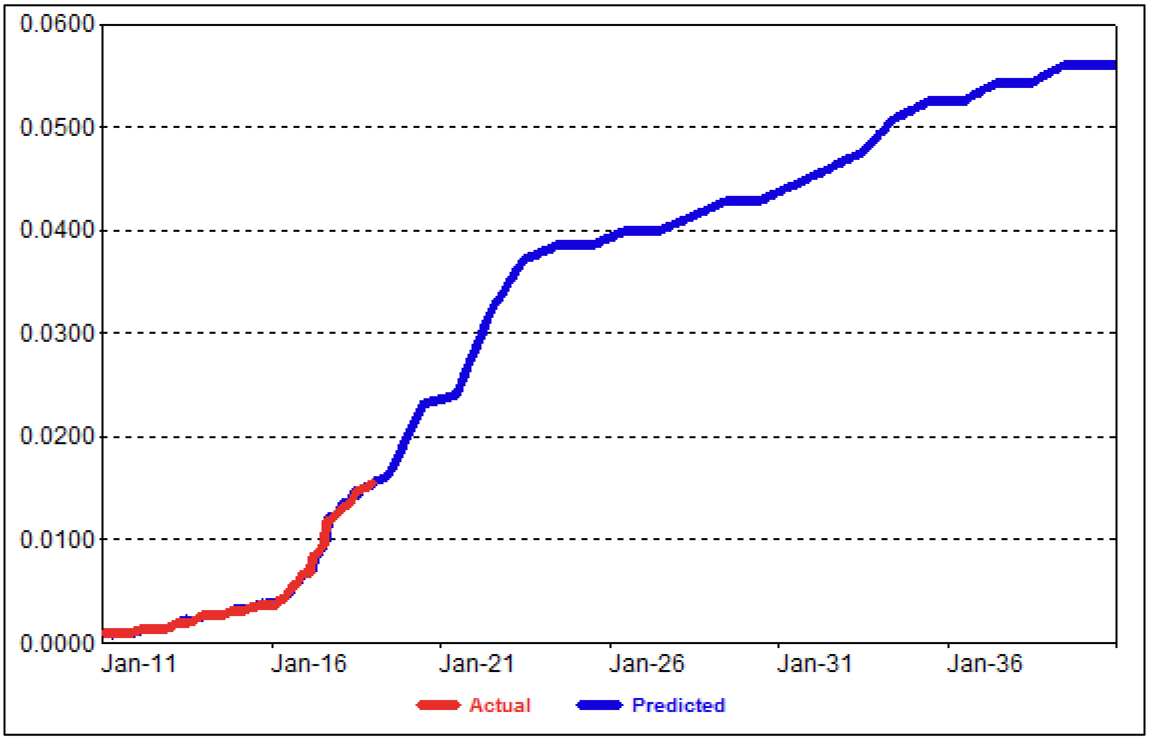
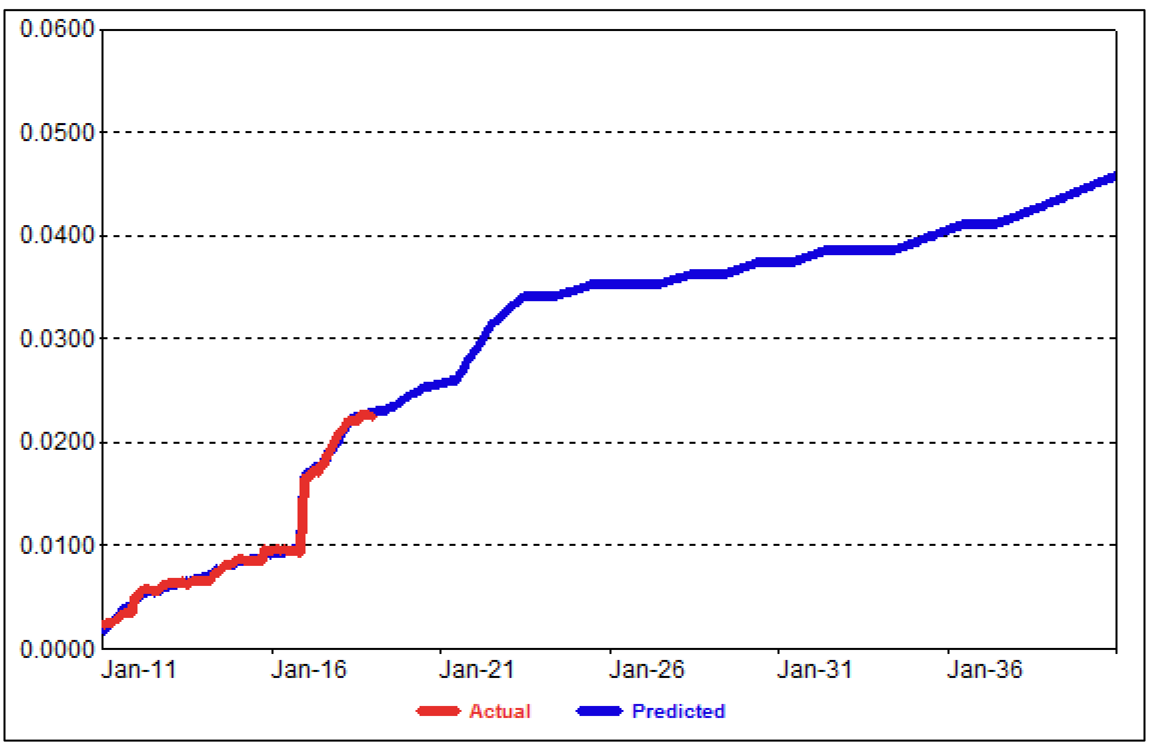


Figure 13: Commercial Solar Share Forecast



As of December 2018, there were 268 residential and 88 commercial solar customer accounts, which amount to 1.6% and 2.3% market shares. With declining system costs and incentives, residential share doubles over the next three years. Commercial solar saturation also increases but at a slower rate. Table 3-3 shows the solar share and resulting solar customer forecast.

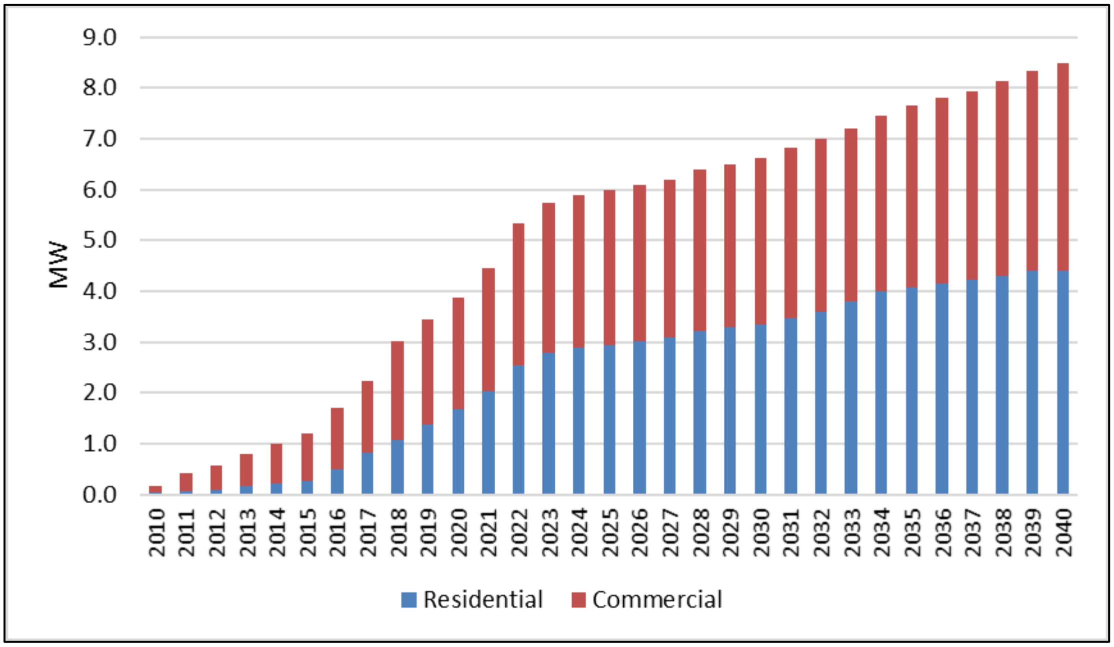
Table 3-3: Solar Customer Forecast

Year	Residential	Share of Total	Commercial	Share of Total
2010	12	0.1%	6	0.2%
2011	15	0.1%	12	0.3%
2012	22	0.1%	22	0.6%
2013	34	0.2%	24	0.7%
2014	47	0.3%	29	0.8%
2015	58	0.3%	34	0.9%
2016	84	0.5%	39	1.0%
2017	168	1.0%	72	1.8%
2018	246	1.4%	86	2.2%
2019	295	1.7%	91	2.3%
2020	396	2.3%	98	2.5%
2021	449	2.5%	103	2.7%
2022	578	3.2%	121	3.1%
2023	675	3.7%	132	3.4%
2024	711	3.8%	134	3.4%
2025	724	3.9%	138	3.5%
2026	747	4.0%	139	3.5%
2027	757	4.0%	139	3.5%
2028	784	4.1%	143	3.6%
2029	811	4.3%	144	3.7%
2030	821	4.3%	148	3.7%
2031	849	4.4%	150	3.8%
2032	882	4.6%	153	3.9%
2033	919	4.8%	154	3.9%
2034	977	5.1%	155	3.9%
2035	1,010	5.2%	160	4.0%
2036	1,021	5.3%	164	4.1%
2037	1,049	5.4%	166	4.1%
2038	1,060	5.5%	171	4.2%
2039	1,088	5.6%	177	4.4%
2040	1,093	5.6%	182	4.5%

3.2.2 Solar Capacity and Generation

The installed solar capacity forecast is the product of the solar customer forecast and an assumed average system size, both for the residential and commercial classes. The average assumed size is 4.0 KW for residential systems and 22.0 KW for commercial systems (average system size of all the systems installed through 2018). Figure 14 shows the installed solar capacity forecast.

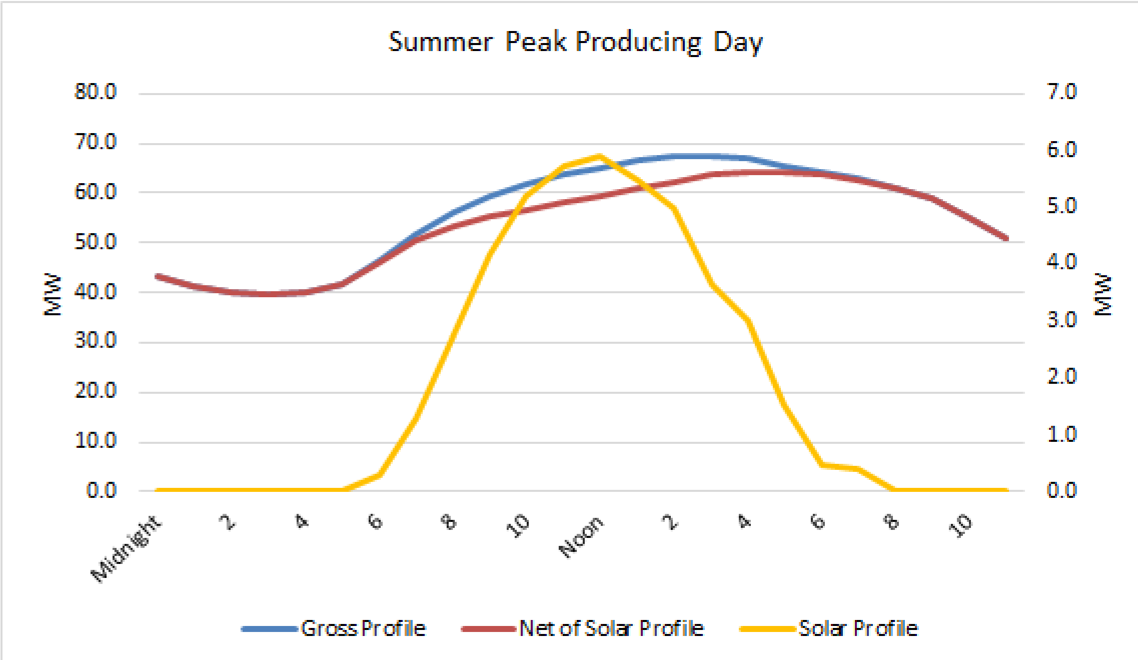
Figure 14: Solar Capacity Forecast



The capacity forecast is translated into a monthly generation forecast by applying monthly solar load factors to the capacity forecast. The monthly load factors are derived from a typical PV load profile for Burlington VT. The PV shape is from the National Renewable Energy Laboratory (NREL) and represents a typical meteorological year (TMY).

The impact of solar on peak demand is a function of the timing between solar load generation and system hourly demand. Even though solar capacity reaches 8.5 MW by 2040, solar load reduces system peak demand by only 1.5 MW. Given the system profile is relatively flat, solar generation effectively just shifts the peak out shifting peak demand from 3:00 p.m. to 4:00 p.m. The reduction in load between the 3:00 hour and 4:00 hour is smaller than the installed solar capacity. Figure 15 shows the gross system profile, solar adjusted system profile, and solar profile for a peak producing summer day.

Figure 15: Solar Hourly Load Impact



PV capacity has no impact on the winter peak demand as the winter peak is late in the evening when there is no solar generation.

Table 3-4 shows the PV capacity forecast and expected annual generation impacts.

Table 3-4: Solar Capacity and Generation

Year	Installed Capacity MW (July)	Generation MWh
2010	0.1	117.4
2011	0.3	293.9
2012	0.5	584.2
2013	0.6	811.8
2014	0.9	1,098.6
2015	1.0	1,311.6
2016	1.3	1,615.3
2017	1.9	2,398.2
2018	2.9	3,459.4
2019	3.2	3,946.6
2020	3.8	4,677.2
2021	4.0	5,036.4
2022	5.1	6,182.3
2023	5.7	6,999.2
2024	5.8	7,255.1
2025	6.0	7,393.5
2026	6.1	7,535.9
2027	6.1	7,599.3
2028	6.3	7,859.6
2029	6.5	8,013.3
2030	6.6	8,163.7
2031	6.7	8,342.5
2032	6.9	8,634.4
2033	7.1	8,814.8
2034	7.4	9,131.8
2035	7.6	9,432.9
2036	7.7	9,632.5
2037	7.9	9,792.2
2038	8.0	9,975.3
2039	8.3	10,278.9
2040	8.4	10,491.2

3.3 Electric Vehicle Forecast

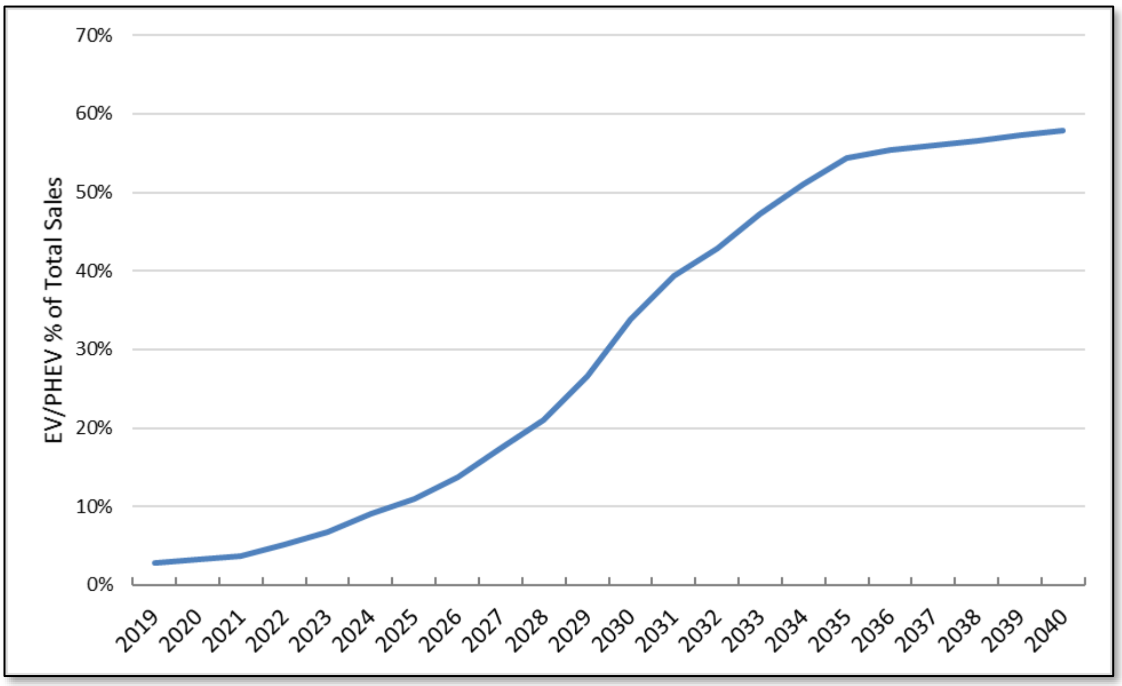
The BED forecast incorporates the impact of electric vehicle adoption and charging. At the time of the forecast there were 222 registered electric vehicles (EV) and plug-in hybrid electric vehicles (PHEV) in the BED service territory. With 25,335 total registered light-duty vehicles, EV/PHEV account for less than 1% of all vehicle on the road. While

EV/PHEV currently represent a small percentage of vehicle, improvements in charging infrastructure and continued state and federal incentives will ensure their growth.

3.3.1 EV/PHEV Adoption Forecast

The EV/PHEV adoption forecast is based on a recent Bloomberg New Energy Finance forecast of EV/PHEV sales as a percentage of total new vehicle sales. Currently EV/PHEV sales account for 2-3% of new vehicle sales nationally, this is forecasted to increase to nearly 60% by 2040. Figure 16 shows the Bloomberg EV/PHEV sales share forecast.

Figure 16: Bloomberg EV/PHEV Sales Forecast



The forecast also accounts for the changing mix of EV and PHEV sales, currently the mix is approximately 50/50, but EVs are forecasted to increase to nearly 90% of all EV/PHEV sales by 2040.

Assumptions regarding annual kWh per vehicle are based on the average efficiency ratings of 5 popular EV/PHEV models. Its assumed vehicles drive 8,000 miles annually with the PHEVs operating in all electric mode 50% of the time or 4,000 miles. As a result, EVs consume 2,544 kWh annually and PHEVs consume 1,344 kWh annually. The EV/PHEV registered vehicle and energy consumed forecast is shown in Table 3-5.

