CONFIDENTIAL

VERMONT ELECTRIC COOPERATIVE 2019 LOAD FORECAST

AUGUST 10, 2018

PREPARED FOR

VERMONT ELECTRIC COOPERATIVE

PREPARED BY

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I. LOAD FORECAST TECHNICAL REPORT EXECUTIVE SUMMARY

Vermont Electric Cooperative, Inc. (VEC) is a member-owned rural electric cooperative established in 1938. Its approximately 39,000 members are spread over 75 towns and 8 counties in northern Vermont. The customer breakdown is as follows:

Customer Class	AVG 2017 Members	% of Total Customers	Total Sales	% of Total Sales
Residential and Seasonal	34,430	88.4%	215,434,784	48.5%
Large Commercial and Small Commercial	4,017	10.3%	112,366,624	25.3%
Industrial	15	0.04%	99,639,588	22.5%
Public Authorities	443	1.1%	15,633,278	3.5%
Lighting	58	0.2%	744,927	0.2%
Total	38,963	100%	443,819,201	100%

Table 1: VEC Customer and Sales (kWh) Distribution

In 2018, Daymark Energy Advisors (Daymark) prepared separate 3-year univariate (i.e. time series) and 20-year multivariate (i.e. econometric) forecasts of VEC system energy and peak demand. Customer class forecasts, based in some cases on forecasts of number of customers and energy use per customer, were also prepared, but not utilized in the IRP modeling. Rather, they were provided to VEC for internal revenue forecasting and other uses, and do not directly integrate with the IRP system energy and peak demand forecasts, which were developed using different forecast models.

The separate system energy and peak demand univariate and multivariate forecasts used in the IRP were prepared in order to:

Minimize the effects of model specification error and forecast bias that may accompany any single methodology;

Utilize all available information to make projections. That is, information contained in both the monthly historical values of VEC sales and loads (univariate methodology), and information contained in aggregated annual VEC sales and load data in relation to exogenous economic and weather data (multivariate methodology); and to

Provide a means of calibrating and blending the typically more accurate shorter-term univariate methods with the longer-term outlook offered by economic and weather data in econometric multivariate models.

Monthly forecasts produced by the separate methods were analyzed individually and then blended, along with expert judgment provided by VEC and Daymark Energy Advisors staff, into a single annual point forecast, with accompanying upper and lower bounds. These upper and lower bounds were derived using 95% confidence interval boundaries for the fitted equations, and then altering projections of some of the independent economic variables underlying the econometric forecasts based again on the boundaries associated with 95% confidence intervals. As a consequence, the upper and lower boundaries reflect a composite confidence interval approaching 100%.

The purpose of the point forecasts is to enable certain types of VEC planning. These objectives include near-term budget-setting, resource planning, rate and financial forecasting and power project financing support. However, the forecasting exercise explained in this report is intended not to lead the reader to any specific point forecast of load, because of the high probability that the forecast will ultimately have been in error by some amount, especially the further out in the forecast horizon one projects.

Instead, the reader is directed to the bounding of uncertainty about future VEC load levels, between an upper and lower boundary. Utilizing a bounding approach more appropriately captures the concept that specific future load levels will take the shape of an assumed approximately normal frequency distribution of possible loads, centered about the midpoint of the upper and lower boundaries (not necessarily the point forecast), but which could and will vary from that midpoint. Reasons for variance include seasonal weather patterns, net immigration into VEC's service territory, regional economic conditions, electricity prices, and other factors.

Importantly, the derivation of upper and lower boundaries over the forecast horizon, in this case utilizing a 95% confidence interval approach (approximately +/- two standard deviations from the mean) for the fitted equations, together with high and low scenario forecasts of the independent variables, allows for testing of the effects of different load growth trajectories on projected VEC system power supply and transmission costs. As explained further in the IRP report in Section~~s 2 &~~ 3.2~~6~~, the IRP modeling approach VEC utilized was Monte Carlo simulation, which projects costs based on a predefined sampling approach simulating the interaction of a host of variables which drive those costs. The load forecast trajectory was but one of numerous variables simulated in the IRP cost projections, though the Monte Carlo simulation software utilized, ***Crystal Ball***™, allows isolation of the impacts of load growth while other variables are held constant.

The results are discussed and presented graphically below.

VEC SYSTEM ENERGY REQUIREMENTS

VEC System Energy requirements were forecast by first forecasting total system sales using an average for the first three years of a monthly time series specification and a monthly econometric specification described further herein and in *Appendix A – Multivariate Models Technical Appendix.* High and low boundaries associated with these models reflect 95% confidence intervals around the fitted base case point estimates. Thereafter, the econometric forecasts were used to complete the low, reference (aka "base") and high case 20-year long-term forecasts**.**

The best fitting time series model was a Box-Jenkins with log transform model with an adjusted R^2 of 0.89, which means that the statistical model explained roughly 89% of the variance in actual monthly loads.

The econometric model was fit using a combination of independent explanatory variables including weather (heating degree-days) and macroeconomic (real price of electricity). The econometric specification produced a well-fit model using historical data, with an adjusted R^2 of 0.87, meaning that variance in the independent variables explained roughly 87% of the variance in actual VEC system load.

In order to develop low and high boundaries around the reference econometric forecast, we developed high and low scenarios for certain independent variables, particularly heating degree days (HDD) at Burlington and the real average price of electricity. The lower boundary is determined by the lower limit of the 95% confidence interval for the low case, and the high boundary is determined by the upper limit of the 95% confidence

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interval for the high case. As a consequence, the confidence interval represented by the low and high case projections approaches 100%.

The results are presented below. Total class sales are expected to decrease from about 444,000 MWh in 2017, to almost 434,000 MWh by 2022, implying a compound annual growth rate (CAGR) of -0.005% in that time frame.

Long-term, VEC is projected to have total sales of approximately 434,000 MWh by 2037, implying a 20-year CAGR of -0.1% in the reference case. This long-term CAGR could vary from as low as -1.0~~0.7~~% in the low case lower limit, to 0.~~4~~5% in the high case upper limit.

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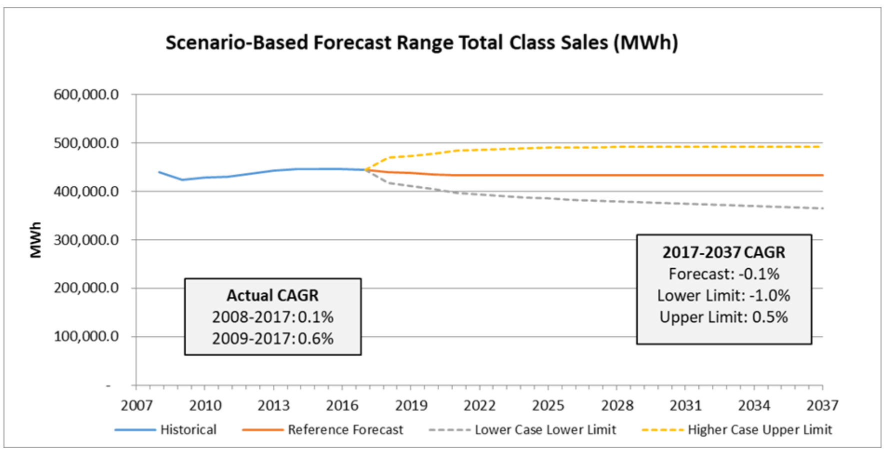

Figure 1: Scenario-based Forecast Range for Total Class Sales (MWh)

Additionally, we wanted to investigate the price-sensitivity of customers' ~~towards~~ consumption. Accordingly, the price-elasticity associated with the real price of electricity variable featured in the multivariate econometric model for total class sales was calculated. The price-elasticity value was approximately -0.29. Suggesting, t~~T~~herefore, that for every 10% increase in real electricity price, there is a long-term decrease in consumption of 2.9%, *ceteris paribus*. The details of this calculation are featured in *Appendix A – Multivariate Models Technical Appendix*.

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VEC GROSS SYSTEM LOAD

In order to "bulk up" total system sales to gross system load, we compared historical gross system load (with SPEED resources[1] included) to total class sales. Between 2014 and 2017, system load averaged 7% greater than total sales, falling within a tight range of 6.3% to 8.2% on an annual basis. We applied this average factor to our forecast of total class sales to develop a forecast of gross system load.

The results are presented below. System energy requirements are expected to decrease from about 475,000 MWh in 2017, to almost 464,000 MWh by 2022 and increasing to 465,000 MWh by 2037. The CAGRs are the same as total customer sales CAGRs because the forecast is adjusted by a constant bulk-up factor.

