2019 Load Forecast Report

REDACTED

April 30, 2019

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Table of Contents

List of Figures

Appendices

Appendix A: 2018 NS Power Forecast

Appendix B: Forecast Model Details

Appendix C: Forecast Comparison

Appendix D: Forecast Sensitivity

1.0 EXECUTIVE SUMMARY

In accordance with the Nova Scotia Wholesale Electricity and Renewable to Retail Market Rules, Nova Scotia Power Inc. (NS Power, the Company) is required to provide the Nova Scotia Utility and Review Board (UARB, Board) with its 10-year energy and demand forecast by the end of April each year for the 10-year period beginning in the following January (Load Forecast Report).

The 2019 Load Forecast provides an outlook on the energy and peak demand requirements of in-province customers for the period 2019 to 2029. As well, it describes the considerations, assumptions, and methodology used in the preparation of the forecast. The NS Power Load Forecast provides the basis for the planning and overall operating activities to serve the Company's customer load.

The load forecast is based on analyses of sales history, weather, end-use saturations and efficiencies, economic indicators, customer surveys, technological and demographic changes in the market and the price and availability of other energy sources.

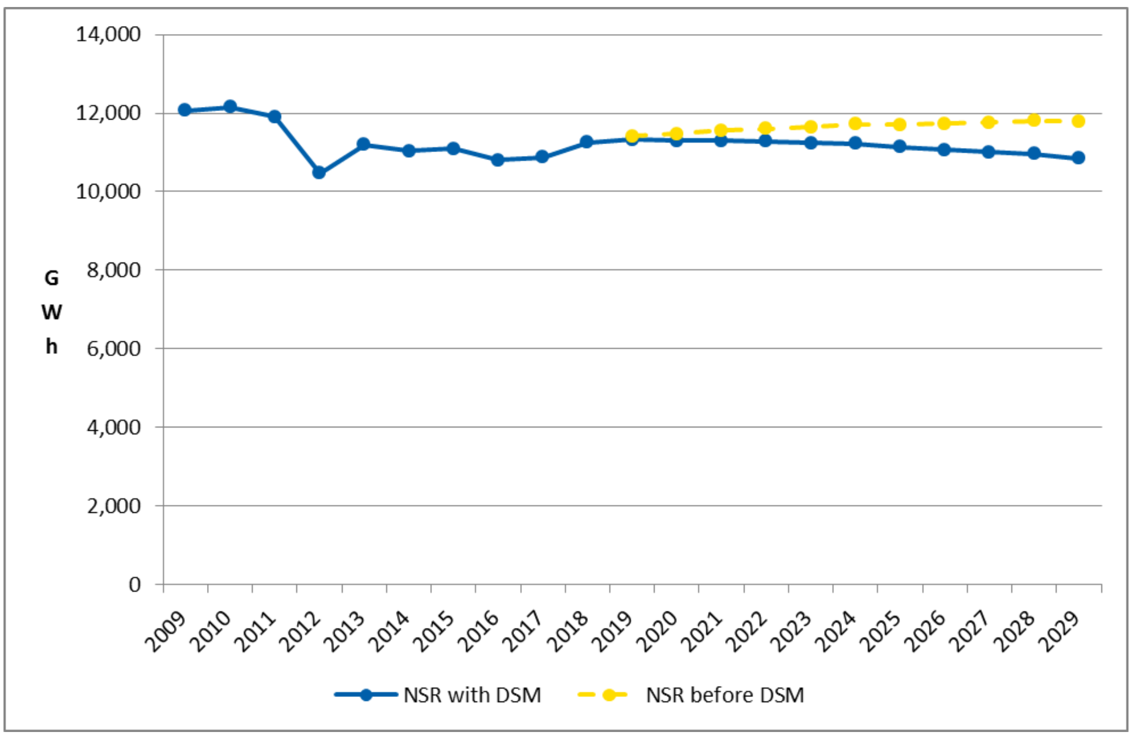
As with any forecast, there is a degree of uncertainty around actual future outcomes. In electricity forecasting, much of this uncertainty is due to the impact of variations in weather, energy efficiency program effectiveness, the health of the economy, changes in large customer loads, the number of electric appliances and end-use equipment installed, as well as the manner and degree to which they are used.

NS Power continues to use and refine Statistically Adjusted End-Use (SAE) models to forecast load for the residential and commercial rate classes. The SAE models explicitly incorporate end-use energy intensity projections into the load forecast. End-use energy forecasts derived from the residential and commercial SAE models are then combined with an econometric based industrial forecast and customer specific forecasts for NS

Power's large customers to develop an energy forecast for the province, also referred to as a Net System Requirement (NSR).

In general, the NSR is expected to grow slowly over the forecast period before the impact of DSM. Anticipated growth is expected to be driven by increased electric heating in the residential sector as well as industrial growth. These will be offset by Demand Side Management (DSM) initiatives and natural energy efficiency improvements outside of structured DSM programs, as well as increased behind-the-meter small scale solar installations. The net result of these inputs is an annual decline of 0.4 percent. Annual NSR is shown below in **Figure 1**.

Figure 1: Historical and Predicted Annual Net System Requirement



In addition to annual energy requirements, NS Power forecasts system peak demand. After accounting for the effects of DSM savings, system peak demand is expected to remain flat on average over the forecast period, as shown in **Figure 2**.

Figure 2: Historical and Predicted Annual System Peak

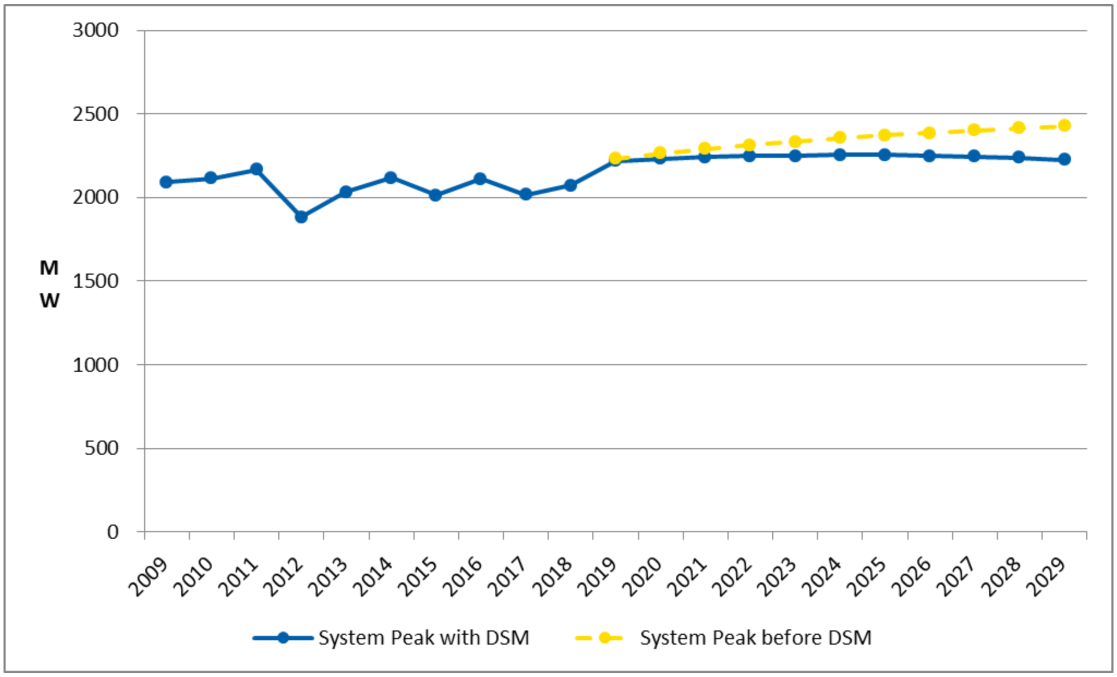


Figure 3, below, shows the changes to system load and system peak over the historic and forecast periods.

Figure 3: Historic and Forecast Net System Requirement and System Peak

Year	NSR (GWh)	Growth (%)	System Peak (MW)	Growth (%)
2009	12,073	-3.7%	2,092	-4.5%
2010	12,158	0.7%	2,114	1.0%
2011	11,907	-2.1%	2,168	2.5%
2012	10,475	-12.0%	1,882	-13.2%
2013	11,194	6.9%	2,033	8.0%
2014	11,037	-1.4%	2,118	4.2%
2015	11,099	0.6%	2,015	-4.9%
2016	10,809	-2.6%	2,111	4.8%
2017	10,873	0.6%	2,018	-4.4%
2018	11,250	3.5%	2,073	2.7%
2019	11,331	0.7%	2,221	7.2%
2020	11,300	-0.3%	2,234	0.6%
2021	11,303	0.0%	2,243	0.4%

2022	11,278	-0.2%	2,247	0.2%
2023	11,240	-0.3%	2,249	0.1%
2024	11,220	-0.2%	2,255	0.3%
2025	11,135	-0.8%	2,255	0.0%
2026	11,069	-0.6%	2,249	-0.2%
2027	11,005	-0.6%	2,244	-0.2%
2028	10,958	-0.4%	2,238	-0.3%
2029	10,844	-1.0%	2,227	-0.5%

2.0 INTRODUCTION

NS Power annually develops a forecast of energy sales and peak demand requirements to assess the effects of customer, demographic and economic factors on the future power system load and load shape. It is a foundational input to the overall planning, budgeting and operating activities of the Company. Produced in the winter of 2018-2019 and using information available at the time, this forecast covers the period of 2019-2029. Unless otherwise noted, reported average annual growth rates are for the 2019-2029 period.

In 2018, the Nova Scotia Utility and Review Board (UARB or Board) initiated a paper hearing process to review the 2018 Load Forecast Report, as it had for the 2017 Load Forecast Report.[1] Interventions were made by the Consumer Advocate (CA), the Small Business Advocate (SBA), the Industrial Group (IG), Port Hawkesbury Paper LP (PHP), EfficiencyOne (E1), and Heritage Gas Limited (Heritage). In addition, Board Counsel engaged Synapse Energy Economics (Synapse) to review and provide a report on NS Power's 2018 Load Forecast Report.

Following response to Information Requests (IRs), filing of evidence by intervenors and Board Counsel and Reply Evidence by NS Power, the Board issued a decision respecting NS Power's 2018 Load Forecast Report. The Board recognized the progress and refinements that have been made in developing NS Power's load forecast in recent years and directed areas for continued improvement. In particular, the Board stated as follows:

[1] M08670 - Nova Scotia Power Inc. - 10 Year Energy and Demand Forecast - 2018 Load Forecast - P-194.

> As noted in prior years, the Board recognizes the progress and refinements that have been made in developing recent load forecast reports. The fundamental importance of the load forecast in relation to NS Power's overall operations, including generation requirements, capital program, fuel forecasts, and customer rates, makes it essential that the input assumptions and resulting forecast present a highly accurate projection of future requirements. Variations in growth rates presented in recent annual reports highlight the lack of consistency in future projections and suggest that further refinements and detailed explanations are still needed to ensure that all relevant factors are fully considered in the analysis.
>
> One specific issue that seems to warrant greater analysis is the adjustment factor applied to DSM savings, both energy and peak demand. Both the CA and the SBA have raised this concern. Although not raised in this year's review, Synapse also raised that concern during its review of the 2017 Load Forecast. In its memorandum dated September 26, 2017, Synapse stated:
>
> > We note that the DSM energy load adjustments based on statistical calculations are roughly of the right order of magnitude, although some statistical measures are weak. We also raise the issue that if the DSM targets increase in the future, then an adjustment factor based on the historic DSM levels needs to be appropriately modified when applied to different future savings levels. For example, if the adjustment factor is based on historic DSM levels of 1 percent and the targets are doubled to 2 percent, the DSM adjustment reduction should be less for these greater savings levels. All this needs to be looked at carefully going forward.
>
> In an effort to resolve these concerns prior to filing the 2019 Load Forecast report, NS Power is directed to meet with stakeholders to address this DSM adjustment issue. Also, NS Power is directed to follow through with all of the enhancements identified in this proceeding.
>
> The Board looks forward to NS Power's filing of the 2019 Load Forecast report by April 30, 2019.[2]

Synapse's evidence provided the following comments and recommendations:

[2] M08670 - Nova Scotia Power Inc. - 10 Year Energy and Demand Forecast - 2018 Load Forecast - P-194, UARB Decision, October 26, 2018, pages 4-5.

> Overall the forecast is comprehensive and contains all the important elements. NSPI's assumptions seem reasonable, although more supporting information could be provided in some cases. Yet, while the key pieces are there, it is not always clear how they fit together to produce the final forecast.
>
> For example, in the residential sector there are the end-use intensities as presented in Figures 8 and 14 and the various adjustments and add-ins presented in Figures 9-13. NSPI does not describe the relationship between these components as they relate to the final forecast. Such a description would help in understanding the forecast. We have suggested a possible approach in our review of the residential forecast, but we encourage NSPI to consider alternative approaches.
>
> Some recommendations are:
>
> 1. The forecast report should identify and explain the differences between the most recent historical year values and those of the first forecast year. For example, how much is weather related and how much is associated with the model itself.
>
> 2. Provide a step-by-step explanation, following our residential example, of how the various components of the forecast fit together to produce the final result.
>
> 3. Further investigation and reporting of the precise impacts of equipment saturation and new technology in future forecasts should better identify the changes that are taking place.
>
> 4. Further refinement of the peak forecast to better identify system needs and measures that can be taken control and moderate them.
>
> 5. At several locations throughout this report (pages 5, 6, 7, 8, 11, and 12) we have asked for NSPI to provide further explanations of some aspects of the forecast. These explanations should be provided in NSPI's Reply materials if possible. Otherwise they should be included in the next forecast report.

In accordance with the Board's direction, NS Power has revised and enhanced the 2019 Load Forecast Report in the following manner:

- An explanation of the difference between the most recent historic year and the first forecast year for NSR and peak is provided in sections 9 and 10. (Synapse recommendation 1)

- A step by step explanation of the impact of various components of the forecast and clarification of the various components provided in sections 5 and 6, and in Appendix B. (Synapse recommendation 2)
- Analysis of various end uses is ongoing, they are discussed in detail in section 4. (Synapse recommendation 3)
- Analysis of the components of the peak is ongoing, and is discussed in detail in section 10. (Synapse recommendation 4)
- Further explanation of the large customer impacts and assumptions are included in sections 6 and 7. (Synapse recommendation 5 items that were not already addressed in NS Power's reply evidence).

Summary of Stakeholder Consultations

As noted above, in its decision on the 2018 Load Forecast Report, the UARB directed NS Power to meet with stakeholders prior to the filing of the 2019 Load Forecast Report to discuss the treatment of DSM in the load forecast. Below is the summary of relevant stakeholder consultations undertaken by NS Power in advance of completing this year's Load Forecast Report.

On December 5, 2018, members of the Load Forecast team held a WebEx meeting with David White and Jamie Hall of Synapse to discuss the issue of treatment of DSM in the forecast and enhancements to be undertaken as a result of the Board's decision on the 2018 Load Forecast Report. NS Power reviewed Synapse's recommendations as filed in its Evidence, and discussed its intended approach to address those recommendations in the 2019 Load Forecast. NS Power understood from this discussion that Synapse was generally comfortable with NS Power's approach to its recommendations and with the current method of using DSM as an input to the regression model and applying the resulting coefficient to future DSM, provided that future levels of DSM are similar to historic levels of DSM.

On April 9, 2019, NS Power held a WebEx meeting with representatives from Synapse, E1, the SBA, the CA, and counsel for the IG to discuss the treatment of DSM in the forecast and to respond to any questions. At the conclusion of the meeting, NS Power offered the opportunity for any of the participants, and/or their consultants if they wished, on the phone call to follow up with NS Power with any questions or to schedule a further discussion.

The Small Business Advocate confirmed that he would like a follow up discussion with his consultant. On April 10, 2019 NS Power held a follow-up meeting with representatives from Daymark Energy Advisors, consultant for the Small Business Advocate. The discussion focused on clarifications as to how DSM is accounted for in the forecast, and the outcome was a recommendation from Daymark to update the explanation in the load forecast report. Specifically, the requested clarifications were as follows:

- Generally try to clarify the explanation of the treatment of DSM
- Explain that the adjustment is a way of accounting for DSM that is captured elsewhere in the forecast rather than an adjustment or assumption of the effectiveness of future DSM activities
- Explain that the methodology employed is not specific to DSM but could also be used to account for any variable in the forecast provided they have similar characteristics (historical trend, potentially included in other inputs, and some information about future impact).

NS Power agreed with Daymark's recommendation and has incorporated it into the 2019 Load Forecast Report. (Please refer to the section on Demand Side Management).

Continuing Forecast Improvement Activities

In 2019 NS Power engaged Itron Inc. (Itron) for a review of the load forecast. The review is in progress and recommendations will be implemented in the 2020 load forecast. Preliminary findings show that the forecast would be improved if the heat pump and water heater end uses were modeled within the intensities/regression. Work is also under way to try and develop an end-use based peak model using end-use component peak contributions (rather than current method of using the end use components from the energy model) that fits historic data as well as the current peak model.

A large scale residential customer survey was completed by NS Power in late 2018, and included several questions on end uses within residential homes. Findings from that survey are still being analyzed and will be used to inform the 2020 load forecast.

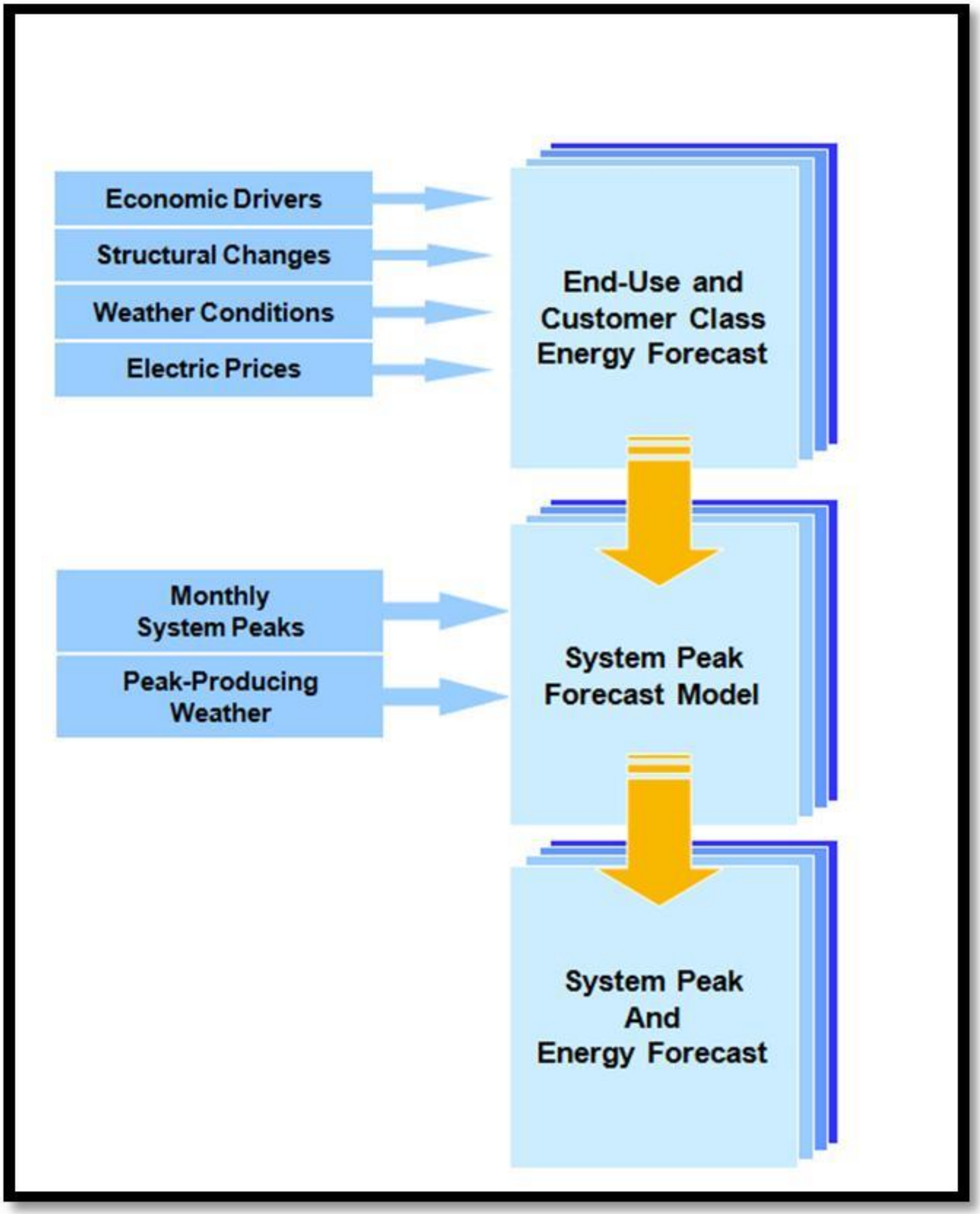
3.0 FORECASTING APPROACH

NS Power continues to use a set of SAE models for the residential and commercial rate classes, an econometric model for the small and medium industrial classes, and uses customer surveys and historical data for the large customer classes.

The SAE model is a hybrid of the econometric and end-use methodologies, incorporating economic and end-use forecast variables into one model. An end-use model is a bottom-up approach that estimates the energy consumption of a customer group by summing the energy usage of all the appliances and equipment used by those customers. End-use forecasts are driven by trends in appliance usage and efficiency trends for that equipment. An econometric model describes the historical relationship between electricity consumption and independent economic indicators, onto provincial economic forecasts to forecast future electricity sales.

The SAE model variables explicitly incorporate end-use saturation and efficiency projections, as well as changes in population, economic conditions, price, and weather. End-use efficiency projections include the expected impact of new standards and naturally-occurring efficiency gains. In the long-term, both economics and structural changes drive energy and demand growth. Structural changes are captured in the residential forecast model through the SAE model specifications. **Figure 4** shows the general forecast approach used in the SAE models.

Figure 4: Forecast Approach



4.0 DISCUSSION OF MAJOR INPUTS

Historical Class Sales and Energy Data

The load forecast is developed using NS Power "billed" sales rather than "accrued" sales. Billed sales refer to the amount of energy billed to customers in a given time period such as a calendar month or a year. Accrued sales recognize the amount of energy actually generated and consumed during that specific time period. Due to the periodic nature and delays inherent in any meter reading and billing process, billed sales will vary from accrued sales.

Historical monthly billed sales are the primary dependent variables in the linear regression models used in developing the forecast. For the 2019 forecast, the residential and commercial energy forecasts are estimated using monthly billed sales data for the period January 2009 to December 2018. The industrial forecasts use the period January 2005 to December 2018 to improve the model fit.

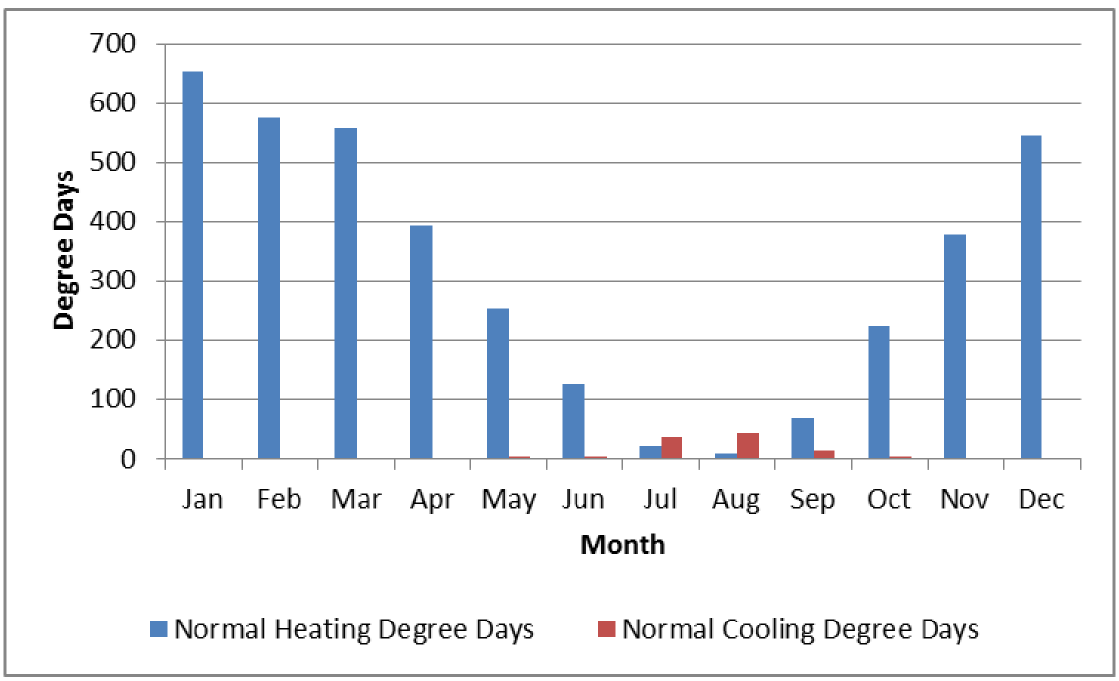
For the peak demand forecast, historical system monthly energy and monthly demand data is derived from system hourly load data for the period January 2009 to December 2018. Large customer peak demand is forecast separately.

