VOLUME 3:

LOAD ANALYSIS AND LOAD FORECASTING

KCP&L GREATER MISSOURI OPERATIONS COMPANY (GMO)

INTEGRATED RESOURCE PLAN

4 CSR 240-22.030

CASE NO. EO-2012-0324

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VOLUME 3 – LOAD ANALYSIS AND LOAD FORECASTING

PURPOSE: This rule sets minimum standards for the maintenance and updating of historical data, the level of detail required in analyzing loads, and the purposes to be accomplished by load analysis and by load forecast models. The load analysis discussed in this rule is intended to support both demand-side management efforts of 4 CSR 240-22.050 and the load forecast models of this rule. This rule also sets the minimum standards for the documentation of the inputs, components, and methods used to derive the load forecasts.

SECTION 1: SELECTING LOAD ANALYSIS METHODS

The utility may choose multiple methods of load analysis if it deems doing so is necessary to achieve all of the purposes of load analysis and if the methods are consistent with, and calibrated to, one another. The utility shall describe and document its intended purposes for load analysis methods, why the selected load analysis methods best fulfill those purposes, and how the load analysis methods are consistent with one another and with the endues consumption data used in the demand-side analysis as described in 4 CSR 240-22.050. At a minimum, the load analysis methods shall be selected to achieve the following purposes:

1.1 PURPOSE: IDENTIFICATION OF END-USE MEASURES

(A) To identify end-use measures that may be potential demand-side resources, generally, those end-use measures with an opportunity for energy and/or demand savings;

1.2 PURPOSE: DERIVATION OF DATA SET OF HISTORICAL VALUES

(B) To derive a data set of historical values from load research data that can be used as dependent and independent variables in the load forecasts;

1.3 PURPOSE: ANALYSIS OF IMPACTS OF IMPLEMENTED DSM AND DEMAND-SIDE RATES ON LOAD FORECASTS

(C) To facilitate the analysis of impacts of implemented demand-side programs and demand-side rates on the load forecasts and to augment measurement of the effectiveness of demand-side resources necessary for 4 CSR 240-22.070(8) in the evaluation of the performance of the demand-side programs or rates after they are implemented; and

1.4 PURPOSE: PRESERVATION OF LOAD ANALYSIS IN HISTORICAL DATABASE

(D) To preserve, in a historical database, the results of the load analysis used to perform the demand-side analysis as described in 4 CSR 240-22.050, and the load forecasting described in 4 CSR 240-22.030.

SECTION 2: HISTORICAL DATABASE FOR LOAD ANALYSIS

The utility shall develop and maintain data on the actual historical patterns of energy usage within its service territory. The following information shall be maintained and updated on an ongoing basis and described and documented in the triennial compliance filings:

2.1 CUSTOMER CLASS DETAIL

(A) Customer Class Detail. At a minimum, the historical database shall be maintained for each of the major classes;

Beginning with this IRP filing, GMO forecasts its loads for each major class, which are Residential, Small General Service (SGS), Large General Service (LGS), Large Power (LP), Lighting and Sales for Resale (SFR). In addition, SGS, LGS and LP are split into the subclasses Commercial and Industrial. This data begins in January 1996 for SJLP and January 1994 for MPS and will be maintained with at least 10 years of history going forward.

2.2 LOAD DATA DETAIL

(B) The historical load database shall contain the following data:

2.2.1 ACTUAL AND WEATHER NORMALIZED ENERGY, AND NUMBER OF CUSTOMERS

1. For each jurisdiction for which it prepares customer and energy and demand forecasts, for each major class, to the actual monthly energy usage and number of customers and weather-normalized monthly energy usage;

MetrixND files are used to maintain this data for each subclass listed in 22.030 (2) (A). These files also contain the models used to forecast the number of customers and weather-normalize and forecast monthly energy sales.

2.2.2 ACTUAL AND WEATHER NORMALIZED DEMANDS

2. For each jurisdiction and major class, estimated actual and weather-normalized demands at the time of monthly system peaks; and

Actual and weather-normalized coincident demands are provided in the *load research* folder of the workpapers. This data is available beginning in 2003 for both SJLP and MPS. Some earlier years are also available.

2.2.3 ACTUAL AND WEATHER NORMALIZED SYSTEM PEAK DEMANDS

3. For the system, actual and weather normalized hourly net system load;

Actual and weather-normalized Net System Input (NSI) is maintained in the MetrixLT files, which are provided in the workpapers.

2.3 LOAD COMPONENT DETAIL

(C) The historical database for major class monthly energy usage and demands at time of monthly peaks shall be disaggregated into a number-of-units component and a use-per-unit component, for both actual and weather-normalized loads.

2.3.1 UNITS COMPONENT

1. The number-of-units component shall be the number of customers, square feet, devices, or other units as appropriate to the customer class and the load analysis method selected by the utility. The utility shall select the units component with the intent of providing meaningful load analysis for demand-side analysis and maintaining the integrity of the database over time.

The number-of-units is the number of customers for residential and SGS commercial. For the other subclasses, mWh sales are modeled because it is more stable than kWh sales per customer and the model fit statistics are higher. In the large customer classes, the size of customers varies more than in the smaller classes and use per customer can change substantially as customers enter or exit the class.

2.3.2 UPDATE PROCEDURE

2. The utility shall develop and implement a procedure to routinely measure and regularly update estimates of the effect of departures from normal weather on class and system electric loads. The estimates of the effect of weather on historical major class and system loads shall incorporate the nonlinear response of loads to daily weather and seasonal variations in loads.

GMO has developed a MetrixND model for each subclass of kWh sales that both forecasts and weather normalizes sales or sales per unit. These models will update weather normalized sales at the subclass level whenever these models are updated. This procedure is automatic. Major class level demands are currently weather normalized only for a rate case and this process is not automatic as it requires a large number of manual steps. Heating and cooling degree days calculated with different base temperatures were tested and kept in the models if statistically significant so that nonlinear weather response functions could be represented.

2.3.3 WEATHER MEASURES AND ESTIMATION OF WEATHER EFFECTS DESCRIPTION AND DOCUMENTATION

3. The utility shall describe and document the methods used to develop weather measures and the methods used to estimate the effect of weather on electric loads. If statistical models are used, the documentation shall include at least: the functional form of the models; the estimation techniques employed; and the relevant statistical results of the models, including parameter estimates and tests of statistical significance. The data used to estimate the models, including the development of model input data from basic data, shall be included in the workpapers supplied at the time the compliance report is filed;

In this IRP filing, GMO used different methods to model the effects of weather for normalization and for forecasting. One reason for using different methods is that the sample period for WN needed to cover the entire period that historical data was available so that data could be WN. On the other hand, the forecasting models often need a more recent shorter sample period since the focus is on calibrating an end-use forecast to recent data. The method of WN used in this IRP filing is different than that used in the rate cases because it is designed to WN many years of data whereas the rate case models are based on only two years of data. Also the method used here is much less labor intensive and can be updated more routinely.

Degree days computed at different base temperatures were tested in explaining the effects of weather on sales and system load. Degree days computed with more than one base temperature were tested in the same model to determine if the load response is nonlinear. The statistical results of model estimation in the weather normalization models of monthly sales are presented in this section. Additional information is available in the MetrixND model files that are included in the electronic workpapers. This additional information includes formulas that define the explanatory variables, plots and tables of residuals, plots and tables of actual, weather-normalized and predicted values, plots and tables of explanatory variables and model statistics and coefficients. The model coefficients were estimated using ordinary least squares regression in MetrixND.

Table 1 WN Model for MPS Residential Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	665	9	71.5	0.00%
BinaryVars.trend1	4.3	2.3	1.9	6.49%
BinaryVars.trend2	-95	42	-2.3	2.43%
BinaryVars.trend3	-36	26	-1.4	17.16%
BinaryVars.Jan	97	12	8.1	0.00%
BinaryVars.Dec	39	11	3.7	0.03%
WthrTrans.cdd65shoulder_CCOS	-1,204	272	-4.4	0.00%
WthrTrans.cddTrend1_CCOS	-75	24	-3.2	0.17%
WthrTrans.cddTrend2_CCOS	-541	259	-2.1	3.78%
WthrTrans.hddTrend1_CCOS	128	27	4.7	0.00%
WthrTrans.hddTrend2_CCOS	-3	290	0.0	99.20%
WthrIndex_RES.CDD65	5,245	83	62.9	0.00%
WthrIndex_RES.HDD55	4,054	112	36.3	0.00%

Table 2 WN Model for MPS Small GS Commercial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	1,785	39	46.0	0.00%
WthrTrans.Cdd55trend1_SML	-205	85	-2.4	1.67%
WthrTrans.Cdd55trend2_SML	-1,344	921	-1.5	14.63%
WthrTrans.Hdd55trend1_SML	30	76	0.4	69.56%
WthrTrans.Hdd55trend2_SML	-530	822	-0.6	52.00%
WthrIndex_SML.CDD60	4,931	2,082	2.4	1.88%
WthrIndex_SML.CDD55	3,425	2,551	1.3	18.09%
WthrIndex_SML.HDD55	5,402	371	14.6	0.00%
BinaryVars.trend1	-6.8	7.1	-1.0	34.12%
BinaryVars.trend2	33	112	0.3	76.61%
BinaryVars.trend3	48	64	0.7	45.76%
SML_WNAvgUse.Apr05	-550	96	-5.7	0.00%

Table 3 WN Model for MPS Large GS Commercial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	48,496	682	71.2	0.00%
WthrTrans.Cdd55trend1_LRG	-4,920	2,271	-2.2	3.15%
WthrTrans.Cdd55trend2_LRG	-6,776	24,595	-0.3	78.32%
WthrTrans.Hdd55trend1_LRG	-464	2,038	-0.2	82.01%
WthrTrans.Hdd55trend2_LRG	-5,076	21,974	-0.2	81.76%
WthrIndex_LRG.CDD55	162,838	7,669	21.2	0.00%
WthrIndex_LRG.HDD55	64,193	7,145	9.0	0.00%
BinaryVars.trend1	-941	210	-4.5	0.00%
BinaryVars.trend2	-831	3,471	-0.2	81.10%
BinaryVars.trend3	22,939	6,768	3.4	0.09%
BinaryVars.trend4	16,147	3,858	4.2	0.00%
LRG_WNAvgUse.Apr05	-17,503	2,570	-6.8	0.00%

Table 4 WN Model for MPS Large Power Commercial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	432,728	6,776	63.9	0.00%
WthrTrans.Cdd55trend1_LP	-14,224	25,437	-0.6	57.67%
WthrTrans.Cdd55trend2_LP	83,755	272,178	0.3	75.86%
WthrIndex_LP.CDD55	995,778	83,715	11.9	0.00%
BinaryVars.trend1	-3,898	2,339	-1.7	9.72%
BinaryVars.trend2	5,507	48,967	0.1	91.06%
BinaryVars.trend3	139,224	112,839	1.2	21.87%
BinaryVars.trend4	95,664	64,241	1.5	13.80%

Table 5 WN Model for MPS Small GS Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	225,065	13,405	16.8	0.00%
WthrTrans.Cdd65trend1_SML	-27,005	20,634	-1.3	19.21%
WthrTrans.Hdd55trend1_SML	-1,631	22,143	-0.1	94.13%
WthrIndex_SML.CDD65	338,572	128,660	2.6	0.91%
WthrIndex_SML.HDD55	382,305	148,492	2.6	1.07%
BinaryVars.trend1	-4,181	2,611	-1.6	11.09%
BinaryVars.trend2	317,736	60,428	5.3	0.00%
BinaryVars.trend3	154,881	44,760	3.5	0.07%

Table 6 WN Model for MPS Large GS Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	3,837,387	240,973	15.9	0.00%
WthrTrans.Cdd55trend1_LRG	-781,448	925,449	-0.8	39.94%
WthrTrans.Cdd55trend2_LRG	-11,760,697	9,828,570	-1.2	23.29%
WthrIndex_LRG.CDD55	8,429,594	3,016,500	2.8	0.57%
BinaryVars.trend1	-422,944	83,268	-5.1	0.00%
BinaryVars.trend2	5,004,218	1,729,090	2.9	0.42%
BinaryVars.trend3	8,216,975	3,986,505	2.1	4.06%
BinaryVars.trend4	1,443,180	2,270,151	0.6	52.57%

Table 7 WN Model for MPS Large Power Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	55,617,031	795,169	69.9	0.00%
WthrTrans.Cdd55trend1_LRG	-2,161,405	3,224,755	-0.7	50.35%
WthrTrans.Cdd55trend2_LRG	-24,113,732	34,372,843	-0.7	48.38%
WthrIndex_LP.CDD55	71,495,588	10,230,747	7.0	0.00%
BinaryVars.trend1	127,292	208,703	0.6	54.26%
BinaryVars.trend2	-18,615,637	5,064,492	-3.7	0.03%
BinaryVars.trend3	-9,319,628	3,519,442	-2.6	0.87%
LP_WNSales.Mar05	-18,772,607	5,282,807	-3.6	0.05%

Table 8 WN Model for SJLP Residential Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	678	13	53.1	0.00%
BinaryVars.trend1	7.4	3.2	2.3	2.12%
BinaryVars.trend2	-127	66	-1.9	5.77%
BinaryVars.trend3	-137	52	-2.6	0.89%
WNAvgUse_CCOS.Dec	23	15	1.6	11.45%
WNAvgUse_CCOS.Jan	98	16	6.0	0.00%
WthrTrans.cddTrend1	-56	32	-1.7	8.54%
WthrTrans.cddTrend2	-551	461	-1.2	23.37%
WthrTrans.hddTrend1	239	37	6.4	0.00%
WthrTrans.hddTrend2	-33	496	-0.1	94.69%
WthrTrans.cdd65shoulder	-1,411	374	-3.8	0.02%
WthrIndex_RES.CDD65	3,991	115	34.7	0.00%
WthrIndex_RES.HDD55	6,020	154	39.1	0.00%

Table 9 WN Model for SJLP Small GS Commercial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	1,000	16	63.7	0.00%
BinaryVars.trend1	-0.3	5.3	0.0	96.07%
BinaryVars.trend2	135	89	1.5	13.32%
BinaryVars.trend3	413	222	1.9	6.43%
BinaryVars.trend4	240	164	1.5	14.63%
BinaryVars.Jan	92	20	4.5	0.00%
BinaryVars.Dec	12	18	0.7	50.07%
WthrIndex_SML.HDD55	4,976	191	26.1	0.00%
WthrIndex_SML.CDD60	4,486	166	27.0	0.00%
WthrTrans.Cdd60trend1_SML	-112	49	-2.3	2.42%
WthrTrans.Cdd60trend2_SML	-1,336	693	-1.9	5.54%
WthrTrans.Hdd55trend1_SML	92	49	1.9	6.43%
WthrTrans.Hdd55trend2_SML	-536	666	-0.8	42.15%
SML_WnAvgUse.May01	375	63	6.0	0.00%
SML_WnAvgUse.Sep01	-511	63	-8.2	0.00%

Table 10 WN Model for SJLP Large GS Commercial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	23,488,330	206,899	113.5	0.00%
BinaryVars.trend1	520,930	72,130	7.2	0.00%
BinaryVars.trend2	-6,380,994	1,227,407	-5.2	0.00%
BinaryVars.trend3	-15,959,832	3,172,037	-5.0	0.00%
BinaryVars.trend4	-10,017,758	2,355,310	-4.3	0.00%
WthrIndex_LRG.HDD50	34,325,680	2,356,321	14.6	0.00%
WthrIndex_LRG.CDD60	61,827,459	2,244,171	27.6	0.00%
WthrTrans.Cdd60trend1_LRG	-743,424	664,245	-1.1	26.46%
WthrTrans.Cdd60trend2_LRG	-15,973,823	9,373,393	-1.7	9.01%
WthrTrans.Hdd50trend1_LRG	1,318,648	598,981	2.2	2.90%
WthrTrans.Hdd50trend2_LRG	2,518,948	8,119,148	0.3	75.68%
BinaryVars.Jan	1,587,665	295,158	5.4	0.00%
BinaryVars.Dec	860,799	258,255	3.3	0.11%

Table 11 WN Model for SJLP Large Power Commercial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	23,488,330	206,899	113.5	0.00%
BinaryVars.trend1	520,930	72,130	7.2	0.00%
BinaryVars.trend2	-6,380,994	1,227,407	-5.2	0.00%
BinaryVars.trend3	-15,959,832	3,172,037	-5.0	0.00%
BinaryVars.trend4	-10,017,758	2,355,310	-4.3	0.00%
WthrIndex_LRG.HDD50	34,325,680	2,356,321	14.6	0.00%
WthrIndex_LRG.CDD60	61,827,459	2,244,171	27.6	0.00%
WthrTrans.Cdd60trend1_LRG	-743,424	664,245	-1.1	26.46%
WthrTrans.Cdd60trend2_LRG	-15,973,823	9,373,393	-1.7	9.01%
WthrTrans.Hdd50trend1_LRG	1,318,648	598,981	2.2	2.90%
WthrTrans.Hdd50trend2_LRG	2,518,948	8,119,148	0.3	75.68%
BinaryVars.Jan	1,587,665	295,158	5.4	0.00%
BinaryVars.Dec	860,799	258,255	3.3	0.11%

Table 12 WN Model for SJLP Small GS Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	1,519	332	4.6	0.00%
WthrIndex_SML.HDD55	33,970	4,182	8.1	0.00%
WthrIndex_SML.CDD65	-3,098	3,013	-1.0	30.83%
WthrTrans.Hdd55trend1_SML	-11,319	1,587	-7.1	0.00%
WthrTrans.Cdd65trend1_SML	2,332	1,266	1.8	7.08%
BinaryVars.trend1	-540	242	-2.2	2.97%
BinaryVars.trend2	135,937	16,918	8.0	0.00%
BinaryVars.trend3	-155,452	30,880	-5.0	0.00%
SML_SalesWn.Jan08	-3,703	867	-4.3	0.01%
SML_SalesWn.Jan09	2,446	844	2.9	0.54%
SML_SalesWn.Dec07	-3,072	834	-3.7	0.05%

Table 13 WN Model for SJLP Large GS Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	4,717,643	159,465	29.6	0.00%
WthrIndex_LRG.HDD50	2,522,104	1,169,273	2.2	3.24%
WthrIndex_LRG.CDD55	5,242,394	1,387,347	3.8	0.02%
BinaryVars.trend1	-235,904	42,375	-5.6	0.00%
BinaryVars.trend2	146,006	690,971	0.2	83.29%
BinaryVars.trend3	1,804,117	468,211	3.9	0.02%
LRG_SalesWn.Aug04	4,885,477	448,344	10.9	0.00%
LRG_SalesWn.Apr01	3,460,394	448,734	7.7	0.00%
WthrTrans.Cdd55trend1_LRG	-431,032	405,957	-1.1	28.98%
WthrTrans.Cdd55trend2_LRG	-6,260,775	5,656,819	-1.1	26.99%
WthrTrans.Hdd50trend1_LRG	-283,521	326,787	-0.9	38.68%
WthrTrans.Hdd50trend2_LRG	-1,491,363	4,402,046	-0.3	73.52%
(year+month/100)<2007.10	-450,936	171,753	-2.6	0.94%
LRG_SalesWn.Sep03	1,566,748	449,341	3.5	0.06%

Table 14 WN Model for SJLP Large Power Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	40,635,483	523,547	77.6	0.00%
WthrIndex_LP.CDD65	24,045,123	5,309,512	4.5	0.00%
WthrTrans.Cdd65trend1_LP	179,769	1,021,155	0.2	86.05%
BinaryVars.trend1	905,261	123,400	7.3	0.00%
BinaryVars.trend2	9,602,722	3,844,201	2.5	1.34%
BinaryVars.trend3	8,371,667	3,661,004	2.3	2.34%
LP_SalesWn.Jun05	17,127,376	3,568,986	4.8	0.00%
LP_SalesWn.Dec01	14,002,215	3,572,373	3.9	0.01%
LP_SalesWn.Dec03	13,194,704	3,565,285	3.7	0.03%
LP_SalesWn.Oct07	13,427,066	3,567,628	3.8	0.02%
LP_SalesWn.Apr01	-11,986,335	3,571,676	-3.4	0.10%

2.4 ASSESSMENTS

(D) For each major class specified pursuant to subsection (2)(A), the utility shall provide, on a seasonal and annual basis for each year of the historical period—

For the current GMO filing, historical sales and customers broken out by class cost of service and commercial and industrial customers was available beginning in January 1994 for MPS and January 1996 for SJLP. Going forward, GMO will maintain this data for at least the previous 10 years.

2.4.1 HISTORIC END-USE DRIVERS OF ENERGY USAGE AND PEAK DEMAND

1. Its assessment of the historical end-use drivers of energy usage and peak demand, including trends in numbers of units and energy consumption per unit;

Historical plots of customers and kwh/customer for energy usage and peak demand can be found in *Appendix 3A*.

Residential customer growth for SJLP was slower in the early 2000s than in the late 1990s, 0.4% per year vs. 0.8%, and then even slower after that. Growth for MPS was about the same in the late 1990s and early 2000s, about 2.3%, and then much slower after that.

SGS customer growth was very high for MPS in the late 1990s, 3.3% per year, and much slower in the early 2000s, 2.1% with no growth after that. There was no growth in this segment for SJLP during the late 1990s, but growth picked up in the 2000s.

Customer growth for LP has been high for MPS since 1996, initially 5.3% in the late 1990s, slowing to 4.0% in the early 2000s, and slowing even more to 3.3% in the late 2000s. SJLP has also seen robust growth for this segment, 3.5% in the late 1990s, and about 1% after that.

The plots for residential mWh use per customer show a very interesting pattern. Summer use is relatively flat from 1996 through 2010 whereas winter use is trending up due to increasing saturations of electric space heating, mostly heat pumps. That upward trend has slowed in the last several years due to slow customer growth. The penetration of heat pumps has been much higher than the saturation so that customer growth has been the prime cause of the rising saturation and this growth has stalled in recent years. Weather normalization has smoothed out the trends especially for the summer months.

For SGS, summer use is declining slowly for MPS and is flat for SJLP. Non-summer use is flat for MPS and rising slightly for SJLP.

LGS usage patterns are declining for MPS during the summer and winter and are nearly flat for SJLP.

LP usage in both the summer and winter is flat or perhaps declining slightly for MPS. For SJLP, the trend is up slightly in the summer whereas winter use trends down from 1996 until 2005, then jumps up in 2006 and continues a slow decline after that. The jump in 2006 may have been caused by a large customer switching out of this class or a new large customer coming to this class.

2.4.2 WEATHER SENSITIVITY OF ENERGY AND PEAK DEMAND

2. Its assessment of the weather sensitivity of energy and peak demand; and

The following plots illustrate the weather response function of daily energy and peak demand for each major class. This data is weather normalized in the rate case process during which the weather response function is represented with an equation estimated with statistical regression analysis. The blue symbols in the plot represent weekdays and the red symbols represent weekends.