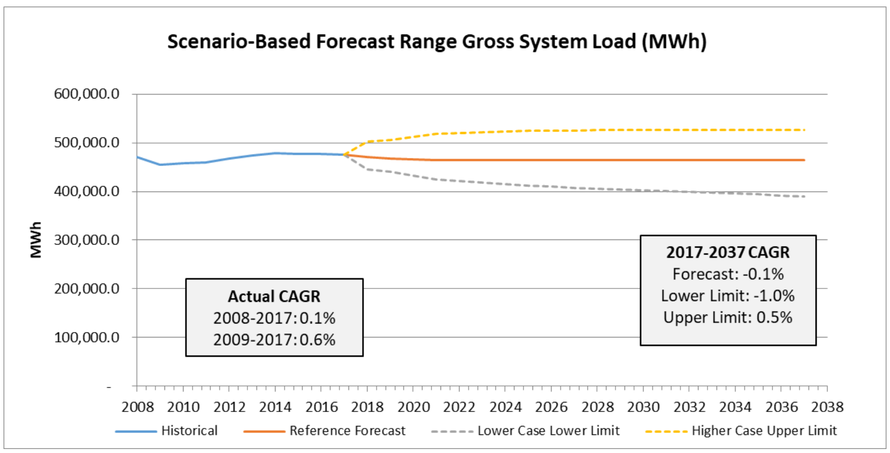

Figure 2: Scenario-Based Forecast Range for Gross System Load (MWh)

[1] Distributed generators that reduce metered load.

VEC SYSTEM (WINTER) PEAK

Better statistical models for load factor (the ratio of average load to peak load) were fit than models for peak loads by themselves. The best fitting time series model utilized exponential smoothing, with an adjusted R^2 of 0.75; the statistical model explained roughly 75% of the variance in actual monthly load factor. The 2018 forecast of monthly load factors for the forecast and 95% confidence intervals were held constant throughout the study period.

We forecasted monthly peaks as a multiple of each month's forecast average hourly gross system load and the forecast monthly load factor. The low boundary was developed by using the gross system load low case low limit (discussed above) with the 95% confidence interval upper limit load factor (because it is a divisor, this serves to further lower the peak forecast). Conversely, the high boundary was developed using the gross system load high case upper limit divided by the 95% confidence interval lower limit load factor. By compounding the low and high cases in this manner, the confidence interval represented by the low and high case projections approaches 100%.

System peak demand is expected to decrease from about 85.4 MW in 2017, to about 80.9 MW by 2022, implying a CAGR of -~~0~~1.1% in that time frame. Long-term, VEC is projected to see peak demand continue to decrease, reaching 79.8 MW by 2037. The boundary cases show projected 20-year CAGRs ranging anywhere from -1.5% to 0.7%, with 2037 system peaks ranging from potentially as low as 63 MW to potentially as high as 97.8 MW.

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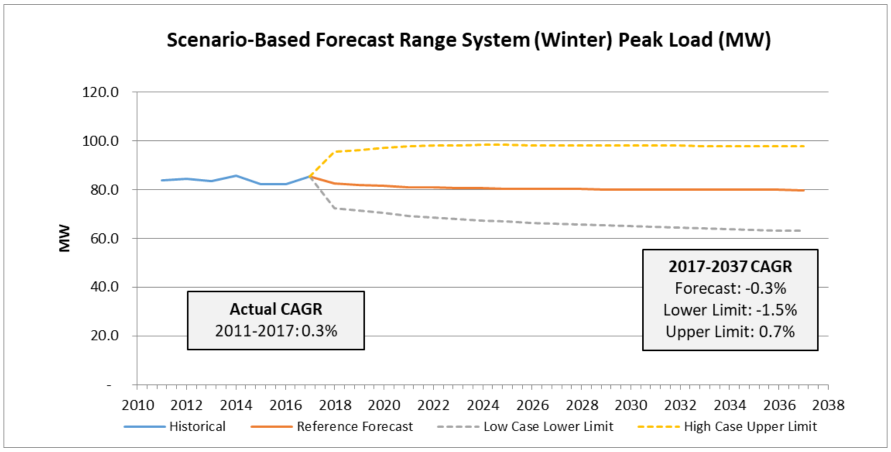

Figure 3: Scenario-Based Forecast Range for System (Winter) Peak Load (MW)

VEC SUMMER PEAK

Using the same approach to estimation of monthly peak load numbers derived above, we next forecast the highest monthly peak load in the summer months. The results are presented below. Summer peak load is expected to decrease from about 73.2 MW in 2017, to about 70.7 MW by 2022, implying a CAGR of -0.~~01~~7% in that time frame. Long-term, VEC summer peak demand is expected to decrease at a rate of about -0.2% annually on average, reaching 70.8 MW by 2037. The boundary cases show projected 20-year CAGRs ranging anywhere from -1.4% to 0.9%, with 2037 system peaks ranging from as low as 55 MW to as high as 88.2 MW.

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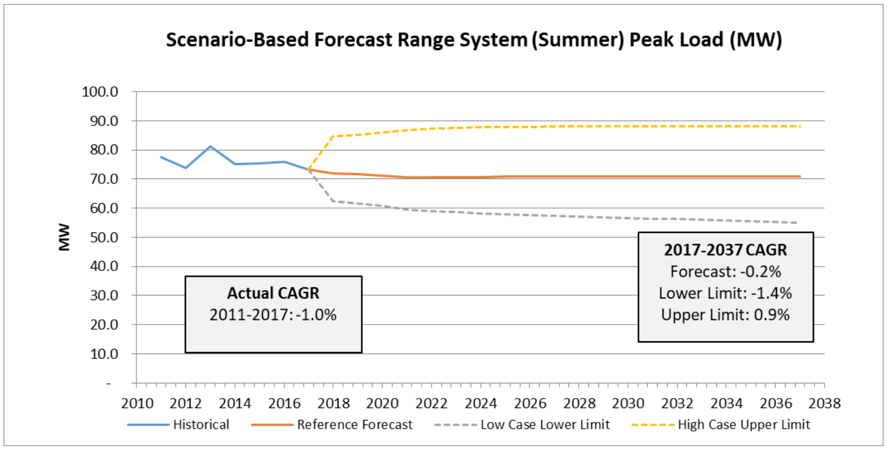

Figure 4: Scenario-Based Forecast Range of Summer Peak Load (MW)

II. INTRODUCTION AND OBJECTIVES

Daymark Energy Advisors was commissioned by VEC to prepare a load forecast with short-term accuracy and shorter-to-longer-term integrated resource planning utility as the primary objectives, with cost containment also a prominent objective.

These objectives suggested the use of both univariate and multivariate methodologies. The former, also known as time-series methods, utilize monthly data and can yield the most accurate predictions among all forecast methods for the next 12–24 months, particularly if recent trends in loads continue without major disruption. That is because univariate methods model future loads on the basis of trends in the historical load data, especially recent trends. Because they utilize only the historical values for the series being forecast, they are inexpensive and easy to prepare.[2]

The least costly and potentially most accurate longer-term multivariate forecasting methods include econometric models, which utilize exogenous economic and weather data to fit relationships between loads and regional economic and weather conditions. In situations where economic and weather data can be found that provide at least a theoretical basis for explaining load variance, and reasonable, unbiased projections of those variables can be made for the future, econometric approaches can be used to project load.

There are other ways to forecast electric load, including engineering calculations and end-use approaches, and other more exotic approaches like systems dynamics or neural network models. These methodologies can yield models that produce quite accurate predictions of load over the shorter or even longer-term, but are data and calculation-intensive, and therefore expensive to produce.[3] It is often not possible to justify the added expense (which can be significant) of these data and time-consuming approaches to achieve potentially marginally better accuracy.

In consideration of the foregoing, the univariate and multivariate econometric approaches utilized herein were chosen to satisfy VEC's current forecast objectives.

[2] However, in some cases, such as with Box-Jenkins models, they may be mathematically difficult to comprehend.

[3] In addition, many of these approaches can also be mathematically difficult to explain.

III. LOAD FORECASTING METHODOLOGIES AND RESULTS

As discussed above, the load forecast methodology utilized the results of short-term univariate modeling and long-term multivariate modeling to produce a blended load forecast at the VEC system level of total energy requirements and seasonal peak demands. These system level forecasts were developed for and utilized directly in the 2019 IRP.

The same techniques were also employed to forecast consumption for the main customer classes (residential & seasonal, Industrial, and combined public, other, VEC facilities, and small & large commercial ("Commercial & Other")). Due to the small consumption values of the public and other classes, these classes, along with VEC facilities consumption, were combined with the large and small commercial classes into a single category known as "Commercial & Other." The public class consists of street lighting, while the other class is composed of public authorities. The class level load forecasts were independent models developed for VEC internal revenue forecasting and other purposes and were not utilized directly in the 2019 IRP.

