Use of Seasonal forecasts in Electrical Load Prediction

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1. Introduction

The electricity industry is moving towards a competitive market, where users will have the liberty to choose their electricity provider in the same way that people get to choose the type of toothpaste they use. As a result this industry needs to improve efficiency in its operations. The operations in the electricity industry are highly dependent on weather conditions, especially air temperature. Knowledge of future temperatures makes forecasted power requirements (load forecasting) possible. It also helps in the management of their generators. Climate forecasts play a vital role in decision making in the electric power industry. For example if the decision makers know what weather to expect, they can estimate the amount of power they need to trade or acquire. If the power requirement for a particular area is known it would be possible to acquire more or trade off some electricity depending on the forecasted needs. For example, if it is going to be very hot, extra power could be purchased well in advance to provide enough power for the population while the prices are cheap. This in effect, could increase sales and profits for the decision maker.

Electricity is generally cheaper to buy in advance, and power producers need to run their generators at the most efficient rate (Keener, 1997). People use more or less electricity depending on the need for heating or cooling. For this reason, power companies make use of the relationship between temperature and electricity demand to prepare for future energy needs. Depending on the specific needs of the power plant, they use different kinds of forecasts ranging from short-term to seasonal forecasts (Changnon, 1995). It is important that the forecasts be accurate, because companies can lose money and service to customers can be disrupted if the load forecasts are incorrect.

In this paper we are going to formulate a relationship between mean temperature and power usage to see how climate forecasts of temperature can be used to make load forecasts. We will also compare forecasts using different lead times to the actual mean temperatures to assess the accuracy of seasonal temperature forecasts.

2. Data

The main goal of this study was to determine the accuracy of summer temperature forecasts in the prediction of energy usage. This was done by analyzing hindcast from the National Center for Environmental Prediction (NCEP) and comparing them to actual mean temperature data obtained from various U.S. National Weather Service (NWS) Cooperative Observer Program (COOP) stations (see Appendix I).

Hindcasts are atmospheric general circulation model (ACGM) runs forced with global observed sea surface temperatures. They forecast average monthly near-surface temperature, 200-mb heights and precipitation for the period 1984 to 1999. NCEP's model has a horizontal grid resolution of 250 km and its domain covers the entire globe. Temperature was the only variable needed in this study, therefore mean temperature hindcasts were retrieved from the NCEP model. For each year from 1984 to 1999, the model provides a six month forecast with a lead time of one month. For each month, ten simulations using different initial conditions are provided. The initial conditions used in the simulations are the initial atmospheric fields during the first five days of the month before the first forecast is valid. These initial conditions are from the 00 UTC and 12 UTC initial atmospheric fields.

3. Analysis Procedures

To determine the accuracy of a forecast we compared it to what was observed, and concluded how much damage the typical forecast errors had on the electricity usage predictions. A forecast will not be a useful tool if the errors found in a seasonal weather forecast are too large, because the benefit of planning ahead will be out-weighed by the cost of preparing for incorrect temperatures.

A method was devised that directly relates the mean monthly forecasted temperature to the electrical load to determine how much forecast error impacts electrical generation error. Power companies have conducted studies that relate air temperature to their customer's energy consumption. We adopted a formula that was derived by the Climaton Research Company (1997) using data from 1986 through 1995. The equation uses weekly averaged high temperatures to find the electrical usage in gigawatt-hours. It was specifically designed for the power needs of the mid-Atlantic region, which includes New York, Delaware, Maryland, New Jersey, and eastern Pennsylvania. Since the seasonal forecasts predict monthly mean temperatures a new energy equation had to be created to relate energy usage to monthly mean temperature. The power consumed was calculated using the Climaton equation and daily high-temperature COOP data for June, July and August for the years 1984 to 1999. Once the power usage was calculated it was related to the mean-temperature COOP data. Summer monthly energy consumption was found to have a linear relation to the monthly mean temperature.

$$\text{Gwatt/hr}_{\text{(per month)}} = 465.0883 * \text{mean temperature}_{\text{(F)}} - 1730.7 \qquad (1)$$

This equation is not corrected for population or temporal effects so it is only valid for the summer power needs of the mid-Atlantic region during the period 1984 to 1999.

Using (1), hindcasted energy usage was calculated with the seasonal hindcast data and compared to the actual energy obtained from COOP data. This gives a measure as to how much impact hindcast temperature errors have on the calculated electrical load.

