

September 17, 2015

Ms. Kirsten Walli, Board Secretary **Ontario Energy Board** P.O. Box 2319 2300 Yonge Street, 27th Floor Toronto, Ontario M4P 1E4



ONTARIO ENERGY BOARD

Dear Ms. Walli:

RE: Kingston Hydro Corporation - 2016 Custom IR Rate Application EB 2015-0083 - Interrogatory Responses

Please find enclosed, 4 additional complete sets of Interrogatory Responses as requested by Ms. Lillian Ing.

In addition, the following are enclosed and have been filed on RESS:

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 addition, the following are enclosed and have been filed on RESS:

 1. 3 sets of Attachments 1-5 for Interrogatory 1-Staff-15 which were inadvertently left out of the original 3 sets delivered by courier on September 15, 2015

 2. 7 copies of the revised Weather Normalized Distribution (Ediblit 3 fto 1/Sch. System Load Forecast: 2016-2020 Custom IR Elenchus Attachment 1

 Incerely,

 Arol Belanger recutive Assistant to the President and CEO illities Kingston

Sincerely,

Carol Belanger

Executive Assistant to the President and CEO **Utilities Kingston**

Lelenchus

Weather Normalized Distribution System Load Forecast: 2016 - 2020 Custom IR

A Report Prepared by Elenchus Research Associates Inc.

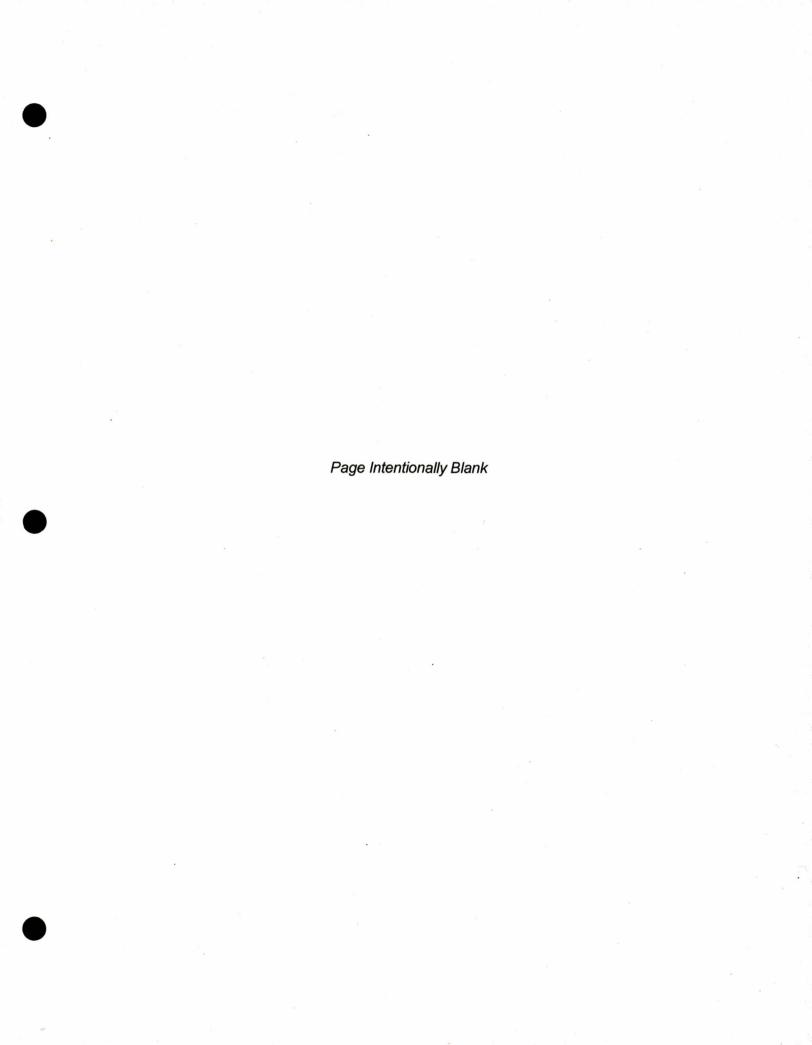
On Behalf of Kingston Hydro

09/09/2015



Table of Contents

1 0	able of	Contents	1
1	ln	troduction	1
	1.1	Summarized Results	2
2	С	lass Specific kWh Regression	5
	2.1	Residential	5
	2.2	GS < 50	7
	2.3	GS > 50	9
	2.4	Large Use	12
3	W	eather Normalization and Economic Forecast	14
3 4		lass Specific Normalized Forecasts	
			16
	C	lass Specific Normalized Forecasts	16 16
	C 4.1	lass Specific Normalized Forecasts	16 16 17
	4.1 4.2	lass Specific Normalized Forecasts Residential GS < 50	16 16 17
	4.1 4.2 4.3 4.4	lass Specific Normalized Forecasts Residential GS < 50 GS > 50	16 16 17 19





1 Introduction

This report outlines the results and methodology used to derive the weather normal load forecast prepared for use in the Custom IR application for 2016-2020 rates for Kingston Hydro Corporation ("Kingston Hydro").

The regression equations used to normalize and forecast Kingston Hydro's weather sensitive load use monthly heating degree days and cooling degree days as measured at Environment Canada's Hartington IHD to take into account temperature sensitivity. This location is approximately 30 km north of the City of Kingston near Harrowsmith and is the closest location to Kingston that has nearly uninterrupted temperature observations for the 1995-2014 period. There was however a stoppage of readings on May 15, 2011 which lasted 109 days. For those readings, the weather station Kingston Climate was used. Kingston is winter peaking and does not exhibit a substantial summer peak. Environment Canada defines heating degree days and cooling degree days as the difference between the average daily temperature and 18°C for each day (below for heating, above for cooling).

Overall economic activity also impacts energy consumption. In order to measure the impact of change in economic activity on energy consumption, a data series must be chosen which represents, as much as possible, that of the service territory. There is no known agency that publishes monthly economic accounts on a regional basis for Ontario. However, regional employment levels are available. Given that income from employment and labour sources accounts for the largest portion of GDP on an income basis, and a study by Statistics Canada that has indicated that "turning points in the growth of output and employment appear to have been virtually the same over the past three decades"¹, employment has been chosen as the economic variable to incorporate into the analysis. Specifically, the monthly full-time employment level for Ontario, as reported in Statistics Canada's Monthly Labour Force Survey (CANSIM series Table 282-0116) is used. A localized employment indicator for Kingston is available, but the Ontario measure is a more statistically significant predictor of energy use in Kingston Hydro's service territory.

In order to isolate demand determinants at the class specific level, equations to weather normalize and forecast kWh consumption for the Residential, GS<50 and GS>50 classes as well as the Large User class, which is comprised of three large institutional users that has significant cooling load, have been estimated.

In addition to the weather and economic variables, a time trend variable, number of days and number of working days in each month, number of customers, and month of year variables, have been examined for all rate classes. More details on the individual class specifications are provided in the next section.

In order to isolate the impact of CDM related approved CDM initiatives, actual data has been adjusted for past CDM. The adjustment consists of adding back savings realized in the years 2009-2014 from

¹ Philip Cross, "Cyclical changes in output and employment," Canadian Economic Observer, May 2009.



programs delivered in 2009-2014. Annual savings are as measured by the IESO. It is assumed that program delivery and savings are realized at a uniform rate throughout the year. Therefore, the input to the statistical regression reflects a scenario where no CDM was run 2009-2014, and the results of the regression produce a forecast for a scenario with no CDM from 2009-2020. The delivered persisting results of 2009-2014 programs are then subtracted from the forecast to arrive at a traditional unadjusted forecast. This reflects CDM savings from programs delivered in 2009-2014, but forecasts no savings for CDM program delivery in 2015-2020 through trend variables or otherwise.

Finally, for classes with demand charges, an annual kW to kWh ratio is calculated using actual observations for each historical year and applied to the normalized kWh to derive a weather normal kW observation. For forecast values, the actual kW to kWh ratio for 2014 is applied.