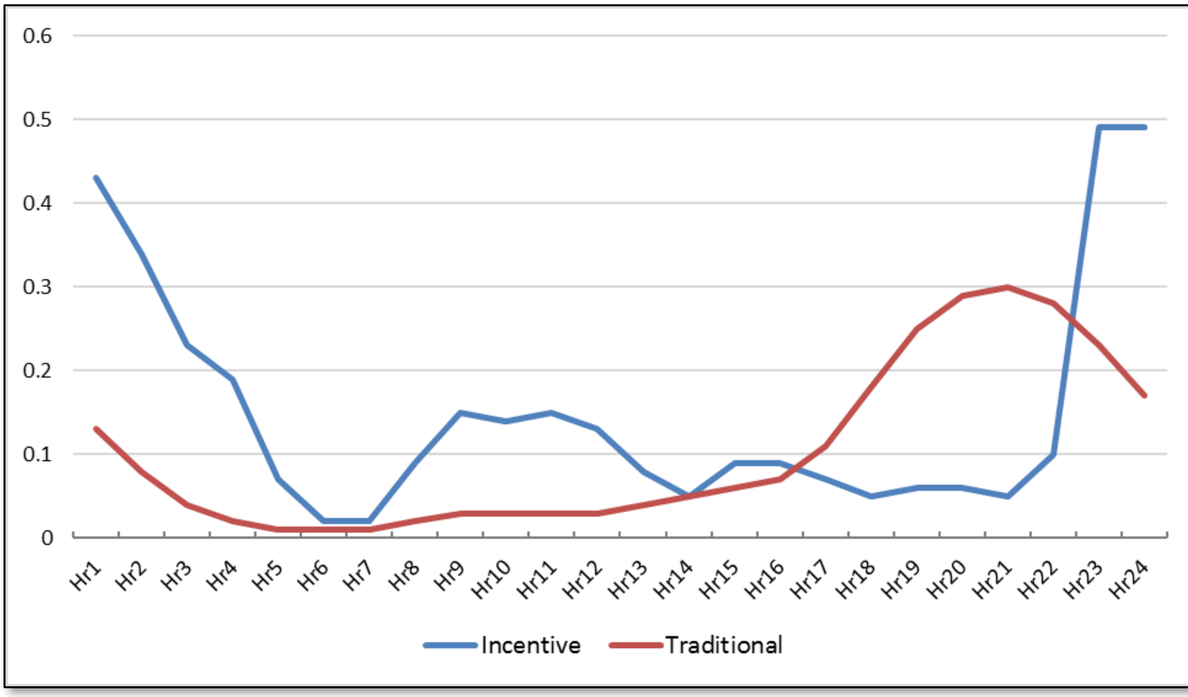
Table 3-5: EV/PHEV Forecast

Year	EV Count	PHEV Count	Total Count		EV MWh	PHEV MWh	Total MWh
2019	145	149	294		369	200	569
2020	183	176	358		464	236	701
2021	228	203	431		580	273	854
2022	296	238	534		752	320	1,072
2023	388	278	666		987	373	1,360
2024	519	325	844		1,321	437	1,758
2025	679	372	1,051		1,728	500	2,228
2026	873	426	1,299		2,222	572	2,794
2027	1,120	492	1,611		2,848	661	3,509
2028	1,421	569	1,990		3,615	765	4,380
2029	1,808	666	2,474		4,601	895	5,496
2030	2,312	787	3,099		5,883	1,058	6,940
2031	2,905	923	3,827		7,390	1,240	8,630
2032	3,554	1,063	4,616		9,040	1,428	10,469
2033	4,267	1,208	5,475		10,854	1,624	12,478
2034	5,034	1,355	6,390		12,808	1,822	14,629
2035	5,848	1,501	7,348		14,876	2,017	16,893
2036	6,657	1,633	8,291		16,936	2,195	19,131
2037	7,451	1,750	9,201		18,954	2,353	21,307
2038	8,222	1,851	10,073		20,917	2,488	23,405
2039	8,966	1,935	10,901		22,810	2,600	25,411
2040	9,681	2,001	11,682		24,628	2,689	27,317

3.3.2 EV/PHEV Charging Profile

Electric vehicles' impact on the BED system profile will depend on when owners choose to charge their vehicles. Off-peak charging can be promoted by providing TOU incentive electric rates for vehicle owners. The forecast uses 2 different charging profiles, a traditional profile in which vehicles begin to charge as owner return home, the other an incentive profile in which charging is delayed to later in the evening with the use of a TOU incentive rate. BED assumes that 80% of the EV energy will be charged based on the incentive profile and 20% on the traditional charge profile. All PHEV energy is assumed to be charged on the traditional profile. Figure 17 shows the traditional and incentive EV/PHEV charging profiles.

Figure 17: EV/PHEV Charging Profile

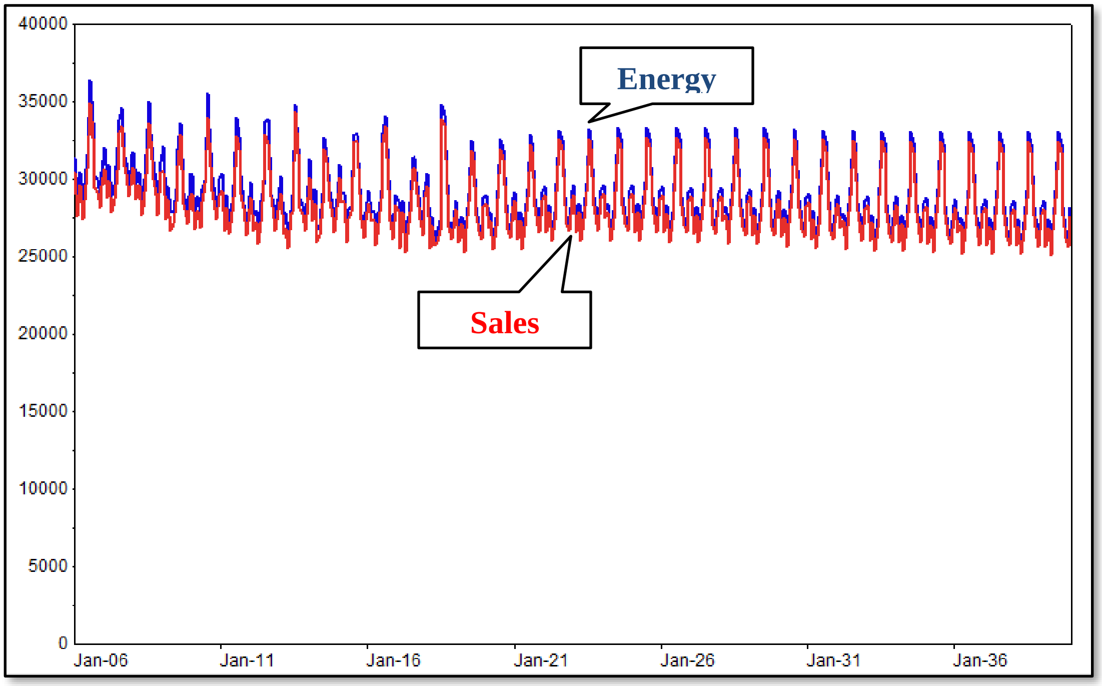


3.3 Energy, Peak, and Hourly Load Forecast

3.3.1 Energy Forecast

The BED energy forecast is derived directly from the sales forecast by applying a monthly energy adjustment factor to the monthly sales forecast. The energy adjustment factor includes line losses and any differences in timing between monthly sales estimates and delivered energy (*unaccounted for energy*). Adjustment factors are calculated as the average monthly ratio of energy to sales. Figure 18 shows the resulting monthly sales and energy forecast.

Figure 18: Long-Term Energy and Sales Forecast (MWh)



3.3.2 Peak Forecast

The long-term system peak forecast is based on a monthly peak linear regression model that relates monthly peak demand to heating, cooling, and base load requirements:

$$Peak_m = B_0 + B_1 HeatVar_m + B_2 CoolVar_m + B_3 BaseVar_m + e_m$$

The model variables ($HeatVar_m$, $CoolVar_m$, and $BaseVar_m$) incorporate changes in heating, cooling, and base-use energy requirements derived from the class sales forecast models as well as peak-day weather conditions.

Heating and Cooling Model Variables

Heating and cooling requirements are derived from the sales forecast models and incorporate customer growth, economic activity, changes in end-use saturation, and improving end-use efficiency. Estimated model coefficients for the heating (XHeat) and cooling variables (XCool) combined with heating and cooling variable for normal weather conditions (*NrmXHeat* and *NrmXCool*) gives an estimate of the monthly heating and cooling load requirements. Heating requirements are calculated as:

- $HeatLoad_m = B_1 \times ResNrmXHeat_m + C_1 \times ComNrmXheat_m$

B_1 and C_1 are the coefficients on *XHeat* in the residential and commercial models.

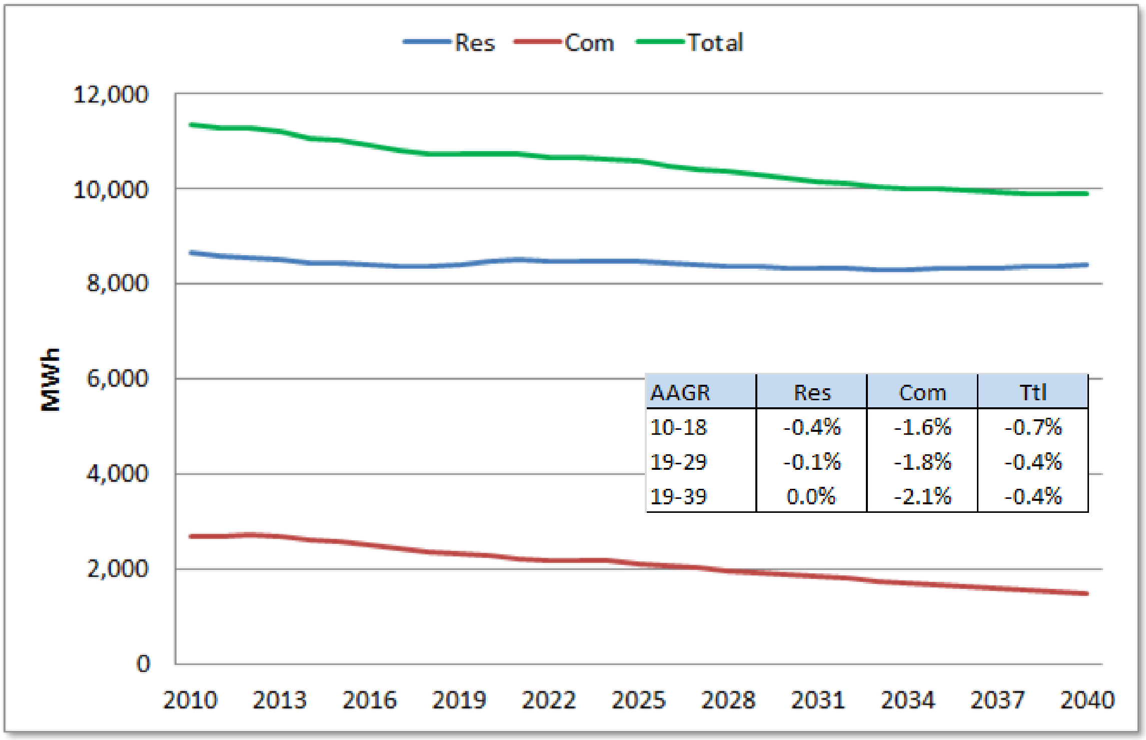
Cooling requirements are estimated in a similar manner:

- $CoolLoad_m = B_2 \times ResNrmXCool_m + C_2 \times ComNrmXCool_m$

B_2 and C_2 are the coefficients on XCool in the residential and commercial models.

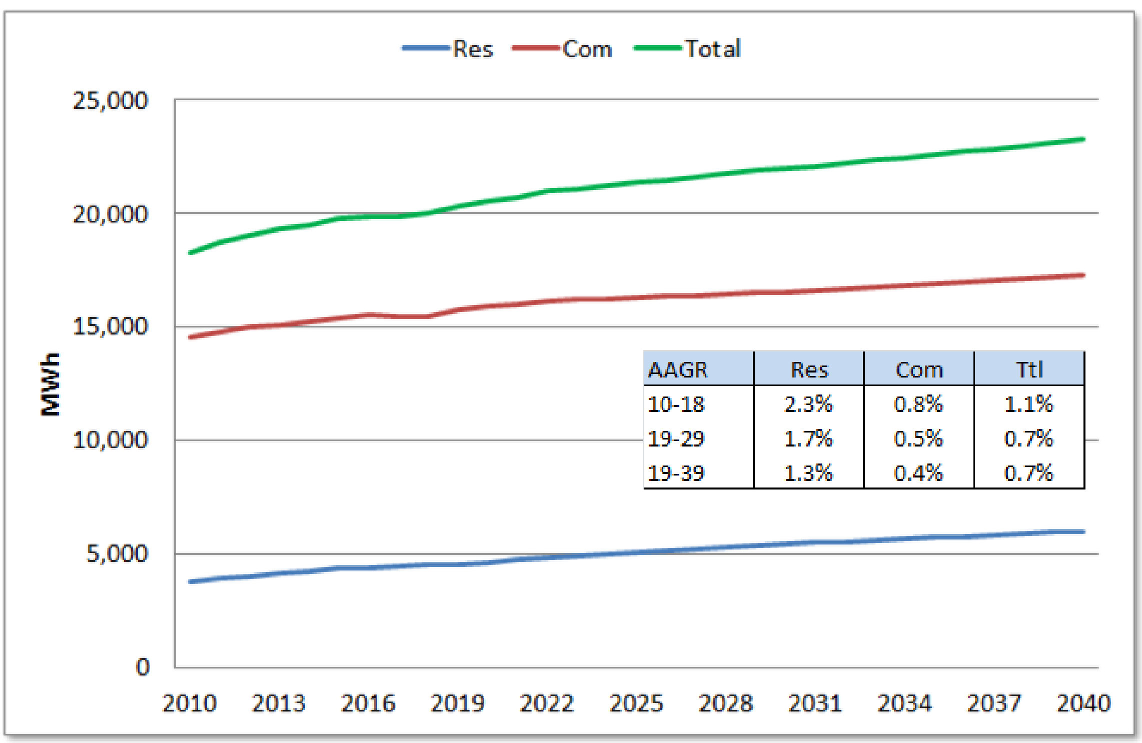
Figure 19 and Figure 20 show resulting historical (weather normalized) and forecasted heating and cooling load requirements.

Figure 19: Annual Heating Load (MWh)



AAGR	Res	Com	Ttl
10-18	-0.4%	-1.6%	-0.7%
19-29	-0.1%	-1.8%	-0.4%
19-39	0.0%	-2.1%	-0.4%

Figure 20: Annual Cooling Load (MWh)



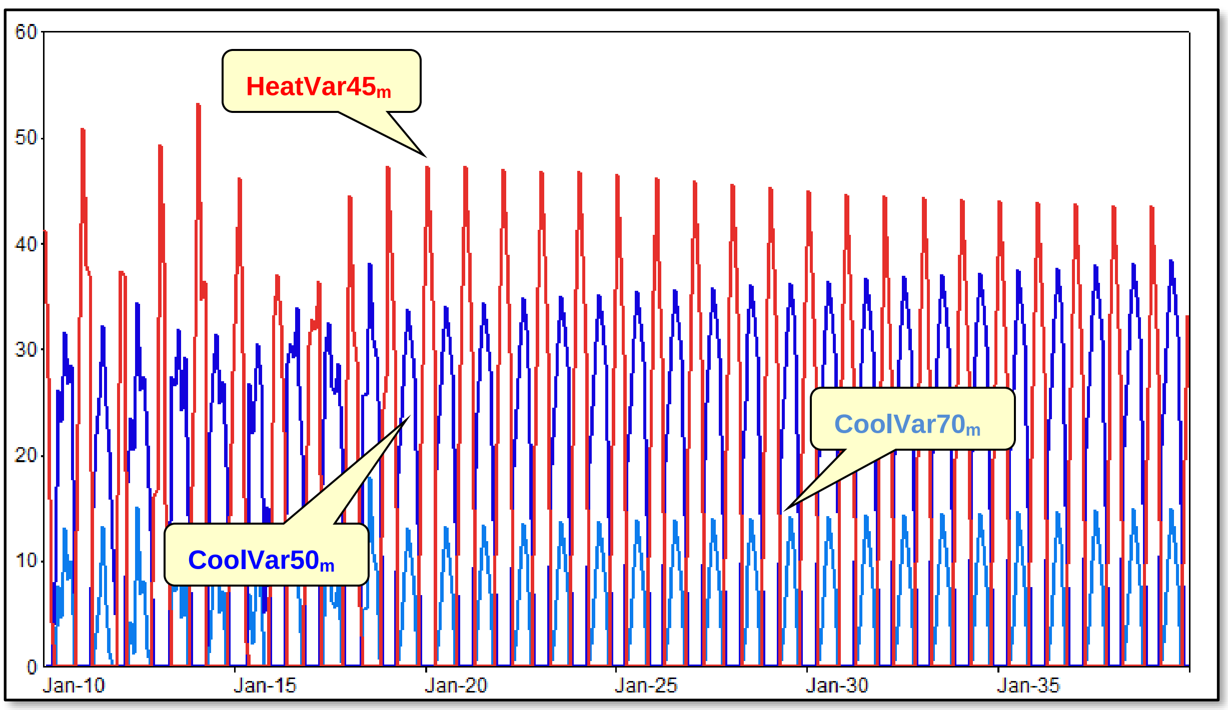
AAGR	Res	Com	Ttl
10-18	2.3%	0.8%	1.1%
19-29	1.7%	0.5%	0.7%
19-39	1.3%	0.4%	0.7%

The impact of peak-day CDD will increase over time with increasing cooling requirements; peak-days HDD impacts will decline given projected decline in heating related load. Peak-day HDD and CDD impact are captured by interacting peak-day HDD and CDD with monthly heating and cooling load requirements. Heating and cooling load requirements are indexed to a base year (2015). The peak model heating and cooling variables are calculated as:

- $HeatVar_m = HeatLoadIdx_m \times PkHDD_m$
- $CoolVar_m = CoolLoadIdx_m \times PkCDD_m$

Figure 21 shows the resulting peak model heating and cooling variables.

