APPENDIX A

Vermont Electric Cooperative, Inc.
2015 Load Forecast

La Capra Associates

APPENDIX A

Vermont Electric Cooperative 2015 Load Forecast

PREPARED BY

La Capra Associates, Inc.
One Washington Mall – Floor 9
Boston, MA 02108

Stan Faryniarz
Principal Consultant

Dan Koehler
Consultant

Laura Kier
Analyst

TECHNICAL REPORT

TABLE OF CONTENTS

Load Forecast Technical Report Executive Summary

Vermont Electric Cooperative, Inc. (VEC) is a member-owned rural electric cooperative established in 1938. Its approximately 38,000 members are spread over 74 towns and 8 counties in northern Vermont. The customer breakdown is as follows:

Customer Class	AVG 2014 Members	% of Total Customers	Total Sales	% of Total Sales
Residential and Seasonal	34,123	88.9%	222,328,586	49.8%
Small Commercial and Public Authority	4,181	10.9%	121,677,558	27.2%
Large Commercial	13	0.03%	101,698,144	22.8%
Lighting	64	0.17%	1,127,158	0.3%
Total	38,380	100%	446,831,446	100.0%

Table 1: VEC Customer and Sales (kWh) Distribution

In early 2015, La Capra Associates (La Capra) 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 La Capra Associates 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 northern Vermont, 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.

The results are discussed and presented graphically below.

VEC SYSTEM SALES

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), macroeconomic (price of electricity, Vermont real disposable income) and a series of dummy variables representing certain months of the year. The econometric specification produced an excellent fitting model using historical data, with an adjusted R^2 of 0.92, meaning that variance in the independent variables explained roughly 92% 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, real disposable income for Vermont 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 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 customer sales are expected to grow from about 447,000 MWh in 2014, to almost 460,000 MWh by 2019, implying a compound annual growth rate (CAGR) of 0.7% in that time frame. The CAGR from 2010 to 2014 was 1.1%, but that includes a substantial boost from a new development at Jay Peak beginning in 2012.

Long-term, VEC is projected to have total sales of 510,000 MWh by 2034, implying a 20-year CAGR of 0.7% in the reference case. This long-term CAGR could vary from as low as -0.7% in the low case lower limit, to 1.5% in the high case upper limit.

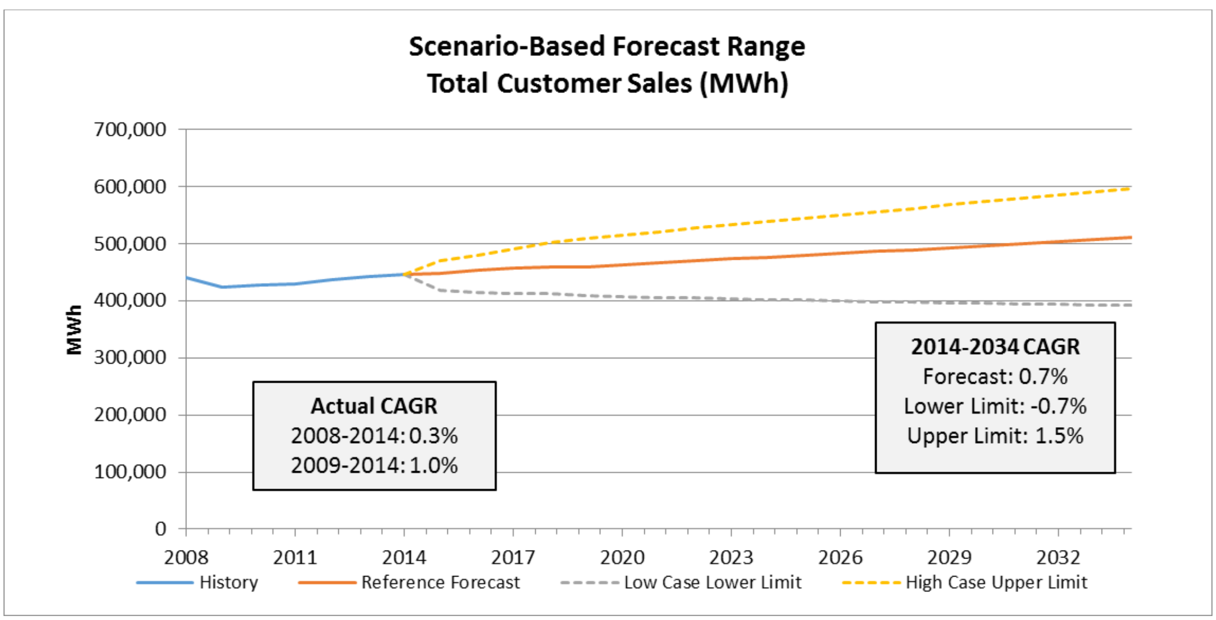


Figure 1: Scenario-based Forecast Range for Total Customer Sales (MWh)

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 customer sales. Between 2011 and 2014, system load averaged 8.3% greater than total sales, falling within a tight range of 7.8% to 9% on an annual basis. We applied this average factor to our forecast of total customer sales to develop a forecast of gross system load.

The results are presented below. System energy requirements are expected to grow from about 484,000 MWh in 2014, to almost 498,000 MWh by 2019 and 553,000 MWh by 2034. The CAGRs are the same as total customer sales CAGRs because the forecast is adjusted by a constant bulk-up factor.

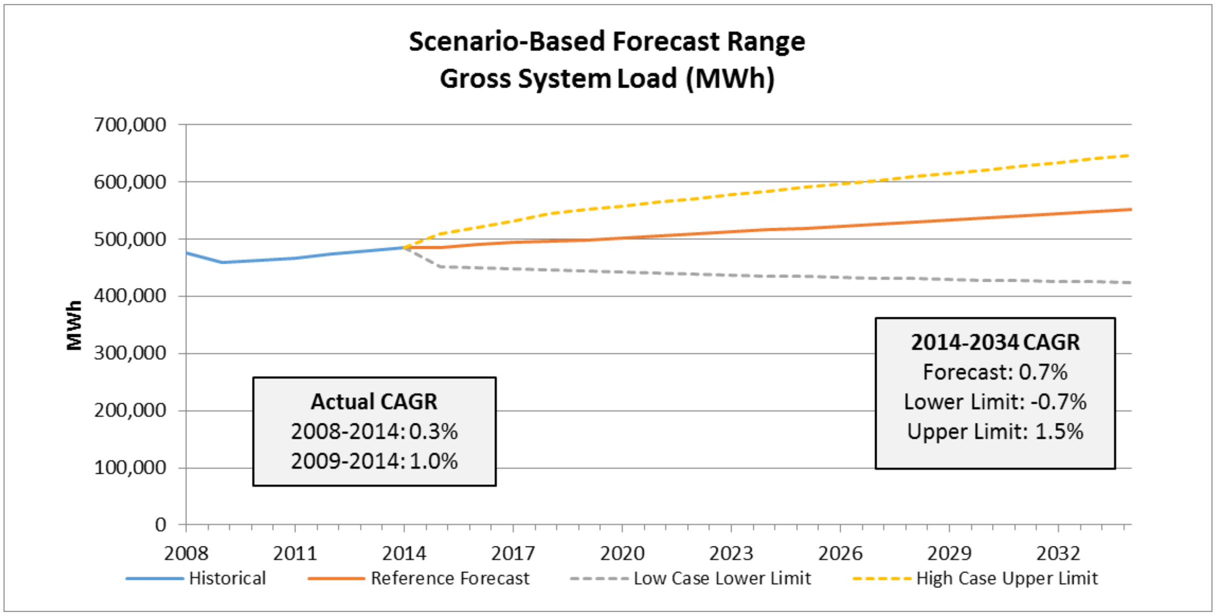


Figure 2: Scenario-Based Forecast Range for Gross System Load (MWh)

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 was a Box-Jenkins model, with an adjusted R^2 of 0.86; the statistical model explained roughly 86% of the variance in actual monthly load factor. The 2015 forecast of monthly load factors for the forecast and 95% confidence intervals were held constant throughout the study period.

[1] Distributed generators that reduce metered load.

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%.

The results are presented below. VEC System Peak Demand is expected to continue to occur in the wintertime, maintaining its historical winter-peaking pattern, though summertime peak loads could approach the winter peaks as they have a couple of times in the past several years.

System peak demand is expected to grow from about 85.6 MW in 2014, to about 88.1 MW by 2019, implying a CAGR of 0.6% in that time frame. Long-term, VEC is projected to see peak demand continue to grow at the same pace, reaching 96 MW by 2034. The boundary cases show projected 20-year CAGRs ranging anywhere from -1.1% to 1.8%, with 2034 system peaks ranging from potentially as low as 69 MW to potentially as high as 122 MW.

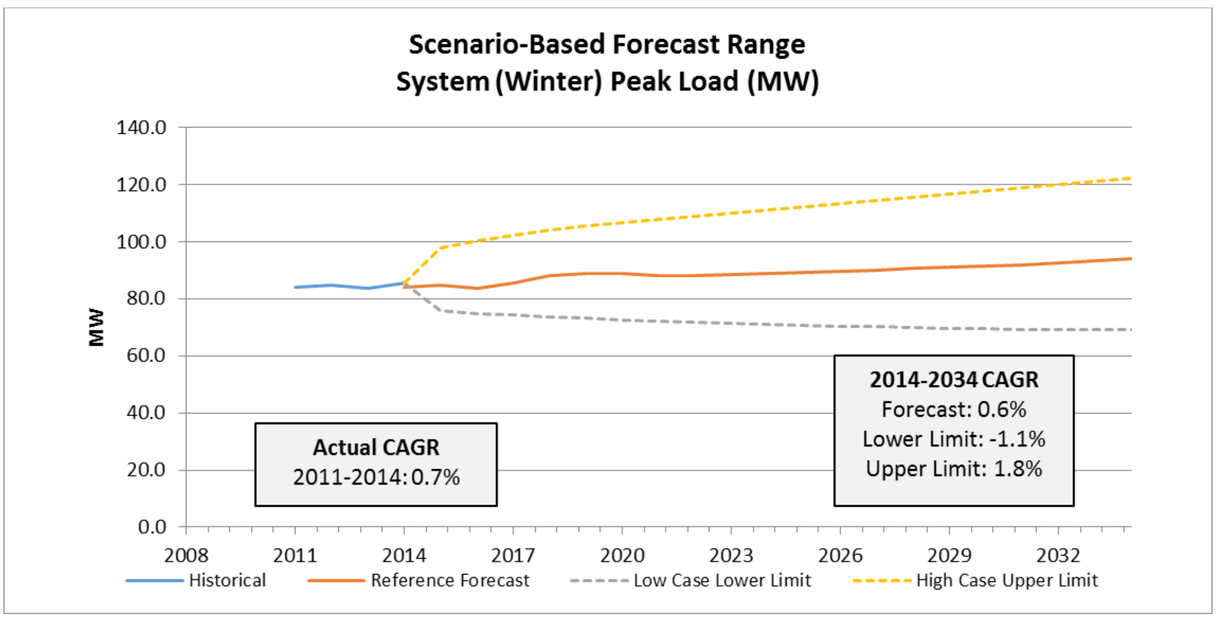


Figure 3: Scenario-Based Forecast Range for System (Winter) Peak Load (MW)

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 grow from about 75.2 MW in 2014, to about 86.7 MW by 2019, implying a CAGR of 2.9% in that time frame. Long-term, VEC summer peak demand is expected to grow more steadily, at a rate of about 1.2% annually on average, reaching 95 MW by 2034. The boundary cases show projected 20-year CAGRs ranging anywhere from -0.6% to 2.4%, with 2034 system peaks ranging from as low as 66 MW to as high as 121 MW. Notably, were the summer peak to grow faster than the winter peak, VEC could become a summer peaking system within the 20-year forecast horizon.

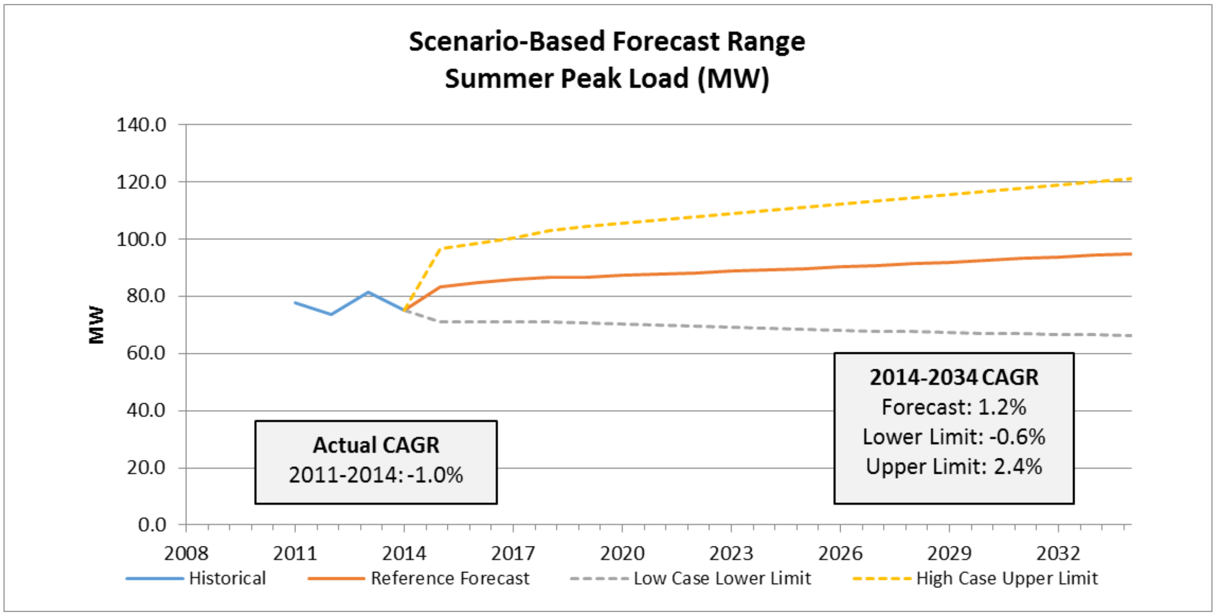


Figure 4: Scenario-Based Forecast Range of Summer Peak Load (MW)

Introduction and Objectives

La Capra Associates 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 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.

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 2015 IRP.

The same techniques were also employed to forecast consumption for the main customer classes (residential & seasonal, small commercial & public, and large commercial). The class level load forecasts were independent models developed for VEC internal revenue forecasting and other purposes, and were not utilized directly in the 2015 IRP.
Below, we discuss the results of each modeling exercise.

Data Sources

A 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 2014 Forecast Report of Capacity, Energy, Loads, and Transmission (2014 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] Daylight hours data was obtained from the United States Naval Observatory.[7] Data was also obtained from VEC's RUS Form 7 on revenue per customer by customer class to forecast electricity price.

The economic forecast data from CELT, which only covers the period from 2014-2025, was extended through 2034 at the last five years (2021-2025) average growth rate. A 10 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 assumed to be held constant in real terms as the average of the last five years of actual data (2009-2013) 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.

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***™.

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.
7 http://aa.usno.navy.mil/data/docs/RS_OneDay.php

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 2015–2017.

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

	Class	Year		
		2015	2016	2017
Class Consumption (MWh)	LG. COM.	100,055	99,480	99,397
	OTHER	15,994	15,994	15,994
	PUBLIC	1,124	1,124	1,124
	RESIDENTIAL	222,719	223,049	223,389
	SM. COM.	107,165	107,165	107,165
Total Customer Sales* (MWh)		446,832	446,832	446,832

** Total customer sales forecast separately, so it does not exactly equal the sum of individual class forecasts. The difference is <0.1% in all three years.*

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 using 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.

Overall, the fit of these equations was very good, with R-squared statistics in the high 80 to high 90 percent range.

