SHORT TERM ELECTRIC LOAD FORECASTING

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree
of
MASTER OF TECHNOLOGY
in
HYDROELECTRIC SYSTEM ENGINEERING AND MANAGEMENT

By

MUSLIM BUDI SANTOSO

WATER RESOURCES DEVELOPMENT TRAINING CENTRE
INDIAN INSTITUTE OF TECHNOLOGY ROORKEE
ROORKEE – 247 667 (INDIA)
June, 2004

DECLARATION

I here declare that the dissertation titled **"SHORT TERM ELECTRIC LOAD FORECASTING"** which is being submitted for partial fulfillment of the requirements for the award of Master's of Technology Degree in **Hydroelectric System Engineering and Management** at Water Resources Development Training Centre (WRDTC), Indian Institute of Technology Roorkee is an authentic record of my own work carried out during the period of 16.07.2003 to 01.06.2004 under the supervision and guidance of **Professor Devadutta Das**, Professor WRDTC, IIT Roorkee and **Dr. N.P. Padhy**, Assistant Professor Electrical Engineering Department IIT Roorkee.

I have not submitted the matter embodied in this dissertation previously for the award of any other Degree.

Place : Roorkee, India

Date : 01.06.2004

(Muslim Budi Santoso)

HSEM

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

(Dr. N.P. Padhy)
Assistant Professor
Electrical Eng. Dept., IIT Roorkee

Devadutta Das

(Devadutta Das)
Professor
WRDTC, IIT Roorkee

ACKNOWLEDGEMENTS

I would like to thank my guides Professor Devadutta Das, Professor in Hydroelectric System Engineering and Management of WRDTC and Dr. N.P. Padhy, Assistant Professor of Electrical Engineering Department IIT Roorkee.

I also wish to thank Vikas Nagar Sub Station IIT Roorkee officer and National Institute of Hydrology (NIH) Roorkee officer. They all helped me during collecting data.

I want to thank Ashburn Shannon and Itron Inc., USA for gave me permission using MetrixND software in my dissertation work.

I am most grateful to all the faculty members of WRDTC for their guidance and family affection shown to me during all my study time in WRDTC.

Last but by no means least, I am grateful to the Indonesian Embassy, New Delhi and to my Head of an office for his encouragement and support throughout my studies.

Muslim Budi Santoso

SHORT TERM ELECTRIC LOAD FORECASTING

ABSTRACT

Short term electric load forecasting is one of the important issues in the operation and system planning. Short term electric load forecasting is predicting a system load with a leading time of one hour to seven days, which is necessary for adequate scheduling and operation of power system .

Short term electric load forecasting parameters have been categorically classified into day types (work days, holidays, special days), weather information (temperature, relative humidity, wind velocity, rainfall, evaporation) and historical part electric load data .

Electric load forecasting problem has been solved using both conventional and non conventional (ANN) methods and the result are compared. The performance of the proposed algorithm has been validated for the IIT Roorkee daily peak load forecasting. The results so obtained are encouraging and useful in the field.

Accurate short-term electric load forecasts represent a great potential savings for electric utility corporations. The accuracy of the forecasted peak-load influences decision-making in economic dispatch, unit commitment, hydro-thermal coordination, fuel allocation, and off-line network analysis, etc.

TABLE OF CONTENTS

CHAPTER	DESCRIPTION	PAGE No

LIST OF FIGURES

FIGURES	PAGE No

FIGURES **PAGE No**

FIGURES PAGE No

LIST OF TABLES

TABLES **PAGE No**

CHAPTER I
INTRODUCTION

1.1. BACKGROUND

Load forecasting is an important problem in the operation and planning of electrical power generation . The countrywide energy estimation, the planning of new plant, the routine maintaining and scheduling of daily electrical generation are all depended on accurate load forecasting in the future .

Load forecasting can be divided into very short, short, medium and long term forecasting according to the time span . In short term forecasting the prediction time can be as short as one hour, while in long term forecasting it is from a few years up to several decades . This dissertation work concentrates on Short term load forecasting (STLF), where the prediction time varies between a few hours and about one week .

Generally, there are two categories of forecasting models, traditional models and modern techniques. Traditional load forecasting models are time series and regression analysis. Where as in modern techniques, fuzzy logic, neural network and genetic algorithms are used for load forecasting.

In recent years, Artificial Neural Networks (ANN) is commonly used for electric load forecasting. The main reason should be the ANN ability to learn complex input-output relationship that are difficult to model with traditional technique. The capability enables the ANN-based system to model the correlations between the electricity load and such factors as temperature and other climatic conditions, time and type of the day effect, season effect, etc.

1.2. PURPOSE AND PERIOD OF FORECASTING

The purpose of electric load forecasting is governed by the period of forecast. Normally the electric load forecasting can be classified into four categories :

1. Long term load forecasting, the time horizon covering is two years or more.
2. Medium term load forecasting, the time horizon covering is three months to two years
3. Short term load forecasting, time horizon covering is one to three months
4. Very short term load forecasting, time horizon covering is less than one month

Long term load forecasting mainly for system planning.

Long term forecasting is useful in the following areas :

- Capital planning
- Plant location
- Plant layout or expansion
- New product planning
- Research and development planning
- Technology management, etc

Medium term load forecasting is used mainly to determine the allocation of resources among competing activities and to revise long range plans in view of more recent development.

Medium term forecasting is vary useful in the following areas :

- Sales planning and sales force decisions
- Productions planning
- Capital and cash planning
- Inventory planning, etc

Short term load forecasting is used mainly for scheduling purposes.

Short term forecasting useful in :

- Economic allocation of generation
- Energy transaction
- System security analysis
- Optimal energy interchange between utilities
- Maintenance scheduling

Because of the short time span between planning and implementation, short term load forecasting impact is much more operational than that of either long term or medium term load forecasting. It is used most effectively as a coordinating and control device for taking corrective action when short term deviations from longer term forecasts and plan occur. It is also used to adjust production schedules, determine inventory levels, and maintain an acceptable working capital position for the organization.

Very short term load forecasting is concerned with the day to day operational aspects of running the organization. The purpose of the very short term load forecasting is to finely adjust operations through incremental improvements, rather than to change the course of future events.

Some related applications are :

- Scheduling of operation and interconnection
- Scheduling of maintenance
- Load dispatching
- Scheduling proper and economic import of power from other sources
- Estimating surplus and secondary sales
- Arranging power factor correction.

1.3. SCOPE OF THE DISSERTATION WORK

This dissertation work studies the applicability of time series and regression analysis methods, Artificial Neural Networks (ANN) technique on short term load forecasting. The models are using daily model forecasting.

1.4. STRUCTURE OF THE DISSERTATION WORK

The dissertation is divided into six chapters.

Chapter I reviews the Background, Purpose and Period of Forecasting, Scope of The Dissertation Work.

Chapter II presents Factor Affecting The Load, Time Series and Regression Analysis.

Chapter III present Artificial Neural Networks .

Chapter IV discusses STLF by Time Series and Regression Analysis .

In Chapter V discusses STLF by Artificial Neural Networks .

The last Chapter presents the Conclusions of the dissertation work.

CHAPTER II

SHORT TERM LOAD FORECASTING (STLF)

2.1. FACTOR AFFECTING THE LOAD

Many factors are influential to the electric power generation and consumption . The factor can be classified into calendar, economical or environmental, weather and unforeseeable random events .

Calendar factors consist of :

- Seasonal variation of load, such as : summer, winter, change of number of daylight hours, graduate change of temperature, start of school year, vacation.
- Daily variation of load : night, morning, noon, afternoon .
- Weekly cyclic.
- Holidays : like Christmas, New years and other days .

Economical or Environmental factors consist of :

- Service area demographics (rural, residential) .
- Industrial growth .
- Emergence of new industry, change of farming .
- Penetration or saturation of appliance usage .
- Economical trends (recession or expansion) .
- Change of the price of electricity .
- Demand side load management .

Weather factors consist of :

- Temperature .
- Relative humidity .
- Wind velocity .

- Thunderstorm .
- Rain, fog, snow .
- Cloud cover or sunshine .

Not all weather factor are important . Some are typical random like wind velocity and thunderstorms . Some factors are interrelated, as temperature is partly controlled by cloud cover, rain and snow . Temperature is the most important because it has direct influence on many kind of electrical consumption. It can be noticed that it is common for the electricity load to increase in winter seasons due to the usage of heater, as well as in the summer seasons due to the usage of air conditioning and refrigeration.

Unforeseeable random event factors consist of :

- Start or stop of large loads (steel mill, factory, furnace) .
- Widespread strikes .
- Sporting events (football games) .
- Popular television shows .
- Shut down of industrial facility .

2.2. TIME SERIES AND SIMPLE REGRESSION ANALYSIS

2.2.1. Time Series Analysis

A time series is a sequence of measurements of some numerical quantity made at or during successive periods of time .

Searching for systematic and recurrent relationships in the historical data and making predictions on future based on these relationships is the key feature of time series methods .

In general, time series is considered consisting of the following components :

- Trend component
- Cyclical component

- Seasonal component
- Irregular component

Trend Component

The gradual shifting of the time series, which is usually due to long term factors such as changes in population, changes in technology etc . Usually the trend is represented by a straight line in the medium term .

Cyclical Component

Any regular pattern of sequences of points above and below the trend line lasting more than one year. In general it is believed that this component represents multiyear cyclical movements in the economy .

Seasonal Component

The trend and cyclical components of a time series are considered attributable to the multiyear movements in the historical data. Many time series show a regular pattern of variability within one year periods. This component represents the variation in regional load within summer, autumn, winter and spring in medium term load forecasting.

Irregular Component

This is the residual of the time series if the trend, cyclical and seasonal components are removed from the time series. If the trend, cyclical and seasonal components have been reasonably accurately removed, the residual component represents the random variability of the time series under consideration and can be attributable to short term, unanticipated and nonrecurring factors which are not predictable .

However it is possible to analysis the variability of this component and then attempt to work out margins with certain confidence levels.

Several methods are available for the analysis such as moving average, Exponential Smoothing, Stochastic modeling etc.

The commonly used time series methods are:

1. Moving average
2. Exponential Smoothing
3. Auto Regressive Integrated Moving Average (ARIMA)

2.2.1.1. Moving Average

The time series technique of moving average consists of taking a set of observed values, finding the average of those values, then using that average as the forecast for the next period. The actual number of past observations included in the average must be specified at the outset. The term moving average is used because as each new observation becomes available a new average can be computed by dropping the oldest observation from the average and including the newest one. The new average is then used as the forecast for the next period. Thus, the number of the data point from the series used in the average is always constant and includes the most recent observations.

The moving average model estimates next period's demand as the average of the actual demand of the last m periods, that is

$$\hat{y}_{t+1} = \frac{y_t + y_{t-1} + \cdots + y_{t-m+1}}{m}$$

Where,

m = periods to be averaged (= 3 or more)

y_t = Observed data at time t

2.2.1.2. Exponential Smoothing

This is another time series forecasting technique where the forecast for the next period is calculated as weighted average of all the previous values. It is based on the premise that the most recent value is the most important for predicting the future value.

For the single exponential smoothing, the forecast $\hat{y}_{t+1}$ is given by

$$\hat{y}_{t+1} = \alpha y_{t-1} + (1-\alpha)\hat{y}_{t-1}$$

Where,

$\hat{y}_{t+1}$ = Current forecast level

$\hat{y}_{t-1}$ = Previous forecast level

y_{t-1} = Previous actual

α = a smoothing constant, $0 < \alpha < 1$

in practice, the value α is chosen between 0.1 and 0.3

The exponentially smoothing is a special kind of moving average that does not require the keeping of long historical record. The moving average technique assumes that data have no value after n periods. Some value (although possibly very little) remains in any datum, and a model that uses all the data with appropriate weightings should be superior to a model that discards data.

Like most forecasting techniques, exponential smoothing uses historical data as its prediction basis. It is a special type of moving average where past data are not given equal weight. The weight given to past data decrease geometrically with increasing age of the data. More recent data are weighted more heavily than less recent ones. The major advantage of this method is that the effect of all previous data is included in the previous forecast figure, so only one number needs to be retained to represent the demand history.

The exponential smoothing approach to forecasting is more ad hoc in character. Models are not explicitly built. Rather, a collection of intuitively plausible prediction algorithms that proved useful in practical applications has been assembled.

2.2.1.2. Auto Regressive Integrated Moving Average (ARIMA)

This forecasting procedure was developed by G.E.P Box and G.M. Jenkins in 1970, and is still very popular for forecasting. The Box-Jenkins approach to time series model building is a method of finding, for a given set of data, an Auto Regressive Integrated Moving Average (ARIMA) model that adequately represents the data generating process.

Box-Jenkins modeling relies heavily on the use of three familiar time series tools : differencing, the autocorrelation function (acf) and the partial autocorrelation function (pacf). Differencing is used to reduce nonstationary series to stationary ones. The acf and pacf are then used to identify an appropriate ARIMA model and the required number of parameters.

After the model is identified, parameter estimates are obtained, that is, the selected model is fit to the available data.

Box-Jenkins models can only be applied to stationary series or series which have been made stationary by differencing. The models fall into one of the following three categories :

- Purely Auto Regressive (AR) models
- Purely Moving Average (MA) models
- Mixed Auto Regressive Moving Average (ARMA) models

If differencing is required to achieve stationarity, then the series will eventually have to be undifferenced or integrated before forecasting. In this case, an I is added to the names of the three models, giving ARI models, IMA models and ARIMA models.

The different Box-Jenkins models are identified by the number of Auto Regressive parameters (p), the degree of differencing (d) and the number of Moving Average parameters (q). Any such model can be written using the uniform notation ARIMA (p,d,q) : An Auto Regressive (of order p), Moving Average (of order q) model applied to series that has been differenced d times.

The stages in Box-Jenkins procedure are : identification, estimation, diagnostic checking and forecasting.

2.2.1.2.a. Auto Regressive Models

Auto Regressive (AR) models, are based on the application of regression analysis to lagged value of the y_t series. In the context of Box Jenkins modeling, parameters of AR models are conventionally denoted by $\phi_i^{'}$s instead of the $\beta_i^{'}$s of regression analysis.

Auto Regressive model of order p, AR (p) is defined by

$$y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \ldots + \phi_p y_{t-p} + \varepsilon_t$$

Where,

y_t = the actual value of the series at time t

y_{t-1} = the actual value of the series at time t - 1

ϕ_1 = the Auto Regressive parameter for y_{t-1}

ε_t = the irregular fluctuation at time t, not correlated with past values of the y_ts

2.2.1.2.b. Moving Average Model

Moving Average model of order q, MA (q) is defined by

$$y_t = \theta_0 + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$$

Where,

y_t = the actual value of the series at time t

θ_1 = the Moving Average parameter for ε_{t-1}

ε_{t-1} = the error term at time t - 1

ε_t = the error term at time t

Auto Regressive Moving Average model of order p and q, ARMA (p,q) can be defined as

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_0 + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$$

Where,

y_t = the actual value of the series at time t

y_{t-1} = the value of the series at time t - 1

ε_t = the error term at time t

ε_{t-1} = the error term at time t - 1

ϕ_1 = the Auto Regressive parameter for y_{t-1}

θ_1 = the Moving Average parameter for ε_{t-1}

Auto Regressive Integrated Moving Average model of order p, d and q, ARIMA (p,d,q) can be defined as

$$w_t = \phi_1 w_{t-1} - \phi_2 w_{t-2} + \dots + \phi_p w_{t-p} + \varepsilon_t + \theta_0 - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q}$$

ε_t, ε_{t-1}, ε_{t-2}, . . . are uncorrelated with one another

By convention, in mixed models the constant term is denoted by θ_0 rather than ϕ_0

2.2.2. SIMPLE LINEAR REGRESSION

Regression or "least squares" analysis, is a statistical method for estimating the functional relationship between a response variable and one or more independent, prediction variables.

In regression analysis, the mathematical form of the relationship between a response variable y and the independent variables x_1, x_2, . . . , x_k, is assumed to be

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \epsilon$$

Where,

β_0, β_1, β_2, . . ., β_k, are fixed constants called regression parameters and ϵ is the error term.

This equation is called the general linear model, and it is the purpose of linear regression analysis to generate estimates of the parameters $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ from the data on the variables y, $x_1, x_2, \ldots, x_k$.

Regression models are simple when only one predictor variable is involved. The standard model of Simple linear regression can be defined :

$$y = \beta_0 + \beta_1 x + \in$$

Simple Linear Regression parameter estimates

Given : A sample of n pairs observations on x and y, (x_1, y_1), $(x_2, y_2), \ldots, (x_n, y_n)$

Estimates : $\hat{\beta}_1 = \dfrac{SS_{xy}}{SS_{xx}}$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

Where,

$$SS_{xx} = \sum x^2 - \frac{(\Sigma x)^2}{n}$$

$$\bar{x} = \frac{\sum x}{n}$$

$$SS_{yy} = \sum y^2 - \frac{(\Sigma y)^2}{n}$$

$$\bar{y} = \frac{\sum y}{n}$$

$$SS_{xy} = \sum xy - \frac{(\sum x).(\sum y)}{n}$$

Estimated Regression model : $\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$

Forecast (at time t for p periods ahead) : $\hat{y}_{t+p} = \hat{\beta}_0 + \hat{\beta}_1 x_{t+p}$

Note : SS_{yy} used in estimating σ_ϵ^2 should be calculated now.

σ_ϵ^2 = Variance of the error terms

Given : SS_{xy}, SS_{yy} and $\hat{\beta}_1$ (from previous calculations)

Estimated : $s_\varepsilon = \sqrt{\dfrac{SSE}{n-2}}$

Where,

SSE = SST – SSR

SST = SS_{yy}

and

SSR = $\hat{\beta}_1 \cdot SS_{xy}$

SSE = Sum Squares Error

SST = Sum of Squares Total

SSR = Sum of Squares Regression

2.3. MEASURING FORECAST ACCURACY

Measure of forecast accuracy are used to :

- Provide a single, easily interpreted measure of model's usefulness, or reliability.
- Compare the accuracy of two different models.

- Search for an optimal model.
- Monitor a model's performance.

2.3.1. Mean Absolute Deviation (MAD)

The mean absolute deviation (MAD) measures forecast accuracy by averaging the magnitudes of the forecast errors, that is, the absolute values of the e_t's.

The formula for the mean absolute deviation of the error series is :

$$\text{MAD} = \frac{\sum |forecast\ error|}{no.of\ forecasts}$$

$$= \frac{\sum \left| y_t - \hat{y}_t \right|}{n} = \frac{\sum |e_t|}{n}$$

2.3.2. Mean Square Error (MSE) & Root Mean Square Error (RMSE)

The descriptive mean square error (MSE) is similar to the MAD in that it attempts to average the sizes of the forecast errors, avoiding the canceling of positive and negative terms, however, by averaging the squares rather than the absolute values of these errors.

MSE gives more weight to the large forecast errors than does the MAD. Thus, it more sensitive to unusually large error than MAD.

The mean square error is calculated from the formula :

$$\text{MSE} = \frac{\sum (forecast\ error)^2}{no.of\ forecasts}$$

$$= \frac{\sum\left(y_t - \hat{y}_t\right)^2}{n} = \frac{\sum e_t^2}{n}$$

The MSE is measured in the squares of the units of the original series, which makes it harder to be interpreted. For this reason, the root mean square error can be evaluated, that is given simply by the equation

RMSE $= \sqrt{MSE}$

and is measured in the same units as the original time series

2.3.3. Mean Absolute Percent Error (MAPE)

Error in measurement are often expressed as a percentage of relative error in order to introduce a unit free scale of evaluation. Forecasting errors can be converted by expressing each e_t, as percentage of the corresponding y_t.

The mean absolute percent error is calculated from the formula :

$$\text{MAPE} = \frac{\sum\left|{forecast\ error}/{actual\ value}\right|}{no.of\ forecasts}$$

$$= \frac{\sum\left|{e_t}/{y_t}\right|}{n} \cdot 100\ \%$$

CHAPTER III
ARTIFICIAL NEURAL NETWORKS

3.1. BASIC CONCEPTS OF NEURAL NETWORKS

A neural network is a computer program or hardwired machine that is designed to learn in a manner similar to the human brain.

Haykin (1994) describes neural networks as an adaptive machine or more specifically:

A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects: Knowledge is acquired by the network through a learning process and interneuron connection strengths known as synaptic weights are used to store the knowledge.

The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objective.

The basic building block of a brain and the neural network is the neuron.

The basic human neuron is shown in Figure 3.1.

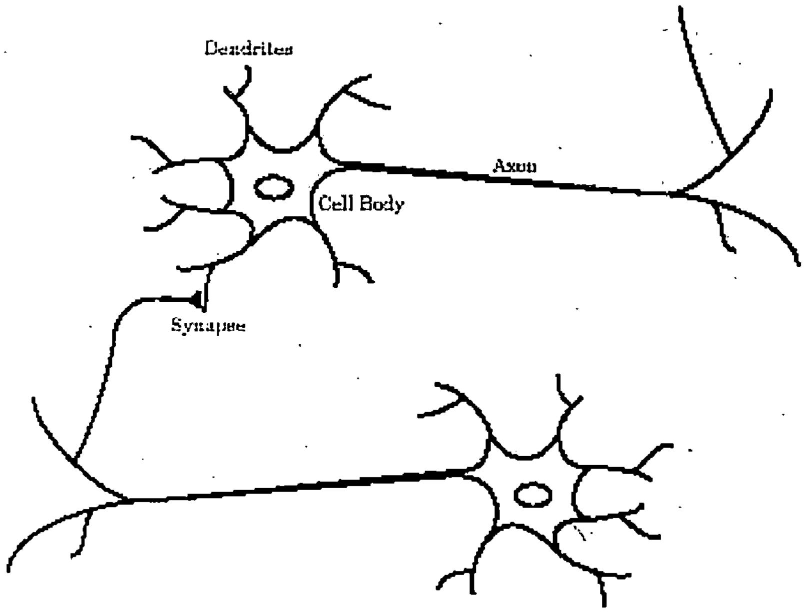


Figure 3.1. Biological Neuron

The brain consists of a large number (approximately 10^{11}) of highly connected elements (approximately 10^4 connections per element) called neurons. Neurons have three principal components: the dendrites, the cell body and the axon. The dendrites are tree-like receptive networks of nerve fibers that carry electrical signals into the cell body. The cell body effectively sums and thresholds these incoming signals. The axon is a single long fiber that carries the signal from the cell body out to other neurons. The point of contact between an axon of one cell and a dendrite of another cell is called a synapse. It is the arrangement of neurons and the strengths of the individual synapses, determined by a complex chemical process, that establishes the function of the neural network.

3.2. NEURAL NETWORK ARCHITECTURES

In general, there are three different classes of neural network architectures :

1. Single Layer Feedforward Network

This type of network comprises of two layer, namely the input layer and the output layer. The input layer neurons receive the input signals and the output layer neurons receive the output signals. The synaptic links carrying the weights connect every input neuron to the output neuron but not vice-versa. Such a network is said to be feedforward in type or acyclic in nature. Despite the two layers, the network is termed single layer since it is the output layer, alone which performs computation. The input merely transmits the signals to the output layer. Hence, the name single layer feedforward network.

Figure 3.2. illustrates an example a single layer feedforward network

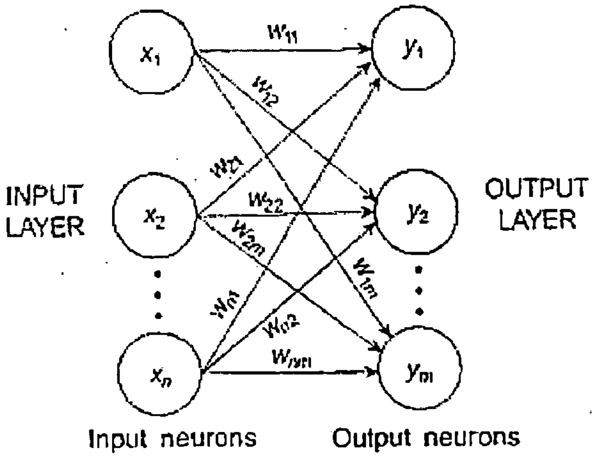


Figure 3.2. Single Layer Feedforward Network

2. Multilayer Feedforward Network

This network is made up of multiple layers. Architecture of this class besides possessing an input and output layer also have one or more intermediary layers called hidden layers. The computational units of the hidden layer are known as the hidden neurons or hidden units. The hidden layer aids in performing useful intermediary computations before directing the input to the output layer. The input layer neuron are linked to the hidden layer neurons and the weight on these links are referred to as input hidden layer weights. Again, the hidden layer neuron are linked to the output layer neurons and the corresponding weight are referred to as hidden output layer weights.

A multilayer feedforward network with l input neurons, m_1 neurons in the first hidden layer, m_2 neurons in the second hidden layer and n output neurons in the output layer is written as $l - m_1 - m_2 - n$

Figure 3.3. Illustrated a multilayer feedforward network with a configuration $l - m - n$.

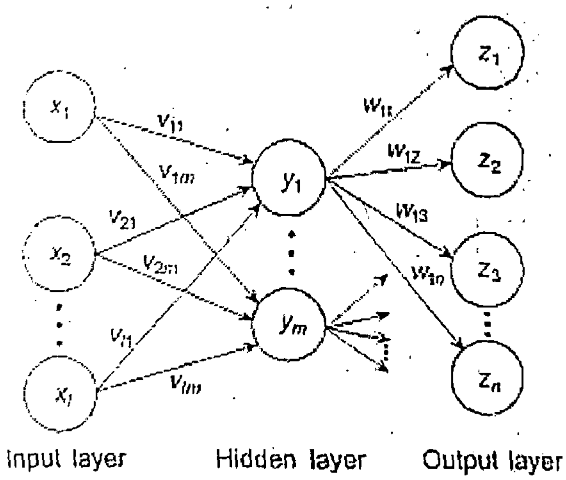


Figure 3.3. Multilayer Feedforward Network ($l - m - n$ configuration)

3. Recurrent Networks

These networks differ from feedforward network architectures in the sense that there is at least one feedback loop. In these networks, for example, there could exist one layer with feedback connections as shown in Figure 3.4. There could also be neurons with self-feedback links, i.e. the output of a neuron is fed back into itself as input.

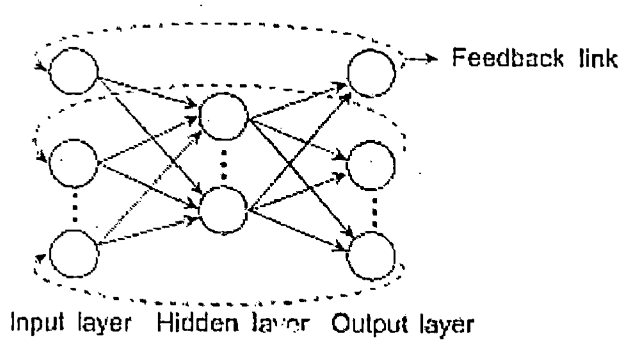


Figure 3.4. Recurrent Neural Network

3.3. LEARNING METHODS

Learning is a process by which the free parameters of a neural network are adapted through a process of stimulation by the environment in which the network is embedded. The type of learning is determined by the manner in which the parameter changes take place.

This definition of the learning process implies the following sequence of events:

- The neural network is simulated by an environment.
- The neural network undergoes changes in its free parameters as a result of this simulation.
- The neural network responds in a new way to the environment because of the changes that have occurred in its internal structure.

Learning methods in neural networks can be broadly classified into three basic types: supervised, unsupervised and reinforced.

1. Supervised Learning

In this, every input pattern that is used to train the network is associated with an output pattern, which is the target or the desired pattern. A teacher is assumed to be present during the learning process, when a comparison is made between the network's computed output and the correct expected output, to determine the error. The error can then be used to change network parameters, which result in an improvement in performance.

2. Unsupervised Learning

In this learning method, the target output is not presented to the network. It is as if there is no teacher to present the desired patterns and hence, the system learns of its own by discovering and adapting to structural features in the input patterns.

3. Reinforced Learning

In this method, a teacher through available, does not present the expected answer but only indicates if the computed output is correct or incorrect. The information provided helps the network in its learning process. A reward is given for a correct answer computed and a penalty for a wrong answer. Reinforced learning is not one of the popular forms of learning. Supervised and unsupervised learning methods are most popular forms of learning.

3.4. BACKPROPAGATION ALGORITHM

The backpropagation algorithm was developed for training multilayer perceptron networks. It was popularized by Rumelhart, Hinton and Williams (1986), although similar ideas had been developed previously by others (Werbos, 1974; Parker, 1985).

The backpropagation algorithm is a generalization of the least mean squared algorithm that modifies network weight to minimize the mean square error between the desired and actual outputs of the network. Backpropagation uses supervised learning in which the network is trained using data for which inputs as well as desired outputs are known. Once trained, the network weights are frozen and can be used to compute output values for new input sample.

The feedforward process involves presenting an input pattern to input layer neurons that pass the input value onto the first hidden layer. Each of the hidden layer nodes computes a weighted sum of its input, passes the sum through its activation function and presents the result to the output layer.

Basically, error backpropagation algorithm learning consist of two passes through the different layers of the network : a forward pass and backward pass. In the forward pass, an activity pattern (input vector) is applied to the sensory nodes of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of the networks are all fixed. During the backward pass, on the other hand, the synaptic weight are all adjusted in accordance with an error correction rule. Specifically, the actual response of the network is subtracted from a desired (target) response to produce an error signal. This error signal is then propagated backward through the network, against the direction the direction of synaptic connections, hence the name error backpropagation.

Backpropagation is based on steepest descent method as shown in Figure 3.5. The error surface is given by

$$E = \sum_{p=1}^{nset} E^p(V,W,I) \qquad (1)$$

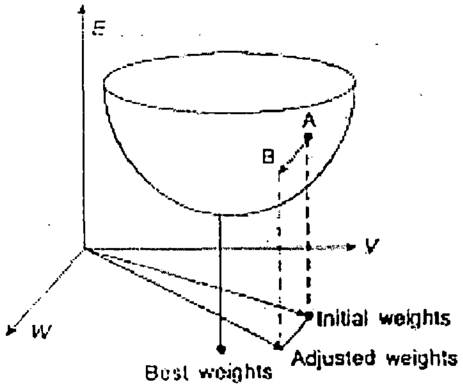


Figure 3.5. Euclidian Norm of Errors

At the start training process, gradient descent search begins at a location with error value E determined by initial weight assignments $W(O), V(O)$ and the training pattern pair (I^P, O^P) where,

$$E = \frac{1}{nset}\sum_{p=1}^{nset} E^p = \frac{1}{2\ x\ nset}\sum_{p=1}^{k}\left(T_k^p - O_{Ok}^p\right)^2 \qquad (2)$$

During training, the gradient descent computations incrementally determine how the weights should be modified at each new location to move most rapidly in the direction opposite to the direction of steepest descent. After the incremental adjustments to the weight have been made, the location is shifted to a different E location on the error weight surface. This process is repeat for each, training pattern (or each epoch $\{(I^P, O^P)\ p = 1, 2, \cdots, nset\}$, progressively shifting the location to lower level until a threshold error value is reached or until a limit on the total number of training cycles is reached.

