Review of Newfoundland Power Load Forecasting Methodology

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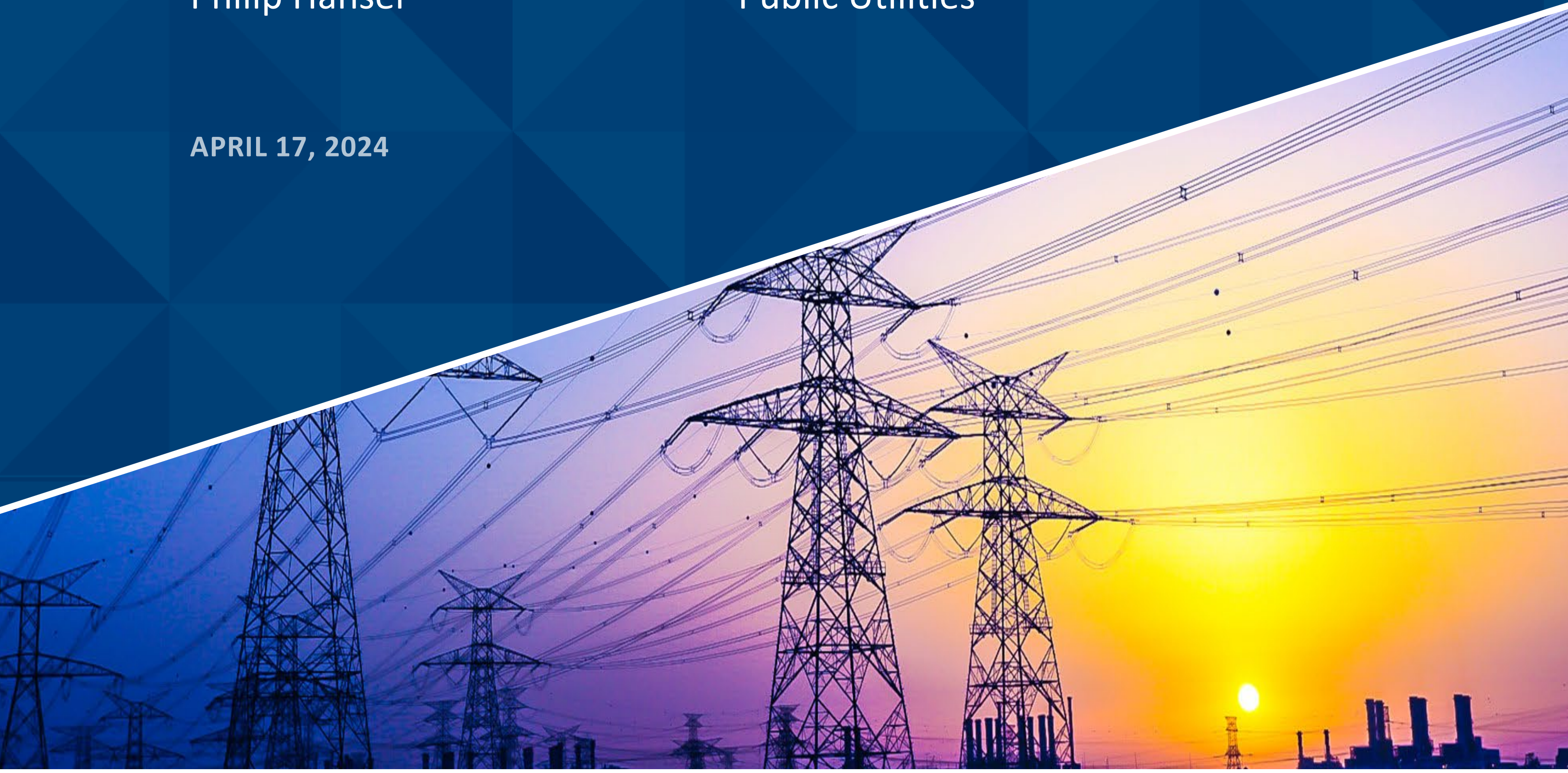

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I. Introduction

The Newfoundland and Labrador Board of Commissioners of Public Utilities ("Board") engaged The Brattle Group ("Brattle") to review various elements of the Newfoundland Power Inc. ("Newfoundland Power" or the "Company") general rate application for 2025/2026. Specifically, the Board requested Brattle to review the Company's energy sales and peak forecasts. In this report, we review the Company's energy and peak demand forecasting methodology as detailed in their submissions for the 2025/2026 General Rate Application ("GRA"). While the Company's proposed load forecast for the 2025/2026 General Rate Application appears to exhibit reasonable forecast performance, our review presents several recommendations that the Company should take into consideration for load forecasts in future rate cases.

Newfoundland Power is primarily an electricity distribution utility that provides service to over 270,000 customers accounting for approximately 87% of all electricity customers in Newfoundland and Labrador.[1] While the Company has some generation assets, it predominantly relies on Newfoundland Hydro ("Hydro") to supply electricity to its customers. The Company provided a load forecast for total energy sales and system peak demand in this rate case. It explained that these forecasts are essential as they help the Company determine its purchased power requirements from Hydro. Relatedly, load forecasts are a key element of revenue requirements for the Company, and they are used to set rates for its customers. While Hydro also directly serves approximately 24,000 customers on the Island Interconnected System, the rates that Hydro charges those customers are the same as Newfoundland Power. Therefore, the Company's rates affect all customers on the Island Interconnected System. It is unclear if the Company's load forecast has any impact or considerations for system reliability and resource adequacy, which the Company mentions is Hydro's responsibility.[2]

Section I provides a brief overview of the importance of load forecasting for electric utilities, shares findings from a utility survey we have conducted in prior work on typical utility load forecasting techniques in the industry and summarizes the materials we have reviewed in the preparation of this report. Section II details our assessment of the Company's methodology by

[1] See Volume 1, Application, Company Evidence and Exhibit, Section 1 Introduction

[2] See Company's response to PUB-NP-158.

describing their methodology; providing a comparison of the Company's overall methodology to that typically observed among utilities; assessing various elements of the Company's forecast and offering recommendations for the Company to improve its forecasting process in the future. Section III concludes the report.

A. Utility Load Forecasting

Electric utilities forecast load so that they can plan exactly how much generation to have on hand to meet their anticipated load. Such planning and investment decisions hold for distribution utilities as well as for vertically integrated utilities that own significant generation and deploy those assets to meet customer demand. In Newfoundland Power's case, they rely primarily on Hydro for generation planning. Nonetheless, as primarily a distribution utility, the Company also requires accurate forecasts to determine the level of purchased power requirements and to ensure that it sizes its distribution system to provide reliable service to customers.