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.*

Table 3: Multivariate Forecast Results- Base Case Annual Projections

	2015	2016	2017
MWh Sales Forecasts			
LG Com	106,483	109,262	110,679
Residential	219,089	220,456	217,909
Small Commercial	103,732	103,654	103,576
Total System	451,203	459,452	459,456
Customer Number Forecasts			
Residential	34,110	34,158	34,155

Forecast Blending Procedure

In previous sections, La Capra Associates 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 2015 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 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, however, 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., the pace of Vermont's economic recovery 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 or end-use stock or efficiency changes), 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 2015–2017, the univariate and multivariate forecasts are combined using a simple weighted average of the forecasts associated with each model. In the years beyond 2017, 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.

Table 4: Forecast weighting for standard blending methodology

Forecast Year	Univariate Forecast Weighting	Multivariate Forecast Weighting
2015	75%	25%
2016	50%	50%
2017	25%	75%
2018 and beyond	0%	100%

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 real disposable income and 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 real disposable income and Burlington HDDs and a high forecast for the real price of electricity. These forecasts were taken from ISO New England's 2014 CELT report, NOAA weather data, and scenario-based adjustments to VEC real retail rates just below and just above 2010-2013 average prices. After the high and low econometric forecasts were constructed, they were blended into the time series forecasts for the period of 2015-2017 in the manner described above.

Final Blended Class Sales Forecasts

RESIDENTIAL AND SEASONAL

The residential class (including seasonal customers) represented about 50% of VEC's total sales in 2014, and about 89% 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 real disposable income in Vermont as well as "dummy variables" to adjust for historical discontinuities in VEC's membership (e.g. the April 2004 acquisition of Citizens Communication Company's Vermont Electric division.) The independent variables in the residential *average energy use per customer equation* included heating degree-days for Burlington airport, heating degree-days squared, the real price of electricity, the Vermont unemployment rate, and real disposable income. Details of econometric model specifications, 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 222,000 MWh in 2014 to over 240,000 MWh in 2034, which translates to a 0.4% CAGR. This compares to the historical CAGR for the past five years of 0.2%. The high case boundary for residential consumption is projected to grow to over 266,000 MWh by 2034, at a CAGR of 0.9%. The low boundary case is projected to decline to below 216,000 MWh by 2034, at a CAGR of -0.2%.

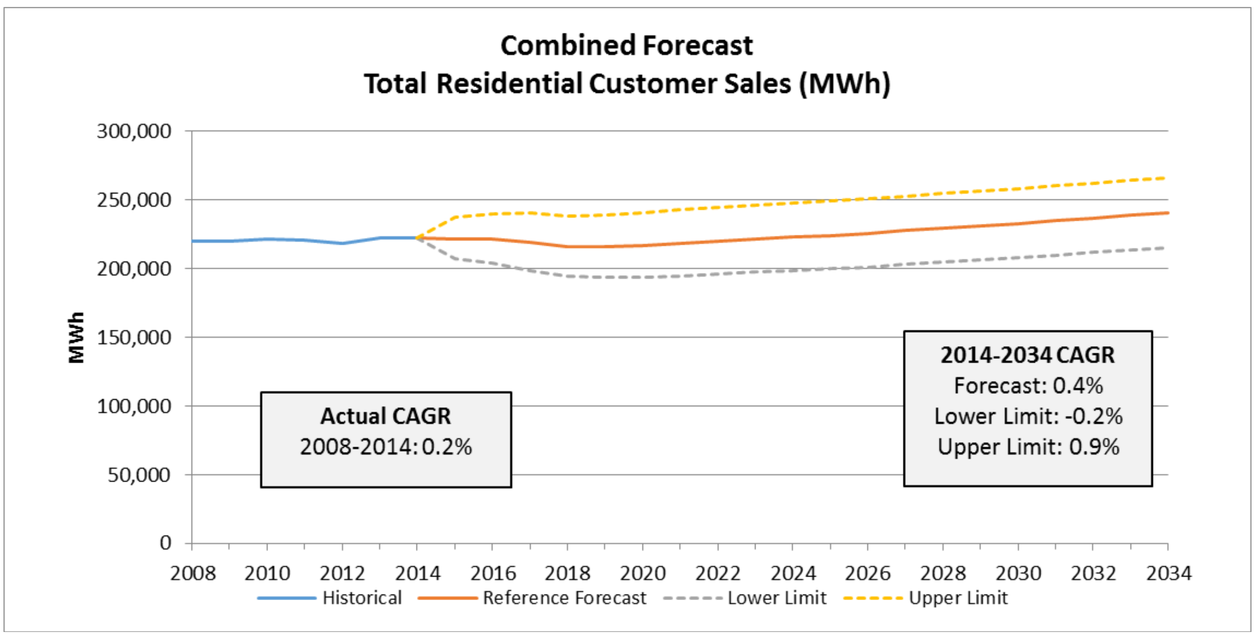


Figure 5: Combined Forecast – Total Residential Customer Sales (MWh)

SMALL COMMERCIAL

The small commercial class represented some 24% of VEC's total sales in 2014, and 10% of its members.

Small commercial sales were forecast directly, without separately forecasting number of customers and average energy use per customer. The independent variables in the multivariate equation were heating degree-days, cooling degree-days, Vermont population and a series of dummy variables representing the month of the year. These equations were fit and highs and lows were developed in the same manner as for the residential class.

The small commercial sales reference forecast was blended in the standard manner using the weightings shown in Table 4 above. The small commercial class is projected to fall slightly from almost 106,000 MWh in 2014 to 104,000 MWh in 2034, which translates to a -0.1% CAGR. This compares to the historical CAGR growth rate for the past six years of 0.5%.

The blending for the high and low boundary cases was done differently than for other forecasts due to the wide disparity between univariate and multivariate confidence intervals. For these cases, 100% weighting was placed on the univariate forecast (which had a wider confidence interval than the multivariate forecast) for the year 2015 – 2017. After 2017 the high and low boundary forecasts were assumed to grow at the rate of the multivariate high and low forecasts, respectively. The high case boundary for small commercial sales is projected to grow to over 155,000 MWh by 2034, at a CAGR of 1.9%. The low case boundary for small commercial sales is projected to fall below 60,000 MWh by 2034, at a CAGR of negative 2.8%.

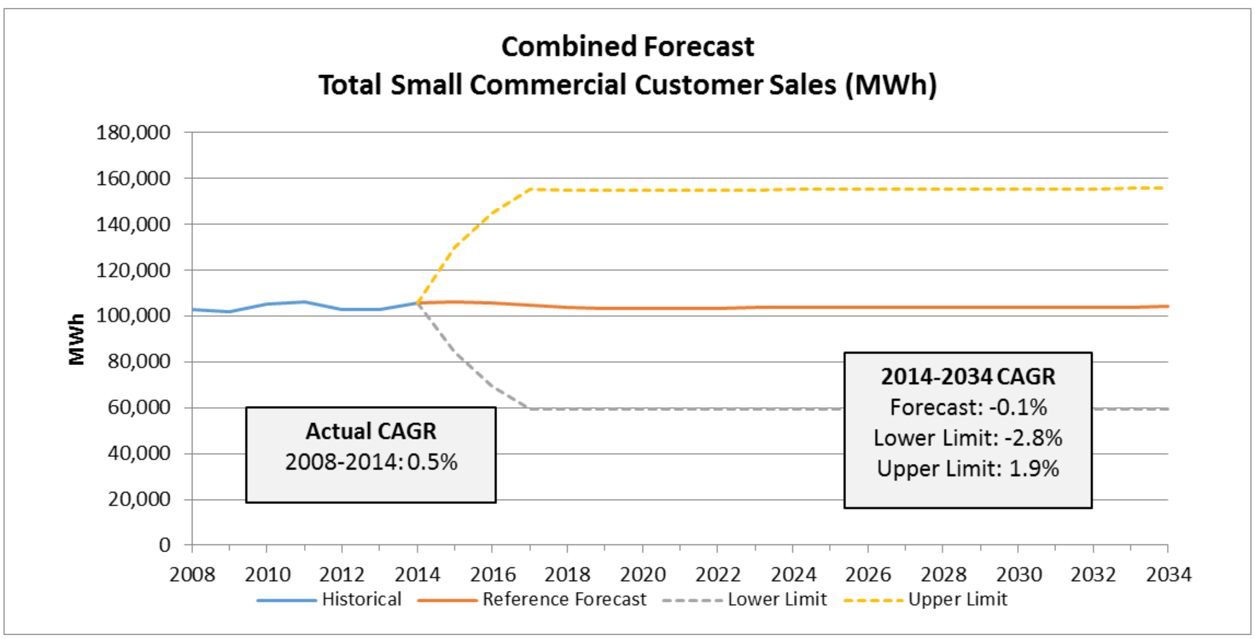


Figure 6: Combined Forecast – Small Commercial Customer Sales (MWh)

LARGE COMMERCIAL

The 13 customers in the large commercial class represented nearly 23% of VEC's total sales in 2014. Long-term forecasts of sales to the large commercial class are likely the most uncertain, because the actions, growth prospects, or departure of any of these largest customers will noticeably affect actual sales. Large commercial sales were forecast directly, without separately forecasting number of customers and average energy use per customer.

The independent variables in the total class energy equation were heating degree-days, cooling degree-days, employment, real price of electricity, and a series of dummy variables representing the month of the year and specific periods with step changes due to customer reclassification or the significant Jay Peak load addition.

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 2015. We assumed that the forecasts would increase linearly from 2016 to 2034 to reach the 2034 multivariate forecast value.

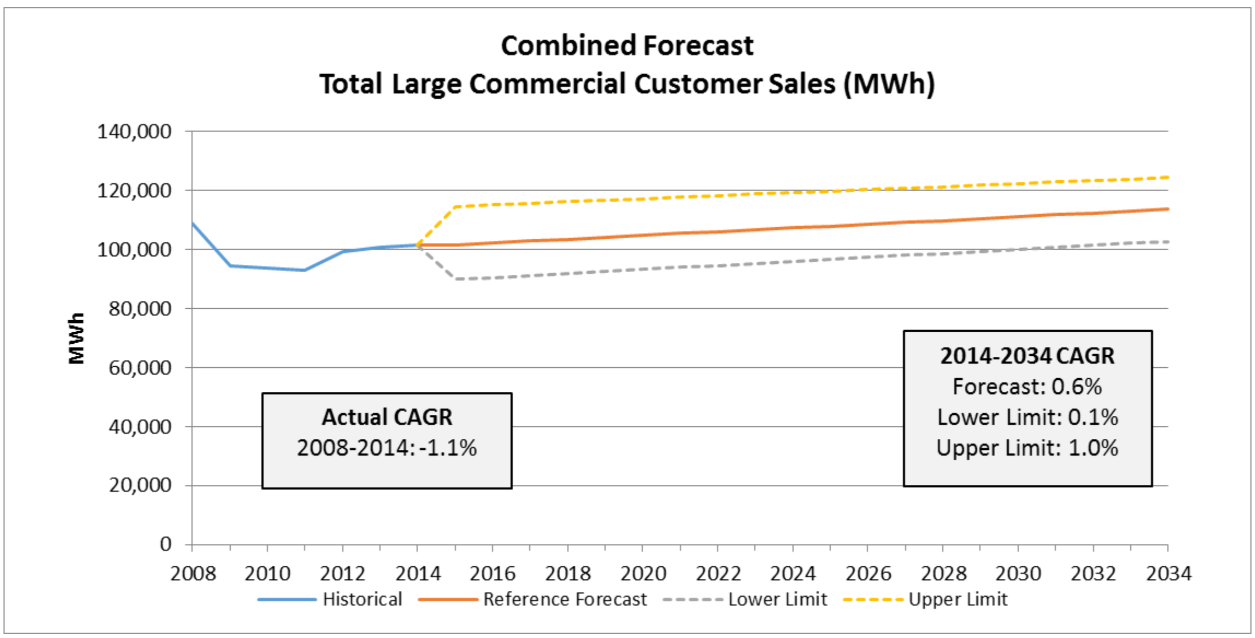


Figure 7: Combined Forecast – Large Commercial Customer Class Sales (MWh)

STREET AND HIGHWAY LIGHTING

The lighting class represented only about 0.3% of VEC's total sales in 2014.

No statistically satisfactory multivariate model could be fit to public street and lighting data. The univariate forecast was extended by assuming consistent year-over-year growth beyond the last year of the univariate forecast period. The final public lighting class sales forecast reflects the extended univariate forecast exclusively.

The public lighting class is projected to remain constant at just over 1,100 MWh in our reference case forecast. Sales have been at about this level since 2008. The lower limit case shows class sales falling just below 1,000 MWh by 2034 at a CAGR of negative 0.8%. The upper limit case shows class sales increasing at a CAGR of 0.7% to almost 1,300 MWh by 2034.

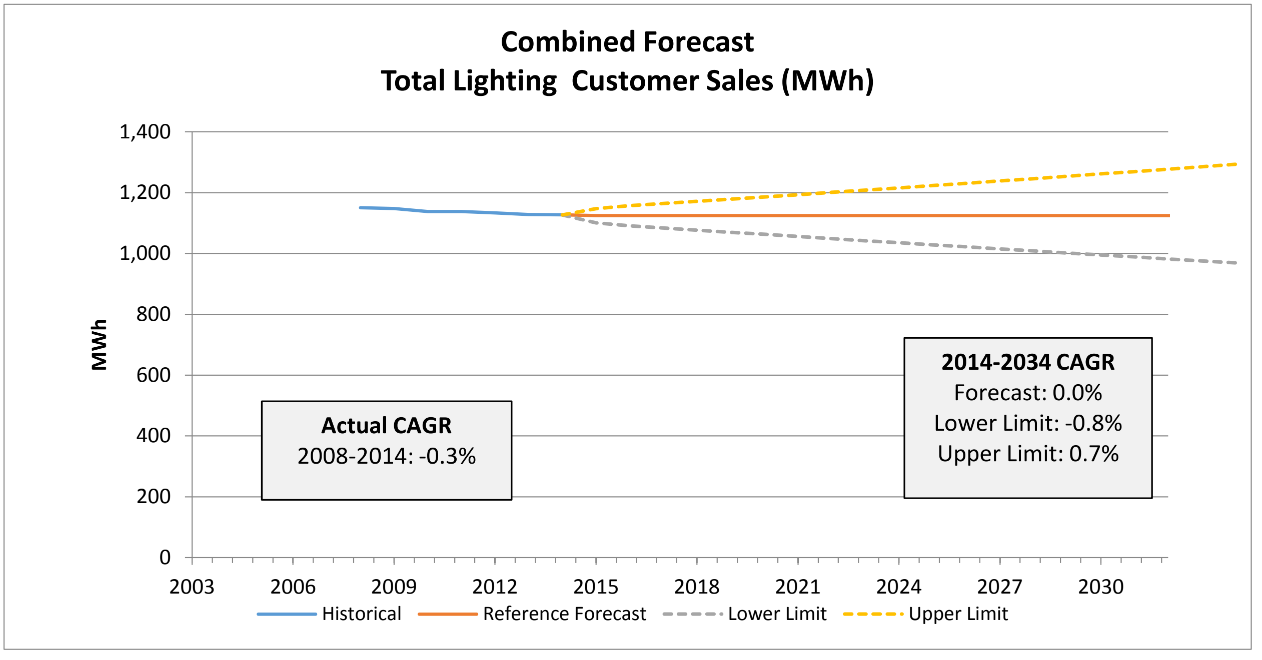


Figure 8: Combined Forecast – Lighting Customer Sales (MWh)

OTHER SALES TO PUBLIC AUTHORITIES

Other sales to public authorities represented 1.2% of VEC's customer base and 4% of total sales in 2014.

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 public authorities class sales forecast reflects the extended univariate forecast exclusively.

The public authorities class is projected to remain constant at about 16,000 MWh in our reference case forecast. The lower limit case shows class sales falling almost to zero by 2034 (representing a true low bound) at a CAGR of negative 19.4%. The upper limit case shows class sales increasing at a CAGR of 9.1% to almost 91,000 MWh by 2034.