The Renewable to Retail (RtR) electricity market was established in Nova Scotia in 2016, to enable independent licensed retailers to sell renewable energy directly to NS Power's retail customers. At present, there is no indication of forthcoming market entrants so no effect on NS Power load is forecast. The two fundamental principles under the RtR legislative regime are that customers of NS Power are not to be negatively affected if some retail customers choose to purchase electricity in the RtR market, and that retail suppliers and their customers are to be responsible for all costs related to the provision of the renewable low-impact electricity in this new market. As such, from a net system requirement perspective, NS Power must continue to plan to serve this load. Any new information on RtR uptake will be incorporated into future annual reports, if appropriate.

Weather Data

Weather conditions have the largest single impact on month-to-month variation in electric sales. The impacts of temperature are captured by monthly heating degree-day (HDD) and cooling degree-day (CDD) variables. HDDs are a common measure of heating requirement based on the degree departure between the daily mean temperature and a given reference temperature. The reference temperature of 18°C is used for these calculations. 18°C is assumed to be a comfortable room temperature below which space heating is generally required and above which space cooling is also required. Monthly HDD and CDD are calculated from Environment Canada hourly temperature information for the Shearwater Airport. Normal monthly HDD and CDD, seen in **Figure 5**, are calculated using 10 years of actual weather data covering the period January 2009 to December 2018. The average temperature continues to show a warming trend – the 30-year average annual HDD is 3,964, while the 10-year average is 3,807.

Figure 5: Normal Monthly HDDs and CDDs



Economic Information

Economic and other provincial statistics used in the load forecast are from the Conference Board of Canada's *Economic Outlook*. This forecast provides a provincial perspective and considers specific Nova Scotia projects and demographics.

In the SAE framework, economic data drives the utilization of the end-use stock over the forecast period. For 2019, the residential model continues to use both the retail sales (RRTS) and household income (RPDI) variables, weighted at 50/50. The retail sales variable grows at a slower rate in the near term compared to the growth in the household income variable, so weighting the two variables produces a more modest increase related to economics. New housing completions for both single family and multi-unit buildings are used in generating residential customer forecasts. In the non-residential models, non-manufacturing Gross Domestic Product (NMANGDP) and non-manufacturing employment (NMANEMP) continue to be used. In the Industrial sector, rate classes are forecast using an Econometric framework, with manufacturing GDP (MANGDP) and manufacturing employment (MANEMP) used as economic variables. The regression timescale for the industrial models was increased from 10 years to 14 years to help improve the relevance of the economic variable in the small industrial model (the model produces a high P-value on the economic variable using a 10-year timeframe) and to help improve the fit in the medium industrial model (adjusted R squared of 0.445 for 10-year vs 0.832 for 14 year). **Figures 6, 7,** and **8** summarize the economic drivers, on an annual basis, used in the 2019 forecast. For financial measures, the variables have been adjusted to constant dollars, eliminating the inflation effects from the series.

Figure 6: Residential Economic Drivers

Year	New Construction	% Change	RPDI (mil $02)	% Change	RRTS (mil $02)	% Change
2009	3,836		18,924		10,460	
2010	3,960	3.3%	19,460	2.8%	10,699	2.3%
2011	3,662	-7.5%	19,217	-1.2%	10,674	-0.2%
2012	3,958	8.1%	19,416	1.0%	10,562	-1.0%
2013	4,670	18.0%	19,920	2.6%	10,776	2.0%
2014	3,259	-30.2%	20,022	0.5%	10,886	1.0%
2015	3,212	-1.4%	20,295	1.4%	10,861	-0.2%
2016	3,406	6.0%	20,670	1.9%	11,239	3.5%
2017	3,707	8.8%	21,385	3.5%	11,981	6.6%
2018	4,237	14.3%	21,336	-0.2%	11,970	-0.1%
2019	3,541	-16.4%	21,305	-0.1%	11,984	0.1%
2020	3,036	-14.3%	21,371	0.3%	12,003	0.2%
2021	2,913	-4.0%	21,494	0.6%	12,054	0.4%
2022	2,814	-3.4%	21,608	0.5%	12,101	0.4%
2023	2,659	-5.5%	21,763	0.7%	12,175	0.6%
2024	2,394	-10.0%	21,853	0.4%	12,244	0.6%
2025	2,200	-8.1%	21,965	0.5%	12,307	0.5%
2026	2,103	-4.4%	22,073	0.5%	12,379	0.6%
2027	1,994	-5.2%	22,189	0.5%	12,456	0.6%
2028	1,888	-5.3%	22,311	0.6%	12,533	0.6%
2029	1,781	-5.7%	22,440	0.6%	12,613	0.6%
09-18		1.1%		1.3%		1.5%
19-29		-6.6%		0.5%		0.5%

Figure 7: Commercial Economic Drivers

Year	NMANGDP (mil $07)	% Change	NMANEMP (thou)	% Change
2009	29,018		414	
2010	29,625	2.1%	419	1.1%
2011	29,664	0.1%	420	0.3%
2012	29,465	-0.7%	425	1.2%
2013	29,455	0.0%	422	-0.6%
2014	29,891	1.5%	418	-1.0%
2015	30,224	1.1%	419	0.4%
2016	30,496	0.9%	417	-0.5%
2017	30,816	1.0%	418	0.3%
2018	31,077	0.8%	424	1.3%
2019	31,393	1.0%	426	0.6%
2020	31,677	0.9%	428	0.3%
2021	31,919	0.8%	429	0.2%
2022	32,210	0.9%	429	0.1%
2023	32,501	0.9%	430	0.3%
2024	32,673	0.5%	430	-0.2%
2025	32,869	0.6%	428	-0.3%
2026	33,156	0.9%	427	-0.4%
2027	33,475	1.0%	425	-0.4%
2028	33,834	1.1%	423	-0.4%
2029	34,174	1.0%	421	-0.4%
09-18		0.8%		0.3%
19-29		0.9%		-0.1%

Figure 8: Industrial Economic Drivers

Year	MANGDP (mil $07)	% Change	MANEMP (thou)	% Change
2009	2,491		35	
2010	2,705	8.6%	33	-7.7%
2011	2,763	2.1%	33	1.1%
2012	2,651	-4.1%	33	-0.8%
2013	2,564	-3.3%	31	-6.0%
2014	2,455	-4.3%	30	-2.5%
2015	2,499	1.8%	29	-4.4%
2016	2,570	2.8%	29	1.2%
2017	2,644	2.9%	31	5.9%
2018	2,820	6.7%	31	2.1%
2019	2,840	0.7%	31	-0.2%
2020	2,895	2.0%	31	-0.3%
2021	2,997	3.5%	31	0.5%
2022	3,052	1.8%	31	-0.8%
2023	3,090	1.2%	31	-0.6%
2024	3,127	1.2%	31	-1.0%
2025	3,151	0.8%	30	-1.5%
2026	3,190	1.2%	30	-1.5%
2027	3,237	1.5%	29	-1.3%
2028	3,285	1.5%	29	-1.4%
2029	3,347	1.9%	29	-0.9%
09-18		1.4%		-1.3%
19-29		1.7%		-0.9%

End-Use Intensity Trends

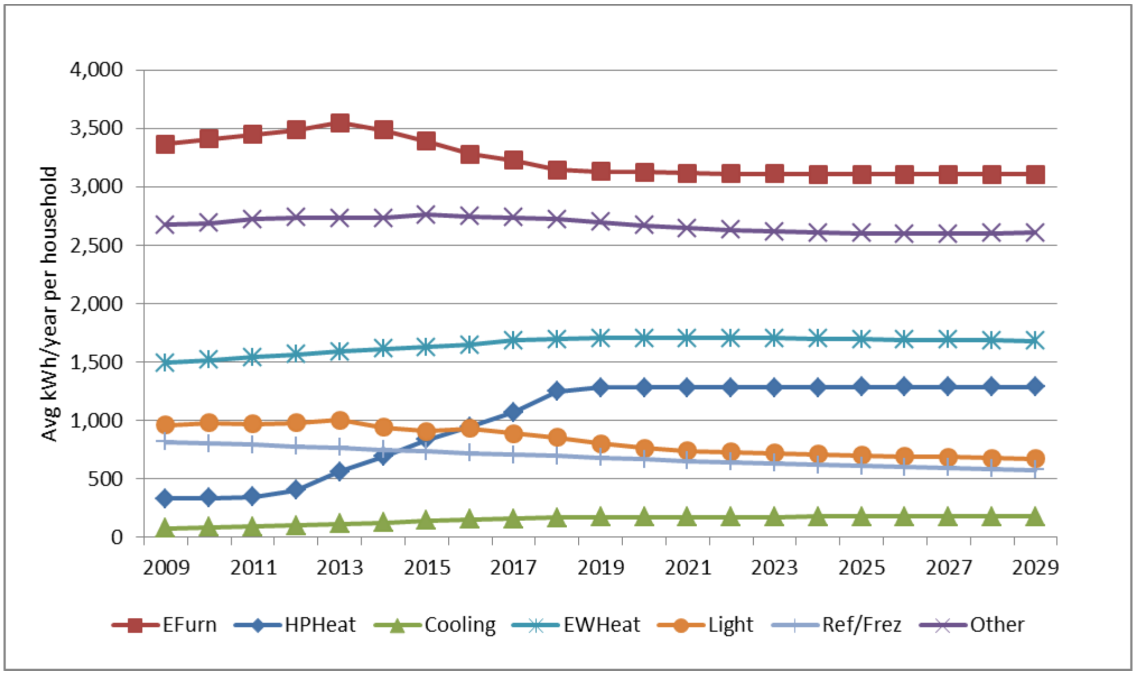
In addition to the economic variables listed above, the SAE model also uses end-use data, in the form of saturations and efficiencies, from Natural Resources Canada (NRCan) and the US Energy Information Agency (EIA). NRCan data for the Residential sector is specific to Nova Scotia, while NRCan data for the Commercial sector is for Atlantic Canada. EIA data is for New England and is calibrated to fit existing Nova Scotia data.

The approach to developing the individual end-use intensities is to start with historical NRCan end-use saturation trends and use year-over-year changes in saturation projections and end-use efficiency estimates for the New England Census Division. The resulting end-use intensity trend is then compared with end-use energy estimates from NRCan. If necessary, it is then adjusted so that the resulting intensities are consistent with NRCan reported end-use consumption and actual average use derived from NS Power billing data. The forecast for the end use intensities is shown in **Figure 9** below. The end uses listed include:

- EFurn: electric baseboard and electric forced air furnaces and secondary electric heaters
- HPHeat: heat pump electric heat
- Cooling: room and central air conditioners, as well as heat pump cooling
- EWHeat: electric water heaters
- Lights: indoor lighting
- Ref/Frez: primary and secondary refrigerators and deep freezes
- Other: all other major appliances (stoves, dishwashers, clothes washers and dryers, televisions) as well as smaller appliances such as computers, dehumidifiers, microwaves, etc.

In the case of end uses where there is little historical activity or where future behaviour is expected to vary significantly from the existing data set due to targeted programs, these are modeled outside of the average use intensities. This was done for heat pumps and hot water heaters, as well as electric vehicles (EV) and rooftop solar generation (PV) as they have little historic data. This method also allows these items to be tracked more directly to help fine-tune future forecasts. For 2019, water heater estimates and PV estimates have been updated based on recent analysis. **Figure 8** below does not include the external forecast inputs listed above; these inputs are discussed individually further on in this report. This figure represents the intensities that are inputs to the XHeat, XCool and XOther variables, they are not direct inputs to the forecast. The relative contribution of each will change based on the coefficient that is applied to the XHeat, XCool and XOther variables. A summary of the impact of the different variables post regression is included in section 5, while a complete breakdown of each element before and after the regression is provided in **Appendix B**.

Figure 9: Historical and Projected Residential End-Use Intensities Before Add-ins



Heat Pumps

Heat pump usage is on the rise as heat pumps are an efficient way for customers to heat and cool a building. Converting to a heat pump can help customers reduce their energy costs by up to 62 percent, and carbon emissions by up to 50 percent. At the end of 2018, the market penetration for heat pumps as both a primary and secondary source of heat was estimated at 25 percent. Compared to the 2018 load forecast, estimated installations are expected to be higher in the non-electric heat segment (65 percent vs 61 percent in 2018). This is due to higher than expected residential electricity sales in 2018 which is assumed to be mainly a result of more heat pump conversions in the non-electric heat segment than previously forecast. The market penetration is held constant in the forecast and the estimates for conversions are added in outside of the model. **Figure 10** shows the forecast number of installs and is broken down by existing heating types (non-electric and electric). New customers are not included in these numbers as they are already captured by the new customer forecast. The installs are in-year totals and the corresponding load and peak values have been profiled annually to account for timing of installations.

Figure 10: Heat Pump Contribution to Energy and Peak Forecasts (cumulative)

Year	Total New Installs	% Non-Electric	% Electric	Load (GWh)	Peak (MW)
2019	15,180	65%	35%	34	17
2020	28,173	65%	35%	55	31
2021	41,329	65%	35%	76	46
2022	54,540	65%	35%	97	60
2023	67,784	65%	35%	118	75
2024	81,078	65%	35%	135	89
2025	90,442	65%	35%	147	98
2026	94,957	65%	35%	153	103
2027	99,101	65%	35%	158	107
2028	102,977	65%	35%	163	111
2029	105,983	65%	35%	167	111

The resulting change to load per install was based on an internal study conducted in 2015 that was similar to the results from a 2014 study carried out by Northeast Energy Efficiency Partnerships.[3] The estimated impacts for different types of heat pumps are shown in **Figure 11**. Most of the targeted installs are ductless units.

[3] http://www.neep.org/northeastmid-atlantic-air-source-heat-pump-market-strategies-report-january-2014

Figure 11: Estimated Heat Pump Impacts per Household

	Ductless		Ducted	
	Change in Energy (annual kWh)	**Change in Peak (kW)**	**Change in Energy (annual kWh)**	**Change in Peak (kW)**
Non-Electric Heat Install	+3700	+1.3	+7000	+5
Electric Heat Install	-3000	0	-7000	-1

<u>Water Heaters</u>

It is expected that some customers who convert their oil heating systems to heat pumps will also convert their hot water supply to electric hot water tanks due to the annual operating savings. Compared to the 2018 load forecast, expected growth from water heaters is much lower due to revised estimates of potential market penetration. Water heater load is estimated to be 3,200 kWh per tank (decreasing over time with increasing efficiency) based on a 10-year average of NRCan data for hot water heaters in Nova Scotia (2005-2014). The corresponding peak contribution is estimated to be 0.57 kW per tank, also decreasing over time, based on internal research on metered hot water tanks (the average tank is around 3kW and the coincident system peak from water heaters shows that approximately one in five water heaters is on). In the case of hot water heaters, the peak impact can potentially be mitigated through AMI enabled technology such as direct load control, the impact of which is currently being evaluated. The annual impact is shown in **Figure 12**. Note that like heat pumps, the impact of the additions is profiled throughout the year.

Figure 12: Water Heater Contribution to Energy and Peak Forecasts (cumulative)

Year	Total New Installs	Load (GWh)	Peak (MW)
2019	275	0	0
2020	804	2	0
2021	1,333	3	0
2022	1,861	5	1
2023	2,388	7	1
2024	2,916	8	1
2025	3,442	10	2
2026	3,968	12	2
2027	4,492	13	2
2028	4,492	14	3
2029	4,492	14	3

Electric Vehicles (EVs)

Estimates for EV penetration are similar to those used in the 2018 load forecast. According to Electric Mobility Canada, at the end of 2018 there were approximately 223 EVs in Nova Scotia, and there are currently no incentives for purchasing an EV in Nova Scotia. Although the federal government recently announced a national incentive program, no details have been provided and it has not been taken into account for this load forecast. The current EV forecast is a high-level estimate that considers future vehicle availability, vehicle battery range, Electric Mobility Canada's forecast growth of the Canadian EV market, and several global forecasts. Compared to Electric Mobility Canada's forecast, a more conservative projection has been developed for Nova Scotia to account for local demographics and current limitations on purchase and infrastructure incentives. This forecast has EVs making up approximately 7 percent of total vehicle stock (around 46,000 vehicles) by 2029, with approximately 70 percent being battery EVs and 30 percent being plug in hybrids. A report prepared for the New York State

Energy Research and Development Authority[4] provides a range of per vehicle peak demand of 0.3 kW (where an off-peak charging incentive exists) to 1.0 kW (for no incentive) in the evening (hours of 1700-1800). The 0.6 kW value assumes there will be some mechanism in place (likely rate based) to discourage charging on peak. This value corresponds to around 10-15 percent of vehicles charging on peak. Although there is no mechanism in place at present, the impact to peak is not forecast to be significant until 2024 – 2026. In **Figure 13** the estimated energy and peak impacts are listed, along with potential peak impact without mitigation measures, which assumes an average of 1.3 kW/vehicle, or around 20-30 percent charging on peak depending on the mix of vehicle and charger types. NS Power is currently looking to obtain data sets that will help in validating peak impacts of residential EV charging (for example from the Amherst smart grid project announced in January).

Figure 13: EV Impact to Energy and Peak Forecasts (cumulative)

Year	New EVs	Load (GWh)	Peak @ 0.6kW/vehicle (MW)	Peak @ 1.3kW/vehicle (MW)
2019	195	1	0	0
2020	567	2	0	1
2021	1,272	4	1	2
2022	2,539	8	2	3
2023	4,743	15	3	6
2024	8,464	26	5	10
2025	14,540	45	9	18
2026	21,919	69	14	28
2027	29,298	94	19	38
2028	36,677	118	24	48
2029	45,531	147	30	59

[4] NYSERDA. 2015. "Electricity Pricing Strategies to Reduce Grid Impacts from Plug-in Electric Vehicle Charging in New York State," NYSERDA Report 15-17. Prepared by M.J. Bradley & Associates LLC. nyserda.ny.gov/about/publications

Solar Generation (PV)

Solar generation consists of two main types – distributed small-scale solar (mainly rooftop) that falls under NS Power's net metering program and small to large-scale generation that is fed directly onto the grid via power purchase agreements. In the load forecast, only the former is considered, as it serves as a reduction in load mainly in the residential class. As of 2018 there were 532 residential solar installations and 49 installations in all other customer classes in the net metering program. As of 2018, the average installed capacity is approximately 6.3kW for residential customers and 16.8kW for non-residential, and total annual net metering solar generation is estimated at 5.3 GWh based on contractor estimates using a capacity factor of around 14 percent, which is higher than the capacity factor of 12-12.5 percent estimated by NRCan's "Photovoltaic Potential and Insolation Dataset" for Nova Scotia. The number of solar installations is expected to increase in the coming years as a result of initiatives such as Property Assessed Clean Energy Programs (e.g. Solar City in Halifax) as well as the provincial SolarHomes rebate of $1/W of installed capacity. The number of new residential installations in the forecast has been updated based on a study by Dunsky for the Canadian Solar Industries Association[5]. This study modeled the uptake of solar generation between 2019 and 2025 based on several possible scenarios – the scenario used for this forecast is "Maintain Current Market Activity", which assumes the SolarHomes rebate continues for several years into 2023. Based on that scenario, the overall number of installs is reduced from previous forecasts, but the average installed capacity is estimated to be 8 kW, with a total of 42 MW added by 2025 in the residential sector and 170 MW added by 2030. The 2019 load forecast also includes an assumption for commercial installations based on actual data for 2018, which indicates non-residential installs accounting for approximately 20 percent of total installed capacity.

[5] Nova Scotia Residential Solar Market Outlook and Labour Force Study Final Report - April 2019 prepared by Dunsky Energy Consulting.
https://www.cansia.ca/uploads/7/2/5/1/72513707/cansia_nova_scotia_residential_solar_market_outlook_and_labor_force_study_-_final_report__2019-04-09_.pdf

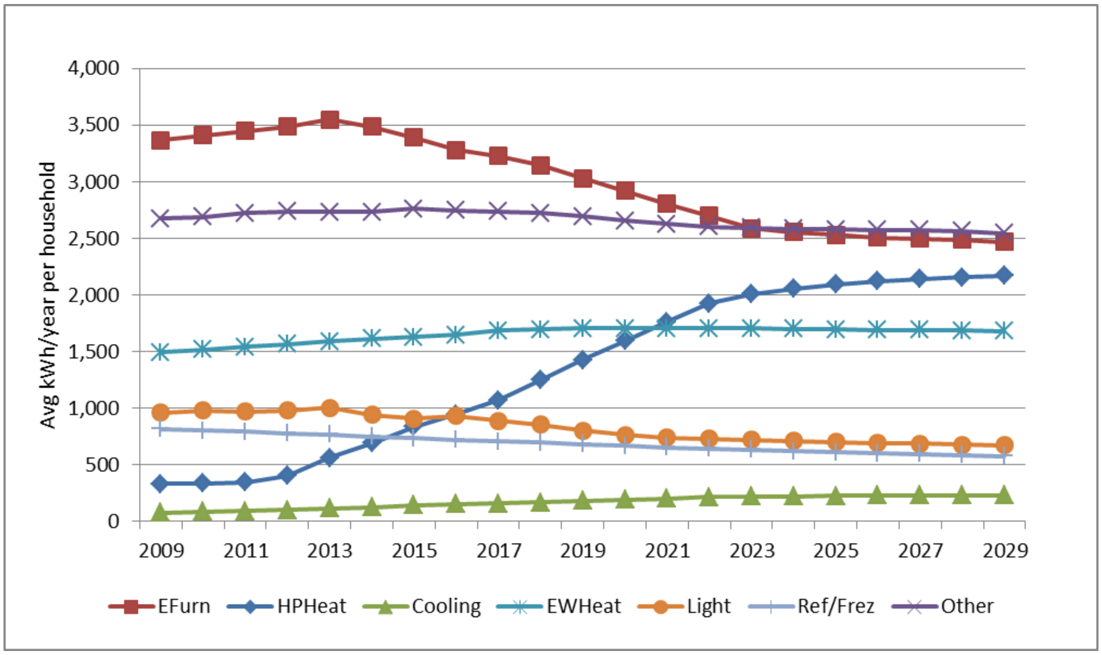
The overall impact is shown in **Figure 14**. Energy amounts are forecast based on a capacity factor of 12.5 percent as used in the Dunsky study. There is no anticipated impact to peak as generation occurs at times non-coincident with NS Power's system peak (winter evenings). This also assumes there is no significant amount of combined solar/battery storage. The estimated number of installs for 2019 is significantly higher than 2018 but is in line with the number of recent net metering applications received by NS Power. This increase is mainly related to the SolarHomes rebate on solar installations.

Figure 14: PV Impact to Energy (cumulative)

Year	Total New Installs	Load (GWh)	Peak (MW)
2019	483	-5	0
2020	966	-10	0
2021	1,476	-15	0
2022	2,037	-20	0
2023	2,651	-27	0
2024	3,839	-39	0
2025	5,537	-56	0
2026	8,019	-81	0
2027	10,435	-105	0
2028	13,579	-137	0
2029	17,670	-178	0

Figure 15 shows an estimate of the resulting end use intensities with these forecasts included. PV and EV are included in the "Other" category.

Figure 15: Residential End-Use Intensities Including Estimated Add-ins



The intensity trends are similar to those in the 2018 load forecast and show a decreasing trend overall. Electric heating is expected to show a small increase over the forecast period with heat pumps displacing both baseboard electric and oil heat due to the annual savings from heat pump efficiency. Heat pumps also drive cooling intensity up over time but not during periods of peak demand. Water heat is expected to remain stable over the forecast period as increased penetration is offset by increased efficiency. Lighting and refrigerators/freezers show a slow decline related to natural increases in efficiency, and increases in the "Other" category (which includes EVs) are now expected to be offset by PV generation.

The end use intensities for the commercial models are done on a per square metre basis, rather than per customer. The forecast for the end use intensities are set out in **Figure 16 and 17** below. The end uses listed include:

- Heat: electric heating
- Cool: air conditioning

- Vent: ventilation
- EWHeat: electric water heaters
- Cooking: electric stoves
- Refrig: refrigerators
- Light: indoor and outdoor lighting
- Office: computers and printers
- Misc: other loads including motors, servers, escalators, medical equipment, etc.