There are two essential metrics that utilities attempt to forecast—total energy and system peak demand. The former refers to the total amount of energy that the utility anticipates its customers will consume on an annual basis. These forecasts will help measure the total operating costs the utility may incur in providing service to customers reliably. They are also used to set retail rates for customers. The latter, system peak demand, refers to the single highest observed demand in a given year. It represents the point at which the electrical system is most constrained, and vertically integrated utilities plan their generation resource buildout so that there is enough capacity on hand (plus a reserve margin) to meet this peak. While we acknowledge that forecasting comes with inherent uncertainty, having a robust forecasting process will help ensure that the consequences of deviating from the perfect forecast will be minimal. Utilities set revenue requirements based on these load forecasts. Over-forecasting load can lead to revenue recovery issues in the absence of a decoupling or deferral mechanism. On the other hand, under-forecasting load can potentially lead to resource adequacy concerns if the utility does not have enough capacity on hand to meet customer load. Furthermore, it can lead to excess revenues that the utility can retain if there is no path to pass the differences in actual revenue collections and revenue requirements to the customers. Therefore, accuracy in load forecasting is imperative to ensure an economically efficient allocation of resources and fairness of utility rates.

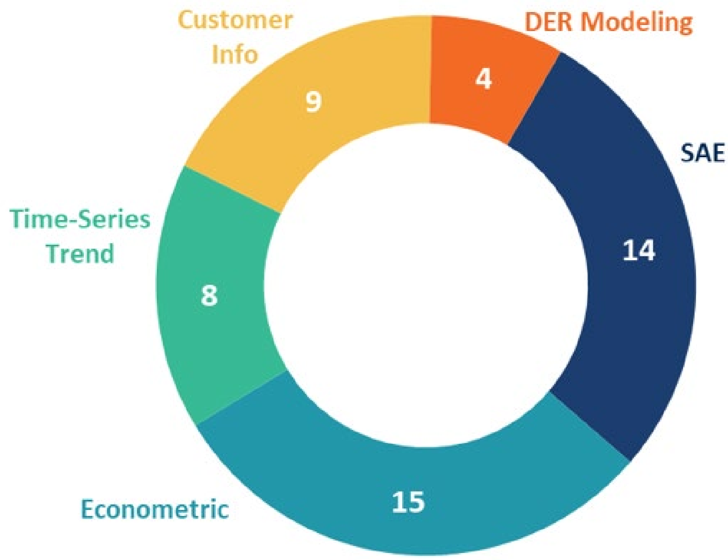
B. Typical Utility Load Forecasting Techniques

As mentioned in the previous Section, load forecasting is an integral part of the utility planning process. Electric utilities have increasingly adopted sophisticated load forecasting techniques to ensure that their overall resource portfolio reflects reasonable future scenarios of load consumption.

In our prior work, we surveyed 20 North American utilities across the United States and Canada to understand how utilities conduct load forecasting for their integrated resource plans and the level of complexity involved. These methods have evolved over a long time as companies have experienced significant load growth in recent decades and as they grapple with the increasing penetration of distributed energy resources (DER), electrification, and conservation measures. We also observe heterogeneity in modeling techniques across customer classes where sophisticated statistical techniques may be used for customer classes that account for a larger share of the customer base, like the residential class, but more tailored and individualized forecasts for smaller customer classes, like the large industrial customers.

Based on our survey, we created summaries of the types of techniques utilities use to forecast both energy and system peak demand. Figure 1 below summarizes the types of forecasting methods that the surveyed North American utilities use for energy sales alone. Note that the responses do not correspond to a single utility. Depending on the customer class, a utility may use one or more of the techniques depicted for energy. The survey revealed that a considerable number of utilities use statistical regression, either using time series regressions or other econometric models, to forecast energy sales for some if not all customer classes. While statistically adjusted end-use (SAE) models also account for a significant share, these were used for a subset of customer classes and at times, in conjunction with econometric modeling. Therefore, it is evident that econometric techniques, whether time series or otherwise, are predominantly used for energy sales forecasting. It is also worth noting that SAE models are often used to model demand for different end-uses, including DERs and energy efficiency. So, most respondents accounted for demand-side load adjustments either through SAE or some other form of DER modeling.

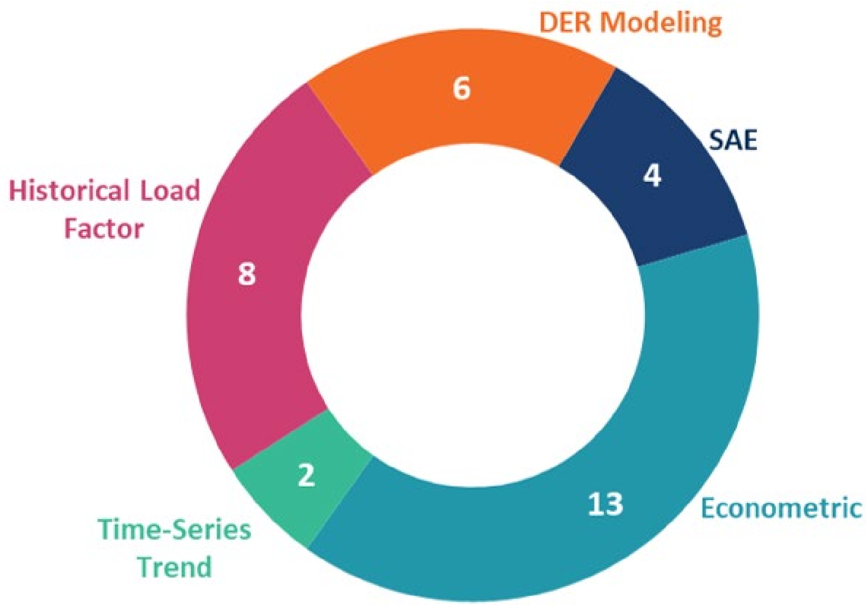
FIGURE 1: SUMMARY OF ENERGY FORECASTING TECHNIQUES



Source: The Brattle Group, 2021

Most utilities we surveyed maintained a separate model for forecasting system peak demand. Some are dependent on the energy sales forecast while others are entirely independent models. Figure 2 below summarizes the type of forecasting techniques the surveyed utilities use for forecasting system peak alone. A good number use their historical load factor to forecast system peak demand. However, this was seldom the only technique for a utility to use for system peak—in most cases, this technique was used for forecasting peak demand for specific customer classes while the system level peak demand was determined using another technique. Similar to energy sales, regression techniques account for the highest share of peak demand forecasting. Furthermore, utilities appear to account for demand-side load adjustments separately for system peak demand as well through the use of DER modeling and SAE.

