Exhibit No. 16
Issue: Weather Normalization
Witness: Mr. Mark Quan
Type of Exhibit: Direct Testimony
Sponsoring Party: Empire District Electric Co.
Case No.
Date Testimony Prepared: October 2007

Before the Public Service Commission
Of the State of Missouri

Direct Testimony

of

Mr. Mark Quan

October 2007

DIRECT TESTIMONY
OF
MR. MARK QUAN
ON BEHALF OF
THE EMPIRE DISTRICT ELECTRIC COMPANY
BEFORE THE
MISSOURI PUBLIC SERVICE COMMISSION

Q. PLEASE STATE YOUR NAME, TITLE, AND BUSINESS ADDRESS FOR THE RECORD.

A. My name is Mark Quan. I am a Principal Consultant for Itron's Forecasting Solution group. My business address is 11236 El Camino Real, San Diego, California 92130

Q. WOULD YOU PLEASE DESCRIBE YOUR EDUCATIONAL BACKGROUND AND PRIOR ACADEMIC EXPERIENCE?

A. I graduated from the University of California at Los Angeles with a Bachelor's Degree in Applied Mathematics with a specialization in Computer Studies. I graduated from Stanford University with a Master's Degree in Operations Research.

From 1989 to 1997, I was employed by Pacific Gas & Electric in San Francisco, California. My responsibilities at PG&E were in the areas of resource planning, gas supply planning, power contracts, and revenue requirements.

In 1997, I joined the consulting staff of Regional Economic Research ("RER"). RER was acquired by Itron in 2002. My responsibilities at

RER/Itron include performing and managing statistical analysis of client loads for the purpose of long-term forecasting and short-term forecasting. The analysis includes developing time series, multivariate regression, and neural network models for use in short term system dispatch forecasts and long-term budget, planning, and rate setting forecasts. In addition to performing analysis for clients, I am responsible for portions of Itron's forecasting training curriculum teaching introduction to forecasting, load modeling, and statistical software training classes.

Q. WHAT IS THE PURPOSE OF YOUR TESTIMONY?

A. The purpose of my testimony is to support work I conducted to develop weather-normalized sales estimates for The Empire District Electric Company ("Empire"). Using a statistical-based modeling approach, I develop weather-normalized sales for the historical test year. The test year is from July 1, 2006 through June 30, 2007. Weather-normalized sales are estimated for the following five classes: Residential RG, Commercial CB, General Power GP, Small Heating SH, and Total Electric Building TEB. I am submitting Schedules MQ-1 and MQ-2 as part of my testimony. Schedule MQ-1 provides a summary of the weather normalization models. Schedule MQ-2 provides a detailed description of the weather-normalization methodology, calculation of normal weather, model statistics, and weather-normal sales results.

Q. WHAT ARE THE RESULTS FROM THE WEATHER NORMALIZATION?

A. Applying the method described in the testimony and detailed in Schedule MQ-2, the normal values I calculated are shown in **Table 1** to **Table 5** for each class.

Table 1: Residential Normal Values

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)	Normal Calendar Sales (kWh)
Jul 2006	166,086,722	158,264,857	172,235,884
Aug 2006	186,842,355	161,069,164	165,977,908
Sep 2006	156,389,932	159,413,630	114,342,868
Oct 2006	96,952,192	96,708,155	100,652,263
Nov 2006	112,602,205	109,434,810	124,294,037
Dec 2006	156,114,458	158,607,904	184,454,051
Jan 2007	161,511,406	183,060,767	167,595,398
Feb 2007	191,850,265	182,319,043	182,920,793
Mar 2007	142,968,625	149,812,624	141,875,705
Apr 2007	108,153,019	110,609,469	94,225,984
May 2007	103,548,434	96,405,809	108,424,533
Jun 2007	113,418,042	108,022,855	125,341,491

Table 2: Commercial Normal Values

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)	Normal Calendar Sales (kWh)
Jul 2006	33,921,516	32,965,699	34,489,040
Aug 2006	35,299,802	32,381,498	34,229,700
Sep 2006	33,285,385	33,652,217	25,946,288
Oct 2006	24,700,287	24,744,956	25,410,149
Nov 2006	23,055,964	22,977,259	23,059,776
Dec 2006	27,110,206	27,318,680	29,335,313

Jan 2007	27,628,434	29,164,835	26,751,948
Feb 2007	29,922,604	29,194,406	29,371,951
Mar 2007	25,346,106	25,786,847	25,723,211
Apr 2007	23,260,000	23,087,475	21,467,997
May 2007	23,866,554	22,583,186	25,862,342
Jun 2007	26,279,007	25,226,153	28,032,825

1 **Table 3: GP Normal Values**

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)	Normal Calendar Sales (kWh)
Jul 2006	80,865,634	80,094,449	80,377,781
Aug 2006	81,969,462	79,472,149	86,679,179
Sep 2006	79,820,887	80,039,860	67,743,418
Oct 2006	64,537,361	64,533,550	68,592,362
Nov 2006	61,387,703	61,613,571	58,153,883
Dec 2006	62,578,748	62,791,459	61,530,181
Jan 2007	61,221,276	62,591,597	62,026,544
Feb 2007	59,178,755	58,704,720	62,521,996
Mar 2007	58,934,260	59,129,540	59,260,246
Apr 2007	62,161,660	61,493,130	59,476,880
May 2007	65,134,633	63,957,202	69,734,367
Jun 2007	72,606,068	71,790,154	73,801,277

2 **Table 4: SH Normal Values**

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)	Normal Calendar Sales (kWh)
Jul 2006	9,409,895	9,205,578	9,290,389
Aug 2006	9,708,077	9,059,209	9,485,222
Sep 2006	8,819,376	8,856,292	7,470,731

Oct 2006	6,720,062	6,716,261	7,011,773
Nov 2006	7,177,999	7,216,989	7,361,009
Dec 2006	9,051,843	8,996,591	10,269,974
Jan 2007	9,257,166	10,401,255	9,811,722
Feb 2007	10,760,431	10,232,839	10,212,899
Mar 2007	8,722,343	8,884,954	8,830,800
Apr 2007	6,740,952	6,662,847	6,197,805
May 2007	6,932,307	6,649,454	7,366,790
Jun 2007	7,356,940	7,165,233	7,562,020

Table 5: TEB Normal Values

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)	Normal Calendar Sales (kWh)
Jul 2006	34,501,869	33,831,247	35,234,907
Aug 2006	35,275,162	33,144,287	34,374,957
Sep 2006	32,765,930	32,982,645	27,400,044
Oct 2006	26,348,346	26,324,265	27,848,186
Nov 2006	27,416,010	27,390,383	28,957,585
Dec 2006	32,291,633	32,527,963	33,688,008
Jan 2007	29,347,202	32,131,950	30,498,736
Feb 2007	31,634,065	30,378,352	30,713,060
Mar 2007	27,609,493	28,205,322	27,712,436
Apr 2007	25,652,459	25,527,026	23,785,567
May 2007	27,889,673	26,832,470	29,937,007
Jun 2007	30,060,032	29,296,047	30,859,009

Q. WHAT IS WEATHER NORMALIZATION?

A. Weather Normalization is the process of determining what historical consumption would have been if normal weather conditions existed. The process is a mathematical method to adjust the existing monthly sales for a class based on a statistical model and normal weather conditions.

Q. CAN YOU DESCRIBE THE WEATHER NORMALIZATION PROCESS?

A. The weather-normalization process entails adjusting actual sales based on the difference between what would have happened under normal weather conditions versus what happened under actual weather conditions. The fundamental equation used in the process is shown below.

$$NormalSales_{month} = \frac{ModelNormalSales_{month}}{ModelActualSales_{month}} \times ActualSales_{month}$$

In this equation, actual monthly sales are multiplied by the ratio of modeled sales under normal conditions to modeled sales under actual conditions.

Q. HOW DO YOU OBTAIN THE MODELED SALES UNDER ACTUAL CONDITIONS?

A. To obtain modeled sales under actual conditions, I developed a multivariate regression model for each class and used the model to estimate sales using actual weather data over the test period. The regression model predicts daily load as a function of actual daily weather. The regression model is developed using customer class load research data. The independent variables include weather splines for heating and cooling responses, daytype and holiday variables for seasonal variations, and sunlight variables for lighting effects. These variables capture the changing customer consumption patterns throughout the year. The weather spline variables capture the nonlinear interaction between load and weather. I have included the regression model specifications and results for the five classes in Schedule MQ-1.

Q. HOW DO YOU OBTAIN THE MODELED SALES UNDER NORMAL CONDITIONS?

A. To obtain modeled sales under normal conditions, I used the same multivariate regression model mentioned above and forecasted the sales using normal weather data through the test period.

Q. IN THE MODELS, WHAT ARE THE MWH PER DEGREE CHANGE IMPACTS CONTAINED IN THE MODEL?

A. Because the load-weather relationship is non-linear, a single MWh/degree number is not applicable for any class. Instead, the MWh/degree change depends on the degree at which the value is calculated. Embedded in the regression model for each class are heating and cooling degree day variables that describe the MWh/degree change at different temperature points.

In the Residential Class model, I used CDD65 and CDD70 temperature splines for cooling impacts. Associated with these variables are model coefficients that describe the MWh/degree change when temperature increases above 65 degrees. Between 66 and 70 degrees, a one degree change results in a 1.05075 MWh increase. The 1.05075 is the coefficient on the CDD65 variable. Above 70 degrees, a one degree change results in a 1.66772 (1.05075 + 0.61697) MWh increase. The 1.66772 is the sum of the coefficients on the CDD65 and CDD70 variables.

In the Residential Class, I used HDD55 , HDD60, and HDD55Trend temperature splines for heating impacts. Excluding the HDD55Trend variable, a one degree change between 56 and 60 degrees results in a 0.52222 MWh increase and a one degree change below 60 degrees, a one degree change results in a 0.54751 (0.52222 + 0.02529) MWh increase. When accounting for the HDD55_Trend variable, the impact increases below 55 degrees by 0.03483 MWh multiplied by a trend factor (Year-2002 + days in year/366) based on 2002. For example, on January 1, 2007, the impact is 5.00273 (2007-2002 + 1/366) multiplied with 0.03483 MWh, or 0.174245 MWh.

For the other classes, the model coefficients are interpreted the same way. These coefficients are shown in Schedule MQ-1.

Q. HOW DID YOU DEVELOP NORMAL WEATHER CONDITIONS FOR THE SALES MODEL?

A. Normal weather conditions are developed using a 30-year average of historical weather from 1977 through 2006. The averages are obtained by first developing historical heating and cooling degree days ("HDD" and "CDD") for multiple temperature reference point. Second, the HDD and CDD values are averaged over the 30-year period by day. For example all the HDD values for January 1st dates from 1977 through 2006 were averaged together to obtain the normal HDD value for January 1st.

Q. WHAT ADJUSTMENT DID YOU MAKE FOR BILLING CYCLES?

A. The fundamental equation includes billing cycle variations in the calculation. To calculate billed normal sales, I forecasted the daily consumption under normal and actual conditions and aggregated the consumption based on monthly billing cycle dates. To calculate calendar normal sales, I aggregated consumption under normal condition based on the calendar dates.

Q. WHAT IS THE RESULT OF THE WEATHER NORMALIZATION PROCESS FOR THE FIVE CLASSES?

A. The results for the normalization process are summarized for each class in Schedule MQ-2.

Q. DOES THIS CONCLUDE YOUR TESTIMONY?

A. Yes, it does.

Schedule MQ-1

REGRESSION MODEL SPECIFICATIONS AND RESULTS

RESIDENTIAL RG MODEL

Model fit statistics

- R-Squared 0.963
- Adjusted R-Squared 0.962
- Mean Abs. Dev. (MAD) 1.61
- Mean Abs. % Err. (MAPE) 4.66%
- Durbin-Watson Statistic 2.103

Variable Statistics

Variable	Coefficient	T-Stat
CONST	27.07364	33.442
DailyAverageTemperature.HDD60	0.02529	0.567
DailyAverageTemperature.HDD55	0.52222	10.469
WeatherTransforms.HDD55_Trend	0.03483	6.580
DailyAverageTemperature.CDD65	1.05075	19.696
DailyAverageTemperature.CDD70	0.61697	9.075
MonthlyBinary.Jan	5.29393	8.245
MonthlyBinary.Feb	4.93770	9.639
MonthlyBinary.Mar	2.75340	5.793
MonthlyBinary.May	1.06322	2.268
MonthlyBinary.Jun	4.26603	8.240
MonthlyBinary.Jul	6.92336	12.722
MonthlyBinary.Aug	7.04515	12.950
MonthlyBinary.Sep	2.97502	5.934
MonthlyBinary.Oct	0.07376	0.141
MonthlyBinary.Nov	1.48287	2.270
MonthlyBinary.Dec	4.13106	4.747
DOWBinary.Monday	-1.33392	-9.054
DOWBinary.Tuesday	-1.61488	-9.124
DOWBinary.Wednesday	-1.58516	-8.390
DOWBinary.Thursday	-1.69977	-8.958
DOWBinary.Friday	-2.01896	-11.330
DOWBinary.Saturday	-0.40617	-2.803

SunTimes.FracDark17	6.15178	2.602
SunTimes.FracDark8	1.45003	0.931
US_Holidays.NYHol	0.55615	0.679
US_Holidays.MLKing	0.40192	0.485
US_Holidays.PresidentDay	1.11588	1.472
US_Holidays.July4thHol	1.40310	1.707
US_Holidays.LaborDay	3.91177	4.332
US_Holidays.Thanksgiving	0.49016	0.533
US_Holidays.FriAftThanks	0.87574	0.952
US_Holidays.XMasHol	1.14770	1.395
MonthlyBinary.Year2006	-2.04694	-2.849
MonthlyBinary.Year2005	-2.38485	-3.266
MonthlyBinary.Year2004	-2.83457	-3.805
MonthlyBinary.Year2003	-2.70131	-3.542
MonthlyBinary.Year2002	-2.78864	-3.572
AR(1)	0.53888	27.222

COMMERICAL CB MODEL

Model fit statistics

- R-Squared 0.958
- Adjusted R-Squared 0.957
- Durbin-Watson Statistic 2.076
- Mean Abs. Dev. (MAD) 1.88
- Mean Abs. % Err. (MAPE) 3.94%

Variable Statistics

Variable	Coefficient	T-Stat
CONST	29.30443	25.049
DailyAverageTemperature.HDD55	0.35847	31.047
DailyAverageTemperature.CDD65	0.98455	14.266
DailyAverageTemperature.CDD60	0.28479	5.095
MonthlyBinary.Jan	3.74126	4.799
MonthlyBinary.Feb	2.95913	3.899
MonthlyBinary.Mar	0.88582	1.278
MonthlyBinary.May	2.51353	3.642
MonthlyBinary.Jun	6.35200	8.243
MonthlyBinary.Jul	8.89172	11.118

MonthlyBinary.Aug	8.87395	11.048
MonthlyBinary.Sep	5.70808	7.458
MonthlyBinary.Oct	2.49691	3.336
MonthlyBinary.Nov	2.26319	2.412
MonthlyBinary.Dec	3.29767	3.019
DOWBinary.Monday	11.65550	72.125
DOWBinary.Tuesday	12.42438	61.586
DOWBinary.Wednesday	12.72190	58.266
DOWBinary.Thursday	12.43160	56.717
DOWBinary.Friday	11.98953	59.074
DOWBinary.Saturday	3.34087	20.799
SunTimes.FracDark17	5.07655	1.547
US_Holidays.MemorialDay	-11.84689	-12.987
US_Holidays.NYHol	-7.80537	-8.675
US_Holidays.July4thHol	-14.53288	-16.120
US_Holidays.LaborDay	-12.31420	-13.497
US_Holidays.Thanksgiving	-14.26096	-13.861
US_Holidays.FriAftThanks	-5.27290	-5.123
US_Holidays.XMasHol	-8.95085	-9.915
MonthlyBinary.Year2006	0.79097	0.738
MonthlyBinary.Year2005	-1.27332	-1.171
MonthlyBinary.Year2004	-3.40168	-3.137
MonthlyBinary.Year2003	-1.77885	-1.638
MonthlyBinary.Year2002	0.58691	0.536
AR(1)	0.67802	38.946

GENERAL POWER GP MODEL

Model fit statistics

- R-Squared 0.967
- Adjusted R-Squared 0.964
- Durbin-Watson Statistic 2.022
- Mean Abs. Dev. (MAD) 218.34
- Mean Abs. % Err. (MAPE) 2.79%