1.1 SUMMARIZED RESULTS

The following table summarizes the historic and forecast kWh for 2009-2020:

Normal Forecast

kWh	Residential	GS < 50	GS > 50	Large Use	Street Light	USL	Total
2009 Actual	196,461,750	93,350,687	270,117,290	148,002,869	3,992,185	2,256,949	714,181,729
2010 Actual	197,410,764	94,126,083	273,806,098	149,058,790	4,076,824	2,229,012	720,707,571
2011 Actual	191,104,338	93,008,635	273,712,584	154,491,718	4,142,238	1,517,655	717,977,169
2012 Actual	184,953,209	88,608,641	274,473,668	155,448,435	4,555,371	1,484,560	709,523,884
2013 Actual	189,348,696	86,375,577	279,458,000	153,943,746	3,336,835	1,499,820	713,962,674
2014 Actual	192,061,408	91,470,555	272,498,127	151,518,193	1,817,917	1,247,036	710,613,237
2009 Normalized	198,884,446	96,064,962	271,411,676	148,687,034	3,992,185	2,256,949	721,297,251
2010 Normalized	195,591,927	94,490,081	272,384,595	150,173,340	4,076,824	2,229,012	718,945,778
2011 Normalized	192,163,011	93,776,077	276,283,654	154,138,390	4,142,238	1,517,655	722,021,025
2012 Normalized	187,471,244	90,457,595	275,227,380	152,025,145	4,555,371	1,484,560	711,221,296
2013 Normalized	188,263,211	87,793,270	278,459,749	154,963,792	3,336,835	1,499,820	714,316,678
2014 Normalized	190,835,981	92,804,877	272,240,655	153,804,618	1,817,917	1,247,036	712,751,085
2015 Forecast	189,417,832	90,135,229	273,909,928	154,864,222	1,814,577	1,221,326	711,363,113
2016 Forecast	188,560,878	87,729,830	276,480,202	156,314,904	1,818,158	1,196,145	712,100,117
2017 Forecast	187,842,287	86,574,290	279,259,356	157,466,056	1,821,740	1,171,483	714,135,212
2018 Forecast	186,889,965	85,112,366	281,887,678	158,640,435	1,825,321	1,147,330	715,503,095
2019 Forecast	185,977,037	82,749,000	284,542,723	159,878,759	1,828,903	1,123,675	716,100,097
2020 Forecast	185,141,745	80,540,933	287,775,925	161,354,888	1,832,484	1,100,508	717,746,483

Table 1 kWh forecast by class



The following table summarizes 2015-2020 CDM Adjusted Load Forecast kWh. Details for this calculation can be found in Schedule 6 of this report.

CDM Adjusted

kWh	Residential	GS < 50	GS > 50	Large Use	Street Light	USL	Total
2015 Forecast	189,236,126	89,999,498	273,308,735	154,564,804	1,814,577	1,221,326	710,145,065
2016 Forecast	188,042,904	86,732,020	273,255,734	147,081,903	1,818,158	1,196,145	698,126,864
2017 Forecast	187,260,718	84,778,808	273,818,458	144,444,566	1,821,740	1,171,483	693,295,774
2018 Forecast	186,243,142	82,438,874	273,991,419	144,385,384	1,825,321	1,147,330	690,031,470
2019 Forecast	185,263,300	79,142,304	274,077,767	144,455,963	1,828,903	1,123,675	685,891,912
2020 Forecast	184,359,435	75,933,648	274,516,295	144,705,330	1,832,484	1,100,508	682,447,699

Table 2 CDM Adjusted kWh forecast

The following table summarizes the historic and forecast kW for 2009-2020. The calculations can be found as follows:

Normal Forecast

kW	GS > 50	Large Use	Street Light	Total
2009 Actual	721,617	240,786	11,246	973,649
2010 Actual	747,917	289,659	11,251	1,048,827
2011 Actual	766,581	294,114	11,237	1,071,932
2012 Actual	781,260	323,212	10,984	1,115,456
2013 Actual	767,156	291,732	8,304	1,067,192
2014 Actual	743,905	286,452	5,045	1,035,402
2015 Forecast	747,759	292,778	5,036	1,045,573
2016 Forecast	754,776	295,520	5,046	1,055,342
2017 Forecast	762,363	297,697	5,056	1,065,115
2018 Forecast	769,538	299,917	5,066	1,074,521
2019 Forecast	776,786	302,258	5,076	1,084,120
2020 Forecast	785,613	305,049	5,086	1,095,747

Table 3 kW Forecast

The following table summarizes 2015-2020 CDM Adjusted Load Forecast kW. Details for this calculation can be found at the end of in Schedule 6 of this report.

CDM Adjusted

kW	GS > 50	Large Use	Street Light	Total
2015 Forecast	746,118	292,212	5,036	1,043,366
2016 Forecast	745,973	278,065	5,046	1,029,084
2017 Forecast	747,509	273,079	5,056	1,025,644
2018 Forecast	747,982	272,967	5,066	1,026,014
2019 Forecast	748,217	273,101	5,076	1,026,394
2020 Forecast	749,414	273,572	5,086	1,028,072

Table 4 CDM Adjusted kW Forecast



The following table summarizes the historic and forecast customer/connections for 2009-2020:

Customer Connections

					Street		
	Residential	GS < 50	GS > 50	Large Use	Light	USL	Total
2009 Actual	23,107	3,319	295	3	5,114	163	32,002
2010 Actual	23,163	3,300	294	3	5,117	158	32,036
2011 Actual	23,212	3,298	291	3	5,120	156	32,079
2012 Actual	23,193	3,250	307	3	5,126	152	32,030
2013 Actual	23,468	3,213	318	3	5,385	151	32,537
2014 Actual	23,853	3,051	325	3	5,228	147	32,606
2015 Forecast	24,004	3,000	331	3	5,337	143	32,819
2016 Forecast	24,157	2,950	337	3	5,349	141	32,937
2017 Forecast	24,311	2,901	343	3	5,361	138	33,057
2018 Forecast	24,466	2,853	350	3	5,373	135	33,179
2019 Forecast	24,622	2,805	357	3	5,385	132	33,303
2020 Forecast	24,779	2,758	364	3	5,397	129	33,429

Table 5 Customer / Connection Forecast for 2009-2020



2 CLASS SPECIFIC KWH REGRESSION

2.1 RESIDENTIAL

For the Residential Class kWh consumption the equation was estimated using 72 observations from 2009:01-2014:12.

Heating and Cooling Degree days were used, as measured at the Hartington weather station as described in the introduction. A Trend variable was used, indicating 1 in January 2009, and incrementing once each month, reaching 72 in the last month of the regression, December 2014. A customer count, reflecting the number of residential customers in each month was used. Finally, binary indicator variables for February, March, April, December, and the summer vacation for most faculty and students at the post-secondary educational institutions (indicating 1 in the months May, June, July, and August) were used.

Several other variables were examined, and found to not show a statistically significant relationship to energy usage. Those included an economic indicator of full time employment, the number of days in the month, and a binary indicator designating spring and fall shoulder seasons.