Figure 1: MPS Residential Daily Energy vs Average Temp

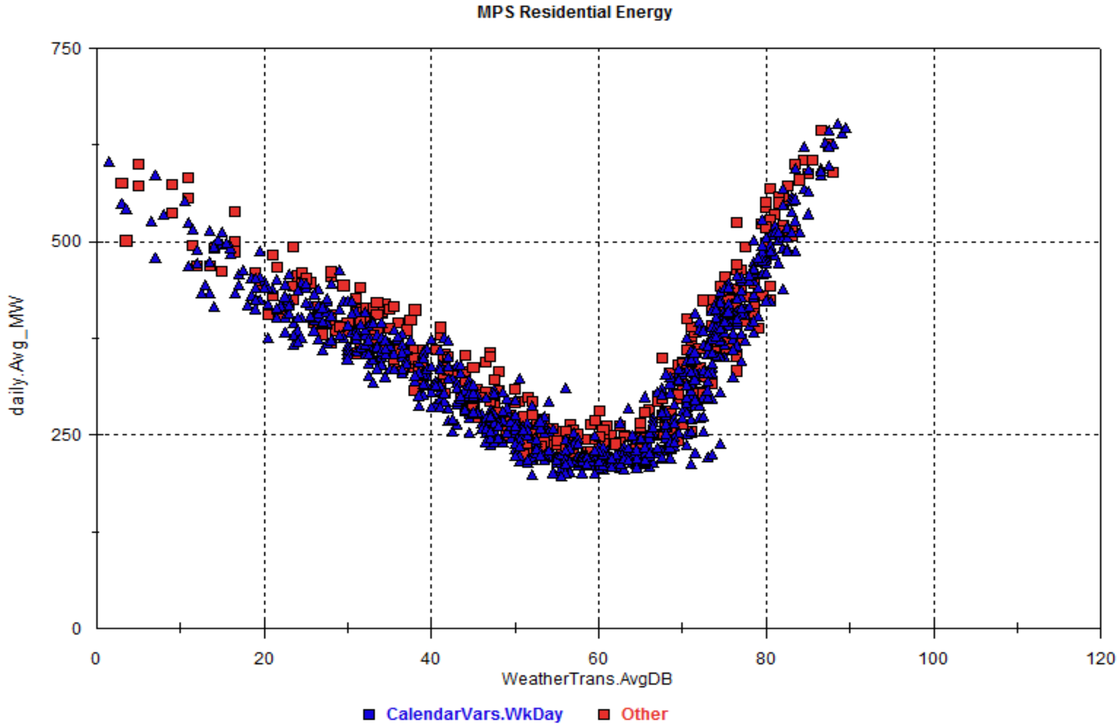


Figure 2: MPS Residential Daily Peak Demand vs Average Temp

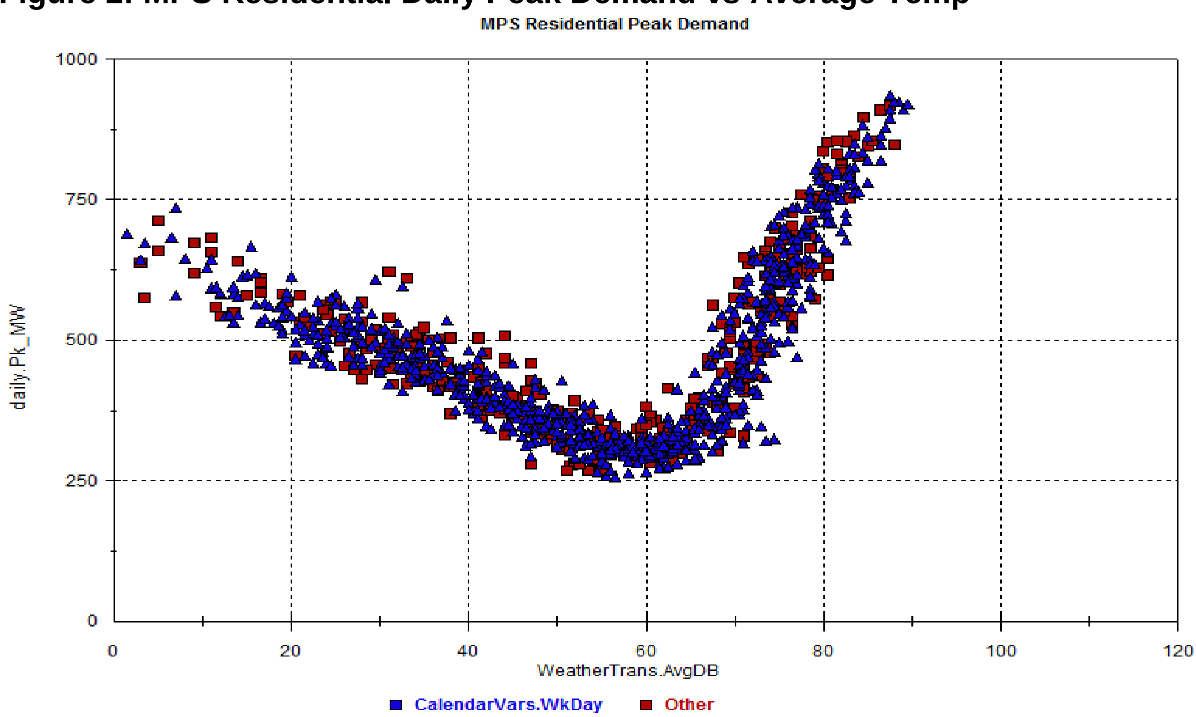


Figure 3: MPS Small General Service Daily Energy vs Average Temp

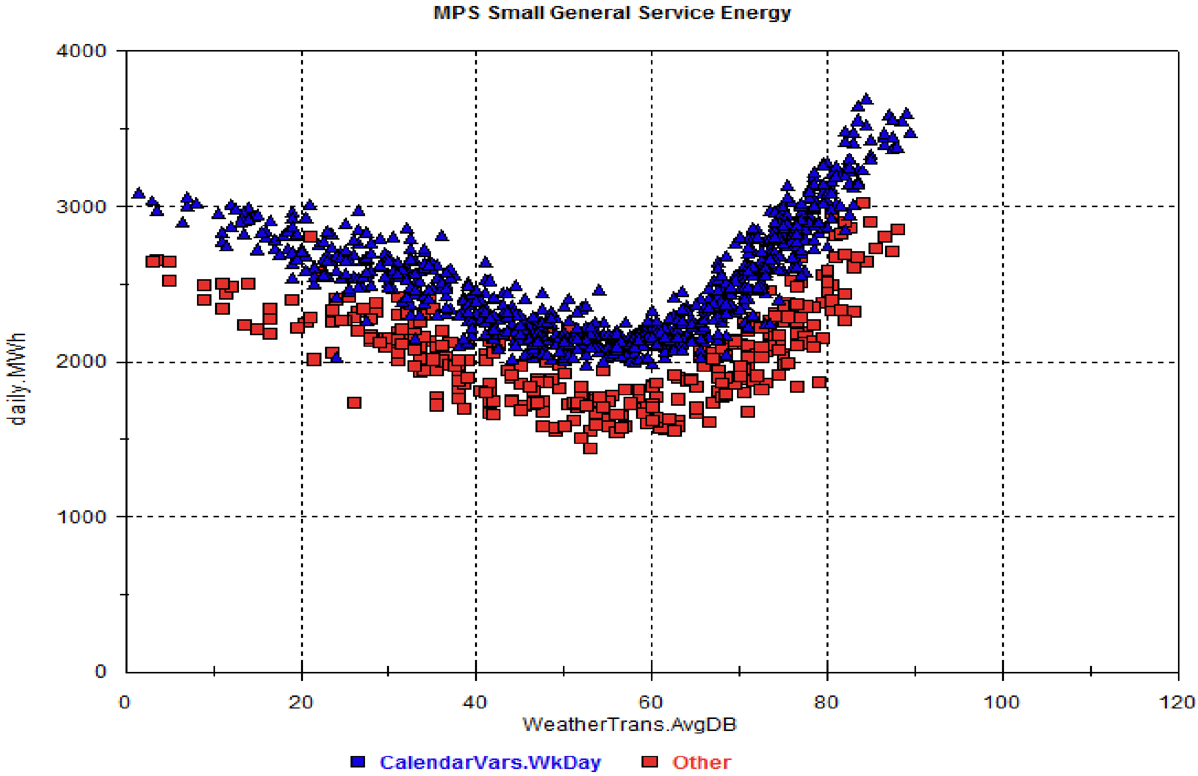


Figure 4: MPS Small General Service Daily Peak vs Average Temp

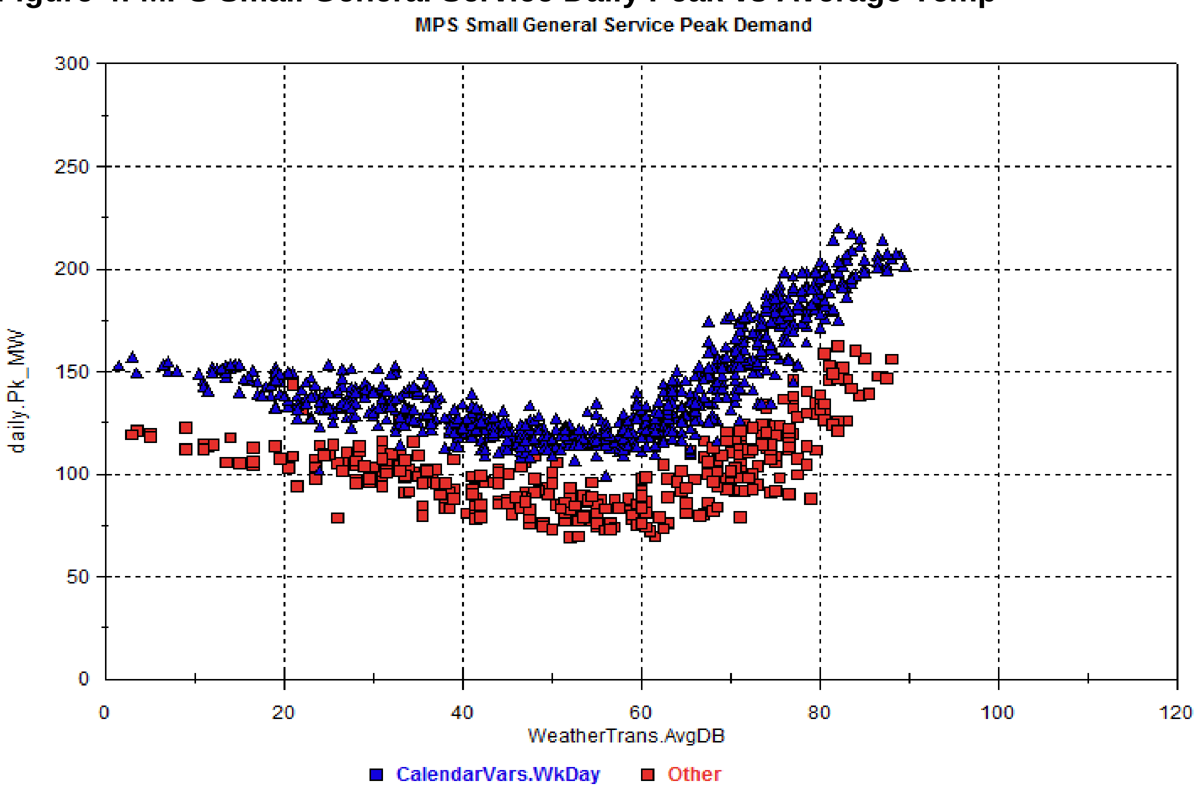


Figure 5: MPS Large General Service Daily Energy vs Average Temp

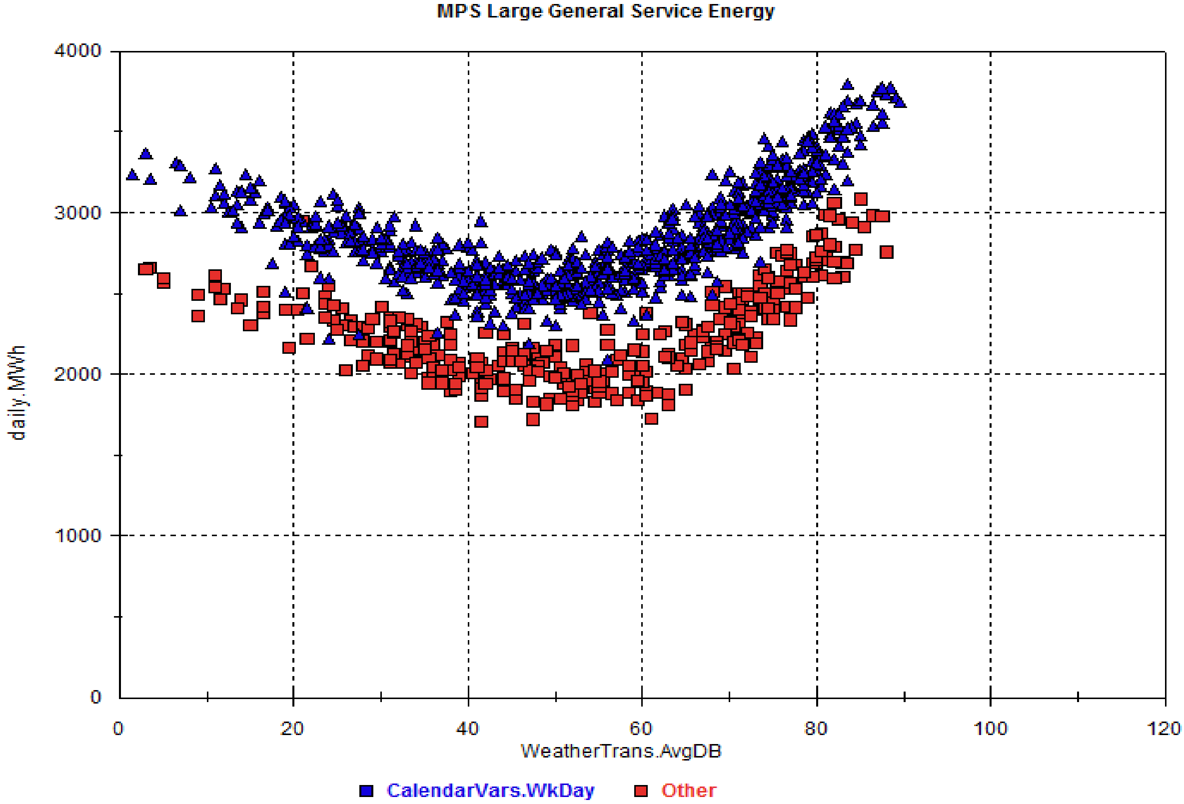


Figure 6: MPS Large General Service Daily Peak Demand vs Average Temp

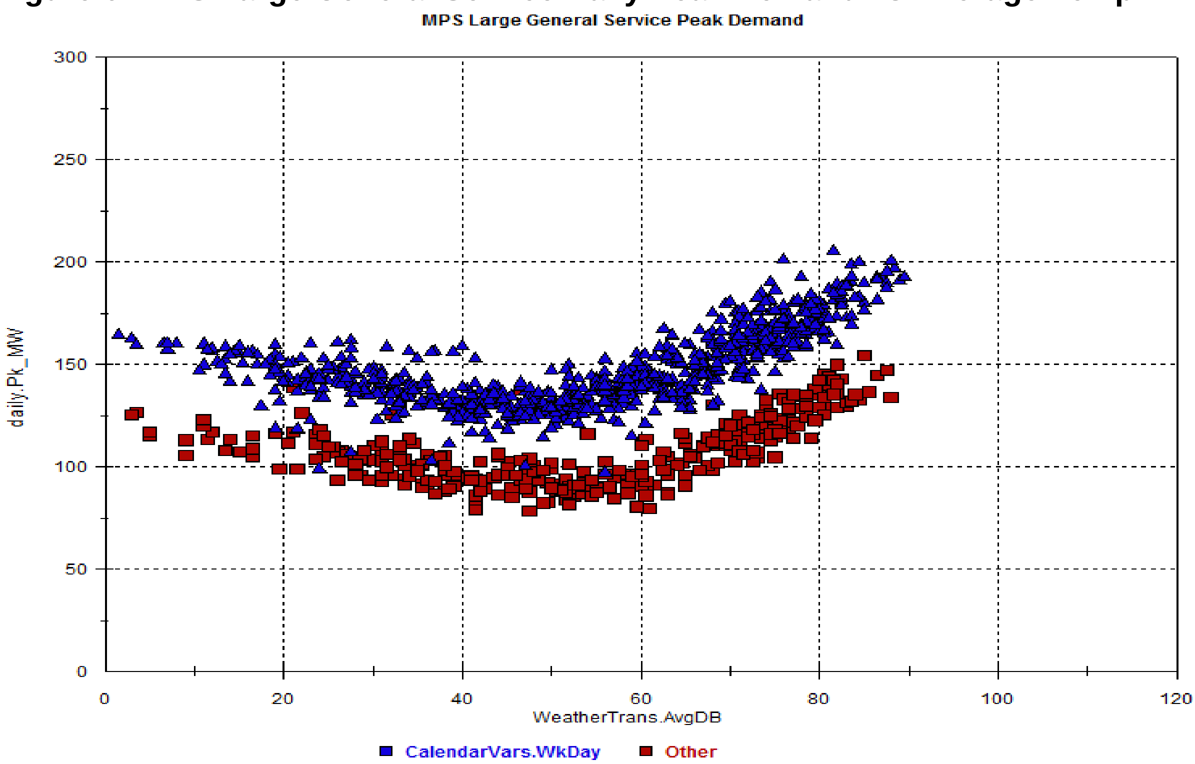


Figure 7: MPS Large Power Daily Energy vs Average Temp

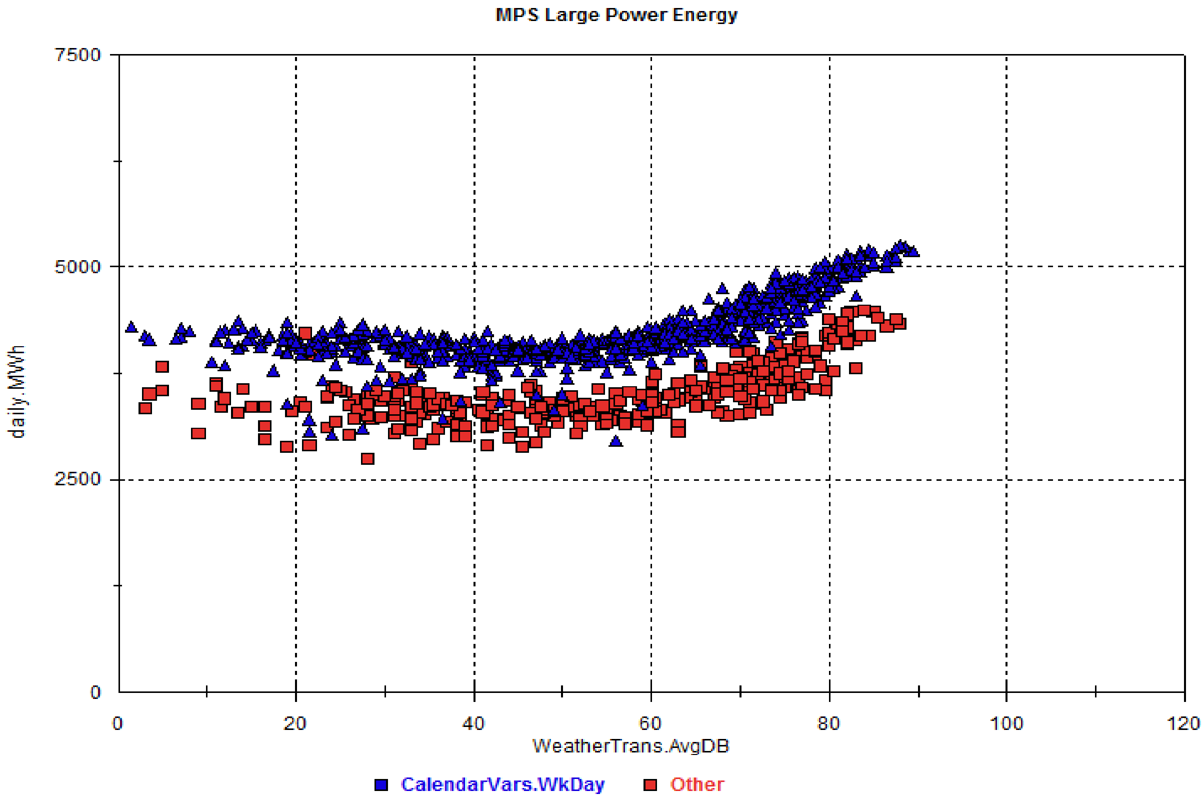


Figure 8: MPS Large Power Daily Peak Demand vs Average Temp

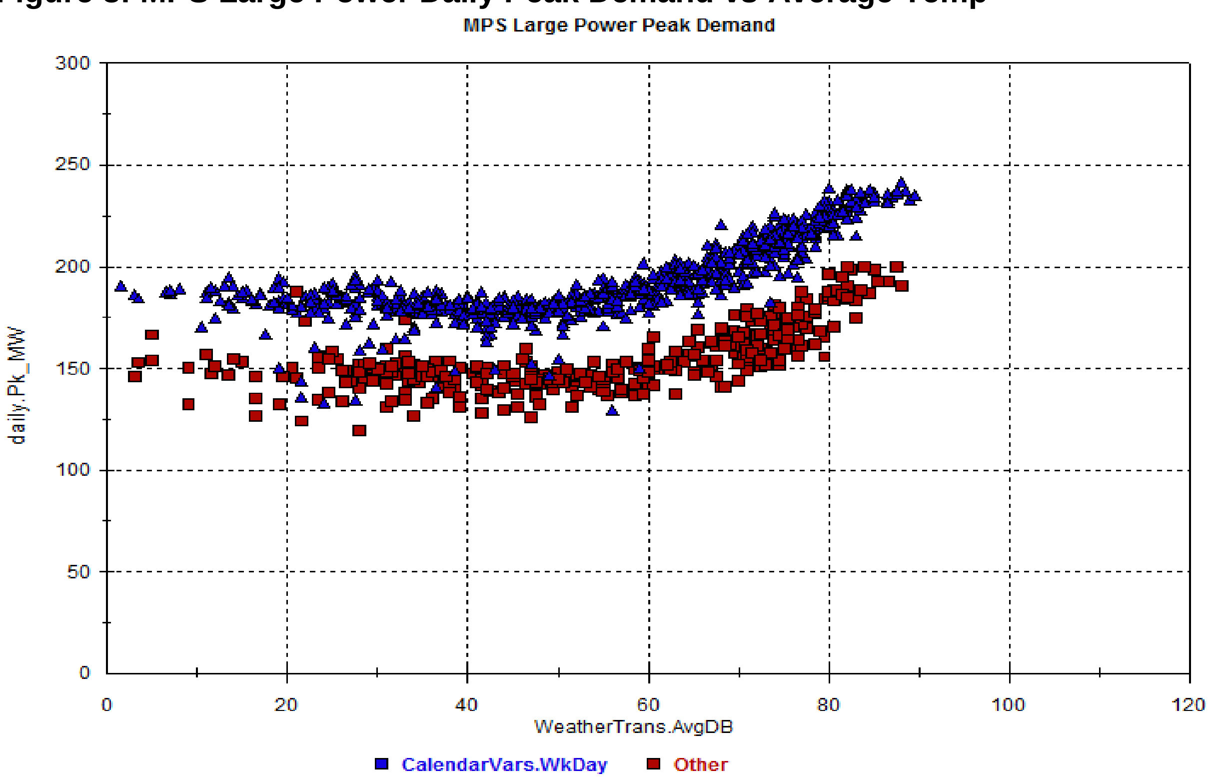


Figure 9: MPS Sales for Resale Daily Energy vs Average Temp

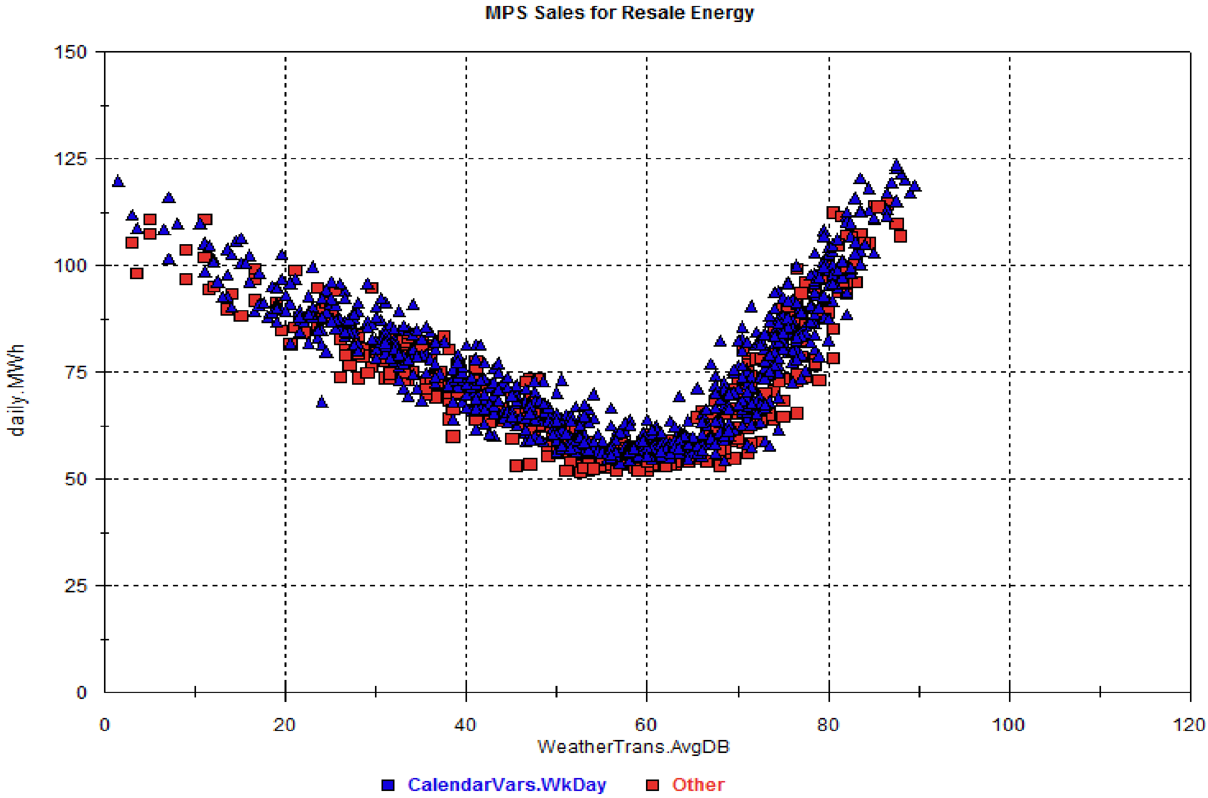


Figure 10: MPS Sales for Resale Daily Peak Demand vs Average Temp

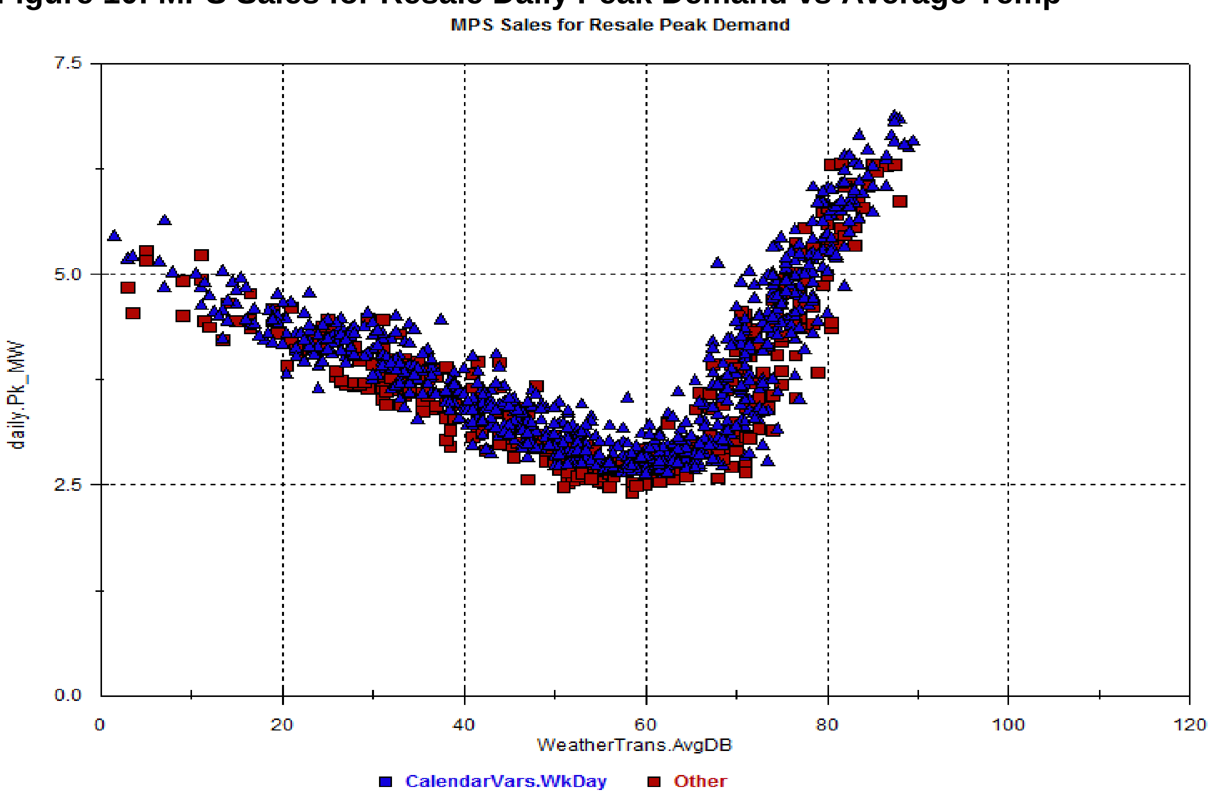


Figure 11: SJ Residential Daily Energy vs Average Temp

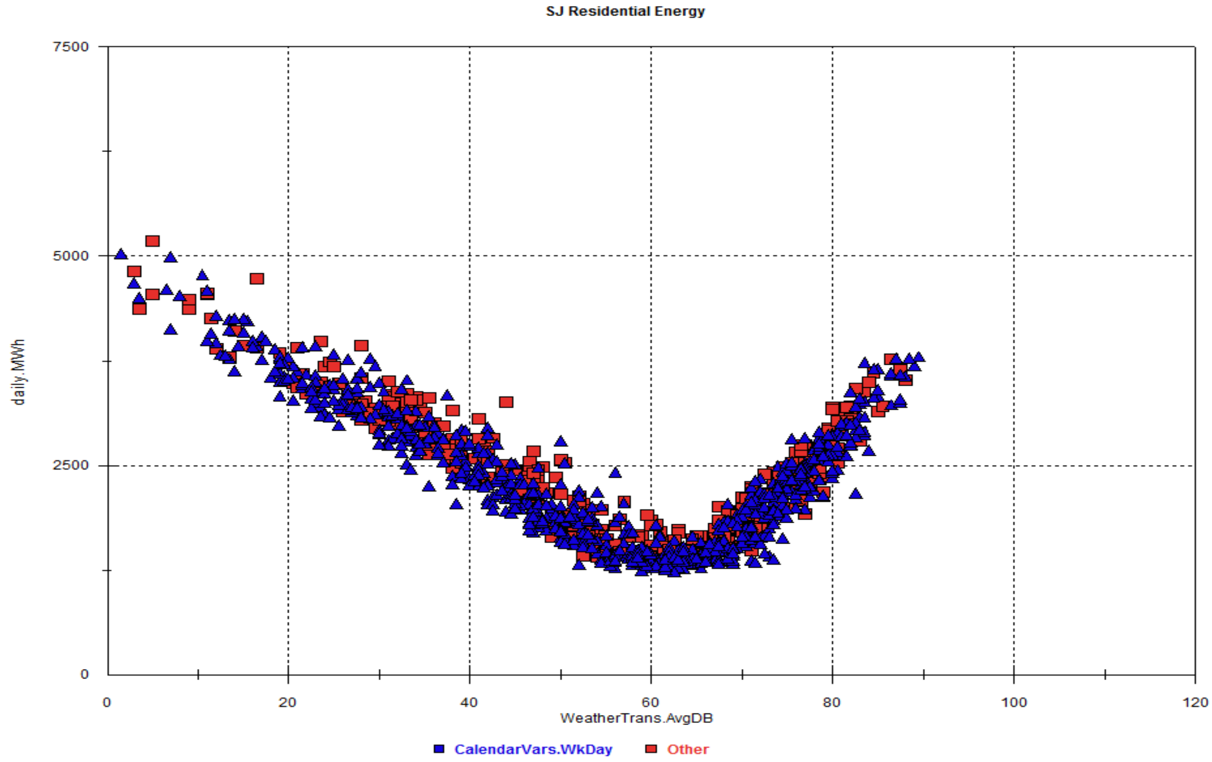


Figure 12: SJ Residential Daily Peak Demand vs Average Temp

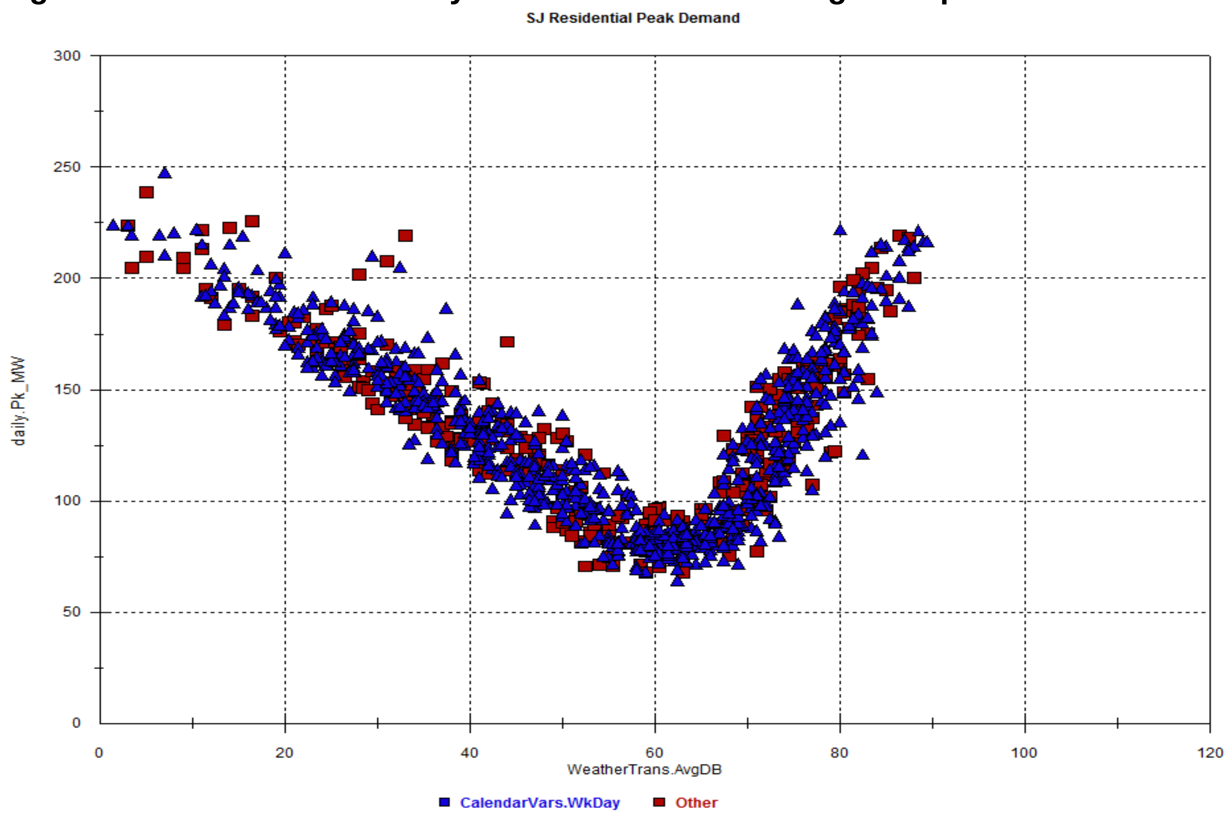


Figure 13: SJ Small General Service Daily Energy vs Average Temp

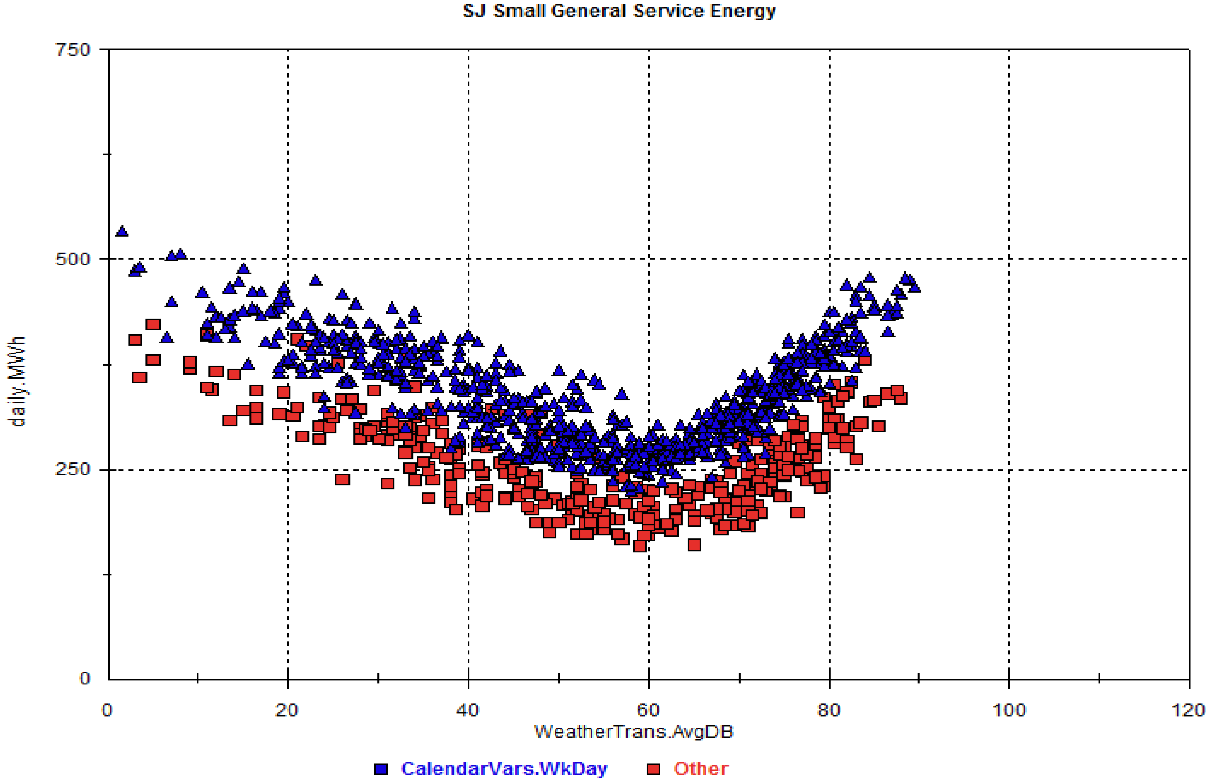


Figure 14: SJ Small General Service Daily Peak Demand vs Average Temp

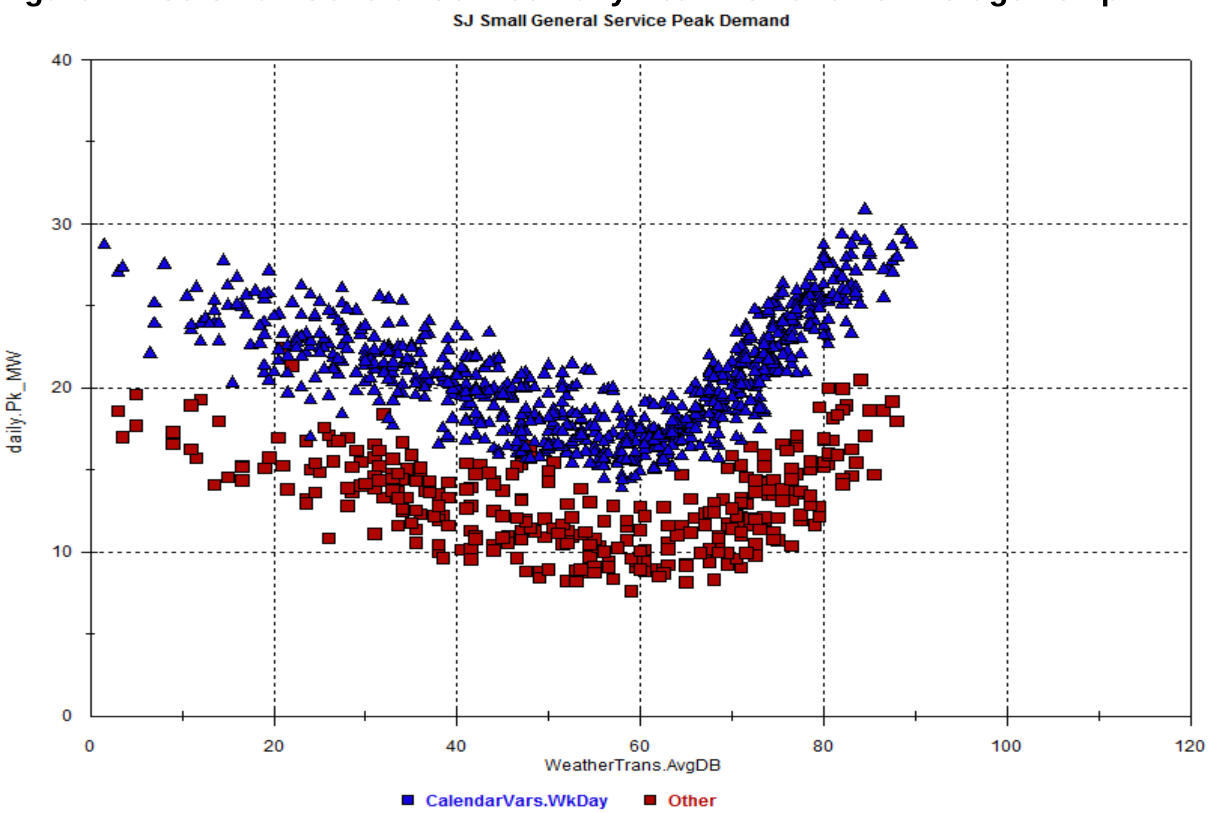


Figure 15: SJ Large General Service Daily Energy vs Average Temp

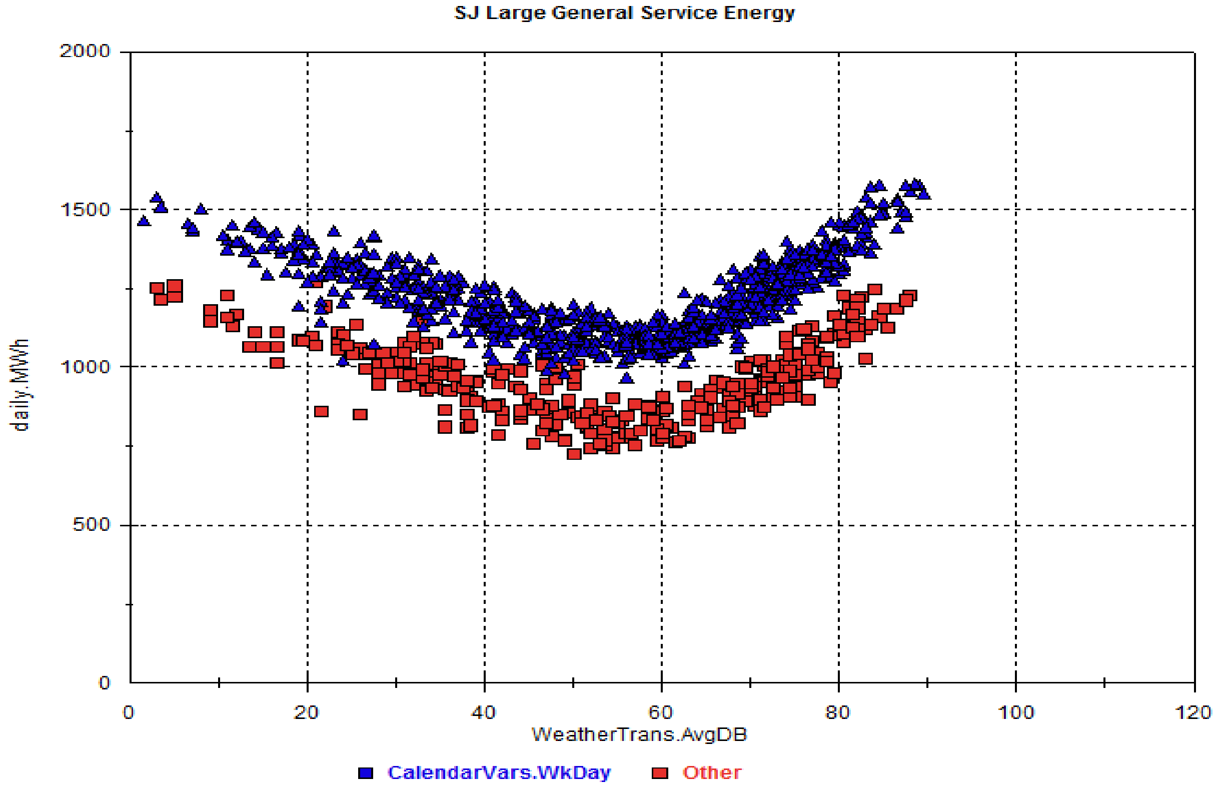


Figure 16: SJ Large General Service Daily Peak Demand vs Average Temp

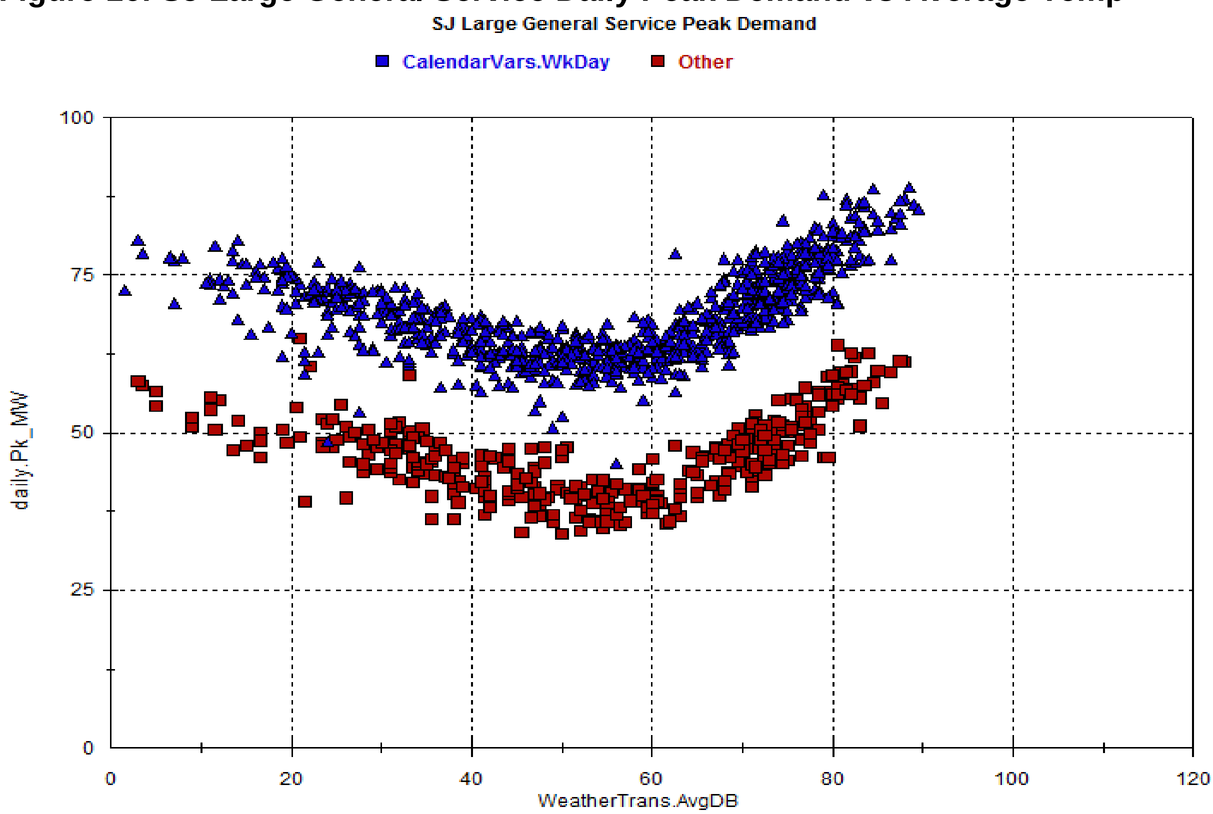


Figure 17: SJ Large Power Daily Energy vs Average Temp

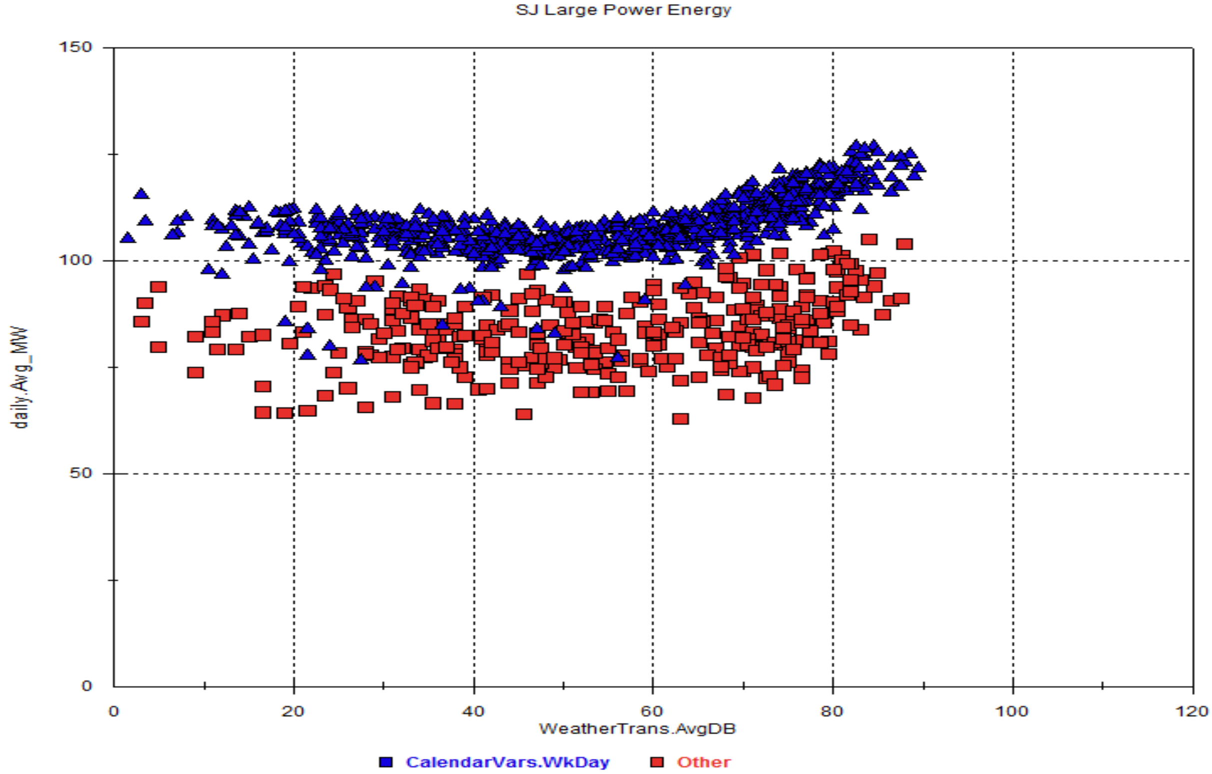
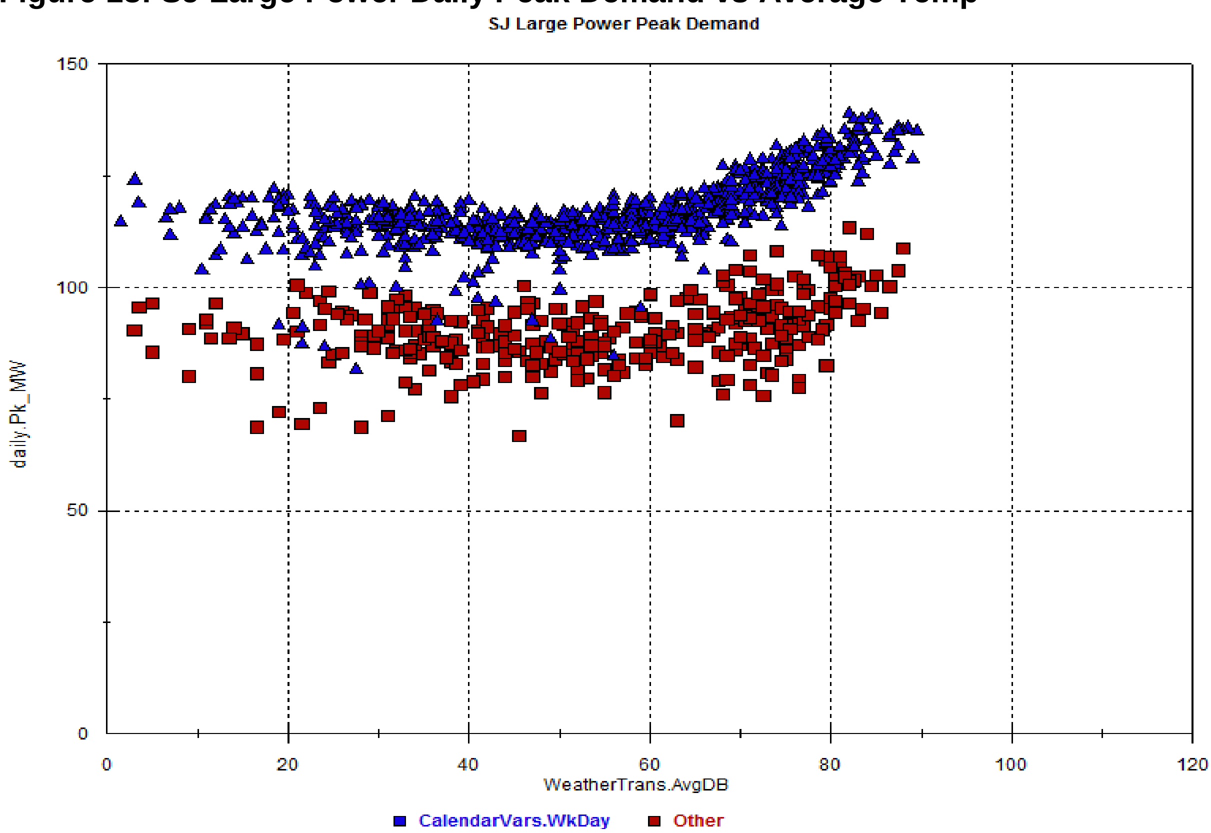


Figure 18: SJ Large Power Daily Peak Demand vs Average Temp



3. Plots illustrating trends materially affecting electricity consumption over the historical period;

Historical class plots of customers, kwh, average use and peak are provided in *Appendix3A1* and were discussed in the section for rule (2) (D) 1.

2.5 ADJUSTMENTS TO HISTORICAL DATA DESCRIPTION AND DOCUMENTATION

(E) The utility shall describe and document any adjustments that it made to historical data prior to using it in its development or interpretation of the forecasting models; and

GMO used binary variables in regression models to explain outliers rather than make adjustments to the data***.***

2.6 LENGTH OF HISTORICAL DATABASE

(F) Length of Historical Database. The utility shall develop and retain the historical database over the historical period.

For GMO, historical sales and customers broken out by class cost of service and commercial and industrial customers was available beginning in January 1994 for MPS and January 1996 for SJLP. Going forward, GMO will maintain this data for at least the previous 10 years.

SECTION 3: ANALYSIS OF NUMBER OF UNITS

For each major class, the utility shall describe and document its analysis of the historical relationship between the number of units and the economic and/or demographic factors (explanatory variables) that affect the number of units for that major class. The analysis may incorporate or substitute the results of secondary analyses, with the proviso that the utility analyze and verify the applicability of those results to its service territory. If the utility develops primary analyses, or to the extent they are available from secondary analyses, these relationships shall be specified as statistical or mathematical models that relate the number of units to the explanatory variables.

3.1 IDENTIFICATION OF EXPLANATORY VARIABLES

(A) Choice of Explanatory Variables. The utility shall identify appropriate explanatory variables as predictors of the number of units for each major class. The critical assumptions that influence the explanatory variables shall also be identified and documented.

A forecast of the number of households in the KC and SJ metro areas from Moody's Analytics was the driver for the number of residential customers of MPS and SJLP, respectively. The KC and SJ metro areas are the same as the Metropolitan Statistical Areas (MSA) defined by the US Census Bureau for KC and SJ and it includes some counties that are not served by GMO. Also, GMO's service areas includes some counties that are not included in the MSA. Despite these inconsistencies in geographic areas, the number of households in the metro areas is a good driver to predict the number of our residential customers because the metro areas each functions economically as a single entity and the metro areas includes the vast majority of our customers. Many people live on one side of the state line and work on the other side. Many people shop on both sides of the state line. And many companies each year move from one side of the state line to the other. Documentation for Moody's forecast of economic activity is provided in the workpapers in the folder *\models\GMO Base Case\Data\Economics*.

KCP&L tested the use of county level forecasts from Moody's several years ago, but saw no improvement in forecasting accuracy. This might be because it is difficult to forecast economic activity for a small geographic area, or because economic activity crosses county lines in the metro area.

The main driver for the number of small general service customers was the number of residential customers. This driver was chosen because it has worked well in the past and because most small commercial customers exist to serve households and these customers will increase in areas where there are new housing developments. Examples of small commercial customers that serve households are medical offices, grocery stores, drug stores, restaurants, churches, schools, hair salons, and movie theaters.

In the models for Large GS and Large Power commercial customers, both non-manufacturing employment and non-manufacturing gross metro product were tested as drivers and the one with the best fit was chosen. If neither was significant or had a positive coefficient, the driver was tested without a constant term in the model, and if still insignificant, a driver was not used.

3.2 STATISTICAL MODEL DOCUMENTATION

(B) Documentation of statistical models shall include the elements specified in subsection (2)(C) of this rule. Documentation of mathematical models shall include a specification of the functional form of the equations if the utility develops primary analyses, or to the extent they are available if the utility incorporates secondary analyses.

The following tables show the statistics for the variables in the regression models. Additional statistics and residual plots are available in the Metrix ND model files.

Table 15 MPS Residential Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
Economics.Households	272	10	26.3	0.00%
RUCust_CCOS.Jan05	-3,307	372	-8.9	0.00%
RUCust_CCOS.Mar05	3,434	429	8.0	0.00%
RUCust_CCOS.Apr05	1,721	429	4.0	0.01%
RUCust_CCOS.Jul08	1,167	372	3.1	0.20%
RUCust_CCOS.May10	-1,855	372	-5.0	0.00%
RUCust_CCOS.Dec07	1,753	372	4.7	0.00%
RUCust_CCOS.AugJul00	5,302	215	24.7	0.00%
RUCust_CCOS.Dec00	3,562	429	8.3	0.00%
RUCust_CCOS.Nov00	-3,376	429	-7.9	0.00%
RUCust_CCOS.Mar11	-373	372	-1.0	31.65%
AR(1)	0.99	0.00	249.0	0.00%

Table 16 MPS Small GS Commercial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	-19,941	11,021	-1.8	7.19%
ClassCustomers_CCOS.RU_Cust_CCOS	0.21	0.00	57.7	0.00%
SML_Customer.Apr00	1,119	198	5.6	0.00%
SML_Customer.Aug98	-115	198	-0.6	56.12%
SML_Customer.Feb02	-1,687	172	-9.8	0.00%
SML_Customer.Jan05	913	172	5.3	0.00%
SML_Customer.Mar00	-1,337	198	-6.8	0.00%
SML_Customer.Jul98	1,170	198	5.9	0.00%
AR(1)	0.995	0.009	115.9	0.00%

Table 17 MPS Large GS Commercial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
Economics.GP_Non_Man	0.016	0.002	7.2	0.00%
LRG_Customer.Apr05	460	14	33.0	0.00%
LRG_Customer.Apr00	50	16	3.1	0.20%
LRG_Customer.Mar00	-90	16	-5.6	0.00%
LRG_Customer.Aug00	56	14	4.0	0.01%
AR(1)	0.99	0.01	96.1	0.00%

In the model for Large GS commercial customers of MPS, the intercept term was dropped so that an economic driver would be statistically significant.

Table 18 MPS Large Power Commercial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	-131	18	-7.3	0.00%
Economics.GP_Non_Man	0.0030	0.0000	11.1	0.00%
LP_Customer.Apr05	54.54	2.57	21.2	0.00%
LP_Customer.Mar10	8.20	2.39	3.4	0.07%
LP_Customer.Feb01	-11.19	2.35	-4.8	0.00%
LP_Customer.Sept10	-5.69	2.38	-2.4	1.76%
LP_Customer.May00	-5.29	2.38	-2.2	2.73%
LP_Customer.LagDep(1)	-0.12	0.04	-3.2	0.17%
AR(1)	0.948	0.023	40.5	0.00%

Table 19 MPS Small GS Industrial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
SML_Customer.Apr05	27.4	1.2	22.6	0.00%
SML_Customer.Apr06	-4.10	1.21	-3.4	0.09%
SML_Customer.Feb02	-10.44	1.21	-8.6	0.00%
Economics.Emp_Man	0.44	0.02	21.0	0.00%
year<2008	5.24	1.54	3.4	0.08%
AR(1)	0.92	0.03	33.0	0.00%

Table 20 MPS Large GS Industrial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
Economics.Emp_Man	0.75	0.02	31.6	0.00%
LRG_Customer.Apr05	30.39	1.43	21.3	0.00%
LRG_Customer.Feb02	-11.36	1.43	-8.0	0.00%
LRG_Customer.Sep98	-8.00	1.43	-5.6	0.00%
LRG_Customer.Jul99	3.06	1.43	2.1	3.32%
LRG_Customer.Mar00	-6.95	1.43	-4.9	0.00%
AR(1)	0.93	0.02	39.0	0.00%

Table 21 MPS Large Power Industrial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	29.1	4.2	6.9	0.00%
Economics.Emp_Man	0.28	0.05	5.5	0.00%
LP_Customer.Apr05	29.1	2.0	14.3	0.00%
LP_Customer.Feb01	-15.3	2.0	-7.5	0.00%
LP_Customer.Mar10	4.2	2.0	2.0	4.34%
LP_Customer.Jul02	7.8	2.0	3.9	0.02%
LP_Customer.Jun03	7.4	2.0	3.6	0.04%
LP_Customer.May02	8.0	2.0	3.9	0.01%
LP_Customer.Mar00	-12.4	2.2	-5.7	0.00%
LP_Customer.Feb00	-7.6	2.2	-3.5	0.07%
AR(1)	0.37	0.08	4.4	0.00%

Table 22 SJLP Residential Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
Economics.Households	272	10	26.3	0.00%
RUCust_CCOS.Jan05	-3,307	372	-8.9	0.00%
RUCust_CCOS.Mar05	3,434	429	8.0	0.00%
RUCust_CCOS.Apr05	1,721	429	4.0	0.01%
RUCust_CCOS.Jul08	1,167	372	3.1	0.20%
RUCust_CCOS.May10	-1,855	372	-5.0	0.00%
RUCust_CCOS.Dec07	1,753	372	4.7	0.00%
RUCust_CCOS.AugJul00	5,302	215	24.7	0.00%
RUCust_CCOS.Dec00	3,562	429	8.3	0.00%
RUCust_CCOS.Nov00	-3,376	429	-7.9	0.00%
RUCust_CCOS.Mar11	-373	372	-1.0	31.65%
AR(1)	0.99	0.00	249.0	0.00%

Table 23 SJLP Small GS Commercial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	3,086	646	4.8	0.00%
ClassCustomers_CCOS.RU_Cust_CCOS	0.052	0.011	4.6	0.00%
SML_Customer.Apr05	762	147	5.2	0.00%
SML_Customer.Feb02	-94	21	-4.5	0.00%
SML_Customer.Jul04	113	21	5.4	0.00%
SML_Customer.Jul08	-83	21	-3.9	0.01%
SML_Customer.May01	78	21	3.7	0.03%
SML_Customer.Jan08	51	24	2.1	3.57%
Year<2009	-64	28	-2.3	2.39%
AR(1)	0.94	0.03	36.6	0.00%

Table 24 SJLP Large GS Commercial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
Economics.Emp_NonMan	23	0	86.8	0.00%
LRG_Customer.Apr05	474	6	80.8	0.00%
LRG_Customer.Nov06	-22	6	-3.8	0.02%
LRG_Customer.Jan00	11	6	1.9	6.01%
LRG_Customer.feb06	12	7	1.8	6.92%
LRG_Customer.mar06	18	7	2.6	0.95%
AR(1)	0.951	0.022	43.4	0.00%

Table 25 SJLP Large Power Commercial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	-21.8	6.6	-3.3	0.11%
Economics.GP_Non_Man	0.015	0.002	7.7	0.00%
LP_Customer.Apr05	11.4	1.1	10.8	0.00%
LP_Customer.Dec03	5.6	1.2	4.6	0.00%
LP_Customer.Jan08	-5.0	1.1	-4.7	0.00%
Year<2009	-3.1	1.2	-2.5	1.28%
LP_Customer.Nov03	-3.7	1.2	-3.1	0.25%
LP_Customer.Jan03	-2.6	1.1	-2.5	1.35%
LP_Customer.Jan02	-3.0	1.1	-2.8	0.51%
AR(1)	0.84	0.05	18.3	0.00%

Table 26 SJLP Small GS Industrial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	0.028	0.017	1.6	10.50%
AR(1)	0.973	0.014	69.0	0.00%

SJLP has only one small industrial customer, so a simple model was used to forecast the number of customers for this class.

Table 27 SJLP Large GS Industrial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	81.9	3.6	22.8	0.00%
LRG_Customer.Apr05	26.3	1.8	14.6	0.00%
LRG_Customer.Sep07	7.6	1.8	4.2	0.01%
LRG_Customer.Oct08	-6.3	1.8	-3.5	0.07%
Economics.Emp_Man	-2.3	0.4	-6.1	0.00%
AR(1)	0.7	0.1	10.8	0.00%

Table 28 SJLP Large Power Industrial Customers

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	33.8	2.5	13.6	0.00%
Economics.Emp_Man	0.55	0.23	2.4	2.00%
LP_Customer.Apr05	25.5	1.3	19.9	0.00%
LP_Customer.Sept07	7.9	1.3	6.2	0.00%
LP_Customer.Aug10	4.2	1.3	3.2	0.19%
LP_Customer.Apr11	-4.5	1.3	-3.5	0.08%
LP_Customer.Mar09	3.5	1.3	2.8	0.73%
Year<2009	-2.2	0.7	-3.2	0.19%
AR(1)	0.51	0.10	5.0	0.00%

SECTION 4: USE PER UNIT ANALYSIS

For each major class, the utility shall describe and document its analysis of historical use per unit by end use.

4.1 <u>END-USE LOAD DETAIL</u>

(A) End-Use Load Detail. For each major class, use per unit shall be disaggregated, where information permits, by end-uses that contribute significantly to energy use or peak demand.

4.1.1 <u>END-USE LOAD INFORMATION</u>

1. The utility shall consider developing information on at least the following end-use loads:

4.1.1.1 <u>Residential Sector</u>

A. For the residential sector: lighting, space cooling, space heating, ventilation, water heating, refrigerators, freezers, cooking, clothes washers, clothes dryers, television, personal computers, furnace fans, plug loads, and other uses;

The list of residential enduses for which GMO maintains the number of units and energy use per unit include electric furnaces, heat pumps with electric resistance backup, heat pumps with natural gas backup, ground source heat pumps, central air conditioning without a heat pump, window or wall AC units, electric water heaters, electric ovens, cook tops and ranges, full-sized refrigerators, small refrigerators and wine coolers, freezers, dishwashers, clothes washers, electric dryers, TVs, air cleaners, computers, video game systems, hot tubs, swimming pools, electric vehicles and miscellaneous uses.

4.1.1.2 <u>Commercial Sector</u>

B. For the commercial sector: space heat, space cooling, ventilation, water heat, refrigeration, lighting, office equipment, cooking equipment, and other uses; and

GMO maintains information on saturations per square foot of floor space and energy use per square foot (EUI) for enduses including heating, cooling, ventilation, electric water heating, electric cooking, refrigeration, outdoor lighting, indoor lighting, and office equipment and miscellaneous uses. In this filing, secondary data from the U.S. DOE for the West North Central region was adopted for both MPS and SJLP. The region includes the states of North Dakota, South Dakota, Minnesota, Iowa, Nebraska, Kansas and Missouri. The results are combined across building types using building type weights. The building types include assembly (theaters, libraries, churches etc.), education, food sales, food service, health care, lodging, small office, large office, mercantile/service, warehouse and other. This data is maintained in *ComIndices_MPS.xls* and *ComIndices_StJoe.xls*. The building types are defined in *2007 NAICS Index File-AEO commercial sectorrev.xls*. These spreadsheets were provided to GMO by Itron Inc. through the Energy Forecasting Group (EFG). The spreadsheets are documented in *2011_CommercialSAE.pdf*. These files are provided in the workpapers.

4.1.1.3 Industrial Sector

C. For the industrial sector: machine drives, space heat, space cooling, ventilation, lighting, process heating, and other uses.

GMO has a relatively small industrial sector, accounting for approximately 16% of retail sales. GMO lacks the concentration of heavy industry that some utilities have. As such, we have modeled our industrial sector with commercial sector drivers. Major enduses are heating, cooling and other.

4.1.2 MODIFICATION OF END-USE LOADS

2. The utility may modify the end-use loads specified in paragraph (4)(A)1.

4.1.2.1 Removal or Consolidation of End-Use Loads

A. The utility may remove or consolidate the specified end-use loads if it determines that a specified end-use load is not contributing, and is not likely to

contribute in the future, significantly to energy use or peak demand in a major class.

In the last few years, GMO has dropped several enduses from its residential survey including VCRs, DVD players, printers, fax machines, copier/scanners and attic fans since these do not contribute significantly to energy use or peak demand.

4.1.2.2 Additions to End-Use Loads

B. The utility shall add to the specified end-use loads if it determines that an end-use load currently not specified is likely to contribute significantly to energy use or peak demand in a major class.

GMO has recently added electric vehicles (including PHEVs) to our database. We are currently using DOE projections for this enduse and plan to add a question for this enduse on our next residential appliance saturation survey.

In our previous residential survey conducted in 2010, we added mini/wine refrigerators and video game systems and, in 2008, we added well pumps to the residential survey questionnaire.

4.1.2.3 Modification of End-Use Documentation

C. The utility shall provide documentation of its decision to modify the specified end-use loads for which information is developed, as well as an assessment of how the modifications can be made to best preserve the continuity and integrity of the end-use load database.

GMO dropped the enduses listed in the previous section A because VCRs, DVD players, printers, fax machines and copier/scanners are mainly plug loads that do not contribute significantly to energy use. We added well pumps, video game systems and mini\wine refrigerators because these use substantial amounts of energy and we believed that these had a significant saturation in our service areas.

We added electric vehicles because these are likely to significantly impact our energy and peak load in the future based on various projections published in different studies. These studies are included in our workpapers.

4.1.3 SCHEDULE FOR ACQUIRING END-USE LOAD INFORMATION

3. For each major class and each end-use load, including those listed in paragraph (4)(A)1., if information is not available, the utility shall provide a schedule for acquiring this end-use load information or demonstrate that either the expected costs of acquisition were found to outweigh the expected benefits over the planning horizon or that gathering the end-use load information has proven to be infeasible.

GMO has chosen a contractor to conduct a DSM potential study that is scheduled for completion in 2013. This study will collect detailed end-use saturation and efficiency data from our customers in the residential, commercial and industrial sectors. GMO has provided copies of the contractor's proposal to the Stakeholders' group.

4.1.4 WEATHER EFFECTS ON LOAD

4. The utility shall determine the effect that weather has on the total load of each major class by disaggregating the load into its cooling, heating, and non-weather-sensitive components. If the cooling or heating components are a significant portion of the total load of the major class, then the cooling or heating components of that load shall be designated as enduses for that major class.

GMO used statistical regression analysis applied to the load research data to develop HELM like hourly load profiles for each month, for three different day types and for base, heating and cooling loads. The three day types are weekdays, weekends and peak days. Daily temperature was used in the regression models to identify the heating and cooling portions of the loads. The profiles were developed for each CCOS. The regressions were performed in Eviews with the program *createloadshapesccos.prg*. The data for Eviews was created in SPSS with the program *dataprep2007CCOS.SPS* which matches actual and normal temperatures to the hourly loads.

These load profiles are used in this IRP filing to allocated monthly base, heating and cooling energy to each hour of the month. These profiles are stored in *DTShapesGMOCCOS.mdb*.

4.2 END-USE DEVELOPMENT

(B) The database and historical analysis required for each end use shall be developed from a utility-specific survey or other primary data. The database and analysis may incorporate or substitute the results of secondary data, with the proviso that the utility analyze and verify the applicability of those results to its service territory. The database and historical analysis required for each end use shall include at least the following:

4.2.1 MEASURES OF THE STOCK OF ENERGY-USING CAPITAL GOODS

1. Measures of the stock of energy-using capital goods. For each major class and end-use load identified in subsection (4)(A), the utility shall implement a procedure to develop and maintain adequate data on the energy-related characteristics of the building, appliance and equipment stock including saturation levels, efficiency levels, and sizes, where applicable. The utility shall update the data before each triennial compliance filing; and

GMO has conducted a residential appliance saturation survey every other year since its acquisition by KCP&L. The surveys have been conducted by mail. The last survey was conducted in the first half of 2010. Questionnaires were sent to 2,500 households in each jurisdiction and 803 and 857 responses were received from customers of MPS and SJLP. The survey responses were matched with each customers' billing records for the previous 12 months and with heating and cooling degree days computed for the billing period and the combined data was used in a conditional demand study to estimate the energy used by each type of appliance.

In addition, GMO has chosen a contractor to conduct a DSM potential study that is scheduled for completion in 2013. This study will collect detailed end-use saturation and efficiency data from our customers in the residential, commercial and industrial sectors. GMO has provided copies of the contractor's proposal to the Stakeholders' group.

4.2.2 END-USE ENERGY AND DEMAND ESTIMATES

2. Estimates of end-use energy and demand. For the end-use loads identified in subsection (4)(A), the utility shall estimate monthly energies and demands at the time of monthly system peaks and shall calibrate these energies and demands to equal the weather-normalized monthly energies and demands at the time of monthly peaks for each major class for the most recently available data.

Monthly energies for the enduses that are included in our SAE models are calibrated in the SAE models to monthly billed sales for each CCOS. The coefficients for the base, heating and cooling loads calibrate those loads and the coefficient for the base load raises or lowers all the components of the base load when the base load is calibrated to monthly billed sales.

Monthly demand for the major enduses that are included in our SAE models are calibrated to the time of the monthly system peaks. This is done in the models by taking the hourly system demands and matching them to the hourly class enduse demands. This computes the coincident peak by class and enduse. To calibrate class enduse demands to the weather normalized system peak, the system peak and weather normalized peaks are used to develop a calibration factor that is applied to each class and enduse. This process is done for both MPS and SJLP. This process is completed in an Excel worksheet which is provided in the workpapers.

SECTION 5: SELECTING LOAD FORECASTING MODELS

The utility shall select load forecast models and develop the historical database needed to support the selected models. The selected load forecast models will include a method of end-use load analysis for at least the residential and small commercial classes, unless the utility demonstrates that end-use load methods are not practicable and provides documentation that other methods are at a minimum comparable to end-use methods. The utility may choose multiple models and methods if it deems doing so is necessary to achieve all of the purposes of load forecasting and if the methods and models are consistent with, and calibrated to, one another. The utility shall describe and document its intended purposes for load forecast models, why the selected load forecast models best fulfill those purposes, and how the load forecast models are consistent with one another and with the end-use usage data used in the demand-side analysis as described in 4 CSR 240-22.050. As a minimum, the load forecast models shall be selected to achieve the following purposes:

5.1 CONSUMPTION DRIVERS AND USAGE PATTERNS

(A) Assessment of consumption drivers and customer usage patterns—to better understand customer preferences and their impacts on future energy and demand requirements, including weather sensitivity of load;

GMO uses the Statistically Adjusted End-use (SAE) method to forecast energy sales and demand for all classes except lighting and sales for resale. The SAE method creates a forecast of sales at the end-use level and then for each class aggregates the forecasts into base, heating and cooling energy and then calibrates these loads to monthly billed sales using statistical regressions. The SAE models were designed and are supported by staff at Itron Inc. This same staff used to support the end-use models REEPS, COMMEND and INFORM for EPRI.

Our end-use level forecasts are developed using both primary data collected by GMO and secondary data and projections produced by the U.S. Department of Energy (DOE) for the West North Central region of the U.S. DOE projections used in our models include projections of saturations for household appliances and equipment used in commercial buildings and projections of efficiencies for appliances, buildings and equipment. DOE has a large professional staff that is responsible for constructing and maintaining energy demand models and for managing contractors. The contractors survey households, businesses and buildings on a regular schedule. Contractors are also used to conduct special studies. DOE's projections are designed to account for changes in consumer preferences, technology and building design practices. Their projections also account for the impacts of appliance and equipment standards. DOE updates its projections at least once a year and we use the most recently available projections whenever we update our models.

GMO calibrates DOE appliance saturation projections to the saturation numbers that we obtain from our residential surveys. We also calibrate DOE's projections of unit energy consumption (UEC) for appliances to the results of our conditional demand study.

Itron hosts an annual meeting for the Energy Forecasting Group (EFG), which supports utilities that use the SAE method to forecast their sales. DOE staff attends the meeting of the EFG (which we attend) to explain changes in the assumptions, data and methods that have occurred during the previous year. Their slide decks provided during these meetings for the past several years are included in our workpapers. On their website, DOE provides detailed documentation and computer code for their models and assumptions.

5.2 LONG-TERM LOAD FORECASTS

(B) Long-term load forecasts—to serve as a basis for planning capacity and energy service needs. This can be served by any forecasting method or methods that produce reasonable projections (based on comparing model projections of loads to actual loads) of future demand and energy loads;

GMO believes that the SAE methodology is the best available for producing our load forecasts. REEPS, COMMEND and INFORM are no longer supported and never were supported as well as the DOE projections. DOE forecasts the impacts of all appliance and equipment standards most of which will substantially increase efficiency.[i] DOE also models trends in appliance ownership and utilization. For example, they have a model that tracks ownership of HDTV by technology and this model was updated this year:

> AEO 2011 also includes updated modeling of TVs. In particular, EIA aligns its projections more closely with the data coming from Energy Star savings calculators and with actual product availability. More efficient new televisions combined with higher penetration of Energy Star products and the phase out of CRT (Cathode Ray Tube) televisions results in substantial downward adjustment in UEC projections.[ii]

Other changes for 2011 include:

> AEO 2011 includes new consensus agreements between efficiency advocates and equipment/appliance manufacturers for a number of products including room air conditioners, dishwashers, clothes washers and dryers, refrigerators and freezers. These agreements provide EIA with a reasonable efficiency level to expect in future rulemakings by the Department of Energy (DOE) and are modeled as expected efficiency standards. This translates into stronger efficiency projections for the appliances in question and impacts energy usage for a number of end-uses. More information on the consensus agreements can be found here - http://www.aham.org/ht/a/GetDocumentAction/i/49956 .
>
> In addition to these standards, AEO 2011 also incorporates 2010 DOE rulemaking for water heaters. This new standard singled out water heaters above 55 gallon capacity for extra efficiency gains. For more information on this ruling, please see the following - http://www1.eere.energy.gov/buildings/appliance_standards/residential/pdfs/htgp_finalrule_fedreg.pdf .
>
> In addition to stronger efficiency growth projection, clothes dryer energy usage was impacted by benchmarking to the most recent data. This change is the result of DOE analysis that lowered the estimated number of loads per year from 322 to 215 thus significantly lowering the starting usage estimates. In addition, it was found that most modern clothes washers have a longer and/or more effective spinning cycle, resulting in laundry that is less wet and reducing the amount of

moisture for the dryers to remove. These results translate into a substantial downward shift in clothes dryer energy usage on top of efficiency improvements.

The structural index reflects both improvements in thermal shell efficiency and changing housing square footage. Changes in the structural index drive heating and cooling use through its interaction with the heating and cooling efficiency and saturation trends. Thermal shell efficiency is slightly stronger in the 2011 forecast reflecting EIA's assumption that recent efficiency measures (including ARRA) result in somewhat stronger adoption of home insulation and highly efficient windows.

5.3 POLICY ANALYSIS

(C) Policy analysis—to assess the impact of legal mandates, economic policies, and rate designs on future energy and demand requirements. The utility may use any load forecasting method or methods that it demonstrates can adequately analyze the impacts of legal mandates, economic policies, and rate designs.

GMO believes that the SAE approach is the best available method to incorporate the impacts of appliance and equipment efficiency standards because the DOE is the best qualified institution to estimate these impacts. DOE will also incorporate any federal legal impacts into its forecasts. For example, DOE has incorporated CAFÉ regulations into its forecasts of electric vehicle unit sales, which in turn impacts kWh sales for recharging EVs.

