Appendix 4.3
Long Term Load and Demand Forecast
2016-2035

Knowledge to Shape Your Future

Electric | Gas | Water
information collection, analysis and application

Long Term Load and Demand Forecast

Yukon Energy Corporation (YEC)

Submitted to:

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Contents

1 Overview

Itron, Inc. (Itron) was contracted by the Yukon Energy Corporation (YEC) to develop a process for forecasting system energy and peaks using a bottom up class level forecasting approach. Itron's modeling approach incorporates the 2015 SAE (Statistically Adjusted End-Use) indices, as well as current economic data. This document outlines underlying data, the structure of the models, and the modeling process.

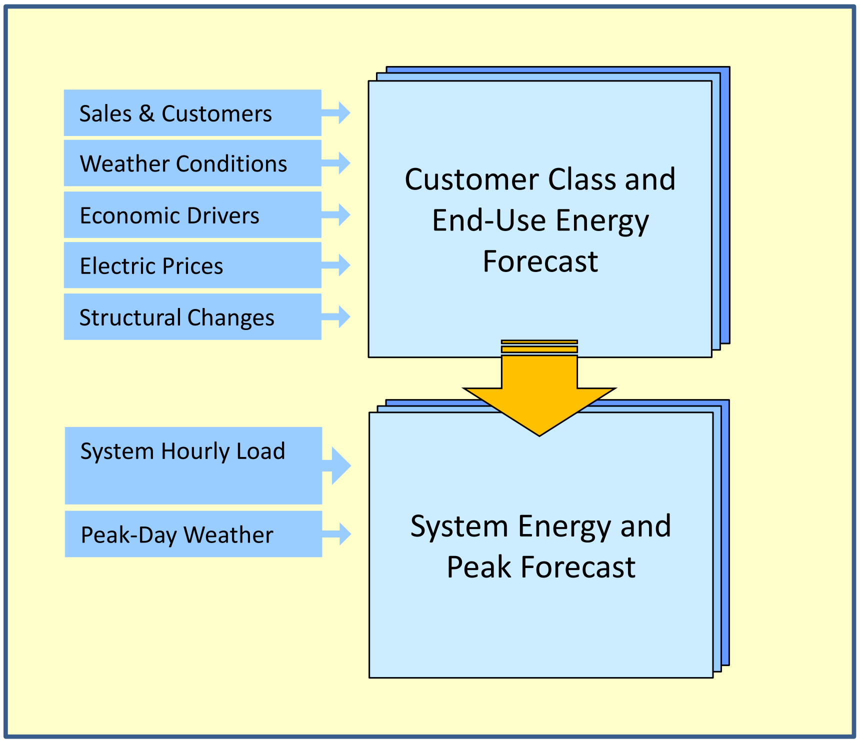
Itron constructed all forecasting and weather normalization models in MetrixND, Itron's statistical modeling application. MetrixND is ideally suited for this purpose as Itron designed and developed the software specifically to meet the needs of the utility industry. In this case, MetrixND generates monthly sales and peak demand. Further, MetrixND acts as the forecasting engine that supports hourly and sub-hourly processes for long-term planning, as well as real-time and day-ahead forecasting to support generation dispatch and load scheduling. Table 1-1 summarizes YEC energy and demand forecast (excluding industrial).

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

Year	Energy (MWh)		Peak (MW)	
2015	374,882		76.9	
2016	389,806	4.0%	82.2	6.9%
2017	393,583	1.0%	83.8	1.9%
2018	399,238	1.4%	85.9	2.5%
2019	406,423	1.8%	88.2	2.7%
2020	413,561	1.8%	90.8	2.9%
2021	418,684	1.2%	92.8	2.2%
2022	425,589	1.6%	95.2	2.6%
2023	432,219	1.6%	97.4	2.3%
2024	439,363	1.7%	99.8	2.4%
2025	443,536	0.9%	101.2	1.4%
2026	447,317	0.9%	102.5	1.3%
2027	451,336	0.9%	103.8	1.3%
2028	455,839	1.0%	105.2	1.4%
2029	457,568	0.4%	105.8	0.5%
2030	458,274	0.2%	106.1	0.3%
2031	457,059	-0.3%	105.8	-0.3%
2032	456,036	-0.2%	105.6	-0.2%
2033	452,276	-0.8%	104.6	-1.0%
2034	448,774	-0.8%	103.7	-0.8%
2035	444,998	-0.8%	102.8	-0.9%
2016-2025		1.4%		2.3%
2016-2035		0.7%		1.2%

The long-term energy and demand forecast is developed using a “build-up” approach. This approach entails first estimating class and end-use energy requirements and then using class and end-use sales projections to drive system peak demand. The forecast models capture not only economic activity and population projections, but also expected weather conditions, the impact of improving end-use efficiency and standards, and electricity prices. The forecast does include the impact of future conservation programs savings. Figure 1-1 shows the general approach.

Figure 1-1: Forecast Approach



In the long-term, both economic growth and structural changes drive sales 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 and naturally occurring efficiency gains. The industrial sales forecast is derived using a generalized econometric model that relates industrial sales to regional industrial GDP growth. The Street Light (ST) sales forecast is also derived using a generalized econometric model that relates ST sales to the residential customer forecast. Table 1-2 summarizes customer class sales forecast excluding industrial saels.

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

Year	Residential		Commercial		ST		SP		Total	
2015	155,443		173,005		291		14		328,754	
2016	162,786	4.7%	175,799	1.6%	291	0.2%	14	0.2%	338,890	3.1%
2017	165,192	1.5%	176,657	0.5%	292	0.2%	14	0.0%	342,154	1.0%
2018	168,663	2.1%	178,079	0.8%	292	0.2%	14	0.0%	347,048	1.4%
2019	172,670	2.4%	180,300	1.2%	293	0.2%	14	0.0%	353,277	1.8%
2020	177,242	2.6%	181,919	0.9%	294	0.2%	14	0.0%	359,469	1.8%
2021	180,655	1.9%	182,937	0.6%	294	0.2%	14	0.0%	363,900	1.2%
2022	185,015	2.4%	184,559	0.9%	295	0.2%	14	0.0%	369,884	1.6%
2023	189,096	2.2%	186,226	0.9%	295	0.2%	14	0.0%	375,632	1.6%
2024	193,618	2.4%	187,904	0.9%	296	0.2%	14	0.0%	381,832	1.7%
2025	196,057	1.3%	189,080	0.6%	296	0.1%	14	0.0%	385,447	0.9%
2026	198,401	1.2%	190,013	0.5%	297	0.1%	14	0.0%	388,725	0.9%
2027	200,882	1.3%	191,017	0.5%	297	0.1%	14	0.0%	392,211	0.9%
2028	203,768	1.4%	192,043	0.5%	297	0.1%	14	0.0%	396,122	1.0%
2029	204,709	0.5%	192,601	0.3%	298	0.1%	14	0.0%	397,621	0.4%
2030	205,508	0.4%	192,416	-0.1%	298	0.0%	14	0.0%	398,235	0.2%
2031	205,253	-0.1%	191,620	-0.4%	298	0.0%	14	0.0%	397,186	-0.3%
2032	205,298	0.0%	190,696	-0.5%	298	0.0%	14	0.0%	396,306	-0.2%
2033	203,568	-0.8%	189,165	-0.8%	298	-0.1%	14	0.0%	393,044	-0.8%
2034	202,212	-0.7%	187,484	-0.9%	297	-0.1%	14	0.0%	390,008	-0.8%
2035	200,789	-0.7%	185,631	-1.0%	297	-0.1%	14	0.0%	386,731	-0.8%
2016-2025		2.1%		0.8%		0.2%		0.0%		1.4%
2016-2035		1.1%		0.3%		0.1%		0.0%		0.7%

The strong growth in Residential sales is the result of increasing saturation of electric heat. Residential electric heat saturation grows from approximately 12% in 2015 to 21% by 2025 before flattening out at 23% by 2031. This saturation is driven by the assumption that 95% of all new residential customers will have electric heat. Residential average use increases 1.0% annually through 2025. Commercial sales are also driven by increases in electric heat saturation. Growth rates in all classes begin to decline in the out years, driven by significant declines in the population and GDP forecasts.

2 Forecast Data and Assumptions

2.1 Historical Class Sales and Energy Data

The process begins by estimating long-term monthly sales models at the revenue class level. Forecast models are estimated for residential, commercial, industrial, and street lighting revenue classes. Regression models are estimated using historical monthly billing data that includes sales, customers, and revenue. The residential and commercial models are estimated using monthly billed sales, customer and price data for the period January 2006 to September 2015. The industrial model is estimated using monthly data for the period January 2006 to September 2015. Street light models are estimated using monthly billed sales data from January 2006 to September 2015.

System monthly energy and monthly demand data are derived from historical hourly load data for the period January 1, 2006 to September 30, 2015 with estimated hourly loads for the Elsa and Minto mines removed.

Hourly Elsa mine loads are approximated subtracting the Elsa SCADA data hourly load from the system loads to obtain a monthly system demand modifier. The modifier is further reduced by 0.28 MW which approximates the non-Elsa mine load from hourly SCADA data based on the average of the SCADA data demand after the Elsa mine closed in August 2013.

Hourly Minto mine loads are approximated by subtracting the Minto mine loads from the system loads to obtain a monthly system demand modifier from January 2013 through September 2015. The demand modifier for data prior to January 2013 is estimated by applying the average ratio of the demand modifier to the Minto non-coincident billing peaks and applying the ratio to the January 2006 through December 2012 time period.

2.2 Weather Data

YEC provided daily historical minimum and maximum dry bulb temperature data for Whitehorse, Canada for the period January1, 1970 to September 30, 2015. These data are obtained from Environment Canada and used as the proxy weather station for the entire YEC service territory.

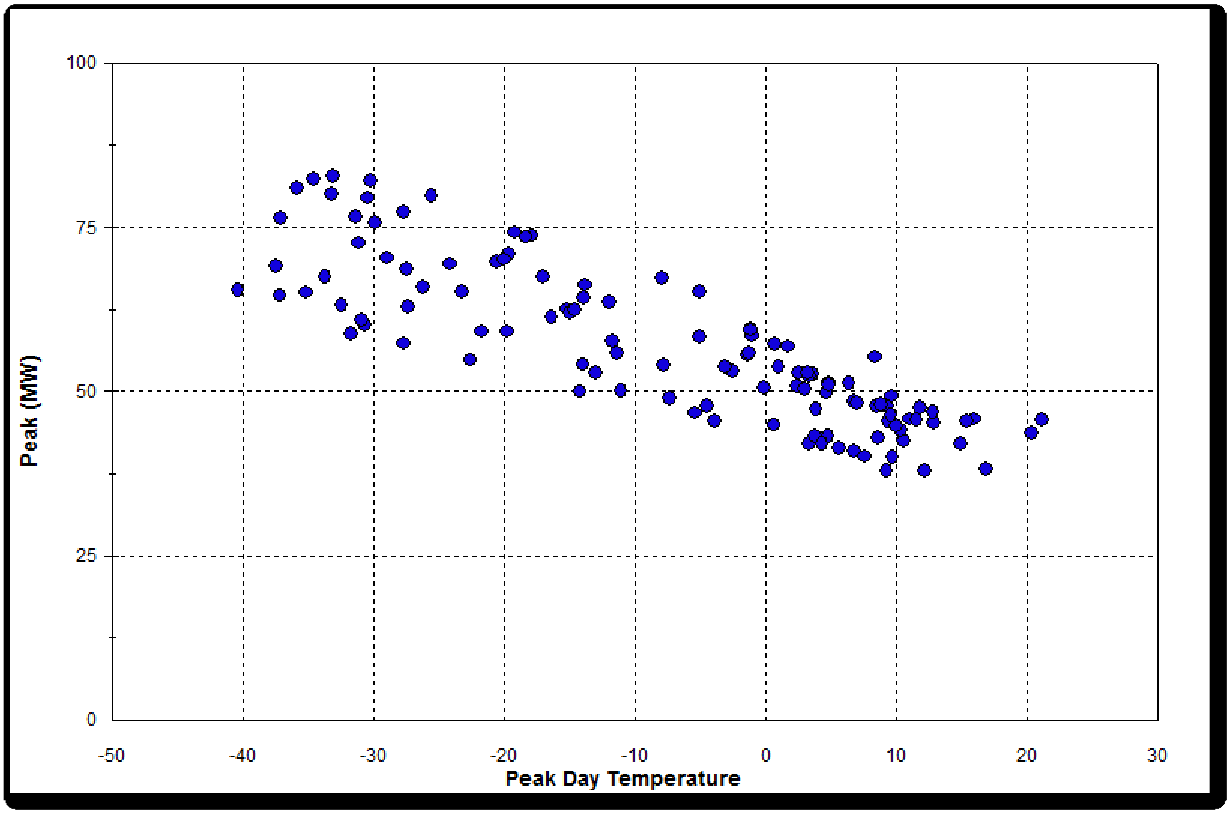
Using these data, a daily average temperature concept is calculated, as well as daily Heating Degree Day (HDD) and Cooling Degree Day (CDD) concepts for numerous breakpoints. As class sales data is measured on a billing month basis, models are estimated using billing-month or cycle-weighted HDD and CDD. These cycle-weighted HDD and CDD concepts are calculated using a meter read schedule, which sums the daily HDD and CDD concepts over the monthly billing cycles. Ultimately, our objective is to generate calendar-month sales and energy forecasts. To derive calendar month sales forecasts, simulation objects are used where billing month HDD and CDD in the estimated model are replaced with calendar month normal HDD and CDD and the number of billing days used in the estimated model is replaced with the number of calendar days.

Normal calendar and cycle-weighted degree days are calculated based on the 30-year period January 1, 1981 to December 31, 2010 using an average by date method.

Peak-Day Weather Variables

The peak forecast is generated from a monthly peak regression model. Peak-day HDD and CDD are derived from historical daily average weather data. 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 2-1.

Figure 2-1: Monthly Peak Demand vs. Temperature Relationship



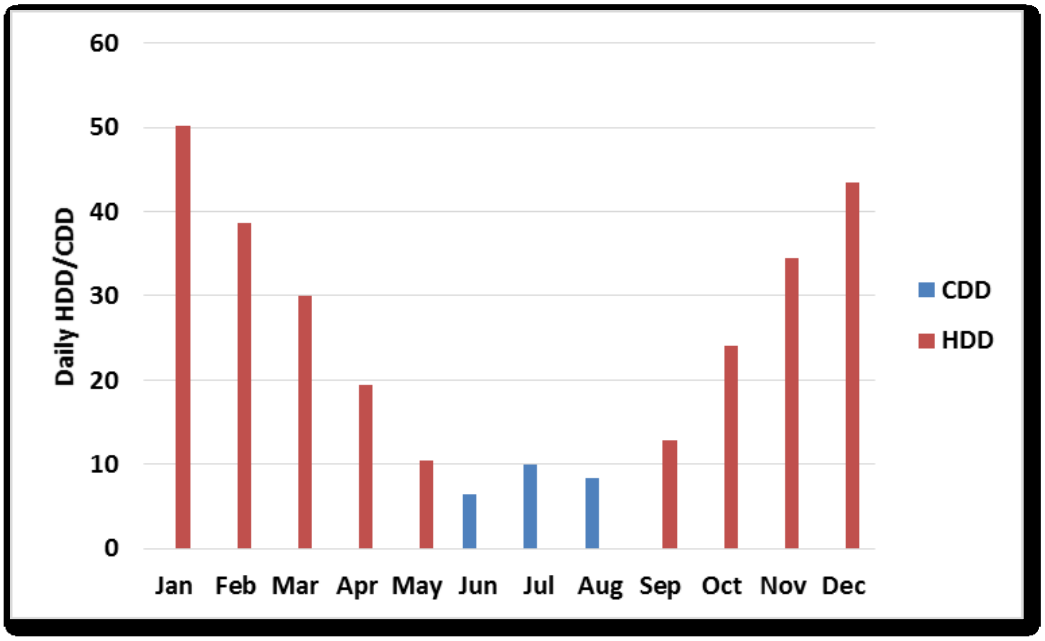
Monthly peak-day HDD and CDD are calculated for the estimation period – January 2006 to September 2015 based on these temperature relationships.