The following table outlines the resulting regression model:

Model 1: OLS, using observations 2009:01-2014:12 (T = 72)
Dependent variable: ResnoCDM

	Coefficient	Std. Error	t-ratio	p-value	
const	-2.18295e+07	1.07698e+0	7 -2.0269	0.04705	**
HDD	12279.7	834.602	14.7132	< 0.00001	***
CDD	33835.9	3298.89	10.2568	< 0.00001	***
Trend	-27107.4	6164.04	-4.3977	0.00004	***
Res_Cust	1540.27	470.287	3.2752	0.00174	***
Fall	-2.24763e+06	513417	-4.3778	0.00005	***
DFEB	-1.15577e+06	355290	-3.2530	0.00186	***
DAPR	-2.20237e+06	512339	-4.2987	0.00006	***
DDEC	-1.22403e+06	356151	-3.4368	0.00107	***
PostSecondarySu	-2.43622e+06	636255	-3.8290	0.00031	***
DMAR	-837789	395864	-2.1164	0.03840	**
Moon dependent ver	1610	2838 S.I	D. denendent ver	26	200020
Mean dependent var			D. dependent var		590038
Sum squared resid			E. of regression		5636.1
R-squared	0.97	78360 Ac	ljusted R-squared	0.9	74812
F(10, 61)	275.	.7800 P-	value(F)	7.	61e-47
Log-likelihood	-105	2.388 Ak	aike criterion	21	26.775
Schwarz criterion	215	1.819 Ha	annan-Quinn	21	36.745
rho	0.13	2692 Du	ırbin-Watson	1.7	709622

0.23791

Table 6 Residential Regression Model

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Using the above model coefficients we derive the following:

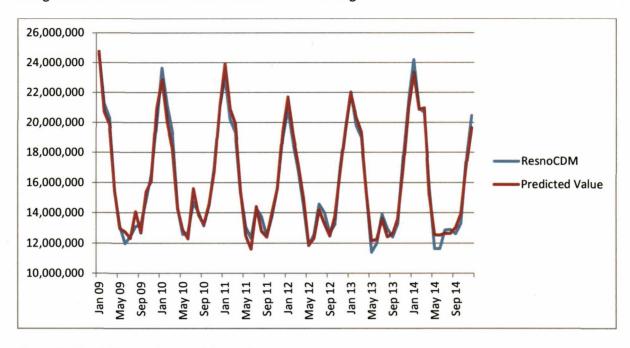


Figure 1 Residential Predicted vs Actual observations

Annual estimates using actual weather are compared to actual values in the table below. Mean absolute percentage error (MAPE) for annual estimates for the period is 0.5%. Annual errors are calculated as the model is used to derive annual forecasts. However, in proceedings Elenchus has been involved in, intervenors and Board Staff have requested MAPE calculated on a monthly basis and this has been provided as well. The MAPE calculated monthly over the period is 2.8%.

	Res kWh		Absolute					
Year	Actual	Predicted	Error (%)					
2009	196,719,829	197,973,758	0.6%					
2010	198,092,958	195,487,619	1.3%					
2011	192,211,502	192,894,724	0.4%					
2012	186,486,715	187,132,016	0.3%					
2013	191,269,649	191,529,542	0.1%					
2014	194,623,695	194,386,688	0.1%					
Mean Absolute Percentage Error (Annual)								
Mean Abso	2.8%							
Table 7 Reside	ential model error							



2.2 GS < 50

For the GS < 50 class, the regression equation was estimated using 72 observations from 2009:01-2014:12.

In January 2014 there was a bulk reclassification of customers between GS < 50 and GS > 50. This resulted in a net transfer of 53 customers from GS > 50 to GS < 50. A binary variable, "Reclassification" was used to capture the effect on the GS < 50 energy usage – indicating 0 from January 2009 – December 2013 and 1 January 2014 onwards.

Heating degree days and cooling degree days were used, as measured at the Hartington weather station as described in the introduction.

A binary variable representing fall months' consumption has also been included. In recent cost-of-service filings in which Elenchus has participated, both Board Staff and intervenors have requested that separate variables for spring and fall be included for testing. The fall variable designates the months of September, October and November as fall months. Therefore, the variable takes a value of 1 in these months and a value of 0 in all other months. Binary variables for the months of February and April were also used.

Several other variables were examined, and found to not show a statistically significant relationship to energy usage. Those included an economic indicator of full time employment, a trend variable indicating 1 in January 2009, incrementing to 72 in December 2014, the number of calendar and working days in the month, an indicator of the Spring months including March, April, and May, and an indicator of the summer vacation for most faculty and students at the post-secondary educational institutions.

The following table outlines the resulting regression model:



Model 3: OLS, using observations 2009:01-2014:12 (T = 72)
Dependent variable: GSlt50noCDM

	Coefficient	Std. Err	or t-ratio	p-value	
const	-6.87535e+06	2.01463e	+06 -3.4127	0.00112	***
HDD	3224.2	144.08	5 22.3770	< 0.00001	***
CDD	15172.4	1221.4	4 12.4217	< 0.00001	***
GS_50_Cust	4135.85	621.94	7 6.6498	< 0.00001	***
Reclassificatio	911880	12791	1 7.1290	< 0.00001	***
Fall	-165990	73969	-2.2440	0.02830	**
DFEB	-326866	10347	9 -3.1588	0.00242	***
DAPR	-430573	10292	4 -4.1834	0.00009	***
Mean dependent var	777	'0470	S.D. dependent var	78	0296.5
Sum squared resid	3.13	8e+12	S.E. of regression	22	1246.2
R-squared	0.92	7531	Adjusted R-squared	0.9	919604
F(7, 64)	117.	.0190	P-value(F)	5.	56e-34
Log-likelihood	-984	.0296	Akaike criterion	19	84.059
Schwarz criterion	200	2.273	Hannan-Quinn	19	91.310
rho	0.27	0745	Durbin-Watson	1.4	443678
Theil's U	0.3	1546			

Table 8 GS < 50 Regression Model

Using the above model coefficients we derive the following:

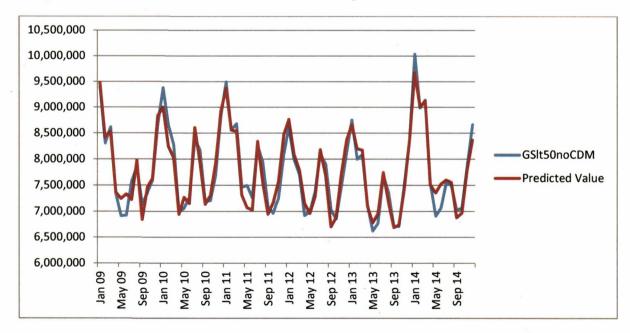


Figure 2 GS < 50 Predicted vs Actual observations

Annual estimates using actual weather are compared to actual values in the table below. Mean absolute percentage error (MAPE) for annual estimates for the period is 0.5%. Annual errors are calculated as the model is used to derive annual forecasts. However, in recent proceedings Elenchus has been involved in,



intervenors and Board Staff have requested MAPE calculated on a monthly basis and this has been provided as well. The MAPE calculated monthly over the period is 2.2%.

	GS<50 kWh		Absolute Error				
,	Actual	Predicted	(%)				
2009	93,692,209	94,278,755	0.6%				
2010	95,078,833	94,432,919	0.7%				
2011	94,563,721	93,907,877	0.7%				
2012	91,104,095	91,533,424	0.5%				
2013	89,694,903	89,980,786	0.3%				
2014	95,340,092	95,340,092	0.0%				
Mean Absolute Percentage Error (Annual) Mean Absolute Percentage Error (Monthly)							

Table 9 GS < 50 model error

2.3 GS > 50

For the GS > 50 class, the regression equation was estimated using 72 observations from 2009:01-2014:12.

In January 2014 there was a bulk reclassification of customers between GS < 50 and GS > 50. This resulted in a net transfer of 53 customers from GS > 50 to GS < 50.

Heating degree days and cooling degree days were used, as measured at the Hartington weather station as described in the introduction. A Trend variable was used, indicating 1 in January 2009, and incrementing once each month, reaching 72 in the last month of the regression, December 2014.

An economic indicator of full time employment in the province of Ontario was used. An indicator for Kingston, Ontario was examined, but the provincial indicator demonstrated a more statistically significant relationship to energy use in the Kingston Hydro service territory of downtown Kingston.

An indicator of the number of GS > 50 customers was used.

A binary variable representing fall months' consumption has also been included. In recent cost-of-service filings in which Elenchus has participated, both Board Staff and intervenors have requested that separate variables for spring and fall be included for testing. The fall variable designates the months of September, October and November as fall months. Therefore, the variable takes a value of 1 in these months and a value of 0 in all other months. A Binary variable representing the summer vacation of the post-secondary educational institutions in Kingston was used. Those months are May, June, July, and August. Binary variables for the months of February, April, and December, were also used.

