ALBERTA ELECTRIC SYSTEM OPERATOR

Confidence Band Intervals for the *Future Demand and Energy Outlook* (2008 – 2028)

Table of Contents

Executive Summary **1**

1.0 Introduction **2**

2.0 Monte Carlo Approach **3**

2.1 Industrial (without Oilsands) Customer Sector 3
2.2 Oilsands Customer Sector 4
2.3 Commercial Customer Sector 5
2.4 Residential Customer Sector 6
2.5 Farm Customer Sector 7

3.0 Total Energy and Peak Demand **8**

3.1 Monte Carlo Results 8

4.0 Appendix 1 Other Approaches **12**

4.1 NERC Methodology 12
4.2 Econometric Theory to Derive Confidence Intervals 12
4.2.1 Industrial (without Oilsands) Customer Sector 14
4.2.2 Commercial Customer Sector 15
4.2.3 Farm Customer Sector 15
4.2.4 Aggregate Results 16
4.2.5 Econometric Approach Summary 17

5.0 Appendix 2 .... **18**

List of Reference Documents **20**

Glossary **21**

FIGURES

Figure 2.1-1: Monte Carlo Approach – Industrial (without Oilsands) Sector Confidence Intervals........................4
Figure 2.2-1: Monte Carlo Approach – Oilsands Sector Confidence Intervals...5
Figure 2.3-1: Monte Carlo Approach – Commercial Sector Confidence Intervals..6
Figure 2.5-1: Monte Carlo Approach – Farm Sector Confidence Intervals..7
Figure 3.1-1: Monte Carlo Approach – AIL Energy Confidence Intervals..8
Figure 3.1-2: Monte Carlo Approach - AIL Peak Demand Confidence Intervals..9
Figure 4.2-1: Econometric Approach - Industrial (without Oilsands) Sector Confidence Intervals......................14
Figure 4.2-2: Econometric Approach - Commercial Sector Confidence Intervals 15
Figure 4.2-3: Econometric Approach - Farm Sector Confidence Intervals 16
Figure 4.2-4: Econometric Approach - AIL Energy Confidence Intervals 16
Figure 4.2-5: Econometric Approach - AIL Peak Demand Confidence Intervals...17

TABLES

Table 3.1-1: Monte Carlo Approach – AIL Energy Confidence Intervals..10
Table 3.1-2: Monte Carlo Approach – AIL Peak Demand Confidence Intervals 11

Executive Summary

Confidence Band Intervals for the *Future Demand and Energy Outlook (2008-2028)* report ("Report") describes the methodology and results of constructing confidence band intervals around the Alberta Electric System's long run load forecast, as laid out in *Future Demand and Energy Outlook (2008-2028)* ("FC2008").

The FC2008 is the Alberta Electric System Operator's (AESO) long-term load forecast. The FC2008 describes the assumptions, methodology, and processes that the AESO uses to assess Alberta's most likely future demand and energy requirements.

The FC2008 includes a 20-year peak load and electricity consumption forecast for Alberta. The load forecast is generated from economic growth (GDP), oilsands production forecast, and population projections by select customer sectors in conjunction with regional adjustments based on historical results and customer-driven growth expectations.

The Report shows confidence intervals on a sector by sector basis at the 80% (P10 to P90) and 95% (P2.5 to P97.5) confidence levels. Three methodologies are discussed in the Report for comparison purposes. However, the AESO believes the Monte Carlo approach is a more reasonable estimate of the confidence band intervals since the approach incorporates variation of all the relevant input variables including those provided by the Conference Board of Canada.

The results of the Monte Carlo approach show that by 2018 a P10/90 low/high peak demand values of 13,856 MW (-5.5%) and 15,268 MW (+4.2%) respectively as compared to the most likely forecast of 14,659 MW. The results for 2028 show a wider spread for the P10/P90 of 17,951 MW (-6.8%) and 20,350 MW (+5.6%) respectively as compared to the most likely forecast of 19,271 MW.

1.0 Introduction

The AESO's long-term load forecast is a study of past energy use patterns and future economic indicators, that are, in simple terms, combined to produce a future energy forecast. The AESO annually updates this energy forecast with a 20-year outlook of Alberta's electric energy consumption and peak load demand. The estimates of future electricity market needs are one of the drivers the AESO uses in analyzing and planning the timely development of the transmission system. The annual forecast is based on economic, demographic and customer information collected from January through June of 2008.

Completed in the third quarter of 2008, the AESO's *Future Demand and Energy Outlook (2008-2028)* describes the assumptions, methodology and processes that the AESO employs to assess Alberta's most likely future demand and energy requirements.

The AESO requires, along with its long-term load forecast, high and low confidence bands that reflect a reasonable expected range of the forecast. Potential sources of error exist with any forecast and it is important to recognize and attempt to measure the potential effect that any error may have on the forecast. The assumptions used and the underlying methodology of forecasting are explained in order to justify why the confidence bands represent a relatively likely forecast.

Forecasts cannot precisely predict the future. Variation in the key factors that drive electrical usage may deviate the actual demand from the forecasted demand in any given year. To account for this, the AESO reports its energy and demand forecast as a baseline or most likely outcome as well as a range of possible outcomes based on probabilities around the base case. For planning and analytical purposes, it is useful to have an estimate not only of the most likely case but also of the distribution of probabilities around the forecast.

The AESO developed upper and lower confidence bands around the 2008 load forecast for each sector. The P2.5/P97.5 confidence band corresponds to a 95% confidence interval. This means that there is a 95% chance that the actual energy demand will fall within this interval and there is a 5% chance the actual demand will fall outside of this interval. Similarly, the P10/P90 confidence band corresponds to an 80% confidence interval for which there is an 80% chance that the forecast will fall within its bands.

Three approaches to calculating confidence band intervals were examined. The Monte Carlo simulation method was used to calculate confidence band intervals for each sector as well as for total Alberta Internal Load (AIL) and peak demand. The North America Electric Reliability Corporation's (NERC) methodology was explored and an econometric approach was also examined. However, due to certain limitations, it was determined that the Monte Carlo simulation method is the preferred choice. For analytical and comparison purposes, the other approaches are included in the Report in Appendix 1.