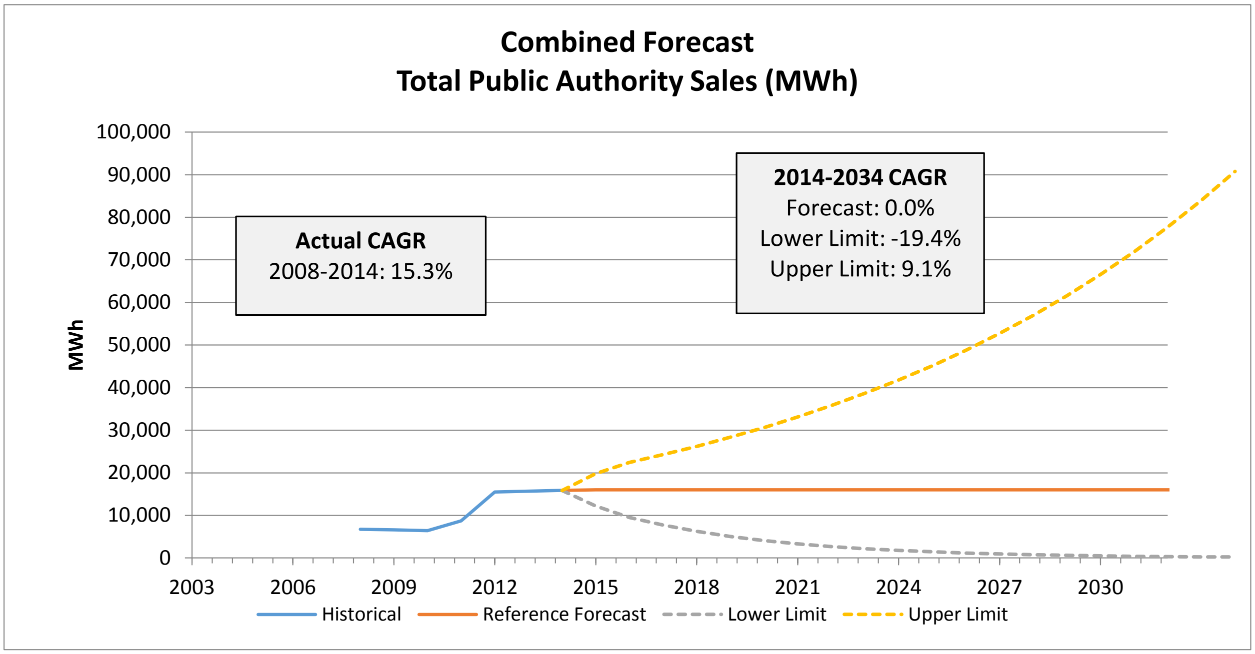


Figure 9: Combined Forecast – Other Customer Class Sales (MWh)

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 sales 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. 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 SALES

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), microeconomic (real price of electricity), macroeconomic (Vermont real disposable income) and a series of dummy variables representing certain months of the year. The econometric specification produced an excellent fitting model using historical data, with an adjusted R^2 of 0.92, meaning that variance in the independent variables explained roughly 92% 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, real disposable income for Vermont and the real average price of electricity. High and low boundaries were based on the model parameters derived for the 95% 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 customer sales are expected to grow from about 447,000 MWh in 2014, to almost 460,000 MWh by 2019, implying a compound annual growth rate (CAGR) of 0.7% in that time frame. The CAGR from 2010 to 2014 was 1.1%, but that includes a substantial boost from a new development at Jay Peak beginning in 2012.

Long-term, VEC is projected to have total sales of 510,000 MWh by 2034, implying a 20-year CAGR of 0.7% in the reference case. This long-term CAGR could vary from as low as -0.7% in the low case lower limit, to 1.5% in the high case upper limit.

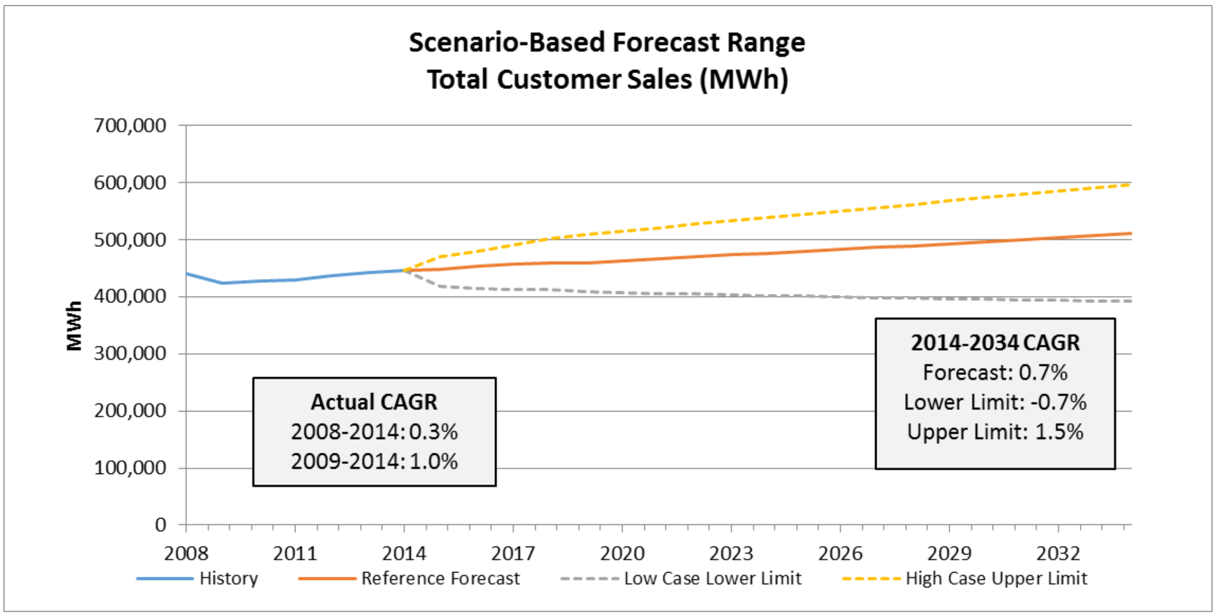


Figure 10: Scenario-based Forecast Range for Total Customer Sales (MWh)

VEC GROSS SYSTEM LOAD

In order to “bulk up” total system sales to gross system load, we compared historical gross system load (with SPEED distributed energy resources included) to total customer sales. Between 2011 and 2014, system load averaged 8.3% greater than total sales, falling within a tight range of 7.8% to 9% on an annual basis. We applied this average factor to our forecast of total customer sales to develop a forecast of gross system load.

The results are presented below. System energy requirements are expected to grow from about 484,000 MWh in 2014, to almost 498,000 MWh by 2019 and 553,000 MWh by 2034. The CAGRs are the same as total customer sales CAGRs because the forecast is adjusted by a constant bulk-up factor.

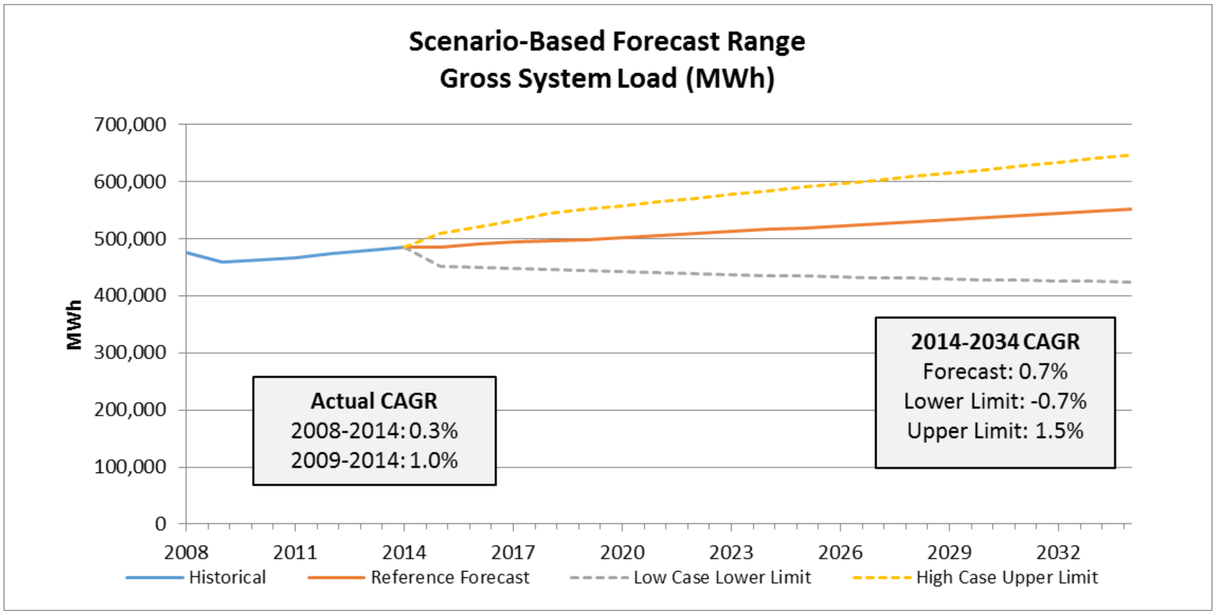


Figure 11: Scenario-Based Forecast Range for Gross System Load (MWh)

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 was a Box-Jenkins model, with an adjusted R^2 of 0.86; the statistical model explained roughly 86% of the variance in actual monthly load factor. The 2015 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%.

The results are presented below. VEC System Peak Demand is expected to continue to occur in the wintertime, maintaining its historical winter-peaking pattern, though summertime peak loads could approach the winter peaks as they have a couple of times in the past several years.

System peak demand is expected to grow from about 85.6 MW in 2014, to about 88.1 MW by 2019, implying a CAGR of 0.6% in that time frame. Long-term, VEC is projected to see peak demand continue to grow at the same pace, reaching 96 MW by 2034. The boundary cases show projected 20-year CAGRs ranging anywhere from -1.1% to 1.8%, with 2034 system peaks ranging from potentially as low as 69 MW to potentially as high as 122 MW.

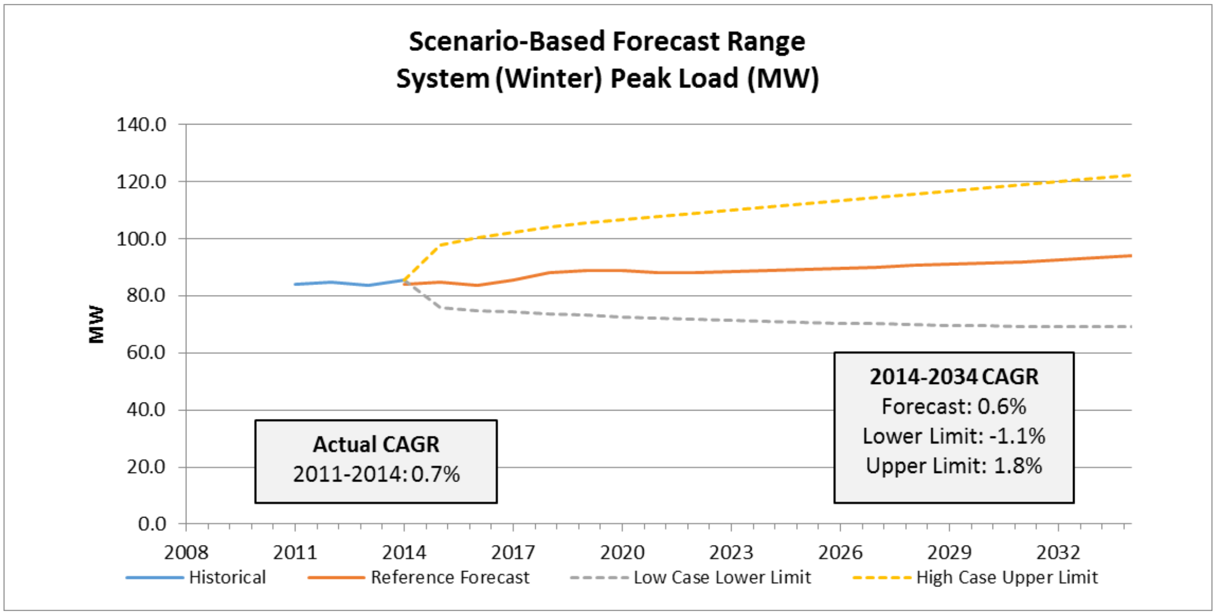


Figure 12: Scenario-Based Forecast Range for System (Winter) Peak Load (MW)

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 grow from about 75.2 MW in 2014, to about 86.7 MW by 2019, implying a CAGR of 2.9% in that time frame. Long-term, VEC summer peak demand is expected to grow more steadily, at a rate of about 1.2% annually on average, reaching 95 MW by 2034. The boundary cases show projected 20-year CAGRs ranging anywhere from -0.6% to 2.4%, with 2034 system peaks ranging from as low as 66 MW to as high as 121 MW. Notably, were the summer peak to grow faster than the winter peak, VEC could become a summer peaking system within the 20-year forecast horizon.

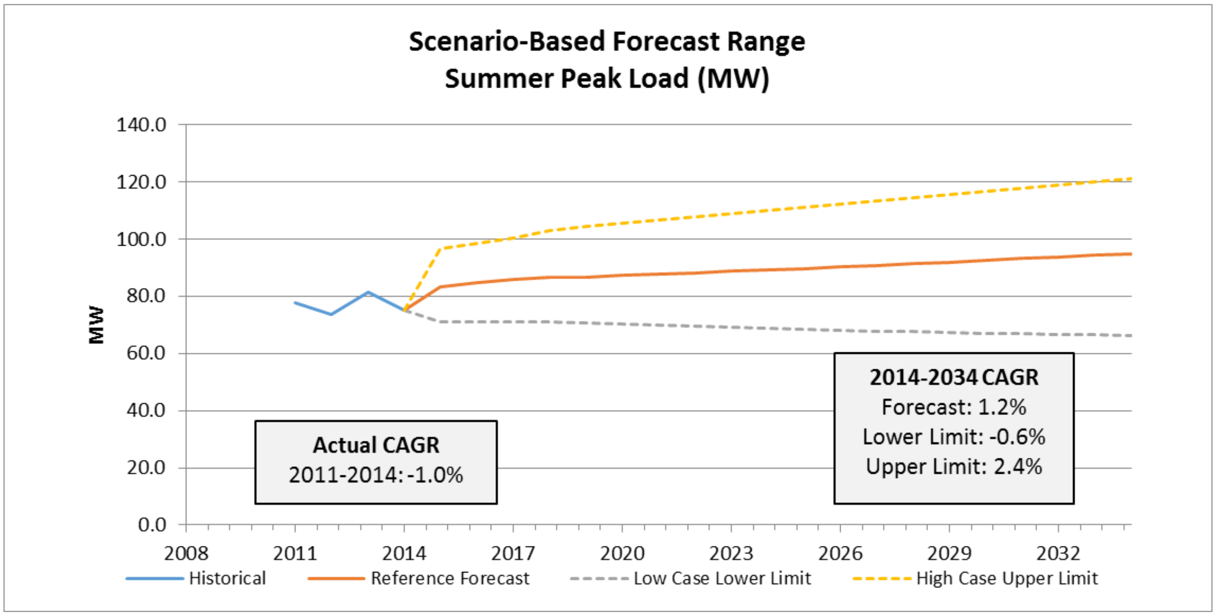


Figure 13: Scenario-Based Forecast Range of Summer Peak Load (MW)

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.

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. 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. 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

La Capra Associates

MULTIVARIATE MODEL DETAILS

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.[8]

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 204-2023 Forecast Report of Capacity, Energy, Loads, and Transmission (2014 CELT).[9] Weather data was obtained from ISO New England monthly data[10] and the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NOAA).[11] Daylight hours data was obtained from the United States Naval Observatory.[12] 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 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 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.

ISO New England. (May 2013). Model Structures: 2013 Forecasts. http://www.iso-ne.com/trans/celt/fsct_detail/2013/forecast_model_structures_2013.pdf. p 4.