Normal peak-day CDD and HDD are calculated from monthly extreme temperature observations. This method is chosen because historic load data is not available prior to 2006; therefore peak day weather cannot be determined. For the months of June, July, and August the monthly maximum temperature is used, for all other months the monthly minimum is used. Normal peak-day HDD and CDD are calculated using 30 years of historical weather data (1981 to 2010). The calculation process entails using a *rank and average* approach as described below:

1. Find the lowest or highest temperature observation for a given month. This calculation occurs within the Loads.NDM.
2. *Rank* the monthly HDD and CDD in each year from the highest value to the lowest value.
3. *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.

4. 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 July. Figure 2-2 shows the calculated peak-day normal HDD and CDD

Figure 2-2: Peak-Day Normal HDD and CDD



2.3 Economic Data

Economic data was provided by YEC. These data are obtained from the Centre for Spatial Economics (C4SE) and include a base case and nine economic scenarios. The main differing factor among the scenarios is mining activity. The economic scenarios and their impact on the load and demand forecast will be covered in detail in the Forecast Scenarios section of this document.

The primary economic drivers in the residential model include income per capita, households, and population. Commercial sales are driven by commercial regional non-mining output, which represents territorial GDP without the contribution of the mining industry, and employment. The economic driver used in estimating the industrial sector model is mining output. Table 2-1 summarizes the primary economic drivers for the residential class.

Table 2-1: Residential Drivers: Base Case

Year	Population		HouseHolds		Per Capita Income	
2015	37.4		15.7		36.1	
2016	37.9	1.2%	16.0	1.5%	36.3	0.6%
2017	38.2	0.9%	16.2	1.2%	36.4	0.3%
2018	38.6	0.9%	16.3	1.2%	36.4	0.0%
2019	38.9	1.0%	16.5	1.2%	37.2	2.2%
2020	39.3	1.0%	16.8	1.3%	37.7	1.3%
2021	39.8	1.1%	17.0	1.3%	37.6	-0.3%
2022	40.2	1.0%	17.2	1.2%	38.1	1.3%
2023	40.6	0.9%	17.4	1.0%	38.6	1.3%
2024	40.9	0.8%	17.5	1.0%	39.3	1.8%
2025	41.2	0.7%	17.7	0.8%	39.8	1.3%
2026	41.4	0.6%	17.8	0.7%	40.1	0.8%
2027	41.6	0.6%	17.9	0.7%	40.7	1.5%
2028	41.9	0.5%	18.0	0.6%	41.0	0.7%
2029	42.0	0.4%	18.1	0.4%	41.3	0.7%
2030	42.1	0.2%	18.1	0.3%	41.6	0.7%
2031	42.1	0.0%	18.2	0.1%	42.0	1.0%
2032	42.0	-0.3%	18.1	-0.2%	42.5	1.2%
2033	41.8	-0.5%	18.1	-0.4%	43.0	1.2%
2034	41.5	-0.7%	18.0	-0.6%	43.4	0.9%
2035	41.1	-0.8%	17.8	-0.7%	43.8	0.9%
2016-2025		0.9%		1.1%		1.0%
2016-2035		0.4%		0.6%		1.0%

Table 2-2 and Table 2-3 show output and employment drivers used in commercial and industrial forecasts.

Table 2-2: Commercial Drivers: Base Case

Year	Non-Mining GDP		Total Employment	
2015	1,938.2		19.7	
2016	1,947.6	0.5%	19.7	-0.1%
2017	1,977.0	1.5%	20.0	1.3%
2018	2,003.6	1.3%	20.0	0.4%
2019	2,089.3	4.3%	20.5	2.1%
2020	2,133.1	2.1%	20.6	0.9%
2021	2,123.0	-0.5%	20.5	-0.7%
2022	2,168.9	2.2%	20.5	-0.1%
2023	2,210.0	1.9%	20.7	0.8%
2024	2,238.7	1.3%	20.9	1.1%
2025	2,272.3	1.5%	21.0	0.6%
2026	2,300.6	1.2%	21.1	0.2%
2027	2,333.3	1.4%	21.1	0.3%
2028	2,359.1	1.1%	21.1	-0.1%
2029	2,382.0	1.0%	21.0	-0.3%
2030	2,402.2	0.8%	21.0	-0.2%
2031	2,423.5	0.9%	21.0	-0.1%
2032	2,443.6	0.8%	20.9	-0.1%
2033	2,457.6	0.6%	20.9	-0.3%
2034	2,466.5	0.4%	20.8	-0.5%
2035	2,470.7	0.2%	20.6	-0.6%
2016-2025		1.7%		0.7%
2016-2035		1.3%		0.2%

Table 2-3: Industrial Drivers: Base Case

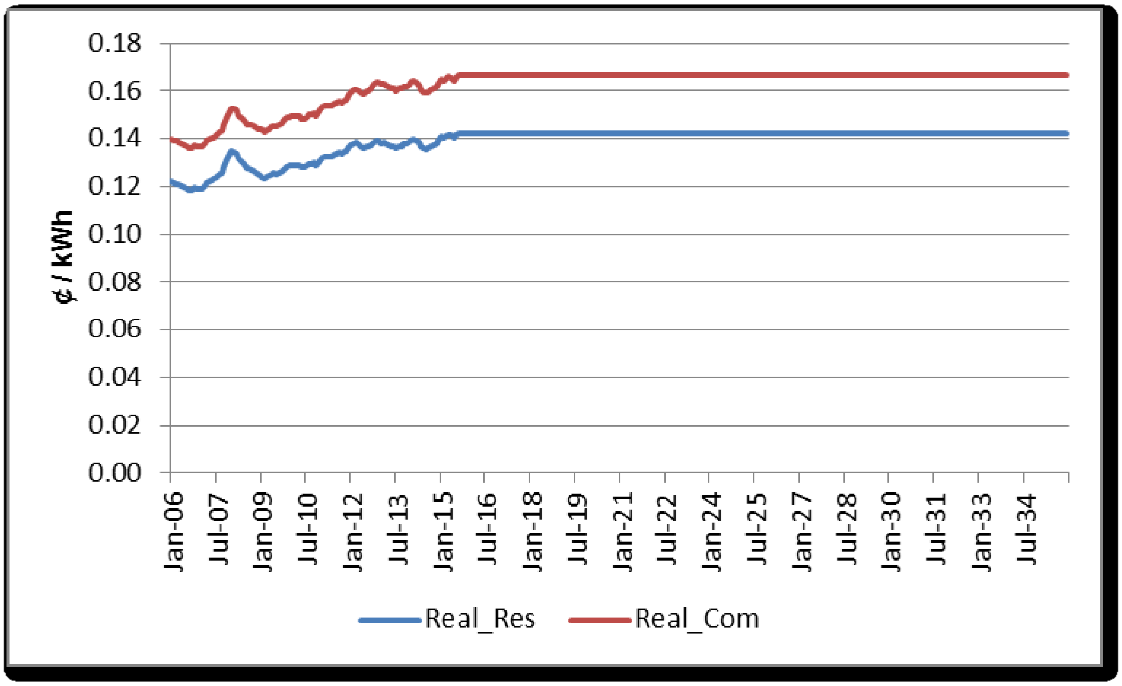
Year	Mining GDP	
2015	287.9	
2016	347.7	20.8%
2017	325.4	-6.4%
2018	316.4	-2.8%
2019	308.8	-2.4%
2020	291.9	-5.5%
2021	278.8	-4.5%
2022	353.9	26.9%
2023	334.0	-5.6%
2024	416.7	24.8%
2025	409.2	-1.8%
2026	375.0	-8.4%
2027	395.0	5.3%
2028	367.5	-7.0%
2029	354.2	-3.6%
2030	321.2	-9.3%
2031	327.4	1.9%
2032	343.4	4.9%
2033	344.8	0.4%
2034	346.0	0.3%
2035	318.4	-8.0%
2016-2025		2.5%
2016-2035		0.0%

2.4 Price Data

Historical average real prices are derived from historical billing and revenue data. Prices impact the class sales through imposed price elasticities. The residential and commercial price elasticity is -0.10. Itron's 2006 Price Effects survey identifies the range of price elasticities from 0.0 to 0.35 for residential customers and 0.0 to 0.5 for commercial customers. The selection of the price elasticity is based on adjusting the elasticity in the model and determining the impact on overall model fit.

Though the elasticities are small, relatively strong price increases through 2015 have a measurable impact on near-term usage. Over the long-term, constant real prices are assumed rendering the impact of elasticity in the forecast as unimportant while leaving the forecast unbiased regarding unadopted price increases and decreases. Figure 2-3 shows price forecasts by class.

Figure 2-3: Historical and projected real electricity prices (cents per kWh)

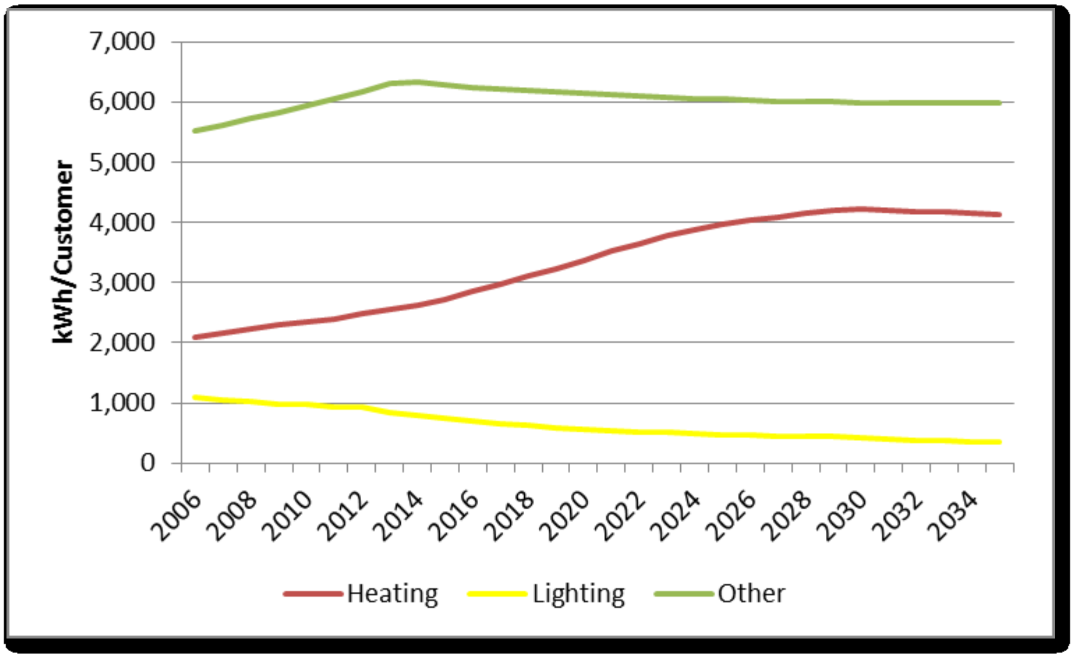


2.5 Appliance Saturation and Efficiency Trends

Over the long-term, changes in end-use efficiency and equipment stock impact energy and peak demand. These trends 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 efficiency are derived from the U.S. Energy Information Administration's (EIA) 2015 West North Central Census Division forecast. Historic and projected residential end-use saturations are based on a combination of data from Natural Resources Canada (NRCan),a 2011 potential study, *Yukon Conservation and Demand Management Potential Review* (CPR), and a 2016 CPR study. The residential electric heat saturation projection is calculated using the assumption that 95% of all new customers use electric heat as their primary heating source.

Residential sales forecast are 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-uses; heating, lighting, and other use, no residential cooling is present in YEC's service territory, per the 2011 potential study. Figure 2-4 shows the resulting aggregated end-use intensity projections.

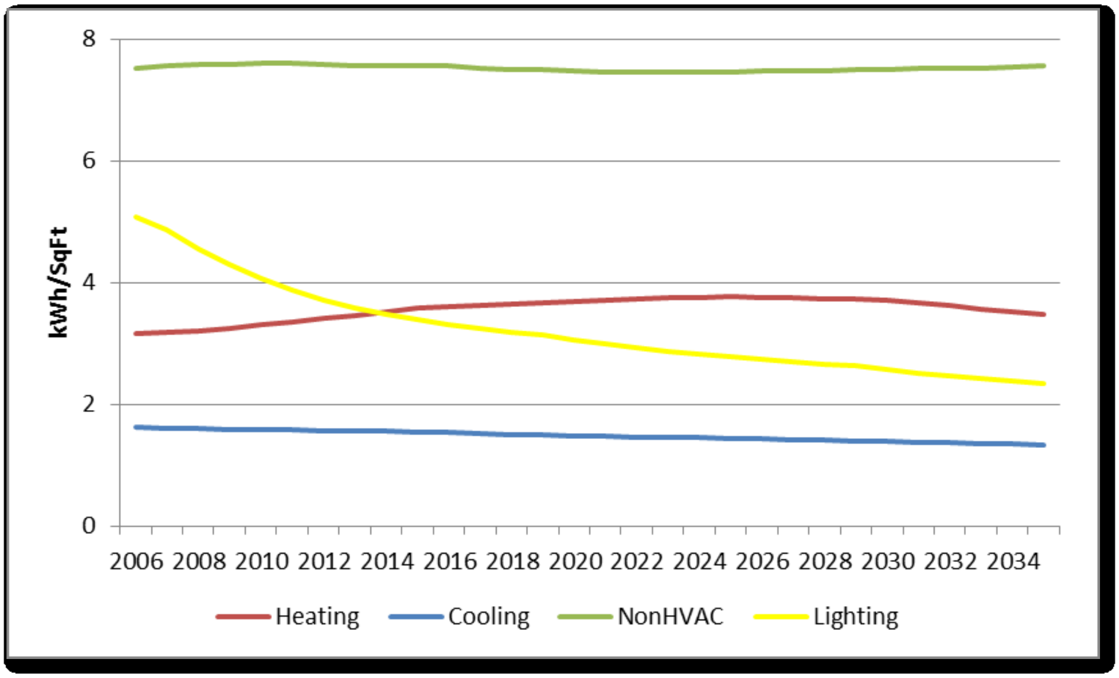
Figure 2-4: Residential End-Use Energy Indices [kWh per Customer]



The heating intensity increases 2.9% annually through the first 10 years of forecast period, driven by the assumption that 95% of all new customers will use electric heat. The 95% electric heat assumption is based on the Energy Solution Centre's work showing that 97% of new homes since 2013 use electric heat as their primary fuel source. After 2032, heating intensity begins to flatten out as the customer forecast declines driven by negative household growth projections. Non-weather sensitive use, "Other", which includes all appliances, plug loads, and water heating declines 0.4% through the first 10 years of the forecast, mainly driven by efficiency improvement in water heating and refrigeration, although this is partially offset by increases in plug loads. Lighting declines fairly steadily as the impact of the new lighting standards (that effectively eliminate traditional incandescent light bulbs) begin to take effect, intensity declines 2.4% through the first 10 years of forecast period.