Below, we discuss the results of each modeling exercise.

A. Data Sources

Historical time series data for dependent and independent variables was collected, as well as forecasts of the independent variables. Historical economic data was obtained from ISO New England's 2018 Forecast Report of Capacity, Energy, Loads, and Transmission (2018 CELT).[4] Weather data was obtained from ISO New England monthly data[5] and the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NOAA).[6] Data was also obtained from VEC's RUS Form 7 on revenue per customer by customer class to model and forecast real electricity price.

The economic forecast data from CELT, which only covers the period from 2018-2027, was extended through 2037 at the last five years (2024-2028) average growth rate. A 13-year average or "normal" for the weather data by month was assumed as constant for the remaining forecast period. The electricity price obtained from the RUS Form 7 was

4 http://www.iso-ne.com/system-planning/system-plans-studies/celt

5 http://www.iso-ne.com/markets/hstdata/znl_info/monthly/index.html

6 http://www.ncdc.noaa.gov/cdo-web/datasets/GHCNDMS/stations/GHCND:USW00014742/detail.

assumed to be held constant in real terms as the average of the last five years of actual data (2013-2017) in the reference case forecast, though scenarios were run in determining low and high case boundaries by considering changes in real electricity price, higher and lower respectively.

B. Univariate Modeling

Univariate (also known as time series) models decompose the historic data into auto-regressive, trend, cyclical and seasonal patterns, and then use these patterns to produce forecasts. As a result, time series forecasts tend to be very accurate in the short term. Time series models considered included exponential smoothing and Box-Jenkins models, both of which were fit automatically using the software product ***Forecast Pro***™.

Univariate models were specified for each major customer class to forecast class consumption through one of two approaches: a) modeling consumption directly; or b) modeling number of customers and usage per customer separately and calculating consumption as the product of the two forecasts. The same approaches were also used to forecast VEC's total system sales and load factor for use in the IRP. A monthly forecast for each series was generated for the three years 2018–2020.

	Class	Year		
		2018	2019	2020
Class Consumption (MWh)	INDUSTRIAL	99,078	99,195	99,253
	COMMERCIAL & OTHER	130,828	130,828	130,828
	RESIDENTIAL	216,455	216,858	217,289
Total Class Sales* (MWh)		442,259	441,328	441,328

Table 2: Time Series Base Case Forecast Results – Annual Consumption by Customer Class

***** *Total class sales forecast separately, so it does not exactly equal the sum of individual class forecasts. The difference is <1.4% in all three years.*

C. Multivariate Modeling

Macroeconomic data from the ISO New England CELT Database, and weather data and customer data compiled by VEC, were used to develop long-term, multivariate forecast models for projections of total system energy for IRP modeling purposes. Separately, independently-developed class sales, class number of customers, and class sales per customer were developed for internal VEC revenue forecasting purposes. A number of the forecast models utilize the ***Forecast Pro™*** software and its dynamic regression functionality. Dynamic regression enhances conventional regression on independent variables by also supporting the use of lagged dependent and independent variables and Cochrane-Orcutt autoregressive error terms. These models therefore represent a hybrid of traditional univariate-times series approaches and linear regression with independent variables. This technique combines the short-term accuracy of time series approaches with the long-term predictive power of econometric models.

The results of the econometric multivariate forecasting are summarized below. A substantial amount of further modeling detail and statistical results are presented in *Appendix A – Multivariate Models Technical Appendix.*

	2018	2019	2020
MWh Sales Forecasts			
Industrial	99,351	99,394	99,437
Commercial & Other	130,609	129,971	128,804
Total System	440,072	437,457	435,569
Customer Number Forecasts			
Residential	34,562	34,829	35,232

Table 3: Multivariate Forecast Results- Base Case Annual Projections

IV.FORECAST BLENDING PROCEDURE

In previous sections, Daymark Energy Advisors discussed the results of separate univariate and multivariate forecasts for each of the major classes, and total system requirements and peak demand for use in the 2019 IRP. These forecasts used different statistical techniques and relied upon different vintages and aggregation levels of underlying data.

The univariate methods forecast based on the trend, cyclical and seasonal patterns contained solely in the monthly historical data, while the multivariate econometric techniques utilized relationships uncovered between regional demographics, economics, weather, and VEC loads. Univariate models focus upon the recent past load history to a much greater extent, while the multivariate econometric techniques focus upon long-term structural relationships between loads and economic conditions and other drivers like weather.

The multivariate econometric models use the relationship between load and explanatory independent variables and are therefore useful for forecasting over a long forecast horizon. For this reason, they drive the long-term VEC load forecast used in the IRP. By necessity, therefore, an accurate load forecast relies upon an accurate forecast of the independent driver variables going forward. Further, the multivariate econometric methods place equal importance on all of the historical data over which the models were fit. This is an especially important and notable feature of the multivariate econometric modeling approach. The econometric models presume long-term structural stability between VEC loads and economic and weather conditions and may not yield reliably accurate forecasts if economic conditions change (e.g., a change in the pace of Vermont's economic growth and its effect on real disposable income, VEC real retail rates, net immigration into VEC service territory, etc.), the independent variables are seriously misforecast, or both. For this reason, we have developed high and low boundaries based on the model parameters derived for the 95% confidence intervals associated with the econometric reference case forecast models, and high and low scenarios for some key independent variables to derive high case upper limit and low case lower limit boundaries on a confidence interval that approaches 100%.

In contrast, the univariate methods place the most weight on the most recent load data. These methods can produce very accurate results in the short run but as the forecast horizon increases, or structural relationships between loads and factors affecting loads change (e.g., economic conditions, end-use stock or efficiency changes, more saturated distributed generation like rooftop solar), univariate forecasts will become less reliable.

To capture the benefits of each method, the univariate and multivariate econometric forecasts for each class and for the VEC system as a whole are blended together during the first three years of the forecast horizon. In the three years 2018–2020, the univariate and multivariate forecasts are combined using a simple weighted average of the forecasts associated with each model. In the years beyond 2020, the forecasts are those developed under the multivariate econometric forecast. The relative weight of each forecast in the blending is shown in the table below.

Forecast Year	Univariate Forecast Weighting	Multivariate Forecast Weighting
2018	75%	25%
2019	50%	50%
2020	25%	75%
2020 and beyond	0%	100%

Table 4: Forecast weighting for standard blending methodology

The high and low boundaries for individual customer class forecasts were developed using the upper and lower limits of the 95% confidence intervals of the respective univariate or multivariate models. For the VEC system as a whole, the highs and lows were developed by additionally varying the independent variables in the econometric models. For instance, the "high case" consisted of a high forecast for heating degree days (HDDs) at Burlington International Airport and a low forecast for the real price of electricity, while the "low case" consisted of a low forecast for Burlington HDDs and a high forecast for the real price of electricity. These forecasts were taken from ISO New England's 2018 CELT report, NOAA weather data, and scenario-based adjustments to VEC real retail rates just below and just above 2013-2017 average prices. After the high and low econometric forecasts were constructed, they were blended into the time series forecasts for the period of 2018-2020 in the manner described above.

V. FINAL BLENDED CLASS SALES FORECASTS

RESIDENTIAL AND SEASONAL

The residential class (including seasonal customers) represented about 49% of VEC's total sales in 2017, and about 88% of its members.

Residential sales were broken up into two monthly time-series: *residential customers* and *average energy use per customer*. Each of these series was forecast independently, and the results combined to form the overall residential sales model. In this way, the forecast captures both the customer demographic and end-use changes.

For the econometric model, the independent variables in the *number of customers equation* included population, Vermont heating degree-days, real personal income, heating degree-days for Burlington airport, real price of electricity, as well as monthly seasonal "dummy variables" to adjust for monthly effects. No statistically satisfactory multivariate model could be fit to the residential *average energy use per customer* data. Therefore, the univariate forecast was extended by assuming consistent year-over-year growth beyond the year of the univariate forecast period. The final average energy use per customer sales forecast reflects the extended univariate forecast exclusively. Details of econometric model specifications for the number of residential customers forecast, parameter details and within-sample statistics can be found in Appendix A.

The multivariate and univariate forecasts are averaged according to the weights shown in the previous section. Residential class consumption is projected to grow from just over 215,000 MWh in 2017 to approximately 222,000 MWh in 2037, which translates to a 0.2% CAGR. This compares to the historical CAGR for the past nine years of -0.3%. The high case boundary for residential consumption is projected to grow to approximately 253,000 MWh by 2037, at a CAGR of 0.8%. The low boundary case is projected to decline to below 193,000 MWh by 2037, at a CAGR of -0.6%.