Variable Statistics

Variable	Coefficient	T-Stat
CONST	5004.77278	34.666

DailyAverageTemperature.HDD50	22.71948	6.788
DailyAverageTemperature.CDD70	28.67405	2.496
DailyAverageTemperature.CDD55	33.90578	5.491
MonthlyBinary.Jan	282.99461	1.586
MonthlyBinary.Feb	452.83537	2.566
MonthlyBinary.Mar	-37.57302	-0.209
MonthlyBinary.May	51.17962	0.284
MonthlyBinary.Jun	327.71844	1.658
MonthlyBinary.Jul	402.87136	1.926
MonthlyBinary.Aug	897.85083	4.341
MonthlyBinary.Sep	292.02897	1.519
MonthlyBinary.Oct	299.86544	1.579
MonthlyBinary.Nov	-126.82545	-0.640
MonthlyBinary.Dec	227.44113	1.074
DOWBinary.Monday	3177.42275	70.780
DOWBinary.Tuesday	3600.81974	65.155
DOWBinary.Wednesday	3690.21106	61.909
DOWBinary.Thursday	3705.03544	61.747
DOWBinary.Friday	3378.53964	60.198
DOWBinary.Saturday	1105.10116	24.677
US_Holidays.NYHol	-2589.43326	-13.438
US_Holidays.July4thHol	-2889.25441	-9.838
US_Holidays.LaborDay	-2790.96132	-10.643
US_Holidays.Thanksgiving	-3836.09599	-12.576
US_Holidays.FriAftThanks	-2920.18975	-8.516
US_Holidays.SatAftThanks	-819.65328	-2.686
US_Holidays.XMasHol	-3054.62101	-10.570
US_Holidays.XMASAft	-1817.39593	-6.959
US_Holidays.July4thMonFri	-2188.84836	-7.452
US_Holidays.MemorialDay	-3091.87384	-11.791
AR(1)	0.63208	15.593

SMALL HEATING SH MODEL

Model fit statistics

- R-Squared 0.937
- Adjusted R-Squared 0.934
- Durbin-Watson Statistic 1.866
- Mean Abs. Dev. (MAD) 3.45
- Mean Abs. % Err. (MAPE) 3.77%

Variable Statistics

Variable	Coefficient	T-Stat
CONST	70.44023	32.043
DailyAverageTemperature.HDD40	0.99691	8.921
DailyAverageTemperature.HDD50	0.86858	11.655
DailyAverageTemperature.CDD55	0.43953	4.548
DailyAverageTemperature.CDD65	1.00770	5.632
DailyAverageTemperature.CDD75	0.24522	1.213
MonthlyBinary.Jan	5.97624	3.281
MonthlyBinary.Feb	5.14113	2.810
MonthlyBinary.Mar	1.44216	0.830
MonthlyBinary.May	1.15074	0.660
MonthlyBinary.Jun	4.73939	2.416
MonthlyBinary.Jul	5.55136	2.707
MonthlyBinary.Aug	7.22772	3.525
MonthlyBinary.Sep	2.94438	1.589
MonthlyBinary.Oct	0.09868	0.055
MonthlyBinary.Nov	0.88221	0.484
MonthlyBinary.Dec	9.12726	4.887
DOWBinary.Monday	17.82648	34.045
DOWBinary.Tuesday	18.08035	28.523
DOWBinary.Wednesday	18.65826	27.579
DOWBinary.Thursday	18.05714	26.431
DOWBinary.Friday	17.72166	27.693
DOWBinary.Saturday	8.65963	16.546
US_Holidays.NYHol	-14.22113	-4.711
US_Holidays.July4thHol	-17.03295	-5.751
US_Holidays.MemorialDay	-13.94027	-4.685
US_Holidays.LaborDay	-17.52870	-5.871
US_Holidays.Thanksgiving	-23.46091	-5.248
US_Holidays.FriAftThanks	-4.80019	-1.361
US_Holidays.XMasHol	-10.31514	-3.463
MonthlyBinary.Year2005	-10.07402	-5.785
MonthlyBinary.Year2006	-10.31305	-5.960

AR(1)	0.54683	18.298

TOTAL ELECTRIC TEB MODEL

Model fit statistics

- R-Squared 0.936
- Adjusted R-Squared 0.935
- Durbin-Watson Statistic 1.940
- Mean Abs. Dev. (MAD) 38.22
- Mean Abs. % Err. (MAPE) 3.19%

Variable Statistics

Variable	Coefficient	T-Stat
CONST	888.70650	39.411
DailyAverageTemperature.HDD55	5.88275	9.486
DailyAverageTemperature.HDD45	10.58025	13.190
DailyAverageTemperature.CDD60	8.33865	6.071
DailyAverageTemperature.CDD65	9.05103	4.669
DailyAverageTemperature.CDD75	1.78477	1.072
MonthlyBinary.Jan	63.32638	3.250
MonthlyBinary.Feb	59.28185	3.690
MonthlyBinary.Mar	14.73697	0.995
MonthlyBinary.May	31.41207	2.133
MonthlyBinary.Jun	82.31469	5.066
MonthlyBinary.Jul	131.41655	7.782
MonthlyBinary.Aug	122.75476	7.255
MonthlyBinary.Sep	89.05683	5.592
MonthlyBinary.Oct	58.07416	3.503
MonthlyBinary.Nov	81.36285	4.001
MonthlyBinary.Dec	93.71623	3.634
DOWBinary.Monday	153.24079	39.760
DOWBinary.Tuesday	162.86442	34.214
DOWBinary.Wednesday	181.79897	35.359
DOWBinary.Thursday	177.15110	34.312
DOWBinary.Friday	188.35985	39.186
DOWBinary.Saturday	70.44889	18.376
SunTimes.FracDark17	121.51060	1.679
SunTimes.FracDark8	-128.28461	-2.825

US_Holidays.NYHol	-135.49184	-6.369
US_Holidays.July4thHol	-125.31082	-5.787
US_Holidays.LaborDay	-164.68142	-7.508
US_Holidays.Thanksgiving	-221.05762	-8.997
US_Holidays.FriAftThanks	-31.28766	-1.272
US_Holidays.XMasHol	-102.21046	-4.707
MonthlyBinary.Year2006	-46.09005	-2.308
MonthlyBinary.Year2005	-10.69552	-0.530
MonthlyBinary.Year2004	-33.97553	-1.691
MonthlyBinary.Year2003	-0.12718	-0.006
AR(1)	0.62341	31.235

Schedule MQ-2

WEATHER NORMALIZATION FOR TEST YEAR

REPORT

Proposal for

Weather Normalization For Test Year

Submitted to:

Empire District Electric Company
602 Joplin Street
Joplin, Missouri 64801

Submitted by:

Itron, Inc.
11236 El Camino Real
San Diego, California 92130
(858) 724-2620

Itron

August 31, 2007

Table of Contents

1

Project Summary

In this project, the Empire District Electric Company (Empire) engaged Itron's forecast consulting services to develop a weather normalized forecast for July 1, 2006 to June 30, 2007. The weather normalized forecast was developed for the following five Empire classes.

- Residential (Res)
- Commercial (Com)
- Small Heating (SH)
- General Power (GP)
- Total Electric (TEB)

The weather normalization process employed by Itron uses load research data provided by Empire and is described in Section 2. This method includes the development of daily statistical models (Section 3) and daily normal weather (Section 4). Final results are show in Section 5.

2

Normalization Method

Weather normalization is the process of mathematically adjusting actual energy sales so that it represents energy typically used under a normal year condition. This process accounts for weather differences from between actual conditions and normal conditions.

Because the process is mathematical, two key assumptions are necessary to account for the differences between actual and normal sales. First, energy consumption is modeled based on historical relationships between actual consumption and historical weather. The model incorporates a set of descriptive variables to capture a statistical correlation between the variables and consumption. Second, normal conditions are assumed based on historical weather data. In this section, Itron describes the steps used to normalize historical sales based on the models and the normal weather developed by Itron in Sections 3 and 4.

Step 1. Daily Sales Models. In this step, Itron developed five regression models to capture the relationship between actual consumption and historical weather. The regression models were developed for the following classes.

- Residential (Res)
- Commercial (Com)
- General Power (GP)
- Small Heating (SH)
- Total Electric (TEB)

The models utilize Empire's Load Research data to articulate the models in Section 3.

Step 2. Simulate Daily Sales With Actual Weather. In this step, Itron used the five regression models developed in Step 1 to forecast the historical daily sales using actual weather. This steps results in the model prediction of sales under actual weather conditions.

Step 3. Simulate Daily Sales With Normal Weather. In this step, Itron used the five regression models developed in Step 1 to forecast the historical daily sales using normal weather. This steps results in the model prediction of sales under normal weather conditions.

Step 4. Calculate the Normal Revenue Cycle Month Sales. In this step, Itron adjusts the historical monthly revenue cycle sales provided by Empire for normal weather conditions. The result of this step is a monthly series of revenue cycle sales under normal conditions.

To calculate the normal revenue cycle sales, the following steps were taken.

1. Calculate the model sales with actual weather over the revenue cycle (***Model Actual Sales***). This step estimates the model predicted monthly revenue sales with actual weather.
2. Calculate the model sales with actual weather over the revenue cycle (***Model Normal Sales***). This step estimates the model predicted monthly revenue sales with normal weather.
3. Calculate the ***Normal Revenue Cycle Sales*** by adjusting the actual revenue sales (***Actual Revenue Cycle Sales***) using the ratio of the (1) and (2)

$$NormalRevenueCycleSales_{month} = \frac{ModelNormalSales_{month}}{ModelActualSales_{month}} \times Actual\,RevenueCycleSales_{month}$$

In calculating ***Normal Revenue Cycle Sales***, ***Model Actual Sales***, and ***Model Normal Sales*** are summed over the historic billing cycle month provided by Empire. Because the meter read schedule is not read on fixed dates, the "**Last Read Date**" is used to define the meter read schedule for the purposes of calculating the ***Normal Revenue Cycle Sales***.

In this approach, the use of the ratio of ***Model Actual Sales*** to ***Model Normal Sales*** removes the model bias from the normal calculation and directly adjusts the ***Actual Revenue Cycle Sales*** using normalization models developed with load research data.

Step 5. Calculate the Normal Calendar Month Sales. In this step, Itron uses the same adjustment in Step 4 to adjust the ***Actual Revenue Cycle Sales*** to calendar month sales. The calculation is identical except that the ***Model Normal Sales*** are summed over the calendar month instead of the revenue month. This approach embeds into the ***Model Actual Sales*** and ***Model Normal Sales*** ratio the adjustment from revenue cycle sales to calendar month sales.

The final products of the weather normalization method are monthly normal sales based on both billing (revenue) cycles and calendar months. The results are show in Section 5.

3

Models

The energy consumption models capture the load response to weather and other conditions. In developing these models, historical load research data were examined and used to estimate linear regression models using daily data. This section discusses the regression.

3.1 Residential Model

The Residential Daily Sales model was developed to articulate the relationship between the Residential class consumption and actual weather patterns. Hourly load research data (load research means) were provided by Empire from January 1, 1995 through February 28, 2007. These hourly data are shown in Figure 1. The hourly data aggregated to daily energy data are shown in Figure 2. Upon inspecting these data, data from January 2002 through February 2007 are used in the residential model.

Figure 1: Residential Hourly Load Research Data

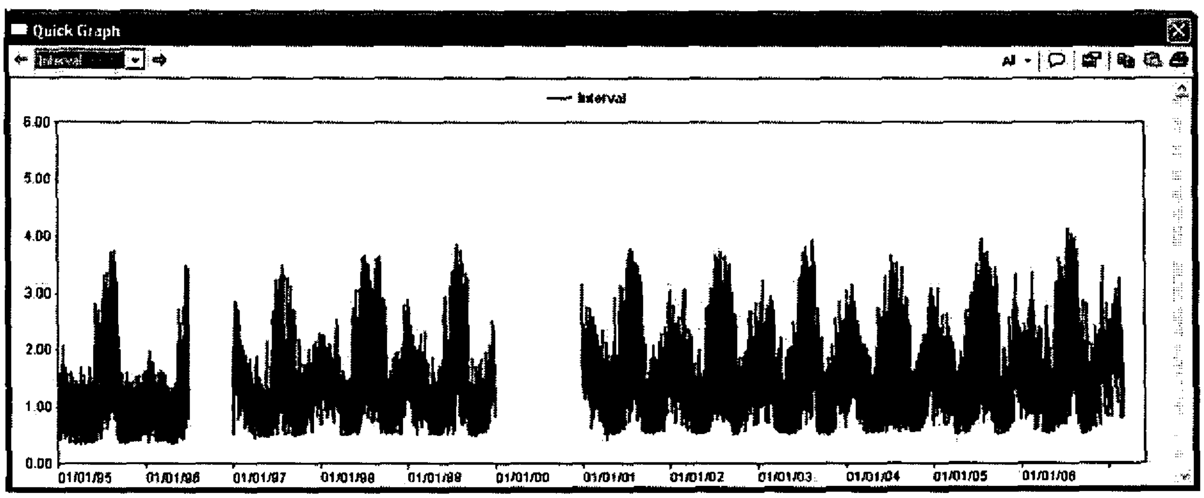
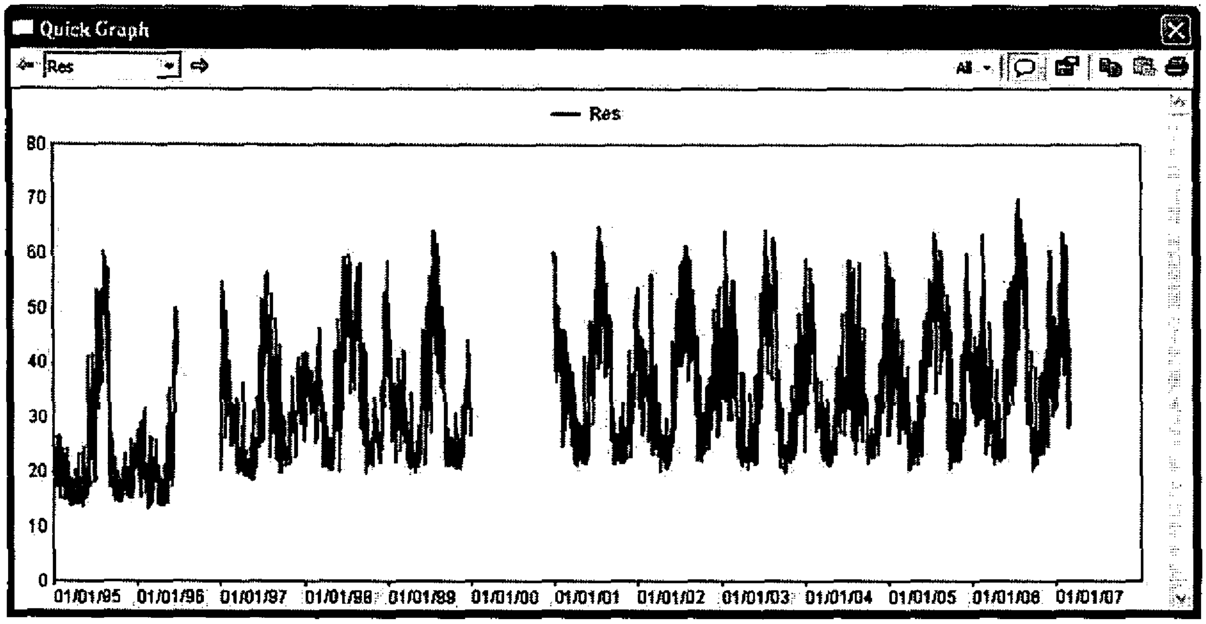


Figure 2: Residential Daily Energy



The load-weather relationship is best viewed using the scatter plots shown in Figure 3 and Figure 4. In these figures, daily energy is shown in the Y-axis and daily average temperature is shown on the X-axis. These figures demonstrate the non-linear load response to actual weather. Two main observations are seen in these figures. In Figure 3, data outside the general load-weather relationship are show in red triangles. These data points are removed from model estimation. In Figure 4, the heating response is seen as changing between 2002 (brown squares) and 2006 (green triangles). The model is constructed to account for this changing heating response.