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

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

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

12 http://aa.usno.navy.mil/data/docs/RS_OneDay.php

Data Series	Name	Source	Granularity	Historic Data
VT Real Price of Electricity	RELPR	2014 CELT	Annual	1996-2013
VT Total Non-Agricultural Employment	EMP	2014 CELT	Annual	1996-2013
VT Population	POP	2014 CELT	Annual	1996-2013
VT Unemployment Rate	UER	2014 CELT	Annual	1996-2013
VT Real Total Personal Income	RPI	2014 CELT	Annual	1996-2013
VT Real Total Gross State Product	RGSP	2014 CELT	Annual	1996-2013
VT Real Total Disposable Income	RDI	2014 CELT	Annual	1996-2013
VT Cooling Degree Days (base 65F)	CDD	ISO-NE SMD	Monthly	Mar03-Dec14
VT Heating Degree Days (base 65F)	HDD	ISO-NE SMD	Monthly	Mar03-Dec14
Daylight Hours in Burlington, VT	DayHrs	Naval Observatory	Monthly	Jan96-Dec14
Cooling Degree Days (base 65F) at Burlington Airport	BurCDD	NOAA Climate Data	Monthly	Jan96-Dec14
Heating Degree Days (base 65F) at Burlington Airport	BurHDD	NOAA Climate Data	Monthly	Jan96-Dec14
Cooling Degree Days (base 65F) at Burlington Airport, squared[13]	BurCDDsq	NOAA Climate Data	Monthly	Jan96-Dec14
Heating Degree Days (base 65F) at Burlington Airport, squared	BurHDDsq	NOAA Climate Data	Monthly	Jan96-Dec14
VT Price of Electricity from RUS7	RUSPRICE	RUS 7	Annual	2007-2013

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

[13] Squaring an independent variable in a multivariate regression is one way to test for a non-linear relationship with the dependent variable.

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.
PreMAR04	= 1, March 2004 and prior = 0, After March 2004	In April 2004, VEC acquired Citizens Communication Company's Vermont Electric division that more than doubled the membership base.
SUMMER	= 1, if month is Jun, Jul, Aug or Sept; = 0, all other months	Test for consistent summer seasonal variance not explained by other variables.
04to06	=1 from April 2004 through November 2006 =0 after November 2006	In December 2006, VEC sold its Southern District in Windham and Windsor counties to Central Vermont Public Service.
07to08	=1 from July 2007 through January 2008 =0 otherwise	To account for reclassification of customers.
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. Table 7 below summarizes the source or methodology of forecasting values through 2034 for those data series that appear in final multivariate regression models.

Data Series	Name	Forecast Source/Methodology
VT Population	POP	2014 CELT forecast (2014-2025); continue at 2021-2025 average growth rate through 2034.
VT Real Price of Electricity	RELPR	2014 CELT forecast (2014-2025); continue at 2021-2025 average growth rate through 2034.
VT Real Total Disposable Income	RDI	2014 CELT forecast (2014-2025); continue at 2021-2025 average growth rate through 2034.
VT Price of Electricity from RUS7	RUSPRICE	2009-2013 value held constant for 2014-2034
VT Total Non-Agricultural Employment	EMP	2014 CELT forecast (2014-2025); continue at 2021-2025 average growth rate through 2034.
VT Unemployment Rate	UER	2014 CELT forecast (2014-2025); continue at 2021-2025 average growth rate through 2034.
Cooling Degree Days (base 65F) at Burlington Airport	BurCDD	12-year normal (average by month of 2003-2014)
Heating Degree Days (base 65F) at Burlington Airport	BurHDD	12-year normal (average by month of 2003-2014)
Heating Degree Days (base 65F) at Burlington Airport, squared	BurHDDsq	12-year normal (average by month of 2003-2014)

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.

Residential and Seasonal Sales

Number of Residential[14] Customers

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

$$\mathrm{Re}\,sSeasCust = \alpha_1 + \beta_1 04to06_{-1} + \beta_2 \,\mathrm{Pr}\,eMAR04 + \beta_3 RDI + \varepsilon$$

Where

04to06 = Dummy variable for April 2004 through November 2006
PreMAR04 = Dummy variable for March 2004 and prior
RDI = Real Disposable Income

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

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

Statistic	Value	Statistic	Value
Sample Size	156	Number of Parameters	4
Mean	31,150	Standard Deviation	7,159
Adjusted R-square	1.00	Durbin-Watson	.81
Ljung-Box(18)	175.6 P=1	Forecast Error	232
BIC	244.42	Mean Absolute Percent Error (MAPE)	0.51%
MAD	152.3		

Table 8: Within-Sample Statistics for ResSeasCust model.

The adjusted R-square for this model is 1.00, indicating that nearly 100% 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
04to06[-1]	2237	78.87
PreMAR04	-17810	105.8
RDI	0.1433	0.0291
_CONST	30455	703.3

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.

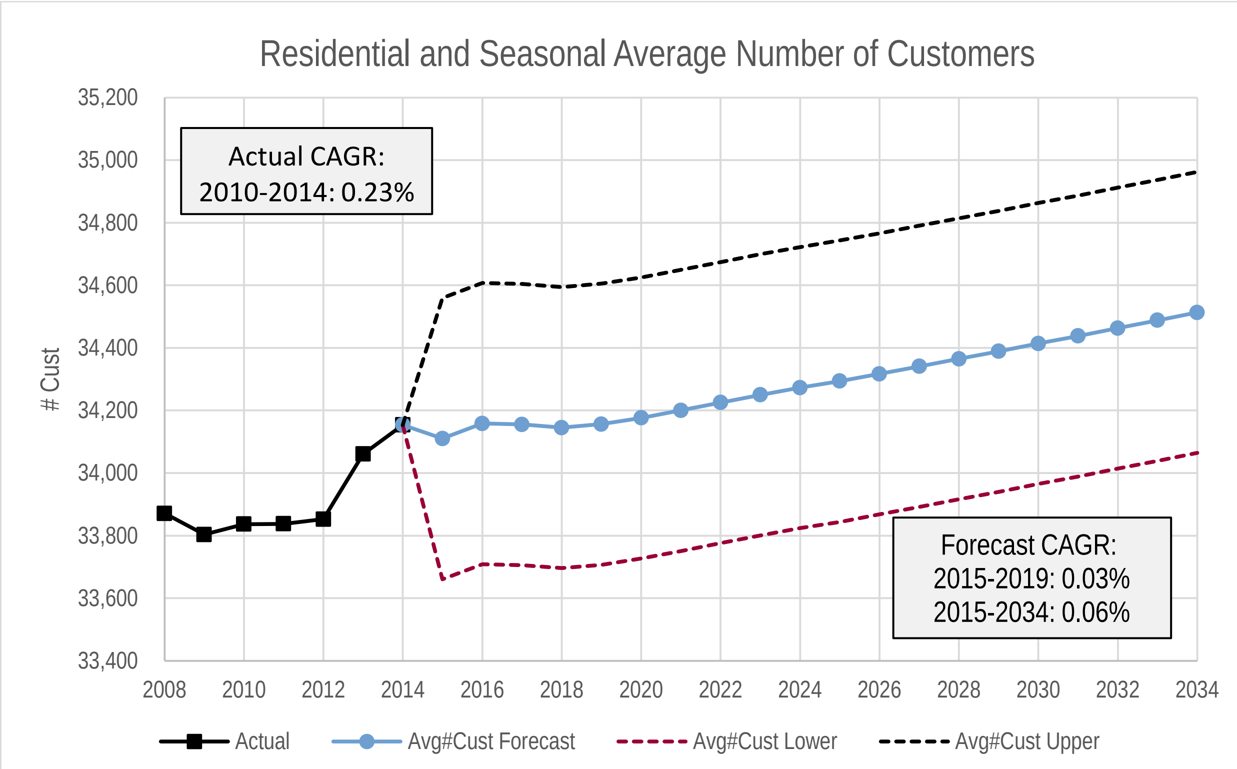


Figure 14: Number of Residential and Seasonal Customers (annual average)

Residential Sales Per Customer

The regression equation for the average sales (in kilowatt-hours, or kWh) per residential customer is specified as a monthly model with the following form:

$$\mathrm{Re}\,sKWHavg = \alpha_1 + \beta_1 UER + \beta_2 HDD + \beta_3 HDD^2 + \beta_4 RUSPRICE + \beta_5 RDI + \beta_6 AUTO_{[-12]} + \varepsilon$$

Where
UER = Unemployment rate
BurHDD = Heating Degree-days
$BurHDD^2$ = Heating Degree-days squared
RUSPRICE = Price of electricity
RDI = Real disposable income
$AUTO_{[-12]}$ = 12 month lagged Cochrane-Orcutt autoregressive error term

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

Statistic	Value	Statistic	Value
Sample size	79	No. parameters	6
Mean	541.18	Std. deviation	56.43
Adj. R-square	0.92	Durbin-Watson	1.7
Ljung-Box(18)	40.2 P=1.00	Forecast error	15.5
BIC	17.58	MAPE	2.22
MAD	11.86		

Table 10: Within-Sample Statistics for ResKWHavg model

The adjusted R-square for this model is 0.92, indicating that just over 92% of the variation observed in the average sales per residential customer is explained by the model parameters. The Mean Absolute Percent Error (MAPE) is reasonably low (2.22%), which also indicates a good model fit. The Durbin-Watson statistic is very close to 2, indicating a lack of autocorrelation in the residual error terms that might be a sign of a biased model. The model parameter coefficients are shown in Table 12 below.

Term	Coefficient	Standard Deviation
BurHDD	0.03297	0.01437
RUSPRICE	-1644	687.5
RDI	0.02755	0.003975
UER	9.987	4.086
BurHDDsq[-1]	0.05287	0.008037
_AUTO[-12]	0.8392	0.04625

Table 11: Parameter Details for ResKWHavg model

The figure below shows the forecast of average sales per residential customer 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.

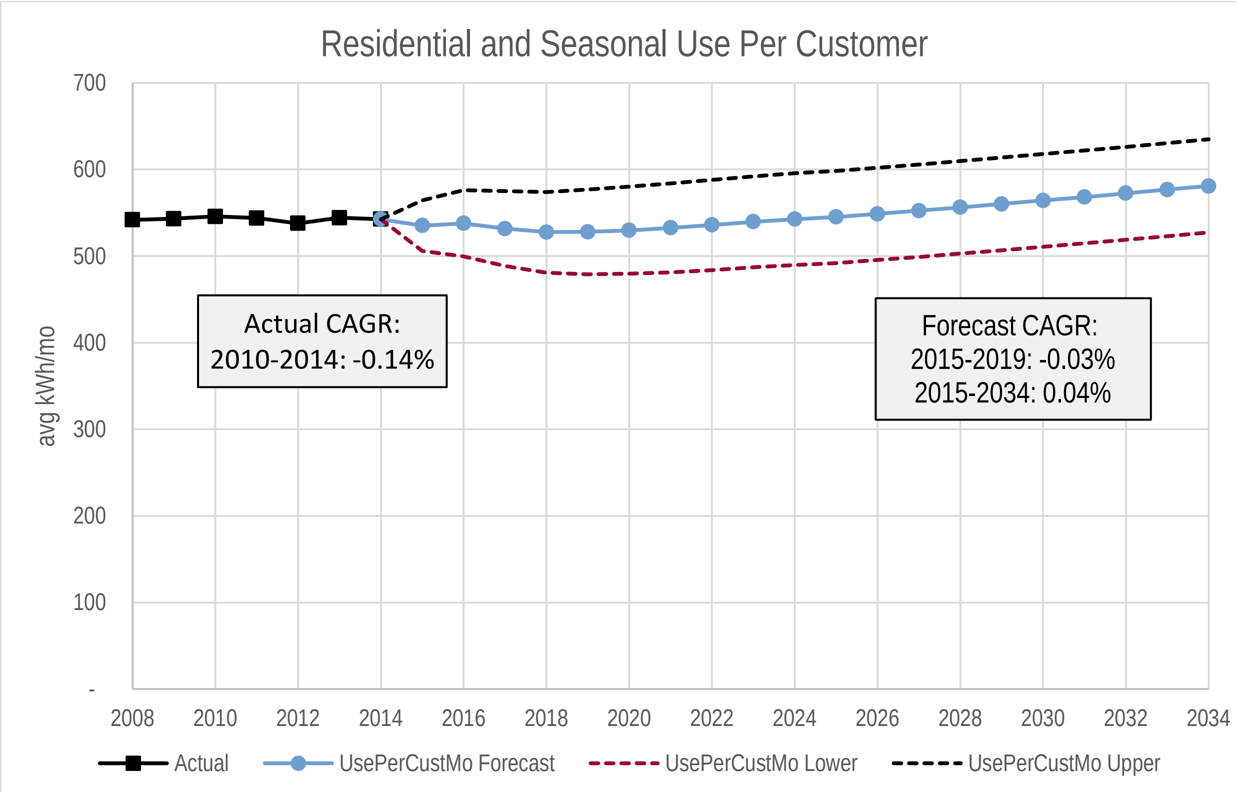


Figure 15: Annual average sales (kWh) per residential or seasonal customer

Residential Sales

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

$$ResSeasKWH = ResSeasCust * ResKWHavg \quad (3)$$

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.

Small Commercial Sales

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

$$SmComMWH = \alpha_1 + \beta_1 AUG + \beta_2 BurCDD + \beta_3 BurHDD + \beta_4 DEC + \beta_5 FEB + \beta_6 MAY + \beta_7 NOV + \beta_8 POP + \beta_9 SEP + \varepsilon$$

Where

AUG = August dummy variable

BurCDD = Cooling degree-days
BurHDD = Heating degree-days
DEC = December dummy variable
FEB = February dummy variable
MAY = May dummy variable
NOV = November dummy variable
SEP = September dummy variable
POP = Population

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

Statistic	Value	Statistic	Value
Sample size	83	No. parameters	9
Mean	8696.04	Std. deviation	700.27
Adj. R-square	0.83	Durbin-Watson	1.53
Ljung-Box(18)	53.8 P=1.00	Forecast error	292.35
BIC	350.78	MAPE	2.59
MAD	223.08		

Table 12: Within-Sample Statistics for SmComMWH model

The adjusted R-square for this model is 0.83, indicating that about 83% 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 just under 2.6%, which is within reasonable tolerance. The Durbin-Watson statistic is very close to 1.5, 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 Table 13 below.

Term	Coefficient	Std. Error
AUG	1143	132.4
BurCDD	5.069	0.6989
BurHDD	0.4388	0.1252
DEC	-504	132.4
FEB	421.6	132.3
MAY	-338.7	132.3
NOV	-608.9	123
POP	12.97	0.1785
SEP	1017	130.6

Table 13: Parameter Details for SmComMWH model

The figure below shows the forecast of small commercial 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.