For the commercial average use model, end-use intensity projections (use per square foot) are aggregated into four generalized end-uses; heating, cooling, lighting, and non-HVAC. It is important to point out that although a cooling intensity projection is developed there is no cooling variable in the commercial average use model; the variable was statistically insignificant. End-use consumption and commercial square footage data from the 2011 CPR was used to calibrate into base year end-use intensities. Projected end-use consumption figures from the 2016 CPR were then used as the basis for deriving intensity projections. Figure 2-5 shows commercial end-use energy intensity forecasts for the aggregated end-use categories.

Figure 2-5: Commercial End-Use Energy Intensity [kWh/SqFt]



Similar to the Residential intensity, Commercial heating intensity (use per square foot) is also increasing. The strong decline in historic and future lighting intensity is largely the result of improving lighting efficiency.

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
- Industrial
- Street Lights (ST)
- Space Lights (SP)

While Itron developed an Industrial model, YEC decided to remove the Industrial model (Appendix D) to manually manage the addition and subtraction of major industrial customers.

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. The technique is fully described in Appendix B and has been adopted by 60 companies across North America.

While a traditional approach to forecasting sales is developing an econometric model that relates monthly sales to weather, seasonal variables, and economic conditions, the approach cannot explicitly capture changes in the underlying energy efficiency of end-uses. In contrast, end-use models capture energy efficiency changes, but are cumbersome and require costly databases that track technology changes over time. The SAE approach blends econometric models with end-use information based on studies conducted by the U.S. Energy Information Administration. The SAE model exploits the strengths of econometric and end-use models by using national-level end-use data and local economic drivers calibrated to utility specific sales to capture growth based on changes in end-use technology.

The SAE approach begins by defining average use as a function of the four primary end-uses -- heating (XHeat), other use (XOther), and lighting (XLight)

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

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

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

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

XOther captures non-weather sensitive end-uses, not including lighting:

$$XOther = OtherUse \ \times OtherIndex$$

Where

$$OtherUse = f(Seasonal\ Use\ Pattern, Household\ Income, Household\ Size, Price, Days)$$

$$OtherIndex = g(Other\ Appliance\ Saturation\ and\ Efficiency\ Trends)$$

XLight captures lighting end-use,

$$XLight = OtherUse \ \times LightIndex$$

Where

$$OtherUse = f(Seasonal\ Use\ Pattern, Household\ Income, Household\ Size, Price)$$

$$LightIndex = g(Lighting\ Saturation\ and\ Efficiency)$$

The specific calculations of the end-use variables are presented in Appendix B. Figure 3-1 to Figure 3-3 show the constructed monthly end-use variables.

Figure 3-1: Residential XHeat: Base Case (kWh per month)

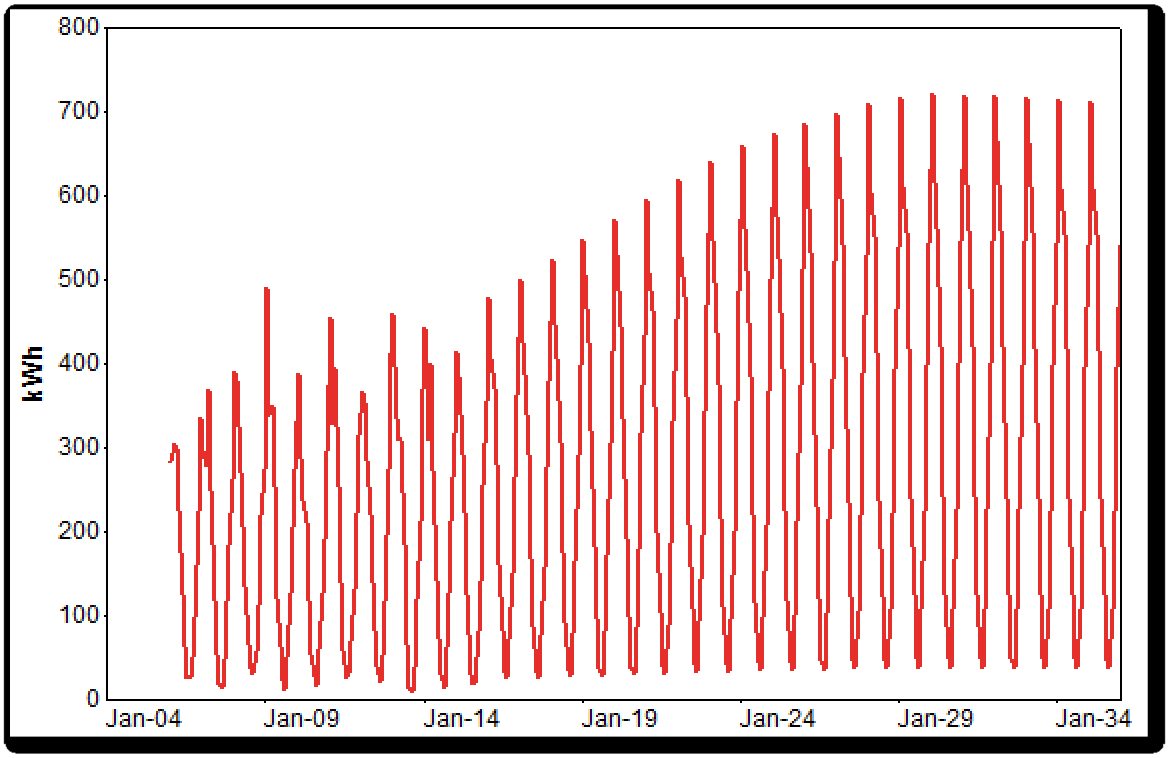


Figure 3-2: Residential XOther: Base Case (kWh per month)

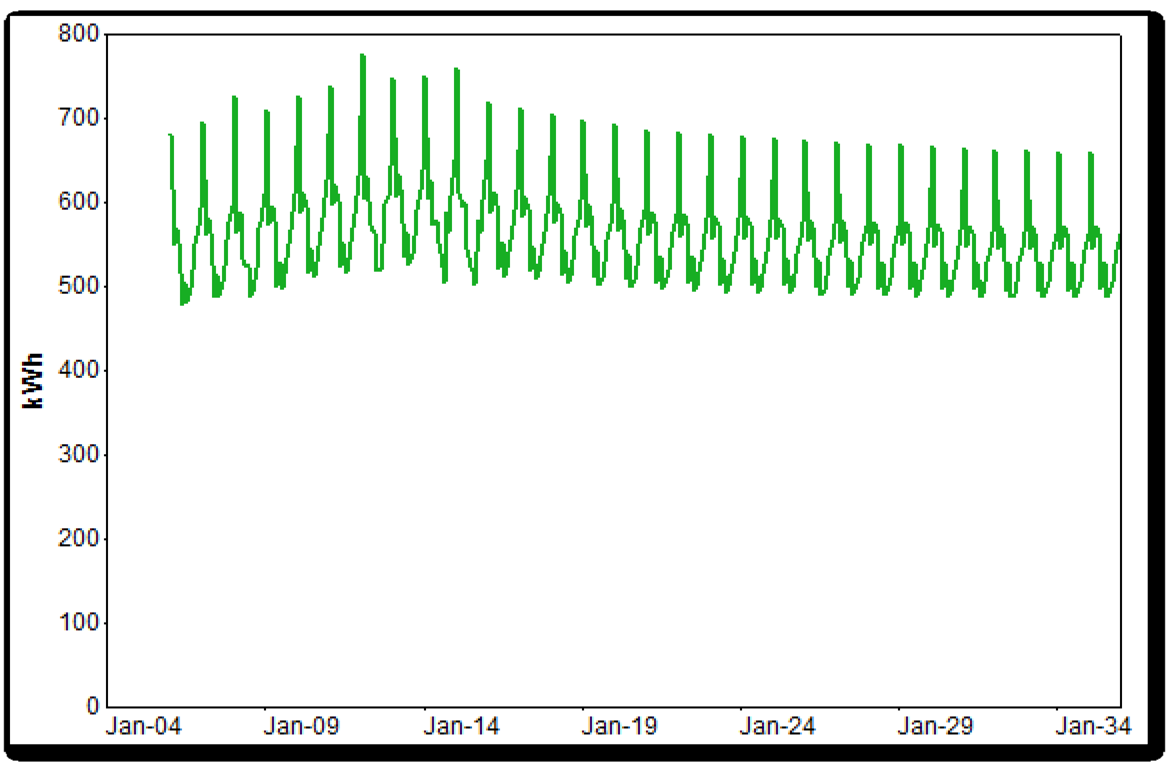
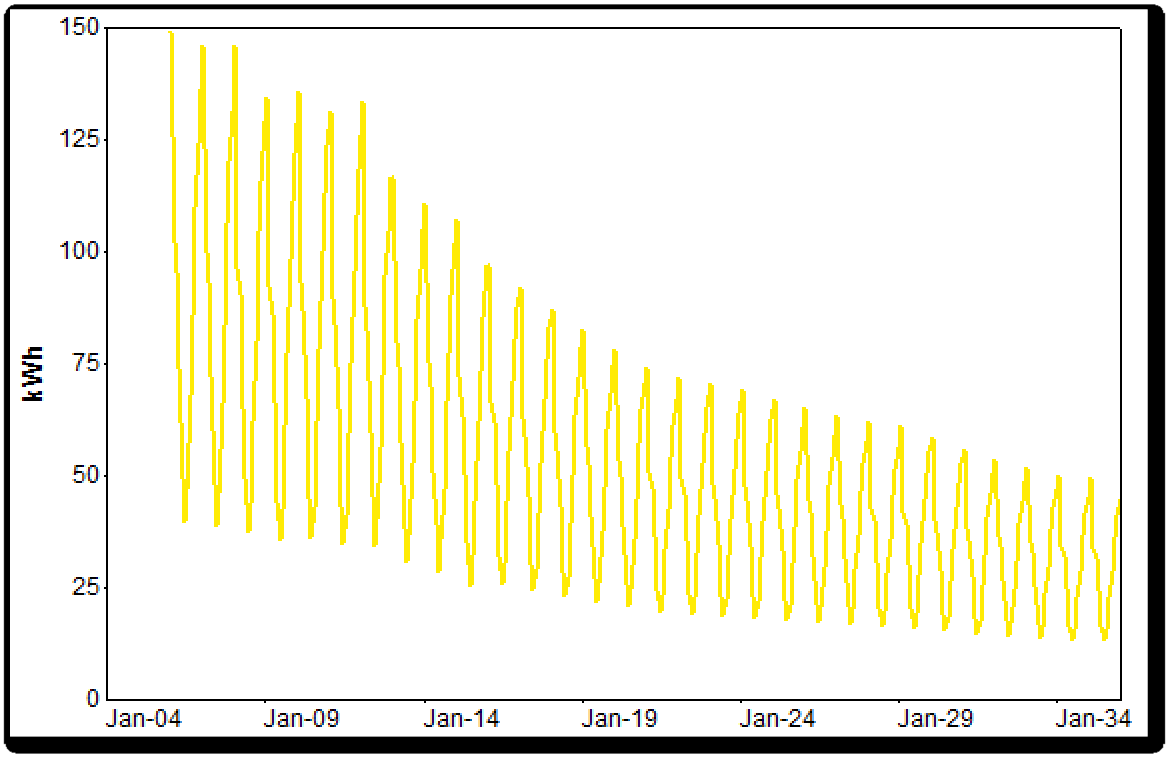
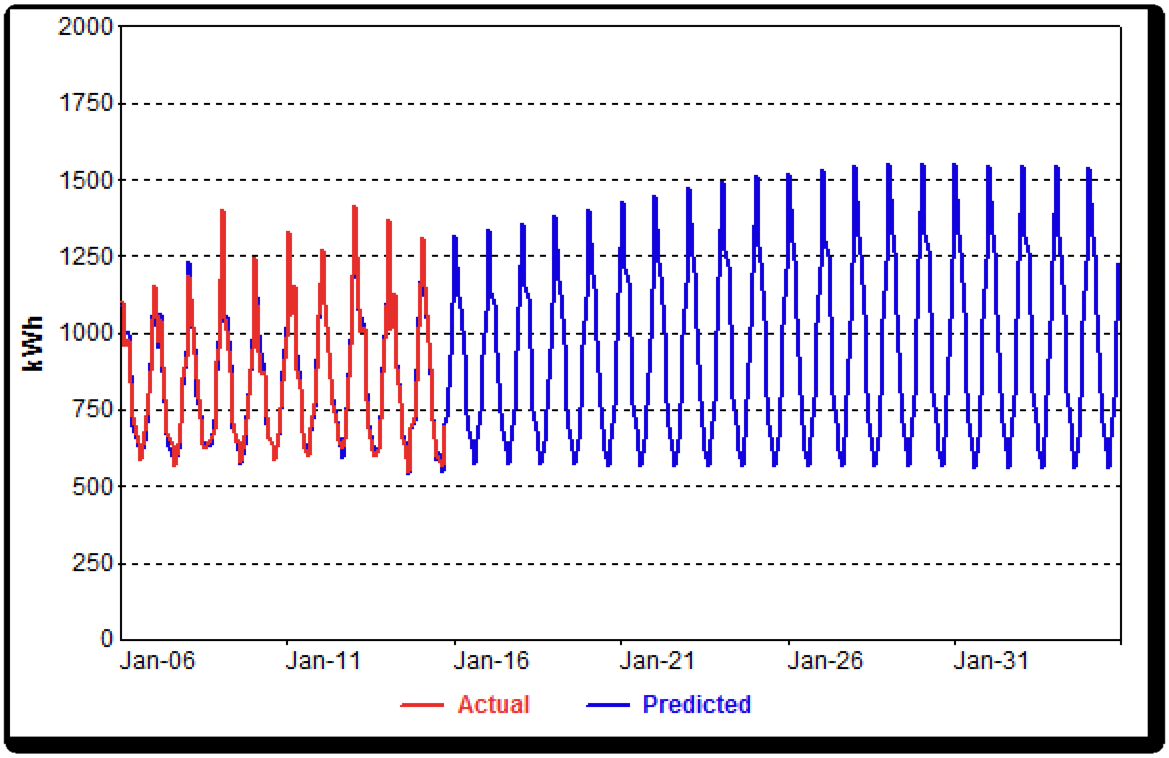


Figure 3-3: Residential XLight: Base Case (kWh per month)



The average use model is estimated over the period January 2006 through September 2015. The model explains historical average use well with an Adjusted R^2 of 0.98 and in-sample Mean Absolute Percent Error (MAPE) of 2.28%. The model accuracy was tested by estimating the model through September 2014 and calculating out of sample model statistics for the 12 withheld observations. The out of sample MAPE of 2.45% confirms that accuracy and robustness of the model. Figure 3-4 shows actual and predicted average use.

Figure 3-4: Actual and Predicted Residential Average Use: Base Case (kWh)



Model coefficients and statistics are provided in Appendix A: Model Statistics.

Use per customer is increasing by 1.0% annually through 2025. This is due to the increase in the electric heat saturation, the result of the assumption that 95% of new customers will use electric heat. Average use begins to flatten in the later years as customer growth declines and eventually becomes negative.

Residential Customer Forecast

The residential customer forecast is based on a monthly regression model that relates the number of customers to household projections. There is a strong correlation, 0.99, between the number of customers and households - customer growth tracks household projections with customers averaging 1.1% annual growth through 2025.