Table 29 Products Covered by DOE Standards[iii]

Covered Product Categories		
Lighting Products: • 3-Way Incandescent Lamp • Candelabra base incandescent lamp • Ceiling Fan Light Kits • Ceiling Fans • Fluorescent lamp ballasts • General Service Fluorescent Lamps • General Service Incandescent Lamps • Incandescent Reflector Lamps • Intermediate Base Incandescent Lamps • Light Emitting Diodes (LEDs) • Medium Base Compact Fluorescent Lamps • Organic Light Emitting Diodes (OLEDs) • Rough Service Lamp • Shatter-Resistant Lamp • Torchieres • Vibration Service Lamp • Mercury Vapor Lamp Ballasts • Metal Halide Lamp Ballast • Metal Halide Lamp Fixtures • High-intensity discharge lamps • Traffic Signal Modules and Pedestrian Modules • Illuminated Exit Signs	**Heating Products:** Residential: • Direct heating equipment • Furnace Fans • Furnaces • Mobile Home Furnace • Pool heaters (Gas Fired) • Residential Boilers • Residential Water heaters • Small Furnaces Commercial: • Commercial warm air furnaces • Packaged boilers • Storage water heaters, instantaneous water heaters, and unfired hot water storage tanks • Unit Heaters	**Space Cooling Products:** Residential: • Central Air Conditioners and Central Air Conditioning Heat Pumps • Room Air Conditioners Commercial: • Packaged terminal air conditioners and packaged terminal heat pumps • Single package vertical air conditioners and single package vertical heat pumps • Small commercial package air conditioning and heating equipment • Large commercial package air conditioning and heating equipment • Very large commercial package air conditioning and heating equipment

Table 30 Products Covered by DOE Standards, continued

Covered Product Categories		
Commercial Refrigeration Products: • Automatic commercial ice makers • Commercial refrigerators, freezers, and refrigerator-freezers • Refrigerated Beverage Vending Machines • Walk-in coolers and walk-in freezers	**Appliances:** Residential: • Clothes dryers • Dehumidifiers • Dishwashers • Kitchen ranges and ovens • Microwave ovens • Refrigerators, Freezers and Refrigerator-Freezers • Residential Clothes washers Commercial: • Commercial clothes washers	**Computers and Electronics:** • Battery Chargers • External Power Supplies, Class A and non-Class A • Television sets
Transformers and Motors: • Electric Motors (medium to large) • Small Electric Motors • Distribution Transformers, MV Dry and Liquid-Immersed	**Plumbing Products:** Residential: • Faucets • Showerheads (except safety shower showerheads) • Urinals • Water closets Commercial: • Commercial Pre-rinse Spray Valves	**Building Products** • None

SECTION 6: LOAD FORECASTING MODEL SPECIFICATIONS

6.1 <u>DESCRIPTION AND DOCUMENTATION</u>

(A) For each load forecasting model selected by the utility pursuant to section 4 CSR 240-22.030(5), the utility shall describe and document its—

6.1.1 DETERMINATION OF INDEPENDENT VARIABLES

1. Determination of appropriate independent variables as predictors of energy and peak demand for each major class. The critical assumptions that influence the independent variables shall also be identified.

In the models of residential use per customer, the independent variables were appliance saturations, appliance UECs, the real price of electricity, real per capita income and persons per household. The appliance saturations and UEC forecasts were adopted from DOE's forecast for the west north central region. The critical assumptions influencing the forecasts of saturations and UECs are discussed in *m067(2010).pdf*, which is supplied in the electronic workpapers and which describes the model assumptions, computational methodology, parameter estimation techniques, and FORTRAN source code. These forecasts incorporate appliance ownership trends, trends in efficiency, updated building standards and technological change.

The forecasts of real per capita income and persons per household were produced by Moody's analytics for the KC and SJ metro areas. Moody's documents its assumptions in *macromodel.pdf*, *state-model-methodology.pdf* and *assum_metro_midwest.pdf*, which are supplied in the workpapers. These independent variables were used to construct an end-use forecast of residential use per customer for three major enduses: heating, cooling and other, and these were then calibrated to monthly billed sales per customer in a linear regression. This is described in *Residential SAE Modeling Framework* in the file *Res2011SAEUpdate.pdf*.

In the models of commercial and industrial sales and use per customer, the independent variables were equipment saturations and EUIs, the real price of electricity and economic variables. Economic variables were non-manufacturing employment or non-manufacturing GMP or manufacturing employment or manufacturing GMP. The forecasts from DOE incorporate trends in equipment saturations, equipment efficiencies, equipment standards, building standards and technological change. These independent variables were used to construct an end-use forecast of commercial use for three major enduses: heating, cooling and other, and these were then calibrated to monthly billed sales or sales per customer in a linear regression. This is described in *Commercial Statistically Adjusted End-Use Model* in the file *2011_CommercialSAE.pdf*.

A. The utility shall assess the applicability of the historical explanatory variables pursuant to subsection (3)(A) to its selected forecast model.

The explanatory variables used by GMO in its forecasting models incorporate the most important drivers of energy use. These drivers are energy standards, building standards, trends in saturations and equipment efficiency, economic growth at the sector level and existing company energy efficiency and DSM programs.

B. To the extent that the independent variables selected by the utility differ from the historical explanatory variables, the utility shall describe and document those differences;

GMO has used the SAE approach since 2009 to forecast its loads. The economic drivers for the residential sector have been the number of households in the KC and SJ metro areas during this time period. This filing is the first time that GMO has modeled commercial and industrial sales at the CCOS level, so these models are new.

For this filing, we are using updated projections from DOE for 2011 and June 2011 vintage economic forecasts of the KC and SJ metro areas from Moody's Analytics.

2. Development of any mathematical or statistical equations comprising the load forecast models, including a specification of the functional form of the equations; and

Table 31 MPS Residential kWh per Customer

Variable	Coefficient	StdErr	T-Stat	P-Value
StrucVars.XHeat55_CCOS	2.50	0.07	36.2	0.00%
StrucVars.XCool65_CCOS	2.59	0.16	16.6	0.00%
StrucVars.XCool70_CCOS	-0.23	0.13	-1.8	7.39%
StrucVars.XOther_CCOS	0.88	0.02	55.7	0.00%
RUAvgUse_CCOS.Jan05	237	37	6.5	0.00%
RUAvgUse_CCOS.Apr05	17	36	0.5	64.08%
RUAvgUse_CCOS.Sept94	-103	37	-2.8	0.53%
Year<2009	-61	10	-6.3	0.00%
RUAvgUse_CCOS.Jan04	-110	36	-3.0	0.27%
AR(1)	0.27	0.07	3.8	0.02%

Table 32 MPS Small GS Commercial kWh per Customer

Variable	Coefficient	StdErr	T-Stat	P-Value
StrucVars.XHeat55_SML	1.61	0.14	11.5	0.00%
StrucVars.XCool55_SML	3.07	1.35	2.3	2.36%
StrucVars.XCool60_SML	2.19	1.11	2.0	4.90%
StrucVars.XOther_SML	0.94	0.02	45.8	0.00%
SML_AvgUse.Apr05	-560	82	-6.8	0.00%
SML_AvgUse.Jan05	433	83	5.2	0.00%
AR(1)	0.68	0.06	12.1	0.00%

Table 33 MPS Large GS Commercial kWh per Customer

Variable	Coefficient	StdErr	T-Stat	P-Value
StrucVars.XHeat55_LRG	0.63	0.11	5.5	0.00%
StrucVars.XCool55_LRG	4.35	0.17	25.2	0.00%
StrucVars.XOther_LRG	0.96	0.03	30.5	0.00%
LRG_AvgUse.Apr05	-17,730	2,151	-8.2	0.00%
LRG_AvgUse.Sep01	7,509	2,151	3.5	0.06%
LRG_AvgUse.Jan05	9,855	2,160	4.6	0.00%
LRG_AvgUse.Jan04	-10,399	2,170	-4.8	0.00%
Year<2009	4,338	1,475	2.9	0.36%
AR(1)	0.71	0.05	13.7	0.00%

Table 34 MPS Large Power Commercial kWh per Customer

Variable	Coefficient	StdErr	T-Stat	P-Value
StrucVars.XCool55_LP	40	2	23.8	0.00%
StrucVars.XOther_LP	11.14	0.10	111.5	0.00%
LP_AvgUse.Apr05	-180,378	33,289	-5.4	0.00%
LP_AvgUse.Nov01	249,250	33,790	7.4	0.00%
LP_AvgUse.Mar01	229,291	33,471	6.9	0.00%
LP_AvgUse.Jul00	217,071	33,802	6.4	0.00%
LP_AvgUse.Oct02	141,329	33,230	4.3	0.00%
LP_AvgUse.Mar00	128,790	33,319	3.9	0.02%
LP_AvgUse.Sep10	-120,068.69	33,426.34	-3.6	0.04%
LP_AvgUse.Feb10	135,389	33,579	4.0	0.01%
AR(1)	0.18	0.07	2.5	1.18%

Table 35 MPS Small GS Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	250,395	57,214	4.4	0.00%
StrucVars.XHeat55_SML	6.83	1.40	4.9	0.00%
StrucVars.XCool65_SML	9.97	1.55	6.4	0.00%
StrucVars.XOther_SML	0.07	0.07	1.0	34.08%
SML_Sales.Jul07	-53,039	30,110	-1.8	7.98%
SML_Sales.Dec05	-72,799	30,413	-2.4	1.77%
SML_Sales.May96	-172,549	30,227	-5.7	0.00%
SML_Sales.Apr95	-179,702	30,253	-5.9	0.00%
SML_Sales.Feb95	60,059.44	30,207.68	2.0	4.83%
SML_Sales.Oct98	146,370	30,148	4.9	0.00%
SML_Sales.Mar02	151,412	30,133	5.0	0.00%
AR(1)	0.92	0.03	34.8	0.00%

Table 36 MPS Large GS Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	2,904,212	806,863	3.6	0.05%
StrucVars.XCool55_LRG	178	26	6.7	0.00%
StrucVars.XOther_LRG	0.74	1.34	0.6	58.02%
LRG_Sales.Sep05	755,037	323,897	2.3	2.13%
LRG_Sales.Mar01	1,384,332	370,974	3.7	0.03%
LRG_Sales.Apr06	-629,670	320,837	-2.0	5.19%
LRG_Sales.May01	1,058,016	364,656	2.9	0.44%
Year<2008	1,443,155	147,353	9.8	0.00%
MA(1)	0.69	0.07	10.4	0.00%

Table 37 MPS Large Power Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	34,102,086	4,690,386	7.3	0.00%
StrucVars.XCool55_LP	1,263	196	6.4	0.00%
StrucVars.XOther_LP	33	8	4.3	0.00%
LP_Sales.Mar05	-17,937,020	3,380,914	-5.3	0.00%
LP_Sales.Feb10	10,110,894	3,354,512	3.0	0.29%
LP_Sales.Aug08	7,986,678	3,362,016	2.4	1.85%
LP_Sales.Sep05	-10,570,288	3,351,922	-3.2	0.19%
LP_Sales.Nov01	45,869,701	3,357,798	13.7	0.00%
LP_Sales.Apr94	28,786,856	3,362,113	8.6	0.00%
LP_Sales.Mar01	13,036,966	3,746,026	3.5	0.06%
LP_Sales.Feb01	-15,845,647	3,726,471	-4.3	0.00%
LP_Sales.Aug00	14,319,775	3,350,099	4.3	0.00%
LP_Sales.Dec00	9,172,040	3,744,861	2.4	1.52%
LP_Sales.Nov00	-11,893,811	3,747,480	-3.2	0.18%
Year<2008	-4,190,779	1,550,847	-2.7	0.75%
AR(1)	0.59	0.06	9.8	0.00%

Table 38 SJLP Residential kWh per Customer

Variable	Coefficient	StdErr	T-Stat	P-Value
StrucVars.XHeat55_CCOS	3.52	0.10	36.0	0.00%
StrucVars.XCool65_CCOS	2.03	0.05	42.9	0.00%
StrucVars.XOther_CCOS	0.88	0.02	37.5	0.00%
RUAvgUse_CCOS.Mar07	144	55	2.6	1.02%
RUAvgUse_CCOS.Dec07	-117	55	-2.1	3.53%
RUAvgUse_CCOS.Jun06	-106	55	-1.9	5.52%
RUAvgUse_CCOS.Jan05	227	55	4.1	0.01%
RUAvgUse_CCOS.Dec00	-206	55	-3.7	0.03%
BinaryVars.Apr	22	14	1.5	12.42%
Year<2009	-70	16	-4.3	0.00%
AR(1)	0.33	0.07	4.4	0.00%

Table 39 SJLP Small GS Commercial kWh per Customer

Variable	Coefficient	StdErr	T-Stat	P-Value
StrucVars.XHeat55_SML	7.0	0.5	14.4	0.00%
StrucVars.XCool60_SML	18.3	0.7	26.3	0.00%
StrucVars.XOther_SML	3.3	0.1	47.9	0.00%
SML_AvgUse.May01	486	61	8.0	0.00%
SML_AvgUse.Sep01	-540	59	-9.2	0.00%
SML_AvgUse.Jan04	-232	61	-3.8	0.02%
SML_AvgUse.Apr05	-277	61	-4.6	0.00%
SML_AvgUse.Jan05	209	61	3.4	0.08%
SML_AvgUse.Jan09	126	61	2.1	4.10%
BinaryVars.Jan	99	25	3.9	0.01%
BinaryVars.Feb	113	27	4.2	0.01%
BinaryVars.Mar	127	25	5.1	0.00%
BinaryVars.Apr	78	23	3.4	0.08%
BinaryVars.May	33	20	1.7	9.59%
AR(1)	0.61	0.06	9.9	0.00%

Table 40 SJLP Large GS Commercial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
StrucVars.XHeat50_LRG	4,584	543	8.4	0.00%
StrucVars.XCool60_LRG	21,570	998	21.6	0.00%
StrucVars.XOther_LRG	6,793	147	46.1	0.00%
BinaryVars.Jan	-568,998	377,955	-1.5	13.40%
BinaryVars.Mar	208,286	296,613	0.7	48.35%
BinaryVars.Dec	-862,206	356,095	-2.4	1.65%
Year<2009	-1,298,450	472,784	-2.7	0.66%
AR(1)	0.50	0.07	7.4	0.00%

Table 41 SJLP Large Power Commercial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
StrucVars.XCool55_LP	16,456	1,738	9.5	0.00%
StrucVars.XOther_LP	7,942	216	36.8	0.00%
LP_Sales.Jan07	-4,522,651	1,735,717	-2.6	1.00%
LP_Sales.Jan08	-9,634,056	1,803,015	-5.3	0.00%
LP_Sales.Feb08	6,021,547	1,849,359	3.3	0.14%
LP_Sales.Jul08	-7,079,039	1,810,156	-3.9	0.01%
LP_Sales.Oct08	6,300,905	1,657,438	3.8	0.02%
LP_Sales.Mar06	4,967,953	1,658,830	3.0	0.32%
LP_Sales.Jun08	7,218,048	1,810,286	4.0	0.01%
(year+month/100)<2007.01	-9,151,641	766,474	-11.9	0.00%
Year<2009	-1,632,731	895,415	-1.8	7.00%
BinaryVars.Feb	793,144	435,009	1.8	7.00%
AR(1)	0.47	0.07	6.7	0.00%

Table 42 SJLP Small GS Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
StrucVars.XOther_SML	0.016	0.006	2.6	1.26%
SML_Sales.Feb09	-1,308	842	-1.6	12.53%
SML_Sales.Jun11	1,265	841	1.5	13.76%
SML_Sales.May06	-1,713	842	-2.0	4.64%
SML_Sales.Feb08	2,383	841	2.8	0.63%
SML_Sales.Apr07	-2,438	841	-2.9	0.52%
AR(1)	1.00	0.03	35.8	0.00%

Small industrial sales has only one customer.

Table 43 SJLP Large GS Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	3,126,656	371,387	8.4	0.00%
StrucVars.XHeat50_LRG	146	42	3.4	0.10%
StrucVars.XCool55_LRG	514	97	5.3	0.00%
StrucVars.XOther_LRG	8.1	3.0	2.7	0.91%
LRG_Sales.Feb05	736,665	222,413	3.3	0.15%
LRG_Sales.Sep08	805,188	196,944	4.1	0.01%
LRG_Sales.Jul08	-571,129	195,784	-2.9	0.48%
LRG_Sales.Jul11	-1,253,763	214,391	-5.8	0.00%
LRG_Sales.Jan11	-634,853	200,650	-3.2	0.23%
AR(1)	0.36	0.10	3.5	0.08%

Table 44 SJLP Large Power Industrial Sales

Variable	Coefficient	StdErr	T-Stat	P-Value
CONST	15,409,087	3,579,722	4.3	0.00%
StrucVars.XCool65_LP	2,585	659	3.9	0.01%
StrucVars.XOther_LP	230	28	8.2	0.00%
LP_Sales.Jun05	20,313,098	4,176,901	4.9	0.00%
LP_Sales.Dec01	15,593,785	4,153,912	3.8	0.02%
Year<2009	-2,324,801	978,212	-2.4	1.85%
AR(1)	0.044	0.075	0.6	55.95%

3. Assessment of the applicability of any load forecast models or portions of models that were utilized by the utility but developed by others, including a specification of the functional forms of any equations or models, to the extent they are available.

The load forecasting models rely on a forecast of economic activity for the KC and SJ metro areas that was produced by Moody’s Analytics. The metro areas are the same as the Metropolitan Statistical Area (MSA) defined by the US Census Bureau and it includes some counties in both states that are not served by GMO. Also, GMO's service area includes some counties that are not included in the MSA. Despite these inconsistencies in geographic areas, there are reasons why this forecast is representative of our service areas. Many people live on one side of the state line and work on the other side. Many people shop on both sides of the state line. And many companies each year move from one side of the state line to the other. Documentation for Moody's forecast of economic activity is provided in the workpapers in the folder \GMO Base Case\Data\Economics.

The load forecasting models also rely on saturation and appliance and equipment utilization forecasts from the DOE. The advantages of the projections from these models is 1) DOE's Forecasting and Analyst staff includes dozens of experts and maintains a large budget for data collection and consultants, 2) DOE has a focus on measuring the impacts of appliance and equipment standards and legal mandates and 3) DOE is very transparent, making available its work and computer code on its website.[iv] GMO also relies on the staff that developed and maintained some of EPRI's end-use models recommended and developed the SAE approach for GMO and many other utilities. EPRI no longer maintains its end-use forecasting models.

A potential downside of these projections for GMO is that the data and models developed by DOE are developed at a regional level rather than specifically for GMO, although this can be an advantage when one service area or region has insufficient variation to measure the impact of a variable such as electric price. Cross sectional variation in the data can be an advantage in situations where price or income elasticities are being modeled.

(B) If the utility selects load forecast models that include end-use load methods, the utility shall describe and document any deviations in the independent variables or functional forms of the equations from those derived from load analysis in sections (3) and (4).

GMO is not aware of any such deviations.

(C) Historical Database for Load Forecasting. In addition to the load analysis database, the utility shall develop and maintain a database consistent with and as needed to run each forecast model utilized by the utility. The utility shall describe and document its load forecasting historical database in the triennial compliance filings. As a minimum, the utility shall—

1. Develop and maintain a data set of historical values for each independent variable of each forecast model. The historical values for each independent variable shall be collected for a period of ten (10) years, or such period deemed sufficient to allow the independent variables to be accurately forecasted over the entire planning horizon;

The independent variables acquired from Moody's are available back to 1990. These are updated every time that GMO acquires a new economic and demographic forecast as revisions to this data far back in time are common.

The independent variables acquired from DOE are also available back to 1990 and these too replace the historical values when each year new spreadsheets are provided to GMO. New studies or data can revise historical estimates of efficiencies and saturations.

The independent variables for natural gas prices of local utilities are maintained back to 1991.

Temperature data is maintained back to 1971 when the Kansas City International Airport opened for business.

2. Explain any adjustments that it made to historical data prior to using it in its development of the forecasting models;

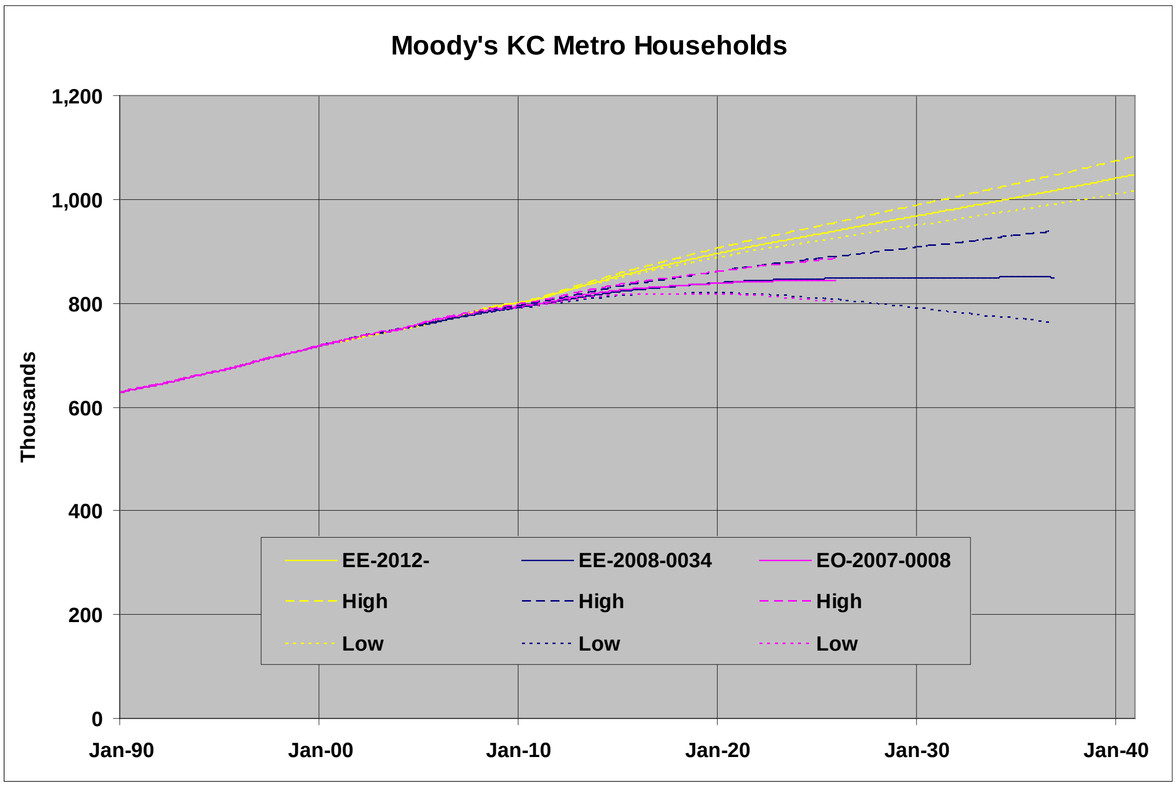
GMO staff is not aware of any adjustments made to independent variables used in its load forecasting models.

3. Archive previous projections of all independent variables used in the energy usage and peak load forecasts made in at least the past ten (10) years and provide

a comparison of the historical projected values in prior plan filings to actual historical values and to projected values in the current compliance filing; and

GMO still posses the electronic files that it received with the independent variables used in producing energy and peak forecasts during the last ten years. Below we plot the base, high and low bands for the most important economic and demographic independent variables used in the current and two previous IRP filings.

Figure 19: KC Households



When asked about the change in the household forecast that occurred with that used in this filing, Moody's responded

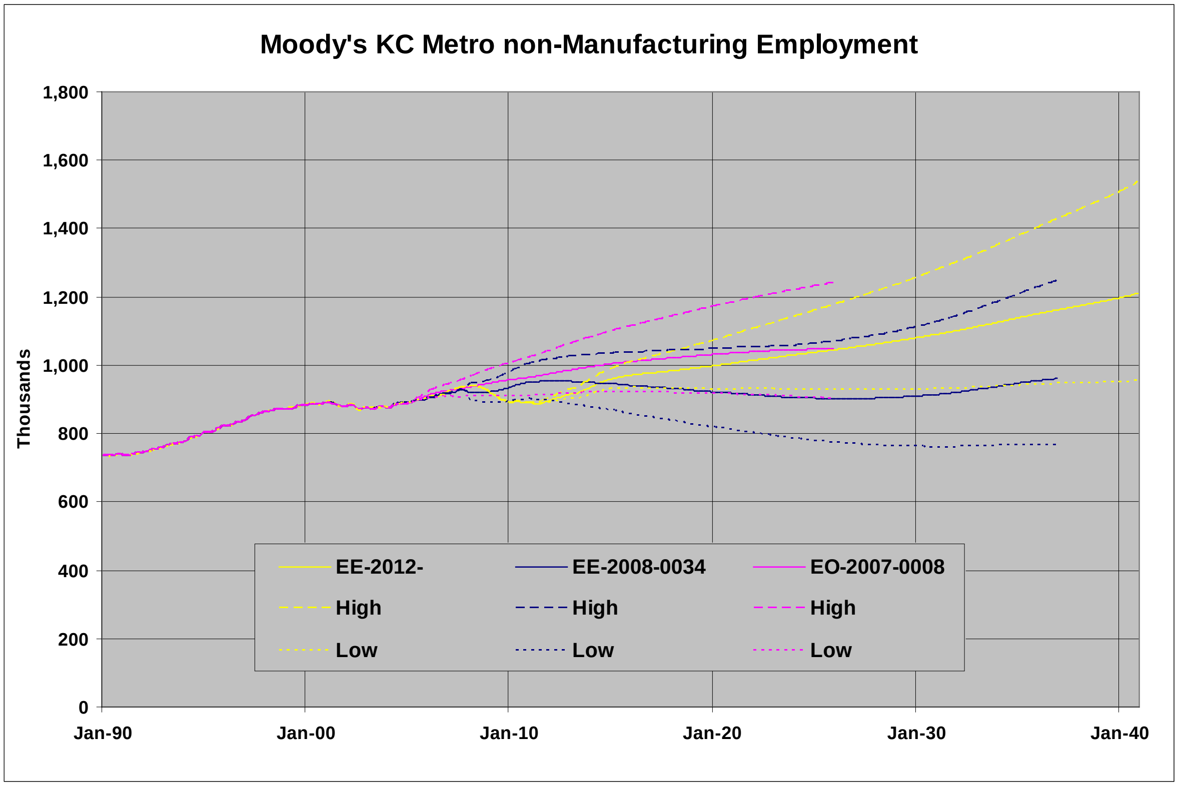
> "we view the metro area as having solid growth drivers that should enable population growth to outpace the nation. It has below average costs and an extremely diversified economy. Its workforce has an above average educational attainment when compared with the regional average, which will help it attract new businesses. In light of these characteristics, a severe decline in the rate of population growth beginning immediately in the forecast period simply couldn't be

> justified, hence the revisions. The changes in the household forecast follow directly from changes to population."[v]

The high and low bands for the current forecast are closer together compared to the two previous forecasts. We ask to explain, Moody's responded

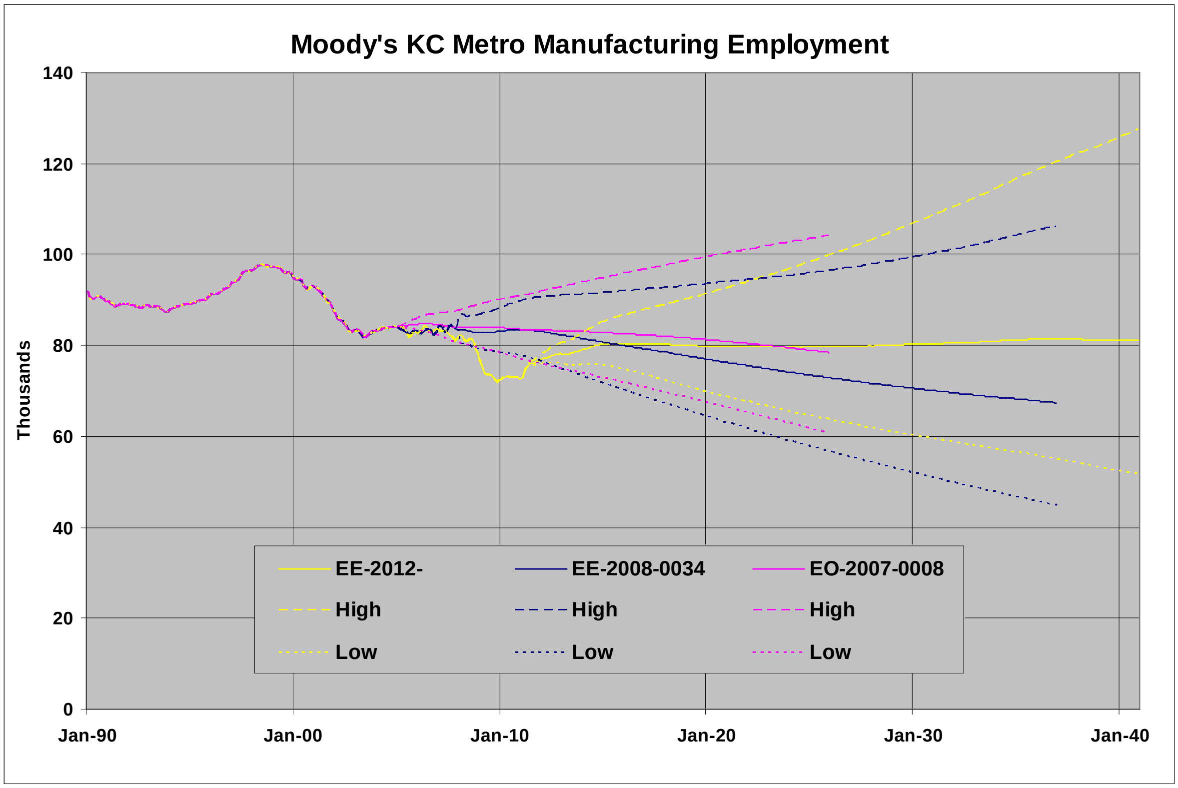
> "The different properties of the high/low bands I sent most recently are a result of the newer methodology I mentioned. Previously, your data delivery used a different, older methodology, but it will be migrated to the new one going forward. Since you requested an update of the households data, I used the new methodology since it will match what you will be receiving in the future.
>
> "The new methodology relies on the historical variation in the growth rates of the time series. Growth in households (both in general and for Kansas City) are quite consistent compared with many other economic time series. For KAN, quarterly growth has ranged only from about 0.1% and 0.7%, with a standard deviation of just over 0.1%. This is what is causing the high and low bands to have relatively small divergence. To illustrate slightly further: If households for KAN were 10% higher than the baseline in 2035, that would be equivalent to a quarterly growth rate about a full standard deviation higher than the baseline expectation in every single quarter. We view that as being too unlikely for the purposes of these high/low bands."[vi]

Figure 20: KC Employment Non-Manufacturing



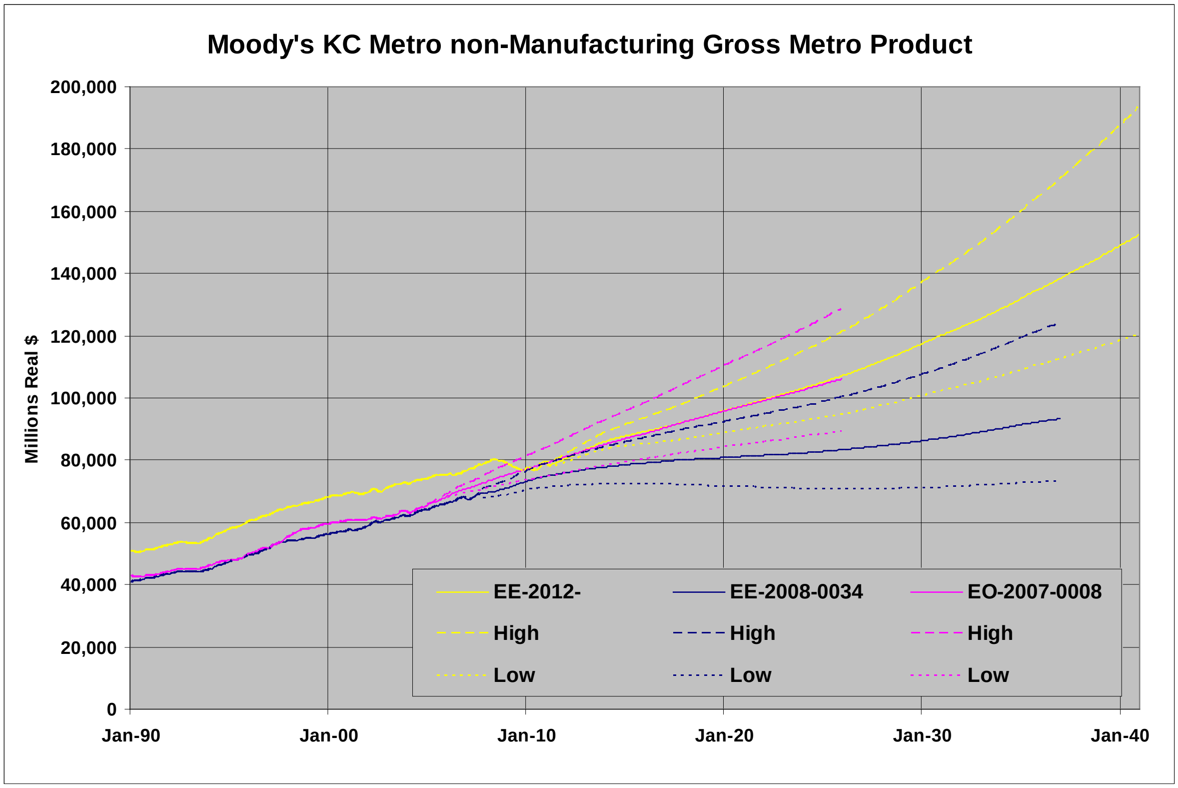
The current forecast of non-manufacturing employment shows a substantial drop during and several years after the last recession, then a rapid rebound and then steady robust growth. The previous forecast shows only a small drop and no increases until the mid 20s. The current forecast reflects a change in assumptions mentioned in the paragraph above for households for the competitiveness of the KC metro economy.

Figure 21: KC Employment Manufacturing



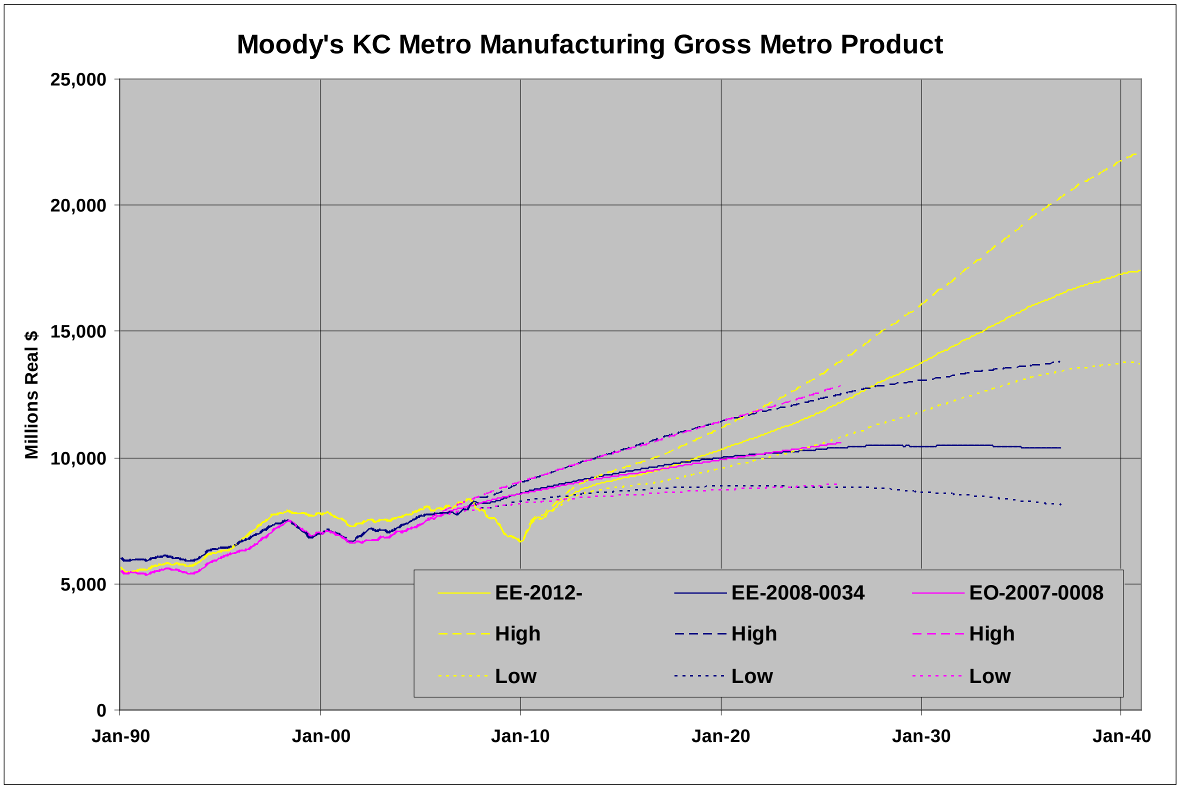
In the current forecast, manufacturing employment shows a huge decline during and several years after the last recession. After a strong rebound, employment is flat thereafter.

Figure 22: KC Gross Metro Product Non-Manufacturing



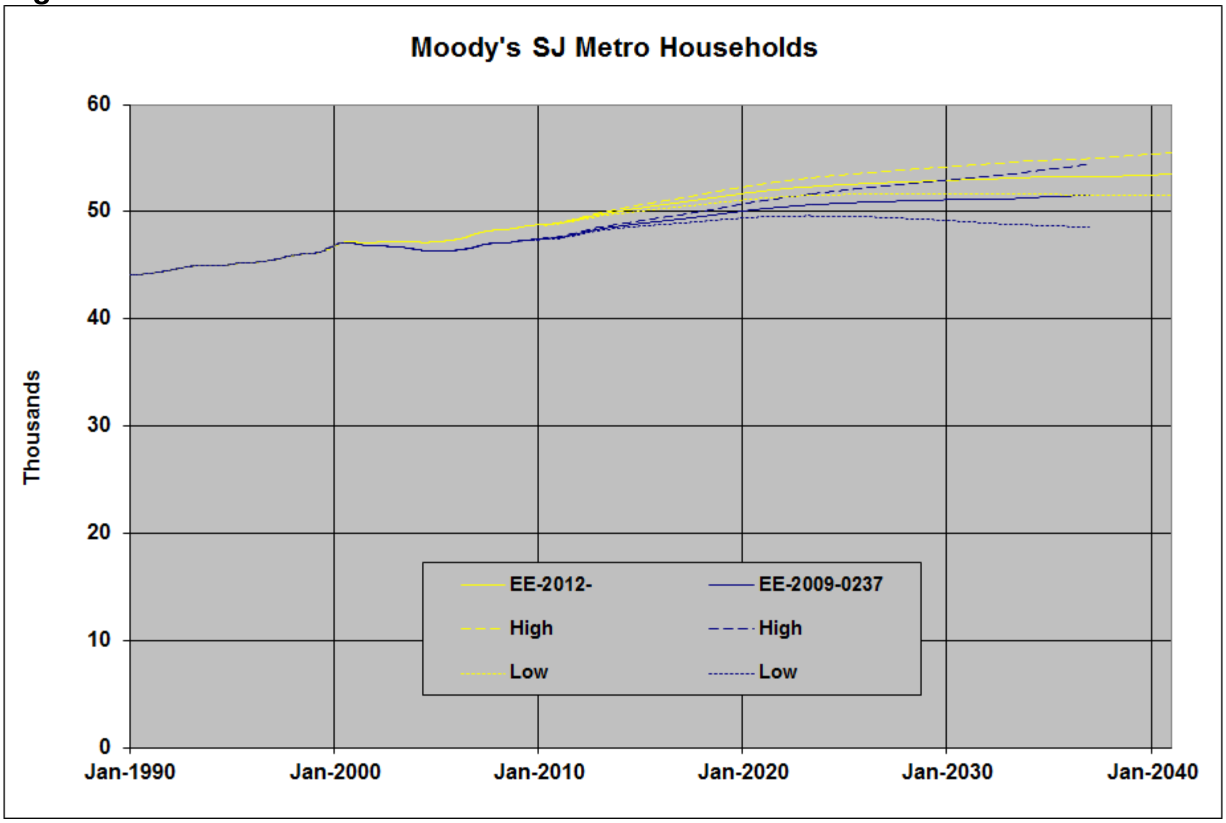
Real non-manufacturing GMP is growing much faster than employment in all three scenarios due to rising productivity. The current forecast shows a drop during and after the last recession. Real GMP in the current forecast was rebased to 2005 $.

Figure 23: KC Gross Metro Product Manufacturing



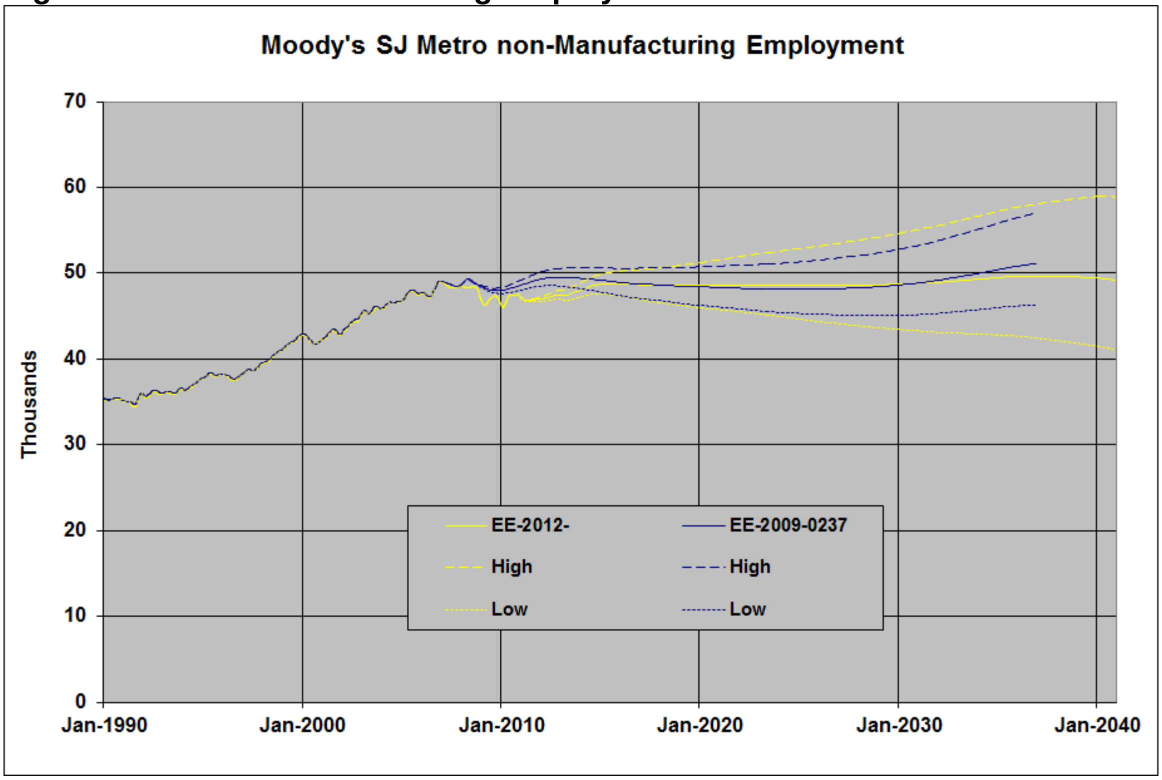
While manufacturing employment is flat after 2015, real manufacturing GMP shows strong growth. The current forecast shows the strongest growth.

Figure 24 SJ Households



The number of households measured in the last Census was higher than previously estimated for 2010. Basic demographic variables such as population and the number of households are not known with any certainty except when a Census is taken.

Figure 25 SJ non-Manufacturing Employment



Recent historical employment numbers have been revised down.

Figure 26 SJ Manufacturing Employment

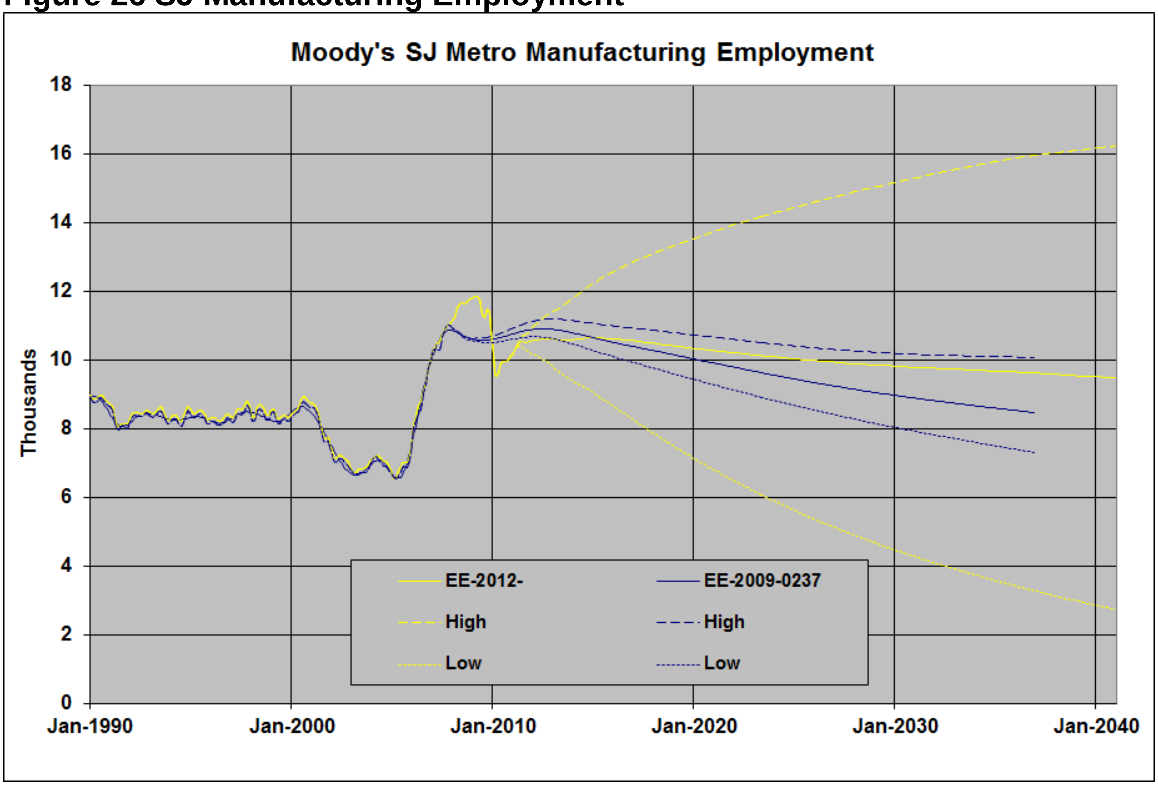
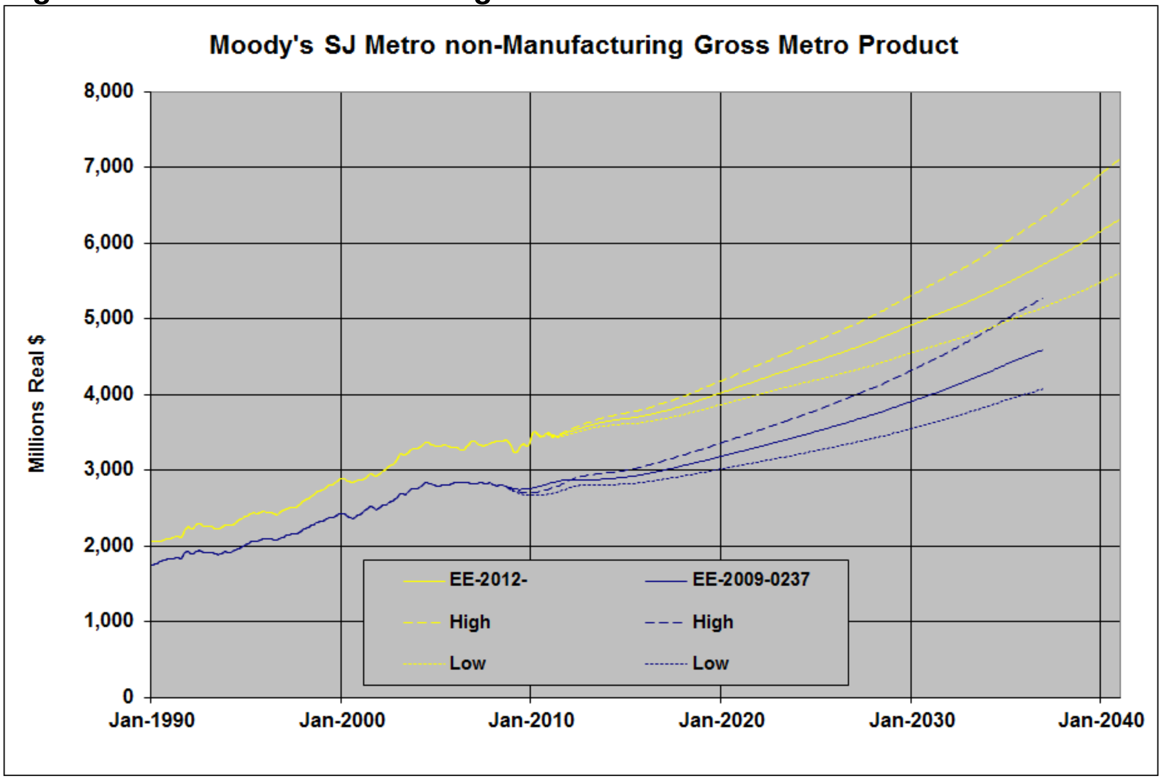
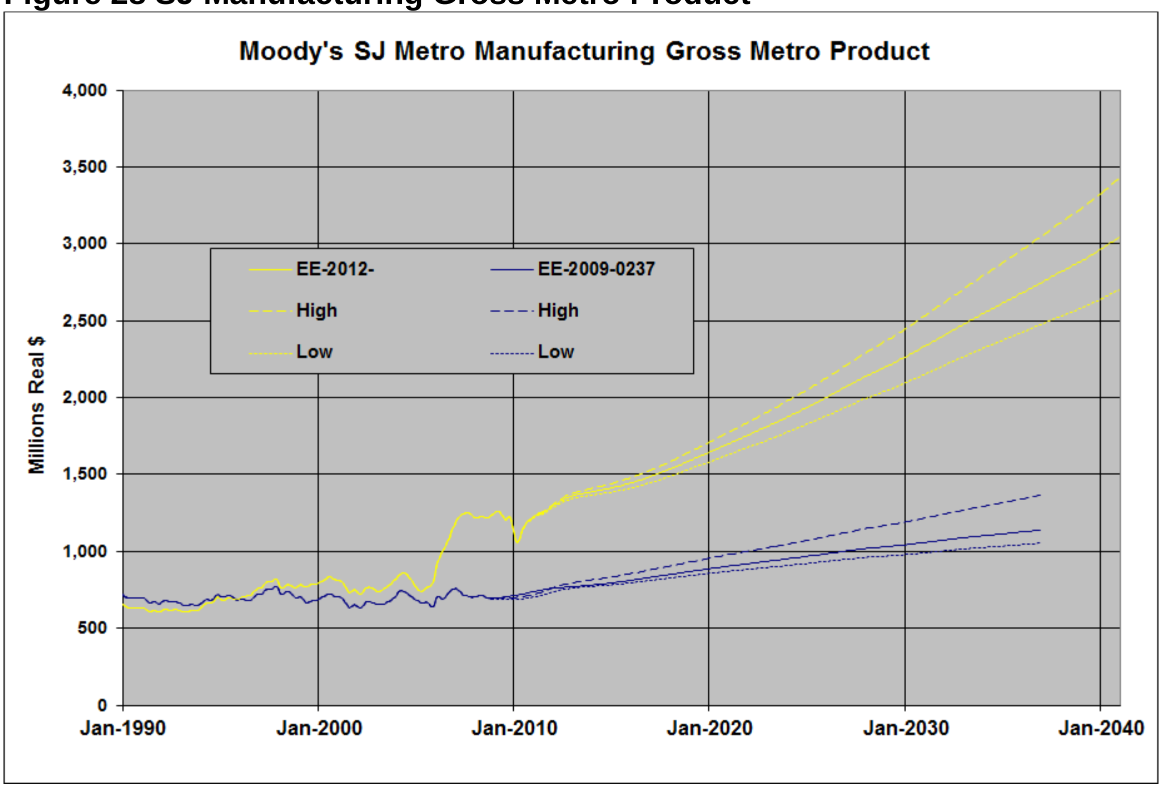


Figure 27 SJ non-Manufacturing Gross Metro Product



Real GMP in the current forecast was rebased to 2005 $.

