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2016 Long-Term Electric Energy and Demand Forecast Report

Burlington Electric Department

Submitted to:

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May 19, 2016

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1 Overview

Burlington Electric Department (BED) serves approximately 20,500 electric customers in Burlington, Vermont. The service area includes a large commercial base with small and large commercial sales accounting for about 75 % of BED deliveries. BED has no significant industrial load. In 2015, total system deliveries (including losses) was 350,936 MWh (a 0.7% increase over 2014) with system peak reaching 64.7 MW.

Over the next ten years (2016 to 2026), energy deliveries are projected to average 0.3% annual growth. The system is expected to see relatively strong growth in 2017 to 2019 as a result of completion of several large construction projects. Over the twenty-year planning period, annual energy averages 0.2% annual growth and peak demand averages 0.1% average annual growth. Table 1-1 shows the BED energy and demand forecast.

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

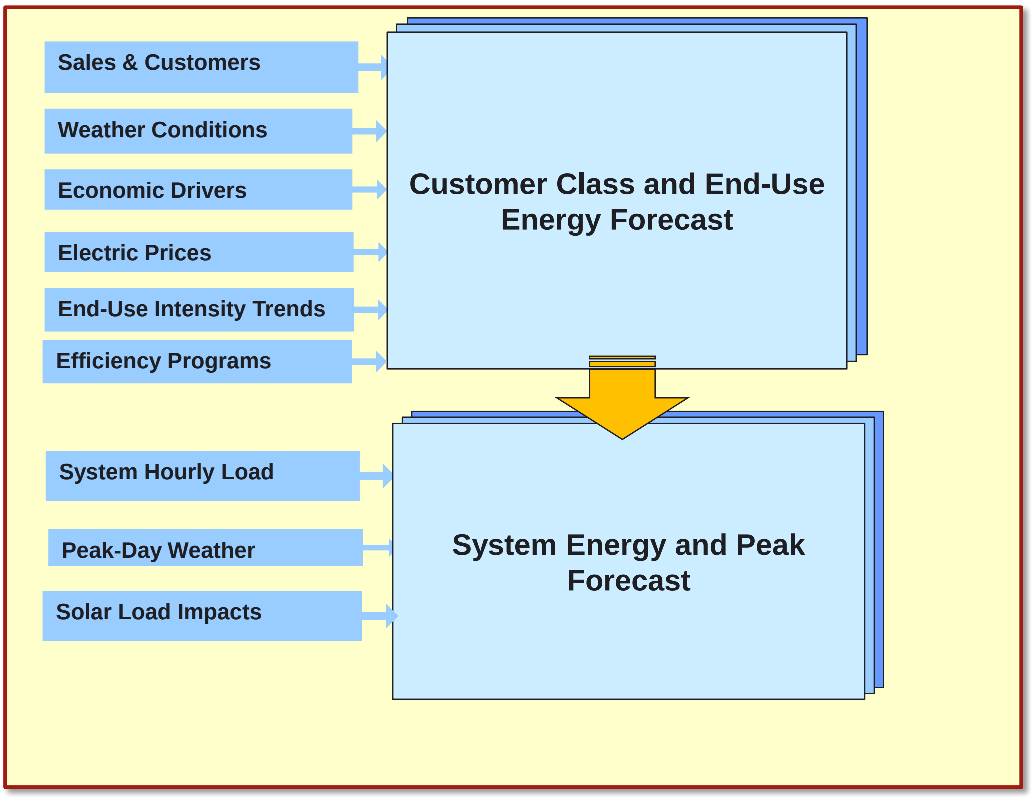
Year	Energy (MWh)	% Chg.	Sum Pk (MW)	% Chg.	WinPk (MW)	% Chg.
2006	369,591		72.3		53.7	
2007	375,232	1.5%	69.1	-4.4%	55.4	3.2%
2008	368,912	-1.7%	67.8	-1.9%	54.2	-2.2%
2009	356,422	-3.4%	64.9	-4.2%	54.9	1.3%
2010	358,868	0.7%	70.4	8.5%	52.2	-4.9%
2011	353,211	-1.6%	65.8	-6.6%	53.5	2.5%
2012	350,753	-0.7%	63.6	-3.3%	50.9	-4.9%
2013	349,150	-0.5%	67.2	5.6%	53.1	4.3%
2014	348,338	-0.2%	64.1	-4.6%	53.5	0.8%
2015	350,936	0.7%	64.7	0.9%	53.0	-0.9%
2016	346,108	-1.4%	66.9	3.4%	51.2	-3.4%
2017	357,437	3.3%	68.2	1.9%	52.3	2.1%
2018	362,158	1.3%	68.9	1.0%	53.1	1.5%
2019	365,460	0.9%	69.2	0.4%	53.6	0.9%
2020	364,091	-0.4%	68.7	-0.7%	54.0	0.7%
2021	361,111	-0.8%	68.2	-0.7%	53.7	-0.6%
2022	359,811	-0.4%	67.9	-0.4%	52.9	-1.5%
2023	358,922	-0.2%	67.6	-0.4%	53.2	0.6%
2024	359,314	0.1%	67.6	0.0%	52.9	-0.6%
2025	358,094	-0.3%	67.4	-0.3%	53.2	0.6%
2026	358,246	0.0%	67.5	0.1%	53.3	0.2%
2027	358,767	0.1%	67.5	0.0%	53.1	-0.4%
2028	360,058	0.4%	67.6	0.1%	52.6	-0.9%
2029	360,055	0.0%	67.6	0.0%	53.0	0.8%
2030	360,018	0.0%	67.6	0.0%	52.7	-0.6%
2031	360,326	0.1%	67.6	0.0%	53.0	0.6%
2032	361,395	0.3%	67.8	0.3%	53.4	0.8%
2033	361,053	-0.1%	67.7	-0.1%	52.7	-1.3%
2034	361,480	0.1%	67.7	0.0%	53.1	0.8%
2035	362,124	0.2%	67.8	0.1%	52.8	-0.6%
2036	363,674	0.4%	67.9	0.3%	53.1	0.6%
06-15		-0.6%		-1.2%		-0.1%
16-26		0.3%		0.1%		0.4%
16-36		0.2%		0.1%		0.2%

** Actual through 2015*

While the forecast methodology is the same, BED’s long-term sales growth is slightly stronger than GMP and VELCO. The primary reason is the mix of customer’s served. BED has a much larger commercial market share (which has the strongest class growth) and no industrial sales (which has tended to be the weakest state sector in terms of sales growth).

The long-term energy and demand forecast is developed using a “build-up” approach. This approach entails first developing class and end-use level sales forecasts from class-level sales and customer forecast models. Energy requirements are then derived by adjusting sales forecast for line losses. End-use energy estimates for heating, cooling, and other-use coupled with peak-day weather conditions drive system peak demand. Constructed forecast model variables capture improvements in end-use efficiency as well as the impact of economic activity and population projections, monthly and peak-day normal weather conditions, and electricity prices. The forecast also includes the impact of future energy efficiency (EE) program savings and solar load impacts. Figure 1 shows the general approach.

Figure 1: Class 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. Street light sales are forecasted using a simple trend and seasonal model. Table 1-2 shows customer class sales forecast.

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

Year	Residential	% Chg.	Commercial	% Chg.	Other	% Chg.	Total	% Chg.
2006	90,793		264,090		3,312		358,194	
2007	90,263	-0.6%	269,653	2.1%	3,051	-7.9%	362,967	1.3%
2008	87,703	-2.8%	267,434	-0.8%	3,052	0.0%	358,189	-1.3%
2009	85,222	-2.8%	256,442	-4.1%	3,053	0.0%	344,717	-3.8%
2010	85,311	0.1%	260,165	1.5%	3,053	0.0%	348,528	1.1%
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%	340,909	-0.6%
2013	85,320	2.1%	251,892	-1.0%	2,744	-7.2%	339,956	-0.3%
2014	83,404	-2.2%	253,271	0.5%	2,597	-5.4%	339,272	-0.2%
2015	83,177	-0.3%	257,445	1.6%	2,525	-2.8%	343,146	1.1%
2016	81,402	-2.1%	253,767	-1.4%	2,508	-0.7%	337,677	-1.6%
2017	83,652	2.8%	262,031	3.3%	2,554	1.8%	348,237	3.1%
2018	84,709	1.3%	265,556	1.3%	2,558	0.2%	352,823	1.3%
2019	84,715	0.0%	268,770	1.2%	2,547	-0.4%	356,031	0.9%
2020	84,025	-0.8%	268,135	-0.2%	2,529	-0.7%	354,689	-0.4%
2021	83,012	-1.2%	266,254	-0.7%	2,513	-0.6%	351,778	-0.8%
2022	82,427	-0.7%	265,584	-0.3%	2,498	-0.6%	350,509	-0.4%
2023	82,005	-0.5%	265,150	-0.2%	2,485	-0.5%	349,639	-0.2%
2024	82,014	0.0%	265,535	0.1%	2,473	-0.5%	350,022	0.1%
2025	81,406	-0.7%	264,960	-0.2%	2,462	-0.4%	348,828	-0.3%
2026	81,199	-0.3%	265,323	0.1%	2,452	-0.4%	348,974	0.0%
2027	81,160	0.0%	265,876	0.2%	2,443	-0.4%	349,479	0.1%
2028	81,433	0.3%	266,870	0.4%	2,434	-0.4%	350,737	0.4%
2029	81,353	-0.1%	266,949	0.0%	2,427	-0.3%	350,729	0.0%
2030	81,210	-0.2%	267,067	0.0%	2,413	-0.6%	350,689	0.0%
2031	81,191	0.0%	267,396	0.1%	2,400	-0.5%	350,988	0.1%
2032	81,466	0.3%	268,174	0.3%	2,389	-0.5%	352,029	0.3%
2033	81,386	-0.1%	267,927	-0.1%	2,378	-0.5%	351,691	-0.1%
2034	81,593	0.3%	268,143	0.1%	2,368	-0.4%	352,104	0.1%
2035	81,882	0.4%	268,487	0.1%	2,360	-0.3%	352,729	0.2%
2036	82,453	0.7%	269,434	0.4%	2,352	-0.3%	354,239	0.4%
06-15		-1.0%		-0.3%		-3.0%		-0.5%
16-26		0.0%		0.4%		-0.2%		0.3%
16-36		0.1%		0.3%		-0.3%		0.2%

** Includes impacts of projected PV installations.*

After adjusting for expected efficiency savings and new solar installations, total sales average 0.2% annual growth over the forecast period. There is a relatively large jump in residential sales in 2017 and 2018 as a result of the expected completion of a few large residential multi-family projects. Commercial sales are expected to average 0.3% annual growth through 2036. Expected near-term economic growth contributes to relatively strong sales growth through 2020.

The BED forecast approach is consistent with the approach used by VELCO and GMP in their most recent IRP filings. This approach has been vetted through the process of working with the Vermont Load Forecasting Sub-Committee (LFC). The LFC played a significant role in developing the VELCO forecast input and reviewing and recommending changes to the forecast methodology.

2 Forecast Data and Assumptions

2.1 Historical Class Sales and Energy Data

Forecast models are estimated for residential, commercial, and street lighting revenue classes. Linear regression models are estimated using historical monthly billing data that includes sales, customers, and revenue. The residential model is estimated using monthly billed sales, customer and price data for the period January 2006 to March 2016. Commercial and street light models are estimated using monthly billed sales data from January 2006 to March 2016.

System monthly energy and monthly peak demands are derived from historical hourly load data for the period January 1, 2006 to March 31, 2016. System energy is derived by applying average monthly loss factors to the monthly sales forecast and system peak demand is estimated using a linear regression model.

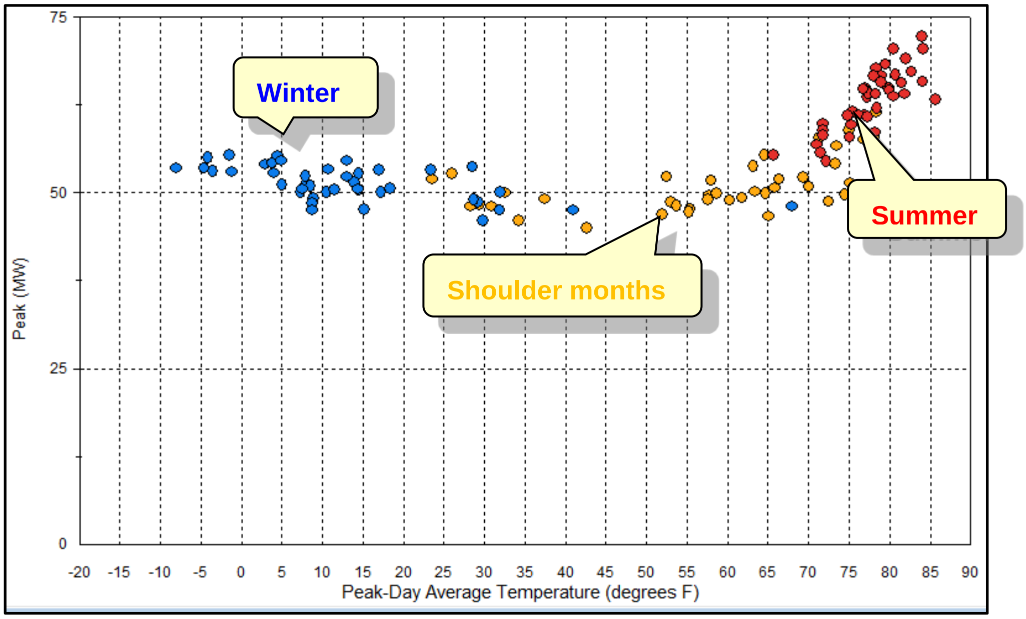
2.2 Weather Data

Historical and normal monthly HDD and CDD were provided by BED. Normal degree days are based on the 20-year period 1996 to 2015.

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

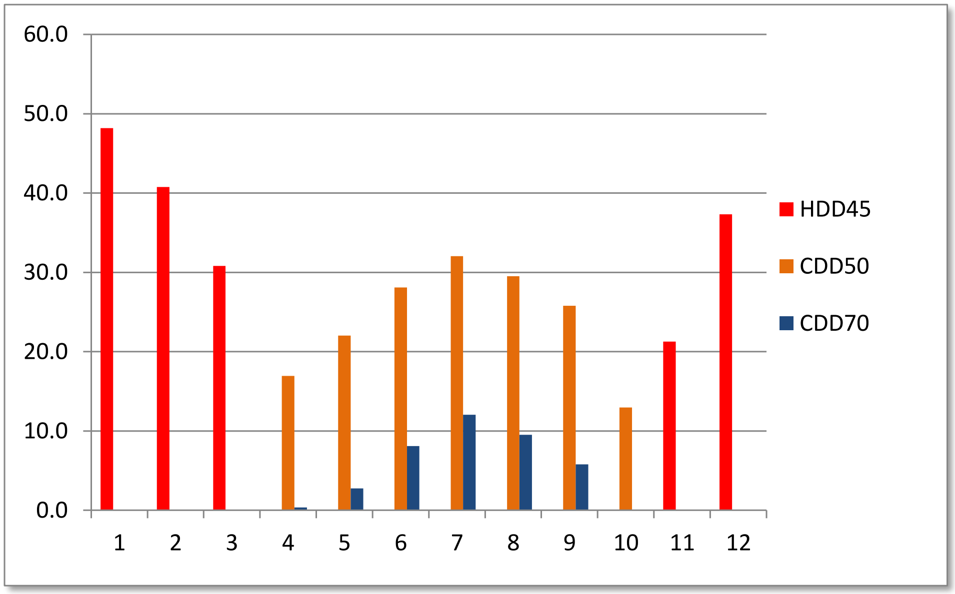


Winter peaks occur when temperatures are below 45 degrees and summer peaks occur when temperatures exceed 70. However, significant amount of cooling occurs during shoulder months and, to account for these, we used second cooling breakpoint accounting for the interval between 50 and 70 degrees. Monthly peak-day HDD and CDD are calculated for the estimation period – January, 2006 to March, 2016 based on these temperature breakpoints.

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 (1996 to 2015). 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* February 2016 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.