2.0 Monte Carlo Approach

Monte Carlo simulations were performed individually on all five sector models as well as on an aggregated model which combines all the sectors together. Within the models there are econometrically forecasted coefficients as well as externally-forecasted values of input variables. All of these variables are allowed to vary according to defined probability distributions that are based on historical data wherever possible. It should be noted that in many instances, historical data was not available or not adequate to produce a reasonable probability distribution estimate. In these instances, the AESO formulated its own estimate of probability distribution using the forecasted values plus a reasonable assessment of potential variation for those forecasted values.

2.1 Industrial (without Oilsands) Customer Sector

The Industrial sector is the largest sector in terms of load and energy consumption, comprising roughly 49 per cent of total Alberta Internal Load (AIL) energy use. The forecast for this sector is a function of real economic growth and historical usage.

The industrial forecast was completed using the following OLS econometric regression:

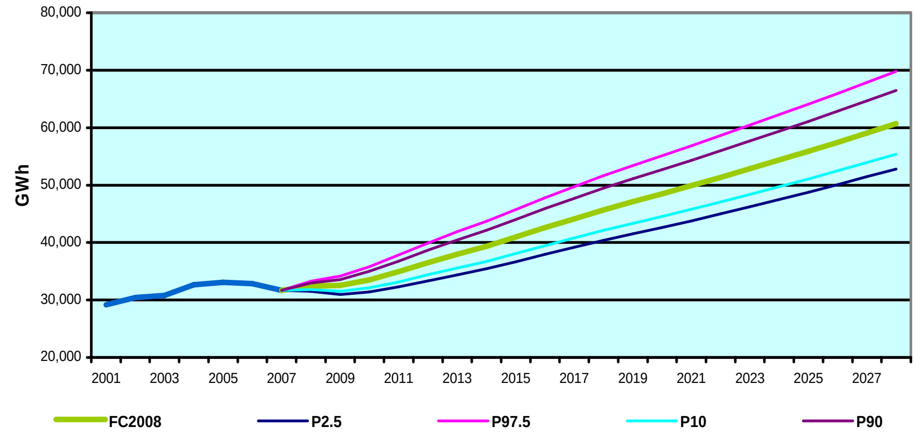
$$IND_t = \beta(MINGDP_t) + \delta(IND_{t-1}) + u_t \qquad (1)$$

Where:

- IND_t is industrial sales in year *t*
- $MINGDP_t$ is Alberta mining, oil and gas extraction GDP ("mining GDP")
- β, δ are unknown coefficients that were estimated
- u_t is an independent and identically distributed stochastic error

Within the Industrial (without Oilsands) sector model, there are two input variables (the estimated coefficients from the econometric regression) plus the Conference Board of Canada's mining, oil and gas GDP forecast. A normal distribution was assumed for both of the regression coefficients and for the growth rates of the GDP forecast in each year. Altogether there are 23 total input variables which received a probability distribution. A random sample from each of those 23 probability distributions was put into the model to calculate the corresponding forecasted value. This process was repeated 100,000 times providing 100,000 forecasted values for each year of the forecast. Using these values, the 80% and 95% forecast confidence band intervals were calculated. These values are shown in Figure 2.1-1.

Figure 2.1-1: Monte Carlo Approach – Industrial (without Oilsands) Sector Confidence Intervals



Source: AESO and ERCB

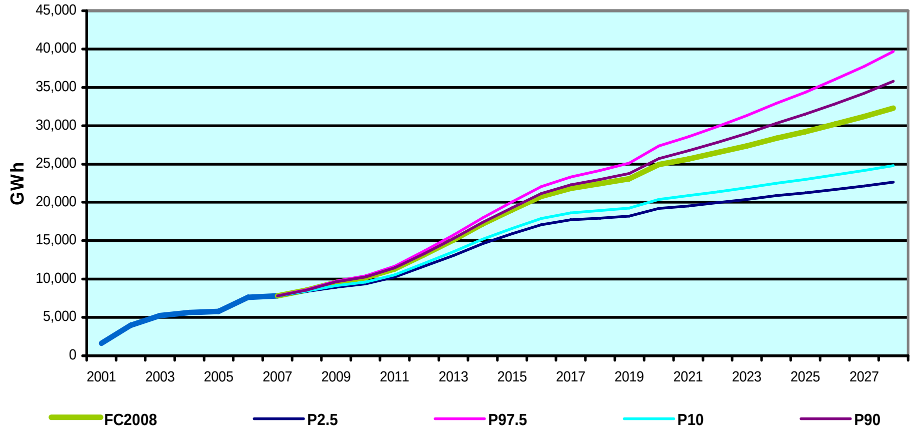
2.2 Oilsands Customer Sector

The Oilsands model has several variable inputs. Production from the oilsands is broken into mining and In-Situ production. Using historical data, estimates are made on the energy intensity of the two production types. Then production estimates for each production type are combined with the estimated energy intensity to produce an oilsands forecast.

As outlined in the FC2008, the oilsands production estimates up to 2020 are based on an adjusted Canadian Association of Petroleum Producers (CAPP) oilsands production forecast. Thereafter, the AESO estimates of growth are used. Probability distributions are estimated for the growth of each year. Up to 2020, the AESO estimates a negatively-skewed probability distribution for each year of the adjusted CAPP production forecast with the most likely value occurring equal to the estimated production value. The negatively-skewed distribution maintains that the most likely case will still be the adjusted CAPP forecast. However, if the Monte Carlo simulation draws a sample that is less than the adjusted CAPP forecast, it may be much lower whereas if the simulation draws a sample that is greater than the forecast, it may only be a little higher. This increases the range of the lower confidence bands and better reflects the possibility of project deferrals and cancellations. After 2020, a normal probability distribution is placed on the moderate annual oilsands production growth forecasts.

The energy intensities of mining and In-Situ production are permitted to vary in the model but only over time. A normal probability distribution with mean equal to zero is placed on the annual growth rate. This allows the confidence bands to incorporate the possibility that energy intensity of either mining or In-Situ may independently increase or decrease over time. 100,000 random samples were taken from each probability distribution of each input variable then put into the model to calculate the corresponding forecast values which were used to calculate the confidence intervals. Figure 2.2-1 shows the calculated 80% and 95% confidence band intervals.

Figure 2.2-1: Monte Carlo Approach – Oilsands Sector Confidence Intervals



Source: AESO and ERCB

2.3 Commercial Customer Sector

The Commercial sector represents approximately 19 per cent of total energy use in Alberta. The Commercial sector forecast assumes commercial energy use is a function of Alberta's economic growth and historical commercial sales.