Figure 21: Peak Model Heating and Cooling Variables (degree days)



Base Load Variable

The base-load variable ($BaseVar_m$) captures the non-weather sensitive load at the time of the monthly peak. The base load variable is defined as:

$$BaseVar_m = ResOtherCP_m + ComOtherCP_m + StLightingCP_m$$

Where

- *ResOther CPm = residential coincident peak load*
- *ComOther CPm = commercial coincident peak load*
- *StLightingCPm = street lighting coincident peak load*

Base load sales estimates are derived for each revenue class by subtracting out heating and cooling load requirements from total sales forecast. Using the SAE modeling framework, class annual base load requirements are then allocated to end-uses at the time of monthly peak demand. For example, the residential water heating coincident peak load estimate is derived as:

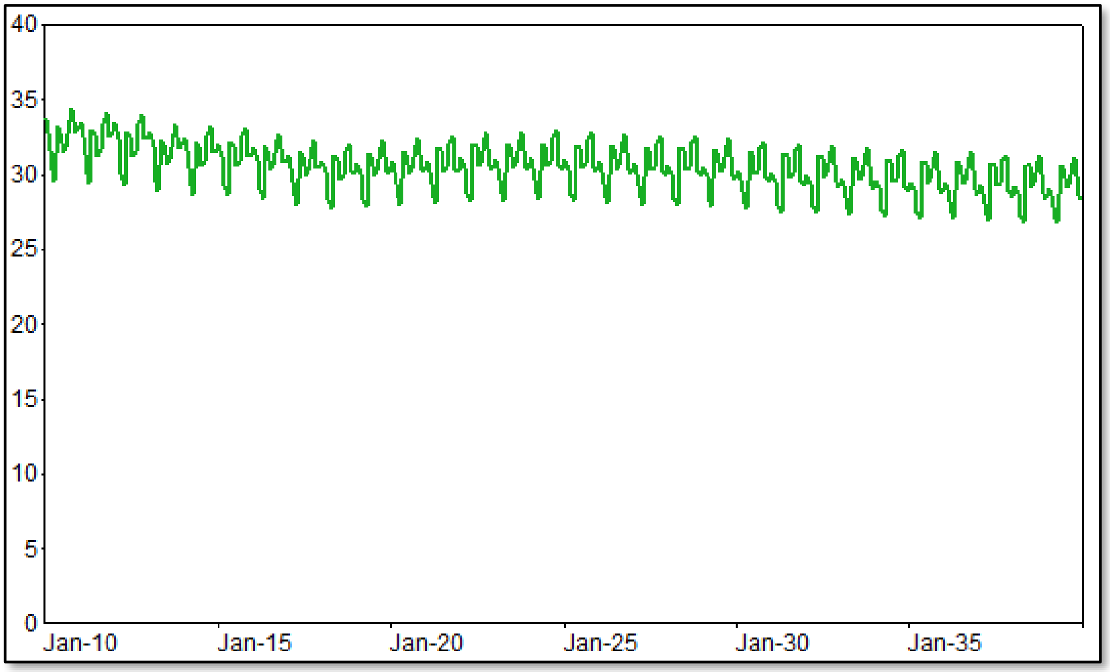
$$ResWaterCP_m = ResBaseLoad_a \times \left({ResWaterEI_a}/{ResBaseEI_a} \right) \times ResWaterFrac_m$$

Where

- *ResBaseLoad* = Annual non-residential non-weather sensitive sales
- *ResWaterEI* = Annual water heating intensity (water use per household)
- *ResBaseEI* = Annual base-use intensity (non-weather sensitive use per household)
- *ResWaterFrac* = Monthly fraction of usage at time of peak

End-use coincident peak load estimates are aggregated to revenue class and then summed across revenue classes. Figure 22 shows the peak model base load variable.

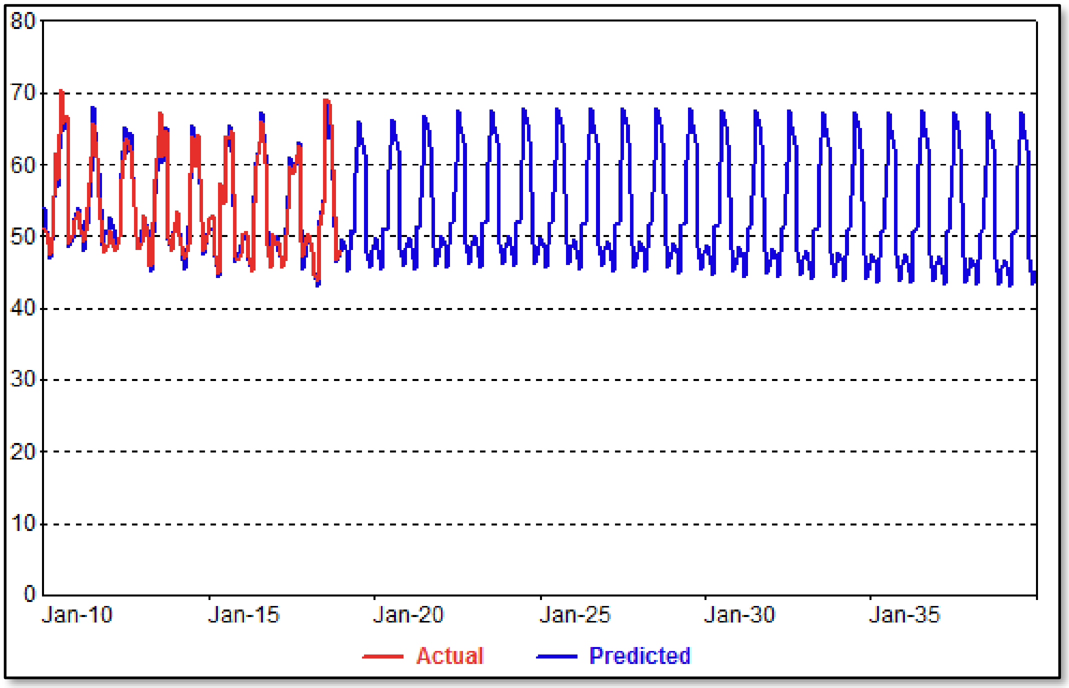
Figure 22: Base Load Variable



Model Results

The peak model is estimated over the period January 2010 to December 2018. The model explains monthly peak variation well with an adjusted R^2 of 0.95 and an in-sample MAPE of 2.0%. Figure 23 shows actual and predicted results. Model statistics and parameters are included in Appendix A.

Figure 23: Peak Model (MW)



The peak demand forecast is adjusted for solar load and electric vehicle impacts. Table 3-6 shows total energy and peak demand.

Table 3-6: Energy and Peak Forecast

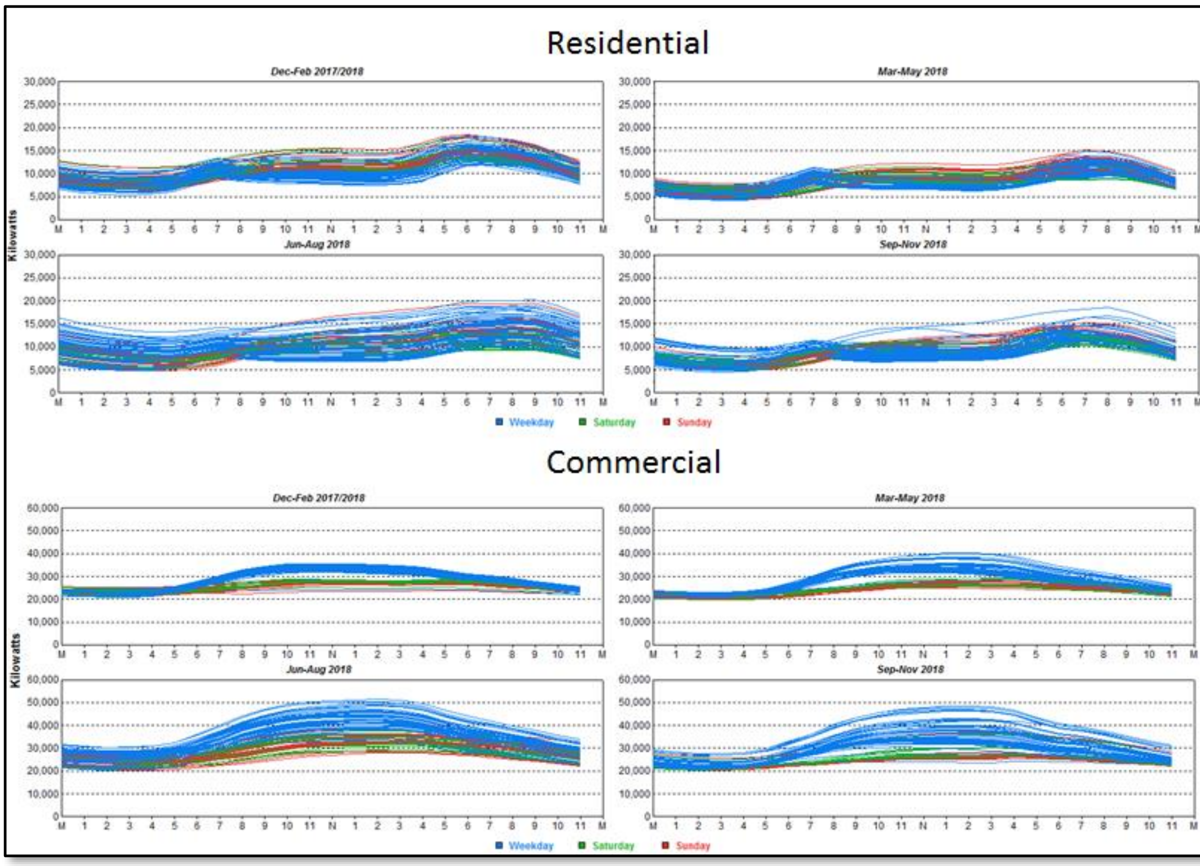
Year	Energy (MWh)	% Chg	SumPk (MW)	% Chg	WinPk (MW)	% Chg
2010	358,868		70.4		52.2	
2011	353,211	-1.6%	65.8	-6.5%	53.5	2.5%
2012	350,753	-0.7%	63.6	-3.3%	50.9	-4.9%
2013	349,150	-0.5%	67.2	5.7%	53.1	4.3%
2014	348,338	-0.2%	64.1	-4.6%	53.5	0.8%
2015	350,950	0.7%	64.7	0.9%	53.0	-0.9%
2016	347,309	-1.0%	65.2	0.8%	50.5	-4.7%
2017	338,936	-2.4%	61.7	-5.4%	49.7	-1.6%
2018	341,234	0.7%	67.3	9.1%	50.3	1.2%
2019	336,402	-1.4%	64.5	-4.1%	51.0	1.4%
2020	338,299	0.6%	64.8	0.4%	50.9	-0.2%
2021	339,933	0.5%	65.2	0.6%	51.7	1.6%
2022	342,348	0.7%	65.4	0.3%	51.6	0.0%
2023	342,126	-0.1%	65.2	-0.2%	51.8	0.3%
2024	343,500	0.4%	65.4	0.3%	51.9	0.2%
2025	343,029	-0.1%	65.4	-0.1%	51.8	-0.3%
2026	342,657	-0.1%	65.3	0.0%	51.8	0.1%
2027	342,650	0.0%	66.3	1.5%	51.8	0.1%
2028	343,789	0.3%	65.5	-1.3%	51.8	-0.1%
2029	343,693	0.0%	65.4	-0.1%	51.6	-0.5%
2030	343,418	-0.1%	65.3	-0.2%	51.5	-0.1%
2031	343,637	0.1%	65.2	-0.1%	51.5	-0.1%
2032	345,036	0.4%	65.3	0.1%	51.7	0.4%
2033	345,130	0.0%	65.2	-0.1%	51.6	-0.1%
2034	346,245	0.3%	65.3	0.0%	51.6	-0.1%
2035	347,589	0.4%	65.3	0.1%	51.6	0.0%
2036	349,961	0.7%	65.5	0.3%	51.9	0.6%
2037	350,755	0.2%	65.6	0.2%	52.2	0.7%
2038	352,314	0.4%	65.8	0.4%	52.4	0.3%
2039	353,667	0.4%	66.0	0.3%	52.3	-0.2%
2040	355,190	0.4%	66.4	0.5%	52.1	-0.3%
10-18		-0.6%		-0.4%		-0.4%
19-29		0.2%		0.1%		0.1%
19-39		0.3%		0.1%		0.1%

3.3.3 System Hourly Load Forecast

The baseline hourly load forecast is the sum of the residential, commercial, and street lighting hourly load forecasts. Class hourly load forecasts are derived by combining class hourly load profiles estimated from AMI data with class sales forecast. Hourly loads are expressed as a function of daily HDD and CDD, binary for day of the week, months, seasons, and holidays, and hours of light.

Figure 24 shows the residential and commercial load profiles by season.

Figure 24: Class Profiles by Season



Class hourly load forecasts are constructed using MetrixLT *Batch Transforms*. Batch Transforms are used to combine class sales forecast with the hourly profile forecast; the forecast is also adjusted for line losses. Figure 25 and Figure 26 show the residential and commercial hourly load forecast for 2019.

Figure 25: Residential Hourly Load Forecast

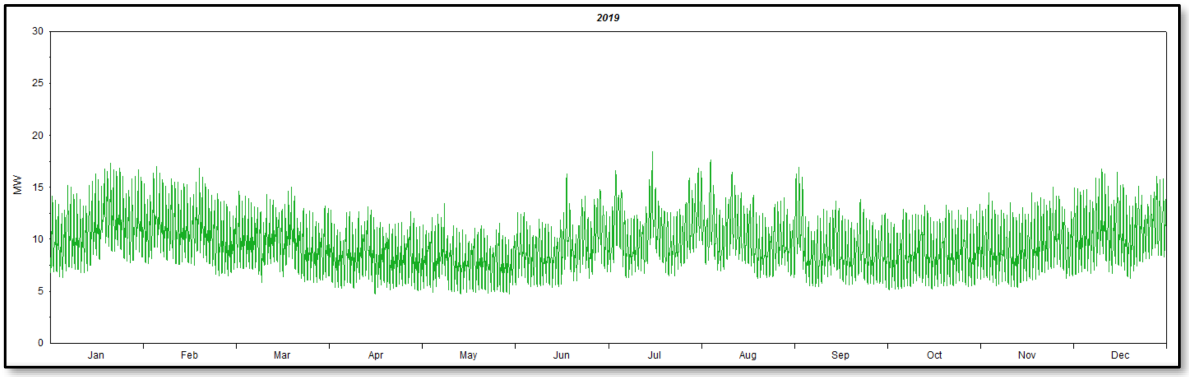
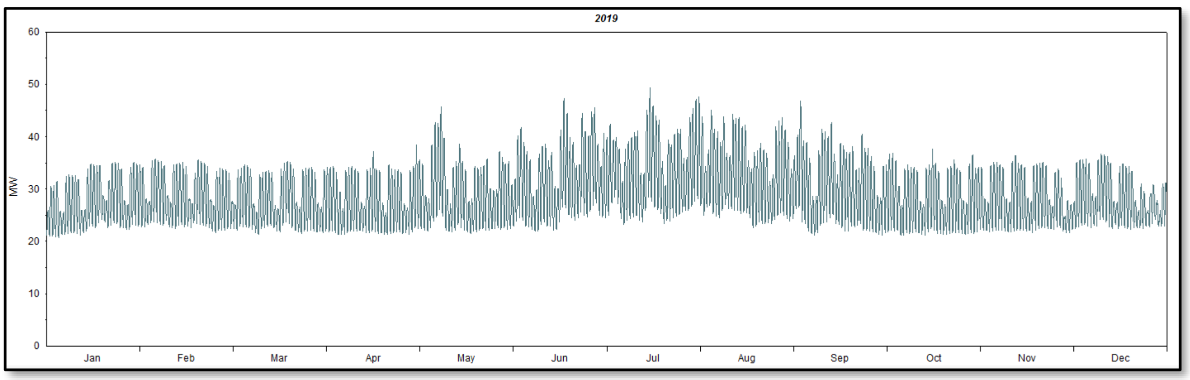
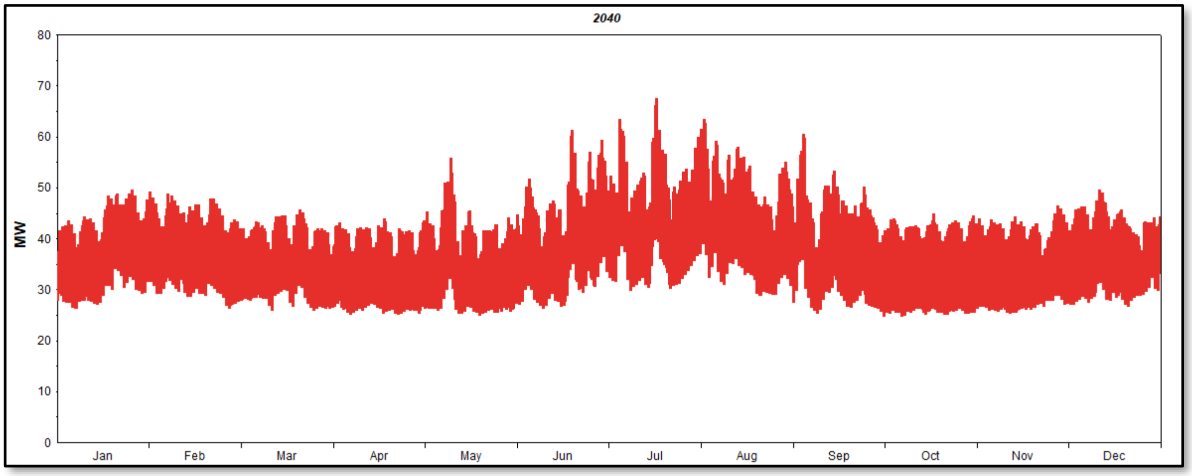


Figure 26: Commercial Hourly Load Forecast



Baseline system hourly load forecast is generated through 2040 by adding residential, commercial, and street lighting load and calibrating this to system energy and peak demand forecast. Figure 27 shows the resulting 2040 baseline hourly load forecast.