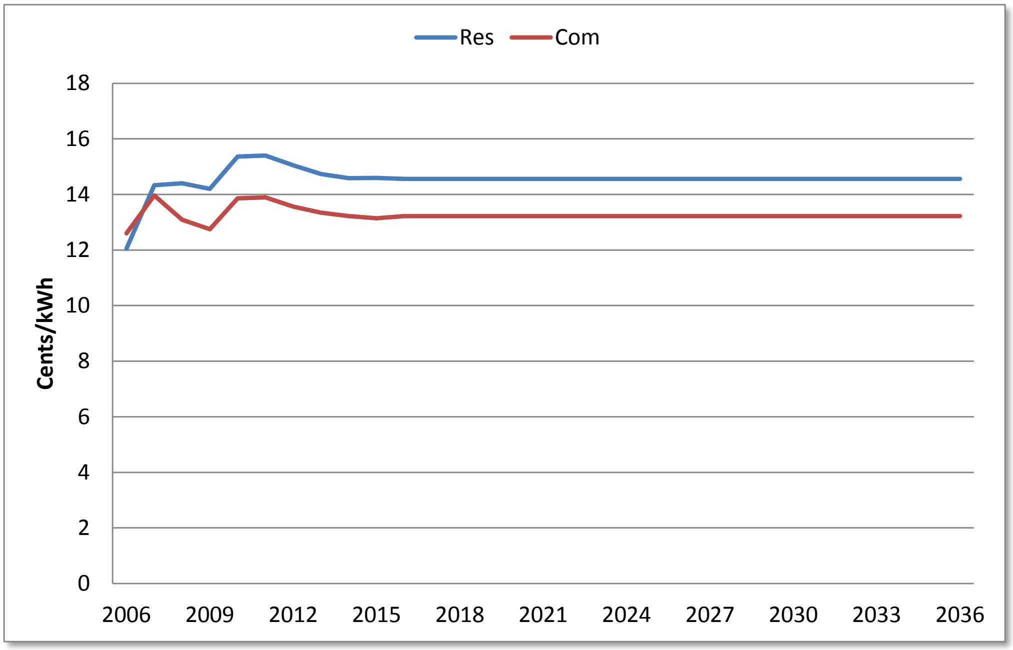
Table 2-1: Economic Forecast (Burlington MSA)

Year	HHs (thou)	% Chg	HHInc ($ thou)	% Chg	GDP ($ mil)	% Chg	Emp (thou)	% Chg
2006	80.8		107.1		9,959		116.0	
2007	81.5	0.8%	108.8	1.6%	9,900	-0.6%	116.8	0.7%
2008	82.2	0.9%	109.5	0.7%	10,127	2.3%	117.0	0.2%
2009	82.9	0.9%	106.5	-2.7%	10,009	-1.2%	114.5	-2.1%
2010	83.6	0.8%	106.3	-0.1%	10,513	5.0%	115.7	1.0%
2011	84.2	0.7%	111.8	5.1%	10,948	4.1%	117.8	1.8%
2012	84.8	0.7%	113.3	1.4%	11,210	2.4%	119.6	1.5%
2013	85.3	0.6%	112.7	-0.5%	11,015	-1.7%	120.5	0.8%
2014	85.4	0.2%	114.8	1.9%	11,125	1.0%	121.0	0.4%
2015	85.5	0.1%	117.5	2.4%	11,304	1.6%	123.5	2.1%
2016	86.0	0.5%	120.1	2.2%	11,633	2.9%	124.3	0.6%
2017	86.5	0.5%	121.9	1.4%	11,924	2.5%	125.6	1.0%
2018	86.9	0.6%	122.9	0.8%	12,126	1.7%	126.8	1.0%
2019	87.4	0.5%	123.5	0.5%	12,285	1.3%	127.7	0.7%
2020	87.8	0.4%	124.0	0.4%	12,412	1.0%	128.1	0.3%
2021	88.1	0.4%	124.7	0.6%	12,562	1.2%	128.5	0.3%
2022	88.5	0.4%	125.5	0.7%	12,731	1.3%	129.1	0.5%
2023	88.8	0.4%	126.4	0.7%	12,903	1.3%	129.7	0.5%
2024	89.2	0.4%	127.2	0.7%	13,076	1.3%	130.3	0.5%
2025	89.5	0.4%	128.1	0.7%	13,251	1.3%	130.9	0.5%
2026	89.9	0.4%	129.0	0.7%	13,435	1.4%	131.5	0.5%
2027	90.3	0.4%	130.0	0.8%	13,633	1.5%	132.2	0.5%
2028	90.6	0.4%	131.0	0.8%	13,839	1.5%	133.0	0.6%
2029	91.0	0.4%	132.1	0.8%	14,048	1.5%	133.8	0.6%
2030	91.4	0.4%	133.1	0.8%	14,264	1.5%	134.6	0.6%
2031	91.7	0.4%	134.2	0.8%	14,482	1.5%	135.5	0.7%
2032	92.1	0.4%	135.4	0.9%	14,708	1.6%	136.4	0.7%
2033	92.4	0.4%	136.6	0.9%	14,943	1.6%	137.3	0.7%
2034	92.8	0.4%	137.9	0.9%	15,185	1.6%	138.2	0.7%
2035	93.1	0.4%	139.2	1.0%	15,441	1.7%	139.2	0.7%
2036	93.4	0.4%	140.6	1.0%	15,707	1.7%	140.2	0.7%
06-15		0.6%		1.1%		1.4%		0.7%
16-26		0.4%		0.7%		1.5%		0.6%
16-36		0.4%		0.8%		1.5%		0.6%

2.4 Price Data

Historical prices (real dollars) are derived from historical billed sales and revenue data. 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 class.

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

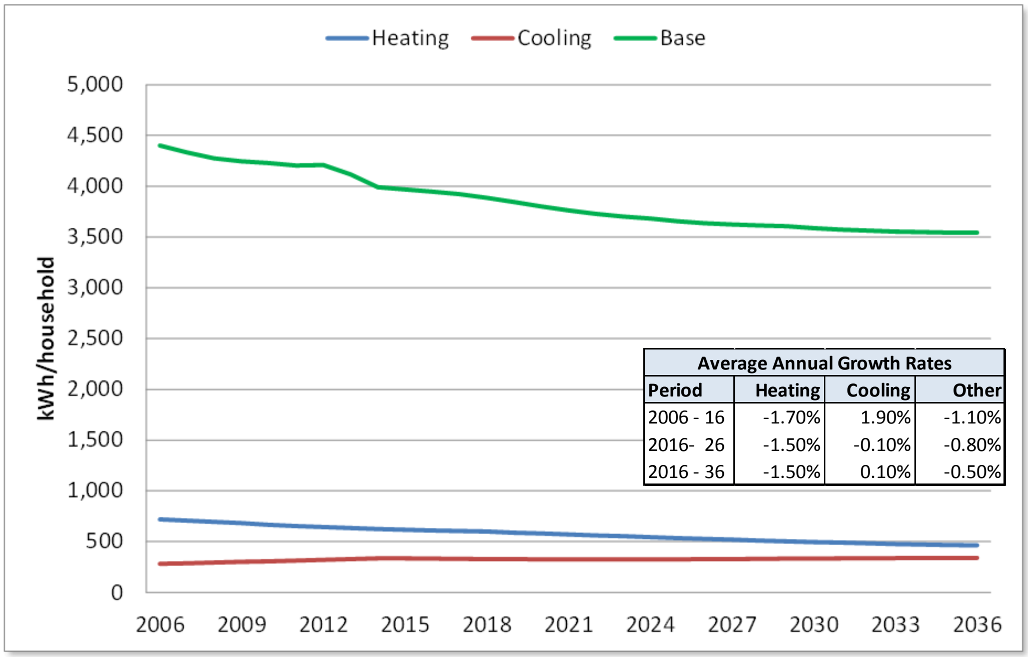


2.5 Appliance Saturation and Efficiency Trends

Over the long-term, changes in end-use saturation and stock efficiency impact class sales, system energy, and peak demand. End-use energy intensities (expressed in kWh per household) are derived from saturation and efficiency projections and are explicitly captured in the forecast model variables. The residential sector incorporates saturation and efficiency trends for seventeen end-uses. The commercial sector captures end-use intensity projections for ten end-use classifications across ten building types. Residential end-use efficiency and commercial end-use intensity projections are derived from the Energy Information Administration's (EIA) 2015 New England Census Division forecast. EIA saturation projections are adjusted to reflect BED residential appliance saturation surveys and mix of multi-family and single-family homes.

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 (use per household) are aggregated into three generalized end-use - heating, cooling, and other use. Figure 5 shows the resulting aggregated end-use intensity projections.

Figure 5: Residential End-Use Energy Intensities

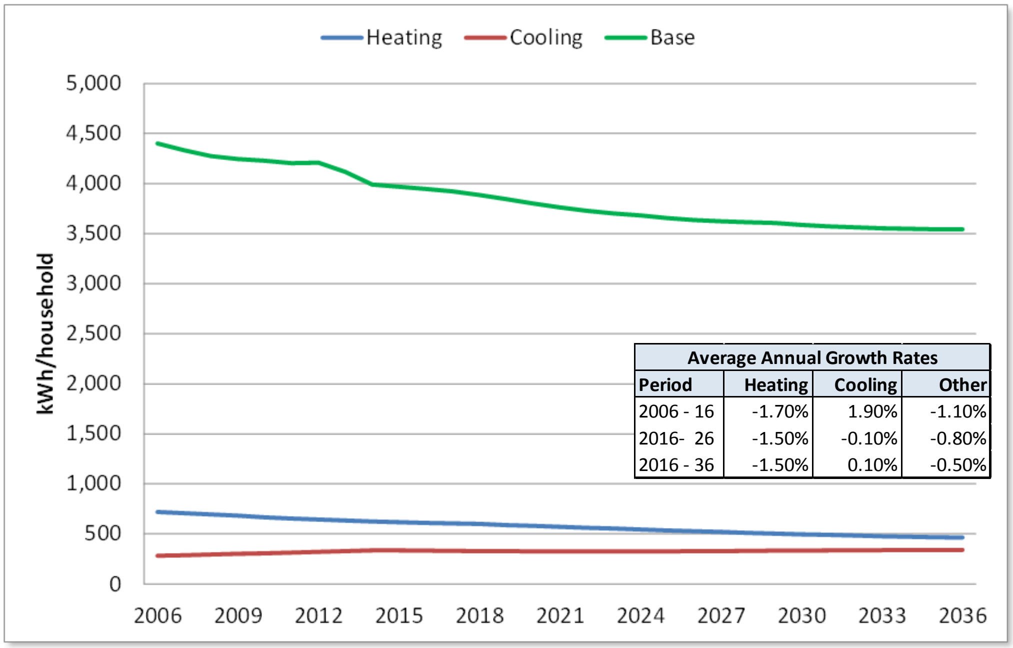


** Incorporates impact of BED Funded EE Programs*

The heating intensity declines 1.5% annually through the forecast period reflecting declining share in electric heat saturation. Through 2016, BED experienced strong growth in cooling intensity averaging 1.9% 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 sq. ft.) 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.

Adjusting for EE Program Impacts

End-use intensity projections are adjusted for the impact of future EE program impacts. Adjusted residential end-use intensities include heating, cooling, water heating, refrigeration, kitchen and laundry, and lighting, and miscellaneous use. To avoid "double-counting" EE savings projections (other than lighting) are adjusted to reflect future EE savings embedded in the baseline sales forecast. The EE adjustment factor is estimated by incorporating historical EE savings as a model variable. In the residential model the EE savings variable is statistically significant with a coefficient of -0.187 indicating that 81.3% (1-.187) of future efficiency savings is embedded in the model; the EE adjustment factor is 0.187. EE lighting savings are not adjusted. The lighting program is a new technology program promoting LED lighting. As there is likely no significant LED lighting yet in the historical sales data (and as result the forecast model) double-counting future LED program savings is not an issue yet. With adjustments for EE programs total residential intensity (kWh per household) averages 0.6% annual decline over the forecast period.

The estimated commercial EE adjustment factor is 0.301. The adjustment factor is calculated from the commercial sales forecast model where historical commercial EE program savings are included as a model variable. Results indicate that 70% of future EE program savings are already captured by the baseline forecast. Commercial end-use intensities that are adjusted for EE program impacts include heating, cooling, ventilation, refrigeration, and miscellaneous use. With adjustments for future EE programs, total commercial building energy intensity (kWh per sq. ft.) declines 0.7% annually through the forecast period.

2.6 Emerging Technologies

Emerging technologies such as photovoltaic (PV) systems, electric vehicles, cold climate heat pumps, energy storage, and other fuel switching technology will likely reshape future demand. The base case forecast incorporates just the impact of expected PV adoption as there has been enough historical adoption to reasonably model and forecast future adoptions. Other emerging technologies where there is little historical adoption data are addressed in other sections in the IRP report.

Compared with the rest of state, photovoltaic (PV) saturation is relatively small. There are currently about 90 residential and 30 commercial solar accounts. Limited market penetration likely reflects the large share of the multifamily housing stock, large rental market, historic structures, limited open land, limited commercial rooftop space and commercial market hurdles (property ownership vs. leasing and customer business opportunity costs). Even given these restraints we expect to see additional solar load growth as a result of declining PV system costs, coupled with federal tax credit, net metering treatment, and state solar generation incentives. A simple payback model is used to project PV growth. The underlying logic is that adoption is driven by customer's return on investment with simple payback being a close proxy. The model is described in detail in the Methodology Section. Based on system cost and electricity price projections, PV saturation is projected to increase from 0.5% to over 2.0% of the homes by 2036. Installed commercial solar systems increase from 0.8% of the commercial customers to 1.9% in 2036. PV capacity projections are based on system average size. Capacity is then translated into monthly generation forecasts from solar profile forecast derived from metered PV hourly load. The demand impact is calculated by subtracting the PV generation hourly load forecast from the system hourly load forecast. The impact on demand is relatively small as the primary impact of increase in solar load is to shift the system peak (which occurs in the summer) to later in the day.

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.

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)

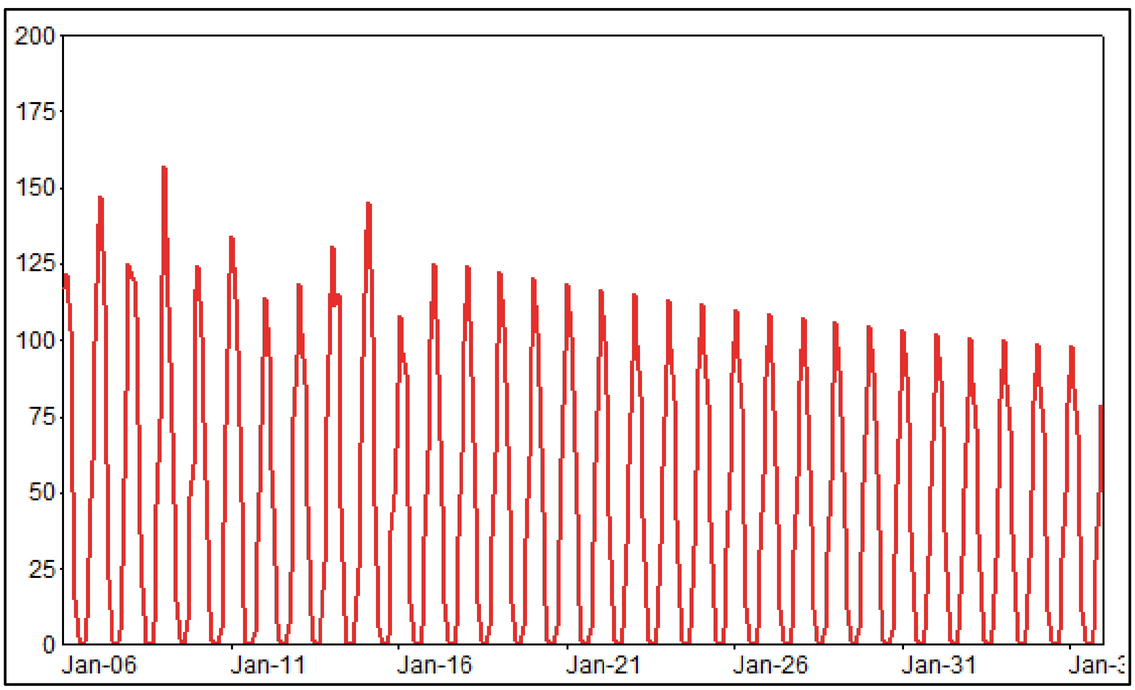


Figure 8: Residential *XCool* (kWh per month)