FIGURE 2: SUMMARY OF PEAK DEMAND FORECASTING TECHNIQUES



Source: The Brattle Group, 2021

The results above show that statistical regression, either through time series or other econometric modeling, is the most common technique North American utilities appear to employ for both energy and system peak demand. While historical load factors also appear to be used to determine system peak demand, they are not used as commonly as econometric models.

C. Brattle's Approach to Assessing Newfoundland Power's Forecast

We base our assessment of Newfoundland Power's forecast on a comprehensive review of the Company's submissions in their 2025/2026 General Rate Application pertaining to the load forecast. Specifically, we have reviewed the results and methodology laid out in Section 5.2 of Volume 1 and the Customer, Energy and Demand Forecast Section of Volume 2.[3] [4] In addition, we have reviewed the detailed responses and data that the Company has provided in Requests for Information ("RFI"). In the following Section, we detail our assessment of the Company's forecasting methodology for energy sales and system peak demand. We also provide a list of

3 See Volume 1, Application, Company Evidence and Exhibit, Section 5.2 Customer, Energy and Demand Forecast ("Volume 1").

4 See Volume 2, Supporting Materials, Section 3 Customer, Energy and Demand Forecast ("Volume 2").

recommendations for both areas that are informed by our prior work on load forecasting, as summarized in Section A.

II. Assessment of Newfoundland Power's Methodology

The Company detailed its forecasting methodology for customer, energy, and demand forecasts in two submissions as part of the 2025/2026 General Rate Application. Volume 1 presents the results of the Company's forecasting process while Volume 2 provides supporting materials detailing the forecasting methodology for total energy sales and peak demand.[5] [6] In addition, the Company provided detail on modeling assumptions and results in responses to RFIs from multiple parties. We base our analysis of the Company's work on our review of the GRA submissions and the Company's responses to RFIs. This Section has two sub-sections. First, we review the Company's methodology for forecasting total energy sales and offer recommendations to incorporate in future load forecasts. In the second, we do the same for the Company's peak demand forecast.

A. Energy Sales Forecasting

1. Newfoundland Power's Methodology

a. Energy Forecast by Customer Class

Newfoundland Power adopts a different forecasting approach for each customer class. The forecast for the **Domestic customer class** employs an econometric approach using historical data between 1980 and 2022 for the class, modeling average customer usage as a function of a set of independent variables.[7] Given a forecast for the total count of customers for the class,

[5] See Volume 1.

[6] See Volume 2.

[7] Independent variables refer to a set of variables that are considered to drive the change in the dependent variable. Dependent variable refers to the variable that is being estimated as a function of the independent variables.

the Company forecasts the total energy sales by multiplying the predicted average customer usage for a given year by the customer count forecast for that year.

The **General Service class**, which refers to commercial, institutional, and industrial customers, is split into two groups for forecasting. The first, known as Small General Service ("SGS"), includes Rate#2.1 General Service 0–100 kW (110 kVA) customers. The forecast for this class also employs an econometric model in which total energy sales for the class is the dependent variable. The second group, known as Large General Service, includes customers in Rate#2.3 General Service 110 kVA (100 kW)–1000 kVA and Rate#2.4 General Service 1000 kVA and over. Per the Company's report, given the small number of customers in the Large General Service category, the forecast for this class is based on informed opinion on an individual customer basis.

Equations 1 and 2 below provide the general framework of the model that the Company has adopted for the Domestic and Small General Service customer classes, respectively. We provide the general form of the regression equation because it is unclear what functional form the Company uses for the econometric models.[8] Given the data provided, it is likely that the Company employed an Ordinary Least Squares ("OLS") estimator to model historical usage patterns. Once the model is estimated, they use forecasted series for the independent variables to predict energy sales in the future, specifically, for the years 2023 through 2026.

$$Avg.Use_{Res,t} = f(Market\ Share_t, Marginal\ Price\ Index_t, Marginal\ Price\ Index_{t-1}, CDM\ Impact\ Index_t, Dummy-2022+, \frac{income}{cust}_t, Dummy-2020) \quad [1]^9$$

where:

1. $Avg.Use_{Res,t}$ is the domestic average annual usage in kWh
2. $Market\ Share_t$ is the market share of electric heat
3. $Marginal\ Price\ Index_t$ is the indexed electricity price in the current year "t"
4. $Marginal\ Price\ Index_{t-1}$ is the indexed electricity price in the prior year "t-1"

8 Volume 2 of the Company's GRA submission provides an overview of the Customer, Energy and Demand Forecast but does not specify the functional form of the regression equation. In PUB-NP-94, we requested the Company to provide the programming code for each of the customer classes. In response, however, the Company mentioned that they perform regression analyses in Microsoft Excel but did not provide detailed representations of the regression equations.

9 See Company's response to PUB-NP-094.

5. $CDM\ Impact\ Index_t$ is the indexed energy conservation and demand management ("CDM") program impact
6. $Dummy - 2022 +$ is a dummy variable for the 2022 base year
7. $\frac{income}{cust}_t$ is the indexed household disposable income per customer
8. $Dummy - 2020$ is a dummy variable for the 2020 pandemic year

$$Sales\ MWh_{SGS,t} = f(GDP - SS_t, Unit\ Price_t, CDM\ Impact\ Index_t, Dummy - 2022+, Customers_t, Dummy - 2020) \quad [2]$$

where:

1. $Sales\ MWh_{SGS,t}$ is the Rate#2.1 sales MWh
2. $GDP - SS_t$ is the service-sector real GDP
3. $Unit\ Price_t$ is the indexed unit electricity price
4. $CDM\ Impact\ Index_t$ is the indexed energy conservation CDM program impact
5. $Dummy - 2022 +$ is a dummy variable for the 2022 base year
6. $Customers_t$ is the count of Rate#2.1 customers
7. $Dummy - 2020$ is a dummy variable for the 2020 pandemic year

The third customer class is **Street and Area Lighting**. Unlike the Residential and SGS classes, the Company does not utilize an econometric forecast for this class. Instead, the Company determines the energy sales forecast by multiplying the number of forecasted high-pressure sodium ("HPS") and light-emitting diode ("LED") fixtures by the amount of electricity consumed for each fixture type and wattage.

