2019 Long-Term Electric Energy and Demand Forecast Report

Vectren

Submitted to:

Vectren, a CenterPoint Energy Company
Evansville, Indiana

Submitted by:

Itron, Inc.
20 Park Plaza
Suite 428
Boston, Massachusetts 02116
(617) 423-7660

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Contents

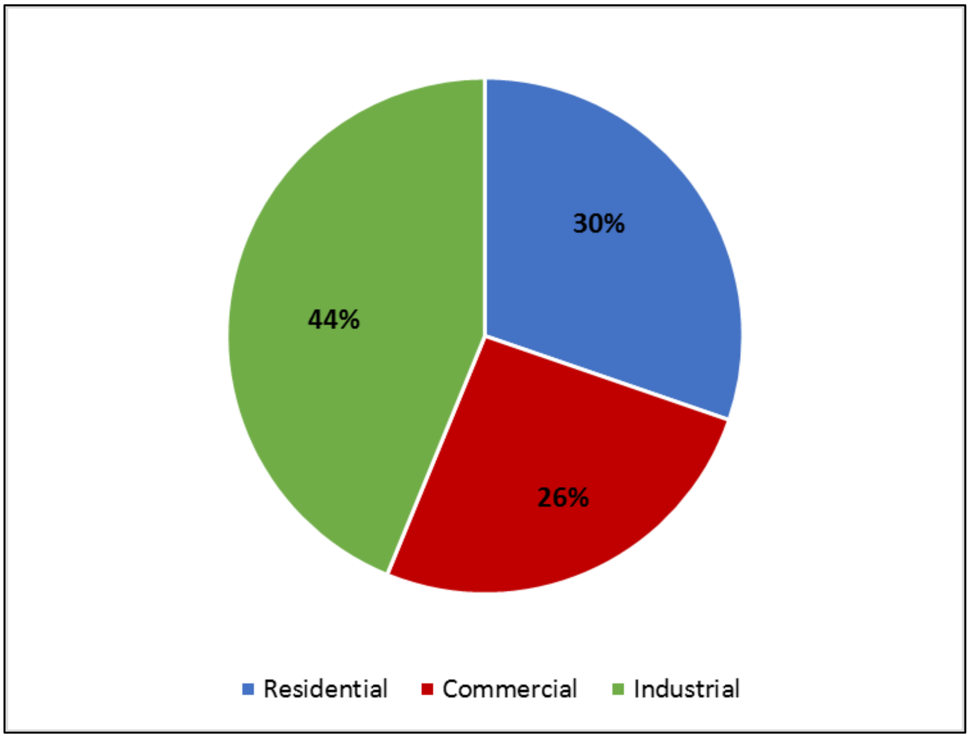
1 Overview

Itron, Inc. was contracted by Vectren to develop a long-term load forecast to support the 2019/20 Integrated Resource Plan. The energy and demand forecasts extend through 2039. It is based on a bottom-up approach that starts with residential, commercial, and industrial load forecasts that then drive system energy and peak demand. In addition, the forecast includes developing long-term behind-the-meter solar and electric vehicle load forecasts. This report presents the results, assumptions, and overview of the forecast methodology.

1.1 VECTREN Service Area

Vectren serves approximately 146,000 electric customers in Southwest Indiana; Evansville is the largest city within the service area. The service area includes a large industrial base with industrial customers accounting for approximately 44% of sales in 2018. The residential class accounts for 30% of sales with approximately 128,000 customers and the commercial class 26% of sales; there are approximately 18,000 nonresidential customers. System 2018 energy requirements are 5,308 GWh with non-weather normalized system peak reaching 1,039.2 MW. Figure 1 shows 2018 class-level sales distribution.

Figure 1: 2018 Annual Sales Breakdown



Despite relatively weak economic growth, since 2010, customer growth has been modest with residential customer growth averaging 0.5% and commercial customer growth 0.3%. GDP has averaged 1.2% growth until recently with 2018 GDP increasing to 3.9% and an expected 3.6% increase in 2019. GDP growth slows to expected 1.9% growth over the next twenty years with employment growth of 0.6%. Steady economic and employment growth contributes to continued moderate long-term customer growth.

Appliance efficiency standards coupled with DSM program activity has held sales growth in check. Since 2010 weather-normalized average use has declined on average 1.4% per year; this translates into 0.9% annual decline in residential sales. Commercial sales have also been falling; normalized sales have declined 0.6% per year. The industrial sector is the only sector showing positive growth with industrial sales averaging 1.8% average annual growth (excluding loss of a large customer account). When combined, total normalized sales have averaged 0.3% annual growth.

While DSM activity has had a significant impact on sales, for the IRP filing, the energy and demand forecasts do not include future DSM energy savings; DSM savings are treated as a resource in determining the most cost-effective options. Excluding future DSM, energy requirements and peak demand are expected to increase on average 0.6% over the next twenty years. Table 1-1 shows the VECTREN energy and demand forecasts. The forecast excludes future DSM savings, but includes the impact of customer-owned distributed generation (mostly behind-the-meter solar) and electric vehicles. Vectren utility scale solar and other distributed generation are not included in this report but are accounted for within the IRP and the forecast submitted to MISO.

Table 1-1: Energy and Demand Forecast (Excluding DSM Program Savings)

Year	Energy (MWh)		Summer Peak (MW)		Winter Peak (MW)	
2019	5,169,366		1,075		786	
2020	5,395,568	4.4%	1,105	2.7%	834	6.1%
2021	5,402,326	0.1%	1,107	0.2%	831	-0.3%
2022	5,527,069	2.3%	1,131	2.1%	850	2.2%
2023	5,763,459	4.3%	1,173	3.7%	888	4.5%
2024	5,795,986	0.6%	1,178	0.5%	891	0.4%
2025	5,811,218	0.3%	1,181	0.3%	891	0.0%
2026	5,828,820	0.3%	1,184	0.3%	892	0.1%
2027	5,849,607	0.4%	1,188	0.3%	894	0.2%
2028	5,880,148	0.5%	1,194	0.5%	897	0.4%
2029	5,895,966	0.3%	1,197	0.3%	897	0.0%
2030	5,912,671	0.3%	1,201	0.3%	897	0.0%
2031	5,930,819	0.3%	1,205	0.3%	898	0.0%
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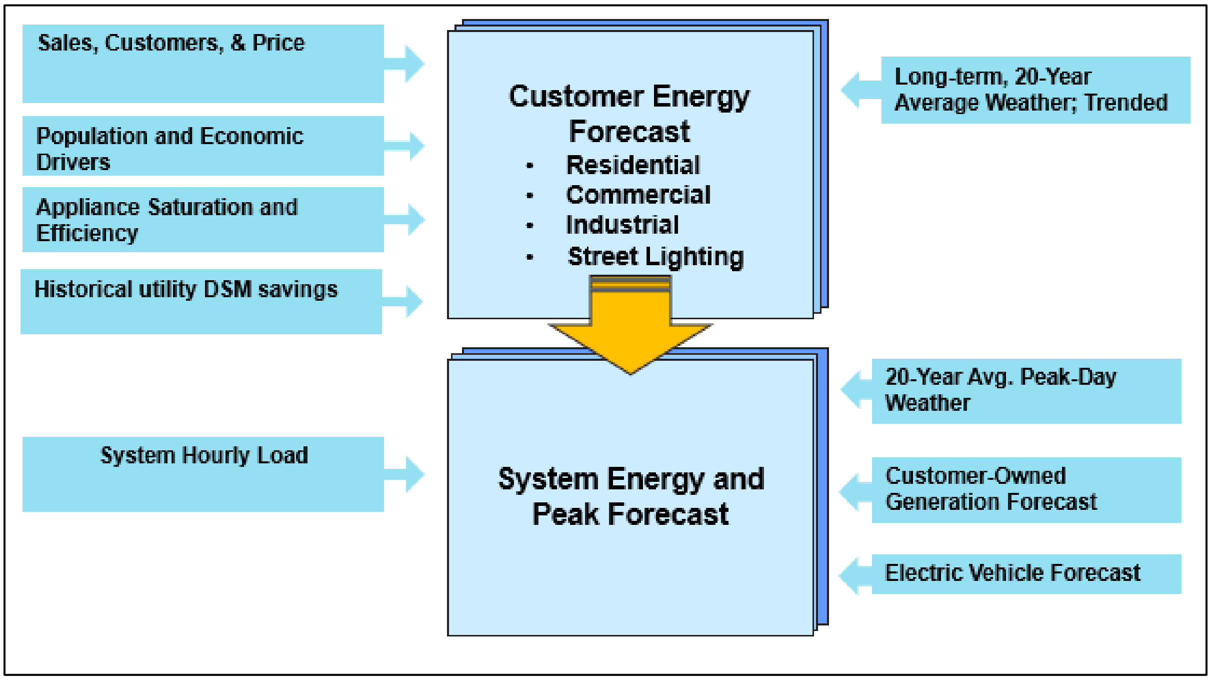
2033	5,970,297	0.2%	1,214	0.3%	899	-0.1%
2034	5,991,229	0.4%	1,219	0.4%	900	0.1%
2035	6,013,551	0.4%	1,224	0.4%	901	0.1%
2036	6,040,644	0.5%	1,230	0.5%	903	0.3%
2037	6,055,140	0.2%	1,234	0.4%	902	-0.1%
2038	6,074,726	0.3%	1,239	0.4%	903	0.1%
2039	6,093,472	0.3%	1,244	0.4%	904	0.1%
CAGR 20-39		0.6%		0.6%		0.4%

2 Forecast Approach

The long-term energy and demand forecasts are based on a build-up approach. End-use sales derived from the customer class sales models (residential, commercial, industrial, and street lighting) drive system energy and peak demand. Energy requirements are calculated by adjusting sales forecast upwards for line losses. Peak demand is forecasted through a monthly peak-demand linear regression model that relates peak demand to peak-day weather conditions and end-use energy requirements (heating, cooling, and other use). System energy and peak are adjusted for residential and commercial PV adoption and EV charging impacts. Figure 2 shows the general framework and model inputs.

Figure 2: Class Build-up Model



In the long-term, both economic growth and structural changes drive energy and demand requirements. Structural changes include the impact of changing appliance owner-ship trends, end-use efficiency changes, increasing housing square footage, and thermal shell efficiency improvements. Changing structural components are captured in the residential and commercial sales forecast models through a specification that combines economic drivers with end-use energy intensity trends. This type of model is known as a Statistically Adjusted End-Use (SAE) model. The SAE model variables explicitly incorporate end-use saturation and efficiency projections, as well as changes in population, economic conditions, price, and weather. Both residential and commercial sales are forecasted using an SAE specification. Industrial sales are forecasted using a two-step approach, which includes a generalized econometric model that relates industrial sales to seasonal patterns and industrial economic activity. Streetlight sales are forecasted using a simple trend and seasonal model.

2.1 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.

Average Use. The residential average use model relates customer monthly average use to a customer's heating requirements (XHeat), cooling requirements (XCool), other use (XOther), and DSM activity per customer:

$$ResAvgUse_{ym} = \left(B_1 \times XHeat_{ym}\right) + \left(B_2 \times XCool_{ym}\right) + \left(B_3 \times XOther_{ym}\right) + \left(B_4 \times DSM_{ym}\right) + e_{ym}$$

Where:

y = year
m = month

The model coefficients (B_1, B_2, B_3, and B_4) are estimated using a linear regression model. Monthly average use data is derived from historical monthly billed sales and customer data from January 2010 to June 2019.

The model variables incorporate end-use saturation and efficiency projections, as well as changes in household size, household income, price, weather, and DSM activity. The model result is an estimate of monthly heating, cooling, and other use energy requirements on a kWh per household basis, which includes the impact of DSM. Incremental future DSM is then added back to the model results to arrive at an average use forecast that does not include the impact of future DSM.

Figure 3 to Figure 5 show the constructed monthly heating, cooling, and other end-use variables. The specific calculations of the end-use variables are presented in Appendix B.