With 1.0% increase in average use and 1.1% customer growth, total residential sales average 2.1% growth between 2016 and 2025. Table 3-1 summarizes the residential forecast.

Table 3-1: Residential Forecast: Base Case

Year	Sales (MWh)		Customers		Avg Use (kWh)	
2015	155,443		15,179		10,241	
2016	162,786	4.7%	15,350	1.1%	10,605	3.6%
2017	165,192	1.5%	15,507	1.0%	10,653	0.4%
2018	168,663	2.1%	15,684	1.1%	10,754	0.9%
2019	172,670	2.4%	15,871	1.2%	10,880	1.2%
2020	177,242	2.6%	16,065	1.2%	11,033	1.4%
2021	180,655	1.9%	16,268	1.3%	11,105	0.7%
2022	185,015	2.4%	16,464	1.2%	11,238	1.2%
2023	189,096	2.2%	16,641	1.1%	11,363	1.1%
2024	193,618	2.4%	16,803	1.0%	11,523	1.4%
2025	196,057	1.3%	16,935	0.8%	11,577	0.5%
2026	198,401	1.2%	17,052	0.7%	11,635	0.5%
2027	200,882	1.3%	17,166	0.7%	11,702	0.6%
2028	203,768	1.4%	17,269	0.6%	11,800	0.8%
2029	204,709	0.5%	17,350	0.5%	11,799	0.0%
2030	205,508	0.4%	17,397	0.3%	11,813	0.1%
2031	205,253	-0.1%	17,405	0.0%	11,793	-0.2%
2032	205,298	0.0%	17,380	-0.1%	11,813	0.2%
2033	203,568	-0.8%	17,317	-0.4%	11,755	-0.5%
2034	202,212	-0.7%	17,226	-0.5%	11,739	-0.1%
2035	200,789	-0.7%	17,114	-0.7%	11,733	-0.1%
2016-2025		2.1%		1.1%		1.0%
2016-2035		1.1%		0.6%		0.5%

3.1.2 Commercial Model

Like the residential sector commercial average use and customers are modeled separately. The commercial sales forecast is then generated as the product of the average use and customer forecasts. The commercial SAE average use model is fully described in Appendix C and expresses monthly average use as a function of XHeat, XOther, and XLight. It is important to point out that an XCool variable was constructed and incorporated into the model at first but the variable was statistically insignificant and therefore removed. The end-use variables are constructed by interacting annual end-use intensity projections (EI) that capture end-use efficiency improvements, with non-mining GDP and employment ($ComVar_m$), real price ($Price_m$), and monthly HDD: Non-mining GDP still includes the associated economic impact of mining activities in the non-mining sectors.

$$XHeat_m = EI_{heat} \times Price_m^{-0.10} \times ComVar_m \times HDD_m$$
$$XOther_m = EI_{other} \times Price_m^{-0.10} \times ComVar_m \times Days_m$$
$$XLight_m = EI_{light} \times Price_m^{-0.10} \times ComVar_m \times Days_m$$

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

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

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

$$ComVar_m = (Employ_m^{0.25}) \times (Non - MiningOutput_m^{0.75})$$

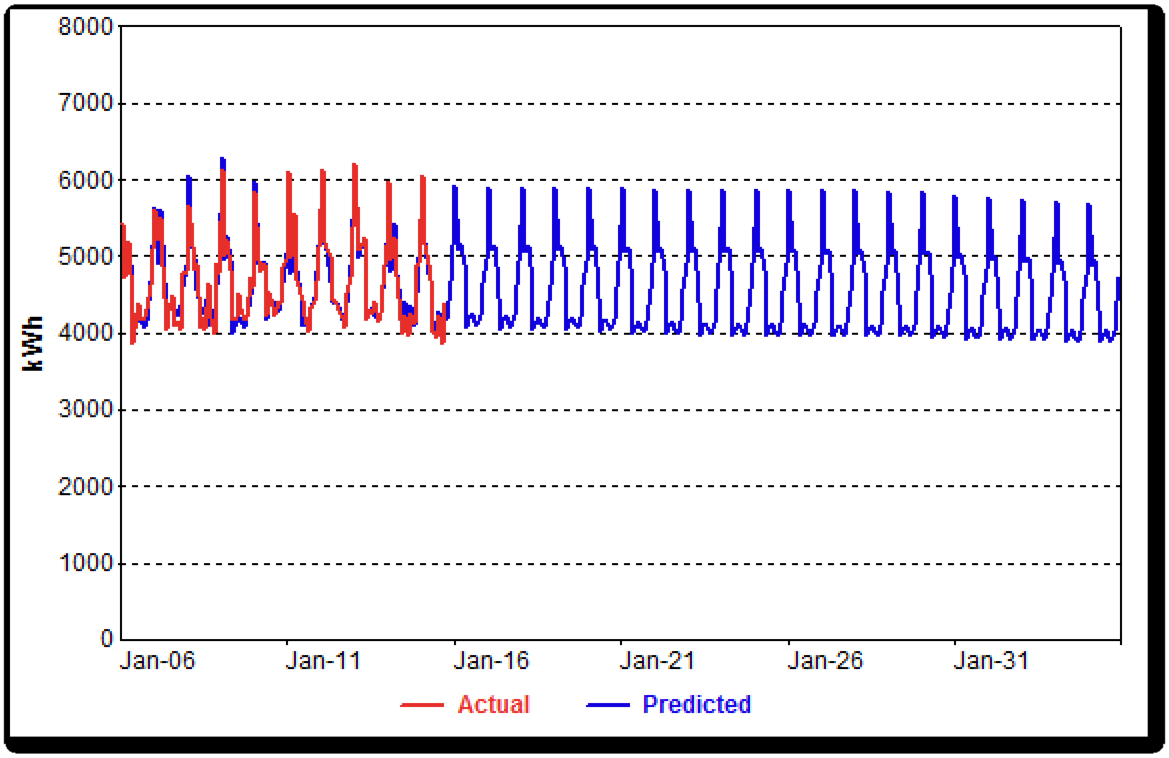
The ComVar uses a weight of 0.25 on employment and 0.75 on non-mining output. The weights were determined by evaluating the in-sample and out-of-sample model statistics for different sets of employment and output weights.

The resulting commercial average use model performs well with an Adjusted R^2 of 0.92 and an in-sample MAPE of 2.5%. The model accuracy was tested by estimating the model through September 2014 and calculating out of sample model statistics for the 12 withheld observations. The out of sample MAPE of 2.01% confirms that accuracy and robustness of the model Figure 3-5 shows actual and predicted monthly commercial average use.

Commercial Customer Forecast

The commercial customer forecast is based on a monthly regression model that relates the number of commercial customers to the residential customer forecast. There is a strong correlation, 0.96, between commercial and residential customers. With an implied elasticity of 0.92 on the residential customer variable commercial customer growth will be slightly less than residential. Commercial customer growth averages 1.0% through 2025.

Figure 3-5: Actual and Predicted Commercial Average Use: Base Case (kWh)



Model coefficients and statistics are provided in Appendix A: Model Statistics.

With 0.2% decrease in average use and 1.0% customer growth, total commercial sales growth average 0.8% between 2016 and 2025. The estimated model coefficients and model statistics are included in Appendix A: Model Statistics. Table 3-2 shows detailed commercial forecast.

Table 3-2: Commercial Forecast: Base Case

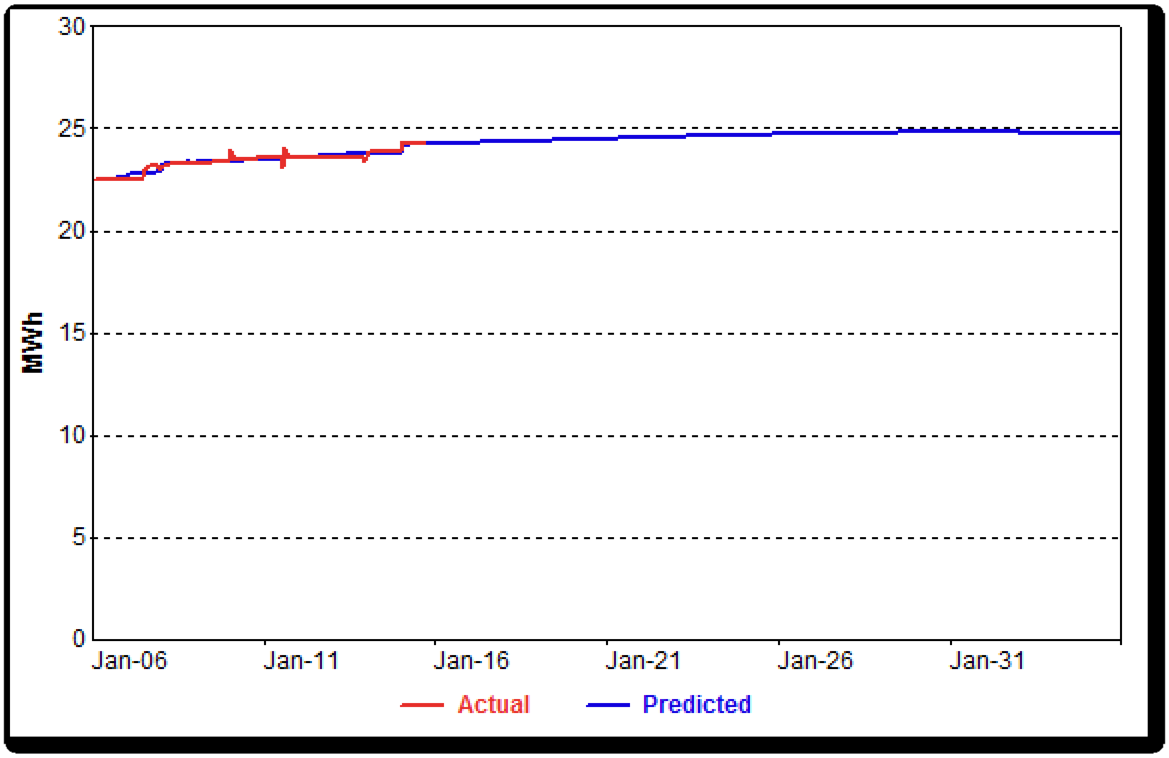
Year	Sales (MWh)		Customers		Avg Use (kWh)	
2015	173,005		3,105		55,719	
2016	175,799	1.6%	3,141	1.1%	55,977	0.5%
2017	176,657	0.5%	3,171	1.0%	55,717	-0.5%
2018	178,079	0.8%	3,204	1.1%	55,573	-0.3%
2019	180,300	1.2%	3,240	1.1%	55,646	0.1%
2020	181,919	0.9%	3,277	1.1%	55,507	-0.2%
2021	182,937	0.6%	3,316	1.2%	55,167	-0.6%
2022	184,559	0.9%	3,354	1.1%	55,034	-0.2%
2023	186,226	0.9%	3,387	1.0%	54,975	-0.1%
2024	187,904	0.9%	3,418	0.9%	54,969	0.0%
2025	189,080	0.6%	3,444	0.7%	54,907	-0.1%
2026	190,013	0.5%	3,466	0.6%	54,823	-0.2%
2027	191,017	0.5%	3,488	0.6%	54,768	-0.1%
2028	192,043	0.5%	3,508	0.6%	54,751	0.0%
2029	192,601	0.3%	3,523	0.4%	54,669	-0.1%
2030	192,416	-0.1%	3,532	0.3%	54,477	-0.4%
2031	191,620	-0.4%	3,534	0.0%	54,229	-0.5%
2032	190,696	-0.5%	3,529	-0.1%	54,042	-0.3%
2033	189,165	-0.8%	3,517	-0.3%	53,791	-0.5%
2034	187,484	-0.9%	3,499	-0.5%	53,578	-0.4%
2035	185,631	-1.0%	3,478	-0.6%	53,376	-0.4%
2016-2025		0.8%		1.0%		-0.2%
2016-2035		0.3%		0.5%		-0.3%

3.1.3 ST & SP Sales

The Street Light (ST) sales forecast is based on a generalized monthly regression model where ST sales are specified as a function of residential customers and year binaries. ST sales increase 0.2% annually through 2025, although the magnitude of sales in this class is insignificant in terms of its impact on total sales or system load. Figure 3-6 shows actual and predicted monthly ST sales.

Space Lights (SP) sales are fitted with a simple seasonal exponential smoothing model which holds the forecast constant.

Figure 3-6: Actual and Predicted ST Sales: Base Case (MWh)

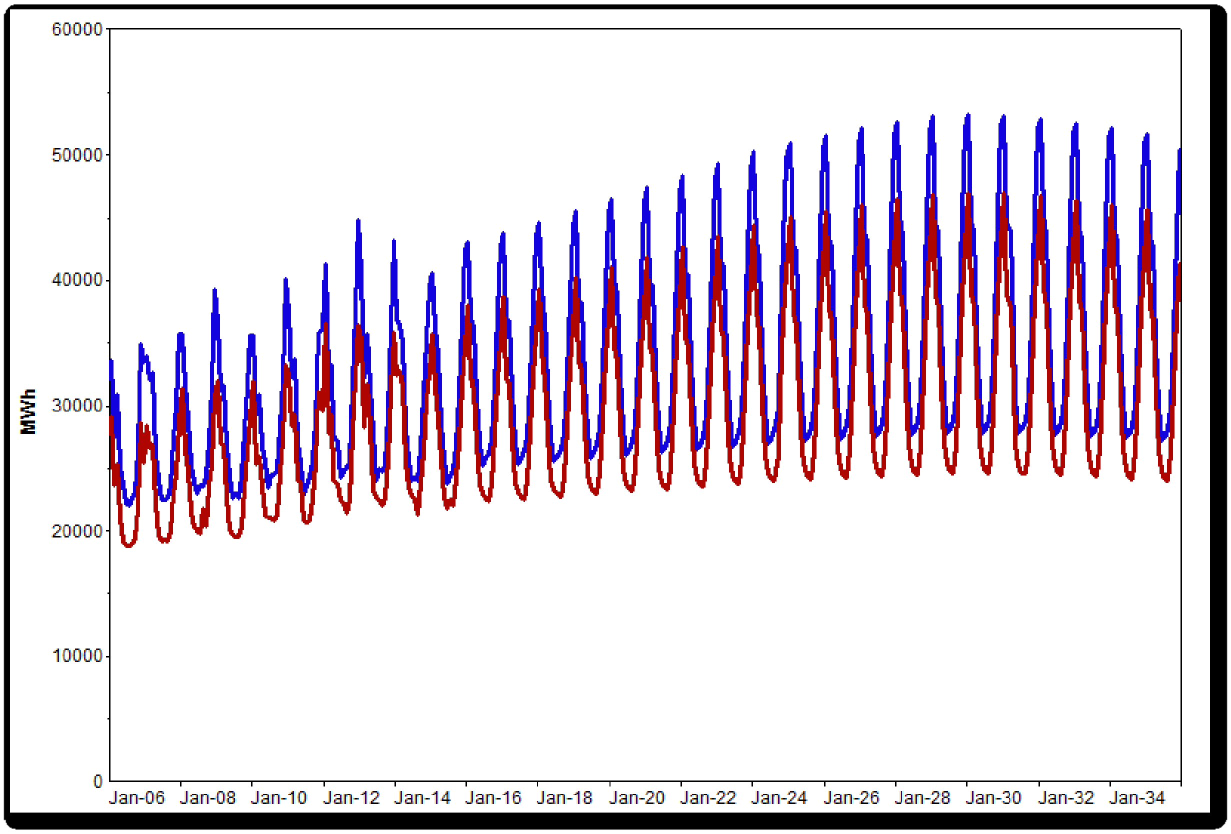


3.2 Energy and Peak Forecast

3.2.1 Energy Forecast

The YEC system energy forecast is derived directly from the sales forecast by applying a monthly energy adjustment factor to the monthly *calendarized* total sales forecast (excluding industrial). 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 3-7 shows the resulting monthly **sales** and **energy** forecast.