There was also a desire to determine errors in forecasted energy usage with different lead times. The differences in energy usage associated with these lead times were determined and then compared to the actual energy usage. This was done by using hindcasts of temperature for June, July and August with different lead times. For the remainder of the study, "Month 5" refers to the model run that used initial conditions from May, “Month 4” used the initial conditions from April, “Month 3” used initial conditions from March and “Month 2” used the initial conditions from February.

4. Results

The biases in this paper were computed by subtracting the forecasted from the observed temperature. The average error is the mean of the absolute value of all the differences. Monthly time series plots of model mean temperature and energy usage errors can be found in Appendix II and Appendix III, respectively.

a) Month 5

When comparing the observed mean temperatures with the hindcasted mean temperatures the model was too cold for most of the hindcast period. The model was cooler than the observed mean temperature by as much as 7 °F in June of 1995. The average error during the hindcast period was 2.37°F and the bias was 2.16°F. When the simulated and observed mean temperatures were fed into the energy equation, the model predicted energy usage in gigawatts per month was generally lower. The model deviated the most from the actual energy usage in June of 1995 when it under predicted energy usage by 3000 gigawatts .

b) Month 4

With a lead time of two months, the hindcasted mean temperatures were colder than the observed mean temperatures throughout the hindcast period. The average error and bias were 3.14°Fand 2.99°F respectively. The model error was the greatest in June of 1995 when the predicted mean temperature was colder by nearly 10 °F. With under predicted mean temperatures the energy usage was also under predicted. The largest error in energy usage occurred in June of 1995 when the difference from the actual energy usage came close to 4,600 gigawatts per month.

c) Month 3

With a lead time of three months the model did a poor job in predicting the mean temperatures. The average error and the bias were 17.79°F. In general, the model predicted temperatures colder by 5 to 30 °F. This, in turn, resulted in a severe under prediction of energy usage throughout the time period. During this time period the model always under predicted energy usage with deviations from the actual energy usage often greater than 10000 gigawatts.

d) Month 2

With a lead time of four months, the model predicted mean temperature was cooler than the observed mean temperature during most of the hindcast period. The model deviated the most from the actual mean temperature in August 1994 and June 1995. In August 1994 the model was warmer than the observed mean temperature by nearly 2° F, and in June 1995 the model was cooler by about 10° F. The average error for this month was 3.4° F, and the bias was 3.25° F. The predicted energy usage was less than the observed energy usage throughout most of the time period. The largest error occurred in June 1995 when the model under predicted energy usage by nearly 4000 gigawatts per month.

5. Discussion

The biases for all the lead times were positive because the hindcasted temperatures were almost always cooler than those observed. Month 3 was the worst of the four lead times with a standard deviation 8.34 °F. The forecast for month 3 had too large of an error to be of any use in forecasting energy usage. Month 2, 4 and 5 had standard deviations of 2.38°F, 2.49°F and 2.05°F, which made month 5 the most consistent. Month 5 also has the best average error and bias. Since the relationship between energy and mean temperature is linear it follows that the month with the lowest errors will have the best energy forecast.

6. Conclusion

The shorter the lead time the more accurate the forecast, but only by a small amount. It is not very clear as to why the forecast for month three was so bad. We can only speculate that March, being a transition month from winter to spring, makes it very hard for the model to resolve what is going to happen later. It could be that the hindcast file for month three was altered.

Typically, monthly mean temperatures during Mid-Atlantic summer months do not exceed four or five degrees difference from the climatological average. Model error is often greater than five degrees, so power companies may choose to plan for average weather rather than use this seasonal forecast model. The forecasts could be useful if they were improved. One way the forecast could be improved is by correcting for bias. We corrected for bias in month 5 and it centered the output over the observed values better. The correction did not reduce the standard deviation but it reduced the average error to nearly zero. The graph of the corrected temperature forecast error is in appendix II.