Figure 3: Residential XHeat

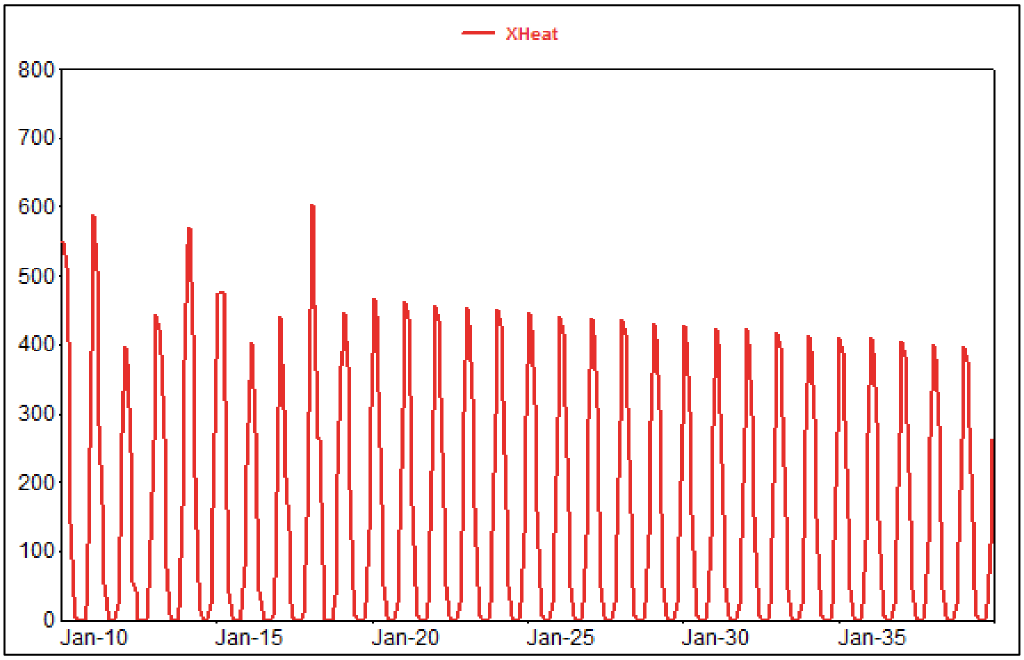


Figure 4: Residential XCool

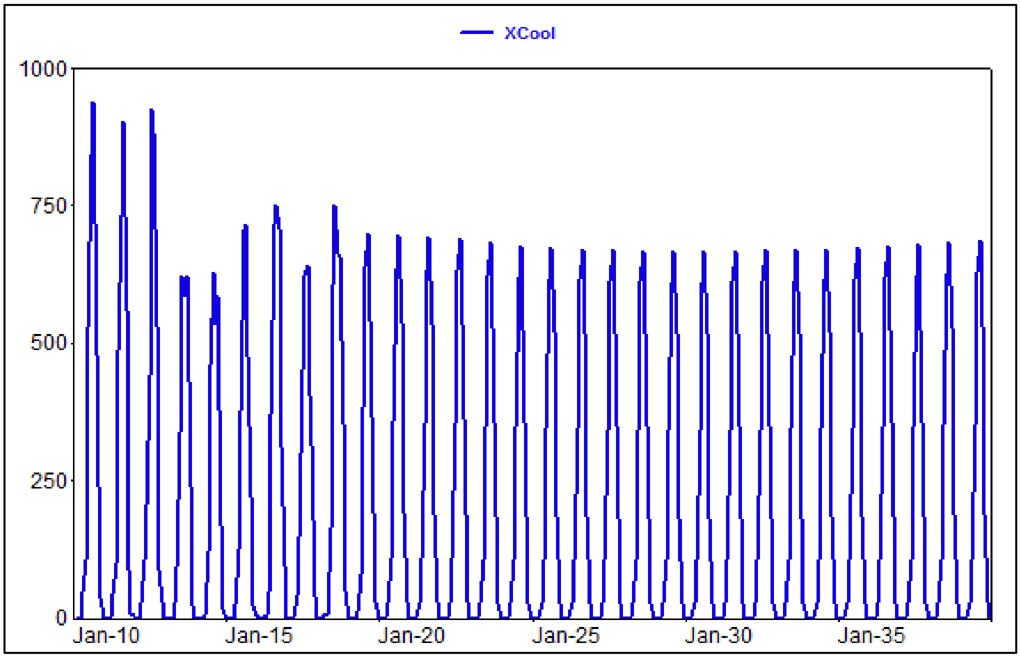
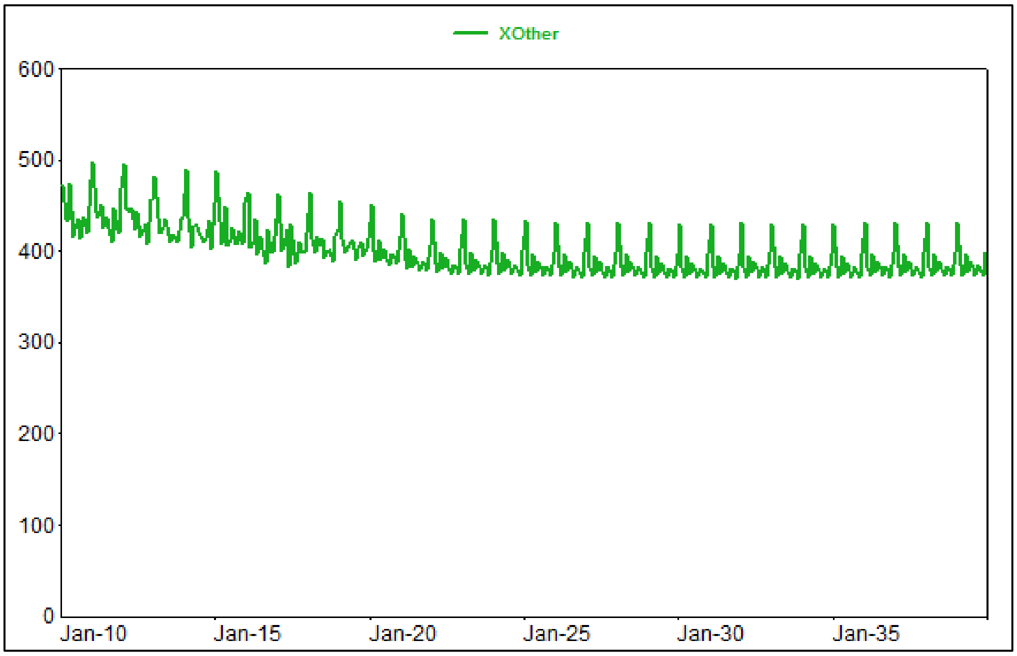


Figure 5: Residential XOther



The average use model is estimated over the period January 2010 through June 2019. The model explains historical average use well with an Adjusted R^2 of 0.98 and in-sample Mean Absolute Percent Error (MAPE) of 1.9%. Model coefficients are statistically significant at the 95% level of confidence and higher. Model coefficients and statistics are provided in Appendix A.

Customer Forecast

The customer forecast is based on a monthly regression model that relates the number of customers to Evansville MSA (Metropolitan Statistical Area) household projections. The model results in 0.4% long-term customer growth.

Sales Forecast

Excluding future DSM savings, average use through the forecast period is flat. With flat average use and 0.4% customer growth, residential sales averages 0.4% growth between 2020 and 2039. Table 2-1 summarizes the residential forecast.

Table 2-1: Residential Forecast (Excluding Future DSM)

Year	Sales (MWh)		Customers		AvgUse (kWh)	
2019	1,397,951		128,325		10,894	
2020	1,394,147	-0.3%	129,037	0.6%	10,804	-0.8%
2021	1,385,056	-0.7%	129,808	0.6%	10,670	-1.2%
2022	1,389,250	0.3%	130,762	0.7%	10,624	-0.4%
2023	1,393,879	0.3%	131,653	0.7%	10,588	-0.3%
2024	1,403,897	0.7%	132,458	0.6%	10,599	0.1%
2025	1,406,700	0.2%	133,214	0.6%	10,560	-0.4%
2026	1,412,868	0.4%	133,887	0.5%	10,553	-0.1%
2027	1,419,111	0.4%	134,474	0.4%	10,553	0.0%
2028	1,429,310	0.7%	135,002	0.4%	10,587	0.3%
2029	1,432,393	0.2%	135,503	0.4%	10,571	-0.2%
2030	1,439,085	0.5%	136,007	0.4%	10,581	0.1%
2031	1,446,125	0.5%	136,473	0.3%	10,596	0.1%
2032	1,456,783	0.7%	136,902	0.3%	10,641	0.4%
2033	1,460,392	0.2%	137,288	0.3%	10,637	0.0%
2034	1,467,666	0.5%	137,619	0.2%	10,665	0.3%
2035	1,475,665	0.5%	137,942	0.2%	10,698	0.3%
2036	1,487,624	0.8%	138,236	0.2%	10,761	0.6%
2037	1,492,228	0.3%	138,459	0.2%	10,777	0.1%
2038	1,499,727	0.5%	138,624	0.1%	10,819	0.4%
2039	1,506,655	0.5%	138,751	0.1%	10,859	0.4%
CAGR 20-39		0.4%		0.4%		0.0%

2.2 Commercial Model

The commercial sales model is also estimated using an SAE specification. The difference is that in the commercial sector, the sales forecast is based on a total sales model, rather than an average use and customer model. Commercial sales are expressed as a function of heating requirements, cooling requirements, other commercial use, and DSM activity:

$$\begin{aligned} ComSales_{ym} = {} & (B_1 \times XHeat_{ym}) + (B_2 \times XCool_{ym}) + (B_3 \times XOther_{ym}) \\ & + (B_4 \times DSM_{ym}) + e_{ym} \end{aligned}$$

Where:

y = year
m = month

The constructed model variables include Heating Degree Days (HDD), Cooling Degree Days (CDD), billing days, commercial economic activity variable, price, end-use intensity trends, and DSM activity. Figure 6 to Figure 8 show the constructed model variables. The specific variable construction is provided in Appendix B.