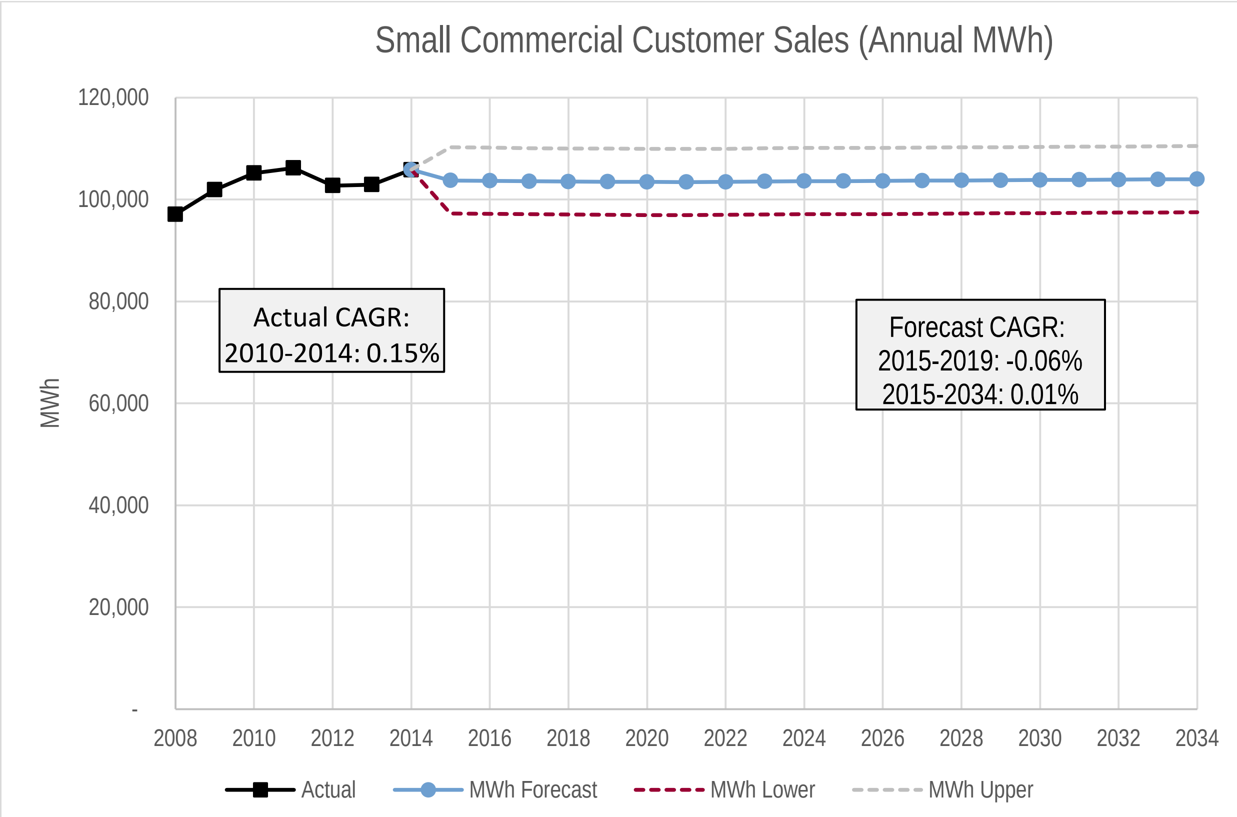


Figure 16: Multivariate Forecast of Small Commercial Total Class Sales (annual)

Large Commercial Sales

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

$$LgComMWH = \alpha_1 + \beta_1 EMP + \beta_2 Jpeak + \beta_3 BurHDD + \beta_4 MAR + \beta_5 FEB + \beta_6 RELPR + \beta_7 07to08 + \varepsilon$$

Where

MAR = March dummy variable
BurHDD = Heating degree-days
Jpeak = Jay Peak dummy variable
FEB = February dummy variable
07to08 = July 2007 to January 2008 dummy variable
EMP = Non-Agricultural Employment
RELPR = Real Price of Electricity

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

Statistic	Value	Statistic	Value
Sample size	91	No. parameters	7
Mean	8607.43	Std. deviation	1703.9
Adj. R-square	0.92	Durbin-Watson	2.24
Ljung-Box(18)	23.9 P=0.84	Forecast error	478.26
BIC	546.55	MAPE	4.12
MAD	359.22		

Table 14: Within-Sample Statistics for LgComMWH model

The adjusted R-square for this model is 0.92, indicating that about 92% 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 5%, which is within reasonable tolerance at the class forecast level. The Durbin-Watson statistic is 2.24 indicating a relative ack of autocorrelation in the residual error terms that might be a sign of a biased model. The model parameter coefficients are shown in Table 15 below.

Term	Coefficient	Standard Deviation
BurHDD	1.247	0.1149
EMP	47.27	6.044
FEB	958.3	206
Jpeak	362.4	113.2
MAR	-868.6	199.6
RELPR	-497.9	130.5
07to08	4713	212

Table 15: Parameter Details for LgComMWH model

The figure below shows the forecast of small commercial 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.

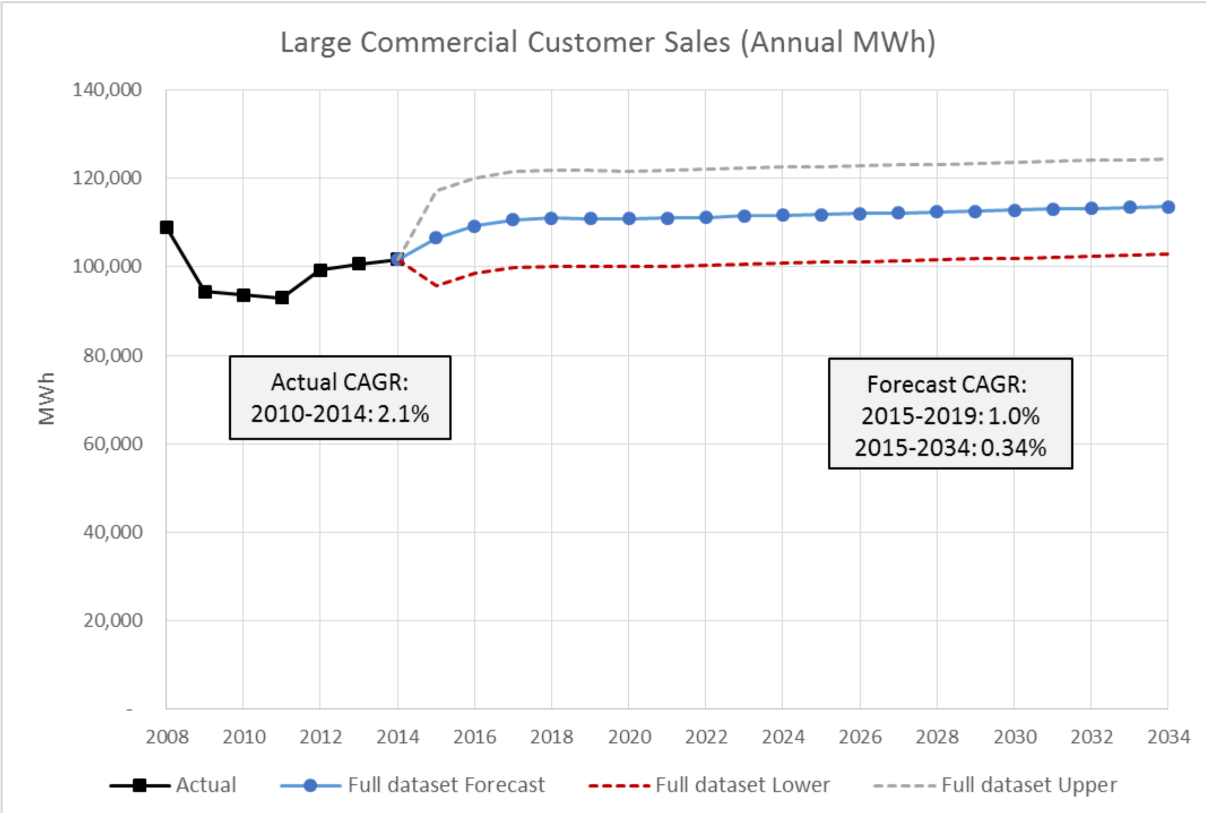


Figure 17: Multivariate Forecast of Large Commercial Total Class Sales (annual)

Lighting Sales

No statistically satisfactory model could be fit to lighting class data. Univariate forecast trends were assumed.

Public Authority Customer Sales

No statistically satisfactory model could be fit to public authority class data. Univariate forecast trends were assumed.

Total System Sales

SYSTEM ENERGY SALES

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

$$EnergySales = \alpha_1 + \beta_1 RUSPRICE + \beta_2 MAR + \beta_3 BurHDD + \beta_4 BurHDD^2{}_{[-1]} + \beta_5 RDI + \beta_6 FEB + \beta_7 AUTO_{[-12]} + \beta_8 AUTO_{[-3]} + \varepsilon$$

Where

$BurHDD^2_{[-1]}$ = 1 period lagged heating degree-days, squared
BurHDD = Heating degree-days
RUSPRICE = Real Price of electricity
RDI = Real disposable income
FEB = February dummy variable
MAR = March dummy variable
$AUTO_{[-12]}$ = 12 month lagged Cochrane-Orcutt autoregressive error term
$AUTO_{[-3]}$ = 3 month lagged Cochrane-Orcutt autoregressive error term

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

Statistic	Value	Statistic	Value
Sample size	79	No. parameters	8
Mean	36170.88	Std. deviation	2861.93
Adj. R-square	0.92	Durbin-Watson	1.66
Ljung-Box(18)	22.8 P=0.80	Forecast error	822.94
BIC	973.34	MAPE	1.69
MAD	612.14		

Table 16: Within-Sample Statistics for System Energy Sales model

The adjusted R-square for this model is 0.92, indicating that about 92% of the variation observed in the historical system sales is explained by variance in the independent variables. The Mean Absolute Percent Error (MAPE) is just under 2%, which is acceptable for the system as a whole. The Durbin-Watson statistic is 1.66 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 Table 17 below.

Term	Coefficient	Standard Deviation
RUSPRICE	-42265	14169
MAR	-3784	763.2
BurHDD	1.845	0.5059
BurHDDsq[-1]	2.188	0.377
RDI	1.685	0.0956
FEB	-1895	855.6
_AUTO[-12]	0.6143	0.05261
_AUTO[- 3]	-0.3355	0.05947

Table 17: Parameter Details for System Load model

The figures below show the forecast of system 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.

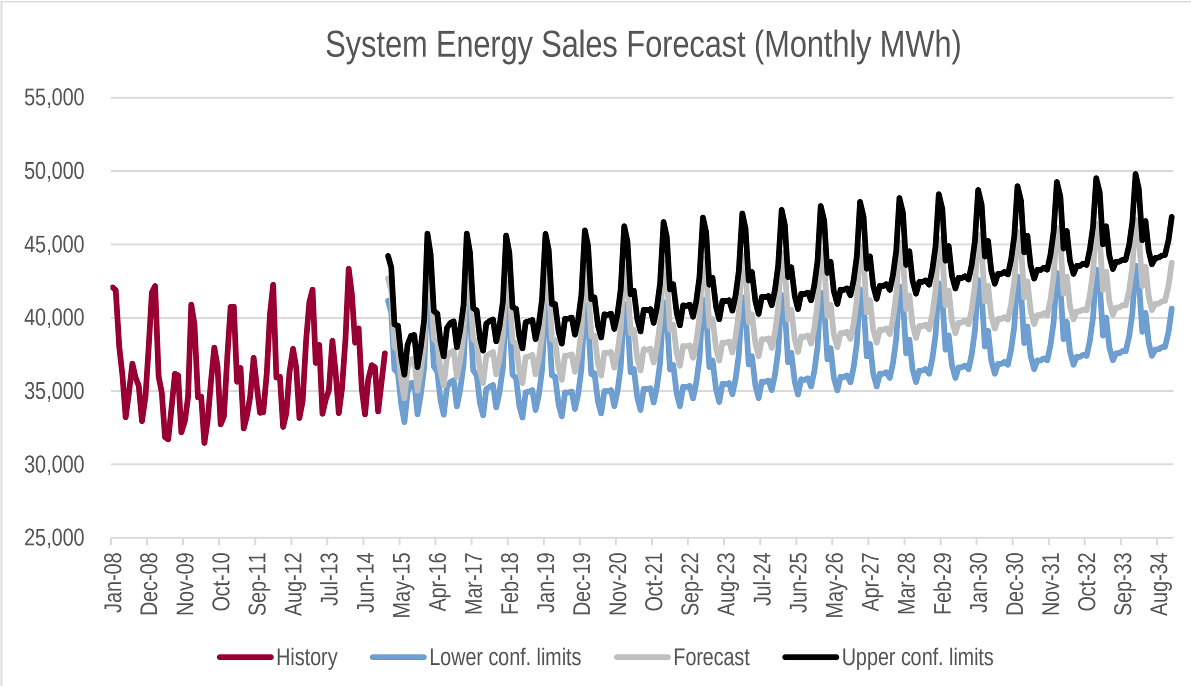


Figure 18: Multivariate Forecast of System Energy Sales (monthly)

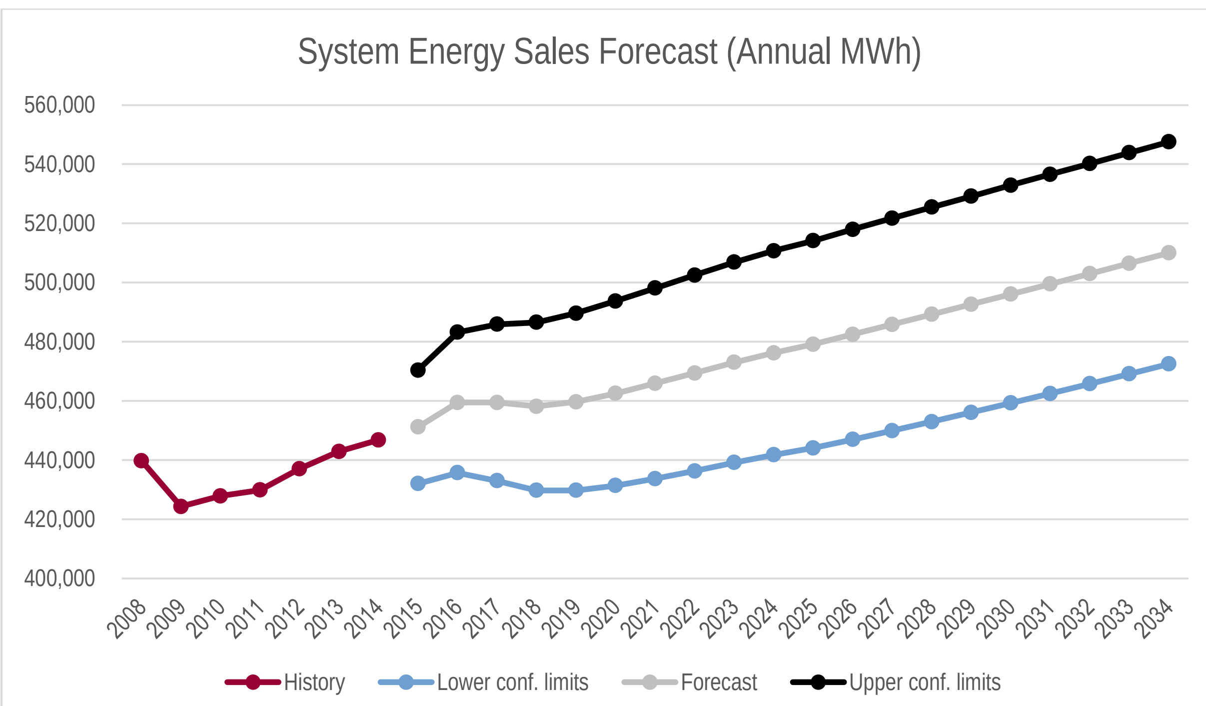


Figure 19: Multivariate Forecast of System Energy Sales (annual)

APPENDIX B

Energy Market Price Forecast

La Capra Associates

To: Craig Kieny, Vermont Electric Cooperative

From: Stan Faryniarz, Dan Koehler, Mary Neal and Doug Smith

Date: March 30, 2015

Re *Energy Market Price Forecast*

Summary

Market energy price projections are derived from the La Capra Associates ("LCA") Northeast Market Model ("NMM"). The NMM uses an hourly chronologic electric energy market simulation model platformed on the AURORAxmp® software ("AURORA"). The model provides a zonal representation of the electrical system of New England, New York, and neighboring regions.

Resulting Vermont zone prices are shown below for reference, high, and low cases. The variance in the three different cases is driven by changes in assumed natural gas and CO_2 prices. Energy prices are very sensitive to natural gas and CO_2 price assumptions, and these assumptions are also subject to a large amount of uncertainty, which is why they were varied to create the three sensitivities. The variation in natural gas and CO_2 price assumptions is summarized in the table below. More details on these inputs and other model inputs are provided in the following section. More details on the results are provided at the end of this memo.