Figure 16: Historical and Projected Small General Commercial End-Use Intensity (kWh/m^2)

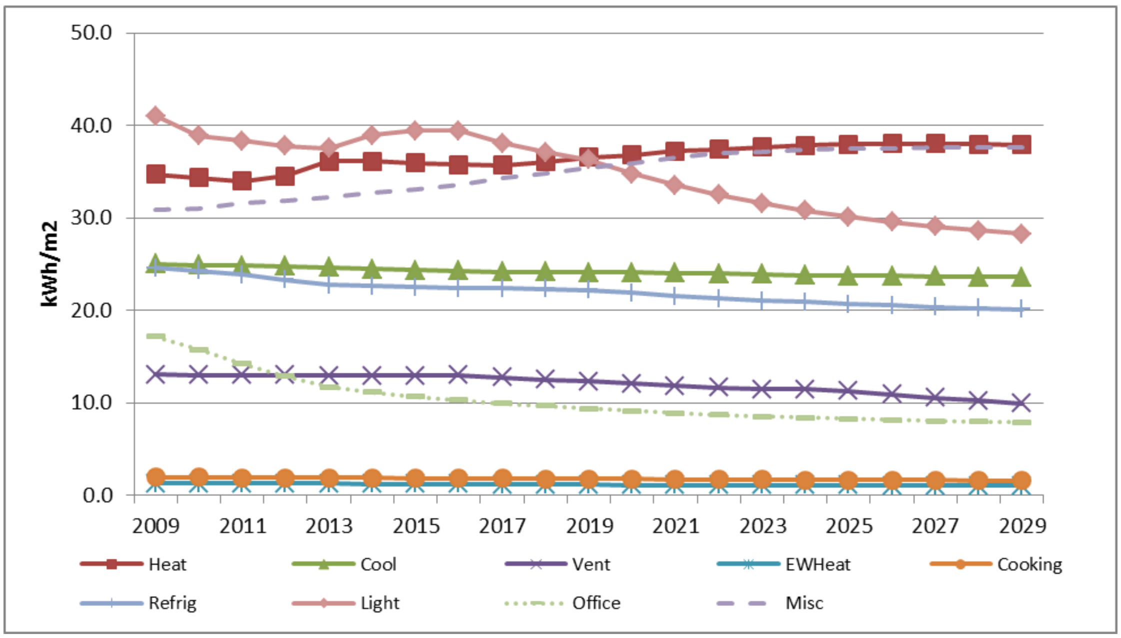
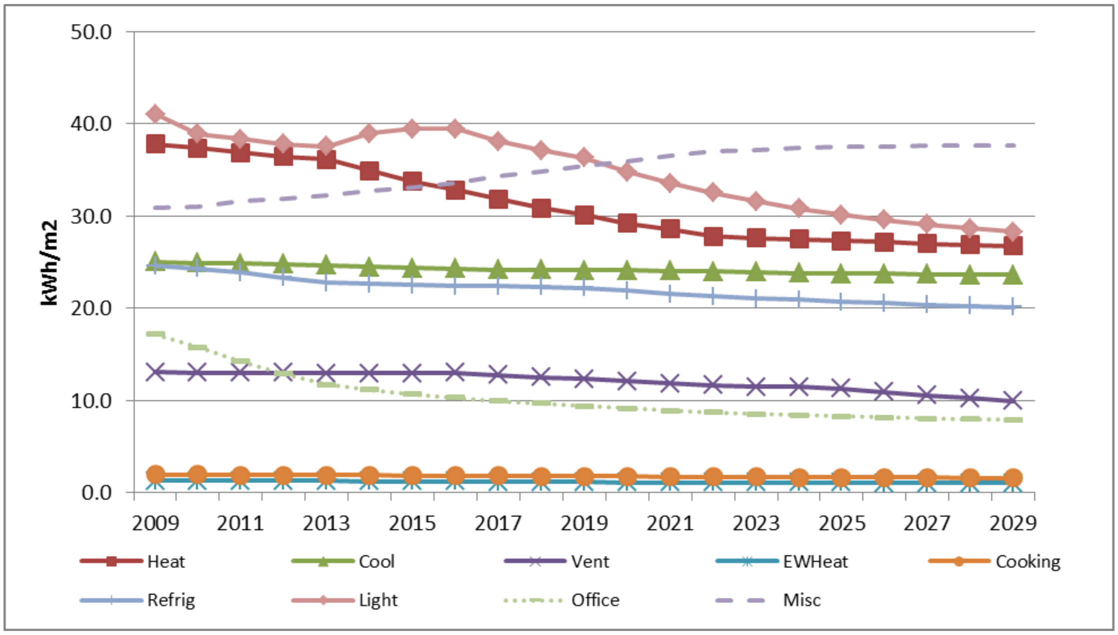


Figure 17: Historical and Projected General Commercial End-Use Intensity (kWh/m²)



For the 2019 forecast, data from the EIA 2018 Annual Energy Outlook uses the same baseline data (2012 Commercial Building Energy Consumption Survey) as the 2018 forecast. The updated historic NRCan data for the commercial class has changed compared to 2018, adjusting overall base year intensity upward from 148 kWh/m^2 in the 2018 forecast to 181 kWh/m^2 in the 2019 forecast. Although all end uses were impacted, the major change was in the heating and lighting intensities. Forecast trends remain the same with an overall declining trend in most categories and an increasing trend in the miscellaneous category.

Commercial and Industrial Programs

Like the residential sector, the commercial and industrial sectors are projected to see targeted growth as a result of electrification programs designed to reduce customers' annual energy usage and lower their carbon emissions. These programs involve converting heating loads to electricity (mainly from oil), accelerating the uptake of electric cooling technologies and looking at opportunities to power industrial processes through electrification (as shown in **Figure 18).** Large industrial customers are evaluated on a case-by-case basis to try to enable the use of electricity while providing benefits to the system (such as through the interruptible rider).

Figure 18: Commercial and Industrial Contribution to Energy and Peak Forecasts

Year	SmGen (GWh)	GenDemand (GWh)	LrgGen (GWh)	SmInd (GWh)	MedInd (GWh)	LrgInd (GWh)	Peak (MW)
2019	4	14	0	0	0	0	2
2020	9	33	0	0	1	0	6
2021	15	53	5	0	1	2	10
2022	20	70	6	1	2	3	14
2023	24	83	6	2	2	5	17
2024	25	88	6	3	3	5	18
2025	26	90	6	3	3	7	18
2026	27	93	6	4	3	7	19
2027	27	94	6	5	3	8	19
2028	27	96	6	6	4	8	20
2029	28	97	6	6	4	8	20

Price Data

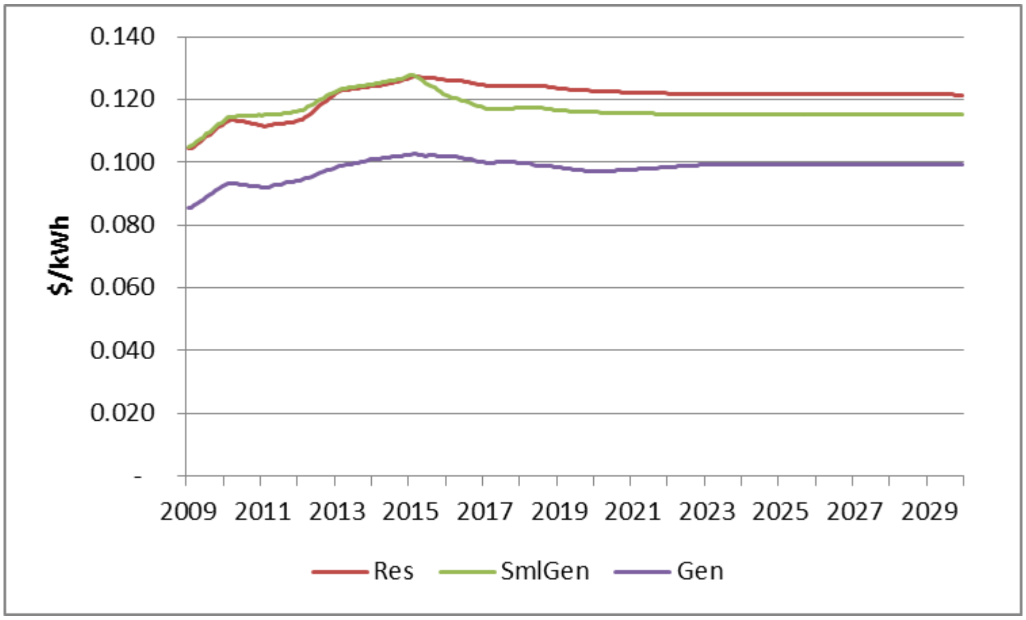
The price series is calculated from historical billed sales and billed revenues. Revenue per kWh is first calculated and translated to a real dollar basis; the price variable itself is then derived as a 12-month moving average of the real revenue per kWh series. The 12-month moving average uncouples the current-month sales/revenue relationship, smooths out the price series, and provides a reasonable expectation as to how customers respond to price over time.

In the forecast period, the nominal price of electricity for each of the calendar years 2017, 2018 and 2019 is based on the rates included in the Company's Fuel Stability Plan and Base Cost of Fuel Reset dated March 7, 2016.[6] For the period from 2017 to 2019

[6] M07348, 2017-2019 Fuel Stability Plan and Base Cost of Fuel Reset, March 7, 2016.

inclusive, the average nominal price is increased at 1.5 percent per year. Beyond 2019, the nominal price of electricity changes at an average of 2 percent per year, or around inflation. **Figure 19** shows price forecasts by class.

Figure 19: Historical and projected real electricity prices (dollars per kWh)



Prices impact the class sales through imposed price elasticities. The SAE models are estimated using a -0.15 price elasticity. This elasticity estimate was provided by Itron during the development of the SAE model and is based on studies and their experience working with other utilities and developing forecasting models. Though the elasticities are small, relatively strong price increases will have a measurable impact on sales.

Demand Side Management

Demand Side Management and conservation plans continue to play a role in the use of electricity in Nova Scotia, and the forecast takes the projected energy and demand savings into account. NS Power uses the DSM targets approved by the Board to modify its forecast. In August 2015, the Board approved a DSM plan covering the 2016–2018 period.[7]

2019 DSM savings are similar to 2018 levels and align with the DSM expenditure level of E1's UARB- approved contract for the 2019 DSM Supply Agreement between E1 and NS Power and projects an incremental annual net energy savings of 127.2 GWh and an incremental annual net demand savings of 20.2 MW. Beyond 2019, DSM savings equal the base DSM scenario from the 2014 Integrated Resource Plan. The base DSM scenario was chosen as the 2020–2029 DSM forecast, because the average annual savings in the base DSM forecast best match the expected average annual DSM savings from the 2017 to 2019 period. It is expected that the DSM forecast will be adjusted for the 2020 load forecast with inputs from the upcoming 2020-2022 DSM agreement, and any other relevant regulatory processes.

In order to highlight the impact of DSM in the province, the forecast amounts are subtracted from the results of the forecast regression models. As with other jurisdictions and utilities with significant DSM activity, NS Power has to address the issue of double counting the impact of DSM savings. The forecast is a regression model based on sales which include past DSM activity, and past DSM also has an influence on other inputs to the load forecast such as price, end use appliance efficiency and even the economic variables. Subtracting 100 percent of forecast DSM activities results in a model that understates sales because it has taken DSM into account in both the regression (via the historic data) and in the projected end use data. The effect of DSM on non-sales related inputs also makes it unrealistic to add historic DSM into past sales to produce a "without DSM" forecast – the impact of DSM would have to also be removed from price, overall appliance efficiency and provincial economics.

[7] Decision 2015 NSUARB 204, M06733, Application for approval of a Supply Agreement for Electricity Efficiency and Conservation Activities between Efficiency One and Nova Scotia Power Inc., August 12, 2015.

To address the issue of double counting, the approach used is the same as that used in the 2018 load forecast – to introduce cumulative historical DSM savings as reported by E1 to the regression model, as a load modifying variable, and allow the model to determine what level of DSM is already included in other variables. Assuming future DSM activities are similar to historic activities, the coefficient applied to historic DSM will also apply to the forecast DSM. This does not imply that a portion of DSM activities is not taking place or that forecast DSM is overstated; rather it is a way of accounting for DSM that is captured elsewhere in the forecast. The methodology is not specific to DSM and could be applied to other variables that need to be highlighted in the forecast provided they have similar characteristics (historical trend, potentially included in other inputs, and some information about future impact).

In the residential model, adding the historic DSM improves the fit of the residential model (adjusted R squared of 0.99 vs 0.986 without the DSM variable). By including this variable the corresponding coefficient, as determined by the regression model, is an indication of the amount of DSM not captured by the other variables. If the coefficient is -1, no DSM is included in other variables, or in practical terms, the regression model determined 100 percent of the DSM savings were required to explain the annual change in historical load levels. If the coefficient is 0, 100 percent of the DSM is included in other variables. As can be seen in the residential model results, the coefficient on the DSM variable is -0.623 (similar to prior values) meaning 38 percent of savings is already accounted for in the regression, and 62 percent is not captured by other variables, and needs to be included in the forecast.

For the commercial and industrial classes a combined model was created to identify the level of DSM already captured by other variables. DSM impacts are not provided for commercial and industrial customers by rate class or by month, so by creating a combined model for these classes, the level of uncertainty around allocating historical DSM savings across rate classes and months of the year is reduced. The DSM variable coefficient is similar to the 2018 value, and the statistics of the model continue to improve and indicate it is a better fit than in 2018 (adjusted R squared of 0.808 vs 0. 795), as well as a more significant DSM variable than in 2018 (p-value of 0.01 percent vs 3.26 percent). The coefficient is -0.623[8] meaning future years in the load forecast should only be adjusted by 62 percent of the forecast DSM amounts. **Figure 20** shows the DSM levels incorporated into the forecast.

[8] For 2019 this is the same as the residential coefficient, but only by coincidence, they are calculated independently.

Figure 20: Annual Forecast DSM Savings

Year	Forecast Residential DSM savings (GWh)	Forecast Commercial and Industrial DSM savings (GWh)	DSM Adjustment for Residential with Coefficient (GWh)	DSM Adjustment for Commercial and Industrial with Coefficient (GWh)
2019	55.5	71.7	34.6	44.7
2020	58.4	75.5	36.4	47.0
2021	56.8	73.3	35.4	45.7
2022	55.7	71.9	34.7	44.8
2023	55.2	71.4	34.4	44.5
2024	55.6	71.8	34.6	44.7
2025	56.8	73.3	35.4	45.7
2026	59.2	76.4	36.9	47.6
2027	62.6	80.9	39.0	50.4
2028	66.9	86.5	41.7	53.9
2029	71.3	92.0	44.4	57.3

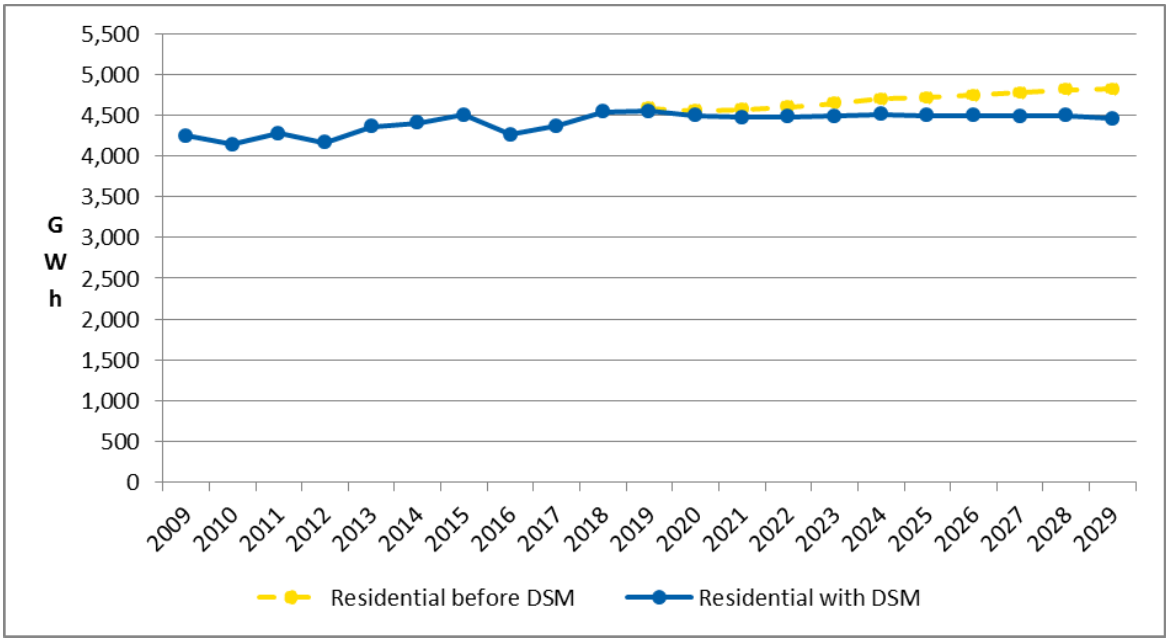
The methodology used to determine the DSM coefficient only works for levels of DSM that have been relatively consistent throughout the historical data set, and does not imply that only a portion of future DSM will impact sales. If forecasts for DSM change significantly then this methodology will have to be revisited. One potential approach might be to treat net new incremental levels of DSM (those above the historical norm) as not being embedded in the forecast variables and subtracted at 100 percent for a period of time, but this will have to be evaluated with any proposed change to DSM levels.

5.0 RESIDENTIAL SECTOR

The residential sales forecast is generated as the product of a residential average use forecast and a customer count forecast. The residential average use model is specified using an SAE model structure and the customer forecast is based on forecast housing starts. Full details on the residential SAE model can be found in **Appendix B**. As outlined in the End Use Intensity Trends, programs related to heat pumps and hot water heaters, as well as projections for EVs and residential solar are added to the modeled load growth projection.

Residential sales dropped between 2015 and 2016, but have been growing since then, driven mainly by increased electric heating. 2018 in particular saw a jump in sales – year over year growth was 4.1 percent, with weather accounting for approximately 1.7 percent. From 2018 to 2019, growth is forecast to be 1.5 percent on a weather normalized basis. The increase in residential load since 2015 has increased projections in the near term, but the overall trend is similar to the 2018 forecast showing a slight decline over the forecast period. Historical and forecast annual residential sector loads are shown in **Figure 21**. Residential sector load is anticipated to decline by 0.2 percent annually during the 10 year forecast period.

Figure 21: Historical and Forecast Annual Residential Sales



New customers in the residential class are separated into single family and multi-unit categories. Analysis of billing data for the past two years for new buildings (built within the last 2-10 years) in both categories has confirmed new single-family homes use around 16,000 kWh per year on average while multi-unit homes use 4,860 kWh per year on average. 1,366 homes were used for the single-family average, of which 1,074 had sufficient billing data history. 1,932 multi-unit homes were used for the multi-unit average, of which 1,492 had sufficient billing data. Most of these samples were in or near the Halifax area, as this corresponds with the location of the majority of new homes being built. In addition to using these averages, a structural index was applied that takes into account building shell efficiency (BSE from the EIA forecast) as well as projected changes in house size. Building efficiency is expected to improve, although based on calibration done in 2013, improvements are expected to be lower in Nova Scotia than the EIA forecast for New England. While efficiency is expected to increase, house size is also expected to continue increasing, albeit at a slower rate than in previous years. These two factors combined lead to a slight expected increase in average use per new residential customer. Building shell efficiency, floor area and the resulting structural index are in

Figure 22. Analysis of both building efficiency and house size is ongoing – in this forecast they are similar to what was forecast in the 2018 load forecast.

Figure 22: Building Characteristics and Structural Index

Year	BSE Heat EIA (New England)	BSE Heat NS	Floor Area (m2)	Structural Index
2019	0.934	0.982	147.0	1.000
2020	0.928	0.980	147.3	1.000
2021	0.922	0.979	147.6	1.000
2022	0.916	0.978	147.8	1.001
2023	0.911	0.977	148.0	1.001
2024	0.905	0.976	148.2	1.002
2025	0.900	0.975	148.4	1.002
2026	0.895	0.974	148.6	1.003
2027	0.890	0.974	148.7	1.003
2028	0.886	0.974	148.9	1.005
2029	0.882	0.974	149.0	1.005

Please refer to Appendix B for tables with a detailed breakdown of the changes from 2019 to 2029. A high level summary of the impact of those changes is as follows:

- Change to existing average use model contributes to a decline of 3.9 percent due to increased efficiency in the underlying end uses;
- New customers add 5.8 percent;
- Heat pumps are expected to add 2.9 percent;
- EVs are expected to add 3.2 percent;
- Hot water heaters are expected to add 0.3 percent;
- Solar is expected to reduce sales by 3 percent; and
- DSM will reduce sales by a further 7.2 percent.

Total change between 2019 and 2029 is a decrease of 2 percent.

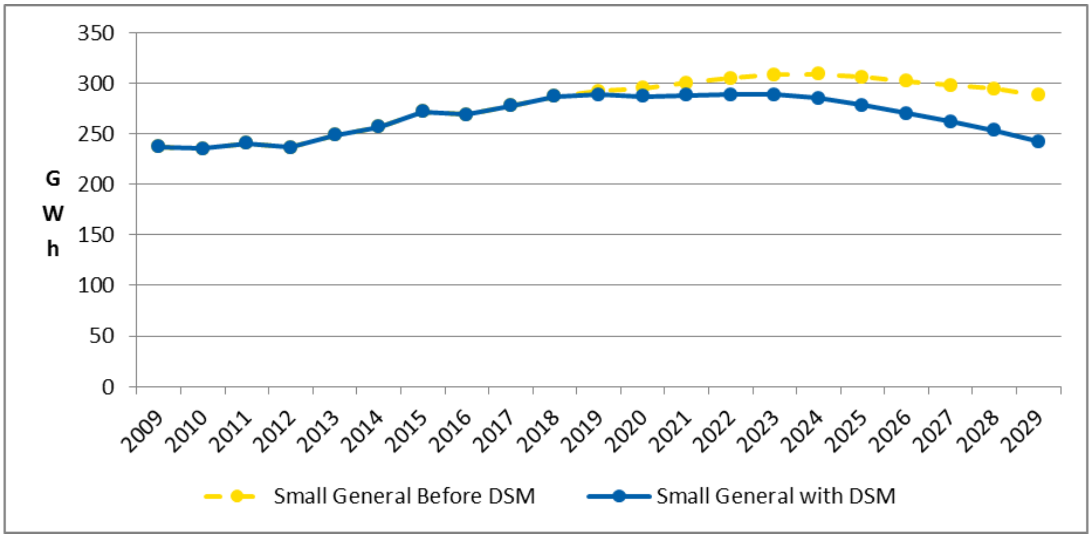
6.0 COMMERCIAL SECTOR

The Commercial SAE model creates a unique forecast for the Small General and General Service rate classes. Like the residential model, the commercial SAE models express monthly sales as a function of heating, cooling, and other loads. The Small General Service forecast is based on a monthly SAE average use model and a separate customer forecast. The General Service rate class model is estimated on a total monthly sales basis (class level sales vs customer level) where total monthly billed sales is a function of total monthly heating requirements, cooling requirements, and other use. The end-use variables are constructed by interacting annual end-use intensity projections (EI) that capture end-use intensity trends, with GDP and employment, real price, monthly HDD and CDD and a variable accounting for the number of days in a given month. A detailed breakdown of the two commercial SAE models is provided in **Appendix B.** Overall sales are expected to be lower than that forecast in the 2018 load forecast.

Small General Service

Historical and forecast Small General Service loads are shown in **Figure 23**. Small General Service load shows a greater decline in the 2019 forecast: 1.7 percent per year over the 10-year forecast period compared to 0.7 percent in the 2018 load forecast. This is driven by a combination of DSM and decreased intensity forecasts for the ventilation, lighting and miscellaneous end uses. The EIA forecast assumes greater LED lighting penetration in the commercial sector, along with greater ventilation efficiency driven by improvements in equipment performance (for example, increased use of variable frequency drives). Partly offsetting these declines is an increase in the heating intensity. For 2019, the year-over-year change in heating penetration from the residential class was applied to the small general class as they are similar in average use characteristics.

Figure 23: Historical and Forecast Annual Small General Sales



Please refer to **Appendix B** for tables with a detailed breakdown of the changes from 2019 to 2029. A high level summary of the impact of those changes is as follows:

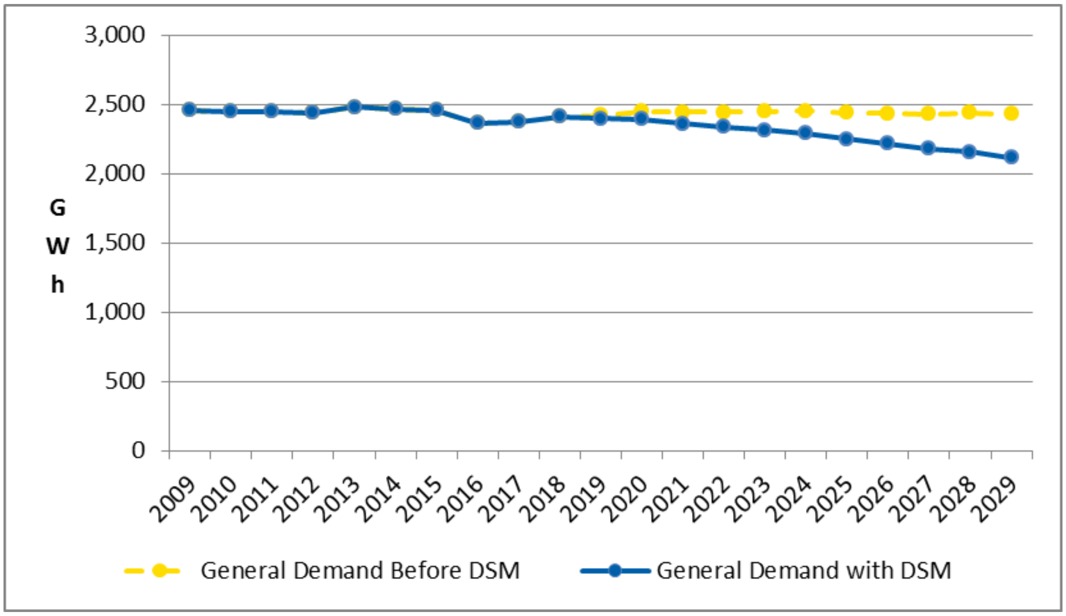
- Change to existing average use model contributes to a decline of 3.6 percent due to increased efficiency in the underlying end uses;
- Growth programs (mainly heat pumps) are expected to add 8.1 percent;
- Solar is expected to reduce sales by 5.9 percent; and
- DSM will reduce sales by a further 14.4 percent.