Commercial energy consumption is forecasted by the AESO according to the following econometric regression:

$$COM_t = \alpha + \beta(ABGDP_t) + \delta(COM_{t-1}) + u_t \qquad (2)$$

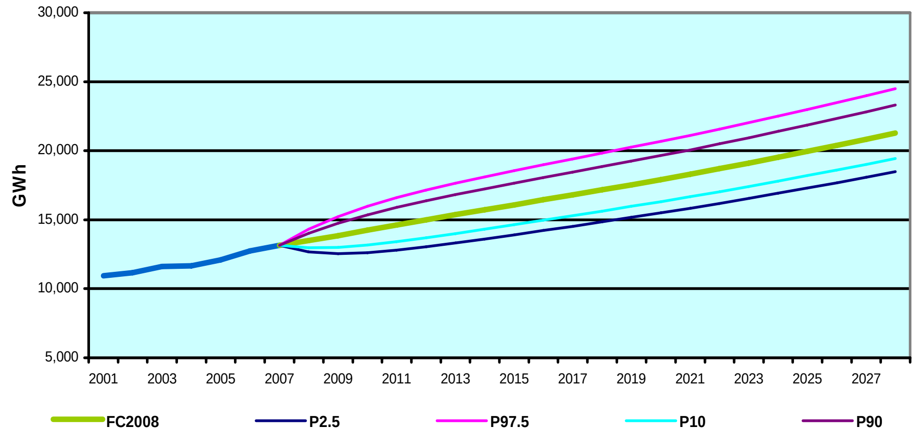
Where;

- COM_t is the commercial sector annual energy consumption,
- $ABGDP_t$ is Alberta's real GDP in 2002 dollars,
- α, β, δ are unknown coefficients that were estimated.
- u_t is an independent and identically distributed stochastic error

The Commercial sector model's inputs include the regression coefficients on Alberta's GDP and on the commercial lag term plus a constant. The other input is the annual growth of Alberta's GDP which is provided by the Conference Board of Canada.

For the Monte Carlo simulation, the regression coefficients are assumed to be normally distributed. The annual GDP growth rates are also assumed to have a normal distribution with the mean centered on the forecasted values. The standard deviation used is calculated from historical values. Similar to the other sectors, 100,000 samples are taken from each input's distribution which are put through the model and used to calculate the forecast confidence intervals. These calculated confidence intervals are displayed in Figure 2.3-1.

Figure 2.3-1: Monte Carlo Approach – Commercial Sector Confidence Intervals



Source: AESO and ERCB

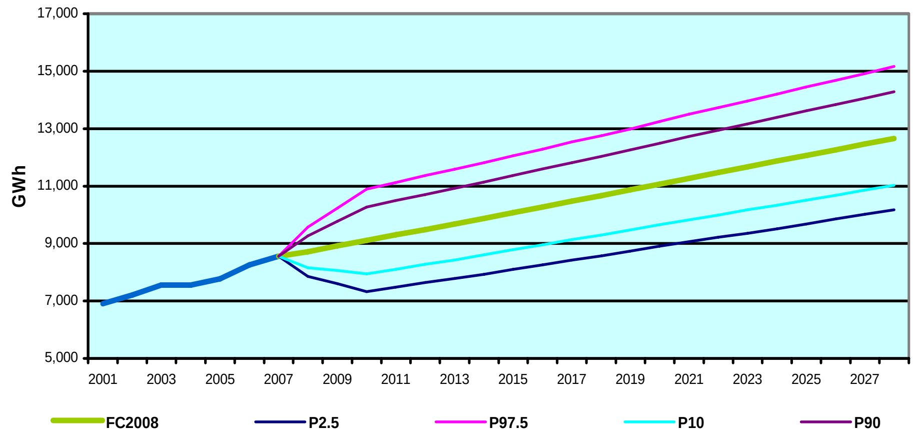
2.4 Residential Customer Sector

The model used to forecast residential demand uses population growth, customers as a fraction of the population, and the average use per customer to estimate future demand. Population growth is provided by the Conference Board of Canada. Customers as a fraction of the population and the average use per customer are estimated using historical trends.

In each year of the Conference Board's population forecast, a normal distribution for the growth rate is assumed. The use per customer in each year is also assumed to be a normal distribution. This implicitly incorporates variation of weather that historically is reflected in energy use per customer.

In a similar fashion to the other sectors, a Monte Carlo simulation of the residential forecast was used to estimate confidence band intervals at 80% and 95%. These estimates are shown in Figure 2.4-1.

Figure 2.4-1: Monte Carlo Approach – Residential Sector Confidence Intervals



Source: AESO and ERCB

2.5 Farm Customer Sector

The Farm sector is the smallest of the forecasted sectors, representing approximately three per cent of total electricity sales. While the FC2008 forecasts farm load to increase over the next 20 years, the farm sector's share of total energy use is expected to fall as industrial and other sectors increase at a more rapid rate.

To forecast farm sector energy use, the following OLS econometric regression was used:

$$farm_t = \alpha + \beta(AGGDP_t) + \delta(HDD_t) + u_t \qquad (3)$$

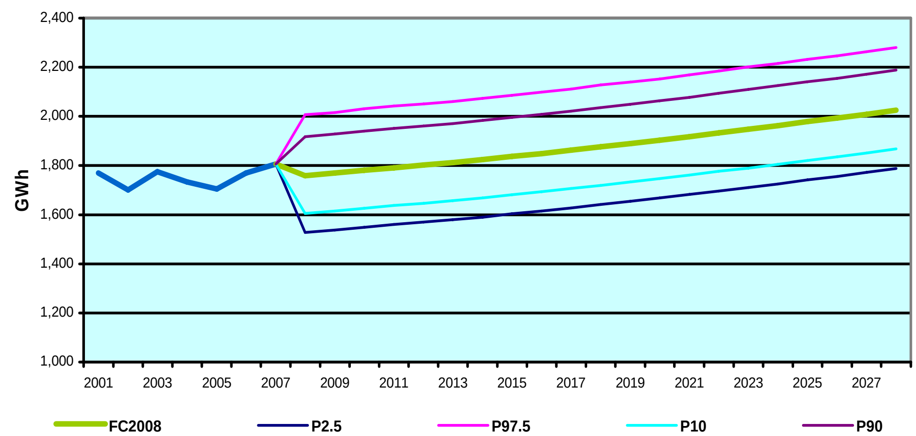
Where:

- $farm_t$ is farm sales
- $AGGDP_t$ is Alberta agricultural GDP
- HDD_t is average annual heating degree days
- α, β, δ are unknown coefficients that were estimated
- u_t is an independent and identically distributed stochastic error

Each of the three estimated coefficients had a normal distribution placed on it with the mean equal to the estimated coefficient. In addition, an agricultural GDP forecast provided by the Conference Board of Canada was used as an input. The growth rates of this forecast in each year were assumed to be normal with the mean equal to the forecasted value. Average historical heating degree days were also used as an input into the model. Historical heating degrees follow a normal distribution which was used in each year for the Monte Carlo simulation.