Figure 28 SJ Manufacturing Gross Metro Product



4. Archive all previous forecasts of energy and peak demand, including the final data sets used to develop the forecasts, made in at least the past ten (10) years. Provide a comparison of the historical final forecasts to the actual historical energy and peak demands and to the current forecasts in the current triennial compliance filing.

GMO maintains an archive of the electronic files associated with our previous forecasts of energy use and peak demand for at least the last ten years. The graphs below compare our previous long-run forecasts of NSI and peak demand. The most recent forecast reflects a significant slowdown in economic growth that began in 2008, expectations for slower economic growth and additional energy standards.

Figure 29: MPS Net System Input (NSI) Historical and Final Forecasts

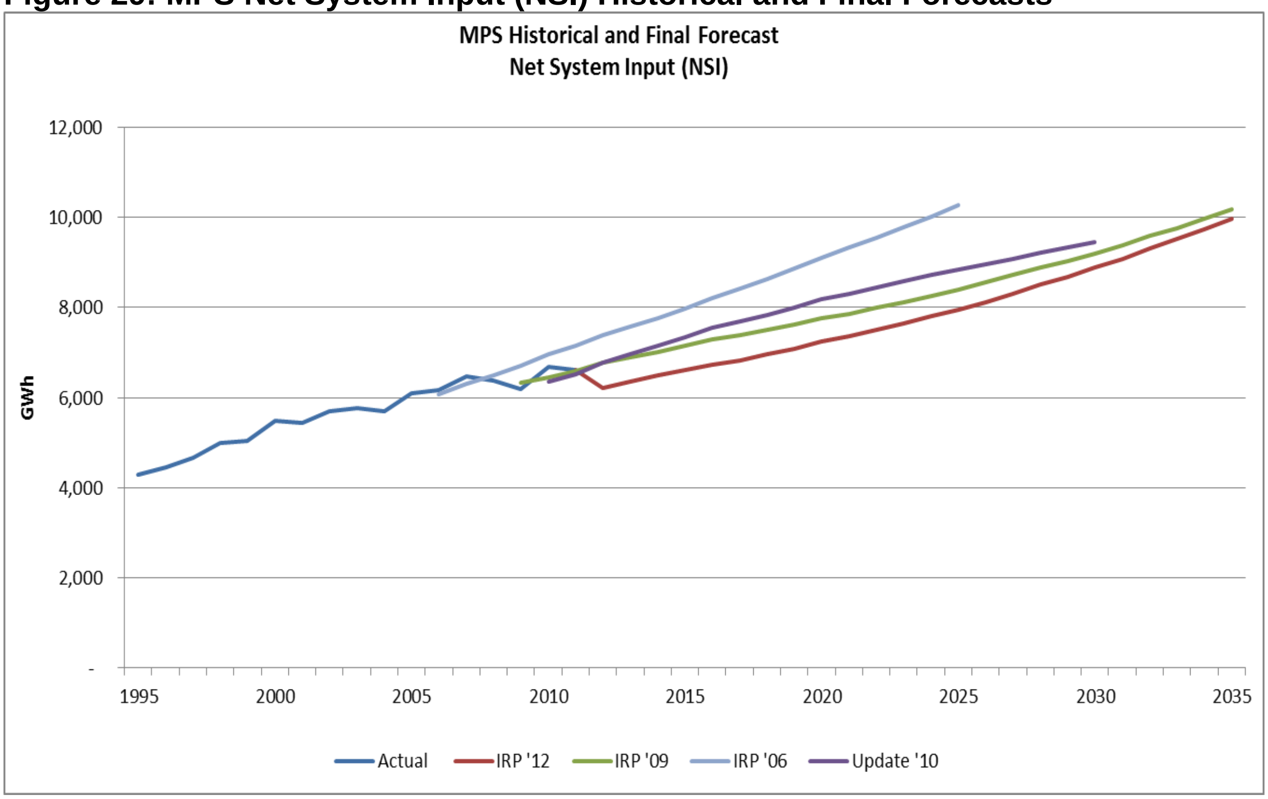


Figure 30: MPS Peak Demand Historical and Final Forecasts

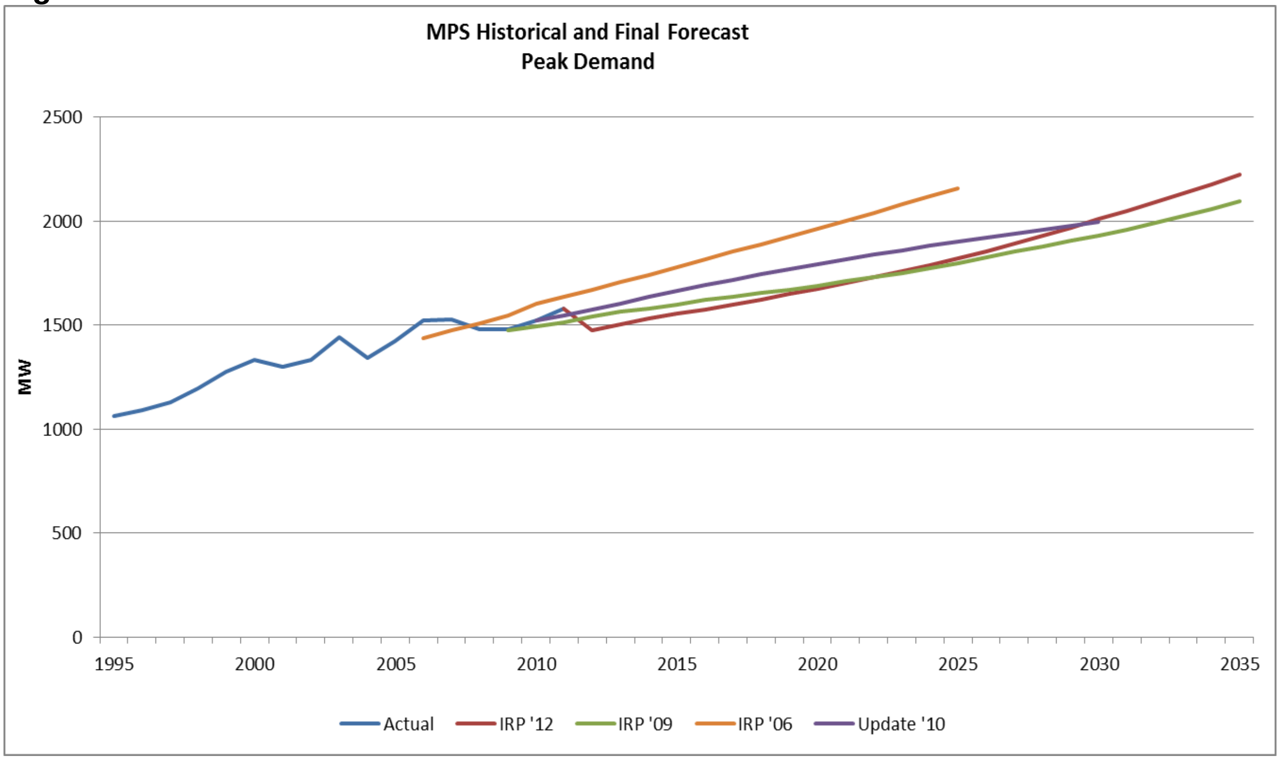


Figure 31: SJ Net System Input (NSI) Historical and Final Forecast

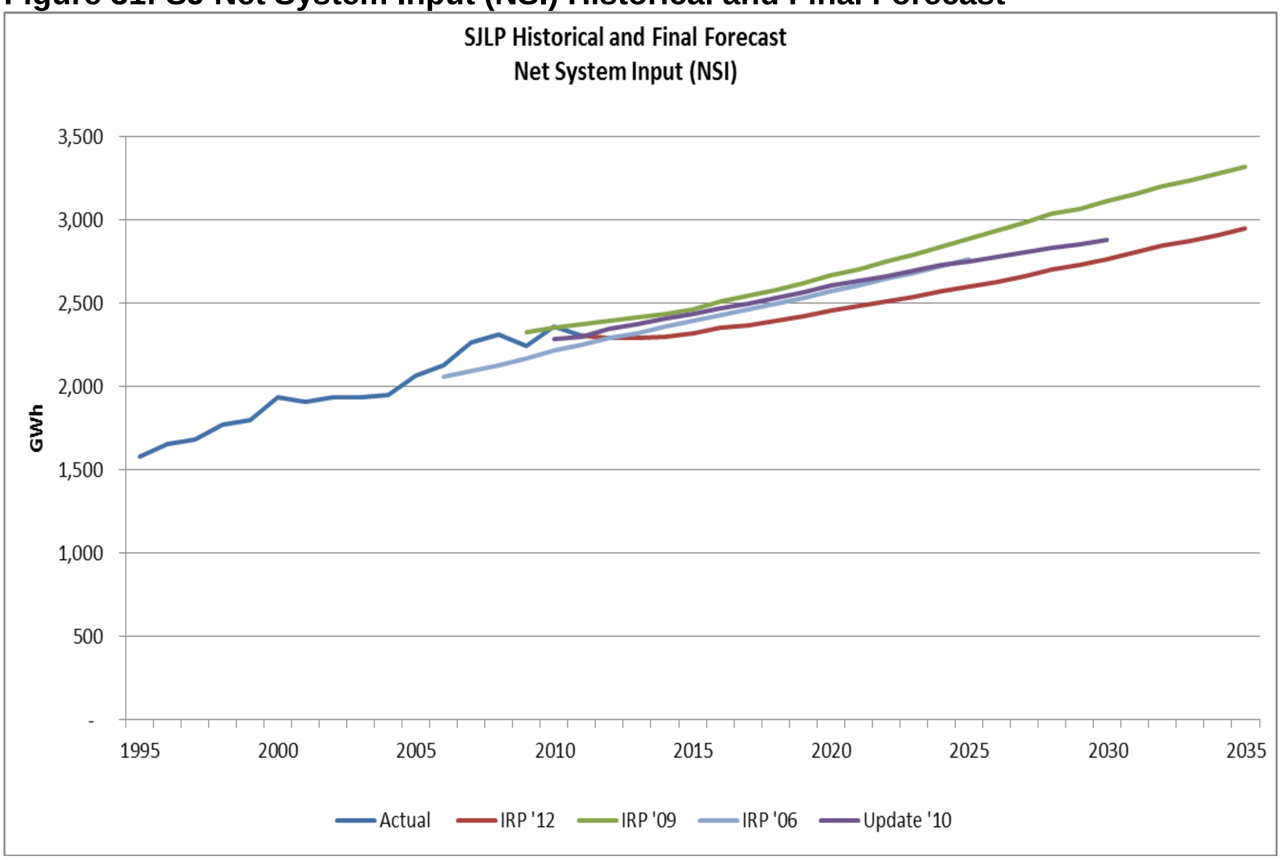
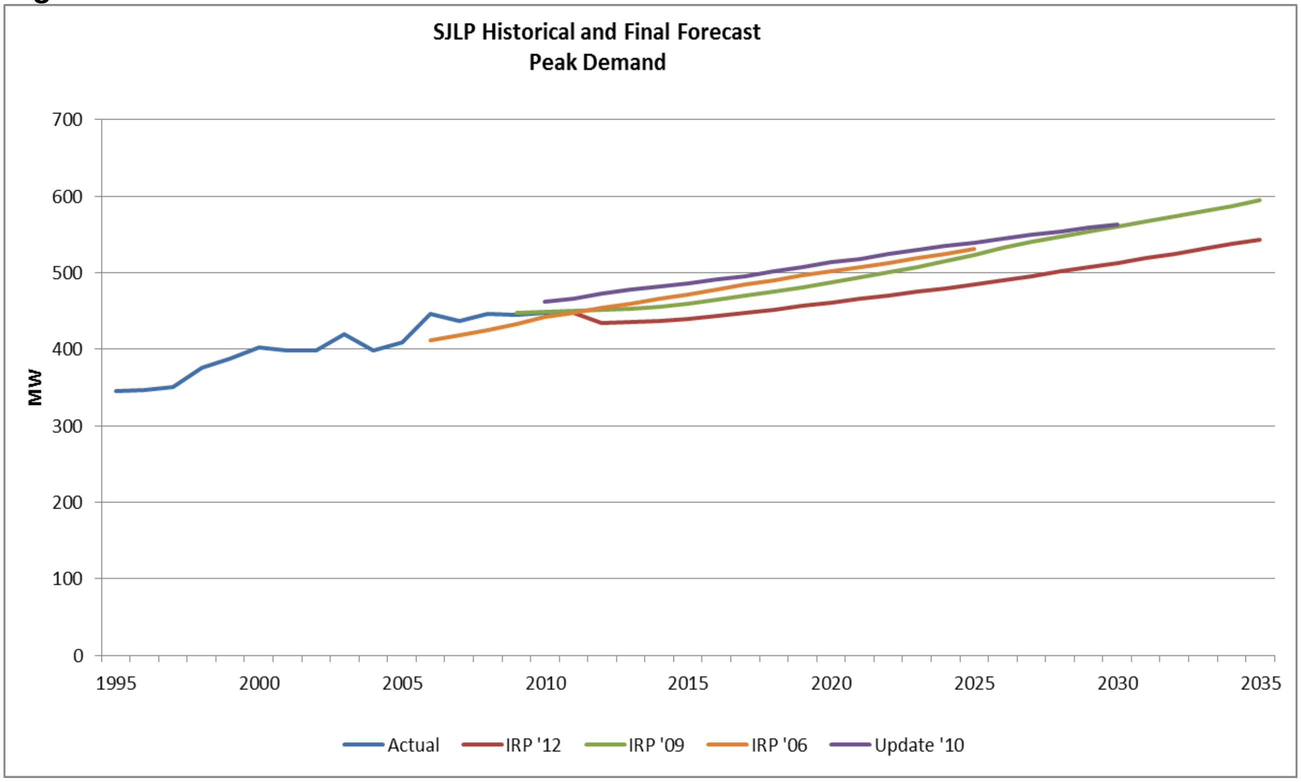


Figure 32: SJ Peak Demand Historical and Final Forecast



SECTION 7: BASE-CASE LOAD FORECAST

The utility's base-case load forecast shall be based on projections of the independent variables that utility decision-makers believe to be most likely. All components of the base-case load forecast shall assume normal weather conditions. The load impacts of implemented demand-side programs and rates shall be incorporated in the base-case load forecast, but the load impacts of proposed demand-side programs and rates shall not be included in the base-case forecast.

GMO's base-case forecast was produced with a base-case economic forecast from Moody's Analytics obtained in June 2011. The forecast included the impacts of GMO's implemented energy efficiency and DSM programs on NSI and peak load. The forecast was produced using normal weather.

7.1 MAJOR CLASS AND TOTAL LOAD DETAIL

(A) Major Class and Total Load Detail.

The utility shall produce forecasts of monthly energy usage and demands at the time of the summer and winter system peaks by major class for each year of the planning horizon, and shall describe and document those forecasts in its triennial compliance filings. Where applicable, these major class forecasts shall be separated into their jurisdictional components.

7.1.1 DESCRIBE AND DOCUMENT RELEVENT ECONOMIC AND DEMOGRAPHICS

1. The utility shall describe and document how the base-case forecasts of energy usage and demands have taken into account the effects of real prices of electricity, real prices of competitive energy sources, real incomes, and any other relevant economic and demographic factors. If the methodology does not incorporate economic and demographic factors, the utility shall explain how it accounted for the effects of these factors.

GMO accounted for the effects of real electricity prices in two ways. First, the prices of electricity and natural gas were used in the models that forecast the saturations of electric space heating for residential and commercial customers. These models are described in the section of this document for rule 7.B.1. Second, GMO assumes a price elasticity of -0.15 in each model of sales or sales per customer. These elasticities are close to the default values in the ERPI models REEPS and COMEND, which ITRON used in the original SAE models that they delivered to KCP&L in 2004. Since, then GMO has made some small changes to these values to improve the fit of the models.

In the residential models of kWh per customer, GMO assumes an income elasticity of 0.2 for heating and cooling and 0.1 for other uses and a persons-per-household elasticity of 0.2. Moody's forecast of households for the KC and SJ metro areas was used in the models of residential customers as was described previously in the section for rule 3.B.

7.1.2 <u>DESCRIBE AND DOCUMENT EFFECTS OF LEGAL MANDATES</u>

2. The utility shall describe and document how the forecasts of energy usage and demands have taken into account the effects of legal mandates affecting the consumption of electricity.

GMO uses the SAE methodology to forecast kWh sales for residential, commercial and industrial sales. This methodology relies on DOE forecasts of UECs and EUIs, which account for appliance efficiency standards and building codes.[vii]

7.1.3 <u>DESCRIBE AND DOCUMENT CONSISTENCY</u>

3. The utility shall describe and document how the forecasts of energy usage and demands are consistent with trends in historical consumption patterns, end uses, and end-use efficiency in the utility's service area as identified pursuant to sections 4 CSR 240-22.030(2), (3), and (4).

GMO forecasts incorporate and thus are consistent with the following trends:

- Electric space heating models explain the rapid rise of electric space heating saturations in the residential and commercial sector as a function of the relative costs of using electricity and natural gas. These costs depend on electricity and natural gas prices and the efficiencies of heat pumps and natural gas furnaces.

- Forecasts of UECs and EUIs used in our models reflect the impacts of energy standards in both the past and the future.

- Forecasts of appliance and equipment saturations reflect the penetration of new devices such as HDTVs and the limitations of further increases for appliances that are reaching equilibrium such as dishwashers and central air conditioners.

7.1.4 DESCRIBE AND DOCUMENT WEATHER NORMALIZED CLASS LOADS

4. For at least the base year of the forecast, the utility shall describe and document its estimates of the monthly cooling, heating, and non-weather-sensitive components of the weather-normalized major class loads.

The estimates are shown below.

Figure 33: Estimates of MPS Residential Monthly Cooling, Heating, and Base

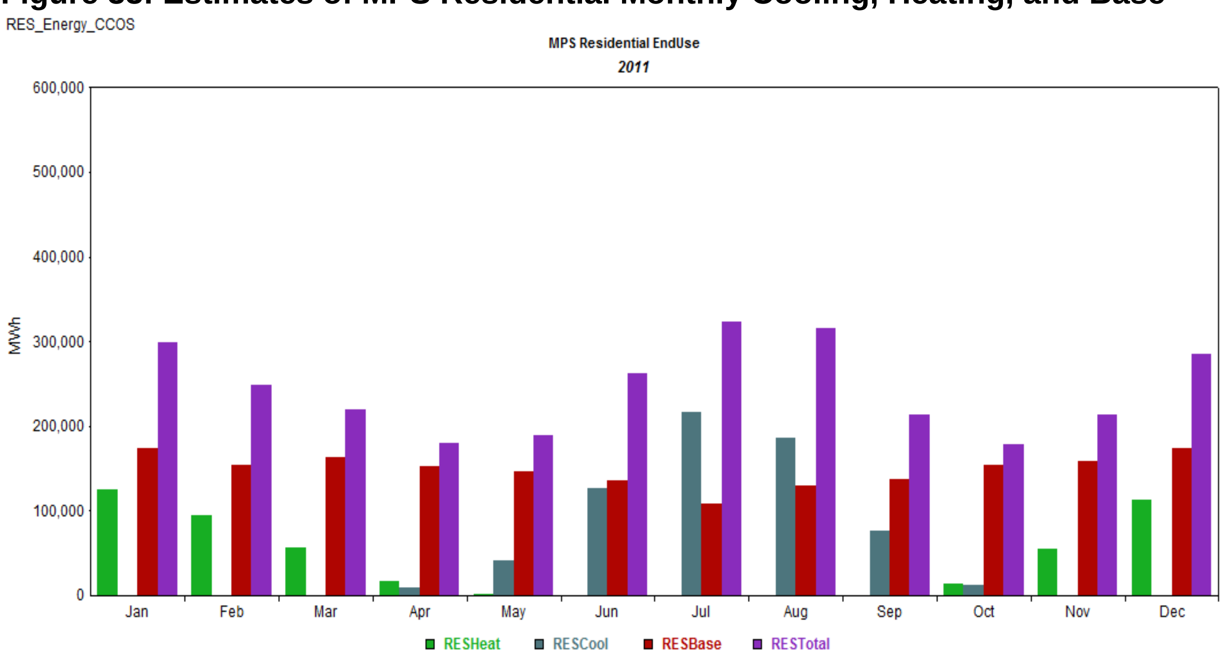


Table 45: Data Table of MPS Residential Monthly Cooling, Heating, and Base

Date	RESHeat	RESCool	RESBase	RESTotal
Jan-11	124,025	-	174,145	298,169
Feb-11	94,254	-	153,585	247,839
Mar-11	55,979	-	163,099	219,078
Apr-11	17,111	9,276	152,900	179,286
May-11	892	41,175	146,658	188,725
Jun-11	-	126,052	135,441	261,493
Jul-11	-	216,394	107,136	323,530
Aug-11	-	185,398	129,397	314,795
Sep-11	412	76,425	136,999	213,836
Oct-11	13,349	11,122	153,770	178,241
Nov-11	54,170	-	158,343	212,513
Dec-11	112,221	-	173,186	285,407

Figure 34: Estimates of MPS Small General Service Monthly Cooling, Heating, and Base

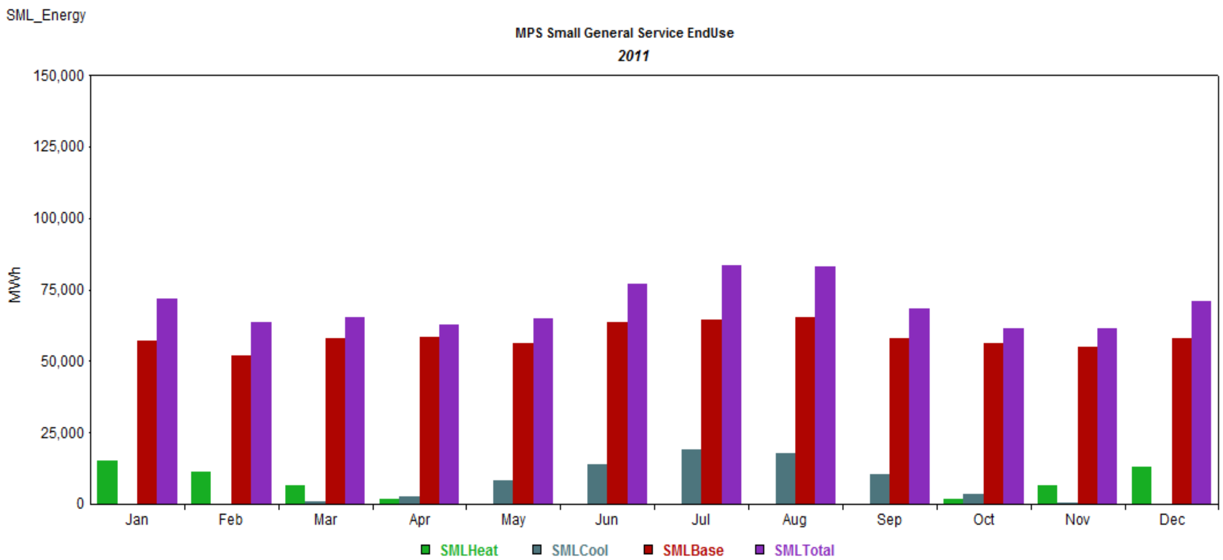


Table 46: Data Table of MPS Small General Service Monthly Cooling, Heating, and Base

Date	SMLHeat	SMLCool	SMLBase	SMLTotal
Jan-11	14,996	-	56,949	71,945
Feb-11	11,344	-	52,059	63,402
Mar-11	6,570	678	58,044	65,292
Apr-11	1,831	2,643	58,421	62,894
May-11	106	8,351	56,280	64,738
Jun-11	-	13,631	63,409	77,039
Jul-11	-	18,858	64,523	83,381
Aug-11	-	17,822	65,235	83,057
Sep-11	48	10,459	57,769	68,277
Oct-11	1,559	3,508	56,336	61,403
Nov-11	6,334	372	54,753	61,459
Dec-11	13,139	-	57,921	71,060

Figure 35: Estimates of MPS Large General Service Monthly Cooling, Heating, and Base

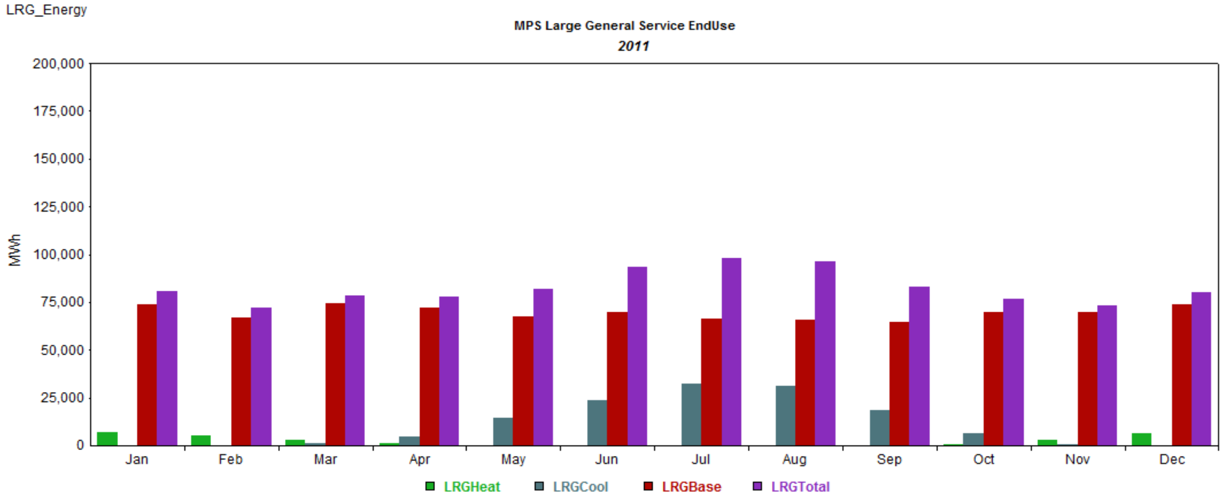


Table 47: Data Table of MPS Large General Service Monthly Cooling, Heating, and Base

Date	LRGHeat	LRGCool	LRGBase	LRGTotal
Jan-11	6,885	-	73,883	80,768
Feb-11	5,274	4	67,096	72,375
Mar-11	3,070	1,175	74,131	78,377
Apr-11	893	4,798	71,986	77,677
May-11	49	14,342	67,510	81,901
Jun-11	-	23,927	69,524	93,450
Jul-11	-	32,078	66,034	98,112
Aug-11	-	31,015	65,432	96,446
Sep-11	22	18,431	64,746	83,199
Oct-11	725	6,265	69,621	76,612
Nov-11	2,947	718	69,791	73,456
Dec-11	6,116	9	73,821	79,946

Figure 36: Estimates of MPS Large Power Monthly Cooling, Heating, and Base

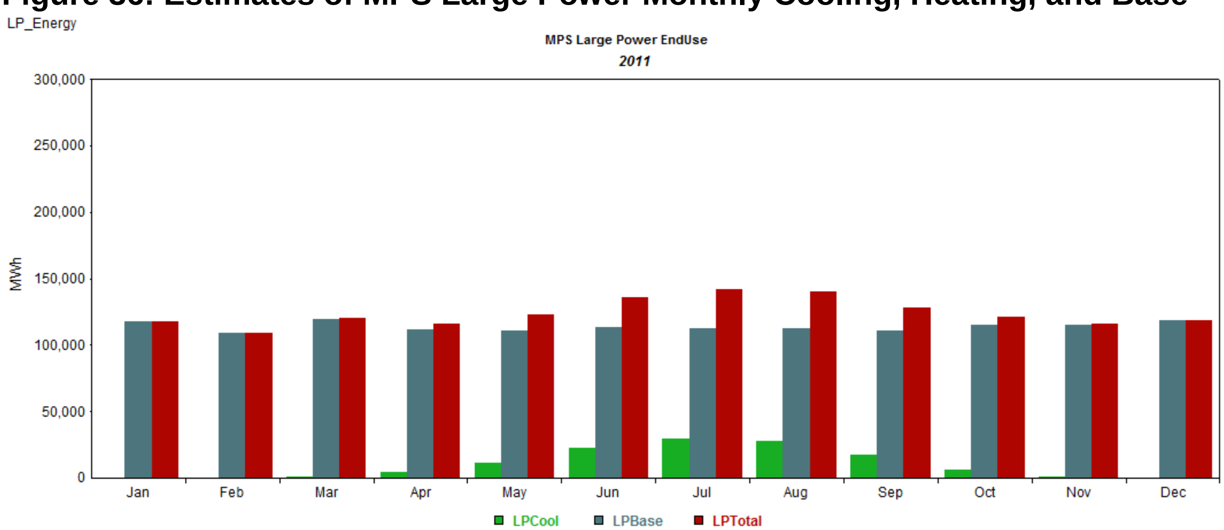


Table 48: Data Table of MPS Large Power Monthly Cooling, Heating, and Base

Date	LPCool	LPBase	LPTotal
Jan-11	-	117,697	117,697
Feb-11	61	108,774	108,835
Mar-11	952	119,335	120,287
Apr-11	4,038	111,667	115,705
May-11	11,429	111,045	122,474
Jun-11	22,490	113,045	135,535
Jul-11	29,485	112,114	141,599
Aug-11	27,617	112,415	140,033
Sep-11	17,637	110,587	128,224
Oct-11	5,976	115,304	121,280
Nov-11	838	114,690	115,529
Dec-11	22	118,845	118,867

Figure 37: Other MPS Load (SFR & Lighting)

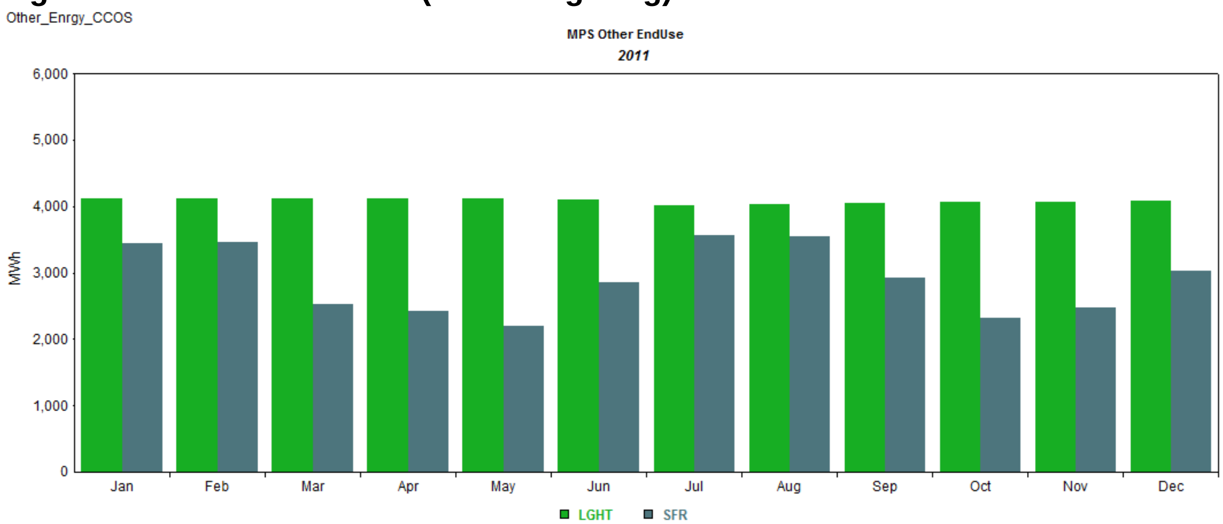


Table 49: Data Table Other MO Load (SFR & Lighting)

Date	LGHT	SFR
Jan-11	4,112	3,449
Feb-11	4,109	3,459
Mar-11	4,119	2,527
Apr-11	4,118	2,426
May-11	4,114	2,191
Jun-11	4,105	2,858
Jul-11	4,018	3,561
Aug-11	4,032	3,547
Sep-11	4,045	2,919
Oct-11	4,057	2,316
Nov-11	4,068	2,477
Dec-11	4,079	3,032

Figure 38: Estimates of SJ Residential Monthly Cooling, Heating, and Base

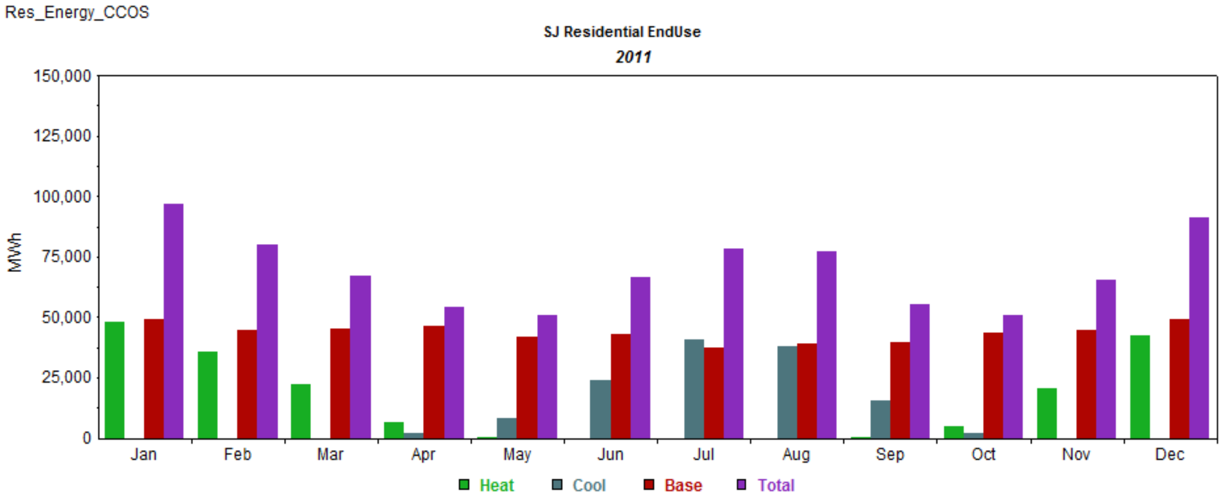


Table 50: Data Table of SJ Residential Monthly Cooling, Heating, and Base

Date	Heat	Cool	Base	Total
Jan-11	47,885	-	49,075	96,960
Feb-11	35,395	-	44,427	79,822
Mar-11	22,023	-	44,996	67,019
Apr-11	6,219	1,826	46,290	54,335
May-11	336	8,405	41,988	50,729
Jun-11	-	23,745	42,990	66,735
Jul-11	-	40,752	37,535	78,287
Aug-11	-	38,070	39,134	77,204
Sep-11	156	15,673	39,491	55,319
Oct-11	5,047	2,278	43,274	50,599
Nov-11	20,452	-	44,634	65,086
Dec-11	42,315	-	49,006	91,321

Figure 39: Estimates of SJ Small General Service Monthly Cooling, Heating, and Base

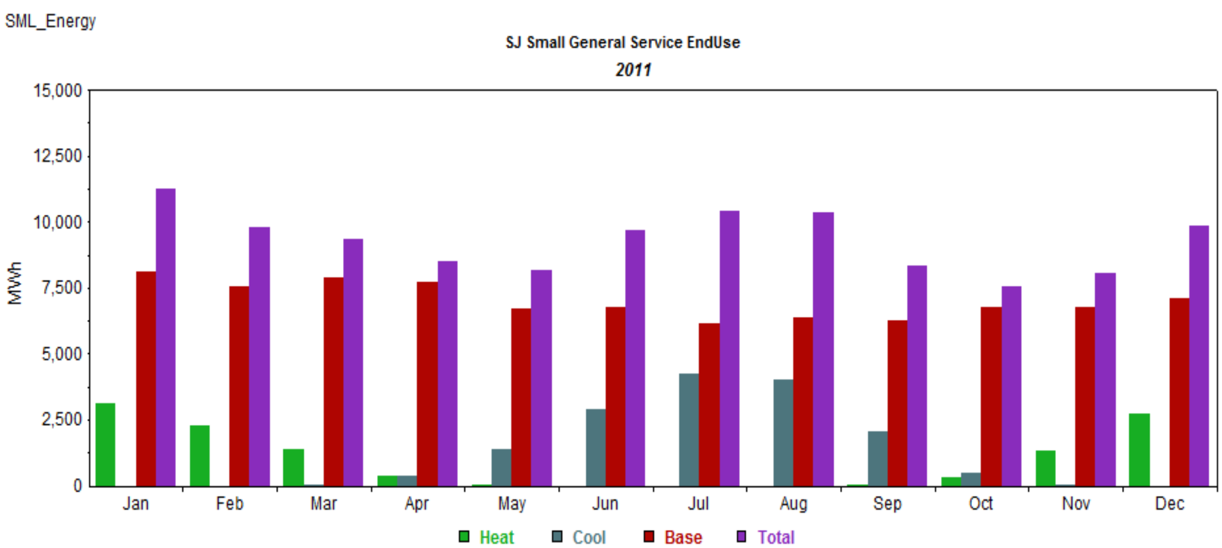


Table 51: Data Table of SJ Small General Service Monthly Cooling, Heating, and Base

Date	Heat	Cool	Base	Total
Jan-11	3,116	-	8,106	11,222
Feb-11	2,290	-	7,525	9,815
Mar-11	1,405	52	7,865	9,321
Apr-11	389	379	7,730	8,499
May-11	22	1,406	6,717	8,145
Jun-11	-	2,905	6,781	9,686
Jul-11	-	4,252	6,164	10,415
Aug-11	-	4,008	6,363	10,372
Sep-11	10	2,020	6,279	8,309
Oct-11	323	483	6,748	7,554
Nov-11	1,311	15	6,740	8,066
Dec-11	2,716	-	7,122	9,838

Figure 40: Estimates of SJ Large General Service Monthly Cooling, Heating, and Base

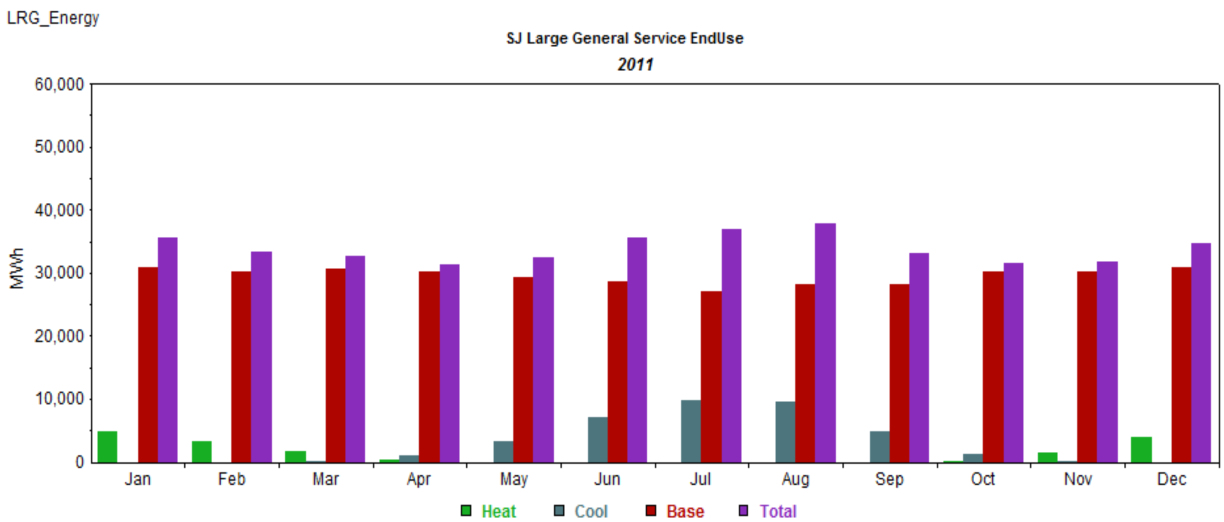


Table 52: Data Table of SJ Large General Service Monthly Cooling, Heating, and Base

Date	Heat	Cool	Base	Total
Jan-11	4,756	-	30,749	35,506
Feb-11	3,188	-	30,094	33,282
Mar-11	1,793	135	30,649	32,578
Apr-11	371	953	30,080	31,404
May-11	5	3,253	29,258	32,516
Jun-11	0	6,983	28,545	35,528
Jul-11	-	9,846	27,101	36,948
Aug-11	-	9,493	28,239	37,732
Sep-11	-	4,834	28,206	33,040
Oct-11	221	1,189	30,195	31,605
Nov-11	1,510	46	30,203	31,759
Dec-11	3,852	-	30,819	34,672

Figure 41: Estimates of SJ Large Power Monthly Cooling, Heating, and Base

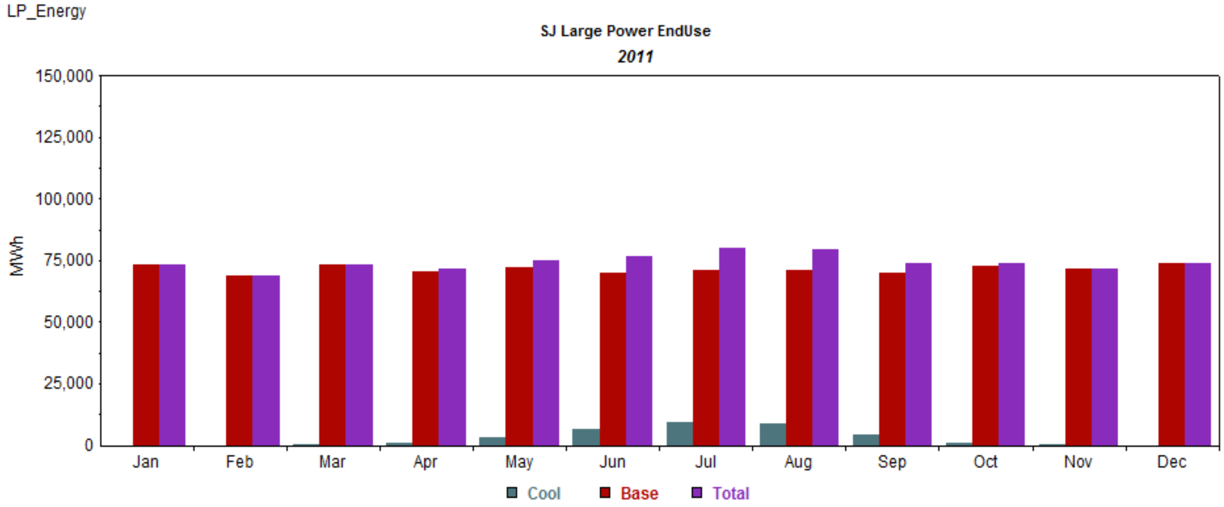


Table 53: Data Table of SJ Large Power Monthly Cooling, Heating, and Base

Date	Cool	Base	Total
Jan-11	-	73,356	73,356
Feb-11	-	68,553	68,553
Mar-11	184	73,132	73,317
Apr-11	1,016	70,585	71,601
May-11	3,074	71,992	75,066
Jun-11	6,452	69,929	76,381
Jul-11	9,024	71,043	80,067
Aug-11	8,501	70,864	79,365
Sep-11	4,356	69,624	73,980
Oct-11	1,180	72,414	73,593
Nov-11	102	71,450	71,552
Dec-11	-	73,931	73,931

Figure 42: Other SJ Load (Lighting)

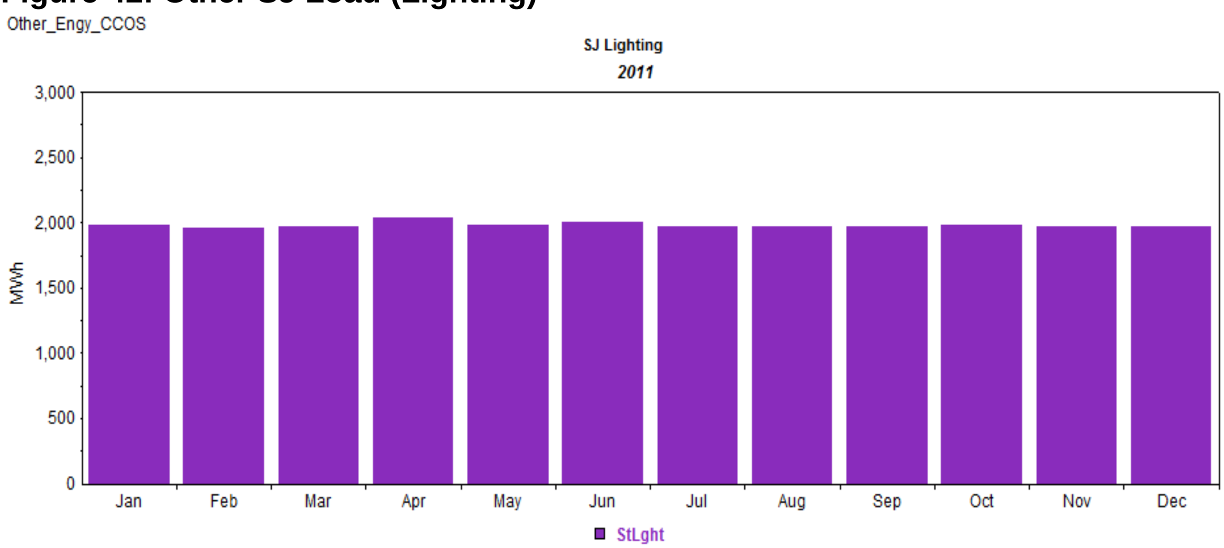


Table 54: Data Table Other SJ Load (SFR & Lighting)

Date	StLght
Jan-11	1,984
Feb-11	1,955
Mar-11	1,965
Apr-11	2,037
May-11	1,982
Jun-11	2,008
Jul-11	1,974
Aug-11	1,964
Sep-11	1,972
Oct-11	1,979
Nov-11	1,967
Dec-11	1,972

7.1.5 DESCRIBE AND DOCUMENT MODIFICATION OF MODELS

5. Where judgment has been applied to modify the results of its energy and peak forecast models, the utility shall describe and document the factors which caused the modification and how those factors were quantified.

The results of all models were used as is except to calibrate the system peak forecast to the weather normalized 2011 peak in each jurisdiction.

The first step is the weather normalization of the jurisdictional hourly load data. After normalizing the hourly loads, the demand side management, mpower and dynamic voltage control reductions at the time of peak are determined. This reduction in load is then added back to the weather normalized data to produce weather normalized monthly gross peaks. The base year weather normalized annual peak is then used to calibrate the jurisdictional peaks that are produced in MetrixLT. This is done by taking the base year normalized peak and using it as the first data point in the calibration process and then applying the annual growth rates from the peak forecast produced in MetrixLT. Then the annual peak is distributed across the months based on the percentage of that month's peak as percent to the annual peak. The percent of each month's contribution to the annual peaks is determined by the output of monthly peaks from MetrixLT. After each jurisdiction has been calibrated, the monthly peaks are then imported back in to MetrixLT and each hour for the peak day is adjusted to reflect the new calibrated peak.

The calibration of the peaks can be found in the jurisdictional system *datalyzer* folder which is provided in the work papers.

7.1.6 PLOTS OF CLASS MONTHLY ENERGY AND COINCIDENT PEAK DEMAND

6. For each major class specified pursuant to subsection (2)(A), the utility shall provide plots of class monthly energy and coincident peak demand at the time of summer and winter system peaks. The plots shall cover the historical database period and the forecast period of at least twenty (20) years. The plots of coincident peak demands for the historical period shall include both actual and weather-normalized peak demands at the time of summer and winter system peaks. The plots of coincident peak demand for the forecast period shall show the class coincident demands for the base-case forecast at the time of summer and winter system peaks.

Plots for class monthly energy and coincident peak demand at the time of summer and winter system loads are provided in *Appendix 3B*. Energy plots by jurisdiction and system are provided in the file *IRP_7.1.6_GMO_MWh-2.xlsx* and peak plots are in the file *IRP_7.1.6_GMO_Peaks-1.xlsx*.

7.1.7 PLOTS OF NET SYSTEM LOAD PROFILES

7. The utility shall provide plots of the net system load profiles for the summer peak day and the winter peak day showing the contribution of each major class. The plots shall be provided in the triennial filing for the base year of the forecast and for the fifth, tenth, and twentieth years of the forecast. Plots for all years shall be included in the workpapers supplied at the time of the triennial filing.

The figures below show the load profiles for the base, fifth, tenth, and twentieth years broken out by summer and winter peak days for each major class of MPS and SJLP and for the system. The plots with data tables are provided in *Appendix 3C*. Plots for additional years can be found in the MetrixLT files (*MPS_Fcst*, *SJ_Fcst*, and *System*) included in the workpapers.