Figure 6: Commercial XHeat

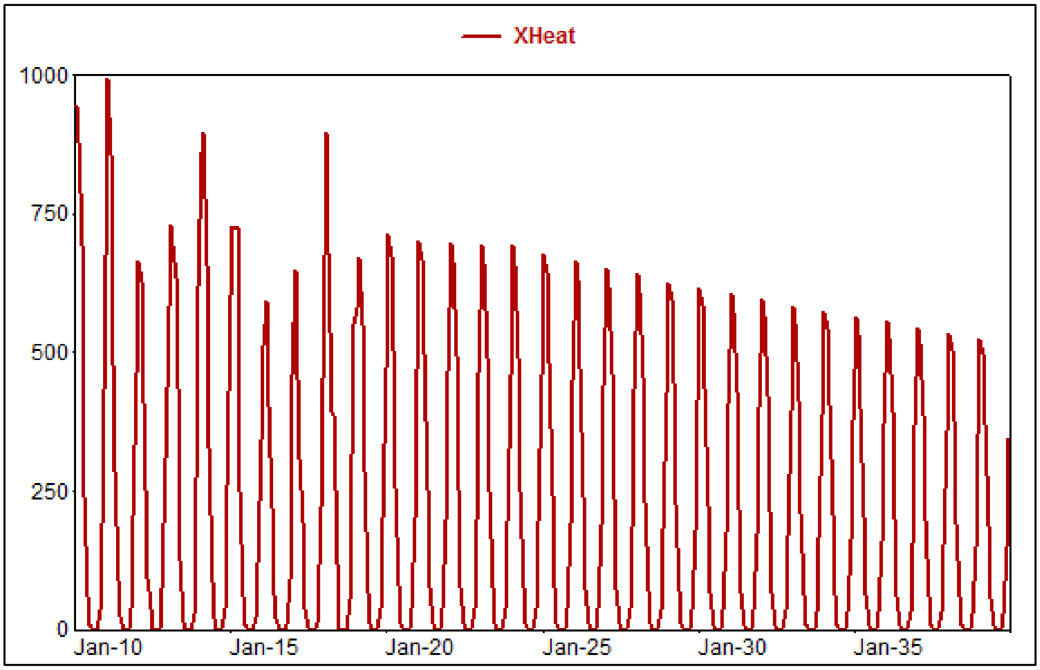


Figure 7: Commercial XCool

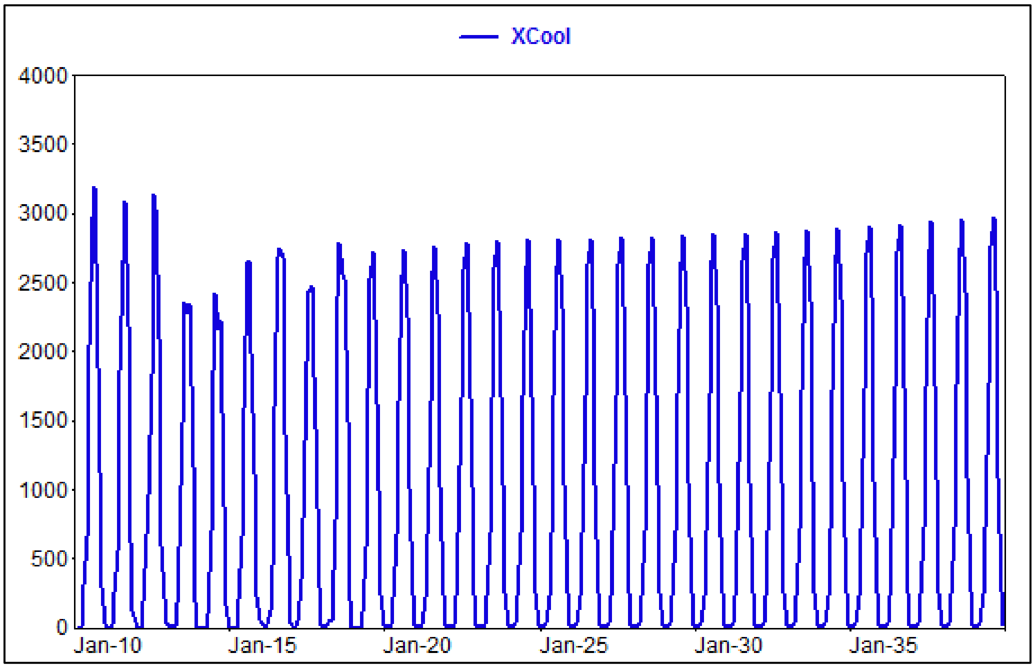
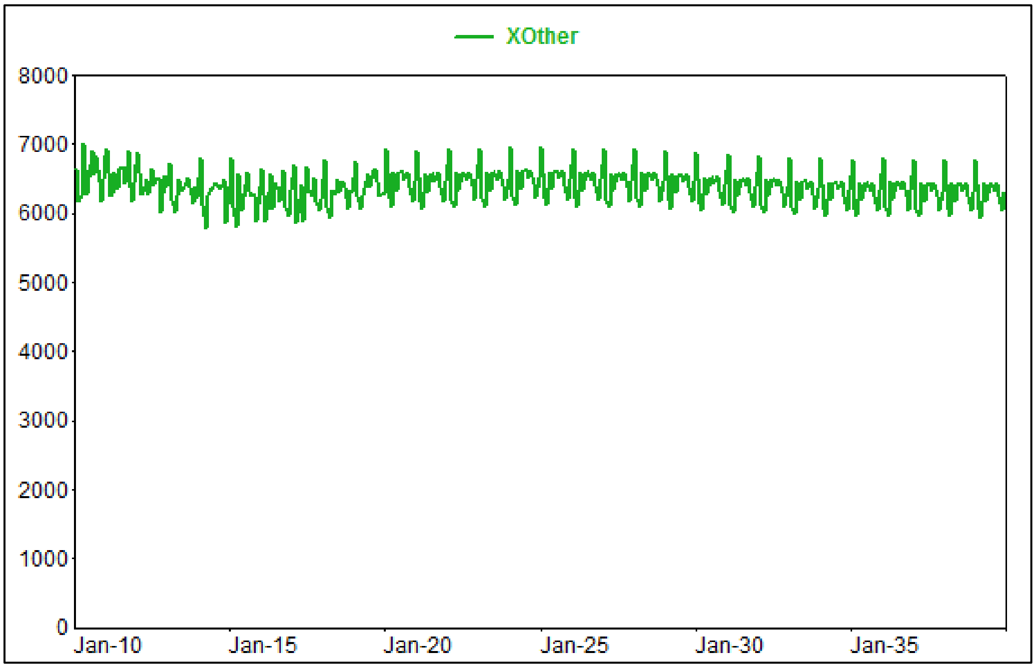


Figure 8: Commercial XOther



The estimated model coefficients (B_1, B_2, B_3, and B_4) calibrate the model to actual commercial sales data. The commercial sales model performs well with an Adjusted R^2 of 0.96 and an in-sample MAPE of 1.8%. The model is estimated with monthly billed sales data from January 2010 to June 2019. The model results include the impact of DSM. Incremental future DSM is then added back to the model results to arrive at a sales forecast that does not include the impact of future DSM.

Commercial sales average 0.2% annual growth through 2039, excluding the impact of future DSM savings. Commercial sales are driven by moderate residential customer and economic growth. Economic activity is captured by combining non-manufacturing output, non-manufacturing employment, and population through a weighted commercial economic variable called *ComVar*. *ComVar* is defined as:

$$ComVar_{ym} = \left(GDP_{ym}^{0.25}\right) \times \left(Employment_{ym}^{0.25}\right) \times \left(Population_{ym}^{0.5}\right)$$

Where:

y = year
m = month

The weights are determined by testing alternative sets of weights that generate the best in-sample and out-of-sample model statistics.

A separate model is estimated for commercial customers; customer projections are based on a monthly regression model that relates the number of customers to non-manufacturing employment in the Evansville MSA. The forecast excludes future DSM savings. Table 2-2 summarizes the commercial forecast.

Table 2-2: Commercial Forecast

Year	Sales (MWh)		Customers	
2019	1,268,993		18,731	
2020	1,281,221	1.0%	18,817	0.5%
2021	1,285,272	0.3%	18,870	0.3%
2022	1,292,595	0.6%	18,935	0.3%
2023	1,297,044	0.3%	18,999	0.3%
2024	1,303,746	0.5%	19,060	0.3%
2025	1,304,199	0.0%	19,122	0.3%
2026	1,305,034	0.1%	19,184	0.3%
2027	1,306,083	0.1%	19,247	0.3%
2028	1,310,084	0.3%	19,309	0.3%
2029	1,309,689	0.0%	19,371	0.3%
2030	1,308,851	-0.1%	19,434	0.3%
2031	1,308,792	0.0%	19,496	0.3%
2032	1,311,763	0.2%	19,560	0.3%
2033	1,310,653	-0.1%	19,624	0.3%
2034	1,312,270	0.1%	19,689	0.3%
2035	1,314,615	0.2%	19,754	0.3%
2036	1,319,551	0.4%	19,820	0.3%
2037	1,320,643	0.1%	19,887	0.3%
2038	1,324,172	0.3%	19,954	0.3%
2039	1,327,364	0.2%	20,021	0.3%
CAGR 20-39		0.2%		0.3%

2.3 Industrial Model

The industrial sales forecast is developed with a two-step approach. The first five years of the forecast is derived from Vectren's expectation of specific customer activity. The forecast after the first five years is based on the industrial forecast model. Vectren determines a baseline volume based on historical consumption use. The baseline use is then adjusted to reflect expected closures and expansions. Near-term sales are also adjusted for the addition of new industrial customers. After five years, the forecast is derived from the industrial sales model; forecasted growth is applied to the fifth-year industrial sales forecast.

The industrial sales model is a generalized linear regression model that relates monthly historical industrial billed to manufacturing employment, manufacturing output, CDD, and monthly binaries to capture seasonal load variation and shifts in sales data. The industrial economic driver is a weighted combination of manufacturing employment and manufacturing output. The industrial economic (*IndVar*) variable is defined as:

$$IndVar_{ym} = \left(ManufEmploy_{ym}^{0.5}\right) \times \left(ManufOutput_{ym}^{0.5}\right)$$

Where:

y = year
m = month

The imposed weights are determined by evaluating in-sample and out-of-sample statistics for alternative weighting schemes. The model Adjusted R^2 is 0.74 with a MAPE of 5.2%. The relatively low Adjusted R^2 and high MAPE are a result of the large month-to-month variations in industrial billing data. The industrial model excludes sales to one of VECTREN's largest customers, which is currently meeting most of its load through onsite cogeneration.

Excluding DSM, industrial sales average 1.0% annual growth with strong near-term growth. After 2023, industrial sales average 0.4% annual growth. Table 2-3 summarizes the industrial sales forecast.

Table 2-3: Industrial Forecast (Excluding Future DSM)

Year	Total Industrial	
2019	2,159,155	
2020	2,347,543	8.7%
2021	2,360,025	0.5%
2022	2,463,638	4.4%
2023	2,669,566	8.4%
2024	2,682,185	0.5%
2025	2,693,010	0.4%
2026	2,702,706	0.4%
2027	2,715,218	0.5%
2028	2,730,260	0.6%
2029	2,742,862	0.5%
2030	2,753,258	0.4%
2031	2,763,983	0.4%
2032	2,774,906	0.4%
2033	2,786,352	0.4%
2034	2,797,969	0.4%
2035	2,809,553	0.4%
2036	2,819,333	0.3%
2037	2,828,251	0.3%
2038	2,837,072	0.3%
2039	2,846,045	0.3%
CAGR 20-39		1.0%

2.4 Street Lighting Model

Streetlight sales are fitted with a simple exponential smoothing model with a trend and seasonal component. Street lighting sales are increasing at 0.2% annually throughout the forecast horizon. Table 2-4 shows the streetlight forecast.

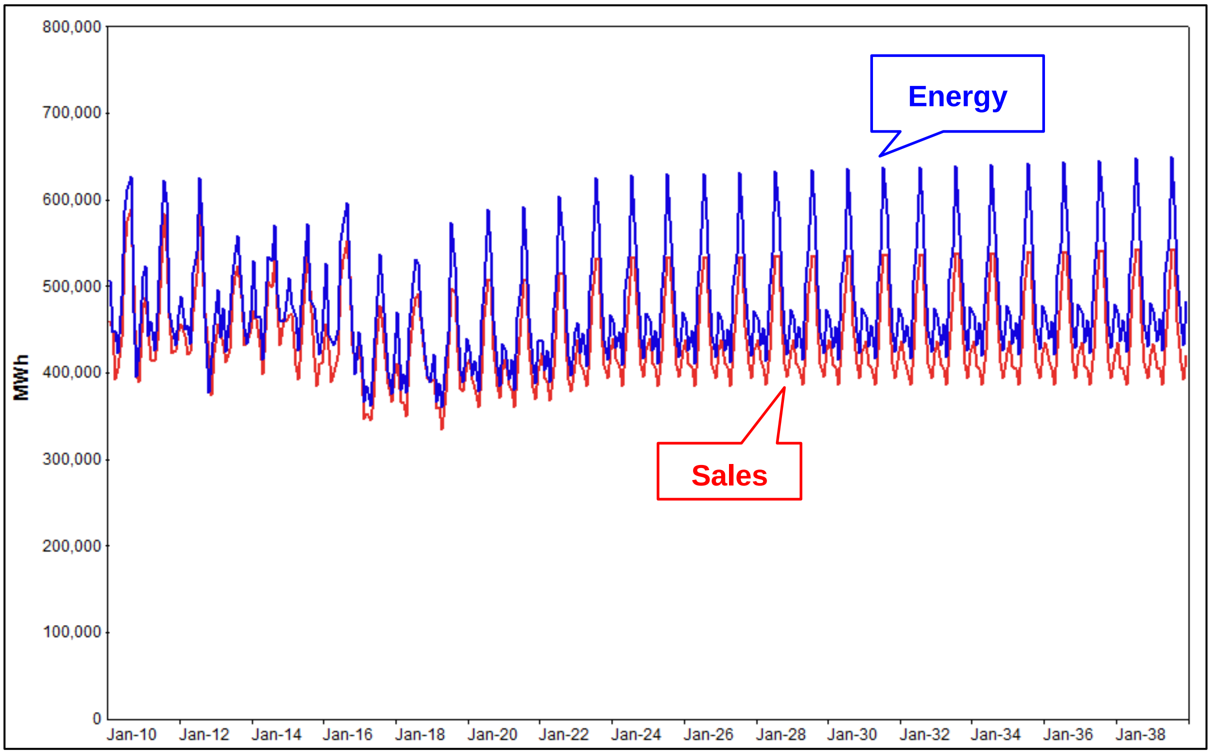
Table 2-4: Street Lighting Forecast

Year	Sales (MWh)	
2019	21,526	
2020	21,645	0.6%
2021	21,680	0.2%
2022	21,715	0.2%
2023	21,749	0.2%
2024	21,784	0.2%
2025	21,819	0.2%
2026	21,854	0.2%
2027	21,889	0.2%
2028	21,924	0.2%
2029	21,959	0.2%
2030	21,994	0.2%
2031	22,029	0.2%
2032	22,064	0.2%
2033	22,098	0.2%
2034	22,133	0.2%
2035	22,168	0.2%
2036	22,203	0.2%
2037	22,238	0.2%
2038	22,273	0.2%
2039	22,308	0.2%
CAGR 20-39		0.2%

2.5 Energy Forecast Model

The energy forecast is derived directly from the sales forecast by applying a monthly energy adjustment factor to the 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 based on the historical relationship between energy and sales. The energy forecast is adjusted for rooftop solar generation and electric vehicles. Figure 9 shows the monthly sales and energy forecast, excluding the impact of future DSM.

Figure 9: Energy and Sales Forecast (Excluding DSM)



2.6 Peak Forecast Model

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

$$Peak_{ym} = B_0 + B_1 HeatVar_{ym} + B_2 CoolVar_{ym} + B_3 BaseVar_{ym} + e_{ym}$$

Where:

y = year
m = month

End-use energy requirements are estimated from class sales forecast models.