Figure 3: Residential Bad Data (Red Triangles)

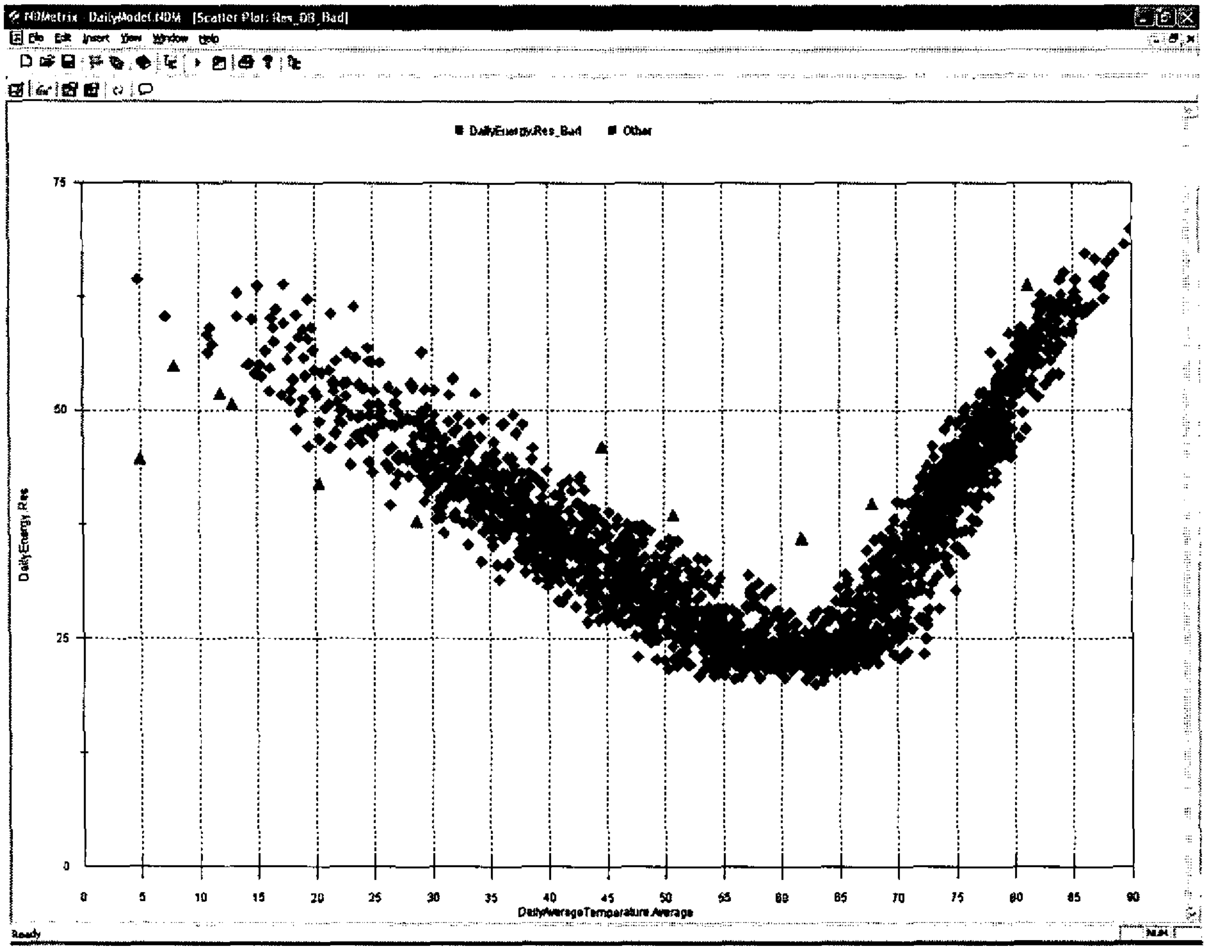
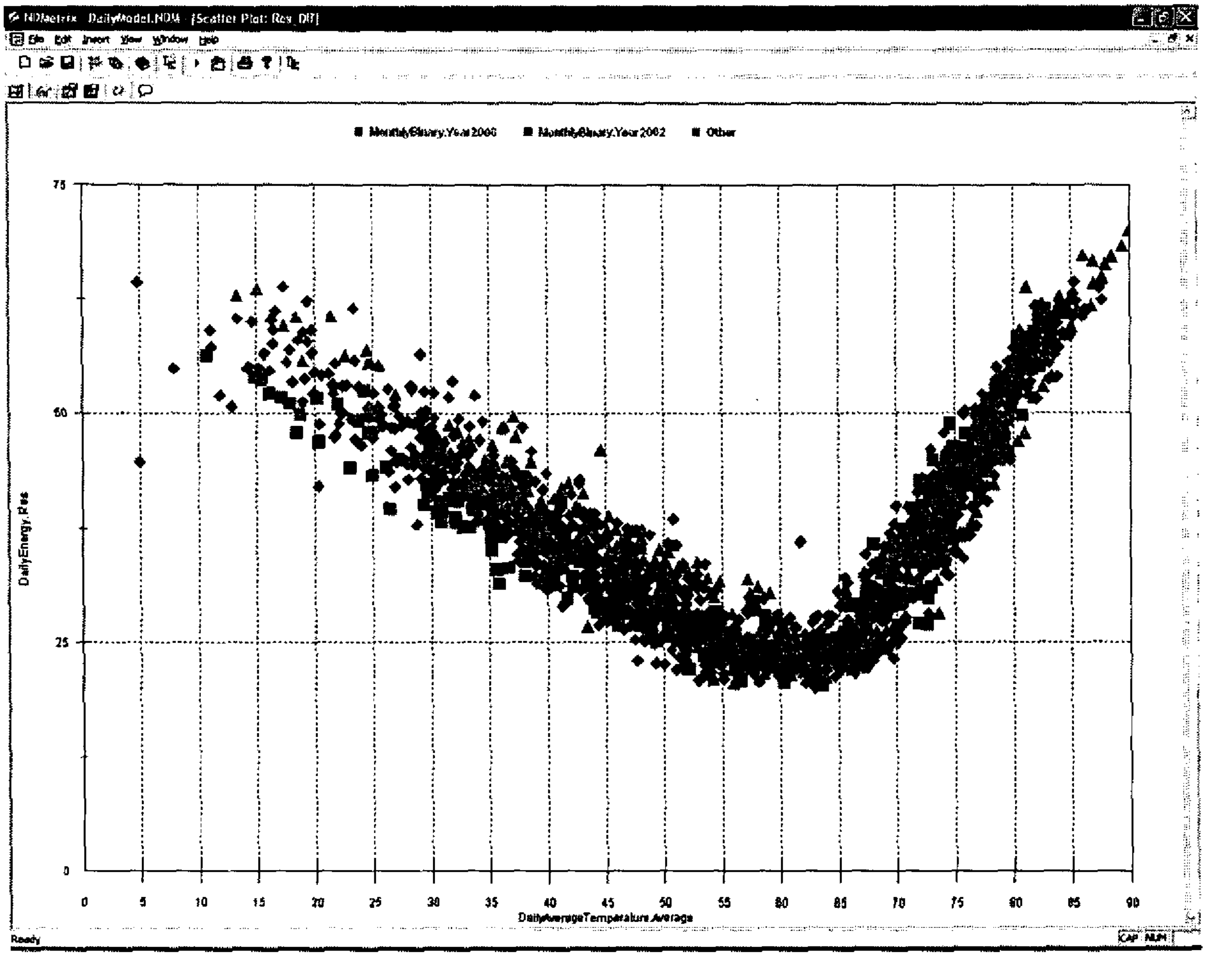


Figure 4: Residential Energy Temperature Scatter Plot



Residential Model. A linear regression model is used to articulate the load-weather relationship. This model contains the following classes of variables and their function in the model context (Table 1). A full description of the model can be viewed in the *MetrixND* project file.

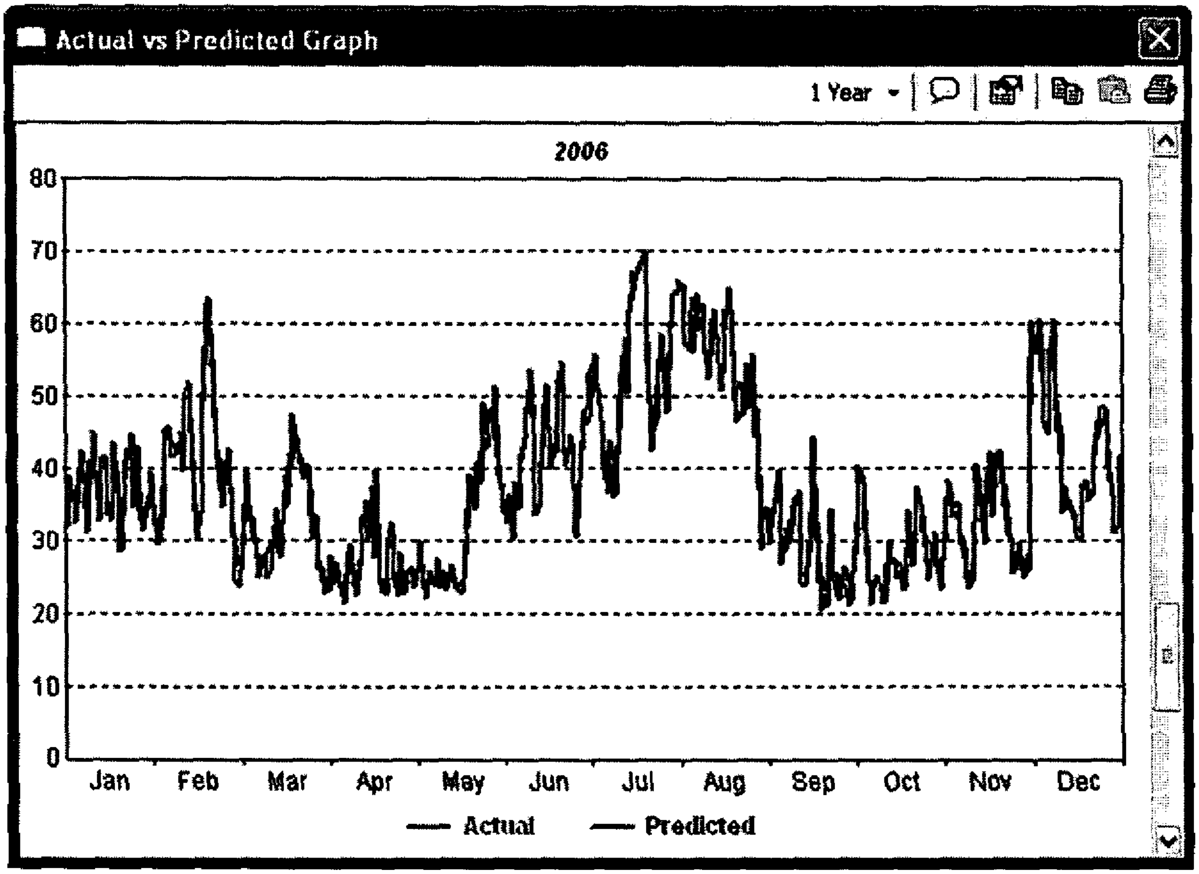
Table 1: Residential Model Variables

Variable Class	Purpose
Monthly Binaries	These variables account for changing seasonal consumption pattern for year.
Day of Week Binaries	These variables account for changing consumption pattern for each day of the week.
Sunlight	These variables account for the changing time of sunrise and sunset.
Holidays	These variables account for changes in consumption as a result of national holidays.
Annual Binaries	These variables account for changes in the load research samples and load growth over the estimation period.
Temperature Splines	These variables account for the nonlinear load response to weather and the changing heating response.
AR Term	This term removes the remaining serial correlation and clarifies the remaining model coefficients.

The overall fit of the regression model can be seen graphically in Figure 5 and numerically in the statistics below.

- R-Squared 0.963
- Adjusted R-Squared 0.962
- Mean Abs. Dev. (MAD) 1.61
- Mean Abs. % Err. (MAPE) 4.66%
- Durbin-Watson Statistic 2.103

Figure 5: Residential Model Fit – Actual Versus Predicted Values



3.2 Commercial

The Commercial Daily Sales model was developed to articulate the relationship between the commercial class consumption and actual weather patterns. Hourly load research data (load research means) were provided by Empire from January 1, 1995 through February 28, 2007. These hourly data are shown in Figure 6. The hourly data aggregated to daily energy data are shown in Figure 7. Upon inspecting these data, data from January 2002 through February 2007 are used in the commercial model.

Figure 6: Commercial Hourly Load Research Data

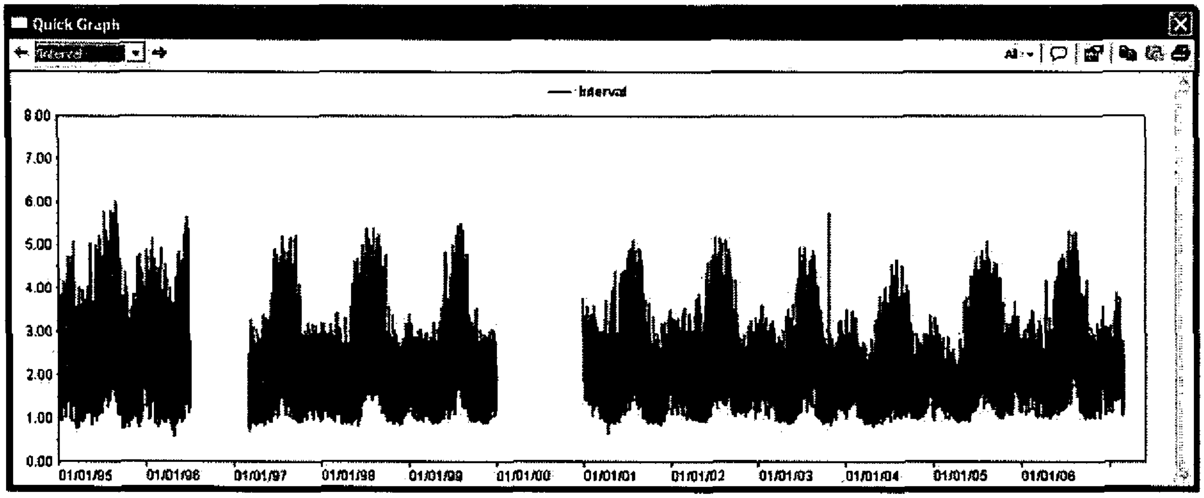
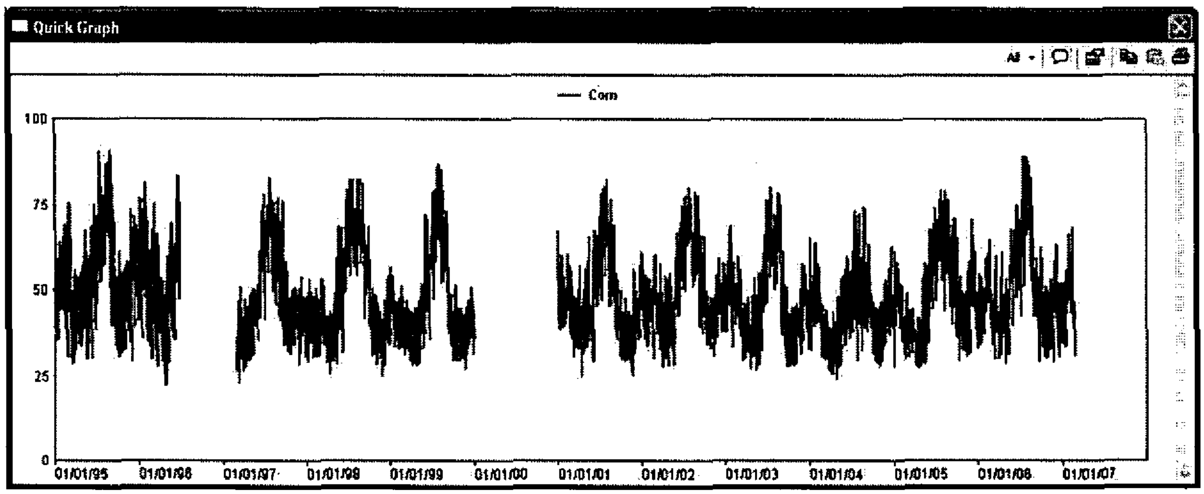


Figure 7: Commercial Daily Energy



The load-weather relationship is best viewed using the scatter plots shown in Figure 8 and Figure 9. In these figures, daily energy is shown in the Y-axis and daily average temperature is shown on the X-axis. These figures demonstrate the non-linear load response to actual weather. Two main observations are seen in these figures. In Figure 8, data outside the general load-weather relationship are show in red triangles. These data points are removed from model estimation. In Figure 9, the weekend response (green triangles) is clearly lower than the weekday response (blue diamonds).