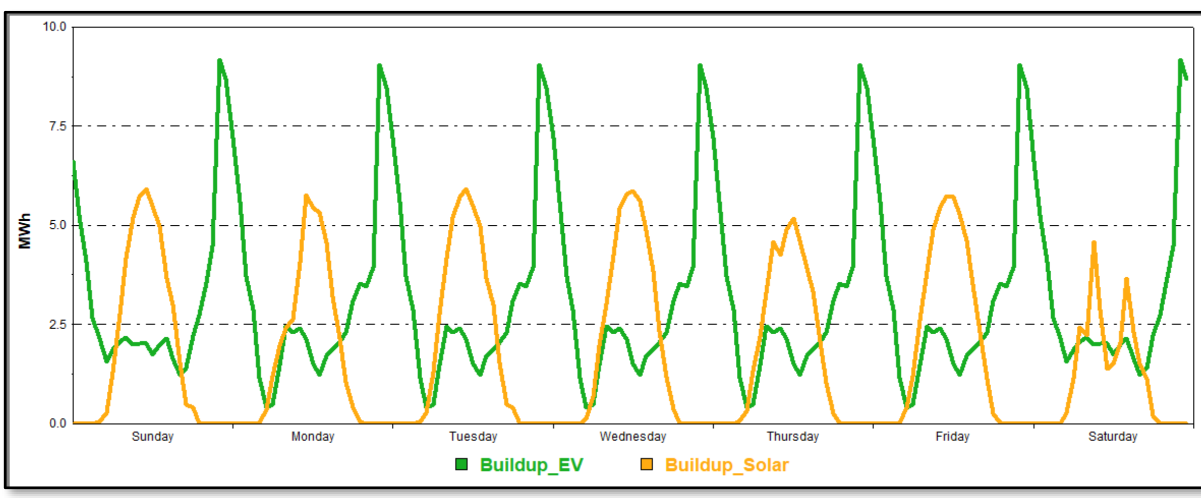
Figure 27: System Hourly Baseline Load Forecast (2040)



Adjustment for New Technologies

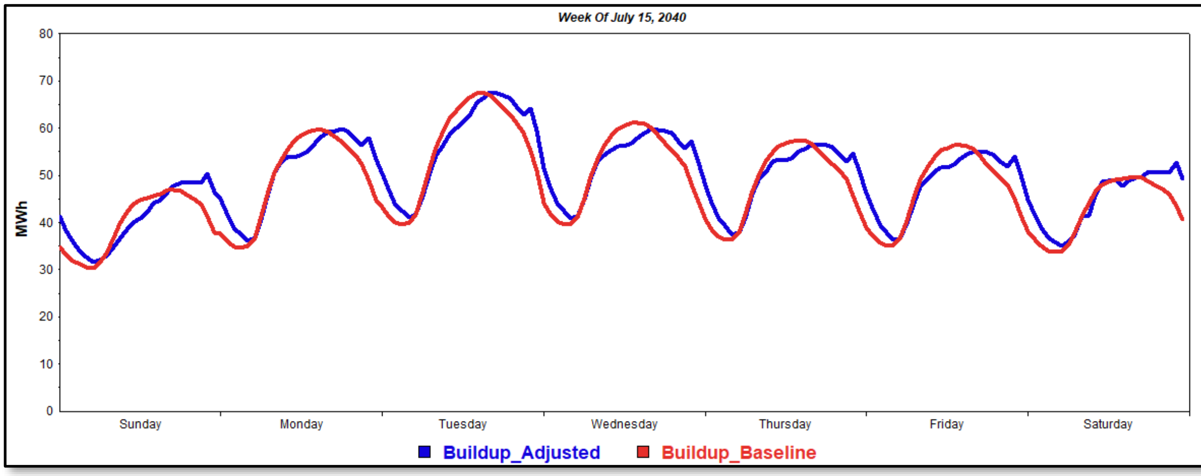
The baseline system load forecast is adjusted for PV and EV adoption. PV reduces system load and demand while EV adds to baseline system load. Figure 28 shows projected PV and EV hourly loads for the July peak week in 2040.

Figure 28: Solar and EV Loads (MWh)



By 2040, EVs add 9 MW of load at 11:00 at night and solar reduces load by 5 MW at noon. The adjusted system load and projected peaks are derived by adding PV and EV hourly load forecast. The combined impact is to shift load and peak to early evening. Figure 29 compares the baseline system load with the adjusted system load forecast.

Figure 29: Baseline vs. Adjusted Loads (MWh)



4 Forecast Scenarios

Peak Weather Scenario

Peak forecast is also estimated for more extreme peak-producing weather conditions. Peak-day weather is calculated for 1 in 10-year conditions (or 90% probability case). The 90% probability peak weather is derived by finding the 90th percentile of historical peak-day weather across the last twenty years. The 90% probability peak-day CDD (base 70 degrees) is 15.9. This compares with expected peak-day temperature of 12.8 CDD. The 90% peak probability temperature is 24% higher than expected peak-day temperature and results in a peak demand forecast that is approximately 4% higher than the base case. Table 4-1 compares baseline and extreme weather peak forecasts.

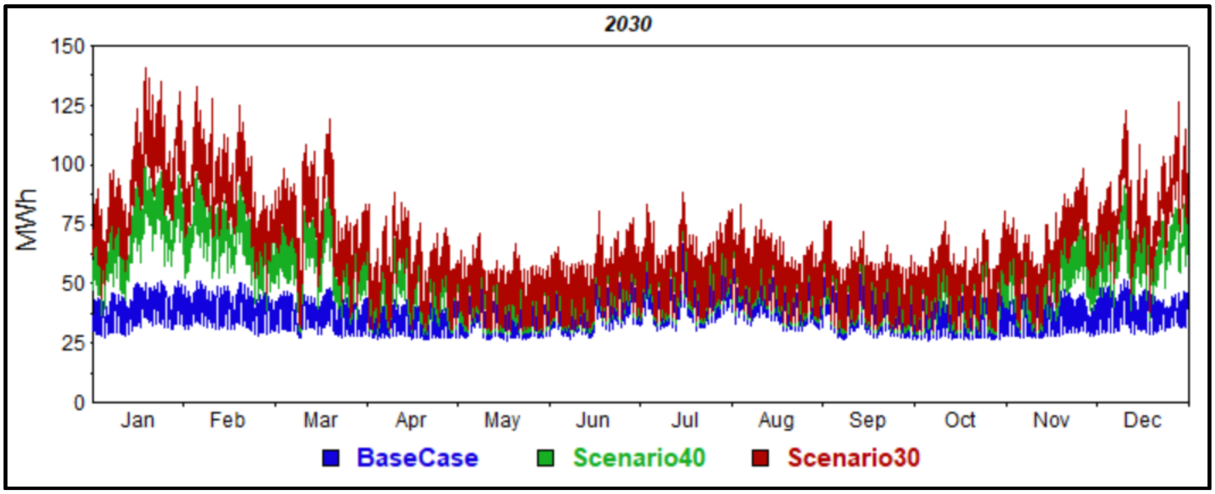
Table 4-1: Comparison with Baseline Peak Forecast (MW)

Year	50% Prob	% Chg	90% Prob	% Chg
2019	64.5		67.2	
2020	64.8	0.4%	67.5	0.4%
2021	65.2	0.6%	67.9	0.6%
2022	65.4	0.3%	68.1	0.3%
2023	65.2	-0.2%	68.0	-0.2%
2024	65.4	0.3%	68.2	0.3%
2025	65.4	-0.1%	68.2	-0.1%
2026	65.3	0.0%	68.1	0.0%
2027	66.3	1.5%	69.2	1.5%
2028	65.5	-1.3%	68.3	-1.2%
2029	65.4	-0.1%	68.3	-0.1%
2030	65.3	-0.2%	68.2	-0.1%
2031	65.2	-0.1%	68.1	0.0%
2032	65.3	0.1%	68.2	0.1%
2033	65.2	-0.1%	68.1	-0.1%
2034	65.3	0.0%	68.2	0.0%
2035	65.3	0.1%	68.2	0.1%
2036	65.5	0.3%	68.4	0.3%
2037	65.6	0.2%	68.5	0.1%
2038	65.8	0.4%	68.6	0.2%
2039	66.0	0.3%	68.7	0.1%
2040	66.4	0.5%	69.1	0.6%
19-29		0.1%		0.2%
19-39		0.1%		0.1%

Electrification Scenarios

BED defined two electrification scenarios – each is to achieve net zero emission targets by specific target years – 2030 (Scenario 30) and 2040 (Scenario 40); the 2030 scenario is the more aggressive scenario. BED provided additional expected electric sales for heating, cooling, water heating in the residential sector and heating, water heating, and cooking in the commercial sector. Each scenario also includes higher EV and solar market penetration as well as higher EE program savings. Figure 30 compares the hourly load impacts with the base case.

Figure 30: Scenario Load Comparison



With strong increase in cold climate heat pump growth, peak demand shifts from the summer months to winter months. By 2030, the aggressive electrification scenario results in peak demand that is more than double the base-case peak demand forecast. Tables 4-2 and 4-3 compare energy and demand forecasts against the base-case.

Table 4-2: Energy (MWh) Scenario Comparison

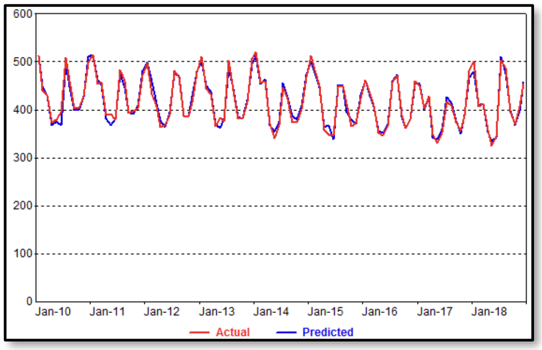
Year	Base	% Chg	Scen40	% Chg	Scen30	% Chg
2019	336,402		339,784		342,871	
2020	338,299	0.6%	347,394	2.2%	365,940	6.7%
2021	339,933	0.5%	359,635	3.5%	390,726	6.8%
2022	342,348	0.7%	376,142	4.6%	417,098	6.7%
2023	342,126	-0.1%	388,429	3.3%	436,852	4.7%
2024	343,500	0.4%	403,762	3.9%	457,413	4.7%
2025	343,029	-0.1%	418,187	3.6%	474,330	3.7%
2026	342,657	-0.1%	431,557	3.2%	488,349	3.0%
2027	342,650	0.0%	444,481	3.0%	500,181	2.4%
2028	343,789	0.3%	457,867	3.0%	511,237	2.2%
2029	343,693	0.0%	467,801	2.2%	529,370	3.5%
2030	343,418	-0.1%	475,770	1.7%	559,027	5.6%
2031	343,637	0.1%	483,133	1.5%	556,901	-0.4%
2032	345,036	0.4%	490,715	1.6%	554,908	-0.4%
2033	345,130	0.0%	495,738	1.0%	551,198	-0.7%
2034	346,245	0.3%	499,275	0.7%	548,188	-0.5%
2035	347,589	0.4%	501,376	0.4%	544,274	-0.7%
2036	349,961	0.7%	503,328	0.4%	540,124	-0.8%
2037	350,755	0.2%	505,876	0.5%	538,026	-0.4%
2038	352,314	0.4%	509,573	0.7%	537,093	-0.2%
2039	353,667	0.4%	511,314	0.3%	534,837	-0.4%
2040	355,190	0.4%	511,634	0.1%	531,247	-0.7%
19-29		0.2%		3.3%		4.5%
19-39		0.3%		2.1%		2.3%

Table 4-3: Peak Scenario Comparison (MW)

Year	Base	% Chg	Scen40	% Chg	Scen30	% Chg
2019	64.5		64.9		65.4	
2020	64.8	0.4%	65.7	1.2%	67.3	2.8%
2021	65.2	0.6%	66.9	1.8%	74.6	10.9%
2022	65.4	0.3%	68.4	2.2%	85.7	14.9%
2023	65.2	-0.2%	70.2	2.7%	95.9	11.9%
2024	65.4	0.3%	75.1	6.9%	102.8	7.2%
2025	65.4	-0.1%	79.8	6.3%	109.4	6.5%
2026	65.3	0.0%	84.3	5.7%	114.2	4.4%
2027	66.3	1.5%	88.9	5.4%	118.1	3.4%
2028	65.5	-1.3%	91.5	2.9%	120.3	1.8%
2029	65.4	-0.1%	96.2	5.1%	126.5	5.1%
2030	65.3	-0.2%	99.1	3.0%	141.2	11.6%
2031	65.2	-0.1%	101.6	2.5%	139.2	-1.4%
2032	65.3	0.1%	102.4	0.8%	135.5	-2.7%
2033	65.2	-0.1%	103.5	1.0%	133.1	-1.7%
2034	65.3	0.0%	106.4	2.8%	132.9	-0.2%
2035	65.3	0.1%	106.4	0.0%	129.8	-2.3%
2036	65.5	0.3%	106.0	-0.4%	126.1	-2.9%
2037	65.6	0.2%	106.9	0.9%	124.7	-1.1%
2038	65.8	0.4%	109.0	2.0%	124.4	-0.2%
2039	66.0	0.3%	109.8	0.7%	123.2	-0.9%
2040	66.4	0.5%	111.3	1.4%	122.6	-0.5%
19-29		0.1%		4.0%		6.9%
19-39		0.1%		2.7%		3.4%

5 Appendix A

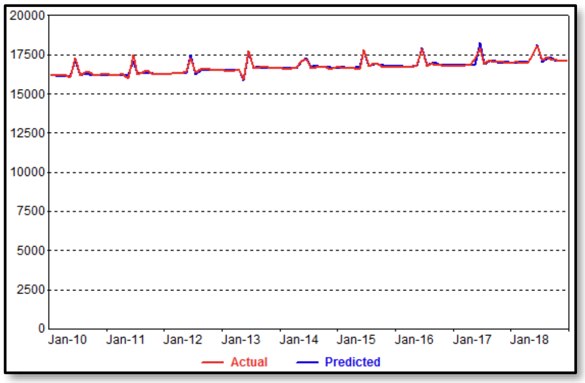
Residential Average Use Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mStructRes.XOther	1.124	0.018	63.002	0.00%
mStructRes.XHeat	0.806	0.055	14.683	0.00%
mStructRes.XCool	1.695	0.105	16.101	0.00%
mBin.AftJul15	-11.599	2.754	-4.212	0.01%
mBin.Mar	-25.449	3.65	-6.973	0.00%
mBin.Apr	-43.102	4.952	-8.704	0.00%
mBin.May	-48.197	5.615	-8.583	0.00%
mBin.Jun	-37.166	4.709	-7.893	0.00%
mBin.Sep	-9.499	4.293	-2.213	2.93%
mBin.Oct	-27.036	5.633	-4.799	0.00%
mBin.Nov	-22.123	3.786	-5.843	0.00%
MA(1)	0.505	0.091	5.546	0.00%

Model Statistics	
Iterations	14
Adjusted Observations	108
Deg. of Freedom for Error	96
R-Squared	0.97
Adjusted R-Squared	0.966
AIC	4.579
BIC	4.877
Log-Likelihood	-388.53
Model Sum of Squares	268,407.61
Sum of Squared Errors	8,427.50
Mean Squared Error	87.79
Std. Error of Regression	9.37
Mean Abs. Dev. (MAD)	6.8
Mean Abs. % Err. (MAPE)	1.64%
Durbin-Watson Statistic	1.809

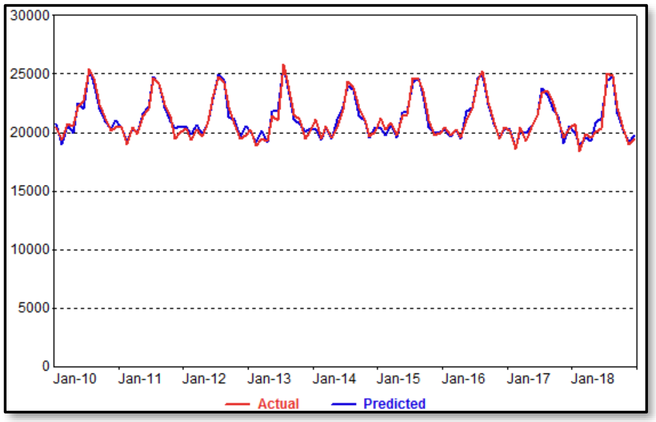
Residential Customer Model



Variable	Coefficient	StdErr	T-Stat	P-Value
Economics.HHs	190.631	0.411	463.48	0.00%
mBin.Jun	1079.33	29.131	37.051	0.00%
mBin.Aug	137.458	30.436	4.516	0.00%
mBin.Sep	105.504	30.435	3.467	0.08%
mBin.May13	-690.79	81.064	-8.522	0.00%
mBin.May14	430.713	90.838	4.742	0.00%
mBin.May18	391.437	81.068	4.829	0.00%
mBin.Jun14	-488.366	95.327	-5.123	0.00%
AR(1)	0.73	0.065	11.18	0.00%

Model Statistics	
Iterations	11
Adjusted Observations	107
Deg. of Freedom for Error	98
R-Squared	0.949
Adjusted R-Squared	0.945
AIC	9.277
BIC	9.502
Log-Likelihood	-639.17
Model Sum of Squares	17,925,460.14
Sum of Squared Errors	967,019.88
Mean Squared Error	9,867.55
Std. Error of Regression	99.34
Mean Abs. Dev. (MAD)	66.86
Mean Abs. % Err. (MAPE)	0.40%
Durbin-Watson Statistic	2.64

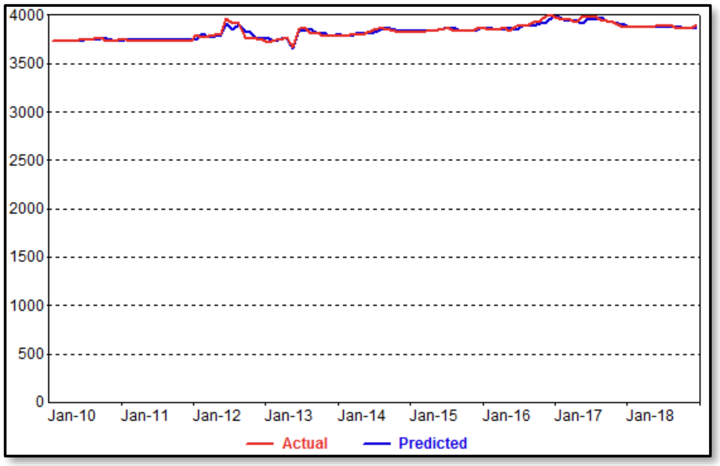
Commercial Sales Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mStructCom.XOther	1753.51	12.05	145.52	0.00%
mStructCom.XHeat	7007.887	2268.64	3.089	0.26%
mStructCom.XCool	18785.915	871.352	21.559	0.00%
mBin.Feb	531.961	123.057	4.323	0.00%
mBin.May12	-1177.846	347.057	-3.394	0.10%
mBin.Jul13	1397.388	354.619	3.941	0.02%
mBin.May15	-816.472	352.308	-2.317	2.26%
mBin.Sep15	833.876	351.38	2.373	1.96%
mBin.Jun17	-769.329	348.175	-2.21	2.95%
mBin.May18	-979.447	349.239	-2.805	0.61%
ComLoadLoss.TotMWh	-0.727	0.357	-2.038	4.43%
MA(1)	0.583	0.091	6.416	0.00%