Repeatedly taking samples from each input's probability distribution allowed the construction of the farm's forecast confidence intervals which are shown in Figure 2.5-1.

Figure 2.5-1: Monte Carlo Approach – Farm Sector Confidence Intervals



Source: AESO and ERCB

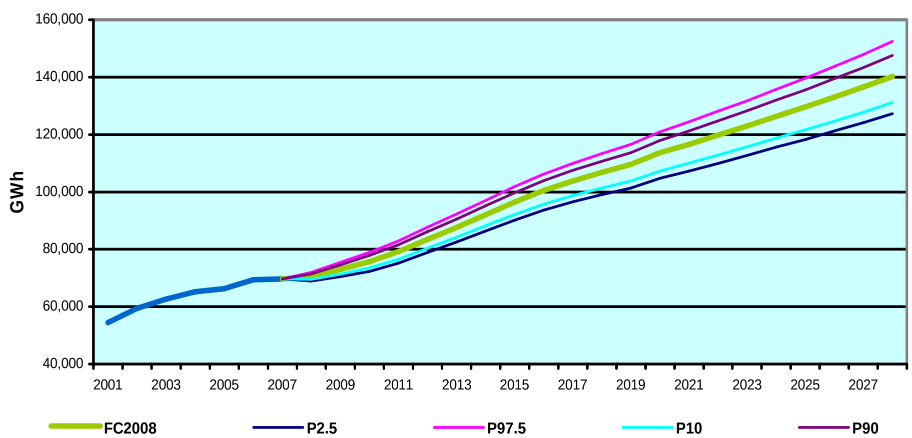
3.0 Total Energy and Peak Demand

Total provincial energy use and peak demand were also calculated using the Monte Carlo simulation which took the inputs from each sector and combined them in a comprehensive model to produce a total energy forecast. This total energy forecast was coverted into peak demand using the FC2008 load factor estimate which was also varied using historical trends.

3.1 Monte Carlo Results

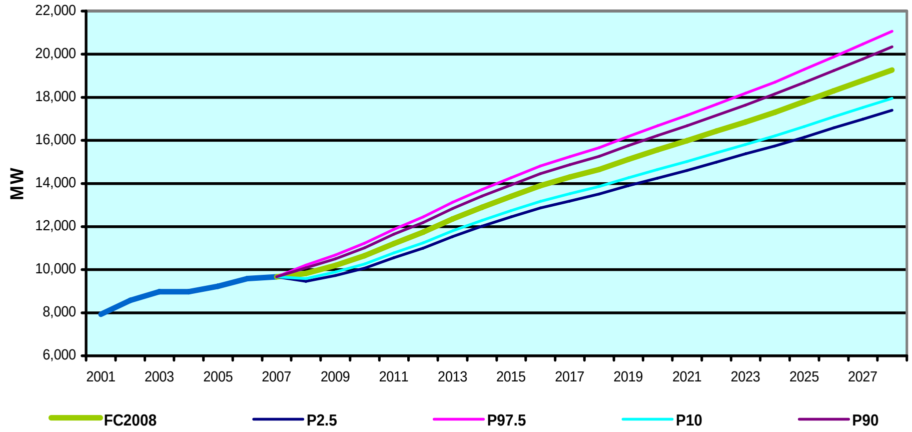
For the Monte Carlo simulation, the five sector models were combined into one model to calculate total AIL energy as well as the corresponding peak demand. The forecasted values remain calculated in the same way. However, the input variables of all five models are permitted to vary simultaneously according to the distributions outlined in section 2. By varying all sector inputs simultaneously, the confidence bands for total AIL and peak energy are dependent on the variation of all inputs. The calculated AIL confidence bands and their corresponding peak demand confidence intervals are displayed in Figures 3.1-1 and 3.1-2.

Figure 3.1-1: Monte Carlo Approach – AIL Energy Confidence Intervals



Source: AESO and ERCB

Figure 3.1-2: Monte Carlo Approach - AIL Peak Demand Confidence Intervals



Source: AESO and ERCB

Tables 3.1-1 and 3.1-2 report the confidence interval results from the Monte Carlo simulation on AIL energy and peak demand respectively. The results of the Monte Carlo approach show that by 2018 a P10/90 low/high peak demand values of 13,856 MW (-5.5%) and 15,268 MW (+4.2%) respectively as compared to the most likely forecast of 14,659 MW. The results for 2028 show a wider spread for the P10/P90 of 17,951 MW (-6.8%) and 20,350 MW (+5.6%) respectively as compared to the most likely forecast of 19,271 MW.

Additional analysis indicates that by 2028, the largest sources of variation in the energy forecast comes from variation in oilsands production growth and oilsands energy intensity. The oilsands sector is expected to represent an increasing share of total energy use and demand in the province. As mentioned in the FC2008, different technologies used to extract crude bitumen from the oilsands use different amounts of electricity. Uncertainty regarding the adoption of these technologies and new technologies creates a wider spectrum of possible electricity use in the sector. In addition, the oilsands production forecast is dependent on large-scale, capital-intensive projects which are economically sensitive, tougher to predict and which cause additional variation in the forecast.