Figure 8: Commercial Bad Data

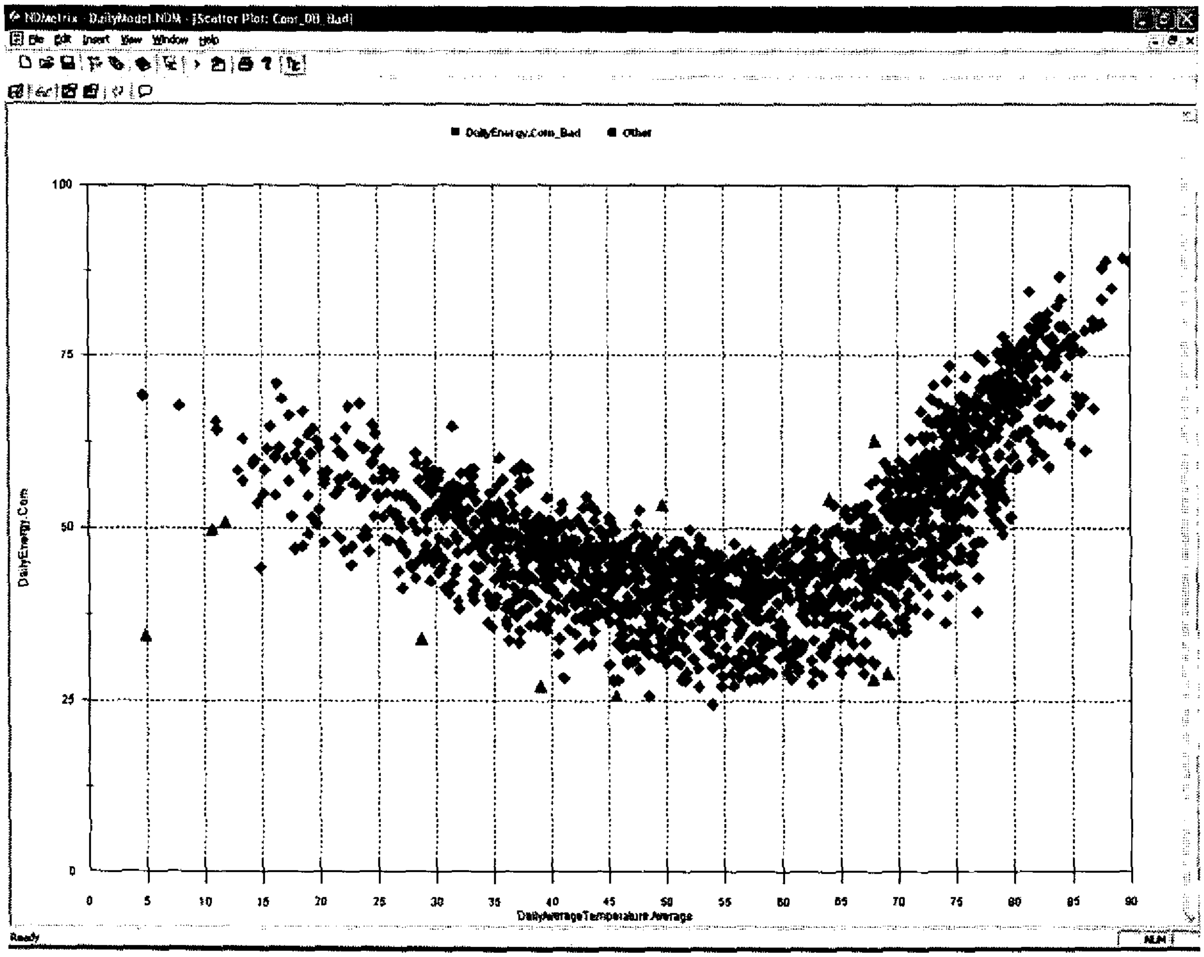
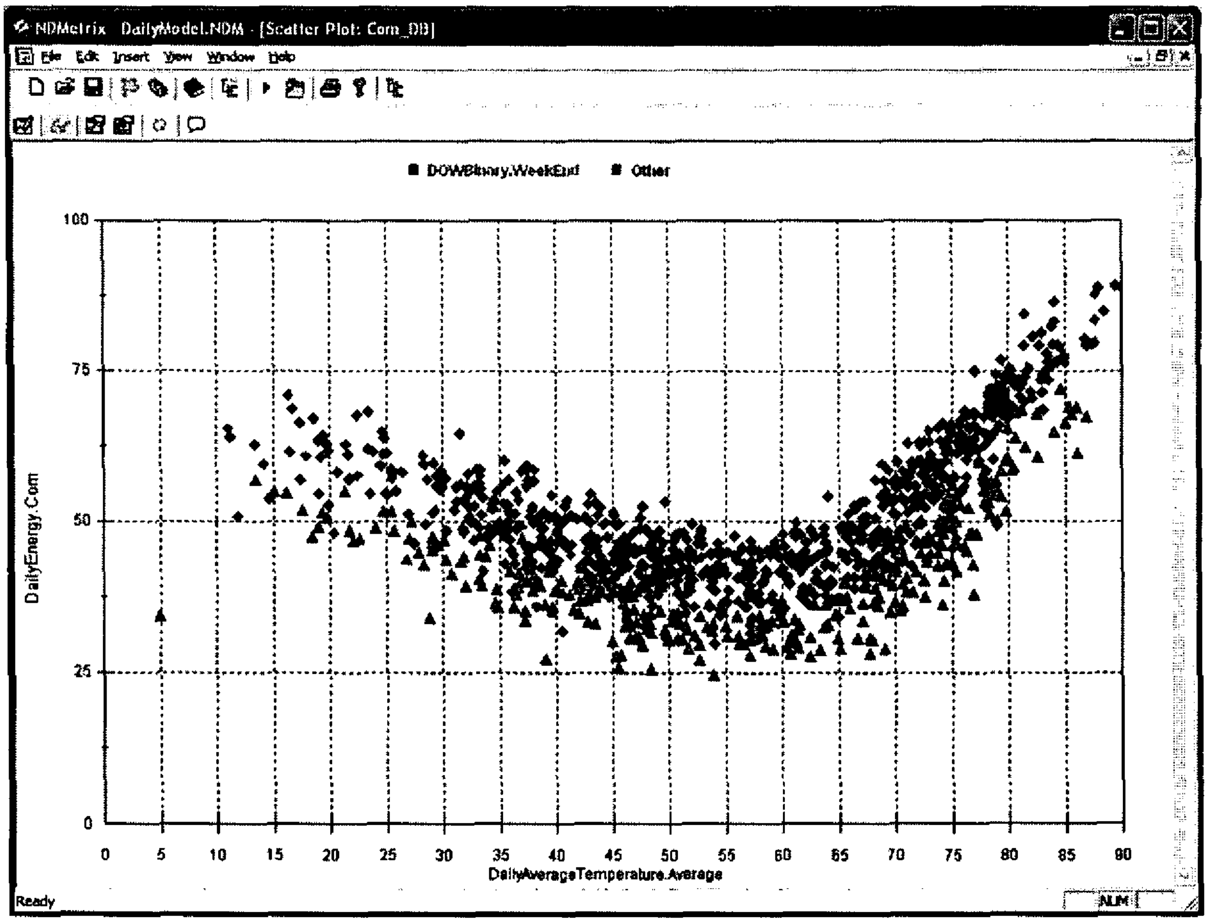


Figure 9: Commercial Energy Temperature Scatter Plot

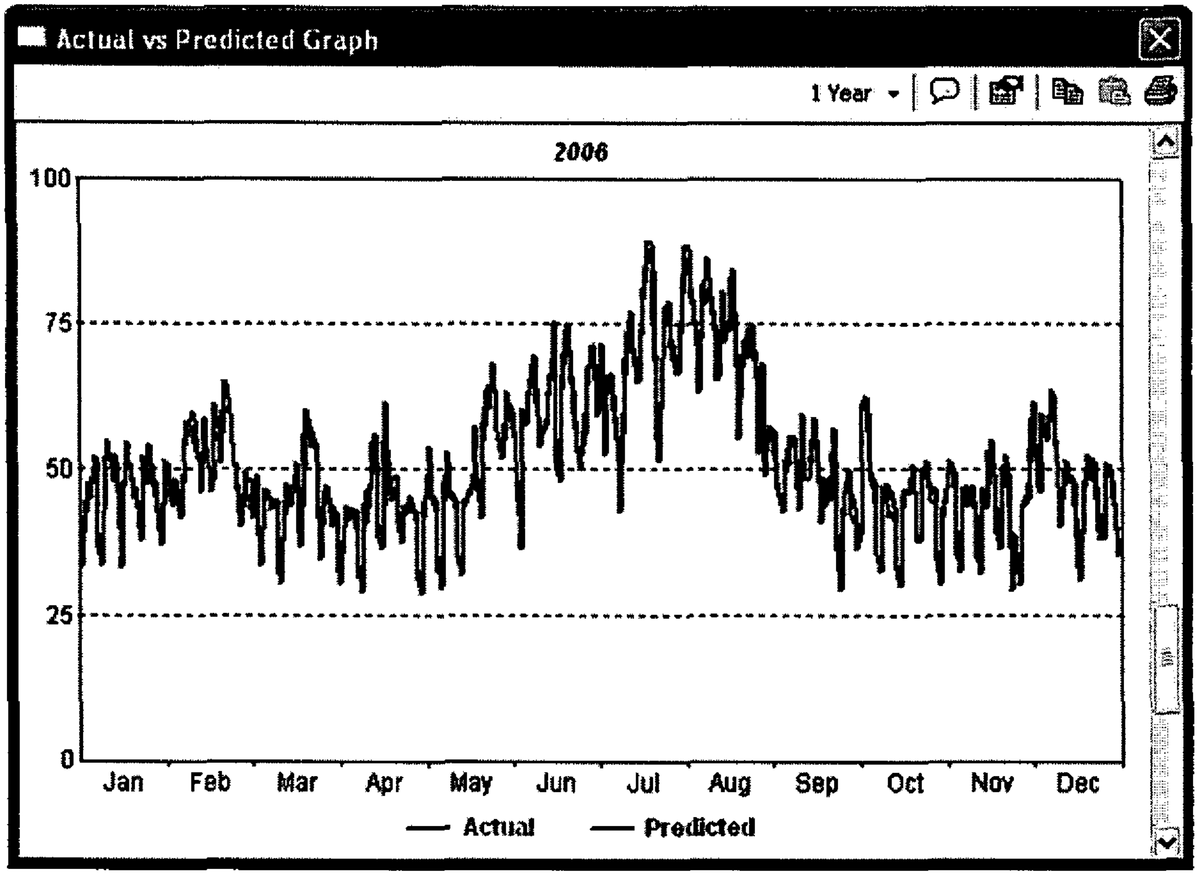


Commercial Model. The commercial model is built with the same classes of variables used in the residential model (Table 1). However, temperature splines have been adjusted for the commercial weather response and no changing weather response is modeled.

The overall fit of the regression model can be seen graphically in Figure 10 and numerically in the statistics below. A full description of the model and the associated model statistics can be viewed in the *MetrixND* project file.

▪ R-Squared	0.958
▪ Adjusted R-Squared	0.957
▪ Durbin-Watson Statistic	2.076
▪ Mean Abs. Dev. (MAD)	1.88
▪ Mean Abs. % Err. (MAPE)	3.94%

Figure 10: Commercial Model Fit – Actual Versus Predicted Values



3.3 General Power

The General Power (GP) Daily Sales model was developed to articulate the relationship between the GP class consumption and actual weather patterns. Hourly load research data (load research means) were provided by Empire from January 1, 1995 through February 28, 2007. These hourly data are shown in Figure 11. The hourly data aggregated to daily energy data are shown in Figure 12. Upon inspecting these data, data from January 2006 through February 2007 are used. The shortened historical series accounts for the significant drop in consumption beginning in 2006.

Figure 11: General Power Hourly Load Research

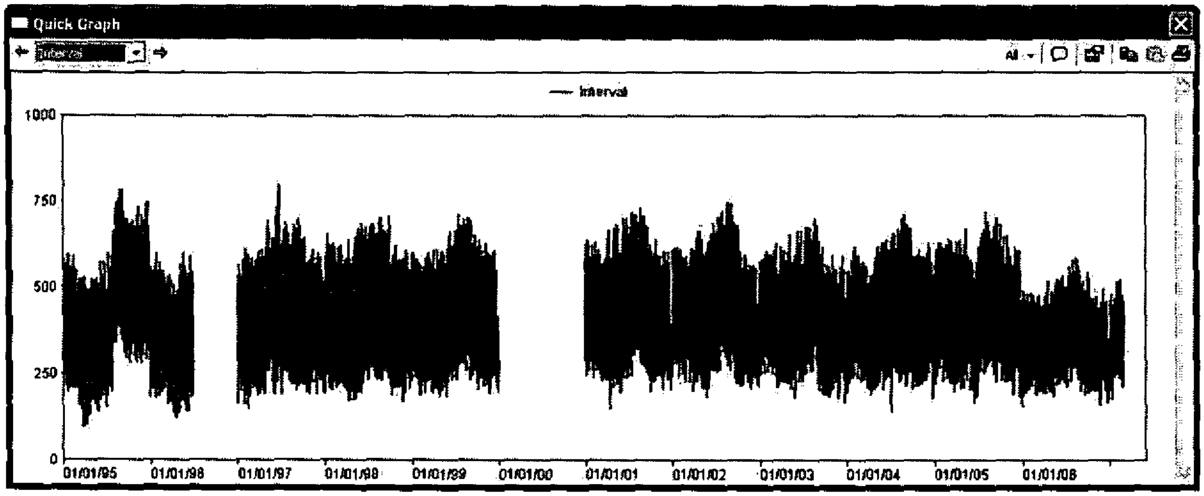
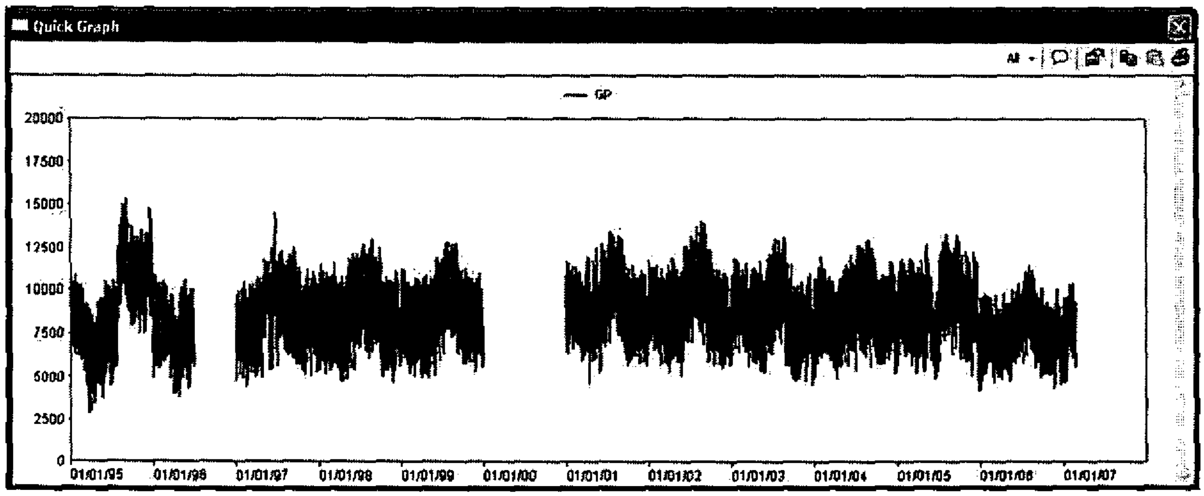


Figure 12: General Power Daily Energy



The load-weather relationship is best viewed using the scatter plots shown in Figure 13 and Figure 14. In these figures, daily energy is shown in the Y-axis and daily average temperature is shown on the X-axis. These figures demonstrate the non-linear load response to actual weather. Two main observations are seen in these figures. In Figure 13, data outside the general load-weather relationship are show in red triangles. These data points are removed from model estimation. In Figure 14, the 2005 data points (red triangles) and the 2006 data points (green squares) are highlighted. Based on visual inspection, the cooling response between 2005 and 2006 clearly changing further demonstrating the need to remove pre-2006 data.