References

Changnon, Stanley A., 1995: Uses and Applications of Climate Forecasts for Power Utilites. *Bull.Amer.Meteor.Soc.*, **76 ,** 711-720

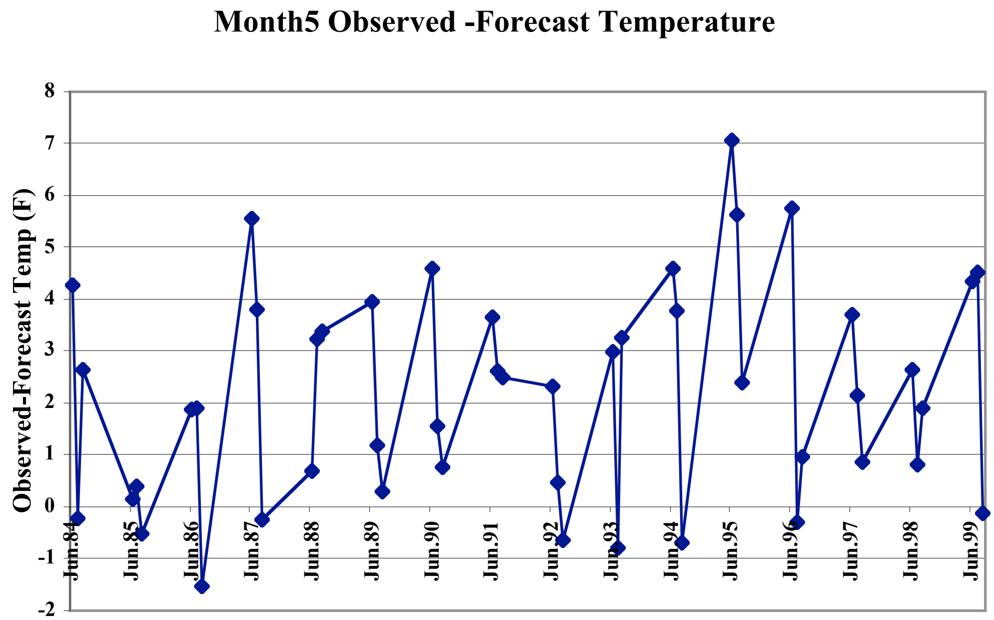
Climaton Research Co., 2003: Scientific Basis of Power Demand Forecast. [http://www.climaton.com/science.html]

Keener, Ronald N., Jr., 1997: The Estimated Impact of Weather on Daily Electric Utility Operations. [http://sciencepolicy.colorado.edu/socasp/weather1/keener.html]