The summation of the forecasts for these three classes results in the Company's total sales forecast.

b. End-Use Load Modifiers

The previous sub-section describes Newfoundland Power's approach to forecasting energy sales for each customer class. These forecasts appear to include some embedded level of demand-side flexible load such as energy efficiency, electric heating, and electric vehicles since the Company has introduced a market share variable and an index variable for CDM. However, this is not wholly certain from the Company's forecasting report. With electrification gaining paramount importance across North American jurisdictions, the Company has conducted some adjustments outside of the econometric models to account for the increasing impacts of conservation and electrification. Specifically, the company has made four external adjustments:

1. Impacts related to CDM
2. Impacts related to electrification
3. Impacts related to the adoption of electric heat pumps
4. Impacts from conversion of traditional oil heating to electric heating

Such adjustments are common in utility load forecasting, as we describe in the following Section. Impacts related to CDM programs have the effect of reducing total energy as customers conserve load. The Company bases its forecasts for CDM program impacts on the estimated energy savings from its latest 5-year CDM plan.[10] Electrification impacts are estimated based on government initiatives on domestic oil to electric conversions, electrification of government buildings, electric conversion of Memorial University's boilers, and the adoption of electric vehicles.[11] The impacts related to the adoption of electric heat pumps assume that customers supplement their existing electric base board heating equipment, which accounts for the majority of domestic heating needs, with more efficient and modern electric heat pumps. This increase in efficiency has a downward impact on the total energy sales forecast.[12] The last impact accounts for increased electricity usage as a result of converting traditional oil heating equipment to electric heating. The source for this data is the Oil to Electric program that takeCHARGE is administering on behalf of the Government of Newfoundland and Labrador. This program provides financial incentives for customers to shift from oil-based heating equipment to electric heating (electric furnace, electric boiler, and electric heat pumps). Based on the Company's response to an RFI, they adjusted the Province-wide heating conversion targets for Newfoundland Power's service territory and customers. The Company provided no additional detail on the exact methodology used to arrive at the Company's forecast for heating oil conversions.[13] They incorporate the net impact of these load modifiers into the energy forecasts described in the previous Section to arrive at the total energy sales forecast.

c. Purchased and Produced Power

Newfoundland Power calculates the total energy sales by summing up the forecasts for the Residential, General Service, and Area/Street lighting classes and the net impact of the demand-side load modifiers above. To this, the Company adds Company use, system losses, and wheeled energy to obtain the total

[10] See Company's response to PUB-NP-091.

[11] *Ibid*.

[12] See Company's response to PUB-NP-093.

[13] See Company's response to PUB-NP-097.

of produced, purchased, and wheeled energy.[14] The Company's forecast of normal hydro production is then subtracted to provide total purchased energy, the largest single expenditure for the Company.

Appendix D of Volume 2 in the 20225/2026 General Rate Application provides the forecast accuracy for the Company's load forecasts. While the company's forecasts show a reasonable range of error between −1.1% and 1.5%, the underestimation of load in 2022 can indicate a downward bias in recent forecast trends. We address this concern in the following Sections, where we first compare the Company's approach to energy sales forecasting to that adopted by other North American utilities and subsequently provide constructive feedback that the Company can incorporate into future load forecasts. We focus on the econometric forecasts for the Residential and SGS classes as well as those for the demand-side load modifiers.

2. Benchmarking to Typical utility practices

Figure 1 summarizes the typical forecasting techniques that North American utilities employ to forecast total energy sales. The Company essentially uses an econometric approach that aligns with the approach used by most utilities. Moreover, the Company uses an average customer usage approach for the Domestic class, i.e., the dependent variable in the econometric model is the average energy consumption per customer, which is also consistent with the approach used by some utilities. Demand-side load modifiers, referring to flexible technology or DERs that customers may own, are accounted for outside of the econometric model, which is also consistent with utilities that conduct DER modeling in addition to econometric models. However, the points above show consistency with typical load forecasting practices at a very high level. When we observe the models closely, certain elements deviate from what we typically see. These pertain to the type of model the Company has selected, the kinds of variables included in the model and the granularity of the model, among others. We provide details of our assessment on each of these factors in the following sub-section.

3. Brattle Assessment

Several areas in the Company's methodology warrant additional discussion. As such, we address these in individual sub-sections below.

[14] Losses refer to the energy that is lost during the transmission and distribution of power from the generation source to the end customer. Wheeled energy refers to the energy that is supplied to Hydro's customers through the Company's electrical system.

a. Model Selection

Forecasting is an iterative exercise with the goal of minimizing forecasting error.[15] Typically, statistical forecasting consists of three fundamental steps—estimation, evaluation, and prediction. Estimation refers to fitting a statistical model on historical data to obtain an explanatory relationship between the dependent and independent variable(s). Evaluation refers to testing the model that has been fit on historical data to calculate the resulting error percentages. Running the estimated model on historical data is appropriate because historical actuals provide a natural basis for comparing predictions. Once a model has been evaluated for forecasting accuracy, prediction follows by using reasonable forecasts for independent variables to obtain predicted values for the dependent variable. Model selection involves an analyst typically employing several different models with different variables and then choosing the one that provides the lowest level of error.

Based on the Company's report, it is unclear how rigorous the model selection process was. The company does not describe any alternative models or estimators that were employed. Nor does it detail any alternative specifications of the chosen model.[16] While the functional form of the Company's chosen model is unclear, it appears to be highly simplistic, and the Company has offered no explicit explanation for the inclusion of the variables in the final model. The lack of such information makes it difficult to gauge whether the Company's proposed model best suits their energy sales forecasting.

b. Forecast Accuracy

The Company's reported forecast accuracy statistics for the domestic class for 2019–2023 indicates a persistent under-forecasting bias with the exception of 2023.[17] The Company's forecast accuracy statistics for total energy sales range from −1.1% to 1.5%.[18] For any forecasting exercise, this range of error is reasonable. However, the highest margin of error is observed in 2022, for which the Company's model under-forecast the actual energy sales in 2022 by 1.5%. The Company acknowledges that it uses these energy forecasts to set revenue requirements for the customer classes. If the Company also uses these forecasts to set rates for

[15] The error refers to the difference between the predicted value and the actual value of the variable of interest.

[16] Specification refers to the functional form and the combination of variables that are included in a given model. It is typical for an analyst to use several different specifications for a given estimator to evaluate model sensitivity.