Heating and Cooling Model Variables

The residential and commercial SAE model coefficients are used to isolate historical and projected weather-normal heating and cooling requirements. Heating requirements are interacted with peak-day HDD and cooling requirements with peak-day CDD; this interaction allows peak-day weather impacts to change over time with changes in heating and cooling requirements. The peak model heating and cooling variables are calculated as:

- $HeatVar_{ym} = HeatLoadIdx_{ym} \times PkHDD_{ym}$
- $CoolVar_{ym} = CoolLoadIdx_{ym} \times PkCDD_{ym}$

  Where $HeatLoadIdx_{ym}$ is an index of total system heating requirements in year *y* and month *m* and $CoolLoadIdx_{ym}$ is an index of total system cooling requirements in year *y* and month *m*. $PkHDD_{ym}$ is the peak-day HDD in year *y* and month *m* and $PkCDD_{ym}$ is the peak-day CDD in year y and month *m*.

Figure 10 and Figure 11 show *HeatVar* and *CoolVar*. The variation in the historical period is a result of variation in peak-day HDD and CDD.

Figure 10: Peak-Day Heating Variable

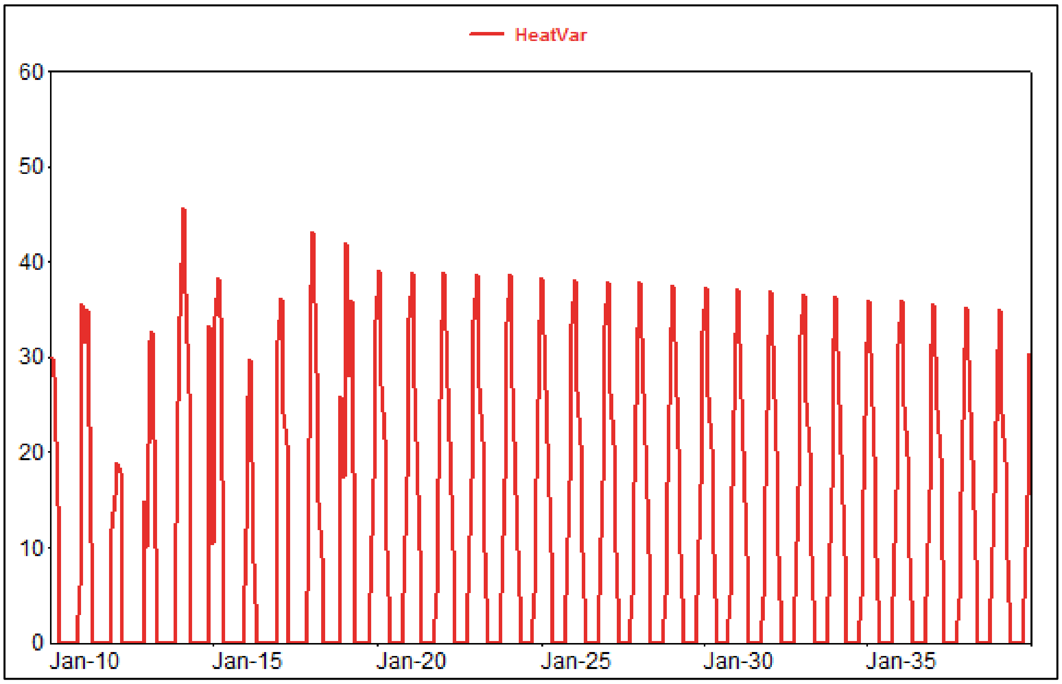
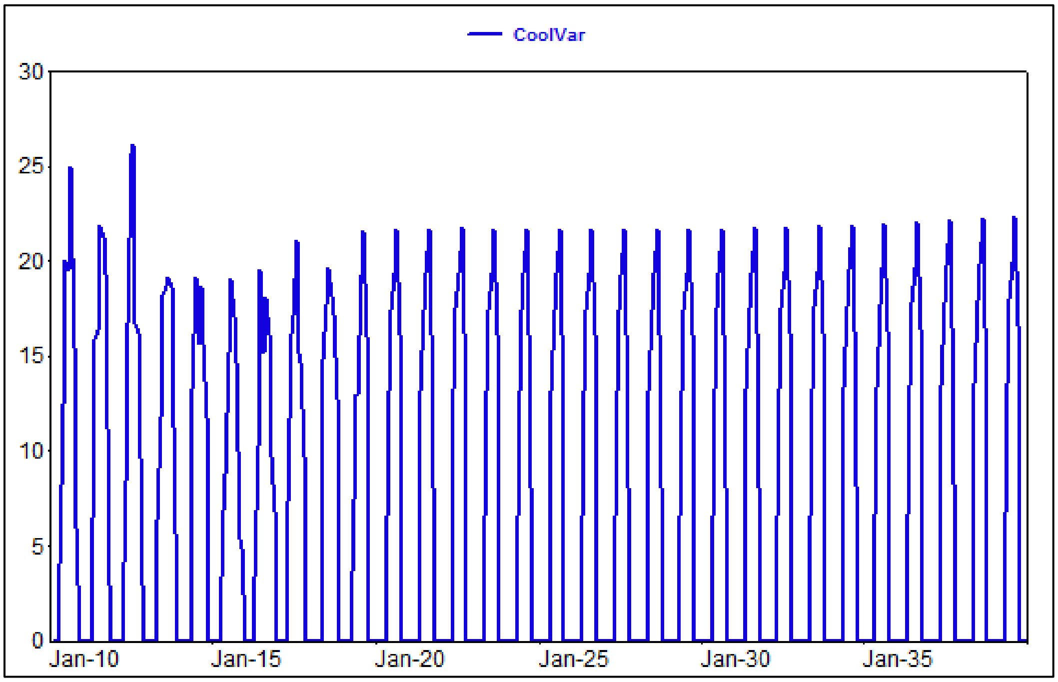


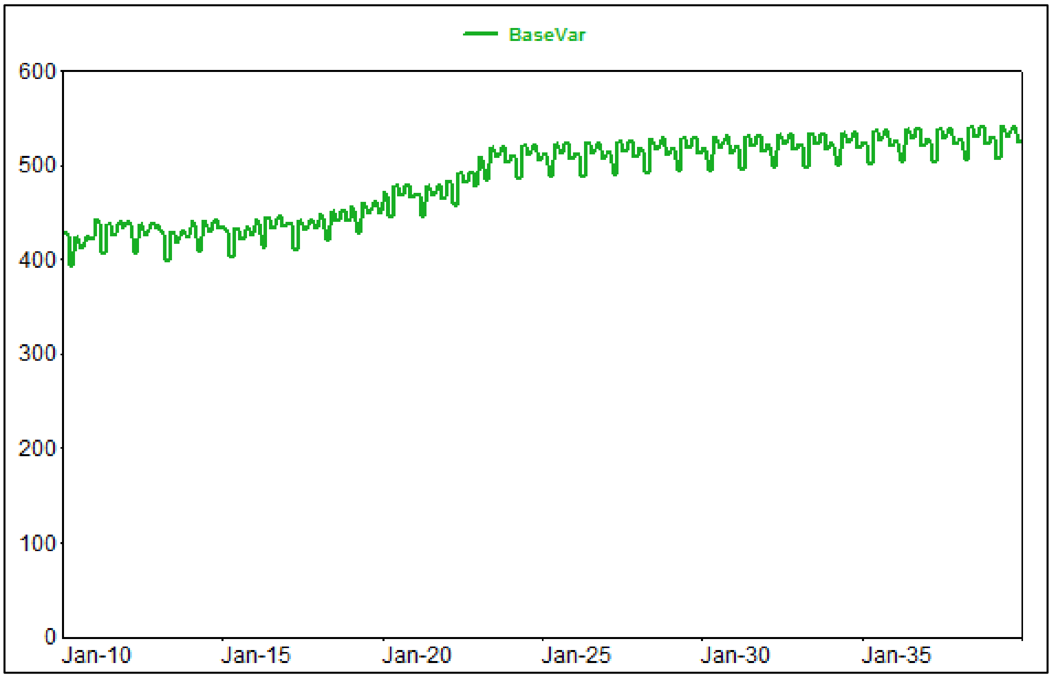
Figure 11: Peak-Day Cooling Variable



Base Load Variable

The base-load variable ($BaseVar_{ym}$) captures non-weather sensitive load at the time of the monthly peak. Monthly base-load estimates are calculated by allocating non-weather sensitive energy requirements to end-use estimates at the time of peak. End-use allocation factors are based on a set of end-use profiles developed by Itron. Figure 12 shows the non-weather sensitive peak-model variable.

Figure 12: Peak-Day Base-Use Variable



Model Results

The peak model is estimated over the period January 2010 to June 2019. The model explains monthly peak variation well with an adjusted R^2 of 0.95 and an in-sample MAPE of 2.81%. The end-use variables – *HeatVar*, *CoolVar*, and *BaseVar* are all highly statistically significant. Model statistics and parameters are included in Appendix A.

The peak demand forecast is adjusted for solar load and electric vehicle impacts, but excludes the impact of future DSM savings. Table 2-5 shows total energy and peak demand.

Table 2-5: Energy and Peak Forecast[1]

Year	Energy (MWh)		Summer Peak (MW)		Winter Peak (MW)	
2019	5,169,366		1,075		786	
2020	5,395,568	4.4%	1,105	2.7%	834	6.1%
2021	5,402,326	0.1%	1,107	0.2%	831	-0.3%
2022	5,527,069	2.3%	1,131	2.1%	850	2.2%
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2028	5,880,148	0.5%	1,194	0.5%	897	0.4%
2029	5,895,966	0.3%	1,197	0.3%	897	0.0%
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2031	5,930,819	0.3%	1,205	0.3%	898	0.0%
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2036	6,040,644	0.5%	1,230	0.5%	903	0.3%
2037	6,055,140	0.2%	1,234	0.4%	902	-0.1%
2038	6,074,726	0.3%	1,239	0.4%	903	0.1%
2039	6,093,472	0.3%	1,244	0.4%	904	0.1%
CAGR 20-39		0.6%		0.6%		0.4%

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[1] Does not include Vectren owned distributed generation or projected DSM

3 Customer Owned Distributed Generation

The energy and peak forecasts incorporate the impact of customer-owned photovoltaic systems. System adoption is expected to increase as solar system costs decline, which is partially offset by changes in net metering laws that will credit excess generation at a rate lower than retail rates in the future. As of June 2019, VECTREN had 421 residential solar customers and 65 commercial solar customers, with an approximate installed capacity of 8.9 MW.

3.1 Monthly Adoption Model

The primary factor driving system adoption is a customer's return-on-investment. A simple payback model is used as proxy. Simple payback reflects the length of time needed to recover the cost of installing a solar system - the shorter the payback, the higher the system adoption rate. From the customer's perspective, this is the number of years until electricity is "free." Simple payback also works well to explain leased system adoption as return on investment drives the leasing company's decision to offer leasing programs. Solar investment payback is calculated as a function of system costs, federal and state tax credits and incentive payments, retail electric rates, and treatment of excess generation (solar generation returned to the grid). Currently, excess generation is credited at the customer's retail rate. In the next few years excess solar generation will be credited at the wholesale cost plus 25%.

One of the most significant factors driving adoption is declining system costs; costs have been declining rapidly over the last five years. In 2010, residential solar system cost was approximately $7.00 per watt. By 2017 costs had dropped to $3.70 per watt. For the forecast period, we assume system costs continue to decline 10% annually through 2024 and an additional 3% annually after 2024. Cost projections are consistent with the U.S. Dept. of Energy's Sun Shot Solar goals and the Energy Information Administration's (EIA), most recent cost projections.[2]

The solar adoption model relates monthly residential solar adoptions to simple payback. Figure 13 shows the resulting residential solar adoption forecast.