Model Statistics	
Iterations	26
Adjusted Observations	108
Deg. of Freedom for Error	96
R-Squared	0.95
Adjusted R-Squared	0.945
AIC	12.203
BIC	12.501
Log-Likelihood	-800.22
Model Sum of Squares	330,067,065.76
Sum of Squared Errors	17,245,443.43
Mean Squared Error	179,640.04
Std. Error of Regression	423.84
Mean Abs. Dev. (MAD)	320.37
Mean Abs. % Err. (MAPE)	1.52%
Durbin-Watson Statistic	1.95

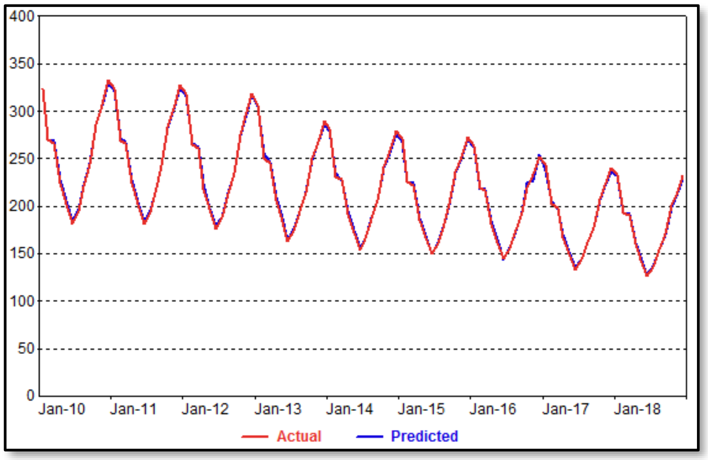
Commercial Customer Model



Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	1571.601	782.937	2.007	4.74%
Economics.Emp	18.516	6.388	2.899	0.46%
mBin.Jun12	106.013	18.048	5.874	0.00%
mBin.Sep12	-63.659	18.16	-3.505	0.07%
mBin.May13	-123.112	20.786	-5.923	0.00%
mBin.Jun13	41.481	20.778	1.996	4.86%
AR(1)	0.865	0.051	16.924	0.00%

Model Statistics	
Iterations	17
Adjusted Observations	107
Deg. of Freedom for Error	100
R-Squared	0.907
Adjusted R-Squared	0.902
AIC	6.413
BIC	6.588
F-Statistic	163.511
Prob (F-Statistic)	0
Log-Likelihood	-487.94
Model Sum of Squares	561,749.45
Sum of Squared Errors	57,258.98
Mean Squared Error	572.59
Std. Error of Regression	23.93
Mean Abs. Dev. (MAD)	16.72
Mean Abs. % Err. (MAPE)	0.44%
Durbin-Watson Statistic	1.801

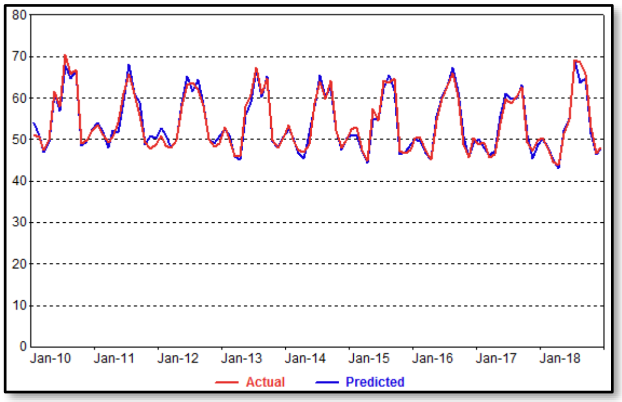
Other Sales Model



Variable	Coefficient	StdErr	T-Stat	P-Value
Simple	1.777	0.061	28.99	0
Trend	0.02	0.008	2.614	0.01
Seasonal	-0.038	0.029	-1.303	0.195

Model Statistics	
Iterations	22
Adjusted Observations	108
Deg. of Freedom for Error	105
R-Squared	0.998
Adjusted R-Squared	0.997
AIC	1.876
BIC	1.95
Log-Likelihood	-251.53
Model Sum of Squares	268,664
Sum of Squared Errors	667
Mean Squared Error	6.35
Std. Error of Regression	2.52
Mean Abs. Dev. (MAD)	2.01
Mean Abs. % Err. (MAPE)	0.94%
Durbin-Watson Statistic	1.376

Peak Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mCPkEndUses.BaseVar	1.544	0.019	80.174	0.00%
mWthr.HeatVar45	0.044	0.018	2.376	1.96%
mWthr.CoolVar50	0.422	0.043	9.79	0.00%
mWthr.CoolVar70	0.415	0.09	4.6	0.00%
mBin.May	-9.311	0.7	-13.31	0.00%
mBin.Jun	-5.566	0.6	-9.273	0.00%
mBin.Sep	-1.823	0.601	-3.033	0.31%
mBin.Oct	-7.686	0.744	-10.34	0.00%
mBin.Nov	-1.831	0.62	-2.954	0.40%
mBin.May10	5.012	1.554	3.226	0.17%
mBin.Mar12	-4.818	1.637	-2.943	0.41%
mBin.Apr12	-7.259	1.66	-4.373	0.00%
mBin.May12	8.154	1.688	4.831	0.00%
mBin.Nov15	-6.047	1.666	-3.629	0.05%
mBin.Apr17	-3.283	1.559	-2.106	3.80%
MA(1)	0.325	0.101	3.218	0.18%

Model Statistics	
Iterations	15
Adjusted Observations	108
Deg. of Freedom for Error	92
R-Squared	0.959
Adjusted R-Squared	0.952
AIC	0.969
BIC	1.367
Log-Likelihood	-189.58
Model Sum of Squares	4,916.19
Sum of Squared Errors	211.67
Mean Squared Error	2.3
Std. Error of Regression	1.52
Mean Abs. Dev. (MAD)	1.08
Mean Abs. % Err. (MAPE)	1.97%
Durbin-Watson Statistic	1.836

6 Appendix B: Residential SAE Modeling Framework

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

There are several advantages to this approach.

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

This section describes the SAE approach, the associated supporting SAE spreadsheets, and the *MetrixND* project files that are used in the implementation. The source for the SAE spreadsheets is the 2018 Annual Energy Outlook (AEO) database provided by the Energy Information Administration (EIA).

6.1 Statistically Adjusted End-Use Modeling Framework

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

$$USE_{y,m} = Heat_{y,m} + Cool_{y,m} + Other_{y,m} \tag{1}$$

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

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

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

6.1.1 Constructing XHeat

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

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

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

$$XHeat_{y,m} = HeatIndex_{y,m} \times HeatUse_{y,m} \qquad (3)$$

Where:

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

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

$$HeatIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \big/ Eff_y^{Type} \right)}{\left(Sat_{09}^{Type} \big/ Eff_{09}^{Type} \right)} \tag{4}$$

The *StructuralIndex* is constructed by combining the EIA's building shell efficiency index trends with surface area estimates, and then it is indexed to the 2009 value:

$$StructuralIndex_y = \frac{BuildingShellEfficiencyIndex_y \times SurfaceArea_y}{BuildingShellEfficiencyIndex_{09} \times SurfaceArea_{09}} \tag{5}$$

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

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

In Equation 4, 2009 is used as a base year for normalizing the index. As a result, the ratio on the right is equal to 1.0 in 2009. In other years, it will be greater than 1.0 if equipment saturation levels are above their 2009 level. This will be counteracted by higher efficiency levels, which will drive the index downward. The weights are defined as follows.

$$Weight^{Type} = \frac{Energy_{09}^{Type}}{HH_{09}} \times HeatShare_{09}^{Type} \tag{7}$$

In the SAE spreadsheets, these weights are referred to as *Intensities* and are defined on the *EIAData* tab. With these weights, the *HeatIndex* value in 2009 will be equal to estimated annual heating intensity per household in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

For electric heating equipment, the SAE spreadsheets contain two equipment types: electric resistance furnaces/room units and electric space heating heat pumps. Examples of weights for these two equipment types for the U.S. are given in Table 6-1.

Table 6-1: Electric Space Heating Equipment Weights

Equipment Type	Weight (kWh)
Electric Resistance Furnace/Room units	255
Electric Space Heating Heat Pump	0

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

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

$$HeatIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \Big/ Eff_y^{Type} \right)}{\left(Sat_{09}^{Type} \Big/ Eff_{09}^{Type} \right)} \times$$

$$\left(TenYearMovingAverageElectricPrice_{y,m}\right)^{\phi} \times \left(TenYearMovingAverageGasPrice_{y,m}\right)^{\gamma} \quad (8)$$

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

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

$$HeatUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{WgtHDD_{y,m}}{HDD_{09}}\right) \times \left(\frac{HHSize_{y}}{HHSize_{09}}\right)^{0.25} \times \left(\frac{Income_{y}}{Income_{09}}\right)^{0.20} \times \left(\frac{ElecPrice_{y,m}}{ElecPrice_{09,7}}\right)^{\lambda} \times \left(\frac{GasPrice_{y,m}}{GasPrice_{09,7}}\right)^{\kappa} \quad (9)$$

Where:

- *BDays* is the number of billing days in year (*y*) and month (*m*), these values are normalized by 30.5 which is the average number of billing days
- *WgtHDD* is the weighted number of heating degree days in year (*y*) and month (*m*). This is constructed as the weighted sum of the current month's HDD and the prior month's HDD. The weights are 75% on the current month and 25% on the prior month.
- *HDD* is the annual heating degree days for 2005
- *HHSize* is average household size in a year (*y*)
- *Income* is average real income per household in year (*y*)
- *ElecPrice* is the average real price of electricity in month (*m*) and year (*y*)
- *GasPrice* is the average real price of natural gas in month (*m*) and year (*y*)

By construction, the $HeatUse_{y,m}$ variable has an annual sum that is close to 1.0 in the base year (2009). The first two terms, which involve billing days and heating degree days, serve to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will reflect changes in the economic drivers, as transformed through the end-use elasticity parameters. The price impacts captured by the Usage equation represent short-term price response.

6.1.2 Constructing XCool

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

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

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

$$XCool_{y,m} = CoolIndex_y \times CoolUse_{y,m} \tag{10}$$

Where

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

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

$$CoolIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \Big/ Eff_y^{Type} \right)}{\left(Sat_{09}^{Type} \Big/ Eff_{09}^{Type} \right)} \tag{11}$$

Data values in 2005 are used as a base year for normalizing the index, and the ratio on the right is equal to 1.0 in 2005. In other years, it will be greater than 1.0 if equipment saturation levels are above their 2005 level. This will be counteracted by higher efficiency levels, which will drive the index downward. The weights are defined as follows.

$$Weight^{Type} = \frac{Energy_{09}^{Type}}{HH_{09}} \times CoolShare_{09}^{Type} \tag{12}$$

In the SAE spreadsheets, these weights are referred to as *Intensities* and are defined on the *EIAData* tab. With these weights, the *CoolIndex* value in 2009 will be equal to estimated annual cooling intensity per household in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

For cooling equipment, the SAE spreadsheets contain three equipment types: central air conditioning, space cooling heat pump, and room air conditioning. Examples of weights for these three equipment types for the U.S. are given in Table 6-2.

Table 6-2: Space Cooling Equipment Weights

Equipment Type	Weight (kWh)
Central Air Conditioning	18
Space Cooling Heat Pump	0
Room Air Conditioning	145

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

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

$$CoolIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \big/ Eff_y^{Type} \right)}{\left(Sat_{09}^{Type} \big/ Eff_{09}^{Type} \right)} \times \tag{13}$$

$$\left(TenYearMovingAverageElectricPrice_{y,m}\right)^{\phi} \times \left(TenYearMovingAverageGasPrice_{y,m}\right)^{\gamma}$$

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

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

$$CoolUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{WgtCDD_{y,m}}{CDD_{09}}\right) \times \left(\frac{HHSize_y}{HHSize_{09}}\right)^{0.25} \times \left(\frac{Income_y}{Income_{09}}\right)^{0.20} \times \left(\frac{ElecPrice_{y,m}}{ElecPrice_{09}}\right)^{\lambda} \times \left(\frac{GasPrice_{y,m}}{GasPrice_{09}}\right)^{\kappa} \quad (14)$$

Where:

- *WgtCDD* is the weighted number of cooling degree days in year (*y*) and month (*m*). This is constructed as the weighted sum of the current month's CDD and the prior month's CDD. The weights are 75% on the current month and 25% on the prior month.
- *CDD* is the annual cooling degree days for 2009.

By construction, the *CoolUse* variable has an annual sum that is close to 1.0 in the base year (2009). The first two terms, which involve billing days and cooling degree days, serve to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will change to reflect changes in the economic driver changes.

6.1.3 Constructing XOther

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

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

The explanatory variable for other uses is defined as follows:

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

The first term on the right hand side of this expression ($OtherEqpIndex_y$) embodies information about appliance saturation and efficiency levels and monthly usage multipliers.

The second term (*OtherUse*) captures the impact of changes in prices, income, household size, and number of billing-days on appliance utilization.

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

$$ApplianceIndex_{y,m} = Weight^{Type} \times \frac{\left(\frac{Sat_y^{Type}}{\frac{1}{UEC_y^{Type}}} \right)}{\left(\frac{Sat_{05}^{Type}}{\frac{1}{UEC_{09}^{Type}}} \right)} \times MoMult_m^{Type} \times \left(TenYearMovingAverageElectricPrice\right)^{\lambda} \times \left(TenYearMovingAverageGasPrice\right)^{\kappa} \quad (16)$$

Where:

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

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

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

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

$$ApplianceUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{HHSize_y}{HHSize_{09}}\right)^{0.46} \times \left(\frac{Income_y}{Income_{09}}\right)^{0.10} \times \left(\frac{ElecPrice_{y,m}}{ElecPrice_{09}}\right)^{\phi} \times \left(\frac{GasPrice_{y,m}}{GasPrice_{09}}\right)^{\lambda} \quad (17)$$

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

$$OtherEqpIndex_{y,m} = \sum_{k} ApplianceIndex_{y,m} \times ApplianceUse_{y,m} \qquad (18)$$

7 Appendix C: Commercial Statistically Adjusted End-Use Model

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

There are several advantages to this approach.

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

This document describes this approach, the associated supporting Commercial SAE spreadsheets, and *MetrixND* project files that are used in the implementation. The source for the commercial SAE spreadsheets is the 2018 Annual Energy Outlook (AEO) database provided by the Energy Information Administration (EIA).

7.1 Commercial Statistically Adjusted End-Use Model Framework

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

$$USE_{y,m} = Heat_{y,m} + Cool_{y,m} + Other_{y,m} \quad (1)$$

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

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

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

7.1.1 Constructing XHeat

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

- Heating degree days,
- Heating equipment saturation levels,
- Heating equipment operating efficiencies,
- Average number of days in the billing cycle for each month, and
- Commercial output and energy price.

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

$$XHeat_{y,m} = HeatIndex_y \times HeatUse_{y,m} \quad (3)$$

where, $XHeat_{y,m}$ is estimated heating energy use in year (y) and month (m),

$HeatIndex_y$ is the annual index of heating equipment, and

$HeatUse_{y,m}$ is the monthly usage multiplier.

The heating equipment index is composed of electric space heating equipment saturation levels normalized by operating efficiency levels. The index will change over time with changes in heating equipment saturations (*HeatShare*) and operating efficiencies (*Eff*). Formally, the equipment index is defined as:

$$HeatIndex_y = HeatSales_{04} \times \frac{\left(HeatShare_y \big/ Eff_y \right)}{\left(HeatShare_{13} \big/ Eff_{13} \right)} \tag{4}$$

In this expression, 2013 is used as a base year for normalizing the index. The ratio on the right is equal to 1.0 in 2013. In other years, it will be greater than one if equipment saturation levels are above their 2013 level. This will be counteracted by higher efficiency levels, which will drive the index downward. Base year space heating sales are defined as follows.

$$HeatSales_{04} = \left(\frac{kWh}{Sqft} \right)_{Heating} \times \left(\frac{CommercialSales_{13}}{\sum_e kWh \big/ Sqft_e} \right) \tag{5}$$

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

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

$$HeatUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5} \right) \times \left(\frac{WgtHDD_{y,m}}{HDD_{13}} \right) \times \left(\frac{Output_y}{Output_{13}} \right)^{0.20} \times \left(\frac{Price_{y,m}}{Price_{13}} \right)^{-0.1} \tag{6}$$

where, *BDays* is the number of billing days in year (y) and month (m), these values are normalized by 30.5 which is the average number of billing days
WgtHDD is the weighted number of heating degree days in year (y) and month (m). This is constructed as the weighted sum of the current month's HDD and the prior

month's HDD. The weights are 75% on the current month and 25% on the prior month.
HDD is the annual heating degree days for 2013,
Output is a real commercial output driver in year (y),
Price is the average real price of electricity in month (m) and year (y),

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

7.1.2 Constructing XCool

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

- Cooling degree days,
- Cooling equipment saturation levels,
- Cooling equipment operating efficiencies,
- Average number of days in the billing cycle for each month, and
- Commercial output and energy price.

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

$$\mathrm{XCool}_{y,m} = \mathrm{CoolIndex}_{y} \times \mathrm{CoolUse}_{y,m} \qquad (7)$$

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

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

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

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

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

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

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

$$CoolUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5} \right) \times \left(\frac{WgtCDD_{y,m}}{CDD_{13}} \right) \times \left(\frac{Output_y}{Output_{13}} \right)^{0.20} \times \left(\frac{Price_{y,m}}{Price_{13}} \right)^{-0.1} \tag{10}$$

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

CDD is the annual cooling degree days for 2013.