Figure 3-7: Energy and Sales Forecast: Base Case (MWh)



3.2.2 Peak Forecast

The long-term system peak forecast is derived through a monthly peak linear regression model that relates monthly peak demand (excluding industrial) 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 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.

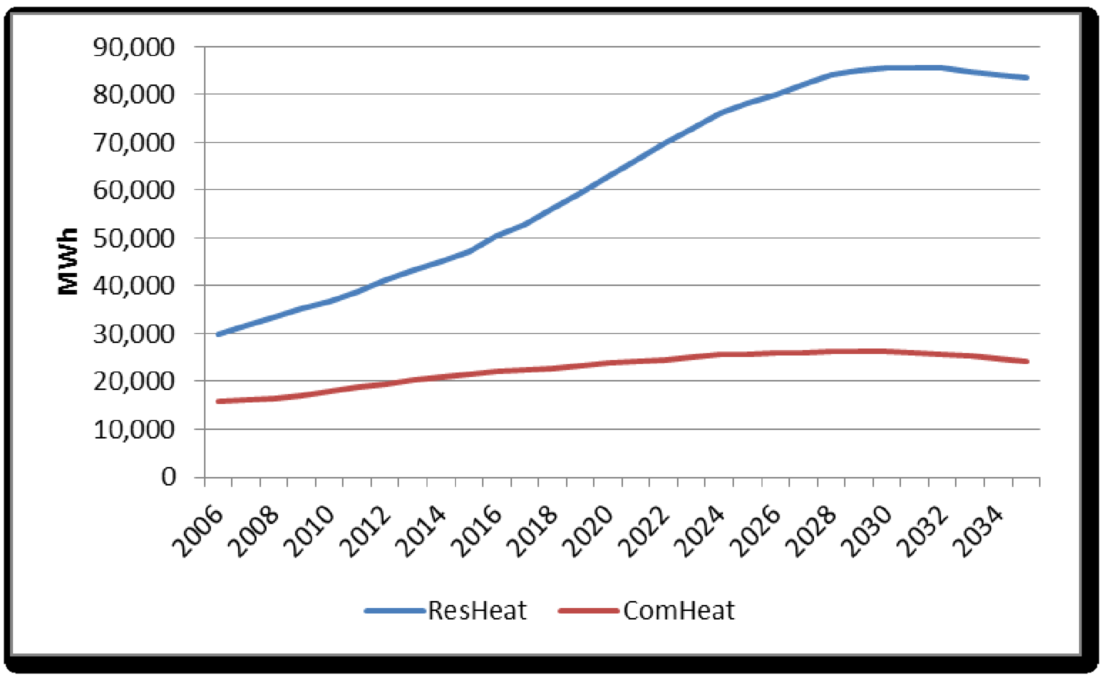
The estimated model coefficients for the heating (XHeat) combined with heating variable for normal weather conditions (*NrmXHeat*) gives us an estimate of the monthly heating load requirements. Heating requirements are calculated as:

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

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

Figure 3-8 show resulting historical (weather normalized) and forecasted heating load requirements.

Figure 3-8: Annual Heating Load: Base Case (MWh)

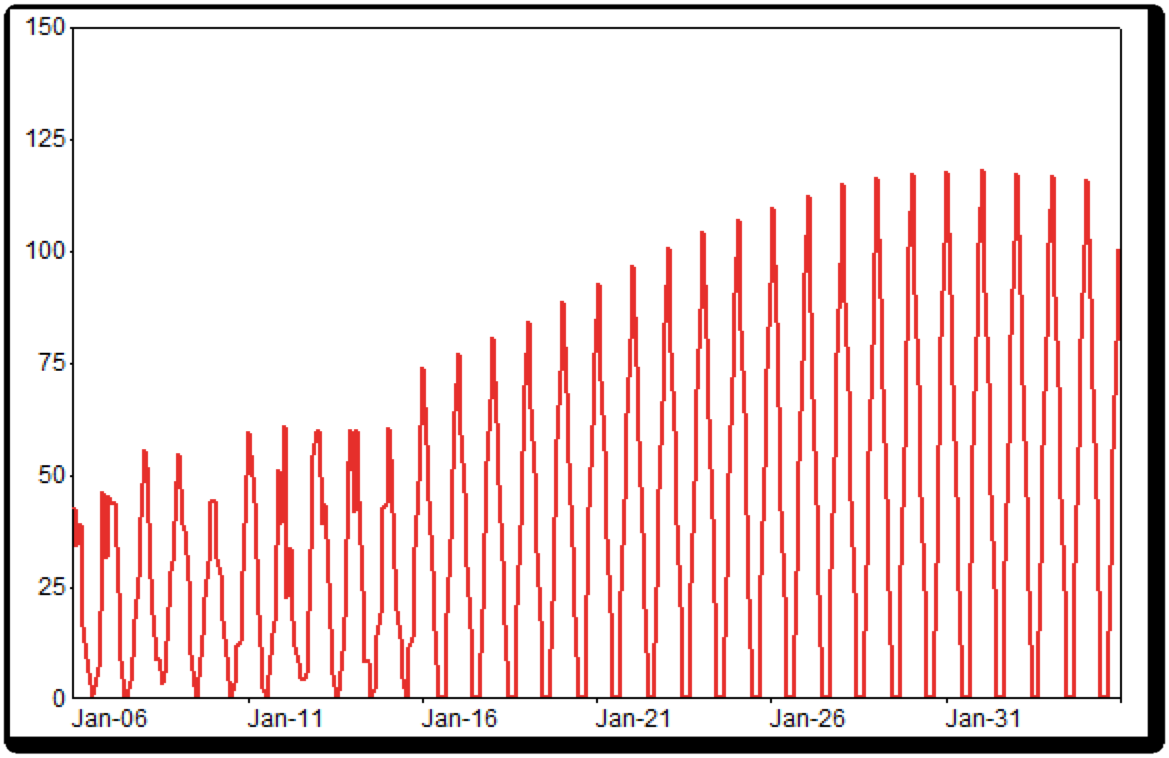


The impact of peak-day weather conditions is captured by interacting peak-day HDD with monthly heating load requirements indexed to a base year (2007). The peak model heating variable is calculated as:

$$HeatVar_m = HeatLoadIdx_m \times PkHDD_m$$

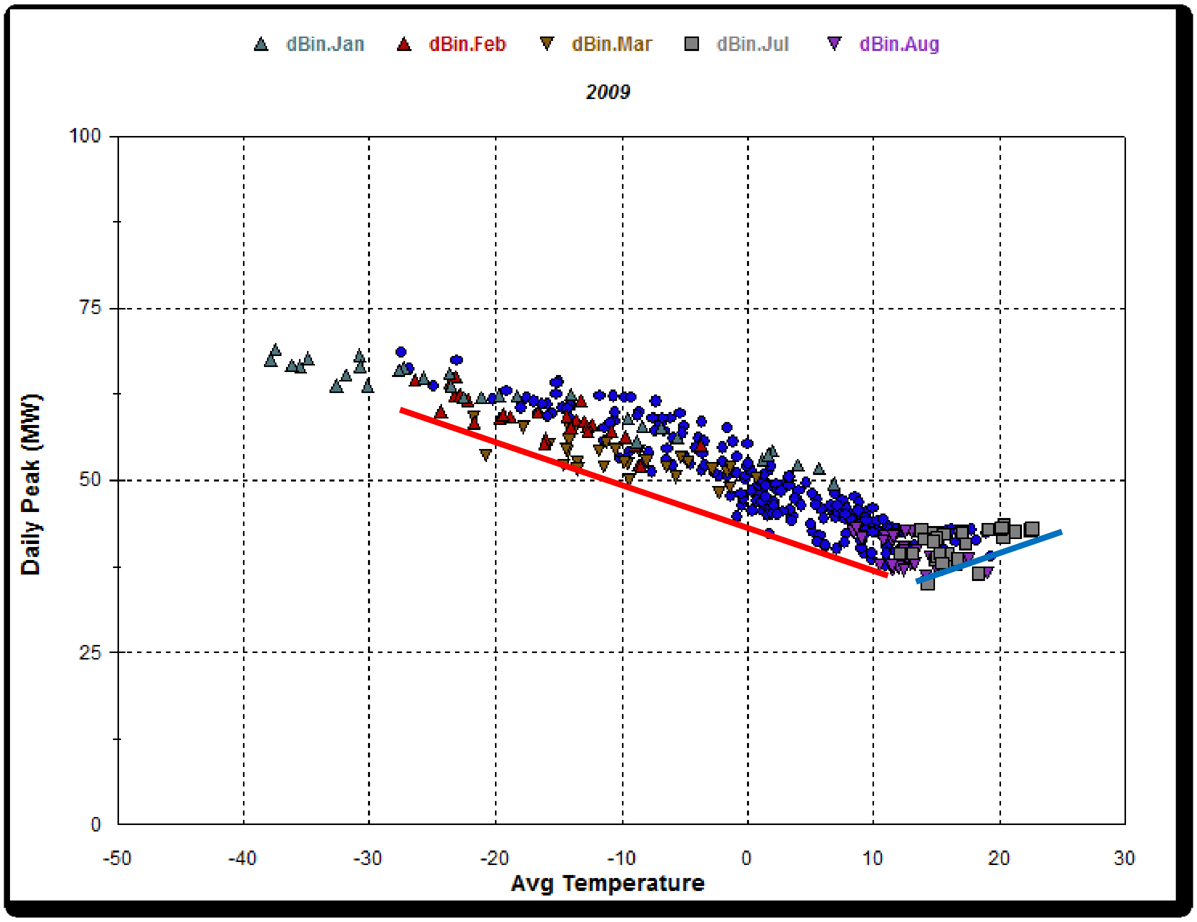
Figure 3-9 shows the resulting peak model heating variable.

Figure 3-9: Peak Model Heating Variable (Index): Base Case



The construction of the peak cooling variable takes on a different form as there is no cooling load associated with the class levels sales. Although there is no cooling variable in any of the class models, as they were statistically insignificant or the coefficients had the incorrect sign, it is likely that commercial cooling load does impact summer peaks. Figure 3-10 shows the relationship between daily peaks and average temperature in 2009. There is clearly a strong heating load that can be seen in the left-hand side of the scatter plot at temperatures below 10 degrees, but what is also evident is the cooling load on the right-hand side at temperatures above 13 degrees.

Figure 3-10: Daily Peaks Vs Temperature Relationship

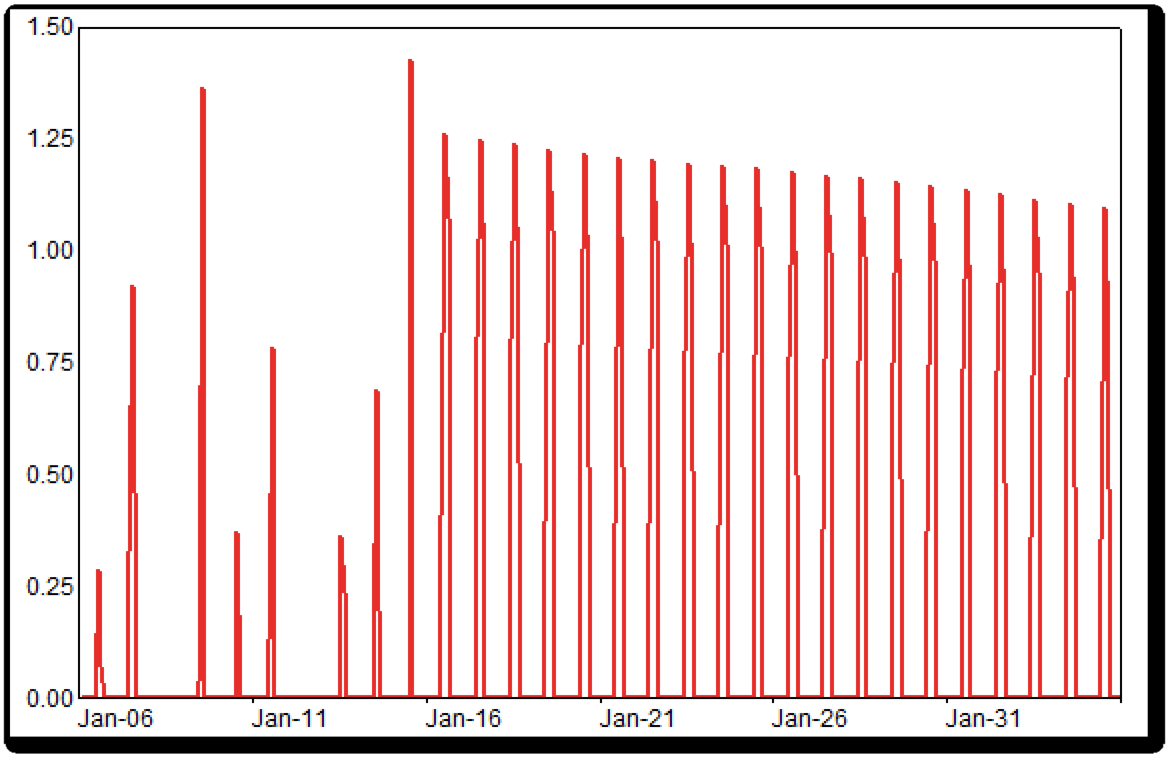


The peak cooling variable is constructed by interacting peak-day CDD with the commercial cooling intensity projections. When used in the peak model the cooling variable is marginally significant and does add additional load to the summer months. The peak model cooling variable is calculated as:

$$CoolVar_m = CommercialCoolingIntensity_y \times PkHDD_m$$

Figure 3-11 shows the resulting peak model cooling variable.