Table 3.1-1: Monte Carlo Approach – AIL Energy Confidence Intervals

	FC2008 (GWh)	P97.5 (GWh)	P90 (GWh)	P10 (GWh)	P2.5 (GWh)
2000	54,054	–	–	–	–
2001	54,467	–	–	–	–
2002	59,437	–	–	–	–
2003	62,716	–	–	–	–
2004	65,259	–	–	–	–
2005	66,268	–	–	–	–
2006	69,370	–	–	–	–
2007	69,660	–	–	–	–
2008	70,511	71,971	71,448	69,508	68,983
2009	73,062	75,476	74,613	71,381	70,527
2010	75,727	78,991	77,824	73,474	72,346
2011	79,146	82,930	81,559	76,489	75,195
2012	83,485	87,733	86,174	80,420	78,956
2013	87,678	92,311	90,568	84,209	82,588
2014	92,106	97,087	95,208	88,233	86,490
2015	96,448	101,846	99,743	92,152	90,220
2016	100,487	106,253	103,974	95,760	93,728
2017	103,841	109,971	107,518	98,789	96,594
2018	106,775	113,321	110,711	101,388	99,070
2019	109,562	116,545	113,748	103,828	101,391
2020	113,652	120,970	117,932	107,355	104,720
2021	116,626	124,435	121,234	110,014	107,271
2022	119,804	128,101	124,733	112,874	109,971
2023	123,028	131,828	128,303	115,770	112,774
2024	126,376	135,796	131,985	118,788	115,584
2025	129,601	139,607	135,560	121,653	118,315
2026	133,049	143,763	139,444	124,708	121,237
2027	136,584	147,998	143,397	127,838	124,223
2028	140,265	152,498	147,572	131,143	127,294

Source: AESO and ERCB

Table 3.1-2: Monte Carlo Approach – AIL Peak Demand Confidence Intervals

	FC2008 MW	P97.5 MW	P90 MW	P10 MW	P2.5 MW
2000	7,785	–	–	–	–
2001	7,934	–	–	–	–
2002	8,570	–	–	–	–
2003	8,967	–	–	–	–
2004	8,967	–	–	–	–
2005	9,236	–	–	–	–
2006	9,580	–	–	–	–
2007	9,661	–	–	–	–
2008	9,833	10,219	10,081	9,581	9,460
2009	10,202	10,679	10,508	9,886	9,728
2010	10,650	11,230	11,024	10,262	10,067
2011	11,217	11,873	11,638	10,774	10,556
2012	11,737	12,451	12,188	11,239	10,999
2013	12,357	13,129	12,839	11,800	11,538
2014	12,897	13,715	13,406	12,290	12,007
2015	13,401	14,263	13,928	12,737	12,442
2016	13,899	14,805	14,451	13,176	12,860
2017	14,290	15,251	14,876	13,529	13,194
2018	14,659	15,668	15,268	13,856	13,505
2019	15,117	16,181	15,766	14,268	13,896
2020	15,573	16,684	16,235	14,648	14,255
2021	15,987	17,159	16,684	15,017	14,607
2022	16,431	17,676	17,167	15,417	14,989
2023	16,860	18,185	17,646	15,801	15,369
2024	17,312	18,705	18,150	16,209	15,752
2025	17,798	19,296	18,689	16,644	16,150
2026	18,298	19,882	19,242	17,088	16,575
2027	18,781	20,465	19,785	17,524	16,978
2028	19,271	21,063	20,350	17,951	17,396

Source: AESO and ERCB

4.0 Appendix 1 Other Approaches

For comparison purposes, the AESO examined two other methods of deriving confidence intervals. The first method follows NERC's method of constructing confidence bands while the second method utilizes an econometric and statistical approach.

4.1 NERC Methodology

The North American Electric Reliability Corporation (NERC) constructs confidence bands around the load forecasts for the various geographic areas within its jurisdiction. The load forecasts come from different organizations and utilize different methodologies. To construct confidence intervals, NERC utilizes a number of univariate time-series models including simple ARIMA models, first order autoregressive models, first order moving average models, and random walk models, with and without drift. Projections of regional demand and net energy for load are modeled as a function of the past peak demand or energy and the optimal model is selected for each region's energy and peak. The confidence bandwidths are then constructed from the in-sample residuals from the univariate time-series models. These bandwidths are then proportionally projected on the original forecasts.

The advantage of this methodology is that it allows NERC to construct confidence bands using historical data without having to deal with the complex modeling used by the various forecasting entities. Combining the various forecasts and attempting to vary all the inputs from all the models would be laborious and time-consuming from NERC's standpoint. The disadvantage of NERC's methodology is it is not based on the variation of the input drivers used to create the original forecasts. Since the actual variation of future load depends on the variation of the factors that drive load, it would be ideal to vary those inputs to determine the confidence intervals. Because the AESO does not have to deal with as many forecasts as NERC, and because the AESO has the ability to vary the inputs of its models, the AESO believes that the Monte Carlo methodology is the better approach to use.

4.2 Econometric Theory to Derive Confidence Intervals

For analytical and comparison purposes, the AESO performed an econometric approach to derive confidence intervals for the Commercial, Farm, and Industrial without Oilsands (Industrial) sectors. This approach offers a theoretical method of constructing confidence intervals that is based off of historical results. The Residential and Oilsands sectors were forecasted without econometric regressions, therefore confidence intervals for these sectors were derived using the Monte Carlo approach described in Section 2. AIL and peak demand confidence bands were estimated by combining the individual sector confidence bands.

The econometric regressions performed to forecast the Commercial, Farm, and Industrial sectors use ordinary least squares (OLS) methodology and assumptions from the Classical Linear Regression Model (CLRM). Following methodology presented in Woolridge, the AESO uses the estimated coefficients to forecast the energy consumption for a particular year in the future using the following formula:

$$y^0 = \beta_0 + \beta_1 x_1^0 + \beta_2 x_2^0 + \ldots + \beta_k x_k^0 + u^0 \quad (4)$$

Where:

- y^0 is the value associated with the forecasted values of x_i^0 .
- x_i^0 is a forecasted value of explanatory variable i in year 0.
- β_i is the estimated coefficient from the OLS regression
- u^0 is a random disturbance

The best forecast of y^0 is the expected value of y^0 given the explanatory variables which are estimated from the OLS regression line:

$$\hat{y}^0 = \hat{\beta}_0 + \hat{\beta}_1 x_1^0 + \hat{\beta}_2 x_2^0 + \ldots + \hat{\beta}_k x_k^0 \quad (5)$$

The forecast error in using $\hat{y}^0$ to predict y^0 is

$$\hat{e}^0 = y^0 - \hat{y}^0 = (\beta_0 + \beta_1 x_1^0 + \beta_2 x_2^0 + \ldots + \beta_k x_k^0) + u^0 - \hat{y}^0 \quad (6)$$

Therefore, the variance of the forecast error, conditional on all in-sample values of the independent variables is the sum of the variances:

$$Var(\hat{e}^0) = Var(\hat{y}^0) + Var(u^0) = Var(\hat{y}^0) + \sigma^2 \quad (7)$$

Where $\sigma^2 = Var(u^0)$ is the error variance. There are two sources of variation in $\hat{e}^0$. The first is sampling error in $\hat{y}^0$, which arises because β_i is estimated. Each $\hat{\beta}_i$ has a variance proportional to $1/n$ which means for large samples, $Var(\hat{y}^0)$ can be very small.