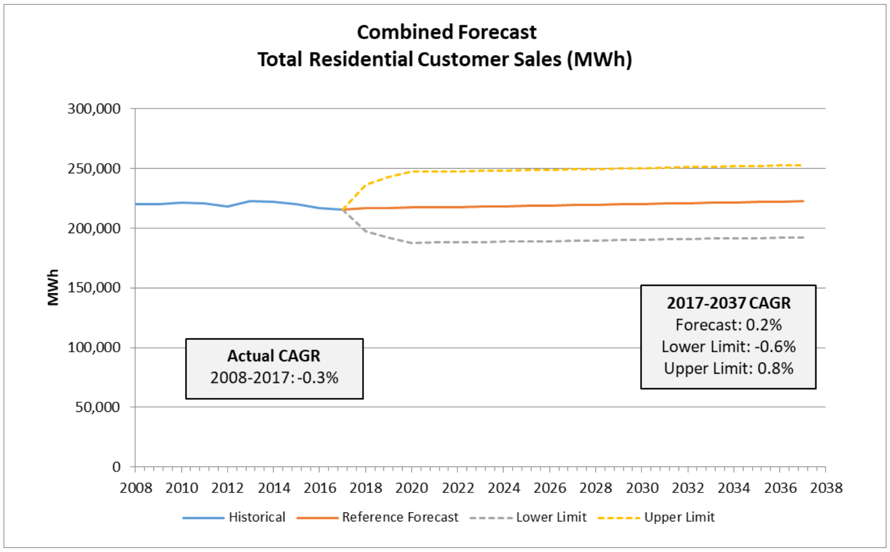

Figure 5: Combined Forecast – Total Residential Customer Sales (MWh)

COMMERCIAL & OTHER (Public, Other, VEC facilities, and Large & Small commercial)

The Commercial & Other class category represented some 29% of VEC's total sales in 2017, and 12% of its members.

No statistically satisfactory multivariate model could be fit for this class. The univariate forecast was extended by assuming consistent year-over-year growth beyond the last year of the univariate forecast period. The final Commercial & Other category sales forecast reflects the extended univariate forecast exclusively.

Sales to the Commercial & Other class are projected to increase from approximately 131,000 MWh in 2017 to 163,000 MWh in 2037, which translates to a 1.1% CAGR. This compares to the historical CAGR growth rate for the past nine years of 1.8%.

The high case boundary for Commercial & Other sales is projected to grow to over 176,000 MWh by 2037, at a CAGR of 1.5%. The low case boundary for Commercial & Other sales is projected to fall below 149,000 MWh by 2037, at a CAGR of 0.6%.

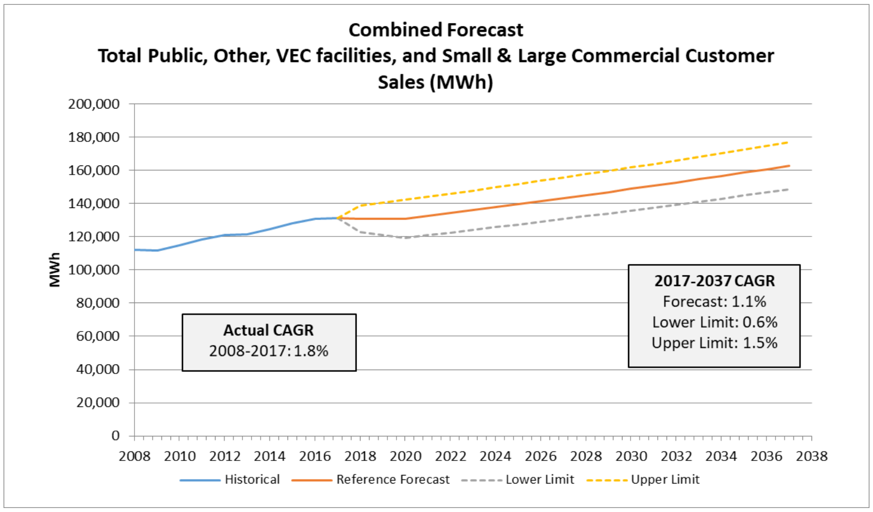

Figure 6: Combined Forecast – Commercial & Other Customer Sales (MWh)

INDUSTRIAL

The 15 customers in the industrial class represented approximately 22% of VEC's total sales in 2017. Industrial sales were forecast directly, without separately forecasting number of customers and average energy use per customer due to the wide variety of customer types.

The independent variables in the total class energy equation were heating degree-days, real price of electricity, and a series of dummy variables reflecting adjustments to some months of the year.

The blending methodology used for the reference, high and low boundary cases was to assume a 75%/25% weighting of the univariate and multivariate forecasts, respectively, in 2018. We assumed that the forecasts would remain linear from 2019 to 2037 to reach the 2037 multivariate forecast value.

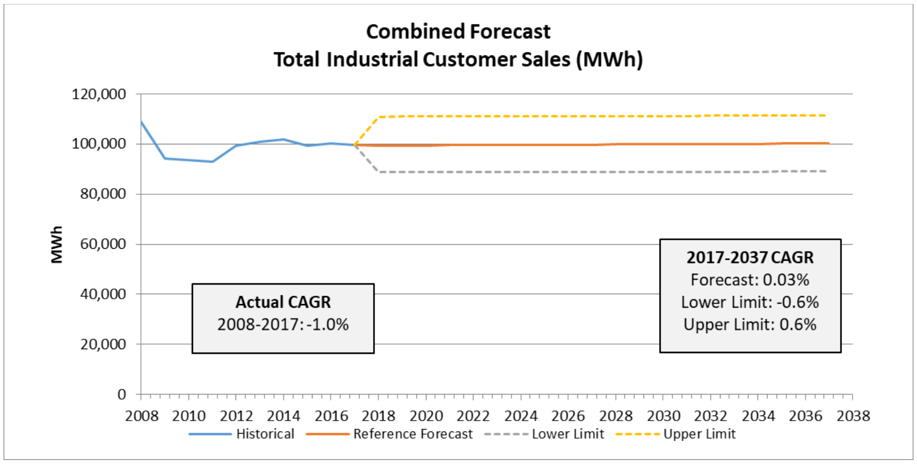

Figure 7: Combined Forecast – Industrial Customer Class Sales (MWh)

VI.FINAL BLENDED SYSTEM LOAD FORECASTS

The class sales forecasts discussed in the previous sections were prepared to enable revenue projections and other types of planning, including demand-side management (DSM). Nevertheless, the IRP utilizes custom-prepared load forecasts at the total system level. These forecasts were developed from separately-specified univariate and econometric models; they are not built up from the class load forecasts discussed in the previous section.

All subsequent Integrated Resource Plan (IRP) modeling was based upon the base, high and low projections made at the VEC total sales level, not by summing the results for individual classes.[7] Good-fitting, separate time series and econometric models were successfully developed at the VEC System level to support the IRP, obviating the need for summing class sales forecasts.

VEC SYSTEM ENERGY REQUIREMENTS

VEC System Energy requirements were forecast by first forecasting total system sales using a weighted average for the first three years of a monthly time series specification and a monthly econometric specification described further herein and in *Appendix A – Multivariate Models Technical Appendix.* High and low boundaries associated with these models reflect 95% confidence intervals around the fitted base case point estimates. Thereafter, the growth rate of the econometric specification was used to project the growth rates of the low, reference (aka "base") and high case 20-year long-term forecasts**.**

The best fitting time series model was a Box-Jenkins with log transform model with an adjusted R^2 of 0.89, which means that the statistical model explained roughly 89% of the variance in actual monthly loads.

The econometric model was fit using a combination of independent explanatory variables including weather (heating degree-days) and macroeconomic (real price of electricity). The econometric specification produced a well-fit model using historical data, with an adjusted R^2 of 0.87, meaning that variance in the independent variables explained roughly 87% of the variance in actual VEC system load.

In order to develop low and high boundaries around the reference econometric forecast, we developed high and low scenarios for certain independent variables, particularly heating degree days (HDD) at Burlington and the real average price of electricity. High and low boundaries were based on the model parameters derived for the 95%

[7] The "High" and "Low" forecast scenarios were created by modifying the VT real price of electricity from RUS7 (RUSPRICE) and Burlington Heating Degree-Days (BurHDD) values. The BurHDD high and low data were based on the values from the years with the largest and smallest number of heating degree days, respectively. The high and low RUSPRICE data used for the scenarios were based on inflating the prices after 2017 by 1% (high price) or holding the 2017 price constant for the remaining years (low price).

confidence intervals associated with the econometric reference case forecast models, and by incorporating high and low scenarios for some key independent variables to derive even wider high case upper limit and low case lower limit boundaries. Because of these scenario adjustments, the confidence interval for this forecast approaches 100%.