Total change between 2019 and 2029 is a decrease of 16.1 percent.

General Service

Historical and forecast General Service sales are shown in **Figure 24**. General Service load is expected to decline by 1.2 percent per year during the 10-year forecast period, compared to a decline of 0.8 percent in the 2018 forecast. Like the small general class, the decline is driven by DSM and changes in the forecasts for ventilation, lighting and miscellaneous end uses.

Figure 24: Historical and Forecast Annual General Demand Sales



Please refer to **Appendix B** for tables with a detailed breakdown of the changes from 2019 to 2029. A high level summary of the impact of those changes is as follows:

- Change to existing average use model contributes to a decline of 2.3 percent due to increased efficiency in the underlying end uses;
- Growth programs (mainly heat pumps) are expected to add 3.4 percent;
- Solar is expected to reduce sales by 0.7 percent; and
- DSM will reduce sales by a further 11.9 percent.

Total change between 2019 and 2029 is a decrease of 11.7 percent.

Large General Service

Large General Service is forecast using a combination of customer survey and historical sales information. Customers are surveyed regularly to determine their electricity requirements over the next three-year period. Details on planned production levels or equipment changes help inform energy requirement expectations. In absence of survey or publicly available information, load levels are forecast as being flat before the impact of any DSM activities. Four of the 19 large general customers replied to the annual survey: one indicated no change, two indicated a slight decrease and one indicated a slight increase in energy consumption. The only major impact to the large general class over the 10 year period is DSM, which accounts for the 9.4 percent decrease overall.

7.0 INDUSTRIAL SECTOR

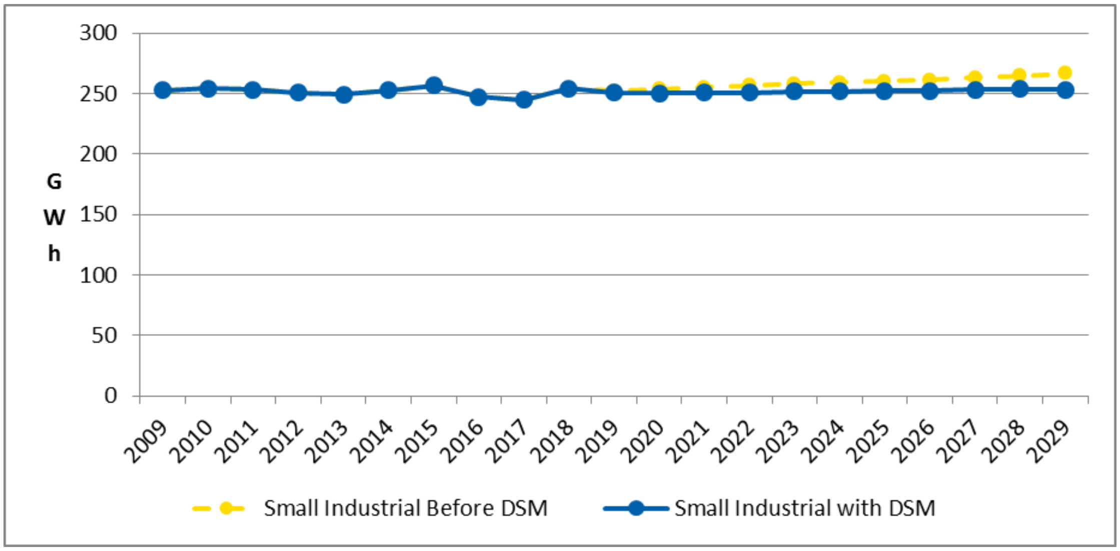
The forecast models for the Small Industrial and Medium Industrial rate classes are econometric-based models (i.e. dependant on economic variables). Provincial GDP is used as the primary economic variable in the Small Industrial forecast and manufacturing employment is used for the Medium Industrial class.

The Small and Medium Industrial rate class models are developed using monthly sales information, as opposed to annual sales, in order to align the timeframes of industrial models with those of the residential and commercial forecast models. This is required in order to implement an end-use based peak forecast for the commercial and residential sectors.

Small Industrial

Figure 25 depicts historical and projected sales for the Small Industrial rate class. Sales in this class have been flat for the last 10 years and are expected to remain essentially flat, with growth of 0.1 percent annually over the forecast period due to underlying economic growth.

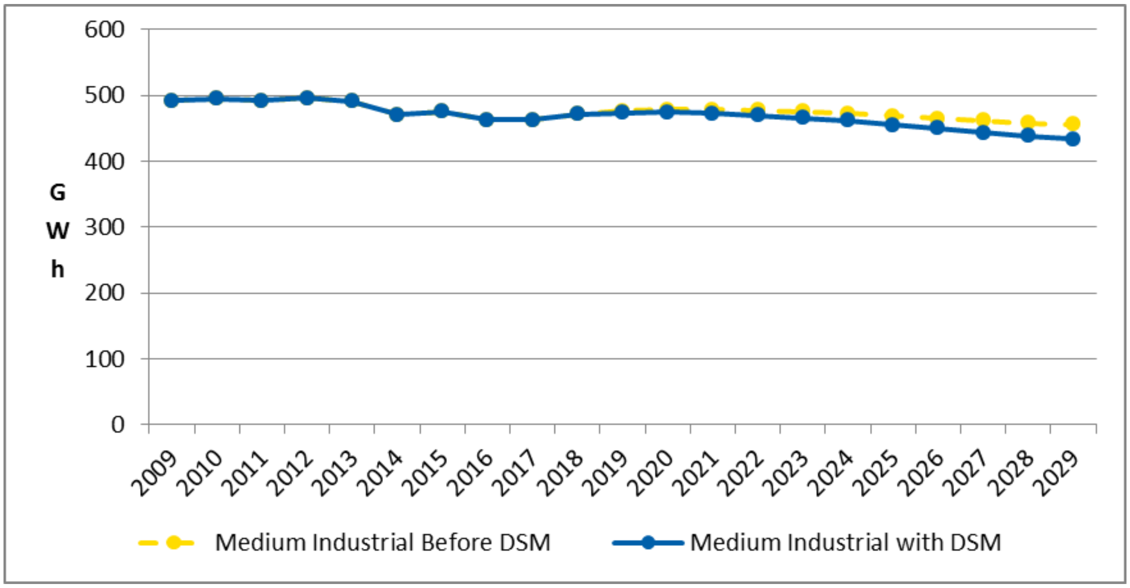
Figure 25: Historical and Forecast Annual Small Industrial Sales



Medium Industrial

Figure 26 depicts historical and projected sales for the Medium Industrial rate class. Load in this class has been decreasing since the 2008 recession, primarily due to the closures or reduced operations of the class participants. Forecast sales are expected to decline over the forecast period, with an average decrease of 0.9 percent driven by a combination of DSM and a declining manufacturing employment forecast.

Figure 26: Historical and Forecast Annual Medium Industrial Sales



Other Industrial Rate Classes

Other Industrial rate classes include Large Industrial, Large Industrial Interruptible, Generation Replacement and Load Following, One-Part Real Time Pricing, Shore Power, and the Load Retention Tariff. The Load Retention Tariff ends in 2019 and a determination will be made as to how the customer currently taking service under that tariff may take service after the end of the Load Retention Tariff term, but pending that determination, for the purposes of this forecast, it is assumed that this customer's load will continue to be served under this tariff for the duration of the forecast.

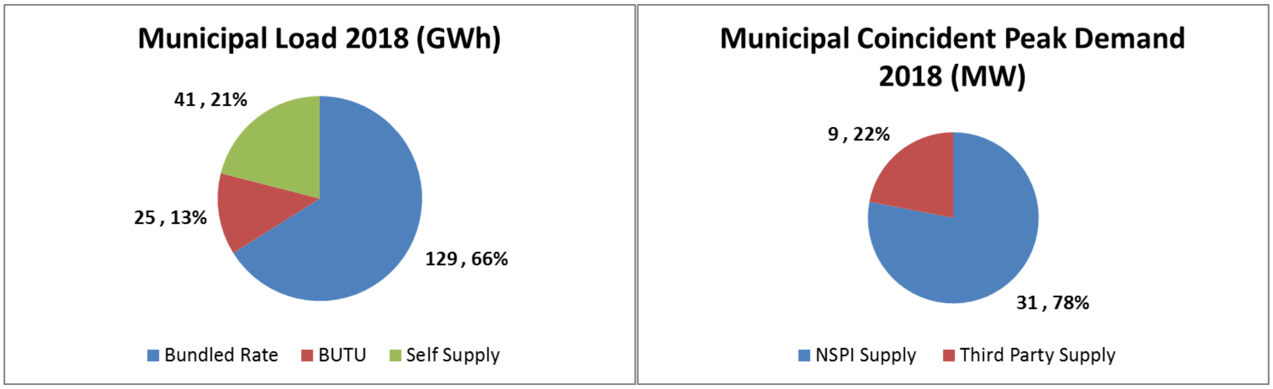
Like the Large General Service rate class, load for these rate classes is forecast using a combination of customer survey and historical sales information. Customers are surveyed regularly in order to gather their forecast monthly electricity requirements over the next three-year period. Details on planned production levels or equipment changes help inform energy requirements expectations. In the absence of any survey or general public information, load levels are forecast as being flat. One response was received from the annual survey, reporting a slight increase in energy use. Regarding changes from 2018, NS Power is aware of several expansion projects, as well as customers who are ramping up operations that are likely to add a total of around 40 GWh in 2019. Several new facilities in the mining and cannabis production sectors are also expected to open in the coming years. Based on discussions with customers, these are expected to add cumulatively 12 GWh in 2019, 55 GWh in 2020 and 95 GWh in 2021 and beyond.

Municipal

This class comprises municipal electric utilities that purchase wholesale electricity from NS Power and distribute it within their own service territories. Utility loads within these municipalities include customers in residential, commercial and industrial sectors. Energy in this class also includes the losses incurred by the municipal utilities in meeting their electricity requirements. These losses are estimated to average approximately 4 percent of sales.

NS Power's Open Access Transmission Tariff (OATT) is available to each of the six municipal utilities. Since 2007 it has been possible for these municipalities to source their electricity from providers other than NS Power. Several municipal customers currently source part of their energy requirement from suppliers other than NS Power, resulting in a reduction in municipal load of around 70 GWh from historic levels. These customers have their load served by a combination of third party generation, the bundled Municipal rate, and the Back-Up Top-Up (BUTU) rate. For the 2019 forecast the BUTU amount is included in the municipal amount. **Figure 27** shows the amount of energy provided to the municipal utilities under the bundled municipal rate, the BUTU rate, and the energy provided by third parties. It also shows the amount of demand provided by each source of supply at the time of the 2018 peak. Even if the municipal customers were to source all of their energy from third parties, their ability to supply their peak demand would depend on the source of the supply.

Figure 27: Energy Supply to Municipalities



8.0 SYSTEM LOSSES AND UNBILLED SALES

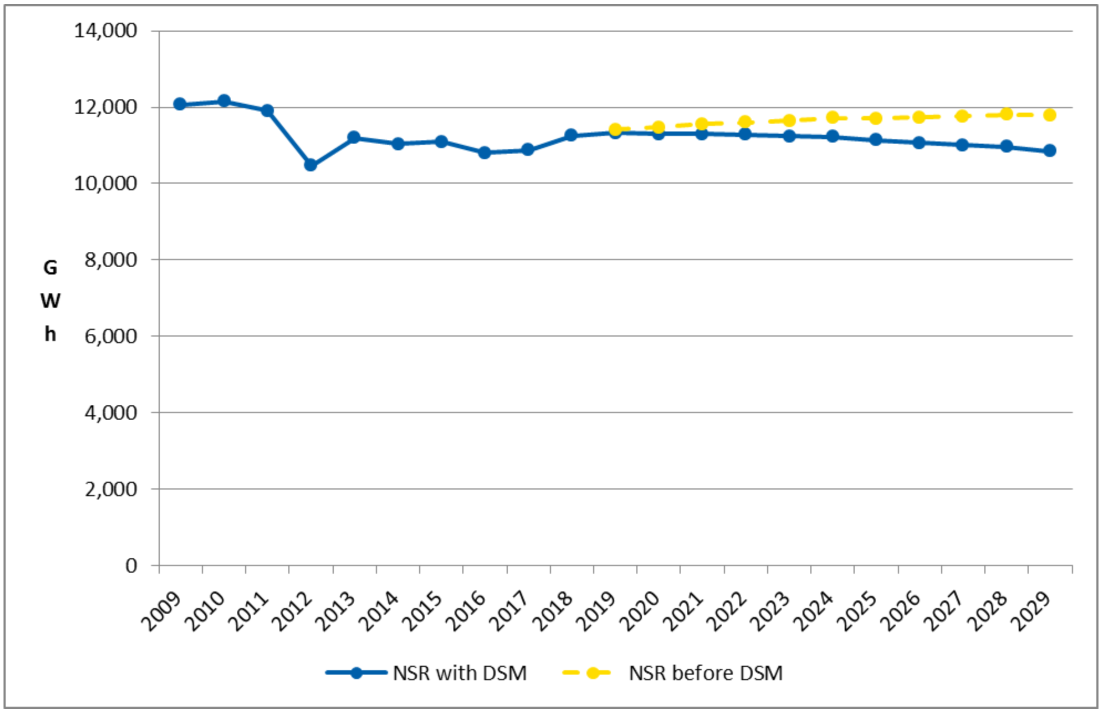
The difference between energy generated for use within provincial borders and the total NS Power billed sales comprises transmission and distribution system losses as well as changes to the level of unbilled sales. Energy generated and sold but not yet billed is referred to as "Unbilled" sales. System losses averaged 6.7 percent of NSR over the past five years and are forecast to remain in the 6.0 to 7.0 percent range over the 10-year forecast period.

9.0 NET SYSTEM REQUIREMENT

The NSR is the energy required to supply the sum of residential, commercial, and industrial electricity sales, plus the associated system losses within the province of Nova Scotia. Loads served by industrial self-generation, exports, and transmission losses associated with energy exports are not included.

In 2018, the NSR for the province increased by 3.5 percent over 2017, primarily due to favourable weather (0.9 percent), higher industrial load (1.3 percent) and underlying growth in the residential and commercial classes (1.4 percent). When adjusted for weather, the growth from 2018 actuals to 2019 forecast is 1.6 percent overall, with almost equal contributions from increased residential load and large industrial customer growth from new customers. From 2019 to 2029, NSR is forecast to decline at 0.4 percent per year, slightly lower than the 2018 load forecast. Without DSM effects, growth would be an average of 0.3 percent annually. Annual NSR is shown in **Figure 28**. Forecast NSR values and the contribution to NSR from the different sectors can be found in **Appendix A**.

Figure 28: Historical and Forecast Annual NSR



10.0 PEAK DEMAND

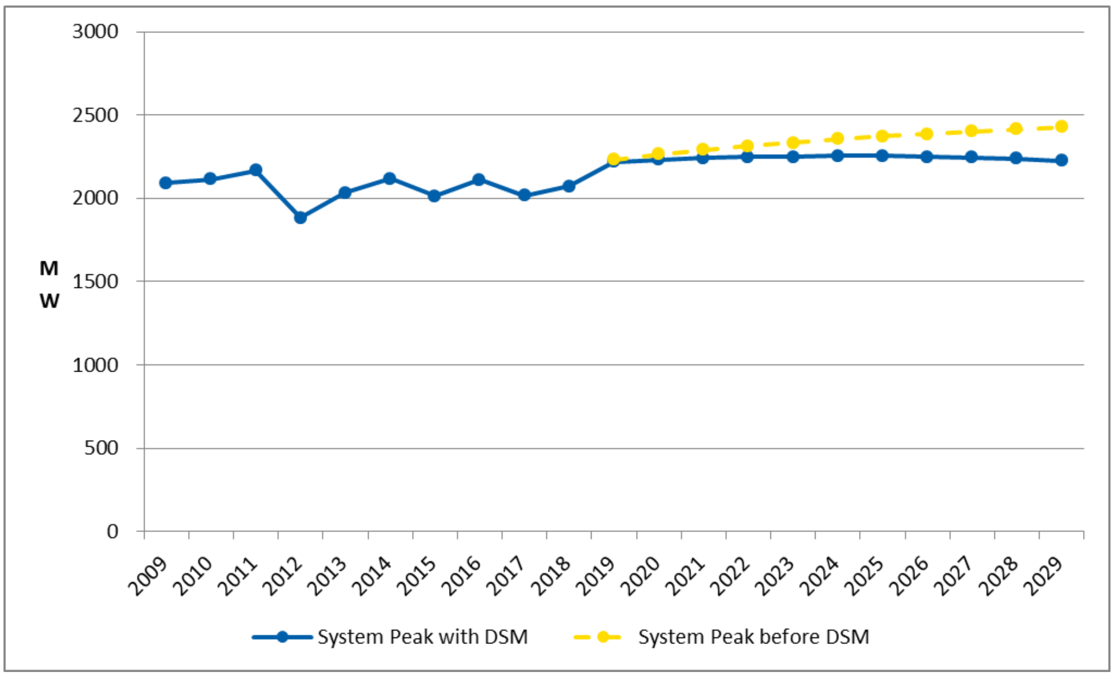
The total system peak is defined as the highest single hourly average demand experienced in a year. It includes both firm and interruptible loads. Due to the weather-sensitive load component in Nova Scotia, the total system peak occurs in the period from December through February.

Since 2015, NS Power has employed an end-use approach to deriving the peak forecast. The breakdown of energy into heating, cooling, and other load components from the energy SAE forecasts was used as an input into the peak forecast. This allowed for the impact of changing heating and cooling requirements, which drive the peak in most months, to be reflected in the peak forecast. Full details about the peak forecast can be found in **Appendix B**.

There are no specific peak mitigation programs taken into account for the forecast, with the exception of the peak contribution of EVs. EVs are expected to be similar to other jurisdictions for which there is some data on the impact of peak mitigation measures. Possibilities for peak mitigation include items such as direct load control (space heating, hot water heating, or EVs), integration of battery storage, or rate design (time of use, critical peak pricing or other rates enabled by an AMI deployment). Critical peak pricing, for instance, is expected to contribute as much as 26MW of savings on peak by 2022. Although combinations of the above are likely to be implemented within Nova Scotia in the next 5-10 years, the amount of uncertainty surrounding the specific combinations or impacts makes it difficult to estimate. As rate design initiatives progress, in particular with the possibilities provided by AMI deployment, estimates for peak reduction will be updated in future load forecasts. The impact of any of these initiatives, at least within the 10 year timeframe of this forecast, is likely to fall within the sensitivity analysis provided in Section 11.

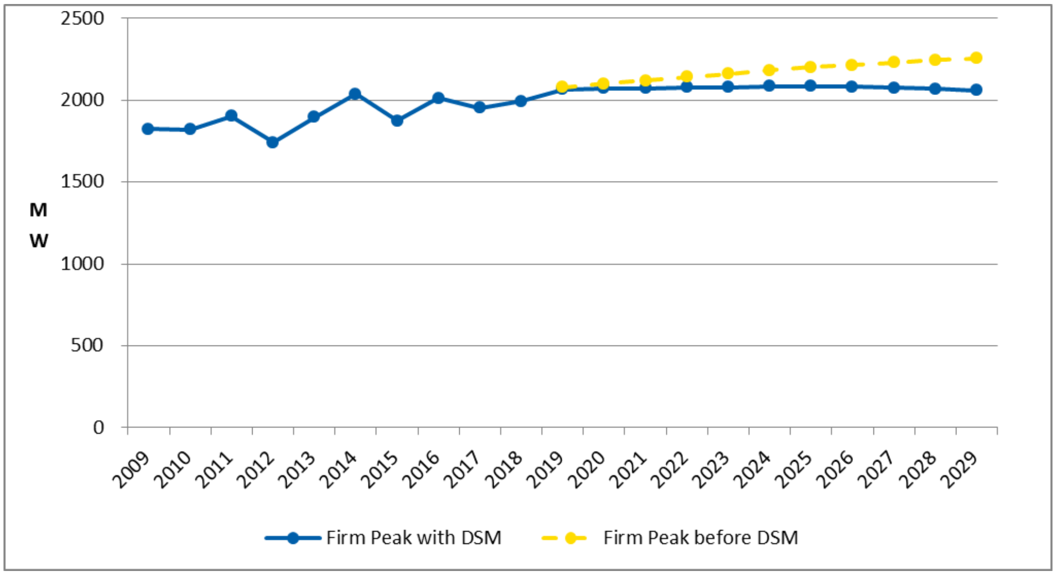
The peak contribution from large customer classes continues to be calculated from historical coincident load factors for each of the rate classes and the large customer forecast is added to the accrued class forecast to get the total system peak. The forecast system peak for 2019 to 2029 is shown below in **Figure 29**. Without DSM, growth would be 0.8 percent annually but growth is forecast to be flat when DSM is included.

Figure 29: Historical and Forecast System Peak



The system peak is made up of firm and interruptible components. As indicated in **Figure 30**, the firm peak is expected to grow by 0.8 percent annually before the impact of DSM. Increased electric heating is the main driver of this increase, but it is expected to be offset by DSM activities, resulting in no growth between 2019 and 2029.

Figure 30: Historical and Forecast Firm Peak



Forecast peak values, along with firm peak and interruptible peak information can be found in **Appendix A**. As discussed in the End Use Intensity section, around half the EV contribution to peak is assumed to be mitigated in the peak forecast. The firm peak without EV peak mitigation (assuming twice the forecast EV peak with mitigation) would grow at 0.1 percent per year, and the overall impact in 2029 would be to add around 35 MW to the peak. **Figure 31** below shows the breakdown of the peak forecast by the various components. Modeled peak is the end-use forecast portion that represents the peak contribution of the residential, small and general demand, small and medium industrial classes, as well as losses. The contributions of the various growth programs discussed in the End Use Intensity section are then added (including their associated losses), as well as large customer and interruptible customer contributions, and finally DSM.

Figure 31: Peak Contribution Components (MW)

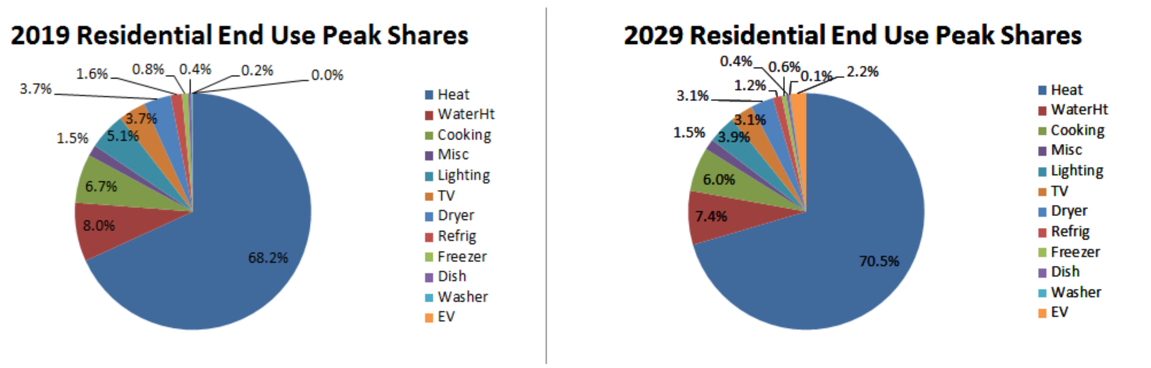
	Modeled Peak	HP	EV	HW	C&I Growth	Large Cust.	Inter. Cust.	DSM	System Peak
2019	1,960	17	0	0	3	98	156	-13	2,221
2029	1,989	111	30	3	20	96	173	-194	2,228
2029 (no EV mitigation)	1,989	111	65	3	20	96	173	-194	2,263

The 2018 firm peak occurred in early January at a temperature of -11.7 degrees C and was 1,993 MW. Although this was close to the 2018 forecast firm peak of 2,001 MW, the peak temperature was warmer than the design temperature of -15 degrees C. Accounting for the warmer temperature, the peak would have likely been around 2,060 MW, which is slightly below the 2019 forecast firm peak of 2,066 MW.

While the forecast is a good statistical fit for the historical data, it present challenges when trying to assess the contribution of individual end uses to peak by class. The overall peak forecast looks at the heating, cooling and other variables across the Residential and Commercial classes. In order to illustrate the impact of the individual end uses on the peak for the individual classes, the coincident peak contribution of each class (Residential, Commercial and Industrial) is derived from load research data and fit to the energy amounts from the end use models. The individual end use shapes are then fit to the end use intensity energy amounts from the end use models.

The residential class saw an increase in heating load in 2018 – peak share was estimated at 60% in the 2018 load forecast versus 68% in the 2019 load forecast. Although sales show a decreasing trend overall, electric heat penetration is expected to increase as can be seen in **Figure 32** below, which shows the breakdown in contribution to peak by residential end use.