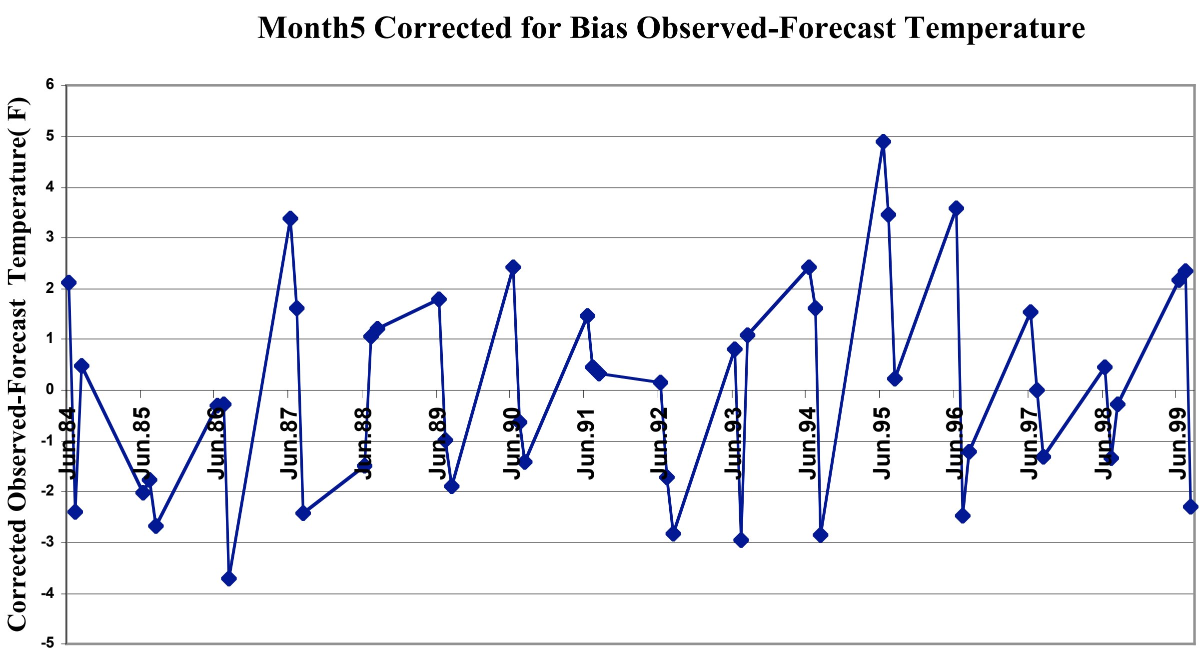
APPENDIX I

State	Station
Delaware	Wilmington New Castle Cnty AP
Maryland	Baltimore Blt-Washington Int'l
	Patuxent River Nas
New York	Binghamton Edwin a Link Field
	Buffalo Niagara Intl AP
	Glens Falls AP
	Massena AP
	Rochester Greater Rochester
	Syracuse Hancock Int'l AP
	Utica Oneida County AP
	Watertown AP
New Jersey	Atlantic City Intl AP
	Millville Municipal AP
	Newark International AP
	Lakehurst
	Allentown
Pennsylvania	Middletown
	Philadelphia
	Wilkes Barre
	Willow Grove

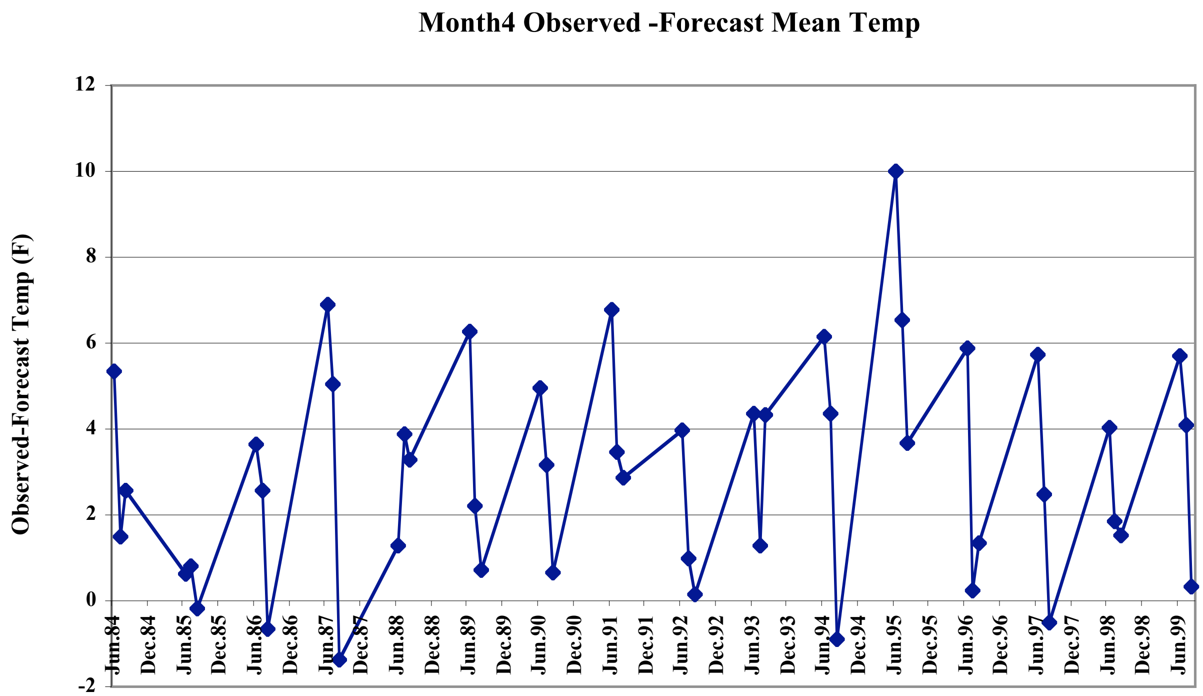
APPENDIX II



Month5 Observed -Forecast Temperature
Observed-Forecast Temp (F)
8
7
6
5
4
3
2
1
0
-1
-2
Jun.84
Jun.85
Jun.86
Jun.87
Jun.88
Jun.89
Jun.90
Jun.91
Jun.92
Jun.93
Jun.94
Jun.95
Jun.96
Jun.97
Jun.98
Jun.99