The results are presented below. Total class sales are expected to decrease from about 444,000 MWh in 2017, to almost 434,000 MWh by 2022, implying a compound annual growth rate (CAGR) of -0.005% in that time frame.

Long-term, VEC is projected to have total class sales of approximately 434,000 MWh by 2037, implying a 20-year CAGR of -0.1% in the reference case. This long-term CAGR could vary from as low as -0.7% in the low case lower limit, to 0.4% in the high case upper limit.

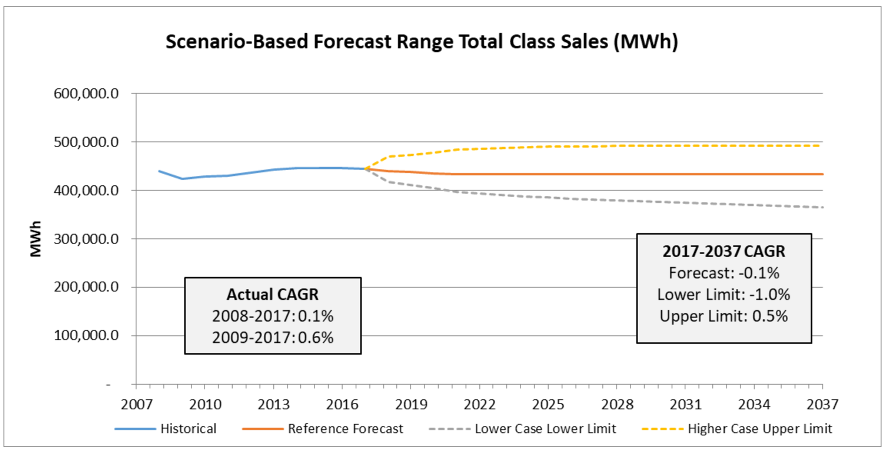

Figure 8~~10~~: Scenario-based Forecast Range for Total Class Sales (MWh)

Additionally, we wanted to investigate the price-sensitivity of customers' ~~towards~~ consumption. Accordingly, the price-elasticity associated with the real price of electricity variable featured in the multivariate econometric model for total class sales was calculated. The price-elasticity value was approximately -0.29. Suggesting, t~~T~~herefore, that for every 10% increase in real electricity price, there is a long-term decrease in consumption of 2.9%, *ceteris paribus*. The details of this calculation are featured in *Appendix A – Multivariate Models Technical Appendix*.

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VEC GROSS SYSTEM LOAD

In order to "bulk up" total system sales to gross system load[8], we compared historical gross system load (with SPEED resources[9] included) to total class sales. Between 2014 and 2017, system load averaged 7% greater than total sales[10], falling within a tight range of 6.3% to 8.2% on an annual basis. We applied this average factor to our forecast of total class sales to develop a forecast of gross system load.

The results are presented below. System energy requirements are expected to decrease from about 475,000 MWh in 2017, to almost 464,000 MWh by 2022 and then increasing slightly to 465,000 MWh by 2037. The CAGRs are the same as total customer sales CAGRs because the forecast is adjusted by a constant bulk-up factor.

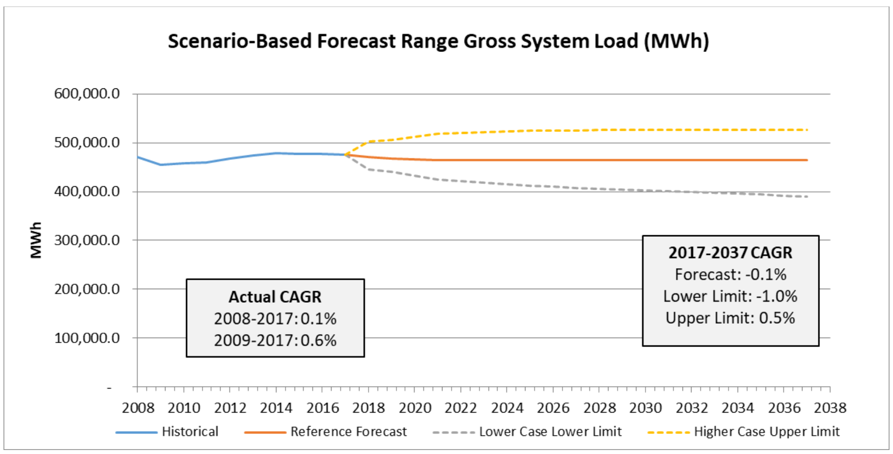

Figure 9~~11~~: Scenario-Based Forecast Range for Gross System Load (MWh)

[8] Also referred to as Real-Time Load Obligation (RTLO).

[9] Distributed generators that reduce metered load.

[10] The difference represents, almost exclusively, losses over the VEC distribution or sub-transmission systems down to the metered sales level.

VEC SYSTEM (WINTER) PEAK

Better statistical models for load factor (the ratio of average load to peak load) were fit than models for peak loads by themselves. The best fitting time series model utilized exponential smoothing, with an adjusted R^2 of 0.75; the statistical model explained roughly 75% of the variance in actual monthly load factor. The 2018 forecast of monthly load factors for the forecast and 95% confidence intervals were held constant throughout the study period.

We forecasted monthly peaks as a multiple of each month's forecast average hourly gross system load and the forecast monthly load factor. The low boundary was developed by using the gross system load low case low limit (discussed above) with the 95% confidence interval upper limit load factor (because it is a divisor, this serves to further lower the peak forecast). Conversely, the high boundary was developed using the gross system load high case upper limit divided by the 95% confidence interval lower limit load factor. By compounding the low and high cases in this manner, the confidence interval represented by the low and high case projections approaches 100%.

System peak demand is expected to decrease from about 85.4 MW in 2017, to about 80.9 MW by 2022, implying a CAGR of -~~0~~1.1% in that time frame. Long-term, VEC is projected to see peak demand continue to decrease, reaching 79.8 MW by 2037. The boundary cases show projected 20-year CAGRs ranging anywhere from -1.5% to 0.7%, with 2037 system peaks ranging from potentially as low as 63 MW to potentially as high as 97.8 MW.

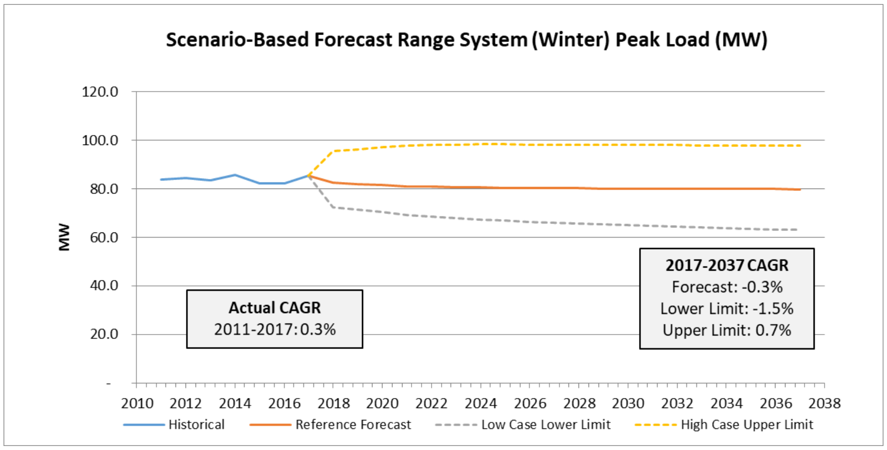

Figure 10~~12~~: Scenario-Based Forecast Range for System (Winter) Peak Load (MW)

VEC SUMMER PEAK

Using the same approach to estimation of monthly peak load numbers derived above, we next forecast the highest monthly peak load in the summer months. The results are presented below. Summer peak load is expected to decrease from about 73.2 MW in 2017, to about 70.7 MW by 2022, implying a CAGR of 0.~~01~~7% in that time frame. Long-term, VEC summer peak demand is expected to decrease at a rate of about -0.2% annually on average, reaching 70.8 MW by 2037. The boundary cases show projected 20-year CAGRs ranging anywhere from -1.4% to 0.9%, with 2037 system peaks ranging from as low as 55 MW to as high as 88.2 MW.