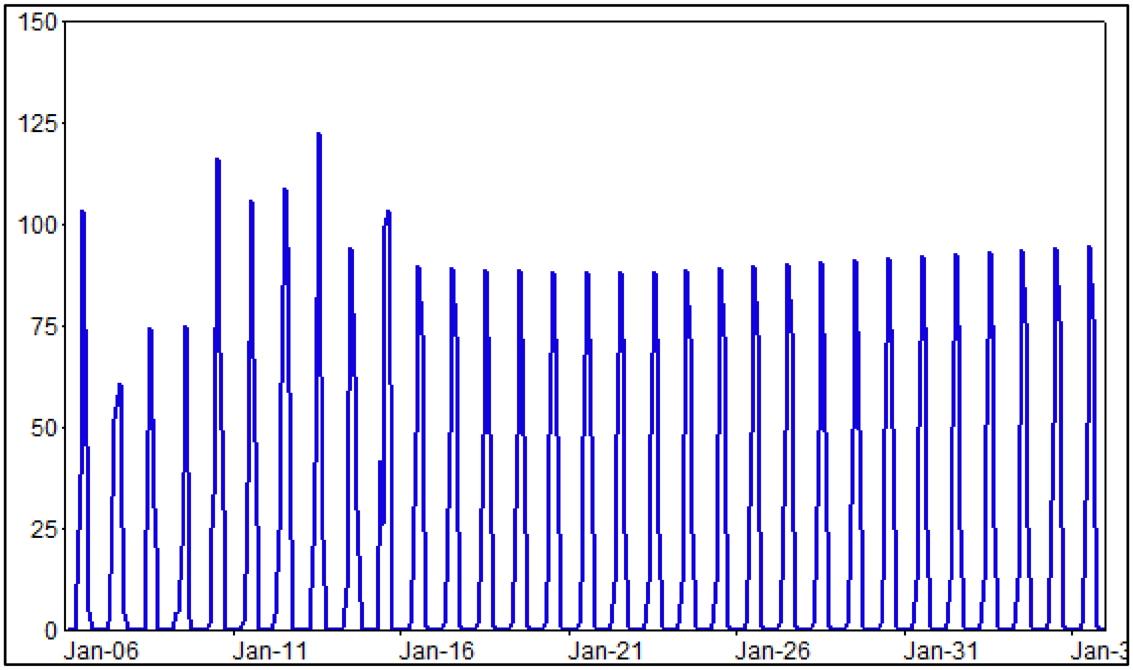
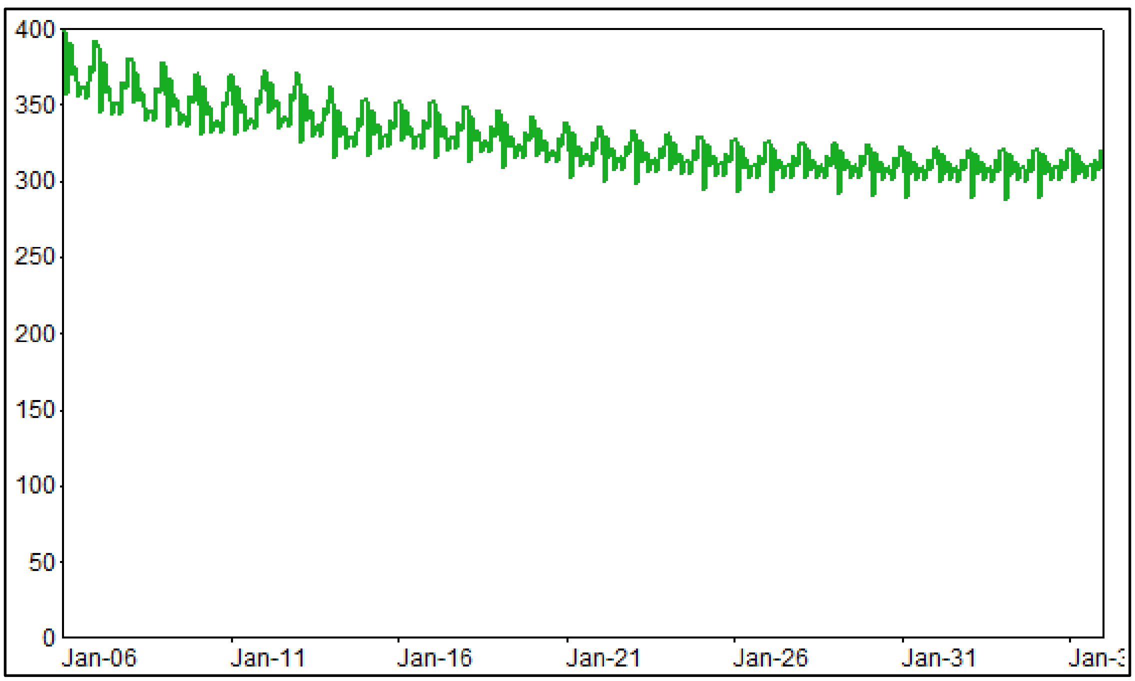
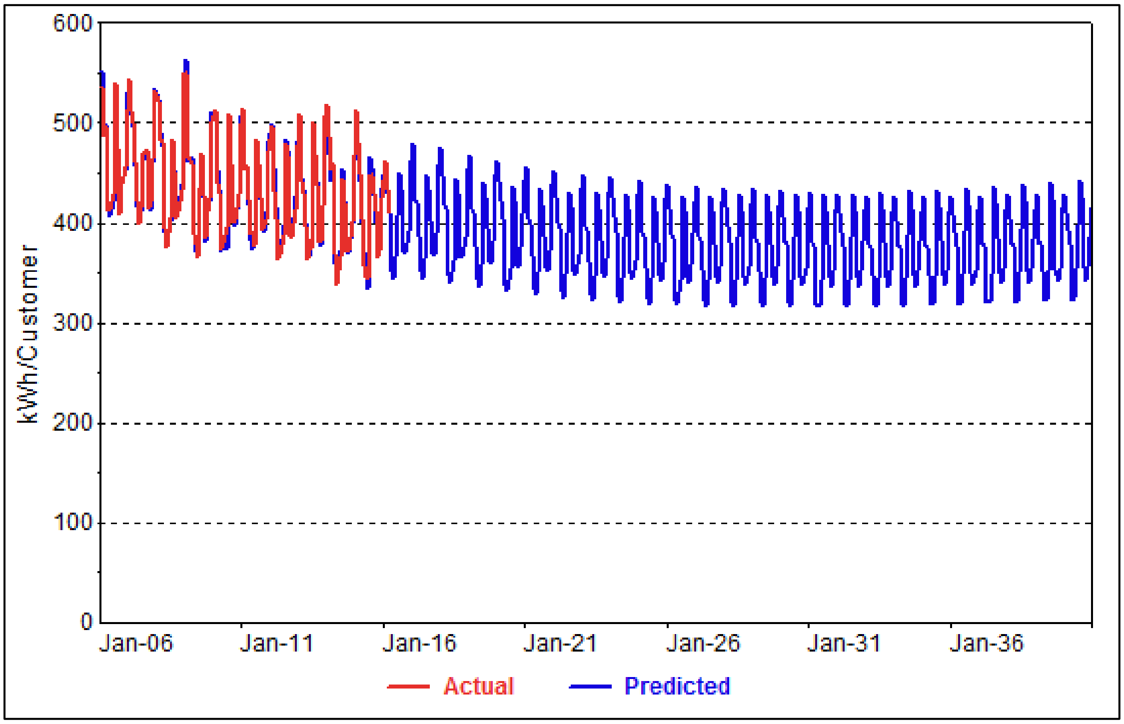


Figure 9: Residential *XOther* (kWh per month)



The average use model is estimated over the period January 2006 through March 2016. 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 over 1.0% per years over the last ten years. It is projected to decline further in the forecast period, albeit at a slightly slower rate. This is largely due to the continuing phase-out of the most common types of incandescent light bulbs mandated by the Energy Independence and Security Act (EISA) and new end-use efficiency standards recently put in place by the Department of Energy. Average use begins to decrease at a slightly slower rate in the later years as the EIA baseline intensity projections only include those end-use 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. Stronger average customer growth rate in the period

2016-26 is explained largely by the completion of construction projects that are expected to add almost a thousand new customers over 2017-19.

Table 3-1 summarizes the residential forecast, before applying impacts from new solar installations. With 0.9% decrease in average use and 0.8% increase in customer growth, total residential sales average -0.1% decrease between 2016 and 2026.

Table 3-1: Residential Forecast

Year	Sales (MWh)	% Chg.	Customers	% Chg.	Avg Use (kWh)	% Chg.
2006	90,793		16,197		5,606	
2007	90,263	-0.6%	16,210	0.1%	5,568	-0.7%
2008	87,703	-2.8%	16,265	0.3%	5,392	-3.2%
2009	85,222	-2.8%	16,293	0.2%	5,231	-3.0%
2010	85,311	0.1%	16,308	0.1%	5,231	0.0%
2011	84,817	-0.6%	16,350	0.3%	5,187	-0.8%
2012	83,579	-1.5%	16,502	0.9%	5,065	-2.4%
2013	85,320	2.1%	16,634	0.8%	5,129	1.3%
2014	83,404	-2.2%	16,737	0.6%	4,983	-2.8%
2015	83,177	-0.3%	16,763	0.2%	4,962	-0.4%
2016	81,461	-2.1%	16,802	0.2%	4,848	-2.3%
2017	83,847	2.9%	17,290	2.9%	4,850	0.0%
2018	85,045	1.4%	17,699	2.4%	4,805	-0.9%
2019	85,143	0.1%	17,928	1.3%	4,749	-1.2%
2020	84,585	-0.7%	17,977	0.3%	4,705	-0.9%
2021	83,667	-1.1%	18,021	0.2%	4,643	-1.3%
2022	83,137	-0.6%	18,065	0.2%	4,602	-0.9%
2023	82,761	-0.5%	18,107	0.2%	4,571	-0.7%
2024	82,819	0.1%	18,150	0.2%	4,563	-0.2%
2025	82,256	-0.7%	18,195	0.2%	4,521	-0.9%
2026	82,096	-0.2%	18,239	0.2%	4,501	-0.4%
2027	82,104	0.0%	18,284	0.2%	4,490	-0.2%
2028	82,425	0.4%	18,329	0.2%	4,497	0.1%
2029	82,390	0.0%	18,375	0.3%	4,484	-0.3%
2030	82,293	-0.1%	18,422	0.3%	4,467	-0.4%
2031	82,320	0.0%	18,468	0.2%	4,458	-0.2%
2032	82,645	0.4%	18,512	0.2%	4,464	0.2%
2033	82,606	0.0%	18,554	0.2%	4,452	-0.3%
2034	82,858	0.3%	18,595	0.2%	4,456	0.1%
2035	83,192	0.4%	18,637	0.2%	4,464	0.2%
2036	83,811	0.7%	18,677	0.2%	4,487	0.5%
06-15		-1.0%		0.4%		-1.3%
16-26		0.1%		0.8%		-0.7%
16-36		0.1%		0.5%		-0.4%

** Prior to adjustments for future PV installations.*

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

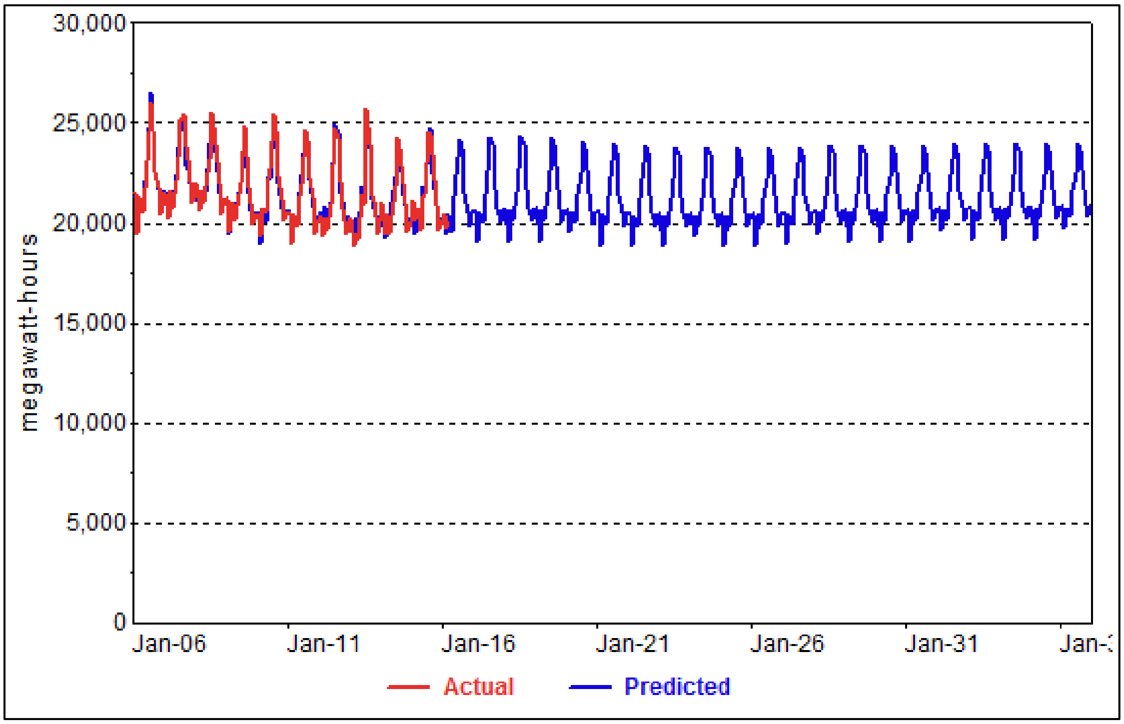
Output and employment are combined through a weighted economic variable where *ComVar* is defined as:

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

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 1.4%. Figure 11 shows actual and predicted monthly commercial energy.

Figure 11: Actual and Predicted Commercial Sales (MWh)



Commercial sales growth averages 0.3% per year through 2026, as economic growth projections are relatively modest through this period. Real output is projected to increase at 1.5% with employment increasing 0.6%. 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 final commercial forecast, before applying impacts from new solar installations.

Table 3-2: Commercial Forecast

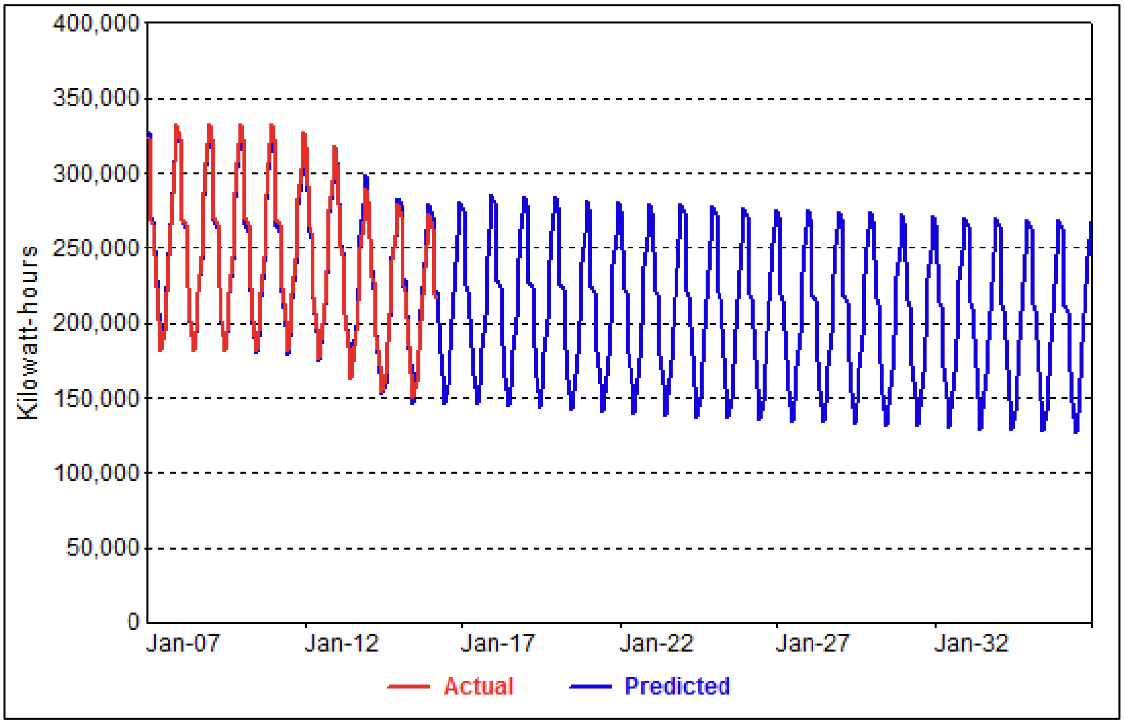
Year	Sales (MWh)	% Chg.	Customers	% Chg.	Avg Use (kWh)	% Chg.
2006	264,090		3,656		72,244	
2007	269,653	2.1%	3,712	1.5%	72,650	0.6%
2008	267,434	-0.8%	3,693	-0.5%	72,415	-0.3%
2009	256,442	-4.1%	3,725	0.9%	68,842	-4.9%
2010	260,165	1.5%	3,742	0.4%	69,530	1.0%
2011	255,031	-2.0%	3,737	-0.1%	68,239	-1.9%
2012	254,374	-0.3%	3,814	2.0%	66,704	-2.2%
2013	251,892	-1.0%	3,780	-0.9%	66,631	-0.1%
2014	253,271	0.5%	3,821	1.1%	66,288	-0.5%
2015	257,445	1.6%	3,829	0.2%	67,233	1.4%
2016	254,049	-1.3%	3,846	0.4%	66,054	-1.8%
2017	262,550	3.3%	3,862	0.4%	67,979	2.9%
2018	266,257	1.4%	3,878	0.4%	68,651	1.0%
2019	269,590	1.3%	3,890	0.3%	69,296	0.9%
2020	269,119	-0.2%	3,896	0.1%	69,078	-0.3%
2021	267,357	-0.7%	3,901	0.1%	68,533	-0.8%
2022	266,756	-0.2%	3,909	0.2%	68,241	-0.4%
2023	266,381	-0.1%	3,917	0.2%	68,002	-0.3%
2024	266,829	0.2%	3,925	0.2%	67,977	0.0%
2025	266,311	-0.2%	3,934	0.2%	67,698	-0.4%
2026	266,733	0.2%	3,943	0.2%	67,653	-0.1%
2027	267,347	0.2%	3,952	0.2%	67,647	0.0%
2028	268,405	0.4%	3,962	0.3%	67,744	0.1%
2029	268,541	0.1%	3,973	0.3%	67,593	-0.2%
2030	268,721	0.1%	3,985	0.3%	67,440	-0.2%
2031	269,113	0.1%	3,997	0.3%	67,334	-0.2%
2032	269,956	0.3%	4,009	0.3%	67,345	0.0%
2033	269,765	-0.1%	4,021	0.3%	67,092	-0.4%
2034	270,043	0.1%	4,034	0.3%	66,950	-0.2%
2035	270,449	0.2%	4,047	0.3%	66,826	-0.2%
2036	271,463	0.4%	4,061	0.4%	66,839	0.0%
06-15		-0.3%		0.5%		-0.8%
16-26		0.5%		0.2%		0.2%
16-36		0.3%		0.3%		0.0%

** Prior to adjustments for future PV installations.*

3.1.3 Street Lighting Sales

Street light sales are fitted with 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 street lights.