From Figure 3.5, the vector $\bar{A}\bar{B}$ is written as:

$$\bar{A}\bar{B} = (V_{i+1} - V_i)\bar{i} + (W_{i+1} - W_i)\bar{j} = \Delta V\bar{i} + \Delta W\bar{j} \tag{3}$$

The gradient is given by

$$\bar{G} = \frac{\partial E}{\partial V}\bar{i} + \frac{\partial E}{\partial W}\bar{j} \tag{4}$$

and hence, the unit vector in the direction of the gradient is given by

$$\bar{e}_{AB} = \frac{1}{\bar{G}}\left\{\frac{\partial E}{\partial V}\bar{i} + \frac{\partial E}{\partial W}\bar{j}\right\} \tag{5}$$

Hence,

$$\bar{A}\bar{B} = -\eta\left[\frac{\partial E}{\partial V}\bar{i} + \frac{\partial E}{\partial W}\bar{j}\right] \tag{6}$$

Where,

$$\eta = \frac{K}{\left|\bar{G}\right|} \text{ ; K is a constant} \tag{7}$$

Comparing Equation (3) with Equation (6) We get

$$\Delta V = -\eta\frac{\partial E}{\partial V} \quad ; \quad \Delta W = -\eta\frac{\partial E}{\partial W} \tag{8}$$

for the k th output neuron, E_k is given by

$$E_k = \frac{1}{2}\left(T_k - O_{ok}\right)^2 \qquad (9)$$

Where, T_k is the target output of the kth output neuron and O_{ok} is the computed output of the kth output neuron.

To compute $\frac{\partial E_k}{\partial W_{ik}}$ We apply chain rule of differentiation as

$$\frac{\partial E_k}{\partial W_{ik}} = \frac{\partial E_k}{\partial O_{ok}} \frac{\partial O_{ok}}{\partial I_{ok}} \frac{\partial I_{ok}}{\partial W_{ik}} \qquad (10)$$

Where,

$$\frac{\partial E_k}{\partial O_k} = -\left(T_k - O_{ok}\right) \qquad (11)$$

and the output of kth output neuron is given by

$$O_{ok} = \frac{1}{\left(1 + e^{-\lambda\left(I_{ok} - O_{ok}\right)}\right)} \qquad (12)$$

Hence,

$$\frac{\partial O_{ok}}{\partial I_{ok}} = \lambda O_{ok}\left(1 - O_{ok}\right) \qquad (13)$$

Hence, the derivative of the sigmoidal function is a simple function of outputs.

Let us evaluate $\frac{\partial I_{ok}}{\partial W_{ik}}$ as

$$I_{ok} = W_{1k}O_{H1} + W_{2k}O_{H2} + \cdots + W_{mk}O_{Hm} \qquad (14)$$

and

$$\Delta W_{ik} = -\eta \frac{\partial E_k}{\partial W_{ik}} \qquad (15.a)$$

Writing in matrix form

$$[\Delta W] = \eta \{O\}_H \langle d \rangle \qquad (15.b)$$

m x n *m x l* *l x n*

Where,

$$\langle d \rangle = \lambda \langle (T_k - O_{ok}) O_{ok} (1 - O_{ok}) \rangle \qquad (16)$$

Now We compute $\frac{\partial E_k}{\partial V_{ij}}$ by applying the chain rule of differentiation as

$$\frac{\partial E_k}{\partial V_{ij}} = \frac{\partial E_k}{\partial O_{ok}} \frac{\partial O_{ok}}{\partial I_{ok}} \frac{\partial I_{ok}}{\partial O_{Hi}} \frac{\partial O_{Hi}}{\partial I_{Hj}} \frac{\partial I_{Hj}}{\partial V_{ij}} \qquad (17)$$

It is already proved that

$$\frac{\partial E_k}{\partial I_{ok}} = \frac{\partial E_k}{\partial O_{ok}} \frac{\partial O_{ok}}{\partial I_{ok}} = -\lambda (T_k - O_{ok}) O_{ok} (1 - O_{ok}) \qquad (18.a)$$

$$\frac{\partial I_{ok}}{\partial O_{Hi}} = W_{ik} \qquad (18.b)$$

$$\frac{\partial O_{Hi}}{\partial I_{Hj}} = \lambda (O_{Hi})(1 - O_{Hi}) \qquad (18.c)$$

$$\frac{\partial I_{Hj}}{\partial V_{ij}} = O_{ij} = I_{ij} \qquad (18.d)$$

Hence,

$$\frac{\partial E_k}{\partial O_{ok}} \frac{\partial O_{ok}}{\partial I_{ok}} \frac{\partial I_{ok}}{\partial O_{Hi}} = -W_{ik} d_k = -e_1 \qquad (19)$$

Where d_k is given by the Equation (16)

Define d_k^* as

$$d_k^* = -e_i \lambda(O_{Hi})(1 - O_{Hi}) \qquad (20.a)$$

$$\frac{\partial E_k}{\partial V_{ij}} = -d_i^* I_{ij} \qquad (20.b)$$

or

$$\underset{l \times m}{[\Delta V]} = \eta \underset{l \times l}{\{O\}_H} \underset{l \times m}{\langle d^* \rangle} \qquad (21)$$

Where,

$$d_i^* = \lambda e_i (O_{Hi})(1 - O_{Hi}) \qquad (22)$$

Combining Equation (15) and Equation (21) We get

$$\underset{m \times n}{[\Delta W]} = \eta \underset{m \times l}{\{O\}_H} \underset{l \times n}{\langle d \rangle} \qquad (23.a)$$

$$\underset{l \times m}{[\Delta V]} = \eta \underset{l \times l}{\{O\}_H} \underset{l \times m}{\langle d^* \rangle} \qquad (23.b)$$

η in Equation (23) is known as learning rate coefficient.

3.5. MULTI LAYER PERCEPTRON IN LOAD FORECASTING

Multi Layer Perceptron (MLP) is the most popular neural network type and most of the reported neural network short term load forecasting models are based on it.

The basic unit (neuron) of the network is a perceptron. This is a computation unit, which produces its output by taking a linear combination of the input signals and by transforming this by a function called activity function.

The output of the perceptron as a function of the input signals can be written :

$$y = \sigma\left(\sum_i^n w_i x_i - \theta\right)$$

Where,

y = the output

x_i = the input signals

w_i = the neuron weight

θ = the bias term (another neuron weight)

σ = the activity function

The MLP network consists of several layers of neurons. Each neuron in a certain layer is connected to each neuron of the next layer. There are no feedback connections. The most often used MLP-network consists of three layers: an input layer, one hidden layer, and an output layer.

The idea behind the use of MLP models in load forecasting is simple: it is assumed that future load is dependent on past load and external factors (i.e. temperature), and the MLP network is used to approximate this dependency. The inputs to the network consist of those temperature values and past load values, and the output is the target load values (for example a load value of a certain hour, load values of many future hours, the peak load of a day, the total load of a day etc).

Therefore, the building of a MLP model for load forecasting can be seen as a nonlinear system identification problem. The determining of the model structure consists of selecting the input variables and deciding the network structure. The parameter estimation is carried out by training the network on load data of the history. This requires choices concerning the learning algorithm and appropriate training data. The model validation is carried out by testing on load data, which has not been used in training.

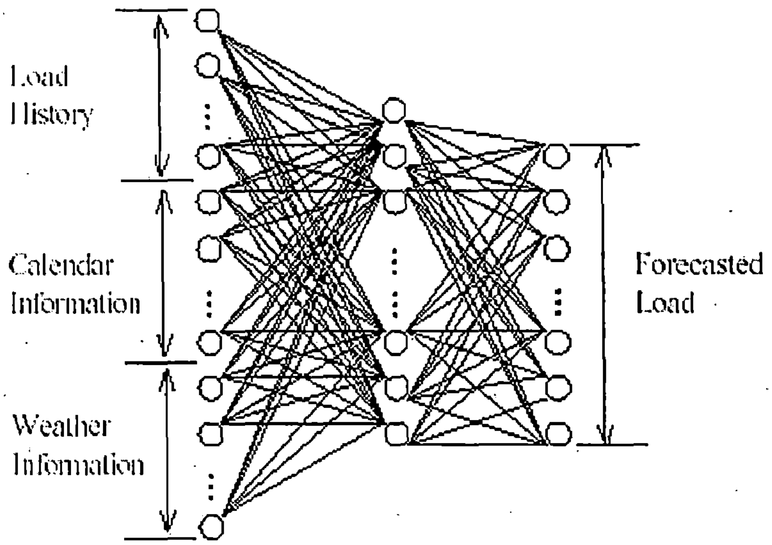


Figure 3.6. Multi Layer Perceptron Network in Load Forecasting

CHAPTER IV

STLF BY TIME SERIES AND REGRESSION ANALYSIS

4.1. FORECASTING BY MOVING AVERAGE

Based on the data at Table 4.1. Daily load maximum in Vikas Nagar Sub Station IIT Roorkee in January 2003, We can calculate the forecast for days 25, 26, 27, 28, 29, 30 and 31, as follows:

$$\hat{y}_{t+1} = \frac{y_t + y_{t-1} + \cdots + y_{t-m+1}}{m}$$

$$\hat{y}_{25} = \frac{443.42 + 518.25 + 531.89}{3} = 497.85$$

$$\hat{y}_{26} = \frac{399.70 + 443.42 + 518.25}{3} = 453.79$$

$$\hat{y}_{27} = \frac{407.26 + 399.70 + 443.42}{3} = 416.79$$

$$\hat{y}_{28} = \frac{459.08 + 407.26 + 399.70}{3} = 422.01$$

$$\hat{y}_{29} = \frac{397.58 + 459.08 + 407.26}{3} = 421.31$$

$$\hat{y}_{30} = \frac{433.43 + 397.58 + 459.08}{3} = 430.03$$

$$\hat{y}_{31} = \frac{415.50 + 433.43 + 397.58}{3} = 415.50$$

With same way, We get the forecast for daily load maximum in 2003 each month, as below:

Table. 4.2. Prediction Load with Moving Average Model

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	25.01.2003	443.42	497.85
Sunday	26.01.2003	399.70	453.79
Monday	27.01.2003	407.26	416.79
Tuesday	28.01.2003	459.08	422.01
Wednesday	29.01.2003	397.58	421.31
Thursday	30.01.2003	433.43	430.03
Friday	31.01.2003	415.50	415.50

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	22.02.2003	388.43	349.40
Sunday	23.02.2003	373.62	368.26
Monday	24.02.2003	307.72	356.59
Tuesday	25.02.2003	302.32	327.89
Wednesday	26.02.2003	319.41	309.82
Thursday	27.02.2003	363.83	328.52
Friday	28.02.2003	328.92	337.39

Day	Date	Actual Load (kW)	Prediction Load (kW)
Tuesday	25.03.2003	331.30	369.49
Wednesday	26.03.2003	332.19	342.42
Thursday	27.03.2003	376.03	346.51
Friday	28.03.2003	423.94	377.39
Saturday	29.03.2003	380.70	393.56
Sunday	30.03.2003	385.98	396.87
Monday	31.03.2003	361.72	376.13

Continued of Table 4.2.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Thursday	24.04.2003	382.00	409.81
Friday	25.04.2003	417.15	406.26
Saturday	26.04.2003	434.95	411.37
Sunday	27.04.2003	383.84	411.98
Monday	28.04.2003	353.90	390.90
Tuesday	29.04.2003	384.62	374.12
Wednesday	30.04.2003	427.97	388.83

Day	Date	Actual Load (kW)	Prediction Load (kW)
Sunday	25.05.2003	490.78	474.01
Monday	26.05.2003	550.02	510.60
Tuesday	27.05.2003	413.42	484.74
Wednesday	28.05.2003	506.91	490.12
Thursday	29.05.2003	492.34	470.89
Friday	30.05.2003	546.74	515.33
Saturday	31.05.2003	515.65	518.24

Day	Date	Actual Load (kW)	Prediction Load (kW)
Tuesday	24.06.2003	422.93	457.01
Wednesday	25.06.2003	540.26	475.30
Thursday	26.06.2003	473.93	479.04
Friday	27.06.2003	472.56	495.58
Saturday	28.06.2003	418.76	455.08
Sunday	29.06.2003	513.24	468.19
Monday	30.06.2003	438.70	456.90

Continued of Table 4.2.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Friday	25.07.2003	642.06	531.92
Saturday	26.07.2003	592.25	571.32
Sunday	27.07.2003	584.98	606.43
Monday	28.07.2003	522.22	566.48
Tuesday	29.07.2003	417.78	508.33
Wednesday	30.07.2003	504.23	481.41
Thursday	31.07.2003	495.62	472.54

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	25.08.2003	476.29	427.06
Tuesday	26.08.2003	547.83	470.85
Wednesday	27.08.2003	421.06	481.73
Thursday	28.08.2003	446.37	471.75
Friday	29.08.2003	516.55	461.33
Saturday	30.08.2003	419.91	460.94
Sunday	31.08.2003	521.54	486

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	24.09.2003	547.15	481.54
Tuesday	25.09.2003	374.72	430.55
Wednesday	26.09.2003	457.88	459.92
Thursday	27.09.2003	433.88	422.16
Friday	28.09.2003	459.08	450.28
Saturday	29.09.2003	407.59	433.52
Sunday	30.09.2003	411.51	426.06

Continued of Table 4.2.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	25.10.2003	545.81	482.36
Sunday	26.10.2003	455.96	493.83
Monday	27.10.2003	450.35	484.04
Tuesday	28.10.2003	446.74	451.02
Wednesday	29.10.2003	401.27	432.79
Thursday	30.10.2003	410.46	419.49
Friday	31.10.2003	358.08	389.94

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	24.11.2003	375.10	417.16
Tuesday	25.11.2003	383.48	388.72
Wednesday	26.11.2003	418.90	392.49
Thursday	27.11.2003	416.65	406.34
Friday	28.11.2003	501.60	445.72
Saturday	29.11.2003	402.05	440.10
Sunday	30.11.2003	350.61	418.09

Day	Date	Actual Load (kW)	Prediction Load (kW)
Thursday	25.12.2003	396.73	373.28
Friday	26.12.2003	433.72	397.74
Saturday	27.12.2003	447.88	426.11
Sunday	28.12.2003	417.12	432.91
Monday	29.12.2003	424.52	429.84
Tuesday	30.12.2003	468.32	436.65
Wednesday	31.12.2003	442.64	445.16

4.2. FORECASTING BY EXPONENTIAL SMOOTHING

Based on the data at Table. Daily load maximum in Vikas Nagar Sub Station IIT Roorkee in January 2003, We can calculate the forecast for days 25, 26, 27, 28, 29, 30 and 31, as follows:

$$\hat{y}_{t+1} = \alpha y_{t-1} + (1-\alpha)\hat{y}_{t-1}$$

taken value of $\alpha = 0.2$

$$\hat{y}_{25} = 0.2 \text{ x } 518.25 + (1-0.2) \text{ x } 518.25 = 518.25$$

$$\hat{y}_{26} = 0.2 \text{ x } 443.42 + (1-0.2) \text{ x } 518.25 = 503.28$$

$$\hat{y}_{27} = 0.2 \text{ x } 399.70 + (1-0.2) \text{ x } 503.28 = 482.56$$

$$\hat{y}_{28} = 0.2 \text{ x } 407.26 + (1-0.2) \text{ x } 482.56 = 467.50$$

$$\hat{y}_{29} = 0.2 \text{ x } 459.08 + (1-0.2) \text{ x } 467.50 = 465.82$$

$$\hat{y}_{30} = 0.2 \text{ x } 397.58 + (1-0.2) \text{ x } 465.82 = 452.17$$

$$\hat{y}_{31} = 0.2 \text{ x } 433.43 + (1-0.2) \text{ x } 452.17 = 448.42$$

With same way, We get the forecast for daily load maximum in 2003 each month, as below:

Table. 4.3. Prediction Load with Exponential Smoothing Model

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	25.01.2003	443.42	518.25
Sunday	26.01.2003	399.70	503.28
Monday	27.01.2003	407.26	482.56

Tuesday	28.01.2003	459.08	467.50
Wednesday	29.01.2003	397.58	465.82
Thursday	30.01.2003	433.43	452.17
Friday	31.01.2003	415.50	448.42

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	22.02.2003	388.43	342.74
Sunday	23.02.2003	373.62	351.88
Monday	24.02.2003	307.72	356.23
Tuesday	25.02.2003	302.32	346.53
Wednesday	26.02.2003	319.41	342.80
Thursday	27.02.2003	363.83	338.12
Friday	28.02.2003	328.92	343.26

Day	Date	Actual Load (kW)	Prediction Load (kW)
Tuesday	25.03.2003	331.30	363.76
Wednesday	26.03.2003	332.19	357.27
Thursday	27.03.2003	376.03	352.25
Friday	28.03.2003	423.94	357.01
Saturday	29.03.2003	380.70	370.40
Sunday	30.03.2003	385.98	372.46
Monday	31.03.2003	361.72	375.16

Day	Date	Actual Load (kW)	Prediction Load (kW)
Thursday	24.04.2003	382.00	419.64
Friday	25.04.2003	417.15	412.11
Saturday	26.04.2003	434.95	413.12
Sunday	27.04.2003	383.84	417.49
Monday	28.04.2003	353.90	410.76
Tuesday	29.04.2003	384.62	399.39
Wednesday	30.04.2003	427.97	396.44

Continued of Table 4.3.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Sunday	25.05.2003	490.78	491.00
Monday	26.05.2003	550.02	490.96
Tuesday	27.05.2003	413.42	502.77
Wednesday	28.05.2003	506.91	484.90
Thursday	29.05.2003	492.34	489.30
Friday	30.05.2003	546.74	489.91
Saturday	31.05.2003	515.65	501.28

Day	Date	Actual Load (kW)	Prediction Load (kW)
Tuesday	24.06.2003	422.93	462.71
Wednesday	25.06.2003	540.26	454.75
Thursday	26.06.2003	473.93	471.85
Friday	27.06.2003	472.56	472.27
Saturday	28.06.2003	418.76	472.33
Sunday	29.06.2003	513.24	461.62
Monday	30.06.2003	438.70	471.94

Day	Date	Actual Load (kW)	Prediction Load (kW)
Friday	25.07.2003	642.06	479.66
Saturday	26.07.2003	592.25	512.14
Sunday	27.07.2003	584.98	528.16
Monday	28.07.2003	522.22	539.52
Tuesday	29.07.2003	417.78	536.06
Wednesday	30.07.2003	504.23	512.40
Thursday	31.07.2003	495.62	510.77

Continued of Table 4.3.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	25.08.2003	476.29	388.43
Tuesday	26.08.2003	547.83	406.00
Wednesday	27.08.2003	421.06	434.37
Thursday	28.08.2003	446.37	431.71
Friday	29.08.2003	516.55	434.64
Saturday	30.08.2003	419.91	451.02
Sunday	31.08.2003	521.54	444.80

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	24.09.2003	547.15	369.79
Tuesday	25.09.2003	374.72	405.26
Wednesday	26.09.2003	457.88	399.15
Thursday	27.09.2003	433.88	410.90
Friday	28.09.2003	459.08	415.50
Saturday	29.09.2003	407.59	424.22
Sunday	30.09.2003	411.51	420.89

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	25.10.2003	545.81	479.71
Sunday	26.10.2003	455.96	492.93
Monday	27.10.2003	450.35	485.54
Tuesday	28.10.2003	446.74	478.50
Wednesday	29.10.2003	401.27	472.15
Thursday	30.10.2003	410.46	457.97
Friday	31.10.2003	358.08	448.47

Continued of Table 4.3.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	24.11.2003	375.10	407.59
Tuesday	25.11.2003	383.48	401.09
Wednesday	26.11.2003	418.90	397.57
Thursday	27.11.2003	416.65	401.84
Friday	28.11.2003	501.60	404.80
Saturday	29.11.2003	402.05	424.16
Sunday	30.11.2003	350.61	419.74

Day	Date	Actual Load (kW)	Prediction Load (kW)
Thursday	25.12.2003	396.73	362.76
Friday	26.12.2003	433.72	369.55
Saturday	27.12.2003	447.88	382.38
Sunday	28.12.2003	417.12	395.48
Monday	29.12.2003	424.52	399.81
Tuesday	30.12.2003	468.32	404.75
Wednesday	31.12.2003	442.64	417.16

4.3. FORECASTING BY ARIMA

The implementation is carried out using MetrixND software.

Input data per month is created in Microsoft Excel file table data. The table data is imported into MetrixND software to build ARIMA (0,1,1) model.

We get the forecast for daily load maximum in 2003 each month, as below:

Table. 4.4. Prediction Load with ARIMA Model

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	25.01.2003	443.42	471.41
Sunday	26.01.2003	399.70	481.64
Monday	27.01.2003	407.26	421.74
Tuesday	28.01.2003	459.08	482.78
Wednesday	29.01.2003	397.58	423.31
Thursday	30.01.2003	433.43	456.53
Friday	31.01.2003	415.50	496.67

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	22.02.2003	388.43	368.48
Sunday	23.02.2003	373.62	314.25
Monday	24.02.2003	307.72	386.14
Tuesday	25.02.2003	302.32	372.25
Wednesday	26.02.2003	319.41	296.34
Thursday	27.02.2003	363.83	358.34
Friday	28.02.2003	328.92	324.24

Day	Date	Actual Load (kW)	Prediction Load (kW)
Tuesday	25.03.2003	331.30	334.36
Wednesday	26.03.2003	332.19	358.99
Thursday	27.03.2003	376.03	378.49
Friday	28.03.2003	423.94	395.78
Saturday	29.03.2003	380.70	342.69
Sunday	30.03.2003	385.98	369.29
Monday	31.03.2003	361.72	366.30

Continued of Table 4.4.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Thursday	24.04.2003	382.00	438.24
Friday	25.04.2003	417.15	388.18
Saturday	26.04.2003	434.95	401.90
Sunday	27.04.2003	383.84	418.49
Monday	28.04.2003	353.90	435.68
Tuesday	29.04.2003	384.62	417.38
Wednesday	30.04.2003	427.97	423.33

Day	Date	Actual Load (kW)	Prediction Load (kW)
Sunday	25.05.2003	490.78	493.34
Monday	26.05.2003	550.02	519.45
Tuesday	27.05.2003	413.42	533.44
Wednesday	28.05.2003	506.91	485.49
Thursday	29.05.2003	492.34	463.20
Friday	30.05.2003	546.74	485.78
Saturday	31.05.2003	515.65	498.12

Day	Date	Actual Load (kW)	Prediction Load (kW)
Tuesday	24.06.2003	422.93	419.03
Wednesday	25.06.2003	540.26	454.58
Thursday	26.06.2003	473.93	481.44
Friday	27.06.2003	472.56	419.54
Saturday	28.06.2003	418.76	401.09
Sunday	29.06.2003	513.24	444.52
Monday	30.06.2003	438.70	431.53

Continued of Table 4.4.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Friday	25.07.2003	642.06	598.97
Saturday	26.07.2003	592.25	449.62
Sunday	27.07.2003	584.98	541.94
Monday	28.07.2003	522.22	503.95
Tuesday	29.07.2003	417.78	437.82
Wednesday	30.07.2003	504.23	489.02
Thursday	31.07.2003	495.62	479.18

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	25.08.2003	476.29	516.00
Tuesday	26.08.2003	547.83	491.09
Wednesday	27.08.2003	421.06	517.82
Thursday	28.08.2003	446.37	496.82
Friday	29.08.2003	516.55	468.04
Saturday	30.08.2003	419.91	436.79
Sunday	31.08.2003	521.54	409.45

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	24.09.2003	547.15	437.16
Tuesday	25.09.2003	374.72	470.37
Wednesday	26.09.2003	457.88	431.06
Thursday	27.09.2003	433.88	455.80
Friday	28.09.2003	459.08	455.04
Saturday	29.09.2003	407.59	488.07
Sunday	30.09.2003	411.51	369.43

Continued of Table 4.4.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	25.10.2003	545.81	415.90
Sunday	26.10.2003	455.96	447.15
Monday	27.10.2003	450.35	404.71
Tuesday	28.10.2003	446.74	405.75
Wednesday	29.10.2003	401.27	443.85
Thursday	30.10.2003	410.46	405.10
Friday	31.10.2003	358.08	451.49

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	24.11.2003	375.10	358.00
Tuesday	25.11.2003	383.48	411.47
Wednesday	26.11.2003	418.90	427.95
Thursday	27.11.2003	416.65	414.67
Friday	28.11.2003	501.60	369.28
Saturday	29.11.2003	402.05	409.79
Sunday	30.11.2003	350.61	414.87

Day	Date	Actual Load (kW)	Prediction Load (kW)
Thursday	25.12.2003	396.73	408.68
Friday	26.12.2003	433.72	420.33
Saturday	27.12.2003	447.88	433.78
Sunday	28.12.2003	417.12	427.41
Monday	29.12.2003	424.52	415.86
Tuesday	30.12.2003	468.32	390.75
Wednesday	31.12.2003	442.64	406.34

4.4. FORECASTING BY SIMPLE LINEAR REGRESSION

Based on the data at Table. Daily load maximum in Vikas Nagar Sub Station IIT Roorkee in January 2003, We can calculate the forecast for days 25, 26, 27, 28, 29, 30 and 31, as follows :

The estimated regression model : $y = \hat{\beta}_0 + \hat{\beta}_1 x$

$$SS_{xy} = \sum xy - \frac{(\sum x).(\sum y)}{n}$$

$$\sum xy = 141{,}261.81$$

$$\sum x = 300$$

$$\sum y = 11{,}093.11$$

$$n = 24$$

$$SS_{xy} = 141{,}261.81 - \frac{(300 \, x \, 11{,}093.11)}{24} = 2{,}597.94$$

$$SS_{xx} = \sum x^2 - \frac{(\sum x)^2}{n}$$

$$\sum x^2 = 4{,}900$$

$$SS_{xx} = 4{,}900 - \frac{(300)^2}{24} = 1{,}150$$

So,

$$\hat{\beta}_1 = \frac{SS_{xy}}{SS_{xx}}$$

$$\hat{\beta}_1 = \frac{2{,}597.94}{1{,}150} = 2.25$$

and,

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

$$\bar{x} = \frac{\sum x}{n} = \frac{300}{24} = 12.5$$

$$\bar{y} = \frac{\sum y}{n} = \frac{11{,}093.11}{24} = 462.21$$

$$\hat{\beta}_0 = 462.21 - (2.25 \text{ x } 12.5) = 434.09$$

The estimated regression model : $\hat{y} = 434.09 + 2.25x$

$X = 25$

$\hat{y}_{25} = 434.09 + (2.25 \text{ x } 25) = 490.34$

$X = 26$

$\hat{y}_{26} = 434.09 + (2.25 \text{ x } 26) = 492.59$

$X = 27$

$\hat{y}_{27} = 434.09 + (2.25 \text{ x } 27) = 494.84$

$X = 28$

$\hat{y}_{28} = 434.09 + (2.25 \text{ x } 28) = 497.09$

$X = 29$

$\hat{y}_{29} = 434.09 + (2.25 \text{ x } 29) = 499.34$

$X = 30$

$\hat{y}_{30} = 434.09 + (2.25 \text{ x } 30) = 501.59$

$X = 31$

$\hat{y}_{31} = 434.09 + (2.25 \text{ x } 31) = 503.84$

With same way, We get the forecast for daily load maximum in 2003 each month, as below:

Table. 4.5. Prediction Load with Simple Linear Regression Model

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	25.01.2003	443.42	490.34
Sunday	26.01.2003	399.70	492.59
Monday	27.01.2003	407.26	494.84
Tuesday	28.01.2003	459.08	497.09
Wednesday	29.01.2003	397.58	499.34
Thursday	30.01.2003	433.43	501.59
Friday	31.01.2003	415.50	503.84

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	22.02.2003	388.43	377.79
Sunday	23.02.2003	373.62	375.86
Monday	24.02.2003	307.72	373.93
Tuesday	25.02.2003	302.32	372.00
Wednesday	26.02.2003	319.41	370.07
Thursday	27.02.2003	363.83	368.14
Friday	28.02.2003	328.92	366.21

Day	Date	Actual Load (kW)	Prediction Load (kW)
Tuesday	25.03.2003	331.30	365.04
Wednesday	26.03.2003	332.19	364.42
Thursday	27.03.2003	376.03	363.80
Friday	28.03.2003	423.94	363.18
Saturday	29.03.2003	380.70	362.56
Sunday	30.03.2003	385.98	361.94
Monday	31.03.2003	361.72	361.32

Continued of Table 4.5.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Thursday	24.04.2003	382.00	432.63
Friday	25.04.2003	417.15	433.93
Saturday	26.04.2003	434.95	435.23
Sunday	27.04.2003	383.84	436.53
Monday	28.04.2003	353.90	437.83
Tuesday	29.04.2003	384.62	431.73
Wednesday	30.04.2003	427.97	440.43

Day	Date	Actual Load (kW)	Prediction Load (kW)
Sunday	25.05.2003	490.78	487.61
Monday	26.05.2003	550.02	487.96
Tuesday	27.05.2003	413.42	488.31
Wednesday	28.05.2003	506.91	488.66
Thursday	29.05.2003	492.34	489.01
Friday	30.05.2003	546.74	489.36
Saturday	31.05.2003	515.65	489.71

Day	Date	Actual Load (kW)	Prediction Load (kW)
Tuesday	24.06.2003	422.93	428.46
Wednesday	25.06.2003	540.26	422.46
Thursday	26.06.2003	473.93	416.46
Friday	27.06.2003	472.56	410.46
Saturday	28.06.2003	418.76	404.46
Sunday	29.06.2003	513.24	398.46
Monday	30.06.2003	438.70	392.46

Continued of Table 4.5.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Friday	25.07.2003	642.06	467.43
Saturday	26.07.2003	592.25	465.74
Sunday	27.07.2003	584.98	464.05
Monday	28.07.2003	522.22	462.36
Tuesday	29.07.2003	417.78	460.67
Wednesday	30.07.2003	504.23	458.98
Thursday	31.07.2003	495.62	457.29

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	25.08.2003	476.29	475.63
Tuesday	26.08.2003	547.83	473.26
Wednesday	27.08.2003	421.06	470.89
Thursday	28.08.2003	446.37	468.52
Friday	29.08.2003	516.55	466.15
Saturday	30.08.2003	419.91	463.78
Sunday	31.08.2003	521.54	461.41

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	24.09.2003	547.15	454.13
Tuesday	25.09.2003	374.72	450.05
Wednesday	26.09.2003	457.88	445.97
Thursday	27.09.2003	433.88	441.89
Friday	28.09.2003	459.08	437.81
Saturday	29.09.2003	407.59	433.73
Sunday	30.09.2003	411.51	429.65

Continued of Table 4.5.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	25.10.2003	545.81	417.04
Sunday	26.10.2003	455.96	416.83
Monday	27.10.2003	450.35	416.62
Tuesday	28.10.2003	446.74	416.41
Wednesday	29.10.2003	401.27	416.20
Thursday	30.10.2003	410.46	415.99
Friday	31.10.2003	358.08	415.78

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	24.11.2003	375.10	408.24
Tuesday	25.11.2003	383.48	407.90
Wednesday	26.11.2003	418.90	407.56
Thursday	27.11.2003	416.65	407.22
Friday	28.11.2003	501.60	406.88
Saturday	29.11.2003	402.05	406.54
Sunday	30.11.2003	350.61	406.20

Day	Date	Actual Load (kW)	Prediction Load (kW)
Thursday	25.12.2003	396.73	401.31
Friday	26.12.2003	433.72	400.58
Saturday	27.12.2003	447.88	399.85
Sunday	28.12.2003	417.12	399.12
Monday	29.12.2003	424.52	398.39
Tuesday	30.12.2003	468.32	397.66
Wednesday	31.12.2003	442.64	396.93

4.5. MEAN ABSOLUTE DEVIATION (MAD) AND MEAN ABSOLUTE PERCENT ERROR (MAPE)

The calculation of the MAD and MAPE for the load of Table 4.2. Prediction Load with Moving Average Model on January 2003 would look as follows:

$$\text{MAD} = \frac{\sum |forecast\ error|}{no.of\ forecasts}$$

$$= \frac{\sum \left| y_t - \hat{y}_t \right|}{n} = \frac{\sum |e_t|}{n}$$

The error of the forecast for day 25 is : 443.42 – 497.85 = - 54.43

The absolute value of – 54.43 = $|-54.43|$ = 54.43

The error of the forecast for day 26 is : 399.70 – 453.79 = - 54.09

The absolute value of – 54.09 = $|-54.09|$ = 54.09

The error of the forecast for day 27 is : 407.26 – 416.79 = - 9.53

The absolute value of – 9.53 = $|-9.53|$ = 9.53

The error of the forecast for day 28 is : 459.08 – 422.01 = 37.07

The error of the forecast for day 29 is : 397.58 – 421.31 = - 23.73

The absolute value of – 23.73 = $|-23.73|$ = 23.73

The error of the forecast for day 30 is : 433.43 – 430.03 = 3.40

The error of the forecast for day 31 is : 415.50 – 415.50 = 0

Total error of the forecast is :

$54.43 + 54.09 + 9.53 + 37.07 + 23.73 + 3.40 + 0 = 182.25$

Number of forecasts is 7

$$\textbf{MAD} = \frac{182.25}{7} = 26.04$$

$$\textbf{MAPE} = \frac{\sum \left| \frac{forecast\ error}{actual\ value} \right|}{no.of\ forecasts} = \frac{\sum \left| \frac{e_t}{y_t} \right|}{n} \cdot 100\ \%$$

The forecast error / actual value for day 25 is : 54.43 / 443.42 = 0.12

The forecast error / actual value for day 26 is : 54.09 / 399.70 = 0.14

The forecast error / actual value for day 27 is : 9.53 / 407.26 = 0.02

The forecast error / actual value for day 28 is : 37.07 / 459.08 = 0.08

The forecast error / actual value for day 29 is : 23.73 / 397.58 = 0.06

The forecast error / actual value for day 30 is : 3.40 / 433.43 = 0.01

The forecast error / actual value for day 31 is : 0 / 415.50 = 0

Total the forecast error / actual value is :

$0.12 + 0.14 + 0.02 + 0.08 + 0.06 + 0.01 + 0 = 0.43$

$$\textbf{MAPE} = \frac{0.43}{7} \times 100\ \% = 6.14\ \%$$

With same way, We get MAD and MAPE for each forecasting model month, is shown in Table 4.6. Comparison MAD and MAPE in Time Series and Regression Analysis Model.