Several other variables were examined, and found to not show a statistically significant relationship to energy usage. Those included an indicator of the number of calendar days in the month, the number of



working days in the month, an indicator of the spring season, and an indicator for the reclassification as used in the GS < 50 class.

The following table outlines the resulting regression model:

Model 4: OLS, using observations 2009:01-2014:12 (T = 72)
Dependent variable: GSgt50noCDM

	Coefficient	Std. Erro	or t-ratio	p-value	
const	-1.70773e+07	8.34542e+	-06 -2.0463	0.04504	**
HDD	7703.57	530.407	14.5239	< 0.00001	***
CDD	32650.1	2888.5	11.3035	< 0.00001	***
OntFTE	5386.23	1334.55	4.0360	0.00015	***
Trend	-24652	10116.1	-2.4369	0.01775	**
GSgt50Cust	8856.97	3450.53	2.5668	0.01273	**
Fall	-1.57356e+06	293720	-5.3573	<0.00001	***
DFEB	-1.51464e+06	216392	-6.9995	< 0.00001	***
DAPR	-1.58967e+06	280696	-5.6633	< 0.00001	***
DDEC	-1.08426e+06	227890	-4.7578	0.00001	***
PostSecondarySu	-1.20721e+06	358270	-3.3696	0.00131	***
Mean dependent var	2312		S.D. dependent var	1	985121
Sum squared resid	1.14		S.E. of regression		32669.6
R-squared	0.95	9186 A	djusted R-squared	0.	952495
F(10, 61)	143.	3582 P	-value(F)		.79e-38
Log-likelihood	-1030	0.592 A	kaike criterion	20	083.183
Schwarz criterion			lannan-Quinn		093.153
rho			urbin-Watson	1.	762987
Theil's U	0.2	2884			

Table 10 GS > 50 model

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Using the above model coefficients we derive the following:

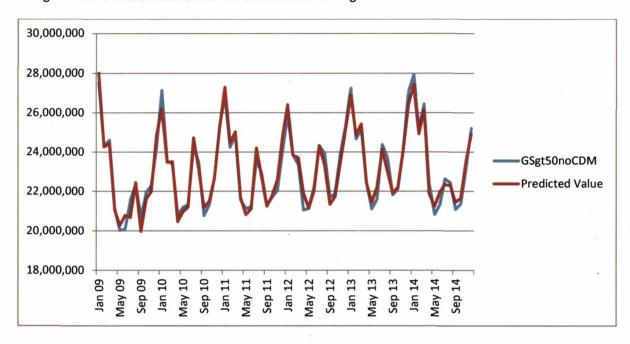


Figure 3 GS > 50 Predicted vs Actual

Annual estimates using actual weather are compared to actual values in the table below. Mean absolute percentage error (MAPE) for annual estimates for the period is 0.3%. Annual errors are calculated as the model is used to derive annual forecasts. However, in recent proceedings Elenchus has been involved in, intervenors and Board Staff have requested MAPE calculated on a monthly basis and this has been provided as well. The MAPE calculated monthly over the period is 1.4%.

		GS>50 kWh		Absolute				
				Error				
		Actual	Predicted	(%)				
	2009	270,757,739	270,291,712	0.2%				
	2010	275,223,188	274,129,393	0.4%				
	2011	275,477,476	277,687,123	0.8%				
	2012	278,251,344	278,425,141	0.1%				
	2013	285,427,115	284,855,695	0.2%				
	2014	279,990,103	279,737,900	0.1%				
Mean Absolute Percentage Error (Annual) 0.3%								
		olute Percentage E	rror (Monthly)	1.4%				
aui	6 11 02 >	ou model error						

Table 11 GS > 50 model error



2.4 LARGE USE

For the GS > 50 class, the regression equation was estimated using 72 observations from 2009:01-2014:12.

Heating degree days and cooling degree days were used, as measured at the Hartington weather station as described in the introduction. An indicator of the number of calendar days in the month, "MonthDays" was used to capture the effect of the differing month lengths. A Trend variable was used, indicating 1 in January 2009, and incrementing once each month, reaching 72 in the last month of the regression, December 2014.

An economic indicator of full time employment in the province of Ontario was used. An indicator for Kingston, Ontario was examined, but the provincial indicator demonstrated a more statistically significant relationship to energy use in the Kingston Hydro service territory of downtown Kingston.

A binary variable representing fall months' consumption has also been included. In recent cost-of-service filings in which Elenchus has participated, both Board Staff and intervenors have requested that separate variables for spring and fall be included for testing. The fall variable designates the months of September, October and November as fall months. Therefore, the variable takes a value of 1 in these months and a value of 0 in all other months. A Binary variable representing the summer vacation of the post-secondary educational institutions in Kingston was used. Those months are May, June, July, and August. Binary variables for the months of April, and December, were also used.

Other variables were examined, and found to not show a statistically significant relationship to energy usage, the number of working days in the month, as well as binary indicators for February, and the spring months of the year.

The following table outlines the resulting regression model:

Model 5: OLS, using observations 2009:01-2014:12 (T = 72)
Dependent variable: LUnoCDM

	Coefficient	Std. En	ror t-ratio	p-value	
const	-3.71606e+07	6.45264e	+06 -5.7590	< 0.00001	***
HDD	-1942.03	396.28	-4.9006	< 0.00001	***
CDD	18776.2	2160.1	6 8.6920	< 0.00001	***
MonthDays	343983	50304	6.8380	< 0.00001	***
OntFTE	6298.19	987.72	8 6.3764	< 0.00001	***
Trend	-33862	7463.	5 -4.5370	0.00003	***
Fall	-1.05988e+06	21279	7 -4.9807	< 0.00001	***
DAPR	-1.03921e+06	20197	1 -5.1454	< 0.00001	***
DDEC	-999622	16874	7 -5.9238	< 0.00001	***
PostSecondarySu	-1.70065e+06	26366	7 -6.4500	< 0.00001	***
Mean dependent var	1278	1801	S.D. dependent var	1	131231
Sum squared resid	6.48	e+12	S.E. of regression	32	23210.9
R-squared	0.92	8714	Adjusted R-squared	0.	918366



F(9, 62)	89.74883	P-value(F)	3.93e-32
Log-likelihood	-1010.177	Akaike criterion	2040.354
Schwarz criterion	2063.120	Hannan-Quinn	2049.417
rho	0.429073	Durbin-Watson	1.140019
Theil's II	0.30843		

Table 12 Large Use Model

Using the above model coefficients we derive the following:

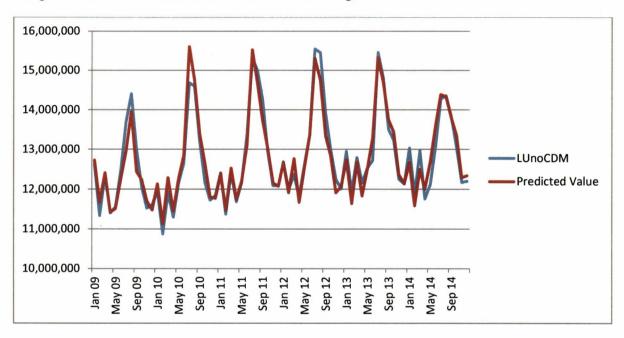


Figure 4 Large Use Predicted vs Actual

Annual estimates using actual weather are compared to actual values in the table below. Mean absolute percentage error (MAPE) for annual estimates for the period is 0.8%. Annual errors are calculated as the model is used to derive annual forecasts. However, in recent proceedings Elenchus has been involved in, intervenors and Board Staff have requested MAPE calculated on a monthly basis and this has been provided as well. The MAPE calculated monthly over the period is 1.7%.