Figure 12: Actual and Predicted Street Lighting Sales (kWh)



3.2 Solar Forecast

The BED energy and peak forecast incorporates the impact of expected photovoltaic adoption. Although relatively small in magnitude compared to the rest of Vermont, BED has experienced a steady growth in the number and size of photovoltaic systems over the past 5 years. This growth is only expected to continue and increase as solar system costs continue to decline. Additionally two recent policy changes, the extension of the Federal Investment Tax Credit (ITC) and the proposed removal of Vermont's Net Metering Cap, should promote greater solar adoption.

3.2.1 Market Share Model

For the solar forecast, we assume that the primary factor driving system adoption is the favorable economics from the customers' perspective that result in reduced energy costs. We use simple payback as a proxy for customer's net savings (annual savings less system costs). The 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. The payback calculation is a function of the total installed cost, annual savings from reduced energy bills, and incentive payment for generated power.

The most significant factor driving the payback trend downwards are system costs (expressed on an installed dollar per watt basis). System costs have been declining rapidly over the last five years. In 2010 the average residential solar system cost $6.37 per watt; by 2015 costs have dropped to $3.55 per watt. For the forecast we assume that system costs continue to decline 10% annually through 2021, at which point costs continue to decline at 3% a year.

The market penetration model relates the share of customers that have adopted solar systems to simple payback, payback squared, and payback cubed. A cubic model specification is chosen to impose an S-shaped adoption curve. Figure 13 and Figure 14 show the resulting market share forecast for the residential class and commercial classes

Figure 13: Residential Solar Share Forecast

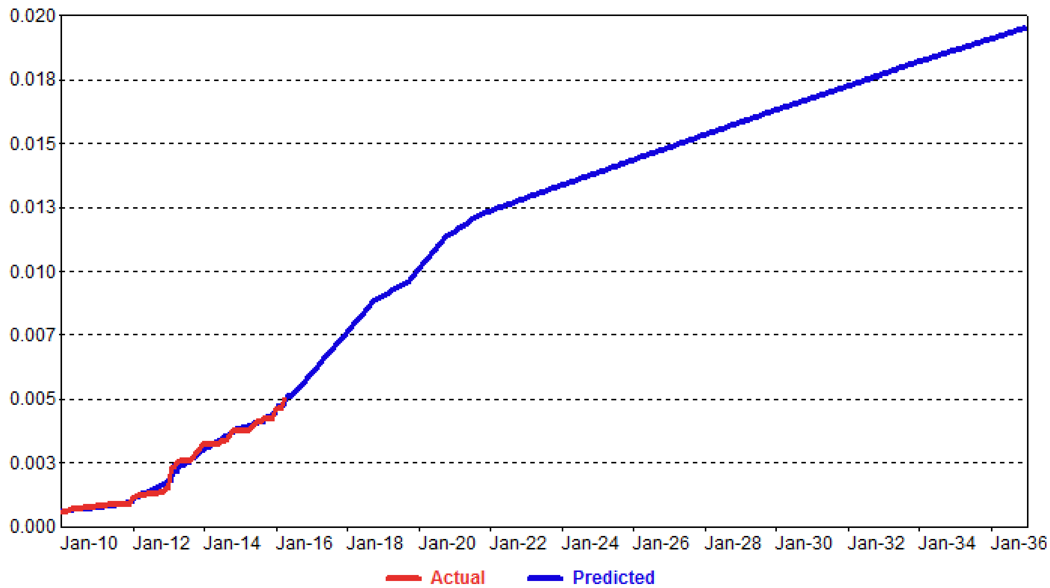
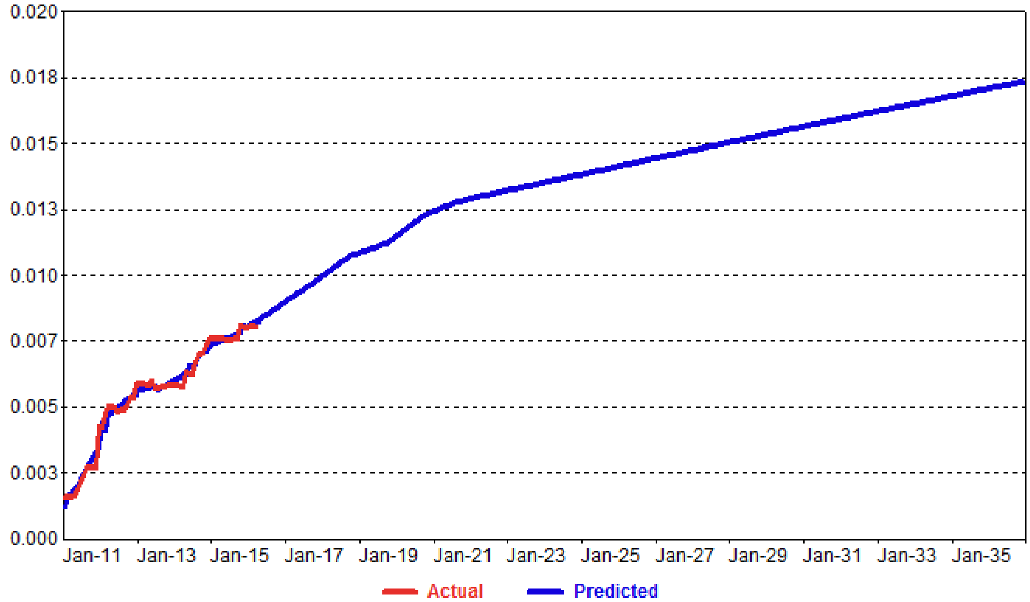


Figure 14: Commercial Solar Share Forecast



As of March 2016 there were 84 residential and 31 commercial solar customer accounts, which amount to a 0.5% and 0.8% market share. With continued declining system costs and continued incentives the residential share doubles within three years. The commercial solar share continues to grow but is limited by factors such as building ownership restrictions. Table 3-3 shows the solar share and resulting solar customer forecast.

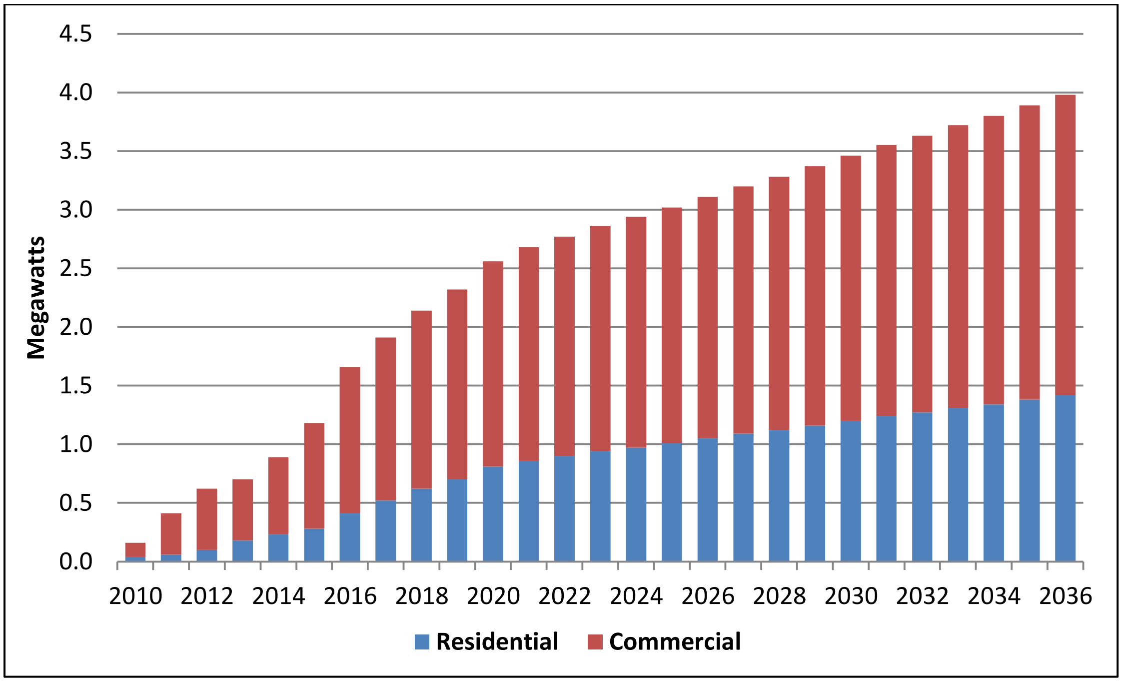
Table 3-3: Solar Customer Forecast

Year	Residential	Share of Total	Commercial	Share of Total
2010	11	0.1%	4	0.1%
2011	14	0.1%	9	0.2%
2012	21	0.1%	19	0.5%
2013	45	0.3%	22	0.6%
2014	57	0.3%	25	0.7%
2015	68	0.4%	30	0.8%
2016	89	0.5%	33	0.9%
2017	115	0.7%	37	1.0%
2018	142	0.8%	41	1.1%
2019	161	1.0%	44	1.1%
2020	186	1.1%	48	1.2%
2021	205	1.2%	51	1.3%
2022	215	1.3%	53	1.4%
2023	225	1.3%	54	1.4%
2024	234	1.4%	56	1.4%
2025	243	1.4%	57	1.5%
2026	252	1.5%	58	1.5%
2027	261	1.5%	60	1.5%
2028	271	1.6%	61	1.6%
2029	280	1.6%	63	1.6%
2030	289	1.7%	64	1.6%
2031	298	1.7%	66	1.6%
2032	307	1.8%	67	1.7%
2033	316	1.8%	69	1.7%
2034	324	1.8%	70	1.7%
2035	333	1.9%	72	1.8%
2036	342	1.9%	73	1.8%

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 4.1 KW for residential systems and 36.3 KW for commercial systems. Figure 15 shows the installed solar capacity forecast.

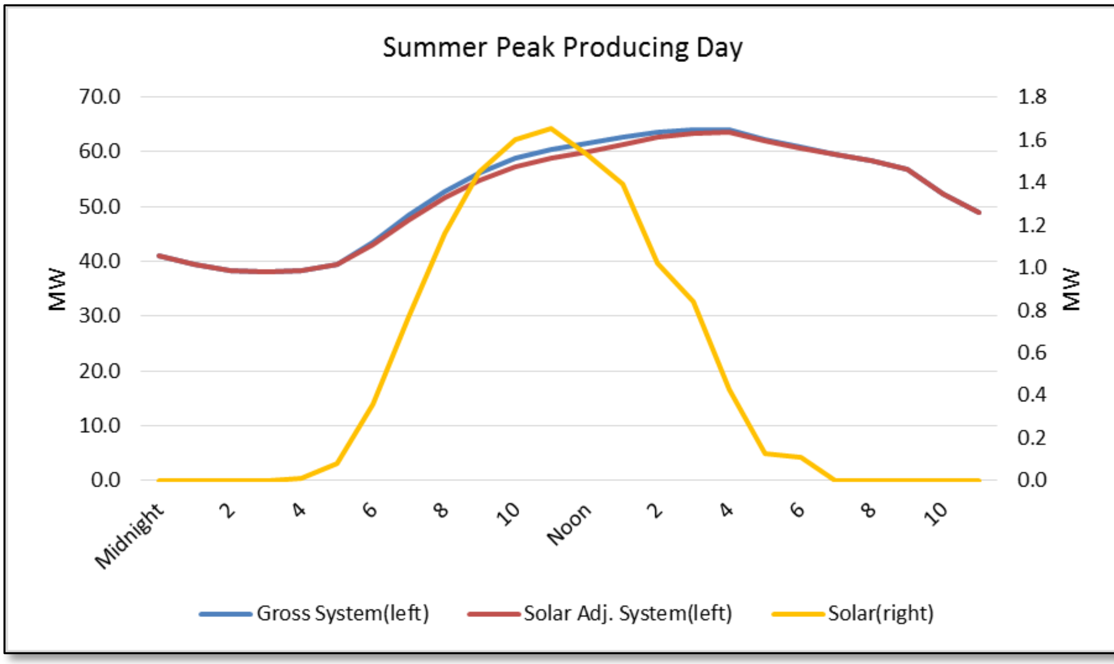
Figure 15: Solar Capacity Forecast



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 sales forecasts are adjusted for incremental new solar generation beginning in March 2016.

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 4 MW by 2036, solar load reduces system peak demand by only 1.3 MW. Given the system profile are relatively flat, solar generation effectively just shifts the peak 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 16 shows the gross system profile, solar adjusted system profile, and solar profile for a peak producing summer day.

Figure 16: Solar Hourly Load Impact



Based on system profile and solar load profile, a MW of PV capacity reduces summer peak demand by 0.33 MW. This adjustment factor is applied to the PV capacity forecast to yield the summer peak demand 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, expected annual generation, and demand impacts given the PV solar load profile.

Table 3-4: Solar Capacity and Generation

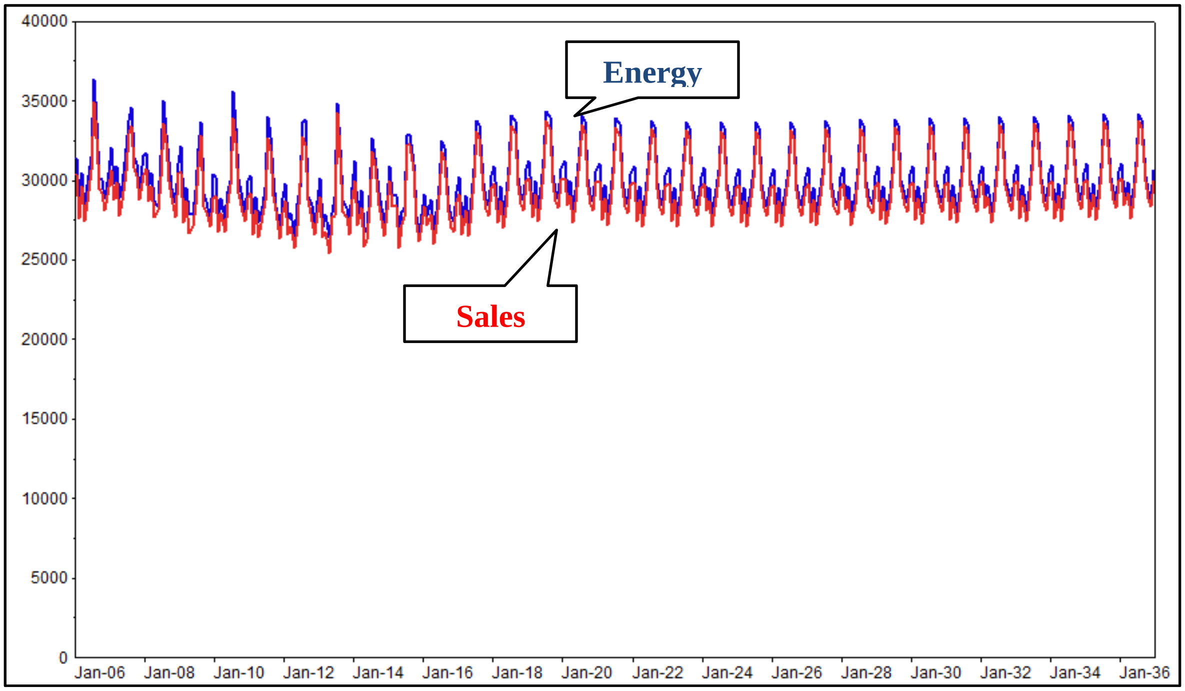
Year	Installed Capacity MW (Jul)	Generation MWh	Peak Demand Impact MW
2010	0.1	98	0.0
2011	0.3	280	0.1
2012	0.5	586	0.2
2013	0.7	828	0.2
2014	0.8	954	0.3
2015	0.9	1,175	0.3
2016	1.6	1,853	0.5
2017	1.8	2,226	0.6
2018	2.1	2,549	0.7
2019	2.2	2,761	0.7
2020	2.5	3,060	0.8
2021	2.6	3,270	0.9
2022	2.7	3,394	0.9
2023	2.8	3,500	0.9
2024	2.9	3,615	1.0
2025	3.0	3,713	1.0
2026	3.1	3,819	1.0
2027	3.2	3,927	1.0
2028	3.3	4,044	1.1
2029	3.3	4,141	1.1
2030	3.4	4,250	1.1
2031	3.5	4,358	1.2
2032	3.6	4,476	1.2
2033	3.7	4,571	1.2
2034	3.8	4,677	1.2
2035	3.9	4,784	1.3
2036	3.9	4,902	1.3

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 *calendar* sales forecast. The energy adjustment factor includes line losses and any differences in timing between monthly sales estimates and delivered energy (*unaccounted for energy*). Monthly adjustment factors are calculated as the average monthly ratio of energy to sales. Figure 17 shows the resulting monthly sales and energy forecast.

Figure 17: Long-Term Energy and Sales Forecast (MWh)



3.3.2 Peak Forecast

The long-term system peak forecast is derived through 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 driven by customer growth, economic activity, changes in end-use saturation, and improving end-use efficiency. These factors are captured in the class sales forecast models. The composition of the models allows us to estimate historical and forecasted heating and cooling load requirement.

The 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 us 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.

