Capacity Market Load Forecast

Date: Februrary 2018
Subject: **Capacity Market Load Forecast Model, Process, and Preliminary 2021 Results**

Purpose

This memo describes the input data, process, and model the AESO will propose for its initial capacity market load forecast.

The load forecast process, methodology, and output described in this document are expected to provide the load forecast data to be used as a key input into resource adequacy modelling and, ultimately, capacity procurement volumes in the capacity market. Key objectives for the AESO's capacity market load forecasting are transparency, accuracy, and following industry best practices. The AESO also intends to establish a load forecasting process which will be as sustainable as possible to minimize future regulatory and administrative costs.

Overview

The AESO intends to leverage its new load forecast tool which completed implementation in May 2017. The tool is based on SAS Energy Forecasting (SEF) and relies on historical data, calendar and weather variables, and economic variables which are forecast by the Conference Board of Canada (CBoC).

SEF brings AESO load forecasting methodologies in-line with industry best practices while providing the AESO with improved modelling and analytical capabilities, flexibility, and efficiencies. These improvements mean the AESO can produce load forecasts which reflect recent economic outlooks and which properly account for weather and other uncertainties. A key intent of the AESO's load forecast models is to minimize model error.

The AESO intends to model and forecast Alberta Internal Load (AIL) as the starting point for its capacity market load forecast. AIL is currently the best measure of total Alberta demand and is best suited to capture the overall behavior between economic activity and load. Depending on capacity market design details such as self-supply options and demand response participation, post-modelling adjustments may be required to the AIL forecast.

The AESO's modelling capability allows it to properly account for weather. Therefore, the AESO plans to produce a weather-normalized reference case load forecast which utilizes the CBoC's most recent provincial economic forecast. Both economic and weather-driven uncertainty is also modelled and quantified to determine ranges of uncertainty. These will also feed into the AESO's resource adequacy modelling.

Inputs

This section describes the input data and processes used to create the forecast.

2500, 330-5th Avenue SW, Calgary, Alberta T2P 0L4 Phone: 403-539-2450 Fax: 403-539-2949
www.aeso.ca www.poweringalberta.com

Economic indicators

For a long-term economic trend variable, the AESO will use a weighted average of real Alberta Gross Domestic Product (GDP), population, and employment. These three variables are taken from the Conference Board of Canada's (CBoC) most recent 20-year or five-year forecasts.[1] The three variables are indexed to a common year, and then weighted based on their relative correlation with average annual AIL over the input data period. The current weights are 28% for real GDP, 32% for population, and 40% for employment. These will be reviewed and updated as required for each forecast. Testing has shown that the index of 3 economic variables is more accurate than any of the individual variables as an input (see the results in Table 1).

Temperature

Temperature data starting from 1986 from Calgary, Edmonton, Fort McMurray, and Lethbridge is used, providing 30+ years of weather profiles. The model uses an equal weight across the four weather stations to estimate the relationship between temperature and AIL. Data from 1986-2008 comes from the Environment Canada website,[2] and data from 2008 to current comes from the AESO's weather data provider (MeteoGroup Weather Services Canada Inc.). Historic hourly weather data from each weather station is run through a data cleaning process that fills in gaps longer than one hour by using the corresponding non-missing sequence in the nearest day available. One hour gaps are replaced by the next value.

Calendar Variables

All calendar variables considered is as follows (see Diagnose Procedure section for more detail on how these are used):

- month of the year,
- day of the week,
- hour of the day,
- day before holiday,
- statutory holiday,
- day after holiday,
- daylight savings time indicator (SEF runs all forecasts in Mountain Standard Time), and
- weighted sunlight indicators (fuzzy indicator that captures the difference in sunrise and sunset times by major cities, Calgary, Edmonton, Fort McMurray, and Lethbridge)

Other

Indicator variables for outliers that are not expected to occur in the future are also utilized. Currently there is an indicator for the Fort McMurray fires (which prevents the model from assuming fire-related impacts will occur again in the future).

Oilsands production is also included. Historical monthly production data is from the Alberta Energy Regulator, and forecast data is obtained from the Canadian Association of Petroleum Producers (CAPP;

[1] The data series for these three trend variables are RQTOA, RHA, and RLEMA.

[2] See Environment Canada's webpage: http://climate.weather.gc.ca/historical_data/search_historic_data_e.html

different forecasts could also be utilized).[3] Forecast annual average oilsands production figures are given a monthly shape based on historic profiles. Including oilsands production results in significant model improvement, especially on peak load, as it captures the seasonal impacts of oilsands production activity on overall provincial demand (see Table 1 for more detail).