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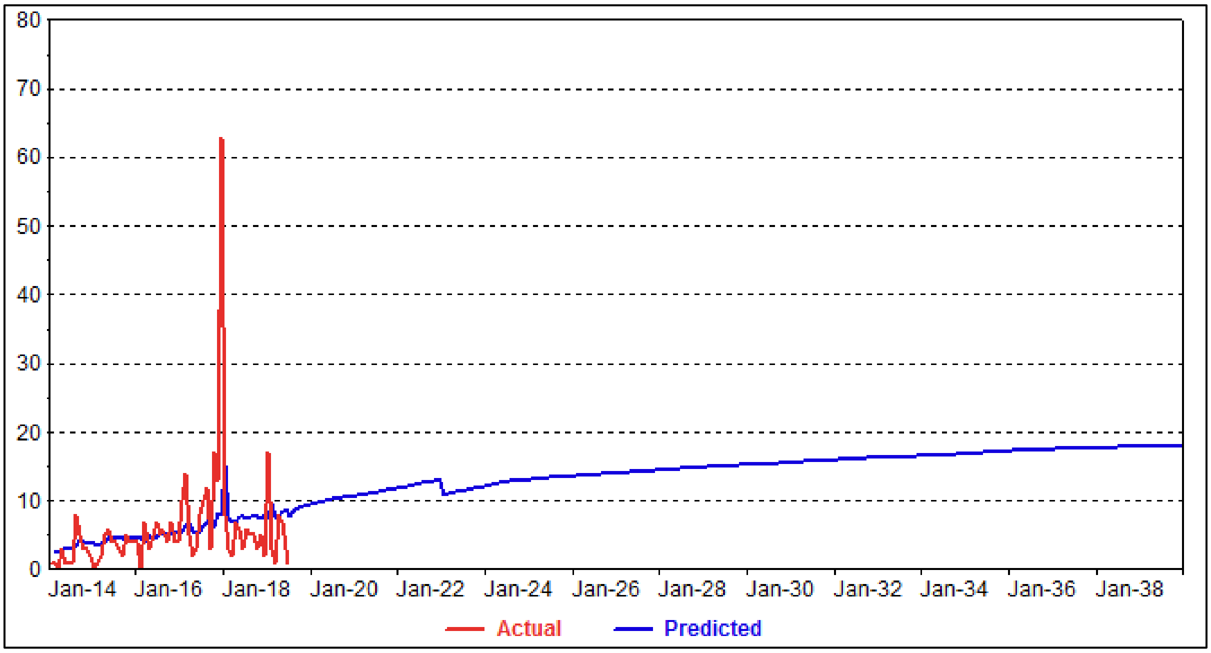
[2] "Tracking the Sun". Lawrence Berkeley National Laboratory. September 2018.

Figure 13: Residential Solar Share Forecast



In the commercial sector, there have been too few adoptions to estimate a robust model; commercial system adoption has been low across the country. Limited commercial adoption reflects higher investment hurdle rates, building ownership issues (i.e., the entity that owns the building often does not pay the electric bill), and physical constraints as to the placement of the system. For this forecast, we assume there continues to be some commercial rooftop adoption by allowing commercial adoption to increase over time, based on the current relationship between commercial and residential adoptions rates.

Declining solar costs continue to drive solar adoption through 2022. Adoptions drop after 2023 with the change in the net metering law, but then continue to increase with declining system costs. Table 3-1 shows projected solar adoption.

Table 3-1: Solar Customer Forecast

Year	Residential Systems	Commercial Systems	Total Systems
2019	431	67	498
2020	541	84	624
2021	671	104	775
2022	814	126	939
2023	957	148	1,105
2024	1,104	170	1,274
2025	1,260	194	1,454
2026	1,424	220	1,644
2027	1,592	246	1,838
2028	1,766	273	2,038
2029	1,946	300	2,246
2030	2,126	328	2,454
2031	2,313	357	2,670
2032	2,505	387	2,892
2033	2,697	416	3,113
2034	2,897	447	3,344
2035	3,101	479	3,579
2036	3,305	510	3,815
2037	3,515	543	4,058
2038	3,731	576	4,307
2039	3,947	609	4,556
CAGR 20-39	11.0%	11.0%	11.0%

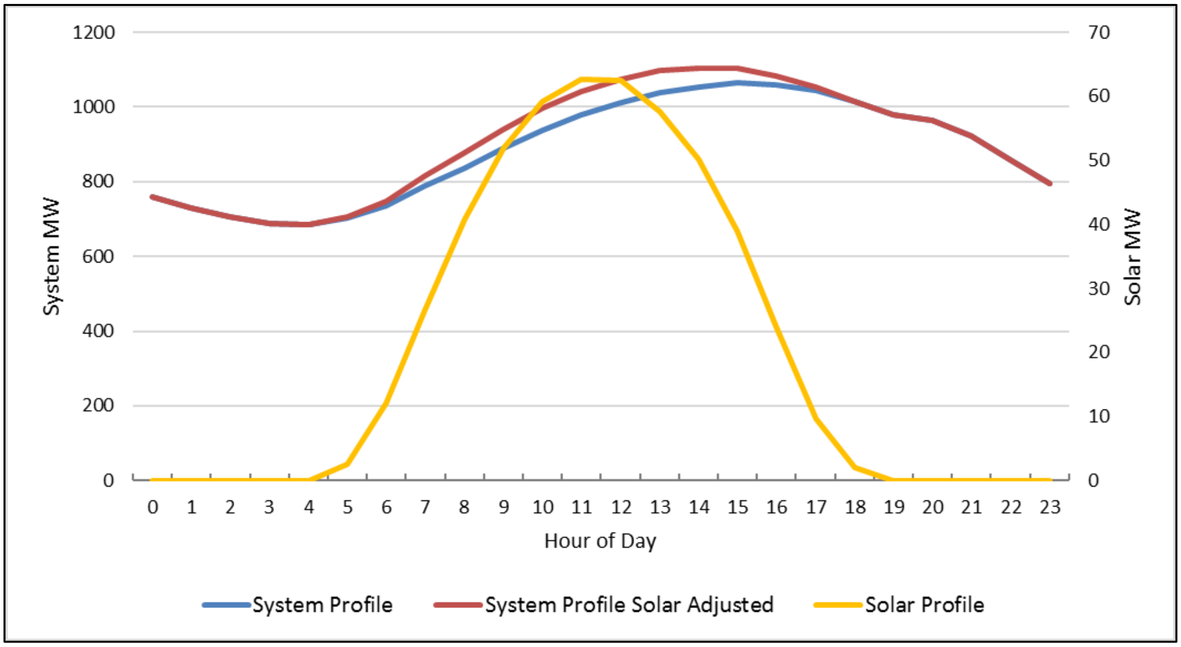
3.2 Solar Capacity and Generation

Installed solar capacity forecast is the product of the solar customer forecast and average system size (measured in kW). Based on recent solar installation data, the residential average size is 10.47 KW, and commercial average system size is 69.5 KW.

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

The impact of solar generation on system peak demand is a function of the timing between solar load generation and system hourly demand. Solar output peaks during the mid-day while system peaks later in the afternoon. Figure 14 shows the system profile, solar adjusted system profile, and solar profile for a peak producing summer day.

Figure 14: Solar Hourly Load Impact



Based on system and solar load profiles, 1.0 MW of solar capacity reduces summer peak demand by approximately 0.29 MW. This adjustment factor is applied to the solar capacity forecast to yield the summer peak demand impact. Solar 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 3-2 shows the PV capacity forecast, expected annual generation, and demand at time of peak.

Table 3-2: Solar Capacity and Generation

Year	Total Generation MWh	Installed Capacity MW (Aug)	Demand Impact MW
2019	12,084	9.3	2.7
2020	15,241	11.8	3.5
2021	18,877	14.6	4.3
2022	22,895	17.6	5.2
2023	26,943	20.7	6.1
2024	31,139	23.8	7.0
2025	35,469	27.1	8.0
2026	40,099	30.6	9.0
2027	44,835	34.2	10.1
2028	49,831	37.9	11.2
2029	54,796	41.7	12.3
2030	59,872	45.6	13.4
2031	65,153	49.6	14.6
2032	70,721	53.6	15.8
2033	75,979	57.7	17.0
2034	81,598	62.0	18.3
2035	87,349	66.3	19.5
2036	93,306	70.6	20.8
2037	99,030	75.1	22.1
2038	105,119	79.7	23.5
2039	111,208	84.3	24.8
CAGR 20-39	11.0%	10.9%	10.9%

4 Electric Vehicle Forecast

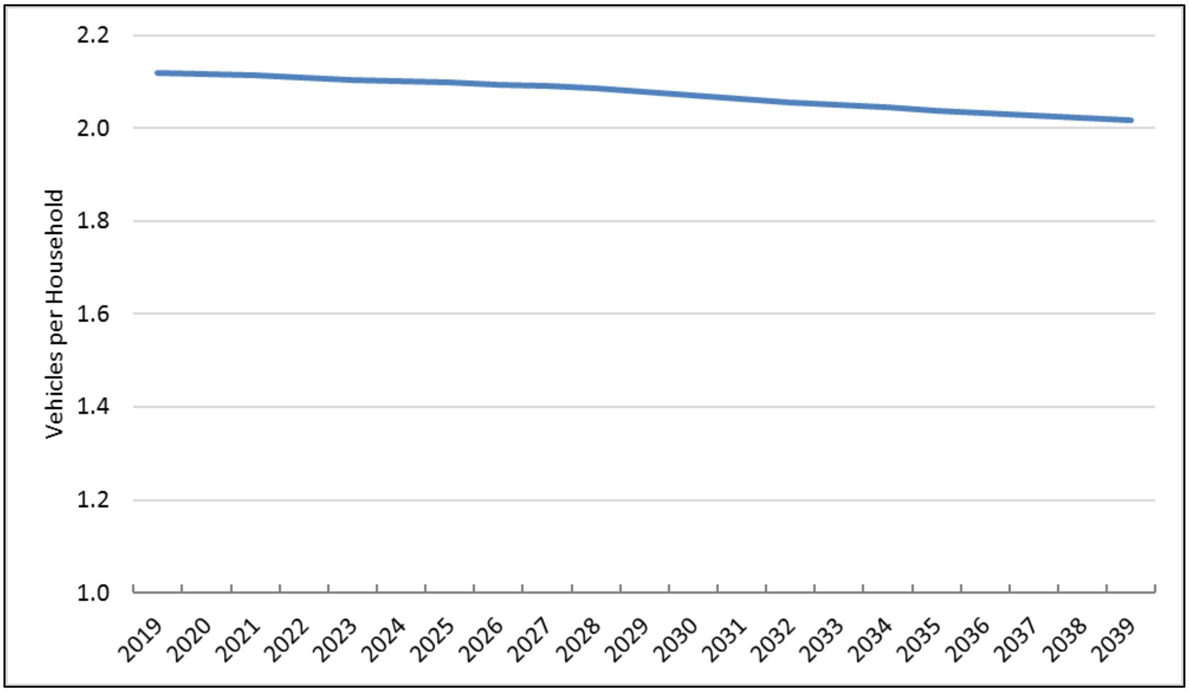
The 2019 Long-Term forecast also includes the impact of electric vehicle adoption. Currently Vectren has relatively few electric vehicles, but this is expected to increase significantly over the next twenty years with improvements in EV technology and declines in battery and vehicle costs. At the time of the forecast Vectren had 238 registered electric vehicles in the counties that Vectren serves: this included full electric (i.e., battery electric vehicles - BEV) as well as plug-in hybrid electric (PHEV) vehicles. The 238 vehicles were comprised of 105 BEVs and 133 PHEVs, with a total of 23 different make/model vehicles represented.

4.1 Methodology

The Energy Information Administration (EIA) produces a transportation forecast as part of their Annual Energy Outlook. One component of this forecast is a vehicle stock forecast by technology type, including electric vehicles. Using these data, we are able to calculate the average number of cars per household and projected electric vehicle share - BEV and PHEV.

Figure 15 shows projected number of vehicles per household. The number of vehicles declines over time as the number of persons per household declines and demand for car services such as Uber and Lyft increases.

Figure 15: EIA Vehicle Per Household

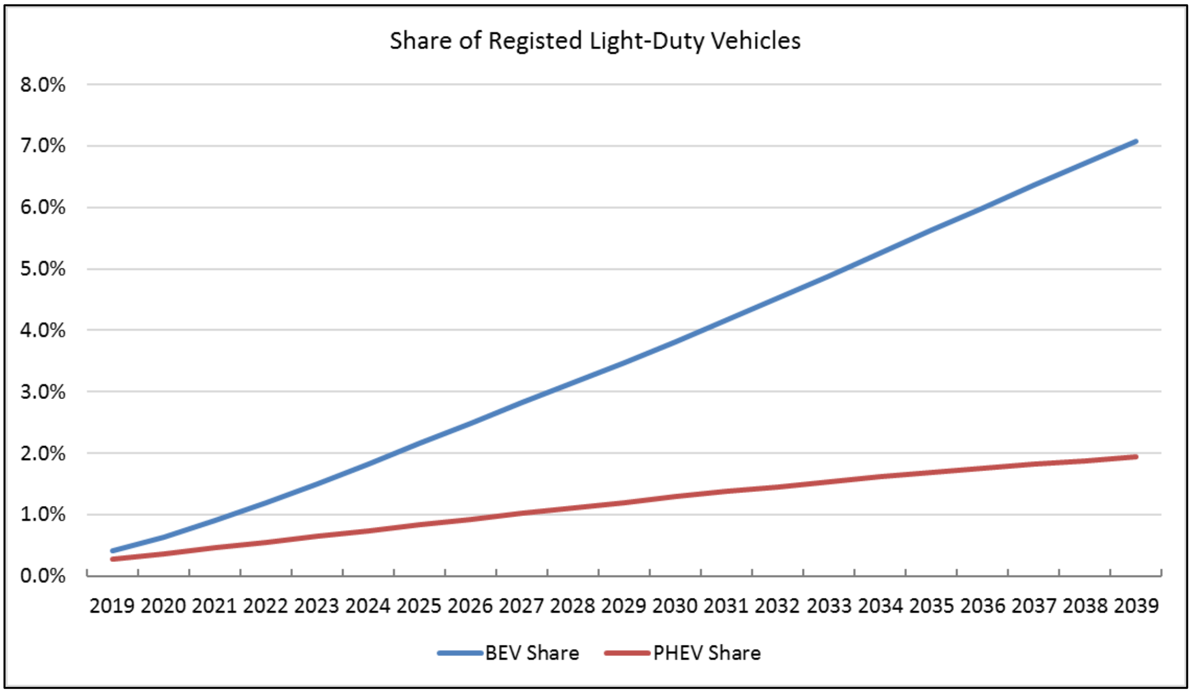


Total service area vehicles are calculated as the product of forecasted customers times EIA projected vehicles per household:

$$Ttl\ Vehicles = \ Custs_{yr} \times EIA\ Vehicle\ Per\ HH_{yr}$$

The number of BEV and PHEV are calculated by applying EIA's projected BEV and PHEV saturation to the service area total vehicle forecast. The share of electric vehicles are projected to increase from 0.5% to 7.1% BEV and 1.9% PHEV by 2039. The BEV and PHEV saturation forecast is shown in Figure 16.