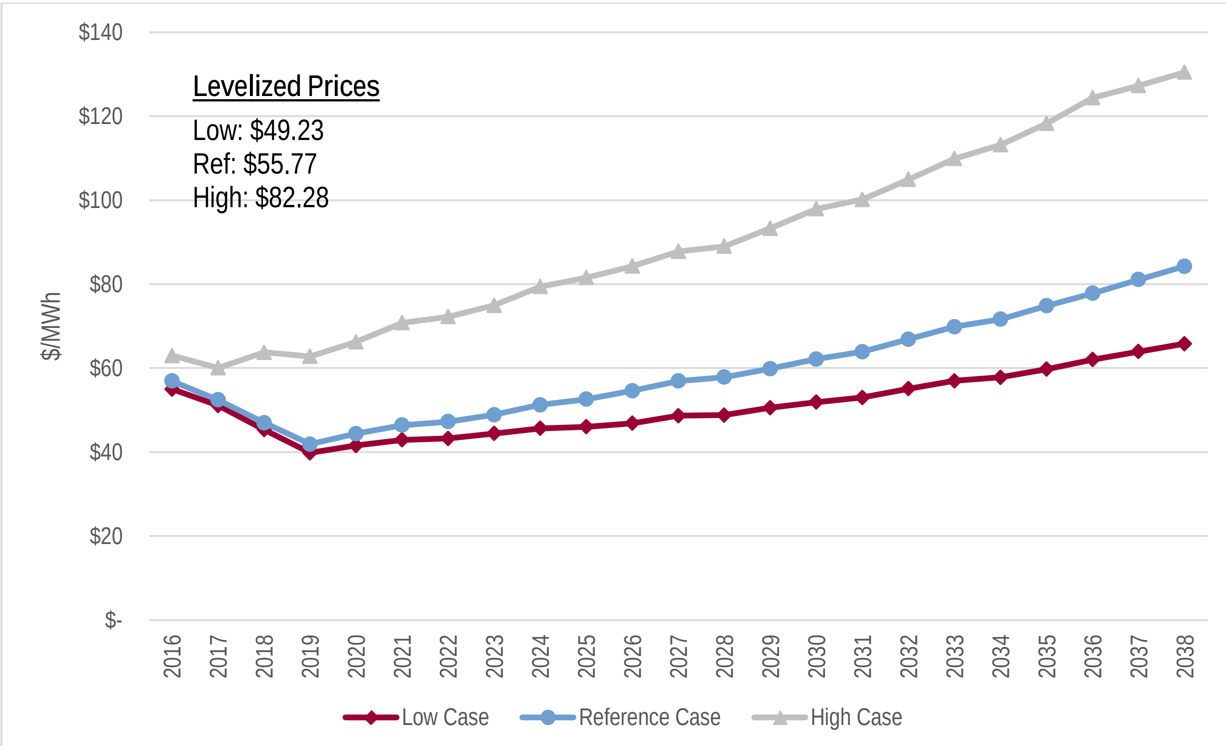


FIGURE 1: VERMONT ZONAL ALL-HOURS PRICE FORECAST COMPARISON. (NOMINAL $)

TABLE 1: HIGH-LEVEL SUMMARY OF NATURAL GAS AND CO_2 PRICE ASSUMPTIONS.

Component	High	Reference	Low
Henry Hub ("HH") Natural Gas	2014 Annual Energy Outlook ("AEO")	Short-term Energy Outlook ("STEO") then extrapolated at 2014 AEO growth rate	March NYMEX quote
Algonquin Citygates Basis	NYMEX quotes, then implied market heat rate applied to Hub futures and netted against HH quotes. Held constant in real terms after 2017	NYMEX quotes, then implied market heat rate applied to Hub futures and netted against HH quotes. Interpolation to zero in 2019 then held constant at zero thereafter	Same as Reference
CO_2 Prices	Regional Greenhouse Gas Initiative ("RGGI")-Only through 2019 then assumed Federal Carbon policy	RGGI-Only	RGGI-Only; Same as Reference

Model Inputs

Natural Gas

The natural gas price delivered to the facility was analyzed in two components:

- Henry Hub "commodity index" price; and
- Basis differential between Henry Hub and Algonquin Citygate.

Our reference, high and low natural gas forecasts are a sum of these two components. A more-detailed summary of our methodology for the high, low and reference case is shown in the table below.

TABLE 2: SUMMARY TABLE OF DELIVERED NATURAL GAS COMPONENTS.

Component	High	Reference	Low
Henry Hub	2014 AEO	STEO Feb 2015 through 2016; 2014 AEO 2016-2038 CAGR	March NYMEX quote
Algon Basis	2016: 30 day average of quotes for Apr15-Mar16 NYMEX. 2017: Implied market heat rate applied to 30 day average of Hub futures and netted against HH quotes. 2018-2021: 2017 constant	2016: 30 day average of quotes for Apr15-Mar16 NYMEX. 2017: Implied market heat rate applied to 30 day average of Hub futures and netted against HH quotes. 2018: Interpolation between 2017 and 2019. 2019: 0	Same as Reference

The resulting delivered natural gas price forecasts are shown in Figure 2 below.

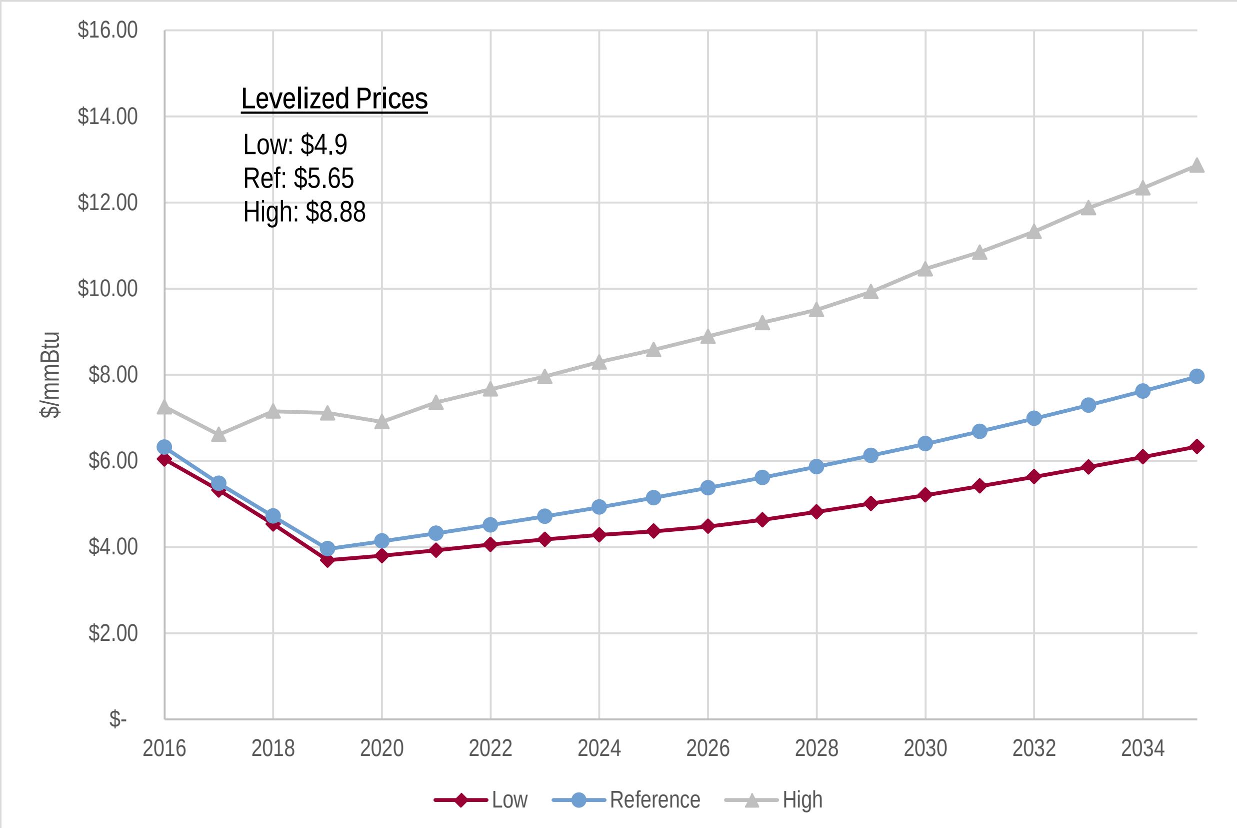


FIGURE 2: DELIVERED NATURAL GAS PRICE COMPARISON. (NOMINAL $)

Henry Hub Forecast

The Henry Hub forecasts rely on data from U.S. Energy Information Administration ("EIA") and NYMEX futures to create high, low and reference case scenarios.

REFERENCE CASE: The EIA produces the AEO annually and a STEO monthly. The most recent AEO is the 2014 AEO, which was released in May 2014. The reference case is created by combining the 2014 AEO trends with updated market information from the March 2015 STEO. The reference forecast relies on the STEO through 2016, the end of the forecast published in that document. The reference case then continues with a 4.5% growth rate, which is the 2014 AEO's 2016-2038 compound annual growth rate.

HIGH CASE: Since the 2014 AEO was published, Henry Hub price expectations have fallen significantly. The March 2015 STEO lists prices that are approximately $1/mmBtu below the 2014 AEO's projections for 2015-2016. The 2014 AEO therefore provides a natural gas forecast that can be used as a reasonable high case for prices.

LOW CASE: NYMEX futures represent our low case. Care must be taken when using NYMEX future quotes as a forecast of future prices. Even though futures are quoted for delivery months through 2027, the later year quotes are based on few if any actual transactions because liquidity drops off significantly for products with delivery beyond several years forward. Long-term forward prices are often based on little to no trading and tend to be disproportionately affected by short-term factors and a bias to either bid or ask participants then in the market. NYMEX futures have fallen over the past several months to reach all-time lows for delivery years coinciding with the forecast period. It is considered unlikely that prices can fall much lower based on fundamental natural gas production economics (though such assurances have been proven wrong in the past), because there will always be minimum cost of extraction and transportation. NYMEX futures prices quoted in early March therefore provide a reasonable low case for prices.

The chart below illustrates the price spread provided by each case for Henry Hub prices.

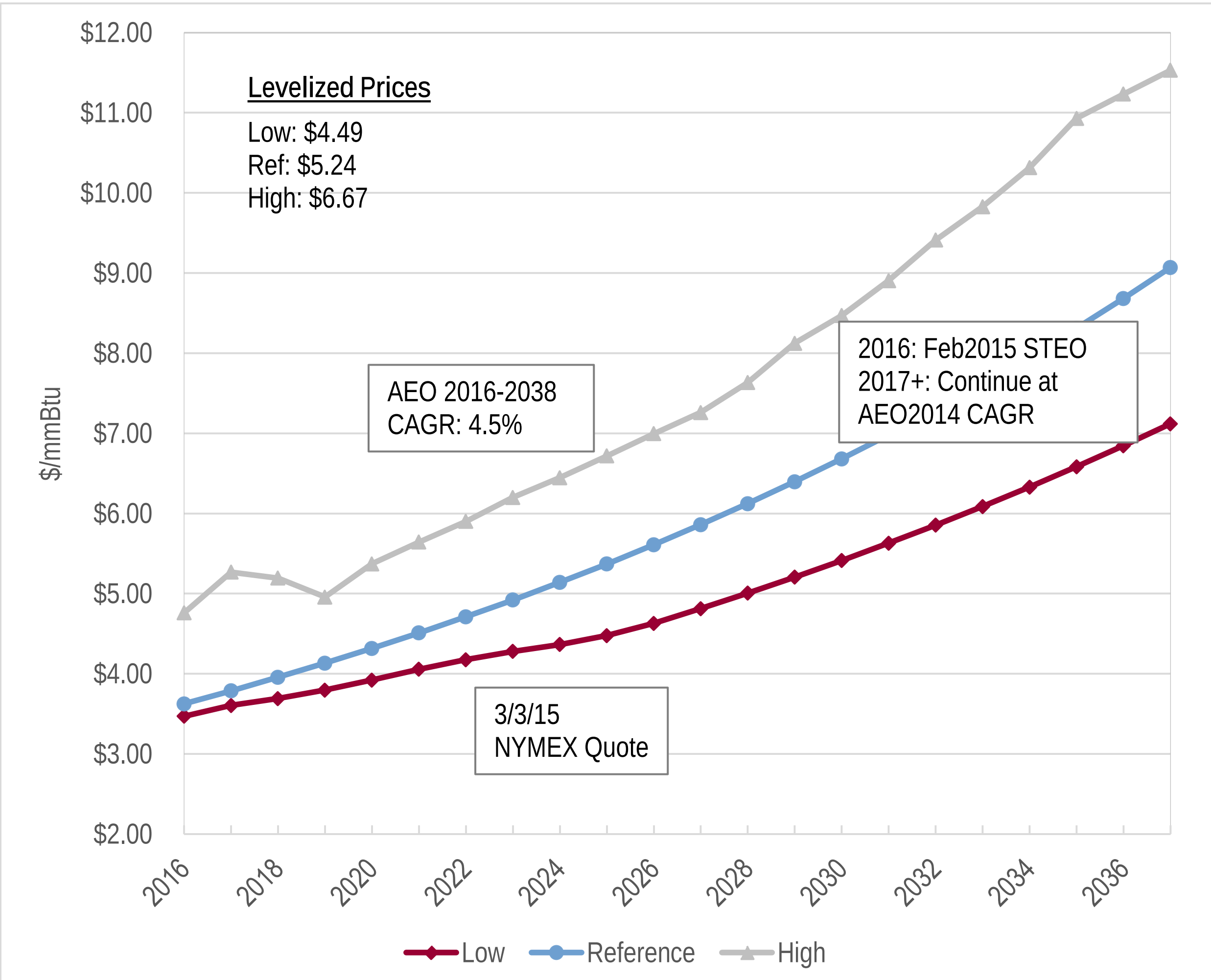


FIGURE 3: HENRY HUB FORECAST COMPARISON. (NOMINAL $)

Algonquin Citygate Basis Differential

Forecasting the basis differential between Henry Hub and the Algonquin Citygate is challenging because there is no publicly available forecast, and futures transactions are sparse and short-term.[1] Historically the annual average basis differential was consistently around $1/mmBtu. In recent years pipeline constraints in the winter months have

---

1 Part of the reason for the sparse transactions is that buyers are reluctant to lock in a long-term deal if they think basis may fall in the future as new pipeline capacity comes into service. Additionally, structural market impediments keep natural gas generators from making longer-term basis commitments.

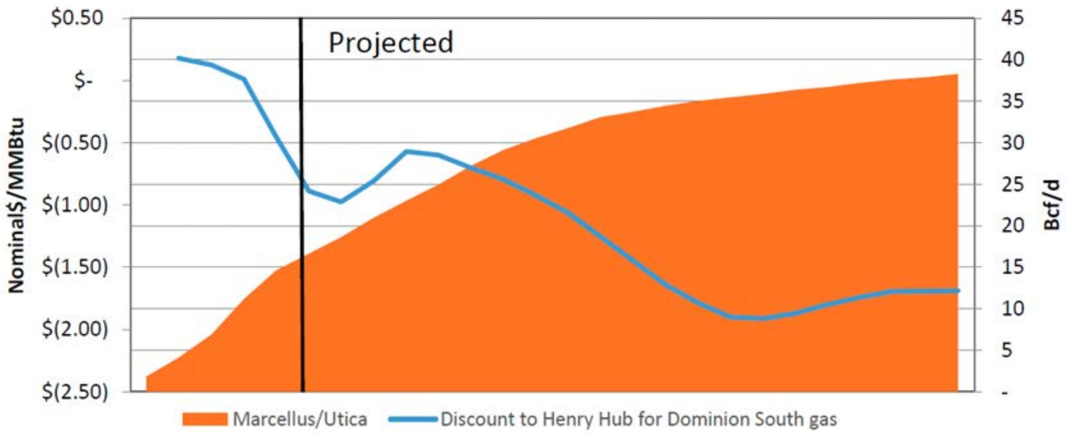
driven the basis differential significantly higher. We expect that the current extreme basis differentials, which ISO-NE has labeled “unsustainable,” will be mitigated over the next few years. There are several reasons behind this expectation including:

- Pipeline expansions underway and being planned;
- ISO New England (“ISO-NE”) market changes and system operations changes;
- Regional policy initiatives to support pipeline expansion in the region; and
- Market responses from alternative fuel suppliers, demand response providers, and imports of power from Canada and New York (where pipeline expansion is leading those efforts in New England).