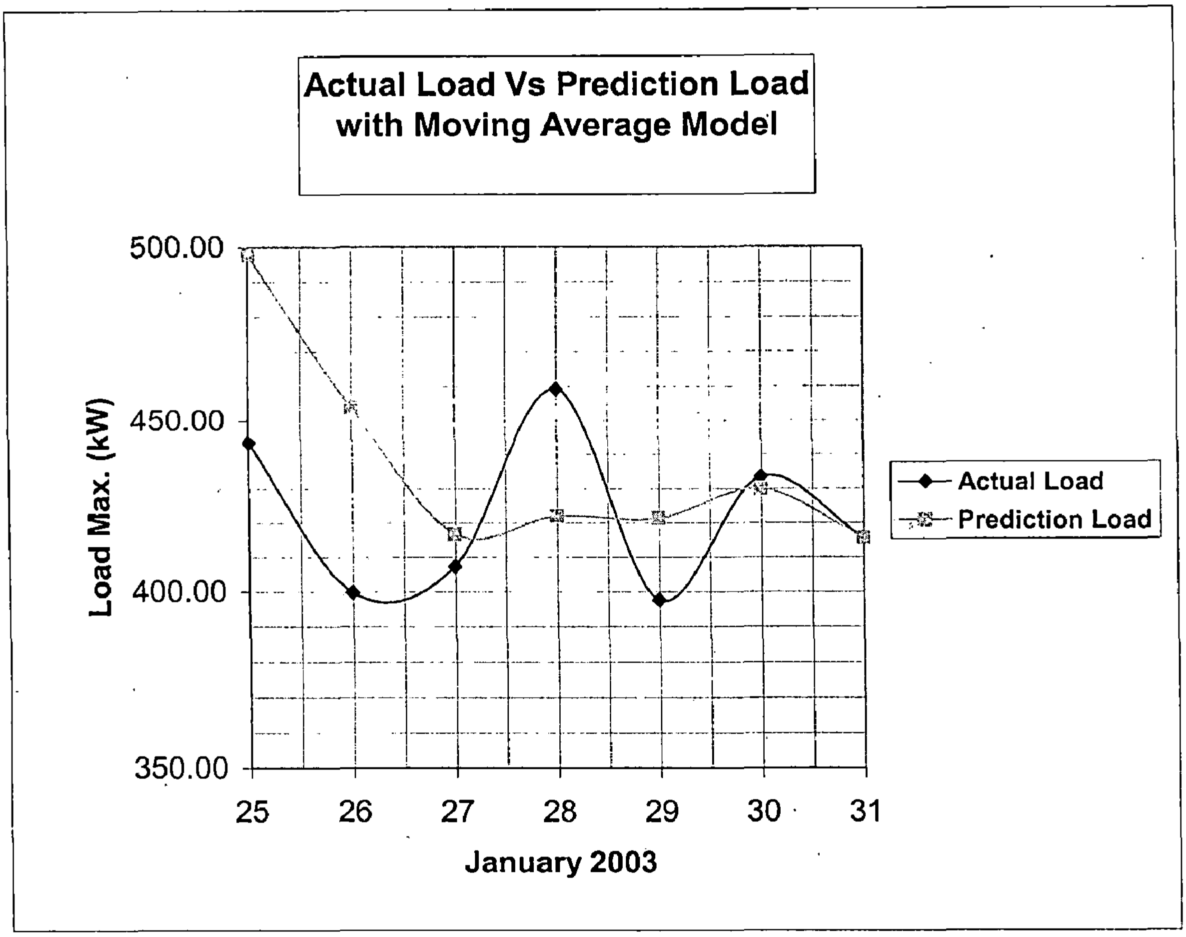
Tabel 4.1. Daily Maximum Load in Vikas Nagar Sub Station During 2003

Day	Jan (kW)	Feb (kW)	March (kW)	April (kW)	May (kW)	June (kW)	July (kW)	August (kW)	Sept (kW)	Oct (kW)	Nov (kW)	Dec (kW)
1	372.75	445.85	356.11	469.44	514.20	506.20	531.89	501.43	563.72	455.58	434.67	373.86
2	388.96	359.43	374.96	424.68	477.35	582.21	508.99	460.92	593.71	384.25	440.46	409.15
3	477.71	398.82	423.05	424.52	433.76	527.97	503.32	396.74	433.10	433.50	394.44	483.12
4	439.28	468.15	330.08	397.40	506.36	645.68	498.58	578.51	625.84	394.19	427.89	408.79
5	456.89	428.73	344.07	382.09	424.52	602.16	436.08	567.24	536.11	468.15	452.95	418.33
6	402.85	475.05	384.58	339.89	465.19	557.91	489.76	624.37	493.52	401.27	425.83	426.28
7	451.96	380.51	454.43	444.84	471.52	482.04	599.33	567.56	411.51	416.65	393.45	407.67
8	418.44	409.23	365.71	335.27	462.56	522.02	542.48	520.61	568.32	359.38	394.44	420.45
9	517.73	328.52	363.27	426.28	481.79	515.85	543.01	507.43	499.30	425.17	416.35	324.56
10	444.84	377.40	391.25	431.97	481.94	481.52	464.95	511.02	500.58	475.05	349.27	429.50
11	515.40	353.90	371.12	348.42	509.61	536.89	414.92	545.81	528.96	481.98	438.79	440.46
12	514.63	329.03	377.84	388.28	514.63	477.35	377.35	491.95	490.34	416.05	459.25	407.59
13	567.99	425.15	392.22	402.82	525.32	440.13	476.45	462.70	472.59	362.75	339.71	449.22
14	544.55	424.02	398.47	495.24	478.78	462.56	484.79	567.56	622.39	424.02	378.54	421.74
15	444.40	424.02	378.69	419.09	471.40	548.05	546.74	385.67	500.45	467.21	387.46	397.56
16	517.80	393.34	330.10	437.58	517.05	467.37	487.41	537.68	469.48	395.86	429.50	442.92
17	416.35	450.35	342.77	455.51	502.03	431.58	468.95	519.21	471.48	416.46	425.64	359.21
18	479.55	477.30	335.79	408.79	445.94	381.62	518.25	517.73	483.19	404.92	356.11	378.50
19	453.61	371.02	380.31	427.10	553.97	523.35	412.64	499.62	450.94	392.76	425.12	420.60
20	258.04	317.02	384.58	482.86	552.35	430.83	515.85	536.78	495.84	427.10	449.29	422.22
21	467.19	342.74	362.67	402.36	468.23	439.36	475.05	470.62	462.37	341.03	387.87	442.53
22	492.05	388.43	327.88	427.80	408.12	485.38	475.05	550.30	527.67	427.56	468.78	443.33
23	531.89	373.62	413.42	419.64	440.24	462.71	474.03	416.46	369.79	421.56	407.59	360.35
24	518.25	307.72	363.76	382.00	491.00	422.93	479.66	388.43	547.15	479.71	375.10	362.76
25	443.42	302.32	331.30	417.15	490.78	540.26	642.06	476.29	374.72	545.81	383.48	396.73
26	399.70	319.41	332.19	434.95	550.02	473.93	592.25	547.83	457.88	455.96	418.90	433.72
27	407.26	363.83	376.03	383.84	413.42	472.56	584.98	421.06	433.88	450.35	416.65	447.88
28	459.08	328.92	423.94	353.90	506.91	418.76	522.22	446.37	459.08	446.74	501.60	417.12
29	397.58	-	380.70	384.62	492.34	513.24	417.78	516.55	407.59	401.27	402.05	424.52
30	433.43	-	385.98	427.97	546.74	438.70	504.23	419.91	411.51	410.46	350.61	468.32
31	415.50	-	361.72	-	515.65	-	495.62	521.54	-	358.08	-	442.64

Table 4.6. MAD and MAPE in Time Series and Regression Analysis Model

FORECASTING	Jan ' 03		Feb '03		March '03		April '03		May '03		June '03	
MODEL	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)
Moving Average	26.04	6.14	24.60	7.30	23.24	6.23	25.29	6.42	28.54	5.96	32.39	6.80
Exponential Smoothing	54.58	13.22	31.94	9.53	26.50	7.05	28.76	7.45	34.98	7.22	38.01	8.02
ARIMA	39.73	9.55	37.27	11.40	17.11	4.55	38.87	10.14	40.31	8.54	34.81	6.98
Simple Linear Regression	74.81	18.03	34.43	10.90	25.93	6.94	37.70	9.99	35.00	7.12	59.75	12.10

FORECASTING	July '03		Aug '03		Sept '03		Oct '03		Nov '03		Dec '03	
MODEL	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)
Moving Average	47.60	9.10	49.15	10.25	26.35	5.98	30.24	6.76	35.06	8.74	19.50	4.49
Exponential Smoothing	65.46	12.12	63.92	12.68	51.31	10.65	54.11	12.80	39.18	9.49	42.72	9.76
ARIMA	42.67	7.54	60.16	12.55	54.43	12.48	52.39	11.86	37.21	8.73	24.61	5.50
Simple Linear Regression	86.91	15.38	43.09	8.90	36.26	8.14	44.30	9.66	33.30	8.00	35.18	7.91



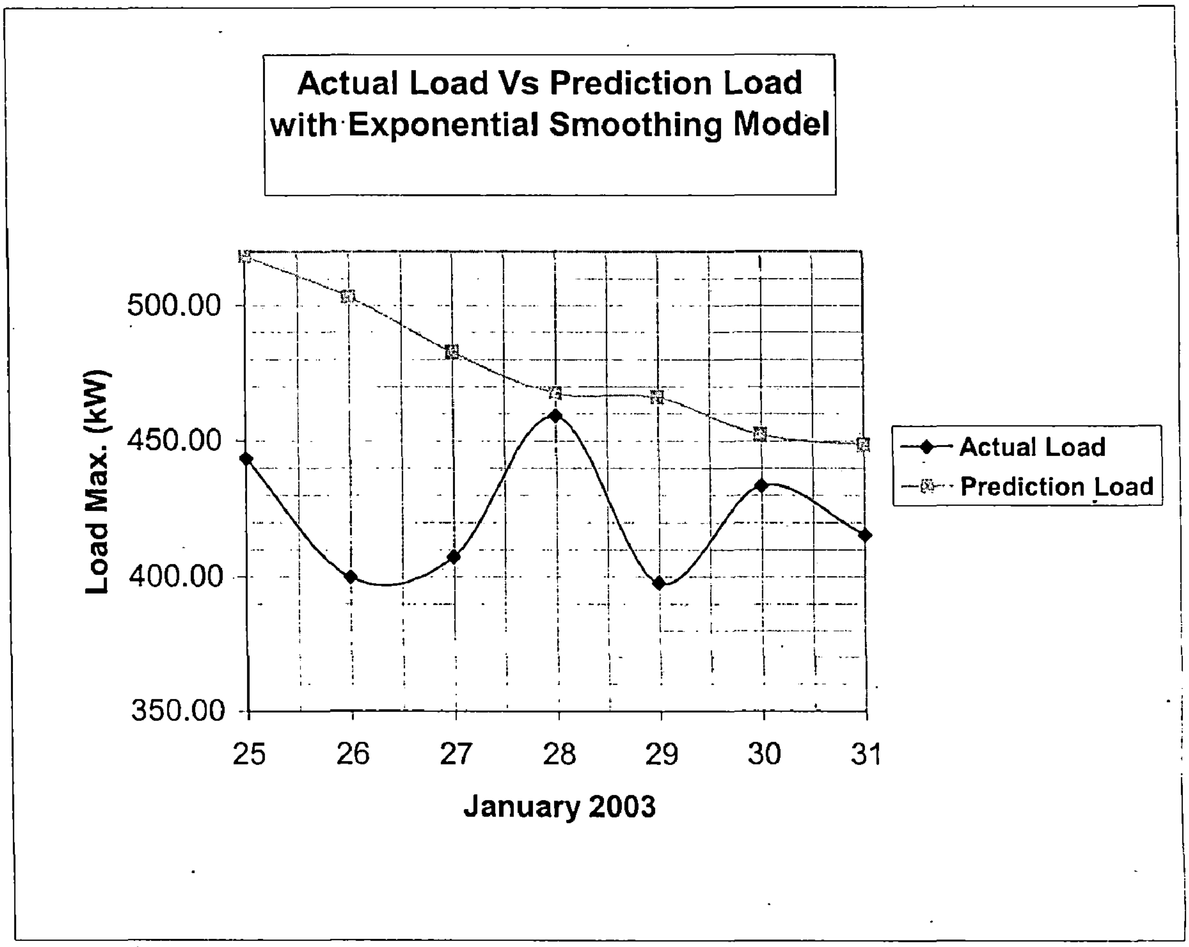
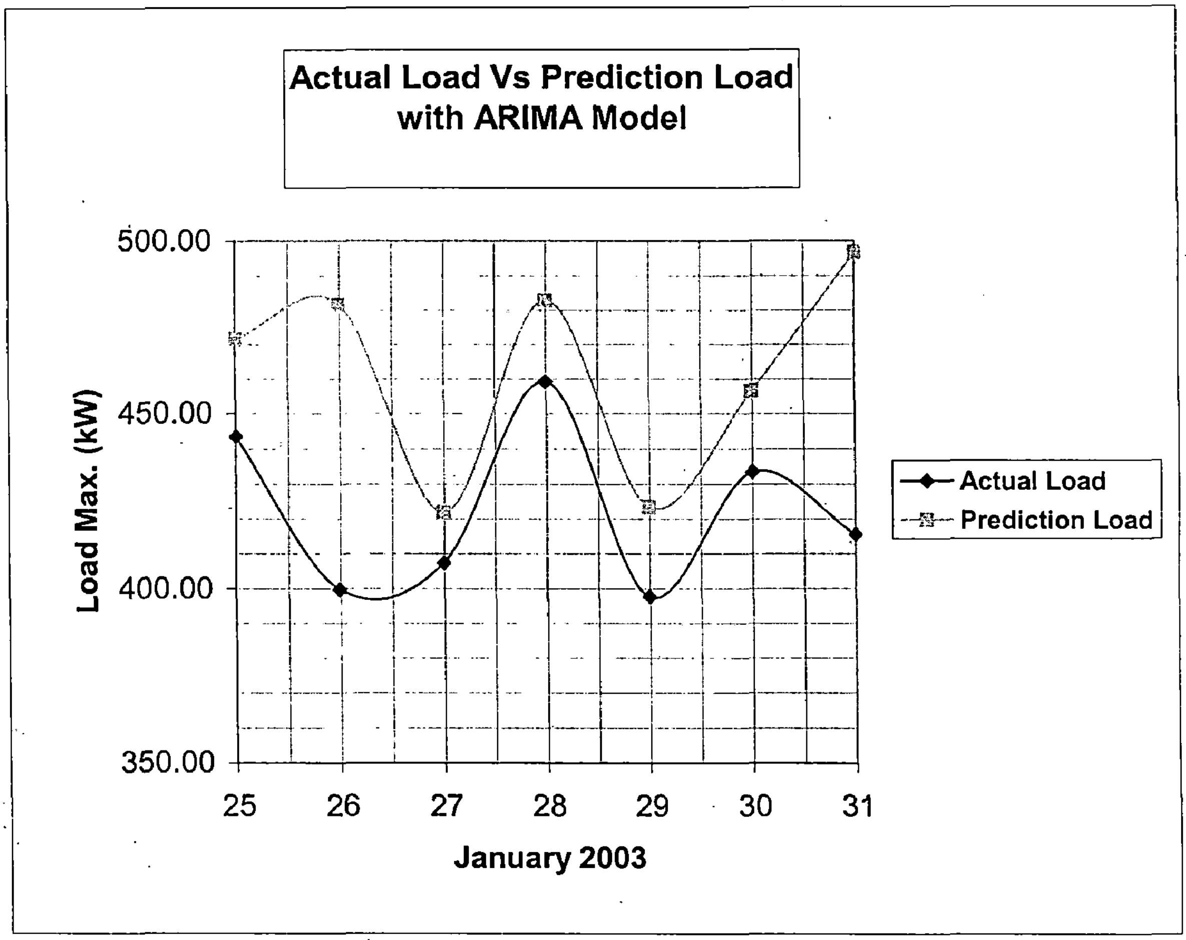
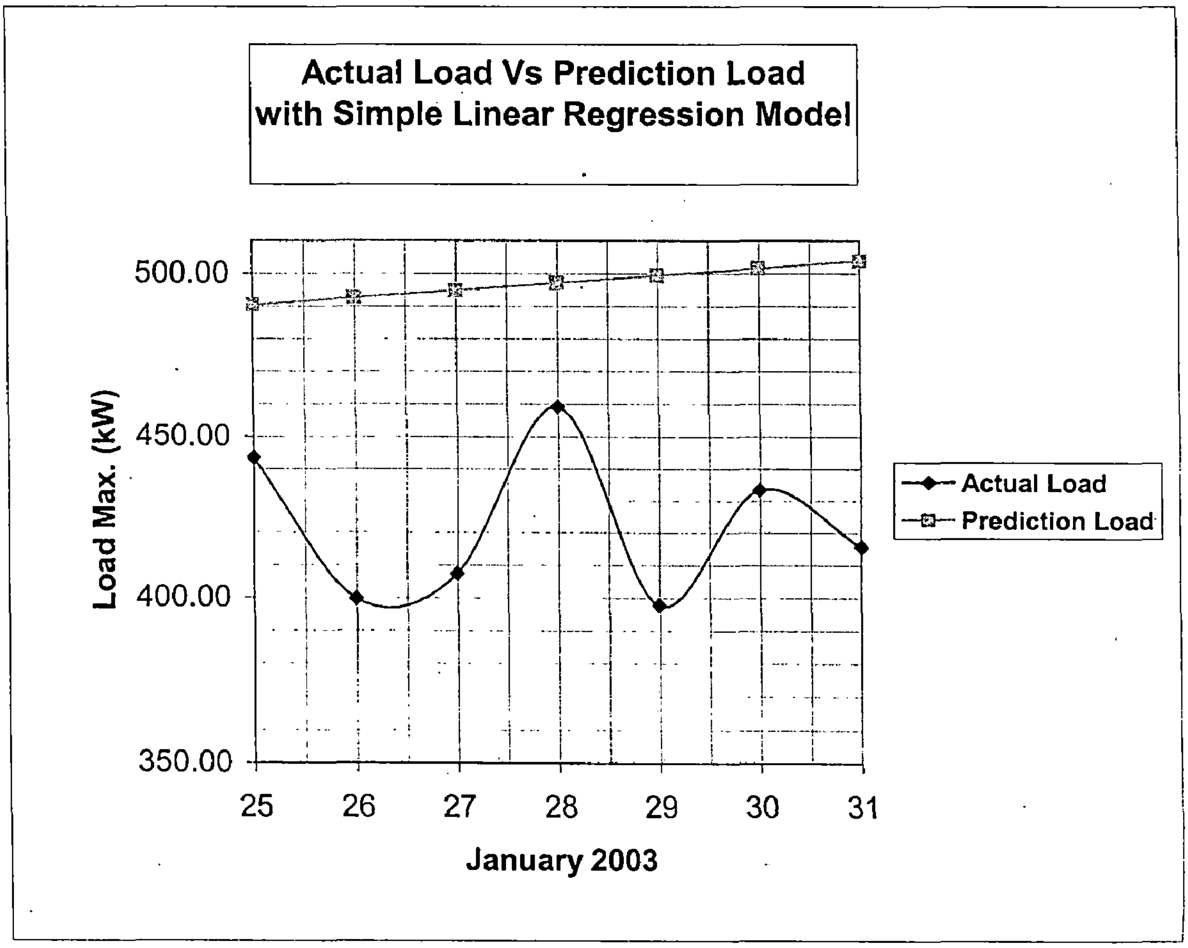
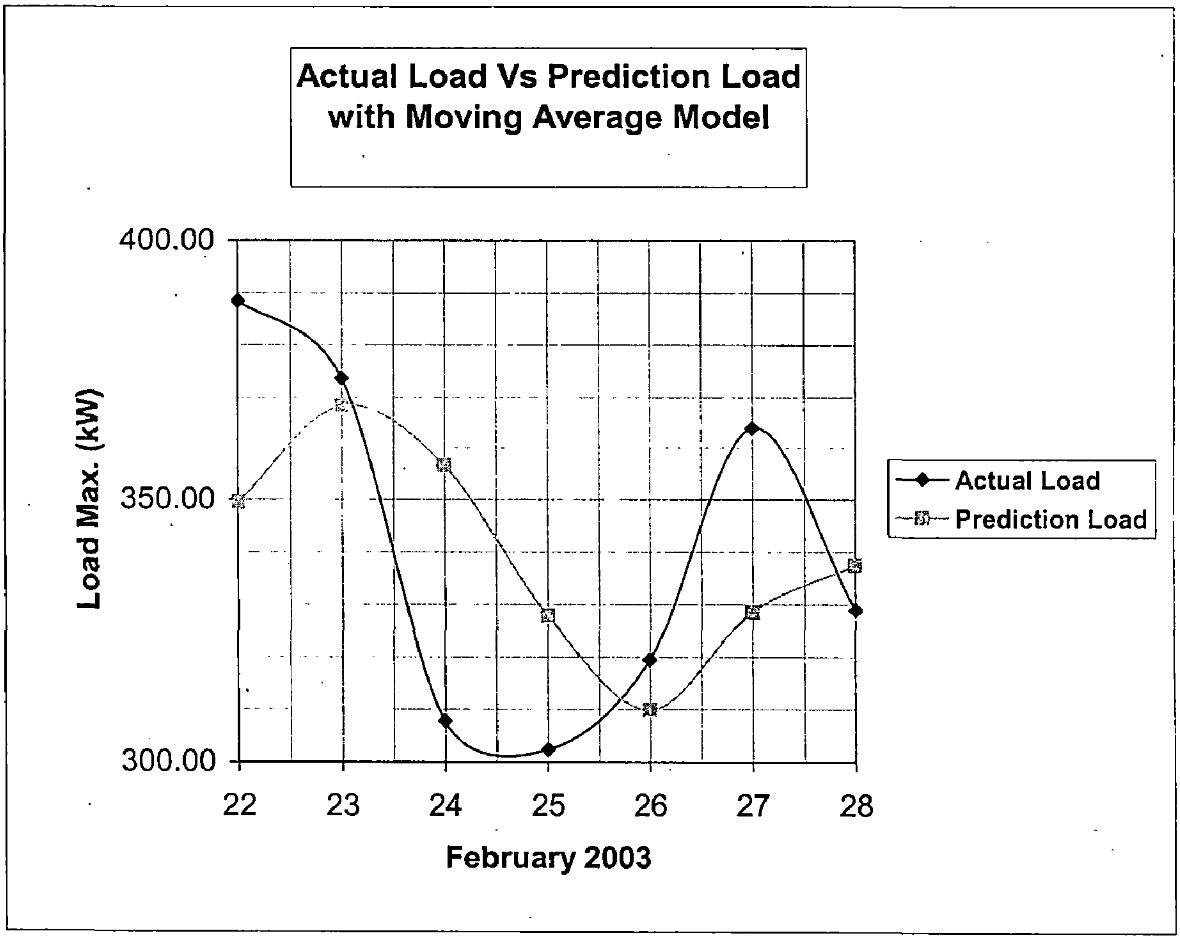


Figure 4.1. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on January 2003

Continued of Figure 4.1.