Figure 13: General Power Bad

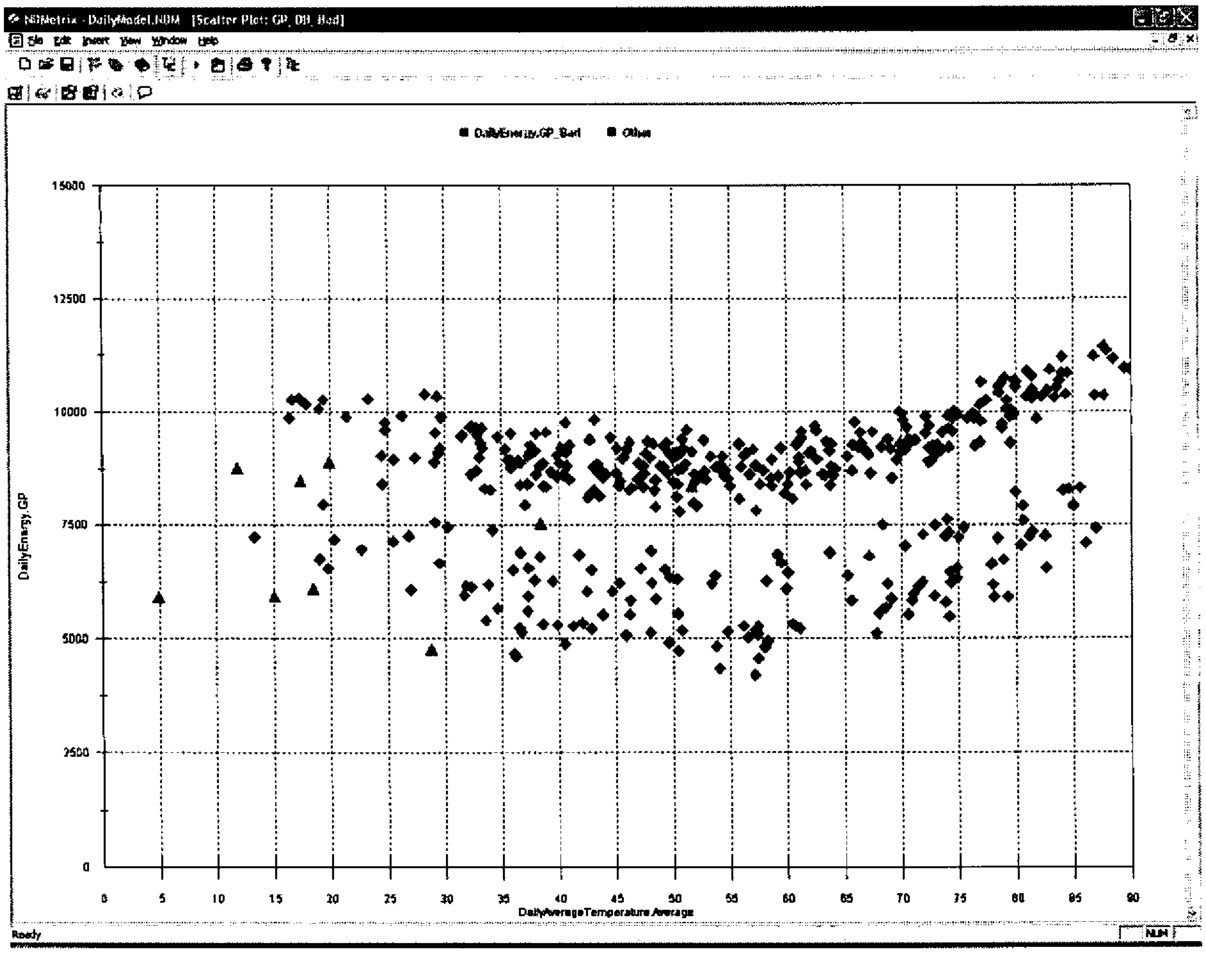
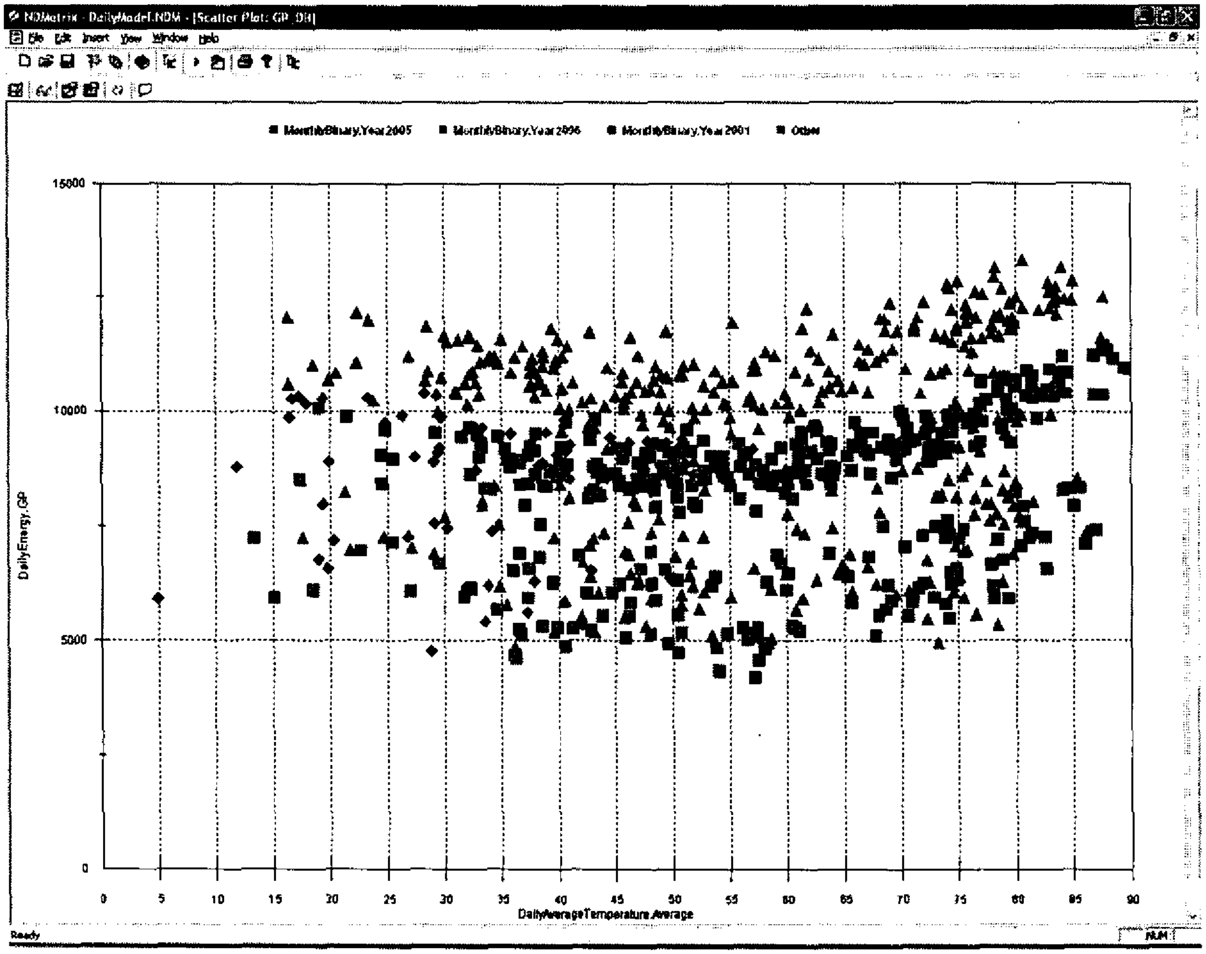


Figure 14: General Power Energy Temperature Scatter Plot

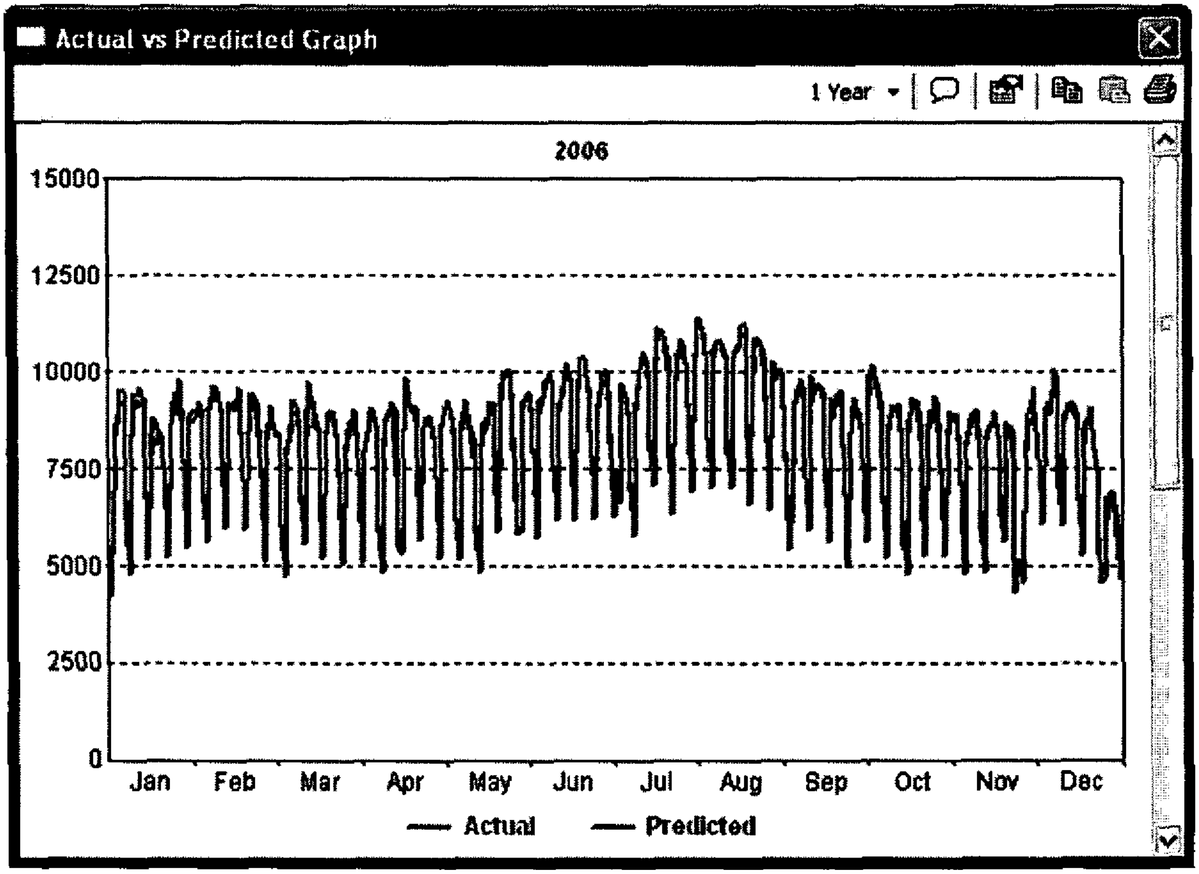


GP Model. The GP model is built with the same classes of variables used in the residential model (Table 1). However, temperature splines have been adjusted for the GP weather response and no changing weather response is modeled.

The overall fit of the regression model can be seen graphically in Figure 15 and numerically in the statistics below. A full description of the model and the associated model statistics can be viewed in the *MetrixND* project file.

▪ R-Squared	0.967
▪ Adjusted R-Squared	0.964
▪ Durbin-Watson Statistic	2.022
▪ Mean Abs. Dev. (MAD)	218.34
▪ Mean Abs. % Err. (MAPE)	2.79%

Figure 15: GP Model Fit – Actual Versus Predicted Values



3.4 Small Heating

The Small Heating (SH) Daily Sales model was developed to articulate the relationship between the SH class consumption and actual weather patterns. Hourly load research data (load research means) were provided by Empire from January 1, 1995 through February 28, 2007. These hourly data are shown in Figure 16. The hourly data aggregated to daily energy data are shown in Figure 17. Upon inspecting these data, data from January 2005 through February 2007 are used. The shortened historical series removes the downward sloping trend that begins in 2001 and stabilizes in 2005.

Figure 16: Small Heating Hourly Load Research

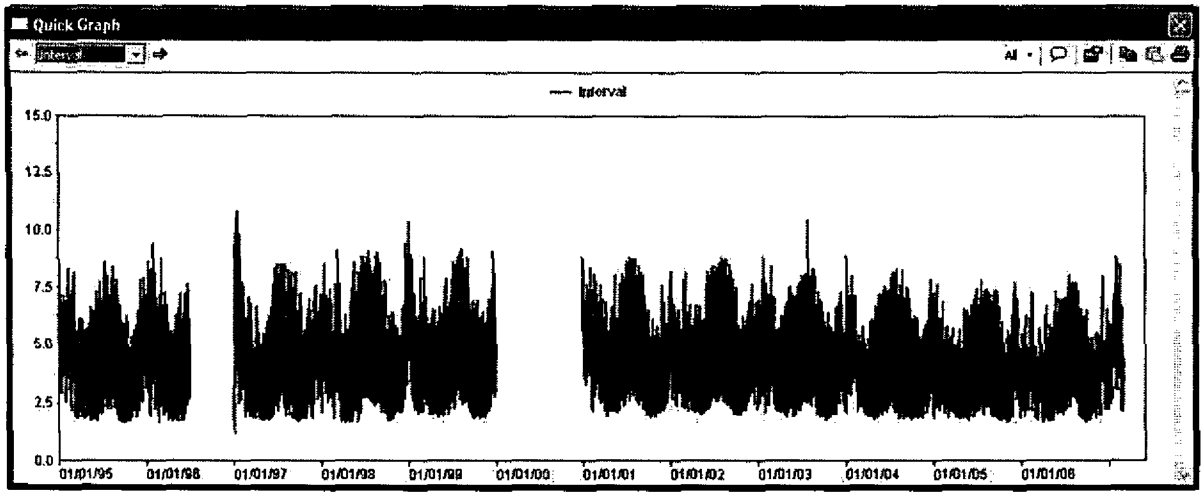
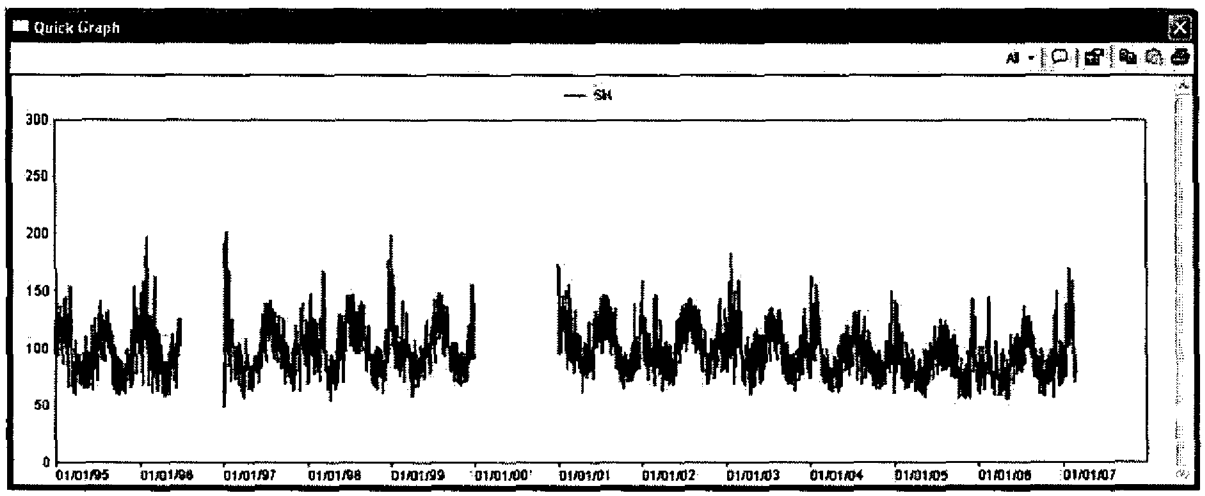


Figure 17: Small Heating Daily Energy



The load-weather relationship is best viewed using the scatter plots shown in Figure 18 and Figure 19. In these figures, daily energy is shown in the Y-axis and daily average temperature is shown on the X-axis. These figures demonstrate the non-linear load response to actual weather. Two main observations are seen in these figures. In Figure 18, data outside the general load-weather relationship are show in red triangles. These data points are removed from model estimation. In Figure 19, the 2004 data points (purple triangles) clearly have a different temperature responses than 2005 (red squares) and 2006 (green circles). The different temperature response demonstrates the need to remove the pre-2005 data.