Load data

Historical AIL data is brought into the model from the same database source as AIL data on the AESO's ETS page (http://ets.aeso.ca/). Data filtering processes check for missing or negative values and replaces with the closest non-negative/missing value. The data quality process also looks for a single number that represents a large portion of the dataset. If a threshold of 70% is hit, the stale data is removed. To ensure that there are no outliers, the process checks to see if there are any values that lie outside of two standard deviations from the mean for a given temperature range. For example, if temperature is zero degrees, the bin for this temperature is [-1, 1]. Within this bin, all loads are used to compute mean and standard deviation. When actual loads are greater than two standard deviations from the mean, those are identified as outliers.

Outlier replacement is done with naïve energy forecasting model, in which the load is a function of trend, month, interaction between day of week and hour, interaction between month and temperature, and interaction between hour and temperature. The stale data is then replaced in to the dataset following this cleaning process.

Process

With the input data described above, the model (see Model Specification for more details) is trained from January 2011 to current, providing approximately five years of historical data as input. Enough data is required to properly train the model and map out the relationship between driver variables and load. However, using the most recent, up-to-date data is the most accurate as it best represents how load currently behaves and is likely to behave in the future. Five years of historical data provides a reasonable balance of using recent data but including enough observations to produce accurate results. AESO testing has shown that models which use older data (i.e. from January 2010 to current) are less accurate. It's expected that the AESO will use five to six years of historical data as inputs into its load forecasts moving forward, subject to checks and reviews of how different data periods impact model error.

Uncertainty

The AESO intends to model key sources of uncertainty in its load forecasts. There are typically three major sources of uncertainty in load forecasts, model uncertainty, economic uncertainty, and weather uncertaity. The AESO is undertaking an extensive process to minimize model uncertainty and error (see Proposed Model Specification below).

For economic and weather uncertainty, the AESO is proposing steps to quantify the impacts of both, using historical data, as described in the following sections. The quantified impacts of these sources of uncertainty will also be incorporated in the AESO's resource adequacy modelling.

Other sources of uncertainty are expected to be addressed through post-modelling adjustments, also described below.

[3] Historic oilsands production data from http://economicdashboard.alberta.ca/OilProduction#type CAPP 2017 forecast: http://www.capp.ca/publications-and-statistics/crude-oil-forecast

Economic Uncertainty

The AESO is proposing to run three economic scenarios to account for economic uncertainty. There will be a high case and low case, relative to the CBoC's forecast. The high and low cases are determined by historic distribution of the weighted economic index's growth rates. The lowest and highest observed growth rates on the weighted economic index are used to adjust the CBoC's forecast to create a high and low growth case. Currently, the 2009 recession represents the lowest downward shock, and the 2006 boom reflects the highest upward shock. The adjustment is applied to the first forecast year, and the remaining years incorporate the CBoC's growth profile.

Temperature Uncertainty

To forecast a range of possible temperature outcomes, SEF runs each historic year's temperature observation (the average across the province for AIL) for a given hour (January 1st at hour ending (HE) 1 for example) through the forecast model. This process is repeated for each weather year creating 30+ profiles for 8760 hours per year. Combined with the three economic scenarios, this generates approximately 100 potential load profiles, each of which has an annual and seasonal peak load which can be assessed. The median peak load from the 30+ weather profiles, for each season, will be used as the weather-normalized reference load forecast. The full set of peak loads can also be used to assess probabilistic high and low peak load values.

Post-Model Adjustments

There are several other factors which create uncertainty within the load forecast. At a high level, the AESO is proposing to address these factors through post model adjustments when required and depending on other capacity market development details.

Energy efficiency

When the load forecast model trains on ~five years of historical data, the model maps out the relationship between AIL and economic drivers. For a change in a dollar of GDP or for a change in the number of Alberta residents, the model determines the corresponding impact to load. That modelled impact is effectively a measure of energy efficiency. The model applies this modelled relationship to future AIL based on the weighted economic trend variable meaning the average energy efficiency observed over the past ~five years is implicitly assumed to persist in the future. For the near term, this is often a reasonable assumption as energy efficiency changes typically take time. However, it may be necessary to make a more explicit assumption of energy efficiency impacts, especially if there is a known driver of efficiency changes such as Energy Efficiency Alberta's (EEA) efficiency programs.

The AESO believes that the best way to make post-model adjustments is to incorporate data from third parties wherever possible. This will increase the credibility and transparency of the process. If the data is available, bottom up modelling of equipment replacement can be netted from the forecast load. If the data is not available, it may be necessary to estimate the impact using alternate techniques such as examining similar programs in other jurisdictions. The AESO is engaged in discussions with EEA to collect the data necessary to make an assessment of the EEA programs and apply their anticipated impact to the load forecast as part of a post-modelling adjustment.