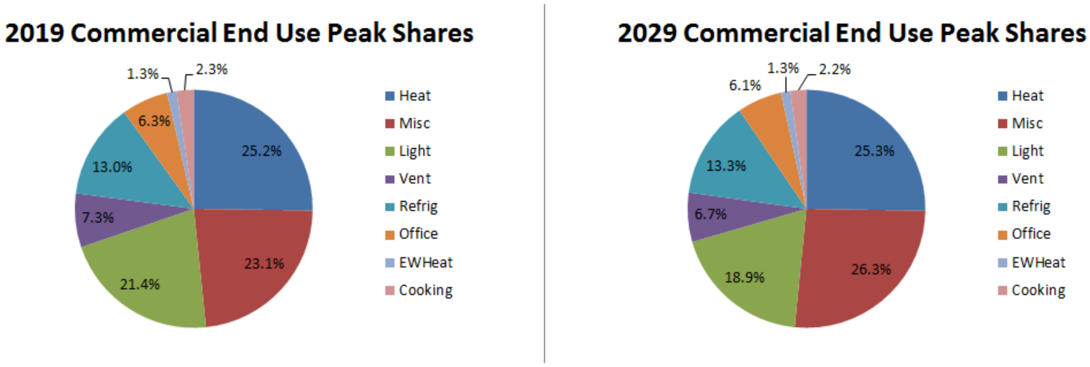
Figure 32: Residential End-Use Peak Shares



Over the forecast period, the peak contribution from heating and EVs grows, while all other end-uses decline as a percentage of the peak. Heating in particular shows a much bigger contribution to peak in 2029 as electric heat becomes more widespread due to a combination of new homes using electric heat and heat pumps being installed in existing homes displacing other heating sources. Efficient heat pumps continue to replace electric baseboard heat and decrease energy sales related to heating, but they have not contributed a similar amount to peak mitigation as resistance heat is still required at peak temperatures. Combined with DSM efforts to reduce energy consumption, this causes the disconnect between the energy forecast that has negative growth in sales and an increasing forecast for firm system peak.

Figure 33 shows the breakdown in the contribution to peak by commercial end use. The largest change in the commercial sector is the peak contribution from miscellaneous end-use growing and lighting declining.

Figure 33: Commercial End-Use Peak Shares



The trend in the commercial class shows that the heating component of the peak is expected to remain unchanged over the forecast period. All other categories decrease through the forecast period. The miscellaneous intensities, which include everything from elevator loads to medical equipment to other office plug-in loads, show an increasing trend over the forecast period and a corresponding increase in peak contribution.

Future Peak Demand Work

In order to further refine the peak forecast model, load research data will be investigated to disaggregate the peak components by class. This would potentially help break out the various end-use components at the class level, as well as potentially allow class level DSM to be integrated directly into the model. Work was completed in 2018 to update the load research sample, and integration of this data with the load forecast is ongoing.

11.0 SENSITIVITY ANALSYSIS

The sales and peak forecasts are fundamentally uncertain and dependent on many variables such as economics, weather, adoption of distributed generation, electricity rates and DSM. Although each of these variables is forecast discretely, the uncertainty in these data sets will impact the load forecast to varying degrees. Additionally, load can be affected by extraordinary events such as economic crises, strikes, trade disputes, natural disasters and volatility in commodities.

In 2017, based on recommendations from Synapse on the 2016 Load Forecast,[9] NS Power developed a P10/P90 probability analysis using the Monte Carlo simulation approach. This was to create a high and low range for the forecast that encompasses possible (not extreme) scenarios. A full description of the sensitivity methodology can be found in **Appendix D**.

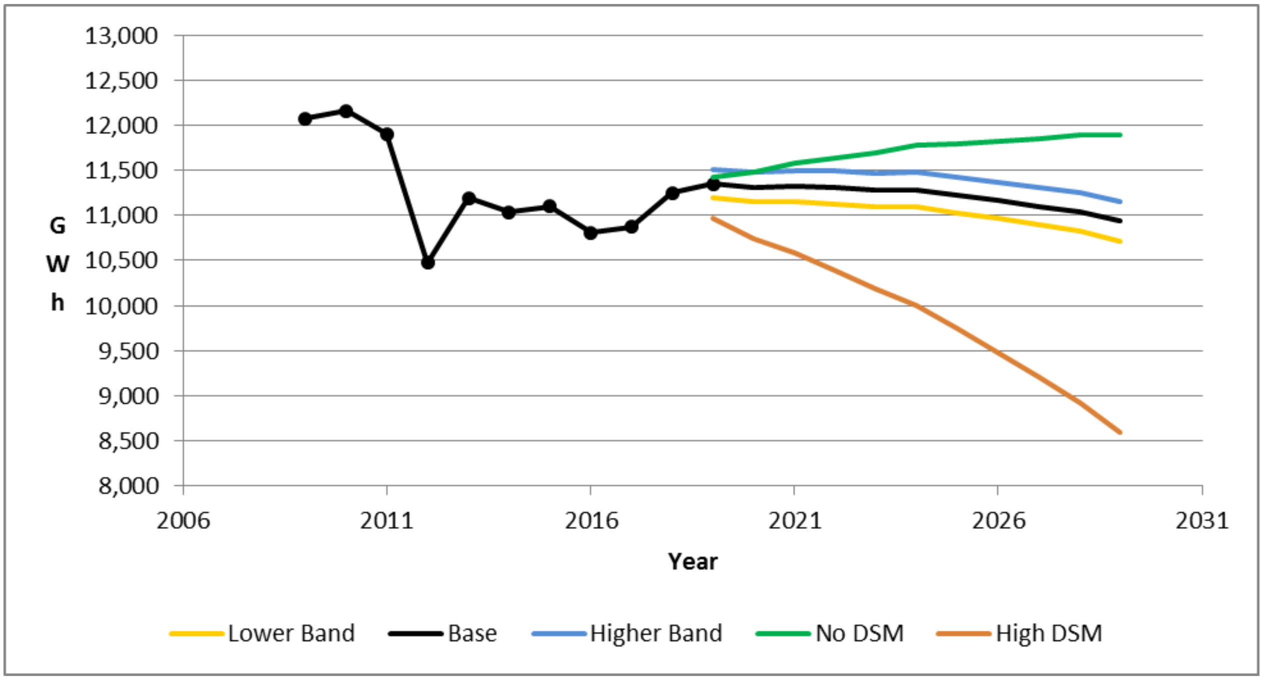
The probable distribution of future load is estimated by sampling 10,000 random trial values of the economic, weather, and price drivers each year using their respective historical distributions. For the 2019 sensitivity model, DSM was added outside of the Monte Carlo simulation based on the Low and High DSM values from the 2014 IRP. Modelling the individual end uses using a Monte Carlo simulation is still in progress and has not been completed for this iteration of the forecast.

Figure 34 shows the 2019 energy forecast in black, surrounded by a low band in yellow representing the 10th percentile, (there is a 90 percent probability that the forecast will be above the yellow line), and by a high band in blue, representing the 90th percentile, (there is a 10 percent probability that the forecast will be above the blue line). These P10/P90 bands cover a range of about 200-400 GWh, which is explained mainly by the impact of weather variation (HDD) and some economic impact in the long term. The green and

[9] M07448, Findings Regarding the NSPI 2016 Load Forecast, Synapse Energy Economics, August 31, 2016.

brown lines represent the envelope of the no (green) and high (orange) DSM amounts. The high DSM line assumes 100 percent of future DSM is impacting the forecast (there is no coefficient applied to future DSM programs).

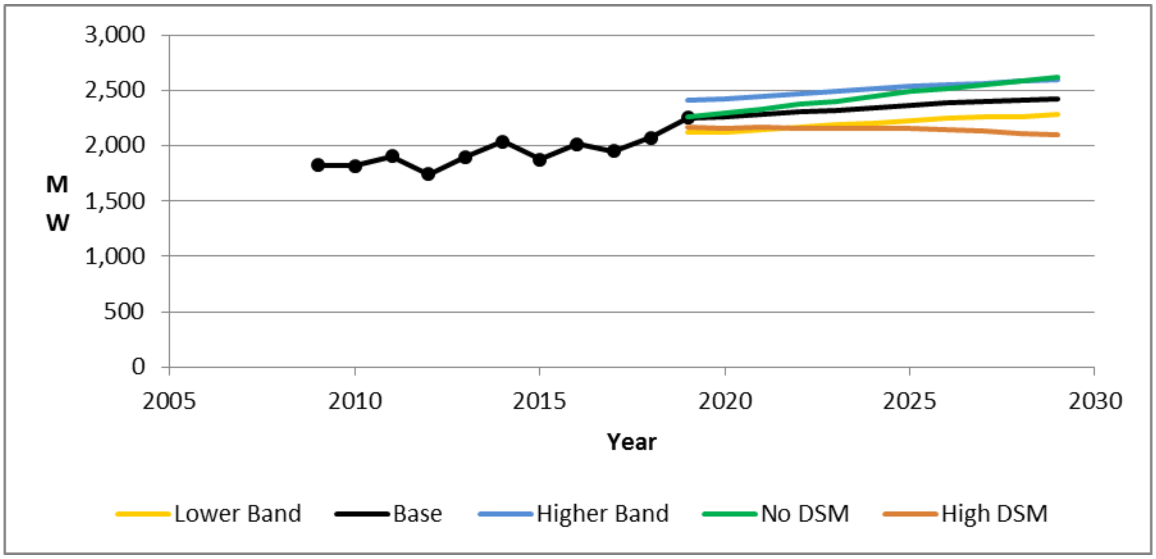
Figure 34: System Energy Sensitivity



DSM represents a much larger source of variability when compared to the potential impact of weather or economics. For a comparison of the impact of various inputs on the forecast, see Figure D9 in in the **Appendix D**.

Similarly, a P10/P90 scenario was created for peak demand using random sampling of weather and economic drivers, overlaid with a no DSM scenario and the 2014 IRP high DSM scenario. The width of the P10/P90 envelope is about 297-313 MW, and unlike the energy forecast, where DSM dominates the variance, the peak is mainly dominated by the variation of Peak day HDD, resulting in enough variation that even the DSM scenarios fall mostly within the bands as seen in **Figure 35**.

1 **Figure 35: System Peak Sensitivity**



2

Load Forecast

Appendices

Appendix A – Forecast Values

2019 NS Power Forecast

Table A1: Energy Requirement – 2019 NS Power Forecast
Energy Forecast with Future DSM Program Effects

Year	Residential Sector	Growth	Commercial Sector	Growth	Industrial Sector	Growth	Municipal	Growth	Losses	Total Energy	Growth
	GWh	%	GWh	%	GWh	%	GWh	%	GWh	GWh	%
2009	4,244	2.1%	3,224	-0.3%	3,638	-12.3%	198	0.3%	769	12,073	-3.7%
2010	4,144	-2.4%	3,211	-0.4%	3,912	7.5%	193	-2.5%	697	12,158	0.7%
2011	4,275	3.2%	3,217	0.2%	3,515	-10.2%	191	-1.0%	709	11,907	-2.1%
2012	4,160	-2.7%	3,196	-0.6%	2,164	-38.4%	191	0.0%	763	10,475	-12.0%
2013	4,362	4.8%	3,244	1.5%	2,604	20.3%	201	4.8%	784	11,194	6.9%
2014	4,404	1.0%	3,222	-0.7%	2,522	-3.1%	198	-1.4%	691	11,037	-1.4%
2015	4,504	2.3%	3,251	0.9%	2,456	-2.6%	197	-0.2%	691	11,099	0.6%
2016	4,264	-5.3%	3,133	-3.7%	2,444	-0.5%	179	-9.2%	789	10,809	-2.6%
2017	4,363	2.3%	3,133	0.0%	2,461	0.7%	163	-9.0%	753	10,873	0.6%
2018	4,542	4.1%	3,181	1.5%	2,614	6.2%	154	-5.7%	758	11,250	3.5%
2019	4,551	0.2%	3,161	-0.6%	2,681	2.6%	152	-1.0%	786	11,331	0.7%
2020	4,493	-1.3%	3,154	-0.2%	2,734	2.0%	150	-1.5%	769	11,300	-0.3%
2021	4,473	-0.5%	3,123	-1.0%	2,795	2.2%	148	-1.5%	765	11,303	0.0%
2022	4,479	0.1%	3,095	-0.9%	2,790	-0.2%	146	-1.1%	767	11,278	-0.2%
2023	4,490	0.2%	3,070	-0.8%	2,785	-0.2%	133	-9.2%	762	11,240	-0.3%
2024	4,511	0.5%	3,040	-1.0%	2,777	-0.3%	132	-0.8%	760	11,220	-0.2%
2025	4,496	-0.3%	2,987	-1.7%	2,768	-0.3%	130	-1.5%	754	11,135	-0.8%
2026	4,492	-0.1%	2,942	-1.5%	2,759	-0.3%	128	-1.2%	748	11,069	-0.6%
2027	4,489	-0.1%	2,896	-1.5%	2,750	-0.3%	127	-1.2%	743	11,005	-0.6%
2028	4,493	0.1%	2,858	-1.3%	2,741	-0.3%	126	-0.9%	739	10,958	-0.4%
2029	4,459	-0.8%	2,801	-2.0%	2,731	-0.4%	124	-1.6%	730	10,844	-1.0%

Table A2: Energy Requirement – 2019 NS Power Forecast

Energy Forecast before Future DSM Program Effects

Year	Residential Sector	Growth	Commercial Sector	Growth	Industrial Sector	Growth	Municipal	Growth	Losses	Total Energy	Growth
	GWh	%	GWh	%	GWh	%	GWh	%	GWh	GWh	%
2009	4,244	2.1%	3,224	-0.3%	3,638	-12.3%	198	0.3%	769	12,073	-3.7%
2010	4,144	-2.4%	3,211	-0.4%	3,912	7.5%	193	-2.5%	697	12,158	0.7%
2011	4,275	3.2%	3,217	0.2%	3,515	-10.2%	191	-1.0%	709	11,907	-2.1%
2012	4,160	-2.7%	3,196	-0.6%	2,164	-38.4%	191	0.0%	763	10,475	-12.0%
2013	4,362	4.8%	3,244	1.5%	2,604	20.3%	201	4.8%	784	11,194	6.9%
2014	4,404	1.0%	3,222	-0.7%	2,522	-3.1%	198	-1.4%	691	11,037	-1.4%
2015	4,504	2.3%	3,251	0.9%	2,456	-2.6%	197	-0.2%	691	11,099	0.6%
2016	4,264	-5.3%	3,133	-3.7%	2,444	-0.5%	179	-9.2%	789	10,809	-2.6%
2017	4,363	2.3%	3,133	0.0%	2,461	0.7%	163	-9.0%	753	10,873	0.6%
2018	4,542	4.1%	3,181	1.5%	2,614	6.2%	154	-5.7%	758	11,250	3.5%
2019	4,582	0.9%	3,195	0.4%	2,689	2.9%	154	0.1%	792	11,412	1.4%
2020	4,556	-0.6%	3,224	0.9%	2,750	2.3%	153	-0.4%	783	11,466	0.5%
2021	4,567	0.2%	3,229	0.1%	2,819	2.5%	153	-0.4%	785	11,552	0.8%
2022	4,604	0.8%	3,236	0.2%	2,822	0.1%	153	0.0%	794	11,608	0.5%
2023	4,646	0.9%	3,245	0.3%	2,824	0.1%	141	-7.8%	795	11,650	0.4%
2024	4,697	1.1%	3,249	0.1%	2,824	0.0%	141	0.4%	800	11,712	0.5%
2025	4,713	0.3%	3,232	-0.5%	2,823	0.0%	141	-0.2%	801	11,709	0.0%
2026	4,742	0.6%	3,222	-0.3%	2,822	0.0%	141	0.1%	802	11,729	0.2%
2027	4,773	0.7%	3,216	-0.2%	2,822	0.0%	141	0.2%	804	11,757	0.2%
2028	4,815	0.9%	3,219	0.1%	2,822	0.0%	142	0.5%	808	11,807	0.4%
2029	4,819	0.1%	3,206	-0.4%	2,822	0.0%	142	0.0%	807	11,797	-0.1%

Table A3: Coincident Peak Demand - 2019 NS Power Forecast

Peak Forecast with Future DSM Program Effects

Year	Interruptible Contribution to Peak (MW)	Firm Contribution to Peak (MW)	Net System Peak (MW)	Growth (%)
2009	268	1,824	2,092	-4.5%
2010	295	1,820	2,114	1.0%
2011	265	1,903	2,168	2.5%
2012	141	1,740	1,882	-13.2%
2013	136	1,897	2,033	8.0%
2014	83	2,036	2,118	4.2%
2015	141	1,874	2,015	-4.9%
2016	98	2,013	2,111	4.8%
2017	67	1,951	2,018	-4.4%
2018	80	1,993	2,073	2.7%
2019	155	2,066	2,221	7.2%
2020	163	2,070	2,234	0.6%
2021	170	2,073	2,243	0.4%
2022	170	2,078	2,248	0.2%
2023	170	2,080	2,249	0.1%
2024	170	2,086	2,255	0.3%
2025	169	2,086	2,255	0.0%
2026	169	2,081	2,250	-0.2%
2027	169	2,076	2,245	-0.2%
2028	168	2,070	2,239	-0.3%
2029	168	2,060	2,228	-0.5%

Table A4: Coincident Peak Demand - 2019 NS Power Forecast

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Peak Forecast before Future DSM Program Effects

Year	Interruptible Contribution to Peak (MW)	Firm Contribution to Peak (MW)	Net System Peak (MW)	Growth (%)
2009	268	1,824	2,092	-4.5%
2010	295	1,820	2,114	1.0%
2011	265	1,903	2,168	2.5%
2012	141	1,740	1,882	-13.2%
2013	136	1,897	2,033	8.0%
2014	83	2,036	2,118	4.2%
2015	141	1,874	2,015	-4.9%
2016	98	2,013	2,111	4.8%
2017	67	1,951	2,018	-4.4%
2018	80	1,993	2,073	2.7%
2019	156	2,078	2,234	7.8%
2020	165	2,100	2,265	1.4%
2021	173	2,119	2,292	1.2%
2022	173	2,141	2,314	1.0%
2023	173	2,160	2,333	0.8%
2024	173	2,183	2,356	1.0%
2025	173	2,201	2,374	0.8%
2026	173	2,214	2,387	0.6%
2027	173	2,229	2,402	0.6%
2028	173	2,244	2,417	0.6%
2029	173	2,255	2,428	0.5%

Appendix B –Forecast Model Details

2018 NS Power Forecast

Residential Model Detail

The residential average use SAE model is defined as a function of the three primary end-uses – cooling (*XCool*), heating (*XHeat*) and other use (*XOther*):

$$ResAvgUse_m = b_1 \times XHeat_m + b_2 \times XCool_m + b_3 \times XOther_m + b_4 \times AvgEESavings_m$$

The end-use variables incorporate both a variable that captures short-term utilization (Use) and a variable that captures changes in end-use efficiency and saturation trends (Index). The heating variable is calculated as:

$$XHeat = HeatUse \times HeatIndex$$

Where

HeatUse = f(HDD, Household Income, Household Size, and Price)

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

The cooling variable is defined as:

$$XCool = CoolUse \times CoolIndex$$

Where

CoolUse = f(CDD, Household Income, Household Size, and Price)

CoolIndex = g(Cooling Saturation, Efficiency, Shell Integrity, Square Footage)

XOther captures non-weather sensitive end-uses:

$$XOther = OtherUse \times OtherIndex$$

Where

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

OtherIndex = g(Other Appliance Saturation and Efficiency Trends)

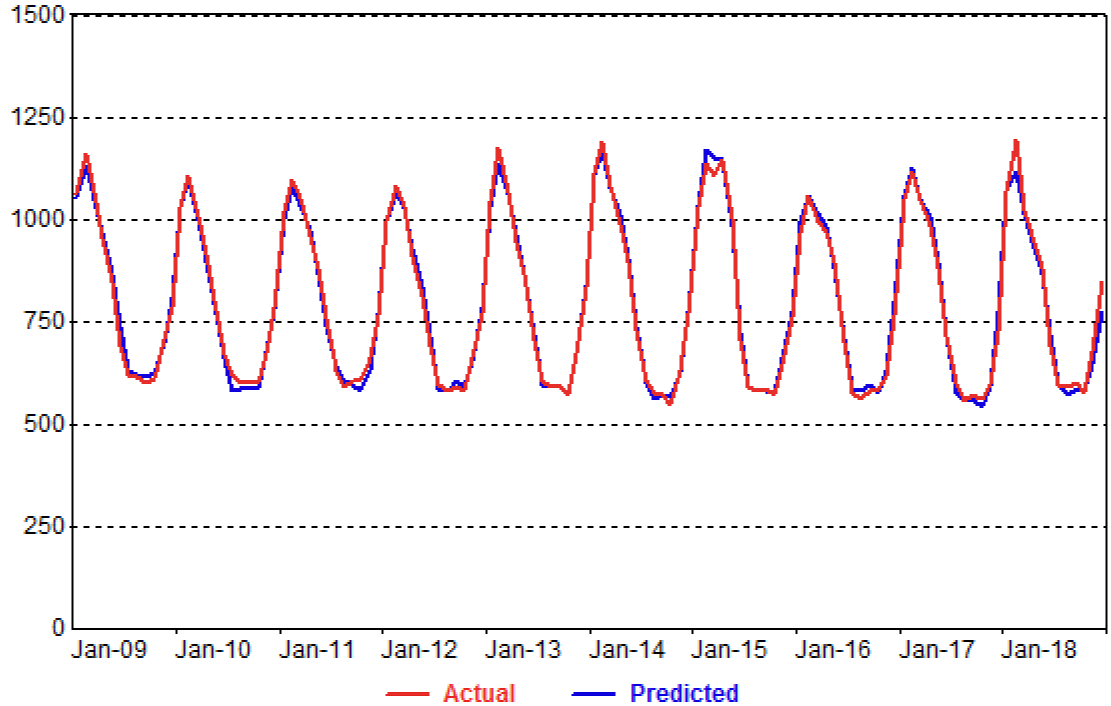
The *AvgEESavings* term captures Efficiency One's DSM past reported savings for the residential class. The associated regression coefficient, b_4, assesses the portion of embedded DSM activity that is already included in the billed sales information. The negative sign of b_4 indicates that DSM activity reduces load. Binary shift variables are added to the model for the months of January, August, September, and October to improve model fit and particular monthly trends, while binaries for April and May of 2015 compensate for an anomaly in the billing data during this period related to delayed meter reads. After running the linear regression with the main variables the residuals show a slight autocorrelation, which happens when a model doesn't take into account relatively small drivers that should explain the dependent variable (in this case, sales). To help eliminate this autocorrelation, a seasonal moving average, SMA, of period 1, SMA(1) were added. SMA(1) estimates the autocorrelation with its the predecessor of 12 months ago.

Variable	Coefficient	StdErr	T-Stat	P-Value
MStructRes.WtXHeat	0.838	0.019	43.996	0.00%
MStructRes.WtXCool	0.845	0.206	4.11	0.01%
MStructRes.WtXOther	0.981	0.019	50.519	0.00%
MSales.AvgEESavings	-0.623	0.094	-6.639	0.00%
MBin.May15	77.312	17.089	4.524	0.00%
MBin.Apr15	88.318	17.25	5.12	0.00%
MBin.Aug	77.19	12.75	6.054	0.00%
MBin.Jan	76.758	10.6	7.241	0.00%
MBin.Sep	86.68	14.662	5.912	0.00%
MBin.Oct	51.621	12.732	4.054	0.01%
SMA(1)	0.58	0.109	5.32	0.00%

Residential Model Statistics

Model Statistics	
Iterations	18
Adjusted Observations	120
Deg. of Freedom for Error	109
R-Squared	0.991
Adjusted R-Squared	0.990
AIC	6.130
BIC	6.385
F-Statistic	#NA
Prob (F-Statistic)	#NA
Log-Likelihood	-527.05
Model Sum of Squares	4,785,246.98
Sum of Squared Errors	45,880.37
Mean Squared Error	420.92
Std. Error of Regression	20.52
Mean Abs. Dev. (MAD)	14.71
Mean Abs. % Err. (MAPE)	1.88%
Durbin-Watson Statistic	1.328
Durbin-H Statistic	#NA
Ljung-Box Statistic	22.96
Prob (Ljung-Box)	0.5221
Skewness	0.655
Kurtosis	5.714
Jarque-Bera	45.397
Prob (Jarque-Bera)	0.0000

Residential SAE Model Fit



Residential Model 2019-2029 Reconciliation

As requested by Synapse, the following tables provide details reflecting the changes between 2019 and 2029 forecast years. Some of the numbers have small discrepancies compared to those used in the final annual figures as there is a conversion between monthly data at the model level to annual data at the system level.

Residential Load – Post Regression (GWh)

	Existing Cust Load (Reg. Model)	New Cust Load	Heat Pumps	EVs	Hot Water	Solar	Res Sales (before DSM)	DSM	Res Sales (with DSM)
2019	4,520	41	34	1	0	(4)	4,592	(31)	4,562
2029	4,341	305	167	147	14	(142)	4,833	(361)	4,472
Change	-3.9%	5.8%	2.9%	3.2%	0.3%	-3.0%	5.2%	-7.2%	-2.0%

Res Sales = Existing Customer Load + New Customer Load + Heat Pump Load + EV Load + Hot Water Load + Solar Load + DSM

Existing customer load is calculated as Res Average Use (9,658 kWh/cust in 2019, 9,275 kWh/cust in 2029) x number of customers as of 2018 (468,049).