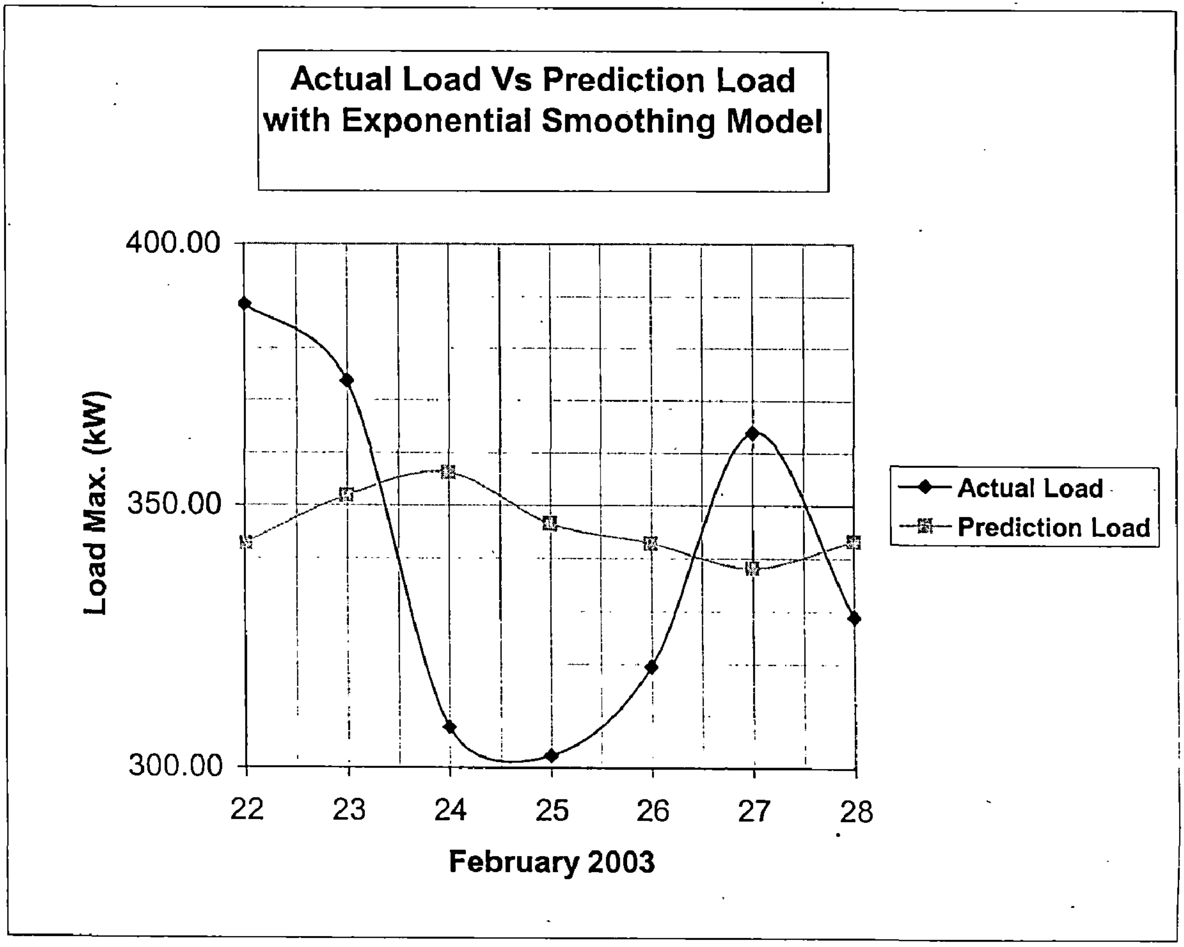
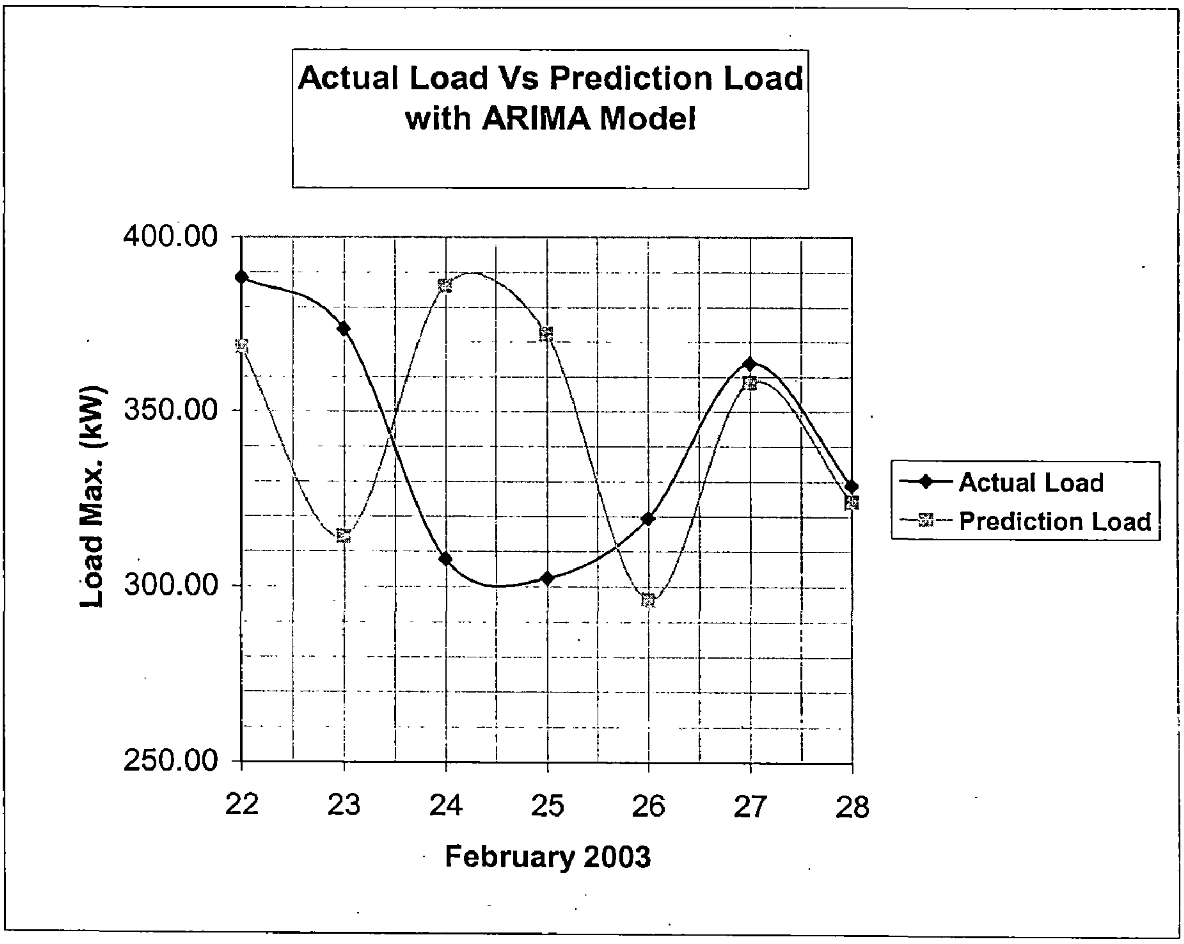
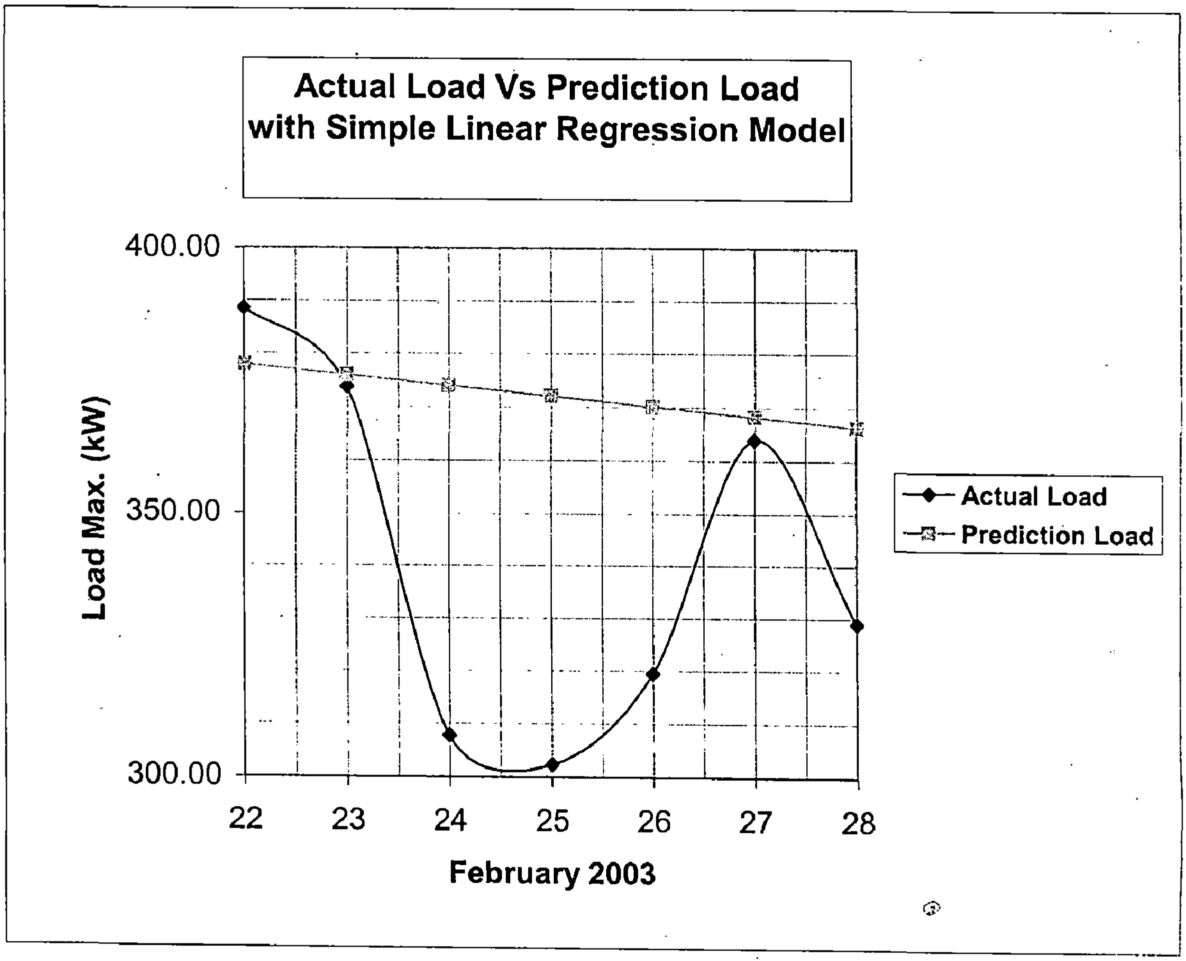
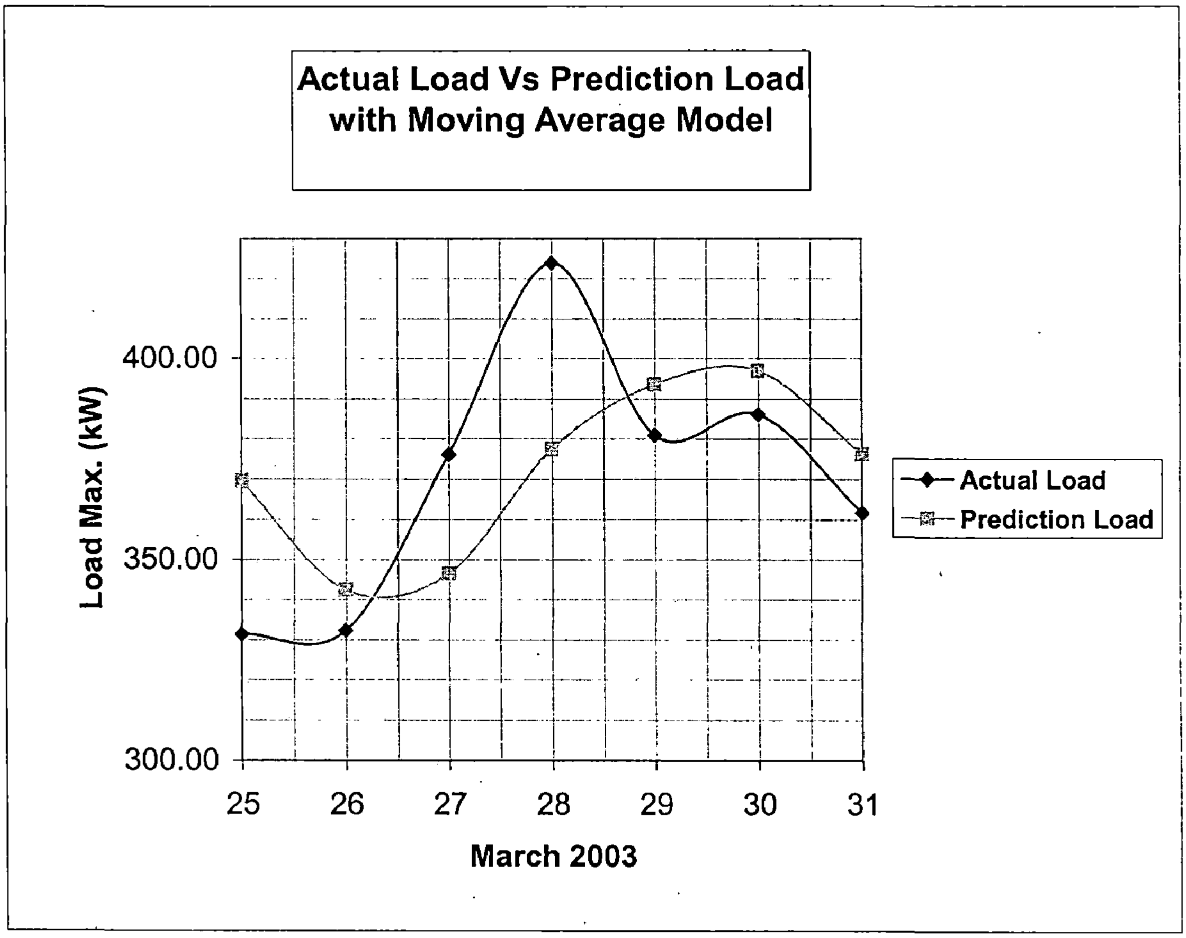


Figure 4.2. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on February 2003

Continued of Figure 4.2.







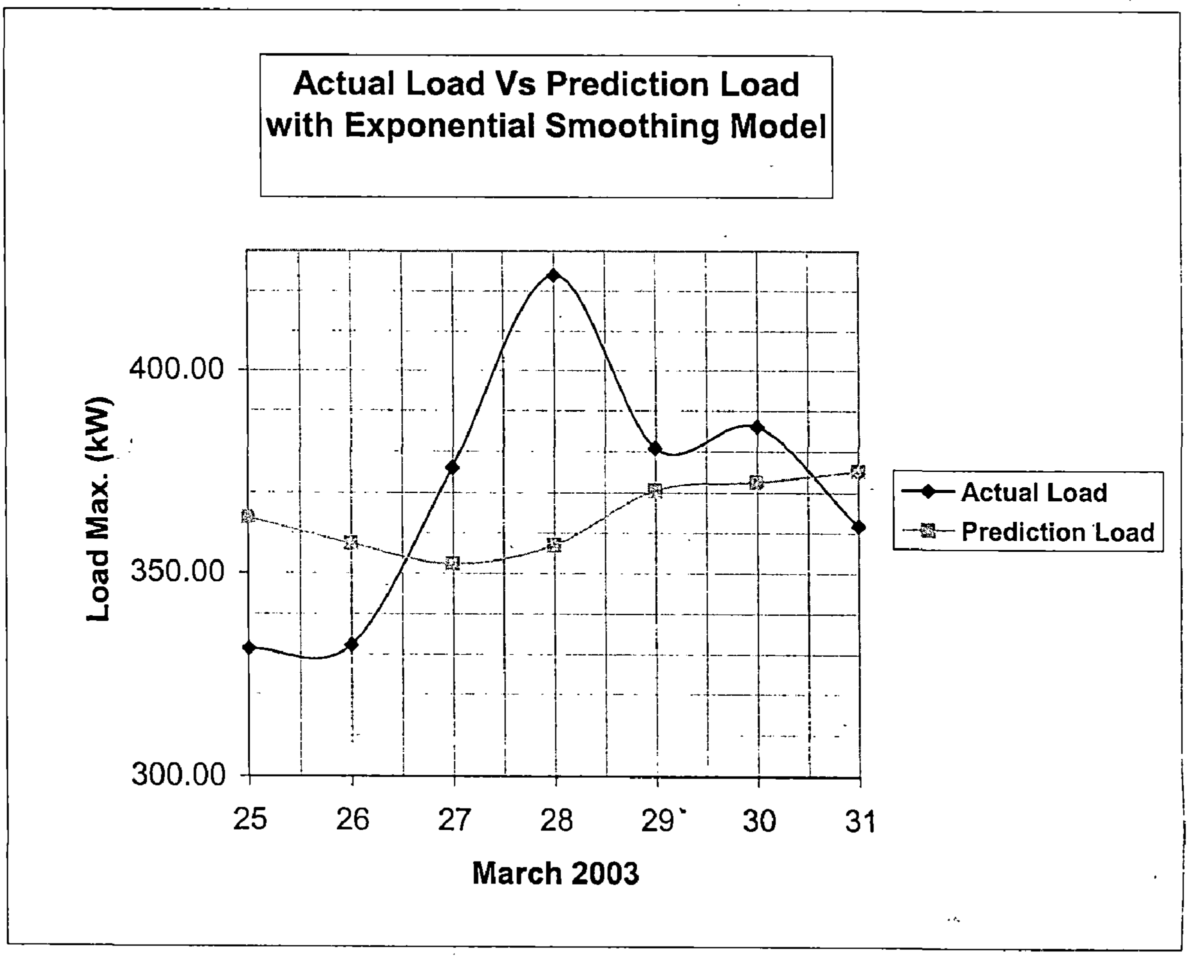
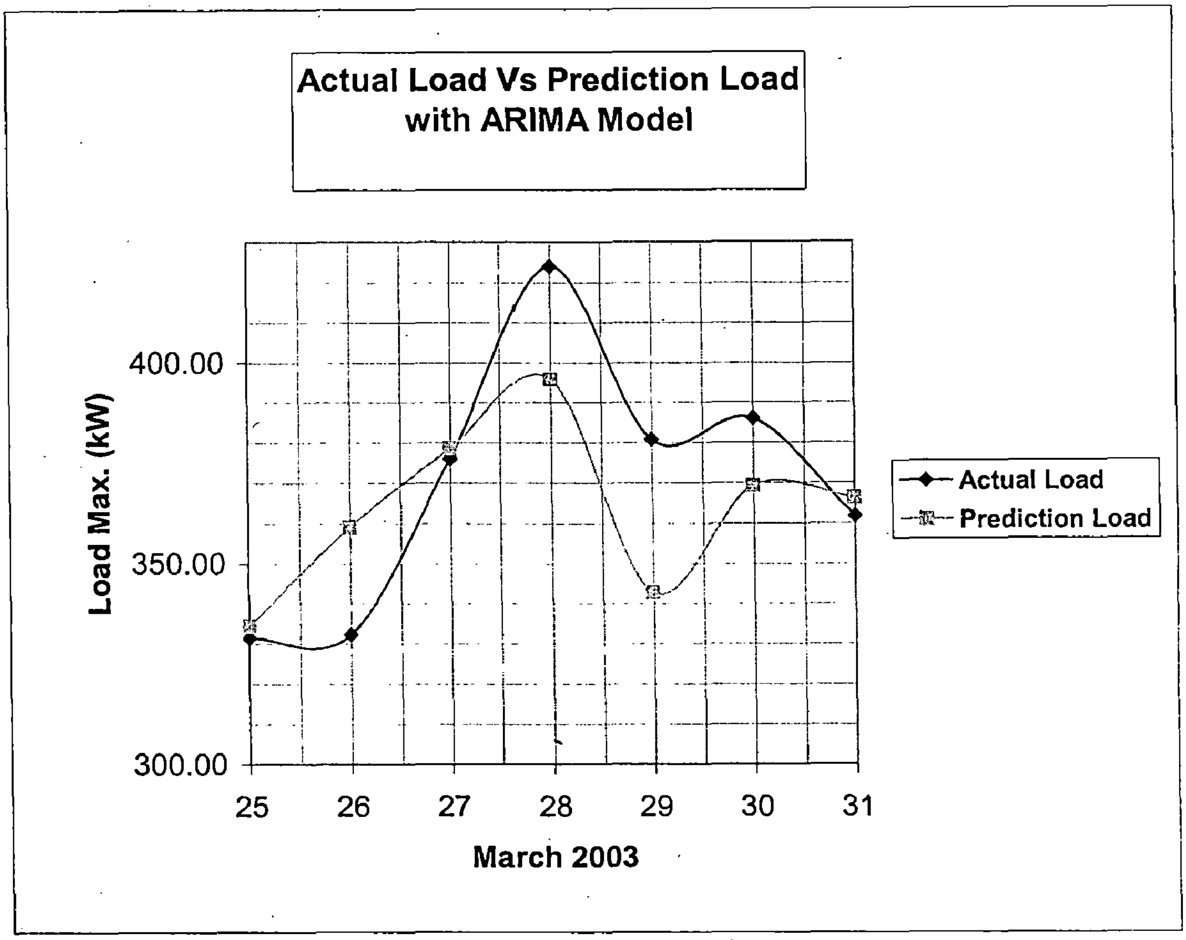
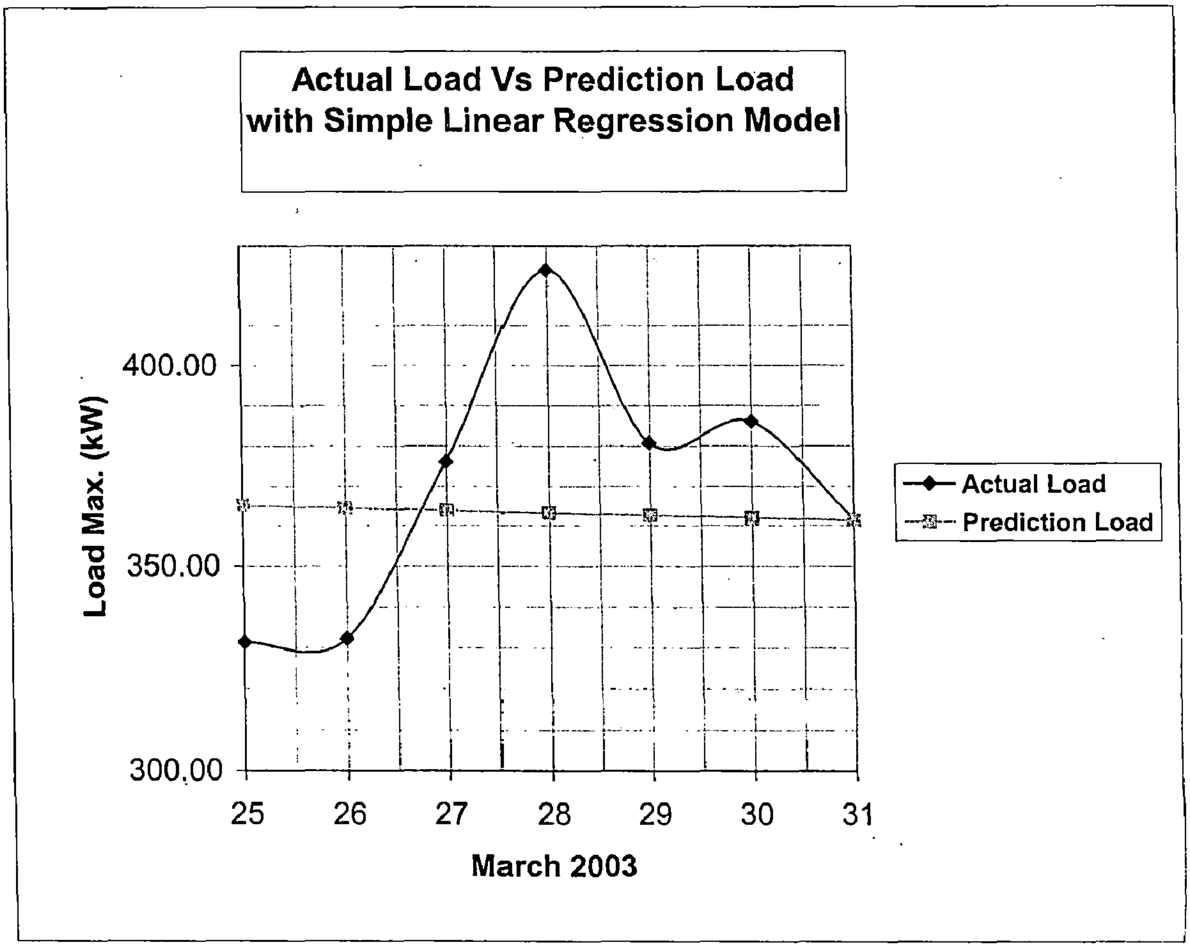
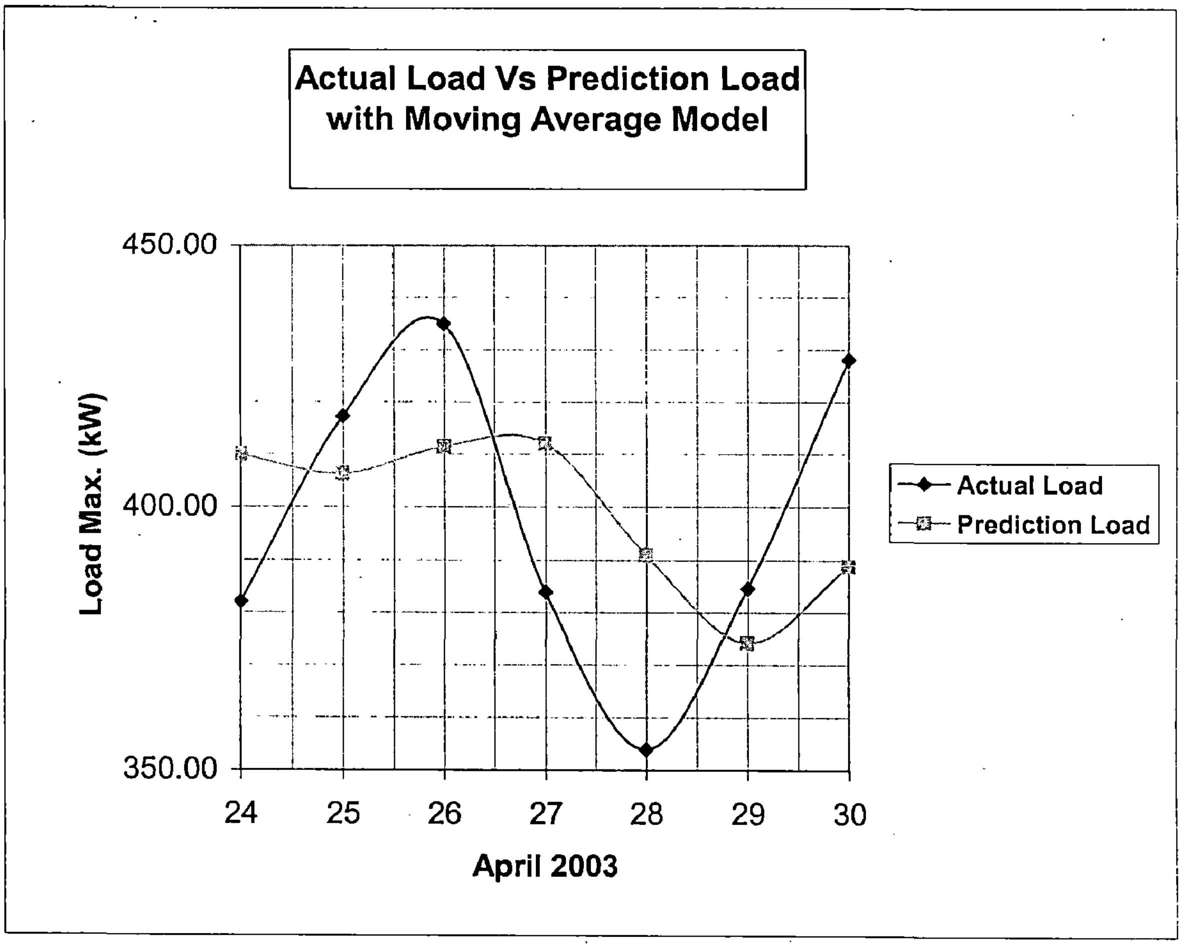


Figure 4.3. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on March 2003

Continued of Figure 4.3.