[17] PUB-NP-087

[18] In-sample tasting refers to a test of forecasting accuracy that uses the data that the model has already been estimated on to come up with predictions. The predictions can then directly be compared against the actual historical values. This is a standard evaluation method in statistics.

customers, a lower energy forecast will produce a higher rate for customers. If the actual sales for a given year exceed the forecast, this will result in excess revenue for the Company. We understand that the Company currently does not have a mechanism to pass excess revenues for higher sales to customers in the form of lower rates or credits, except through an Excess Earnings Account. Since this mechanism is limited in dealing with excess revenues from higher sales, these excess revenues would be retained by the Company unless the requirements of the Excess Earnings accounts are met. Given the risk that such under-forecasting poses, it is essential that the Company's forecasting process is robust enough to choose the best performing model. The Company's under forecasting may also be impacted by how it models the demand-side load modifiers, which is covered below in the following sub-sections.

c. Unit of Observation

Newfoundland Power's forecasting model considers annual data covering the period from 1980 to 2022. These data provide a total of 43 observations for the econometric model. The Company's forecasting may benefit significantly from using monthly observations instead of annual observations as they will be able to capture much more granular variation in customers' consumption decisions and the factors driving consumption. For example, the company uses two indicators of electricity prices in its econometric model—one for marginal electricity prices in a given year and the other for marginal electricity prices in the prior year.[19] The hypothesis here is that customer usage may be driven by both the level of prices today and the level of prices faced last year. In reality, however, consumption decisions in response to prices may be influenced by much shorter units of time—it is much more likely that customers alter their consumption in response to prices differently based on the month or season, and their different use cases for electricity based on the season. Furthermore, using monthly data provides considerably more data for the Company to train its models on, which may produce better forecasting outcomes. At the very least, the company should test whether or not they achieve better forecasting accuracy by using more granular data.

d. Variable Selection and Demand-side Load Modifiers

In Section II.A.3.a. above, we noted that the Company offers no detailed justification for the inclusion of the variables in the final econometric models. We have concerns about some of the variables that the Company has chosen to include in the model and, most importantly, some

[19] See Company's response to PUB-NP-094. The Company only describes the variables but does not provide a source for the data.

potential variables they have not included in the forecasting model. Issues related to the latter are detailed in the following sub-section.

The first concern has to do with the use of the CDM Impact variable in the econometric models. The Company has not provided a detailed description of this variable. From the data provided in response to PUB-NP-094, it appears that this is an indexed variable and does not represent the absolute level of CDM in a given year. The inclusion of this CDM variable means that the econometric forecasts already account for some level of CDM. The value of the CDM variable is also kept constant at 2022 levels for the forecast period.[20] Doing so indicates that the Company expects the same level of CDM in 2022 to continue through the forecast period. However, the Company performs an external adjustment to account for CDM in its forecast.[21] Such an adjustment would only be warranted if it accounts for any CDM that is entirely incremental to the CDM embedded in the econometric forecast. The Company makes no such distinction in its reports.

The second concern pertains to the inclusion of the market share of electric heat in the econometric model. It is unclear if this market share accounts only for customers with electric base board heating and electric boilers or if it includes customers with electric heat pumps. Regardless, as with the inclusion of the CDM variable, the company performs external adjustments to account for the increasing share of electric heat among customers. Again, this would only make sense if the external adjustment accounts for adoption that is entirely incremental to that embedded in the econometric forecast. However, the Company makes no distinction between the electric heat variable in the econometric model and those calculated through the external adjustments.

The inclusion of impacts of CDM and electric heat both, within and outside of the models may result in an overadjustment of the load forecasts. Therefore, the Company should clearly detail the adjustment methodology for each of the demand-side load modifiers and state how the assumptions are different from those included in the econometric model, if at all.

Another demand-side load modifier that warrants discussion is electric vehicles. The Government's Renewable Energy Plan clearly identifies transportation electrification as a key focus area. Therefore, forecasting new load from electric vehicle adoption is vital to the Company's system planning. The Company merely references that it includes electric vehicle

[20] See Company's response to PUB-NP-095.

[21] See Company's response to PUB-NP-096.

adoption in its accounting of electrification impacts.[22] In response to PUB-NP-097, they reference a report by Dunsky Energy + Climate Advisors, which forms the basis of their electric vehicle forecast. However, they do not provide additional details on the forecasting methodology. The Company also notes that they rely on the "low" scenario in the Dunsky report instead of the "base" case, without elaborating on the basis of their decision. The Company should include the details of this forecast within its report on the energy sales forecast.

Additionally, it is unclear if there is some possible double counting of oil to electric conversions in the Company's external adjustments for electrification in the energy sales forecasts. In response to PUB-NP-091, they point out that "electrification impacts are based on government initiatives such as domestic oil to electric conversions." However, the response to PUB-NP-096 includes both electrification impacts and conversions from oil to electric heating as separate line items. It may be that the conversions to electric heating are accounted for separately but the Company must clarify and adequately document each of its individual adjustments to the model.

e. Variable Omission

Omitting important variables in econometric analysis can lead to significant issues. In causal inference, omitting variables can violate the basic assumptions of regression analysis leading to biased and inconsistent coefficient estimates. As a result, any cause-and-effect conclusion drawn from such estimates is flawed. In forecasting, omitting variables that could potentially have strong explanatory power can compromise forecasting accuracy. We observe potential instances of both phenomena in the Company's energy sales forecasts.

The first pertains to a glaring omission that is typically included in most utility forecasting—accounting for the impact of weather. Weather is a crucial factor that drives customer power consumption—customers change how they run their electric heating equipment based on the temperature on a given day. Omitting an indicator of weather in colder climates, heating degree days ("HDD"), and in warmer climates, cooling degree days ("CDD"), from the model may compromise forecasting performance. The omission of this variable may create an omitted variable bias, which we cover below in the following sub-section.

The second omission is the price of oil. The company acknowledges that the recent increase in average usage may be due to higher oil prices that may have aided the adoption of electric heat

[22] See Volume 2 of Newfoundland Power's submission, Section 3.3.

pumps as customers look to take advantage of available federal incentives for converting traditional oil heating systems to electric heat pumps. As such, oil is a substitute for electricity consumption for heating. Excluding the price of a substitute can potentially impact the estimation of demand. As a response to RFI PUB-NP-155, the Company ran an alternative specification including the price of oil as an independent variable that revealed a negative coefficient estimate—in other words, as the price of oil increases, electricity consumption would decrease, contradicting the Company's hypothesis. However, such a result does not necessarily mean that the variable does not belong in the model. The negative sign could indicate that there is some omitted variable bias in the model or strong multicollinearity with another variable in the model, such as the electric heating market share. Due to the exclusion of this variable, there could be an endogeneity bias in the model resulting in the marginal electricity price correlating with the error term, which in turn leads to biased estimates. Testing for the inclusion and exclusion of such variables comprehensively and considering alternative estimation approaches (such as instrumental variables approach) is essential in forecasting.