Residential Average Use –Regression

	XHeat	XCool	XOther	AvgEE Savings	Binaries	ARMA	Res Average Use
2019	3,999	180	5,779	(720)	292	127	9,658
2029	4,021	188	5,493	(720)	292	0	9,275
Change	0.2%	0.1%	-3.0%	0.0%	0.0%	-1.3%	-4.0%

Res Avg Use = XHeat + XCool + XOther + AvgEESavings + Binaries + ARMA

Residential Input Variables – XHeat

	Intensities				Econ + Struct	Regression	
	Efurn	HP Heat	Secondary Heat	Furnace Fans	HeatUse Variable	Coeff	Total XHeat
2019	2,815	1,284	172	148	1.08	0.838	3,999
2029	2,830	1,291	173	108	1.09	0.838	4,021
Change	0.4%	0.2%	0.0%	-0.9%	0.9%	0.0%	0.5%

XHeat = (Efurn + HP Heat + Secondary Heat + Furnace Fans) x HeatUseVariable x Coeff

Note that because these factors are multiplicative, the growth rate for the intensities is multiplied by the coefficients to calculate the overall impact. For example, the contribution of Efurn is calculated as [($Efurn_{2029}$-$Efurn_{2019}$) x HeatUse x Coeff]/$WtXHeat_{2019}$

Residential Input Variables – XCool

	Intensities			Econ + Struct	Regression	
	Central AC	HP Cool	Room AC	CoolUse Variable	Coefficient	Total Xcool
2019	36	82	50	1.3	0.845	180
2029	39	83	52	1.3	0.845	188
Change	1.4%	0.5%	1.5%	0.8%	0.0%	4.4%

XCool = (Central AC + HP Cool + Room AC) x CoolUseVariable x Coeff

Residential Input Variables – XOther

	Intensities							Econ + Struct	Reg	
	Water Heat	Cook	Ref/Frz	Wash/ Dry	TV	Light	Misc	Other Use Var	Coeff	Total Xother
2019	1,705	572	682	740	761	801	630	1.0	0.981	5,779
2029	1,683	569	580	671	701	673	666	1.0	0.981	5,439
Change	-0.4%	0.0%	-1.8%	-1.2%	-1.0%	-2.2%	0.6%	0.0%	0.0%	-5.9%

XOther = (Water Heat + Cook + Ref/Frz + Wash/Dry + TV + Light + Misc) x OtherUseVariable x Coeff

Commercial Model Detail

Small General Service: Small General Service is projected using an SAE average use model and a sales forecast is generated as the product of the average use and customer forecast.

Like the residential model, monthly Small General Service average use is defined as a function of monthly heating requirements (*XHeat*), cooling requirements (*XCool*), and other use (*XOther*). The end-use variables are constructed by interacting annual end-use intensity projections (EI) that capture end-use intensity trends, with *GDP* and employment ($SmlGenVar_m$), real price ($Price_m$), monthly *HDD* and *CDD* and a variable accounting for the number of days in a given month:

$$XHeat_m = EI_{heat} \times Price_m^{-.15} \times SmlGenVar_m \times HDD_m$$
$$XCool_m = EI_{cool} \times Price_m^{-.15} \times SmlGenVar_m \times CDD_m$$
$$XOther_m = EI_{other} \times Price_m^{-.15} \times SmlGenVar_m \times Days_m$$

The coefficients on price are imposed short-term price elasticities.

Several binary shift variables are added to the model to:

(1) Compensate for the change in the rate class specification, which came into effect in November 2014, allowing commercial customers consuming 32,000 to 42,000 kWh per year to choose whether to take service under the Small General rate or the General rate

(2) Improve model fit using monthly binaries for March, September and December.

As in the residential model, analysis of the initial regression results indicated that the model would be improved by adding an ARMA process. A seasonal moving average of period 1, SMA(1), and a autoregressive process of period 1, AR(1) were used. Autocorrelated errors can be understood as a propagation of uncertainty from one month to the immediate next, a sort of momentum between consecutive measurements. The regression model weights all measurements (sales) the same, however more recent measurements may shed better light on the current forecast than measurements from years ago.

The monthly forecast average use sales model is then estimated as:

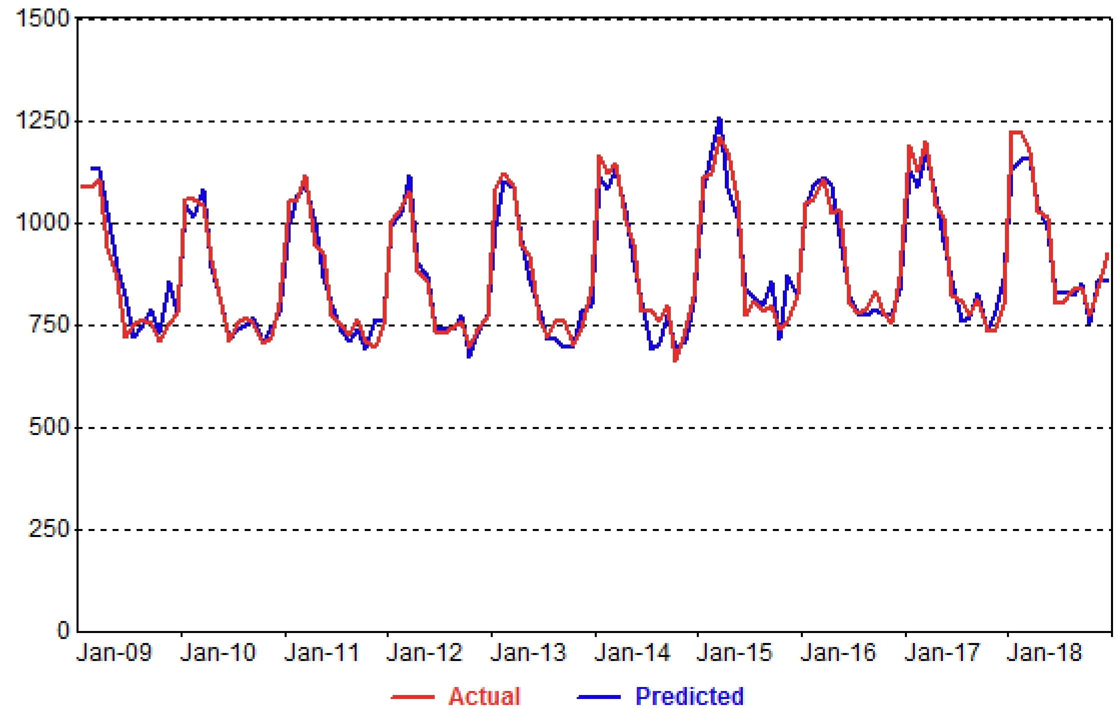
$SmlGen\_AvgUse_m = b_1 \times XHeat_m + b_2 \times XCool_m + b_3 \times XOther_{m} + MBin.Aft15 + MBin.Mar + MBin.Sep + MBin.Dec + SMA(1) + AR(1)$

Variable	Coefficient	StdErr	T-Stat	P-Value
MStructSmlGen.WtXHeat	0.727	0.038	18.943	0.00%
MStructSmlGen.WtXCool	0.137	0.030	4.517	0.00%
MStructSmlGen.WtXOther	0.703	0.019	37.597	0.00%
MBin.Mar	104.264	20.441	5.101	0.00%
MBin.Sep	66.149	21.618	3.060	0.28%
MBin.Dec	-100.238	20.920	-4.791	0.00%
MBin.Aft13	65.642	13.080	5.018	0.00%
AR(1)	0.216	0.100	2.165	3.26%
SMA(1)	0.543	0.085	6.371	0.00%

Small General Model Statistics

Model Statistics	
Iterations	14
Adjusted Observations	119
Deg. of Freedom for Error	110
R-Squared	0.931
Adjusted R-Squared	0.926
AIC	7.587
BIC	7.797
F-Statistic	#NA
Prob (F-Statistic)	#NA
Log-Likelihood	-611.27
Model Sum of Squares	2,735,621.64
Sum of Squared Errors	201,726.28
Mean Squared Error	1,833.88
Std. Error of Regression	42.82
Mean Abs. Dev. (MAD)	32.47
Mean Abs. % Err. (MAPE)	3.67%
Durbin-Watson Statistic	1.981
Durbin-H Statistic	#NA
Ljung-Box Statistic	40.35
Prob (Ljung-Box)	0.0196
Skewness	-0.194
Kurtosis	3.197
Jarque-Bera	0.938

Small General Model Fit



Small General 2019-2029 Reconciliation

The Small General Demand customer forecast model is constructed like the residential model. Adjustments done outside the regression include estimates for commercial and industrial growth programs (mainly heat pumps), PV and DSM.

Historically the XHeat, XCool and XOther variables are constructed with a flat scaling factor to keep regression coefficients close to 1, which allows for easier comparison.

Small General Load – Post Regression (GWh)

	Load from Regression Model	NSPI C&I Programs	Solar	Small Gen Sales (before DSM)	DSM	Small Gen Sales (with DSM)
2019	289	4	(0)	292	(4)	288
2029	278	28	(18)	288	(46)	242
Change	-3.6%	8.1%	-5.9%	-1.5%	-14.4%	-16.1%

Small General Sales = Avg Use Existing x customer count forecast+ NSPI C&I Programs + Solar Load + DSM

The load from the regression model is calculated as Small Gen Average Use (11,300 kWh/cust in 2019, 10,629 kWh/cust in 2029) x number of customers (25,545 in 2019, increasing to 26,158 in 2029).

Small General Average Use –Regression

	XHeat	XCool	XOther	Binaries	ARMA	Avg Sales (kWh)
2019	2,893	211	7,198	858	140	11,300
2029	3,030	209	6,532	858	(0)	10,629
Change	1.2%	0.0%	-5.9%	0.0%	-1.2%	-5.9%

Small General Avg Use = XHeat + XCool + XOther + Binaries + ARMA

Small General Input Variables – XHeat

	Intensities	Econ + Struct	Regression		
	Heating	HeatUse Variable	Coeff	Scaling Factor	Total XHeat (kWh)
2019	50,079	1.14	0.727	0.070	2,893
2029	51,933	1.15	0.727	0.070	3,030
Change	3.7%	1.0%	0.0%	0.0%	4.7%

XHeat = Heating x HeatUseVariable x Coeff x Scaling Factor

Note that because these factors are multiplicative, the growth rate for the intensities are multiplied by the coefficients to calculate the overall impact. For example, the contribution of Heating is calculated as [($Heat_{2029}$-$Heat_{2019}$) x HeatUse x Coeff x Scaling]/$WtXHeat_{2019}$

Small General Input Variables – XCool

	Intensities	Econ + Struct	Regression		
	Cooling	CoolUse Variable	Coefficient	Scaling Factor	Total XCool (kWh)
2019	33,056	1.33	0.137	0.035	211
2029	32,414	1.34	0.137	0.035	209
Change	-2.0%	0.8%	0.0%	0.0%	-1.1%

XCool = Cooling x CoolUseVariable x Coeff x Scaling Factor

Small General Input Variables – XOther

	Intensities							Econ + Struct	Reg		
	Vent	Water Heat	Cook	Refrig	Light	Office	Misc	OtherUse Var	Coeff	Scaling Factor	Total XOther (kWh)
2019	16,880	1,601	2,456	30,418	49,759	12,891	48,551	12.60	0.703	0.005	7,198
2029	13,607	1,425	2,230	27,608	38,837	10,899	51,572	12.71	0.703	0.005	6,532
Change	-2.0%	-0.1%	-0.1%	-1.7%	-6.8%	-1.2%	1.9%	0.9%	0.0%	0.0%	-9.2%

XOther = (Ventilation+ Water Heat + Cook + Refrigeration + Light + Office + Misc) x OtherUseVariable x Coeff x Scaling Factor

General Service: The General Service rate class model is estimated on a total monthly sales basis where total monthly billed sales is a function of total monthly heating requirements (*XHeat*), cooling requirements (*XCool*), and other use (*XOther*). The end-use variables are constructed by interacting annual end-use intensity projections (EI) that capture end-use intensity trends, with *GDP* and employment ($GenVar_m$), real price ($Price_m$), monthly *HDD* and *CDD* and a variable accounting for the number of days in a given month:

$$XHeat_m = EIheat \times Price_m^{-.15} \times GenVar_m \times HDD_m$$

$$XCool_m = EIcool \times Price_m^{-.15} \times GenVar_m \times CDD_m$$

$$XOther_m = EIother \times Price_m^{-.15} \times GenVar_m \times Days_m$$

The coefficients on price are imposed short-term price elasticities.

Like the Small General model, binaries are added for the change in billing rate class threshold.

A monthly forecast sales model is then estimated as:

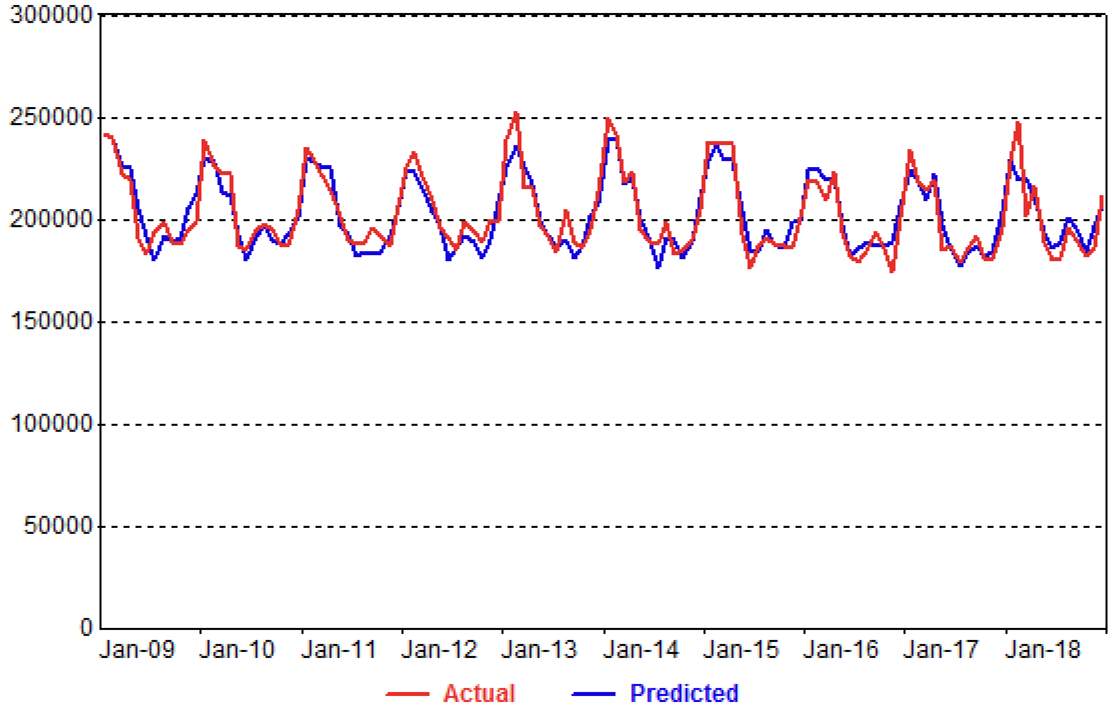
$$GenService_m = b1 \times XHeat_m + b2 \times XCool_m + MBin.Aug08 + MBin.Aft13 + AR(1) + SMA(1)$$

Variable	Coefficient	StdErr	T-Stat	P-Value
MStructGen.WtXHeat	0.696	0.051	13.597	0.00%
MStructGen.WtXCool	0.260	0.051	5.080	0.00%
MStructGen.WtXOther	1.009	0.021	47.168	0.00%
MBin.Aft13	5699.159	2633.310	2.164	3.25%
AR(1)	0.316	0.089	3.540	0.06%
SMA(1)	0.577	0.090	6.389	0.00%

General Service Model Statistics

Model Statistics	
Iterations	14
Adjusted Observations	119
Deg. of Freedom for Error	113
R-Squared	0.843
Adjusted R-Squared	0.836
AIC	17.955
BIC	18.095
F-Statistic	#NA
Prob (F-Statistic)	#NA
Log-Likelihood	-1,231.16
Model Sum of Squares	36,223,779,935.89
Sum of Squared Errors	6,751,754,834.03
Mean Squared Error	59,750,042.78
Std. Error of Regression	7,729.82
Mean Abs. Dev. (MAD)	5,965.25
Mean Abs. % Err. (MAPE)	2.94%
Durbin-Watson Statistic	1.958
Durbin-H Statistic	#NA
Ljung-Box Statistic	32.08
Prob (Ljung-Box)	0.1251
Skewness	0.249
Kurtosis	3.484
Jarque-Bera	2.389
Prob (Jarque-Bera)	0.3029

General Service Model Fit



General Demand 2019-2029 Reconciliation

The general demand class, which makes up the largest portion of the commercial sector, is forecasted as gross total sales rather than average use as is the case in the small general and residential classes.

Like the small general model, a flat scaling factor is used to adjust some of the end-use regression coefficients close to 1, making their interpretation a bit easier. Outside of the SAE regression model, adjustments include for NS Power commercial growth programs (mainly heat pumps), PV and DSM.

General Demand Load – Post Regression (GWh)

	Load Regression Model	NSPI C&I Programs	Solar	Gen Sales (before DSM)	DSM	Gen Sales (with DSM)
2019	2,408	14	(0)	2,421	(27)	2,395
2029	2,351	97	(18)	2,431	(316)	2,115
Change	-2.3%	3.4%	-0.7%	0.4%	-11.9%	-11.7%

Gen Sales = Sales + NSPI C&I Programs+ Solar Load + DSM

General Demand Sales –Regression

	XHeat	XCool	XOther	Binaries	ARMA	Sales (MWh)
2019	345,122	44,887	1,969,713	68,390	(20,405)	2,407,707
2029	329,680	47,369	1,905,996	68,390	0	2,351,435
Change	-0.6%	0.1%	-2.6%	0.0%	0.8%	-2.3%

Sales = XHeat + XCool + XOther + Binaries + ARMA

General Demand Input Variables – WtXHeat

	Intensities	Econ + Struct	Regression		
	Heating	HeatUse Variable	Coeff	Scaling Factor	Total XHeat
2019	412,365	1.20	0.696	1	345,122
2029	366,018	1.29	0.696	1	329,680
Change	-12.1%	7.6%	0.0%	0.0%	-4.5%

XHeat = Heating x HeatUseVariable x Coeff x Scaling Factor

Note that because these factors are multiplicative, the growth rate for the intensities are multiplied by the coefficients to calculate the overall impact. For example, the contribution of Heating is calculated as [($Heat_{2029}$-$Heat_{2019}$) x HeatUse x Coeff x Scaling]/$WtXHeat_{2019}$

General Demand Input Variables – XCool

	Intensities	Econ + Struct	Regression		
	Cooling	CoolUse Variable	Coefficient	Scaling Factor	Total Xcool
2019	330,451	1.41	0.260	0.370	44,887
2029	324,033	1.52	0.260	0.370	47,369
Change	-14.3%	7.6%	0.0%	0.0%	5.5%

XCool = Cooling x CoolUseVariable x Coeff x Scaling Factor

General Demand Input Variables – XOther

	Intensities							Econ + Struct	Reg		
	Vent	Water Heat	Cook	Refrig	Light	Office	Misc	Other Use Var	Coeff	Scaling Factor	Total Xother
2019	168,746	16,008	24,555	304,083	497,421	128,871	485,345	13.35	1.009	0.090	1,969,713
2029	136,023	14,247	22,289	275,987	388,239	108,952	515,549	14.36	1.009	0.090	1,905,996
Change	-2.2%	-0.1%	-0.2%	-1.9%	-7.2%	-1.3%	2.0%	7.6%	0.0%	0.0%	-3.2%

XOther = (Ventilation + Water Heat + Cooking + Refrigeration + Lighting + Office + Miscelaneous) x OtherUseVariable x Coeff x Scaling Factor

Industrial Econometric Model Details

Small Industrial model

$SmlInd\_Sales_m = BinJan_m + BinFeb_m + BinMar_m + BinApr_m + BinMay_m + BinJun_m + BinJul_m + BinAug_m + BinSep_m + BinOct_m + BinNov_m + BinDec_m + BinJul08 + BinAug08 + BinAft17 + b1 \times GDP$

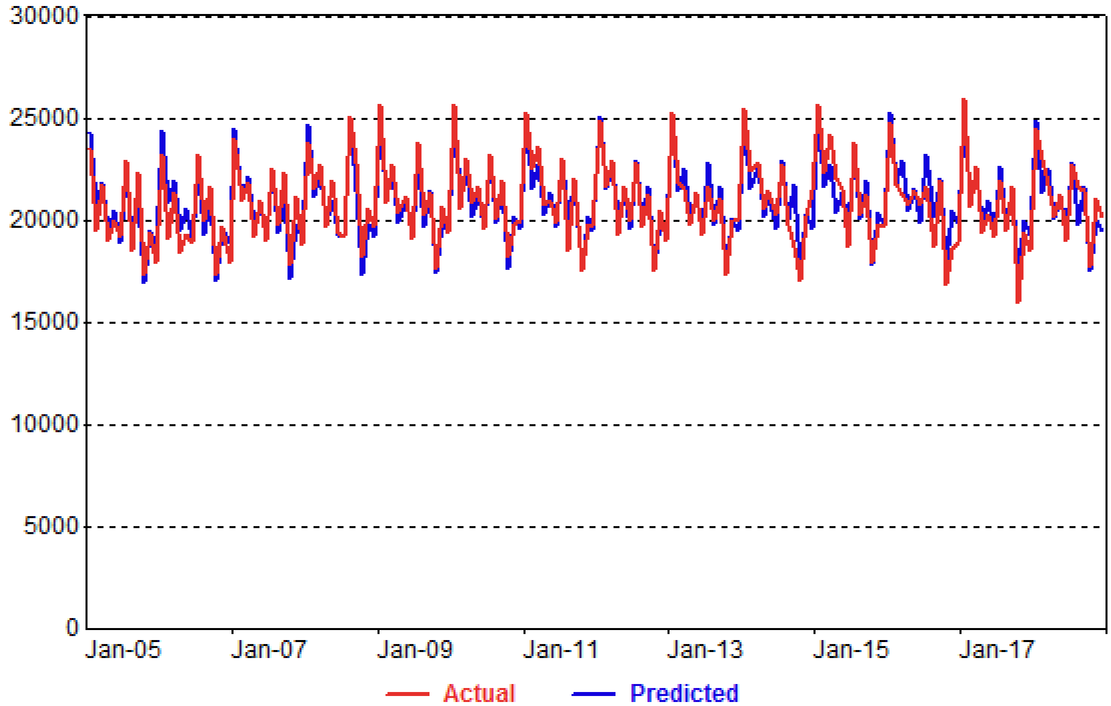
Binary variables for July and August 2008 were added to the model in order to isolate an anomaly in the billing data during this time. Class sales are lower than normal in July and higher than normal in August because billing which was supposed to occur on the last day of July was delayed and actually occurred on the first day of August. A binary was also added for 2017 as the model overestimated the most recent year of sales. As discussed in Section 4.0, a historic period of 2005 – 2018 was used to improve model fit.

Variable	Coefficient	StdErr	T-Stat	P-Value
MBin.Jan	13266.167	2474.615	5.361	0.00%
MBin.Feb	9758.628	2476.479	3.941	0.01%
MBin.Mar	10858.567	2478.342	4.381	0.00%
MBin.Apr	8419.392	2480.206	3.395	0.09%
MBin.May	9472.188	2482.069	3.816	0.02%
MBin.Jun	7832.359	2483.933	3.153	0.20%
MBin.Jul	11154.332	2488.403	4.483	0.00%
MBin.Aug	8110.544	2490.365	3.257	0.14%
MBin.Sep	9921.100	2489.451	3.985	0.01%
MBin.Oct	5818.135	2491.279	2.335	2.08%
MBin.Nov	8385.029	2493.106	3.363	0.10%
MBin.Dec	7722.800	2494.934	3.095	0.23%
MBin.Jul08	-3446.989	820.617	-4.200	0.00%
MBin.Aug08	5422.102	820.680	6.607	0.00%
MBin.Aft17	-697.189	226.233	-3.082	0.25%
MEcon.GDPIdx	11026.329	2354.155	4.684	0.00%

Small Industrial Model Statistics

Model Statistics	
Iterations	1
Adjusted Observations	168
Deg. of Freedom for Error	152
R-Squared	0.864
Adjusted R-Squared	0.851
AIC	13.434
BIC	13.732
F-Statistic	#NA
Prob (F-Statistic)	#NA
Log-Likelihood	-1,350.86
Model Sum of Squares	604,247,555.03
Sum of Squared Errors	94,845,337.60
Mean Squared Error	623,982.48
Std. Error of Regression	789.93
Mean Abs. Dev. (MAD)	568.42
Mean Abs. % Err. (MAPE)	2.76%
Durbin-Watson Statistic	1.525
Durbin-H Statistic	#NA
Ljung-Box Statistic	59.08
Prob (Ljung-Box)	0.0001
Skewness	-0.435
Kurtosis	4.210
Jarque-Bera	15.532
Prob (Jarque-Bera)	0.0004

1 **Small Industrial Model Fit**



2

Medium Industrial Model

$$MedInd\_Sales_m = BinJan_m + BinFeb_m + BinMar_m + BinApr_m + BinMay_m + BinJun_m + BinJul_m + BinAug_m + BinSep_m + BinOct_m + BinNov_m + BinDec_m + BinJul08 + BinAug08 + b1 \times ManEmp + AR(1)$$

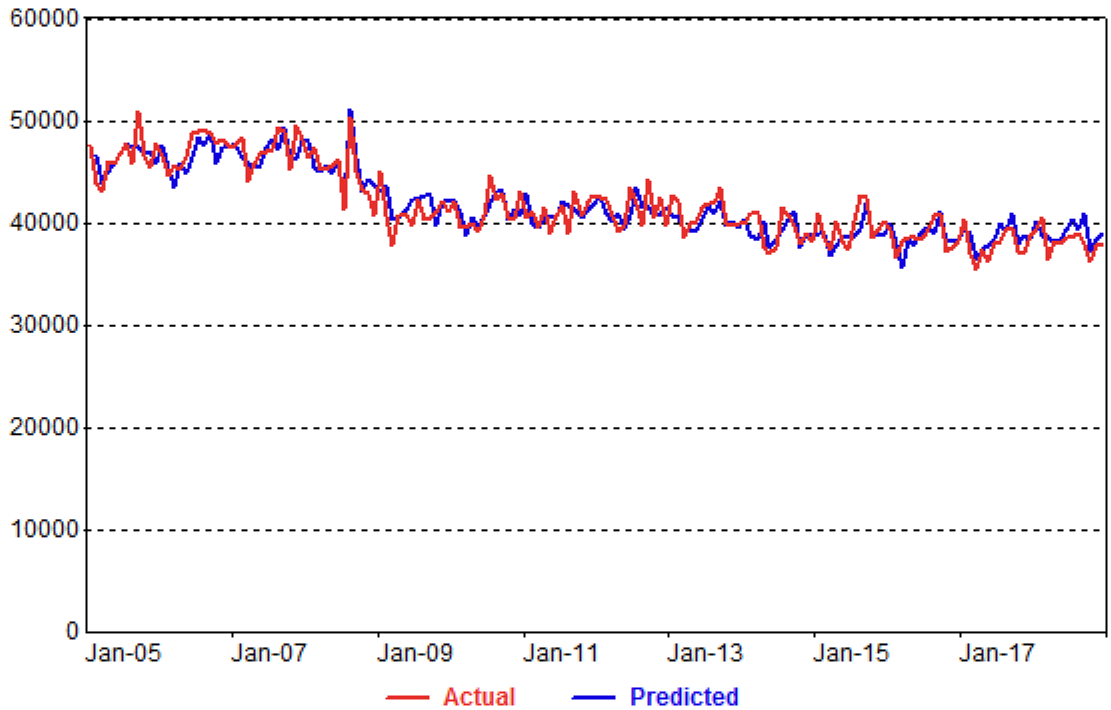
Binary variables for July and August 2008 were added to isolate an anomaly in the billing data during this period. Class sales are lower than normal in July and higher than normal in August because billing which was supposed to occur on the last day of July was delayed and actually occurred on the first day of August. An AR variable was added to improve model results. As discussed in Section 4.0, a historic period of 2005 – 2018 was used to improve model fit.