Month5 Corrected for Bias Observed-Forecast Temperature
Corrected Observed-Forecast Temperature(F)
6
5
4
3
2
1
0
-1
-2
-3
-4
-5
Jun.84
Jun.85
Jun.86
Jun.87
Jun.88
Jun.89
Jun.90
Jun.91
Jun.92
Jun.93
Jun.94
Jun.95
Jun.96
Jun.97
Jun.98
Jun.99


Month4 Observed -Forecast Mean Temp
Observed-Forecast Temp (F)
12
10
8
6
4
2
0
-2
Jun.84
Dec.84
Jun.85
Dec.85
Jun.86
Dec.86
Jun.87
Dec.87
Jun.88
Dec.88
Jun.89
Dec.89
Jun.90
Dec.90
Jun.91
Dec.91
Jun.92
Dec.92
Jun.93
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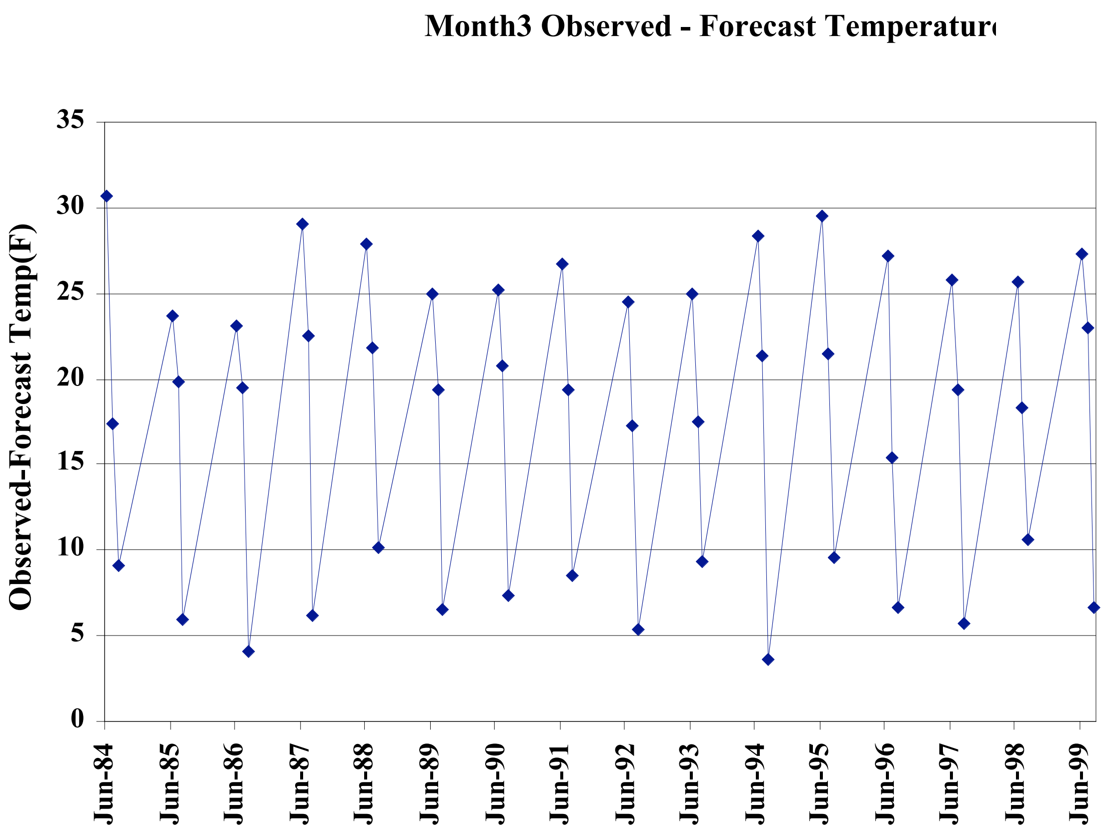
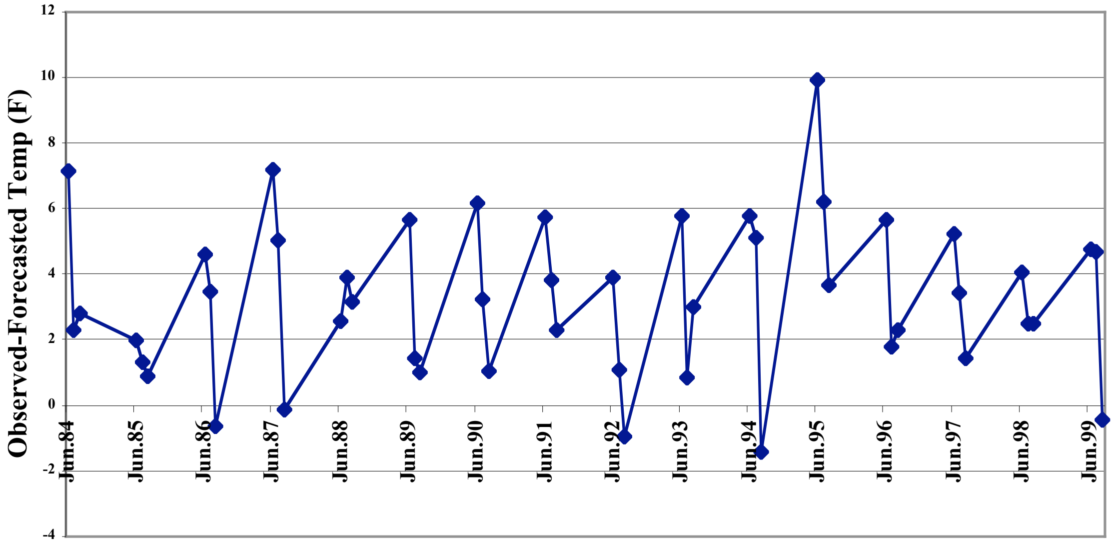
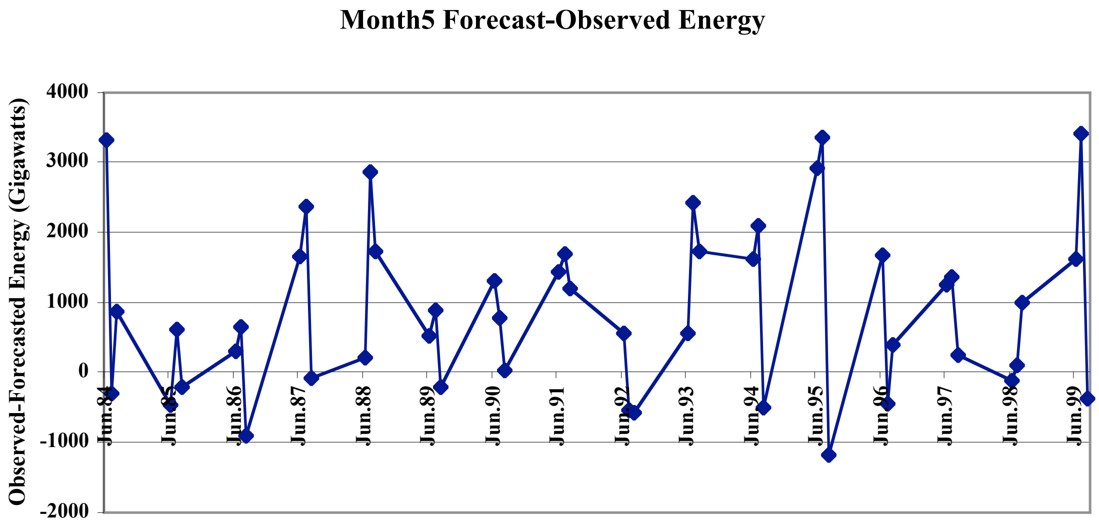
Dec.97
Jun.98
Dec.98
Jun.99