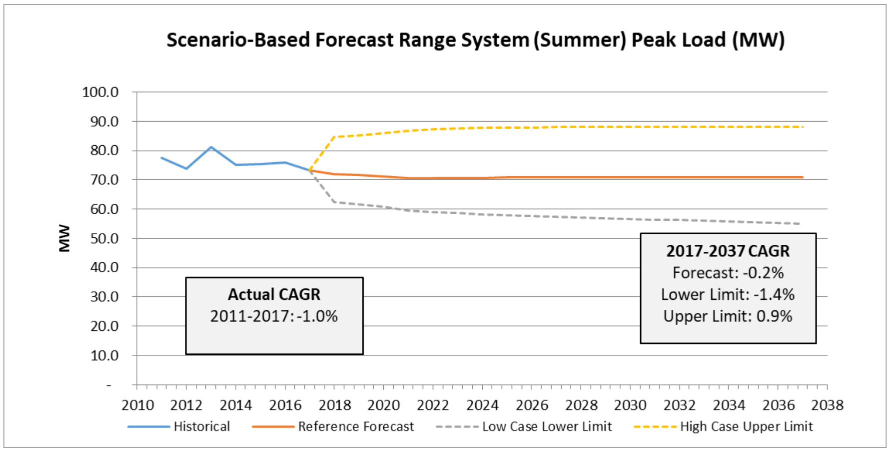

Figure 11~~13~~: Scenario-Based Forecast Range of Summer Peak Load (MW)

VII. USE OF FORECASTS IN BUDGETING AND OPERATIONS

In addition to using these forecasts for long term planning, they may also be used for shorter term budgeting and operations. The primary uses include the capability to forecast class sales for revenue projection purposes, and system energy requirements and system peak taking into account actual observed and forecast average temperatures. For example, the regression for system energy describes, among others, the relationship between heating and cooling degree-days and system energy by month. Should VEC need an estimate of system energy use part way through a quarter all that needs to be done is to integrate the actual degree day observations (i.e. replace the normal degree day values) and input the adjusted degree day forecast into the regression model using the equation coefficients presented in Appendix A. The result is an estimate of system energy for the quarter that takes into account potentially better estimates of actual weather.

There are some limits to bear in mind when using this method in budgeting and operations. First, estimates can only be generated based on the relationship between the degree-day data and loads over the period in which the regression was originally fitted. That data was aggregated and fit on a monthly basis for all equations.

Likewise, predicting actual peak cannot be done with precision using the monthly equation because the coefficients were estimated using *monthly* aggregated data, and we know that seasonal peak demands, which themselves are hourly values, are driven by *daily or hourly* temperatures. Actual peak demands can only be forecast with any precision if VEC accurately forecasts the relationship between cumulative hourly or daily temperatures over an extreme weather spell of perhaps only days, and heating and cooling degree-days aggregated over an entire month. Additionally, the coefficients were estimated based on the *historical relationships* between the dependent load variable and seasonal degree-days, so if the relationship changes, for instance due to a significant change in air conditioning stock or efficiency going forward, the forecast will likely be in error. Regardless, the regression equations do provide another useful tool in monitoring VEC sales and planning its operations.

VIII. EXPECTED ERROR AND ERROR SOURCES

There are four main sources of forecast error: errors in the historic data, poorly fit explanatory models, problems with the forecast of the independent variables for econometric models, and unforeseen events that render historically--fit equations invalid.

Of these four categories, the latter two are at best difficult to control, if not impossible. In this case, the potential error from problematic historic data has been isolated and corrected. VEC has previously made the necessary adjustments to the data to correct for the effects of the Citizens merger and divestiture of the southern portion of its territory. Further, a careful modeling process has produced explanatory forecast models that are statistically fit and sound.

For the econometric forecasts, the error in the forecast of the independent explanatory variables proved to be less of an issue. The forecasts of independent variables used in the VEC system level load forecast models are based on the ISO New England CELT forecasts, which employed empirically-derived econometric forecasts for New England economic and demographic variables at the state level. While these forecasts employed a robust methodology, the wide spreads between high and low cases illustrate how significantly changes to the economy can affect VEC's energy usage.

Unforeseen events are also a potential source of error in both the econometric and univariate forecasts. These events can be major technological changes, such as the development of extremely energy efficient consumer products, such as cold climate heat pump air conditioning. They can also include economic related events such as job cuts by a major employer in the region. In either case, the shock to loads may not have been incorporated in the forecast model, resulting in misforecasting of actual loads.

We have already combined two separate forecasting techniques to minimize specification error. Besides that, the best method for producing accurate forecasts in the presence of these other hard-to-control sources for error is to implement at least an annual review of the forecast and conduct an analysis of the errors.

By reviewing the forecast each year, or issuing new ones, corrections can be made for any unforeseen events and updated independent variable forecasts can be included. This is a particularly relevant point for this forecast exercise given the relatively small dataset available since VEC's southern territory divestiture. As more historic data is added to the dataset, the regression equations should improve. This kind of annual review is the most effective way to ensure accurate load forecasting.

APPENDIX A

Daymark Energy Advisors

Multivariate Model Details

IX. APPENDIX A – MULTIVARIATE MODEL DETAILS

Multivariate regression (or multiple regression) modeling is a key component of the energy and sales forecasts produced for this IRP. Multiple regression analysis is a widely accepted forecasting technique that establishes a relationship between a dependent variable (e.g., the total amount of residential electricity usage) and one or more independent variables. Independent variables employed in electricity usage forecasting often include macroeconomic and demographic variables such as personal income, employment, or population; microeconomic price-related variables such the cost per kWh of electricity consumption; and/or weather data (such as heating or cooling degree-days). ISO New England, for example, uses multivariate modeling in its load forecasting and has recognized real gross state product, New England real retail price of electricity and various weather metrics as key inputs to regional energy and peak forecast models.[11]

Multiple regression modeling was performed with Forecast Pro™ software using the dynamic regression functionality. Dynamic regression enhances conventional regression on independent variables by also supporting the use of lagged dependent and independent variables and Cochrane-Orcutt autoregressive error terms.

In order to perform multiple regression analysis, it is necessary to acquire historical time series data for dependent and independent variables, as well as forecasts of the independent variables. For this forecast, historical economic data was obtained from ISO New England's 2018-2027 Forecast Report of Capacity, Energy, Loads, and Transmission (2018 CELT).[12] Weather data was obtained from ISO New England monthly data[13] and the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NOAA).[14] Data was also obtained from VEC's RUS Form 7 on revenue per customer by customer class. The data that was tested is summarized in **Error! Reference source not found.**~~Table~~ 5 below.

In addition to this economic, weather and population data, a variety of "dummy variables" were also tested as potential independent variables in the model

[11] Forecast Modeling Procedures for 2018 CELT: ISO New England Long-Run Energy and Seasonal Peak Forecasts (May 2018). https://www.iso-ne.com/static-assets/documents/2018/04/modeling_procedure_2018fcst.pdf. p. 3.

[12] https://www.iso-ne.com/system-planning/system-plans-studies/celt/

[13] http://www.iso-ne.com/markets/hstdata/znl_info/monthly/index.html

[14] http://www.ncdc.noaa.gov/cdo-web/datasets/GHCNDMS/stations/GHCND:USW00014742/detail.

formulations. Dummy variables are a means to incorporate qualitative or categorical data into a regression model. A dummy variable is set to equal 1 when a condition is true, and 0 when not true. The dummy variables that were tested in this multiple regression analysis are summarized in Table 6 below.

Data Series	Name	Source	Granularity	Historic Data
VT Real Price of Electricity	RELPR	2018 CELT	Annual	1996-2017
VT Population	POP	2018 CELT	Annual	1996-2017
VT Real Total Personal Income	PI	2018 CELT	Annual	1996-2017
VT Real Total Gross State Product	RGSP	2018 CELT	Annual	1996-2017
VT Actual Net Energy for Load	NEL	2018 CELT	Annual	1996-2017
VT Passive Demand Resources	EE	2018 CELT	Annual	1996-2017
VT Price Responsive Demand Resources	PRD	2018 CELT	Annual	1996-2017
VT Behind-the-Meter Solar PV	SOLAR	2018 CELT	Annual	1996-2017
New England Consumer CPI	CPI	2018 CELT	Annual	1996-2017
VT Cooling Degree Days (base 65F)	CDD	ISO-NE SMD	Monthly	Mar03-Dec17
VT Heating Degree Days (base 65F)	HDD	ISO-NE SMD	Monthly	Mar03-Dec17
Cooling Degree Days (base 65F) at Burlington Airport	BurCDD	NOAA Climate Data	Monthly	Jan96-Dec15
Heating Degree Days (base 65F) at Burlington Airport	BurHDD	NOAA Climate Data	Monthly	Jan96-Dec15
Cooling Degree Days (base 65F) at Burlington Airport, squared	BurCDDsq	NOAA Climate Data	Monthly	Jan96-Dec15
Heating Degree Days (base 65F) at Burlington Airport, squared	BurHDDsq	NOAA Climate Data	Monthly	Jan96-Dec15
VT Real Price of Electricity from RUS7	RUSPRICE	RUS 7	Annual	2007-2017

Table 5: Summary of Historic Data Series Test in Multivariate Modelling

Name	Condition	Purpose
JAN	= 1, if month is January = 0, all other months	Test for consistent monthly variance not explained by other variables.
FEB, MAR, … , DEC	= 1, if month is [NAME] = 0, all other months	See JAN.
PostAPR10	= 1, After April 2010 = 0, April 2010 and prior	In April 2010, some small commercial customers were reclassified as residential customers. This variable may be used to control for the impact on these customer classes, particularly Small Commercial where the impact was proportionately greater.
Jpeak	=1 from January 2012 =0 December 2011 and otherwise	To account for introduction of large commercial customer, Jay Peak.