Figure 43: Base Year (2011) Net System Load Profiles for MPS, SJ, and GMOC

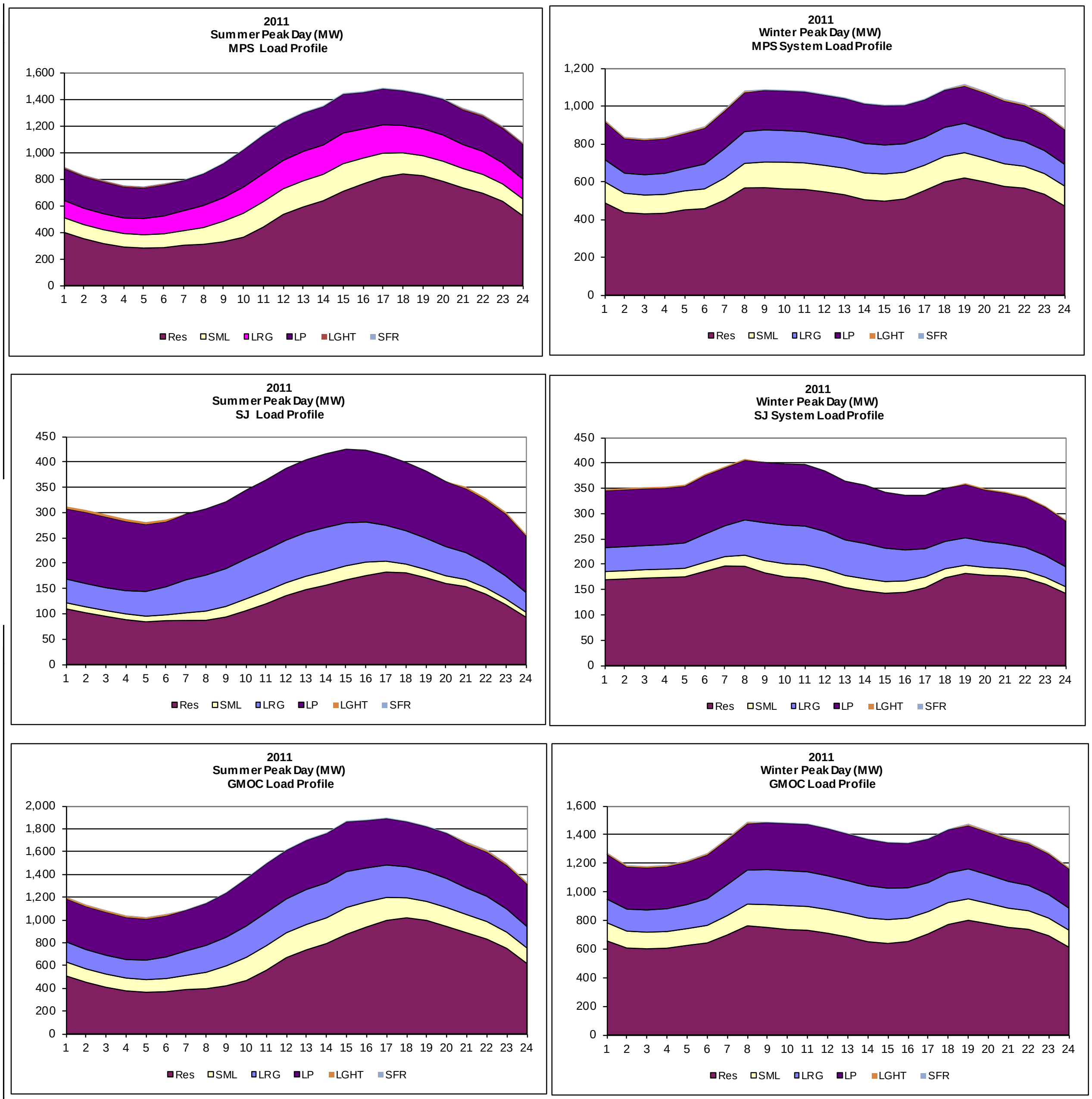


Figure 44: Fifth Year (2016) Net System Load Profiles for MPS, SJ, and GMOC

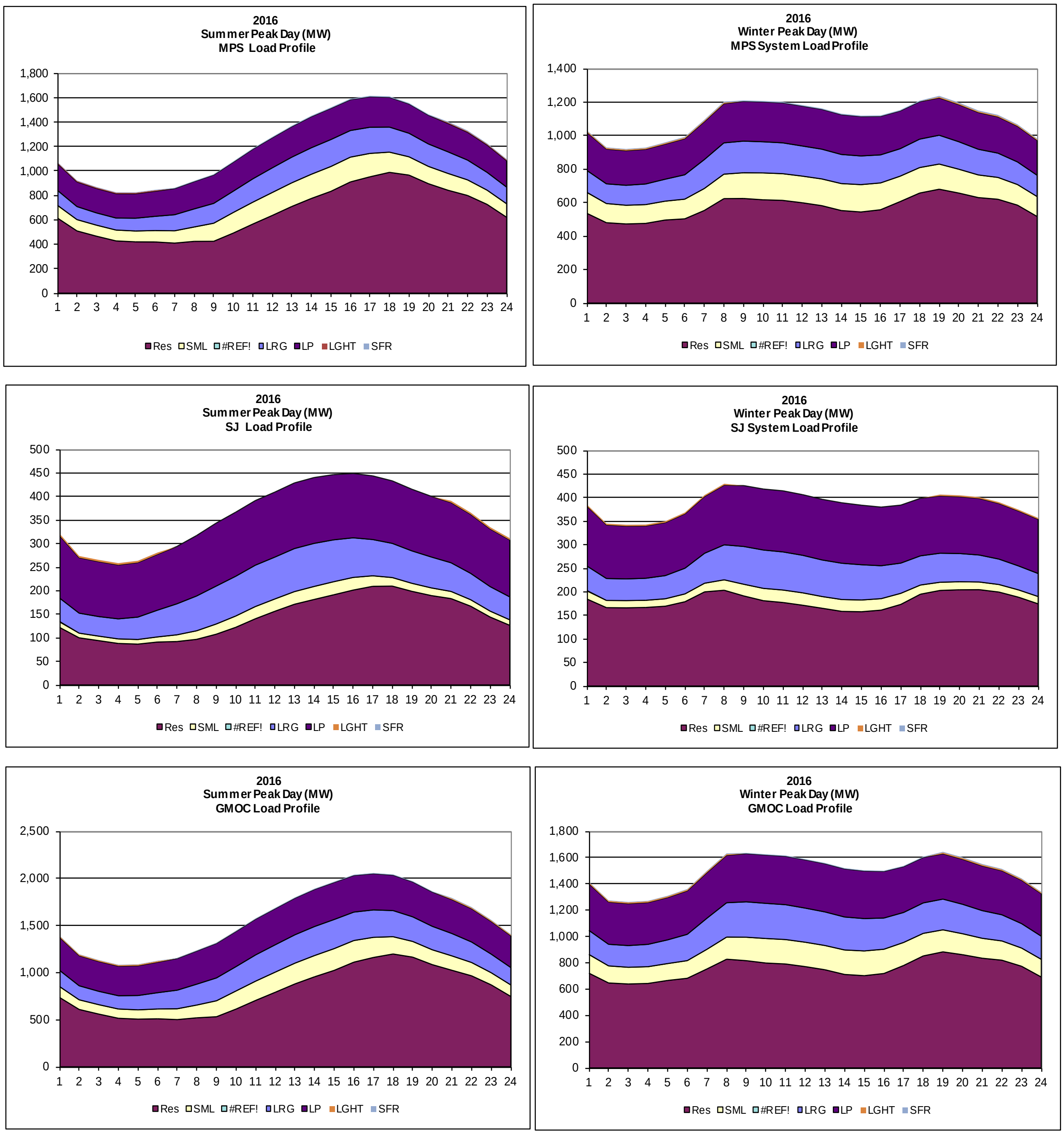


Figure 45: Tenth Year (2021) Net System Load Profiles for MPS, SJ, and GMOC

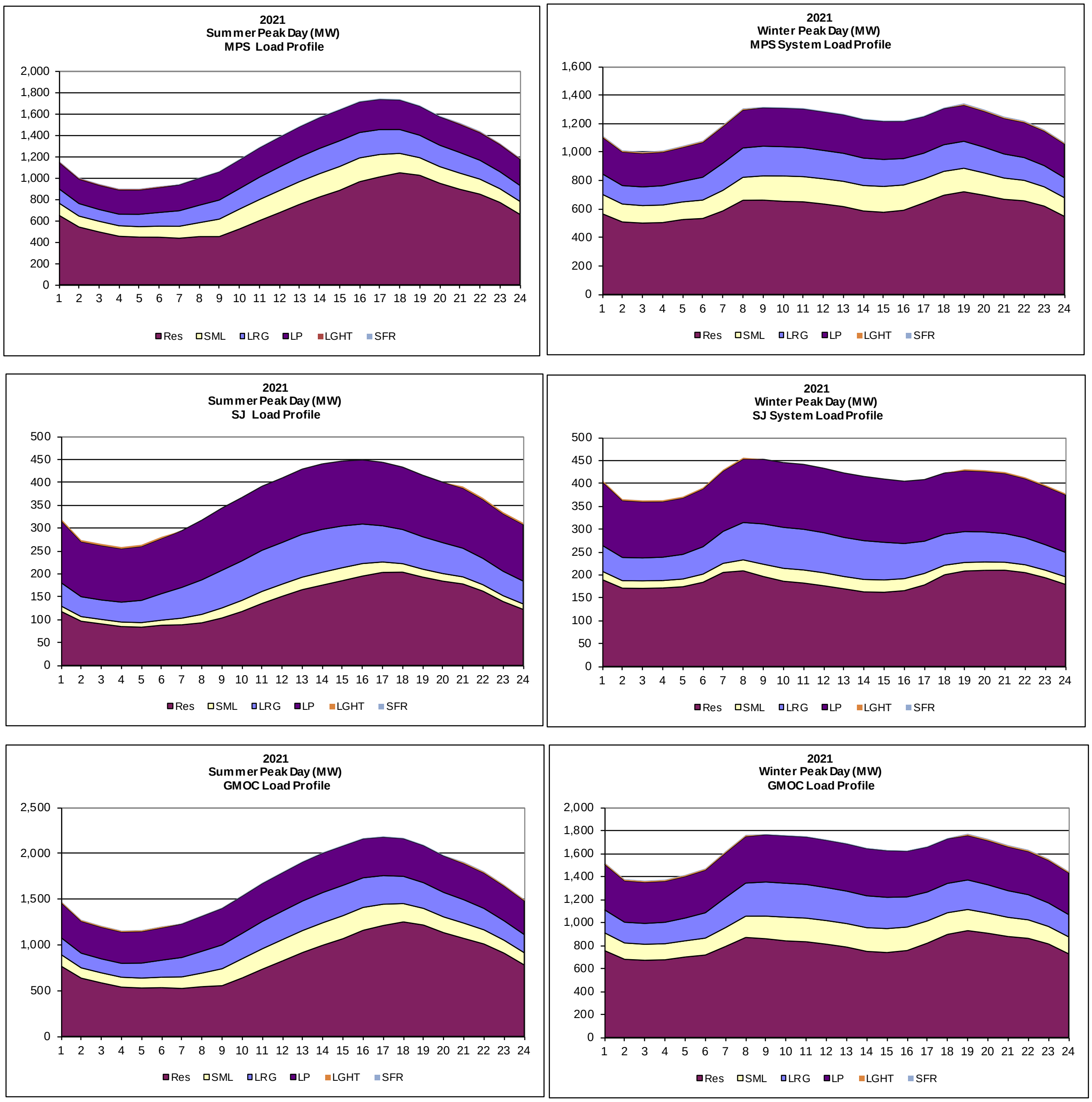
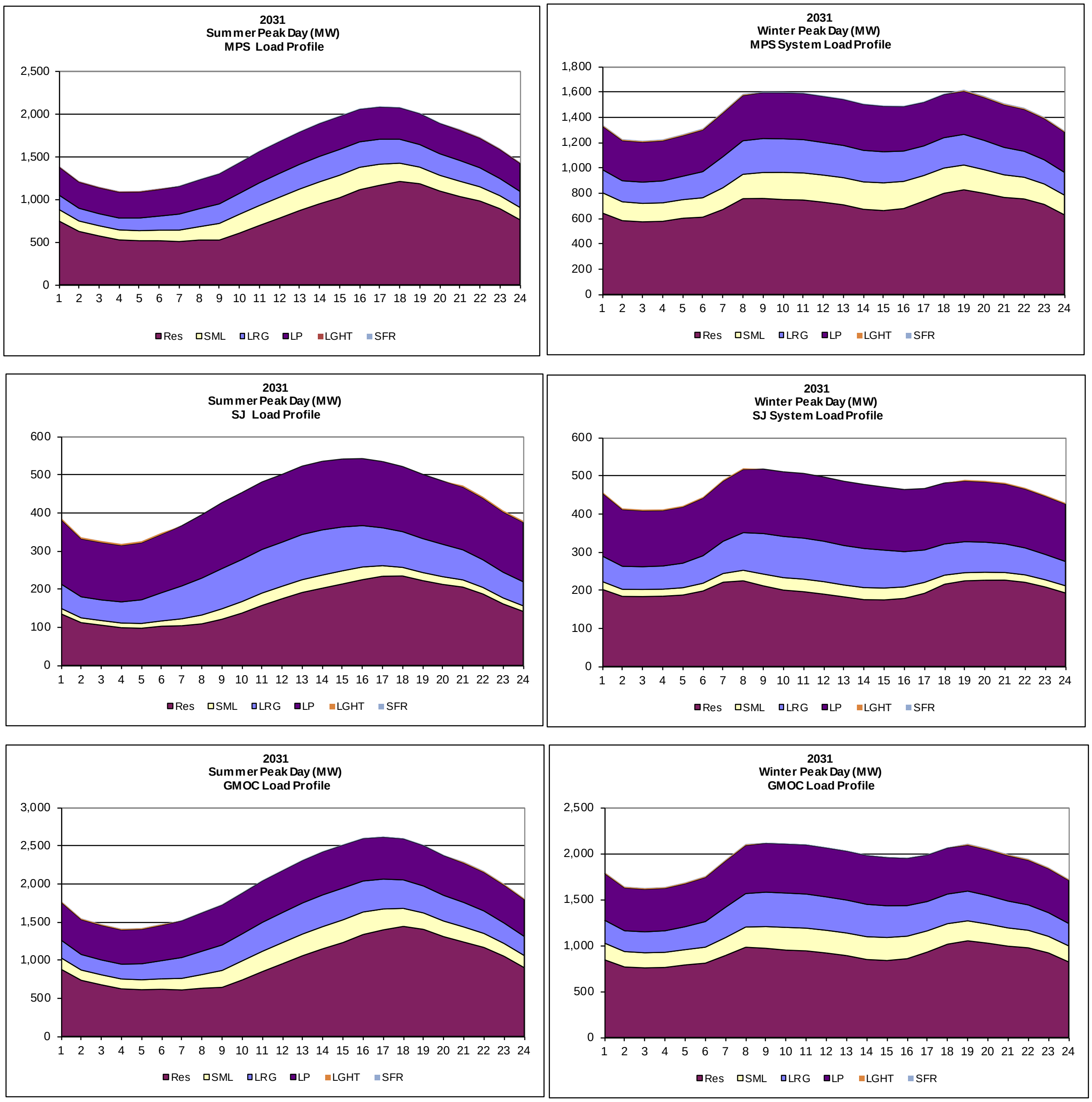


Figure 46: Twentieth Year (2031) Net System Load Profiles for MPS, SJ, and GMOC



7.2 <u>DESCRIBE AND DOCUMENT FORECASTS OF INDEPENDENT VARIABLES</u>

(B) Forecasts of Independent Variables.

The forecasts of independent variables shall be specified, described, and documented.

The forecasts of independent variables were described above in the section for rule 6.C.3 and below in the section for rule for 7.B.3.

7.2.1 DOCUMENTATION OF MATHEMATICAL MODELS

1. Documentation of mathematical models developed by the utility to forecast the independent variables shall include the reasons the utility selected the models as well as specification of the functional form of the equations.

GMO acquired forecasts of independent variables from Moody's and DOE as described previously. GMO developed its own models to forecast the saturation of electric space heating for residential customers (*SpaceHeating.xls*). GMO has discounted tariffs for customers that have electric space heating and the percentage of customers on these tariffs is used as a measure of electric space heating saturations. The models predict both the penetration rate of electric space heating for new customers and the percentage rate of conversion to electric space heating for customers that use natural gas or propane to heat their homes. These rates are driven by the difference in costs to heat a home by electricity and natural gas. These costs are determined by the average natural gas rates for local gas utilities, GMO's winter tail-block rates and heating equipment efficiency rates.

The real price differential per million Btu is computed as

$$\text{PD}= (1{,}000{,}000/1{,}028{,}000/\text{Gas Furnace Efficiency}*\text{Gas rate}$$
$$-1{,}000{,}000/(\text{Heat pump Efficiency}*1{,}000)*\text{Electric tail block rate})*\text{CPI}_{2004}/\text{CPI}_t$$

The heat pump efficiency is Btu out per Watt hour in.

The equation to predict the number of additional customers using electric space heating is

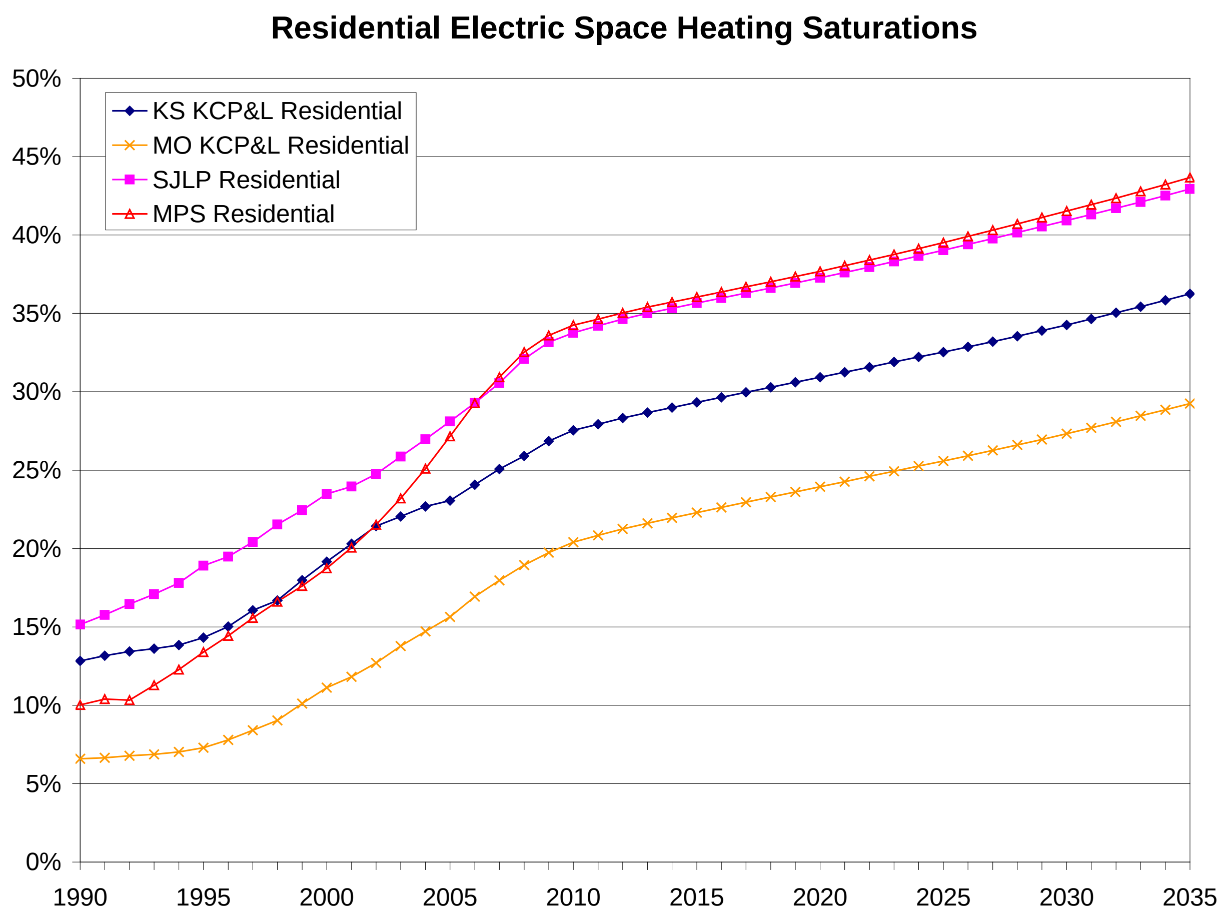
$$\text{New customers}/(1+\text{EXP}(-\text{newCust}*\text{PD}-C_1))+$$
$$\text{customers wo electric heat}/(1+\text{EXP}(-\text{conversions}*\text{PD}+C_2+\text{incentive}*\text{tax credit}))$$

where tax credit = federal tax credits and GMO rebates available, newCust, conversions, incentive, C_1, C_2 are coefficients.

The coefficients were estimated with least squares regression pooling the data for GMO and KCP&L.

The forecasts for KCP&L and GMO are compared in the figure below.

Figure 47: Residential Space Heating Saturations



7.2.2 <u>DOCUMENTATION OF ADOPTED FORECASTS DEVELOPED BY ANOTHER ENTITY</u>

2. If the utility adopted forecasts of independent variables developed by another entity, documentation shall include the reasons the utility selected those forecasts, an analysis showing that the forecasts are applicable to the utility's service territory, and, if available, a specification of the functional form of the equations used to forecast the independent variables.

GMO used a forecast of economic and demographic variables for the KC metro area that was developed by Moody's Analytics. The reasons for using this forecast, the applicability to GMO's service areas and documentation for the forecast were discussed in the sections for rules 3 A and 6 A 3.

GMO used forecasts of saturations, UECs, EUIs and building efficiencies from DOE. The reasons for using these forecasts, the applicability to GMO's service area and documentation for the forecast were discussed in the sections for rules 3 A, 4 A 1 B, 5 A, 5 B AND 6 A 3.

7.2.3 COMPARISON OF FORECAST FROM INDEPENDENT VARIABLES TO HISTORICAL TRENDS

3. These forecasts of independent variables shall be compared to historical trends in the variables, and significant differences between the forecasts and long-term and recent trends shall be analyzed and explained.

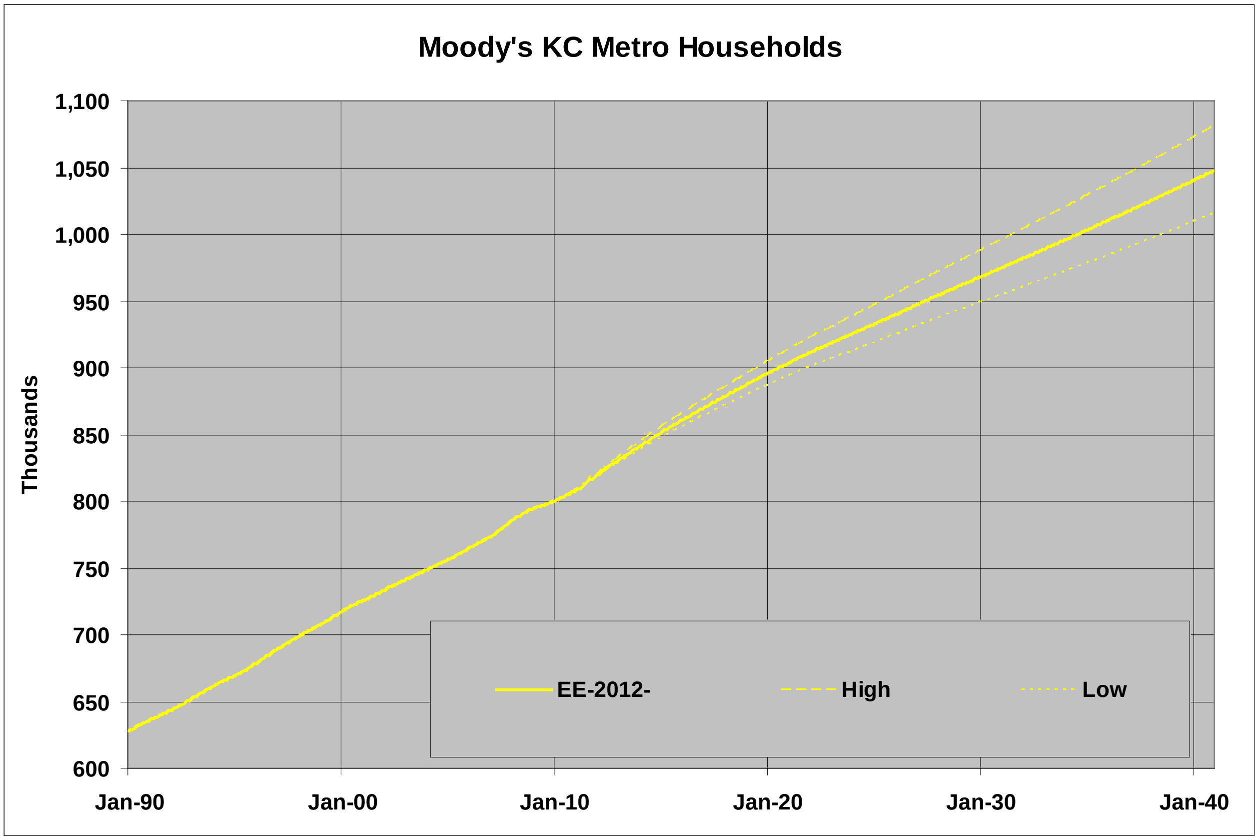
Table 55 Growth Rates for KC Metro Area

	Households	Employment Non-Manufacturing	Employment Manufacturing	Gross Product Non-Manufacturing	Gross Product Manufacturing
1990-2000	1.3%	1.9%	0.3%	3.0%	3.2%
2000-2010	1.1%	0.0%	-2.4%	1.3%	0.0%
2010-2020	1.1%	1.2%	0.9%	2.2%	3.4%
2020-2030	0.8%	0.8%	0.1%	2.1%	3.0%

Table 56 Growth Rates for SJ Metro Area

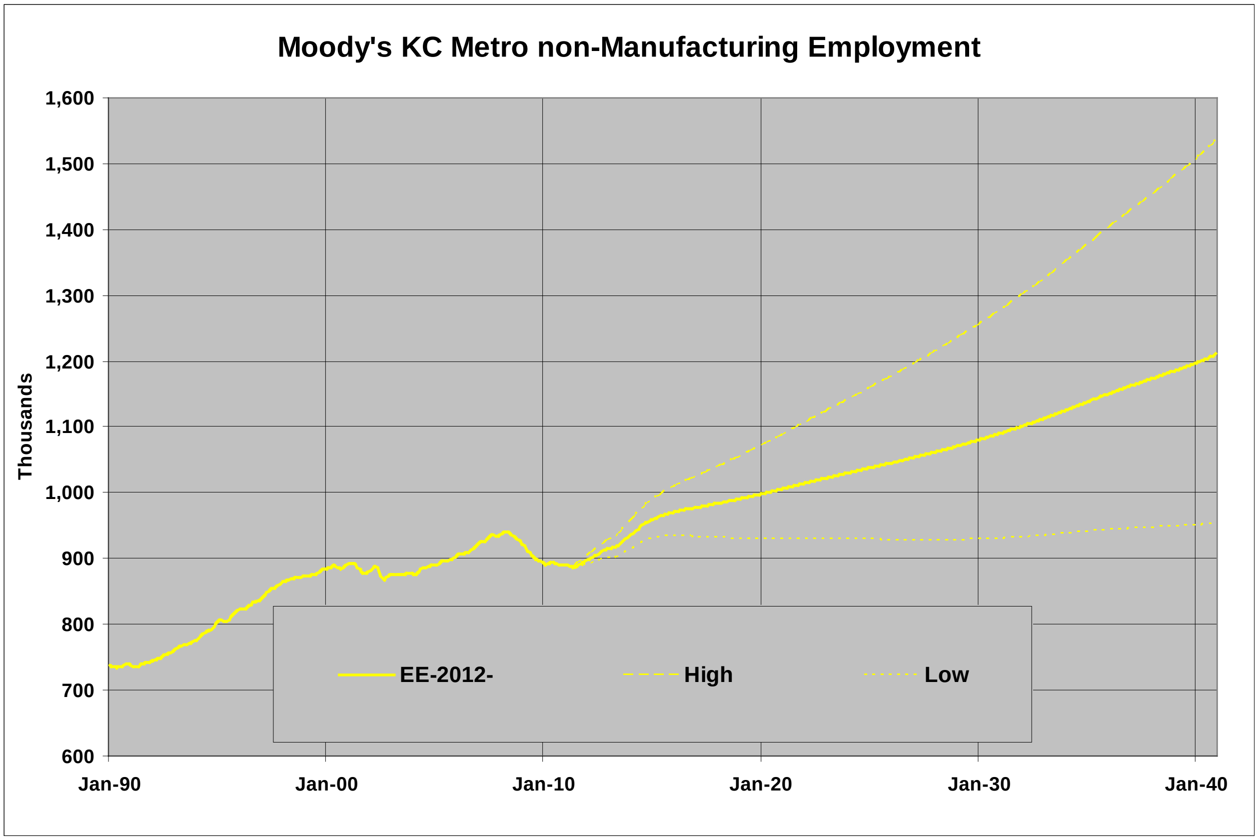
	Households	Employment Non-Manufacturing	Employment Manufacturing	Gross Product Non-Manufacturing	Gross Product Manufacturing
1990-2000	0.6%	1.8%	0.0%	3.2%	2.5%
2000-2010	0.4%	1.2%	1.5%	2.0%	4.1%
2010-2020	0.6%	0.3%	0.1%	1.7%	3.4%
2020-2030	0.2%	0.1%	-0.5%	2.0%	3.2%

Figure 48: KC Metro Households



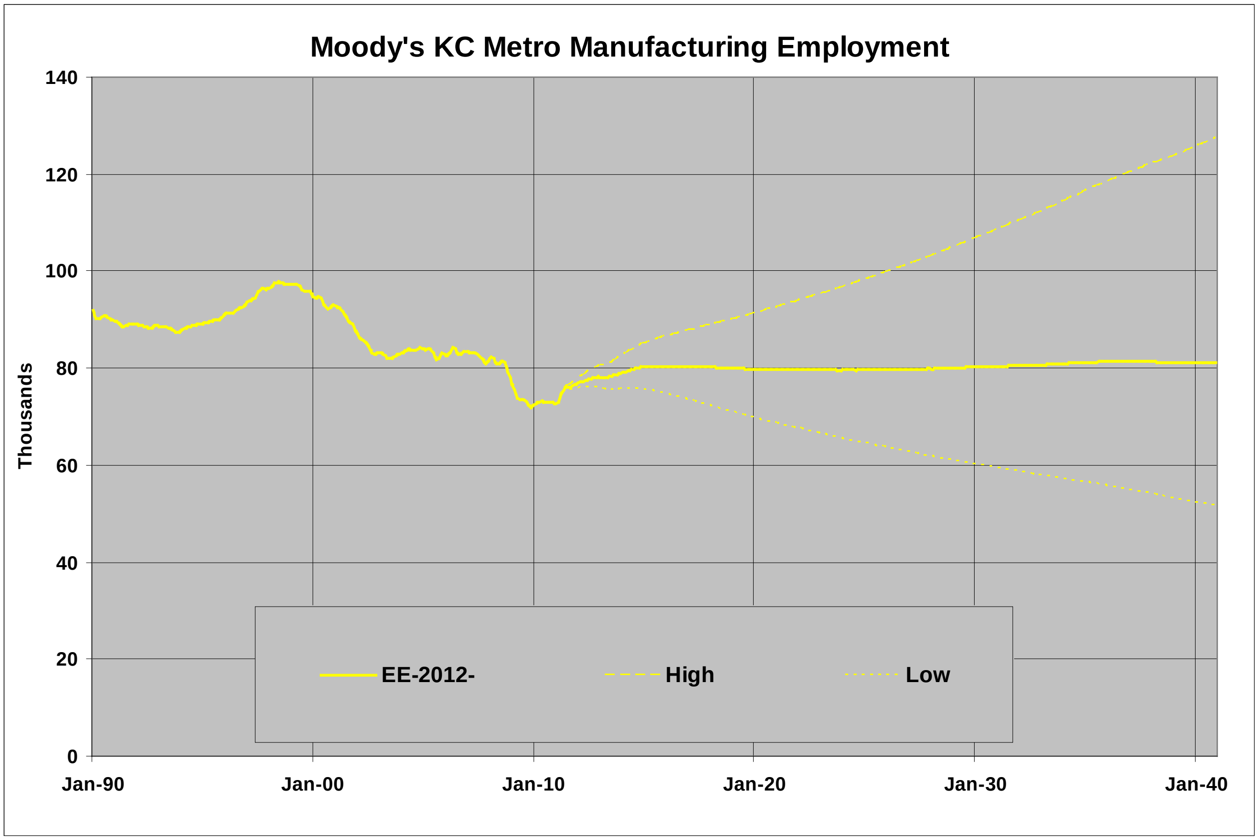
The household data and projection shows robust growth from 1990 until the beginning of the last recession at the end of 2007, at which time growth slowed substantially. The forecast is for the housing stock to growth rapidly again after the current period of low U.S. economic growth to allow the housing stock to catch up with demographic growth. Then growth slows to a level lower than what we have seen in the last two decades.

Figure 49: KC Metro Employment Non-Manufacturing



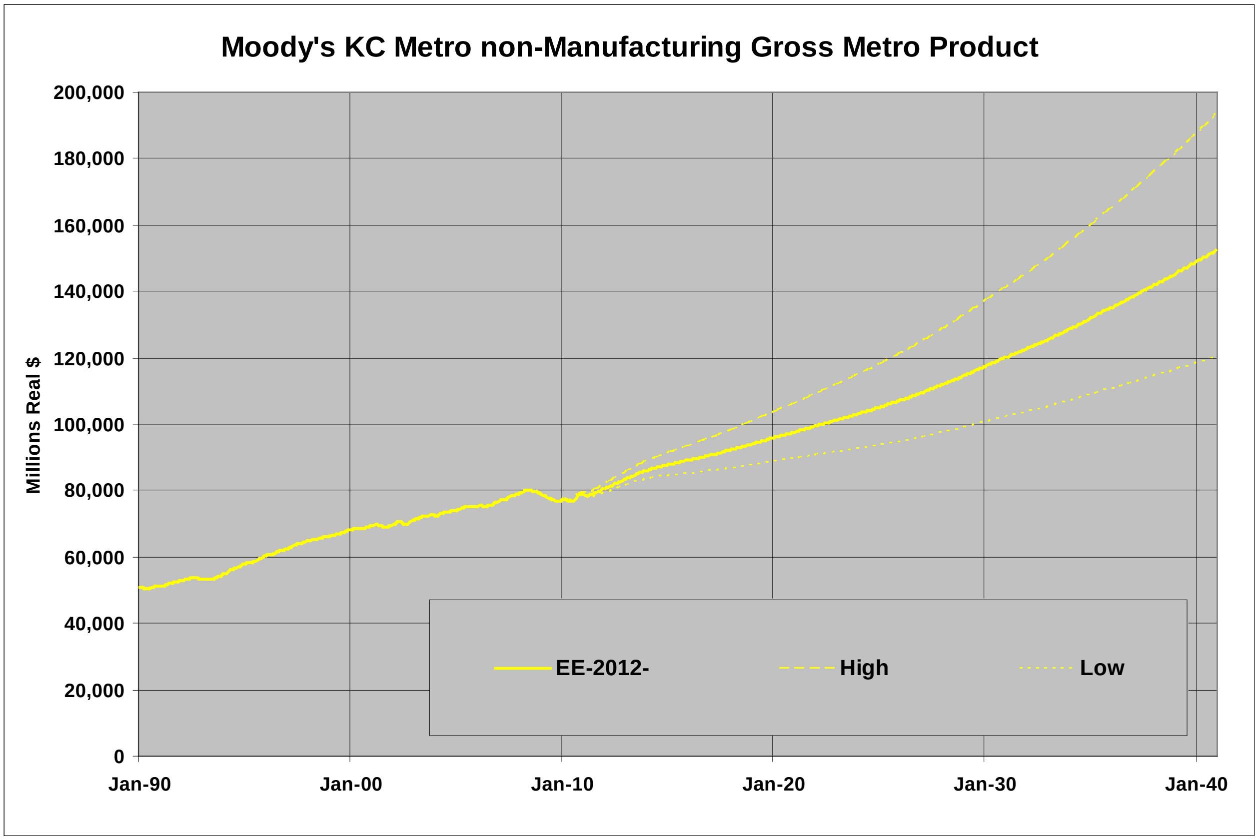
Non-manufacturing showed very strong growth in the 1990s, 1.9% per year, then stalled after the 2001 recession, picked up strongly in 2004 and then turned negative during the last recession. Moody's expects growth to rebound strongly after the current slump and then hold at about 1% after that.

Figure 50: KC Metro Employment Manufacturing



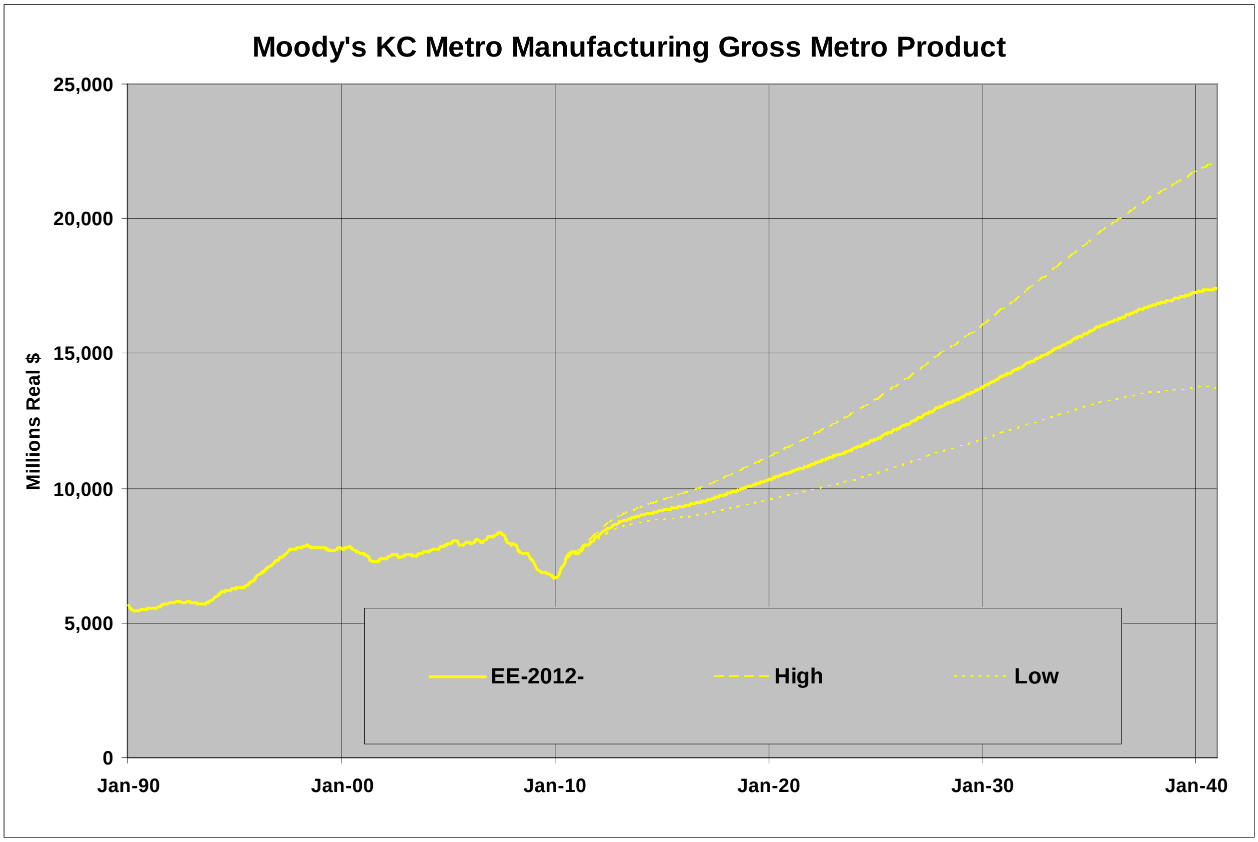
Manufacturing employment peaked in the late 1990s and has fallen since. It fell precipitously between 1999 and 2003 and again during the last recession. Moody's expects flat growth after we bounce back from the current economic slump.

Figure 51: KC Metro Gross Metro Product Non-Manufacturing



Real non-manufacturing gross metro product grew 3% per year during the 1990s, slowed down a bit after that and then declined during the last recession. GMP is growing faster than employment because of increasing productivity, a trend seen nationally and across many service sectors. Moody's expects above trend growth coming out of the current slump and then trend growth after that.

Figure 52: KC Metro Gross Metro Product Manufacturing



Real gross metro product from the manufacturing sector grew strongly during the 1990s and then fell flat until it plunged during the last recession. Moody's expects rebound growth coming out of the current economic slump and then trend growth after that. GMP for this sector is growing while employment is flat or declining because of increasing productivity and because more labor intensive industries tend to move overseas where there is lower cost labor.

Figure 53 SJ Metro Households

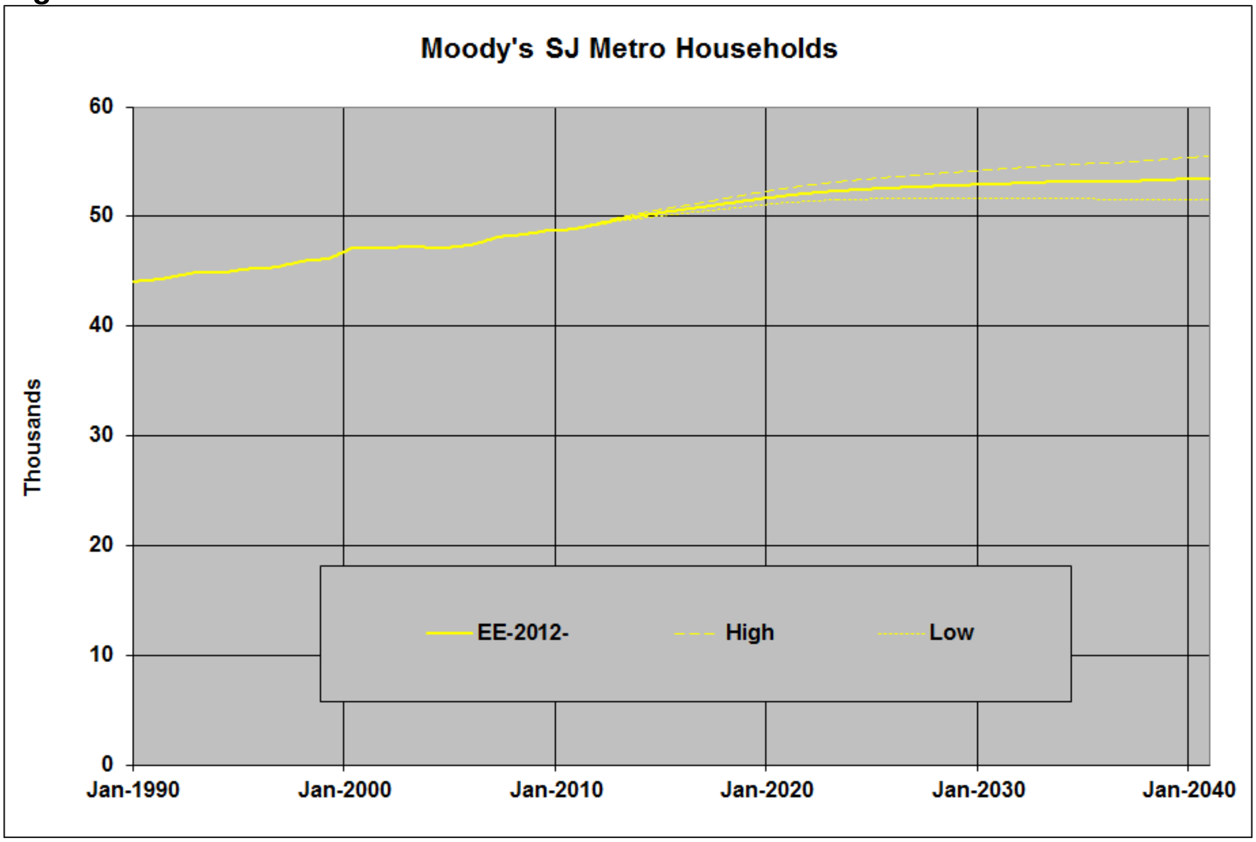


Figure 54 SJ Metro non-Manufacturing Employment

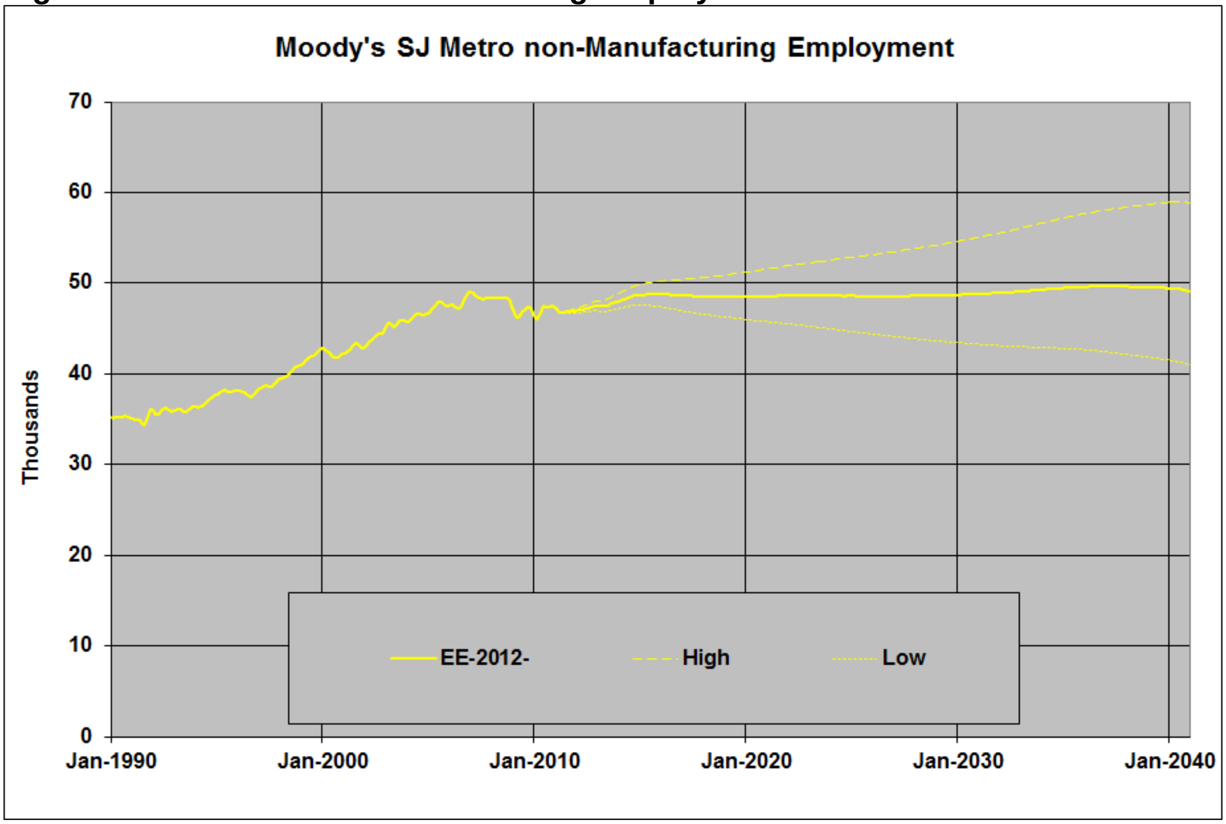


Figure 55 SJ Metro Manufacturing Employment

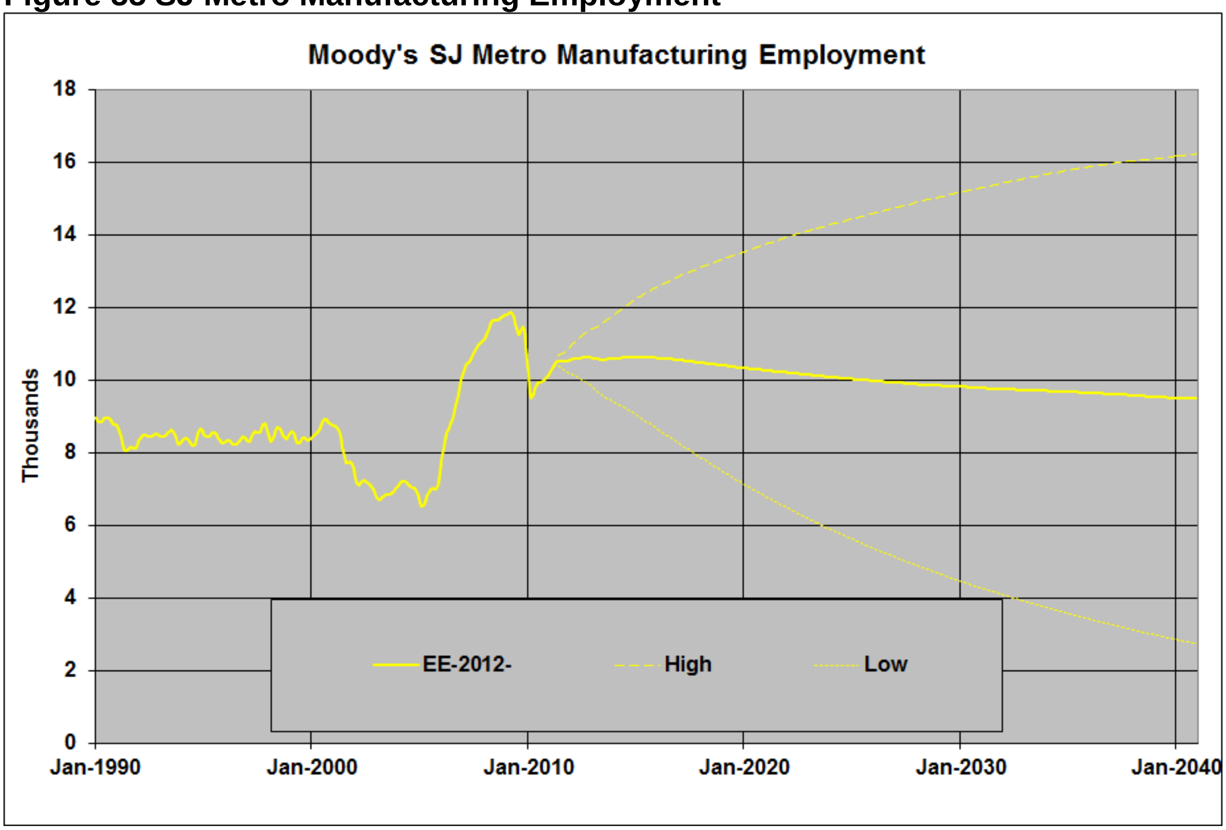


Figure 56 SJ Metro non-Manufacturing Gross Metro Product

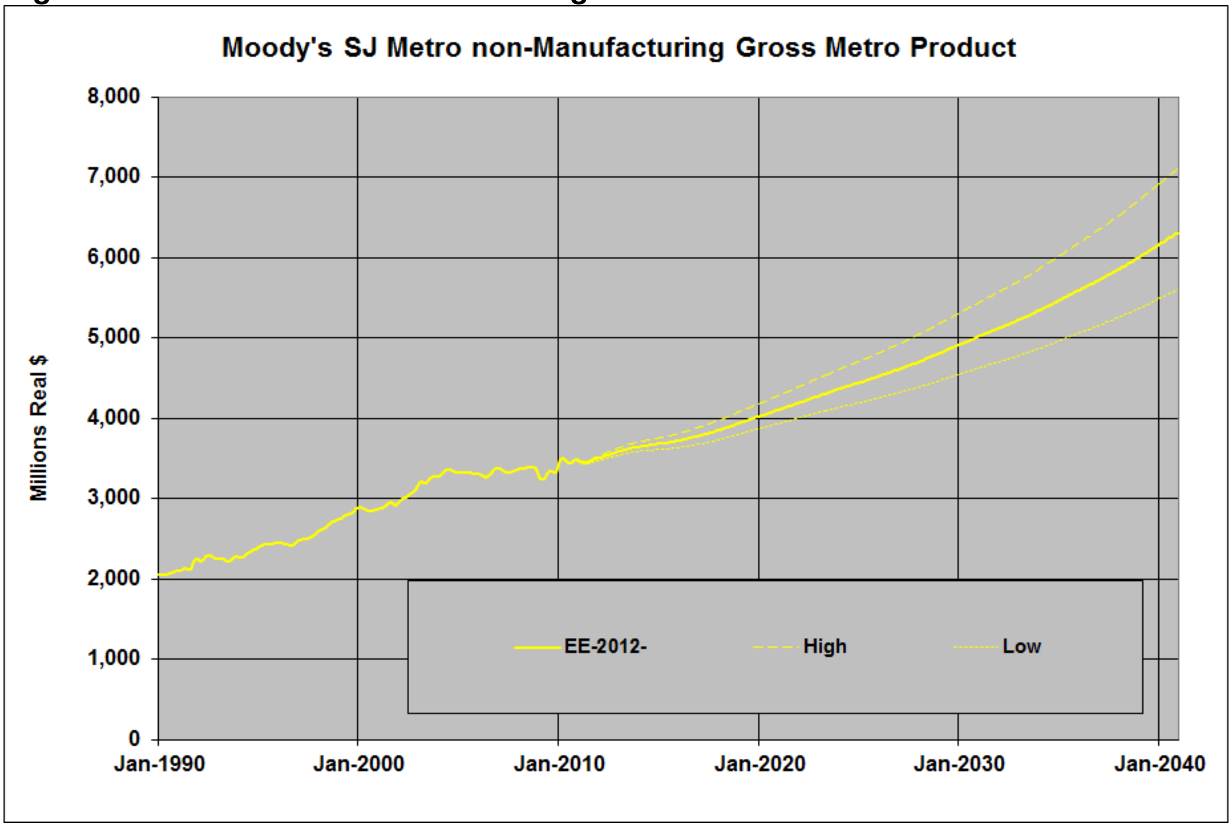


Figure 57 SJ Metro Manufacturing Gross Metro Product

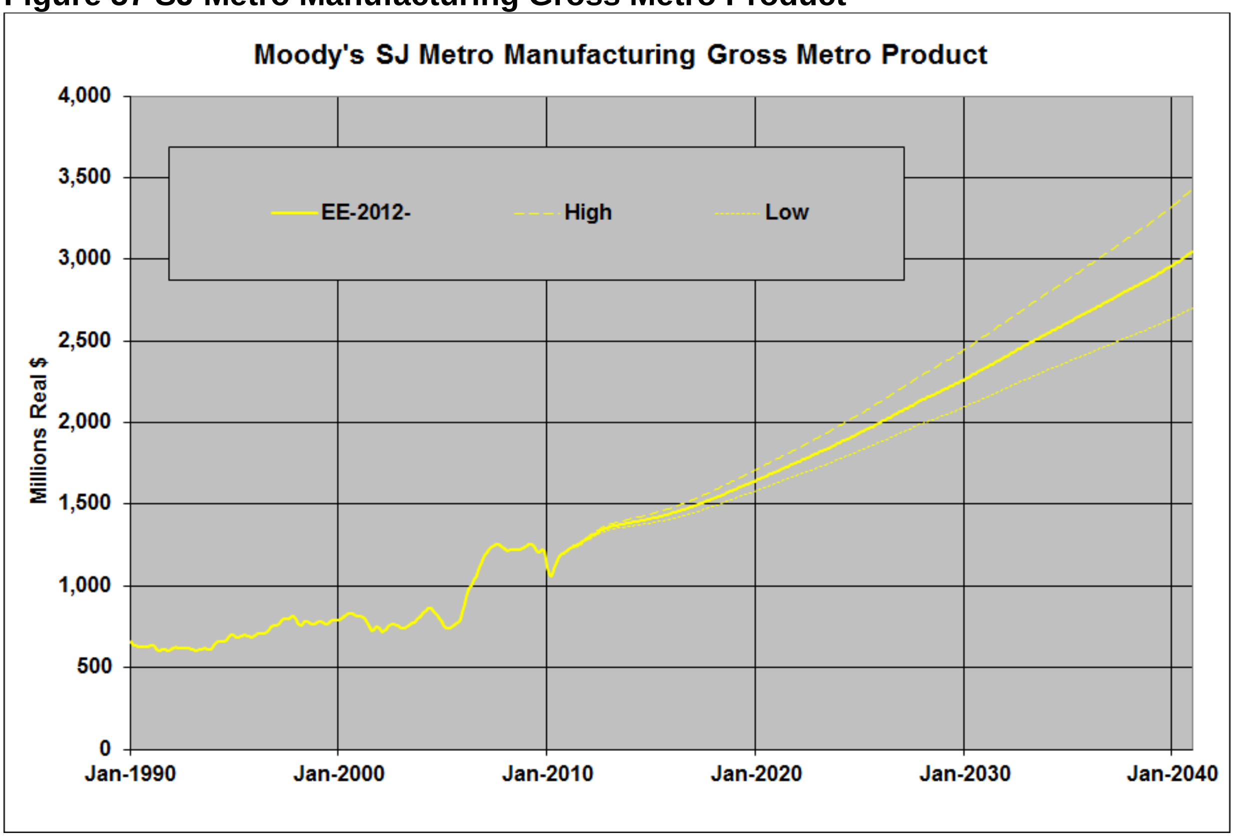
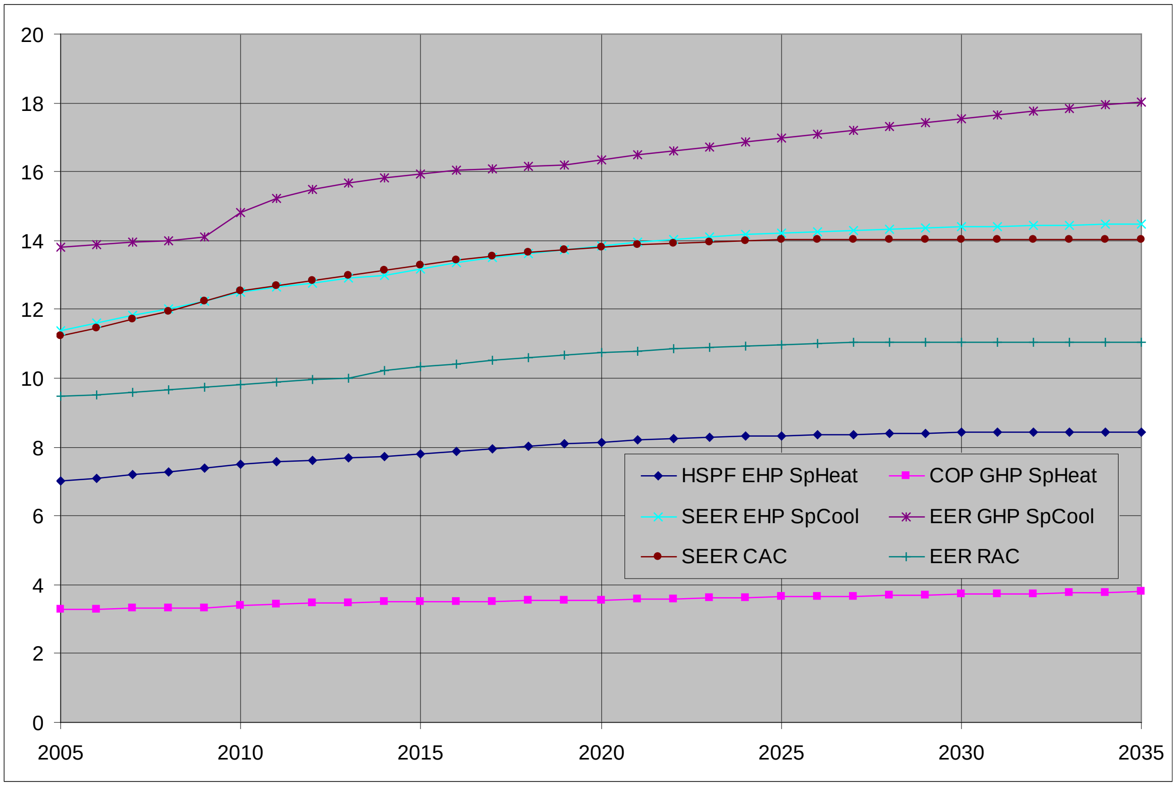
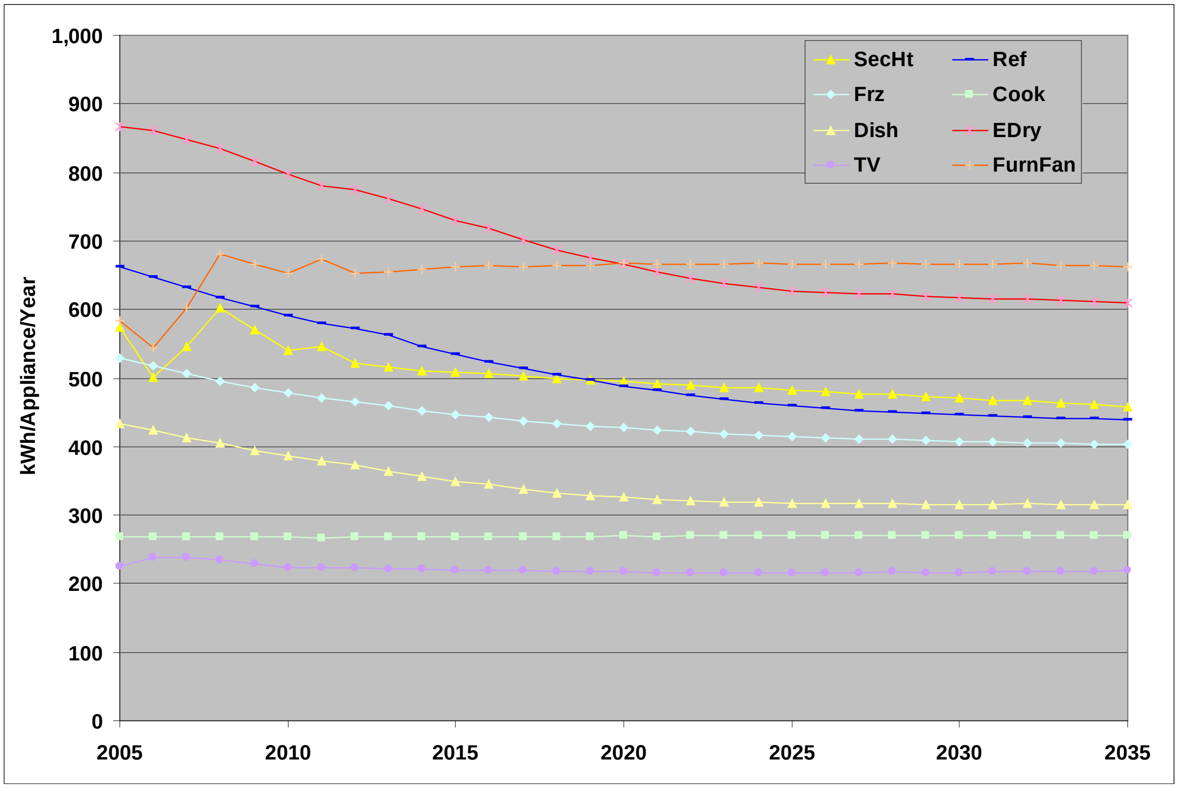