Additional considerations of energy efficiency include windows of eligibility (how far into the future to apply the impacts of an energy efficiency program[4]) and how energy efficiency may be eligible in the capacity market.

Demand response

Similar to energy efficiency, the load forecast model will implicitly factor-in the effects of past demand response behavior into the forecast of load. Based on the relatively low model errors from the AESO's initial models, it is unlikely that demand response behavior is contributing significant amounts of error to the forecast. Therefore, the AESO believes there is low risk to not explicitly modelling current demand response behavior in the forecast.

However, depending on capacity market eligibility and other potential factors in the future, demand response may have a greater impact on future load than it has in the past. The AESO's preferred method of dealing with demand response is to incorporate future impacts by making post-model adjustments using third party data. If demand response providers are able to provide the AESO with data of their capabilities and drivers, it should be possible to make appropriate post-model adjustments to ensure the impacts are accounted for. This is especially important if demand response is able to participate in the capacity market on the demand side. It is not expected that there will be post-model adjustments from demand response participating in the supply side of the capacity market.

Distributed micro-generation

Similar to energy efficiency and demand response, the load forecast model will implicitly apply the historical impact from distributed micro-generation, i.e. behind-the-meter (BTM) generation, to future load. Currently there are small amounts of BTM generation installed.[5] Because of the minimal amounts of BTM generation installed currently, the impacts on load are negligible. However, the AESO anticipates that BTM generation penetration will increase in the future and the impact will need to be accounted for.

The AESO is currently working on BTM models which will allow it to model the impacts of current and future BTM on load. The intent is to account for past impacts which will "gross" up AIL to add back in load which was offset by BTM. Then the forecast process will use the grossed-up load to forecast future demand. This gross future demand will then be adjusted for the BTM forecast, resulting in a load forecast which is net of the anticipated BTM impacts. The AESO is still developing the modelling capability to perform this adjustment along with the required input data but anticipates this process will be undertaken within the SEF tool.

Proposed Model Specification

This section describes the process SEF undertakes to determine the optimal model specification, and the final result. SEF uses the mean absolute percentage error (MAPE) calculation, among many, to evaluate models. MAPE is a typical measure used to forecast accuracy. MAPE can be calculated for each hour, and for each daily, monthly, and seasonal peak. The definition of MAPE used is in this document and by SEF is as follows:[6]

[4] An example of this is a lightbulb replacement program will impact the near term as lightbulb are replaced; however, it can be argued that eventually the bulbs would have been replaced with more efficient bulbs at some in the future without the program. Thus, the impacts of the program only last until when the bulb would have been replaced in absence of the program.

[5] See the AESO's micro-generation reporting here: https://www.aeso.ca/market/market-and-system-reporting/micro-generation-reporting/

[6] See the Wikipedia page on MAPE https://en.wikipedia.org/wiki/Mean_absolute_percentage_error

$$\sum_{t=1}^{n} abs\left(\frac{forecast_t - actual_t}{actual_t}\right) * \frac{100}{n}$$

The Diagnose procedure[7]

SEF utilizes a Diagnose procedure to determine the best model specification for a given time series. It is generally load forecasting best practice to use linear models for long-term (multi-year) load forecasts. Linear models, as opposed to non-linear models like artificial neural networks (ANNs), provide a reasonable trade-off between accuracy and explainability. ANN models tend to work well for near-term (day-ahead) load forecasting accuracy; however, it can be challenging to interpret and explain the relationships mapped out in the process. The AESO believes using a linear modelling framework, in line with best practices, is the appropriate approach to its long-term load forecasting.

SEF tests four different linear model specifications and determines the best fitting one through a one-year holdout period. The first model is the Naïve model, which predicts hourly load as a function of a variety of seasonality, temperature, and independent variables (see Input Data section for more information). The second model specification is the Recency effect. The Recency effect determines the optimal combination of the following lagged temperature effects:

- the simple moving average of the temperatures from the preceding 24 hours
- the temperatures from preceding hours
- the weighted moving average of the temperatures from the preceding 24 hours

The third specification adds the Weekend Effect. This is done by grouping two adjacent days together and calculating the holdout mean absolute percent error (MAPE) generated by this grouping. Only if the holdout MAPE improves, will the energy forecasting procedure continue to group the two adjacent days. All adjacent days are tried: Monday-Tuesday, Tuesday-Wednesday, Wednesday-Thursday, Thursday-Friday, Friday-Saturday, Saturday-Sunday, and Sunday-Monday.

Finally the fourth specification is the Holiday Effect. Models are first developed with the special days (holidays, and the days before and after) modeled as the weekday on which they occur. Models are then developed to test the special day considered to be all other day types of the week. If considering a special day as another day of the week improves model accuracy, then its weekday assignment is modified.