Figure 16: EV & PHEV Market Share



The resulting electric vehicle forecast is summarized in Table 4-1:

Table 4-1: Electric Vehicle Forecast

Year	BEV Count	PHEV Count
2019	115	140
2020	283	266
2021	711	509
2022	1,783	974
2023	3,936	1,712
2024	5,112	2,065
2025	6,069	2,342
2026	7,015	2,613
2027	7,953	2,878
2028	8,884	3,136
2029	9,827	3,390
2030	10,785	3,639
2031	11,771	3,878
2032	12,772	4,109
2033	13,789	4,329
2034	14,816	4,538
2035	15,848	4,736
2036	16,875	4,926
2037	17,887	5,108
2038	18,887	5,279
2039	19,885	5,445

4.2 Electric Vehicle Energy & Load Forecast

Electric vehicles' impact on VECTREN's load forecast depends on the amount of energy a vehicle consumes annually and the timing of vehicle charging. BEVs consume more electricity than PHEVs and accounting for this distinction is important. An EV weighted annual kWh use is calculated based on the current mix of EV models. EV usage is derived from manufacturers' reported fuel efficiency to the federal government (www.fueleconomy.gov). The average annual kWh for the current mix of EVs registered in Vectren's service territory is 3,752kWh for BEV and 2,180 kWh for PHEV based on annual mileage of 12,000 miles.

Electric vehicles' impact on peak demand depends on when and where EVs are charged. Since Vectren does not have incentivized BEV/PHEV off-peak charging rates, it is assumed that the majority of charging will occur at home in the evening hours; this has a minimal impact on summer peak demand. Table 4-2 shows the electric vehicle forecast.

Table 4-2: Electric Vehicle Load Forecast

Year	BEV MWh	PHEV MWh	Total EV MWh	Demand Impact MW (Aug)
2019	432	305	737	0.1
2020	1,063	580	1,643	0.2
2021	2,667	1,110	3,777	0.4
2022	6,691	2,124	8,815	1.0
2023	14,769	3,732	18,501	2.1
2024	19,178	4,503	23,681	2.5
2025	22,770	5,106	27,876	2.9
2026	26,320	5,697	32,017	3.3
2027	29,838	6,275	36,113	3.8
2028	33,334	6,837	40,171	4.2
2029	36,869	7,392	44,261	4.6
2030	40,467	7,933	48,400	5.0
2031	44,164	8,455	52,619	5.5
2032	47,920	8,959	56,878	5.9
2033	51,735	9,438	61,173	6.3
2034	55,591	9,895	65,486	6.8
2035	59,461	10,327	69,788	7.2
2036	63,315	10,741	74,056	7.7
2037	67,111	11,137	78,248	8.1
2038	70,863	11,510	82,373	8.5
2039	74,607	11,872	86,479	8.9

5 Forecast Assumptions

5.1 Weather Data

Historical and normal HDD and CDD are derived from daily temperature data for the Evansville airport. Normal degree-days are calculated by averaging the historical daily HDD and CDD over the last twenty years. In past forecasts, we assumed normal HDD and CDD will occur in each of the forecast years. Recent analysis suggests an alternative approach. In reviewing historical weather data, we found a statistically significant positive, but slow, increase in average temperature. This translates into fewer HDD and more CDD over time. Our analysis showed HDD are decreasing 0.2% per year while CDD are increasing 0.5% per year. These trends are incorporated into the forecast. Starting normal HDD are allowed to decrease 0.2% over the forecast period while CDD increase 0.5% per year through 2039. Figure 17 and Figure 18 show historical and forecasted monthly HDD and CDD.

Figure 17: Heating Degree Days

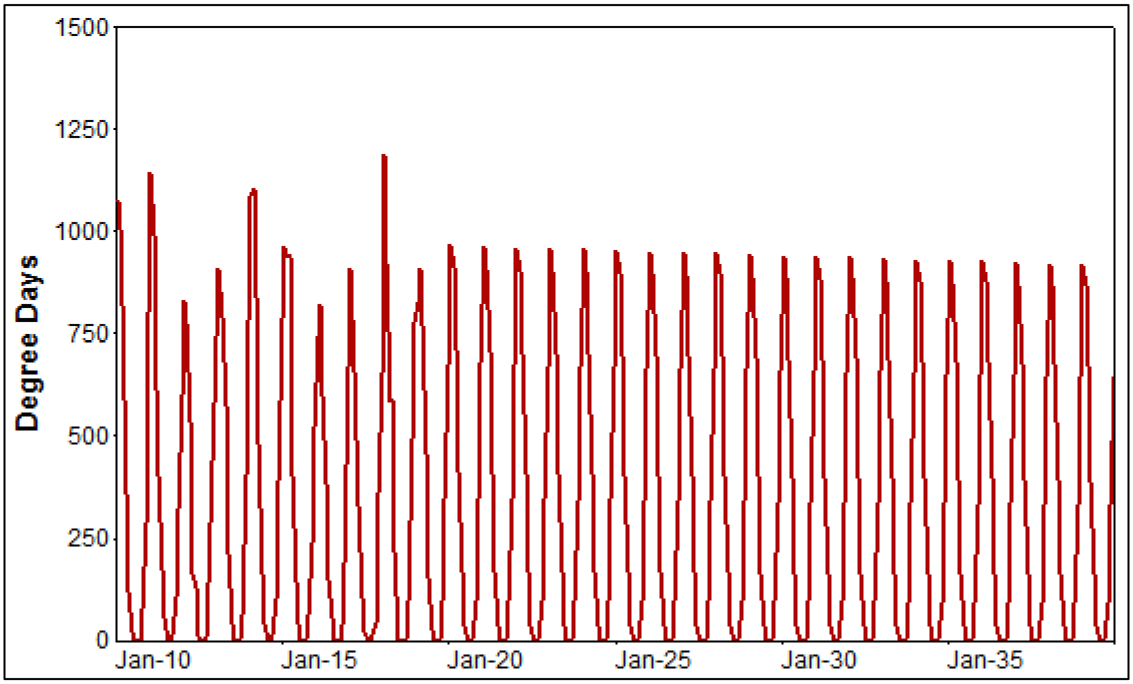
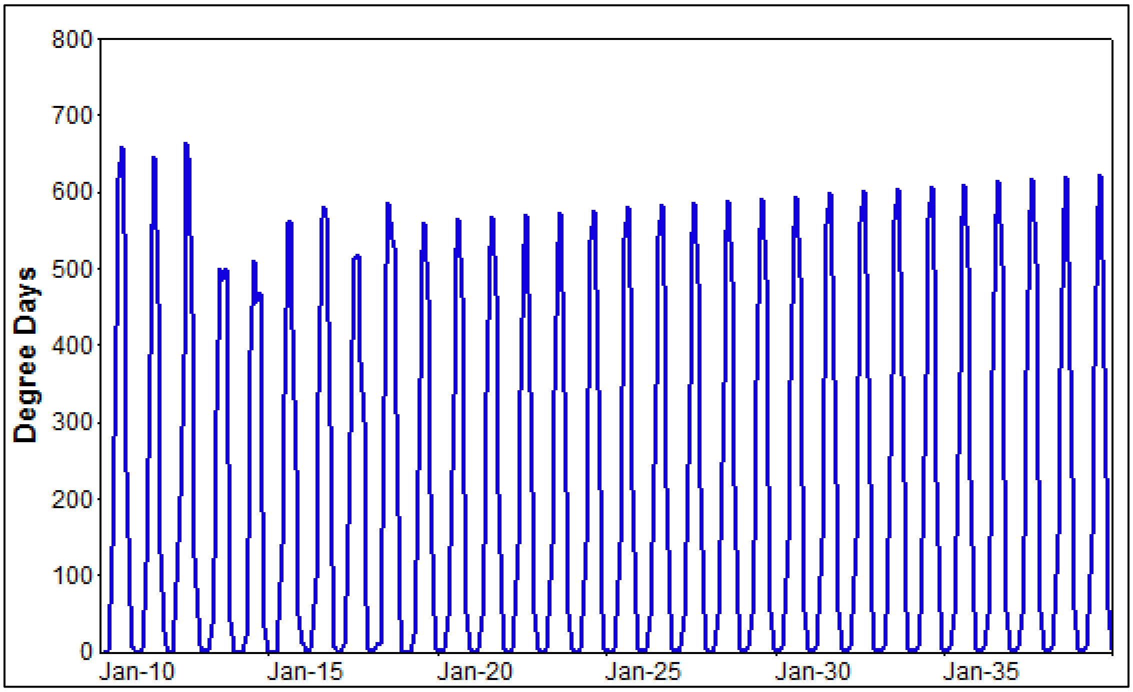


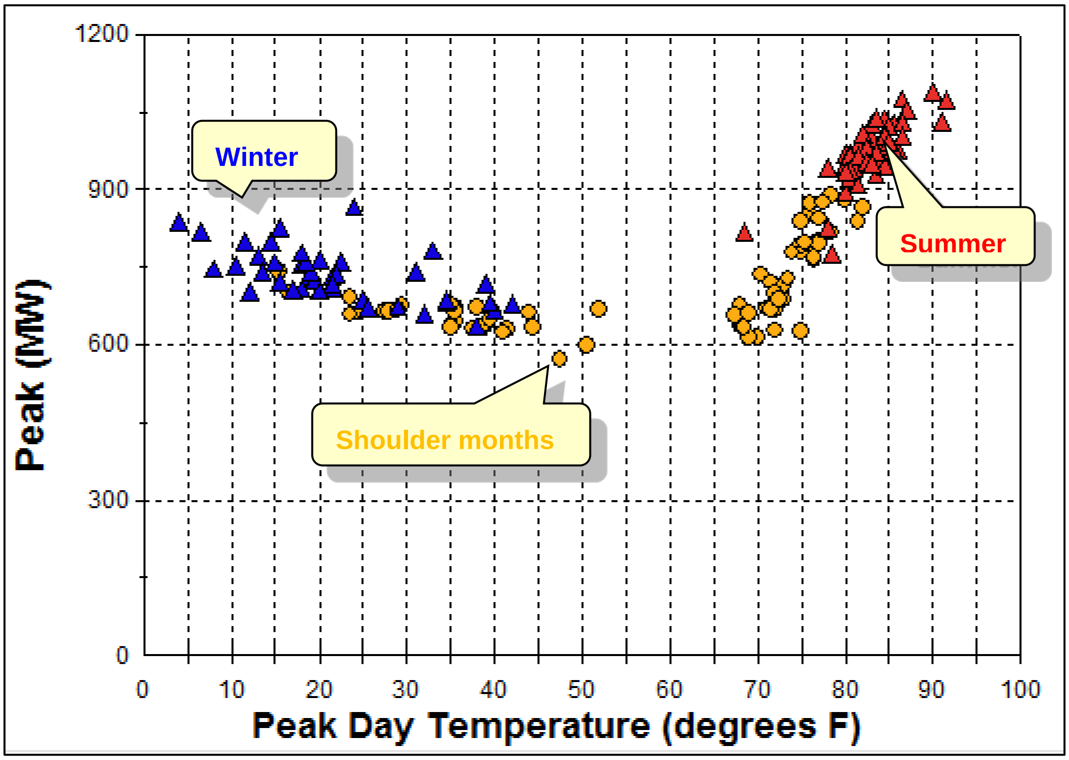
Figure 18: Cooling Degree Days



Peak-Day Weather Variables

Peak-day CDD and HDD are used in forecasting system peak demand. Peak-day HDD and CDD are derived by finding the daily HDD and CDD that occurred on the peak day in each month. The appropriate breakpoints for defining peak-day HDD and CDD are determined by evaluating the relationship between monthly peak and the peak-day average temperature, as shown in Figure 19.