	LU kWh		Absolute
			Error
	Actual	Predicted	(%)
2009	148,002,869	146,702,343	0.9%
2010	149,058,790	152,031,999	2.0%
2011	155,109,163	154,549,328	0.4%
2012	156,990,060	155,119,495	1.2%
2013	156,431,907	156,358,052	0.0%
2014	154,696,877	155,528,449	0.5%
Mean Abso	lute Percentage	Error (Annual)	0.8%
Mean Abso	lute Percentage	Error (Monthly)	1.7%
Table 13 Large	Use Model Error		



3 WEATHER NORMALIZATION AND ECONOMIC FORECAST

It is not possible to accurately forecast weather for months or years in advance. Therefore, one can only base future weather expectations on what has happened in the past. Individual years may experience unusual spells of weather (unusually cold winter, unusually warm summer, etc.). However, over time, these unusual spells "average" out. While there may be trends over several years (e.g., warmer winters for example), using several years of data rather than one particular year filters out the extremes of any particular year. While there are several different approaches to determining an appropriate weather normal, Kingston Hydro has adopted the most recent 10 year monthly degree day average as the definition of weather normal, which to our knowledge, is consistent with many LDCs load forecast filings for cost-of-service rebasing applications.

The table below displays the most recent 10 year average of heating degree days and cooling degree days as reported by Environment Canada for Hartington IHD, which is used as the weather station for Kingston Hydro.

10 Year Average

		HDD	CDD
Hartington IHD	January	784.29	0
Hartington IHD	February	682.51	0
Hartington IHD	March	556.99	0
Hartington IHD	April	326.59	0.39
Hartington IHD	May	144.96	8.67
Hartington IHD	June	41.51	44.41
Hartington IHD	July	5.01	96.91
Hartington IHD	August	12.72	77.23
Hartington IHD	September	86.57	19.9
Hartington IHD	October	270.3	1.21
Hartington IHD	November	444.05	0
Hartington IHD	December	684.01	0

Table 14 10 Year Average HDD and CDD

As part of the minimum filing requirements the OEB has requested monthly degree days calculated using a trend based on 20 years. This is shown in the table below.



20 Year Trend (2016)

		HDD	CDD
Hartington IHD	January	738.32	0.00
Hartington IHD	February	657.50	0.00
Hartington IHD	March	525.81	0.00
Hartington IHD	April	302.45	0.82
Hartington IHD	May	114.01	11.10
Hartington IHD	June	47.66	35.25
Hartington IHD	July	2.26	107.60
Hartington IHD	August	5.45	87.84
Hartington IHD	September	78.63	24.57
Hartington IHD	October	266.10	1.57
Hartington IHD	November	426.33	0.00
Hartington IHD	December	688.11	0.00

Table 15 20 Year Trend HDD and CDD

Forecasts for Ontario's employment outlook for 2015 and 2016 are available from four Canadian Chartered Banks at time of writing. Their forecasts are summarized below.

Employment Forecast - Ontario

(figures in annual percentage change)

	BMO 06-Mar-	TD 26-Jan-	Scotia 26-Feb-	RBC 26-Feb-	Average
	15	15	15	15	
2015	0.90%	1.40%	0.90%	1.40%	1.15%
2016	1.20%	1.10%	1.00%	1.20%	1.13%

Table 16 Employment Forecast

In order to give the annual forecast change in employment a monthly periodicity, monthly employment levels for 2014 are compared to the annual average for that year. For each month, the average ratio of monthly employment level to annual average employment for 2014, is used to project the monthly employment into 2015-2020. The annual average of each forecast year (2014 and 2015) will result in an annual increase over the previous year equal to the percentage averages in Table 2.6 above.



4 CLASS SPECIFIC NORMALIZED FORECASTS

4.1 RESIDENTIAL

Incorporating the forecast economic variables, 10-yr weather normal heating and cooling degree days, and calendar variables, the following weather corrected consumption and forecast values are calculated:

A	Normalized	Persisting		Annual	Res kWh	
Annual		2009-2014		Annual		
Change	Forecast	CDM	Normalized	Change	Actual	Year
	198,884,446	258,079	199,142,525		196,461,750	2009
-1.7%	195,591,927	682,194	196,274,121	0.5%	197,410,764	2010
-1.8%	192,163,011	1,107,163	193,270,174	-3.2%	191,104,338	2011
-2.4%	187,471,244	1,533,506	189,004,750	-3.2%	184,953,209	2012
0.4%	188,263,211	1,920,953	190,184,164	2.4%	189,348,696	2013
1.4%	190,835,981	2,562,287	193,398,268	1.4%	192,061,408	2014
-0.7%	189,417,832	2,884,432	192,302,263			2015
-0.5%	188,560,878	2,663,258	191,224,136			2016
-0.4%	187,842,287	2,321,714	190,164,001			2017
-0.5%	186,889,965	2,232,007	189,121,972			2018
-0.5%	185,977,037	2,121,127	188,098,164			2019
-0.4%	185,141,745	1,950,949	187,092,694			2020

Table 17 Actual vs Normalized Residential kWh

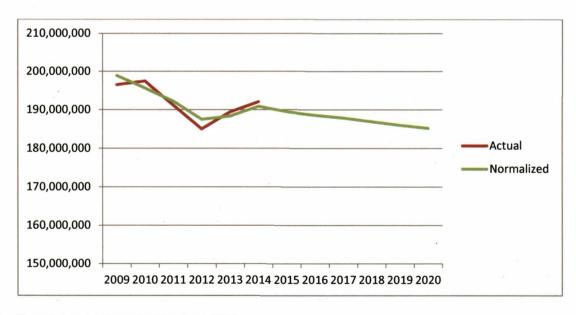


Figure 5 Actual vs Normalized Residential kWh

Customer counts are forecasted for Residential both for the purpose of the regression model as well as for the purpose direct use in rate setting. The Geometric mean of the annual growth from 2009 to 2014



was used to forecast the growth rate from 2015 to 2020. The following table includes the customer Actual / Forecast customer count on this basis:

Re	Annual	
Year	Customers	Change
2009	23,107	
2010	23,163	0.24%
2011	23,212	0.21%
2012	23,193	-0.08%
2013	23,468	1.19%
2014	23,853	1.64%
2015	24,004	0.64%
2016	24,157	0.64%
2017	24,311	0.64%
2018	24,466	0.64%
2019	24,622	0.64%
2020	24,779	0.64%

Table 18 Forecasted Residential Customer Count

4.2 GS < 50

	GS<50 kWh	Annual		Persisting 2009-2014	Normalized	Annual
Year	Actual	Change	Normalized	CDM	Forecast	Change
2009	93,350,687		96,406,484	341,522	96,064,962	
2010	94,126,083	0.8%	95,442,831	952,750	94,490,081	-1.6%
2011	93,008,635	-1.2%	95,331,163	1,555,086	93,776,077	-0.8%
2012	88,608,641	-4.7%	92,953,049	2,495,455	90,457,595	-3.5%
2013	86,375,577	-2.5%	91,112,596	3,319,326	87,793,270	-2.9%
2014	91,470,555	5.9%	96,674,415	3,869,537	92,804,877	5.7%
2015			94,145,237	4,010,008	90,135,229	-2.9%
2016			91,658,299	3,928,470	87,729,830	-2.7%
2017			89,212,896	2,638,606	86,574,290	-1.3%
2018			86,808,333	1,695,967	85,112,366	-1.7%
2019			84,443,930	1,694,929	82,749,000	-2.8%
2020			82,119,014	1,578,081	80,540,933	-2.7%

Table 19 Actual vs Normalized GS < 50 kWh



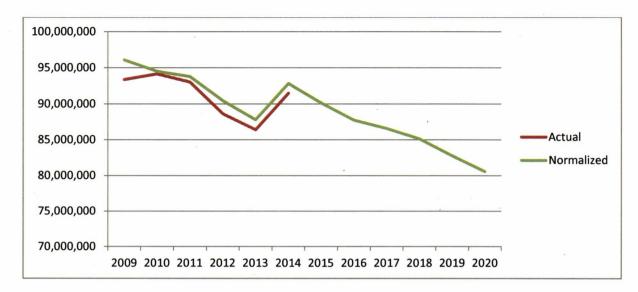


Figure 6 Actual vs Normalized GS < 50 kWh

Customer counts are forecasted for GS < 50 both for the purpose of the regression model as well as for the purpose direct use in rate setting. The Geometric mean of the annual growth from 2009 to 2014 was used to forecast the growth rate from 2015 to 2020. In order to appropriately reflect the growth rate in the class, without being skewed by the 2014 reclassification, the historic years 2009-2013 were adjusted to reflect the reclassified customers having always been in their present class.