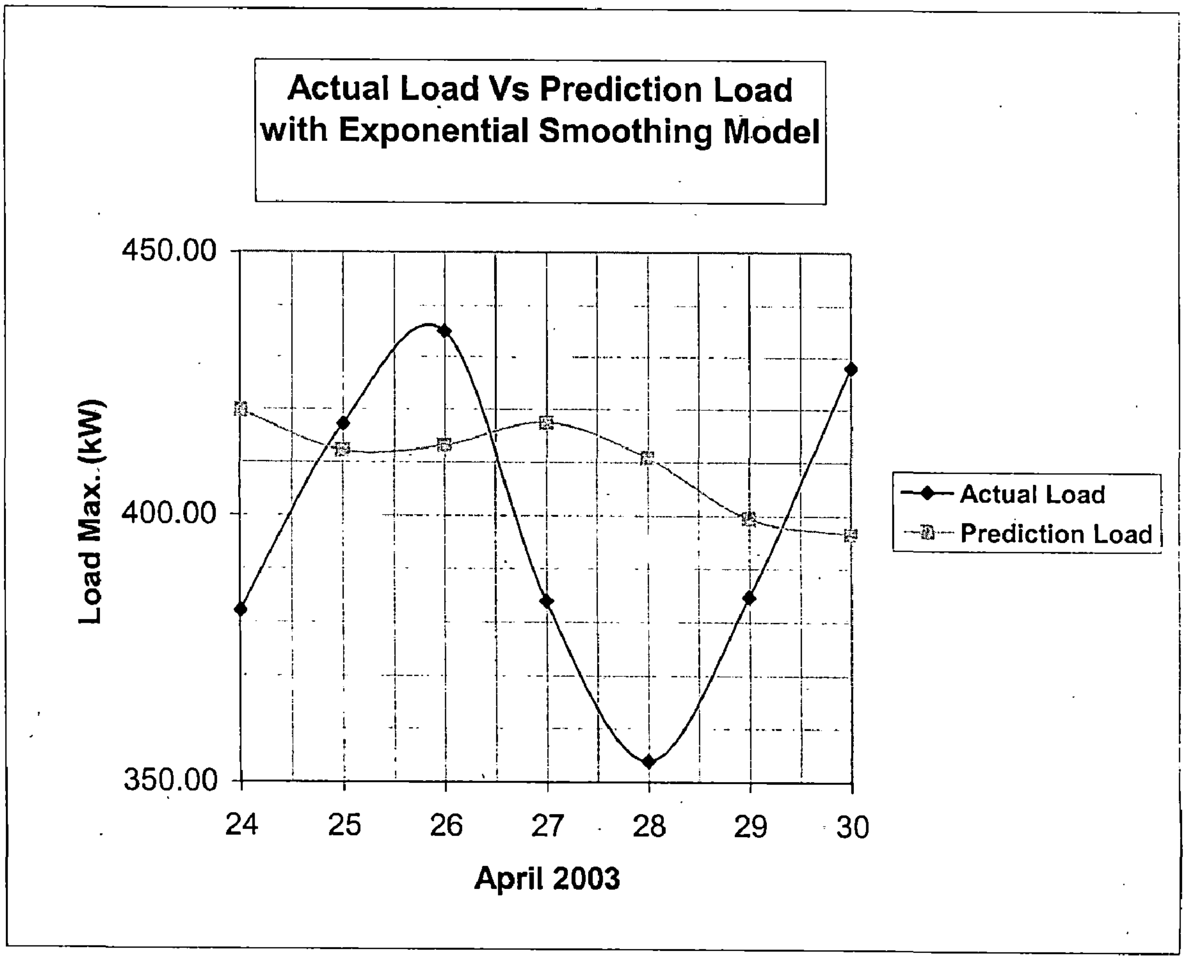
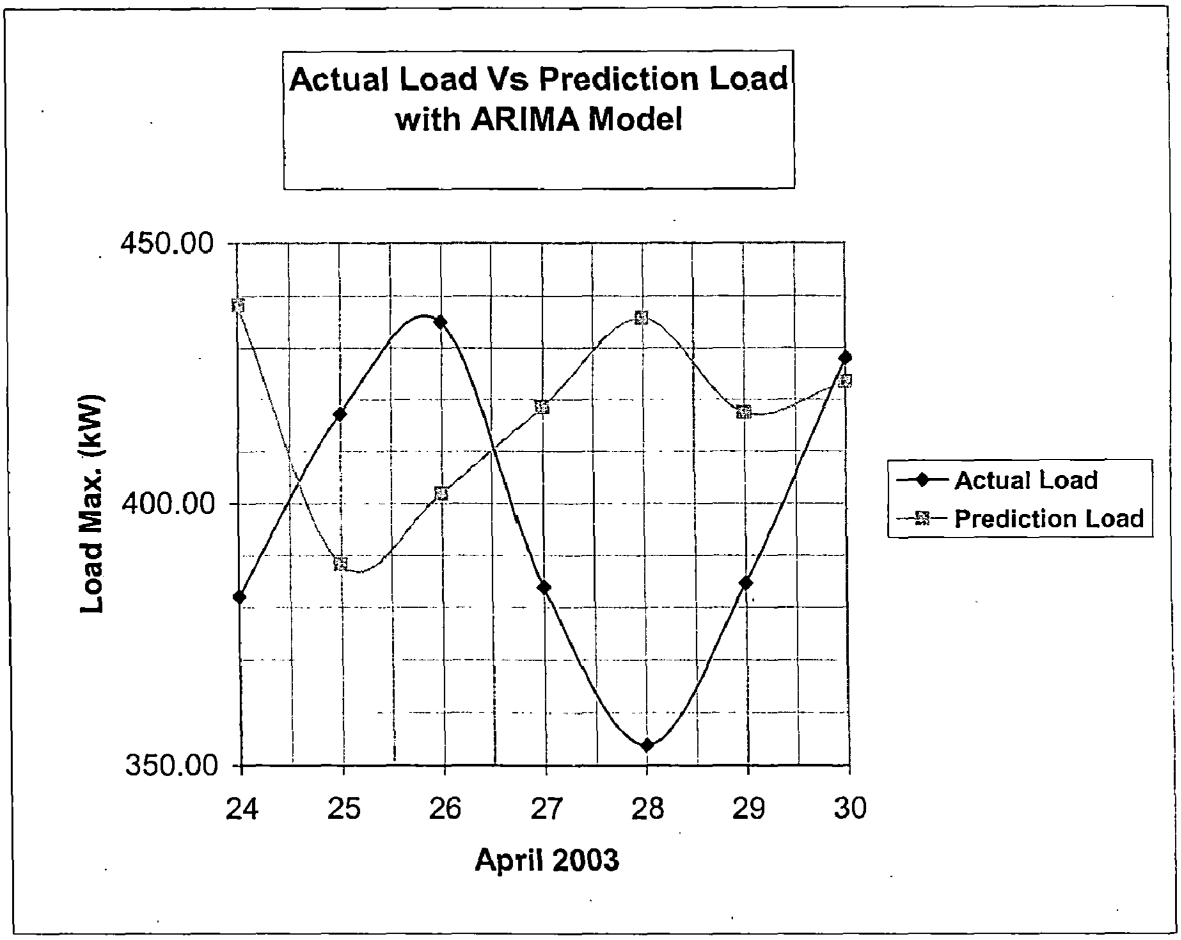
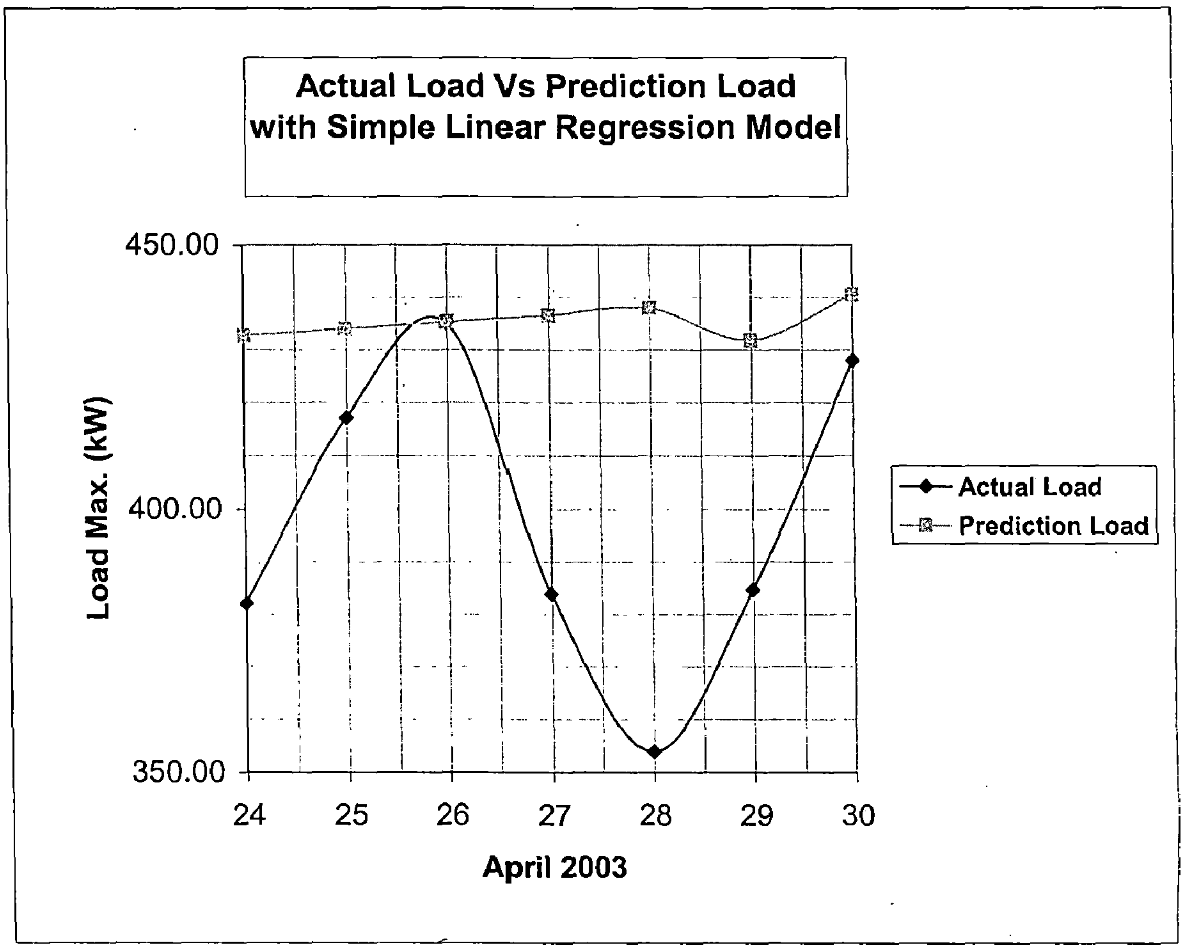
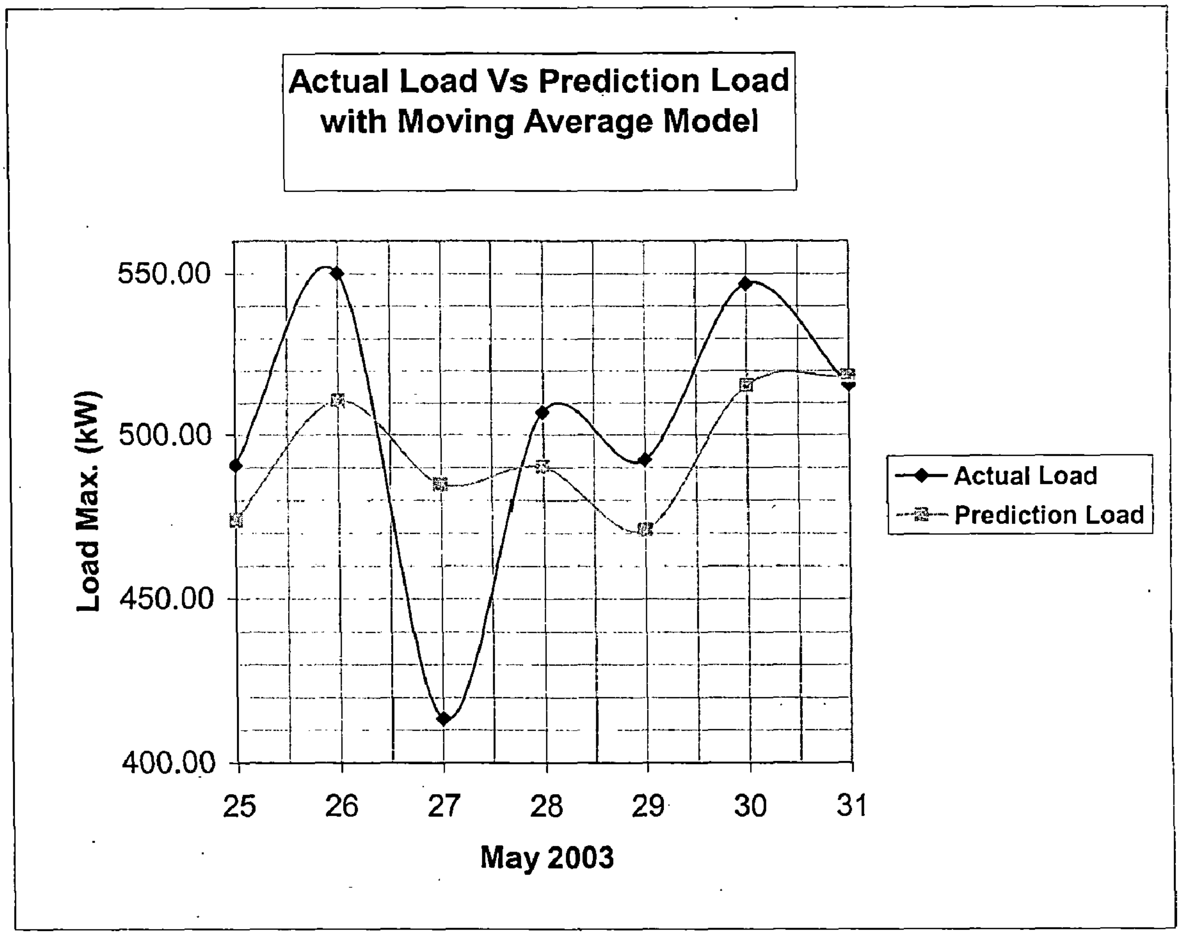


Figure 4.4. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on April 2003

Continued of Figure 4.4.







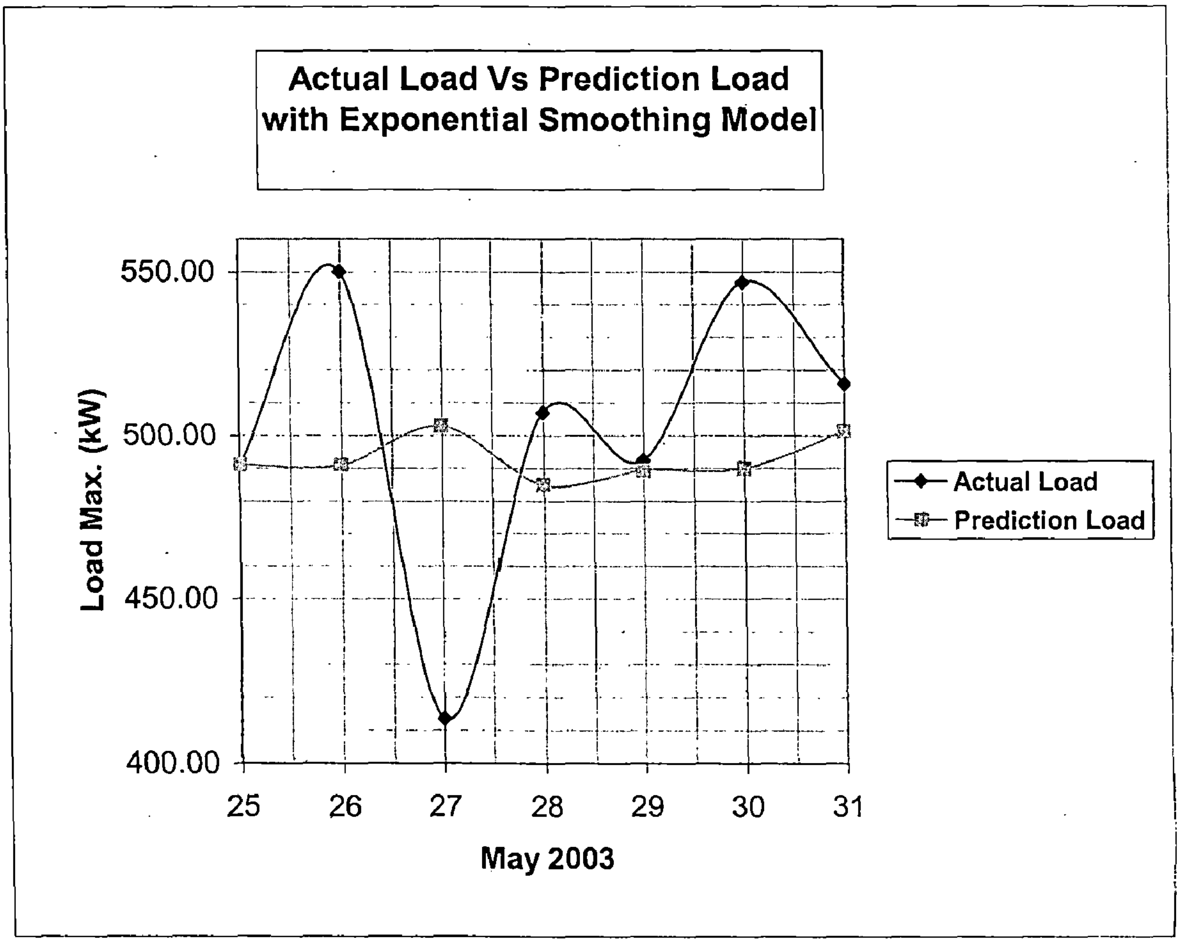
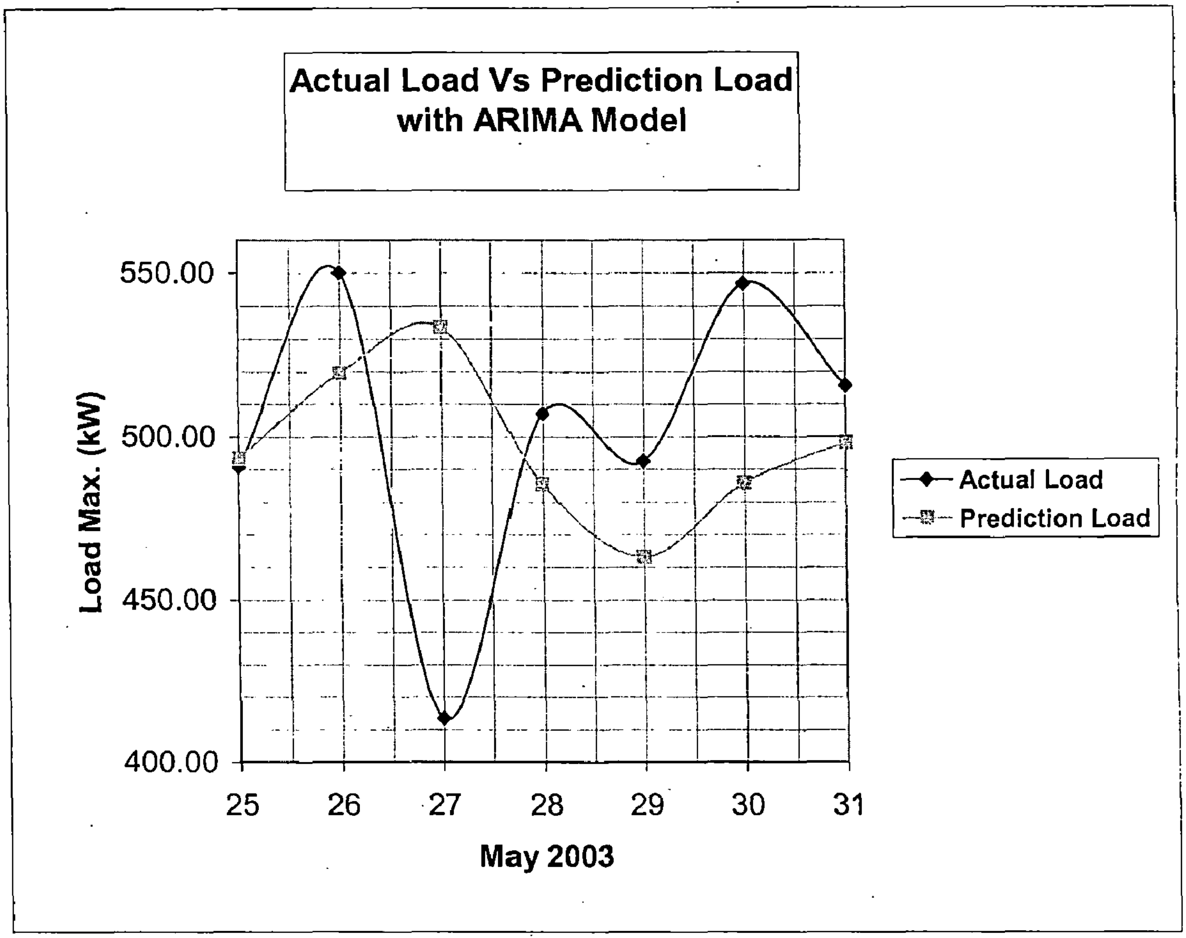
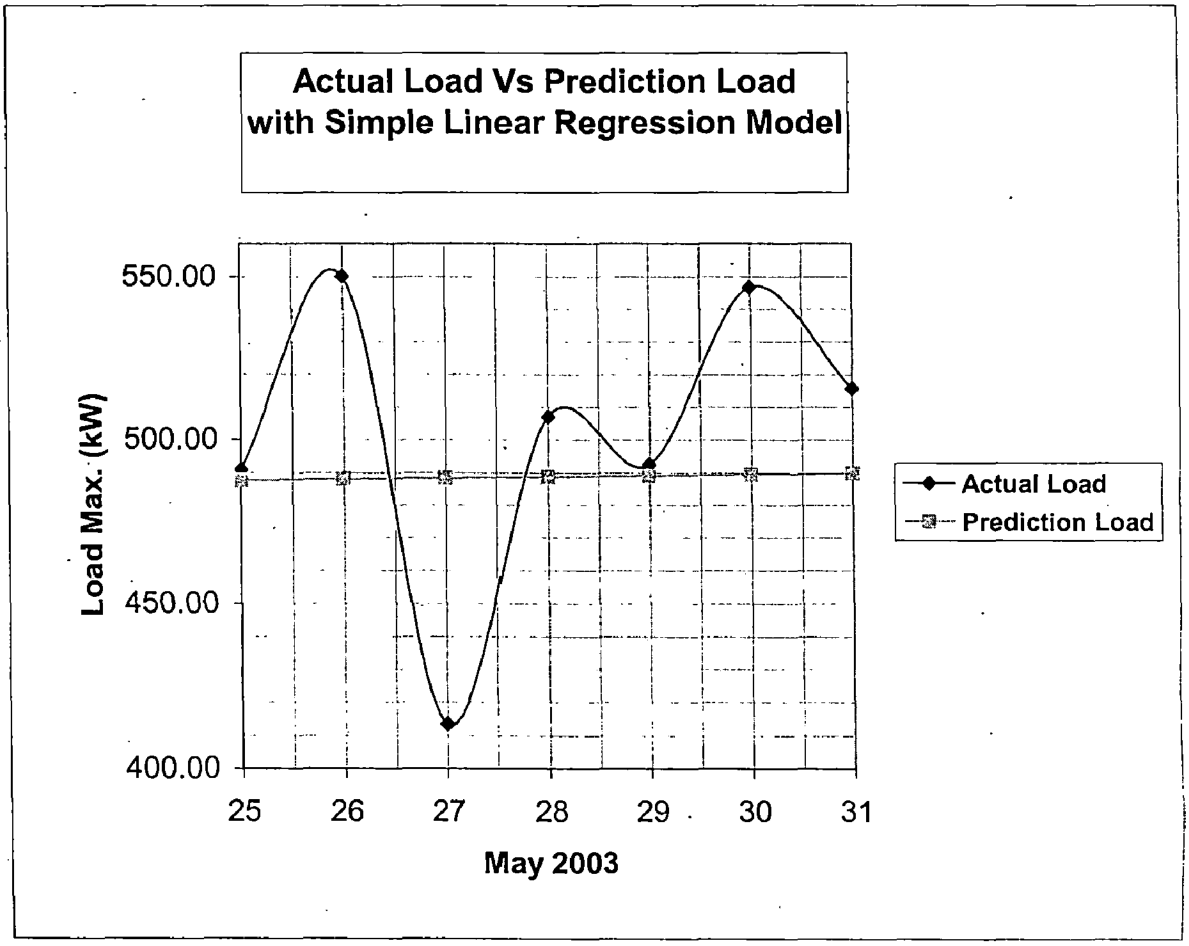
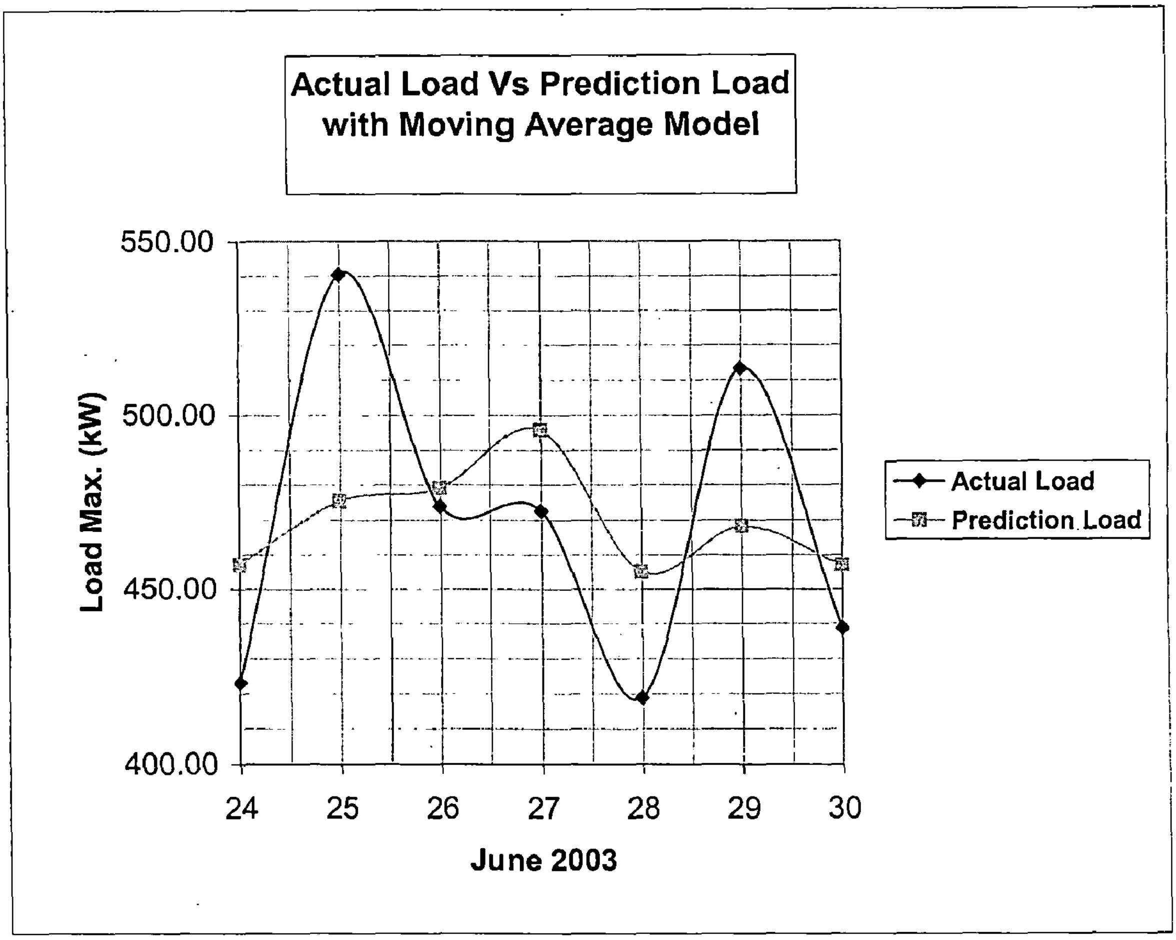


Figure 4.5. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on May 2003

Continued of Figure 4.5.







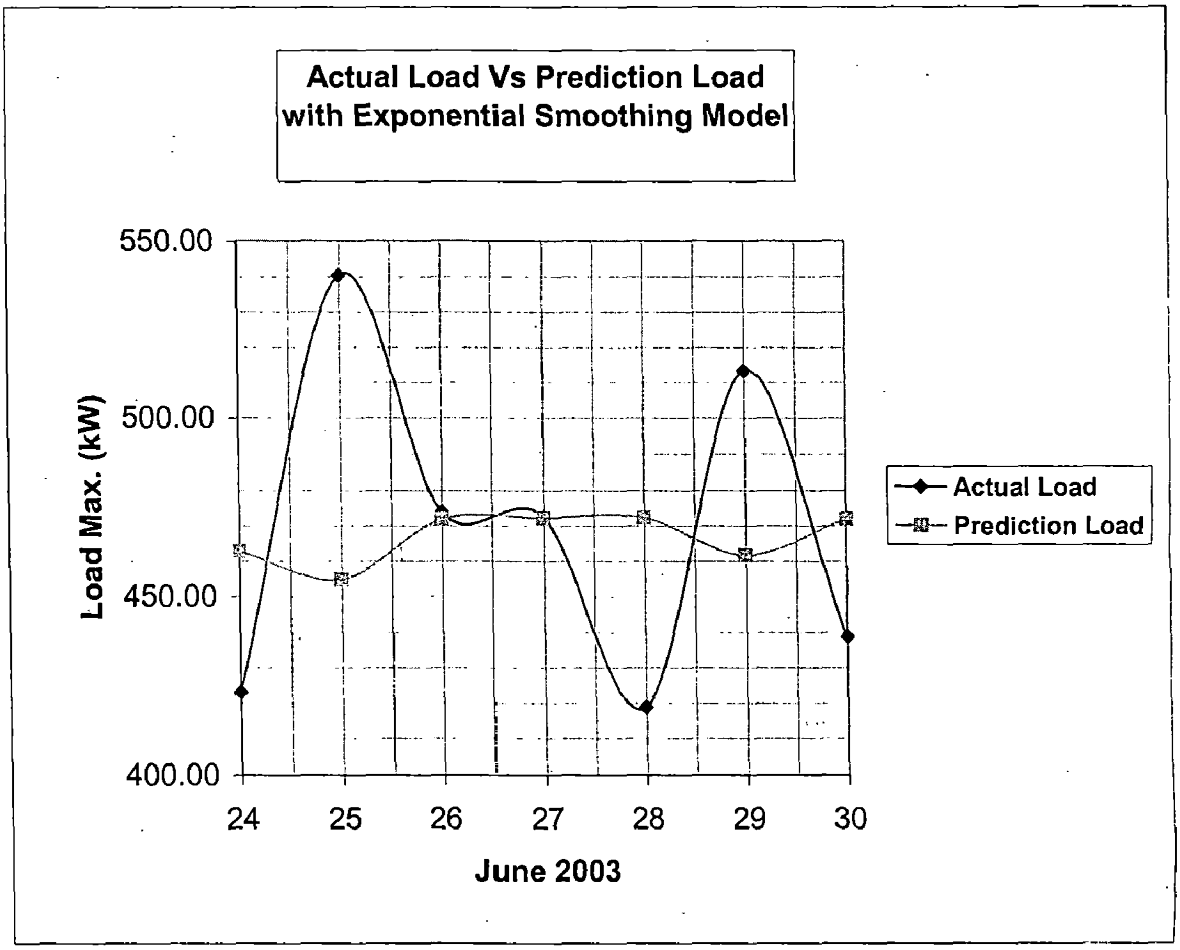
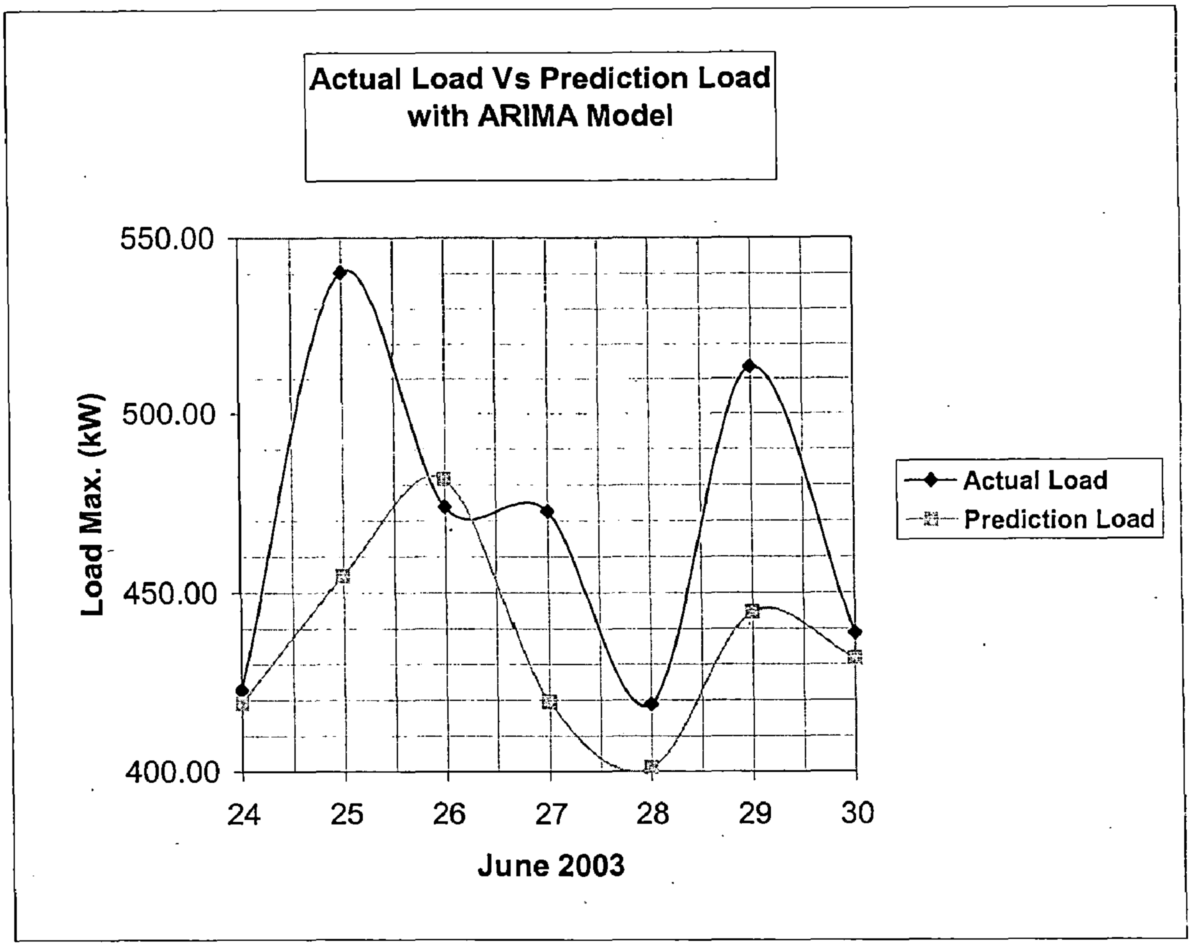
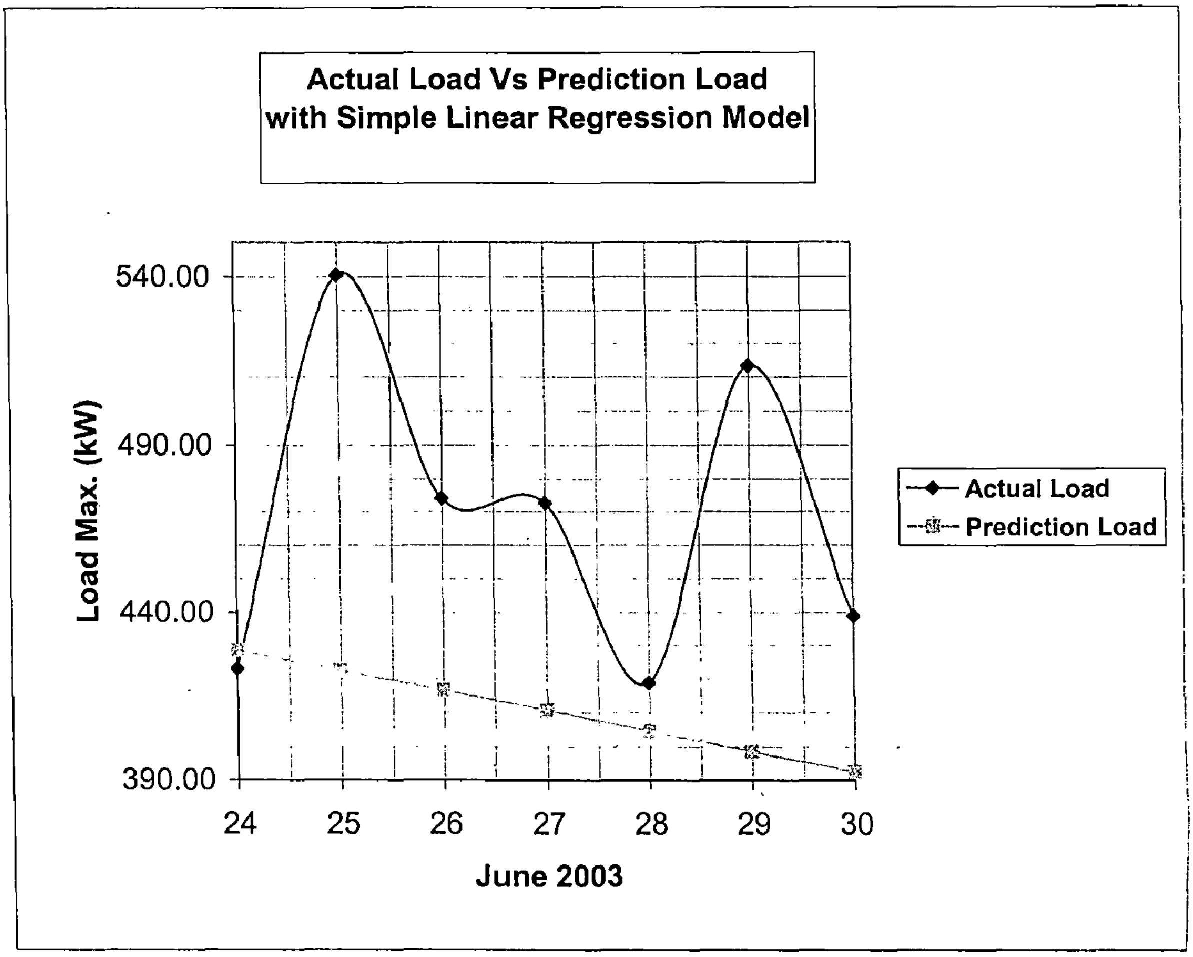
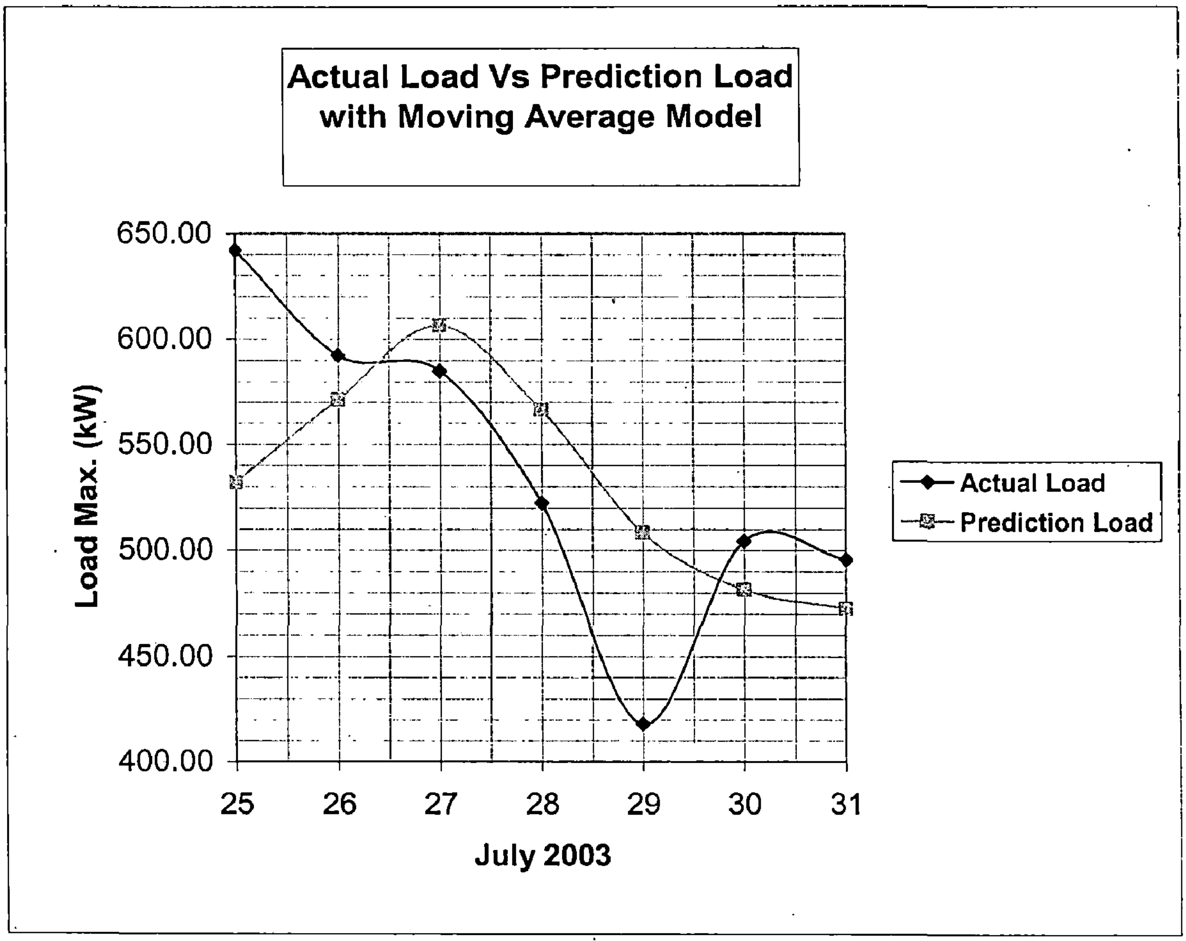