The third issue, related to the omitted variable bias problem outlined above, is the Company's use of the price elasticity of demand. They report an elasticity estimate of −0.19 in their report. However, it is unclear how exactly this is estimated or used. The Company's response to PUB-NP-103 seems to indicate that the elasticity estimate is a result of their energy sales regression analysis. Yet, they do not detail the exact methodology, merely asserting that it is derived from their econometric models.[23] There are two ways to derive price elasticity of demand from an econometric model. If the model uses a log-log functional form, then the coefficient estimate for price directly provides the price elasticity. If the model has a linear functional form, then the coefficient estimate for price has to be transformed to obtain the price elasticity of demand. Either way, the coefficient estimate for price is an essential factor in determining elasticity. However, only if the basic assumptions of regressions are met can the coefficient estimate be reliably used. The two issues regarding the omitted variable bias above point to the possibility of invalid coefficient estimates in the Company's model. If that is the case, the elasticity estimates used by the Company are not valid. Therefore, the Company must detail its methodology for calculating the price elasticity of demand, how it is used, and how it accounts for omitted variables in its econometric models.

23 See Company's response to PUB-NP-103, section B.

4. Energy Forecast Assessment Recap and Recommendations

Based on our assessments, we observe that the Company's domestic energy sales model show trends of under forecasting.[24] The Company's peak demand was over-forecasted by a significant margin in 2023. We believe that these forecasting errors consistently occurring in one direction may signal underlying problems with the econometric model utilized to forecast sales, and the load factor approach utilized to forecast peak demand. Given that the overall accuracy statistics presented for the Company's energy and peak demand forecasts have generally been reasonable, we determine that the Company's forecasts provide reasonable accuracy for the 2025/2026 General Rate Application. However, these accuracy levels are likely to worsen in the future given the shortcomings of the Company's forecasting approach as we discuss below.

1. The Company provides a very high-level description of its load forecasting models in its GRA filing. It is a common expectation for utilities to develop detailed load forecasting reports, that present their model functional form, estimation routines, alternatives tested, and other statistical tests conducted. In the absence of these details, it is difficult for the regulators and intervenors to assess the performance of the load forecasting models. The Company should, at the very least, be required to submit a report that details their forecasting methodology, regression specifications and functional forms, estimated model coefficients along with standard errors, and alternative model specifications explored before settling on the final methodology for the forecasts. This report should also provide a detailed discussion of all of the ex-post model adjustments and the basis for the levels of these adjustments. The Company's load forecasting discussion in Volume 2 of the 2025/2026 GRA is too high-level for a useful load-forecasting methodology document. A comprehensive and transparent methodology document is required to judge the appropriateness of the Company's approach for load forecasting and ratemaking. This requirement holds for both total energy sales and system peak demand forecasts.
2. The Company's domestic forecasting model has a mean absolute percentage error of 0.9%, which represents a good forecasting accuracy on average.[25] However, it has under-forecasted its domestic load four out of five times during this five-year period, which implies that the Company was able to collect more revenues from the domestic class as a result of under-forecasting domestic sales.

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24 See Company's response to PUB-NP-087.

25 *Ibid.*

3. The Company’s sales forecasting model is an annual model and includes 43 years of data spanning 1980 through 2022. The accuracy of the model would improve if the Company used monthly data in its econometric forecasting model.
4. The model is missing a key determinant of electricity sales, which is the weather variable. Especially given the high penetration of electric heating in the Company’s service territory, the weather might be the most important variable explaining the variation in energy sales over time. Weather patterns have been changing significantly throughout the estimation period used in the Company’s model, and not accounting for the impact of weather is a significant omission from the model. Therefore, the Company should consider adding CDD and HDD variables to the model, on a monthly level.
5. Economic literature predicates that the price of its substitute plays a crucial role determining the demand of a given good. In the context of electricity sales, the substitute for electricity is oil in the Company’s service territory. It underlines the importance of the price of oil in affecting the rate of fuel switching, thereby affecting electricity sales in multiple RFI responses.[26] When we pointed to this deficiency in its model, the Company simply included the price of oil in their econometric model and found that it was estimated with the wrong sign (negative sign, while the expectation was to find a positive relationship with electricity sales). This finding does not prove that the price of oil does not belong in the sales model. It potentially indicates that there is an endogeneity problem in the regression, meaning one or more of the explanatory variables are highly correlated with the price of oil, leading to biased and inconsistent estimates for the other variables in the model. We recommend that the Company considers this recommendation more carefully in their future load forecasting model revisions.
6. We understand that the Company’s sales forecasting framework accounts for the impacts of CDM and electrification, but it is unclear whether this accounting is done correctly. There are three widely used methods, when it comes to integrating the impact of “load modifiers.” The first approach assumes that the impacts of existing programs are already baked into the historical sales, therefore these impacts will continue to be reflected in the sales forecasts. To the extent that there are additional programs implemented above and beyond those observed in the historical period, then those “incremental” adjustments are made outside the model. The second approach involves adjusting the historical sales for the impact of load modifiers (e.g., adding back the electricity conserved due to CDM) and implementing the econometric model to generate “gross” electricity forecasts. To obtain

[26] See Company’s responses to PUB-NP-092 and PUB-NP-155.

the net sales forecasts, one would then adjust for the "total" (as opposed to incremental) impact of the load modifiers. The third approach is called the "statistically adjusted end-use modeling," which involves including indices for the load modifiers within the econometric model to capture their impact, explicitly in the econometric model. The Company's sales forecasting model essentially uses the first approach and applies adjustments for CDM, Electrification, Heat Pumps, and Oil to Electric Heating[27] outside of the model. However, the model also includes indices for electric heating market share and CDM programs. We are concerned that the Company may be over-adjusting for some of these factors given that there is a clear overlap between the electric market share index and electrification adjustments and CDM index and CDM adjustments. The intent and rationale for these variables are unclear as the Company has not developed comprehensive documentation for its load forecasting models.

7. In its response to PUB-NP-054, Newfoundland Power reports that it relies on the "low scenario" provided by Dunsky Energy + Climate Advisors for Newfoundland and Labrador Hydro's Resource and Reliability Adequacy Study ("RRAS") 2022 Update. It further explains that it uses the low scenario because "this scenario most closely aligns with current market drivers and conditions for EV adoption". However, it doesn't provide evidence for why the low scenario represents a better forecast than the base scenario.