The second part of the error variance comes from σ^2 which is the variance of the error in the population and, therefore, does not change with sample size.

An unbiased estimator of $\hat{\sigma}^2$ is calculated using the formula:

$$\hat{\sigma}^2 = \left(\sum_{i=1}^{n} \hat{u}_i^2 \right) / (n-k-1) = SSR/(n-k-1) = SSR/df \quad (8)$$

Under the classical linear model assumptions, $\hat{\beta}_i$ and u^0 are normally distributed and so $\hat{e}^0$ is also assumed to be normally distributed. By using these estimators, the standard error of $\hat{e}^0$ is defined as:

$$se(\hat{e}^0) = \left\{ \left[se(\hat{y}^0) \right]^2 + \sigma^2 \right\}^{1/2} \quad (9)$$

$\hat{e}^0$ has a *t* distribution which is used to derive the forecast interval for $\hat{y}^0$:

$$\hat{y}^0 \pm t_{(df, a/2)} \cdot se(\hat{e}^0) \quad (10)$$

Where α is the confidence level (eg 95%) and *df* is the degrees of freedom. Equation (10) is used to estimate confidence intervals for regressions that satisfy the CLRM assumptions. However, of the three sectors estimated using regressions, only Farm satisfies the CLRM assumptions. The Industrial (without Oilsands) and Commercial sectors both incorporate a lag variable which means the assumptions of the CLRM are not satisfied. Using equation (10) to estimate the Industrial (without Oilsands) and Commercial sector confidence intervals is still approximately valid provided that u_t is normally distributed with mean of zero and variance σ^2. Using a Jarque-Bera test, the null hypothesis that u_t is normally distributed was rejected in both the Industrial and Commercial models indicating that u_t is not normally distributed in either model.

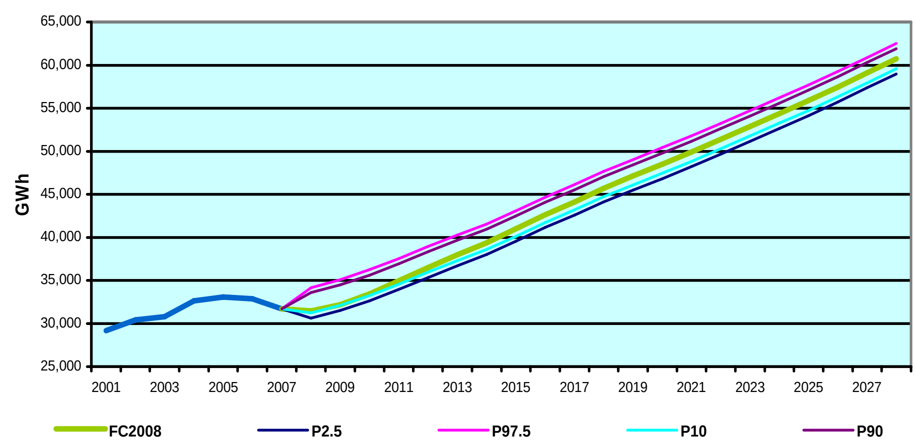
Since the CLRM assumptions are not valid for the Industrial and Commercial models because of the lag term and because the u_t term from the Industrial and Commercial models is not normally distributed, an alternative approach is required. Rather than use statistical assumptions regarding the error term, the standard errors can be computed via simulation, using bootstrapped residuals. This process works by drawing a simple sample, with replacement, of size *T* + *h* from the residuals, where *T* is the number of historical observations (22 for both Industrial and Commercial) and *h* is the number of forecasted periods (21 for both sectors). The sampled residuals, the initial values of the endogenous variables, the exogenous variables, and the estimated coefficients are combined to construct a new sample data set. The simulated endogenous variables are then saved. The bootstrapping simulation is repeated *R* times. For each endogenous variable and each forecast period, the simulated standard error is the estimated standard error of the *R* simulated forecasts. The confidence bands are then estimated using equation (10) but with the simulation-based estimates of the standard errors and the normality assumption. For the purposes of this analysis, *R*, the number of bootstrapping simulations, was made equal to 1,000.

4.2.1 Industrial (without Oilsands) Customer Sector

Applying the econometric approach described in section 4.1 to the Industrial sector regression, 80% and 95% confidence band intervals were constructed. Figure 4.2-1 shows the confidence bands for the non-oilsands industrial sector. Since mining GDP is exogenous in the model, it is taken as given and the model does not take any variation of the GDP forecast into consideration. This causes narrow confidence band intervals around the forecast.

Compared with the Monte Carlo simulation approach, the econometric method constructs narrower confidence intervals which do not increase in width over time. The AESO believes the Monte Carlo results are a more reasonable estimate of the confidence band intervals since the Monte Carlo approach incorporates variation of all the relevant input variables including those provided by the Conference Board of Canada.

Figure 4.2-1: Econometric Approach - Industrial (without Oilsands) Sector Confidence Intervals



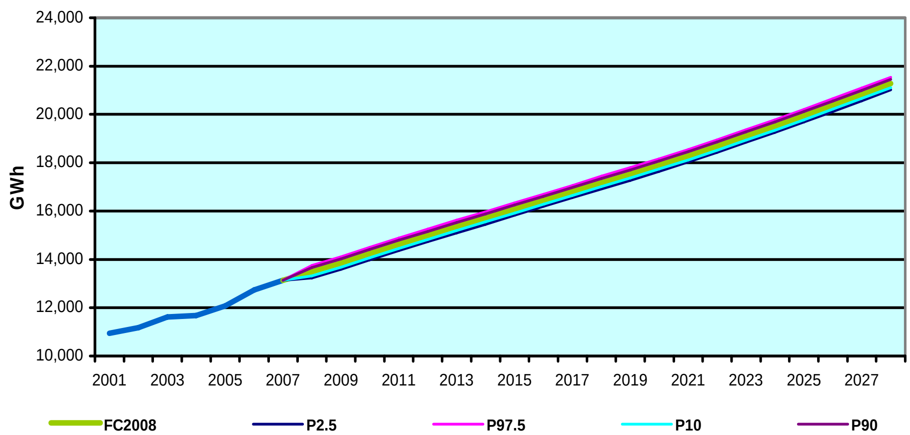
Source: AESO and ERCB

4.2.2 Commercial Customer Sector

The FC2008 uses an OLS econometric regression process described in section 4. Confidence band intervals where constructed with 80% and 95% confidence levels which are shown in Figure 4.2-2.