This multi-stage model testing approach ensures that the load forecast model reasonably and appropriately determines weather and calendar effects on load.

Methodology for determining a winning model

Objectives

The AESO strives to ensure that appropriate driver variables are included in the capacity market load forecast and that those variables are properly modelled. This section outlines model testing the AESO has undertaken to determine the appropriate economic inputs and modelling methodology to include them.

[7] See the following link for more information on the SEF Diagnose procedure: https://support.sas.com/documentation/onlinedoc/ef/3.2/efug.pdf

Specification and inputs

24 different model specifications were tested to determine the most appropriate model. The 24 different model specifications were established through different options in SEF and available control variables. Different models were tested by targeting which type of error is most important to minimize, and by choosing different ways to incorporate economic trend variables in the model. All models were run on AIL.

Of the assorted error minimization options in SEF, two different options were tested to determine which model specification was most accurate; hourly MAPE and daily peak MAPE. Other MAPE options, including monthly, seasonal, and annual peak MAPE minimizations, were not included as they would only utilize 12 or 1-2 observations to minimize errors over a one year hold-out period. Due to the small sample size of these options, it was determined that insufficient confidence would be drawn from the results. The hourly MAPE- and daily peak MAPE-derived model were subsequently tested to determine which specification produced the most accurate results (see Evaluation Criteria below).

With regard to input variables, different model specifications were tested with many combinations of indexed GDP, population, employment, a weighted average of three indices, and oilsands production. Other variables including natural gas and conventional oil production were tested. Ultimately, natural gas and conventional oil production were excluded from the final tests because of negative parameter estimates.[8]

The inclusion of economic trend variables can take three forms in SEF; used as a simple trend variable, interacted with the different independent variables, or as a ratio of load. The ratio specification yielded high error and unstable parameters, and was therefore not chosen.

The model was tested with and without oilsands production over the different MAPE minimization and economic variable scenarios. Oilsands is interacted with month as oilsands production intensity changes with seasonal temperatures, resulting in overall error reduction.

The AESO expects that it will review the chosen modelling approach on a forward basis to ensure that the right specification is used with the goal of forecast error minimization.

Evaluation criteria

Based on the results from the aforementioned hourly MAPE and daily peak MAPE model specifications, four error measures were used to evaluate the 24 final model specifications; hourly MAPE, daily peak MAPE, monthly peak MAPE, and seasonal peak MAPE (e.g. the daily peak MAPE was assessed from the output of the hourly MAPE model, etc.). A weighted average of the four error measures is the final metric used to determine the best model. The weights used were 25 per cent on hourly MAPE, 10 per cent on daily peak, 10 per cent on monthly peak MAPE, and 55 per cent on seasonal peak MAPE. Hourly and seasonal peak MAPE were seen as most important, as having low hourly error ensures that the load shape is appropriate, and seasonal peak MAPE is very important as this metric is what will drive future capacity market procurement and it is what will be used in transmission planning. All error metrics were calculated in-sample over the same training period (Jan 1, 2010 – Sep 31, 2017).[9] Appendix A explains and summarizes the calculated errors from the various models as well as the detailed specification of the proposed final model.