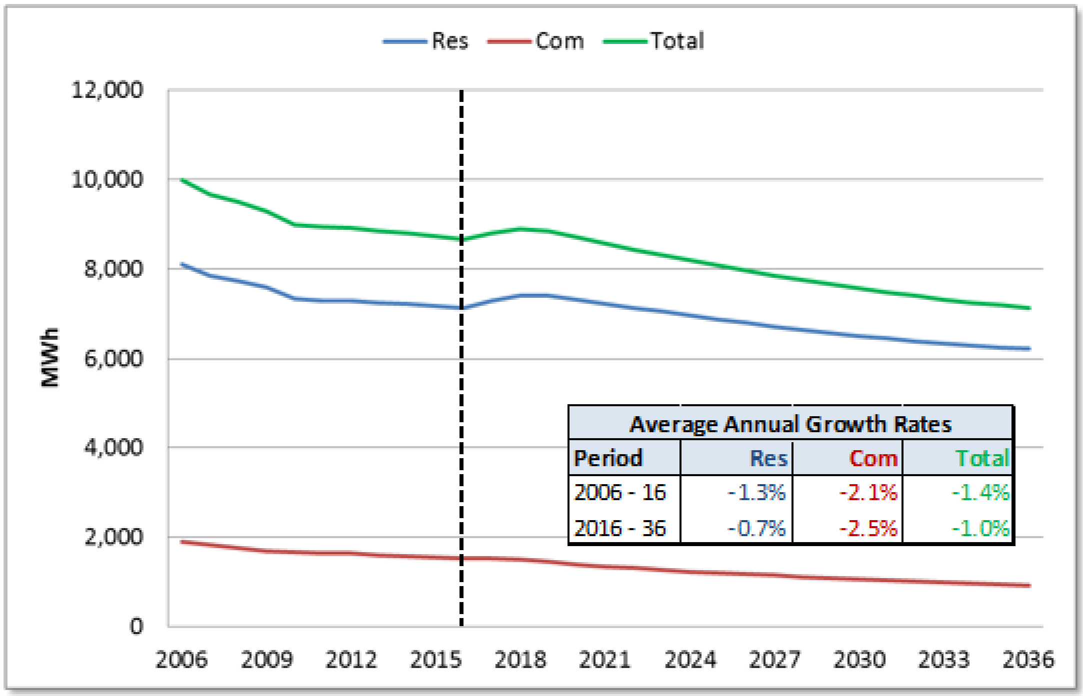
Cooling requirements are estimated in a similar manner:

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

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

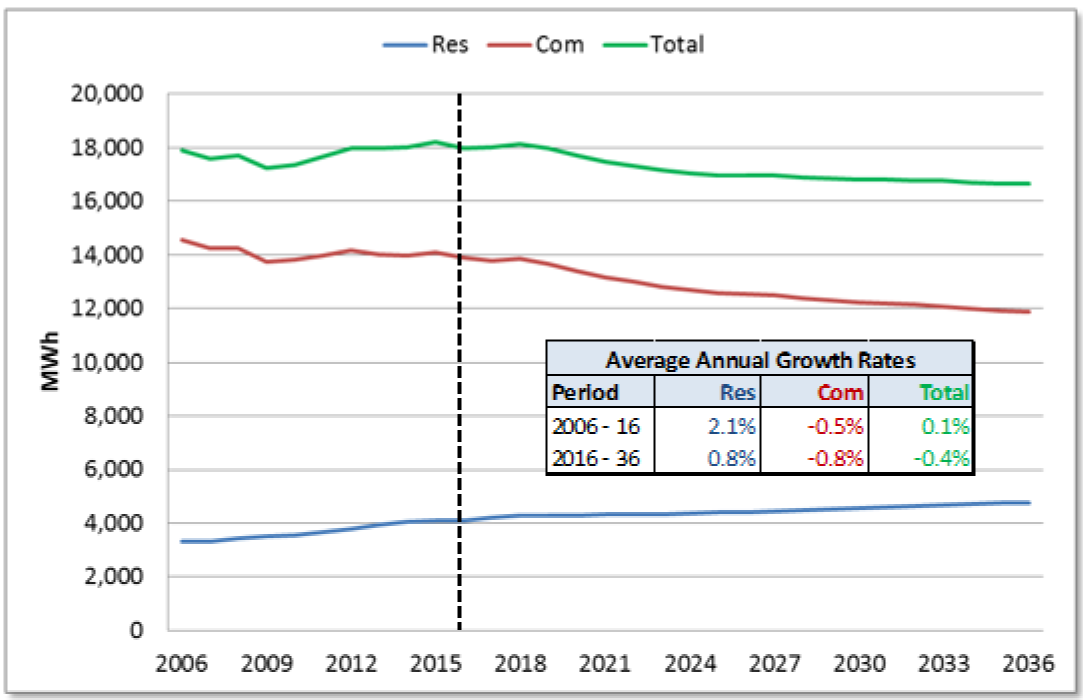
Figure 18 and Figure 19 show resulting historical (weather normalized) and forecasted heating and cooling load requirements.

Figure 18: Annual Heating Load (MWh)



Average Annual Growth Rates			
Period	Res	Com	Total
2006 - 16	-1.3%	-2.1%	-1.4%
2016 - 36	-0.7%	-2.5%	-1.0%

Figure 19: Annual Cooling Load (MWh)



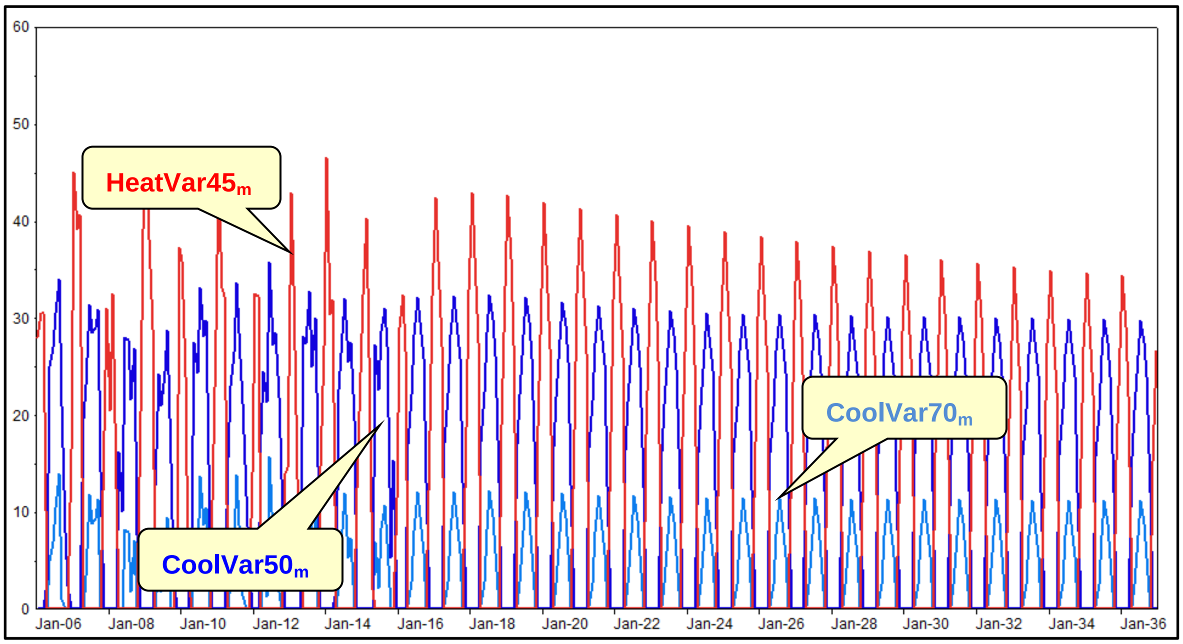
Average Annual Growth Rates			
Period	Res	Com	Total
2006 - 16	2.1%	-0.5%	0.1%
2016 - 36	0.8%	-0.8%	-0.4%

The impact of peak-day weather conditions is captured by interacting peak-day HDD and CDD with monthly heating and cooling load requirements indexed to a base year (2006). 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 20 shows the resulting peak model heating and cooling variables.

Figure 20: 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:

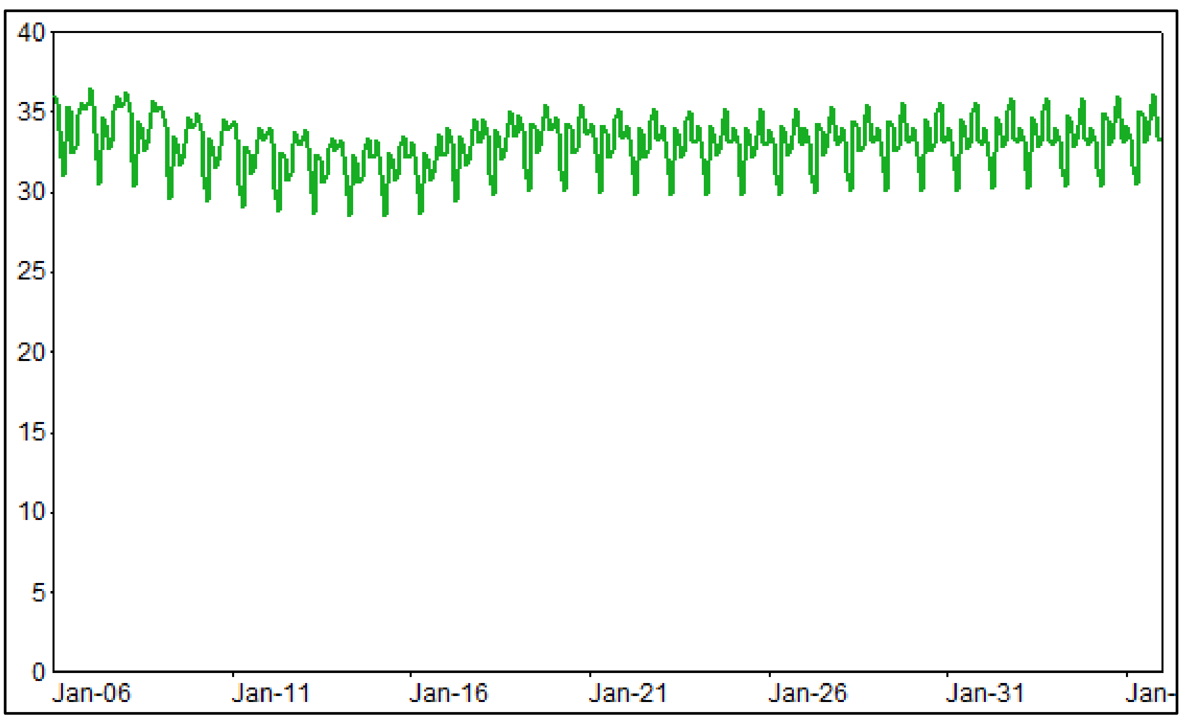
$$ResWaterCP_m = ResBaseLoad_a \times \left({ResWaterEI_a}/{ResBaseEI_a} \right) \times ResWaterFrac_m$$

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 21 shows the peak model base load variable.

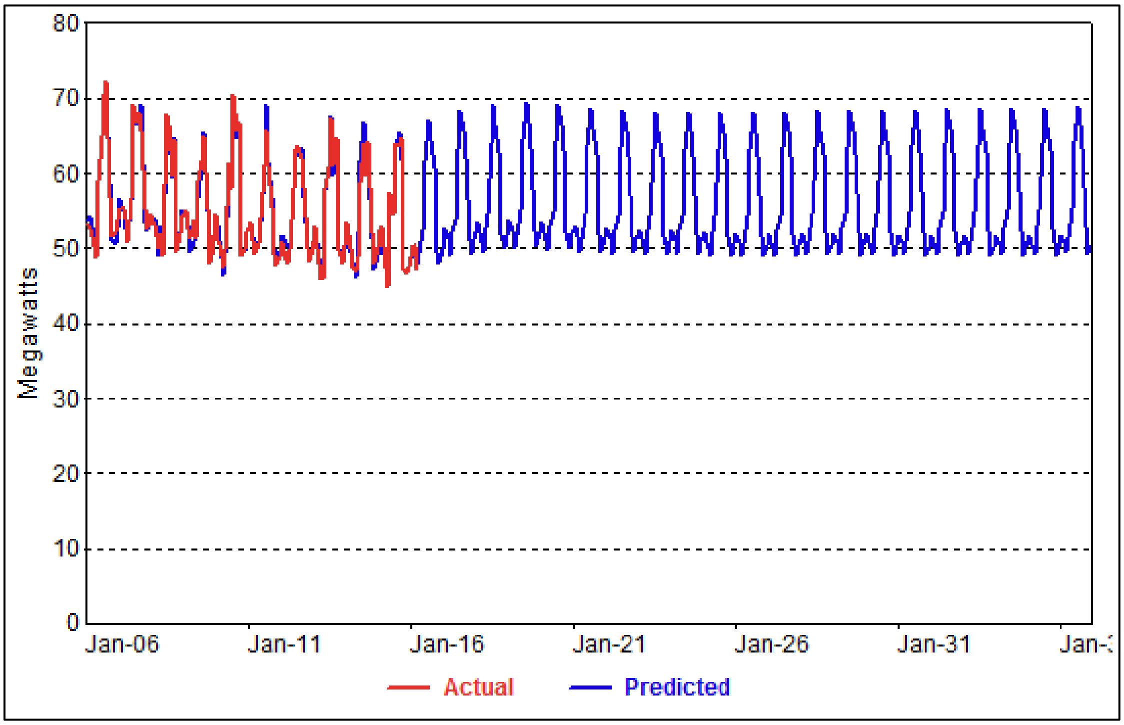
Figure 21: Base Load Variable



Model Results

The peak model is estimated over the period January 2006 to March 2016. The model explains monthly peak variation well with an adjusted R^2 of 0.96 and an in-sample MAPE of 1.7%. Figure 22 shows actual and predicted results. Model statistics and parameters are included in Appendix A.

Figure 22: Peak Model (MW)



The peak demand forecast is adjusted for solar load impacts. Table 3-5 shows total energy and peak demand.

Table 3-5: Energy and Peak Forecast

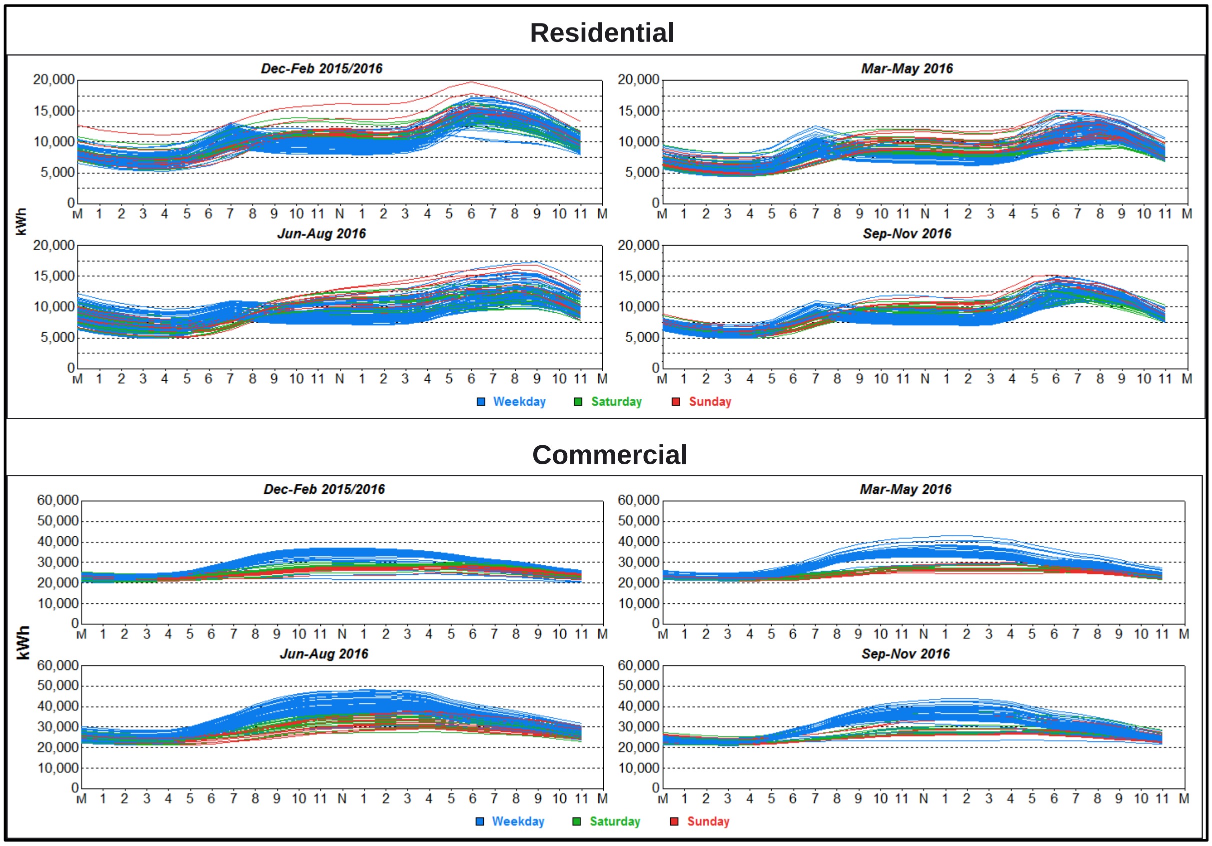
Year	Energy (MWh)	% Chg.	Sum Pk (MW)	% Chg.	WinPk (MW)	% Chg.
2006	369,591		72.3		53.7	
2007	375,232	1.5%	69.1	-4.4%	55.4	3.1%
2008	368,912	-1.7%	67.8	-1.9%	54.2	-2.1%
2009	356,422	-3.4%	64.9	-4.2%	54.9	1.4%
2010	358,868	0.7%	70.4	8.5%	52.2	-4.9%
2011	353,211	-1.6%	65.8	-6.6%	53.5	2.3%
2012	350,753	-0.7%	63.6	-3.3%	50.9	-4.7%
2013	349,150	-0.5%	67.2	5.6%	53.1	4.1%
2014	348,338	-0.2%	64.1	-4.6%	53.5	0.9%
2015	350,936	0.7%	64.7	0.9%	53.0	-1.1%
2016	346,108	-1.4%	66.9	3.4%	50.5	-4.7%
2017	357,437	3.3%	68.2	1.9%	52.7	4.4%
2018	362,158	1.3%	68.9	1.0%	53.4	1.3%
2019	365,460	0.9%	69.2	0.4%	53.8	0.7%
2020	364,091	-0.4%	68.7	-0.7%	53.5	-0.6%
2021	361,111	-0.8%	68.2	-0.7%	53.0	-0.9%
2022	359,811	-0.4%	67.9	-0.4%	52.7	-0.6%
2023	358,922	-0.2%	67.6	-0.4%	52.4	-0.6%
2024	359,314	0.1%	67.6	0.0%	52.4	0.0%
2025	358,094	-0.3%	67.4	-0.3%	52.1	-0.6%
2026	358,246	0.0%	67.5	0.1%	52.0	-0.2%
2027	358,767	0.1%	67.5	0.0%	52.0	0.0%
2028	360,058	0.4%	67.6	0.1%	52.0	0.0%
2029	360,055	0.0%	67.6	0.0%	52.0	0.0%
2030	360,018	0.0%	67.6	0.0%	51.8	-0.4%
2031	360,326	0.1%	67.6	0.0%	51.7	-0.2%
2032	361,395	0.3%	67.8	0.3%	51.8	0.2%
2033	361,053	-0.1%	67.7	-0.1%	51.6	-0.4%
2034	361,480	0.1%	67.7	0.0%	51.6	0.0%
2035	362,124	0.2%	67.8	0.1%	51.6	0.0%
2036	363,674	0.4%	67.9	0.1%	51.7	0.2%
06-15		-0.6%		-1.2%		-0.1%
16-26		0.3%		0.1%		0.3%
16-36		0.2%		0.1%		0.1%

3.3.3 System Hourly Load Forecast

The system hourly load forecast is developed by aggregating residential, commercial, street lighting, and solar (which is a negative curve) hourly load forecasts. Class hourly load forecasts are derived by combining load profiles estimated from AMI data with class sales forecast. Hourly load class profiles are estimated using MetrixND. 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 23 shows the residential and commercial load profiles by season.