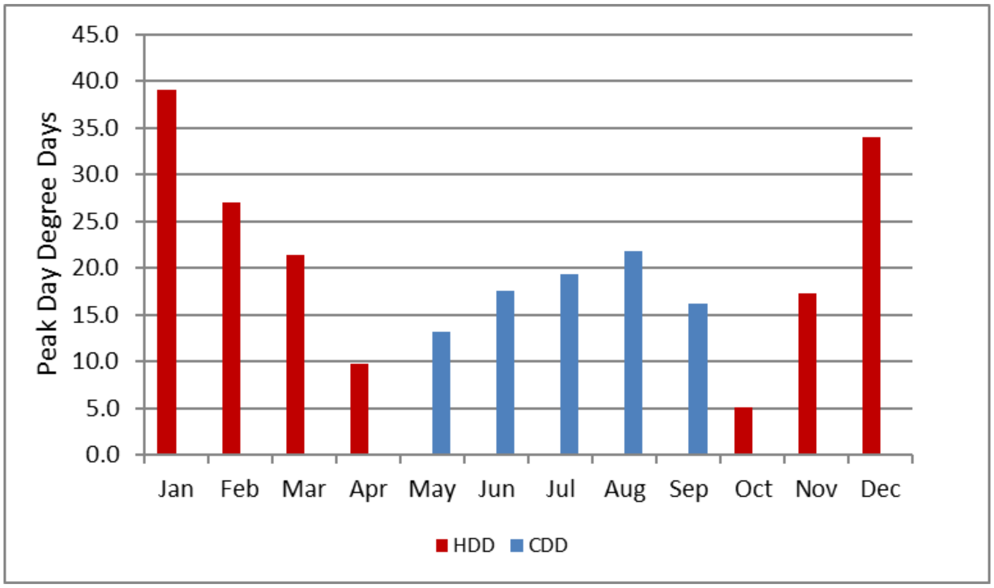
Figure 19: Monthly Peak Demand /Temperature Relationship



Peak-day cooling occurs when temperatures are above 65 degrees and peak-day heating occurs when temperatures are below 55 degrees.

Normal peak-day HDD and CDD are calculated using 20 years of historical weather data, based on a rank and average approach, these are not trended. The underlying rate class sales models incorporate trended normal weather; derived heating and cooling sales from these models are an input into the peak model. Using a trended peak weather would double count the impact of increasing temperatures. Normal peak-day HDD and CDD are based on the hottest and coldest days that occurred in each month over the historical time period. Figure 20 shows the normal peak-day HDD and CDD values used in the forecast.

Figure 20: Normal Peak-Day HDD & CDD



5.2 Economic Data

The class sales forecasts are based on *Moody's Economy.com* May 2019 economic forecast for the Evansville Metropolitan Statistical Area (MSA). The primary economic drivers in the residential sector are household income and the number of new households. Household formation is stable and increasing consistently though the forecast period with 0.4% average annual growth. Real household income growth is modest, averaging 1.6% over the forecast period.

Commercial sales are driven by nonmanufacturing output, nonmanufacturing employment, and population. Non-manufacturing output is forecasted to grow at 1.7% per year through the forecast period with non-manufacturing employment is growing 0.6% per year and population a little over 0.1% per year.

The industrial model relates sales to manufacturing output and employment. Manufacturing output is projected to increase more rapidly over the next 5 years, with output increasing 2.3% per year, over the long-term manufacturing output averages 1.8% annual growth. While output increases, associated manufacturing employment is projected to decline at a 0.5% annual rate.

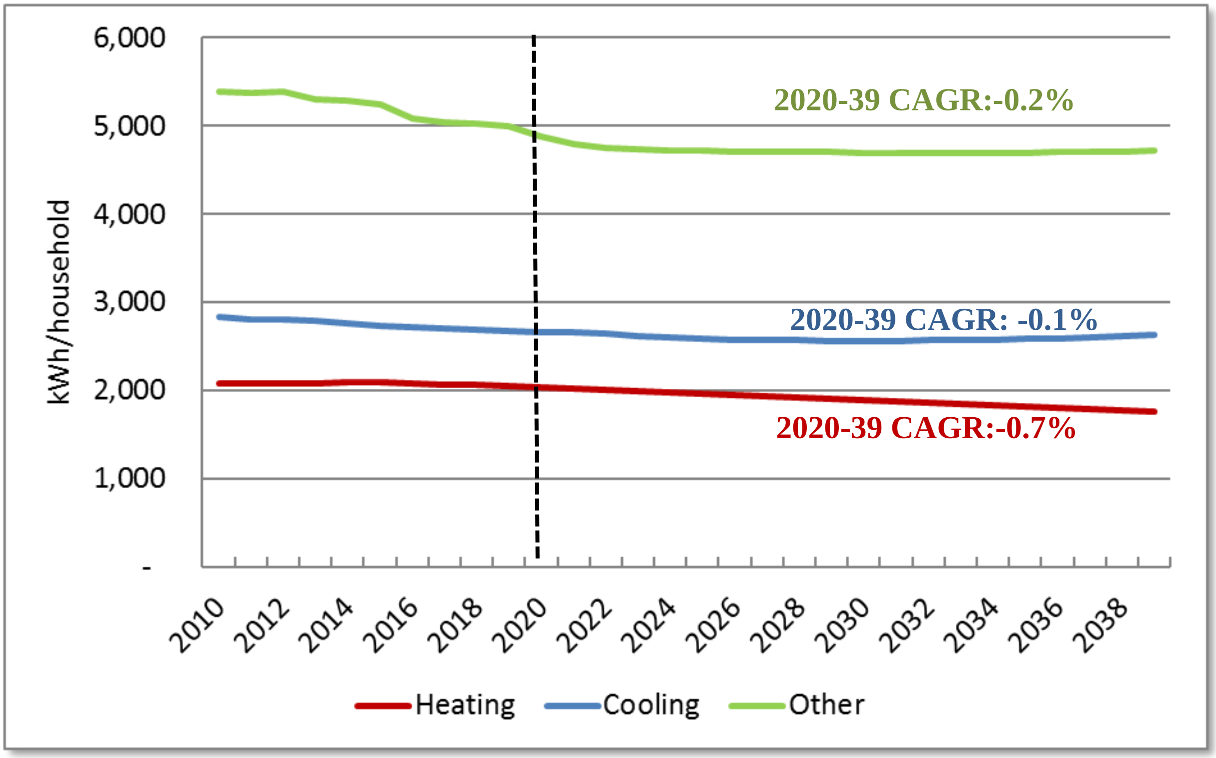
Historical electric prices (in real dollars) are derived from billed sales and revenue data. Historical prices are calculated as a 12-month moving average of the average rate (revenues divided by sales); prices are expressed in real dollars. Prices impact residential and commercial sales through imposed short-term price elasticities. Short-term price elasticities are small; residential and commercial price elasticities are set at -0.10. Price is not an input to the industrial sales model. Price projections are based on the Energy Information Administration's (EIA) long-term real growth rates. Over the forecast period, prices increase 1.5% annually.

5.3 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 for the residential sector and kWh per square foot for the commercial sectors, are incorporated into the constructed forecast model variables. Energy intensities reflect both change in ownership (saturation) and average stock efficiency. In general, efficiency is improving faster than end-use saturation resulting in declining end-use energy use. Energy intensities are derived from Energy Information Administration's (EIA) 2019 Annual Energy Outlook and Vectren's appliance saturation surveys. 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 intensities are used in constructing the model end-use variables. Figure 21 shows the resulting aggregated end-use intensity projections.

Figure 21: Residential End-Use Energy Intensities

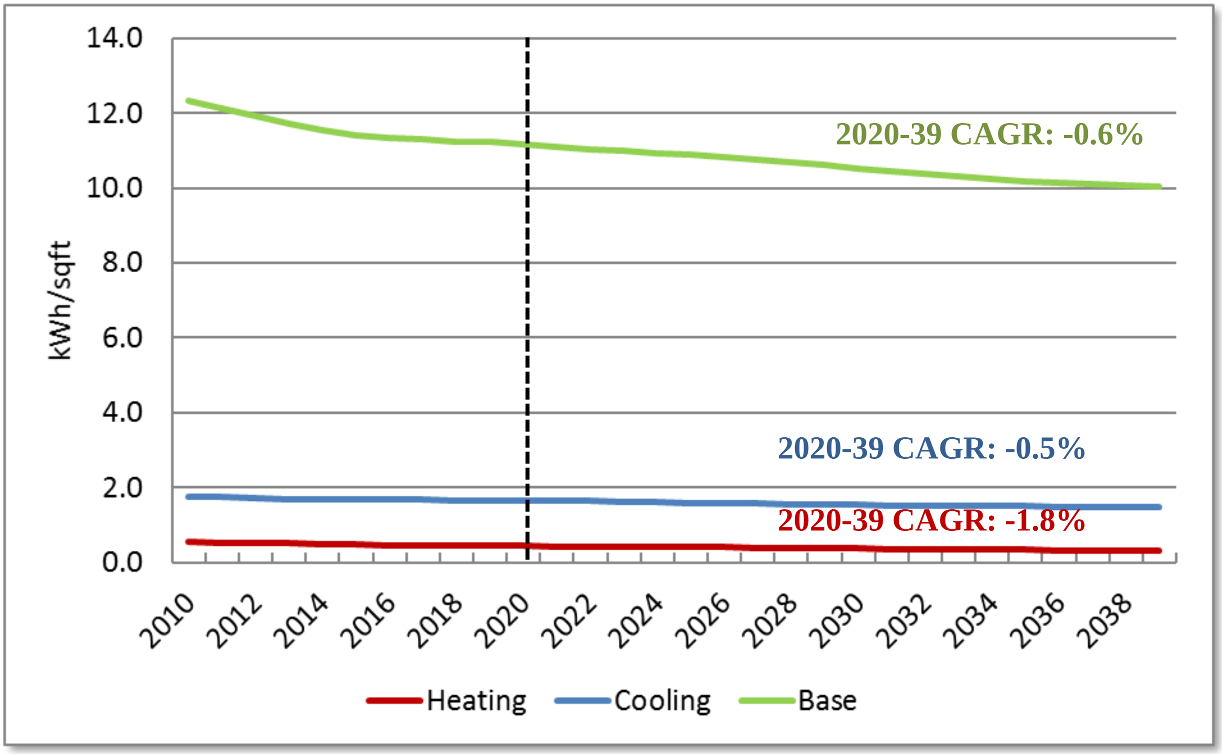


*CAGR=Compound Average Growth Rate

Heating intensity declines 0.7% annually through the forecast period, reflecting declining share in electric heat saturation. Cooling intensity declines 0.1% annually through the forecast period as overall air conditioning efficiency improvements outweigh increase in saturation. Total non-weather sensitive end-use intensity declines 0.2% annually.

Commercial end-use intensities (expressed in kWh per sqft) are based on the EIA's East South Central Census Division forecast; the starting intensity estimates are calibrated to Vectren commercial sales. As in the residential sector, end-use energy use has been declining as a result of new codes and standards and utility DSM programs. Figure 22 shows commercial end-use energy intensity forecasts for total heating, cooling, and non-weather sensitive loads.

Figure 22: Commercial End-Use Energy Intensity



Commercial usage is dominated by non-weather sensitive (Base) end-uses, which over the forecast period are projected to decline 0.6% per year. Cooling intensity declines 0.5% annually through the forecast period. Heating intensity declines even stronger at 1.8% annual rate though commercial electric heating is relatively small.