Figure 3-11: Peak Model Cooling Variable (Index): Base Case



Base Load Variable

The peak model base load variable ($BaseVar_m$) derived from the sales forecast models is an estimate of the non-weather sensitive load at the time of the monthly system peak demand. The base load variable is defined as:

$$BaseVar_m = ResOtherCP_m \times ComOtherCP_m + StLightingCP_m$$

Base load requirements are derived for each revenue class by subtracting out heating and cooling load requirements from total load requirements. 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:

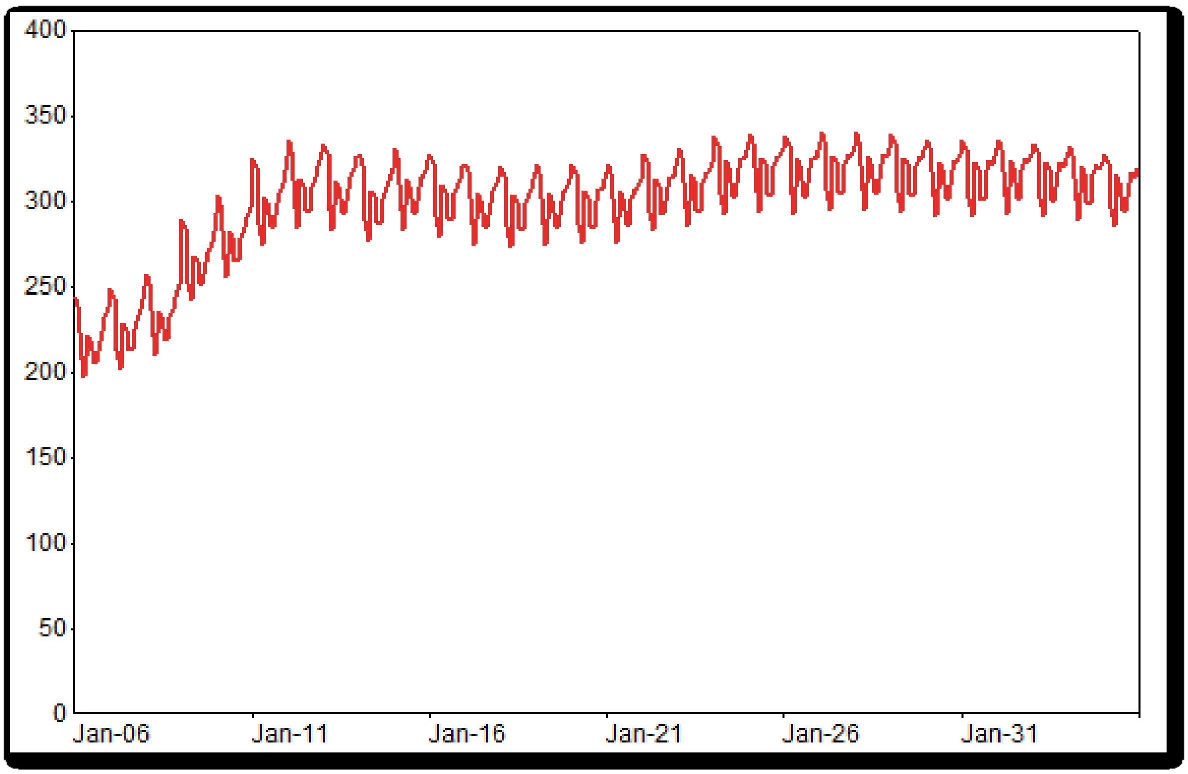
$$ResWaterCP_m = ResBaseLoad_m \times \left({ResWaterEI_a}/{ResBaseEI_a} \right) \times ResWaterFrac_m$$

Where

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 on at peak (estimates are based on Itron's hourly end-use load profile database)

End-use load estimates are aggregated by end-use and then revenue class resulting in the base load variable. Figure 3-12 shows the peak model base load variable.

Figure 3-12: Base Load Variable: Base Case



Model Results

The peak model is estimated over the period January 2006 to September 2015. The model explains monthly peak variation well with an adjusted R^2 of 0.97 and an in-sample MAPE of 2.36%. Figure 3-13 shows actual and predicted results. Model statistics and parameters are included in Appendix A: Model Statistics.

Figure 3-13: Peak Model: Base Case (MW)

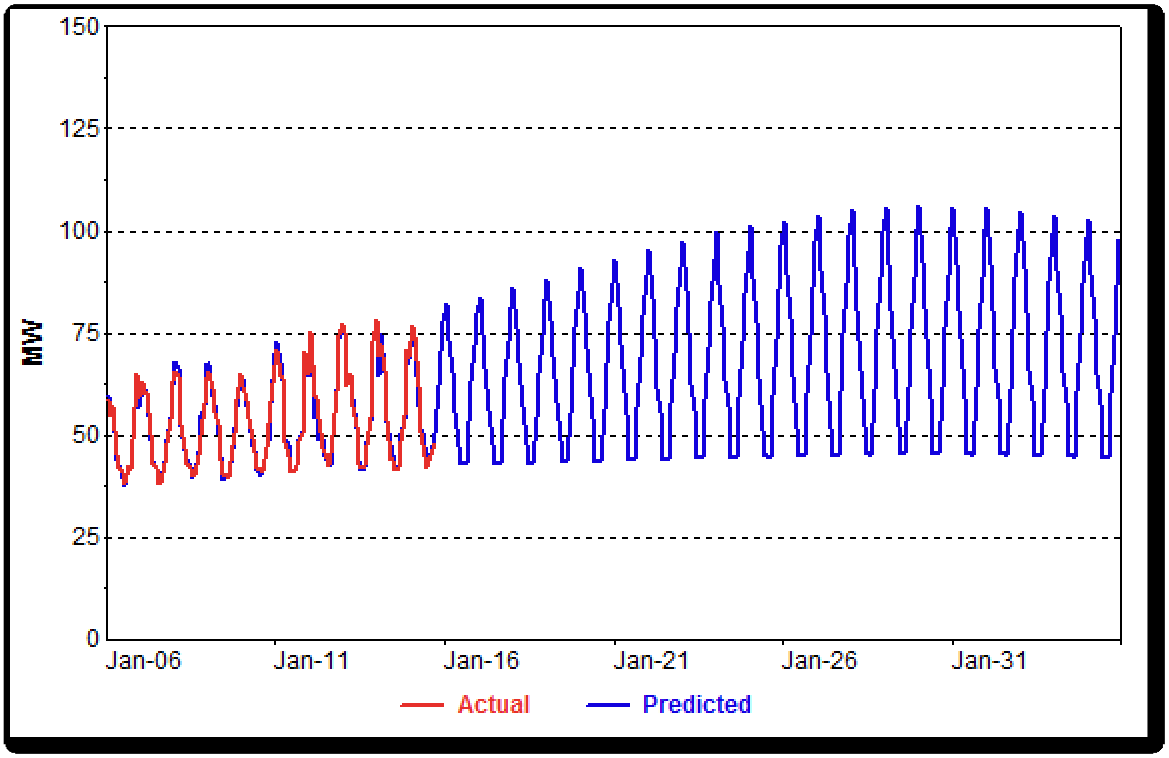


Table 3-3 shows the peak demand forecast (excluding industrial).

Table 3-3: Peak Demand Forecast: Base Case (MW)

Year	Peak (MW)	
2015	76.9	
2016	82.2	6.9%
2017	83.8	1.9%
2018	85.9	2.5%
2019	88.2	2.7%
2020	90.8	2.9%
2021	92.8	2.2%
2022	95.2	2.6%
2023	97.4	2.3%
2024	99.8	2.4%
2025	101.2	1.4%
2026	102.5	1.3%
2027	103.8	1.3%
2028	105.2	1.4%
2029	105.8	0.5%
2030	106.1	0.3%
2031	105.8	-0.3%
2032	105.6	-0.2%
2033	104.6	-1.0%
2034	103.7	-0.8%
2035	102.8	-0.9%
2016-2025		2.3%
2016-2035		1.2%

3.3 Solar Forecast

The forecast includes the impact of expected grid-connected solar generation. Currently there is very little grid-connected solar generation in the YEC service territory and it is not expected to grow to a point where it would significantly impact energy or peaks. Unlike many other parts of Canada and North America where solar is increasing in popularity due to decreases in system costs and utility incentives, which have made the systems economically viable, in Yukon the adaptation is not driven by economics or return on investment.

The solar generation forecast is derived by first forecasting the number of solar customers. Yukon provided 18 months of solar customer data, with a total of 16 grid-connected solar systems as of August 2015. A simple linear trend was imposed to predict the number of solar customers for the next 16 months, reaching 31 solar customers by December 2016. Starting in January 2017 the annual growth rate of solar capacity from the EIA's 2015 Annual Energy Outlook forecast is used to grow the solar customer forecast. Table 3-4 shows the resulting solar customer forecast.

An installed solar capacity forecast is then derived as the product of the solar customer forecast and the assumed average system size of 3.1 kW based on YEC's short-term expectations on size.

Using an 8760 hourly solar load shape for Whitehorse, provided by the National Renewable Energy Laboratory's PV Watt Calculator, monthly specific load factors are calculated. The month specific load factors are applied to the monthly capacity forecast to calculate the MWh solar generation forecast, shown in Table 3-4.

Table 3-4: Solar Forecast

Year	Solar Customers	Solar Capacity (kW)	Generation (MWh)
2015	15	48	45.3
2016	26	82	81.2
2017	32	98	99.2
2018	32	100	101.4
2019	33	103	104.3
2020	35	108	109.2
2021	37	114	115.4
2022	39	122	122.9
2023	42	130	131.4
2024	45	140	141.1
2025	48	150	151.4
2026	52	162	162.7
2027	56	173	174.5
2028	60	185	186.9
2029	64	197	198.7
2030	68	210	211.2
2031	72	222	224.1
2032	76	235	237.4
2033	80	248	250.0
2034	84	261	263.1
2035	88	274	276.6

4 Forecast Scenarios

In addition to the baseline economic forecast YEC provided 9 additional economic scenarios based on changing assumption regarding mining output and government transfer payments. These scenarios are used to generation alternative energy and load forecasts. Figure 4-1 defines the economic scenarios.

Figure 4-1: Economic Scenarios

Scenario Number	Definition
1	Very Low Mining Activity
2	Low Mining Activity
3	**Base Case (Medium Mining Activity)**
4	High Mining Activity + Large Mine
5	Low Mining Activity Scenario with sensitivity on government spending
6	"Base case" scenario with sensitivity on government spending
7a	"Base case" scenario with positive shock to Agriculture, Forestry and Logging industries
7b	"Base case" scenario with increased growth in Accommodations, Transportation and Warehousing, to account for tourism growth
9	"Base case" with sensitivity on large mine (later start of production)
10	Sensitivity on Boom and Bust Cycles in the Mining Industry

Figure 4-2 through Figure 4-6 compare the differences in the economic scenarios for the primary economic drivers of the sales models.