Variable	Coefficient	StdErr	T-Stat	P-Value
MBin.Jan	17947.121	2010.459	8.927	0.00%
MBin.Feb	16762.948	2022.874	8.287	0.00%
MBin.Mar	15296.029	2027.929	7.543	0.00%
MBin.Apr	16285.075	2028.725	8.027	0.00%
MBin.May	16057.486	2027.181	7.921	0.00%
MBin.Jun	17082.943	2024.379	8.439	0.00%
MBin.Jul	18235.241	2016.728	9.042	0.00%
MBin.Aug	17920.584	2014.315	8.897	0.00%
MBin.Sep	18903.354	2015.255	9.380	0.00%
MBin.Oct	16385.886	2012.237	8.143	0.00%
MBin.Nov	17197.431	2009.168	8.559	0.00%
MBin.Dec	17251.425	2006.073	8.600	0.00%
MBin.Aug08	-5262.709	1483.154	-3.548	0.05%
MBin.Jul08	5062.896	1482.394	3.415	0.08%
MEcon.ManEmpIdx	29737.890	2376.599	12.513	0.00%
AR(1)	0.524	0.070	7.541	0.00%

Medium Industrial Model Statistics

Model Statistics	
Iterations	8
Adjusted Observations	167
Deg. of Freedom for Error	151
R-Squared	0.847
Adjusted R-Squared	0.832
AIC	14.679
BIC	14.977
F-Statistic	#NA
Prob (F-Statistic)	#NA
Log-Likelihood	-1,446.64
Model Sum of Squares	1,814,648,983.43
Sum of Squared Errors	326,884,762.41
Mean Squared Error	2,164,799.75
Std. Error of Regression	1,471.33
Mean Abs. Dev. (MAD)	1,106.53
Mean Abs. % Err. (MAPE)	2.66%
Durbin-Watson Statistic	2.200
Durbin-H Statistic	#NA
Ljung-Box Statistic	76.07
Prob (Ljung-Box)	0.0000
Skewness	0.158
Kurtosis	2.640
Jarque-Bera	1.597
Prob (Jarque-Bera)	0.4500

Medium Industrial Model Fit



Combined Model for Commercial and Industrial DSM Coefficient

$NonResSales_m = b1 \times NonResEESavings_m + b2 \times GenWtXHeat_m + b3 \times GenWtXCool_m + b3 \times GenWtXOther_m + BinYr11to14_m + BinDec_m + b4 \times NonResCustomers_m$

Weighted X variables from the General Service model were used to represent the underlying end uses in conjunction with the non-residential portion of historical DSM savings, as well as the number of non-residential customers to help explain underlying sales trends over time. Binary variables were added similar to those used in the underlying commercial and industrial models.

Variable	Coefficient	StdErr	T-Stat	P-Value
MSales.EESavings	-0.623	0.148	-4.201	0.01%
MStructGen.WtXHeat	0.619	0.059	10.559	0.00%
MStructGen.WtXCool	0.900	0.048	18.735	0.00%
MStructGen.WtXOther	0.975	0.359	2.718	0.76%
MBin.Yr11to14	9726.136	2783.344	3.494	0.07%
MBin.Dec	-17918.743	3747.530	-4.781	0.00%
MSales.NonResCusts	5.268	1.636	3.220	0.17%

The coefficient on the EESavings variable represents the amount of DSM needed to explain historical sales trends beyond the changes in the underlying end-uses. When compared with the 2018 model, the significance of this variable has improved (P-value of 0.01% vs 3.26%).

Combined Model Statistics

Model Statistics	
Iterations	1
Adjusted Observations	120
Deg. of Freedom for Error	113
R-Squared	0.818
Adjusted R-Squared	0.808
AIC	18.683
BIC	18.846
F-Statistic	#NA
Prob (F-Statistic)	#NA
Log-Likelihood	-1,284.26
Model Sum of Squares	62,360,366,492.09
Sum of Squared Errors	13,882,459,764.26
Mean Squared Error	122,853,626.23
Std. Error of Regression	11,083.94
Mean Abs. Dev. (MAD)	8,908.34
Mean Abs. % Err. (MAPE)	2.25%
Durbin-Watson Statistic	1.665
Durbin-H Statistic	#NA
Ljung-Box Statistic	32.25
Prob (Ljung-Box)	0.1210
Skewness	0.384
Kurtosis	2.942
Jarque-Bera	2.965
Prob (Jarque-Bera)	0.2271

Peak Forecast (Accrued Classes)

The long-term system peak forecast for the accrued classes is derived through a monthly peak linear regression model that relates monthly peak demand (excluding large customer contribution) to heating, cooling, and base load requirements:

$$Peak_m = b1 \times HeatVar_m + b2 \times CoolVar_m + b3 \times BaseVar_m$$

The model variables ($HeatVar_m$, $CoolVar_m$, and $BaseVar_m$) incorporate changes in heating, cooling, and base-use energy requirements (which are derived from the class sales forecast models) as well as peak-day weather conditions.

The composition of the models allows historical and forecast heating and cooling load requirement to be estimated. The model coefficients for the heating (*XHeat*) and cooling variables (*XCool*) combined with heating and cooling variable for calendar-month normal weather conditions produce an estimate of the monthly heating and cooling load requirements.

Heating requirements are calculated as:

$$HeatLoad_m = B1 \times ResXHeat_m + C1 \times SmlGSXHeat_m + D1 \times GSXHeat_m$$

Where *B1*, *C1*, and *D1* are the coefficients on *XHeat* in the Residential, Small General Service, and General Service sales forecast models.

Cooling requirements are estimated in a similar manner. Cooling requirements are calculated as:

$$CoolLoad_m = B_2 \times ResXCool_m + C_2 \times SmlGSXCool_m + D_2 \times GSCool_m$$

Where B_2, C_2, and D_2 are the coefficients on *XCool* in the residential, Small General Service, and General Service sales forecast models.

In constructing the monthly peak model variables, the heating and cooling load requirements are normalized for the number of days and hours in the month by expressing heating and cooling load requirements on an average MW load basis:

$$HeatAvgMW_m = HeatLoad_m / Days_m / 24$$

$$CoolAvgMW_m = CoolLoad_m / Days_m / 24$$

The impact of peak-day weather conditions are then captured by interacting peak-day HDD and CDD with average monthly heating and cooling load requirements. *HeatAvgMW* and *CoolAvgMW* are indexed to 2005 and interacted with peak-day *HDD* and *CDD* creating the variables $HeatIdx_m$ and $CoolIdx_m$. This interaction allows the impact of peak-day *HDD* and *CDD* to change over the estimation period as the underlying heating and cooling load requirements change.

The peak model heating and cooling variables are calculated as:

$$HeatVar_m = HeatIdx_m \times PkHDD_m$$

$$CoolVar_m = CoolIdx_m \times PkCDD_m$$

The peak model base load variable ($BaseVar_m$) is constructed to capture the impact of loads that are not weather sensitive on peak, including residential, commercial, other end-use components along with industrial and unmetered sales. Base load requirements are calculated as:

$$BaseVar_m = \sum C_{m\times} mBin \times OtherLoad_m$$

Where the C_m coefficients are regression coefficients associated with the portions of $OtherLoad_m$, corresponding to a specific month of the year. In this way $BaseVar_m$ measures the strength of the non-weather sensitive load drivers in each month of the year. $OtherLoad_m$ is comprised of:

$$OtherLoad_m = ResOther_m + SmlGSOther_m + GSOther_m + SmIndSales_m + MedIndSales_m + UnMSales_m$$

Where ResOther$_m$, SmlOther$_m$ and GSOther$_m$ are the non-weather dependent portion of the sales model (including embedded DSM). For example, the energy sales model can be written as:

$$ResSales = b1 \times ResXHeat + b2 \times ResXCool + ResOther$$

Where *b1* and *b2* are regression coefficients found after running the sales model. *ResOther* can be written as:

$$ResOther_m = ResSales_m - b1 \times ResXHeat_m - b2 \times ResXCool_m$$

In this way, $ResOther_m$ (and also $SmlOther_m$ and $GSOther_m$) carries the non-weather dependent variables, including past energy-related DSM activity into the peak model, whose impact was assessed through specific coefficients in the energy sales model.

The $OtherLoad_m$ requirements are normalized for the number of days and hours in the month by expressing the load requirements on an average MW load basis:

$$OtherAvgMW_m = OtherLoad_m / Days_m / 24$$

Variable mBin.Feb10 is used to correct an anomaly in the historic data, and mBin.AftJun18 is a launch variable that helps to align the Peak Forecast with peak values seen in February 2019 actuals (firm peak of 1,954 MW occurring at -15 degrees Celsius at 8am, it would not include the typical lighting load seen in an evening peak).

Variable	Coefficient	StdErr	T-Stat	P-Value
mVars.Cool_Var	1.752	0.709	2.472	1.51%
mVars.Heat_Var	1.537	0.082	18.655	0.00%
mVars.Jan_Other	1.236	0.068	18.283	0.00%
mVars.Feb_Other	1.282	0.071	17.938	0.00%
mVars.Mar_Other	1.410	0.056	25.361	0.00%
mVars.Apr_Other	1.568	0.036	44.121	0.00%
mVars.May_Other	1.557	0.024	65.096	0.00%
mVars.Jun_Other	1.676	0.021	80.646	0.00%
mVars.Jul_Other	1.675	0.024	70.150	0.00%
mVars.Aug_Other	1.560	0.026	59.384	0.00%
mVars.Sep_Other	1.499	0.020	75.652	0.00%
mVars.Oct_Other	1.561	0.020	76.279	0.00%
mVars.Nov_Other	1.709	0.033	51.112	0.00%
mVars.Dec_Other	1.639	0.056	29.410	0.00%
mBin.Feb10	239.055	41.447	5.768	0.00%
mBin.AftJun18	52.988	17.291	3.064	0.28%

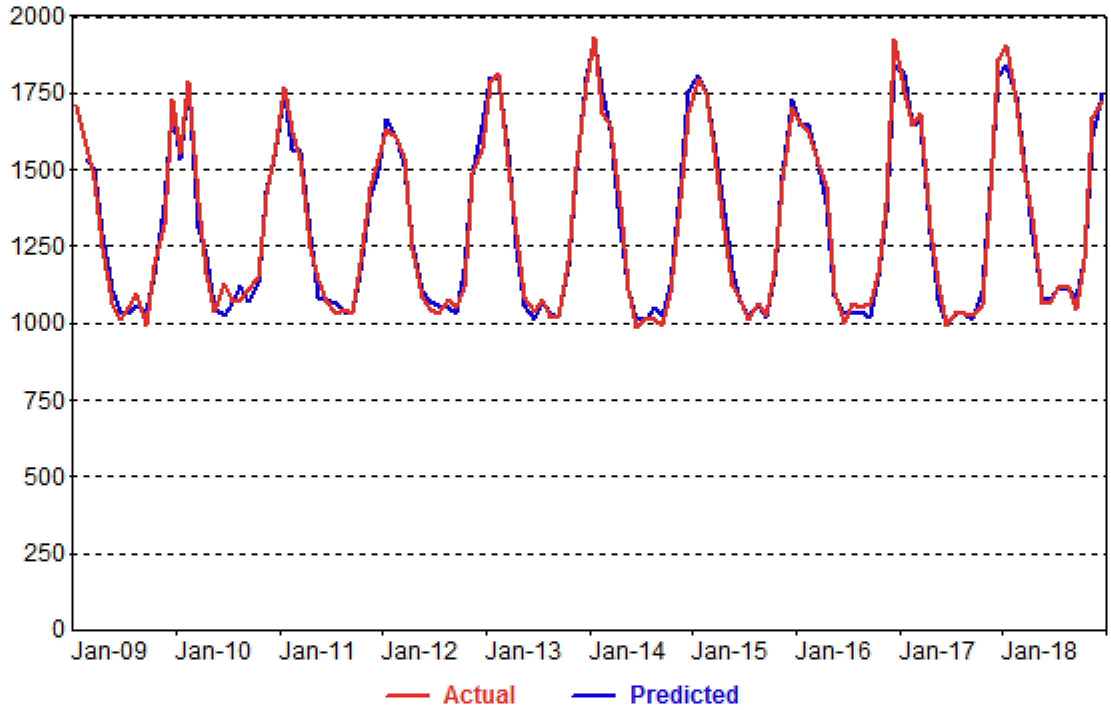
Peak Model Statistics

Model Statistics	
Iterations	1
Adjusted Observations	119
Deg. of Freedom for Error	103
R-Squared	0.984
Adjusted R-Squared	0.982
AIC	7.429
BIC	7.803
F-Statistic	#NA
Prob (F-Statistic)	#NA
Log-Likelihood	-594.89
Model Sum of Squares	9,392,714.58
Sum of Squared Errors	153,189.87
Mean Squared Error	1,487.28
Std. Error of Regression	38.57
Mean Abs. Dev. (MAD)	28.74
Mean Abs. % Err. (MAPE)	2.22%
Durbin-Watson Statistic	2.025
Durbin-H Statistic	#NA
Ljung-Box Statistic	28.68
Prob (Ljung-Box)	0.2326
Skewness	0.239
Kurtosis	2.900
Jarque-Bera	1.180
Prob (Jarque-Bera)	0.5544

Peak Model Fit

As seen in the figure below (and in the model statistics above), this approach produces a good fit with historical data. Although it was not possible to produce a peak model with an explicit peak DSM variable (like the Residential model) as the associated parameters are insignificant, the indirect effects of energy related DSM in the historical data from the end use model are carried over into the peak model. Assuming there is a relationship between the DSM applied to peak savings and DSM applied to energy savings, this will result in a similar amount of DSM embedded in the peak forecast, either through the embedded portion of energy sales DSM that is present on the *OtherLoad*$_m$ or embedded on the accrued demand information measured at the system level.