Appendix A: Model Statistics

Residential Average Use Model

Variable	Coefficient	StdErr	T-Stat	P-Value
mStructRev.XHeat	1.131	0.024	47.002	0.00%
mStructRev.XCool	1.102	0.015	72.536	0.00%
mStructRev.XOther	1.247	0.019	64.464	0.00%
mBin.Jan	41.217	10.23	4.029	0.01%
mBin.Aug	42.865	11.411	3.756	0.03%
mBin.Sep	34.721	10.421	3.332	0.12%
mBin.Oct	30.013	9.805	3.061	0.28%
mDSMF.DSM	-0.628	0.098	-6.44	0.00%

Model Statistics	
Iterations	1
Adjusted Observations	111
Deg. of Freedom for Error	103
R-Squared	0.989
Adjusted R-Squared	0.988
Model Sum of Squares	6,162,873.25
Sum of Squared Errors	70,284.55
Mean Squared Error	682.37
Std. Error of Regression	26.12
Mean Abs. Dev. (MAD)	19.03
Mean Abs. % Err. (MAPE)	1.93%
Durbin-Watson Statistic	1.81

Residential Customer Model

Variable	Coefficient	StdErr	T-Stat	P-Value
Economics.PopEV	960.574	2.859	335.981	0.00%
AR(1)	0.958	0.02	47.011	0.00%
MA(1)	0.438	0.086	5.101	0.00%

Model Statistics	
Iterations	8
Adjusted Observations	113
Deg. of Freedom for Error	110
R-Squared	0.996
Adjusted R-Squared	0.996
Model Sum of Squares	322,162,685.79
Sum of Squared Errors	1,295,103.33
Mean Squared Error	11,773.67
Std. Error of Regression	108.51
Mean Abs. Dev. (MAD)	87.12
Mean Abs. % Err. (MAPE)	0.07%
Durbin-Watson Statistic	1.91

Commercial Sales Model

Variable	Coefficient	StdErr	T-Stat	P-Value
mStructRev.XOther	9.238	1.188	7.776	0.00%
mStructRev.XCool	15.486	0.442	35.027	0.00%
mStructRev.XHeat	20.148	1.804	11.165	0.00%
mBin.Yr14	2763.076	860.831	3.21	0.18%
mBin.Feb	2174.958	1122.048	1.938	5.54%
mBin.Jun	-4324.45	995.223	-4.345	0.00%
mBin.Oct	3652.067	1025.239	3.562	0.06%
mBin.Nov	2720.101	1042.823	2.608	1.05%
mBin.Aug09Plus	29960.933	7537.599	3.975	0.01%
mDSM.DSM	-0.498	0.13	-3.826	0.02%

Model Statistics	
Iterations	1
Adjusted Observations	110
Deg. of Freedom for Error	100
R-Squared	0.964
Adjusted R-Squared	0.961
Model Sum of Squares	18,976,689,674.96
Sum of Squared Errors	712,451,460.27
Mean Squared Error	7,124,514.60
Std. Error of Regression	2,669.18
Mean Abs. Dev. (MAD)	1,974.42
Mean Abs. % Err. (MAPE)	1.82%
Durbin-Watson Statistic	1.586

Industrial Sales Model

Variable	Coefficient	StdErr	T-Stat	P-Value
mEcon.IndVar	118487.802	2254.45	52.557	0.00%
mWthrRev.CDD65	57.963	6.069	9.551	0.00%
mBin.Jul09Plus	29846.553	2190.612	13.625	0.00%
mBin.Feb	11020.029	3029.515	3.638	0.04%
mBin.Apr	7543.537	3000.036	2.514	1.32%
mBin.Sep	19778.485	3582.861	5.52	0.00%
mBin.Nov	17466.878	3505.353	4.983	0.00%
mBin.Yr09	-16514.547	3068.532	-5.382	0.00%
mBin.Yr16Plus	11358.694	1919.002	5.919	0.00%

Model Statistics	
Iterations	1
Adjusted Observations	137
Deg. of Freedom for Error	128
R-Squared	0.757
Adjusted R-Squared	0.742
Model Sum of Squares	37,889,478,247.99
Sum of Squared Errors	12,146,223,745.81
Mean Squared Error	94,892,373.01
Std. Error of Regression	9,741.27
Mean Abs. Dev. (MAD)	7,706.07
Mean Abs. % Err. (MAPE)	5.24%
Durbin-Watson Statistic	1.714

Residential Solar Adoption Model

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	23.491	11.774	1.995	5.04%
Payback.ResPayback	-1.31	0.866	-1.512	13.55%
AR(1)	0.144	0.126	1.143	25.75%

Model Statistics	
Iterations	6
Adjusted Observations	65
Deg. of Freedom for Error	62
R-Squared	0.068
Adjusted R-Squared	0.038
Model Sum of Squares	286.23
Sum of Squared Errors	3,925.31
Mean Squared Error	63.31
Std. Error of Regression	7.96
Mean Abs. Dev. (MAD)	3.71
Mean Abs. % Err. (MAPE)	91.11%
Durbin-Watson Statistic	2.009

Peak Model

Variable	Coefficient	StdErr	T-Stat	P-Value
mCPkEndUses.HeatVar	3.147	0.335	9.405	0.00%
mCPkEndUses.CoolVar	18.522	0.542	34.196	0.00%
mCPkEndUses.BaseVar	1.519	0.024	62.389	0.00%
mBin.Jan16	148.429	30.989	4.79	0.00%
mBin.Nov16	-86.871	31.195	-2.785	0.64%
mBin.Yr15	47.869	10.315	4.641	0.00%
mBin.May	-49.483	10.624	-4.658	0.00%
mBin.Oct	-48.783	11.583	-4.212	0.01%
mBin.Yr12Plus	-35.439	7.391	-4.795	0.00%

Model Statistics	
Iterations	1
Adjusted Observations	111
Deg. of Freedom for Error	102
R-Squared	0.952
Adjusted R-Squared	0.949
Model Sum of Squares	1,908,789.28
Sum of Squared Errors	95,539.47
Mean Squared Error	936.66
Std. Error of Regression	30.6
Mean Abs. Dev. (MAD)	22
Mean Abs. % Err. (MAPE)	2.81%
Durbin-Watson Statistic	1.855

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 2019 Annual Energy Outlook (AEO) database provided by the Energy Information Administration (EIA).

Residential 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.

$$\mathrm{USE}_m = a + b_1 \times \mathrm{XHeat}_m + b_2 \times \mathrm{XCool}_m + b_3 \times \mathrm{XOther}_m + \varepsilon_m \qquad (2)$$

$XHeat_m$, $XCool_m$, 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.

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
- 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:

$$HeatIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \middle/ Eff_y^{Type} \right)}{\left(Sat_{2015}^{Type} \middle/ Eff_{2015}^{Type} \right)} \tag{4}$$

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 2015 value:

$$StructuralIndex_y = \frac{BuildingShellEfficiencyIndex_y \times SurfaceArea_y}{BuildingShellEfficiencyIndex_{2015} \times SurfaceArea_{2015}} \tag{5}$$

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:

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

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 1.

Table 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.

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:

$$HeatUse_{y,m} = \left(\frac{HDD_{y,m}}{HDD_{05}}\right) \times \left(\frac{HHSize_{y}}{HHSize_{05,7}}\right)^{0.25} \times \left(\frac{Income_{y}}{Income_{05,7}}\right)^{0.10} \times \left(\frac{Elec\,Pr\,ice_{y,m}}{Elec\,Pr\,ice_{05,7}}\right)^{-0.10} \tag{7}$$

Where:

- *HDD* is the number of heating degree days in year (*y*) and month (*m*).
- *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*)

By construction, the $HeatUse_{y,m}$ variable has an annual sum that is close to 1.0 in the base year (2005). The first term, which involves 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.

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
- 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,

$$XCool_{y,m} = CoolIndex_{y} \times CoolUse_{y,m} \tag{8}$$

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:

$$CoolIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left({Sat_y^{Type}} \middle/ {Eff_y^{Type}} \right)}{\left({Sat_{2015}^{Type}} \middle/ {Eff_{2015}^{Type}} \right)} \qquad (9)$$

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 2.

Table 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].

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:

$$CoolUse_{y,m} = \left(\frac{CDD_{y,m}}{CDD_{05}}\right) \times \left(\frac{HHSize_y}{HHSize_{05,7}}\right)^{0.25} \times \left(\frac{Income_y}{Income_{05,7}}\right)^{0.10} \times \left(\frac{Elec\,Price_{y,m}}{Elec\,Price_{05,7}}\right)^{-0.10} \qquad (10)$$

Where:

- CDD is the number of cooling degree days in year (y) and month (m).

- *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)

By construction, the *CoolUse* variable has an annual sum that is close to 1.0 in the base year (2005). The first term, which involves 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.

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:

$$XOther_{y,m} = OtherEqpIndex_{y,m} \times OtherUse_{y,m} \qquad (11)$$

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.

$$ApplianceIndex_{y,m} = Weight^{Type} \times \frac{\left(Sat_y^{Type} \Big/ \frac{1}{UEC_y^{Type}} \right)}{\left(Sat_{2015}^{Type} \Big/ \frac{1}{UEC_{2015}^{Type}} \right)} \times MoMult_m^{Type} \times \qquad (12)$$

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:

$$ApplianceUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{HHSize_{y}}{HHSize_{05,7}}\right)^{0.25} \times \left(\frac{Income_{y}}{Income_{05,7}}\right)^{0.10} \times \left(\frac{Elec\ Pr\ ice_{y,m}}{Elec\ Pr\ ice_{05,7}}\right)^{-0.10} \tag{13}$$

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

$$OtherEqpIndex_{y,m} = \sum_{k} ApplianceI\ ndex_{y,m} \times ApplianceU\ se_{y,m} \tag{14}$$

Appendix C: Commercial 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, 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 2019 Annual Energy Outlook (AEO) database provided by the Energy Information Administration (EIA).

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,

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

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.

$$\mathrm{USE}_m = a + b_1 \times \mathrm{XHeat}_m + b_2 \times \mathrm{XCool}_m + b_3 \times \mathrm{XOther}_m + \varepsilon_m \qquad (2)$$

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.

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,
- Commercial output, employment, population, and energy price.

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

$$\mathrm{XHeat}_{y,m} = \mathrm{HeatIndex}_y \times \mathrm{HeatUse}_{y,m} \qquad (3)$$

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:

$$HeatIndex_y = HeatSales_{2013} \times \frac{\left(HeatShare_y / Eff_y\right)}{\left(HeatShare_{2013} / Eff_{2013}\right)} \quad (4)$$

In this expression, 2013 is used as a base year for normalizing the index. The ratio on the right is equal to 1.0 in 2004. In other years, it will be greater than one if equipment saturation levels are above their 201

level. This will be counteracted by higher efficiency levels, which will drive the index downward. Base year space heating sales are defined as follows.

$$HeatSales_{2013} = \left(\frac{kWh}{Sqft}\right)_{Heating} \times \left(\frac{CommercialSales_{2013}}{\sum_e kWh / Sqft_e}\right) \quad (5)$$

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

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

$$HeatUse_{y,m} = \left(\frac{HDD_{y,m}}{HDD_{05}}\right) \times \left(\frac{EconVar_{y,m}}{EconVar_{05,7}}\right) \times \left(\frac{Price_{y,m}}{Price_{05,7}}\right)^{-0.10} \quad (6)$$

Where:

- *HDD* is the number of heating degree days in month (m) and year (y).
- *EconVar* is the weighted commercial economic variable that blends Output, Employment, and Population in month (m), and 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 term, which involves 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).

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,
- Commercial output, employment, population 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:

$$CoolIndex_y = CoolSales_{2013} \times \frac{\left({CoolShare_y}/{Eff_y} \right)}{\left({CoolShare_{2013}}/{Eff_{2013}} \right)} \tag{8}$$

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

$$CoolSales_{2013} = \left(\frac{kWh}{Sqft}\right)_{Cooling} \times \left(\frac{CommercialSales_{2013}}{\sum_e {kWh}/{Sqft_e}}\right) \tag{9}$$

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 2013 will be equal to the estimated annual cooling sales in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

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

$$CoolUse_{y,m} = \left(\frac{CDD_{y,m}}{CDD_{05}}\right) \times \left(\frac{EconVar_{y,m}}{EconVar_{05,7}}\right) \times \left(\frac{Price_{y,m}}{Price_{05,7}}\right)^{-0.10} \qquad (10)$$

Where:

- *HDD* is the number of heating degree days in month (m) and year (y).
- *EconVar* is the weighted commercial economic variable that blends Output, Employment, and Population in month (m), and year (y).
- *Price* is the average real price of electricity in month (m) and year (y).

By construction, the *CoolUse* variable has an annual sum that is close to one in the base year (2004). The first term, which involves 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.

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:

$$\text{XOther}_{\text{y,m}} = \text{OtherIndex}_{\text{y,m}} \times \text{OtherUse}_{\text{y,m}} \qquad (11)$$

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:

$$OtherIndex_{y,m} = \sum_{Type} Weight_{2013}^{Type} \times \left(\frac{Share_{y}^{Type} \big/ Eff_{y}^{Type}}{Share_{2013}^{Type} \big/ Eff_{2013}^{Type}} \right) \qquad (12)$$

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:

$$Weight_{2013}^{Type} = \left(\frac{kWh}{Sqft}\right)_{Type} \times \left(\frac{CommercialSales_{04}}{\sum_e {}^{kWh}/_{Sqft_e}}\right) \qquad (13)$$

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

$$OtherUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{EconVar_{y,m}}{EconVar_{05,7}}\right) \times \left(\frac{Pr\,ice_{y.m}}{Pr\,ice_{05,7}}\right)^{-0.10} \qquad (14)$$