Figure 58: DOE Stock Average Appliance Efficiency Projections



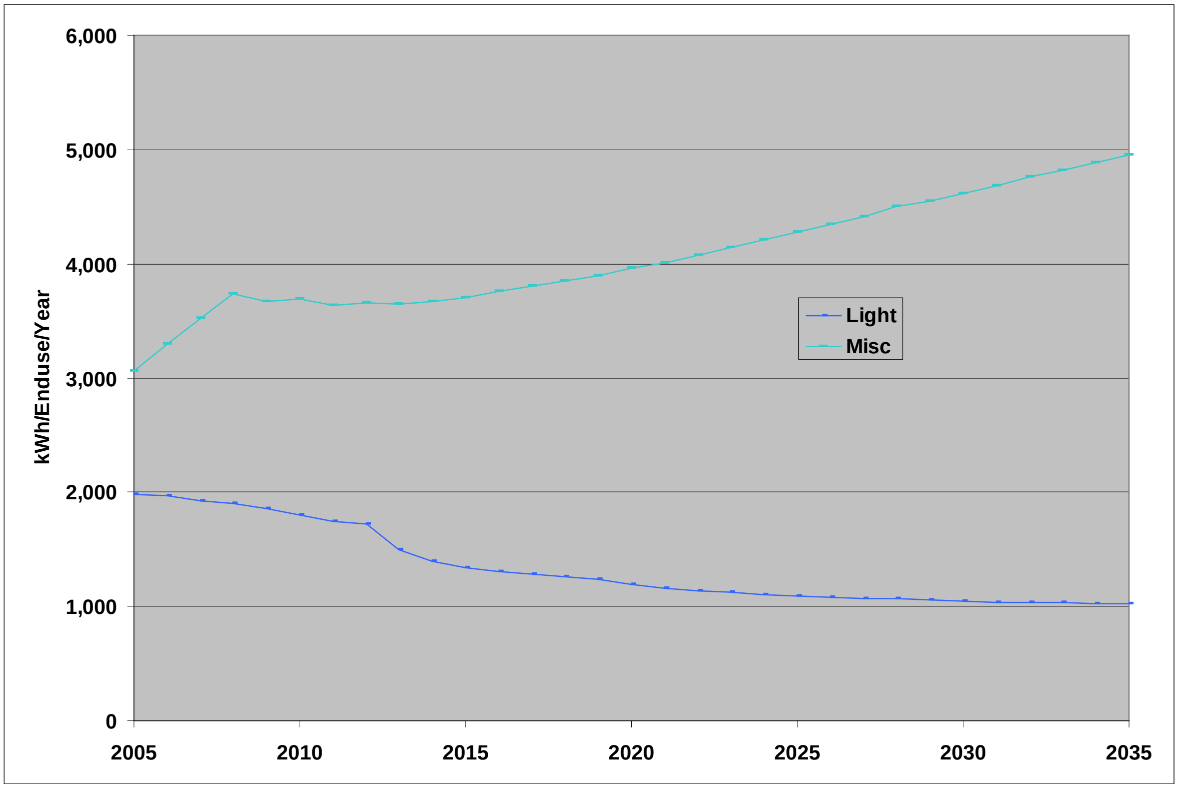
DOE is expecting increases in the stock average appliance efficiencies for residential heating and cooling equipment. This is resulting from appliance standards. In January 2006 a new standard raised the SEER standard by 30 percent for central air conditioners. This standard impacts the stock average efficiency both from new construction and when units are replaced.

Figure 59: DOE UEC Projections (<1000 kWh/year)



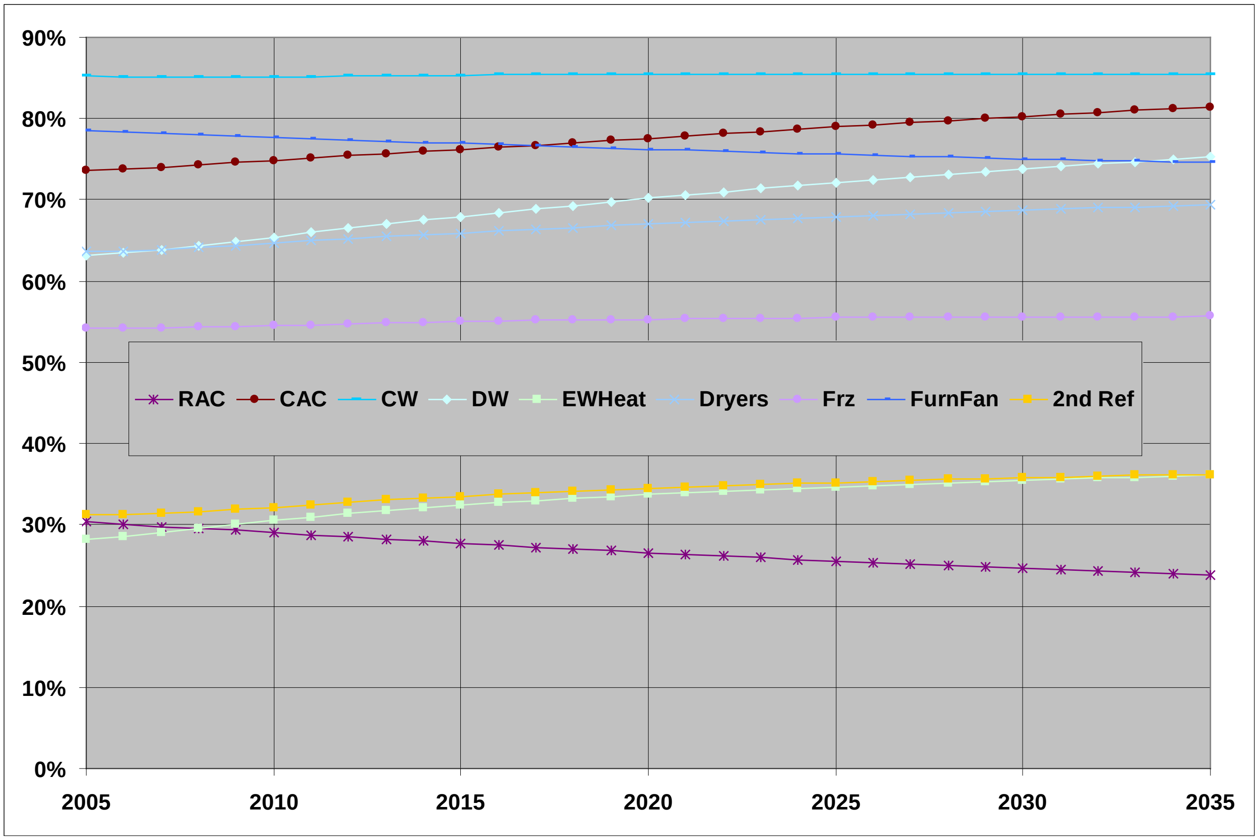
UECs are expected to decline substantially for electric clothes dryers, refrigerators, electric cooking and dishwashers due to appliance efficiency standards.

Figure 60: DOE UEC Projections (>1000 kWh/year)



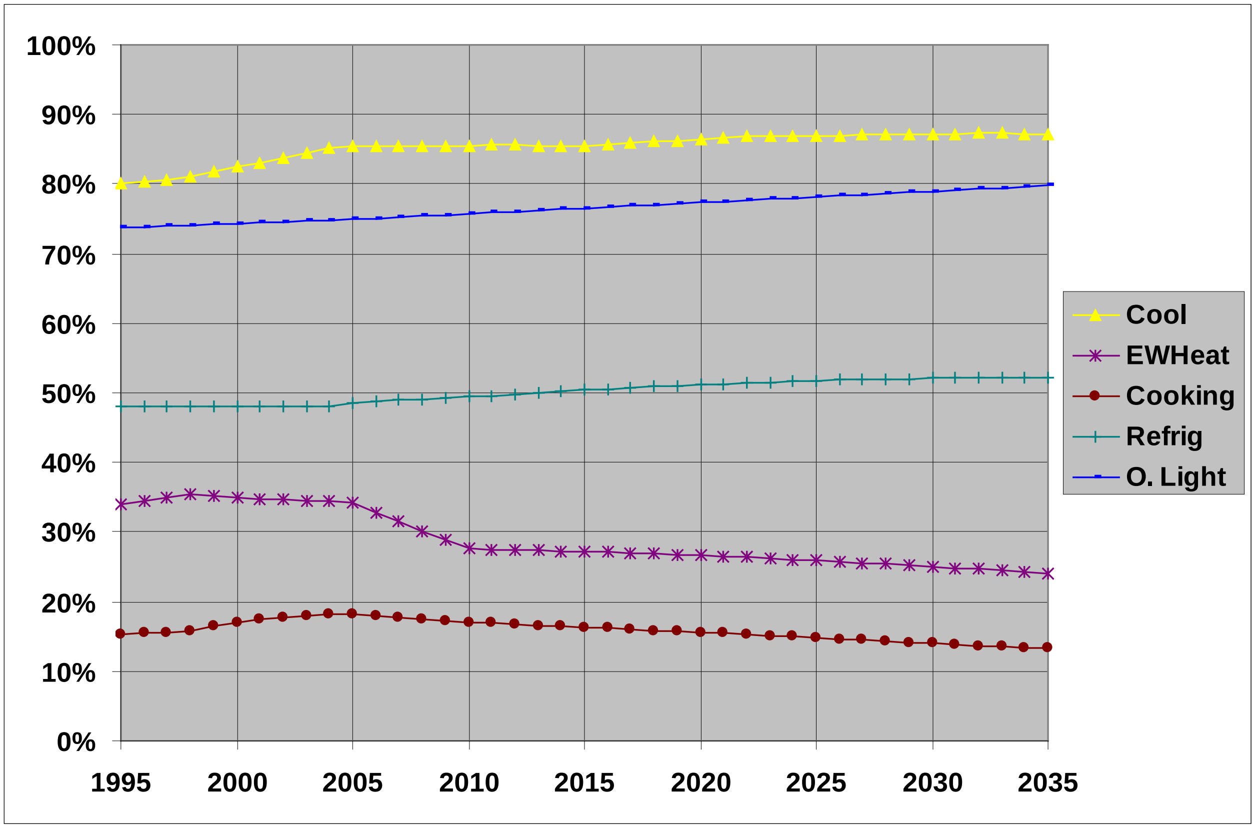
The UEC for lighting is declining because of the increasing sales of CFLs and is expected to decline even more rapidly beginning in 2012 due to a new standard for light bulbs.

Figure 61: DOE Electric Appliance Saturation Projections (< 100%)



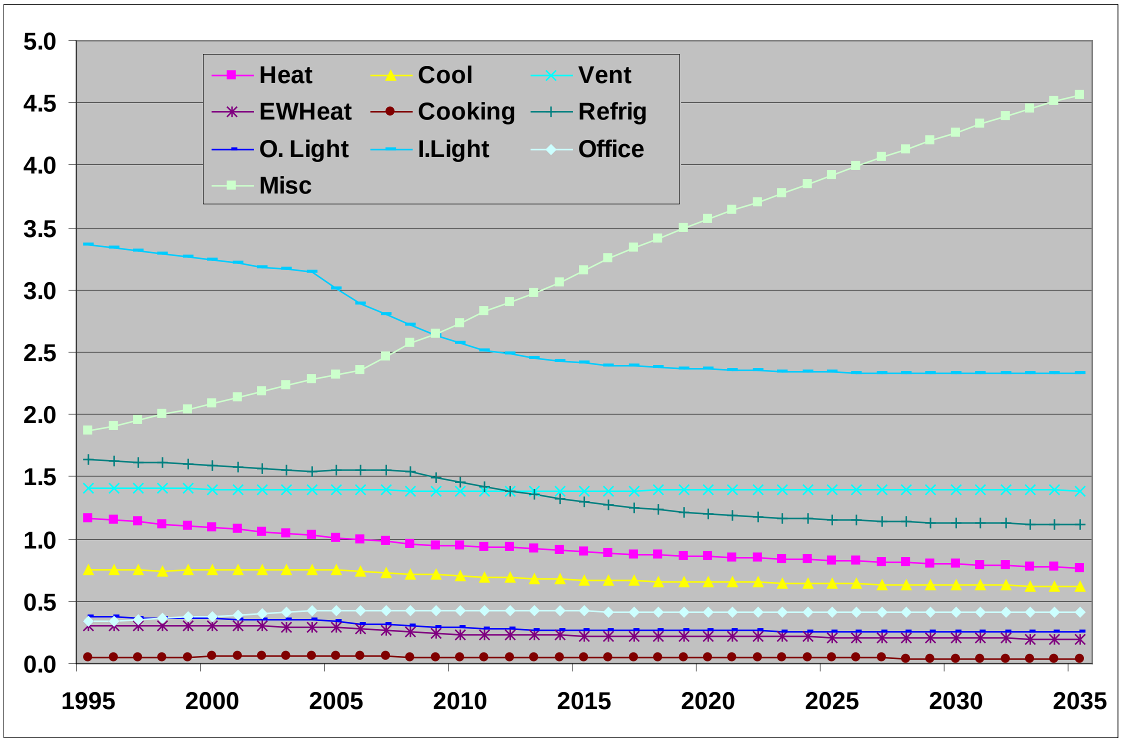
DOE saturation projections shown above are in line with recent historical trends.

**Figure 62: DOE Equipment Saturation Projections
(Average over all Commercial Building Types)**



DOE commercial sector saturations are mostly in line with trends in recent historical data. The saturation of electric water heating dropped from about 34% in 2004 to 28% in 2010 perhaps because natural gas prices have fallen precipitously. Electric cooking saturations are also falling.

Figure 63 DOE EUI Projections
(Average over all Commercial Building Types)



DOE estimates of the EUI for lighting has been declining since 1995 and started falling more rapidly in 2005, probably because of the use of CFLs, especially for lodging and in recessed fixtures in offices. The refrigeration EUI has been declining historically and started a more rapid decline in 2009, which continues with the projection. New standards for commercial refrigeration equipment went into effect at the beginning of 2010.[viii] The heating EUI is declining and expected to further decline. A new standard for commercial heating and cooling equipment became effective in April 2007 and November 2004.[ix] The EUI for miscellaneous equipment has been rising rapidly and is expected to continue that trend.

7.2.4 <u>SPECIFICATION AND QUANTIFICATION OF FACTORS</u>

4. Where judgment has been applied to modify the results of a statistical or mathematical model, the utility shall specify the factors which caused the modification and shall explain how those factors were quantified.

GMO used the forecasts of economic and demographic variables as is from Moody's Analytics.

The projections of appliance saturations from DOE were calibrated to the results of our Residential Appliance Saturation.

7.3 NET SYSTEM LOAD FORECAST

(C) Net System Load Forecast. The utility shall produce a forecast of net system load profiles for each year of the planning horizon. The net system load forecast shall be consistent with the utility's forecasts of monthly energy and peak demands at time of summer and winter system peaks for each major class.

GMO has produced an hourly forecast for each major class and the sum of these forecasts is the hourly forecast of NSI.

SECTION 8: LOAD FORECAST SENSITIVITY ANALYSIS

(8) Load Forecast Sensitivity Analysis.

The utility shall describe and document its analysis of the sensitivity of the dependent variables of the base-case forecast for each major class to variations in the independent variables identified in subsection 4 CSR 240-22.030(8).

To perform a sensitivity analysis, we are using a method that was suggested by the Missouri Public Service Commission Staff for GMO's IRP. For each major class, mwh sales were regressed on important driver variables and degree days and the standardized variables are used to show the relative importance of each explanatory variable. We also show the elasticity for each driver variable as measured by the statistical regression run with monthly data available from 1996 to 2010.

Table 57 displays the results for MPS residential customers. Among the driving variables, the number of heating degree days times the number of households has the largest standardized coefficient, followed by the number of cooling degree days also multiplied by the number of customers. Heating degree days times the number of customers times a trend was the third most important variable because the rising saturation of electric space heating has hugely increased winter sales. The inflation adjusted real price of electricity times the number of customers was not statistically significant. The price of electricity was multiplied by the number of customers because the magnitude of the price impact on kWh sales would be expected to rise proportionally to the number of customers. The variable hddPriceRatio is heating degree days with a base temperature of 55 degrees times the number of customers times the price of natural gas for MGE's residential customers divided by the price of electricity. The purpose of this variable is to measure the impact of gas and electric prices on electric space heating loads. The variable had the expected sign, but was not significant. The variable DAYS is the number of billing days averaged over each billing cycle.

Table 57 MPS Residential

VARIABLE	Standardized Coefficient	t-Statistic	Elasticity
DAYS	1,084	2.0	
CUSTOMERS	9,588	6.1	0.53
PrElecCus	-2,389	-1.4	-0.09
cusHDD55PriceRatio	2,228	0.6	0.01
cdd80_cust	-4,617	-3.8	
cdd65_cust	69,967	32.7	
custCDD65Trend	2,118	1.2	
hdd55_cust	71,277	10.4	
custHDD65Trend	19,704	10.5	
hdd45_cust	-16,572	-3.9	
jan_2005	3,139	5.1	

Table 58 provides the results for MPS SGS customers. As for residential customers, the two variables with the largest standardized coefficients were heating and cooling degree days times the number of customers. The real price of electricity was highly significant with an elasticity of -0.35. The gas to electric price ratio was not significant.

Table 58 MPS SGS

VARIABLE	Standardized Coefficient	t-Statistic	Elasticity
DAYS	1,048	8.1	
CUSTOMERS	4,563	13.9	0.77
PrElecCus	-2,145	-8.0	-0.35
hddPriceRatioCus	-1,553	-1.4	-0.02
cdd70_cust	-4,189	-3.0	
cdd65_cust	13,030	8.7	
cusCDD65Trend	-1,293	-3.0	
hdd50_cust	7,739	5.8	
cusHDD50Trend	1,988	3.7	
Jan_2005	698	3.7	

Cooling degree days times the number of customers had the largest standardized coefficient, followed by the real price of electricity. The electric price elasticity was -0.61.

Table 59 MPS LGS

VARIABLE	Standardized Coefficient	t-Statistic	Elasticity
DAYS	1,030	6.4	
Employment_NonManufacturing	1,819	3.7	1.05
RealPriceElec	-3,446	-2.4	-0.61
cusHDD45PriceRatio	308	0.2	0.00
cdd55_cust	6,634	9.0	
cusCDD55Trend	-1,724	-2.3	
hdd45_cust	2,420	1.7	
Mar2000Apr	-665	-4.8	
Feb2002Mar	-566	-4.2	

The price of electricity was not significant for MPS LP.

Table 60 MPS LP

VARIABLE	Standardized Coefficient	t-Statistic	Elasticity
DAYS	-2,152	-7.4	
Gross_Product_Non_Manufacturing	11,248	28.2	1.45
RealPriceElec	-245	-0.5	-0.02
cdd55_cust	9,418	19.1	
hdd35_cust	1,126	2.1	
Feb_2001	-2,274	-4.7	

Table 61 shows the results for residential customers of SJLP. The variables with the largest standardized coefficients are degree days times the number of customers. The price variables were not significant.

Table 61 SJLP Residential

VARIABLE	Standardized Coefficient	t-Statistic	Elasticity
DAYS	293	1.4	
CUSTOMERS	547	4.0	0.46
PrElecCus	-87	-0.2	-0.02
cusHDD55PriceRatio	13	0.0	0.00
cdd80_cust	-781	-1.9	
cdd65_cust	16,103	23.1	
hdd55_cust	30,696	13.6	
hdd45_cust	-7,559	-5.4	
Jan_2005	844	4.0	
cusCDD65Trend	877	1.9	
cusHDD55Trend	8,709	15.4	

Table 62 shows the results for SJLP SGS. The electric price variable had the wrong sign and was not significant. The gas to electric price ratio also is not significant.

Table 62 SJLP SGS

VARIABLE	Standardized Coefficient	t-Statistic	Elasticity
DAYS	98	4.0	
Employment_NonManufacturing	117	6.4	0.47
cusHDD55PriceRatio	247	1.3	0.02
hdd55_cust	1,365	5.7	
cdd65_cust	1,331	19.5	
cusCDD65Trend	59	0.9	
cusHDD55Trend	456	4.6	

The price variables for LGS were significant. The elasticity for the real electric price is −0.19. There is also a substitution effect for natural gas, which has an elasticity of 0.08.

Table 63 SJLP LGS

VARIABLE	Standardized Coefficient	t-Statistic	Elasticity
DAYS	304	3.8	
Employment_NonManufacturing	695	9.4	0.75
RealPriceElec	-714	-5.0	-0.19
realPriceGas	551	3.1	0.08
hddPriceRatio	910	3.0	0.02
hdd45_cust	832	2.7	

For Large Power customers, the coefficients for price had the wrong sign.

Table 64 SJLP LP

VARIABLE	Standardized Coefficient	t-Statistic	Elasticity
DAYS	-1,420	-6.4	
Gross_Product_Non_Manufacturing	7,276	14.3	1.72
cdd55_cust	3,258	5.4	

8.1 TWO ADDITIONAL NORMAL WEATHER LOAD FORECASTS

(A) The utility shall produce at least two (2) additional normal weather load forecasts (a high-growth case and a low-growth case) that bracket the base-case load forecast. Subjective probabilities shall be assigned to each of the load

forecast cases. These forecasts and associated subjective probabilities shall be used as inputs to the risk analysis required by 4 CSR 240-22.060.

GMO used two additional economic forecasts from Moody's Analytics to produce high-growth and low-growth load forecast scenarios. These additional scenarios represent economic growth one standard deviation above and below the base case forecast.

In addition to these two scenarios, GMO produced an additional scenario to comply with the Commission's on October 19, 2011, *ORDER ESTABLISHING SPECIAL CONTEMPORARY RESOURCE PLANNING ISSUES*:

> Investigate and document the impacts on KCPL-GMO's preferred resource plan and contingency plans of a loss of significant load for the short term and potentially for the long term that may be the result of a prolonged double-dip recession or a large customer or group of customers no longer taking service from KCPL-GMO.

GMO constructed this scenario by subtracting the energy and peak demand from the largest customer for both SJLP and MPS from the results for the base case scenario. The most recent 12 billing records from each customer were used and the energy and peak from each month was used for that particular month in the forecast. Losses were added to the energy and peak demands.

The corresponding figures below show the base-case, low-case, high-case, and significant loss forecasts for energy and demand.

Figure 64: MPS Base, Low, High and Significant Loss Energy (NSI) Forecast

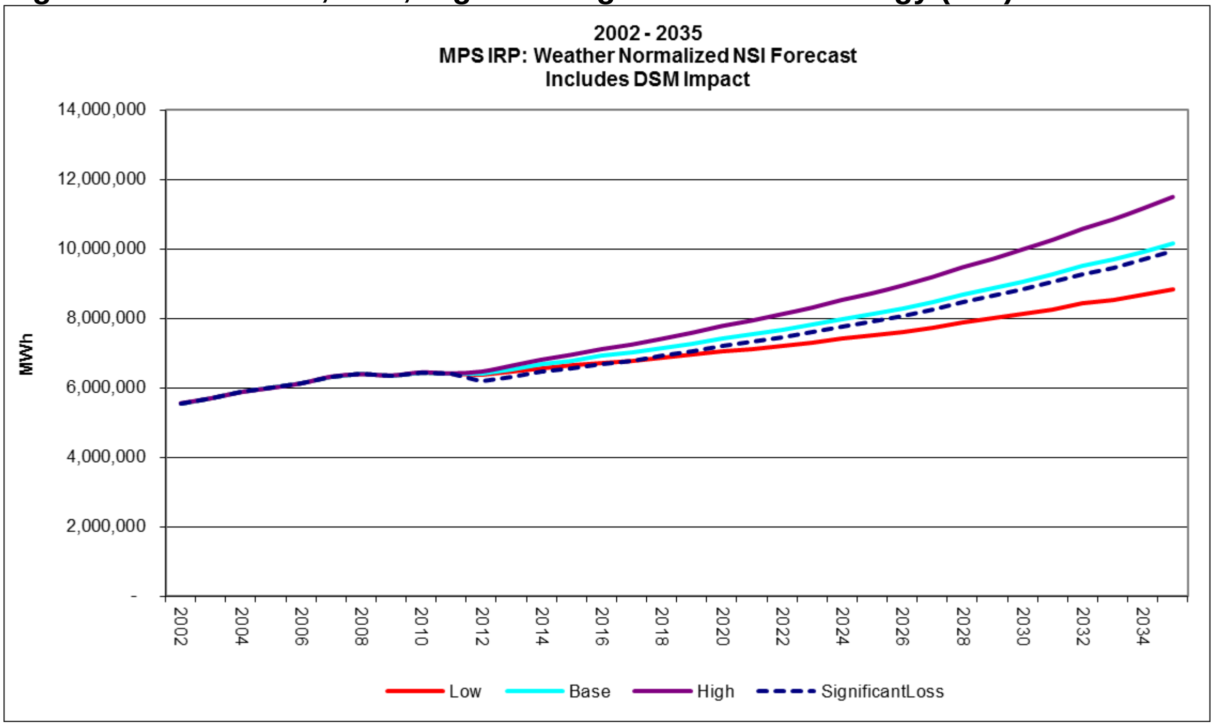


Figure 65: MPS Base, Low, High and Significant Loss Peak Demand Forecast

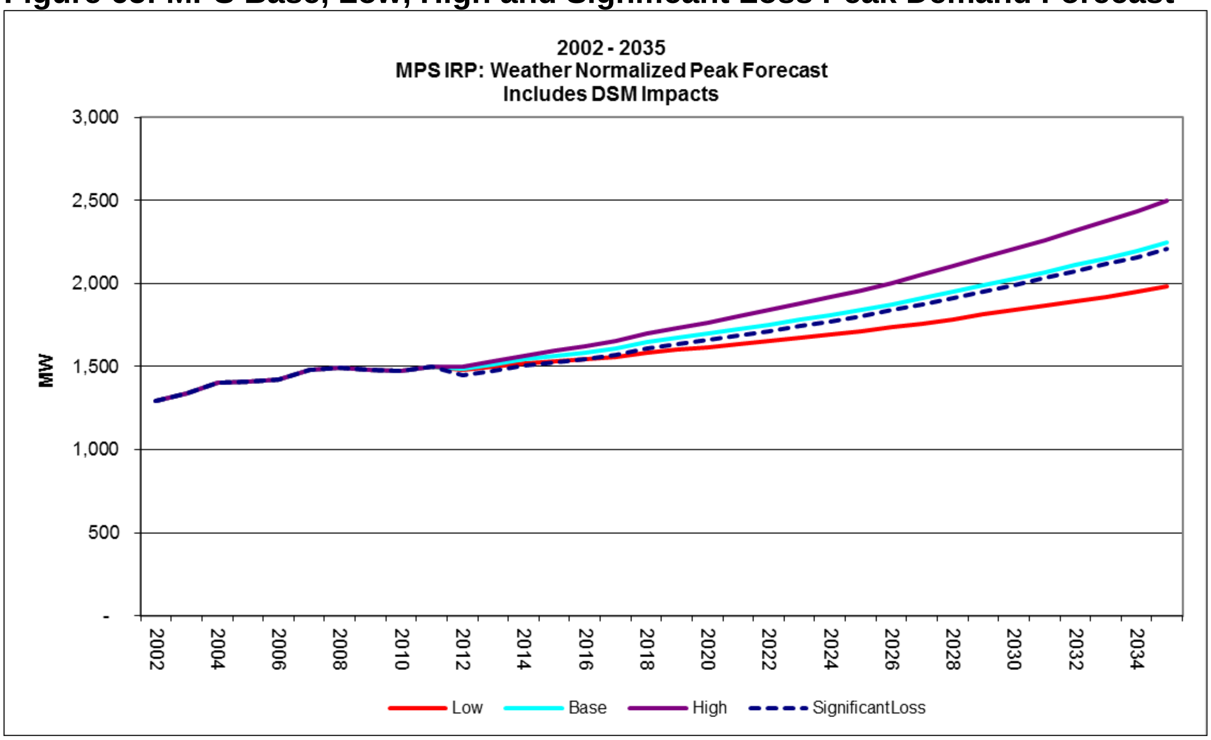


Figure 66: SJLP Base, Low, High and Significant Loss Energy (NSI) Forecast

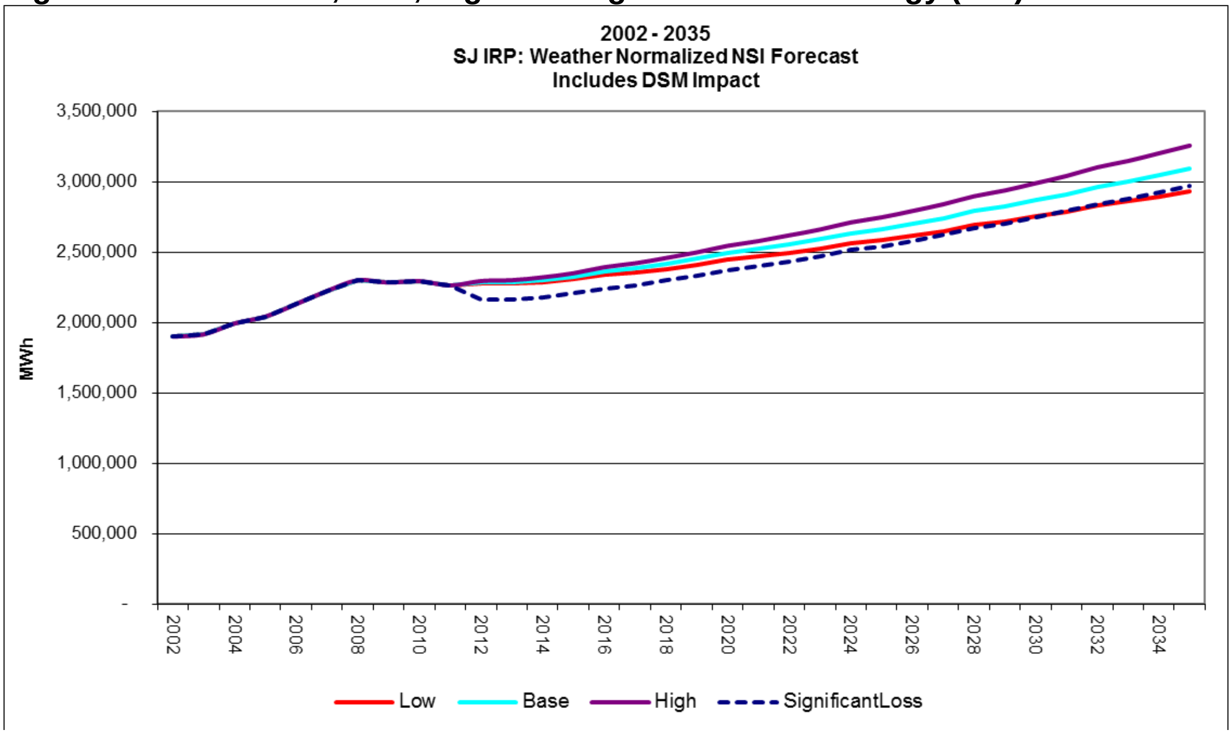


Figure 67: SJLP Base, Low, High and Significant Loss Peak Demand Forecast

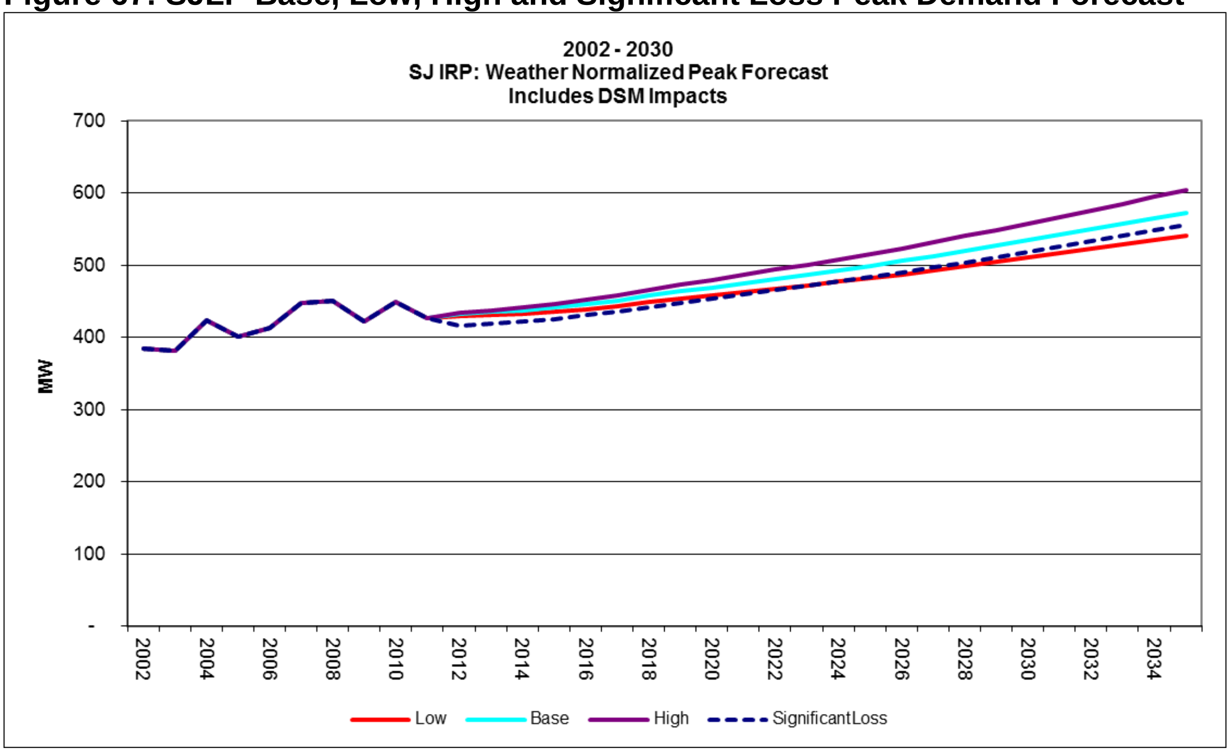


Figure 68: GMOC Base, Low, High and Significant Loss Energy (NSI) Forecast

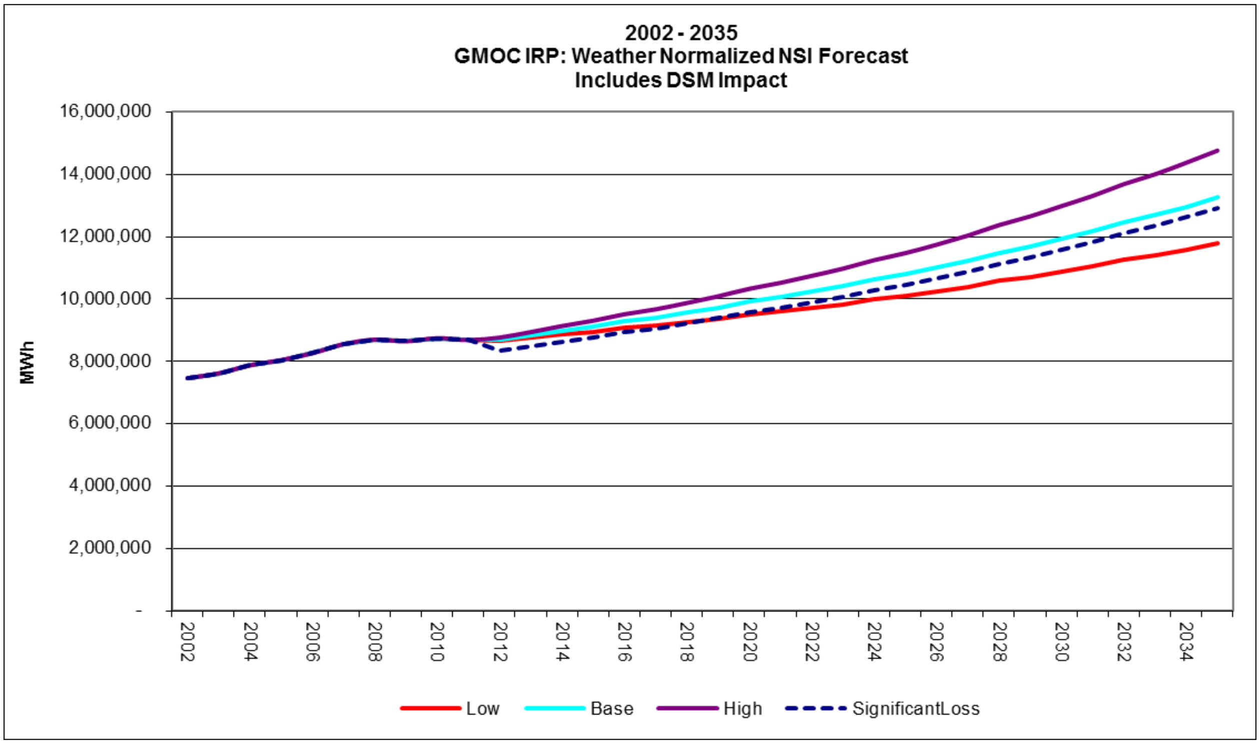
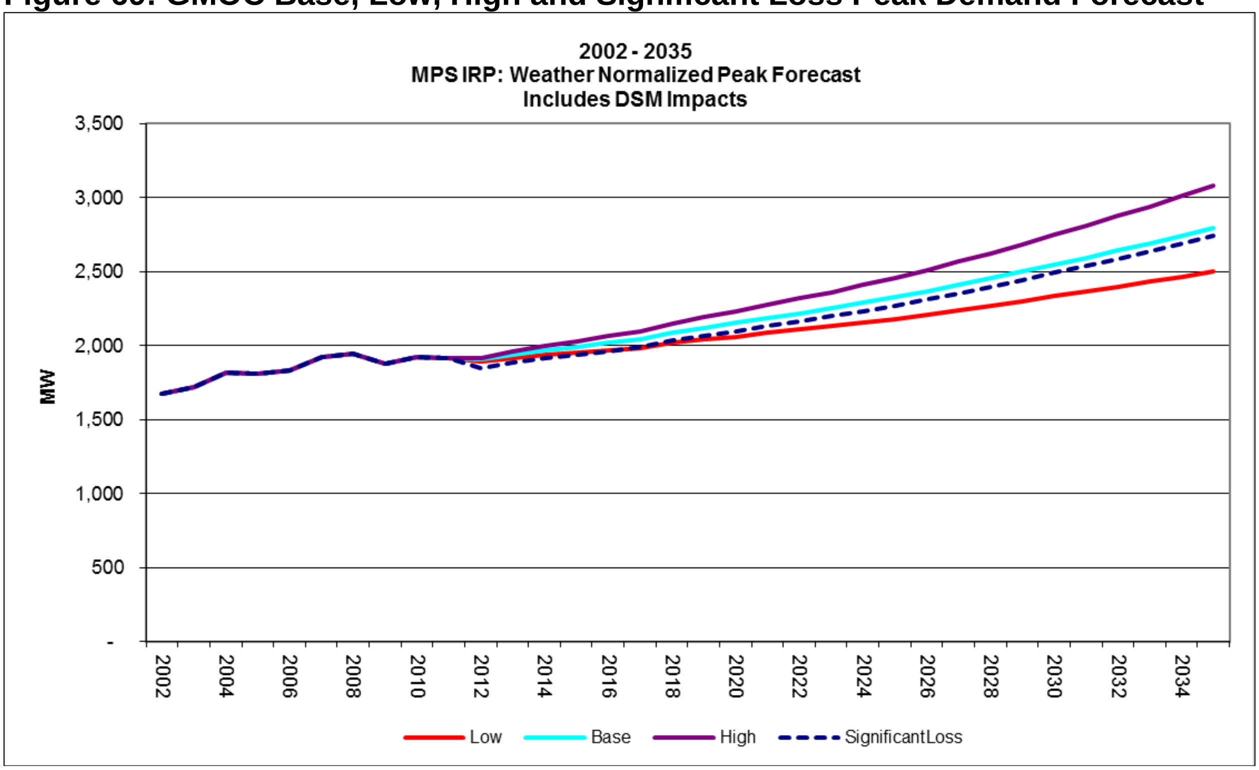


Figure 69: GMOC Base, Low, High and Significant Loss Peak Demand Forecast



8.2 ESTIMATE OF SENSITIVITY OF SYSTEM PEAK LOAD FORECASTS TO EXTREME-WEATHER

(B) The utility shall estimate the sensitivity of system peak load forecasts to extreme weather conditions. This information shall be considered by utility decision-makers to assess the ability of alternative resource plans to serve load under extreme weather conditions when selecting the preferred resource plan pursuant to 4 CSR 240-22.070(1).

GMO created a forecast scenario using the base case economic scenario and weather from the years with more than 1,700 cooling degree days at KCI. These years were 1980, 1988, 2006 and 2010. The number of cooling degree days those years were 1,746, 1,724, 1,724 and 1,705. The scenario was created by running our computer programs with normal weather computed with those four years instead of with 30 years. In 2012, the peak rose from 1,904 mW to 2,015 mW. In 2020, the peak increased from 2,151 to 2,267 under this scenario. The complete set of results is in a file, *GMO Peak Monthly_Annual 12_7_11.xls.* This file contains monthly NSI and peak load for all forecast scenarios.

The corresponding figures below show the base-case, low-case, high-case, and extreme weather forecasts for energy and demand.