Figure 4-2: Real GRP

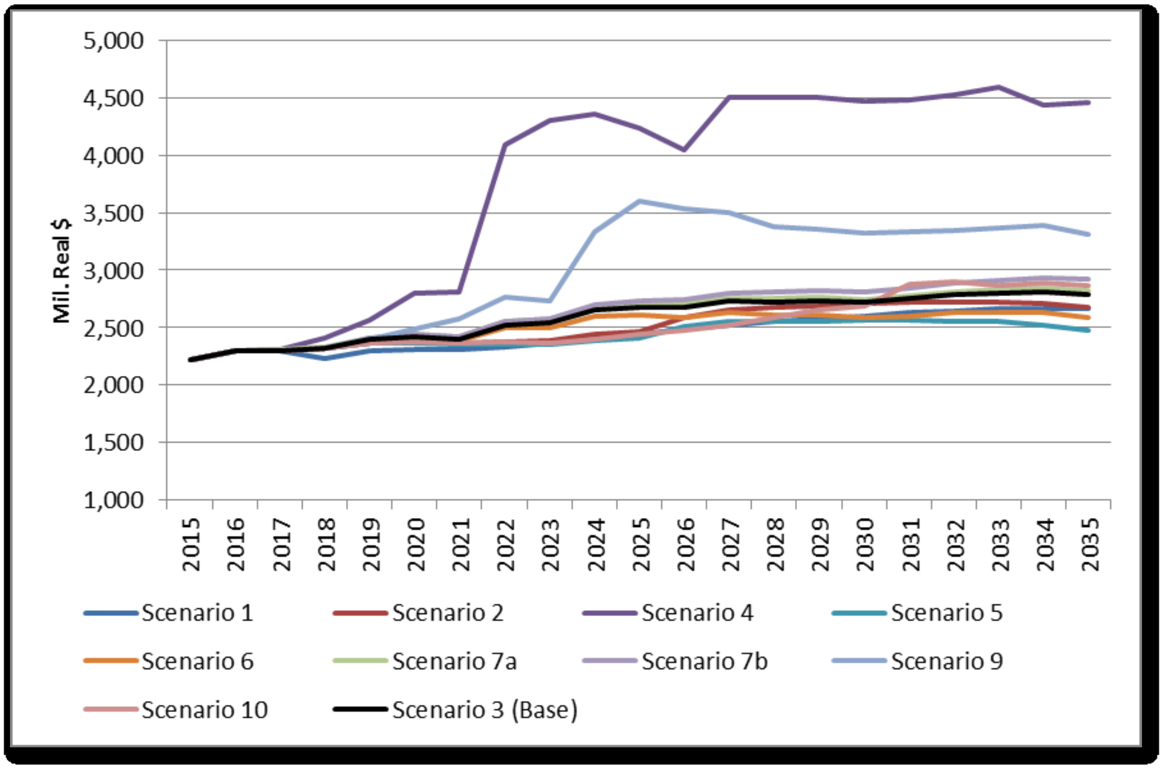


Figure 4-3: Real Mining GRP

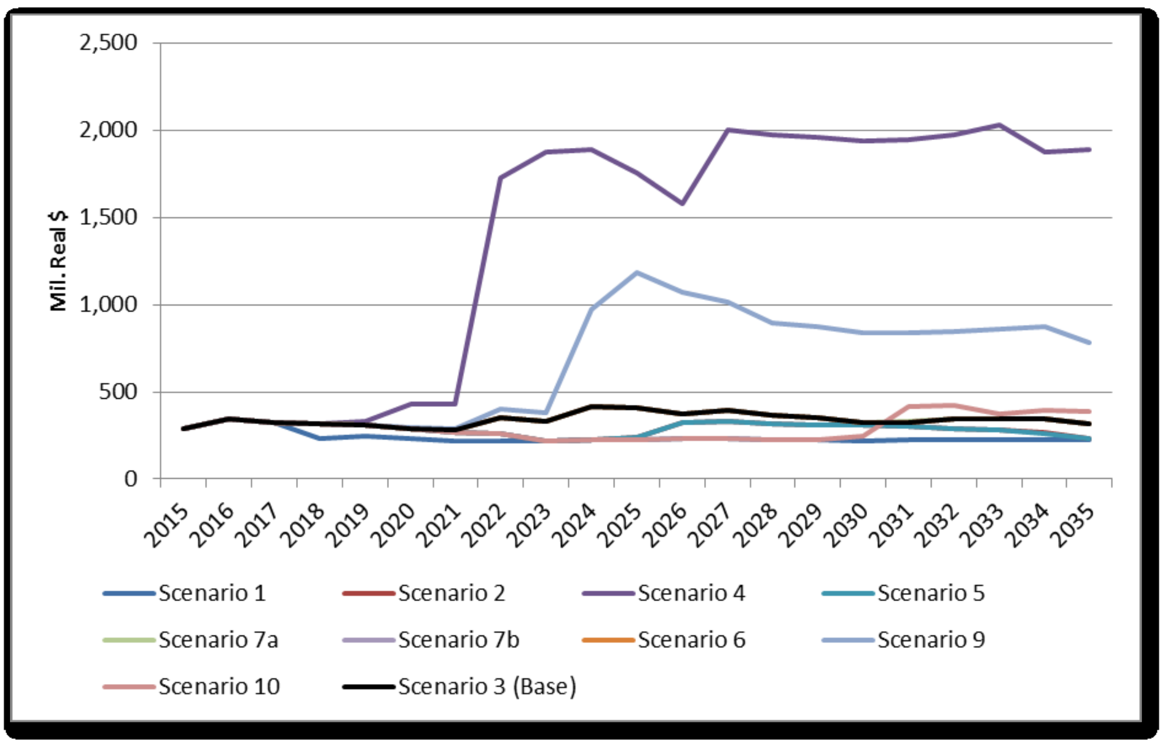


Figure 4-4: Real Income Per Capita

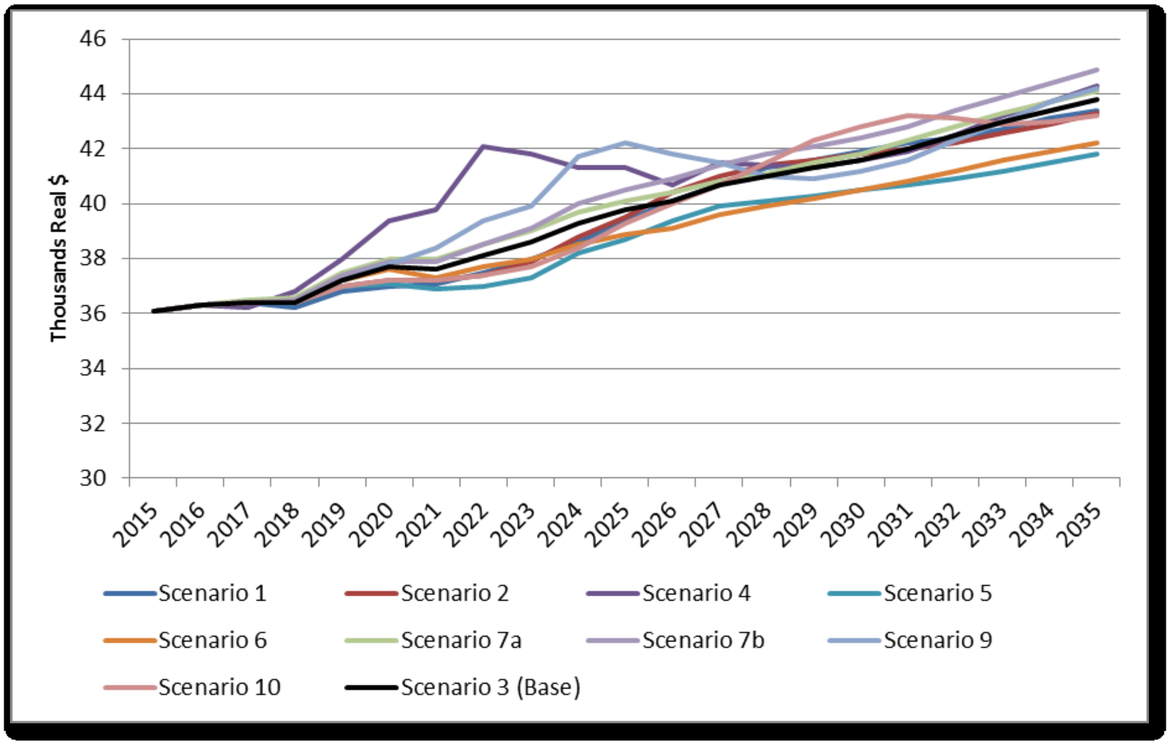


Figure 4-5: Households

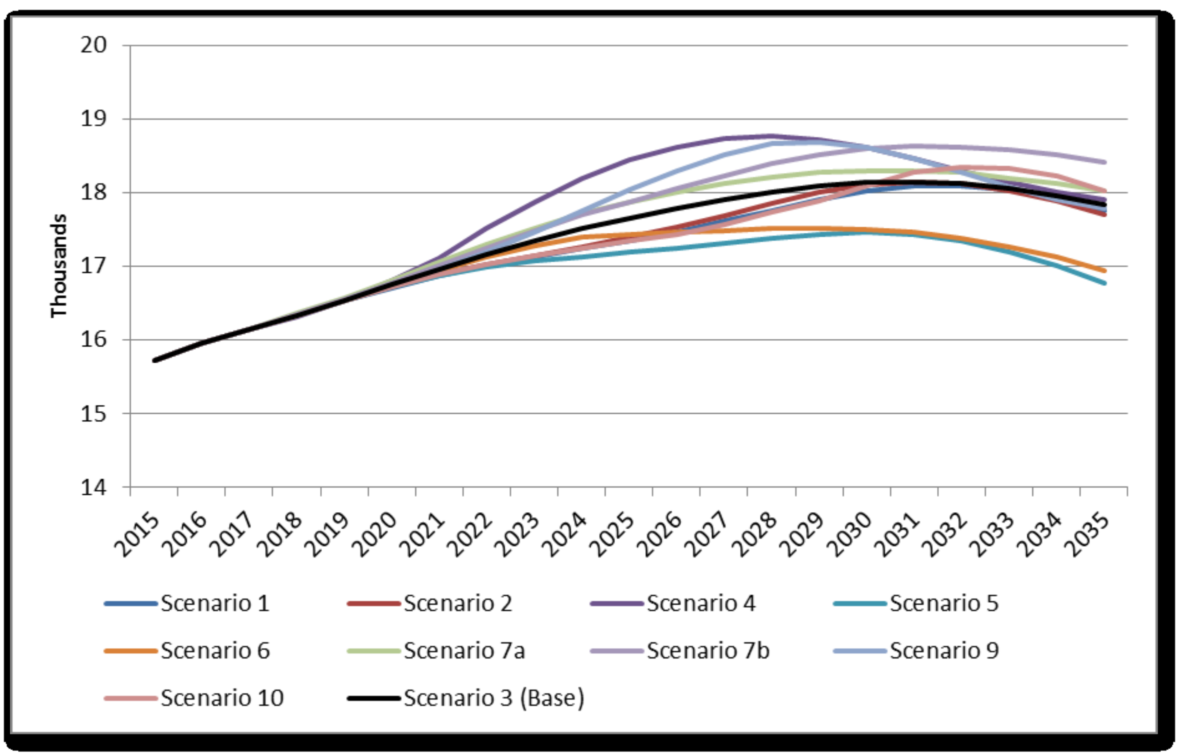
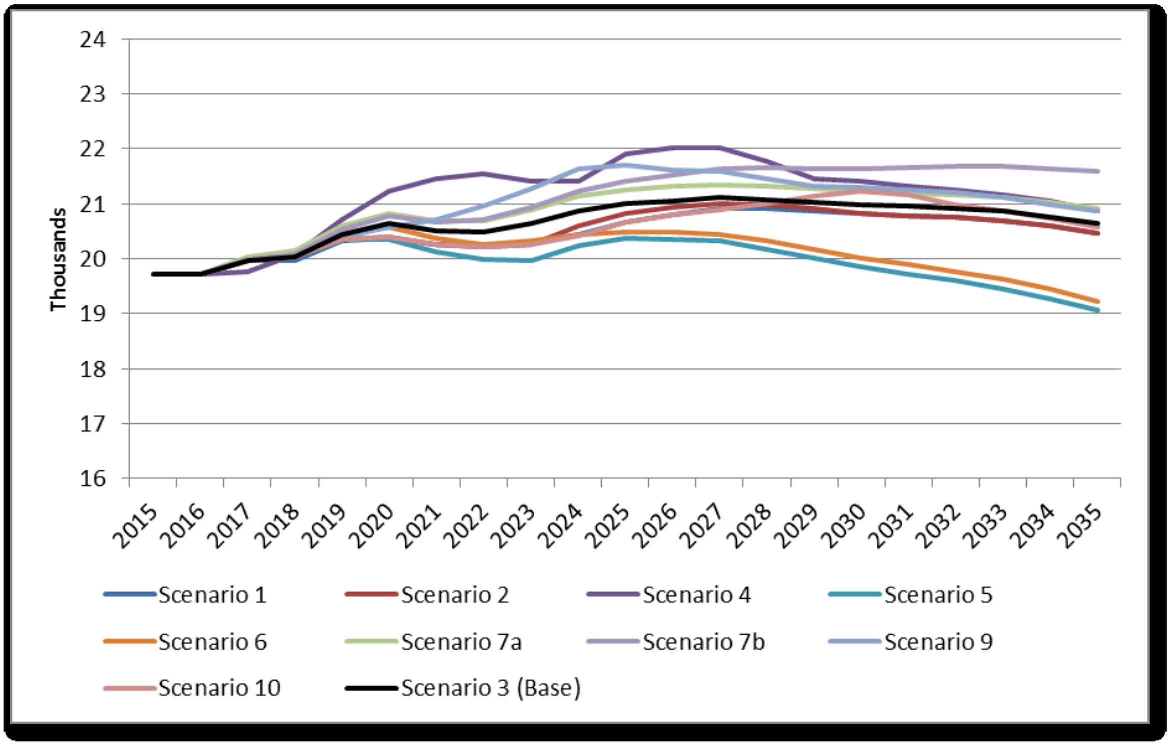


Figure 4-6: Employment



Using the same model specifications and estimation periods these alternative economic drivers are used to estimate class average use, customer, and total sales models, which are used to derive the total energy and peak forecast. Table 4-1 and Table 4-2 summarize the energy and peak forecasts (excluding industrial) under the different economic scenarios.

Table 4-1: Scenario Energy Forecasts (MWh)

Year	Scenario 1	Scenario 2	Scenario 3 (Base)	Scenario 4	Scenario 5	Scenario 6	Scenario 7a	Scenario 7b	Scenario 9	Scenario 10
2015	374,869	374,869	374,882	374,869	374,869	374,869	374,869	374,869	374,869	374,869
2016	389,838	389,838	389,806	389,787	389,838	389,838	389,871	389,845	389,838	389,838
2017	393,471	393,508	393,583	393,229	393,508	393,508	393,813	393,591	393,508	393,508
2018	398,655	398,959	399,238	399,487	398,959	399,033	399,877	399,351	399,022	398,959
2019	404,662	405,259	406,423	408,328	405,231	405,900	407,656	406,669	405,884	405,259
2020	410,315	411,147	413,561	419,071	410,864	412,617	415,850	414,354	413,338	411,147
2021	413,488	414,470	418,684	429,181	413,529	417,101	422,499	420,580	420,103	414,470
2022	417,526	418,476	425,589	443,664	416,432	422,717	430,885	428,846	429,069	418,422
2023	421,327	422,368	432,219	457,208	418,501	427,272	438,861	437,151	438,686	421,896
2024	426,018	427,366	439,363	469,431	421,096	431,495	447,093	446,365	451,128	426,194
2025	429,155	431,217	443,536	477,240	421,840	432,135	451,780	452,668	460,986	428,803
2026	432,997	436,247	447,317	482,259	423,236	431,956	455,580	458,631	469,635	432,080
2027	437,915	441,695	451,336	485,707	424,837	431,911	459,069	464,656	476,595	436,661
2028	444,362	448,292	455,839	486,885	427,419	432,587	462,852	471,134	481,364	443,542
2029	448,642	452,402	457,568	482,903	427,906	431,057	463,761	474,450	480,389	449,499
2030	452,004	455,219	458,274	478,673	427,375	429,285	463,713	476,473	477,130	456,369
2031	452,943	455,204	457,059	473,112	424,872	426,492	462,071	476,292	471,651	461,391
2032	452,646	454,048	456,036	468,669	422,067	424,090	460,920	475,902	466,634	463,667
2033	448,887	449,558	452,276	462,579	416,318	419,189	457,229	472,661	459,778	460,493
2034	444,835	444,855	448,774	458,069	410,492	414,419	454,039	469,885	454,795	456,311
2035	440,007	439,780	444,998	454,687	404,307	409,227	450,704	467,073	451,121	450,476
2016-2025	1.1%	1.1%	1.4%	2.3%	0.9%	1.2%	1.7%	1.7%	1.9%	1.1%
2016-2035	0.6%	0.6%	0.7%	0.8%	0.2%	0.3%	0.8%	1.0%	0.8%	0.8%

Table 4-2: Scenario Peak Forecast (MW)

Year	Scenario 1	Scenario 2	Scenario 3 (Base)	Scenario 4	Scenario 5	Scenario 6	Scenario 7a	Scenario 7b	Scenario 9	Scenario 10
2015	77.9	77.9	77.9	77.9	77.9	77.9	77.9	77.9	77.9	77.9
2016	82.2	82.2	82.2	82.2	82.2	82.2	82.2	82.2	82.2	82.2
2017	83.8	83.8	83.8	83.7	83.8	83.8	83.8	83.8	83.8	83.8
2018	85.8	85.8	85.9	86.0	85.8	85.8	86.0	85.9	85.8	85.8
2019	87.9	88.0	88.3	88.6	88.0	88.1	88.4	88.2	88.1	88.0
2020	90.3	90.4	90.8	91.6	90.3	90.6	91.0	90.9	90.7	90.4
2021	92.0	92.2	92.8	94.3	92.0	92.5	93.2	93.0	93.0	92.2
2022	94.0	94.1	95.2	97.8	93.8	94.7	95.8	95.6	95.7	94.1
2023	95.9	96.0	97.4	100.9	95.4	96.6	98.2	98.0	98.4	95.9
2024	97.9	98.1	99.8	103.8	97.2	98.6	100.7	100.7	101.5	97.9
2025	99.2	99.5	101.2	105.7	98.2	99.5	102.2	102.4	103.6	99.1
2026	100.5	101.0	102.5	107.1	99.1	100.2	103.5	104.0	105.5	100.4
2027	101.9	102.5	103.8	108.3	100.1	101.0	104.7	105.5	107.1	101.8
2028	103.7	104.2	105.2	109.4	101.3	101.9	106.1	107.3	108.6	103.6
2029	104.6	105.1	105.8	109.1	101.6	102.0	106.6	108.1	108.7	104.8
2030	105.3	105.7	106.2	108.6	101.8	102.0	106.8	108.6	108.4	105.9
2031	105.2	105.5	105.8	107.4	101.2	101.4	106.5	108.4	107.3	106.5
2032	105.1	105.2	105.6	106.5	100.6	100.9	106.2	108.3	106.2	106.7
2033	104.1	104.0	104.6	105.0	99.1	99.6	105.2	107.4	104.5	105.7
2034	103.1	102.9	103.7	103.9	97.7	98.4	104.4	106.7	103.4	104.7
2035	101.9	101.7	102.8	103.1	96.3	97.1	103.5	106.0	102.5	103.3
2016-25	2.1%	2.1%	2.3%	2.8%	2.0%	2.1%	2.5%	2.5%	2.6%	2.1%
2016-35	1.1%	1.1%	1.2%	1.2%	0.8%	0.9%	1.2%	1.4%	1.2%	1.2%

5 Appendix A: Model Statistics

Residential Average Use Model

Variable	Coefficient	StdErr	T-Stat	P-Value
mStructResCyc.XHeat	1.177	0.032	37.187	0.00%
mStructResCyc.XOther_MinusLght	1.119	0.018	62.183	0.00%
mStructResCyc.XLight	0.875	0.129	6.785	0.00%
mBin.Feb	22.047	9.737	2.264	2.56%
mBin.Apr	-30.172	9.785	-3.083	0.26%
mBin.Jul	44.623	9.819	4.544	0.00%
mBin.Oct	-26.794	10.308	-2.599	1.07%
mBin.Yr06	29.029	8.516	3.409	0.09%
mBin.Aug08	77.193	27.27	2.831	0.56%
mBin.May11	80.668	27.336	2.951	0.39%
mBin.Sep13Plus	-24.492	6.672	-3.671	0.04%

Model Statistics	
Iterations	1
Adjusted Observations	117
Deg. of Freedom for Error	106
R-Squared	0.985
Adjusted R-Squared	0.984
AIC	6.669
BIC	6.928
Log-Likelihood	-545.13
Model Sum of Squares	5,111,380.58
Sum of Squared Errors	76330.61
Mean Squared Error	720.1
Std. Error of Regression	26.83
Mean Abs. Dev. (MAD)	19.44
Mean Abs. % Err. (MAPE)	2.28%
Durbin-Watson Statistic	2.113

Residential Customer Model

Variable	Coefficient	StdErr	T-Stat	P-Value
mEcon.HHs	954.365	2.83	337.209	0.00%
mBin.Jul12Plus	91.567	37.903	2.416	1.73%
AR(1)	0.901	0.042	21.407	0.00%