Figure 4.6. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on June 2003

Continued of Figure 4.6.







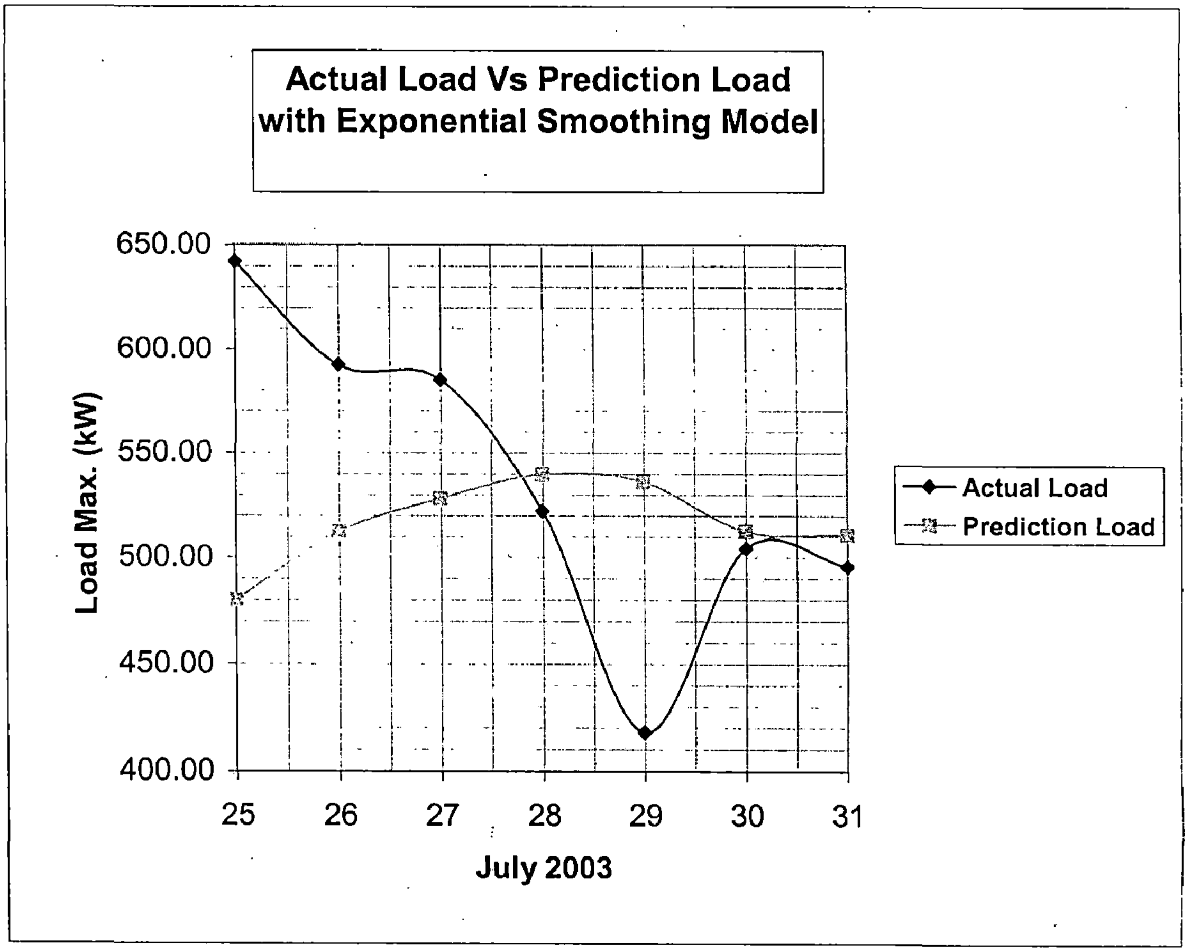
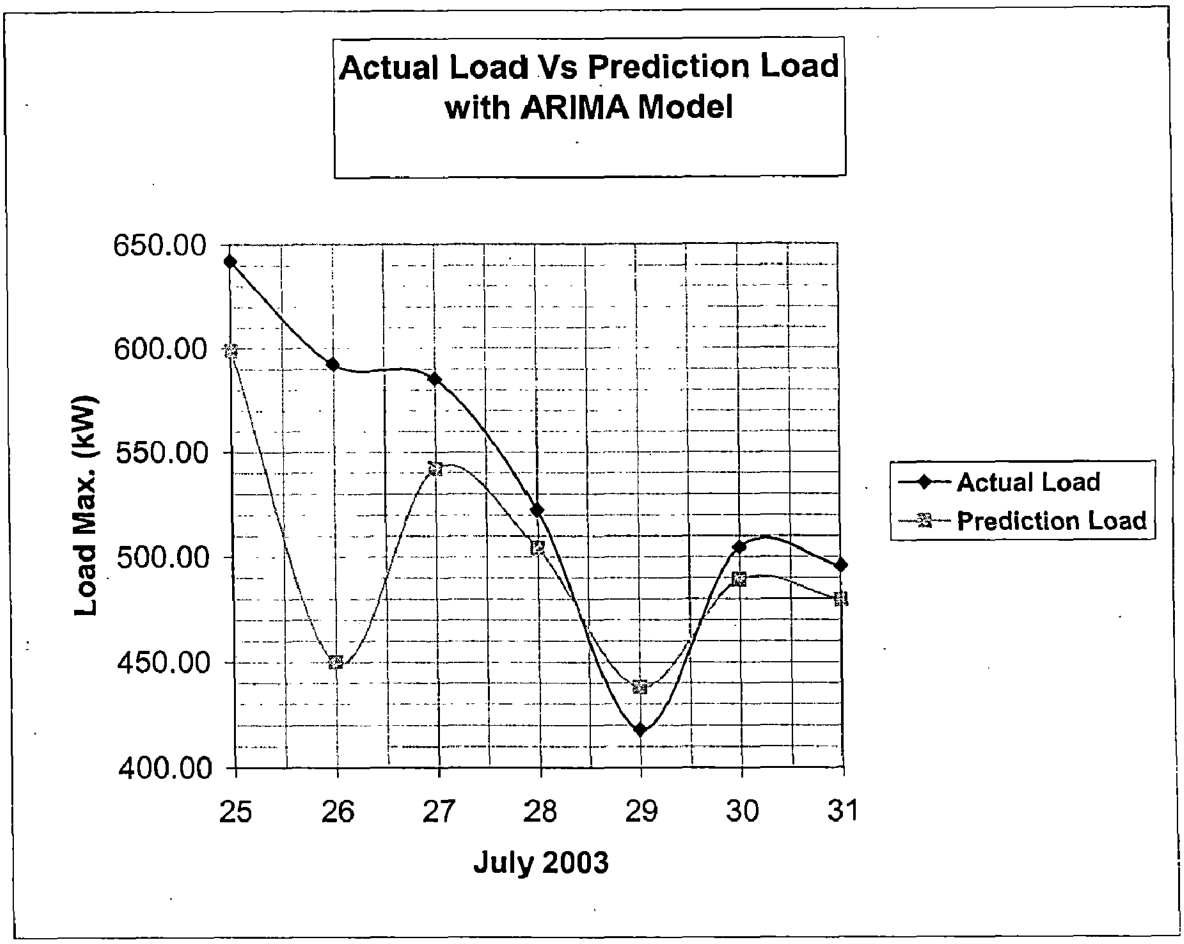
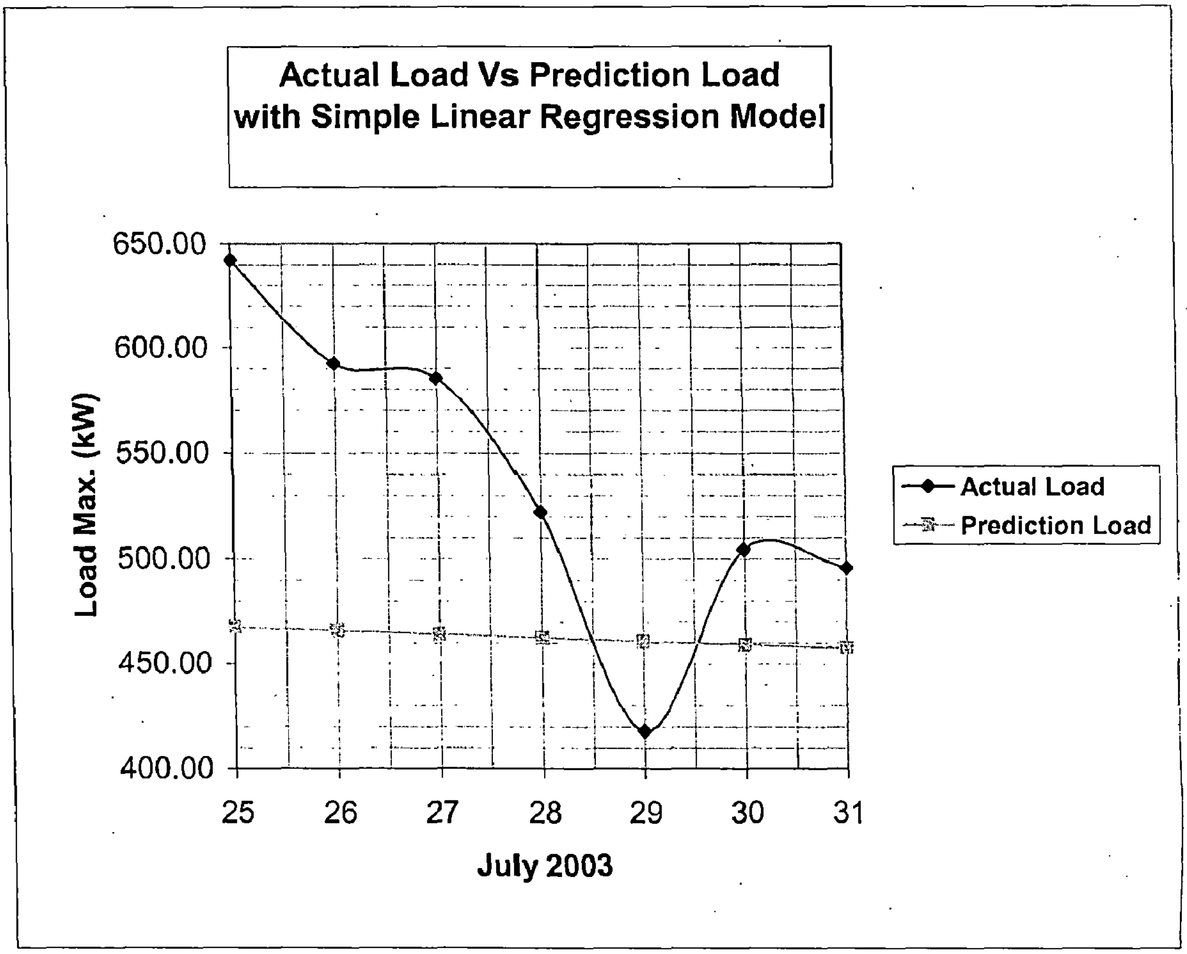
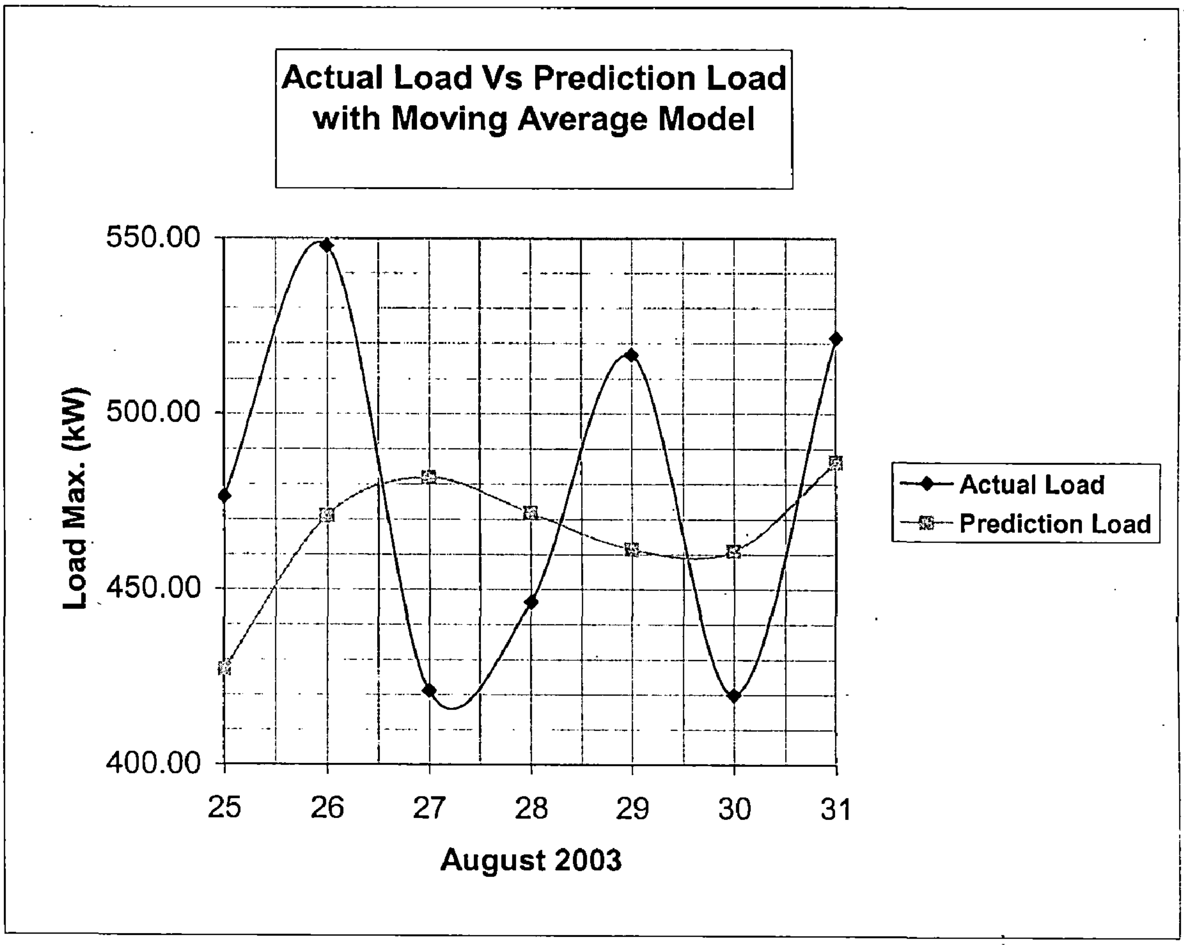


Figure 4.7. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on July 2003

Continued of Figure 4.7.







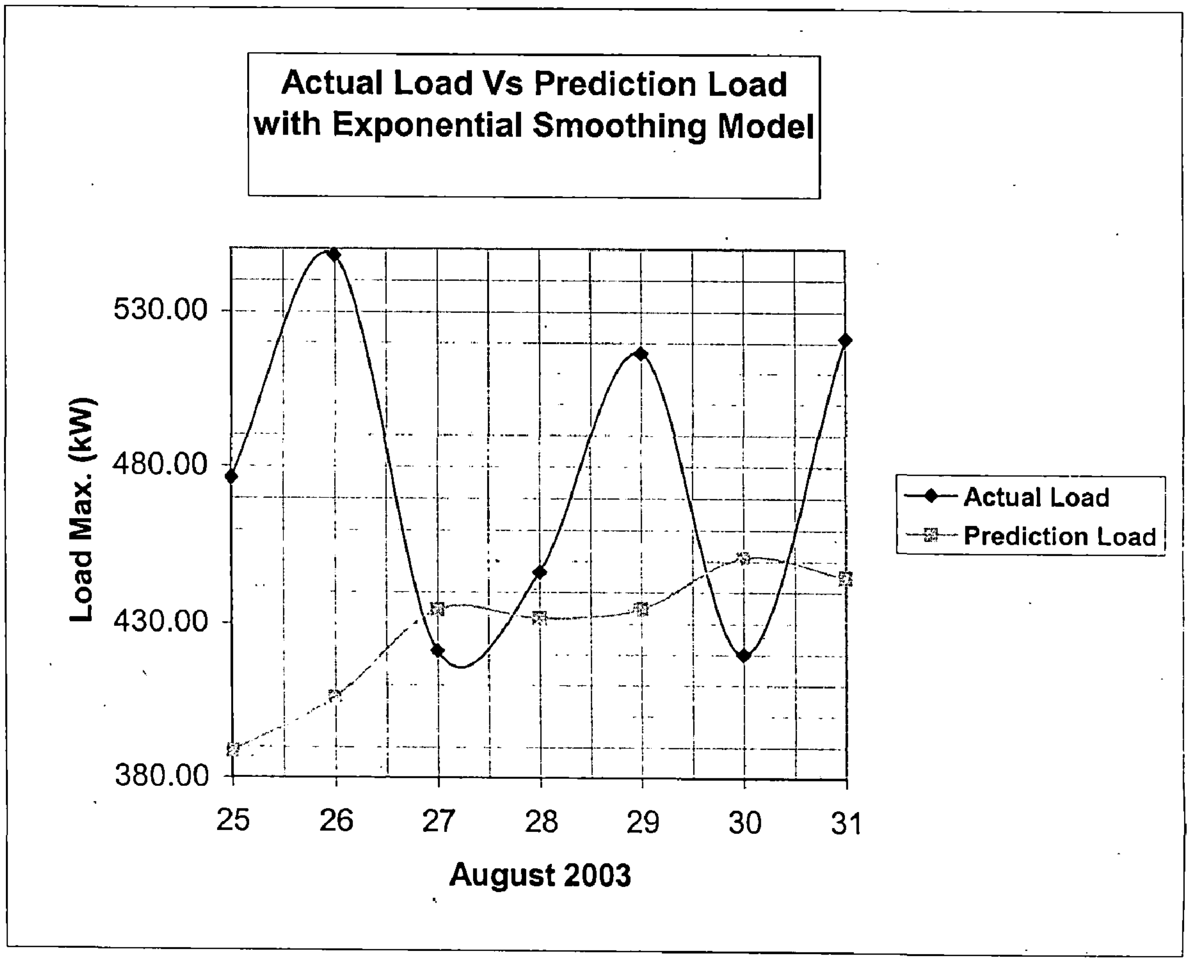
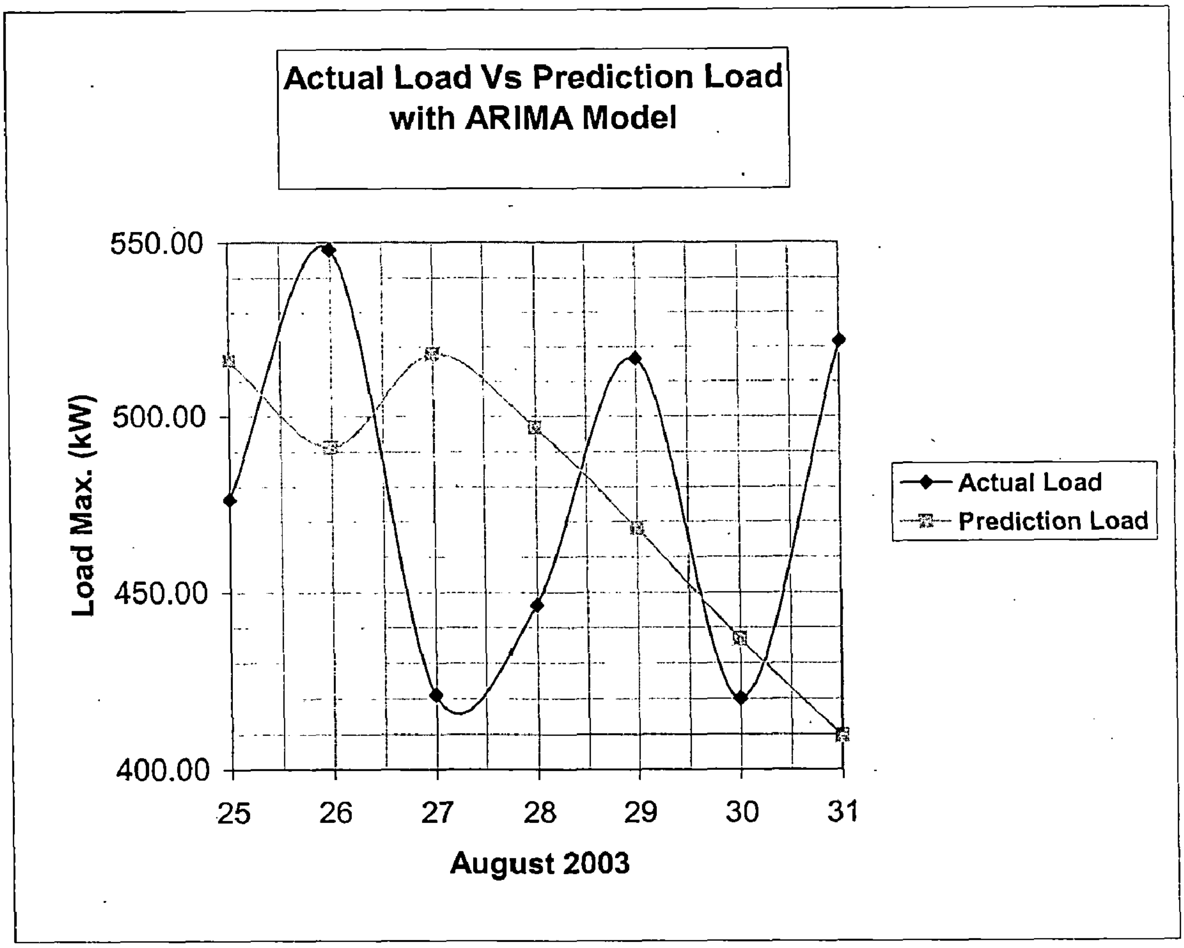
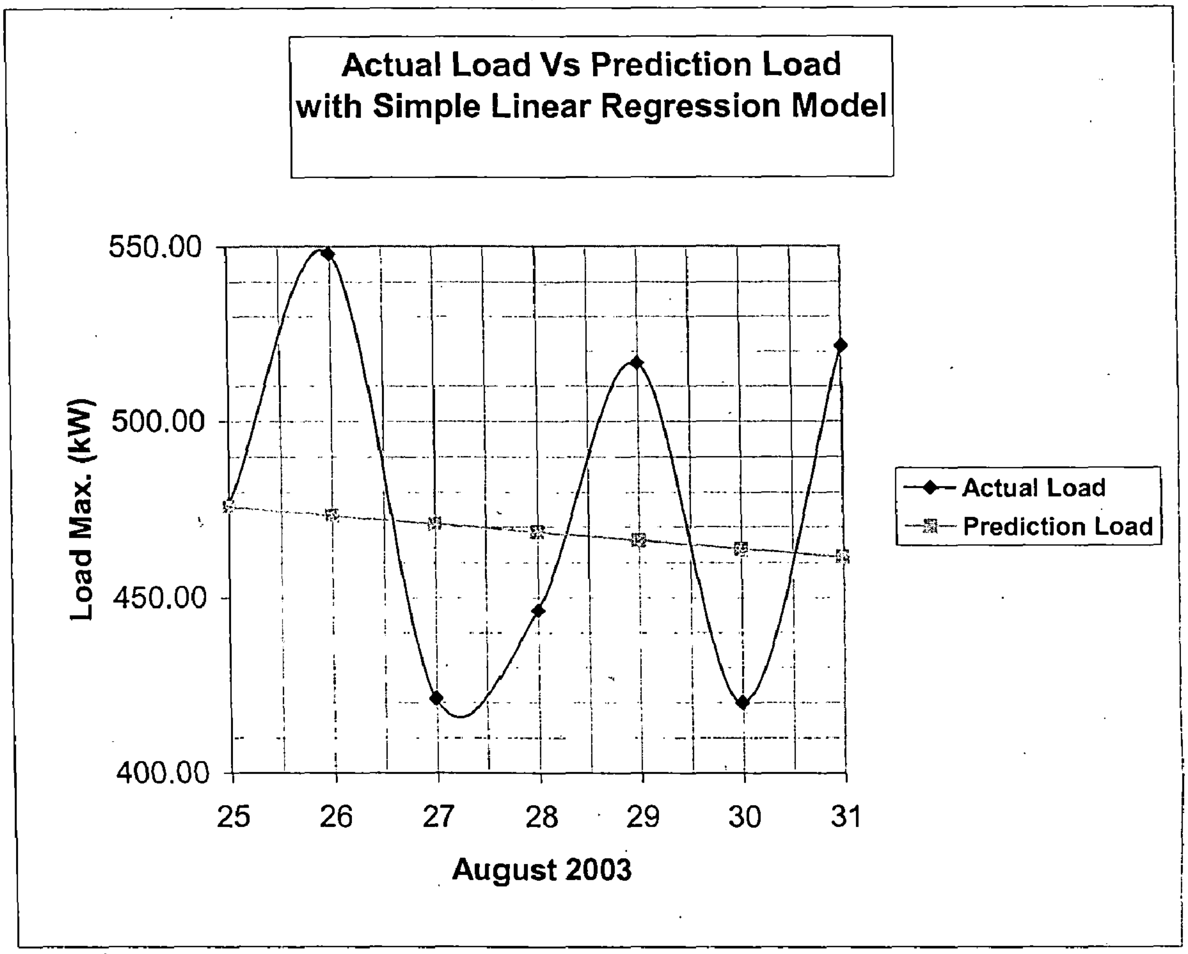
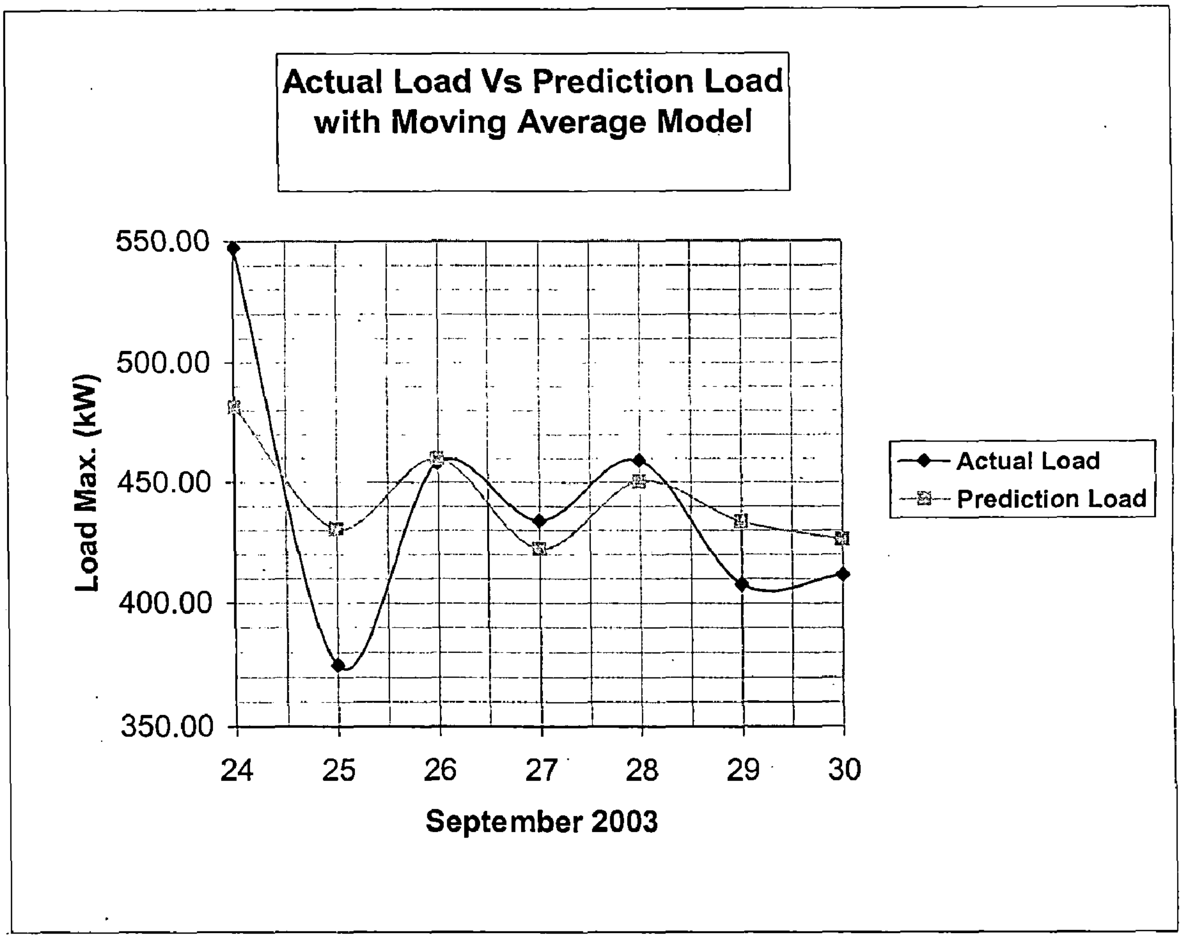


Figure 4.8. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on August 2003

Continued of Figure 4.8.