Table 6: Summary of Dummy Variables Tested in Multivariate Modeling

After fitting the regression models based on historic data, forecasts of the independent variables are needed to forecast the dependent variable. For each model, only a handful of potential independent variables tested were found to be significant enough to appear in the final regression equations. **Error! Reference source not found.**~~Table~~ 7 below summarizes the source or methodology of forecasting values through 2037 for those data series that appear in final multivariate regression models.

Data Series	Name	Forecast Source/Methodology
VT Real Total Personal Income	PI	2018 CELT forecast (2017-2028); continue at 2024-2028 average growth rate through 2037.
VT Real Price of Electricity	RELPR	2018 CELT forecast (2017-2028); continue at 2024-2028 average growth rate through 2037.
VT Population	POP	2018 CELT forecast (2017-2028); continue at 2024-2028 average growth rate through 2037
VT Real Price of Electricity from RUS7	RUSPRICE	2013-2017 value held constant for 2018-2037
VT Heating Degree Days (base 65F)	HDD	14-year monthly average held constant for 2018-2037
Heating Degree Days (base 65F) at Burlington Airport	BurHDD	12-year normal (average by month of 2004-2015)
Heating Degree Days (base 65F) at Burlington Airport, squared	BurHDDsq	12-year normal (average by month of 2004-2015)

Table 7: Forecast Source/Methodology for Variables Included in Multivariate Regression Models

Details of the regression equations and the regression statistics for all of the equations are found below.

D. Residential and Seasonal Sales

Number of Residential[15] Customers

The number of residential customers regression equation is specified as a monthly model with the following form:

[15] In this report, the term "residential customers" includes both the residential and seasonal customer class.

$$ResSeasCust = \propto_1 + \beta_1\, RELRP + \beta_2\, POP + \beta_3\, PI + \beta_4 HDD + \beta_5\, BurHDD_{-1} + \varepsilon$$

Where

RELRP = Real Price of Electricity

POP = Population

PI = Real Personal Income

HDD = Heating Degree-days

BurHDD = One month lagged Burlington Heating Degree-days

The following table provides within-sample statistics for the ResSeasCust model.

Statistic	Value	Statistic	Value
Sample Size	118	Number of Parameters	6
Mean	34,041	Standard Deviation	233
Adjusted R-square	0.91	Durbin-Watson	0.4
Ljung-Box(18)	347.0 P=1	Forecast Error	69.54
BIC	76.49	Mean Absolute Percent Error (MAPE)	0.16
MAD	53.03		

Table 8: Within-Sample Statistics for ResSeasCust model.

The adjusted R-square for this model is 0.91, indicating that 91% of the variation observed in the number of residential customers is explained by the model parameters. The model parameter coefficients are shown in the table below.

Term	Coefficient	Standard Error
RELPR	-247.3	34.55
POP	100.9	16.08
PI	0.2143	0.006636
HDD	0.156	0.02185
BurHDD[-1]	-0.1069	0.01295
_CONST	-32237	9753

Table 9: Parameter Details for ResSeasCust model

The figure below shows the forecast of residential customers produced by the model, as well as actual history, fitted historical values produced by the model, and lower (2.5%) and upper (97.5%) confidence limits. On an annual basis, the customer growth rate is forecasted as slightly lower than the historical CAGR.

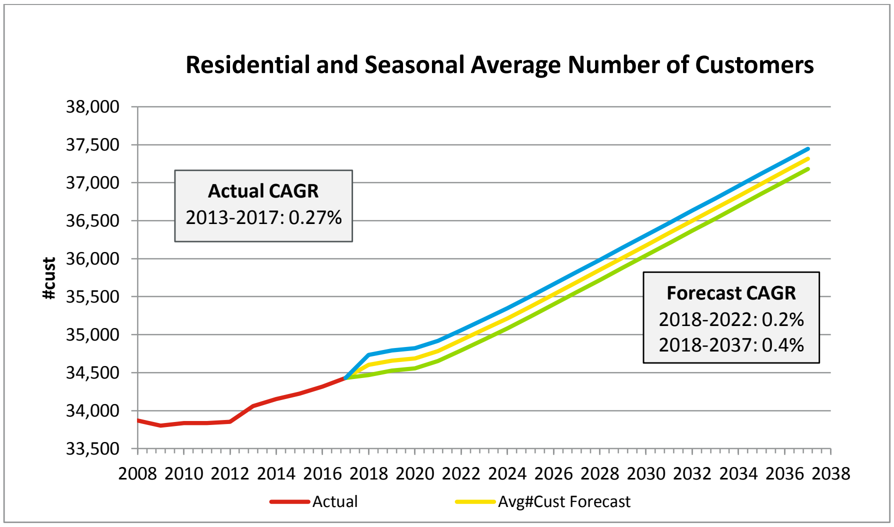

Figure 12~~10~~: Number of Residential and Seasonal Customers (annual average)

Residential Sales Per Customer

No statistically satisfactory model could be fit to the residential sales per customer data. Univariate forecast trends were assumed.

Residential Sales

Residential sales were forecast by multiplying the forecast number of customers and the forecast average sales per customer.

$$ResSeasKWH = ResSeasCust * ResKWHavg$$

As such, no model statistics can be provided for this forecast. It should be noted, however, that the confidence limits, as the product of two 2.5% lower or 97.5% upper limits, provide very conservative (i.e. <1% lower and >99% upper) confidence limits for the combined forecast.

E. Commercial & Other Sales

No statistically satisfactory model could be fit to the Commercial & Other sales data. Univariate forecast trends were assumed.

F. Industrial Sales

The regression equation for the total sales (MWh) for the industrial customer class is specified as a monthly model with the following form:

$$IndustrialCust = \propto_1 + \beta_1\, RUSPRICE + \beta_2\, BurHDD + \beta_3\, JAN + \beta_4 FEB + \beta_5\, DEC + \beta_6\, APR + \varepsilon$$

Where

RUSPRICE = Real price of electricity from RUS7

BurHDD = Burlington Heating degree-days

JAN = January dummy variable

FEB = February dummy variable

DEC = December dummy variable

APR = April dummy variable

The following table provides within-sample statistics for the IndustrialMWH model.

Statistic	Value	Statistic	Value
Sample Size	119	Number of Parameters	7
Mean	8,208	Standard Deviation	916
Adjusted R-square	0.71	Durbin-Watson	1.53
Ljung-Box(18)	63.4 P=1	Forecast Error	490.09
BIC	547.21	Mean Absolute Percent Error (MAPE)	4.53
MAD	376.65		

Table 10~~14~~: Within-Sample Statistics for IndustrialMWH model

The adjusted R-square for this model is 0.71, indicating that about 71% of the variation observed in the historical sales to small commercial customers is explained by variance in the independent variables. The Mean Absolute Percent Error (MAPE) is a little over 4.5%, which is within reasonable tolerance at the class forecast level. The Durbin-Watson statistic is 1.53 indicating a relative lack of autocorrelation in the residual error terms that might be a sign of a biased model. The model parameter coefficients are shown in **Error! Reference source not found.**~~Table 1~~5 below.

Term	Coefficient	Standard Error
RUSPRICE	-15201	4257
JAN	1091	232.8
FEB	1734	208.2
DEC	1075	200.5
BurHDD	0.4619	0.1457
APR	538.9	167.7
_CONST	10131	719.9

Table 11~~15~~: Parameter Details for IndustrialMWH model

The figure below shows the forecast of Industrial sales produced by the model, as well as actual history, fitted historical values produced by the model, and lower (2.5%) and upper (97.5%) confidence limits.