Available market data seems to support this view. Even though public futures trading for New England delivered gas or basis differential swaps does not typically extend beyond the prompt year, electricity at the New England hub experiences a relatively active level of forward trading. Since New England electricity prices are highly correlated to the price of delivered natural gas, an implied market outlook on delivered gas prices can be inferred. Over the last 12-18 months of trading, even though short-term forward prices for electricity spiked during and after the winter of 2013/14, and then retreated this winter, 2017 electricity futures prices remained relatively stable and low. We interpret this to imply that the market outlook is for mitigation of the conditions leading to the sharp spikes in basis differential the past few years.

Historically, gas prices in New England were tied to Henry Hub and basis was a function of congestion and transportation charges from gas travelling to the New England region. The $1/mmBtu average basis between Henry Hub and New England has been seen as a floor, but this is not necessarily true going forward. Growing production in the Marcellus Shale region has provided a significantly-closer supply for New England and it is expected to replace supply from the Gulf coast. The new supply dynamics suggest that supply prices will be tied to Marcellus Shale region prices (represented by Dominion hub) and the New England basis differential from Henry Hub will no longer be a pure adder to commodity costs, but rather a net of congestion and transportation from Marcellus to New England, against the price differential at Marcellus versus Henry Hub.

There is already a significant price disparity between Marcellus and Henry Hub prices and it is expected to continue, maybe increase. An ICF study for the Access Northeast proposed project shows a Henry Hub premium of $1-2 per mmBtu relative to Marcellus as seen in Figure 4 below.



Source: ICF International, SNL

FIGURE 4: ICF CHART OF HISTORICAL AND PROJECTED MARCELLUS/UTICA PRODUCTION AND DOMINION SOUTH POINT TO HENRY HUB BASIS[2]

We developed two basis differential forecasts: low and high. We consider the low case to be the more likely case; therefore, the low basis case is included in both our low and reference delivered gas forecast. Both basis differential forecasts utilize forward market data for 2016 and 2017 that shows declining basis relative to recent highs. The cases differ starting in 2018.

LOW: The low case assumes that additional pipeline capacity such as Algonquin Incremental Market (AIM), Access Northeast and/or other proposals, as well as the other potential mitigating factors discussed above, will bring the market back to equilibrium by 2019. Therefore, the low case assumes that approximately $1/mmBtu in annual transportation and congestion charges will be offset by a $1/mmBtu Marcellus shale supply discount to the Henry Hub price. The positive winter basis will be offset by a negative summer/shoulder basis.

HIGH: The high case assumes that the market will remain constrained during the study period due to delays or scale-downs in additional pipeline capacity and/or the failure of mitigating factors to fully offset rising demand for pipeline transportation. There will be some mitigation in basis between 2015 and 2017, but significant congestion will remain. Prices from 2017 through 2019 will be constant.

We used a hybrid methodology for forecasting the basis:

- 2016. Both cases use a 30 day average (2/3/15-3/4/15) of quotes for April 2015 – March 2016 NYMEX future swaps, which is the furthest forward futures quotes currently available for 2016.
- 2017. An implied Market Heat Rate is calculated from a 30-day average of quotes for April 2015 – March 2016 NYMEX Henry Hub, NYMEX Algonquin Citygate Basis Swap Futures, and NYMEX ISO-NE Hub ATC LMPs. This Market Heat Rate is then applied to the 30-day average of January 2017 – December 2017 ISO-NE Hub Futures to estimate a market view of delivered gas, which is netted against January 2017 – December 2017 NYMEX HH quotes to arrive at a calculation of the Algonquin basis.
- 2018-2021 Low Case. Assume basis of $0 by 2019. Interpolate between 2017 and 2019 to forecast 2018.
- 2018-2021 High Case. Same as 2017.

2 http://accessnortheastenergy.com/wp-content/uploads/2015/02/ICF-Report-on-Access-Northeast-Project.pdf

The high and low cases are shown in Figure 5 below.

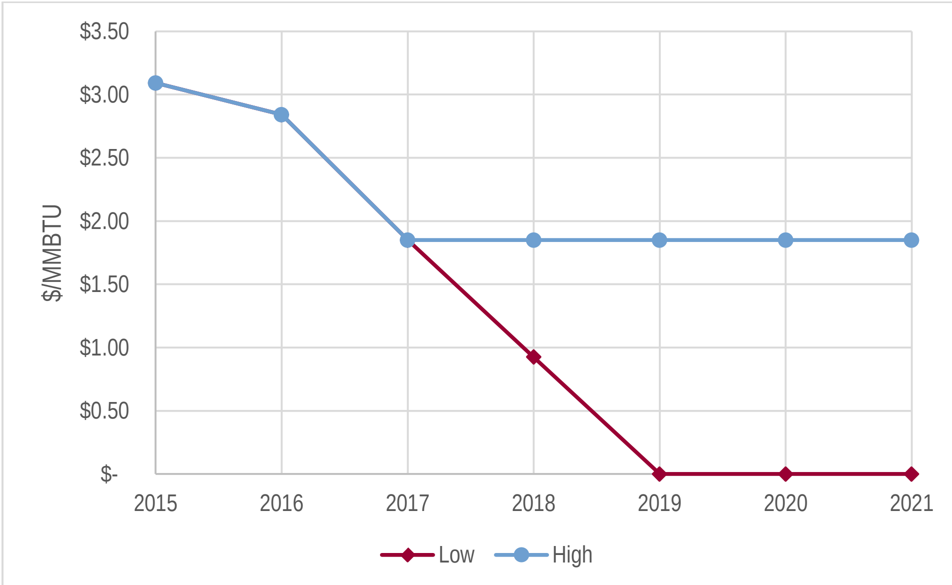


FIGURE 5: HIGH AND LOW ALGONQUIN CITYGATES BASIS FORECAST. (NOMINAL $)

In addition to this basis, Northern New England states (namely Vermont, New Hampshire, and Maine) also have an additional delivery basis added to the delivered monthly Algonquin Citygates natural gas price of about $0.53/mmBTU on an average annual basis. This is to account for the additional expense to transport the gas the additional distance from inexpensive shale gas supplies to the southwest. The forecast is based on backhaul usage rates on the Maritimes and Northeast Pipeline and Portland Natural Gas Transmission System short-term reservation rates.

Monthly Shapes

The annual HH prices and Algonquin basis differentials shown above are also subject to monthly shaping. In general, the shape for the basis differential is far more pronounced than for HH prices. The shaping factors reflect the following:

HENRY HUB: For the reference case in 2016, monthly price projections from the STEO are directly input into the NMM. Otherwise, all annual prices are multiplied by a monthly shaping factor from the default input database provided with the AURORA model.[3]

ALGONQUIN BASIS DIFFERENTIAL: For prices through 2017—and thereafter for the high case—the monthly basis differential reflects monthly futures prices, either directly or implied by the market heat rate based on monthly forward prices. For the low case, once prices reach zero on an annual average basis, a monthly shaping factor is applied based on an average of 2009-2012 actual monthly basis shape. Monthly basis shape was moderately stable over that historical period.

3 EPIS, the developers of AURORAxmp, create this default input database. The iteration of the default database used for this model was released in mid-2014.

CO_2 Prices

Two different CO_2 price outlooks have been used in this analysis. The one used for the reference and low cases only incorporates expected impacts from RGGI. The CO_2 price outlook in the high case assumes federal carbon regulation complements or supersedes the RGGI program beginning in 2020. More detail regarding each of these assumptions is provided below:

RGGI: All New England states participate in RGGI, a cap-and-trade program aimed at reducing CO_2 emissions from the power sector. Pricing carbon emissions through a cap-and-trade program affects New England electric energy prices by increasing the variable costs of fossil fuel-fired generators that are almost always on the margin. RGGI allowance prices have been minimal since the program began in 2009 because actual CO_2 emission levels have fallen well below the initial program caps. On February 7, 2013 the RGGI states announced their commitment to an Updated Model Rule that tightened caps significantly in 2014. A RGGI-commissioned study of the Updated Model Rule projects that emission allowance prices will rise from about $4 (2010$) per ton in 2014 to over $10 (2010$) per ton by 2020.[4] The NMM incorporates this updated outlook on RGGI allowance prices. RGGI auction results to-date have benchmarked well to the Updated Model Rule forecast.

FEDERAL POLICY: Federal policy regarding greenhouse gas emissions presents a potential, though uncertain, outcome. Congress has considered several legislation options that would create a cap-and-trade market for CO_2 emission allowances over the past several years. Legislative activity was high in the 2008-2010 session, although no action was taken. As legislative efforts to regulate CO_2 emissions have since foundered, the U.S. EPA subsequently stepped in with proposed regulations that might achieve similar results. In the past year, the EPA has released proposed rules that would regulate carbon emissions under Section 111 of the Clean Air Act at both new and existing power plants. The proposed regulations on new and modified sources would effectively ban the development of new coal-fired electric generating units without carbon capture and sequestration technology. In June 2014 the EPA released its Clean Power Plan proposal, which aims to cut carbon emissions from existing power plants and enable the US to reduce carbon emissions from the power sector by 30% below 2005 levels.[5] The EPA has proposed each state or multi-state collaboration would develop a plan to meet an individual carbon intensity reduction target through any combination of plant efficiency improvements, shifting generation from higher to lower-emitting resources, maintaining and expanding nuclear and renewable generation, and energy efficiency. New England has already implemented programs and policies that would likely generate more carbon dioxide reductions than required under the EPA's proposal, but the federal proposal would backstop these efforts.

Our federal CO2 emissions price outlook relies on the Synapse Energy Economics, Inc. 2015 Carbon Dioxide Price Forecast.[6] Synapse reviews policy and regulatory developments as well as utility price forecasts to develop Low, Mid and High scenario CO2 emission price forecasts. We believe the Synapse "Low" forecast, which "represents a

---

4 RGGI, Inc. 2/7/2013 Press Release. http://www.rggi.org/docs/PressReleases/PR130207_ModelRule.pdf

5 EPA, "EPA Proposes First Guidelines to Cut Carbon Pollution from Existing Power Plants/Clean Power Plan is flexible proposal to ensure a healthier environment, spur innovation and strengthen the economy", 2 June 2014, http://yosemite.epa.gov/opa/admpress.nsf/bd4379a92ceceeac8525735900400c27/5bb6d20668b9a18485257ceb00490c98!OpenDocument

6 http://www.synapse-energy.com/sites/default/files/2015%20Carbon%20Dioxide%20Price%20Report.pdf

scenario in which the final version of the Clean Power Plan is relatively lenient and readily achieved…"[7], is most appropriate for use as a reference forecast of federal carbon pricing at this point. The high case assumes that a federal CO_2 pricing program is implemented in 2020 as forecast in the Synapse "Low" case.

The CO_2 price outlooks are summarized in the figure below.

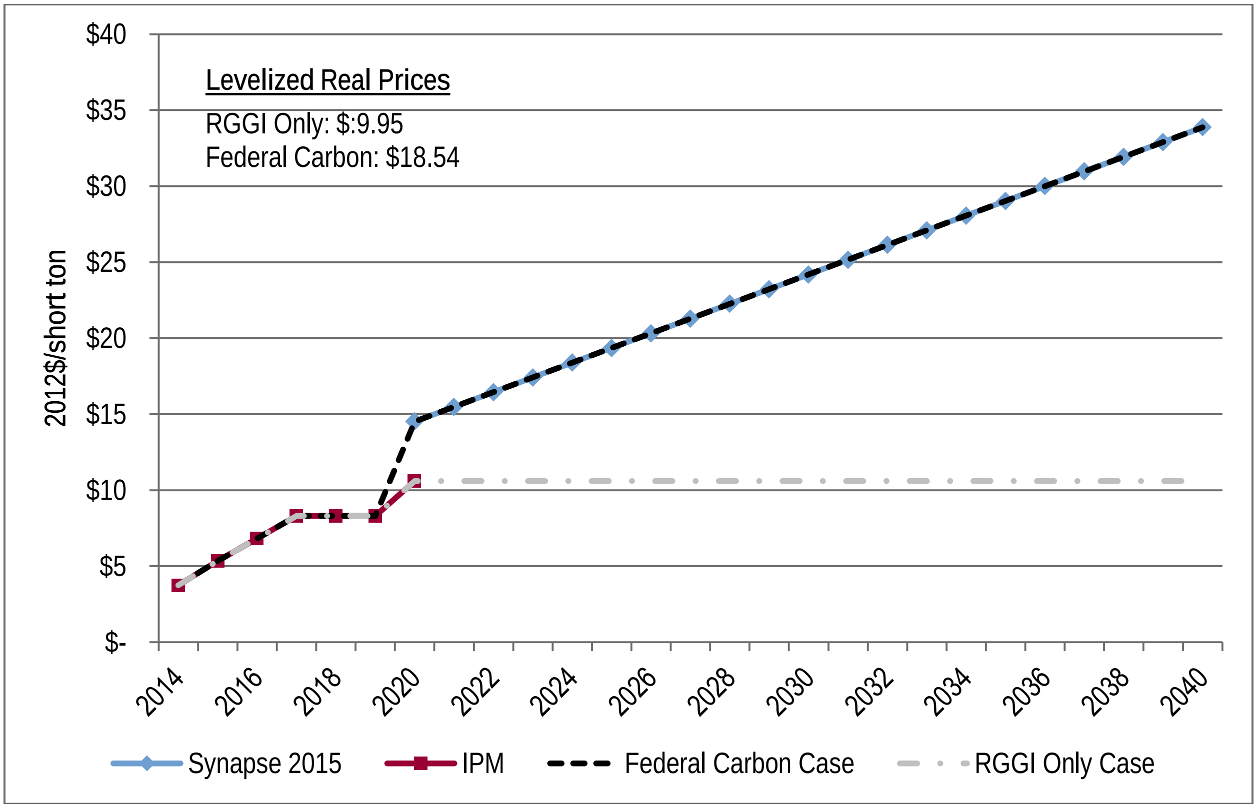


FIGURE 6: CO_2 PRICE FORECAST COMPARISON. (REAL 2012 $)

Other Inputs

Other model inputs are the same between all three cases. Like with natural gas and CO_2, these inputs generally reflect the latest and best publicly-available information. Key sources include the ISO-NE CELT forecast and AURORA's default input database provided by EPIS, the developers of AURORA.

Key assumptions include the following:

- Load and DSM: The 2014 CELT report was used to estimate gross peak and energy load and peak and energy load net of energy efficiency ("EE") through 2023.[8] ISO-NE's EE forecast in the CELT report includes estimates based both on the resources cleared in the New England Forward Capacity Market ("FCM") and the load reduction projected due to state-sponsored EE programs. For extrapolation in the period 2024-2039, gross regional load is assumed to grow at the 2018-2023 compound annual growth rate. EE

7 Synapse report at 3.

8 ISO-NE refers to EE as "passive demand resources" (PDR).

reductions are extrapolated such that EE's percent of gross load, both peak and energy, in 2023 remains constant through the rest of the study period. These extrapolations are done separately for each zone in the system. Additional Demand Response resources are added based on what resources clear in ISO-NE's Forward Capacity Auction ("FCA").