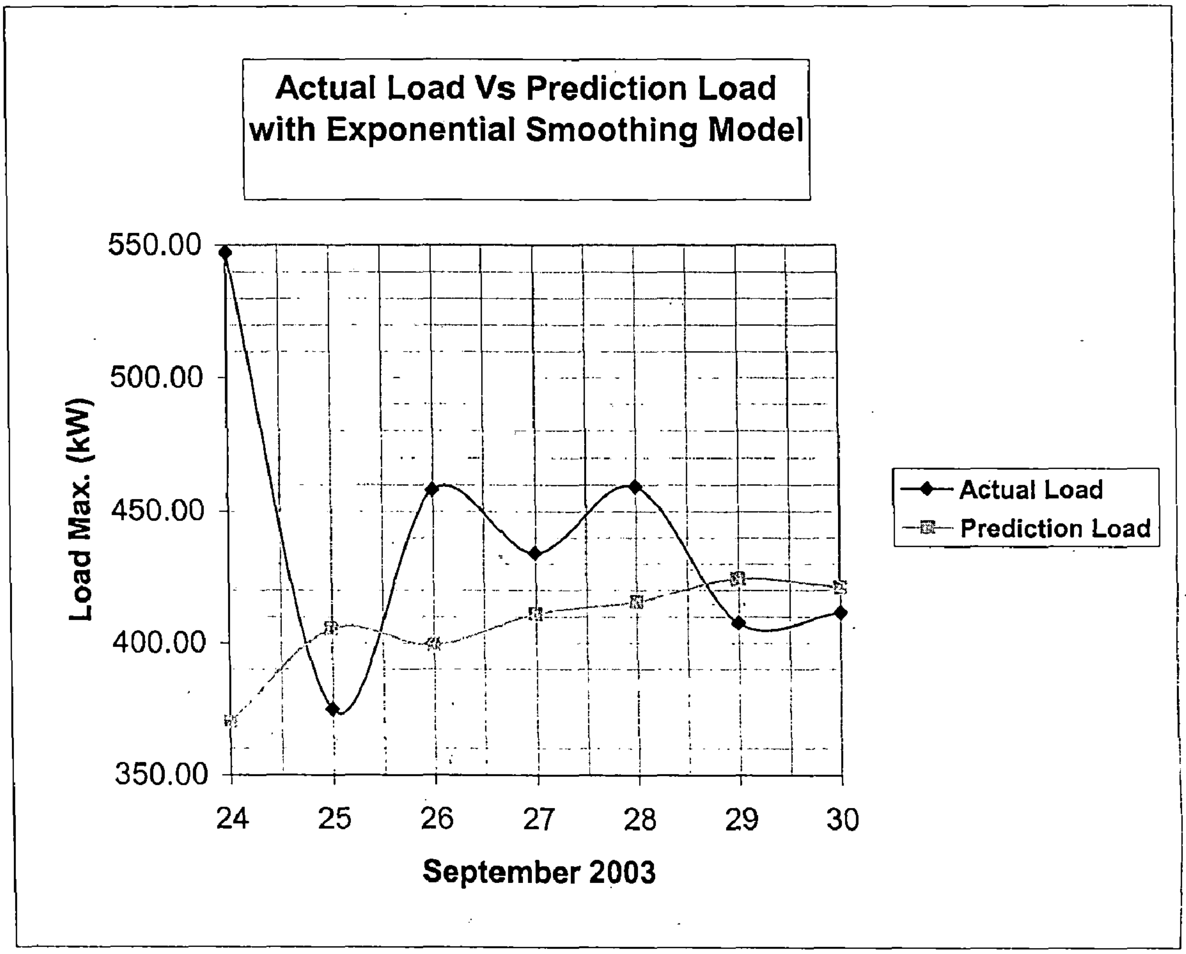
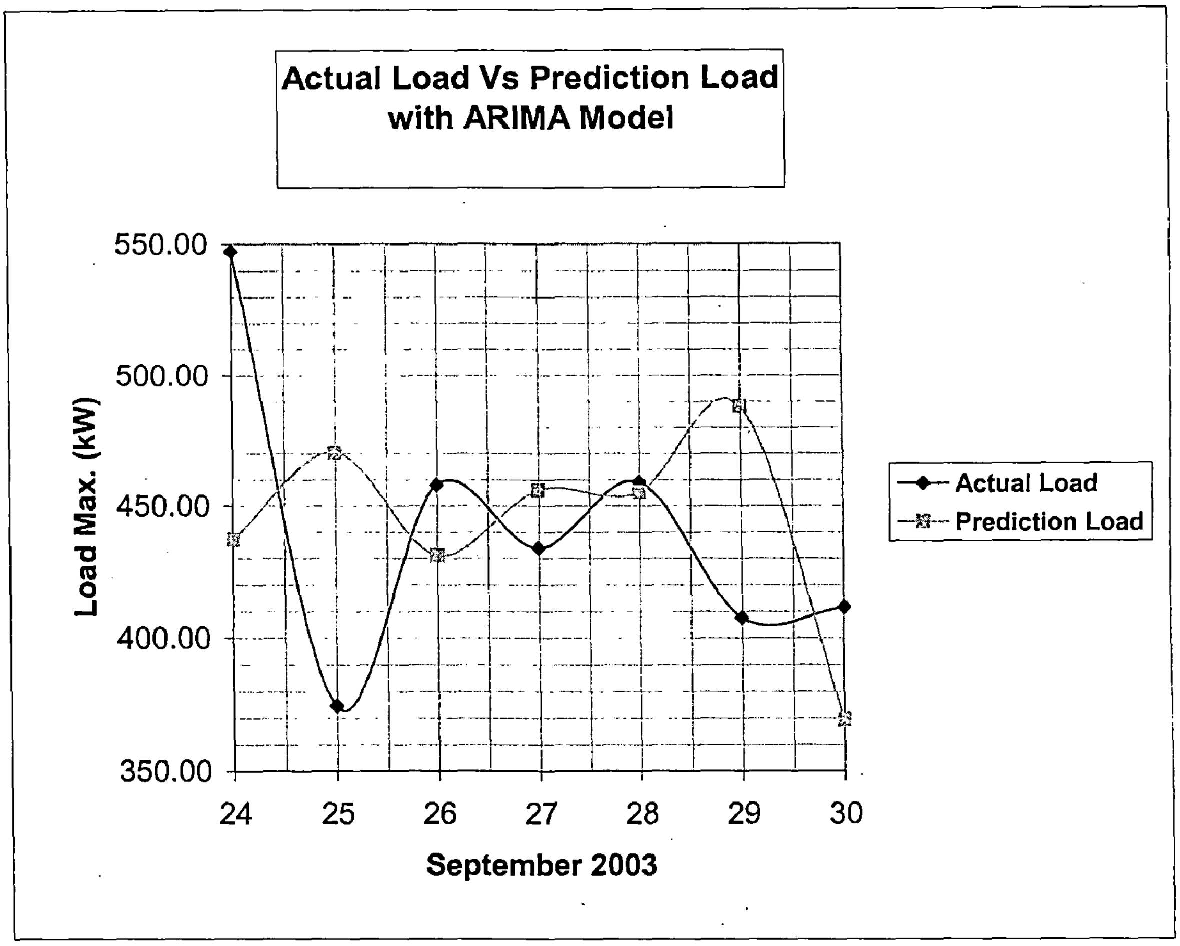
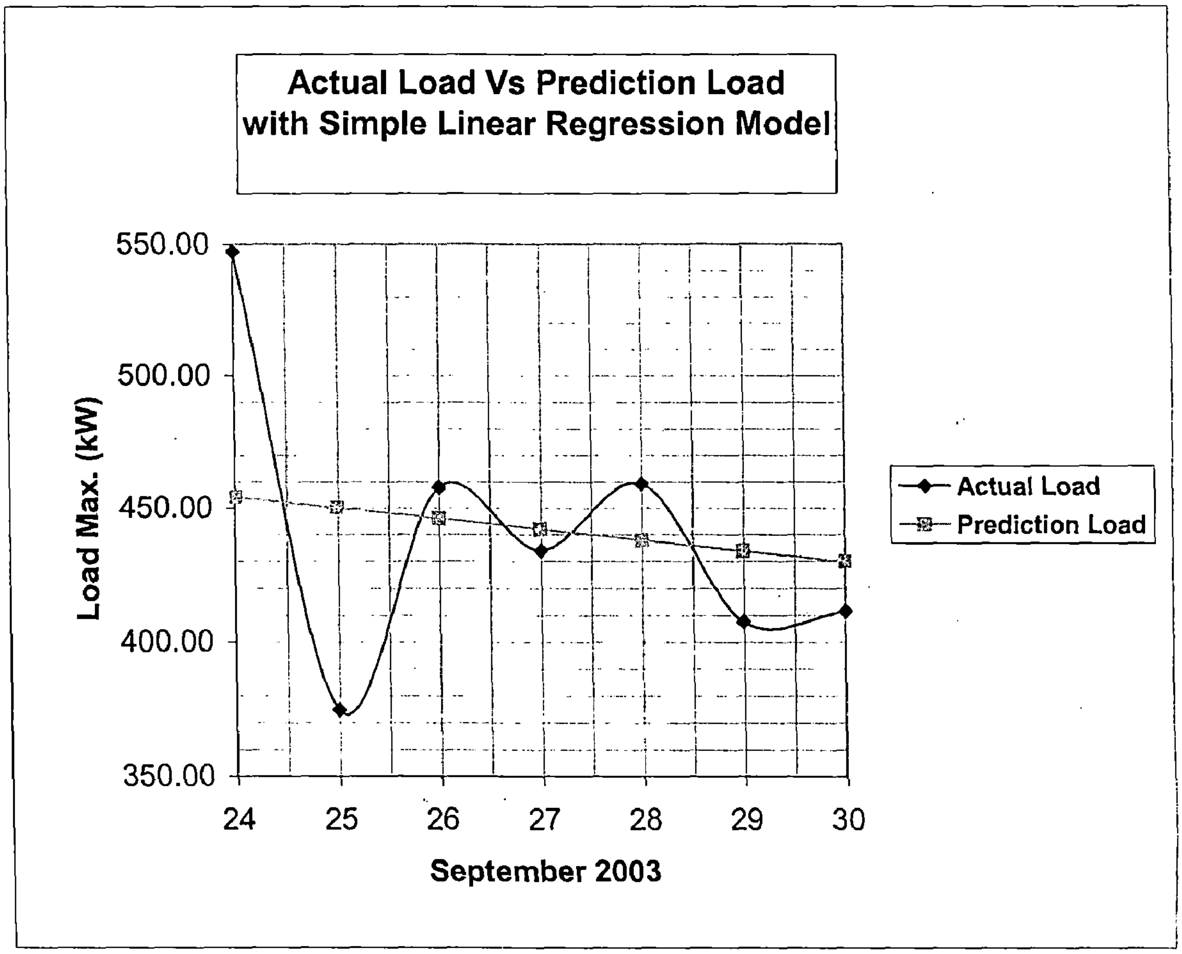
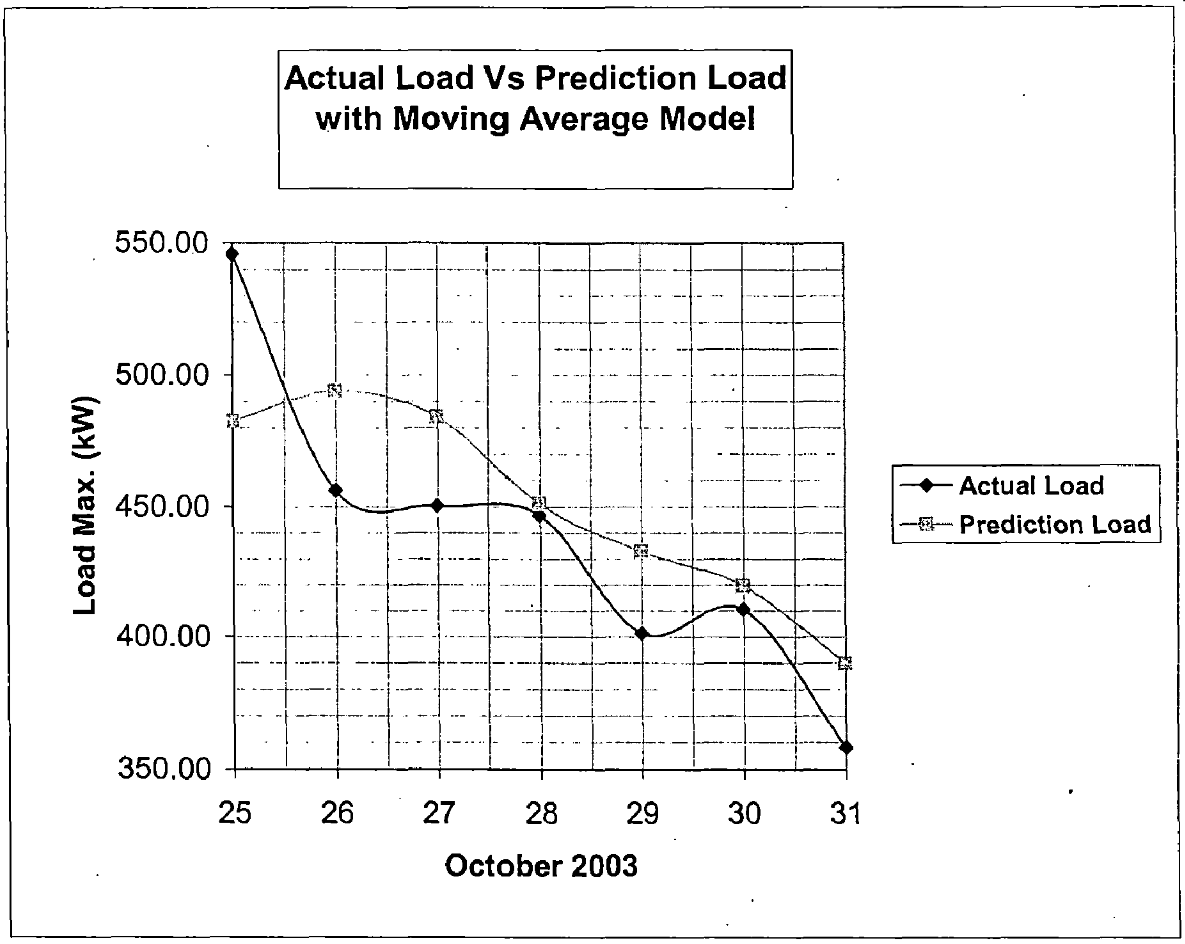


Figure 4.9. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on September 2003

Continued of Figure 4.9.







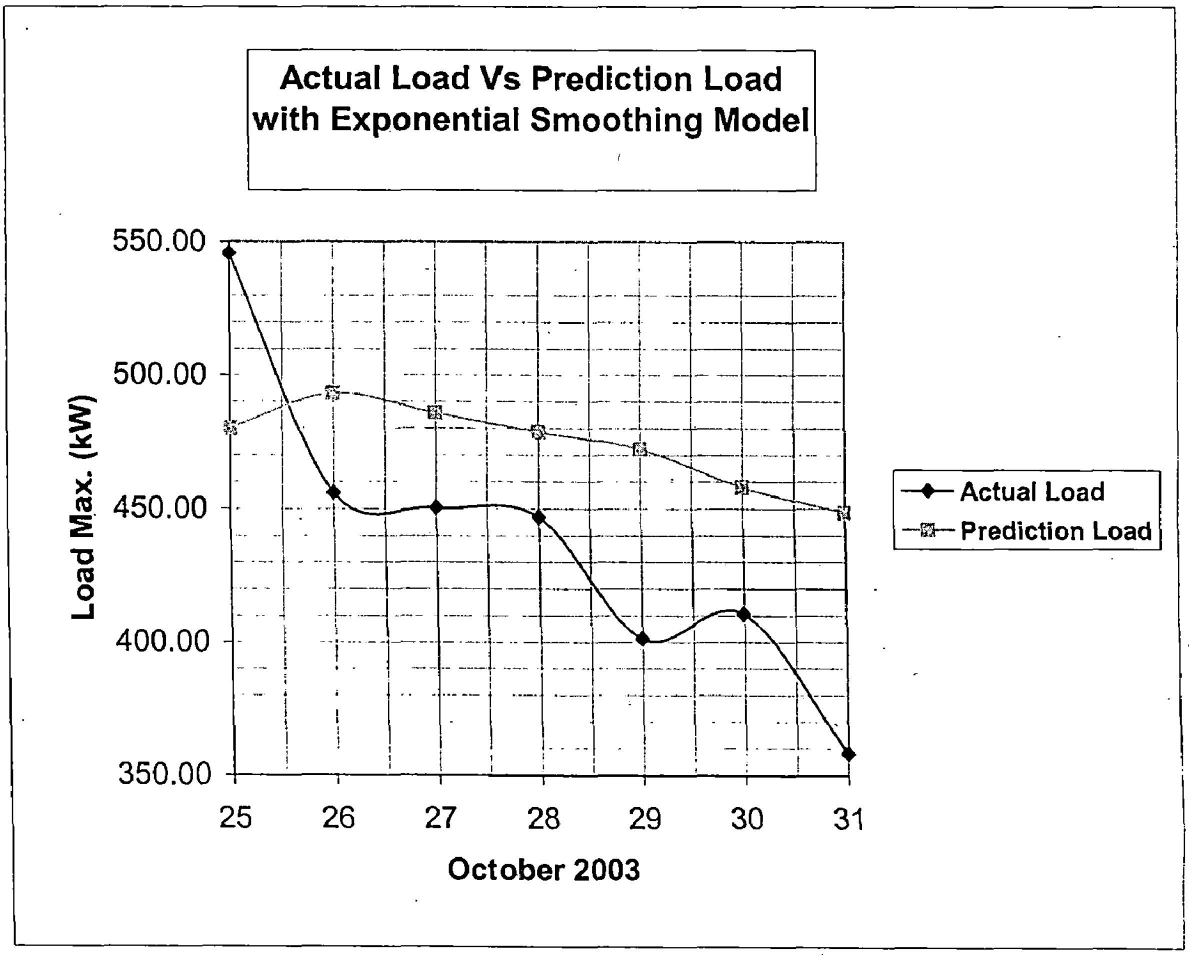
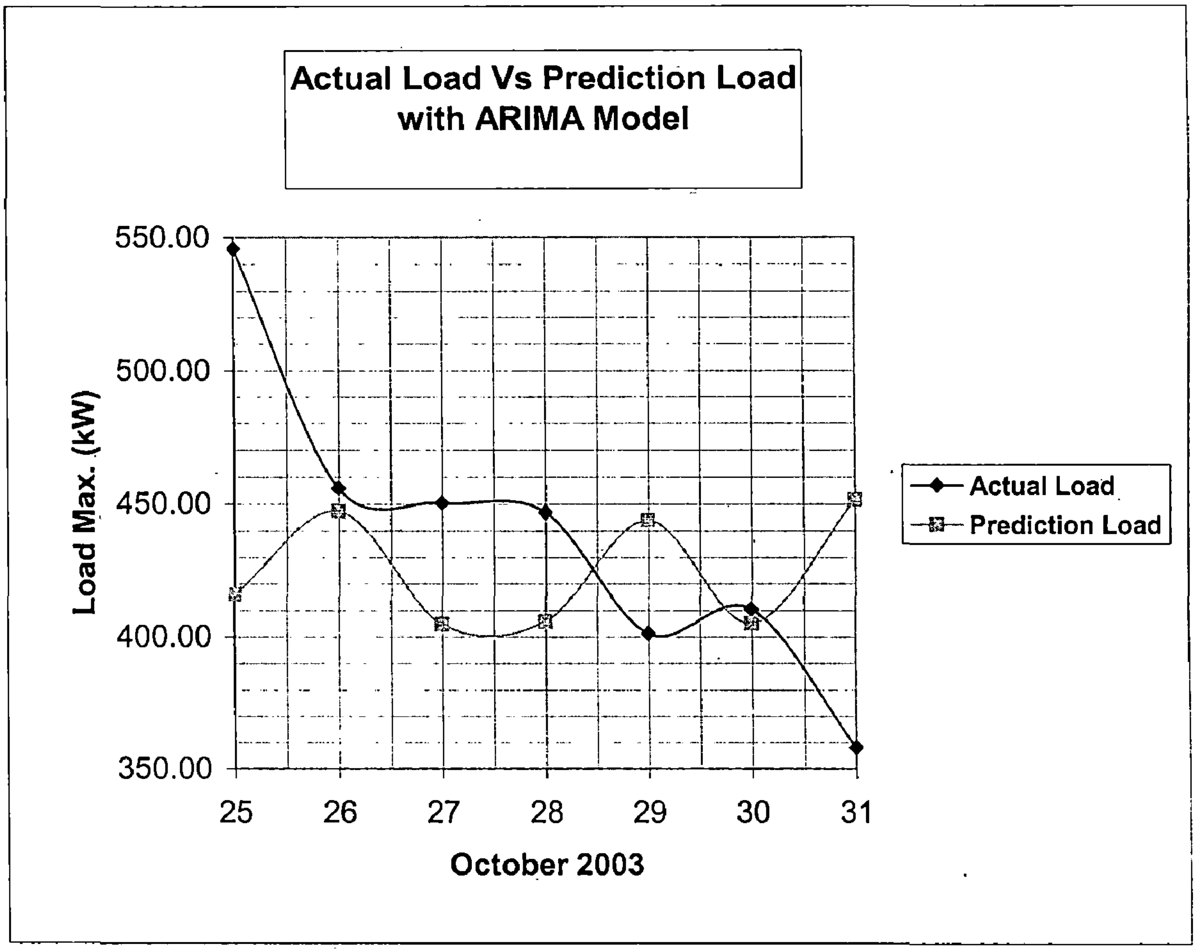
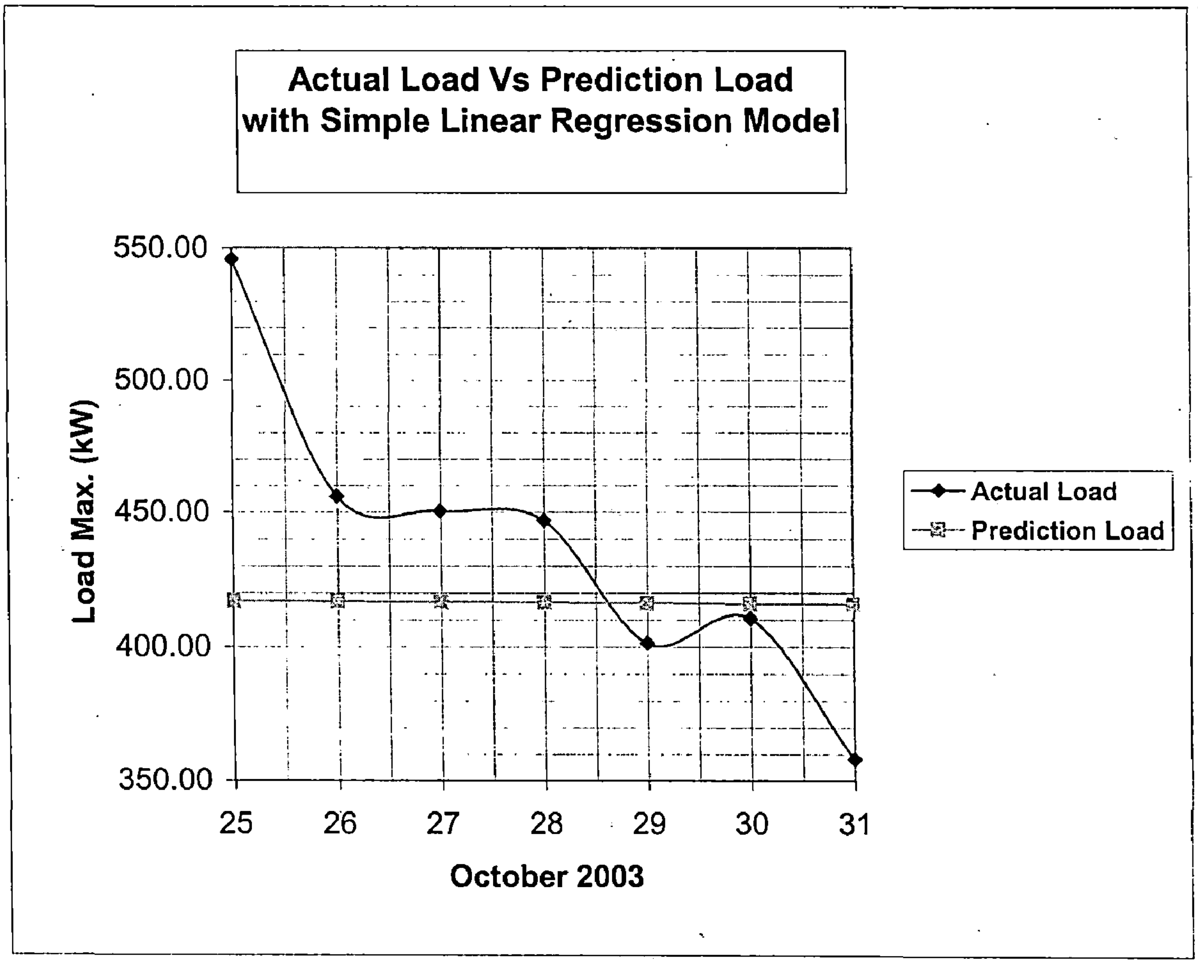
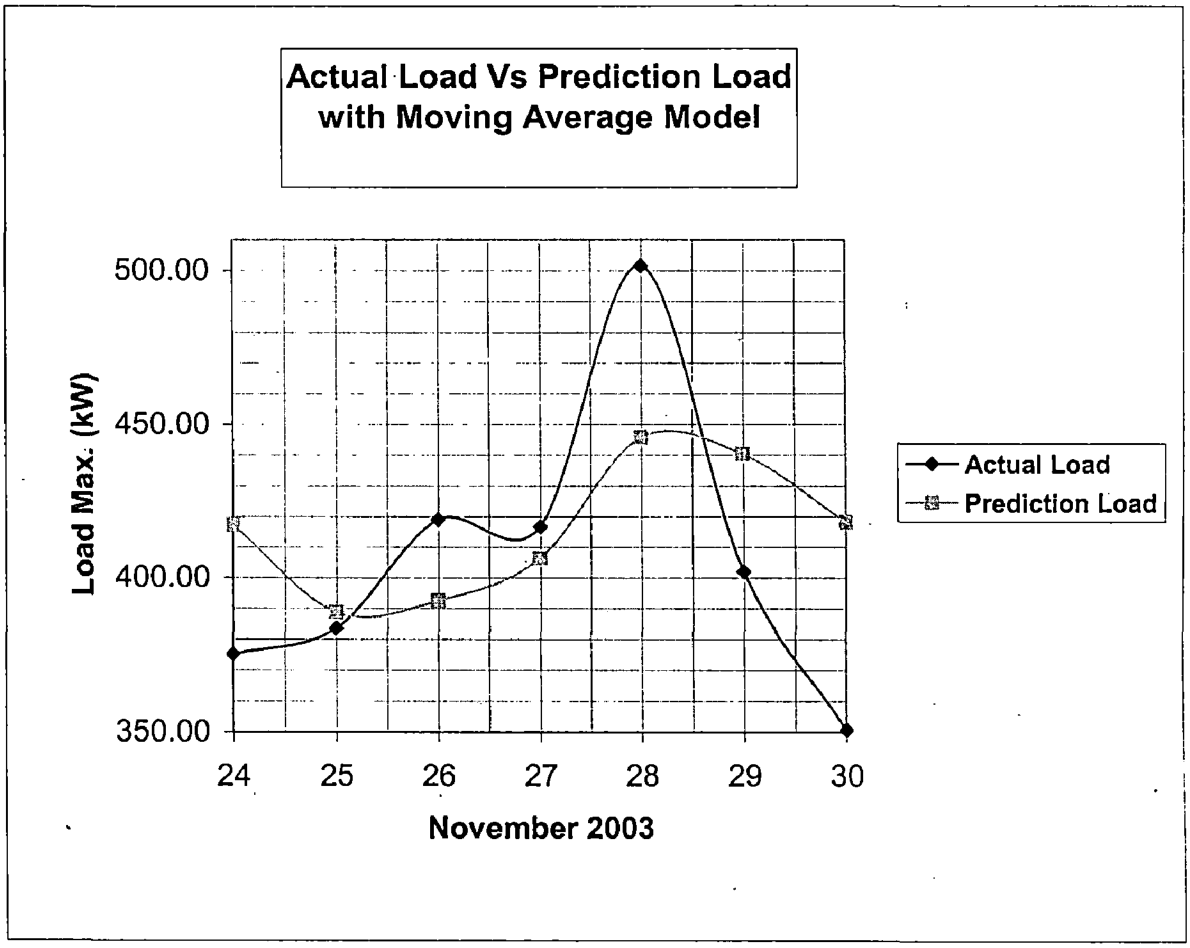


Figure 4.10. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on October 2003

Continued of Figure 4.10.