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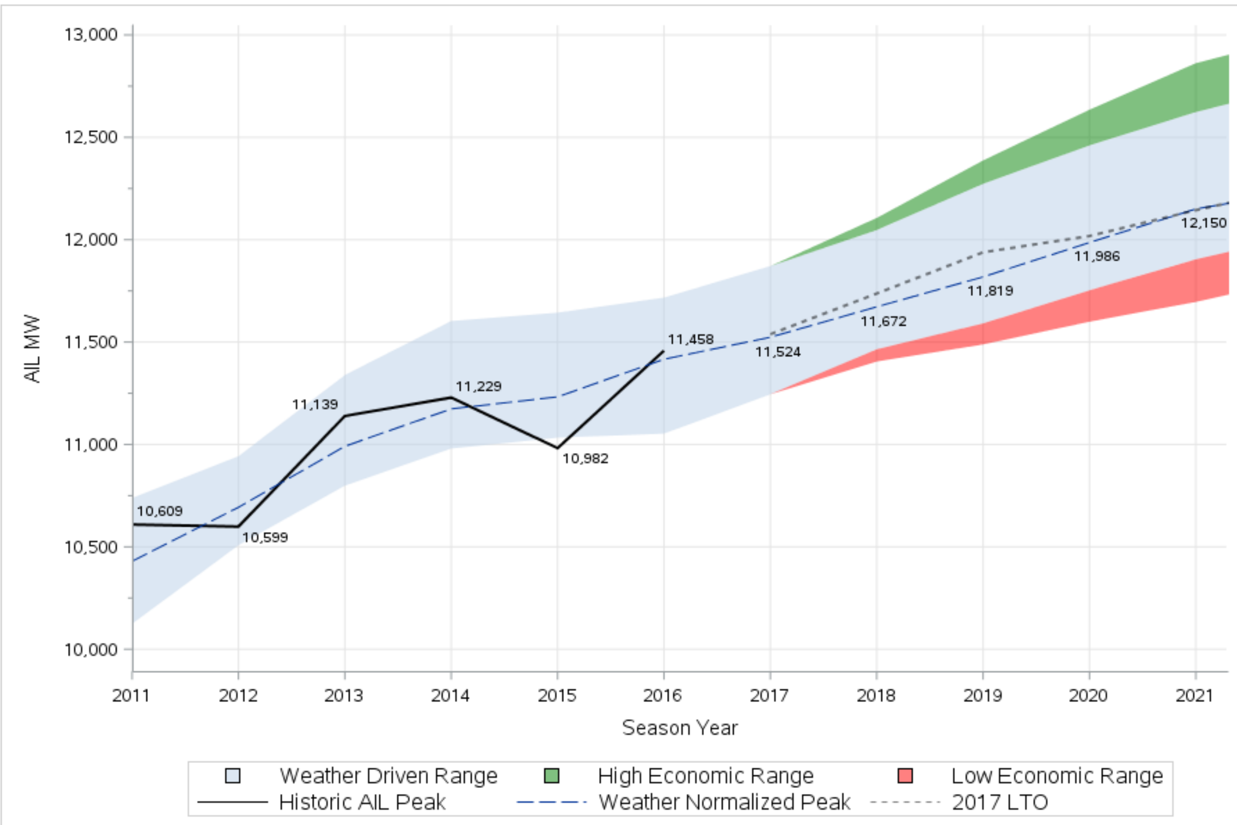
[8] These variables and others including precipitation in Alberta's agricultural region and penetration of air conditioning are targeted to be used on more specific areas for substation-level forecasts to be used in the next LTO. On a more granular level, proper signs are much more attainable for these variables.

[9] Note that the model was refreshed and Table 1 reports different in-sample statistics than Table 2 below.

Preliminary results

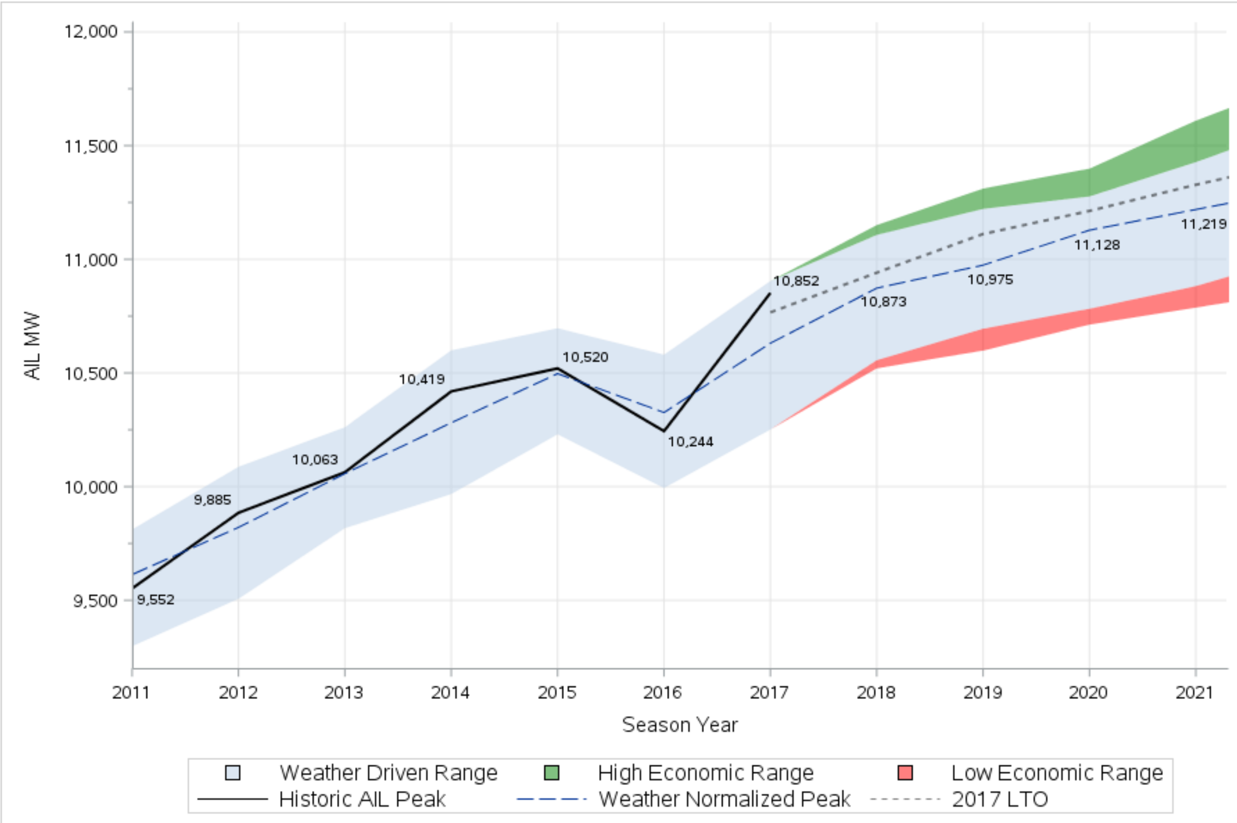
The AESO has run the model described above (the same model as shown in Equation 1 in Appendix A) with 31 weather years, and the proposed economic variability using the CBoC's summer 2017 five year forecast, and CAPP's most June 2017 oilsands production forecast. Figures 1 and 2 display the winter and summer peak results from the proposed model. Historic AIL peaks are also shown alongside the estimated historic range (the blue "weather riven range") based on what load would have been in each weather year.[10] The dashed blue line is the weather normal peak which is the median peak from the 31 historic weather profiles. The green and red ranges show the range of peak values that happen outside the reference case range associated with an economic expansion or contraction. The 2017 LTO forecast is also included for reference. Note that these results are strictly indicative of future capacity market forecasts and may change depending on feedback to the proposed methodology described above and as historical load, weather, and economic drivers are updated.