Figure 70: MPS Base, Low, High, and Extreme Weather Energy (NSI) Forecast

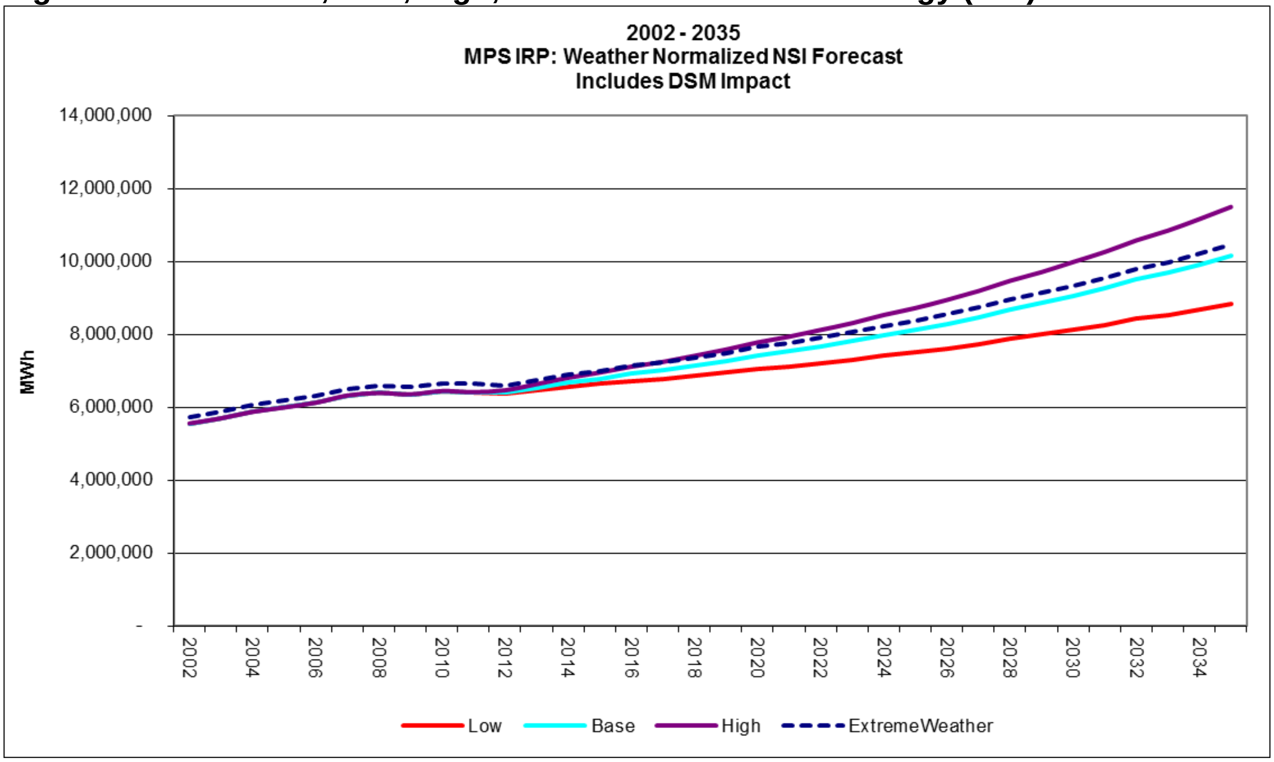


Figure 71: MPS Base, Low, High, and Extreme Weather Peak Demand Forecast

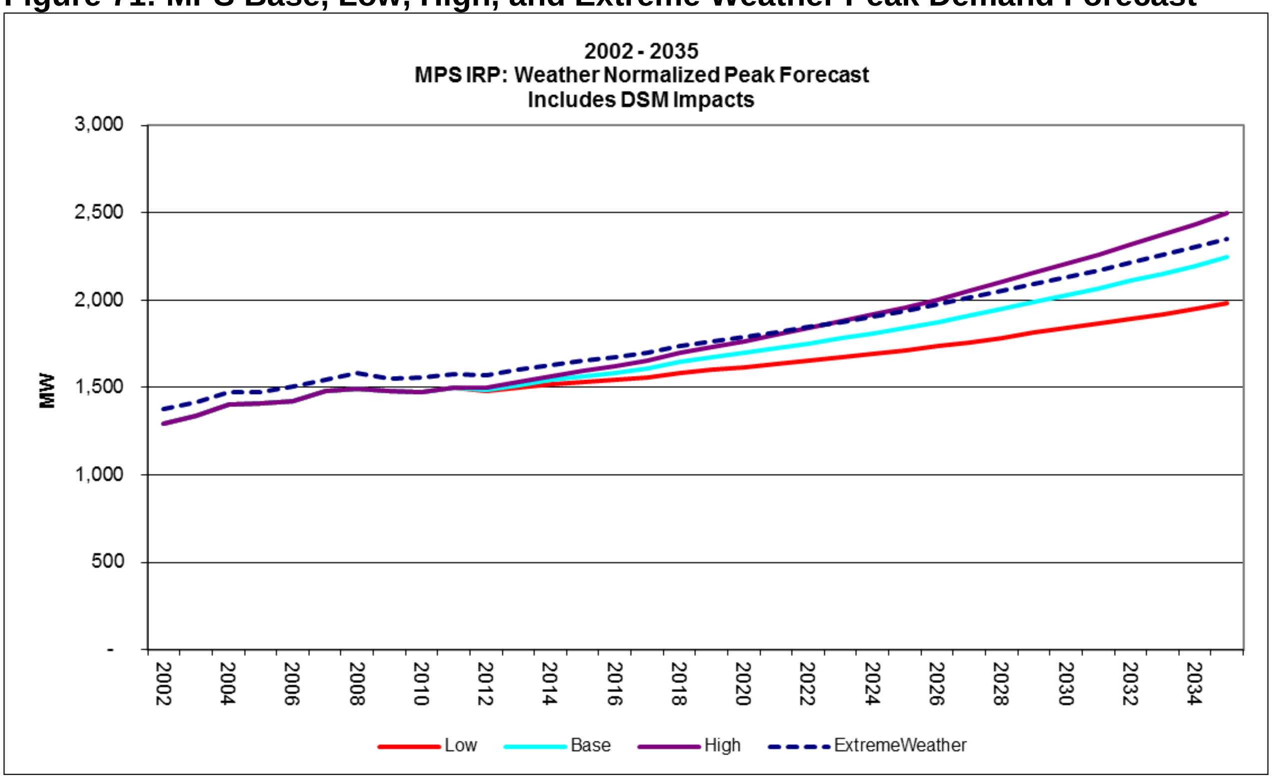


Figure 72: SJLP Base, Low, High and Extreme Weather Energy (NSI) Forecast

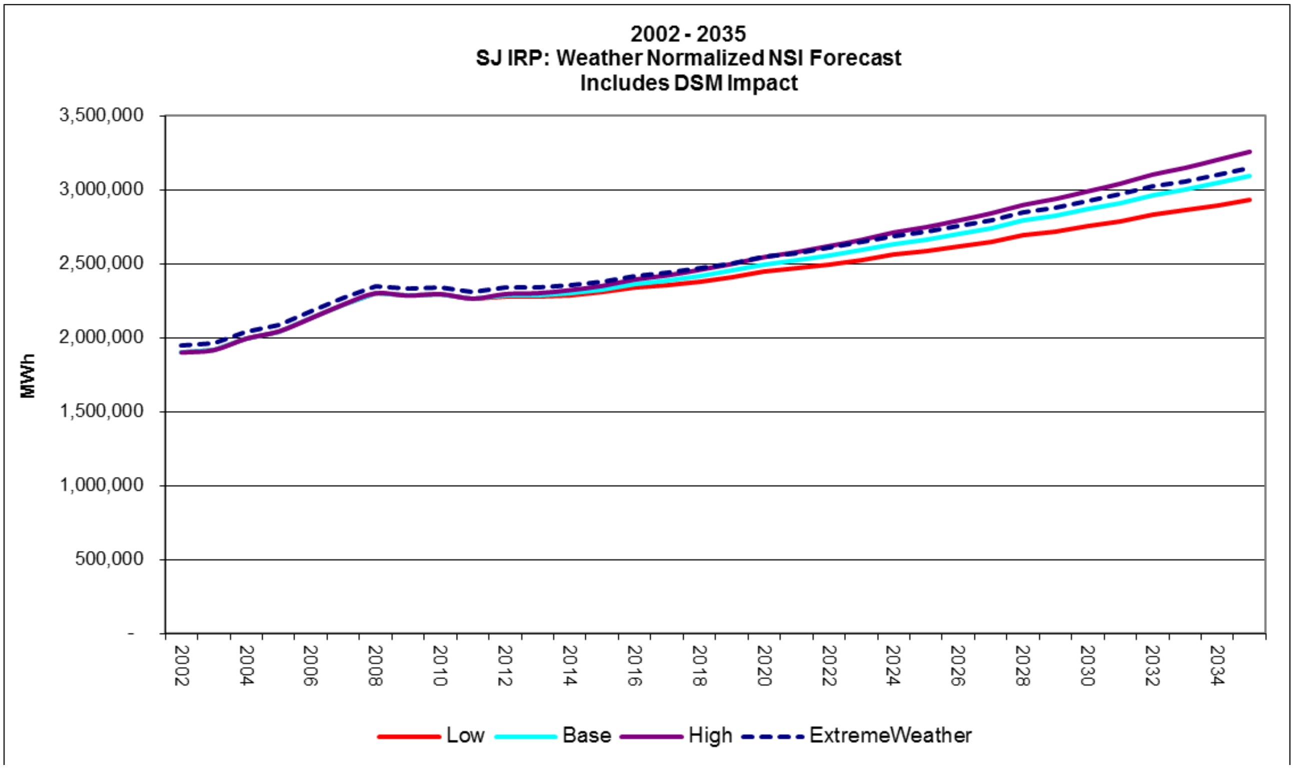


Figure 73: SJLP Base, Low, High and Extreme Weather Peak Demand Forecast

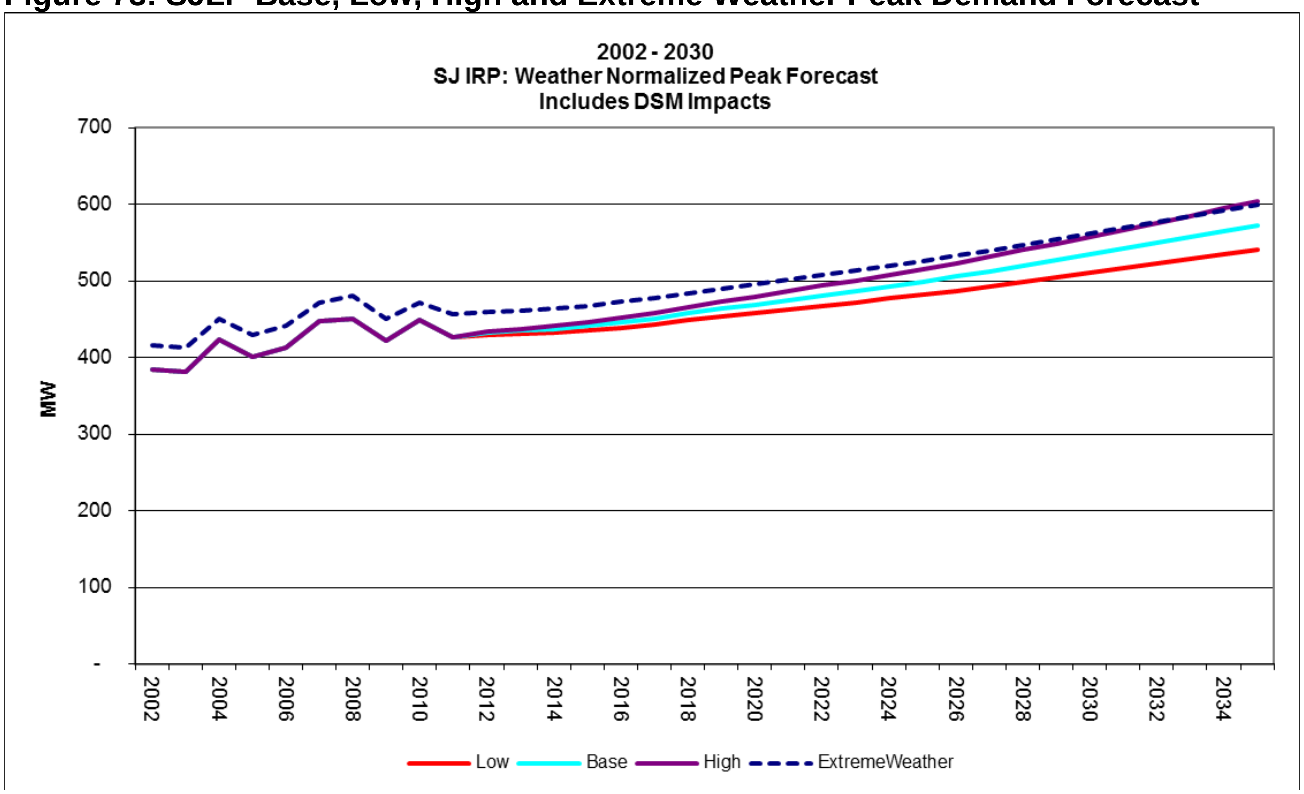


Figure 74: GMOC Base, Low, High and Extreme Weather Energy (NSI) Forecast

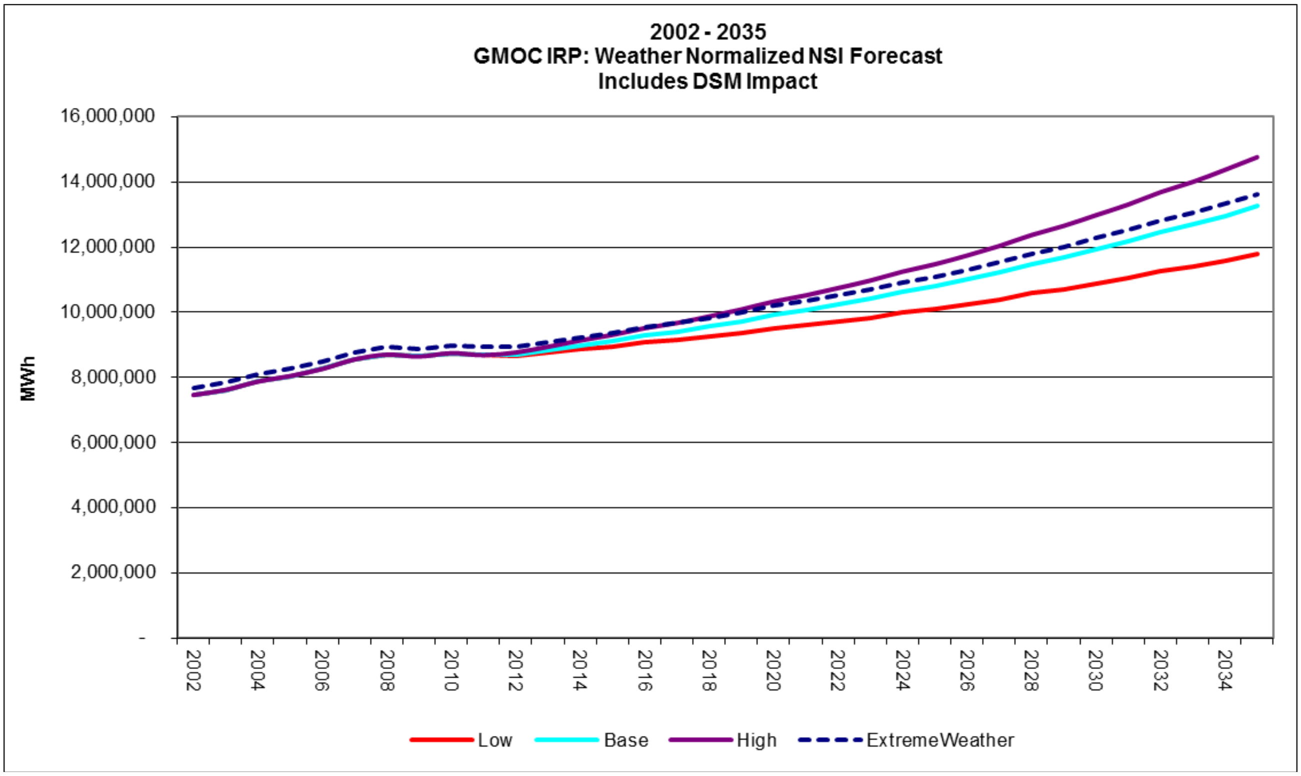
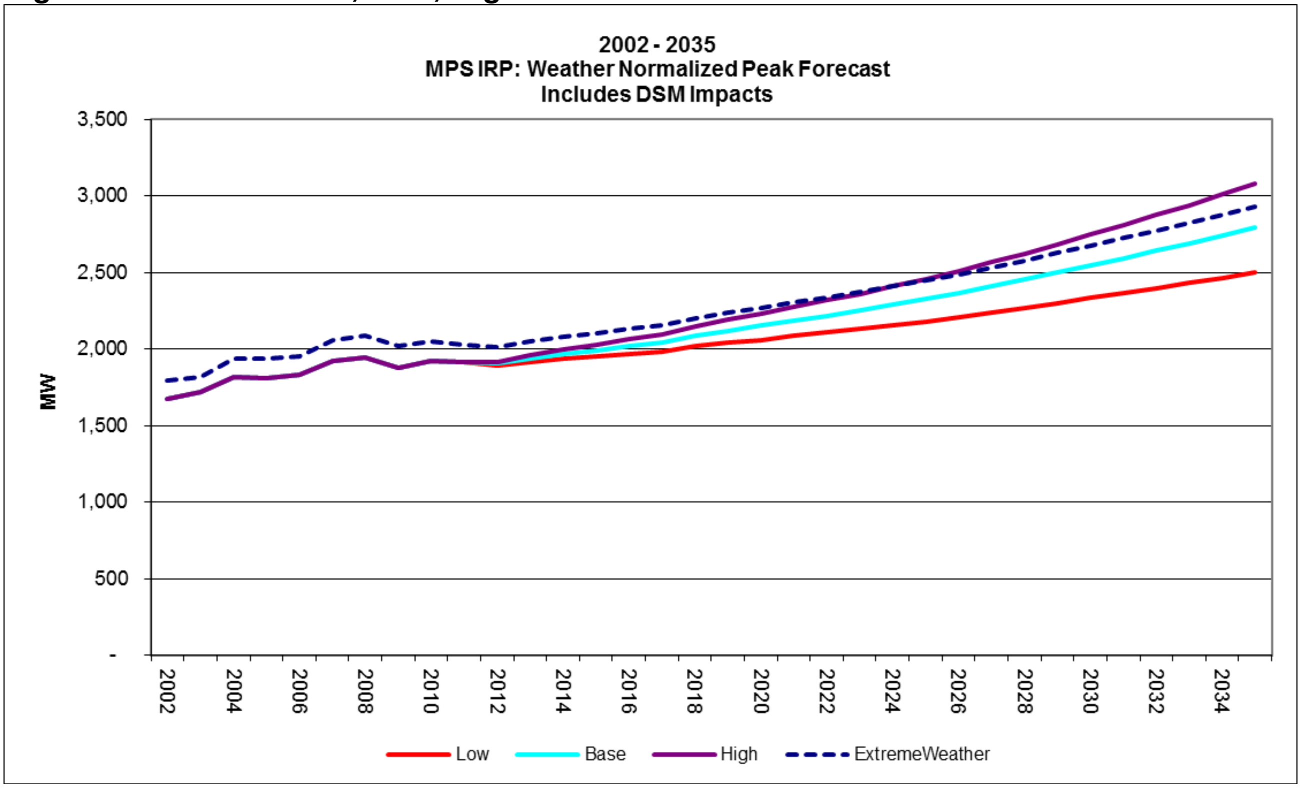


Figure 75: GMOC Base, Low, High and Extreme Weather Peak Demand Forecast



8.3 ENERGY USAGE AND PEAK DEMAND PLOTS

(C) The utility shall provide plots of energy usage and peak demand covering the historical database period and the forecast period of at least twenty (20) years.

1. The energy plots shall include the summer, non-summer, and total energy usage for each calendar year. The peak demand plots shall include the summer and winter peak demands.

The figures below represent actual and weather normalized Net System Input (Energy) for summer, non-summer, and total year for the base case forecast. Corresponding tables can be found in *Appendix 3D*.

Figure 76: MPS Base Case Actual and Weather Normalized Summer Energy Plots

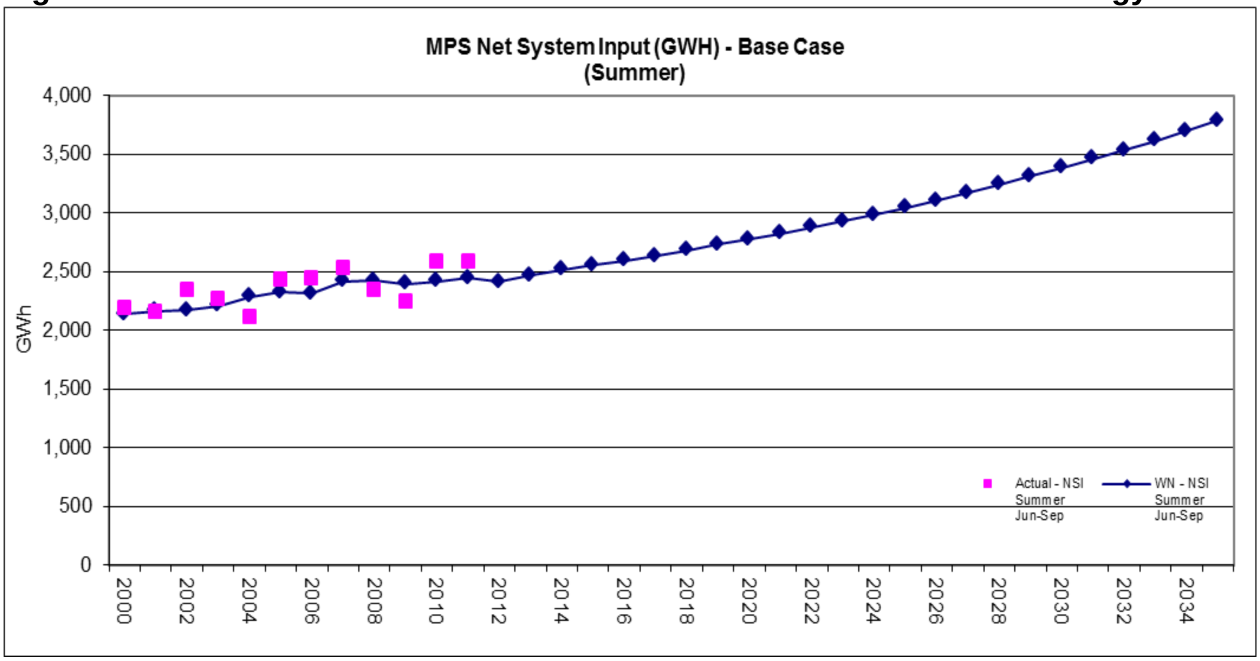


Figure 77: MPS Base Case Actual and Weather Normalized Non-Summer Energy Plots

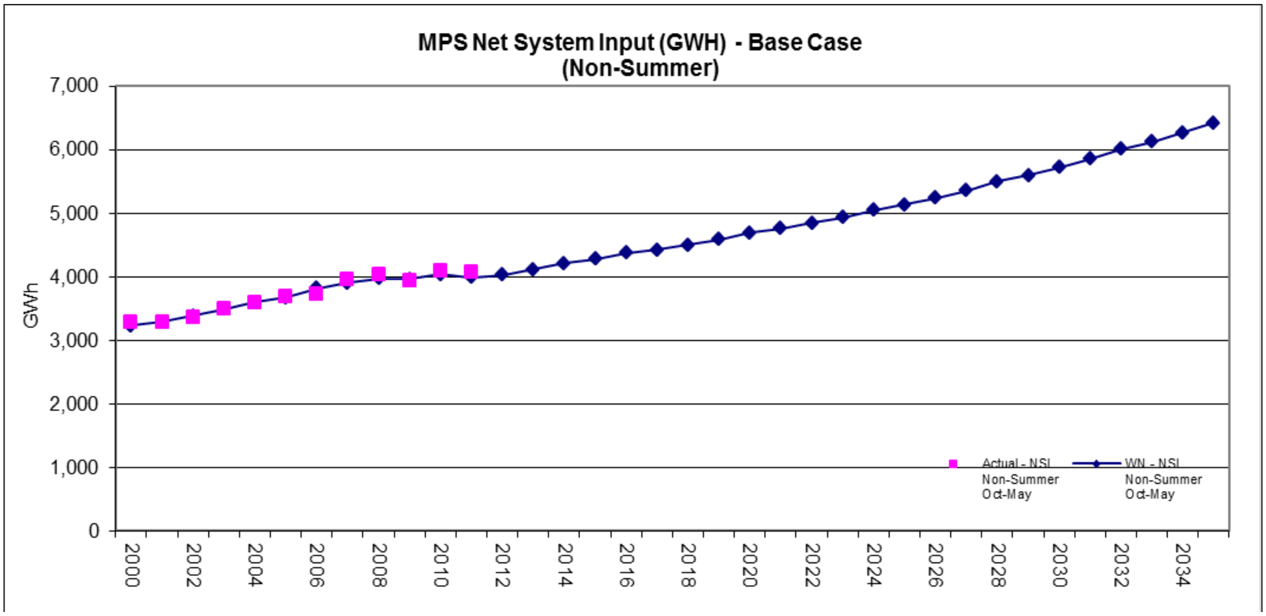


Figure 78: MPS Base Case Actual and Weather Normalized Total Energy Plots

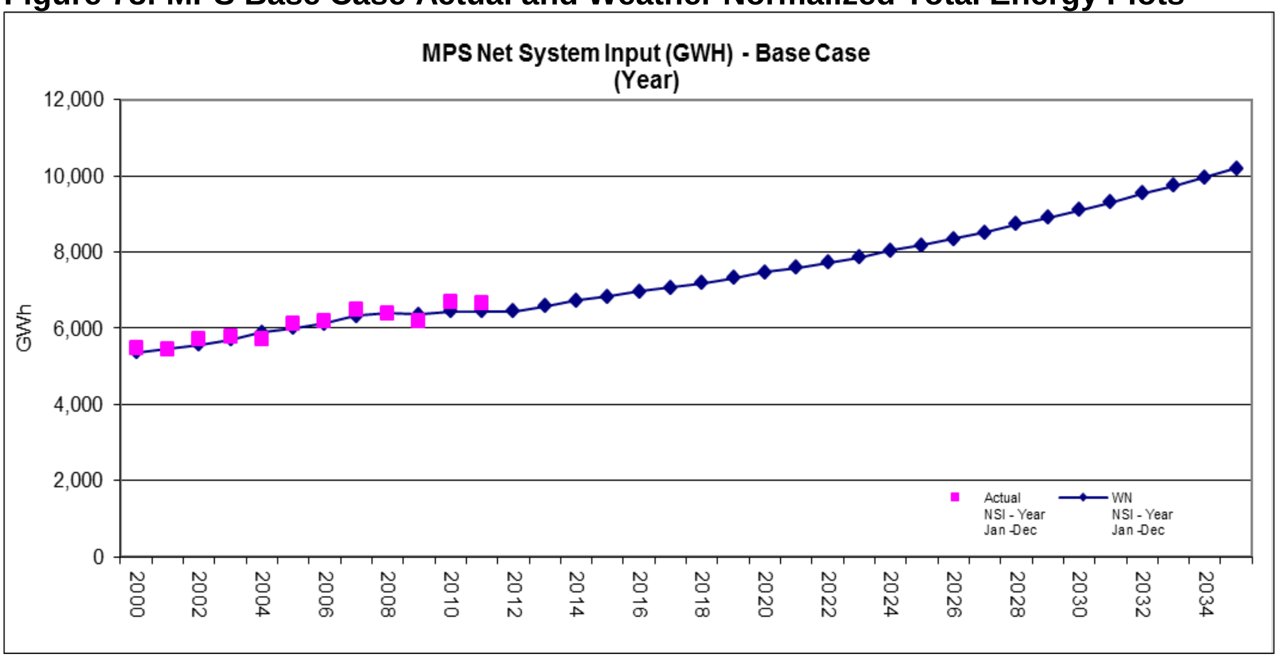


Figure 79: SJLP Base Case Actual and Weather Normalized Summer Energy Plots

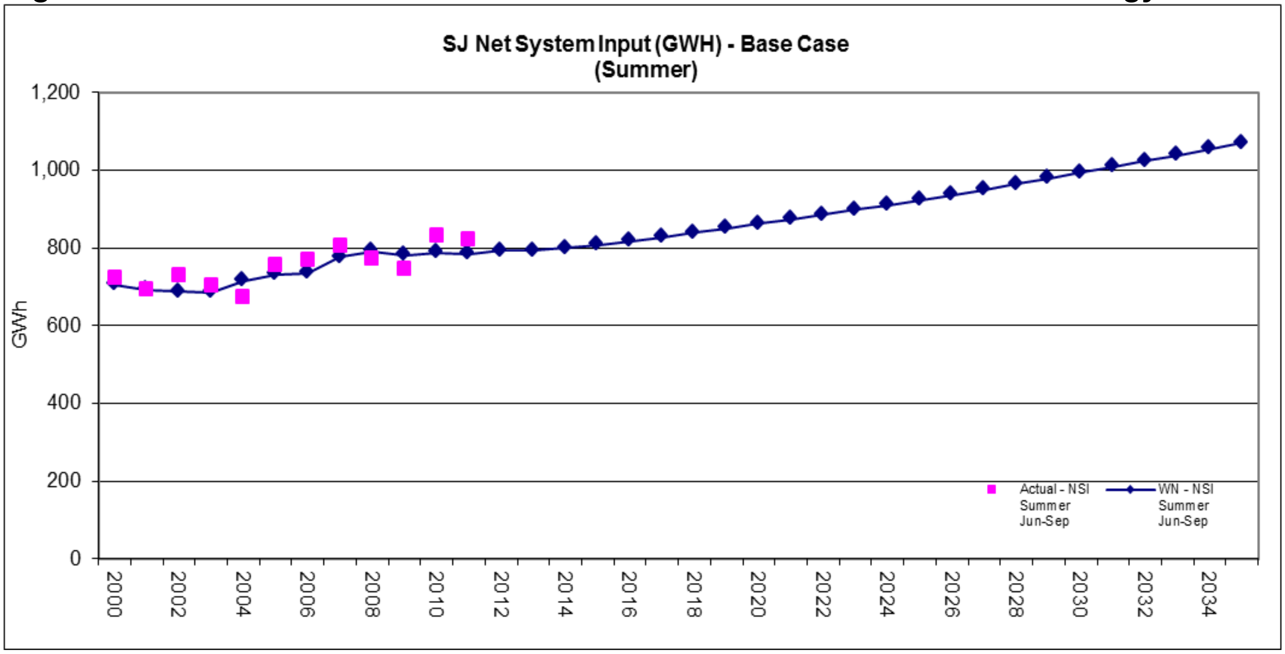


Figure 80: SJLP Base Case Actual Weather and Normalized Non-Summer Energy Plots

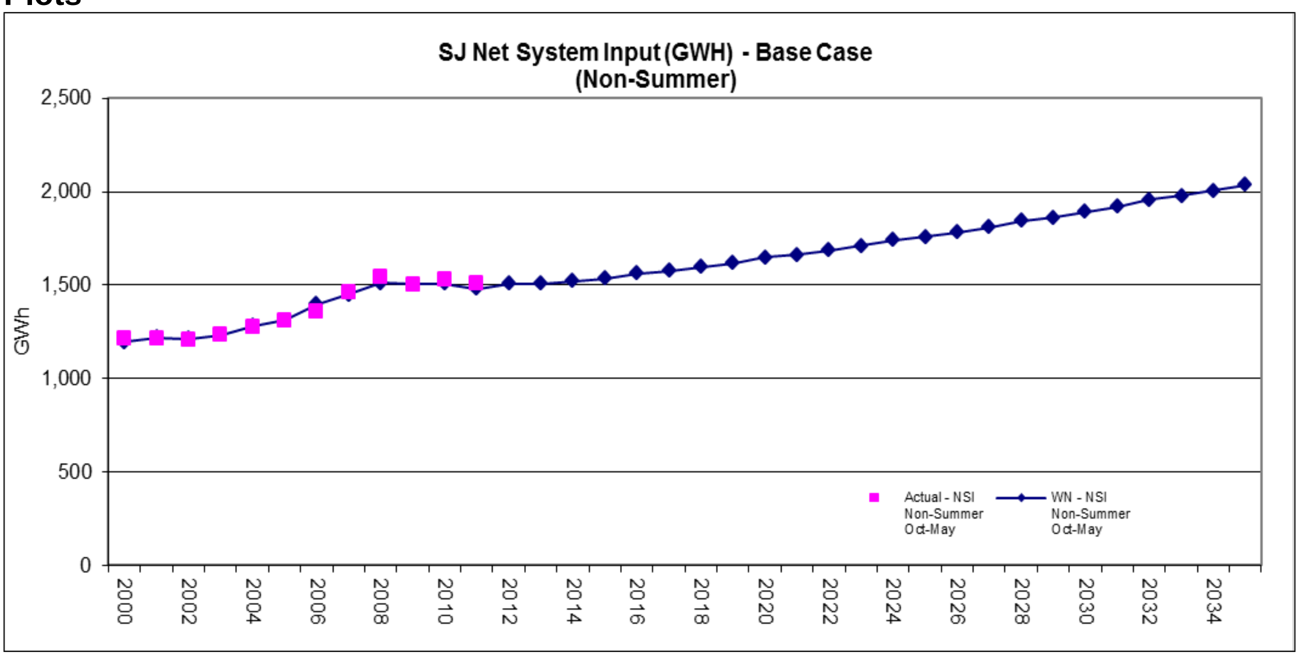


Figure 81: SJLP Base Case Actual and Weather Normalized Total Energy Plots

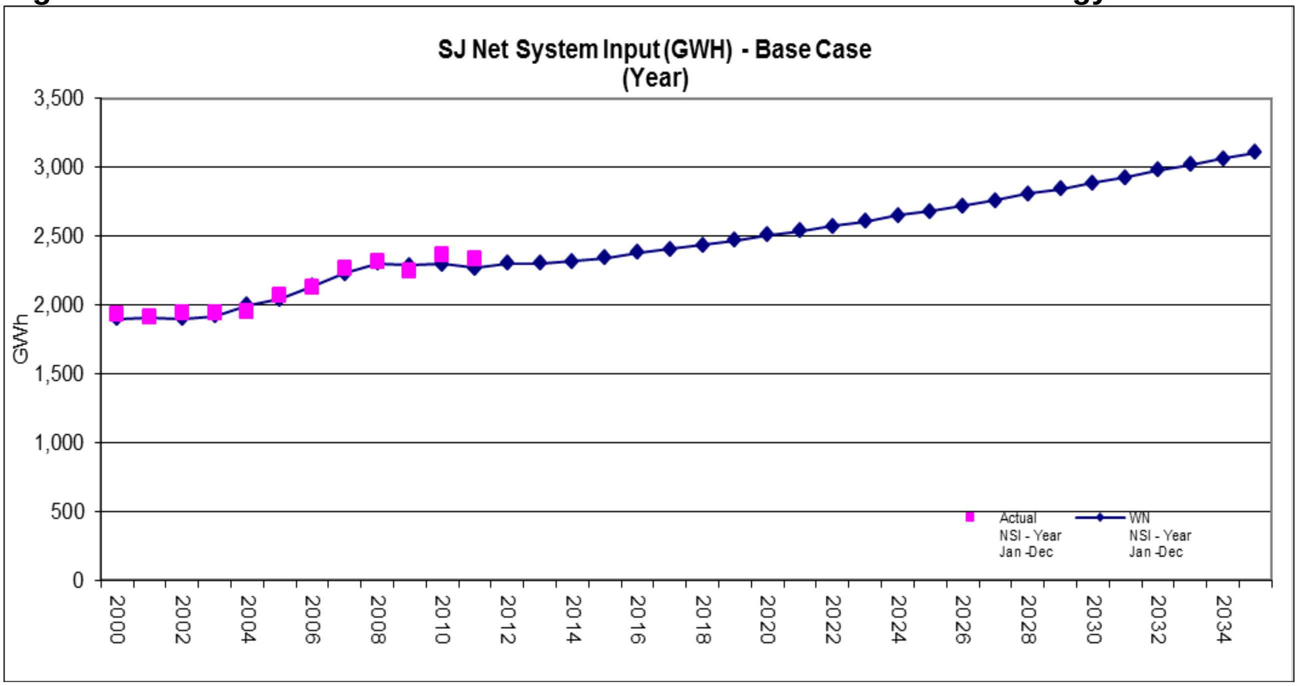


Figure 82: GMOC Base Case Actual and Weather Normalized Summer Energy Plots

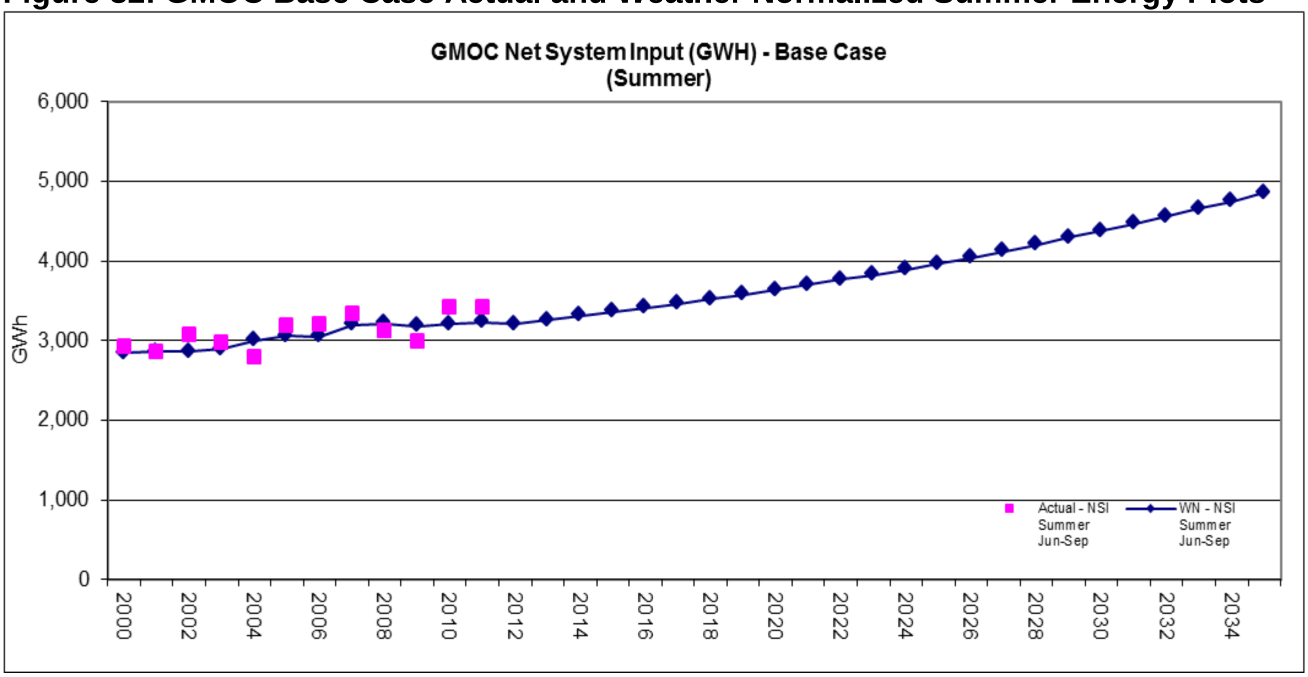


Figure 83: GMOC Base Case Actual and Weather Normalized Non-Summer Energy Plots

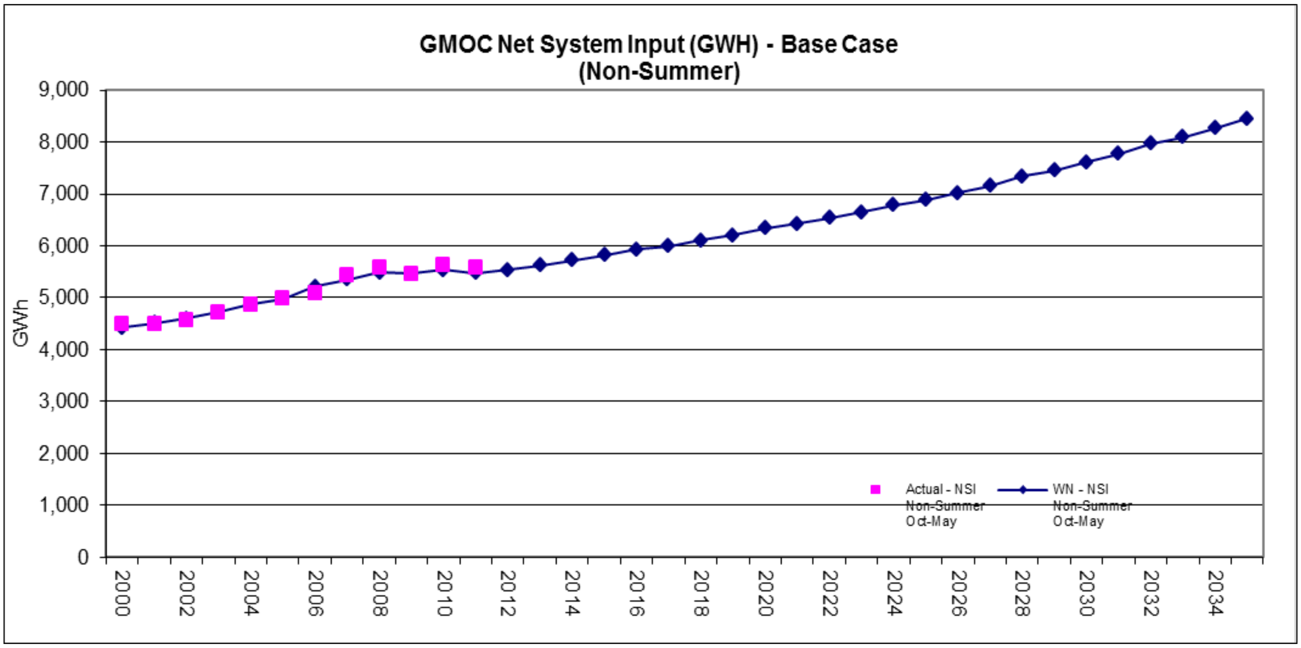
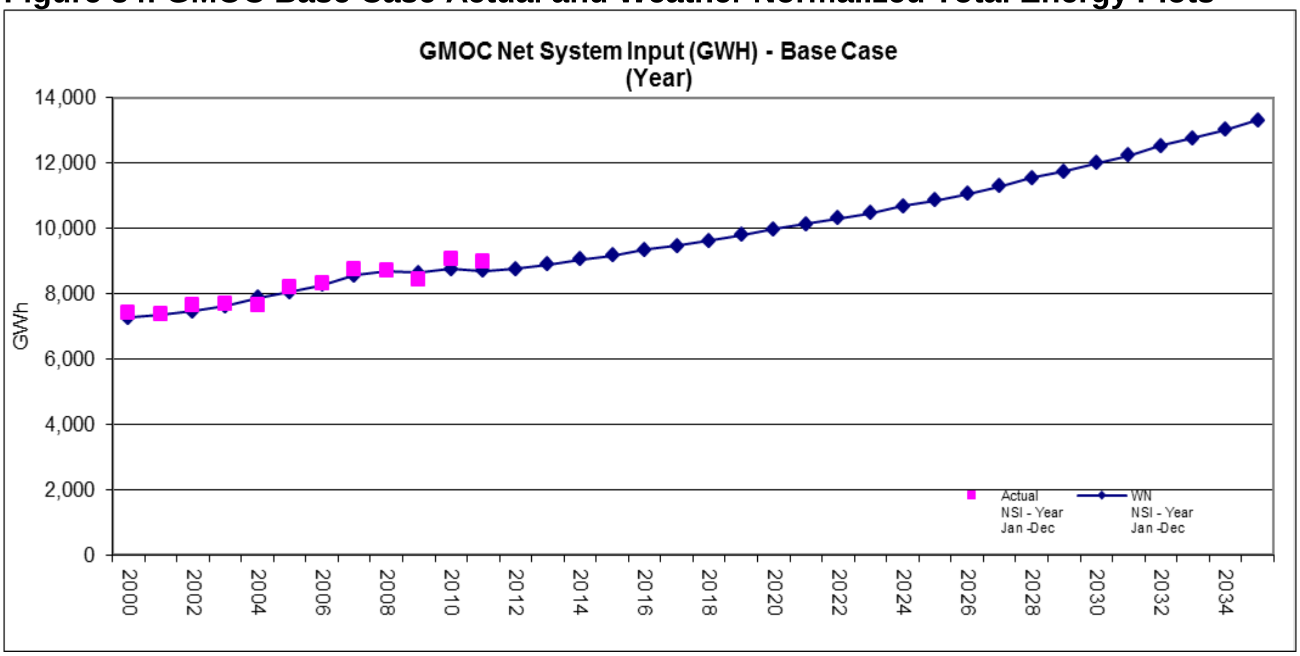


Figure 84: GMOC Base Case Actual and Weather Normalized Total Energy Plots



The figures below represent actual and weather normalized peak demand for summer and non-summer for the base case forecast. Annual demand charts are not shown, since they are the same as summer demand charts. Corresponding tables can be found in *Appendix 3D*.

Figure 85: MPS Base Case Actual and Weather Normalized Summer Peak Demand Plots

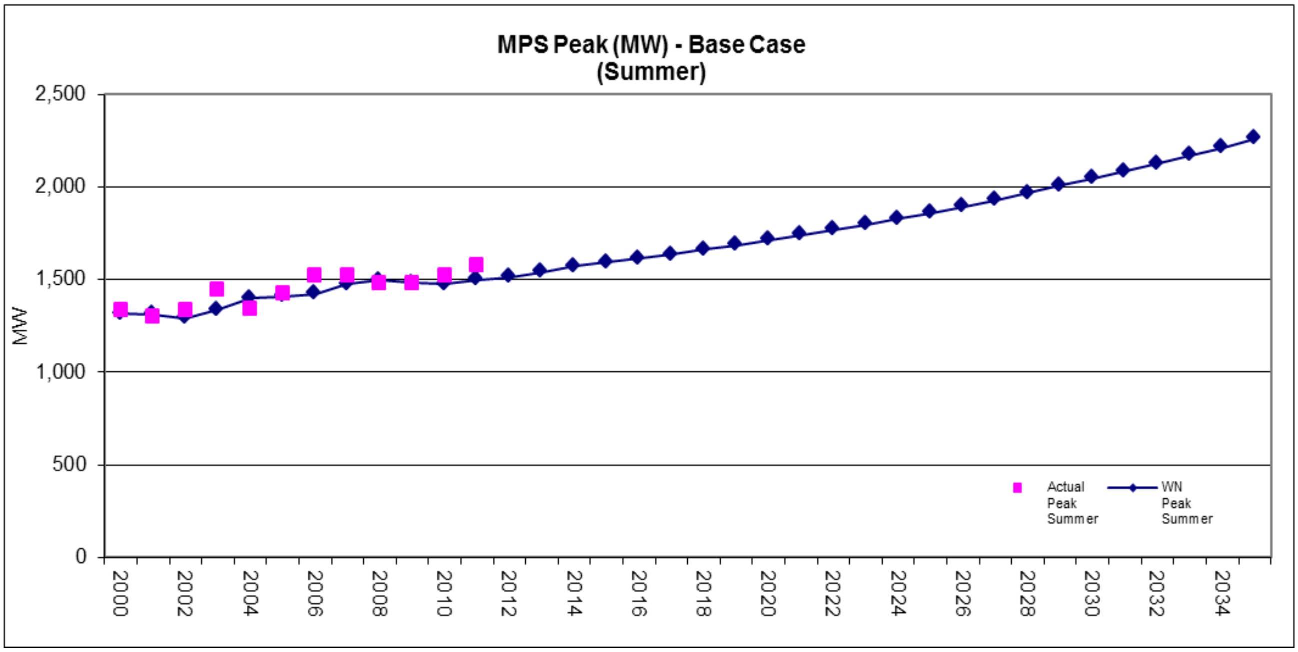


Figure 86: MPS Base Case Actual and Weather Normalized Winter Peak Demand Plots

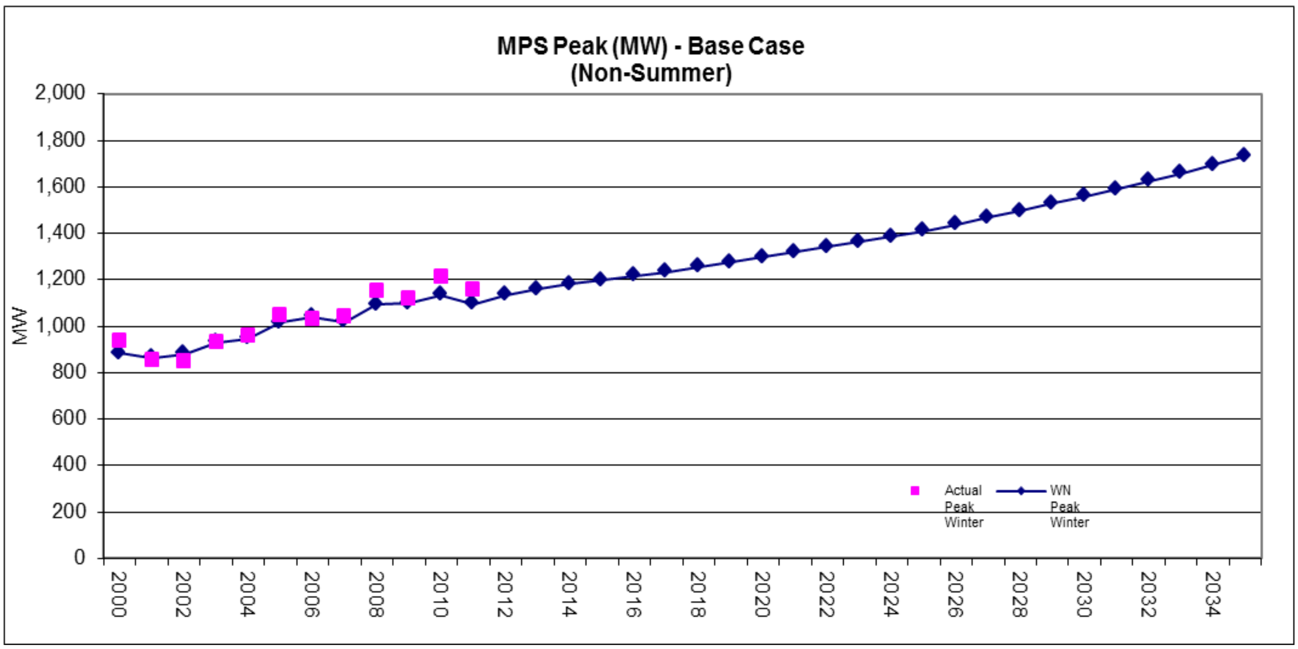


Figure 87: SJLP Base Case Actual and Weather Normalized Summer Peak Demand Plots

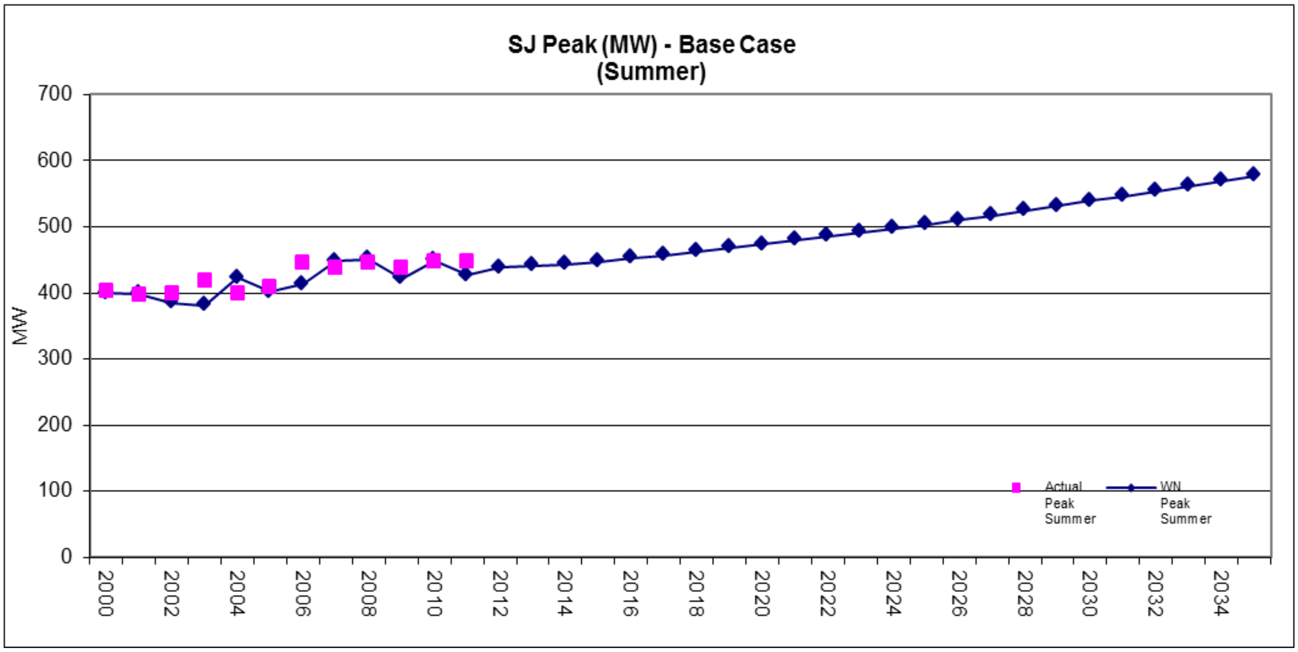


Figure 88: SJLP Base Case Actual and Weather Normalized Winter Peak Demand Plots

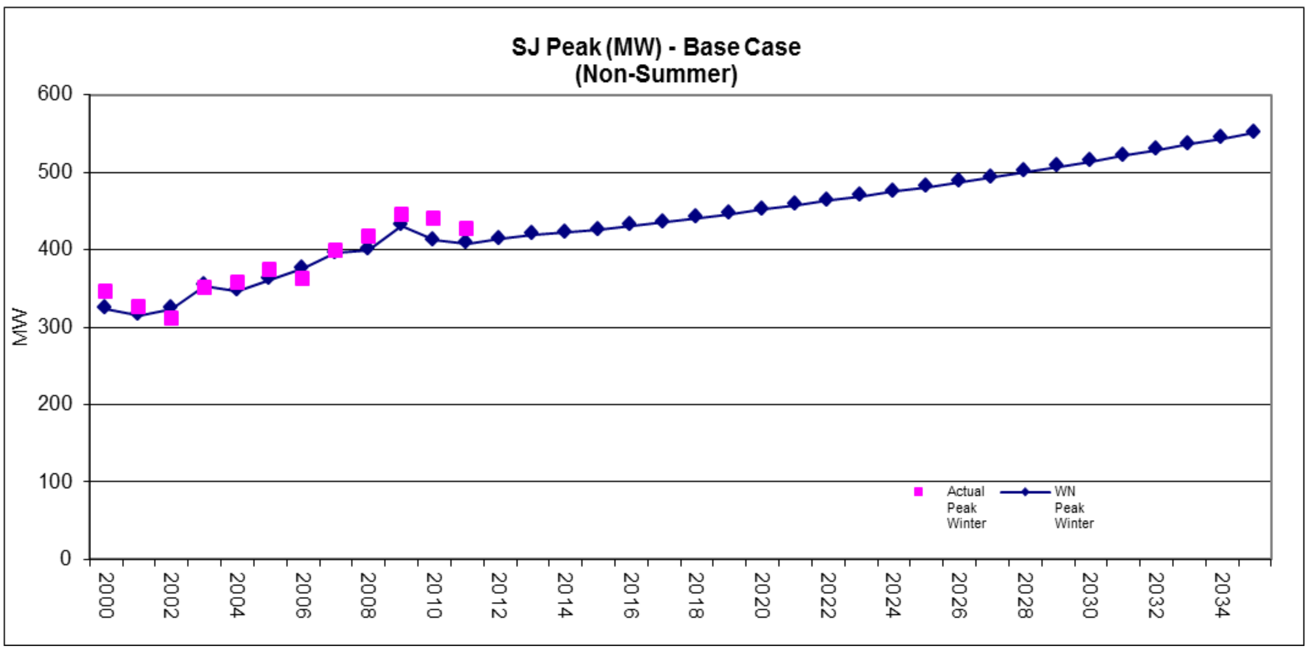


Figure 89: GMOC Base Case Actual and Weather Normalized Summer Peak Demand Plots

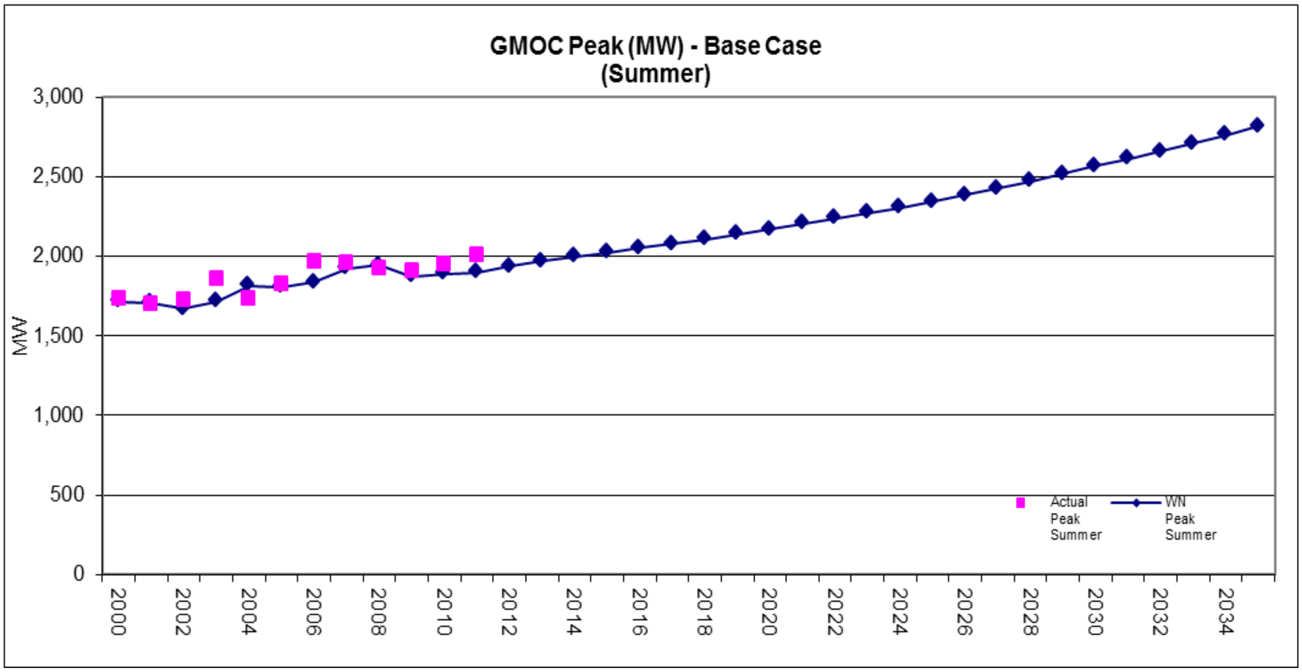
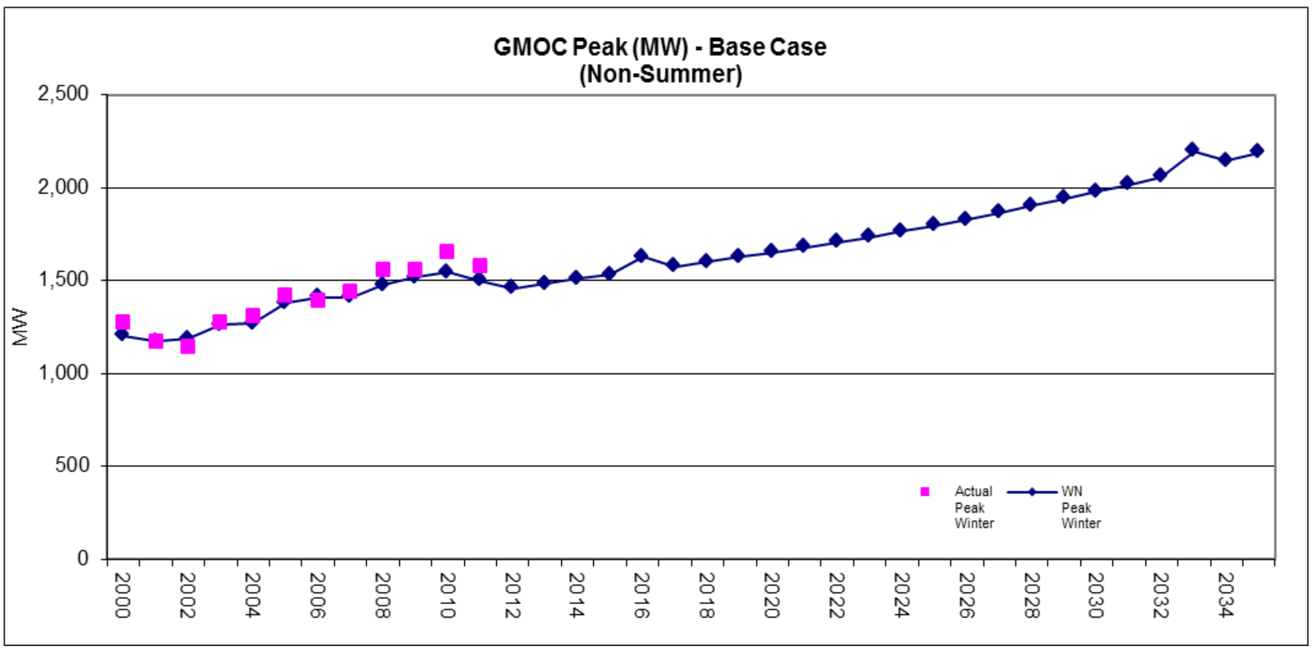


Figure 90: GMOC Base Case Actual and Weather Normalized Winter Peak Demand Plots



2. The historical period shall include both actual and weather-normalized values. The forecast period shall include the base-case, low-case, and high-case forecasts.