Figure 18: Small Heating Bad

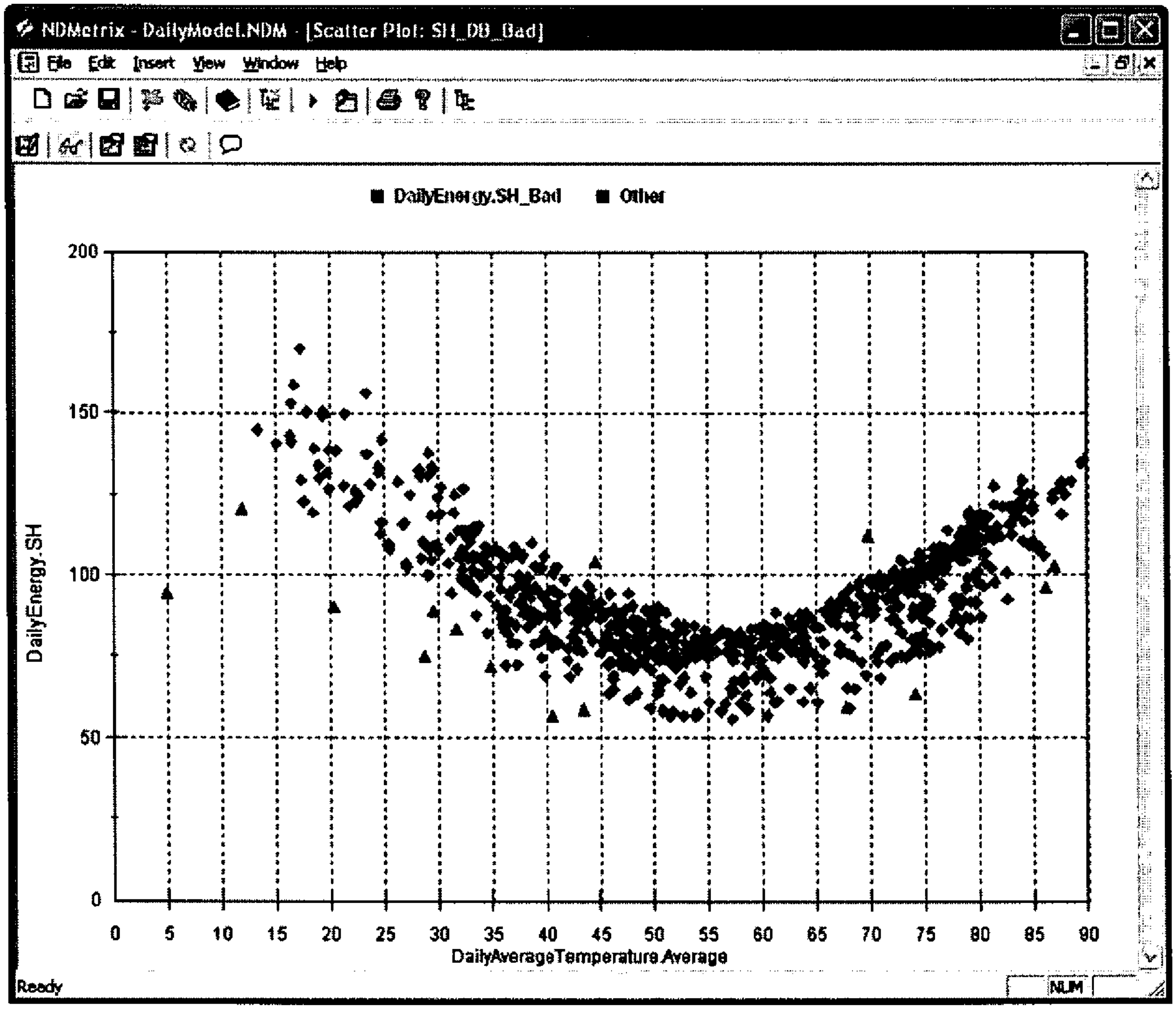
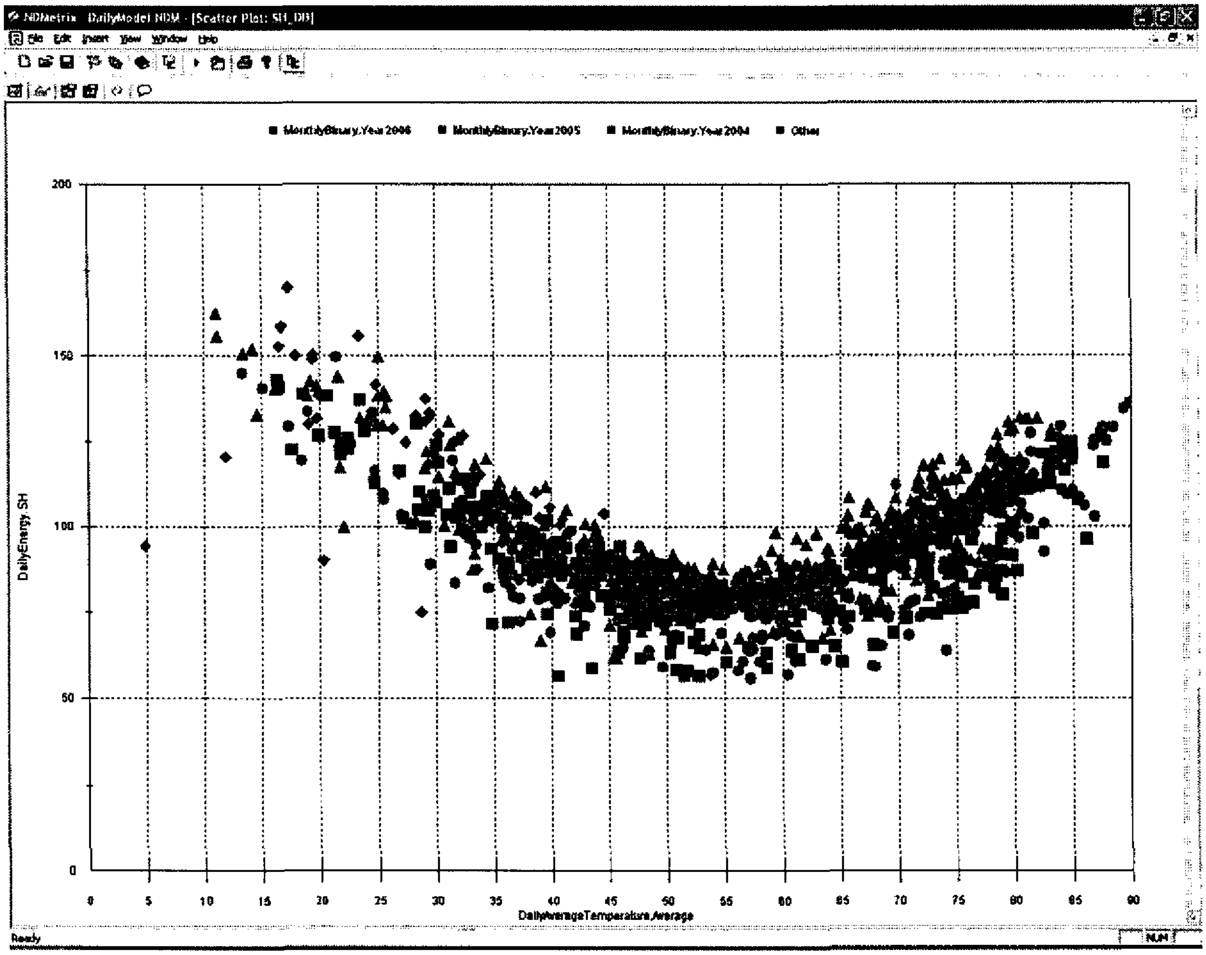


Figure 19: Small Heating Energy Temperature Scatter Plot

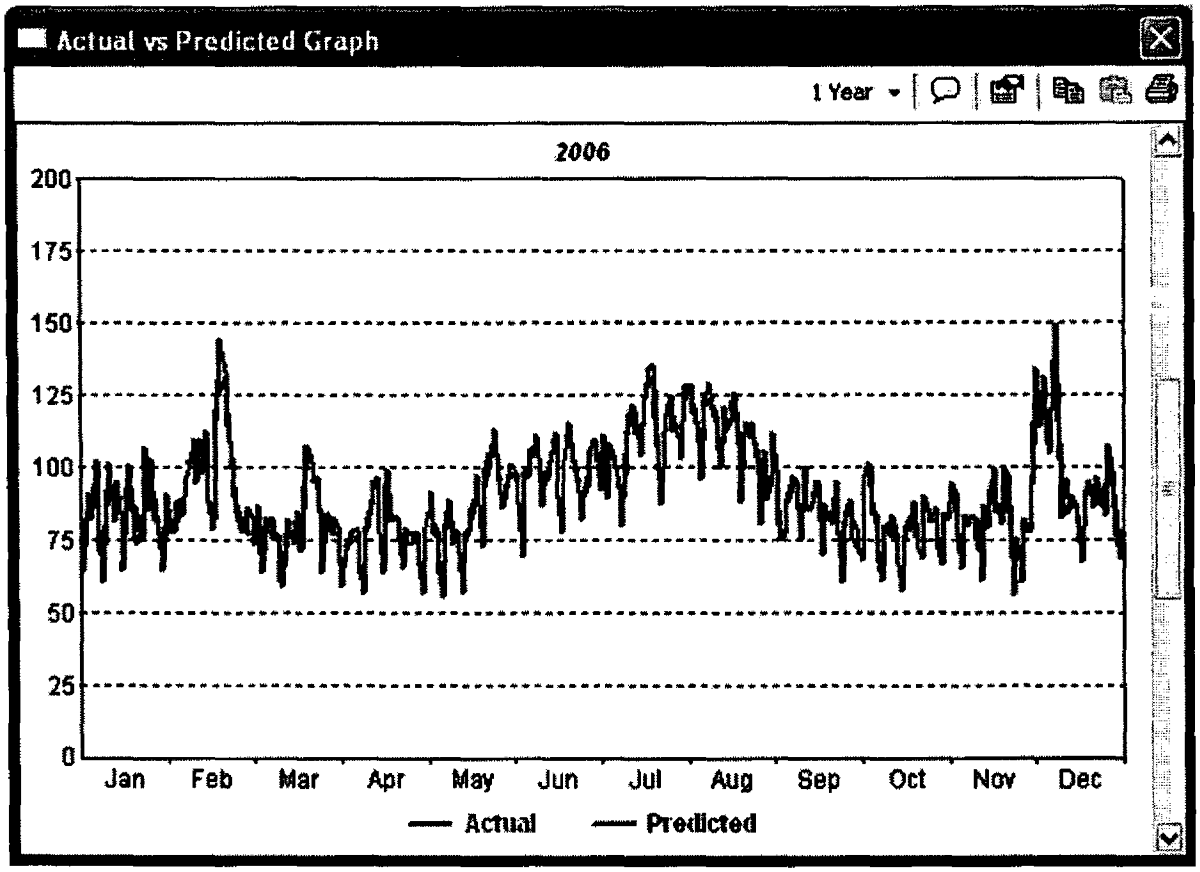


SH Model. The SH model is built with the same classes of variables used in the residential model (Table 1). However, temperature splines have been adjusted for the SH weather response and no changing weather response is modeled.

The overall fit of the regression model can be seen graphically in Figure 20 and numerically in the statistics below. A full description of the model and the associated model statistics can be viewed in the *MetrixND* project file.

▪ R-Squared	0.937
▪ Adjusted R-Squared	0.934
▪ Durbin-Watson Statistic	1.866
▪ Mean Abs. Dev. (MAD)	3.45
▪ Mean Abs. % Err. (MAPE)	3.77%

Figure 20: SH Model Fit – Actual Versus Predicted Values



3.5 Total Electric

The Total Electric (TEB) Daily Sales model was developed to articulate the relationship between the TEB class consumption and actual weather patterns. Hourly load research data (load research means) were provided by Empire from January 1, 1995 through February 28, 2007. These hourly data are shown in Figure 21. The hourly data aggregated to daily energy data are shown in Figure 22. Upon inspecting these data, data from January 2003 through February 2007 are used. The shortened historical series captures the stable level of loads that appears after the beginning of 2003.

Figure 21: Total Electric Hourly Load Research

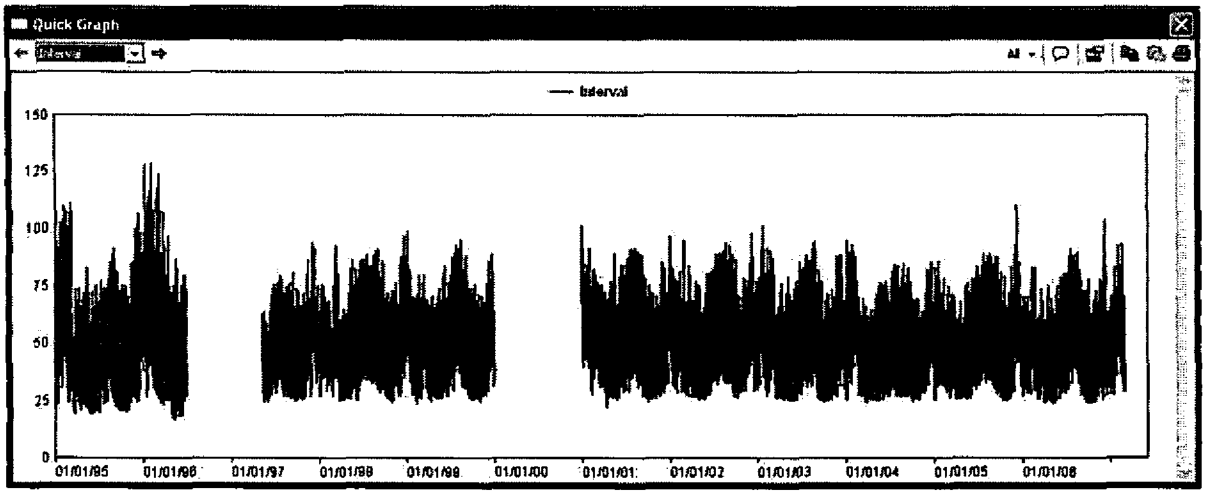
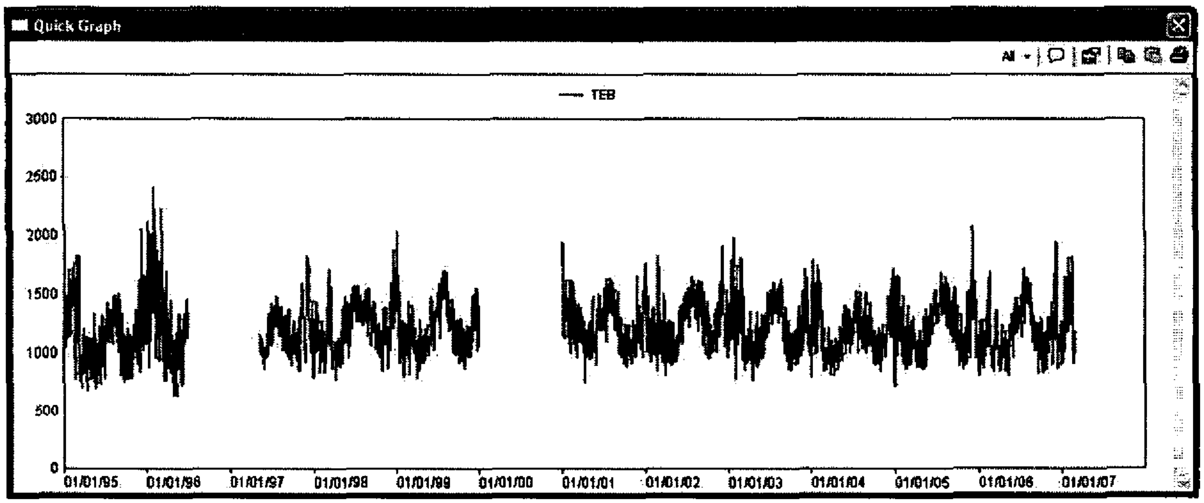


Figure 22: Total Electric Daily Energy



The load-weather relationship is best viewed using the scatter plots shown in Figure 23 and Figure 24. In these figures, daily energy is shown in the Y-axis and daily average temperature is shown on the X-axis. These figures demonstrate the non-linear load response to actual weather. Two main observations are seen in these figures. In Figure 23, data outside the general load-weather relationship are show in red triangles. These data points are removed from model estimation. In Figure 24, the 2002 data points (red triangles) are shown against the 2003 through 2007 data (blue diamonds). This view shows the 2002 data with a higher load and higher cooling weather response, which results in the data being excluded from the model.