The estimated confidence bands around the commercial load forecast are very narrow. This is due to the forecast model specifications and the high correlation of the input drivers with commercial load. The model has two right-hand side variables, GDP and a one-period lag term of commercial sales. Since the GDP input to the forecast is provided by the Conference Board of Canada, it does not vary. GDP and commercial sales are also highly correlated which results in low variation of the error term thus creating a narrow confidence band interval. This is also the partly why the confidence bands do not widen much over time. It is intuitive that the confidence bands should become wider because as the forecast looks further into the future as it becomes more difficult to predict and there is an increased probability that events could occur which deviate the actual number from the forecast.

Figure 4.2-2: Econometric Approach - Commercial Sector Confidence Intervals

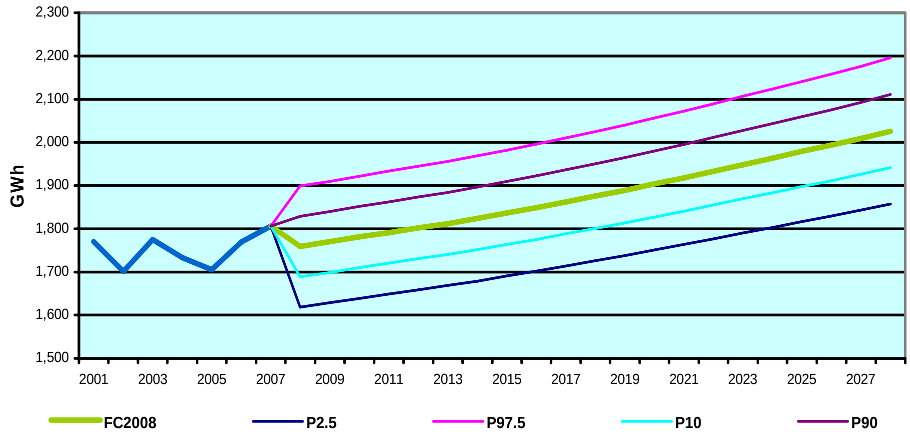


Source: AESO and ERCB

4.2.3 Farm Customer Sector

The confidence band intervals calculated using the econometric approach and the forecasted farm sales from the FC2008 are shown in Figure 4.2-3. The variation of the farm forecast that is used to create the confidence intervals is dependent on the variation of the error term in equation (3). Variation of the input variables, however, is not taken into consideration by the model. Instead, the model assumes that the forecasts for agricultural GDP and for heating degree days are accurate and without variation. As a result, potential variation of agricultural GDP and heating degree days are not included as part of the variation of the forecast and the confidence bands are smaller than they would otherwise be.

Figure 4.2-3: Econometric Approach - Farm Sector Confidence Intervals

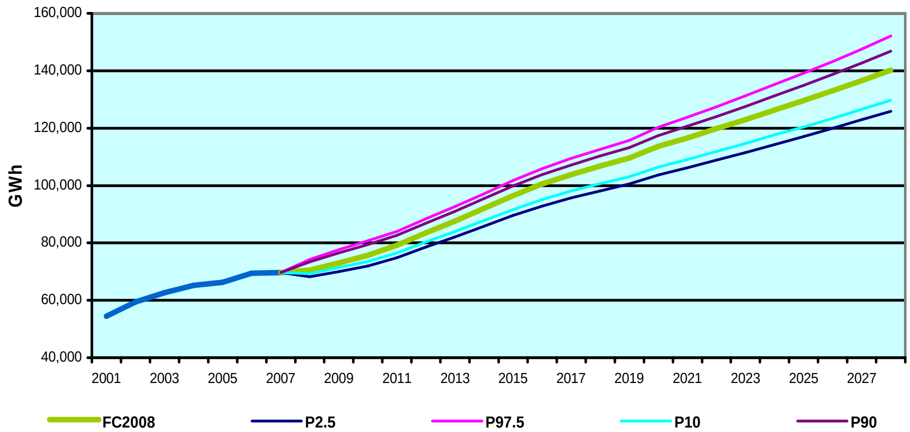


Source: AESO and ERCB

4.2.4 Aggregate Results

Using the confidence band intervals from the econometric approach for the Commercial, Industrial, and Farm sectors, and combining them with the Monte Carlo simulation results for the Residential and Oilsands sectors, the five sectors were aggregated together to provide a total energy sales confidence band intervals at the 80% and 95% levels. The FC2008 forecasted losses were added to each aggregated confidence band in order to determine AIL total energy. It is assumed that losses remain constant in each confidence interval. The confidence bands showing the 80% and 95% confidence intervals for the AIL, which includes losses, are shown in Figure 4.2-4.

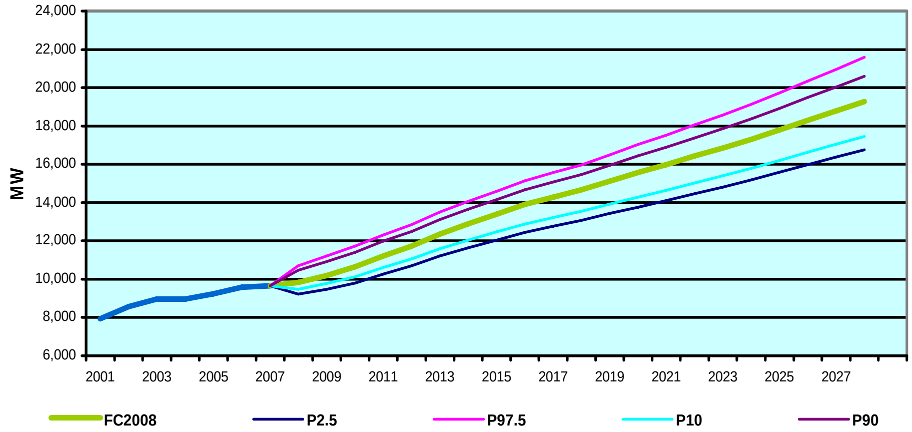
Figure 4.2-4: Econometric Approach - AIL Energy Confidence Intervals



Source: AESO and ERCB

The AIL confidence band intervals were converted into peak energy demand using the FC2008 forecasted load factor confidence band estimates. The estimated confidence intervals for peak demand are shown in Figure 4.2-5.