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

7.1.3 Constructing XOther

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

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

The explanatory variable for other uses is defined as follows:

$$\mathrm{XOther}_{y,m} = \mathrm{OtherIndex}_{y,m} \times \mathrm{OtherUse}_{y,m} \tag{11}$$

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

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

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

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

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

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

$$OtherUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{Output_{y}}{Output_{13}}\right)^{0.20} \times \left(\frac{\mathrm{Pr}ice_{y.m}}{\mathrm{Pr}ice_{13}}\right)^{-0.1} \tag{14}$$

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

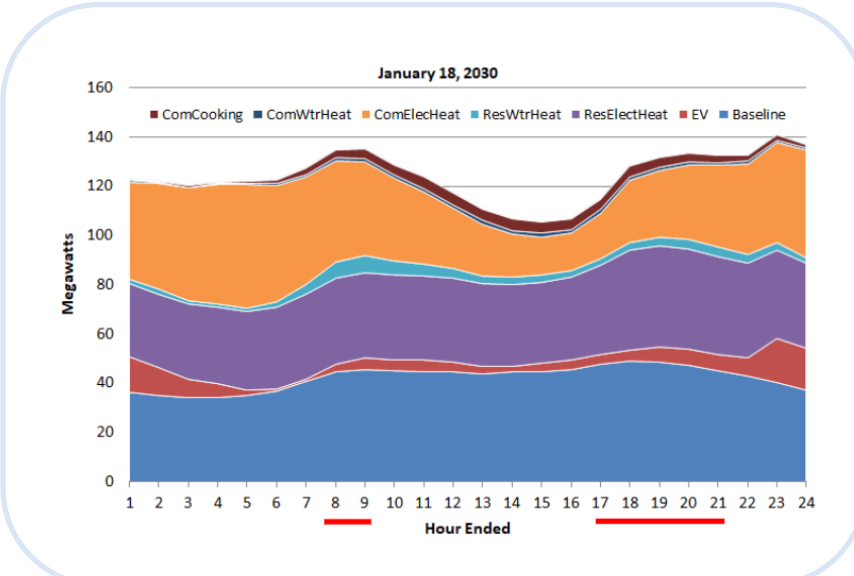
Appendix – Controllable Loads

One of the outcomes of the 2016 IRP was that BED continued researching commercially available measures and technologies that would allow BED to control customer loads remotely and/or through incentive programs. To this end, BED has been focused on several end-use loads that can be strategically controlled through assigned schedules or in real-time (automated when possible) to provide Wholesale Electric Market ("WEM") benefits. End-use loads of interest have included the thermal heating and cooling space with heat pump and commercial HVAC controls along with research into "smart" level 1 electric vehicle charging. The sections below outline the research and development BED has conducted related to load control.

Heat Pump Controls

Heat pumps are a significant focus for BED as they play a crucial role in advancing the 2030 Net Zero Energy Roadmap and will contribute significantly to peak coincident demand if left uncontrolled. Figure 1 shows the contribution of commercial and residential electric heating to morning and evening peak hours.

Figure 1: Net Zero Energy 2030 Disaggregated Load Profile



To date, there are few commercialized solutions that provide device aggregators with accurate submetering and seamless control of heat pump technologies. Additionally, research into customer flexibility regarding thermostatic setpoint adjustments is lacking. It is important to better understand the range of acceptable temperature adjustments to avoid severely impacting quality of service for the customer while maximizing load management.

BED is working to launch a pilot program with Packetized Energy that will deploy heat pump controls with the goals of proving out the operations and accuracy of the controls and submetering and gaining further insight into customer flexibility with size and duration of setpoint adjustments. Initially, this pilot will focus on Mitsubishi air source heat pumps, but

Packetized Energy seeks to engage other manufacturers going forward. BED is currently using Sensibo and Emporia devices at its offices on 585 Pine St. to control and submeter heat pumps.

Level 1 EV Charger

Another research project that BED has engaged in is to identify a suitable smart level 1 electric vehicle charger that provides accurate submetering and ideally the ability for load control. This is of interest to BED as installation of level 2 charging at home can require expensive wiring and in some cases electrical panel upgrades, and many owners of plug-in hybrid electric vehicles or those who don't make frequent long trips can fully charge with a level 1 charger. Identifying such a device could expand the number of customers enrolled in the EV rate.

Currently, BED has been working and researching several companies that are looking to develop a commercialized product. None of these companies have yet gained the necessary UL certification. BED will continue to monitor this technology as it advances and evaluate these products as they reach commercialization.

BED Staff Comments on report on "Economic Impact of McNeil Station" by Innovative Natural Resource Solutions dated 5/7/2020 (the "Report").

BED finds the report informative, particularly as relates to the impact of McNeil's operations on the Vermont economy (relative to the direct costs incurred by the McNeil Joint Owners). BED would like to offer some additional context for the report as the report was contracted for as an independent study and BED staff did not actually edit the report proper. The comments relate to the:

1. The totality of McNeil's financial statements for expenses relative to McNeil's market revenues.
2. Known and potential changes to the 2019 levels of revenue for energy, RECs, capacity, and other market values
3. Activities under way to improve McNeil's economics
4. BED's conclusions regarding the continued operation of McNeil for the foreseeable future.

McNeil's financial statements (expenses) and relative economics

McNeil's financial statements show 2019 expenses of $24,093,818 (which is consistent with page 3 of the Report). The Report indicates that this is outweighed by the direct economic benefit of $25.3 million and dramatically outweighed by the direct, indirect and induced impact to Vermont of $49.8 million and to the local region of $66.5 million. Depreciation and interest on debt related to McNeil amount to an additional $1,590,110.

In CY19 McNeil expensed a major turbine overhaul that typically occurs about every seven years (or 50,000 equivalent operating hours). In prior overhauls, BED had amortized this expense over a seven-year period, but that accounting treatment was not permitted in 2019 pursuant to the PUC's draft rules on accounting orders. Nevertheless, this non-annual expense increased the O&M expenses for McNeil by roughly $2.3 million in calendar year 2019. Adjusted for this, a 2019 cost for McNeil would have been on the order of $23,712,499 including depreciation and interest, but only including 1/7 of the major overhaul expense) (or $0.1043 per KWH produced).

Comparisons to the costs Vermont utilities incur to support the Ryegate facility are informative. McNeil's average cost for 2019 is very similar to the current contract rate for Ryegate of $0.1035 per kwh (within 0.75%). If one compares the McNeil cost to the Ryegate contract rate the following items are noteworthy and more than compensate for the small cost difference:

1. Currently under the Ryegate contract the utilities are only entitled to 50% of the Renewable Energy Credits (RECS).
2. McNeil average energy revenues per MWH from ISO-NE are 8-12% higher than those of Ryegate for 2019. BED tries to optimize McNeil's output based on market price signals whereas Ryegate generally operates base load/all hours. As noted below BED hopes its new wood purchasing strategy will further increase McNeil's relative advantage in this respect.

3. McNeil is owned by the Vermont utilities, and any efficiency cost savings, sch as those that may result from activities described in more detail below, benefit the VT retail electricity customers directly.

CY19 Revenues Per Unit and Potential Changes in Those Values

The key value streams for McNeil in CY19 were:

Source	Revenue per Unit & Units	Percent of Revenues
Energy	$34.86 per MWH	39.7%
RECs	$30.99 per MWH	35.3%
Capacity	$8.29 per kW-Mo	24.8%
VAR Payments	$25,000 annually	0.1%

Energy prices are not expected to fall from these levels. In fact increase operation in the winter relative to other times of the year, and potentially additional cycling capability with the repair of the water wall and replacement of the economizer tubes could increase the average revenue received per MWH even without an increase in the energy markets.

REC prices throughout the trading curve are generally averaging better than the value received in 2019, and BED is pursuing contracts at these higher prices.

CT 1, 2020 - $41.00 bid
CT 1, 2021 - $34.00 bid

CT 1, 2022 - $34.50 bid
CT 1, 2023 - $30.00 bid
CT 1, 2024 - $30.00 bid

Capacity revenues will fall through at least May 2024 based on the currently cleared capacity markets. Capacity revenues however only provided ¼ of McNeil's revenue in 2019.

The above comments are reflected in general terms in a comment at the bottom of page 12 of the Report.

See the discussion of key variables in the body of the IRP for additional discussion on these markets.

Efficiency/Operational Improvement Activities Underway at McNeil

BED continues to engage in improvements to the operations of McNeil wherever an opportunity appears to exist.

District energy represents an opportunity to utilize heat from McNeil for purposes other than the production of electric energy. To the extent waste heat can be used, there will be an improvement in McNeil's overall efficiency.

The McNeil Joint Owners are developing a pilot project for automated settings to control combustion efficiency with ThermoAI (a company that participated in the 2020 DeltaClimeVT program). Modifying air flow to reflect actual (near real time) ambient conditions has a potential to improve McNeil's effective heat rate.

In 2020 McNeil revised its wood contracting to better align wood flow with wholesale energy market prices through a combination of base load, seasonal, and on-call wood supply contracts. This is also hoped to permit suppliers improved ability to plan for their own operations.

Improvements in efficiencies and production timing are hoped to improve the McNeil economics through a combination of reduced cost and increased average revenue per MWH.

<u>BED's Conclusions</u>

McNeil is currently above market prices (reflected by a market revenue less than its cost to the Vermont utilities). On the other hand, no equivalent replacement in Vermont exists, or is likely. Replacing McNeil with a resource from other areas in New England would have the potential to save the McNeil Joint Owners a modest amount of money under present market conditions, but doing so would have a severe adverse economic impact on the Vermont and near regional economy as is indicated in the report. Potential reliability impacts of the loss of Vermont's largest energy producers have not been modelled in detail but the potential for adverse reliability under certain transmission conditions may exist.

This conclusion is supported by the consideration related to potential actions by the VT Legislature regarding the Ryegate generating facility this legislative season. In sponsoring the pending bill to extend the current 10-year contract with Ryegate it was noted:

- "There's a lot of indirect employment that's provided by having this plant. The plant uses low grade wood which there's really limited market for that wood. A lot of the plants over in New Hampshire and Maine have closed so there isn't a readily available market for a lot of these wood chips which are very important to get that junk wood, really low grade wood, to get that cleaned up and out of our forest and into something like electricity which is a renewable energy source."

And as noted in the committee floor report supporting the bill, McNeil harvests sustainability, is exploring efficiency improvements including district energy, and is the largest single purchaser of low-grade wood chips in Vermont (including the Ryegate station).

With the retirement of Vermont Yankee, McNeil is now the largest energy producing resource in Vermont, and moreover is one of the very few renewable resources capable of controlling its output based on market conditions (i.e. in industry terms McNeil is a "intermediate dispatchable renewable resource". Lastly, McNeil has the advantage from reliability terms of producing its energy at the center of the largest load pocket in Vermont. McNeil is a critical renewable asset for BED and for Vermont and a key component of Burlington's Net Zero goal and at this point BED intends its continued operation.

Burlington Electric Department

Economic Impact of McNeil Station

A Report from:

Innovative Natural Resource Solutions, LLC

May 7, 2020

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Introduction

Burlington Electric Department's McNeil Station is a 50 MW wood-fired electricity generating facility[i] that operates in the ISO-New England region. This facility provides an important market for biomass chips, produced in the forests of Vermont and nearby New York, and provides electricity to consumers in the City of Burlington, Vermont and surrounding communities, as well as the entire ISO-New England market.

Innovative Natural Resource Solutions LLC (INRS) was commissioned by Burlington Electric Department to analyze the economic impacts associated with operations of McNeil Station. This economic analysis is for one year, and uses 2019 data whenever possible. There were a few occasions when 2019 data was not available; in those cases, the latest available data was utilized.

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Executive Summary

In 2019, the cost to operate McNeil Station – inclusive of wood fuel, operations, maintenance and other expenses was $24,093,818. The facility generated an estimated $19,933,373 in revenue – from the sale of electricity, Renewable Energy Certificates (RECs), capacity and Volt Ampere Reactive (VAR) payments.

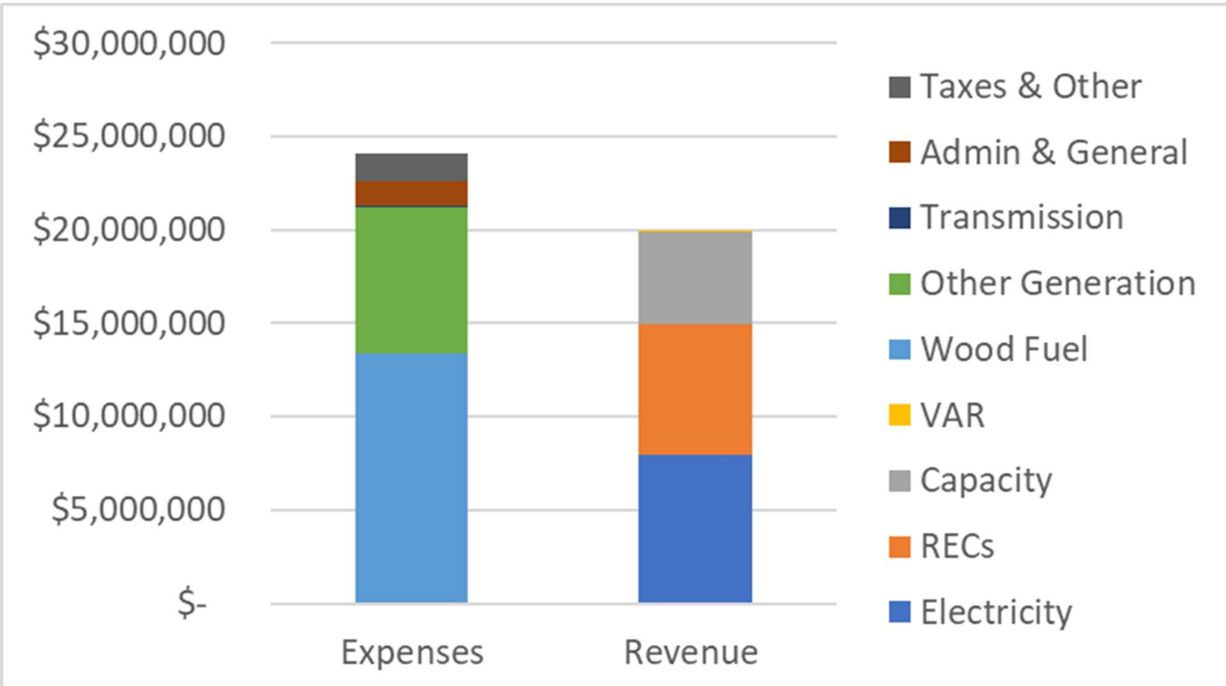

Figure 1. *Expenses and Revenue*

McNeil Station provides significant economic benefit to Vermont and the surrounding region through the operations of the facility, purchase and handling of wood fuel, and avoided cost of carbon emissions. The facility, Vermont's largest wood-using facility, provides:

- $25.3 million in annual direct economic impact, 79 percent of which is in Vermont; and
- $66.5 million in annual direct, indirect and induced economic impact, 75 percent of which is in Vermont.

	Direct, Indirect & Induced	
	Vermont Only	Total Impact
Wood Fuel	$ 12,355,893	$ 29,072,358
* Swanton Yard	$ 2,827,154	$ 2,827,154
* Railroad	$ 3,470,159	$ 3,470,159
* Waste Wood Avoided Cost	$ 745,500	$ 745,500
* Waste Wood Chipping	$ 189,000	$ 189,000
Payroll	$ 15,411,902	$ 15,411,902
Overhead	$ 6,043,109	$ 6,043,109
Property Tax	$ 2,504,561	$ 2,504,561
Misc. General Spending	$ 86,326	$ 86,326
Carbon (avoided $)	$ 6,199,298	$ 6,199,298
Total	*$ 49,832,903*	*$ 66,549,368*

Table 1. *Total Economic Impact*

McNeil Station is also responsible for the creation of 80 jobs at the facility and in the wood fuel supply chain, with total wages for these positions estimated to be $4.5 million annually.

The operations of McNeil Station as a wood-fired electricity generating facility provides benefits to Vermont and the surrounding region.

Wood Fuel

McNeil Station procures biomass fuel from loggers and others in the forest products industry. The vast majority of this fuel (98%) is procured as chips – generally made from the tops and branches of trees that are harvested for other uses, such as sawlogs for lumber or pulpwood for papermaking. McNeil Station does purchase some minor volumes of roundwood, which can be stored and used during time periods when loggers are unable to operate due to soft ground conditions – generally during the spring mud season.

The generation station purchased 334,935 green tons of wood fuel in 2019[ii], making it the largest consumer of wood in Vermont. McNeil Station purchases wood from eight Vermont counties, as well as from proximate counties in New York and a modest volume from Quebec. Unlike fossil fuels that are imported from outside of the State and region, or other renewable generation sources that do not require ongoing fuel expenses (e.g., solar and wind), biomass electricity generation creates local economic benefits through ongoing wood fuel purchases. Assuming an average wood fuel price of $28 per green ton[iii] [iv], McNeil Station purchased $9.4 million in wood fuel in 2019. The figure below shows estimated wood fuel purchases in each Vermont county. In addition to what is shown below, the facility purchased $5.4 million in fuel from Quebec and Clinton, Essex, Franklin and Warren Counties in New York.

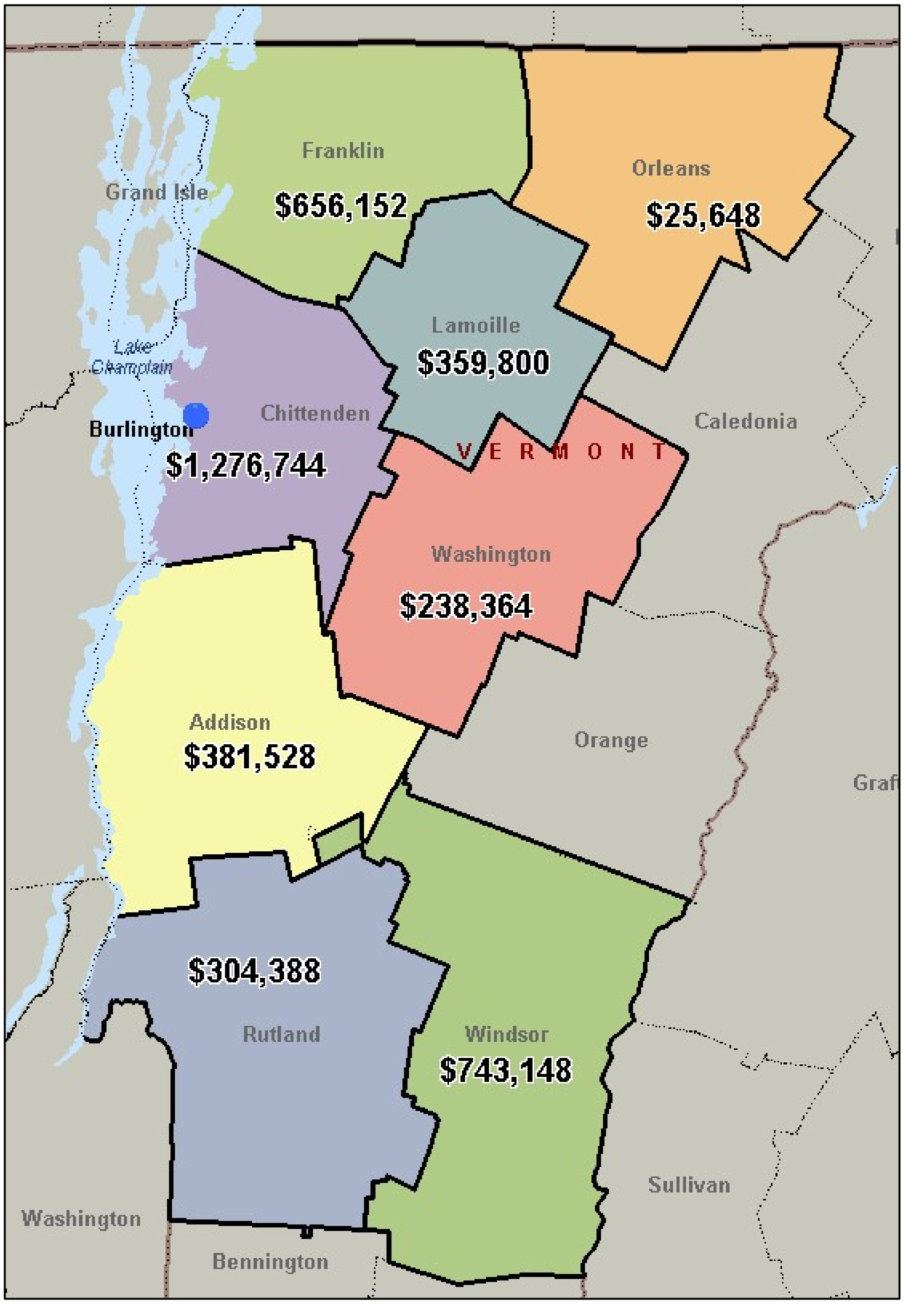

Figure 2. Wood Fuel Purchases by Vermont County, 2019 (green tons)

In addition to dollars, the market for biomass fuel created by McNeil Station creates jobs. Logging crews produce biomass as part of a mix with other forest products, including sawlogs and pulpwood. The figure below shows how multiple products can be generated from a single tree or timber stand.