Figure 23: TEB Bad

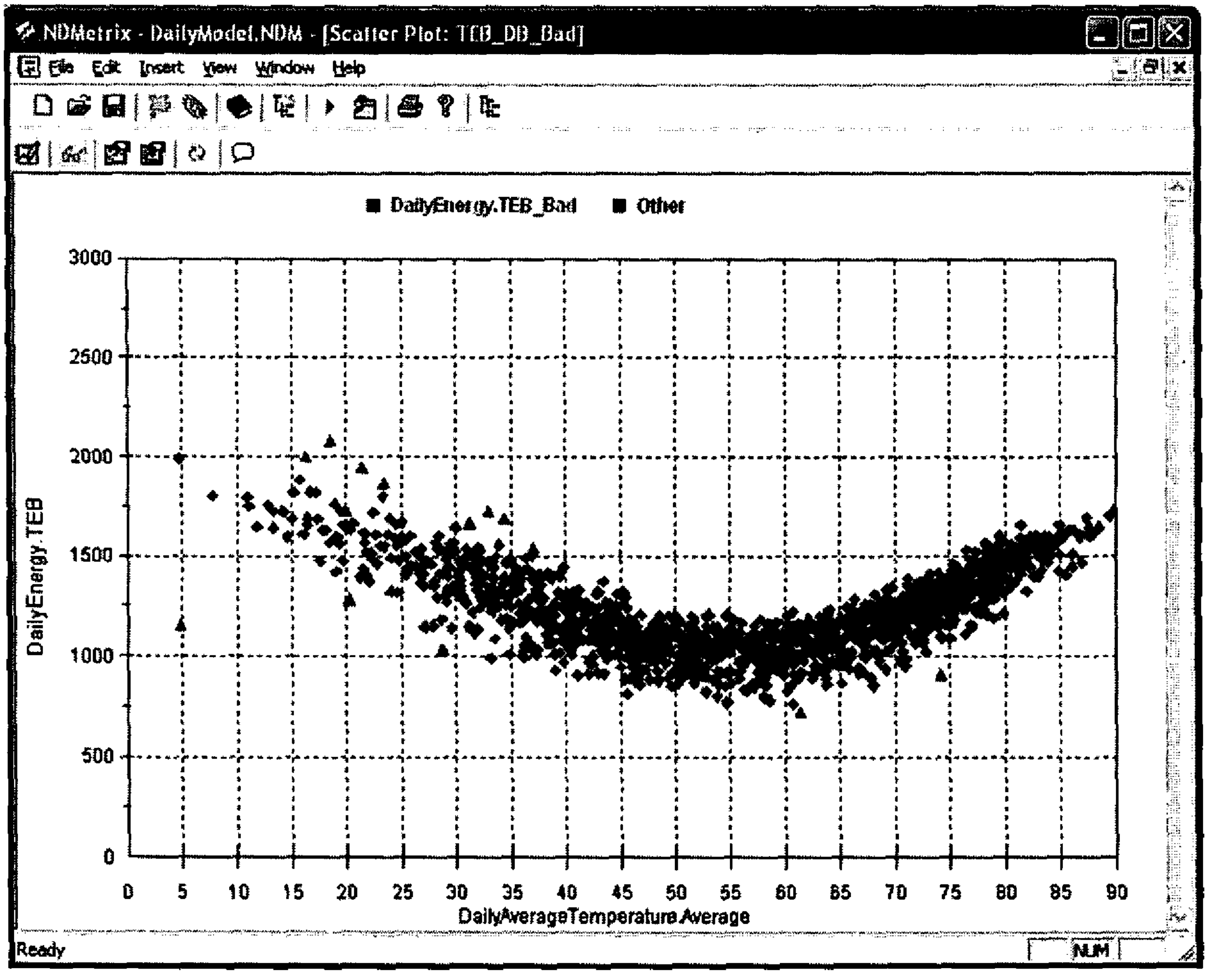
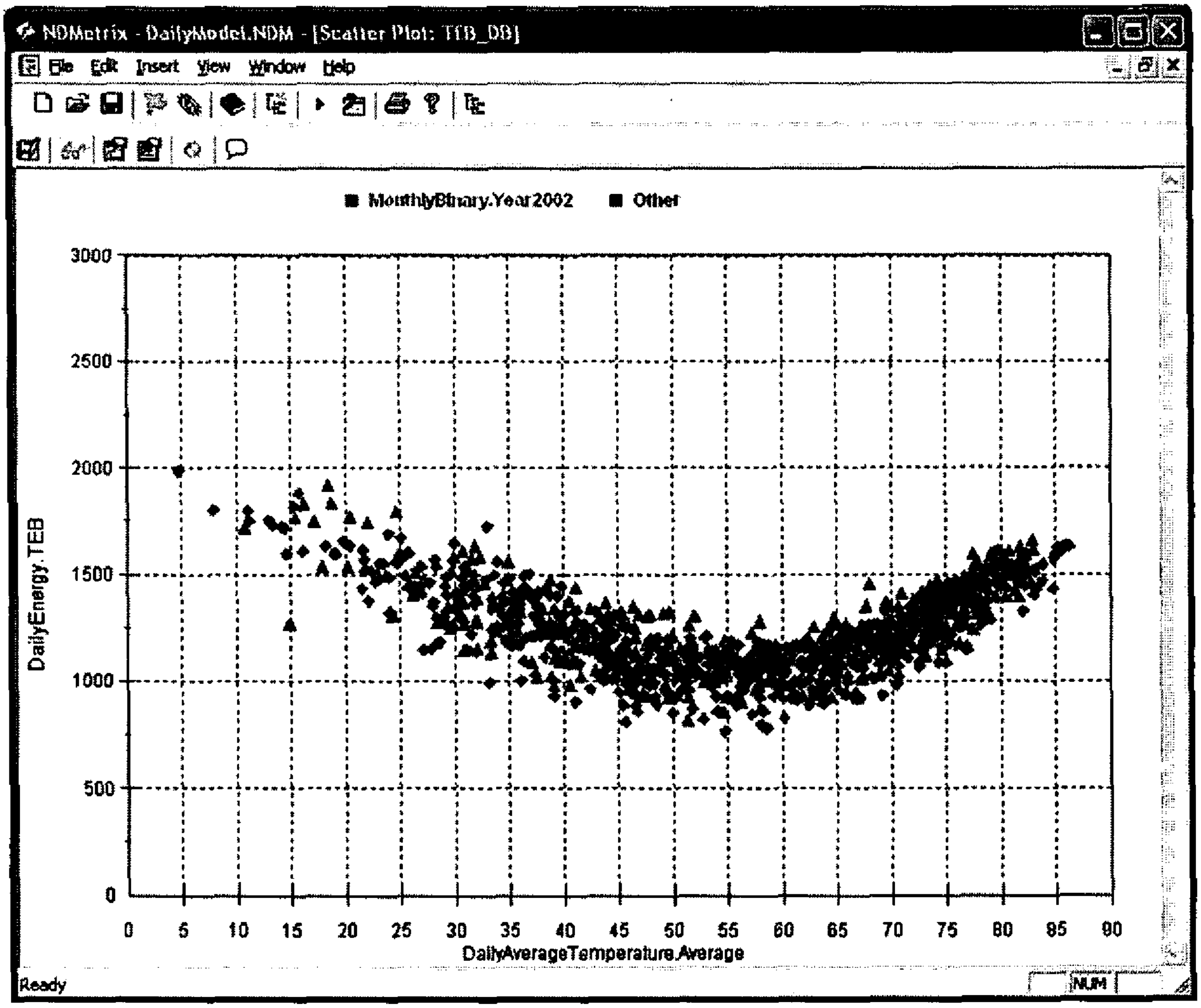


Figure 24: TEB Energy Temperature Scatter Plot

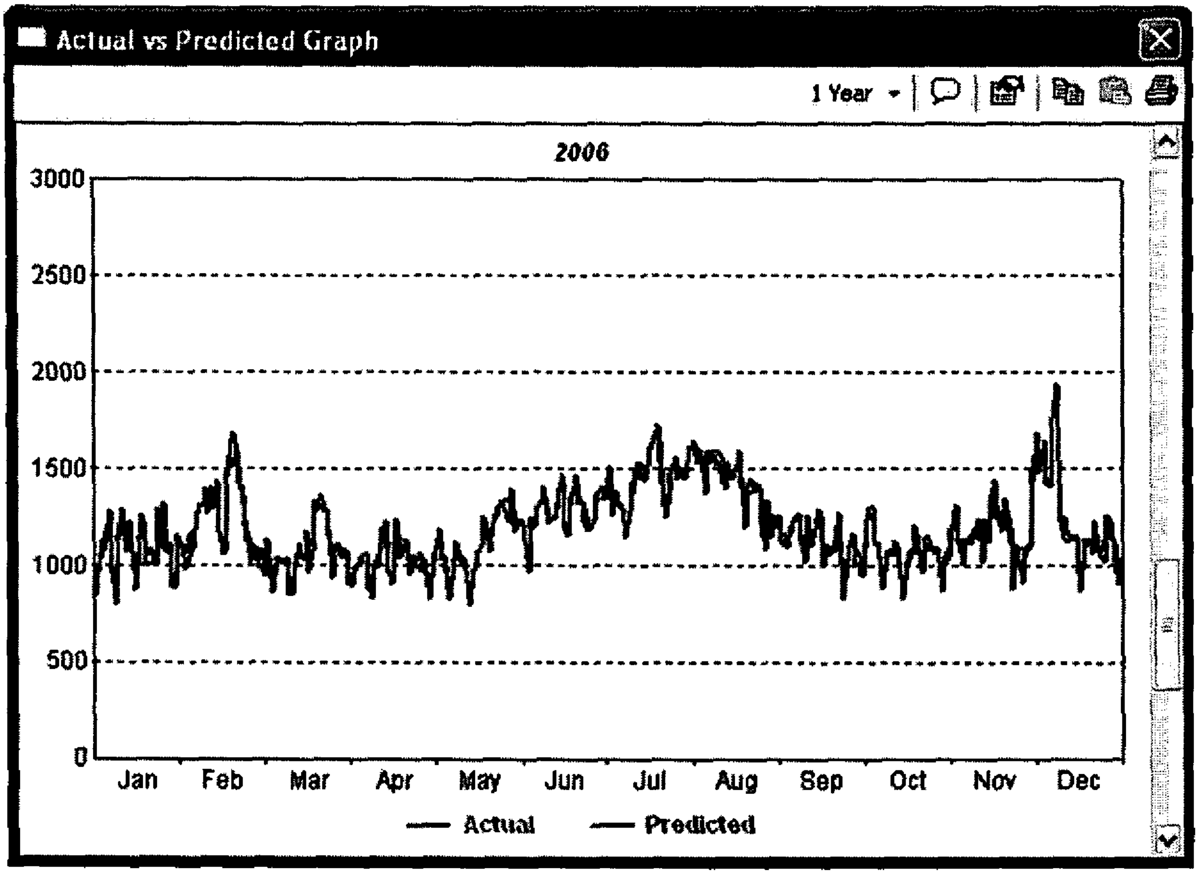


TEB Model. The TEB model is built with the same classes of variables used in the Residential model (Table 1). However, temperature splines have been adjusted for the TEB weather response and no changing weather response is modeled.

The overall fit of the regression model can be seen graphically in Figure 25 and numerically in the statistics below. A full description of the model and the associated model statistics can be viewed in the *MetrixND* project file.

▪ R-Squared	0.936
▪ Adjusted R-Squared	0.935
▪ Durbin-Watson Statistic	1.940
▪ Mean Abs. Dev. (MAD)	38.22
▪ Mean Abs. % Err. (MAPE)	3.19%

Figure 25: TEB Model Fit – Actual Versus Predicted Values



4

Weather Data

Normal weather conditions are a key component in the weather normalization process. In this section, the method to calculate the normal weather is discussed.

Data. Historical hourly weather data from 1977 through 2006 for Springfield, Missouri were provided by Empire. These data were used to develop the daily normal weather used in the weather normalization process.

Method. A daily average method is used to develop daily normal weather. In this method, daily average temperatures by day of the month are used to calculate normal heating degree days (HDD) and cooling degree days (CDD), which are then mapped back to the historical test year. Four steps are used to develop the daily normal HDD and CDD values.

Step 1. Calculate Daily Values. The historical hourly values for each data were used to create the daily average temperatures.

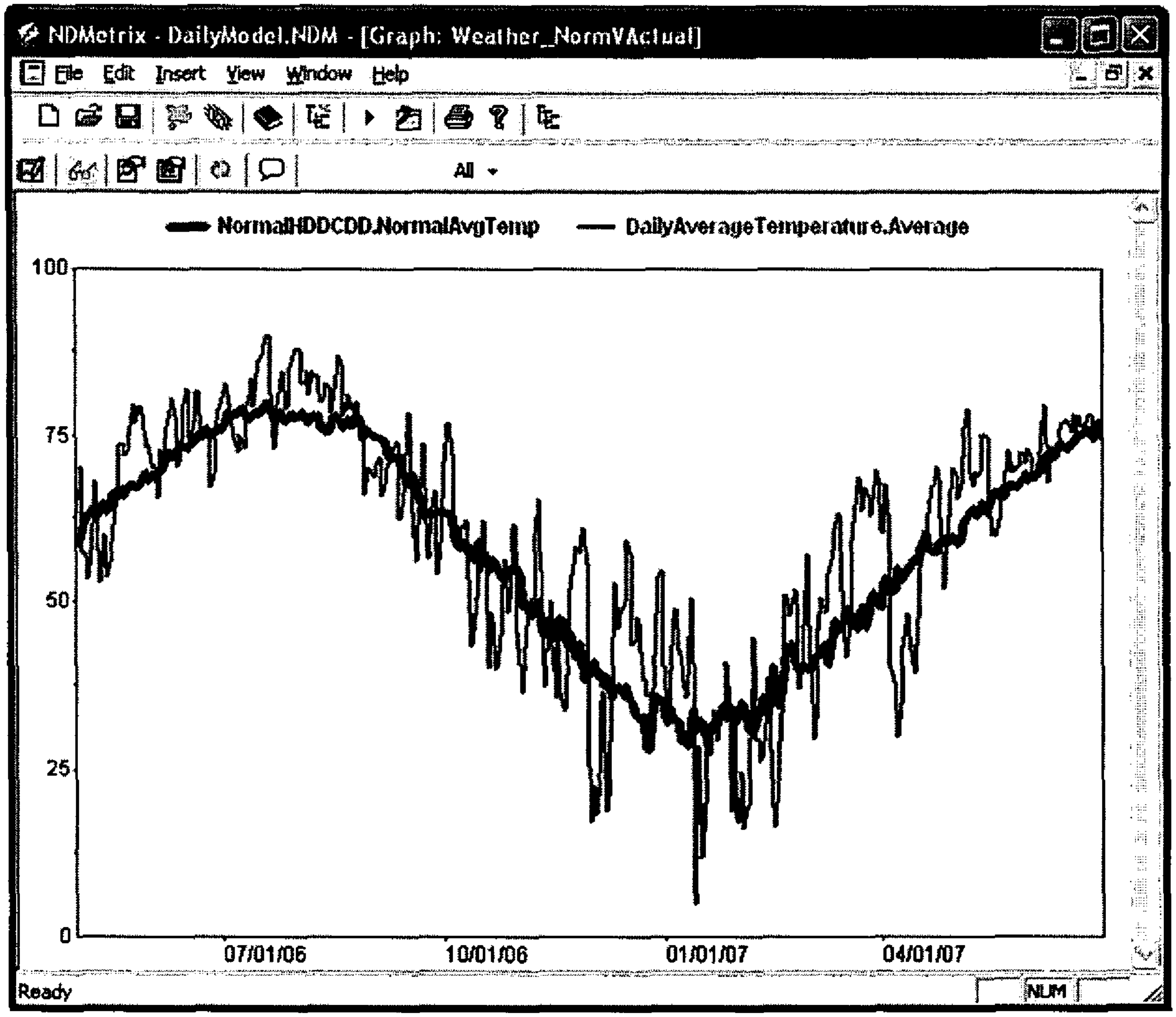
$$AverageTemperature_{day} = \frac{\sum_{hour} Temperature_{hour}}{24}$$

Step 2. Calculate HDD and CDD Values. For each historical day, the HDD and CDD were calculated based on the Average Temperature in Step 1. CDD values were calculated based on temperature reference points of 60, 65, 70, 75, and 80 degrees. HDD values were calculated based on temperature reference points of 40, 45, 50, 55, 60, and 65 degrees.