The following table includes the customer Actual / Forecast customer count on this basis:

G	SS < 50	Annual
Year	Customers	Change
2009	3,319	
2010	3,300	-0.58%
2011	3,298	-0.07%
2012	3,250	-1.45%
2013	3,213	-1.14%
2014	3,051	-5.02%
2015	3,000	-1.67%
2016	2,950	-1.67%
2017	2,901	-1.67%
2018	2,853	-1.67%
2019	2,805	-1.67%
2020	2,758	-1.67%
Company of the Company	CO O PRESIDE	Market Park

Table 20 Forecasted GS < 50 Customer Count*

^{*}NOTE: 2009-2013 historic customer counts have been adjusted for Jan 2014 reclassification of 53 customers



4.3 GS > 50

	GS>50 kWh	Annual		Persisting 2009-2014	Normalized
Year	Actual	Change	Normalized	CDM	Forecast
2009	270,117,290		272,052,125	640,449	271,411,676
2010	273,806,098	1.4%	273,801,685	1,417,090	272,384,595
2011	273,712,584	0.0%	278,048,545	1,764,891	276,283,654
2012	274,473,668	0.3%	279,005,056	3,777,676	275,227,380
2013	279,458,000	1.8%	284,428,864	5,969,115	278,459,749
2014	272,498,127	-2.5%	279,732,631	7,491,976	272,240,655
2015			281,952,432	8,042,504	273,909,928
2016			284,131,255	7,651,052	276,480,202
2017			286,379,824	7,120,468	279,259,356
2018			288,699,026	6,811,348	281,887,678
2019			291,089,758	6,547,035	284,542,723
2020			293,552,931	5,777,005	287,775,925

Table 21 Actual vs Normalized GS > 50 kWh

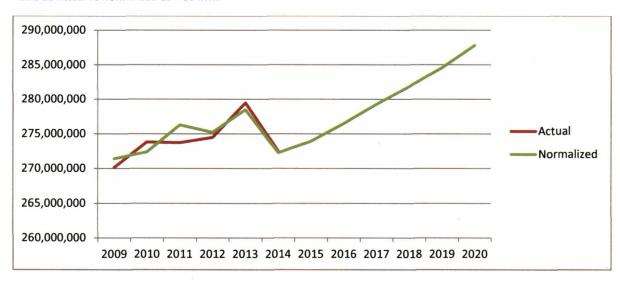


Figure 7 Actual vs Normalized GS > 50 kWh

Customer counts are forecasted for GS > 50 both for the purpose of the regression model as well as for the purpose direct use in rate setting. The Geometric mean of the annual growth from 2009 to 2014 was used to forecast the growth rate from 2015 to 2020. In order to appropriately reflect the growth rate in the class, without being skewed by the 2014 reclassification, the historic years 2009-2013 were adjusted to reflect the reclassified customers having always been in their present class. The following table includes the customer Actual / Forecast customer count on this basis:



G	GS > 50		
Year	Customers	Change	
2009	295		
2010	294	-0.45%	
2011	291	-0.94%	
2012	307	5.32%	
2013	318	3.64%	
2014	325	2.12%	
2015	331	1.91%	
2016	337	1.91%	
2017	343	1.91%	
2018	350	1.91%	
2019	357	1.91%	
2020	364	1.91%	

Table 22 Forecasted GS > 50 Customer Count*

In order to normalize and forecast class kW for those classes that bill based on kW (demand) billing determinants, the relationship between billed kW and kWh is used. The ratio from the most recent historic year is used to forecast kW for all future years.

GS>50							
Year	kWh Actual	Ratio	kW Actual				
	Α	C = B / A	В				
2009	270,117,290	0.002671	721,617				
2010	273,806,098	0.002732	747,917				
2011	273,712,584	0.002801	766,581				
2012	274,473,668	0.002846	781,260				
2013	279,458,000	0.002745	767,156				
2014	272,498,127	0.00273	743,905				
k	Wh Normalized						
k	Wh Normalized D	E	F = D * E				
2015	_	E 0.00273	F = D * E 747,759				
	D	_					
2015	D 273,909,928	0.00273	747,759				
2015 2016	D 273,909,928 276,480,202	0.00273 0.00273	747,759 754,776				
2015 2016 2017	D 273,909,928 276,480,202 279,259,356	0.00273 0.00273 0.00273	747,759 754,776 762,363				
2015 2016 2017 2018	D 273,909,928 276,480,202 279,259,356 281,887,678	0.00273 0.00273 0.00273 0.00273	747,759 754,776 762,363 769,538				

^{*}NOTE: 2009-2013 historic customer counts have been adjusted for Jan 2014 reclassification of 53 customers



4.4 LARGE USE

	LU kWh	Annual		Persisting 2009-2014	Normalized
Year	Actual	Change	Normalized	CDM	Forecast
2009	148,002,869		148,687,034	0	148,687,034
2010	149,058,790	0.7%	150,173,340	0	150,173,340
2011	154,491,718	3.6%	154,755,834	617,444	154,138,390
2012	155,448,435	0.6%	153,566,771	1,541,626	152,025,145
2013	153,943,746	-1.0%	157,451,954	2,488,161	154,963,792
2014	151,518,193	-1.6%	156,983,301	3,178,684	153,804,618
2015			158,082,286	3,218,064	154,864,222
2016			159,462,580	3,147,676	156,314,904
2017			160,565,405	3,099,350	157,466,056
2018			161,735,494	3,095,060	158,640,435
2019			162,973,603	3,094,844	159,878,759
2020			164,280,497	2,925,609	161,354,888

Table 24 Actual vs Normalized Large Use kWh

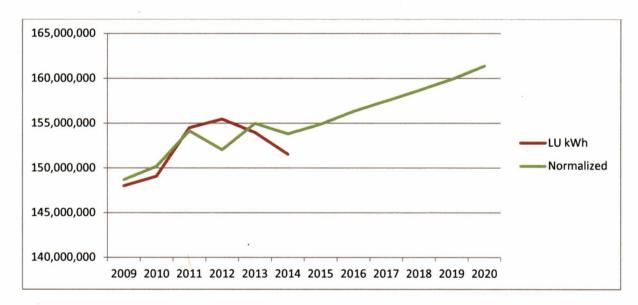


Figure 8 Actual vs Normalized Large Use kWh

Large Use customer count has remained stable at 3 customers for the past several years, and is forecasted to remain at 3 customers throughout the test years.

In order to normalize and forecast class kW for those classes that bill based on kW (demand) billing determinants, the relationship between billed kW and kWh is used. The ratio from the most recent historic year is used to forecast kW for all future years.



	Large	e Use	
Year	kWh Actual	Ratio	kW Actual
	Α	C = B / A	В
2009	148,002,869	0.001627	240,786
2010	149,058,790	0.001943	289,659
2011	154,491,718	0.001904	294,114
2012	155,448,435	0.002079	323,212
2013	153,943,746	0.001895	291,732
2014	151,518,193	0.001891	286,452
	kWh Normalized		
	D	E	F = D * E
2015	154,864,222	0.001891	292,778
2016	156,314,904	0.001891	295,520
2017	157,466,056	0.001891	297,697
2018	158,640,435	0.001891	299,917
2019	159,878,759	0.001891	302,258

305,049

2020 161,354,888 0.001891

Table 25 Forecasted Large Use kW



5 STREET LIGHT AND USL FORECAST

The Street Lighting and Unmetered Scattered Load Classes are non-weather sensitive classes. The tables below summarize the historic annual energy consumption for both classes and the anticipated consumption in the forecast period.