The figures below represent Net System Input (energy) for summer, non-summer, and the whole year for the base, low and high scenario forecasts. Corresponding tables can be found in *Appendix 3D*.

Figure 91: MPS Base-Case, Low-Case, and High-Case Summer Energy Plots

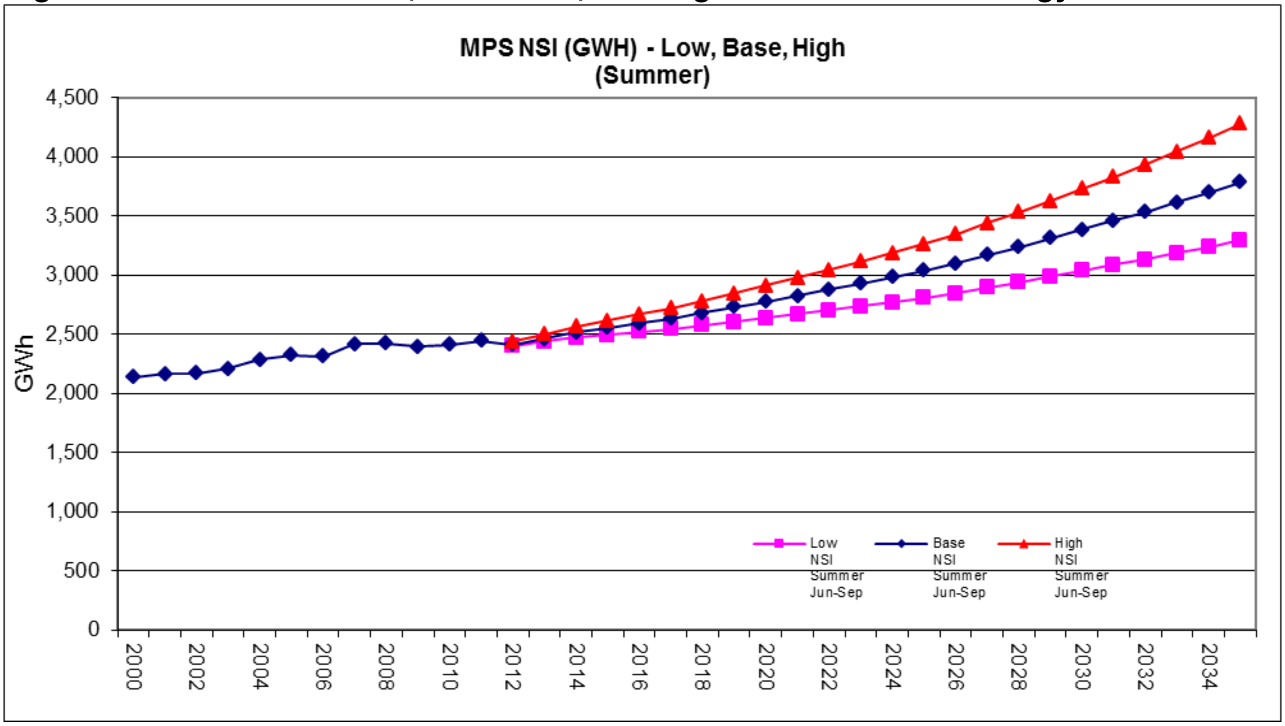


Figure 92: MPS Base-Case, Low-Case, and High-Case Non-Summer Energy Plots

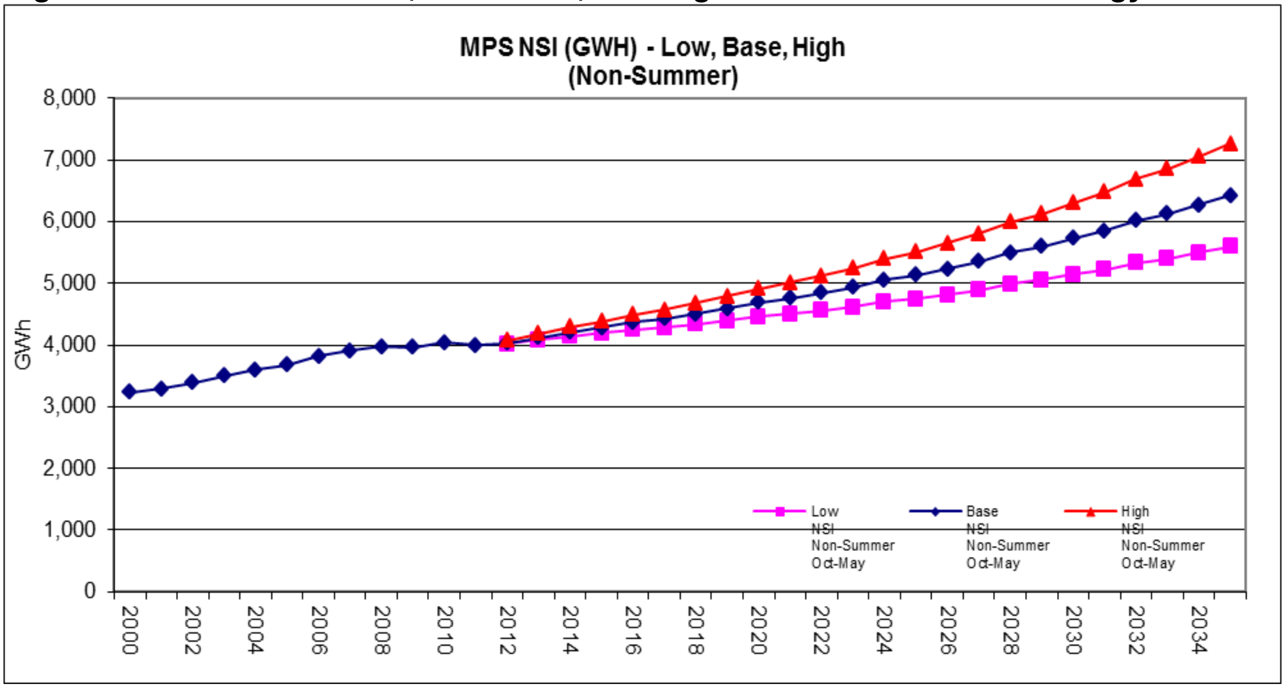


Figure 93: MPS Base-Case, Low-Case, and High-Case Total Energy Plots

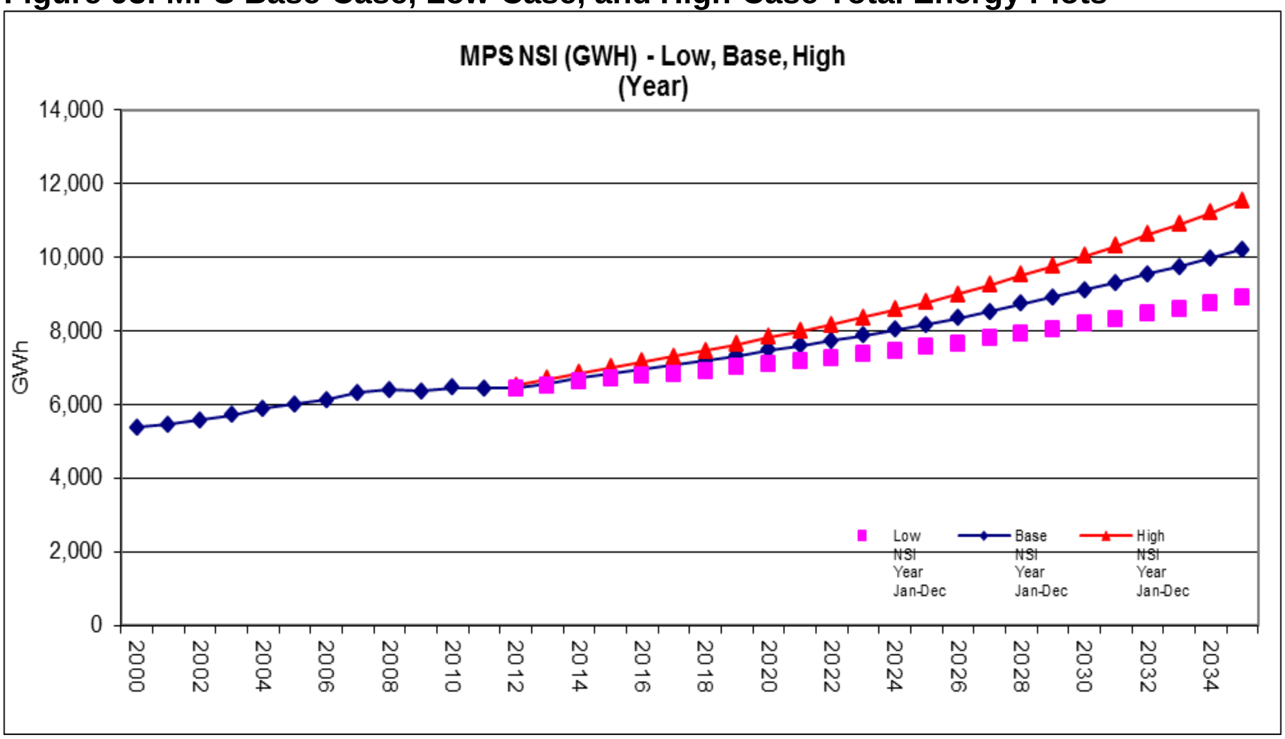


Figure 94: SJLP Base-Case, Low-Case, and High-Case Summer Energy Plots

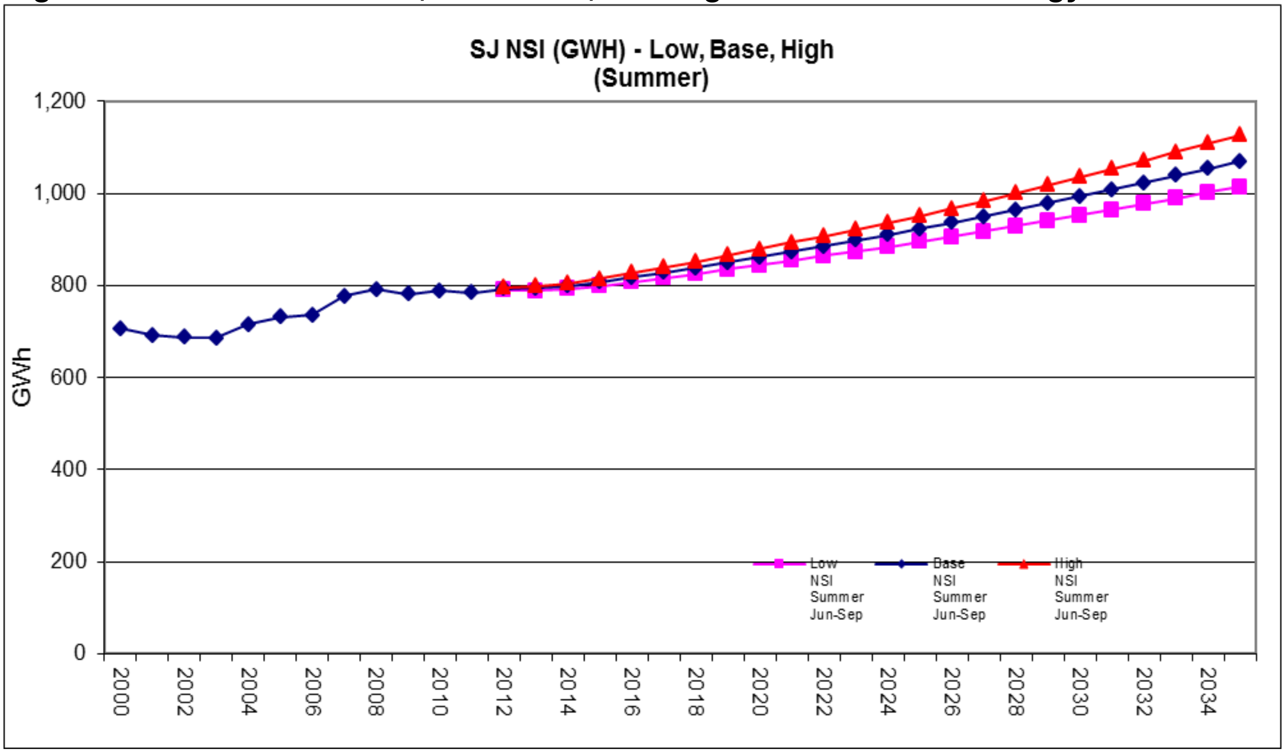


Figure 95: SJLP Base-Case, Low-Case, and High-Case Winter Energy Plots

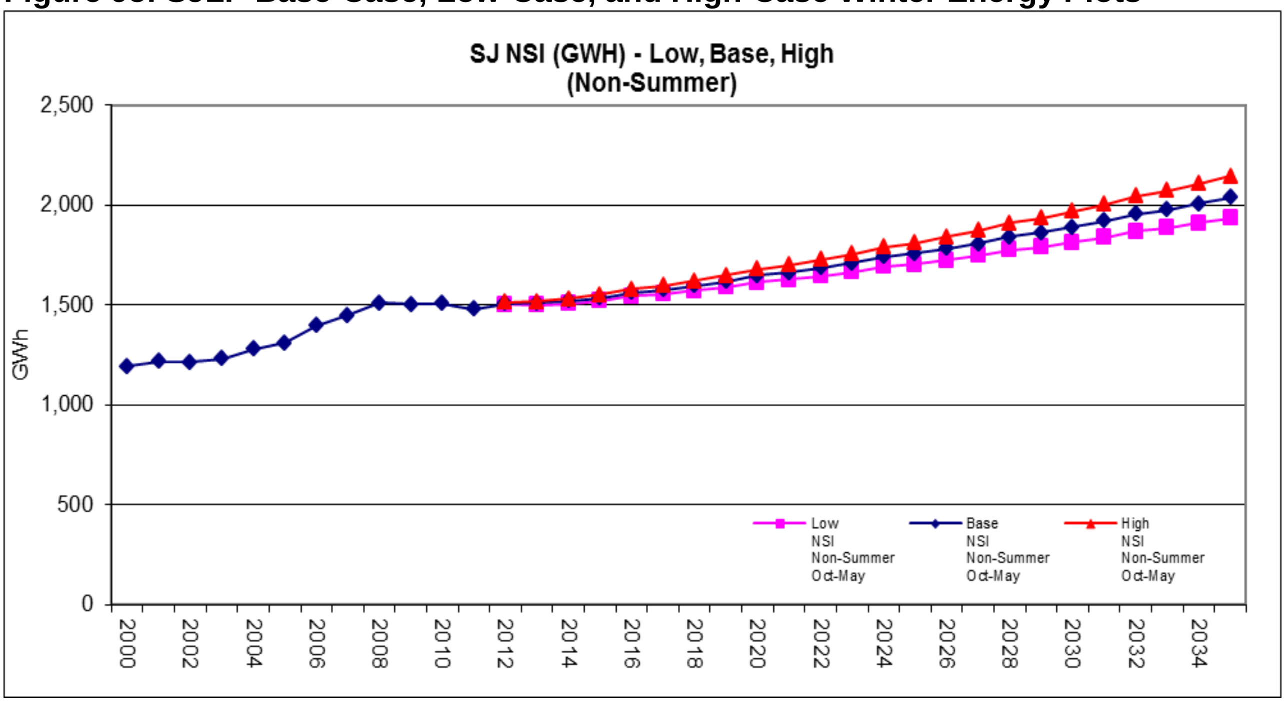


Figure 96: SJLP Base-Case, Low-Case, High-Case Total Energy Plots

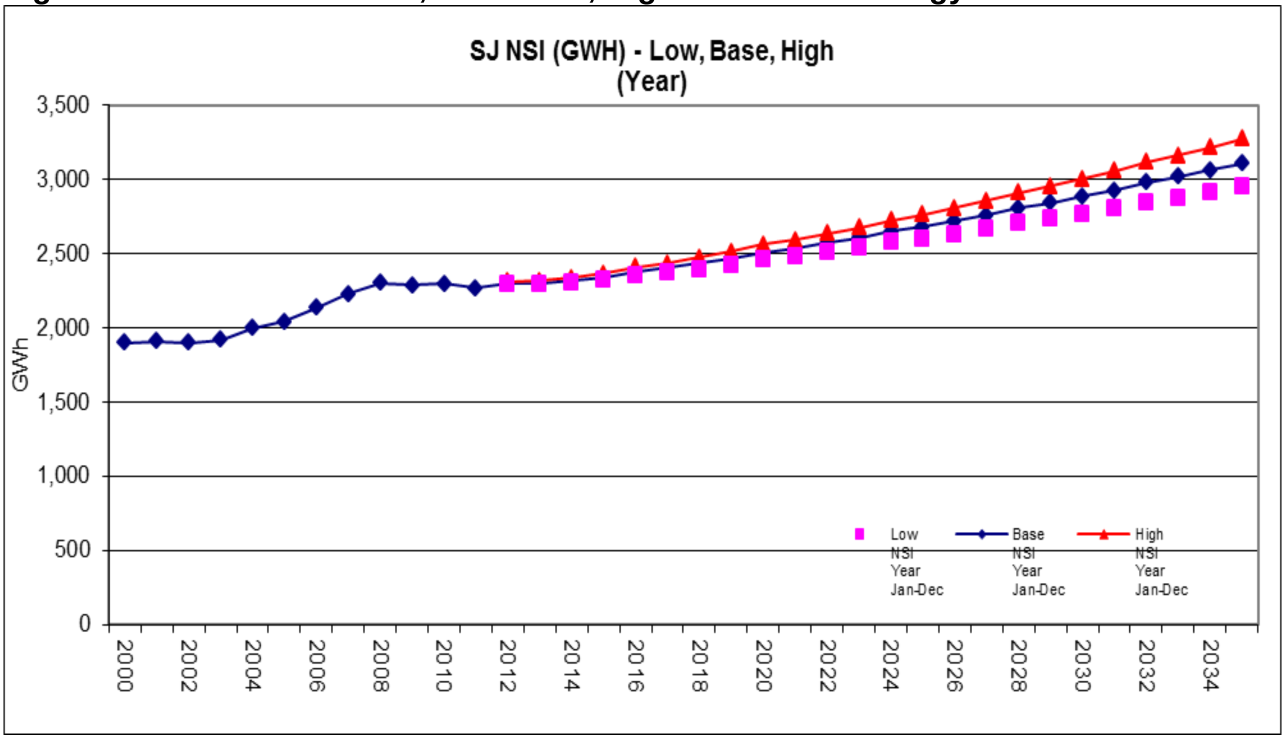


Figure 97: GMOC Base-Case, Low-Case, and High-Case Summer Energy Plots

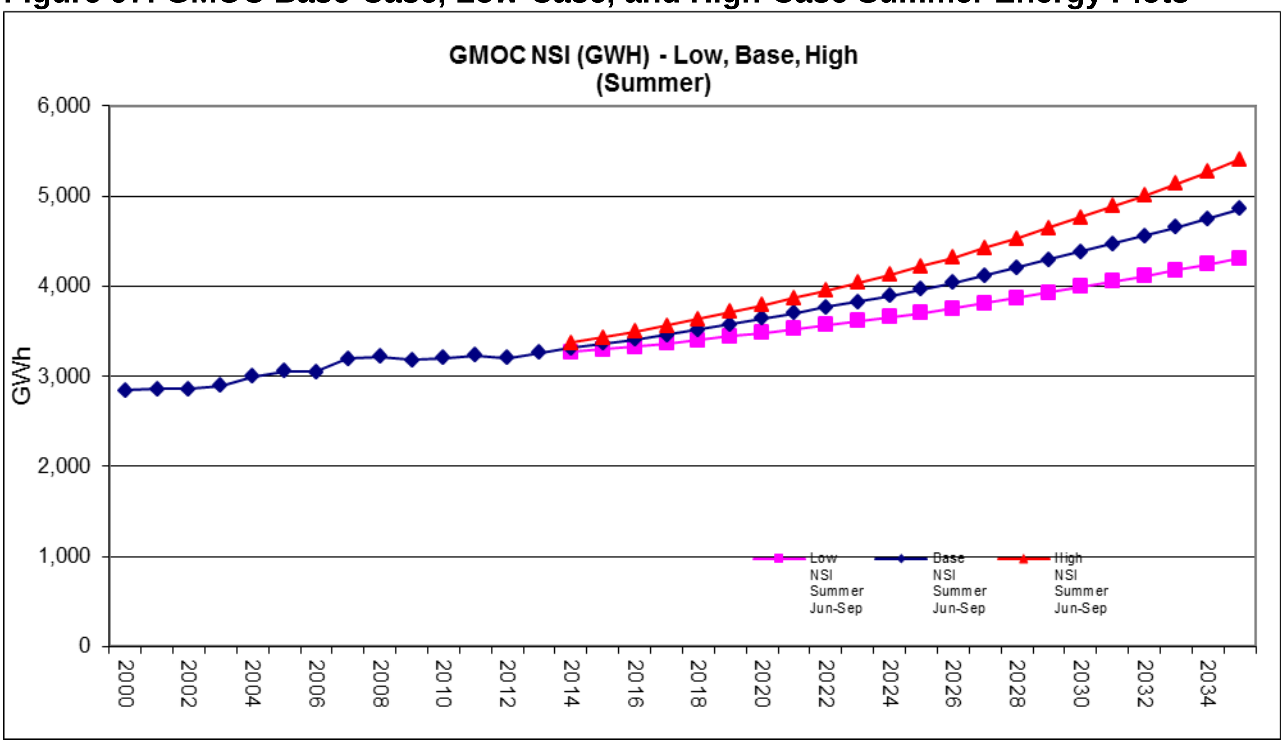


Figure 98: GMOC Base-Case, Low-Case, and High-Case Winter Energy Plots

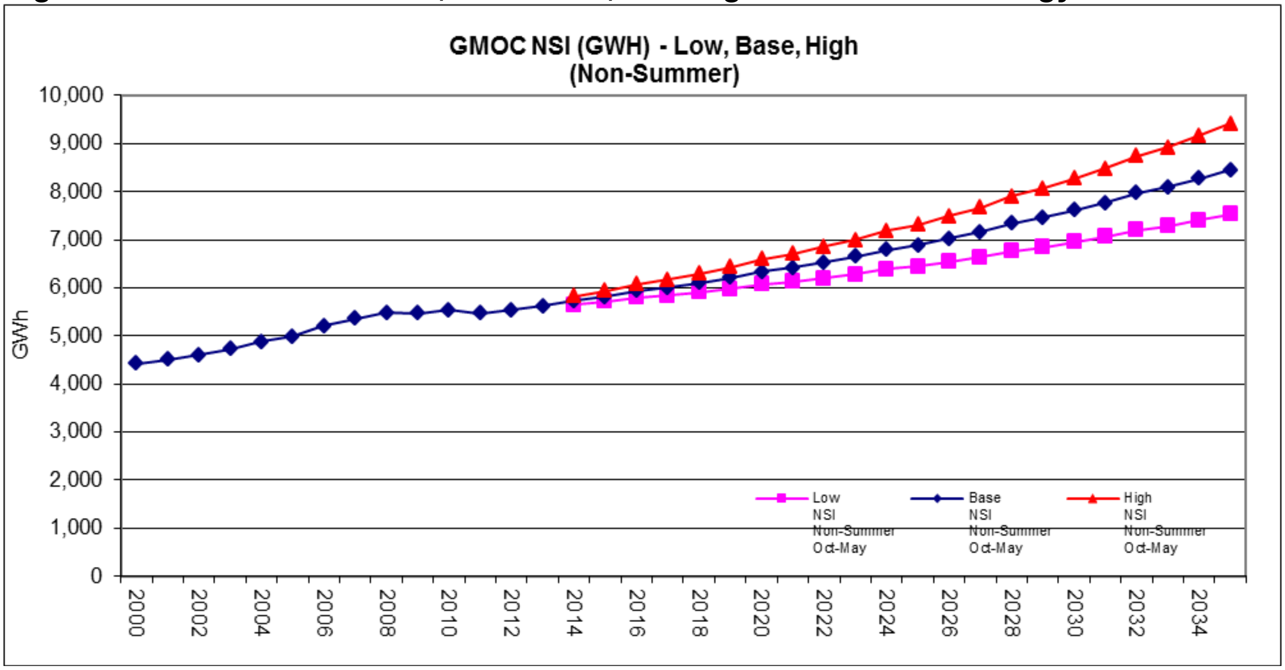
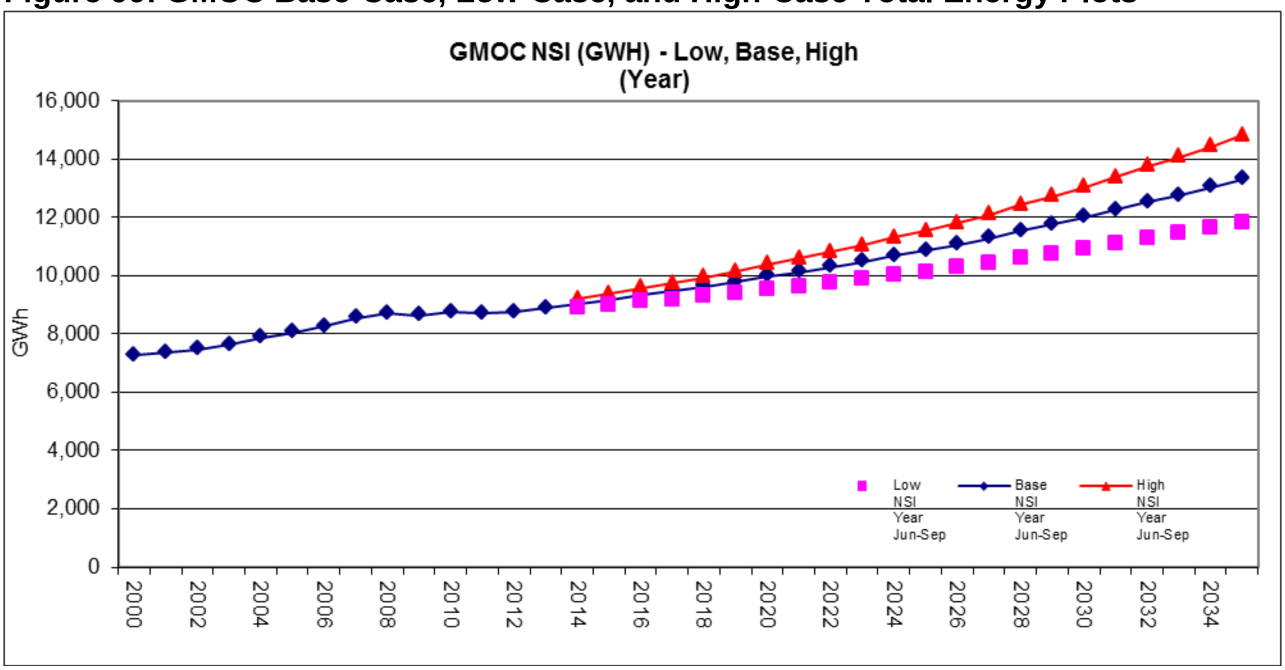


Figure 99: GMOC Base-Case, Low-Case, and High-Case Total Energy Plots



The figures below represent peak demand for summer and non-summer for the base, low, and high scenario forecasts. Annual demand charts are not shown, since they are the same as summer demand charts. Corresponding tables can be found in *Appendix 3D*.

Figure 100: MPS Base-Case, Low-Case, and High-Case Summer Peak Demand Plots

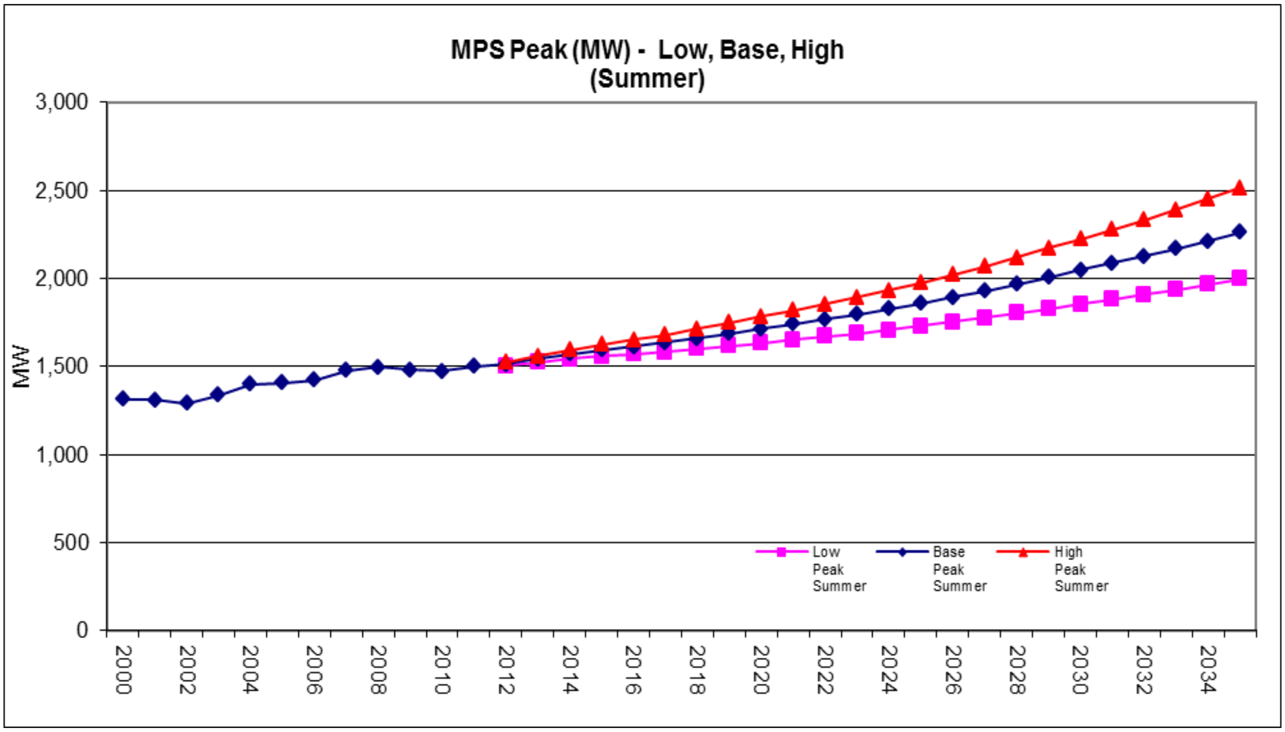


Figure 101: MPS Base-Case, Low-Case, and High-Case Winter Peak Demand Plots

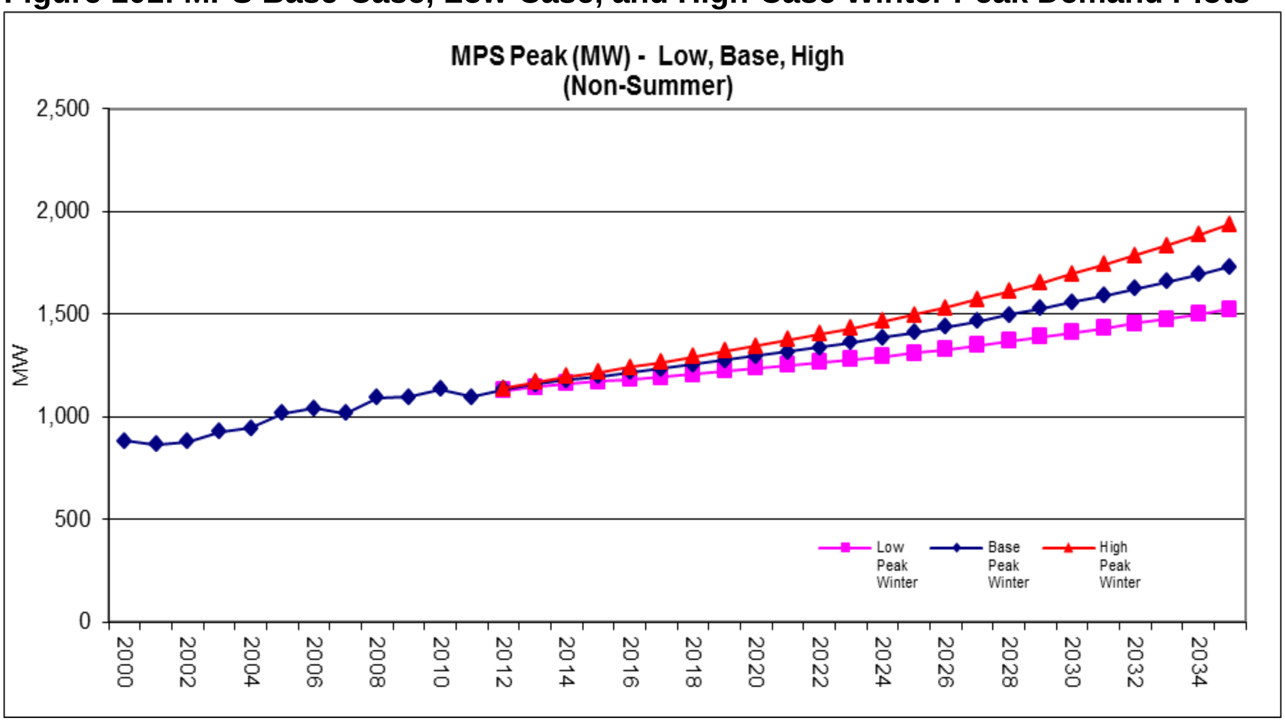


Figure 102: SJLP Base-Case, Low-Case, and High-Case Summer Peak Demand Plots

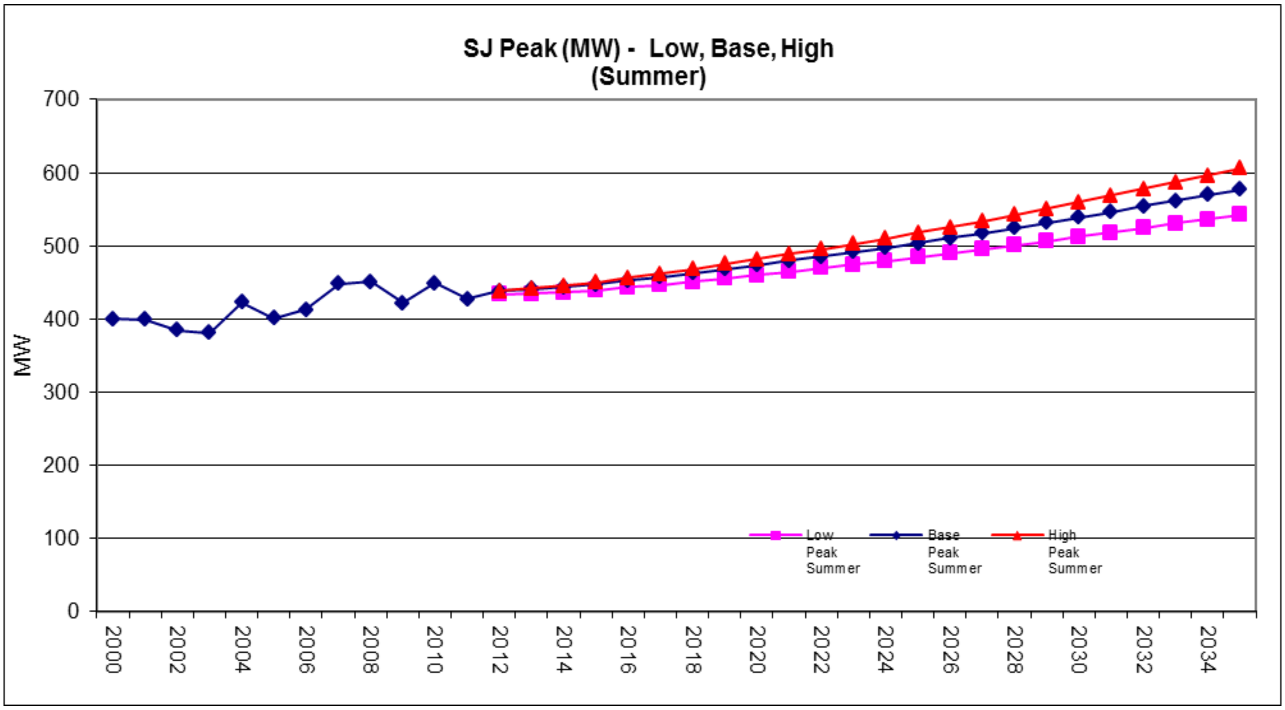


Figure 103: SJLP Base-Case, Low-Case, and High-Case Winter Peak Demand Plots

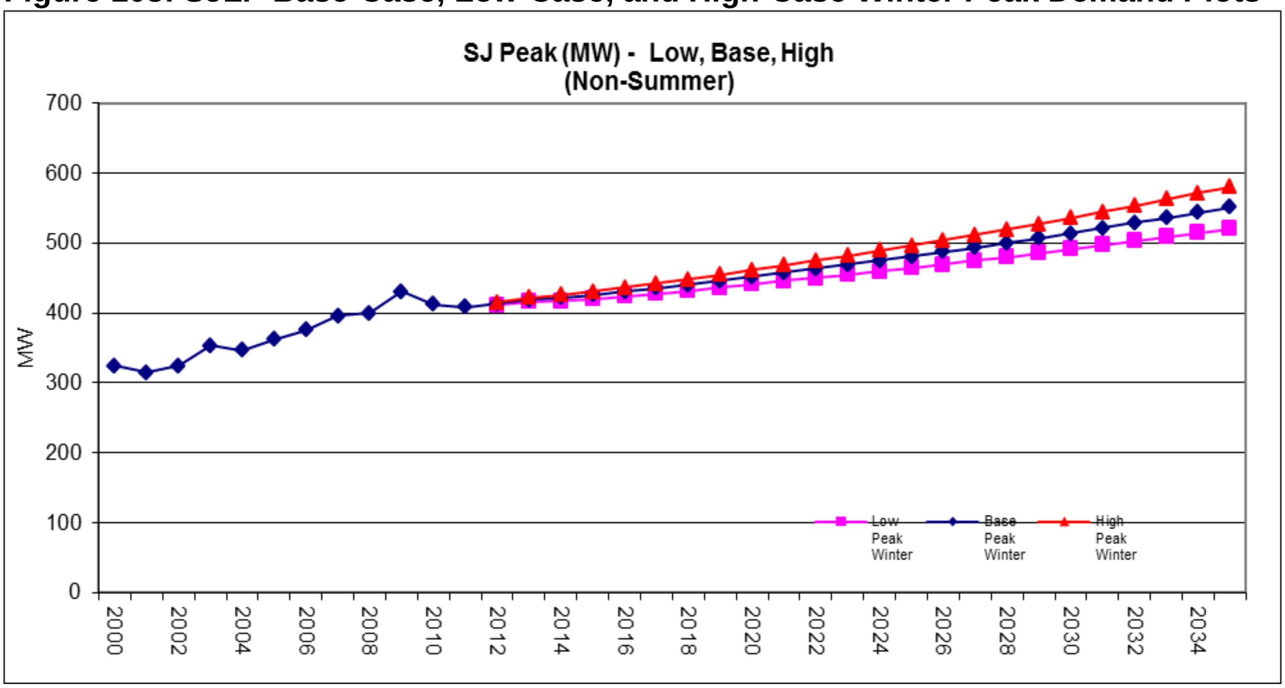


Figure 104: GMOC Base-Case, Low-Case, and High-Case Summer Peak Demand Plots

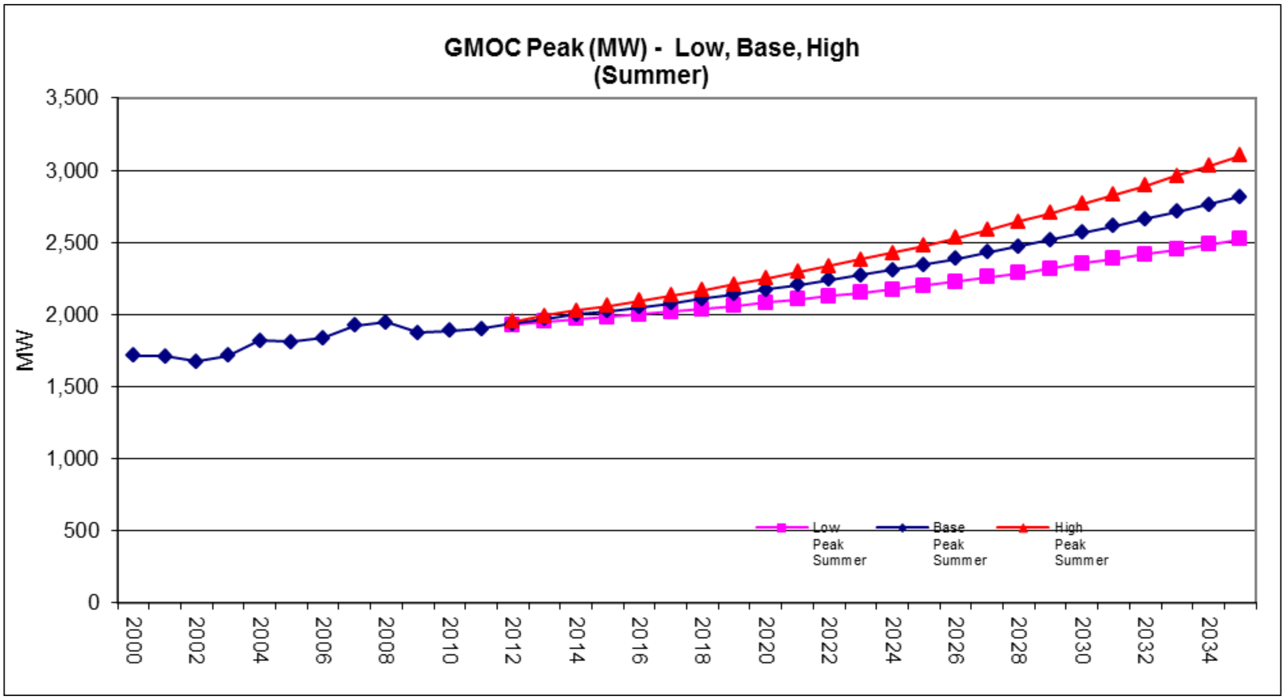
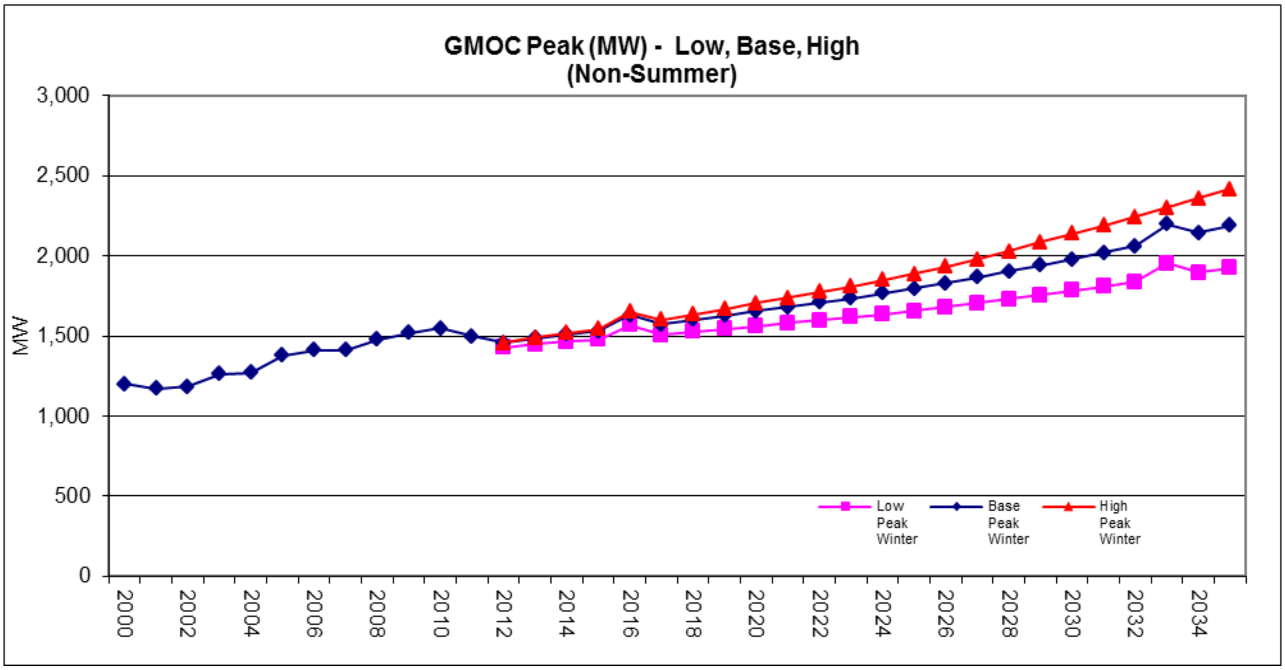


Figure 105: GMOC Base-Case, Low-Case, and High Case Winter Peak Demand Plots



[i] http://www1.eere.energy.gov/buildings/appliance_standards/residential/residential_cac_hp.html
[ii] DOE slide deck *RES2011SAEUpdate.pdf*, provided in the workpapers.

[iii] Multi-Year Program Plan, Building Regulatory Programs, U.S. Department of Energy Energy Efficiency and Renewable Energy Building Technologies Program October 2010.
[iv] http://www.eia.gov/analysis/model-documentation.cfm
[v] Email from Benjamin Kanigel dated 7/6/2010.
[vi] Email to Al Bass from Benjamin Kanigel dated 9/23/2010.
[vii] See regulatory_programs_mypp.pdf .
[viii] www1.eere.energy.gov/buildings/appliance_standards/commercial/refrig_equip_final_rule.html and www1.eere.energy.gov/buildings/appliance_standards/commercial/automatic_ice_making_equipment.html
[ix] www1.eere.energy.gov/buildings/appliance_standards/commercial/ashrae_products_docs_meeting.html