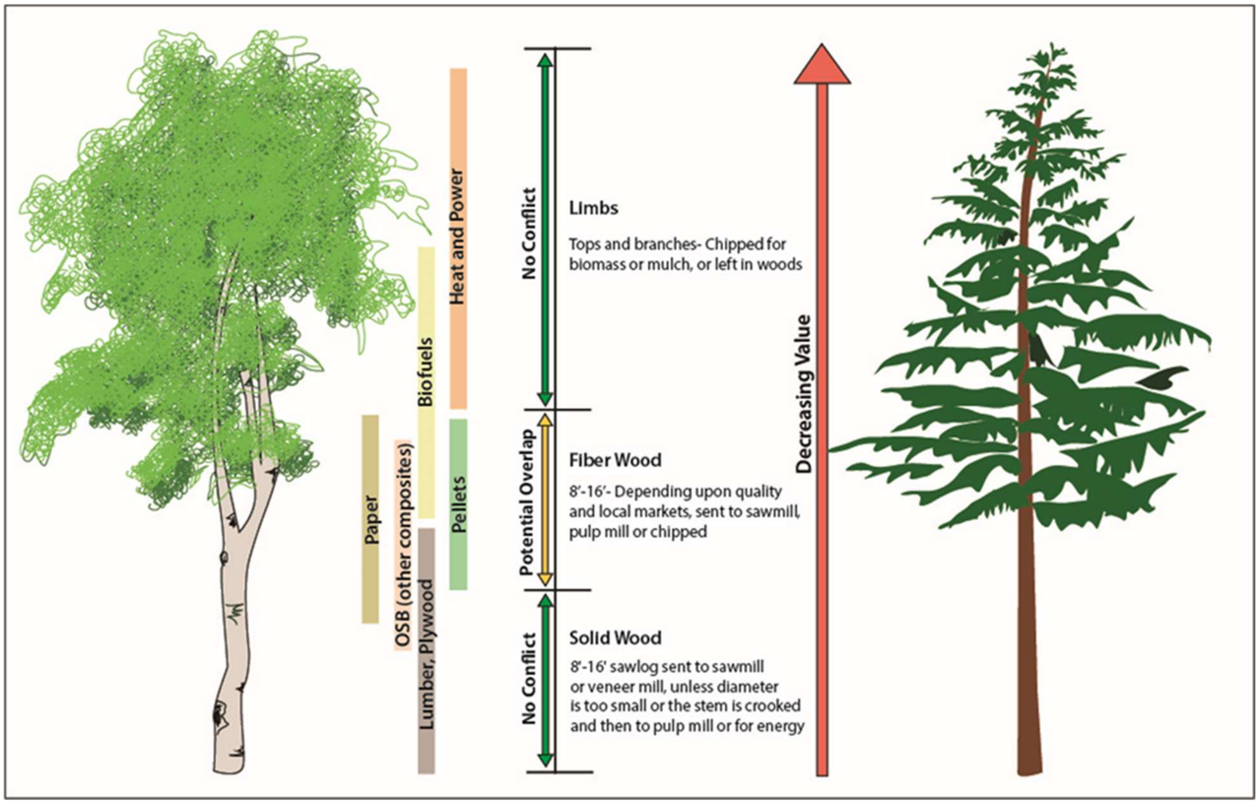

Figure 3. *Sawlogs, Pulpwood and Biomass Can All Be Generated from a Timber Harvest*

Assuming that a 4-person logging crew (exclusive of trucking) can produce 35 loads per week, at 30 tons per load, these 4 loggers would generate an estimated 1,050 tons of wood per week. Because loggers cannot work the entire year (often spring and fall mud season conditions keep loggers from operating for extended periods of time), we assume 45 weeks of operation per year. Given the above assumptions, McNeil Station's annual wood use directly supports the production of 28 full-time (FTE) logging jobs. According to data from the US Bureau of Labor Statistics[v], the average wage for a logging company employee in Vermont is $41,250 per year. Using this wage, the market created by McNeil Station an estimated $1.16 million in logging wages annually.

In addition to logging jobs, providing wood fuel to the facility requires trucks, and thus generates trucking jobs. Again assuming 30 tons per load, McNeil Station's wood use requires 11,165 deliveries per year, or 43 deliveries per day (assumes 260 delivery days). Assuming that each truck can make three deliveries per day, this means that McNeil Station supports 14 trucks and FTE truckers. According to data from the US Bureau of Labor Statistics[vi], the average wage for trucker in Vermont $45,250 per year. Using this wage, the market created by McNeil Station provides $633,500 in trucking wages annually.

Wood Handling

In addition to wood purchases, McNeil Station has a unique situation where much of the wood fuel used at the facility is delivered to a remote yard in Swanton, Vermont and then sent to the facility via a short-line rail carrier. This arrangement, which adds cost to the delivered cost of wood fuel, was established to decrease truck traffic in the area around McNeil Station.

In 2019, roughly 280,000 green tons of wood fuel were delivered to Swanton, unloaded, stored on site, and re-loaded into rail cars. Operations at this yard cost McNeil Station roughly $912,000 in 2019. The Swanton yard employs an estimated 2.5 people to conduct these activities.[vii] Assuming a wage similar to an agricultural equipment operator at $31,050[viii], the Swanton yard provides an estimated $77,625 in wages annually.

Railing this wood from Swanton to McNeil Station in Burlington costs an additional $2 million per year. The vast majority of this is the charge for trains, but also includes switching fees, weather-related delays, and charges for snow trains. The short-line rail uses two individuals to operate each chip train. Assuming a wage of $49,250[ix], these two rail jobs provide $98,500 in wages annually.

> *INRS notes that the yard and rail costs, spread over all wood fuel used (including any delivered directly to McNeil Station via truck) adds $7.80 per ton to the cost of fuel. Assuming 1.6 green tons of wood fuel are used to generate a megawatt hour of electricity[x], this means an increased fuel cost of $12.48 per MWh associated with the Swanton yard and rail.*

In addition to wood procured via forestry operations, McNeil Station has an on-site wood waste yard where individuals can drop off pallets, untreated lumber, tree trimmings and other clean wood for use as a fuel. McNeil Station then pays a contractor to come in three times annually to grind the wood waste, allowing it to be sized for use as biomass fuel. This costs roughly $90,000 per year. In 2019 McNeil Station's waste wood program generated 7,100 tons of wood fuel for use at the facility[xi]. At an avoided cost of $50 per ton (avoided tipping fee)[xii], the waste wood yard provided Chittenden County residents a value of $355,000 in 2019.

Plant Operations

Operating McNeil Station requires a professional staff to operate the facility. As a baseload generator, McNeil Station is staffed around the clock for the entire year, and always available for generation (with the exception of planned maintenance and unplanned outages). McNeil Station employs 33, with an annual payroll of $3.5 million and overhead (benefits, employee costs, etc.) of nearly $1.4 million. Total staffing costs for McNeil Station are roughly $4.9 million annually.

McNeil Station pays a property tax to the City of Burlington. In 2019 that property tax was $1.4 million.

There are a number of costs associated with plant operations that can be described as "Miscellaneous Operating Expenses". These include utilities, materials & supplies, dues, outside technical services, repairs and maintenance, professional trainings, phones, and publications. These costs are a relatively minor expense for McNeil Station – roughly $54,000 per year.

Carbon

While the combustion of biomass to generate electricity generates carbon emissions at the stack, this is offset by the fact that forests absorb carbon from the atmosphere as they grow. Carbon contained in wood fuel is already part of the above-ground carbon cycle, unlike fossil fuels which take ancient carbon that has been sequestered for millions of years and adds it to the atmosphere. It is for these reasons that, at the federal level, both the Environmental Protection Agency and the United States Congress have recognized biomass as "carbon neutral".[xiii]

Timberland in the Vermont and New York counties where Burlington procures wood fuel from have been adding tree carbon since at least 2003.[xiv]

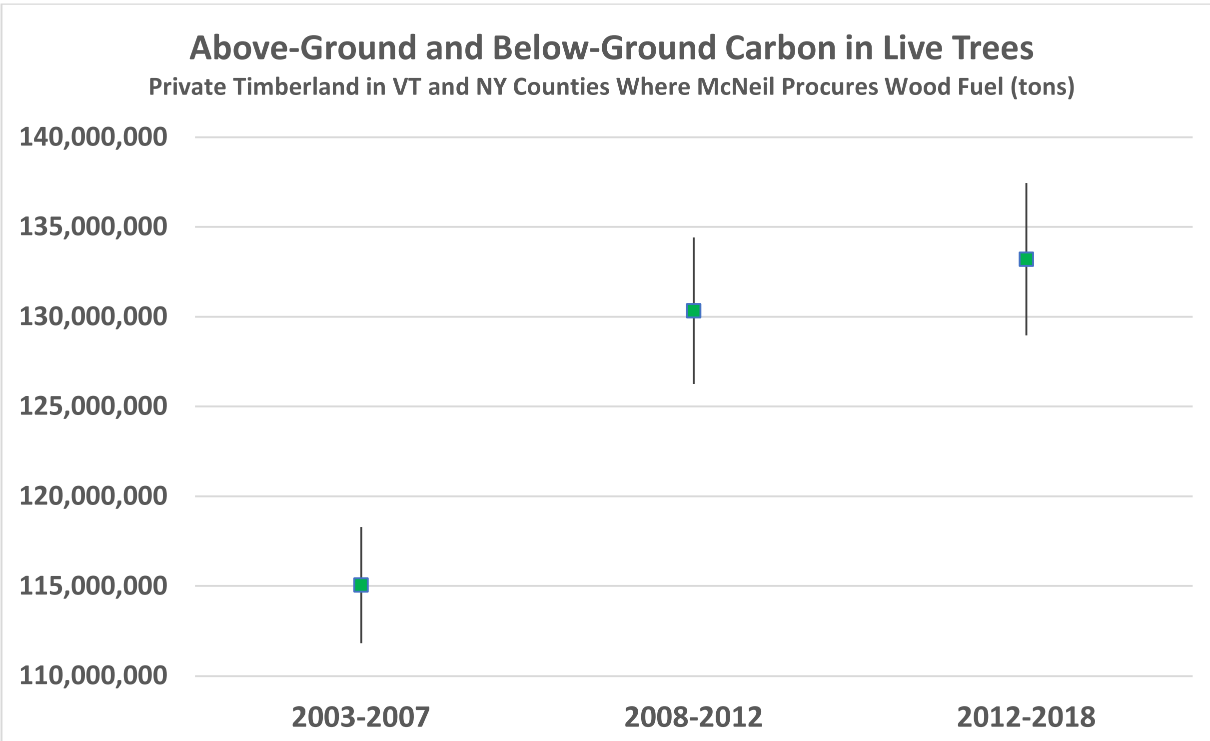

Figure 4. *Tree Carbon on Private Timberland in Vermont (Addison, Chittenden, Franklin, Lamoille, Orleans, Rutland, Washington and Windsor) and New York (Clinton, Essex, Franklin and Warren) Counties - Where McNeil Station Procured Wood Fuel in 2019*

If the 227,247 MWh that McNeil Station generated in 2019 did not come from the plant, they would need to be procured from other generators in ISO-New England. The regional grid has an average carbon dioxide (CO2) emission rate of 682 pounds per MWh, or 0.341 tons per MWh[xv] [xvi]. This means that using biomass at McNeil Station kept 77,491 tons of carbon emissions from occurring at alternative electricity generation facilities.

At a value of $80 per ton for carbon emissions[xvii] (N.B. – this is a placeholder value; there is not currently a mandated market for carbon emissions), this means the avoided carbon cost of generating electricity with biomass at McNeil Station is $6.2 million annually.

Generation Revenue & Operating Expenses

McNeil Station generated 227,247 MWh of electricity in 2019, and received payments for electricity and Renewable Energy Certificates (RECs) associated with this generation. Additionally, the facility received capacity payments from IS)-New England for being available to generate electricity when called upon, and Volt Ampere Reactive (VAR) payments for the value of generation near an electricity load center (the City of Burlington).

As shown in the table below, these generation-related revenues provide an estimated $19.9 million in revenue to McNeil Station annually.

Electricity sales (MWh)[xviii]		227,247	
Electricity			
	Electricity revenue ($/MWh)[xix]	$ 34.86	
	Electricity Revenue		$ 7,921,830
Renewable Energy Certificates			
	REC Revenue ($/MWh)[xx] [xxi]	$ 30.99	
	REC Revenue		$ 7,042,385
Capacity			
	Capacity ($/kW month)[xxii]	$ 8.29	
	Capacity ($/MW month)	$ 8,290	
	MW per month	50	
	Monthly Capacity Payment	$ 414,500	
	Total Capacity Payment		$ 4,944,158
VAR Payments			
	VAR Payments[xxiii]		$ 25,000
Total			
	Total Generation Revenue		*$ 19,933,373*

Table 2. *Generation-based Revenue, 2019 (estimate)*

This is revenue brought in through operations of the facility. Importantly, this is not included in calculating the total economic impact of McNeil Station because it is these same funds that are used to purchase wood fuel, pay employees, and cover other expenses. To include this revenue in the final calculation would be double counting.

Additionally, McNeil Station's operations support the electricity grid in Northwestern Vermont. According to information provided by the Vermont Electric Power Company (VELCO), if McNeil Station was not operating, that would create a "problem for the local area encompassing the City of Burlington, Essex and Winooski", and that "the 34.5 kV lines around McNeil could be overloaded during relatively heavy load days."[xxiv]

While generating an estimated $19,933,373 in revenue, the facility incurred $24,093,818 in expenses[xxv] – wood fuel, operations, maintenance, and taxes.

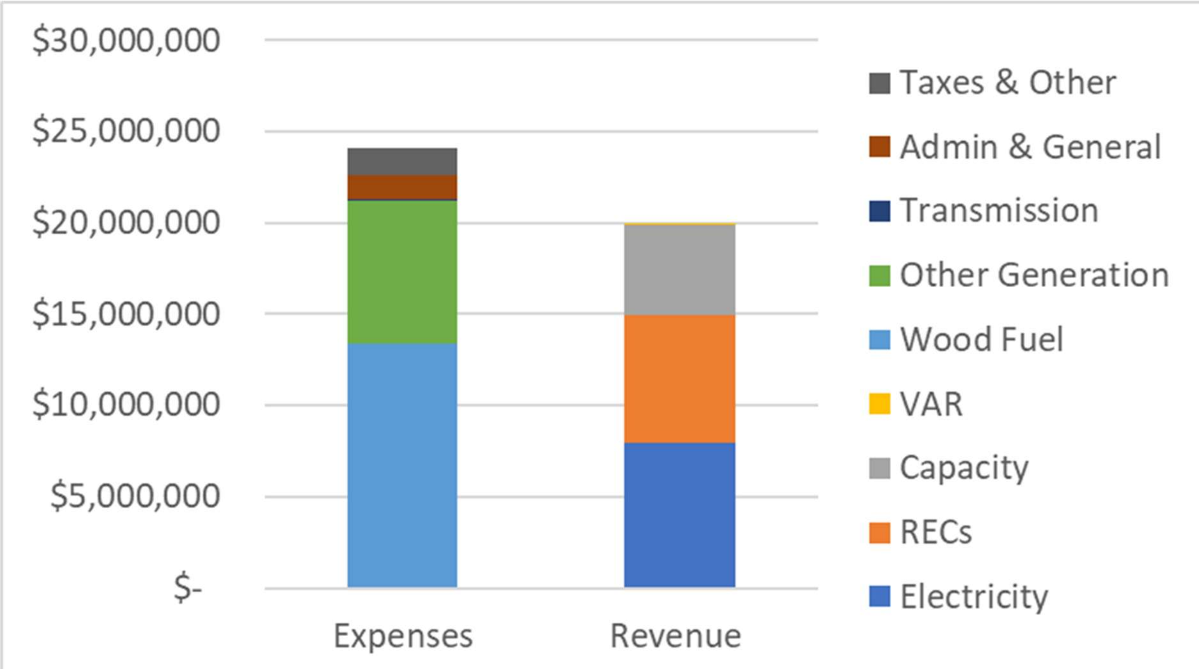

Figure 5. *Expenses and Revenue*

While future revenues and expenses are uncertain, it is known that capacity payments in the ISO-NE market are scheduled to decline in coming years, REC markets can be unpredictable (and subject to rapid change based on either political or market activity), and there is no market indication that wholesale electricity market prices will rise

Summary – Direct Economic Impact

Based on the information above, McNeil Station has a direct economic impact of $25.3 million, 79% of which is in Vermont (the remainder is associated with wood fuel purchases from proximate New York and Quebec).