Step 3. Normal HDD, CDD, and Temperature Values. For each day, the HDD, CDD, and temperature values in Step 2 were averaged across the data from 1977 through 2006. These average values are the normal values for each day of the year. For example, the average HDD value for all January 3 dates between 1977 through 2006 is the normal value for January 3.

Step 4. Map Normal HDD and CDD to Calendar Year. In this step, the Normal HDD and CDD values calculated (Step 3) are mapped to the test year period based on date. The mapped temperatures are used in the weather normalization calculation. The result is shown for average temperatures in Figure 26. In this figure, the bold blue line is the normal temperatures.

Figure 26: Normal Average Temperatures



5

Normal Test Year Results

The test year for normalization is July 2006 to June 2007. Based on the method described in Section 2, normal billed sales and normal calendar sales are calculated from the actual billed sales.

In this section, three series are reported for Empire's Missouri load. The series are defined below.

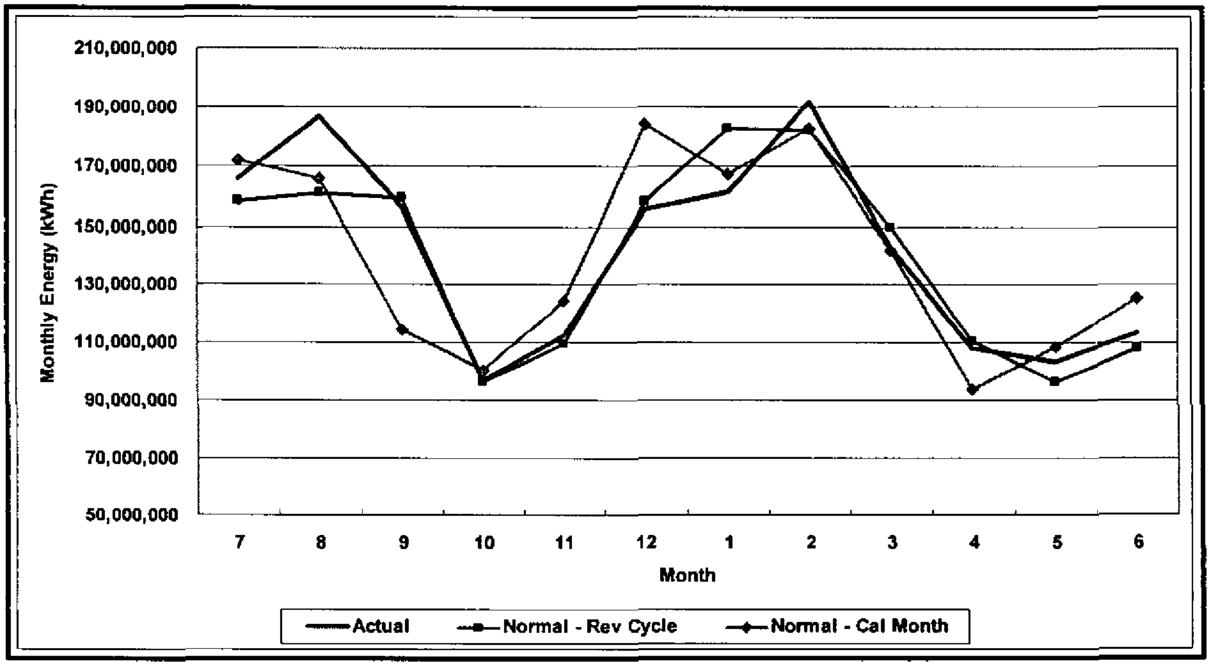
- ***Actual Billed Sales (History).*** This is series is the historical billed sales provided by Empire. The sales represent the billed energy based on the meter read cycle.
- ***Normal Billed Sales (Modeled).*** This series is modeled using the method in Section 2. The series represent historical billed sales (based on the meter read cycle) assuming that normal weather occurred.
- ***Normal Calendar Sales (Modeled).*** This series is modeled using the method in Section 2. The series represent historical sales for each calendar month assuming that normal weather occurred.

Residential Normalization. The result of the weather normalization process on the Residential class is shown in Table 1 and graphically in Figure 27.

Table 1: Residential Normal Values

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)	Normal Calendar Sales (kWh)
Jul 2006	166,086,722	158,264,857	172,235,884
Aug 2006	186,842,355	161,069,164	165,977,908
Sep 2006	156,389,932	159,413,630	114,342,868
Oct 2006	96,952,192	96,708,155	100,652,263
Nov 2006	112,602,205	109,434,810	124,294,037
Dec 2006	156,114,458	158,607,904	184,454,051
Jan 2007	161,511,406	183,060,767	167,595,398
Feb 2007	191,850,265	182,319,043	182,920,793
Mar 2007	142,968,625	149,812,624	141,875,705
Apr 2007	108,153,019	110,609,469	94,225,984
May 2007	103,548,434	96,405,809	108,424,533
Jun 2007	113,418,042	108,022,855	125,341,491

Figure 27: Residential Normalization Results

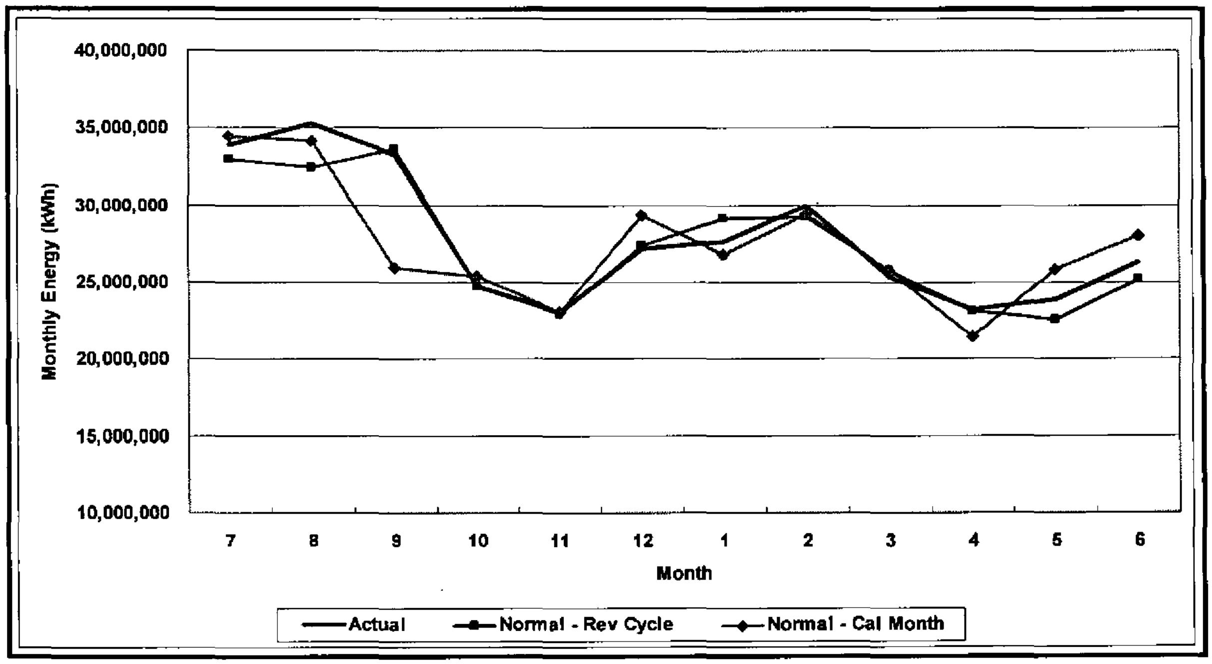


Commercial Normalization. The result of the weather normalization process on the Commercial class is shown in Table 2 and graphically in Figure 28.

Table 2: Commercial Normal Values

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)	Normal Calendar Sales (kWh)
Jul 2006	33,921,516	32,965,699	34,489,040
Aug 2006	35,299,802	32,381,498	34,229,700
Sep 2006	33,285,385	33,652,217	25,946,288
Oct 2006	24,700,287	24,744,956	25,410,149
Nov 2006	23,055,964	22,977,259	23,059,776
Dec 2006	27,110,206	27,318,680	29,335,313
Jan 2007	27,628,434	29,164,835	26,751,948
Feb 2007	29,922,604	29,194,406	29,371,951
Mar 2007	25,346,106	25,786,847	25,723,211
Apr 2007	23,260,000	23,087,475	21,467,997
May 2007	23,866,554	22,583,186	25,862,342
Jun 2007	26,279,007	25,226,153	28,032,825

Figure 28: Commercial Normalization Results

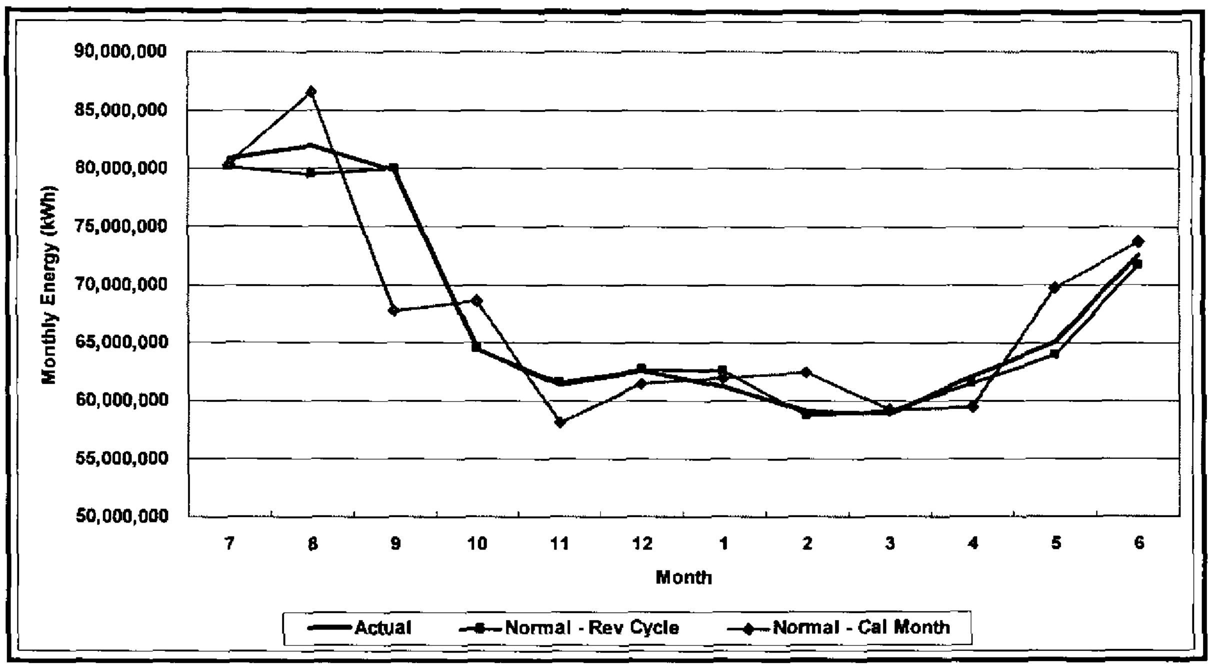


GP Normalization. The result of the weather normalization process on the GP class is shown in Table 3 and graphically in Figure 29.

Table 3: GP Normal Values

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)	Normal Calendar Sales (kWh)
Jul 2006	80,865,634	80,094,449	80,377,781
Aug 2006	81,969,462	79,472,149	86,679,179
Sep 2006	79,820,887	80,039,860	67,743,418
Oct 2006	64,537,361	64,533,550	68,592,362
Nov 2006	61,387,703	61,613,571	58,153,883
Dec 2006	62,578,748	62,791,459	61,530,181
Jan 2007	61,221,276	62,591,597	62,026,544
Feb 2007	59,178,755	58,704,720	62,521,996
Mar 2007	58,934,260	59,129,540	59,260,246
Apr 2007	62,161,660	61,493,130	59,476,880
May 2007	65,134,633	63,957,202	69,734,367
Jun 2007	72,606,068	71,790,154	73,801,277

Figure 29: GP Normalization Results

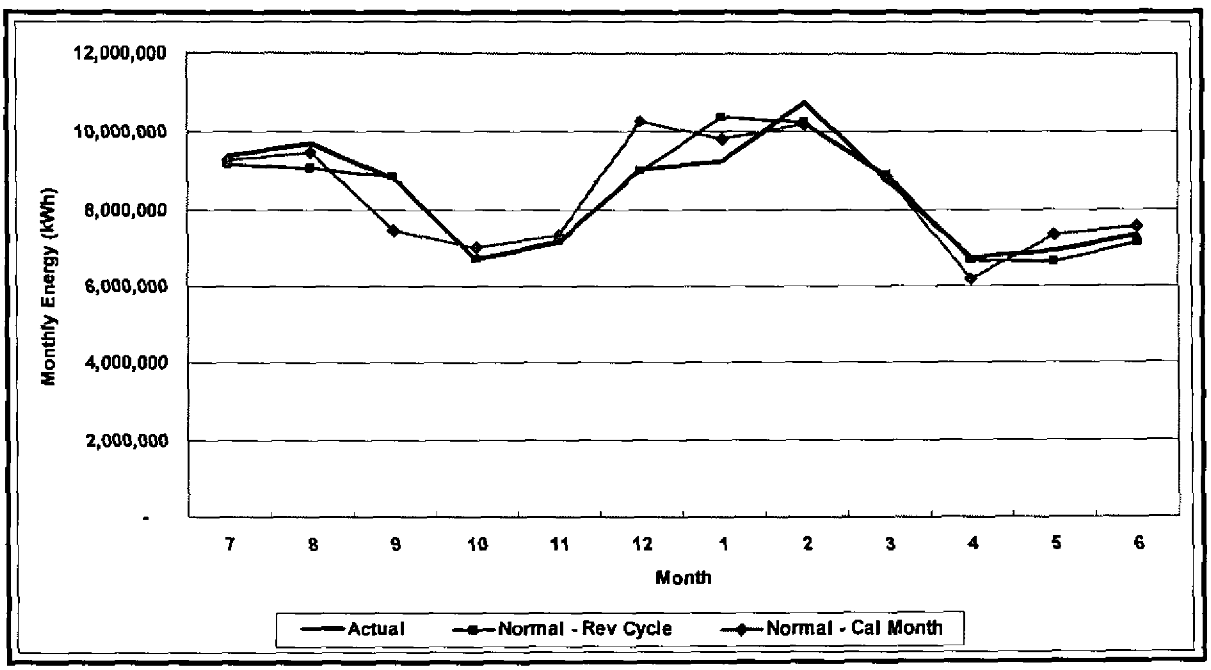


SH Normalization. The result of the weather normalization process on the SH class is shown in Table 4 and graphically in Figure 30.

Table 4: SH Normal Values

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)	Normal Calendar Sales (kWh)
Jul 2006	9,409,895	9,205,578	9,290,389
Aug 2006	9,708,077	9,059,209	9,485,222
Sep 2006	8,819,376	8,856,292	7,470,731
Oct 2006	6,720,062	6,716,261	7,011,773
Nov 2006	7,177,999	7,216,989	7,361,009
Dec 2006	9,051,843	8,996,591	10,269,974
Jan 2007	9,257,166	10,401,255	9,811,722
Feb 2007	10,760,431	10,232,839	10,212,899
Mar 2007	8,722,343	8,884,954	8,830,800
Apr 2007	6,740,952	6,662,847	6,197,805
May 2007	6,932,307	6,649,454	7,366,790
Jun 2007	7,356,940	7,165,233	7,562,020

Figure 30: SH Normalization Results



TEB Normalization. The result of the weather normalization process on the TEB class is shown in Table 5 and graphically in Figure 31.

Table 5: TEB Normal Values

Month	Actual Billed Sales (kWh)	Normal Billed Sales (kWh)	Normal Calendar Sales (kWh)
Jul 2006	34,501,869	33,831,247	35,234,907
Aug 2006	35,275,162	33,144,287	34,374,957
Sep 2006	32,765,930	32,982,645	27,400,044
Oct 2006	26,348,346	26,324,265	27,848,186
Nov 2006	27,416,010	27,390,383	28,957,585
Dec 2006	32,291,633	32,527,963	33,688,008
Jan 2007	29,347,202	32,131,950	30,498,736
Feb 2007	31,634,065	30,378,352	30,713,060
Mar 2007	27,609,493	28,205,322	27,712,436
Apr 2007	25,652,459	25,527,026	23,785,567
May 2007	27,889,673	26,832,470	29,937,007
Jun 2007	30,060,032	29,296,047	30,859,009

Figure 31: TEB Normalization Results