Figure 23: 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 24 and Figure 25 show the residential and commercial hourly load forecast for 2017.

Figure 24: Residential Hourly Load Forecast

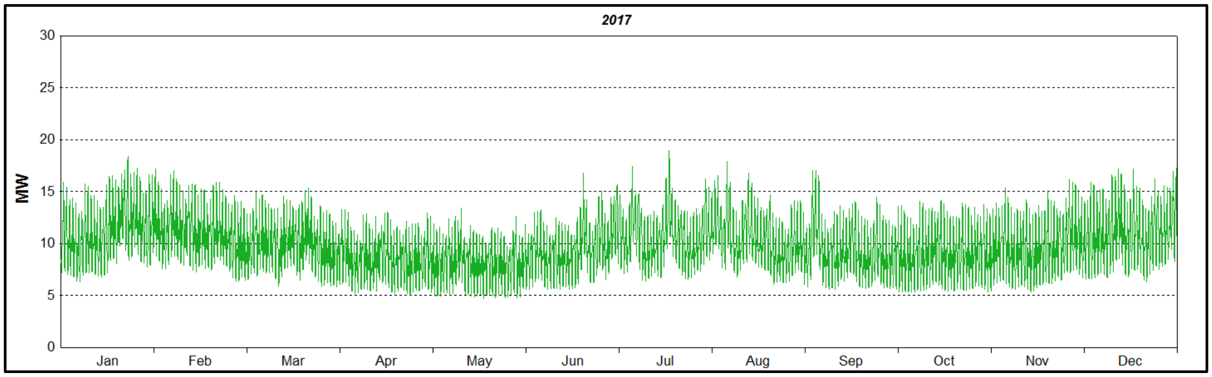
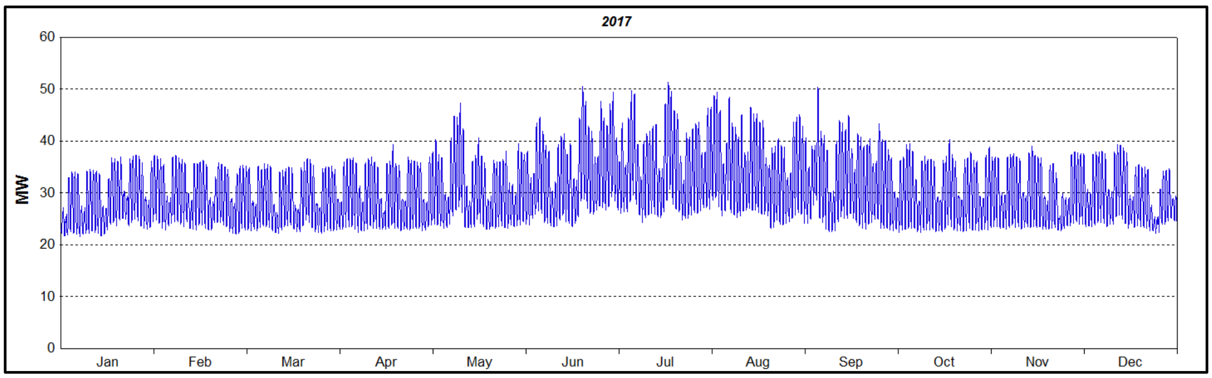
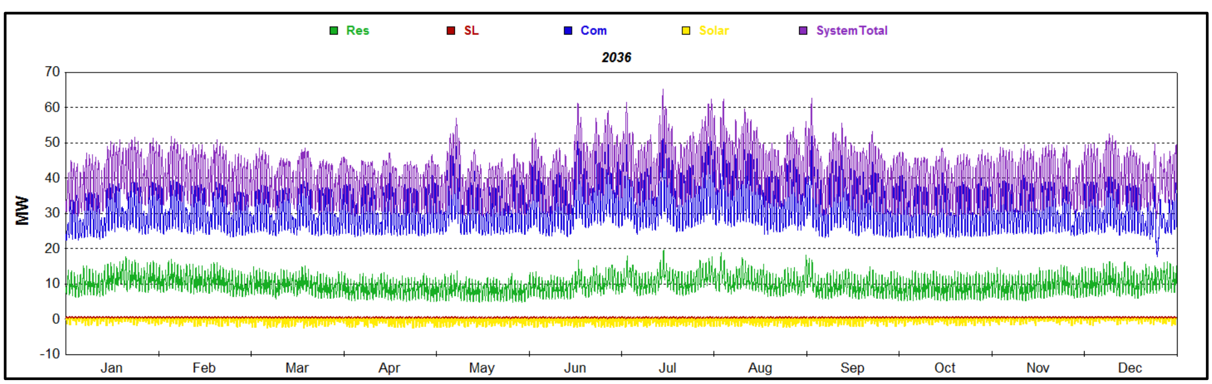


Figure 25: Commercial Hourly Load Forecast



A Batch Transform is used to generate the system hourly load forecast by adding the residential, commercial, street lighting, and solar load forecasts and calibrating the resulting system hourly load forecast to system peak. Class and system hourly load forecasts extend through 2036. Figure 26 shows the resulting 2036 class and system hourly load forecast. The solar load forecast (in yellow) is a negative curve as it reduces system hourly load demand.

Figure 26: Class and System Hourly Load Forecast



4 Forecast Scenarios

A high and low case sales, energy, and demand forecasts were developed for respective economic growth scenarios.

The base case forecast assumes relatively modest regional demographic and economic growth. Households are projected to average 0.4% annual growth through the forecast period, regional output 1.5% annual growth, and employment 0.6% annual growth. The economic forecast is consistent with recent economic activity. Between 2006 and 2015 the number of households has averaged 0.6% annual growth; output has averaged 1.4% annual growth and employment 0.7% average annual growth.

In the high case we assume that the economy (using GDP or output as a proxy) increases 1.0% faster than the base case growth and 1.0% lower growth in the low case. We also assume that the relationship between GPD growth and other economic drivers (including employment, number of households, and real income) is the same in the high and low case as it is in the base case. Table 4-1 through Table 4-3 compare the demographic and economic forecasts.

Table 4-1: Base Case Economics

Year	HHs (thou)	% Chg	HHInc ($ thou)	% Chg	GDP ($ mil)	% Chg	Emp (thou)	% Chg
2006	80.8		107.1		9,959		116.0	
2007	81.5	0.8%	108.8	1.6%	9,900	-0.6%	116.8	0.7%
2008	82.2	0.9%	109.5	0.7%	10,127	2.3%	117.0	0.2%
2009	82.9	0.9%	106.5	-2.7%	10,009	-1.2%	114.5	-2.1%
2010	83.6	0.8%	106.3	-0.1%	10,513	5.0%	115.7	1.0%
2011	84.2	0.7%	111.8	5.1%	10,948	4.1%	117.8	1.8%
2012	84.8	0.7%	113.3	1.4%	11,210	2.4%	119.6	1.5%
2013	85.3	0.6%	112.7	-0.5%	11,015	-1.7%	120.5	0.8%
2014	85.4	0.2%	114.8	1.9%	11,125	1.0%	121.0	0.4%
2015	85.5	0.1%	117.5	2.4%	11,304	1.6%	123.5	2.1%
2016	86.0	0.5%	120.1	2.2%	11,633	2.9%	124.3	0.6%
2017	86.5	0.5%	121.9	1.4%	11,924	2.5%	125.6	1.0%
2018	86.9	0.6%	122.9	0.8%	12,126	1.7%	126.8	1.0%
2019	87.4	0.5%	123.5	0.5%	12,285	1.3%	127.7	0.7%
2020	87.8	0.4%	124.0	0.4%	12,412	1.0%	128.1	0.3%
2021	88.1	0.4%	124.7	0.6%	12,562	1.2%	128.5	0.3%
2022	88.5	0.4%	125.5	0.7%	12,731	1.3%	129.1	0.5%
2023	88.8	0.4%	126.4	0.7%	12,903	1.3%	129.7	0.5%
2024	89.2	0.4%	127.2	0.7%	13,076	1.3%	130.3	0.5%
2025	89.5	0.4%	128.1	0.7%	13,251	1.3%	130.9	0.5%
2026	89.9	0.4%	129.0	0.7%	13,435	1.4%	131.5	0.5%
2027	90.3	0.4%	130.0	0.8%	13,633	1.5%	132.2	0.5%
2028	90.6	0.4%	131.0	0.8%	13,839	1.5%	133.0	0.6%
2029	91.0	0.4%	132.1	0.8%	14,048	1.5%	133.8	0.6%
2030	91.4	0.4%	133.1	0.8%	14,264	1.5%	134.6	0.6%
2031	91.7	0.4%	134.2	0.8%	14,482	1.5%	135.5	0.7%
2032	92.1	0.4%	135.4	0.9%	14,708	1.6%	136.4	0.7%
2033	92.4	0.4%	136.6	0.9%	14,943	1.6%	137.3	0.7%
2034	92.8	0.4%	137.9	0.9%	15,185	1.6%	138.2	0.7%
2035	93.1	0.4%	139.2	1.0%	15,441	1.7%	139.2	0.7%
2036	93.4	0.4%	140.6	1.0%	15,707	1.7%	140.2	0.7%
06-15		0.6%		1.1%		1.4%		0.7%
16-26		0.4%		0.7%		1.5%		0.6%
16-36		0.4%		0.8%		1.5%		0.6%

Table 4-2: High Case Economics

Year	HHs (thou)	% Chg	HHInc ($ thou)	% Chg	GDP ($ mil)	% Chg	Emp (thou)	% Chg
2006	80.8		107.1		9,959		116.0	
2007	81.5	0.8%	108.8	1.6%	9,900	-0.6%	116.8	0.7%
2008	82.2	0.9%	109.5	0.7%	10,127	2.3%	117.0	0.2%
2009	82.9	0.9%	106.5	-2.7%	10,009	-1.2%	114.5	-2.1%
2010	83.6	0.8%	106.3	-0.1%	10,513	5.0%	115.7	1.0%
2011	84.2	0.7%	111.8	5.1%	10,948	4.1%	117.8	1.8%
2012	84.8	0.7%	113.3	1.4%	11,210	2.4%	119.6	1.5%
2013	85.3	0.6%	112.7	-0.5%	11,015	-1.7%	120.5	0.8%
2014	85.4	0.2%	114.8	1.9%	11,125	1.0%	121.0	0.4%
2015	85.5	0.1%	117.5	2.4%	11,304	1.6%	123.5	2.1%
2016	86.0	0.5%	120.1	2.2%	11,633	2.9%	124.3	0.6%
2017	87.0	1.2%	122.0	1.6%	12,041	3.5%	126.1	1.4%
2018	87.8	0.9%	123.5	1.2%	12,365	2.7%	127.5	1.1%
2019	88.5	0.8%	124.8	1.0%	12,651	2.3%	128.8	1.0%
2020	89.1	0.7%	126.0	0.9%	12,908	2.0%	129.9	0.9%
2021	89.8	0.8%	127.2	1.0%	13,193	2.2%	131.0	0.8%
2022	90.5	0.8%	128.6	1.1%	13,502	2.3%	132.3	1.0%
2023	91.3	0.8%	130.0	1.1%	13,820	2.3%	133.6	1.0%
2024	92.0	0.8%	131.3	1.1%	14,143	2.3%	134.9	1.0%
2025	92.7	0.8%	132.7	1.1%	14,474	2.3%	136.2	1.0%
2026	93.5	0.8%	134.2	1.1%	14,820	2.4%	137.6	1.0%
2027	94.3	0.8%	135.7	1.1%	15,186	2.5%	139.0	1.0%
2028	95.1	0.9%	137.2	1.1%	15,567	2.5%	140.4	1.0%
2029	95.9	0.9%	138.8	1.1%	15,959	2.5%	141.9	1.1%
2030	96.8	0.9%	140.4	1.2%	16,364	2.5%	143.4	1.1%
2031	97.6	0.9%	142.0	1.1%	16,777	2.5%	144.9	1.0%
2032	98.5	0.9%	143.6	1.2%	17,207	2.6%	146.4	1.0%
2033	99.3	0.9%	145.3	1.2%	17,654	2.6%	148.0	1.1%
2034	100.2	0.9%	147.0	1.2%	18,116	2.6%	149.6	1.1%
2035	101.2	0.9%	148.8	1.2%	18,602	2.7%	151.3	1.1%
2036	102.1	0.9%	150.6	1.2%	19,109	2.7%	153.0	1.1%
06-15		0.6%		1.1%		1.4%		0.7%
16-26		0.8%		1.1%		2.5%		1.0%
16-36		0.9%		1.1%		2.5%		1.0%

Table 4-3: Low Case Economics

Year	HHs (thou)	% Chg	HHInc ($ thou)	% Chg	GDP ($ mil)	% Chg	Emp (thou)	% Chg
2006	80.8		107.1		9,959		116.0	
2007	81.5	0.8%	108.8	1.6%	9,900	-0.6%	116.8	0.7%
2008	82.2	0.9%	109.5	0.7%	10,127	2.3%	117.0	0.2%
2009	82.9	0.9%	106.5	-2.7%	10,009	-1.2%	114.5	-2.1%
2010	83.6	0.8%	106.3	-0.1%	10,513	5.0%	115.7	1.0%
2011	84.2	0.7%	111.8	5.1%	10,948	4.1%	117.8	1.8%
2012	84.8	0.7%	113.3	1.4%	11,210	2.4%	119.6	1.5%
2013	85.3	0.6%	112.7	-0.5%	11,015	-1.7%	120.5	0.8%
2014	85.4	0.2%	114.8	1.9%	11,125	1.0%	121.0	0.4%
2015	85.5	0.1%	117.5	2.4%	11,304	1.6%	123.5	2.1%
2016	86.0	0.5%	120.1	2.2%	11,633	2.9%	124.3	0.6%
2017	86.4	0.5%	121.0	0.7%	11,808	1.5%	125.1	0.6%
2018	86.6	0.2%	121.4	0.3%	11,890	0.7%	125.5	0.3%
2019	86.7	0.1%	121.5	0.1%	11,927	0.3%	125.6	0.1%
2020	86.7	0.0%	121.5	0.0%	11,931	0.0%	125.6	0.0%
2021	86.8	0.1%	121.7	0.1%	11,956	0.2%	125.8	0.2%
2022	86.9	0.1%	121.8	0.2%	11,997	0.3%	125.9	0.1%
2023	87.0	0.1%	122.0	0.2%	12,039	0.3%	126.1	0.2%
2024	87.1	0.1%	122.2	0.2%	12,080	0.3%	126.3	0.2%
2025	87.2	0.1%	122.4	0.2%	12,121	0.3%	126.5	0.2%
2026	87.3	0.1%	122.6	0.2%	12,168	0.4%	126.7	0.2%
2027	87.5	0.2%	122.9	0.2%	12,226	0.5%	126.9	0.2%
2028	87.6	0.2%	123.2	0.2%	12,288	0.5%	127.2	0.2%
2029	87.8	0.2%	123.5	0.2%	12,351	0.5%	127.5	0.2%
2030	87.9	0.2%	123.8	0.2%	12,417	0.5%	127.7	0.2%
2031	88.1	0.2%	124.1	0.2%	12,483	0.5%	128.0	0.2%
2032	88.3	0.2%	124.4	0.3%	12,553	0.6%	128.3	0.2%
2033	88.4	0.2%	124.7	0.3%	12,628	0.6%	128.6	0.2%
2034	88.6	0.2%	125.1	0.3%	12,706	0.6%	129.0	0.3%
2035	88.8	0.2%	125.5	0.3%	12,793	0.7%	129.3	0.2%
2036	89.1	0.2%	125.9	0.3%	12,886	0.7%	129.7	0.3%
06-15		0.6%		1.1%		1.4%		0.7%
16-26		0.2%		0.2%		0.5%		0.2%
16-36		0.2%		0.2%		0.5%		0.2%

The estimated residential and commercial forecast models are then used to generate high and low sales forecast for the high and low economic scenarios. High and low end-use energy projections then drive the estimated system peak forecast. Table 4-4 through Table 4-6 summarize base, high, and low case energy and peak forecasts.