Model Statistics	
Iterations	11
Adjusted Observations	116
Deg. of Freedom for Error	113
R-Squared	0.998
Adjusted R-Squared	0.998
AIC	7.449
BIC	7.52
Log-Likelihood	-593.62
Model Sum of Squares	81,670,717.77
Sum of Squared Errors	189,190.68
Mean Squared Error	1,674.25
Std. Error of Regression	40.92
Mean Abs. Dev. (MAD)	25.19
Mean Abs. % Err. (MAPE)	0.18%
Durbin-Watson Statistic	2.59

Commercial Average Use Model

Variable	Coefficient	StdErr	T-Stat	P-Value
mStructComCyc.ComXHeat	2070.155	80.337	25.769	0.00%
mStructComCyc.ComXOther_MinusLght	334.946	4.359	76.834	0.00%
mStructComCyc.ComXLight	522.353	148.641	3.514	0.07%
mBin.Jul	156.426	55.407	2.823	0.57%
mBin.Yr06	-225.44	51.274	-4.397	0.00%
mBin.Yr10	261.034	50.148	5.205	0.00%
mBin.Aug08	582.936	156.758	3.719	0.03%
mBin.May11	561.317	156.764	3.581	0.05%
mBin.Sep11Plus	353.772	31.715	11.155	0.00%

Model Statistics	
Iterations	1
Adjusted Observations	117
Deg. of Freedom for Error	108
R-Squared	0.929
Adjusted R-Squared	0.924
AIC	10.146
BIC	10.358
Log-Likelihood	-750.55
Model Sum of Squares	33,411,686.23
Sum of Squared Errors	2,556,679.15
Mean Squared Error	23,672.96
Std. Error of Regression	153.86
Mean Abs. Dev. (MAD)	116.05
Mean Abs. % Err. (MAPE)	2.50%
Durbin-Watson Statistic	2.201

Commercial Customer Model

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	161.017	38.738	4.157	0.01%
ResCusts.Filled	0.191	0.003	69.332	0.00%
mBin.Apr	21.973	5.457	4.027	0.01%
mBin.May	81.281	6.123	13.274	0.00%
mBin.Jun	86.779	6.125	14.168	0.00%
mBin.Jul	89.14	6.129	14.544	0.00%
mBin.Aug	91.462	6.133	14.914	0.00%
mBin.Sep	97.459	6.329	15.398	0.00%
mBin.Oct	59.685	6.361	9.383	0.00%
mBin.Nov	1098.10%	5.692	1.929	5.65%
mBin.Sep10	-110.892	15.352	-7.223	0.00%
mBin.Yr06	11.582	7.404	1.564	12.08%
mBin.Yr09	-31.211	6.499	-4.802	0.00%
MA(1)	0.362	0.096	3.772	0.03%

Model Statistics	
Iterations	14
Adjusted Observations	117
Deg. of Freedom for Error	103
R-Squared	0.993
Adjusted R-Squared	0.992
AIC	5.601
BIC	5.931
F-Statistic	1075.78
Model Sum of Squares	3,384,250.50
Sum of Squared Errors	24,924.87
Mean Squared Error	241.99
Std. Error of Regression	15.56
Mean Abs. Dev. (MAD)	10.98
Mean Abs. % Err. (MAPE)	0.39%
Durbin-Watson Statistic	1.882

ST Model

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	19.923	0.34	58.643	0.00%
mFcstCyc.ResCusts	0	0	10.69	0.00%
mBin.Yr06	-0.642	0.056	-11.437	0.00%
mBin.Yr07	-0.428	0.053	-8.154	0.00%
mBin.YrPlus15	0.387	0.057	6.751	0.00%

Model Statistics	
Iterations	1
Adjusted Observations	117
Deg. of Freedom for Error	112
R-Squared	0.91
Adjusted R-Squared	0.907
AIC	-3.839
BIC	-3.721
Log-Likelihood	63.58
Model Sum of Squares	23.33
Sum of Squared Errors	2.31
Mean Squared Error	0.02
Std. Error of Regression	0.14
Mean Abs. Dev. (MAD)	0.1
Mean Abs. % Err. (MAPE)	0.41%
Durbin-Watson Statistic	1.186

Peak Model

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	10.702	2.474	4.326	0.00%
mCPkEndUses.BaseVar	0.125	0.011	11.628	0.00%
mWthr.HeatVar13	0.526	0.013	39.029	0.00%
mWthr.CoolVar10	1.754	0.827	2.121	3.62%
mBin.Jan	-3.895	0.738	-5.278	0.00%
mBin.Feb	-2.912	0.684	-4.259	0.00%
mBin.Jun	-1.779	0.698	-2.548	1.22%
mBin.Aug06	4.566	1.886	2.421	1.72%
mBin.Jun07	3.684	2.015	1.828	7.04%
mBin.Sep12	4.451	1.885	2.361	2.00%

Model Statistics	
Iterations	1
Adjusted Observations	117
Deg. of Freedom for Error	107
R-Squared	0.974
Adjusted R-Squared	0.972
AIC	1.306
BIC	1.542
Log-Likelihood	-232.43
Model Sum of Squares	13,597.11
Sum of Squared Errors	364.1
Mean Squared Error	3.4
Std. Error of Regression	1.84
Mean Abs. Dev. (MAD)	1.27
Mean Abs. % Err. (MAPE)	2.36%
Durbin-Watson Statistic	1.888

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 the SAE spreadsheets is the 2013 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,

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

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

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

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

6.1.1 Constructing XHeat

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

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

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

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

Where:

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

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

$$HeatIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \middle/ Eff_y^{Type} \right)}{\left(Sat_{05}^{Type} \middle/ Eff_{05}^{Type} \right)} \tag{4}$$

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 2005 value:

$$StructuralIndex_y = \frac{BuildingShellEfficiencyIndex_y \times SurfaceArea_y}{BuildingShellEfficiencyIndex_{05} \times SurfaceArea_{05}} \tag{5}$$

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, 2005 is used as a base year for normalizing the index. As a result, 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.

$$Weight^{Type} = \frac{Energy_{05}^{Type}}{HH_{05}} \times HeatShare_{05}^{Type} \tag{7}$$

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 2005 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	505
Electric Space Heating Heat Pump	190

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,

$$HeatIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \big/ Eff_y^{Type} \right)}{\left(Sat_{05}^{Type} \big/ Eff_{05}^{Type} \right)} \times$$
$$\left(TenYearMovingAverageElectric\,\Pr ice_{y,m}\right)^{\phi} \times \left(TenYearMovingAverageGas\,\Pr ice_{y,m}\right)^{\gamma} \quad (8)$$

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

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

$$HeatUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{WgtHDD_{y,m}}{HDD_{05}}\right) \times \left(\frac{HHSize_y}{HHSize_{05}}\right)^{0.25} \times \left(\frac{Income_y}{Income_{05}}\right)^{0.20} \times \left(\frac{Elec\,Price_{y,m}}{Elec\,Price_{05,7}}\right)^{\lambda} \times \left(\frac{Gas\,Price_{y,m}}{Gas\,Price_{05,7}}\right)^{\kappa} \quad (9)$$

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 (2005). 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:

$$CoolIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \big/ Eff_y^{Type} \right)}{\left(Sat_{05}^{Type} \big/ Eff_{05}^{Type} \right)} \tag{11}$$

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.

$$Weight^{Type} = \frac{Energy_{05}^{Type}}{HH_{05}} \times CoolShare_{05}^{Type} \tag{12}$$

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 2005 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	1,661
Space Cooling Heat Pump	369
Room Air Conditioning	315

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,

$$CoolIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \big/ Eff_y^{Type} \right)}{\left(Sat_{05}^{Type} \big/ Eff_{05}^{Type} \right)} \times \tag{13}$$

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

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

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

$$CoolUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{WgtCDD_{y,m}}{CDD_{05}}\right) \times \left(\frac{HHSize_{y}}{HHSize_{05}}\right)^{0.25} \times \left(\frac{Income_{y}}{Income_{05}}\right)^{0.20} \times \left(\frac{Elec\,Price_{y,m}}{Elec\,Price_{05}}\right)^{\lambda} \times \left(\frac{Gas\,Price_{y,m}}{Gas\,Price_{05}}\right)^{\kappa} \qquad (14)$$

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 2005.

By construction, the *CoolUse* variable has an annual sum that is close to 1.0 in the base year (2005). 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:

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

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

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

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

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

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:

$$ApplianceUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5} \right) \times \left(\frac{HHSize_y}{HHSize_{05}} \right)^{0.46} \times \left(\frac{Income_y}{Income_{05}} \right)^{0.10} \times \quad (17)$$
$$\left(\frac{Elec\,Price_{y,m}}{Elec\,Price_{05}} \right)^{\phi} \times \left(\frac{Gas\,Price_{y,m}}{Gas\,Price_{05}} \right)^{\lambda}$$

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 2010 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,

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

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

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

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,

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

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:

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

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.

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

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:

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

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:

$$CoolIndex_{y} = CoolSales_{04} \times \frac{\left(CoolShare_{y} / Eff_{y} \right)}{\left(CoolShare_{04} / Eff_{04} \right)} \tag{8}$$

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.

$$CoolSales_{04} = \left(\frac{kWh}{Sqft}\right)_{Cooling} \times \left(\frac{CommercialSales_{04}}{\sum_{e} kWh/Sqft_{e}}\right) \tag{9}$$

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:

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

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.

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

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

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

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

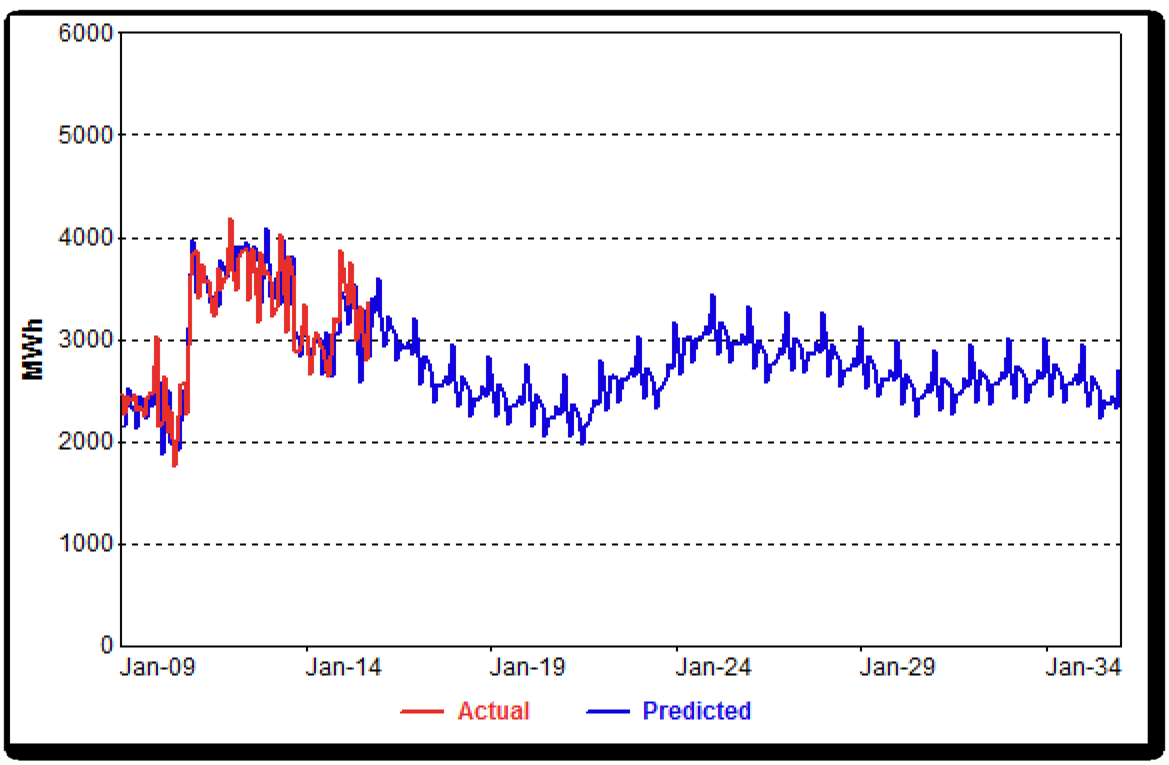
8 Appendix D: Industrial Model

While Itron developed the Industrial model, this model is not used in the final forecast. YEC chose to remove the model results in favor of manually adjusting the forecast based on large industrial customer changes. This Appendix documents the model developed by Itron.

The industrial sales forecast is based on a generalized monthly regression model where industrial sales are specified as a function of mining output and monthly binaries to capture seasonal load variation and shifts in the data.

The final model's Adjusted R^2 is 0.73 with in-sample MAPE of 7.09%. The relatively low Adjusted R^2 and high MAPE are due to the "noisy" nature of industrial monthly billing data. Actual and predicted monthly industrial sales are depicted in Figure 8-1. Model specification and statistics are shown in Table 8-2 and Table 8-3.

Figure 8-1: Actual and Predicted Industrial Sales: Base Case (MWh)



Given the volatility of mining output, industrial sales growth will vary; sales are projected to decrease through 2021 before increasing through the 2022-25 period. Table 8-1 shows the industrial forecast

Table 8-1: Industrial Sales Forecast

Year	Sales (MWh)	
2015	39,782	
2016	36,236	-8.9%
2017	31,919	-11.9%
2018	30,031	-5.9%
2019	29,055	-3.3%
2020	27,827	-4.2%
2021	27,466	-1.3%
2022	31,369	14.2%
2023	31,713	1.1%
2024	36,073	13.7%
2025	36,287	0.6%
2026	34,444	-5.1%
2027	34,978	1.6%
2028	33,551	-4.1%
2029	32,249	-3.9%
2030	30,303	-6.0%
2031	30,415	0.4%
2032	31,391	3.2%
2033	31,653	0.8%
2034	31,520	-0.4%
2035	29,507	-6.4%
2016-2025		0.3%
2016-2035		-0.9%

Table 8-2: Industrial Model Specification

Variable	Coefficient	StdErr	T-Stat	P-Value
Economics.MiningGRP	6.228	1.168	5.332	0.00%
mBin.Nov10Plus	1492.275	319.361	4.673	0.00%
mBin.Sep13Plus	-620.462	301.337	-2.059	4.35%
mBin.Jan	-335.293	121.363	-2.763	0.74%
mBin.Feb	-582.235	157.396	-3.699	0.05%
mBin.Mar	-274.006	181.018	-1.514	13.50%
mBin.Apr	-316.668	196.71	-1.61	11.23%
mBin.May	-369.204	206.264	-1.79	7.81%
mBin.Jun	-641.672	210.491	-3.048	0.33%
mBin.Jul	-455.372	209.665	-2.172	3.35%
mBin.Aug	-455.413	203.57	-2.237	2.87%
mBin.Sep	-422.67	191.929	-2.202	3.12%
mBin.Oct	-322.226	168.599	-1.911	6.04%
mBin.Nov	-396.904	121.54	-3.266	0.17%
AR(1)	0.904	0.055	16.514	0.00%

Table 8-3: Industrial Model Statistics

Model Statistics	
Iterations	13
Adjusted Observations	80
Deg. of Freedom for Error	65
R-Squared	0.778
Adjusted R-Squared	0.73
AIC	11.575
BIC	12.022
Log-Likelihood	-561.52
Model Sum of Squares	20,472,920.14
Sum of Squared Errors	5851872.22
Mean Squared Error	90028.8
Std. Error of Regression	300.05
Mean Abs. Dev. (MAD)	215.38
Mean Abs. % Err. (MAPE)	7.09%
Durbin-Watson Statistic	2.538