Figure 1: Winter Peak Preliminary Results



[10] Note that the 2015 winter peak lies outside the weather driven range. This is because the 2015 weather year in 2015 produced the lowest peak prediction, and that peak prediction is ~50 MW or ~0.4% higher than the actual peak that materialized. The 2015 peak is seen as a low outlier.

Figure 2: Summer Peak Preliminary Results



Governance

The AESO believes that the modelling methodology and inputs discussed in this memo is the appropriate approach to forecasting load for the capacity market. However, further revisions may also be required depending on internal and external stakeholder feedback and the need to further refine some details such as energy efficiency and demand response. At a high level, the AESO intends to keep its load forecasting processes as open and transparent as possible while providing opportunity for stakeholder feedback. The AESO also expects that it will ultimately be responsible for the final model specification including inputs, methodology, and the final output. The AESO is striving for transparency and meeting industry standard to ensure that we will be prepared to meet a range of either internal or external governance requirements.

Alignment with AESO Long-term Outlooks, Forecasts, and Transmission Planning

The AESO intends to align its capacity market forecasts with Long-term Outlooks (LTOs), other internal forecast products, and forecasts used in transmission planning as much as possible. As part of the SEF implementation, the AESO's requirements included substation-level load forecasts which can be reconciled with AIL forecasts which will assist with this alignment. This means that the AESO is capable of creating substation-level load forecasts which, with losses, add-up to AIL. These substation-level load forecasts can then be added up geographically over study regions and used in transmission planning.

The nature and scope of future LTOs are still being defined; however, it is currently expected that the load forecasts used in them will be consistent with capacity market forecasts in the near term then, using the same models, will extend the load forecast into the future for at least 20 years in order to align with current practices and regulatory requirements.

The AESO also intends to align other forecast products including the Mid-Term Load Forecast (MTLF; used in the AESO's 24 Month Supply and Demand Forecast[11]) and budget forecasts with the capacity market forecast. Most budget forecasting requirements are Demand Transmission Service (DTS), or system load, but can be aligned with the capacity market forecast by using the SAS platform and by utilizing the same input variables and model specifications. The AESO is examining what steps are required to align its MTLF with the load forecast used in the capacity market.

Appendix A

This appendix shows the results from the AESO winning model assessment explained in the Methodology for Determining a Winning Model section above.

Results

Table 1 below shows each tested model and their respective MAPE statistics. Table 1 does not show statistics for models without oilsands production as they produced higher errors than *all* models with oilsands production. The following list describes the names of iterations of the model displayed in Table 1:

- HM indicates hourly MAPE minimization, DM indicates daily peak MAPE minimization,
- ET indicates economic data was used only as a trend, and ETI indicates the economic trend was interacted with calendar and temperature variables,
- WI indicates the weighted index is the economic trend, E indicates employment is the economic trend, and GDP indicates GDP is the economic trend[12]