Kingston Hydro performed a forecast of Street Light based on anticipated connections for 2015 and historic growth in the streetlight lamp (device) count. For the USL class, the Geometric Mean growth of the connection count was forecasted. These forecasts are given below:

Street Light	Lamps / Devices	Annual Change	
Year			
2009	5,114		
2010	5,117	0.06%	
2011	5,120	0.05%	
2012	5,126	0.13%	
2013	5,385	5.05%	
2014	5,228	-2.91%	
2015	5,337	2.07%	
2016	5,349	0.22%	
2017	5,361	0.22%	
2018	5,373	0.22%	
2019	5,385	0.22%	
2020	5,397	0.22%	

Table 26 Forecasted Street Light lamps (devices)

USL		Annual Change
Year	Connections	
2009	163	
2010	158	-2.67%
2011	156	-1.74%
2012	152	-2.25%
2013	151	-0.77%
2014	147	-2.87%
2015	143	-2.06%
2016	141	-2.06%
2017	138	-2.06%
2018	135	-2.06%
2019	132	-2.06%
2020	129	-2.06%

Table 27 Forecasted USL connections



In the summer of 2013, the city of Kingston converted the bulk of their street lights to LEDs. The last remaining street lights were converted in 2014.

Light Change Year Actual Normalized
2009 3,992,185 3,992,185
2010 4,076,824 4,076,824 2.12%
2011 4,142,238 4,142,238 1.60%
2012 4,555,371 4,555,371 9.97%
2013 3,336,835 3,336,835 -26.75%
2014 1,817,917 1,817,917 -45.52%
2015 1,814,577 -0.18%
2016 1,818,158 0.20%
2017 1,821,740 0.20%
2018 1,825,321 0.20%
2019 1,828,903 0.20%
2020 1,832,484 0.20%

Table 28 Forecasted Street Light kWh

Causation for changes in USL demand energy, is typically based on connection counts, changes in equipment, and re-classifications. Of these, only changes in connection counts can reasonably be forecasted. Therefore, in forecasting USL, the full year 2014 was used as the basis for forecasting USL energy going forward, with adjustments for forecasted connection counts.

	USL		Annual Change
Year	Actual	Normalized	
2009	2,256,949	2,256,949	
2010	2,229,012	2,229,012	-1.24%
2011	1,517,655	1,517,655	-31.91%
2012	1,484,560	1,484,560	-2.18%
2013	1,499,820	1,499,820	1.03%
2014	1,247,036	1,247,036	-16.85%
2015		1,221,326	-2.06%
2016		1,196,145	-2.06%
2017		1,171,483	-2.06%
2018		1,147,330	-2.06%
2019		1,123,675	-2.06%
2020		1,100,508	-2.06%

Table 29 Forecasted USL kWh



Stree	 	-	L

		g	
Year	kWh Actual	Ratio	kW Actual
	A	C = B / A	В
2009	3,992,185	0.002817	11,246
2010	4,076,824	0.00276	11,251
2011	4,142,238	0.002713	11,237
2012	4,555,371	0.002411	10,984
2013	3,336,835	0.002489	8,304
2014	1,817,917	0.002775	5,045

kWh Normalized

	D	E	F = D * E
2015	1,814,577	0.002775	5,036
2016	1,818,158	0.002775	5,046
2016	1,821,740	0.002775	5,056
2016	1,825,321	0.002775	5,066
2016	1,828,903	0.002775	5,076
2016	1,832,484	0.002775	5,086

Table 30 Forecasted Street Light kW



6 CDM ADJUSTMENT TO LOAD FORECAST

The current Chapter 2 OEB Minimum Filing requirements, consistent with the Board's CDM Guideline EB-2012-0003, expects the distributor to integrate an adjustment into its load forecast that takes into account the six-year (2015-2020) targets for kWh and kW reductions.

The filing requirements note that the distributors license condition targets and the LRAMVA balances are based on the IESO targets, which are annualized. It is recognized that the CDM programs in a year are not in effect for the full year, although persistence of previous year's programs will be. Therefore, the actual impact on the load forecast for the first year of the program should not be the full annualized amount. For this reason, the amount that will be used for the LRAMVA will be related to, but not necessarily equal to, the CDM adjustment for the load forecast.

The following table shows Kingston Hydro's proposed annual CDM targets.

		6 Yea	r (2015-2020)	kWh Target:			
			34,500,0	000			Marie Car
	2015	2016	2017	2018	2019	2020	Total
			%	21			
2015 Programs	7.94%						7.94%
2016 Programs		33.23%					33.23%
2017 Programs			20.39%				20.39%
2018 Programs				14.18%			14.18%
2019 Programs					15.31%		15.31%
2020 Programs		•				16.72%	16.72%
Total in Year	7.94%	33.23%	20.39%	14.18%	15.31%	16.72%	107.78%
			kWh				
2015 Programs	2,740,000						2,740,000
2016 Programs		11,465,768					11,465,778
2017 Programs			7,034,709	W. BAR			7,034,709
2018 Programs				4,893,696			4,893,696
2019 Programs					5,280,676		5,280,676
2020 Programs	solo o		10	N .		5,767,655	5,767,655
Total in Year	2,740,000	11,465,768	7,034,709	4,893,696	5,280,676	5,767,655	37,182,504

Table 31 Proposed CDM Targets



Consistent with recent Board decisions Elenchus includes the full value of the estimated 2015 CDM in 2016. Persistence is included assuming that the full influence of those programs would continue through to 2020. It is also assumed that only one half of the estimated programs would impact the year in which they are delivered.

	Impact Year					
Rate Class	2015	<u>2016</u>	2017	2018	2019	2020
Residential	181,706	517,974	581,569	646,823	713,737	782,310
GS Less Than 50kW	135,732	997,809	1,795,482	2,673,492	3,606,696	4,607,285
GS Greater Than 50kW	601,193	3,224,468	5,440,898	7,896,259	10,464,956	13,259,631
Large User	299,419	9,233,001	13,021,489	14,255,051	15,422,796	16,649,559
TOTAL	1,218,049	13,973,253	20,839,438	25,471,625	30,208,185	35,298,784

Table 32 Proposed CDM Impacts

The following is the proposed allocation of the CDM kWh load forecast adjustment and final proposed load forecast.

	Weather Normalized 2015 Forecast - Classes with CDM	CDM Load Forecast	2015 CDM Adjusted Load	
Retail kWh	programs anticipated	Adjustment	Forecast	
Residential	189,417,832	181,706	189,236,126	
GS < 50	90,135,229	135,732	89,999,498	
GS > 50	273,909,928	601,193	273,308,735	
Large Use	154,864,222	299,419	154,564,804	,
Total	708,327,211	1,218,049	707,109,162	-0.2%

	Weather Normalized 2016 CDM 2016 Forecast - CDM Load Adjusted Classes with CDM Forecast Load			
Retail kWh	programs anticipated	Adjustment	Forecast	
Residential	188,560,878	517,974	188,042,904	
GS < 50	87,729,830	997,809	86,732,020	
GS > 50	276,480,202	3,224,468	273,255,734	
Large Use	156,314,904	9,233,001	147,081,903	
Total	709,085,814	13,973,253	695,112,561	-2.0%

	Weather Normalized		2017 CDM	
	2017 Forecast -	CDM Load	Adjusted	
	Classes with CDM	Forecast	Load	
Retail kWh	programs anticipated	Adjustment	Forecast	
Residential	187,842,287	581,569	187,260,718	
GS < 50	86,574,290	1,795,482	84,778,808	
GS > 50	279,259,356	5,440,898	273,818,458	
Large Use _	157,466,056	13,021,489	144,444,566	
Total	711,141,989	20,839,438	690,302,550	-2.9%
_				



	Weather Normalized		2018 CDM	
	2018 Forecast -	CDM Load	Adjusted	
	Classes with CDM	Forecast	Load	
Retail kWh	programs anticipated	Adjustment	Forecast	
Residential	186,889,965	646,823	186,243,142	
GS < 50	85,112,366	2,673,492	82,438,874	
GS > 50	281,887,678	7,896,259	273,991,419	
Large Use	158,640,435	14,255,051	144,385,384	
Total	712,530,444	25,471,625	687,058,819	-3.6%

	Weather Normalized 2019 Forecast - Classes with CDM	CDM Load Forecast	2019 CDM Adjusted Load	
Retail kWh	programs anticipated	Adjustment	Forecast	
Residential	185,977,037	713,737	185,263,300	
GS < 50	82,749,000	3,606,696	79,142,304	= 2 ×
GS > 50	284,542,723	10,464,956	274,077,767	
Large Use	159,878,759	15,422,796	144,455,963	
Total	713,147,519	30,208,185	682,939,334	-4.2%

Weather Normalized 2020 CDM 2020 Forecast - CDM Load Adjusted Classes with CDM Forecast Load	
Retail kWh programs anticipated Adjustment Forecast	
Residential 185,141,745 782,310 184,359,435	
GS < 50 80,540,933 4,607,285 75,933,648	
GS > 50 287,775,925 13,259,631 274,516,295	
Large Use 161,354,888 16,649,559 144,705,330	
Total 714,813,491 35,298,784 679,514,707 -4	.9%

Table 33 Proposed CDM Adjustment

In order to calculate the kW Elenchus proposes using a proportional ratio utilizing the base load forecast kW and kWh.