Figure 4.2-5: Econometric Approach - AIL Peak Demand Confidence Intervals



Source: AESO and ERCB

It should be noted that the aggregated econometric results are for analytical and comparison purposes only and are not the recommended approach. Generally, for statistical reasons, P-levels should not be aggregated together to produce confidence intervals as these tend to be too large (see Appendix 2 for an explanation of why this occurs). In addition, the econometric method does not allow for the variation of exogenously forecasted variables such as GDP.

4.2.5 Econometric Approach Summary

The Farm, Commercial and Industrial sector models all have exogenous forecasted variables which are taken as given. The statistical model used to determine the confidence band intervals does not take the variation of the forecast inputs into consideration resulting in narrowly defined confidence intervals. In addition, the econometric does not properly estimate AIL and peak demand confidence bands. For these reasons, the econometric approach is not preferred.

5.0 Appendix 2

P-levels from each sector model ideally should not be aggregated as this creates confidence intervals which are too large. Adding the P-levels together implies that the standard error of the combined sectors is equal to the sum of the standard errors of each sector. However, because the distributions of the forecasted values of each sector are independent, the variance of the combined sectors should be equal to the sum of the variances of each sector. To show why this is the case, a simple two-sector model is shown.

Recall equation (10),

$$\hat{y}^0 \pm t_{(df,a/2)} \cdot se(\hat{e}^0)$$

To aggregate, the distributions are added such that

$$\hat{y}_T^0 = \hat{y}_F^0 + \hat{y}_C^0 \qquad (11)$$

Where:

- *T* is the combined sectors
- *F* is the Farm sector
- *C* is the Commercial sector

Combining (10) and (11), the upper bound of the aggregated confidence interval is

$$\hat{y}_T^0 + t_{(df,a/2)} \cdot se(\hat{e}_T^o) = \hat{y}_F^0 + t_{(df,a/2)} \cdot se(\hat{e}_F^o) + \hat{y}_C^0 + t_{(df,a/2)} \cdot se(\hat{e}_C^o) \qquad (12)$$

assuming, $t_{(df,a/2)}$ is the same for each confidence band. Using equation (11) and dividing both sides by $t_{(df,a/2)}$, equation (12) can be rewritten as

$$se(\hat{e}_T^o) = se(\hat{e}_F^o) + se(\hat{e}_C^o) \qquad (13)$$

Taking the square of both sides gives the variance of the combined sectors

$$Var(\hat{e}_T^o) = \left[se(\hat{e}_F^o) + se(\hat{e}_C^o)\right]^2 \qquad (14)$$

However, since *F* and *C* are independent,

$$Var(\hat{e}_T^o) = Var(\hat{e}_F^o) + Var(\hat{e}_C^o) \qquad (15)$$

Combining (14) and (15),

$$Var(\hat{e}_F^o) + Var(\hat{e}_C^o) = \left[se(\hat{e}_F^o) + se(\hat{e}_C^o)\right]^2 \qquad (16)$$

Which implies

$$\left[se(\hat{e}_F^o)\right]^2 + \left[se(\hat{e}_C^o)\right]^2 = \left[se(\hat{e}_F^o) + se(\hat{e}_C^o)\right]^2 \qquad (17)$$

Equation (17) can only hold if either $se(\hat{e}_F^o)$ or $se(\hat{e}_C^o)$ is equal to zero. Since $se(\hat{e}_F^o)$ and $se(\hat{e}_C^o)$ are the standard errors of the forecast, they cannot be equal to zero.

List of Reference Documents

Alberta Electric System Operator (2009) *Future Demand and Energy Outlook, 2008-2028*

Energy Resources and Conservation Board *Table 11: ELECTRIC ENERGY DISTRIBUTION SALES AND NUMBER OF CUSTOMERS*

Canadian Association of Petroleum Producers (June, 2008) *Crude Oil Forecast, Markets and Pipeline Expansions*.

Conference Board of Canada (2008) *Provincial Outlook Long-Term Economic Forecast: 2008*.

Woolridge, J. (2006) *Introductory Econometrics*, Thomson, Canada: 214-217, 665-669

Glossary

Alberta Internal Load (AIL): is the total electricity consumption including behind-the-fence (BTF), the City of Medicine Hat and losses (transmission and distribution).

Behind-the-fence load (BTF): is industrial load that is characterized by being served in whole, or in part, by on-site generation, in other words, plants that are built on the industrial host's site. When these plants have excess power available they sell it into the competitive wholesale marketplace.

Customer Sectors: are used to classify types of load. For the purposes of this report, five sectors are used: Industrial (without Oilsands), Oilsands, Residential, Commercial and Farm.

Demand: (or coincident demand) commonly and for the purpose of this report, refers to a maximum electricity load in a given period of time for a defined area expressed in units of kW (kilowatt) or MW (megawatt)

Energy: commonly and for the purpose of this report, refers to electricity consumption over a given period of time for a defined area expressed in units of kWh (kilowatt hour), MWh (megawatt hour) or GWh (gigawatt hour)

Gigawatt hour (GWh): One billion watt hours.

Gross domestic product: is one of the measures of national income and output for a given country's economy. GDP is defined as the total market value of all final goods and services produced within the country in a given period of time (usually a calendar year). It is also considered the sum of a value added at every stage of production (the intermediate stages) of all final goods and services produced within a country in a given period of time, and it is given a money value.

Heating degree days (HDD): are a quantitative index designed to reflect the demand for energy needed to heat a home or business.

Load factor: is the ratio of average load to the peak load during a specified period of time; expressed in per cent.

Megawatt (MW): One million watts.

Ordinary Least Squares (OLS): is a method for estimating the parameters of a multiple linear regression model. The ordinary least squares estimates are obtained by minimizing the sum of squared residuals.

Transmission Losses: are made up of physical conductors. As a result of this, loss of electrical power occurs on transmission lines.

Transmission System (Electric): is an interconnected group of electric transmission lines and associated equipment for moving or transferring electric energy in bulk between points of supply and points at which it is transformed for delivery over the distribution system lines to consumers, or is delivered to other electric systems.