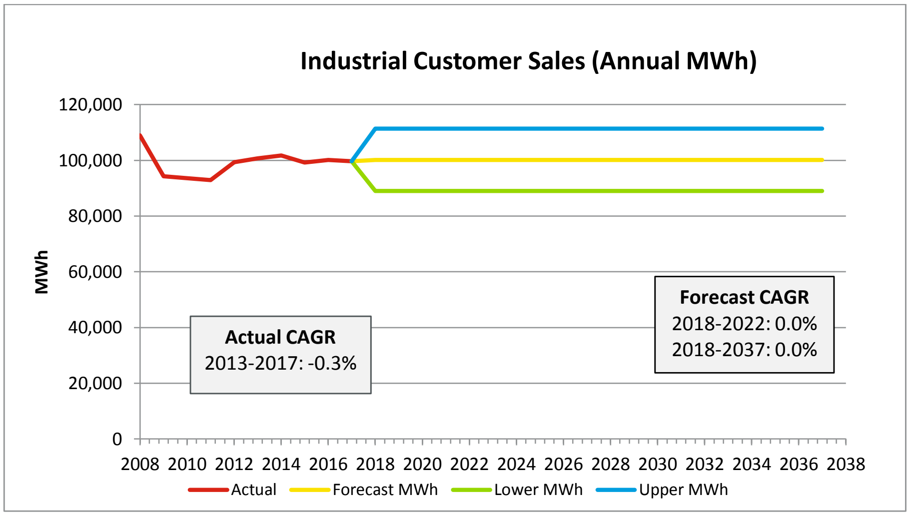

Figure 13: Multivariate Forecast of Industrial Total Class Sales (annual)

G. Total Class Sales

TOTAL CLASS SALES

The energy sales equation is specified as a monthly model with the following form:

$$EnergySales = \propto_1 + \ \beta_1 \ BurHDD^2_{[-1]} + \ \beta_2 \ RUSPRICE + \ \beta_3 \ AUTO_{[-12]} + \ \varepsilon$$

Where

$BurHDD^2_{[-1]}$ = 1 period lagged heating degree-days, squared

RUSPRICE = Real price of electricity from RUS&

AUTO$_{[-12]}$ = 12 month lagged Cochrane-Orcutt autoregressive error term

The following table provides within-sample statistics for the Total Class Sales model.

Statistic	Value	Statistic	Value
Sample Size	106	Number of Parameters	4
Mean	36,423	Standard Deviation	2851.32
Adjusted R-square	0.87	Durbin-Watson	1.46
Ljung-Box(18)	30.5 P=0.97	Forecast Error	1041.38
BIC	1115.5	Mean Absolute Percent Error (MAPE)	2.27
MAD	827.98		

Table 12~~16~~: Within-Sample Statistics for Total Class Sales model

The adjusted R-square for this model is 0.87, indicating that about 87% of the variation observed in the historical class sales is explained by variance in the independent variables. The Mean Absolute Percent Error (MAPE) is approximately 2.27%, which is acceptable for class sales as a whole. The Durbin-Watson statistic is 1.46 indicating a relative lack of autocorrelation in the residual error terms that might be a sign of a biased model. The model parameter coefficients are shown in **Error! Reference source not found.**~~Table 1~~7 below.

Term	Coefficient	Standard Error
RUSPRICE	-66872	18244
BurHDDsq[-1]	2.377	0.3872
_CONST	45435	2878
_AUTO[-12]	0.8639	0.05311

Table 13~~17~~: Parameter Details for Total Class Sales model

The figures below show the forecast of class sales produced by the model, as well as actual history, fitted historical values produced by the model, and lower (2.5%) and upper (97.5%) confidence limits.

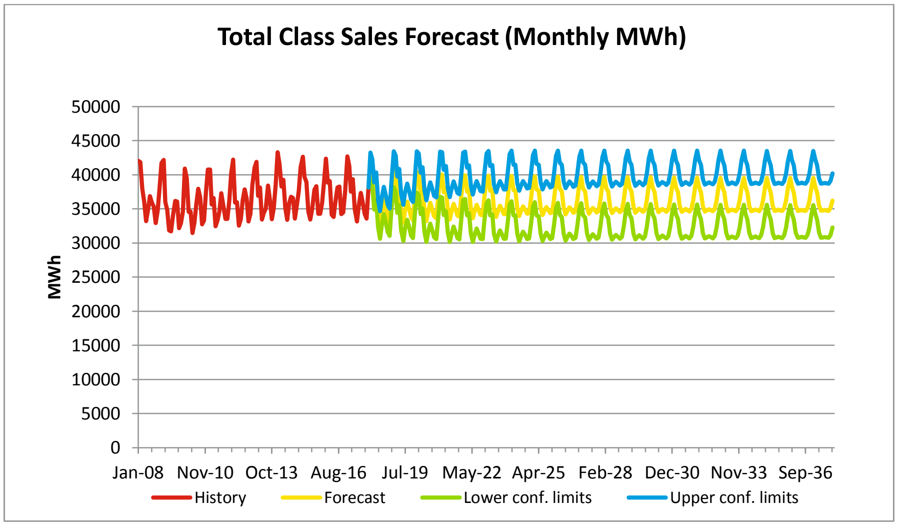

Figure 14: Multivariate Forecast of Total Class Sales (monthly)

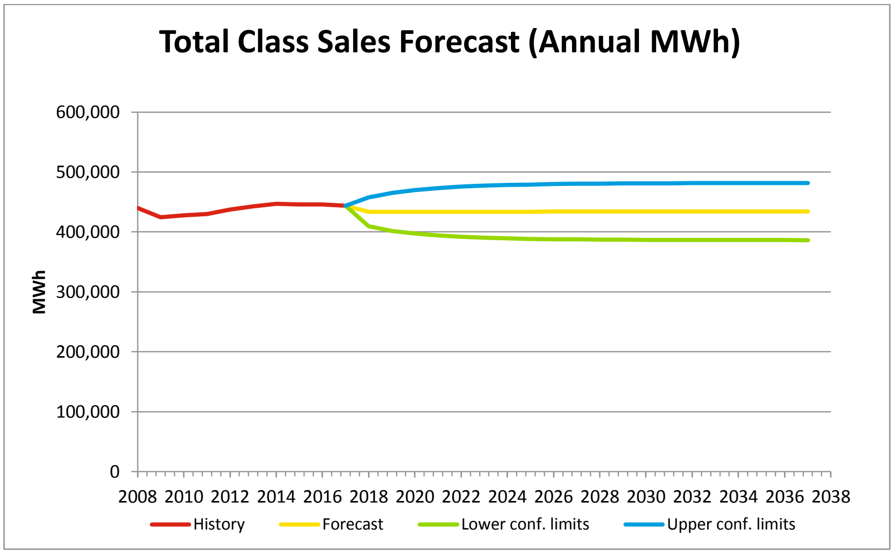

Figure 15: Multivariate Forecast of Total Class Sales (annual)

H. Price-Elasticity for Total Class Sales

To calculate the price-elasticity associated with the real price of electricity (RUSPRICE), the energy sales equation was specified with the following form:

$$ln\ EnergySales = \propto_1 + \ \beta_1\ BurHDD^2_{[-1]} + \ \beta_2\ ln\ RUSPRICE + \ \beta_3\ AUTO_{[-12]} + \ \varepsilon$$

Where

ln Energy Sales = Natural log of total class energy sales

$BurHDD^2_{[-1]}$ = 1 period lagged heating degree-days, squared

ln RUSPRICE = Natural log of real price of electricity from RUS&

$AUTO_{[-12]}$ = 12 month lagged Cochrane-Orcutt autoregressive error term

The following table provides within-sample statistics for the model.

Statistic	Value	Statistic	Value
Sample Size	106	Number of Parameters	4
Mean	10.5	Standard Deviation	0.08
Adjusted R-square	0.86	Durbin-Watson	1.42
Ljung-Box(18)	35.7 P=0.99	Forecast Error	0.03
BIC	0.03	Mean Absolute Percent Error (MAPE)	0..22
MAD	0.02		

Table 18: Within-Sample Statistics for Price-Elasticity model

The adjusted R-square for this model is 0.86, indicating that about 86% of the variation observed in the historical class sales is explained by variance in the independent variables. The Mean Absolute Percent Error (MAPE) is approximately 0.22%. The Durbin-Watson statistic is 1.42 indicating a relative lack of autocorrelation in the residual error terms that might be a sign of a biased model. The model parameter coefficients are shown in **Error! Reference source not found.**~~Table 1~~9 below.

Term	Coefficient	Standard Error
ln RUSPRICE	-0.2891	0.08341
BurHDDsq[-1]	0.00006151	0.00001074
_CONST	9.925	0.1595
_AUTO[-12]	0.8616	0.05335

Table 19: Parameter Details for Price-Elasticity model

The coefficient for ln RUSPRICE represents the price-elasticity for customers in relation to consumption. The price elasticity value was approximately -0.29. Therefore, for every 10% increase in real electricity price, there is a long-term decrease in consumption of 2.9%, ceteris paribus.