Table 1: In-sample MAPEs for all Models

Model	Hourly	Daily	Monthly	Seasonal	Weighted
HM - ETI - WI	1.21%	1.25%	1.41%	1.23%	1.24%
HM - ETI - E	1.27%	1.30%	1.36%	1.20%	1.24%
HM - ET - WI	1.25%	1.28%	1.36%	1.22%	1.25%
HM - ET - E	1.29%	1.32%	1.36%	1.21%	1.25%
HM - ET - GDP	1.25%	1.29%	1.38%	1.24%	1.26%
DM - ETI - WI	1.26%	1.30%	1.47%	1.24%	1.27%
DM - ETI - E	1.31%	1.34%	1.42%	1.23%	1.28%
DM - ET - WI	1.29%	1.33%	1.42%	1.26%	1.29%
HM - ETI - GDP	1.22%	1.26%	1.45%	1.31%	1.30%
DM - ET - GDP	1.29%	1.33%	1.44%	1.28%	1.30%
DM - ET - E	1.33%	1.37%	1.42%	1.26%	1.30%
DM - ETI - GDP	1.27%	1.31%	1.51%	1.32%	1.32%

[11] http://ets.aeso.ca/Market/Reports/Manual/AiesGraphs/24_month_supply_and_demand.html

[12] Because of SEF is only configured to have 3 economic scenarios, population alone was not tested and the economic trend. This is because it population has grown continuously in Alberta even in times of recession, and may not have enough variation on its own to be reliable.

Table 1 demonstrates that the best model is one in which hourly MAPE minimization is chosen, the weighted economic index is used, and the weighted index is interacted with other control variables. This result is encouraging as it supports the hypothesis that if minimizing errors across all hours, peaks should still be captured. Also, the weighted index contains more information than its individual parts; therefore it is not surprising that it produces the best error statistics. Finally, the low error results from interacting the weighted index with other variables indicates that, for example, load is impacted by economic growth more so in hour ending 18 during the week than hour ending one, or on the weekend. If the impacts from economic growth are unequal across all hours based on the data, the AESO believes the model should capture that impact.

The proposed model

The proposed model takes the following form, where:[13,14]

- E represents the weighted economic trend variable,
- M indicates the month, subscript $_i$ refers to the 12 different months,
- W indicates the day of the week, subscript $_j$ refers to the days of the week included,
- HE is the hour ending, subscript k refers to all hours in the day,
- DST indicates hours in mountain daylight time,
- T is temperature,
- TA is an exponentially smoothed average of the past 24 hour's temperature,
- S indicates if there is sunlight,
- O is oilsands production,
- D indicates dummy variables for events,
- The ∝ on each parameter refers the coefficient estimate for each term, and
- Subscript $_t$ indicates the time period (at an hourly granularity) of the estimation

Equation 1: Load forecasting model specification

$$\begin{aligned} AIL_t = \beta_0 &+ \beta_\alpha E_t + \beta_\alpha M_{it} + \beta_\alpha E_t M_{it} + \beta_\alpha W_{jt} HE_{kt} + \beta_\alpha E_t W_{jt} HE_{kt} + \beta_\alpha DST_t W_{jt} HE_{kt} \\ &+ \beta_\alpha E_t M_{it} T_t + \beta_\alpha E_t M_{it} T_t^2 + \beta_\alpha E_t M_{it} T_t^3 + \beta_\alpha E_t HE_{kt} T_t + \beta_\alpha E_t HE_{kt} T_t^2 \\ &+ \beta_\alpha E_t HE_{kt} T_t^3 + \beta_\alpha E_t M_{it} TA_t + \beta_\alpha E_t M_{it} TA_t^2 + \beta_\alpha E_t M_{it} TA_t^3 + \beta_\alpha E_t HE_{kt} TA_t \\ &+ \beta_\alpha E_t HE_{kt} TA_t^2 + \beta_\alpha E_t HE_{kt} TA_t^3 + \beta_\alpha S_t M_{it} W_{it} + \beta_\alpha O_t M_{it} + \beta_\alpha D_t \end{aligned}$$

The proposed model was run on Alberta Internal Load (AIL), and has the following in-sample (Jan 1, 2011 – Sep 31, 2017) and hold-out[15] (Oct 1st, 2016-Sep 31st 2017) mean absolute percentage error (MAPE) statistics:

[13] SAS Energy Forecasting chooses how to include lagged temperature by iterating through and determining whether or not a flat average or some exponentially smoothed function that minimizes a specified error metric errors (in the winning model a smoothed average reduced error the most). Similarly, in the W variable, SAS Energy Forecasting determines the optimal grouping of holidays and weekends through the same process. See the Diagnose Procedure section. The current model uses an exponentially smoothed average of the last 24 hours with an alpha of 0.95.

[14] Because the goal is to minimize errors, as more data becomes available, the AESO will look to update this model specification to minimize errors given the most recent data. This may result in different calendar and other variable configurations, etc.