8. In its response to PUB-NP-159, the Company indicates that "…[its] methodology to determine the elasticity effects on the Company's energy sales involves regression analyses used to forecast energy usage for the Domestic and General Service Rate #2.1 Customers." However, it is entirely unclear how the Company develops its reported price elasticities from its econometric models for domestic and general service customers. In fact, the Company did not even disclose the regression specification used for the sales forecasting model when inquired about the code to run its regressions, and merely indicated that they run these models in Excel. Therefore, we could not replicate its models and evaluate how the Company derives its elasticity estimate from its model. The Company also reports that "for the Domestic customer rate class, Newfoundland Power's current analysis indicates that price elasticity is −0.30. On a total basis, adjustments related to elasticity equate to approximately −0.19."[28] However, it does not explain how it derives −0.3 from its domestic sales regression nor does it detail how the elasticity equates to −0.19 on a total basis.[29] Moreover, the Company refers to a report by Dr. James P. Feehan, which estimates a price

[27] See Company's response to PUB-NP-096.

[28] See Company's response to PUB-NP-103.

[29] *Ibid.*

elasticity for its domestic customers using annual data for the period 1992 to 2016.This regression analysis resulted in a price elasticity for Newfoundland Power's Domestic customers of −0.42.[30] Dr. Feehan estimates a double-log function to explain domestic sales as a function of the price of electricity, price of fuel, disposable income per capita, and lagged consumption. This log-log regression model resulted in a short-run elasticity of −0.15 and a long-run elasticity of −0.42. In our opinion, Dr. Feehan's model is much more robust and comprehensive for estimating energy sales and price elasticities. It is unclear if the Company has considered adopting elements from Dr. Feehan's model such as the price of fuel and the lagged consumption variable. The Company compares their elasticity of −0.3 to Dr. Feehan's long-run elasticity of −0.42, yet its model does not involve the lagged sales variable as an independent variable. As indicated earlier, it is entirely unclear how the Company develops its elasticity estimate from its stylized responses to the RFIs.

B. Peak Demand Forecasting

1. Newfoundland Power's Methodology

Newfoundland Power forecasts peak demand to estimate purchased power from Newfoundland Hydro. This appears to be the system peak demand and uses a simplistic forecasting approach. Based on their explanation, the Company applies a five-year average of their weather-adjusted system load factor to the produced and purchased energy sales forecast to predict the native peak demand in each year.[31] The Company calculates purchased power demand by subtracting the Generation Credit and Curtailable Credit from the native peak.[32] The Company notes that they surveyed twelve Canadian utilities and found that six utilities used a similar methodology and therefore asserted the appropriateness of their adopted approach.

2. Benchmarking to Typical Utility Practices

The company uses a straightforward approach to predict its native peak by applying a measure of the system's average historical load factor to the energy sales forecast. As per the results

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[30] In its response to CA-NP-076, NP provides Attachment A for the July 31, 2018 report of James P. Feehan, MSc(Econ), PhD entitled "The Long-Run Price Elasticity of Demand for Electricity and the Feasibility of Raising Electricity Rates to Finance Muskrat Falls.

[31] The five-year average system load factor is 49.35% for the period from 2018 to 2022 (excluding 2020) as provided in Volume 1 of the Company's submission.

[32] See Volume 2, Section 2.5.

shown in Figure 2, this overall approach aligns with techniques adopted by other North American Utilities. However, in that survey, there were very few utilities among those that reported using historical load factor (2 out of 8) that solely relied on this method for their entire system peak demand forecast. In most cases, this simplistic approach was used only for a subset of the customer classes while the overall system peak demand forecast was determined using an econometric approach. The Company also does not appear to account for the impact of DERs or electrification separately in its peak demand forecast; instead, it relies mainly on the historical impact of these technologies through the use of the historical load factor. Our survey reveals that a good number of utilities account for the impact of these demand-side load modifiers in their peak demand forecast as well. Our detailed assessment of the Company's peak demand forecast follows in the next sub-section.

3. Brattle Assessment

a. Forecast Accuracy

The need to reliably provide service when the system is constrained drives most capital investment in electric utility system planning. The inability to meet peak demand may severely compromise system reliability. Therefore, forecasting system peak demand accurately is of paramount importance, especially so for a vertically integrated utility. In its response to PUB-NP-158, the Company notes that "For reliability and resource adequacy purposes, Hydro has its own system peak forecast for Newfoundland Power." Therefore, Hydro is responsible for procuring capital assets to maintain system reliability for the Company's service territory. While Newfoundland Power has some production of its own, it is significantly smaller than the power it purchases from Newfoundland Hydro. Therefore, the Company is primarily responsible for power delivery and not for power supply.

The Company also notes that it forecasts peak demand to estimate its expected purchased power costs from Hydro and set revenue requirements accordingly.[33] The figure below provides a comparison of the Company's Forecast, Hydro's Forecast, and the actual peak demand observed for the system over the past five years.

[33] See response to PUB-NP-158.

FIGURE 3: NEWFOUNDLAND POWER SYSTEM PEAK DEMAND—ACTUAL VS. FORECAST

System Peak Demand (MW)[1]

Winter Season	Actual	Newfoundland Power Forecast	Hydro Forecast	Newfoundland Power Variance	Hydro Variance
2019-2020	1,367	1,389	1,407	-1.6%	-2.8%
2020-2021	1,300	1,361	1,406	-4.5%	-7.5%
2021-2022	1,383	1,351	1,400	2.4%	-1.2%
2022-2023	1,463	1,368	1,407	6.9%	4.0%
2023-2024	1,487	1,448	1,437	2.7%	3.5%

Source: PUB-NP-157

Newfoundland Power notes that they provide their forecasts to Hydro. The figure above shows that in the past three winters, the Company has under-forecast system peak demand. Given that the Company uses these forecasts to set revenue requirements, it notes that under-forecasting peak demand may lead to financial losses of up to $500,000.[34] While it is unclear what would happen in cases when the Company over forecasts, as was the case in 2019–2020 and 2020–2021, this means that the Company must have incurred some system peak demand-related financial losses for the past three winters, a less than ideal outcome.

Interestingly, Hydro's forecast has also been less than the actual system peak demand over the last two winters. To the extent that Hydro's forecast relies on the Company's forecast in some way, this may have had consequences for resource adequacy. While we acknowledge that peak demand forecasting is nuanced, the observations above indicate that the Company's simplistic load-factor approach may not be the most robust one. The Company could explore a more sophisticated technique to forecast peak demand and assess how its current methodology compares.