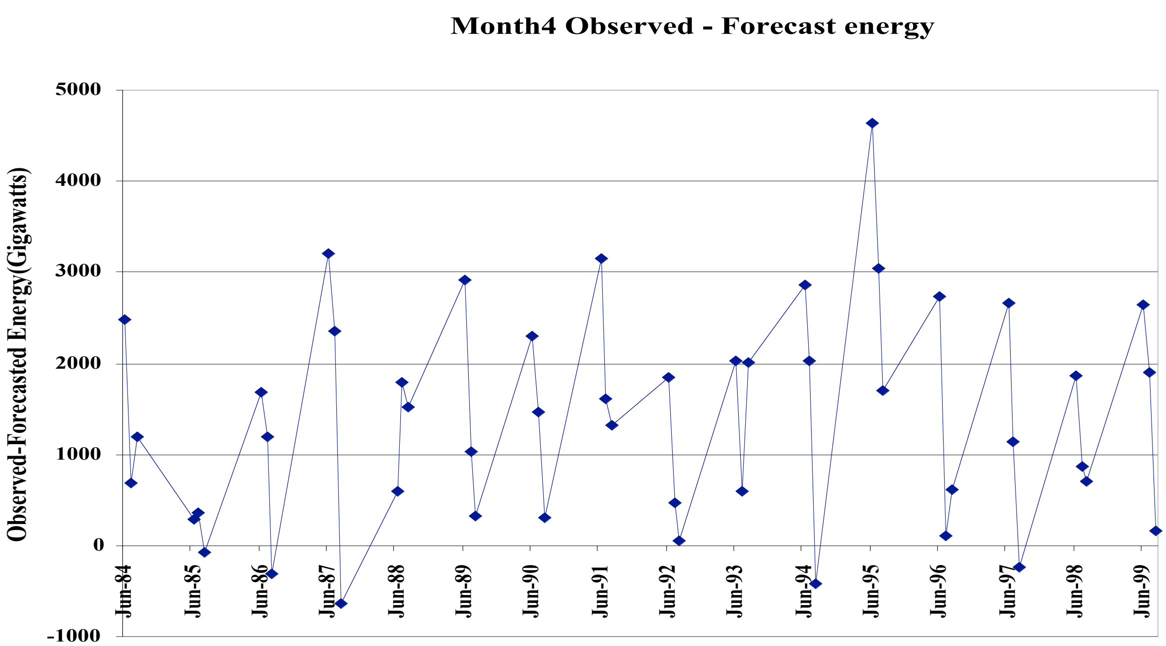

Month3 Observed - Forecast Temperatur
Observed-Forecast Temp(F)
35
30
25
20
15
10
5
0
Jun-84
Jun-85
Jun-86
Jun-87
Jun-88
Jun-89
Jun-90
Jun-91
Jun-92
Jun-93
Jun-94
Jun-95
Jun-96
Jun-97
Jun-98
Jun-99

Month 2 Observed-Forecasted Temperature

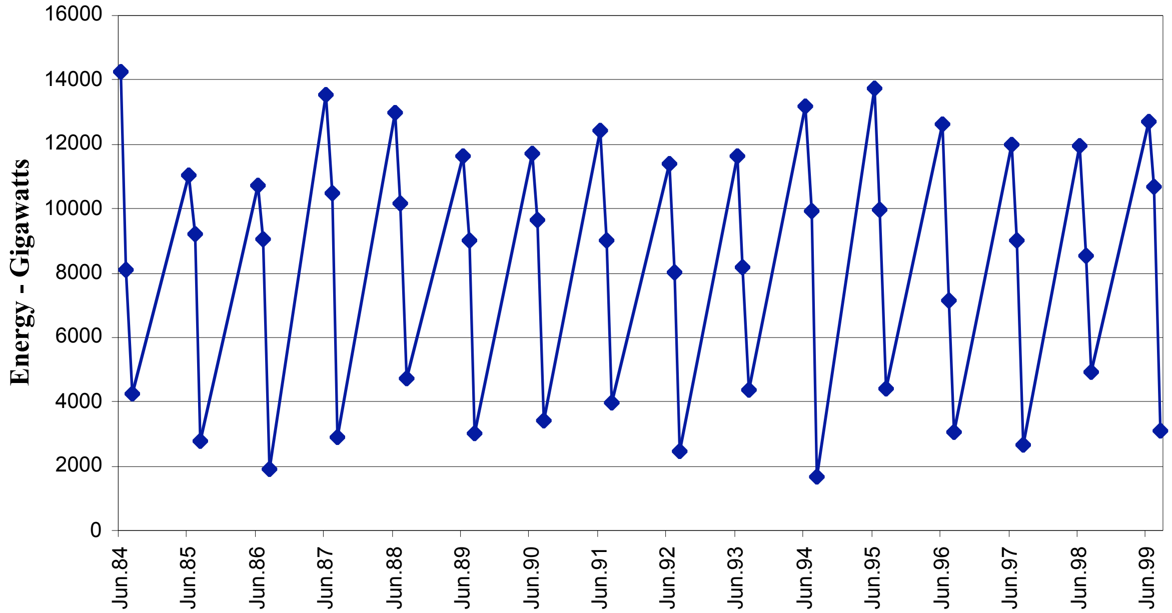


APPENDIX III





Month 3 Observed - Forecast Energy



Month2 Observed- Forecast Energy