Peak Model Fit



Appendix C

Forecast Comparison

Figure C1: Total Nova Scotia Energy Requirement (NSR) with DSM

1

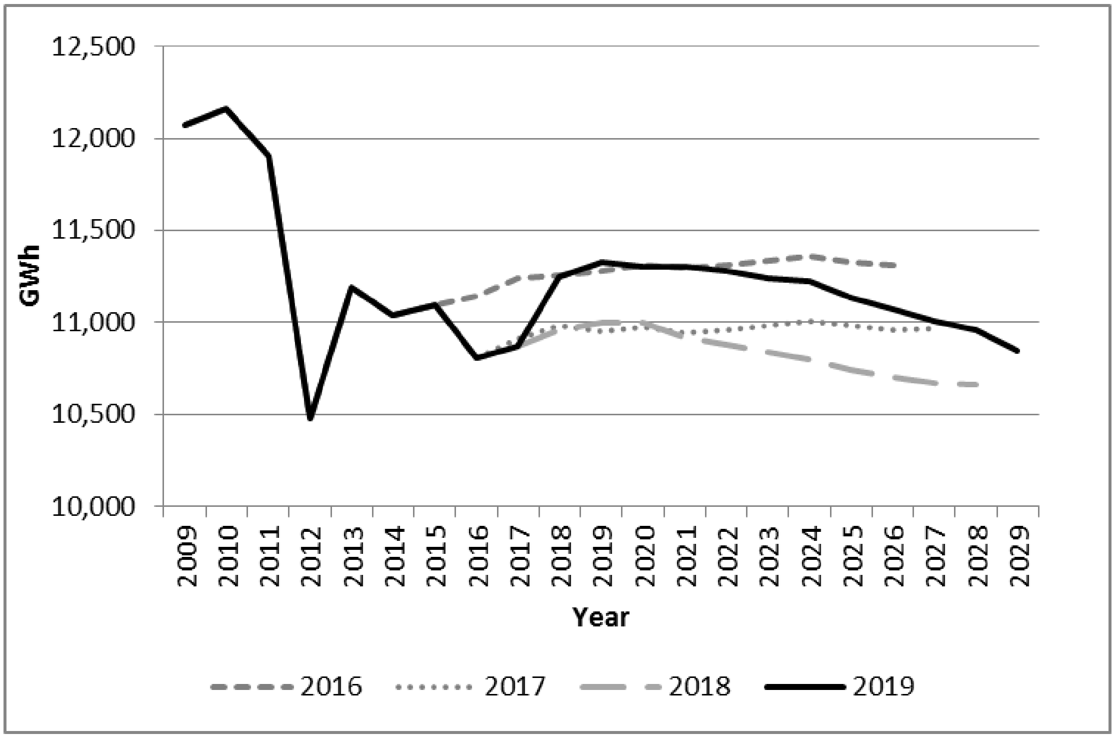


Figure C2: Total Nova Scotia Energy Requirement (NSR) before DSM

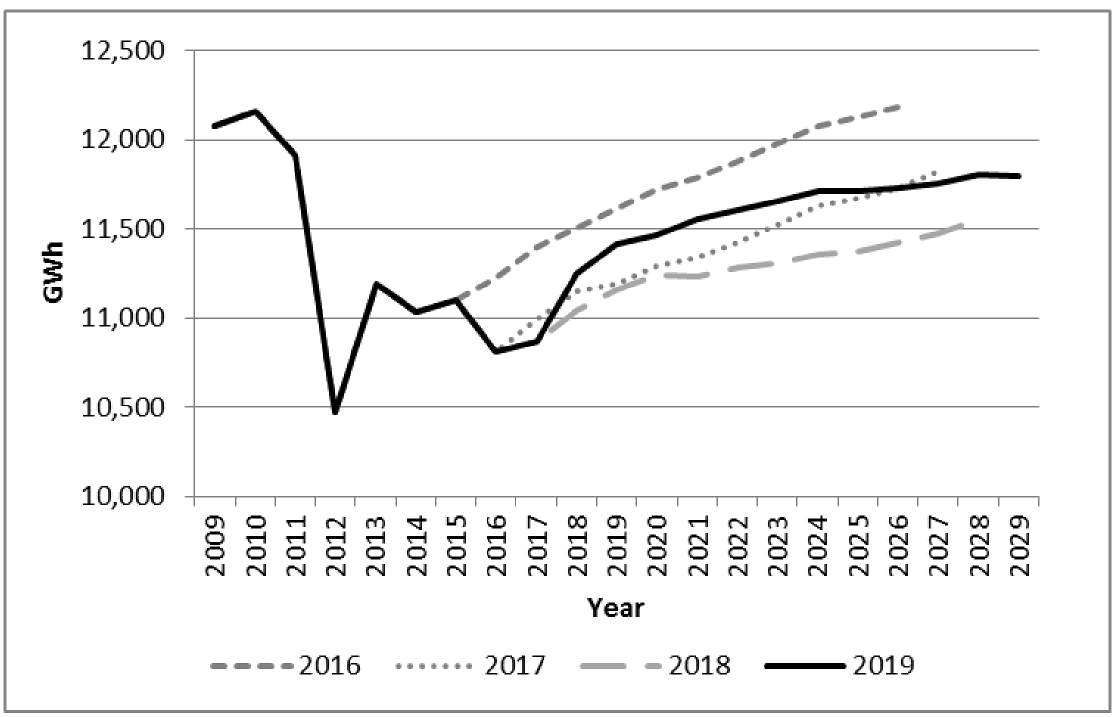


Figure C3: System Peak Demand with DSM

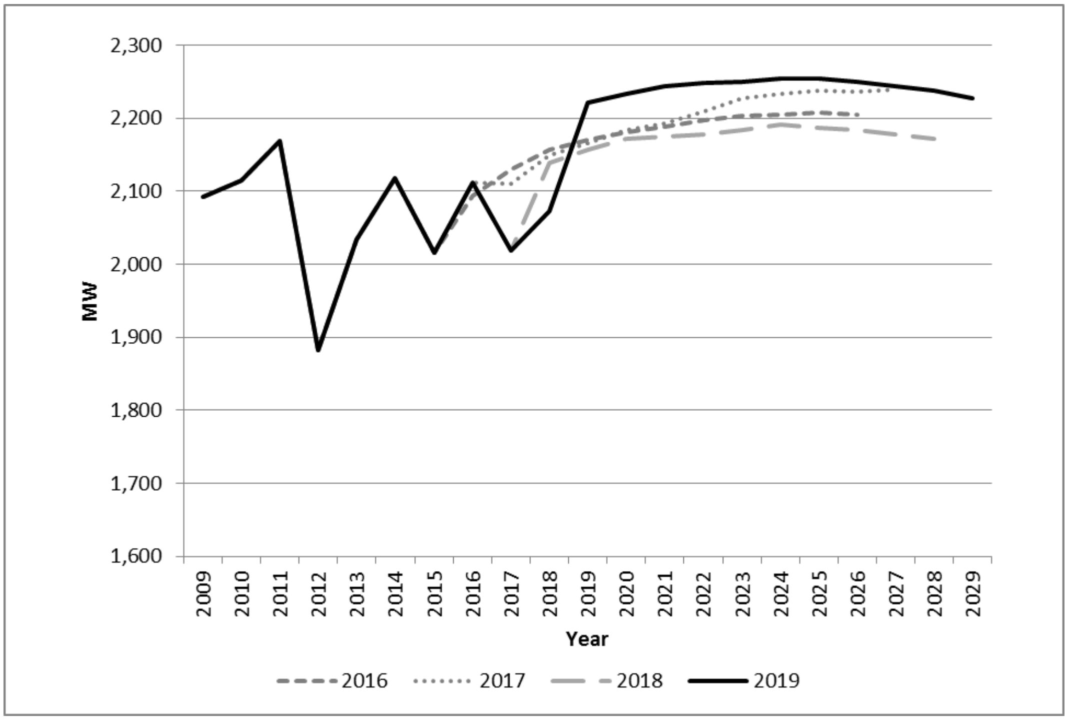


Figure C4: System Peak Demand before DSM

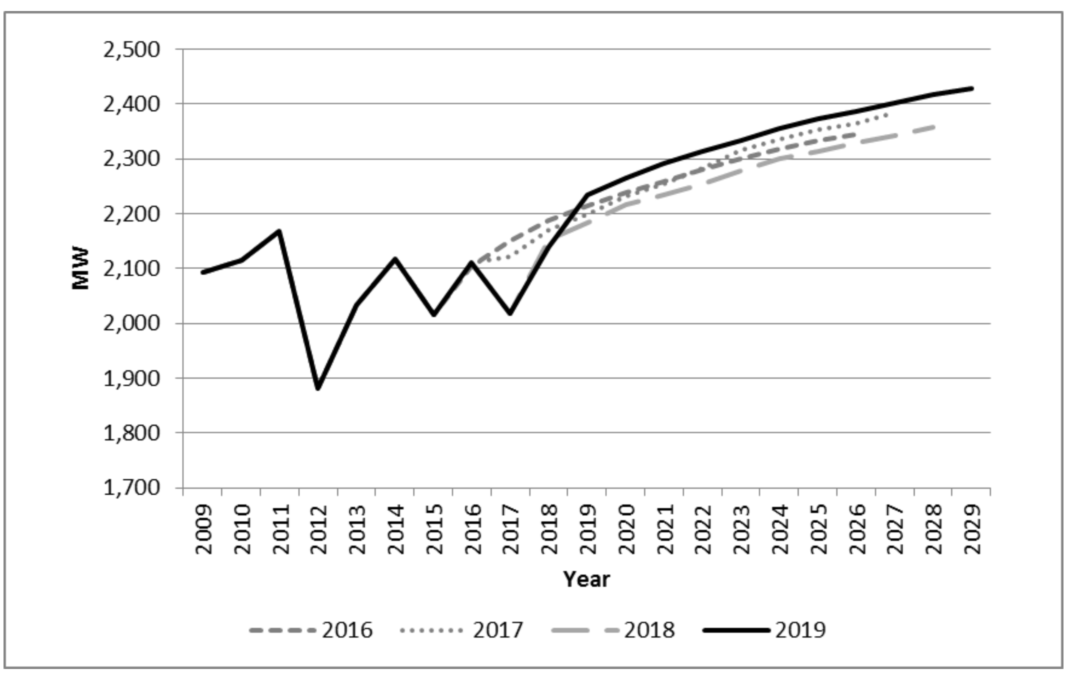


Figure C5: Firm Peak Demand with DSM

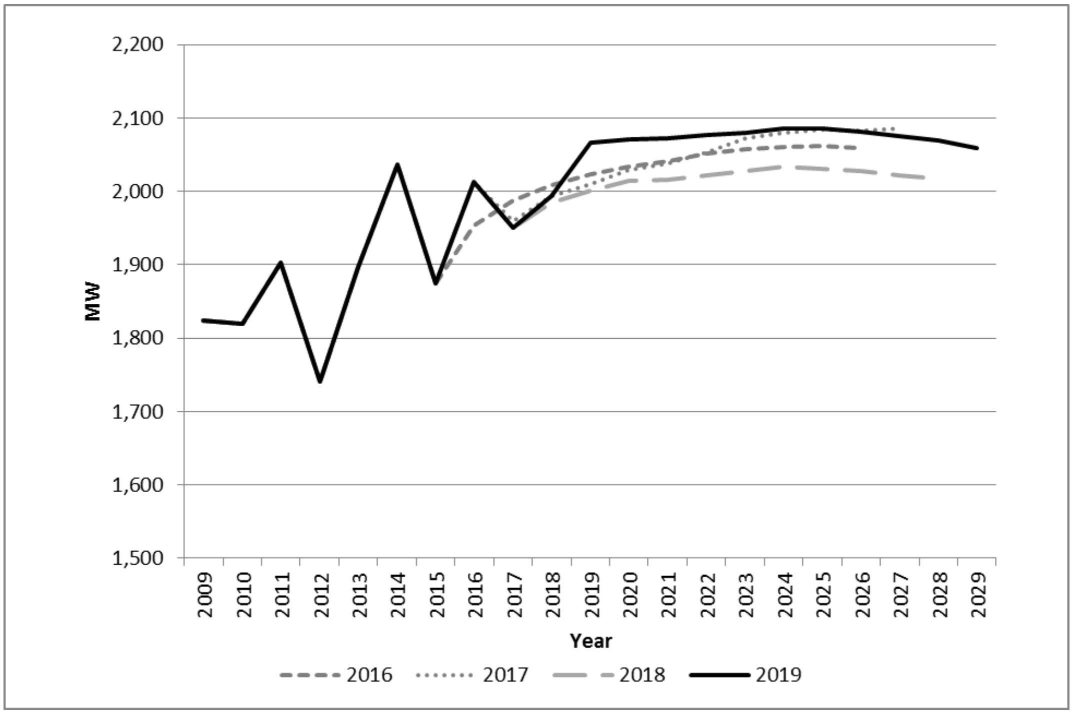
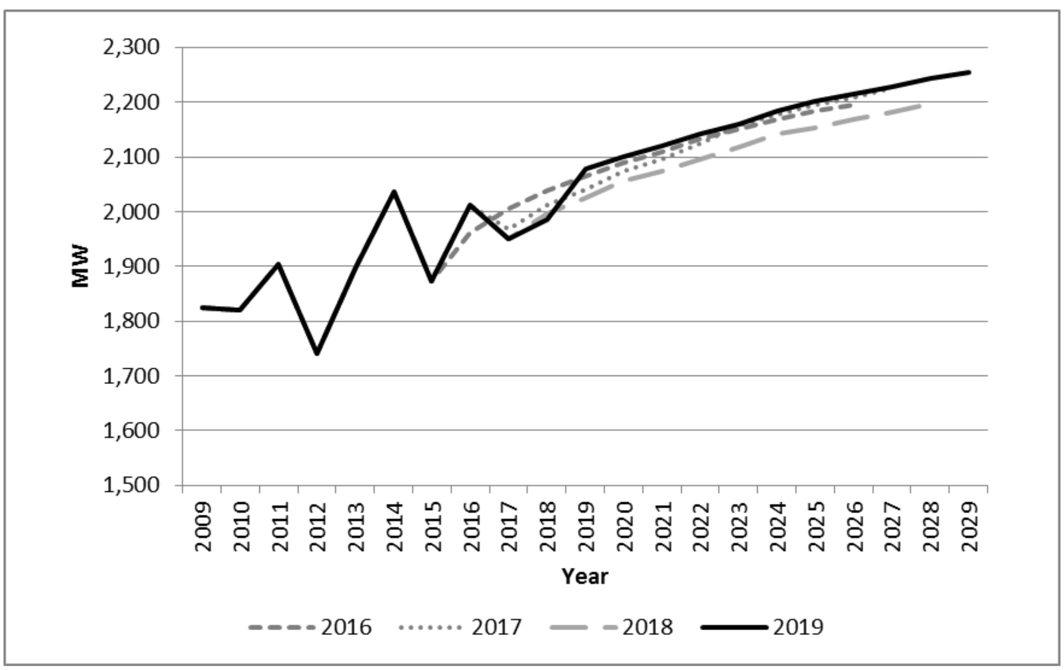
1 

Figure C6: Firm Peak Demand before DSM



Appendix D

Forecast Sensitivity Analysis

Sensitivity Analysis

The P10/P90 sensitivity analysis used Monte Carlo simulation for the economic and weather variables.

The algorithm uses the following sequence

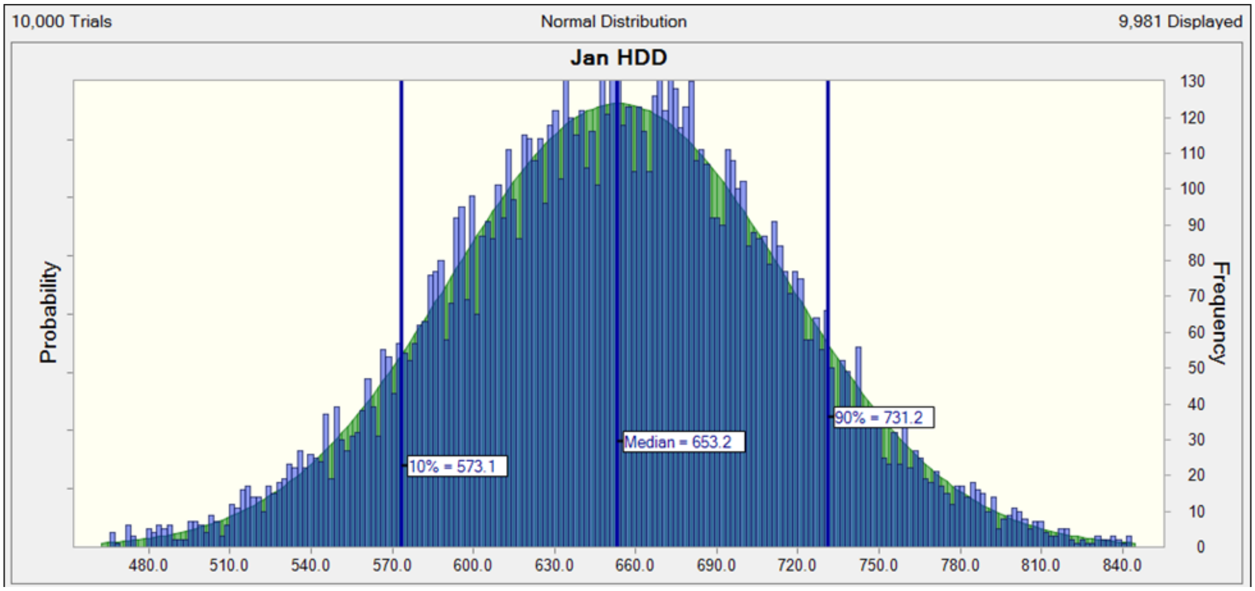
1. Once the deterministic SAE regression models is complete, the regression coefficients are exported into the Monte Carlo tool, called Oracle Crystal Ball (MS Excel add-on).

2. The Monte Carlo process assumes that the regression coefficients are held constant throughout the simulation, the historical variation of the inputs (predictors, independent variables) will affect the forecast prediction, in a probabilistic way. In other words, the simulations help to understand how the underlying SAE forecast responds to changes to the inputs based on historical variation.

3. For 2019 the historical variation of weather (20 years of hourly temperatures expressed in HDDs and CDDs) and economic drivers (as obtained from Conference Board of Canada Economic models) was used.

4. The variation of the weather and economic drivers are treated as Normal distributions (see **Figure D1**).

Figure D1: Distribution of January HDD



5. Since there are high and low DSM scenarios provided by the 2014 IRP, and since a probabilistic DSM forecast would be very difficult to produce given the consistency of prior activity, DSM scenarios have been added outside the Monte Carlo simulation.

6. Oracle's Crystal Ball runs about 10,000 trials, taking a random set of numbers from the aforementioned variables for each trial. For example the random HDD variable for January (above), would have a Normal distributed weight, meaning that after 10,000 trials, a histogram of the variable will have an average and standard deviation that coincides with the distribution of the last 20 years.

7. Incorporating variability in the individual end uses is still in progress, as it is difficult to produce a distribution for historical end use data. EIA and NRCan have revised their historical data sets in recent years, making historical variation studies challenging.

8. At the end of the Monte Carlo run, 10,000 output forecast points are produced, each year represented by 10,000 possible outputs, with Normal distributed averages and standard deviations, which are the result of the different combination of the random variable trials.

These distributions are shown in **Figure D2** for energy and **Figure D3** for peak (both before the impact of DSM). 10th (10%) and 90th (90%) percentiles can easily be obtained from Normal distributions and so they are highlighted in D2.

Figure D2: Distribution of Energy (Before DSM)

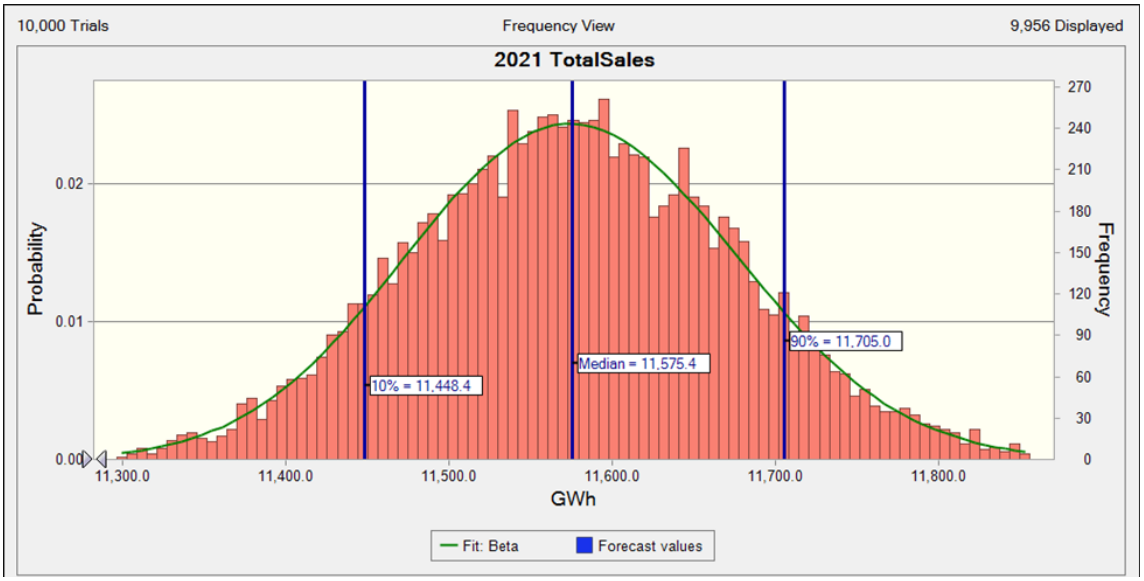
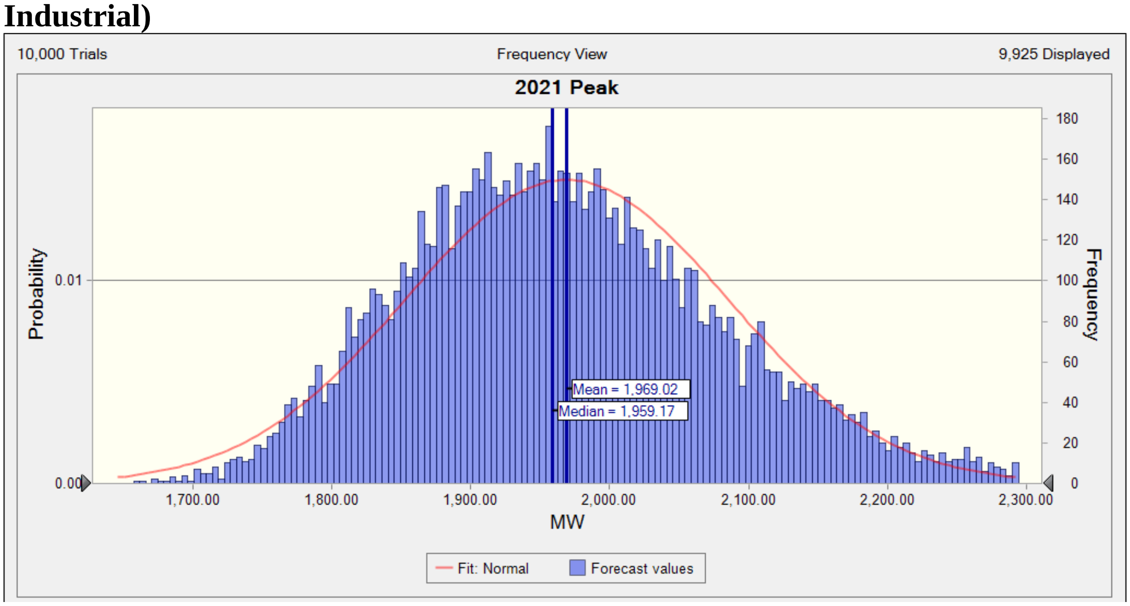
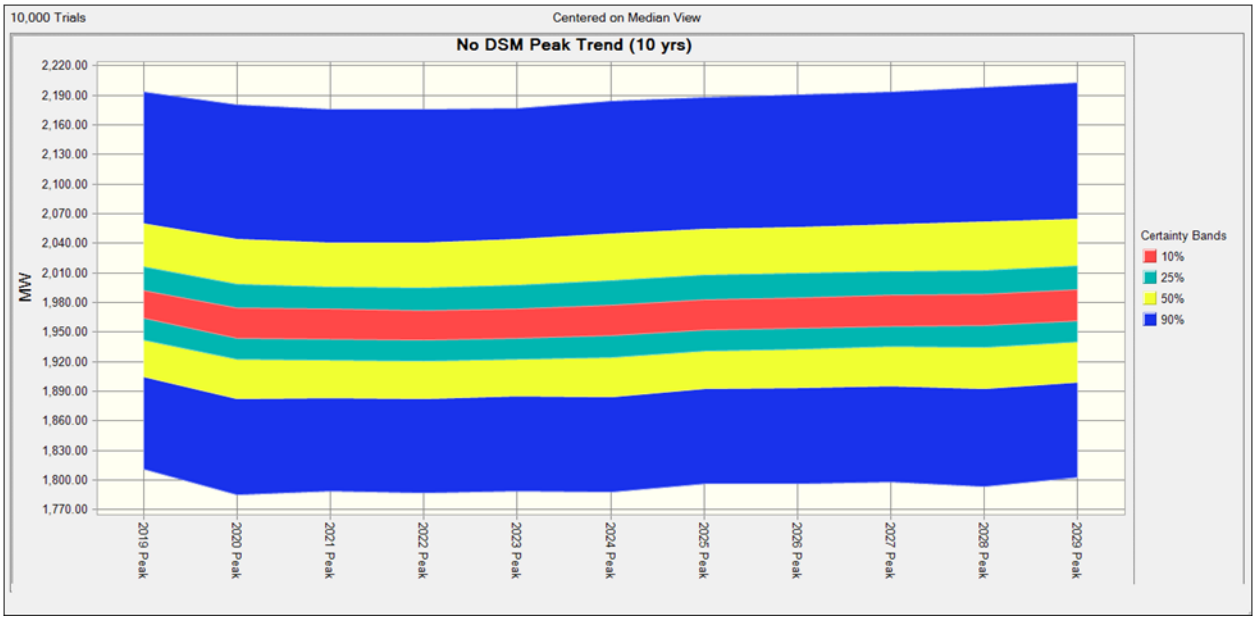


Figure D3: Distribution of Peak (Residential, Commercial and Small and Medium Industrial)



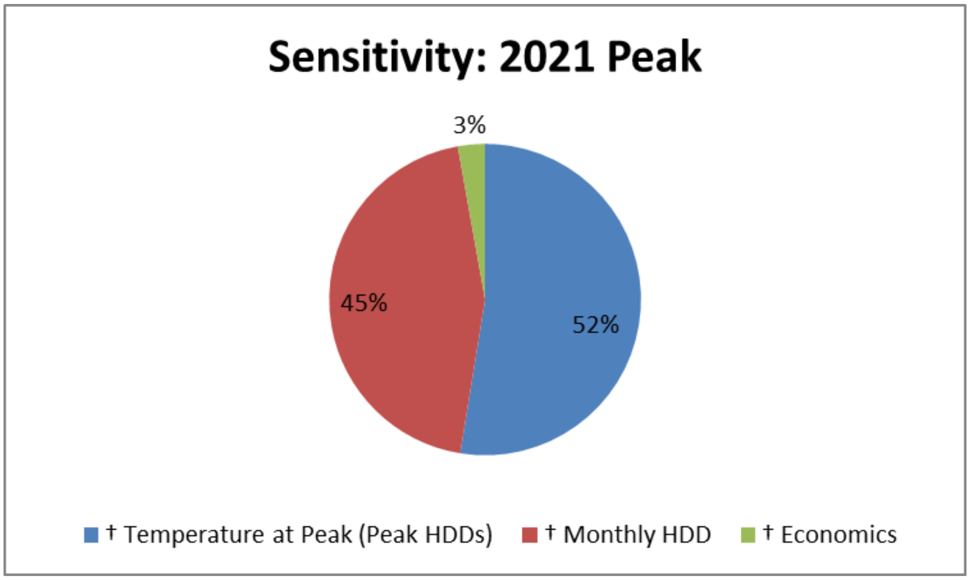
9. From these annual forecast distributions the various probabilistic forecasts can be obtained as well as sensitivity diagrams that show the relative impact of the variables in each year. In **Figure D4** the probabilities of peak forecasts (before DSM) around the median are shown. The area contained between blue borders represents a range of peaks that has a 90% chance of occurring; the yellow area highlights a 50% chance, and so on.

Figure D4 Peak Forecast (Residential, Commercial and Small and Medium Industrial)



The asymmetry in this figure, seen as the off-centre median, is explained by the bias introduced by plotting the maximum monthly Peak of a given year. Every month has a normal distributed daily Peak HDD, however by using the MAX function a skewed quasi-normal distribution is created when it selects the maximum Peak HDD from the 12 available months. Peak Demand and its associated SAE model are mostly sensitive to the Peak HDD temperature, however, as shown in **Figure D5**, the Monthly HDD gained more importance in 2019 as year-long residential heating had an impact on sales, and therefore, some of that impact (sensitive to monthly variations) translated into Peak Demand.

Figure D5: Relative Sensitivity of Peak



In terms of the sensitivity of the energy sales forecast to the various input variables, **Figures D6 and D7** show that in the near term, weather represents the strongest sensitivity, while in the long term, economics start becoming more dominant. This is mainly due to the compounding effect of economics over time, as opposed to weather which will only impact a particular year.

Figure D6 Sensitivity of Energy Forecast (2021)

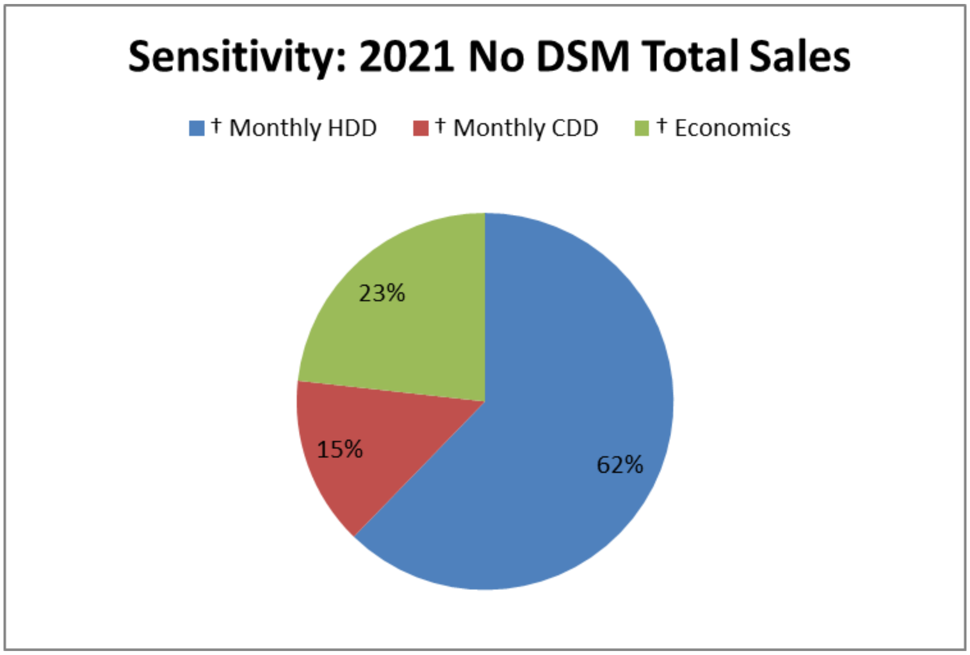
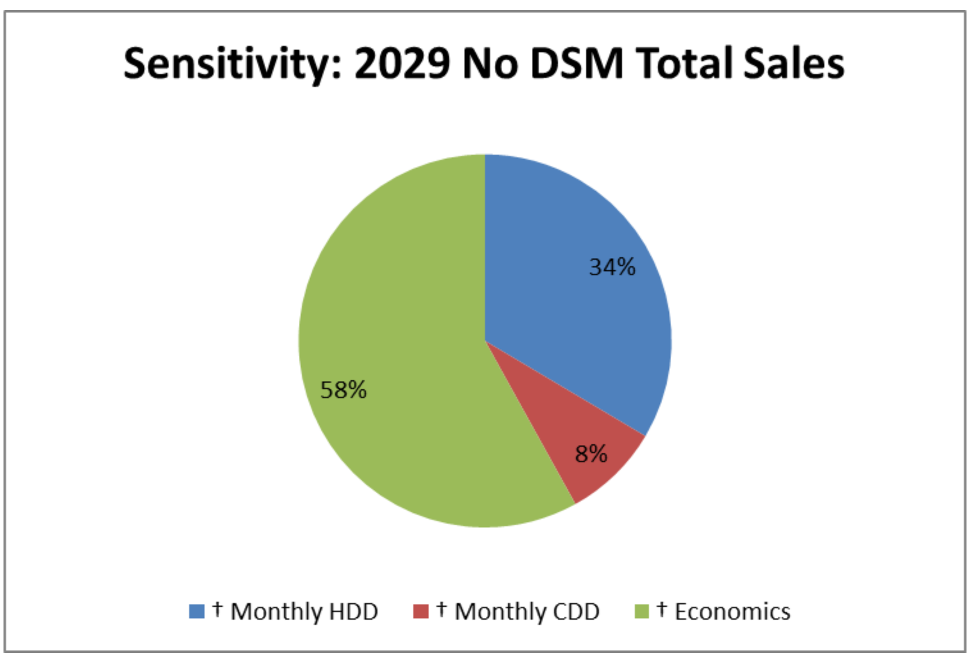


Figure D7 Sensitivity of Energy Forecast (2029)



In terms of relative magnitude of the sensitivities, with the exception of the weather impact on peak, DSM and PHP far outweigh the potential impact from likely changes related to the economy, weather, or underlying end uses. **Figure D8** shows the relative impact of these items.

Figure D8 Relative Impact of Inputs

Item	2021 Energy (GWh)	2021 Peak (MW)	2029 Energy (GWh)	2029 Peak (MW)
Heat Pump Programs	76	46	167	111
EVs	4	1	147	30(1)
Solar PV	-15	0	-178	0
DSM (base case)	-391	-76	-1499	-311
DSM (high case)	-548	-124	-2145	-475
PHP	[redacted]			
Weather/Economics P10/P90	+/-318	+/-297	+/-440	+/-312

(1) This assumes peak mitigation, without mitigation this is estimated to be around 65 MW.