- New Renewable Generation: It was assumed that New England state Renewable Portfolio Standard ("RPS") programs would continue throughout the study period,[9] and the NMM incorporates a renewable build-out that included enough renewable energy to meet the RPS targets each year. Most of the states' required percentages of renewable energy stop increasing at some point in the study period. After this point, additional build-out is based on maintaining the percentage target as load increases.
- Retirement and New Thermal Generation assumptions: The retirement assumptions are developed as part of the thermal expansion development process. The schedule of retirements is based on the de-list bids from the FCA and is adjusted to reflect LCA's most current understanding of likely retirements. Specifically, we incorporated the retirements of Entergy's Vermont Yankee at the end of 2014 and the expected retirement of Dynegy's Brayton Point in 2017.[10],[11] For years in which no FCA had yet cleared, professional judgment was used to determine an expected life for the oil-fired and coal-fired units remaining online in New England. Thermal additions are calculated by first determining a forecast of future New England installed capacity requirement, net of existing tie benefits ("NICR"). The NICR is compared to supply from existing resources less retirements, plus new demand-side management (passive and active), projected imports, and forecasted new renewable generation. The 674 MW Footprint CCGT, slated for the current Salem Harbor site cleared in FCA 7 and is, therefore, assumed to come online in May 2016. Once the net of these resources is determined any shortfall in meeting NICR is met with a combination of generic natural gas fired combined cycle plants and generic simple cycle combustion turbine units.
- Inflation: The NMM uses the GDP Chain-type Price Index from the Macroeconomic Indicators table of the 2014 AEO, and modifies this index to reflect a constant growth rate based on the average growth rate over 25 years. The average growth rate is 1.8%/year.
- Transmission: The NMM assumes the following upgrades to the existing New England transmission system based on ISO-NE's 2014 Regional System Plan:
    - The Maine Power Reliability Project ("MPRP") (in-service 2015);
    - New England East-West Solution ("NEEWS") (Greater Springfield Reliability Project completed by 2013; Interstate Reliability Project completed by 2018).
    - NEMA/Boston upgrades in-service 2014.[12]

---

9 No VT RPS was assumed for the purposes of developing the renewable energy build-out.

10 Boston Business Journal, August 22, 2014, The Brayton Point power plant is being sold again, but new owner will still shut it down, http://www.bizjournals.com/boston/blog/bottom_line/2014/08/the-brayton-point-power-plant-is-being-sold-again.html?page=all.

11 Boston Globe, December 29, 2014, Vermont Yankee nuclear plant shutdown complete, http://www.bostonglobe.com/business/2014/12/29/vermont-nuclear-plant-shuts-down-today/uU0uUect2gVsVhvANHQVTO/story.html.

12 ISO-NE, *2014 Regional System Plan*, p. 64, http://www.iso-ne.com/static-assets/documents/2014/11/rsp14_110614_final_read_only.docx.

Results

The figures below compare the forecasted Vermont zonal prices for the high, reference, and low cases on an annual and monthly basis. On an annual basis, the high case is much higher than the reference case, while the low case is close to the reference case, especially in the near-term. This is a product of the input assumptions. The only difference between the low and reference cases is the Henry Hub price forecast whereas the high case has higher Henry Hub prices, natural gas basis, and CO_2 prices. This reflects the expectation that there is more upside potential to energy prices than downside compared to the reference price forecast. This assumption, ie. a lognormal (aka "skewed to the upside") outlook for natural gas, is consistent with previous VEC IRPs.

The monthly prices show how high winter prices driven by natural gas pipeline constraints during times of high heating demand are expected to change over time. The reference and low cases show a sharp decline in winter prices, as these cases assume natural gas pipeline constraints will ease between 2017 - 2019, while the high case assumes high winter prices persist throughout the study period.

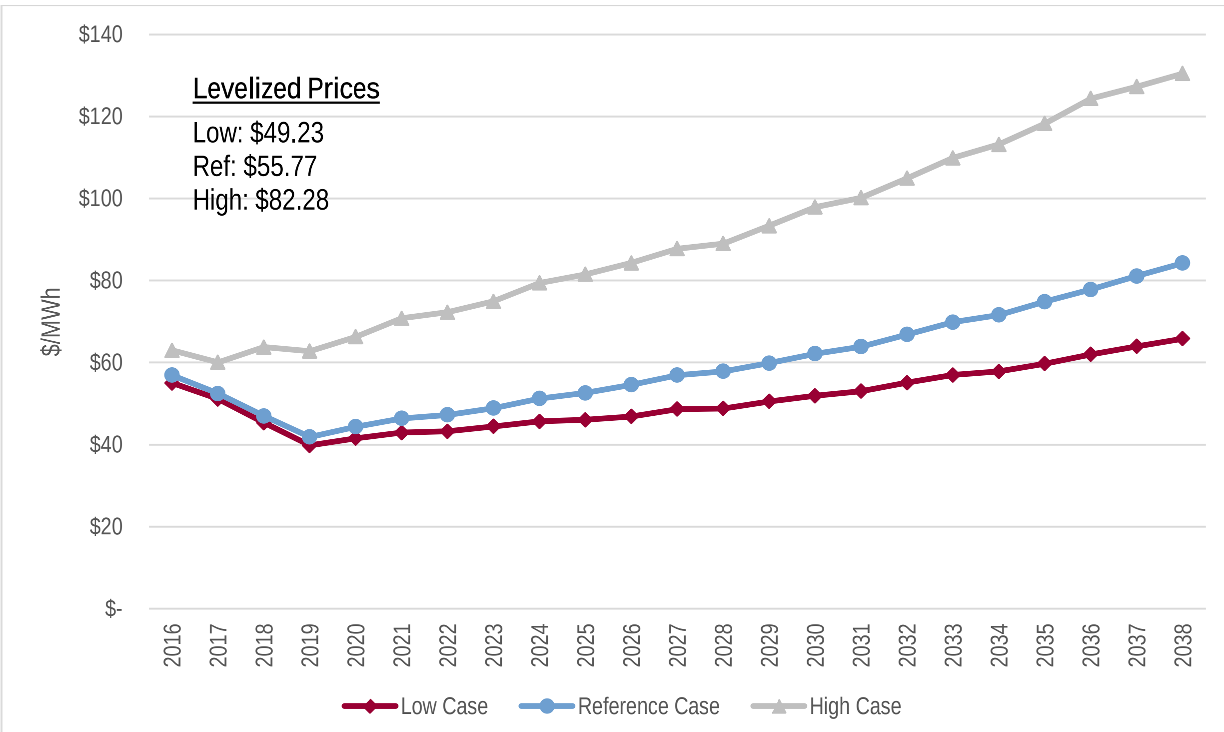


FIGURE 7: VERMONT ZONAL ALL-HOURS ANNUAL PRICE FORECAST COMPARISON. (NOMINAL $)

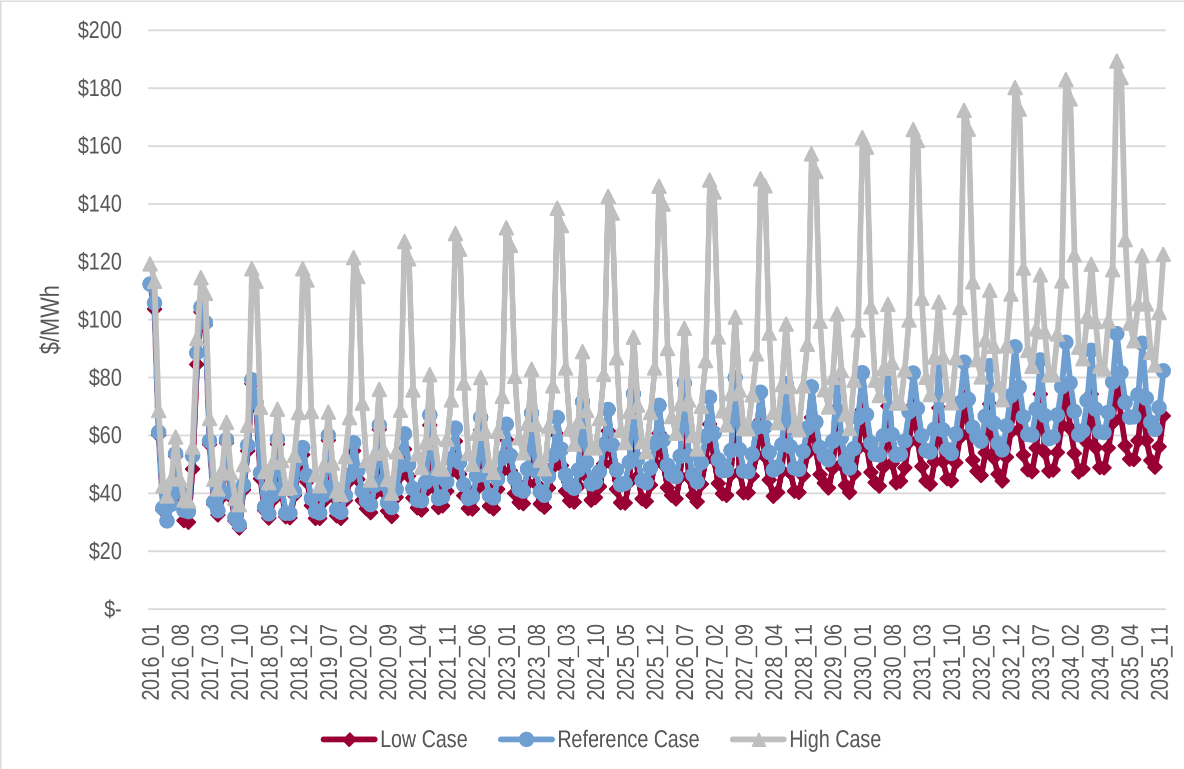


FIGURE 8: VERMONT ZONAL ALL-HOURS MONTHLY PRICE FORECAST COMPARISON. (NOMINAL $)

The following figure visually demonstrates how strongly market energy prices correlate to assumed natural gas and CO_2 prices. This figure shows results only for the reference case, but the other two cases show similar trends.

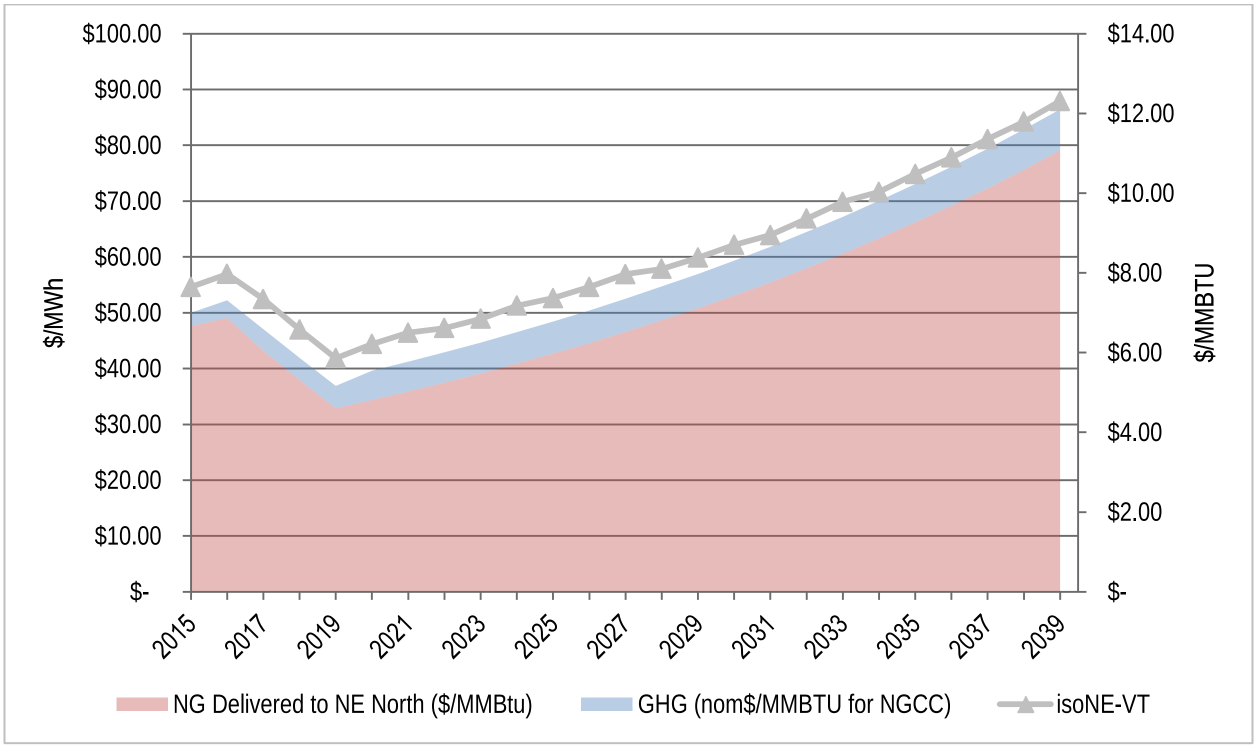


FIGURE 9: COMPARISON OF FORECASTED VERMONT AVERAGE ANNUAL ENERGY PRICES, NATURAL GAS PRICES AND CO_2 PRICES.[13] (NOMINAL $)

Finally, the following figure shows forecasted market heat rates based on Vermont zonal prices and delivered natural gas prices[14] for each of the three sensitivities. Market heat rates tend to be negatively correlated to natural gas prices[15], and these results reflect that trend. The high case also shows a sharp increase in forecasted market heat rate in 2020 when federal carbon pricing is assumed to go into effect.

---

13 Greenhouse Gas ("GHG") prices are expressed in $/MMBTU based on the emissions rate of an efficient natural gas combined cycle plant ("NGCC").

14 Prices reflect the Northern New England price.

15 Another assumption consistent with previous VEC IRPs.

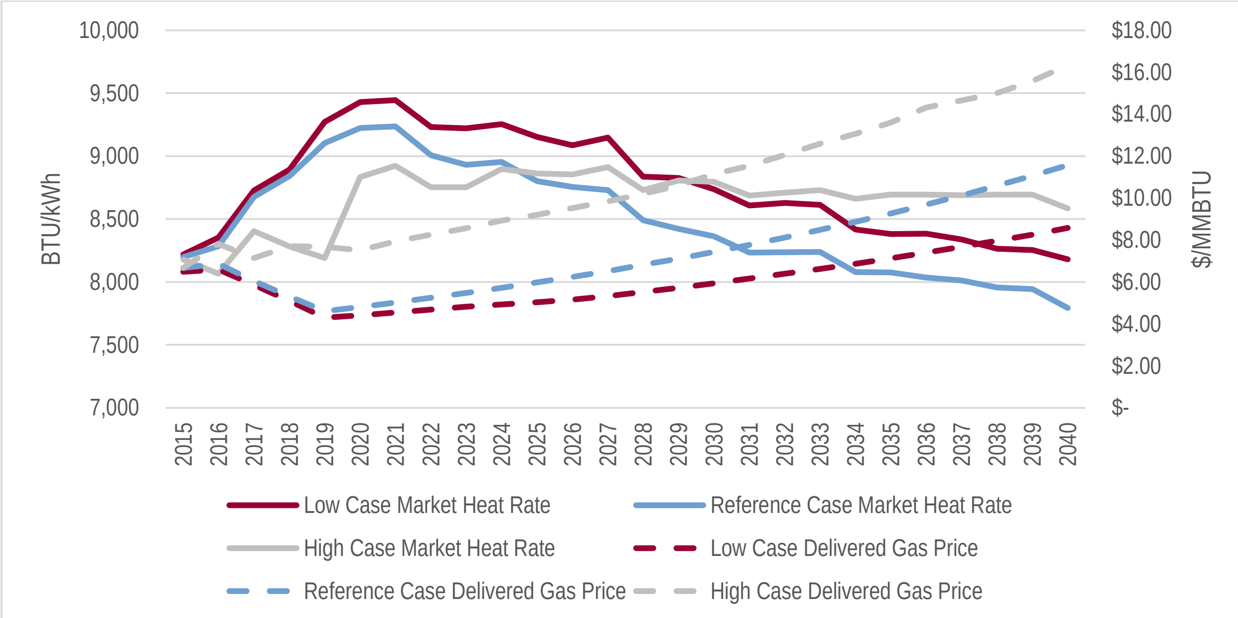


FIGURE 10: COMPARISON OF FORECASTED MARKET HEAT RATES AND DELIVERED NATURAL GAS PRICES. (GAS PRICES ARE IN NOMINAL $)

APPENDIX C

ISO-NE Forward Capacity Market Outlook memo dated March 17, 2015

APPENDIX D

VEC Power Supply Resources

APPENDIX E

Total System Energy Requirements and Committed Resources (MWh)

APPENDIX F
Tier 1 Requirements and Committed Resources (REC)

APPENDIX G
Tier 1 Requirements and Committed Resources (REC) – After Sale of High-Value REC

APPENDIX H
Tier 2 Requirements and Committed Resources (REC)

APPENDIX I

Forward Capacity Market Resources

APPENDIX J
Substation Data Sheets