[15] A hold-out period is where values are forecast, using a model derived from an earlier time period, over different time period then compared to actuals. This allows for a measure of true forecast model error, as actual temperature and economics are available. Note that the model is not trained on the data contained in the hold-out period for hold-out statistics.

Table 2: MAPE statistics on load forecast model

Time Period	Hourly	Daily Peak	Monthly Peak	Seasonal Peak
In-sample	1.21%	1.25%	1.32%	1.17%
Hold-out	1.58%	1.61%	0.93%	0.87%[16]

An explanation of each term:

- β_0 is the intercept
- $\beta_\alpha E_t$ is the coefficient on the long-term economic trend, and drives the long-term growth profile
- $\beta_\alpha M_{it}$ is the coefficient on a dummy for each month, picking up seasonal effects
- $\beta_\alpha E_t M_{it}$ is an interaction between economic and seasonal trends. This picks up an effect of, for example, load being higher in December due to drilling, Christmas light loads (higher retail spending), or other factors being high in December, producing both higher load and higher GDP as a result.
- $\beta_\alpha W_{jt} HE_{kt}$ an interaction of day of the week and hour ending. The impact of 6:00pm is not expected to be the same on Sunday as it is on Monday.
- $\beta_\alpha E_t W_{jt} HE_{kt}$ an interaction of economics, week, and hourly trends. It may be expected that higher economic trends typically have a higher load impact on weekdays during business hours.
- $\beta_\alpha DST_t W_{jt} HE_{kt}$ is the interaction of daylight savings time on the hourly load profile by day of the week. Because the sun rises later and sets later during MDT, load profiles are altered (sunlight is keep on a MST time frame).
- $\beta_\alpha E_t M_{it} T_t$ the interaction of temperature, month, and economic drivers. A 20-degree day in September is expected to be different than in May, and to be different in times of recession or growth. A cubed function is used to capture the relationship between temperature and load.[17]
- $\beta_\alpha E_t HE_{kt} T_t$ the interaction of temperature, hour ending, and economic drivers. A temperature of 20 degrees at 7:00am is expected to have different impacts than 20 degrees at 6:00pm, and to be different in times of recession or growth. A cubed function is used to capture the relationship between temperature and load.
- The interaction between temperature, month, hour, and economics is also applied to a weighted average of previous 24 hours temperature. Typically load is higher if there is consistent hot or cold as insulation in houses or industrial sites is fully utilized.
- $\beta_\alpha S_t M_{it} W_{it}$ this is the interaction between sunlight hours and the month and weekday. When the sun goes down, houses, businesses, and streetlights typically increase lighting load to compensate. The lighting impact may be different across months and days of the week.
- $\beta_\alpha O_t M_{it}$ oilsands production interacted with month. This picks up a seasonal trend in oilsands production intensity. It is more energy intensive to produce bitumen in winter months.
- $\beta_\alpha D_t$ dummy variables for outlier events like the Fort McMurray fires.

[16] The seasonal peaks during the hold-out period were the 2017 summer peak, and the 2016/2017 winter peak.

[17] In some circumstances a 2nd degree polynomial may be chosen instead. If the cubed function is solving such that it has a saturation point where predicted load is decreasing as it get colder, a second degree function will help correct for this inconsistency.

Appendix B

The Appendix discusses the approximate impact to the load forecast from forecast errors in the economic input variables.

Errors in the economic driver variables

As discussed in the Inputs section, the AESO is proposing to use a weighted index of population, employment, and real GDP growth, as well as oilsands production as the long-term trend drivers in the model. The AESO uses forecasts of oilsands production and the variables that create the index from third party vendors. If the vendor's forecasts for these variables turn out to have contained errors, then it follows that the load forecast will have directionally contained the same errors. This risk is inherent in the business of forecasting. This is because to forecast a variable that is explained by other variables, a forecast of those input variables is required.

To assess the risk to the load forecast from third party vendor error, sensitivities were run on the load forecast model with respect to the economic driver input variables. The sensitivities tested included what the impact of a 1 per cent change in the economic index or oilsands production is on predicted load. The results were that for a 1 per cent change in the economic index, load will increase/decrease by 71 MW during winter peak conditions, and 54 MW during summer peak conditions. Likewise a 1% increase in oilsands production results in a 17 MW increase/decrease in forecast load.

The AESO reviewed multiple CBoC forecasts to determine the possible range of errors we can expect moving forward. By calculating what the weighted economic index was from previous forecasts, and comparing it to the actual economic index, we determined what historic forecast errors have been. Three years out, the worst forecast errors are 3.4% and -2.8% (positive number indicates an over-forecast). One year out, the worst case errors have been 1.1% and -1.4%.

The AESO acknowledges these risks, and plans to mitigate them through the use of scenarios, as described above.