Lelenchus

	Weather Normalized				
	2015 Forecast -		CDM Load	2015 CDM	
	Classes with CDM		Forecast	Adjusted Load	
kW	programs anticipated		Adjustment	Forecast	
	G	I = G / H	J = G / A * E	K = G - J	
GS > 50	747,759	72%	1,641	746,118	
Large Use	292,778	28%	566	292,212	
Total	1,040,537	100%	2,207	1,038,330	-0.2%
	Н	_			
	Weather Normalized				
	2016 Forecast -		CDM Load	2016 CDM	
	Classes with CDM		Forecast	Adjusted Load	
kW	programs anticipated		Adjustment	Forecast	
00 - 50	G	I=G/H	J = G / A * E	K = G - J	
GS > 50	754,776	72%	8,803	745,973	
Large Use	295,520	_ 28%_	17,455	278,065	
Total	1,050,296	100%	26,258	1,024,038	-2.5%
	Н				
*					
	Weather Normalized				
	2017 Forecast -		CDM Load	2017 CDM	
	2017 Forecast - Classes with CDM		CDM Load Forecast	2017 CDM Adjusted Load	
kW					
kW	Classes with CDM	I = G / H	Forecast	Adjusted Load	
kW GS > 50	Classes with CDM programs anticipated	I = G / H 72%	Forecast Adjustment	Adjusted Load Forecast	
	Classes with CDM programs anticipated G		Forecast Adjustment J = G / A * E	Adjusted Load Forecast K = G - J	
GS > 50	Classes with CDM programs anticipated G 762,363	72%	Forecast Adjustment J = G / A * E 14,853	Adjusted Load Forecast K = G - J 747,509	-3.7%
GS > 50 Large Use	Classes with CDM programs anticipated G 762,363 297,697	72% 28%	Forecast Adjustment J = G / A * E 14,853 24,618	Adjusted Load Forecast K = G - J 747,509 273,079	-3.7%
GS > 50 Large Use	Classes with CDM programs anticipated G 762,363 297,697 1,060,059	72% 28%	Forecast Adjustment J = G / A * E 14,853 24,618	Adjusted Load Forecast K = G - J 747,509 273,079	-3.7%
GS > 50 Large Use	Classes with CDM programs anticipated G 762,363 297,697 1,060,059 H	72% 28%	Forecast Adjustment J = G / A * E 14,853 24,618	Adjusted Load Forecast K = G - J 747,509 273,079	-3.7%
GS > 50 Large Use	Classes with CDM programs anticipated G 762,363 297,697 1,060,059 H	72% 28%	Forecast Adjustment J = G / A * E 14,853 24,618 39,471	Adjusted Load Forecast K = G - J 747,509 273,079 1,020,588	-3.7%
GS > 50 Large Use	Classes with CDM programs anticipated G 762,363 297,697 1,060,059 H Weather Normalized 2018 Forecast -	72% 28%	Forecast Adjustment J = G / A * E 14,853 24,618 39,471 CDM Load	Adjusted Load Forecast K = G - J 747,509 273,079 1,020,588	-3.7%
GS > 50 Large Use Total	Classes with CDM programs anticipated G 762,363 297,697 1,060,059 H Weather Normalized 2018 Forecast - Classes with CDM	72% 28%	Forecast Adjustment J = G / A * E 14,853 24,618 39,471 CDM Load Forecast	Adjusted Load Forecast K = G - J 747,509 273,079 1,020,588	-3.7%
GS > 50 Large Use Total	Classes with CDM programs anticipated G 762,363 297,697 1,060,059 H Weather Normalized 2018 Forecast - Classes with CDM programs anticipated	72% 28% 100%	Forecast Adjustment J = G / A * E 14,853 24,618 39,471 CDM Load Forecast Adjustment	Adjusted Load Forecast K = G - J 747,509 273,079 1,020,588 2018 CDM Adjusted Load Forecast	-3.7%
GS > 50 Large Use Total kW GS > 50	Classes with CDM programs anticipated G 762,363 297,697 1,060,059 H Weather Normalized 2018 Forecast - Classes with CDM programs anticipated 769,538	72% 28% 100%	Forecast Adjustment J = G / A * E 14,853 24,618 39,471 CDM Load Forecast Adjustment 21,556	Adjusted Load Forecast K = G - J 747,509 273,079 1,020,588 2018 CDM Adjusted Load Forecast 747,982	-3.7%
GS > 50 Large Use Total	Classes with CDM programs anticipated G 762,363 297,697 1,060,059 H Weather Normalized 2018 Forecast - Classes with CDM programs anticipated	72% 28% 100%	Forecast Adjustment J = G / A * E 14,853 24,618 39,471 CDM Load Forecast Adjustment	Adjusted Load Forecast K = G - J 747,509 273,079 1,020,588 2018 CDM Adjusted Load Forecast	-3.7%



	Weather Normalized				
	2019 Forecast -		CDM Load	2019 CDM	
	Classes with CDM		Forecast	Adjusted Load	
kW	programs anticipated		Adjustment	Forecast	
	G	I = G / H	J = G / A * E	K = G - J	
GS > 50	776,786	72%	28,569	748,217	
Large Use	302,258	28%	29,157	273,101	
Total	1,079,044	100%	57,726	1,021,318	-5.3%
	ш				

	Weather Normalized				
	2020 Forecast -		CDM Load	2020 CDM	
	Classes with CDM		Forecast	Adjusted Load	
kW	programs anticipated		Adjustment	Forecast	
	G	I = G / H	J = G / A * E	K = G - J	
GS > 50	785,613	72%	36,198	749,414	
Large Use	305,049	28%	31,477	273,572	
Total	1,090,661	100%	67,675	1,022,986	-6.2%
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Table 34 Proposed kW CDM adjustment

For 2016-2020 For LRAMVA Elenchus reasons that the effects of 2015-2020 IESO CDM programs should be included in the LRAMVA calculation.

Values for calculation of projected LRAMVA 2015-2020							
2015	2016	2017	2018	2019	2020		
181,706	517,974	581,569	646,823	713,737	782,310		
135,732	997,809	1,795,482	2,673,492	3,606,696	4,607,285		
156.91	909.18	1,548.03	2,241.64	2,928.94	3,668.74		
52.56	450.95	807.70	1,178.28	1,497.24	1,825.52		
	2015 181,706 135,732 156.91	2015 2016 181,706 517,974 135,732 997,809 156.91 909.18	2015 2016 2017 181,706 517,974 581,569 135,732 997,809 1,795,482 156.91 909.18 1,548.03	2015 2016 2017 2018 181,706 517,974 581,569 646,823 135,732 997,809 1,795,482 2,673,492 156.91 909.18 1,548.03 2,241.64	2015 2016 2017 2018 2019 181,706 517,974 581,569 646,823 713,737 135,732 997,809 1,795,482 2,673,492 3,606,696 156.91 909.18 1,548.03 2,241.64 2,928.94		

Table 35 Proposed LRAMVA CDM Thresholds by Class