Table 4-4: Base Case Forecast

Year	Energy (MWh)	% Chg.	Sum Pk (MW)	% Chg.	WinPk (MW)	% Chg.
2006	369,591		72.3		53.7	
2007	375,232	1.5%	69.1	-4.4%	55.4	3.2%
2008	368,912	-1.7%	67.8	-1.9%	54.2	-2.2%
2009	356,422	-3.4%	64.9	-4.2%	54.9	1.3%
2010	358,868	0.7%	70.4	8.5%	52.2	-4.9%
2011	353,211	-1.6%	65.8	-6.6%	53.5	2.5%
2012	350,753	-0.7%	63.6	-3.3%	50.9	-4.9%
2013	349,150	-0.5%	67.2	5.6%	53.1	4.3%
2014	348,338	-0.2%	64.1	-4.6%	53.5	0.8%
2015	350,936	0.7%	64.7	0.9%	53.0	-0.9%
2016	346,108	-1.4%	66.9	3.4%	51.2	-3.4%
2017	357,437	3.3%	68.2	1.9%	52.3	2.1%
2018	362,158	1.3%	68.9	1.0%	53.1	1.5%
2019	365,460	0.9%	69.2	0.4%	53.6	0.9%
2020	364,091	-0.4%	68.7	-0.7%	54.0	0.7%
2021	361,111	-0.8%	68.2	-0.7%	53.7	-0.6%
2022	359,811	-0.4%	67.9	-0.4%	52.9	-1.5%
2023	358,922	-0.2%	67.6	-0.4%	53.2	0.6%
2024	359,314	0.1%	67.6	0.0%	52.9	-0.6%
2025	358,094	-0.3%	67.4	-0.3%	53.2	0.6%
2026	358,246	0.0%	67.5	0.1%	53.3	0.2%
2027	358,767	0.1%	67.5	0.0%	53.1	-0.4%
2028	360,058	0.4%	67.6	0.1%	52.6	-0.9%
2029	360,055	0.0%	67.6	0.0%	53.0	0.8%
2030	360,018	0.0%	67.6	0.0%	52.7	-0.6%
2031	360,326	0.1%	67.6	0.0%	53.0	0.6%
2032	361,395	0.3%	67.8	0.3%	53.4	0.8%
2033	361,053	-0.1%	67.7	-0.1%	52.7	-1.3%
2034	361,480	0.1%	67.7	0.0%	53.1	0.8%
2035	362,124	0.2%	67.8	0.1%	52.8	-0.6%
2036	363,674	0.4%	67.9	0.3%	53.1	0.6%
06-15		-0.6%		-1.2%		-0.1%
16-26		0.3%		0.1%		0.4%
16-36		0.2%		0.1%		0.2%

Table 4-5: High Case Forecast

Year	Energy (MWh)	% Chg.	Sum Pk (MW)	% Chg.	WinPk (MW)	% Chg.
2006	369,591		72.3		53.7	
2007	375,232	1.5%	69.1	-4.4%	55.4	3.2%
2008	368,912	-1.7%	67.8	-1.9%	54.2	-2.2%
2009	356,422	-3.4%	64.9	-4.3%	54.9	1.3%
2010	358,868	0.7%	70.4	8.5%	52.2	-4.9%
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	350,936	0.7%	64.7	0.9%	52.9	-1.1%
2016	346,108	-1.4%	66.9	3.4%	51.2	-3.2%
2017	358,851	3.7%	68.4	2.2%	52.5	2.5%
2018	364,532	1.6%	69.3	1.3%	53.5	1.9%
2019	368,931	1.2%	69.7	0.6%	54.1	1.1%
2020	369,074	0.0%	69.6	-0.1%	54.7	1.1%
2021	367,738	-0.4%	69.3	-0.4%	54.6	-0.2%
2022	367,972	0.1%	69.3	0.0%	54.0	-1.1%
2023	368,612	0.2%	69.3	0.0%	54.5	0.9%
2024	370,592	0.5%	69.6	0.4%	54.4	-0.2%
2025	370,866	0.1%	69.7	0.1%	54.9	0.9%
2026	372,593	0.5%	70.0	0.4%	55.2	0.5%
2027	374,742	0.6%	70.3	0.4%	55.3	0.2%
2028	377,705	0.8%	70.7	0.6%	55.0	-0.5%
2029	379,230	0.4%	71.0	0.4%	55.6	1.1%
2030	380,686	0.4%	71.2	0.3%	55.5	-0.2%
2031	382,484	0.5%	71.5	0.4%	56.0	0.9%
2032	385,176	0.7%	71.9	0.6%	56.6	1.1%
2033	386,356	0.3%	72.1	0.3%	56.1	-0.9%
2034	388,370	0.5%	72.4	0.4%	56.8	1.2%
2035	390,613	0.6%	72.7	0.4%	56.7	-0.2%
2036	393,844	0.8%	73.2	0.7%	57.3	1.1%
06-15		-0.6%		-1.2%		-0.2%
16-26		0.7%		0.5%		0.8%
16-36		0.6%		0.5%		0.6%

Table 4-6: Low Case Forecast

Year	Energy (MWh)	% Chg.	Sum Pk (MW)	% Chg.	WinPk (MW)	% Chg.
2006	369,591		72.3		53.7	
2007	375,232	1.5%	69.1	-4.4%	55.4	3.2%
2008	368,912	-1.7%	67.8	-1.9%	54.2	-2.2%
2009	356,422	-3.4%	64.9	-4.2%	54.9	1.3%
2010	358,868	0.7%	70.4	8.5%	52.2	-4.9%
2011	353,211	-1.6%	65.8	-6.6%	53.5	2.5%
2012	350,753	-0.7%	63.6	-3.3%	50.9	-4.9%
2013	349,150	-0.5%	67.2	5.6%	53.1	4.3%
2014	348,338	-0.2%	64.1	-4.6%	53.5	0.8%
2015	350,936	0.7%	64.7	0.9%	52.9	-1.1%
2016	346,108	-1.4%	66.9	3.4%	51.2	-3.2%
2017	356,162	2.9%	68.0	1.6%	52.2	2.0%
2018	359,126	0.8%	68.3	0.4%	52.8	1.1%
2019	360,834	0.5%	68.3	0.0%	53.0	0.4%
2020	358,313	-0.7%	67.7	-0.9%	53.3	0.6%
2021	354,382	-1.1%	67.0	-1.0%	52.8	-0.9%
2022	351,983	-0.7%	66.5	-0.7%	51.9	-1.7%
2023	349,983	-0.6%	66.1	-0.6%	52.0	0.2%
2024	349,236	-0.2%	65.8	-0.5%	51.6	-0.8%
2025	346,900	-0.7%	65.4	-0.6%	51.7	0.2%
2026	345,902	-0.3%	65.3	-0.2%	51.6	-0.2%
2027	345,280	-0.2%	65.1	-0.3%	51.3	-0.6%
2028	345,375	0.0%	65.1	0.0%	50.7	-1.2%
2029	344,168	-0.3%	64.8	-0.5%	50.9	0.4%
2030	342,891	-0.4%	64.6	-0.3%	50.4	-1.0%
2031	341,912	-0.3%	64.4	-0.3%	50.6	0.4%
2032	341,698	-0.1%	64.3	-0.2%	50.8	0.4%
2033	340,175	-0.4%	64.0	-0.5%	50.0	-1.6%
2034	339,367	-0.2%	63.8	-0.3%	50.2	0.4%
2035	338,743	-0.2%	63.7	-0.2%	49.8	-0.8%
2036	338,930	0.1%	63.6	-0.2%	49.9	0.2%
06-15		-0.6%		-1.2%		-0.2%
16-26		0.0%		-0.2%		0.1%
16-36		-0.1%		-0.3%		-0.1%

Peak Weather Scenario

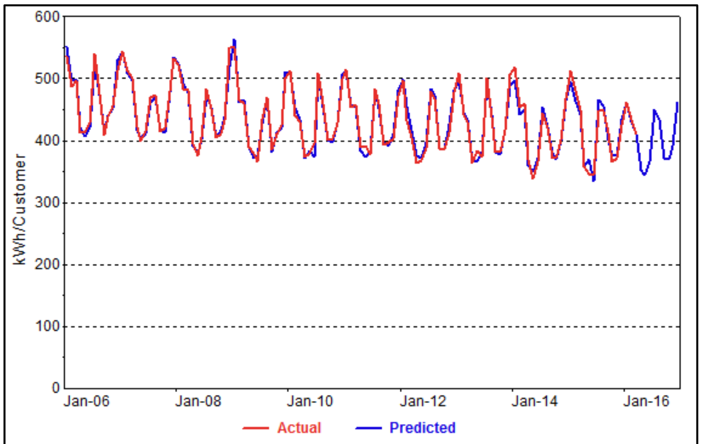
Peak forecast is also estimated for extreme peak weather conditions. We define extreme peak weather conditions as a 1 in 10-year condition (or 10% probability case). The 10% probability peak weather is derived by finding the 90th percentile of historical peak-day weather across the last twenty years. The 10% probability peak-day CDD (base 70 degrees) is 14.74. This compares with expected peak-day temperature of 12.05 CDD. The 10% peak probability temperature is 22% higher than expected peak-day temperature. The extreme weather results in peak demand forecast that is approximately 3.7% higher than the base case. Table 4-7 shows peak forecast with extreme peak-day weather.

Table 4-7: Extreme Peak Weather Scenario

Year	Energy (MWh)	% Chg.	Sum Pk (MW)	% Chg.	WinPk (MW)	% Chg.
2006	369,591		72.3		53.7	
2007	375,232	1.5%	69.1	-4.4%	55.4	3.1%
2008	368,912	-1.7%	67.8	-1.9%	54.2	-2.1%
2009	356,422	-3.4%	64.9	-4.3%	54.9	1.4%
2010	358,868	0.7%	70.4	8.5%	52.2	-4.9%
2011	353,211	-1.6%	65.8	-6.5%	53.5	2.3%
2012	350,753	-0.7%	63.6	-3.3%	50.9	-4.7%
2013	349,150	-0.5%	67.2	5.7%	53.1	4.1%
2014	348,338	-0.2%	64.1	-4.6%	53.5	0.9%
2015	350,936	0.7%	64.7	0.9%	52.9	-1.1%
2016	346,108	-1.4%	69.5	7.4%	52.3	-1.1%
2017	357,437	3.3%	70.8	1.9%	53.4	2.1%
2018	362,158	1.3%	71.5	1.0%	54.2	1.5%
2019	365,460	0.9%	71.8	0.4%	54.7	0.9%
2020	364,091	-0.4%	71.3	-0.7%	55.2	0.9%
2021	361,111	-0.8%	70.7	-0.8%	54.9	-0.5%
2022	359,811	-0.4%	70.4	-0.4%	54.0	-1.6%
2023	358,922	-0.2%	70.1	-0.4%	54.3	0.6%
2024	359,314	0.1%	70.1	0.0%	54.0	-0.6%
2025	358,094	-0.3%	69.9	-0.3%	54.3	0.6%
2026	358,246	0.0%	69.9	0.0%	54.4	0.2%
2027	358,767	0.1%	70.0	0.1%	54.2	-0.4%
2028	360,058	0.4%	70.1	0.1%	53.7	-0.9%
2029	360,055	0.0%	70.1	0.0%	54.1	0.7%
2030	360,018	0.0%	70.0	-0.1%	53.8	-0.6%
2031	360,326	0.1%	70.1	0.1%	54.1	0.6%
2032	361,395	0.3%	70.2	0.1%	54.5	0.7%
2033	361,053	-0.1%	70.1	-0.1%	53.7	-1.5%
2034	361,480	0.1%	70.1	0.0%	54.2	0.9%
2035	362,124	0.2%	70.2	0.1%	53.9	-0.6%
2036	363,674	0.4%	70.3	0.1%	54.2	0.6%
06-15		-0.6%		-1.2%		-0.2%
16-26		0.3%		0.1%		0.4%
16-36		0.2%		0.1%		0.2%

5 Appendix A

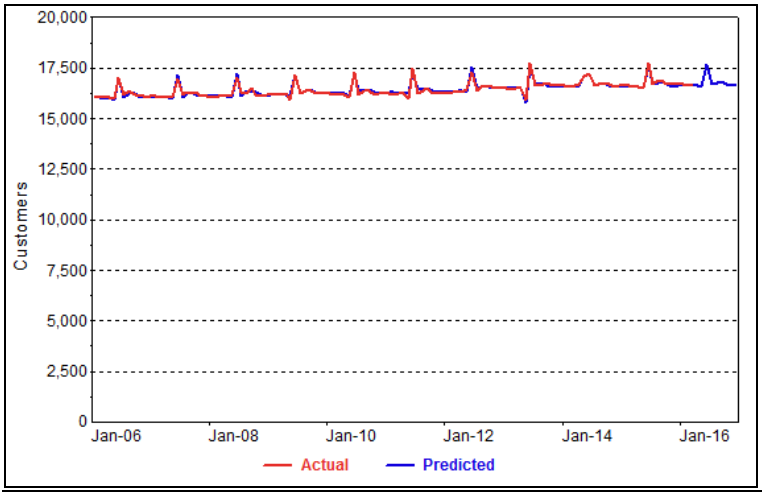
Residential Average Use Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mStructRes.XHeat	0.728	0.049	14.756	0.00%
mStructRes.XCool	0.959	0.059	16.136	0.00%
mStructRes.XOther	1.171	0.016	74.258	0.00%
PastDSM.Res	-0.187	0.035	-5.319	0.00%
mBin.Aug08	18.111	8.959	2.022	4.56%
mBin.Mar	-26.363	3.4	-7.754	0.00%
mBin.Apr	-46.182	4.7	-9.826	0.00%
mBin.May	-49.114	5.24	-9.372	0.00%
mBin.Jun	-37.138	4.289	-8.658	0.00%
mBin.Sep	-12.749	4.288	-2.973	0.36%
mBin.Oct	-32.006	5.111	-6.262	0.00%
mBin.Nov	-23.725	3.673	-6.458	0.00%
MA(1)	0.495	0.084	5.856	0.00%

Model Statistics	
Iterations	15
Adjusted Observations	123
Deg. of Freedom for Error	110
R-Squared	0.968
Adjusted R-Squared	0.965
Model Sum of Squares	320,489.46
Sum of Squared Errors	10,429.55
Mean Squared Error	94.81
Std. Error of Regression	9.74
Mean Abs. Dev. (MAD)	7.09
Mean Abs. % Err. (MAPE)	1.62%
Durbin-Watson Statistic	1.846

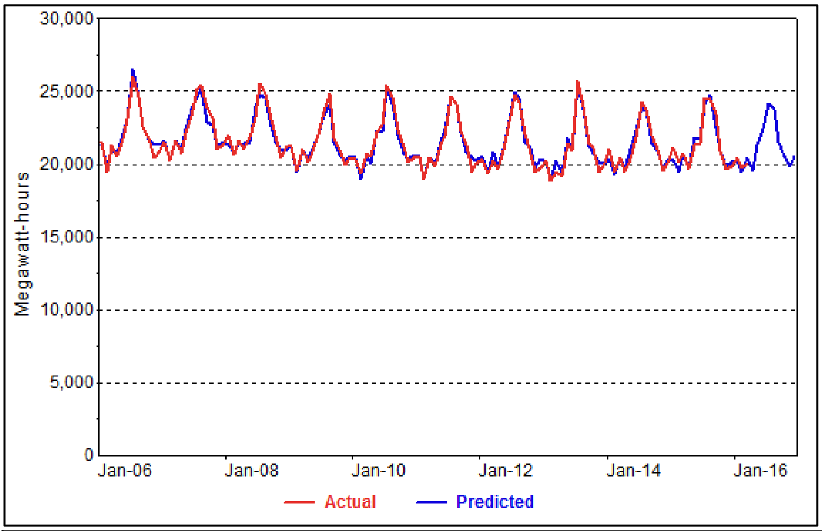
Residential Customer Model



Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	5985.146	1023.872	5.846	0.00%
Economics.HHs	123.472	12.217	10.107	0.00%
mBin.May	-94.3	31.542	-2.99	0.34%
mBin.Jun	1027.159	35.865	28.64	0.00%
mBin.Jul	64.72	36.744	1.761	8.10%
mBin.Aug	165.341	36.74	4.5	0.00%
mBin.Sep	207.153	34.729	5.965	0.00%
mBin.Oct	62.025	28.917	2.145	3.42%
mBin.May13	-613.381	79.654	-7.701	0.00%
mBin.May14	570.039	89.057	6.401	0.00%
mBin.Jun14	-372.549	88.496	-4.21	0.01%
AR(1)	0.596	0.076	7.888	0.00%