	Direct				
		Vermont Only		Total Impact	Jobs (FTE)
Wood Fuel	$	3,985,772	$	9,378,180	42
*** Swanton Yard**	$	911,985	$	911,985	2.5
*** Railroad**	$	2,029,333	$	2,029,333	2
*** Waste Wood Avoided Cost**	$	355,000	$	355,000	
*** Waste Wood Chipping**	$	90,000	$	90,000	
Payroll	$	3,510,684	$	3,510,684	33
Overhead	$	1,376,562	$	1,376,562	
Property Tax	$	1,407,057	$	1,407,057	
Misc. General Spending	$	53,954	$	53,954	
Carbon (avoided $)	$	6,199,298	$	6,199,298	
Total	***$***	***19,919,645***	***$***	***25,312,053***	***80***

Table 3. *Direct Economic Impact*

McNeil Station is also responsible for the creation of 80 jobs at the facility and in the wood fuel supply chain, with total wages for these positions estimated to be $4.5 million annually.

Importantly, these jobs are maintained as long as McNeil Station is operating and using wood fuel. This is in contrast with some other forms of renewable electricity generation, where most jobs are associated with the development and construction of generation units, not their ongoing operations.

Multiplier Effect

INRS has reviewed relevant literature to estimate the multiplier effect for each relevant area of economic activity. The multiplier effect, used in economics to provide an understanding of the economic impact of activities, is defined as:

> *"Multiplier effect: means the cumulative economic activity arising from the fact that the biomass electric power generation industry's direct effect contribution spreads across the state's economy by creating and supporting jobs, incomes, and taxes. The biomass electric power generation industry supports its supply industries in the region by making purchases from them (indirect effect). These supply industries include commercial logging, marketing research, truck transportation, and maintenance and repair construction. In addition, workers in the biomass electric power generation industry and its supply industries spend their earnings in the region's services industries (induced effect), such as restaurants, medical services, grocery stores, real estate, and retail stores."*[xxvi]

The table below shows the multipliers used for each economic activity, and the reference determined through a literature review.

	Multiplier	Reference
Wood Fuel	3.10	Plymouth State[xxvii]
*** Swanton Yard**	3.10	Plymouth State
*** Railroad**	1.71	ASLRRA[xxviii]
*** Waste Wood Avoided Cost**	2.10	Hardy, Stevenson & Assoc[xxix]
*** Waste Wood Chipping**	2.10	Hardy, Stevenson & Assoc
Payroll	4.39	Plymouth State (calculated)
Overhead	4.39	Plymouth State (calculated)
Property Tax	1.78	Plymouth State (calculated)
Misc. General Spending	1.60	Plymouth State (calculated)
Carbon (avoided $)	1.00	xx

Table 4. *Multipliers by Category*

Summary – Total Economic Impact

Using the information above, the total economic impact of McNeil Station is estimated at $66.5 million, 75 percent of this impact is in Vermont.

	Direct, Indirect & Induced	
	Vermont Only	Total Impact
Wood Fuel	$ 12,355,893	$ 29,072,358
*** Swanton Yard**	$ 2,827,154	$ 2,827,154
*** Railroad**	$ 3,470,159	$ 3,470,159
*** Waste Wood Avoided Cost**	$ 745,500	$ 745,500
*** Waste Wood Chipping**	$ 189,000	$ 189,000
Payroll	$ 15,411,902	$ 15,411,902
Overhead	$ 6,043,109	$ 6,043,109
Property Tax	$ 2,504,561	$ 2,504,561
Misc. General Spending	$ 86,326	$ 86,326
Carbon (avoided $)	$ 6,199,298	$ 6,199,298
Total	***$ 49,832,903***	***$ 66,549,368***

Table 5. *Total Economic Impact*

Associated with this activity, McNeil Station generates an estimated $19.9 million annually in generation-based revenue from the sale of electricity, Renewable Energy Certificates, capacity payments and VAR payments.

Endnotes

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[i] https://burlingtonelectric.com/more-mcneil

[ii] Low-Grade Roundwod and Chip Volumes Processed or Consumed: By Vermont County or State of Origin. Form completed by Burlington Electric Department for the Vermont Department of Forest, Parks and Recreation. Calendar Year 2019.

[iii] Personal communication, Burlington Electric Department staff

[iv] https://burlingtonelectric.com/more-mcneil

[v] May 2018 State Occupational Employment and Wage Estimates – Vermont. https://www.bls.gov/oes/2018/may/oes_vt.htm

[vi] May 2018 State Occupational Employment and Wage Estimates – Vermont. https://www.bls.gov/oes/2018/may/oes_vt.htm

[vii] Personal communication, Burlington Electric Department staff

[viii] May 2018 State Occupational Employment and Wage Estimates – Vermont. https://www.bls.gov/oes/2018/may/oes_vt.htm

[ix] May 2018 State Occupational Employment and Wage Estimates – Vermont. https://www.bls.gov/oes/2018/may/oes_vt.htm

[x] "Amended and Restated Power Purchase Agreement, Public Service of New Hampshire and Berlin Station", Approved in Docket DE-10-195 of the New Hampshire Public Utilities Commission. Section 6.1.2(a)(2) implies that facility, a 70 MW biomass unit, would burn 1.6 tons of fuel per MWh.

[xi] Personal communication, Burlington Electric Department staff

[xii] Chittenden Solid Waste District. cswd.net/a-to-z/wood/

[xiii] *EPA Declares Forest Biomass Is 'Carbon Neutral'*. Power Magazine. April 24, 2018. https://www.powermag.com/epa-declares-forest-biomass-is-carbon-neutral/

[xiv] Data from USDA Forest Service, Forest Inventory and Analysis Program, Fri Feb 07 17:41:28 GMT 2020. Forest Inventory EVALIDator web-application Version 1.8.0.01. St. Paul, MN: U.S. Department of Agriculture, Forest Service, Northern Research Station. [Available only on internet: http://apps.fs.usda.gov/Evalidator/evalidator.jsp]. Data analysis by Innovative Natural Resource Solutions LLC.

[xv] 2017 ISO New England Electric Generator Air Emissions Report. April 2019. https://www.iso-ne.com/static-assets/documents/2019/04/2017_emissions_report.pdf

[xvi] The most recent data for grid emissions is from 2017. It is probable that this has changed; INRS used the latest available data.

[xvii] Personal communication, Burlington Electric Department staff

[xviii] *Joseph C. McNeil Generating Station Financial Statements (Calendar Year).* As reported by the Burlington Electric Department Finances and Accounting Group. December 2019.

[xix] Personal communication, Burlington Electric Department staff

[xx] Personal communication, Burlington Electric Department staff

[xxi] REC revenue here is for RECs generated during 2019; given the timing of REC issuance and sales, some of this revenue will be realized in 2020.

[xxii] Results of the Annual Forward Capacity Auctions. ISO-New England. https://www.iso-ne.com/about/key-stats/markets#fcaresults Note – the figure used is the mean of $9.55 per kwM (January-June 2019) and $7.03 per kwM (July-December 2019).

[xxiii] Personal communication, Burlington Electric Department staff

[xxiv] Email from VELCO (Hantz Presume) to Burlington Electric Department (Casey Lamont), July 15, 2019

[xxv] *Joseph C. McNeil Generating Station Financial Statements (Calendar Year).* As reported by the Burlington Electric Department Finances and Accounting Group. December 2019.

[xxvi] Daniel S. Lee, College of Business Administration, Plymouth State University (New Hampshire). *Economic Contribution of the Biomass Electric Power Generation Industry in New Hampshire: Calendar Year 2016.* March 1, 2017

[xxvii] Daniel S. Lee, College of Business Administration, Plymouth State University (New Hampshire). *Economic Contribution of the Biomass Electric Power Generation Industry in New Hampshire: Calendar Year 2016.* March 1, 2017

[xxviii] American Short Line and Regional Railroad Association. *ASLRRA Releases Economic Impact Report*. July 2018.

[xxix] Hardy, Stevenson and Associates, Ltd. *Timber Supply and Community Socio-Economic Sustainability in Ontario.* Ministry of Natural Resources, Forest Resource Assessment Project. 2006.

Appendix – Pilot Reporting

As detailed in 6.b of the Memorandum of Understanding from the 2016 IRP, BED agreed to provide an assessment of the lessons learned from current and future pilot projects. BED's current projects include a water heater program in partnership with Packetized Energy Management ("Packetized"), the Electric Bus program with Green Mountain Transit, and the Residential Electric Vehicle Charging Rate. In addition to these three programs, BED is working to launch three new pilot projects originating from DeltaClimeVT, a Vermont-based accelerator program for clean technology companies in their startup stage. BED was a founding member of DeltaClimeVT and has supported it since inception by providing access to mentorship and potential to engage in a pilot project. The three pilot projects under development involve Medley Thermal, WexEnergy, and ThermoAI. Finally, BED has recently concluded a pilot project that arose from a previous DeltaClimeVT session and was supported by an American Public Power Association DEED grant. BED worked with Omega Grid to craft a demand side management program using Blockchain. Each of these pilot programs will be discussed in further detail in the sections below.

Water Heater Program

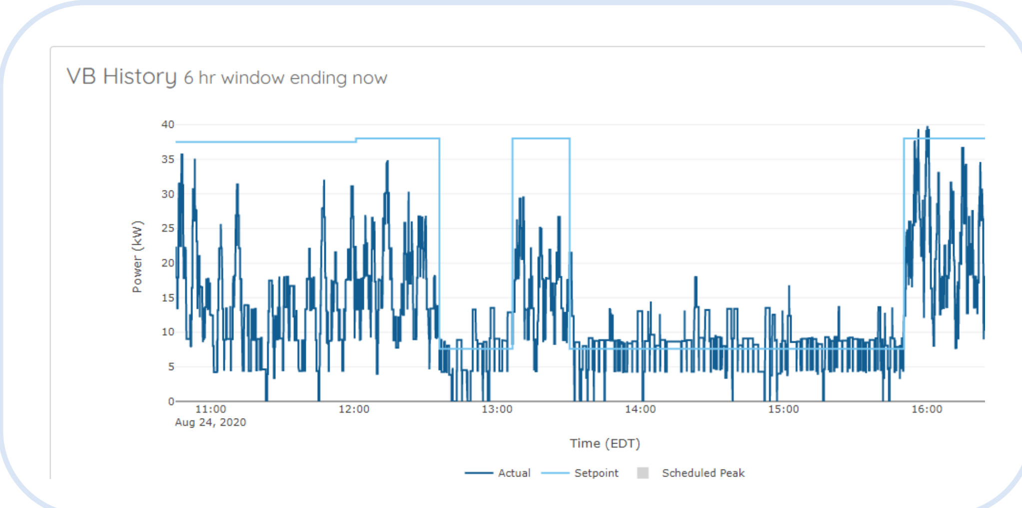
Packetized is a clean technology company that focuses on making demand for electricity flexible with software. BED has partnered with Packetized for over 3 years, and their product offerings have expanded from their initial offering that turned electric resistance hot water heaters into thermal batteries to electric vehicle chargers and heat pumps.

The first device that Packetized produced was the UL-listed Mello smart thermostat (Figure 1) that allows traditional electric resistance water heaters to match energy demand with real-time grid conditions. BED became the first utility to test and deploy this device in 2017 and has since deployed 84 devices. The controls for this device have expanded beyond manual setpoint controls and now allow BED to coordinate large fleets of distributed energy resources with automated peak shaving and energy arbitrage. These two features use predictive analytics that forecast load shapes and market conditions to determine peak probability and identify opportunities to perform energy arbitrage. BED uses its load forecasts to schedule these peak events automatically, while Packetized uses its internal forecasts to optimize the energy market. Figure 2 shows the power being recorded by the fleet of water heaters under control. The dark blue line is the actual power being drawn by the water heaters and the lighter

Figure 1: Packetized Mello device

blue line is the kW setpoint that is determined by the software to select how many water heaters are allowed to begin producing hot water. A signal can be sent to this group of water heaters so that they function as a virtual battery to increase and decrease the amount of electricity that they are consuming in real-time.

Figure 2: Packetized Energy's virtual battery for BED's fleet of water heaters



To attract customers to sign up for the water heater program BED provides a $20 bill credit as well as a reoccurring monthly bill credit of $1.37 if their Mello device is connected. Currently BED has control of 84 water heaters in Burlington and is continually looking to grow the program.

Electric Bus Program

On January 28, 2020, two Proterra electric buses ("e bus") were delivered to Green Mountain Transit, the public transit authority providing transportation services in Chittenden and Washington counties. One e bus (#990) went into full operation on March 2nd and is running assigned routes on regular basis. Through July 31, 2020, Bus #990 has consumed nearly 24,000 kWh and travelled over 8,000 miles, according to GMT. The second e bus (#991) encountered unexpected mechanical problems that were unable to be resolved until August because a Proterra mechanic was prohibited from travelling to Vermont due to the COVID19 pandemic. On August 6th, e bus #991 went into full service. Both #990 and #991, however, have been operating at reduced levels due to the State of Vermont's public health orders in response to COVID-19.

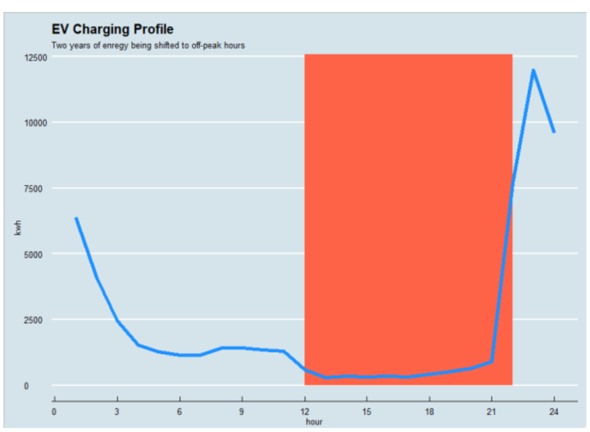
Additionally, both e buses are being evaluated by a team comprised of VTRANs, GMT, VEIC, and BED. This evaluation commenced in July. Over the next several months, the team will evaluate the operating performance of the e buses, the amount of energy consumed, and their efficiency measured in miles per gallon equivalent (i.e., the amount of electric power consumed converted into gallons of diesel fuel).

Residential Electric Vehicle Rate

In January of 2019, BED launched its residential electric vehicle rate that provides a ~$0.07/kWh discount for the electricity used to charge an electric vehicle. Unlike other rates that impose on-peak pricing, all of a customer's monthly charging must take place during designated off-peak times in order to receive any credit on their monthly bill. This programmatic design avoids making the customer any worse off compared to their current billed energy rate while sending strong price signals to avoid peak times. Alternatively, given the significant costs of transmission and capacity peaks, the on-peak rate would need to be very high in order to send the same price signal, but would have the adverse effect of exposing the customer to a downside of a price beyond that of the normal retail rate.

To join the rate a customer must install a BED-approved measuring device that sub-meters the charger's kWh. Upon launching the program, BED approved two charger companies: Packetized Energy and ChargePoint. BED is working to approve more charger providers by testing the accuracy of their telemetry and the accessibility of both their application programming interface and the user interface by which customers manage their charging.

Figure 3: EV rate charging load profile over last 2 years



There are currently 35 residential accounts on this rate. Figure 3 shows the hourly charging that has been shifted outside of the on-peak hours (noon – 10pm). More than 90% of charging occurs during off-peak hours of the day (after 10 pm and before noon).

BED is seeking to expand the number of customers who participate in this rate program. One option being considered is to expand this rate to include commercial customers. The second focus is on testing level 1 smart chargers to lower the installation cost associated with bringing a 220/240v outlet to where the car is parked. As mentioned above, BED is also working to expand the list of approved level 2 chargers that can be used to participate in the rate program.

Medley Thermal

A pilot project in conjunction with BED's facilities staff and Medley Thermal is underway to explore the possibility for price-dispatchable electric load in the form of electric boilers located in parallel with fossil fuel boilers. This pilot will take place at BED's Pine Street location since installation on company property avoids the rate implications during the pilot phase.

ThermoAI

BED is implementing a pilot project with ThermoAI to optimize the efficiency of the J.C. McNeil Generating Station through learning algorithms. The three phases of this pilot include data accumulation and simulation of the plant to determine the potential for fuel savings; use of the algorithms to make suggestions for operational adjustments such as air intake; and allowing the trained algorithm to make supervised adjustments to the facility's combustion operations. BED will be one of the first companies to work with ThermoAI and is excited by the potential for improved efficiencies in fuel use.

WexEnergy

BED is working on a pilot project in conjunction with VGS staff and WexEnergy to test the thermal savings from WexEnergy's product, Window Skins. This product is a lightweight, transparent plastic window treatment that increases the insulation of windows. BED will work with VGS to select a building in Burlington for installation of Window Skins and to run measurement and verification analysis to determine the thermal savings achieved. Considering recent building occupancy changes due to COVID-19, BED and VGS are planning to use benchmarking with comparative building types to better understand savings by controlling for occupancy changes that historical data would not be able to achieve.

Omega Grid

In a wholesale market system such as ISO-NE, under traditional utility rates (or even perhaps most rate structures), there are times where the marginal cost to serve retail load will exceed the retail revenues from that load. This pilot project combined price signals with the probability of occurrence of key cost causation events, customer baselining and optimization algorithms to allow customers to more intelligently choose when to use electricity, while still being served under a traditional rate structure.

BED worked alongside Omega Grid (OG) to design and deploy an opt-in blockchain market incentive program. The program encouraged residential, commercial, and industrial load reduction or generation in response to wholesale market cost drivers (including anticipated monthly peak-based transmission and annual peak-based capacity charges). The project ran for 12 months beginning in the fall of 2018 and concluding at the end of the 2019 summer.

This program allowed BED to avoid excess transmission, capacity, and energy charges on the wholesale market (ISO-NE). The majority of the value of the savings (70%) was allocated to customers participating in the program, 20% was retained as general system benefit, with the remaining peak savings getting passed to OG as performance payment for their work.

The customers received "tokens" for their load reduction or generation with an unalterable record on the OG private blockchain. After the ISO-NE savings had been calculated by BED (which occurred both monthly for energy and transmission based savings and annually for capacity based savings), BED allocated 70% of the dollar value of the savings to the token holders in proportion to the number of tokens they have earned. This credit created a pooled savings funds, which participants were entitled to proportional to the number of "tokens" they produced. The OG record along with other market information is auditable and visible by the other market participants.

Future expansion of this program structure could include more localized price signals such as costs related to constrained distribution areas. Additionally, it is possible that customers with emergency generation may be motivated to install emission controls sufficient to allow that generation to respond to these price signals if the price signals are strong enough.