Another consideration is that the Company has revealed that it maintains a more granular peak forecast that provides peak demand forecasts at the area, substation, and feeder level. It also mentions that it uses this to assess the need for investments to address load growth and overload conditions.[35] It is unclear why the Company would use such a simplistic approach for setting revenue requirements when it has a more sophisticated forecast to project future capital investment need. Any investments that the Company makes would be reflected in its revenue requirement. Therefore, it would follow that the demand determinants used to project capital needs would be highly correlated, if not the same, with those that it uses to set revenue

[34] *Ibid.*

[35] *Ibid.*

requirements. At the very least, the Company should aggregate its area-level peak demand to the system level to see how that compares with those calculated using the average load factor approach.

b. Demand-Side Load Modifiers

Newfoundland Power's peak demand forecasting approach does not appear to account for the demand-side load modifiers separately. Our understanding is that it takes the forecast energy sales, which include the impact of future adoption of demand-side technologies, and applies a historical average of system load factor to it to obtain the native peak for the system. However, the use of the historical factor implicitly assumes that the historical impact of the demand-side load modifiers would continue for the forecast horizon. However, the fact that the Company separately accounted for the increasing impact of these load modifiers in the energy sales forecast indicates that their impact in the future may be different from that historically observed. Given the recent under-forecasting of peak demands relative to actuals, it will be important to account for the granular impact that these demand-side load modifiers may have.

4. Peak Demand Forecast Assessment Recap and Recommendations

Our review of Newfoundland Power's peak demand forecasting methodology reveals consistent under-forecasting of system peak demand in recent years. Such under-forecasting may result from its overly simplistic forecasting approach, notwithstanding the fact that other Canadian utilities use the same approach. While the Company maintains that under-forecasting its peak has no significant implications for its operations, the potential for financial losses is not ideal. We believe there are some changes the Company could explore for in the future.

1. The Company should explore an alternative approach to test the robustness of its existing historical load factor methodology. As is common among other North American utilities, the Company could test an econometric model, as it does with total energy sales, to forecast peak demand.
2. The Company should aggregate its granular area level, substation, and feeder-level peak demand forecasts and compare them with those obtained from its existing approach. Doing so will provide an additional data point against which the Company would calibrate its peak demand forecasting methodology.
3. Just as the Company accounts for the impact of increasing CDM and electrification separately in its energy sales forecasts, it should conduct a similar exercise for the impact of demand-side load modifiers on system peak demand. This exercise could also serve as an

alternative way of forecasting peak demand by using representative load shapes linked with energy consumption by customer class and each of the demand-side technologies to model energy sales on an 8760 basis. Peak demand can then be observed at the hour with the highest energy observation.

III. Conclusions

The Board engaged the Brattle Group to conduct a comprehensive review of the Company's load forecasting framework. In this report, we have provided our assessment of the Company's load forecasting process for total energy sales and system peak demand. Our review was based on the Company's submissions in the 2025/2026 General Rate Application as well as its responses to RFIs submitted by various intervenors. We also offer critique of the Company's methodology, comparing it to approaches we have seen in other North American jurisdictions in our prior work and offer recommendations for the Company to consider in futures load forecasts.

Newfoundland Power uses an econometric approach to forecast total energy sales for the Domestic and Small General Service classes while the Large General Service relies on more individualized customer forecasts and Area/Street lighting relies on the forecast of light fixtures. While we do not have transparency into the actual model or specification that was used, we believe that the Company uses a simple OLS estimator to model historical usage as a function of a group of independent variables. The econometric models use 43 observations of annual data from 1980 through 2022 and use forecasts for the independent variables and the number of customers to predict total energy sales for Domestic and Small General Service classes. The forecast for system peak demand is rather simplistic, applying a historical five-year average of the system load factor to the total energy sales forecast to predict the native peak for the system. The Company uses both these forecasts to estimate its purchased power from Hydro, the single largest expense for the Company.

Based on our review, we have found that the overall accuracy statistics presented for the Company's energy and peak demand forecasts have generally been reasonable. Therefore, we determine that the Company's forecasts provide reasonable accuracy for the 2025/2026 General Rate Application. However, these accuracy levels are likely to worsen in the future given the shortcomings of the Company's forecasting approach. We summarize these potential improvements and considerations for total energy sales and peak demand forecasts as follows:

1. The Company only provides a very high-level description of its load forecasting models in its GRA filing. The Company should, at a minimum, be required to submit a report that details their forecasting methodology, regression specifications and functional forms, estimated model coefficients along with standard errors, and alternative model specifications explored before settling on the final methodology for the forecasts. This report should also provide a detailed discussion of all of the ex-post model adjustments and the basis for the levels of these adjustments.
2. The Company has under-forecasted its domestic load four out of five times during the last five-year period, which implies that the Company was able to collect more revenues from the domestic class as a result of under forecasting domestic sales.[36]
3. The accuracy of the model would improve if the Company used monthly data in its econometric forecasting model instead of annual data.
4. The model is missing a key determinant of electricity sales, which is the weather variable and the Company should consider adding CDD and HDD variables to the model, on a monthly level.
5. The Company's finding that the price of oil has a negative coefficient upon including it in their main specification does not prove that the price of oil does not belong in the energy sales model. It potentially indicates that there is an endogeneity problem in the regression leading to biased and inconsistent estimates for the other variables in the model.
6. We understand that the Company's sales forecasting framework accounts for the impacts of CDM and electrification, but it is unclear whether this accounting is done correctly. As with the overall framework, the Company should submit detailed documentation describing the approach for the impacts of CDM and electrification, and ensure that there is no over-adjustment for these impacts in the forecast. The same holds true for the Company's forecasts for electric vehicles.
7. In its response to PUB-NP-159, the Company indicates that estimates for price elasticity are derived from the econometric models for energy sales forecasting. However, it does not detail exactly how these were obtained. Moreover, it references another report by Dr. James P. Feehan that analyzed price elasticity for the Company's Domestic customers using annual data from 1992 to 2016. This study uses a fairly robust framework for estimating

[36] See Company's response to PUB-NP-087.

elasticity. However, it is unclear if the Company directly uses estimates from this work in its own forecasting process.

8. For system peak demand, the Company should explore an alternative approach to test the robustness of its results using an econometric model, as it does with total energy sales.
9. The Company should aggregate its granular area level, substation, and feeder-level peak demand forecasts and compare them with those obtained from its existing approach. Doing so will provide an additional data point for the Company to calibrate its peak demand forecasting methodology against.
10. Just as the Company accounts for the impact of increasing CDM and electrification separately in its energy sales forecasts, it should conduct a similar exercise for the impact of demand-side load modifiers on system peak demand.