Model Statistics	
Iterations	12
Adjusted Observations	122
Deg. of Freedom for Error	110
R-Squared	0.946
Adjusted R-Squared	0.94
F-Statistic	173.614
Prob (F-Statistic)	0
Model Sum of Squares	14,708,838.29
Sum of Squared Errors	847,214.43
Mean Squared Error	7,701.95
Std. Error of Regression	87.76
Mean Abs. Dev. (MAD)	62.61
Mean Abs. % Err. (MAPE)	0.38%
Durbin-Watson Statistic	2.588

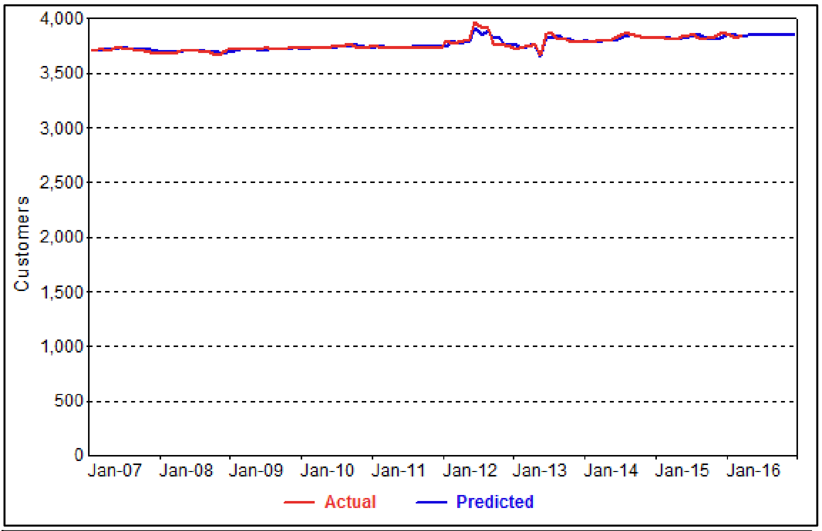
Commercial Sales Model



Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	5415.226	947.869	5.713	0.00%
mStructCom.XHeat	3507.489	1520.4	2.307	2.29%
mStructCom.XCool	31631.286	1405.56	22.504	0.00%
mStructCom.XOther	1525.053	90.009	16.943	0.00%
mBin.BefJul06	-803.376	268.226	-2.995	0.34%
PastDSM.Com	-0.301	0.076	-3.965	0.01%
mBin.May12	-1133.62	337.522	-3.359	0.11%
mBin.Jun13	-1074.132	420.23	-2.556	1.19%
mBin.Jul13	795.626	422.507	1.883	6.23%
mBin.May15	-609.076	342.755	-1.777	7.83%
MA(1)	0.585	0.079	7.372	0.00%

Model Statistics	
Iterations	22
Adjusted Observations	123
Deg. of Freedom for Error	112
R-Squared	0.95
Adjusted R-Squared	0.946
F-Statistic	213.437
Prob (F-Statistic)	0
Model Sum of Squares	360,140,856.09
Sum of Squared Errors	18,898,172.36
Mean Squared Error	168,733.68
Std. Error of Regression	410.77
Mean Abs. Dev. (MAD)	311.41
Mean Abs. % Err. (MAPE)	1.44%
Durbin-Watson Statistic	1.804

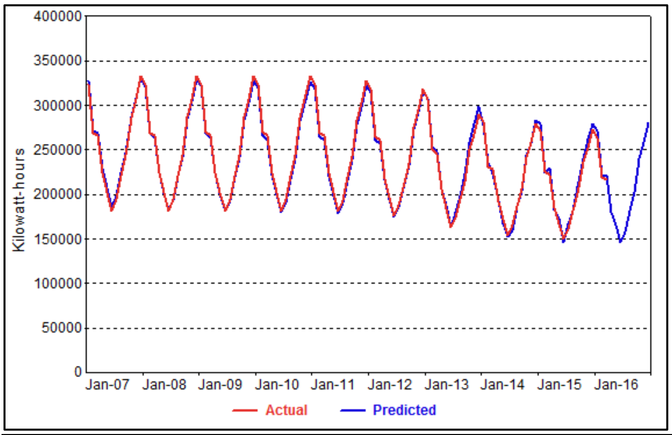
Commercial Customer Model



Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	2142.713	389.252	5.505	0.00%
Economics.Emp	13.683	3.271	4.183	0.01%
mBin.Jun12	107.151	16.346	6.555	0.00%
mBin.Sep12	-63.448	16.585	-3.826	0.02%
mBin.May13	-122.85	18.785	-6.54	0.00%
mBin.Jun13	42.296	18.775	2.253	2.64%
AR(1)	0.811	0.058	13.92	0.00%

Model Statistics	
Iterations	14
Adjusted Observations	110
Deg. of Freedom for Error	103
R-Squared	0.878
Adjusted R-Squared	0.87
F-Statistic	123.066
Prob (F-Statistic)	0
Log-Likelihood	-487.88
Model Sum of Squares	328,718.09
Sum of Squared Errors	45,853.33
Mean Squared Error	445.18
Std. Error of Regression	21.1
Mean Abs. Dev. (MAD)	15.22
Mean Abs. % Err. (MAPE)	0.40%
Durbin-Watson Statistic	1.716

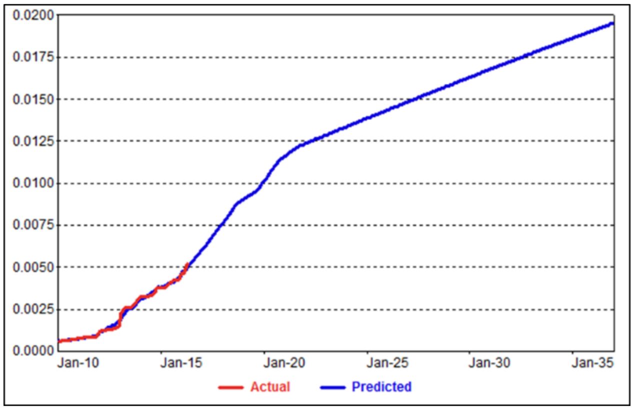
Other Sales Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mEcon.LightEl	318335.578	39164.214	8.128	0.00%
mBin.Jan	233929.197	10583.444	22.103	0.00%
mBin.Feb	182062.339	10259.422	17.746	0.00%
mBin.Mar	178447.236	10243.195	17.421	0.00%
mBin.Apr	138855.57	10275.632	13.513	0.00%
mBin.May	118435.711	10331.722	11.463	0.00%
mBin.Jun	97954.845	10328.848	9.484	0.00%
mBin.Jul	110275.535	10333.795	10.671	0.00%
mBin.Aug	134297.491	10339.046	12.989	0.00%
mBin.Sep	156813.684	10341.507	15.164	0.00%
mBin.Oct	196013.718	10348.822	18.941	0.00%
mBin.Nov	215166.44	10353.321	20.782	0.00%
mBin.Dec	238274.329	10731.543	22.203	0.00%
mBin.Yr14Plus	-14585.721	2813.236	-5.185	0.00%
MA(1)	0.909	0.053	17.217	0.00%
SMA(1)	0.458	0.136	3.381	0.11%

Model Statistics	
Iterations	41
Adjusted Observations	111
Deg. of Freedom for Error	95
R-Squared	0.993
Adjusted R-Squared	0.991
AIC	16.978
BIC	17.368
Model Sum of Squares	265,322,126,717.73
Sum of Squared Errors	1,965,690,475.88
Mean Squared Error	20,691,478.69
Std. Error of Regression	4,548.79
Mean Abs. Dev. (MAD)	3,553.32
Mean Abs. % Err. (MAPE)	1.51%
Durbin-Watson Statistic	0.863

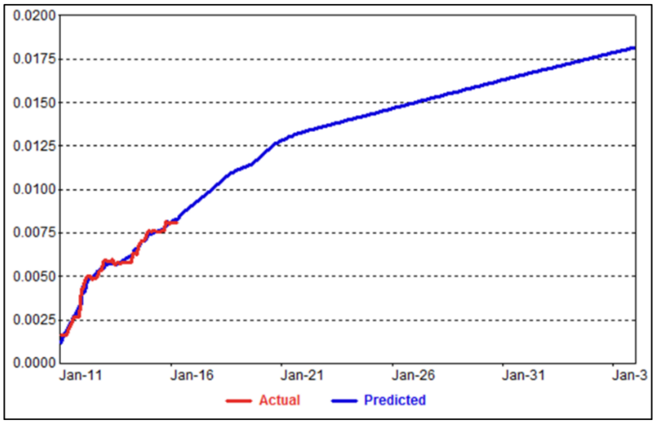
Residential Solar Share Model



Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	0.038	0.004	8.841	0.00%
Payback.ResPayback	-0.006	0.001	-6.35	0.00%
mAdopt.ResPayback_Sq	0.000	0	4.767	0.00%
mAdopt.ResPayback_Cb	0.000	0	-3.673	0.05%
MA(1)	0.631	0.093	6.778	0.00%

Model Statistics	
Iterations	18
Adjusted Observations	75
Deg. of Freedom for Error	70
R-Squared	0.991
Adjusted R-Squared	0.991
F-Statistic	2037.464
Prob (F-Statistic)	0
Model Sum of Squares	0.00
Sum of Squared Errors	0.00
Mean Squared Error	0.00
Std. Error of Regression	0
Mean Abs. Dev. (MAD)	0
Mean Abs. % Err. (MAPE)	4.99%
Durbin-Watson Statistic	1.301

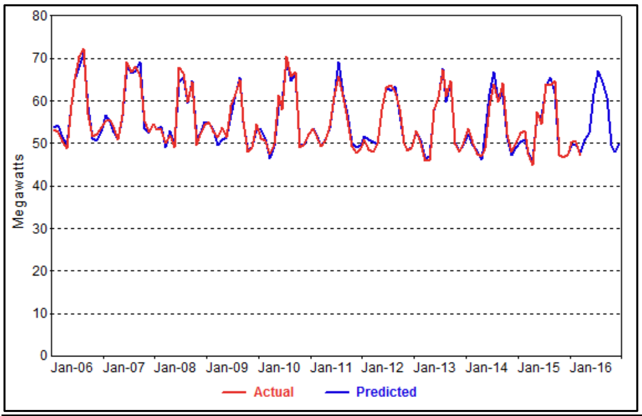
Commercial Solar Share Model



Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	0.031	0.006	4.882	0.00%
Payback.ComPayback	-0.006	0.002	-3.232	0.21%
mAdopt.ComPayback_Sq	0.001	0	2.841	0.63%
mAdopt.ComPayback_Cb	0.000	0	-2.872	0.58%
MA(1)	0.499	0.117	4.259	0.01%

Model Statistics	
Iterations	16
Adjusted Observations	60
Deg. of Freedom for Error	55
R-Squared	0.982
Adjusted R-Squared	0.981
F-Statistic	743.54
Prob (F-Statistic)	0
Model Sum of Squares	0.00
Sum of Squared Errors	0.00
Mean Squared Error	0.00
Std. Error of Regression	0
Mean Abs. Dev. (MAD)	0
Mean Abs. % Err. (MAPE)	4.55%
Durbin-Watson Statistic	1.658

Peak Model



Variable	Coefficient	StdErr	T-Stat	P-Value
mCPkEndUses.BaseVar	1.423	0.015	98.057	0.00%
mWthr.HeatVar45	0.124	0.018	7.008	0.00%
mWthr.CoolVar50	0.3	0.046	6.548	0.00%
mWthr.CoolVar70	0.671	0.082	8.196	0.00%
mBin.Apr07	-3.344	1.574	-2.125	3.60%
mBin.May09	-4.587	1.471	-3.119	0.24%
mBin.Apr12	-6.535	1.597	-4.093	0.01%
mBin.May12	6.492	1.488	4.362	0.00%
mBin.Jun12	-5.998	1.574	-3.81	0.02%
mBin.Nov15	-3.825	1.573	-2.431	1.67%
mBin.Jan	-0.853	0.538	-1.585	11.59%
mBin.Mar	2.004	0.483	4.153	0.01%
mBin.Apr	4.987	0.671	7.437	0.00%
mBin.May	-2.175	1.024	-2.124	3.60%
mBin.Jun	2.139	1.076	1.989	4.94%
mBin.Jul	5.559	1.15	4.834	0.00%
mBin.Aug	4.944	1.093	4.525	0.00%
mBin.Sep	2.352	1.042	2.258	2.60%
mBin.Oct	-1.873	0.747	-2.506	1.38%

Model Statistics	
Iterations	1
Adjusted Observations	123
Deg. of Freedom for Error	104
R-Squared	0.964
Adjusted R-Squared	0.958
AIC	0.795
BIC	1.229
Model Sum of Squares	5,338.63
Sum of Squared Errors	199.9
Mean Squared Error	1.92
Std. Error of Regression	1.39
Mean Abs. Dev. (MAD)	0.93
Mean Abs. % Err. (MAPE)	1.68%
Durbin-Watson Statistic	1.807

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 2015 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,

$$\mathrm{USE}_{y,m} = \mathrm{Heat}_{y,m} + \mathrm{Cool}_{y,m} + \mathrm{Other}_{y,m} \quad (1)$$

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.

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

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

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,

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

Where:

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

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

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

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	767
Electric Space Heating Heat Pump	127

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,

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

$$(TenYearMovingAverageElectric\ Price_{y,m})^{\phi} \times (TenYearMovingAverageGas\ Price_{y,m})^{\gamma} \qquad (8)$$

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	1,219
Space Cooling Heat Pump	240
Room Air Conditioning	177

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,

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

$$(TenYearMovingAverageElectric\,Price_{y,m})^{\phi} \times (TenYearMovingAverageGas\,Price_{y,m})^{\gamma}$$

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.

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

$$(TenYearMovingAverageElectricPrice)^{\lambda} \times (TenYearMovingAverageGasPrice)^{\kappa}$$

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:

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

$$\left(\frac{ElecPrice_{y,m}}{ElecPrice_{09}} \right)^{\phi} \times \left(\frac{GasPrice_{y,m}}{GasPrice_{09}} \right)^{\lambda}$$

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

$$OtherEqpIndex_{y,m} = \sum_{k} ApplianceIndex_{y,m} \times ApplianceUse_{y,m} \tag{18}$$

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 2015 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,

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

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

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

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,

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

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:

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

In this expression, 2004 is used as a base year for normalizing the index. The ratio on the right is equal to 1.0 in 2004. In other years, it will be greater than one if equipment saturation levels are above their 2004 level. This will be counteracted by higher efficiency levels, which will drive the index downward. Base year space heating sales are defined as follows.

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

Here, base-year sales for space heating is the product of the average space heating intensity value and the ratio of total commercial sales in the base year over the sum of the end-use intensity values. In the Commercial SAE Spreadsheets, the space heating sales value is defined on the *BaseYrInput* tab. The resulting $HeatIndex_y$ value in 2004 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:

$$HeatUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5} \right) \times \left(\frac{WgtHDD_{y,m}}{HDD_{04}} \right) \times \left(\frac{Output_y}{Output_{04}} \right)^{0.20} \times \left(\frac{Price_{y,m}}{Price_{04}} \right)^{-0.18} \tag{6}$$

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 2004,
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 (2004). 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,

$$\mathrm{XCool}_{y,m} = \mathrm{CoolIndex}_{y} \times \mathrm{CoolUse}_{y,m} \tag{7}$$

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

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

$$CoolIndex_y = CoolSales_{04} \times \frac{\left(CoolShare_y \middle/ Eff_y \right)}{\left(CoolShare_{04} \middle/ Eff_{04} \right)} \tag{8}$$

Data values in 2004 are used as a base year for normalizing the index, and the ratio on the right is equal to 1.0 in 2004. In other years, it will be greater than one if equipment saturation levels are above their 2004 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.

$$CoolSales_{04} = \left(\frac{kWh}{Sqft} \right)_{Cooling} \times \left(\frac{CommercialSales_{04}}{\sum_e kWh \middle/ Sqft_e} \right) \tag{9}$$

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 2004 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:

$$CoolUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5} \right) \times \left(\frac{WgtCDD_{y,m}}{CDD_{04}} \right) \times \left(\frac{Output_y}{Output_{04}} \right)^{0.20} \times \left(\frac{Price_{y,m}}{Price_{04}} \right)^{-0.18} \tag{10}$$

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

CDD is the annual cooling degree days for 2004.

By construction, the *CoolUse* variable has an annual sum that is close to one in the base year (2004). 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:

$$OtherIndex_{y,m} = \sum_{Type} Weight_{04}^{Type} \times \left(\frac{Share_y^{Type} / Eff_y^{Type}}{Share_{04}^{Type} / Eff_{04}^{Type}} \right) \tag{12}$$

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.

$$Weight_{04}^{Type} = \left(\frac{kWh}{Sqft} \right)_{Type} \times \left(\frac{CommercialSales_{04}}{\sum_e kWh / Sqft_e} \right) \tag{13}$$

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

$$OtherUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{Output_{y}}{Output_{04}}\right)^{0.20} \times \left(\frac{\Pr ice_{y.m}}{\Pr ice_{04}}\right)^{-0.18} \quad (14)$$

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