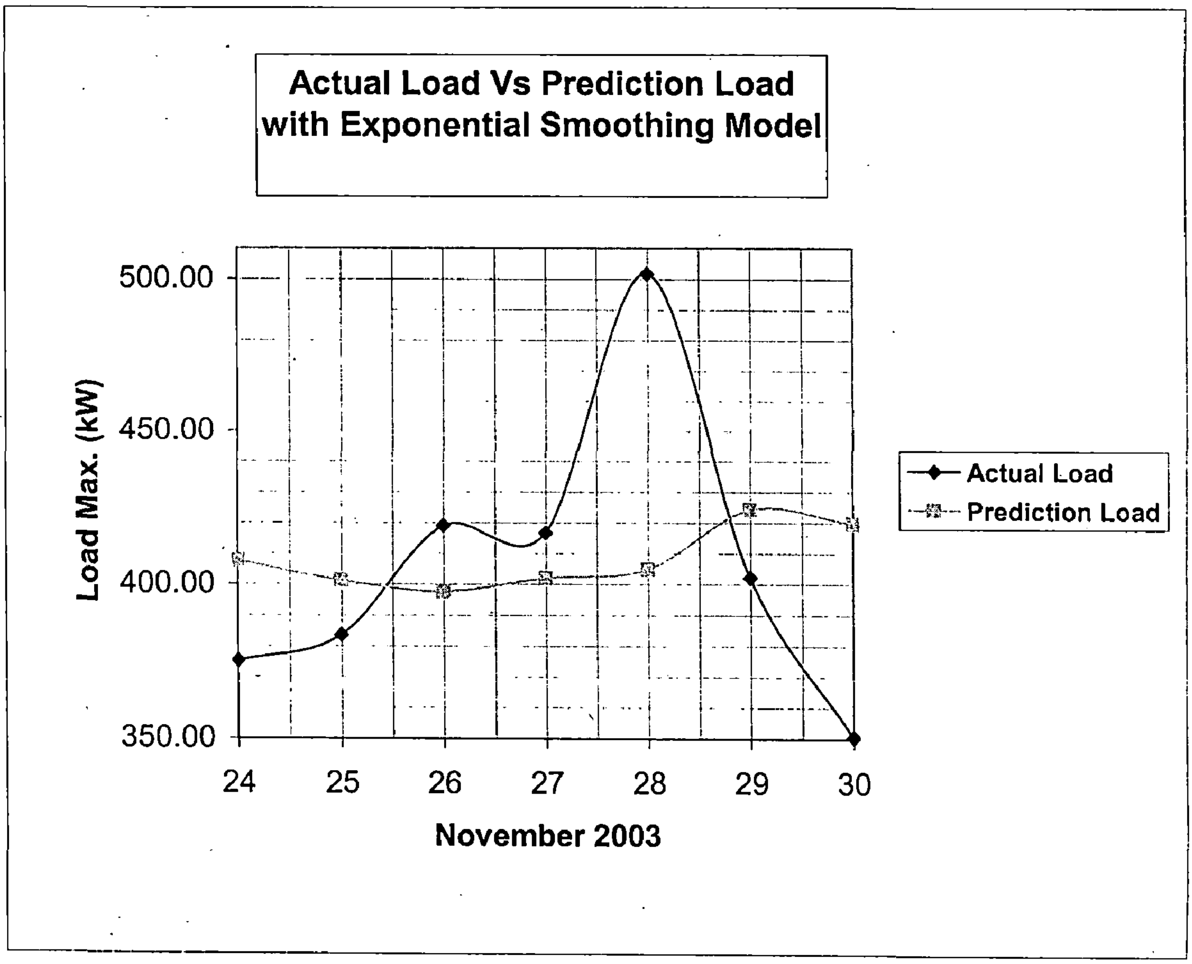
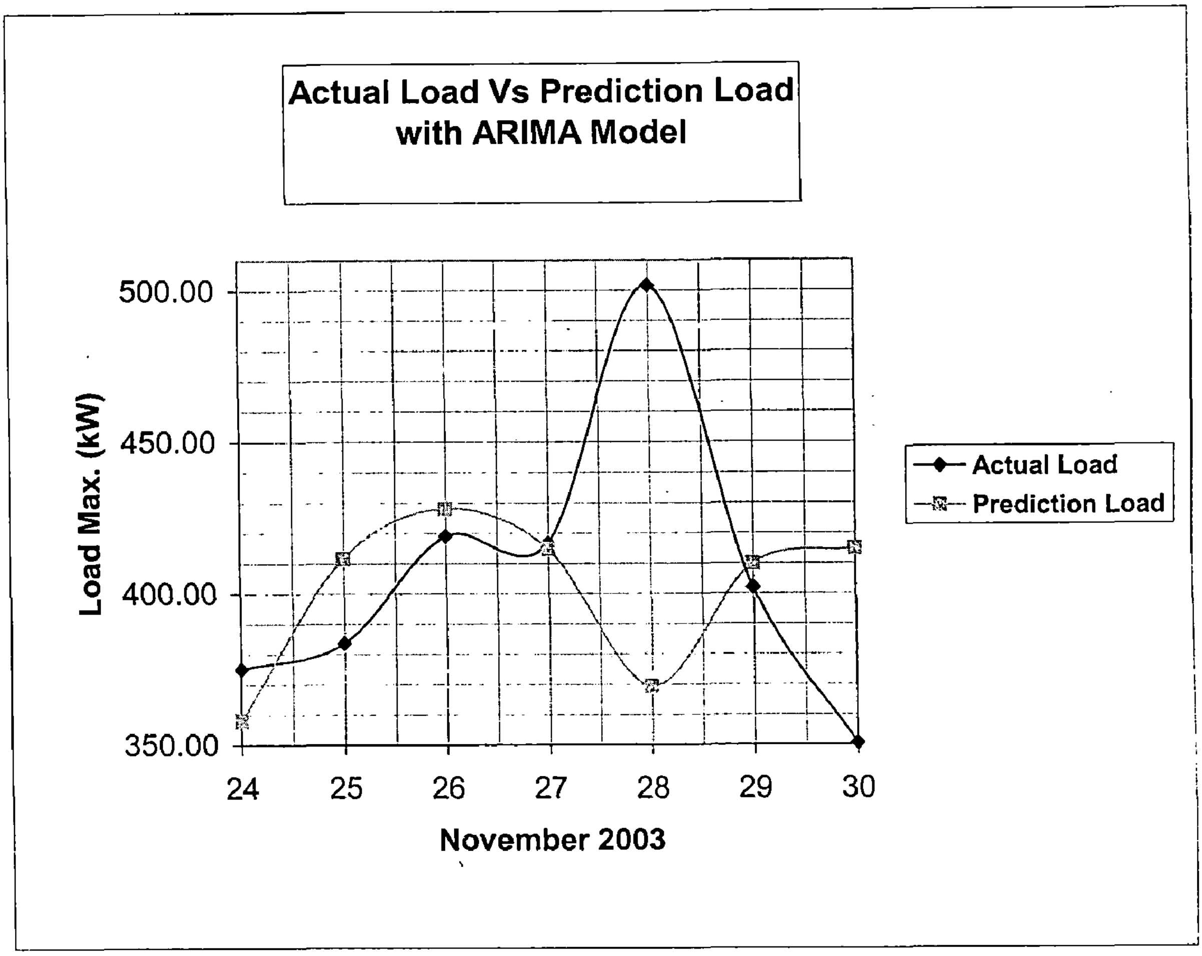
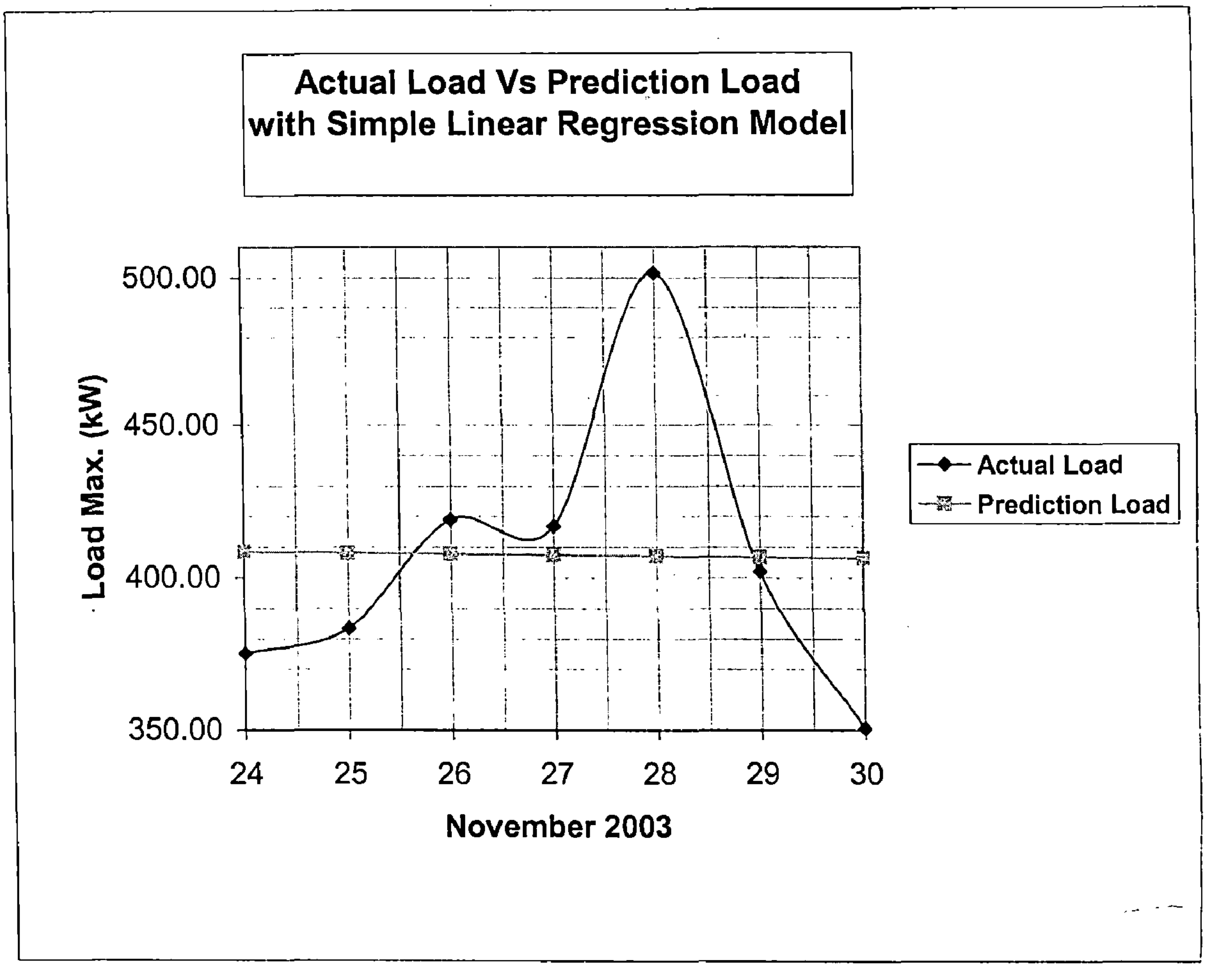
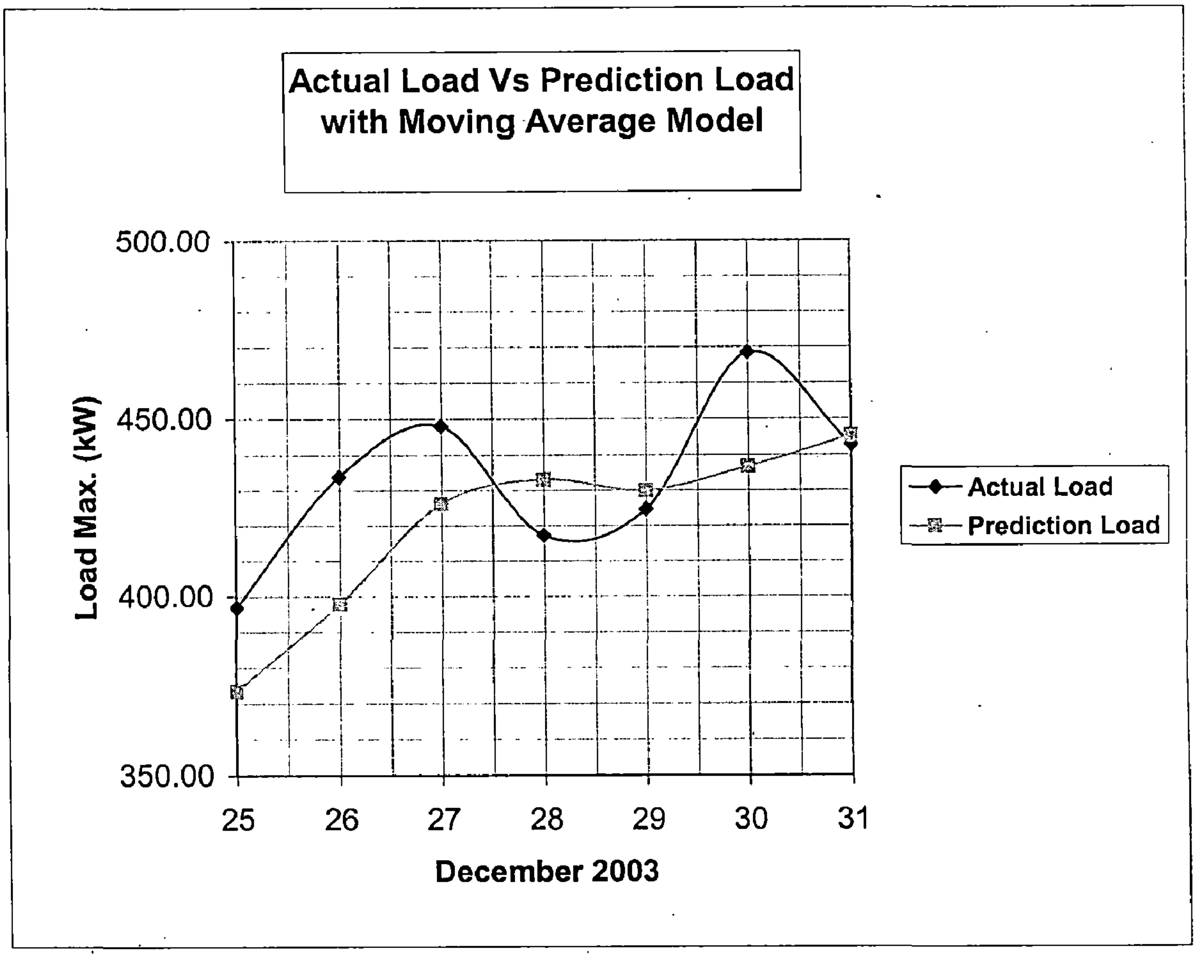


Figure 4.11. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on November 2003

Continued of Figure 4.11.







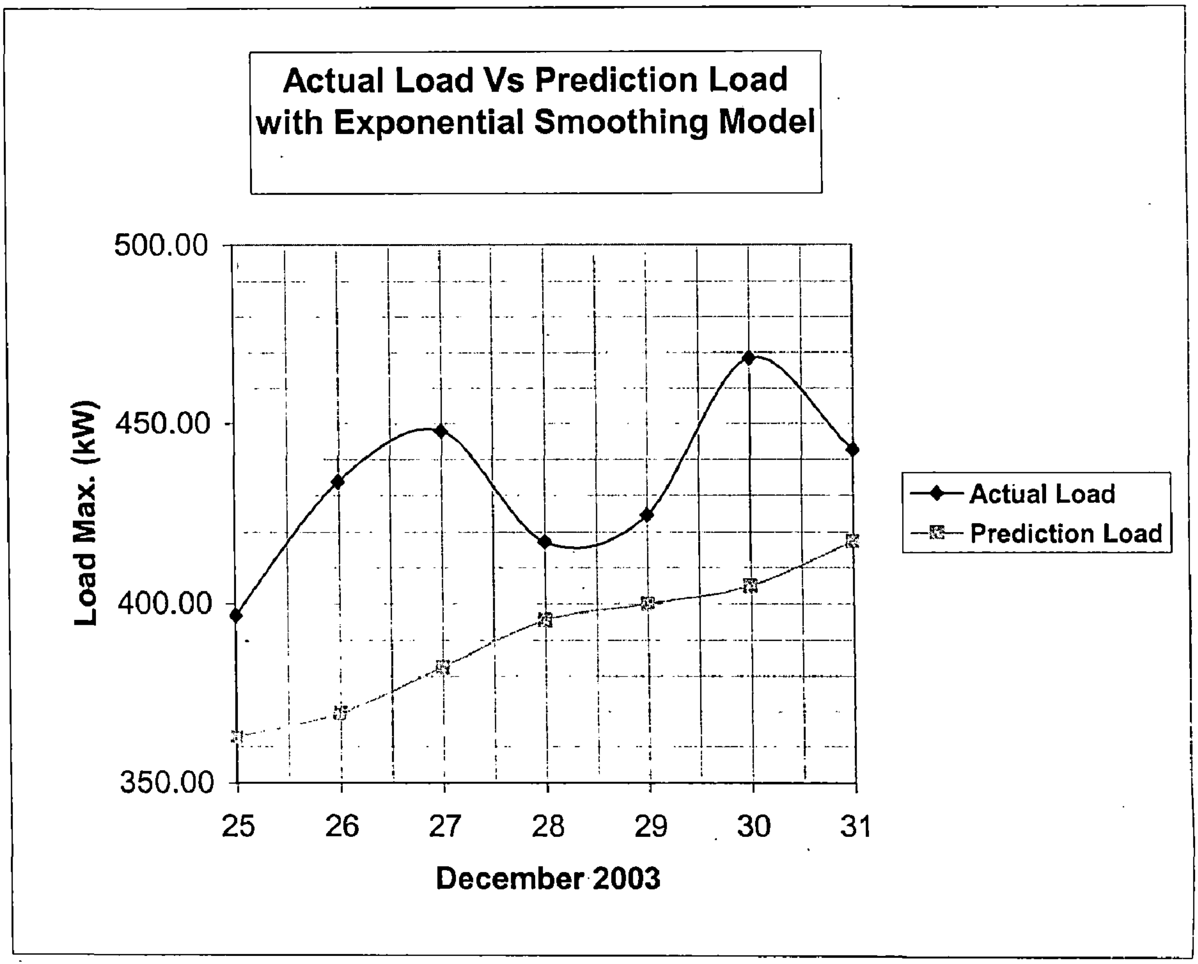
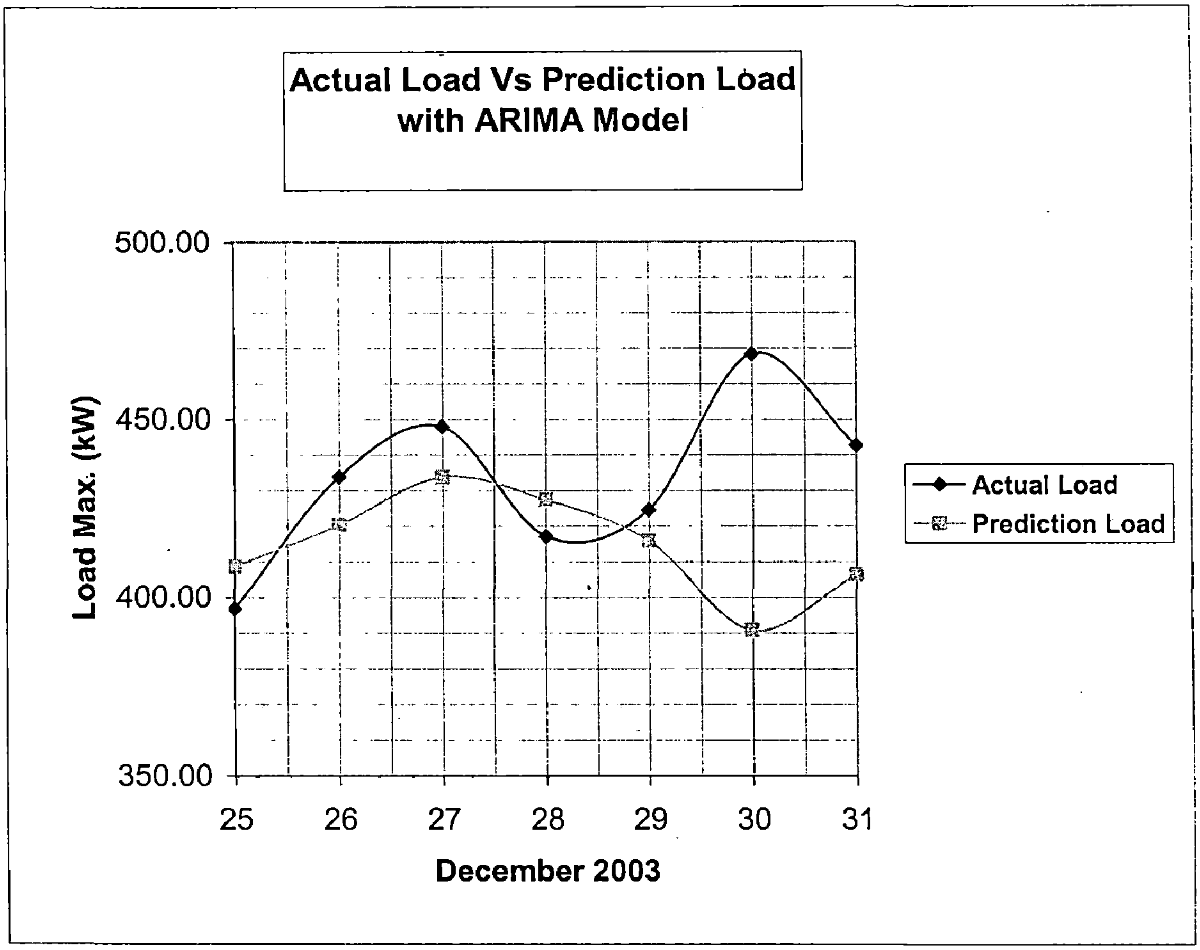
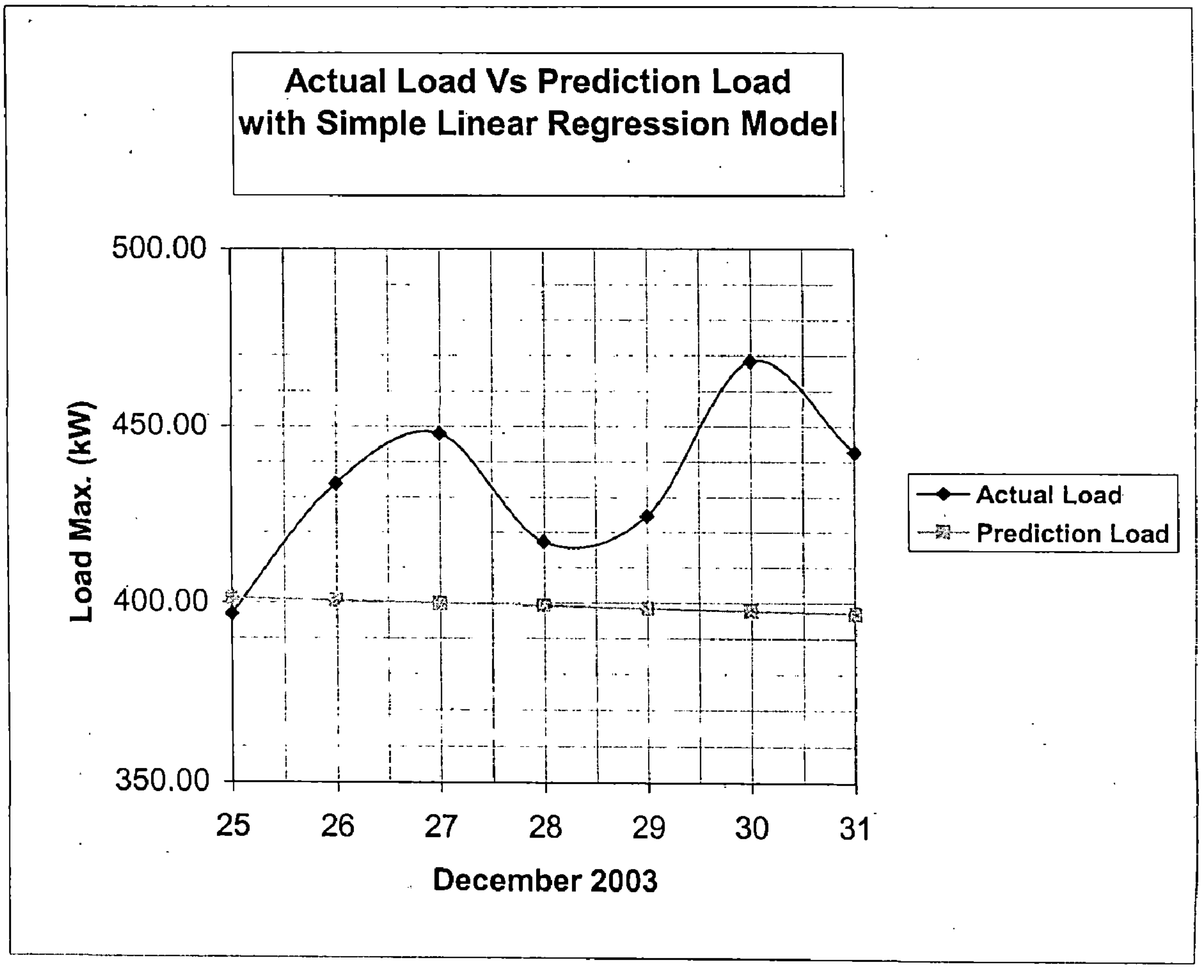


Figure 4.12. Actual Load Versus Prediction Load with Time Series Analysis Model and Simple Linear Regression Model on December 2003

Continued of Figure 4.12





CHAPTER V

STLF BY ARTIFICIAL NEURAL NETWORKS

5.1. FORECASTING BY NEURAL NETWORKS

The implementation is carried out using MetrixND software.

Input data per month is created in Microsoft Excel file table data. The table data is imported into MetrixND software to build neural network model.

Input selection data such as:

- Daily load maximum in Vikas Nagar Sub Station IIT Roorkee from January 2003 to December 2003, shown in Table 4.1.
- Daily average temperature in Roorkee from January 2003 to December 2003, shown in Table 5.1.
- Daily relative humidity in Roorkee from January 2003 to December 2003, shown in Table 5.2.
- Daily average wind velocity in Roorkee from January 2003 to December 2003, shown in Table 5.3.
- Daily evaporation in Roorkee from January 2003 to December 2003, shown in Table 5.4.
- Daily rainfall in Roorkee from January 2003 to December 2003, shown in Table 5.5.
- Indian Calendar 2003 from January 2003 to December 2003.

We divided the day into three categories:

- Work days : Monday to Friday

- Holidays : Saturday and Sunday
- Special days : Indian national holiday and religious celebration , shown in Table 5.6.

We get the forecast for daily load maximum in 2003 each month, as below:

Table. 5.7. Prediction Load with Neural Networks Model

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	25.01.2003	443.42	479.00
Sunday	26.01.2003	399.70	399.70
Monday	27.01.2003	407.26	356.42
Tuesday	28.01.2003	459.08	451.94
Wednesday	29.01.2003	397.58	391.93
Thursday	30.01.2003	433.43	451.52
Friday	31.01.2003	415.50	422.25

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	22.02.2003	388.43	400.33
Sunday	23.02.2003	373.62	316.60
Monday	24.02.2003	307.72	358.96
Tuesday	25.02.2003	302.32	383.80
Wednesday	26.02.2003	319.41	345.46
Thursday	27.02.2003	363.83	322.40
Friday	28.02.2003	328.92	364.39

Continued of Table 5.7.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Tuesday	25.03.2003	331.30	340.28
Wednesday	26.03.2003	332.19	344.95
Thursday	27.03.2003	376.03	388.30
Friday	28.03.2003	423.94	418.89
Saturday	29.03.2003	380.70	345.23
Sunday	30.03.2003	385.98	368.80
Monday	31.03.2003	361.72	364.28

Day	Date	Actual Load (kW)	Prediction Load (kW)
Thursday	24.04.2003	382.00	400.51
Friday	25.04.2003	417.15	417.53
Saturday	26.04.2003	434.95	412.59
Sunday	27.04.2003	383.84	396.74
Monday	28.04.2003	353.90	345.38
Tuesday	29.04.2003	384.62	398.10
Wednesday	30.04.2003	427.97	447.48

Day	Date	Actual Load (kW)	Prediction Load (kW)
Sunday	25.05.2003	490.78	485.81
Monday	26.05.2003	550.02	520.05
Tuesday	27.05.2003	413.42	449.13
Wednesday	28.05.2003	506.91	490.01
Thursday	29.05.2003	492.34	498.15
Friday	30.05.2003	546.74	536.92
Saturday	31.05.2003	515.65	519.48

Continued of Table 5.7.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Tuesday	24.06.2003	422.93	432.05
Wednesday	25.06.2003	540.26	545.85
Thursday	26.06.2003	473.93	512.61
Friday	27.06.2003	472.56	437.55
Saturday	28.06.2003	418.76	391.10
Sunday	29.06.2003	513.24	454.28
Monday	30.06.2003	438.70	434.52

Day	Date	Actual Load (kW)	Prediction Load (kW)
Friday	25.07.2003	642.06	567.26
Saturday	26.07.2003	592.25	515.06
Sunday	27.07.2003	584.98	539.31
Monday	28.07.2003	522.22	558.22
Tuesday	29.07.2003	417.78	450.67
Wednesday	30.07.2003	504.23	516.69
Thursday	31.07.2003	495.62	492.61

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	25.08.2003	476.29	479.77
Tuesday	26.08.2003	547.83	572.00
Wednesday	27.08.2003	421.06	466.63
Thursday	28.08.2003	446.37	490.45
Friday	29.08.2003	516.55	555.13
Saturday	30.08.2003	419.91	454.51
Sunday	31.08.2003	521.54	522.04

Continued of Table 5.7.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	24.09.2003	547.15	539.60
Tuesday	25.09.2003	374.72	460.60
Wednesday	26.09.2003	457.88	454.12
Thursday	27.09.2003	433.88	461.38
Friday	28.09.2003	459.08	453.73
Saturday	29.09.2003	407.59	478.10
Sunday	30.09.2003	411.51	405.65

Day	Date	Actual Load (kW)	Prediction Load (kW)
Saturday	25.10.2003	545.81	545.81
Sunday	26.10.2003	455.96	418.29
Monday	27.10.2003	450.35	429.96
Tuesday	28.10.2003	446.74	414.92
Wednesday	29.10.2003	401.27	410.31
Thursday	30.10.2003	410.46	422.09
Friday	31.10.2003	358.08	409.76

Day	Date	Actual Load (kW)	Prediction Load (kW)
Monday	24.11.2003	375.10	392.02
Tuesday	25.11.2003	383.48	386.38
Wednesday	26.11.2003	418.90	418.90
Thursday	27.11.2003	416.65	408.91
Friday	28.11.2003	501.60	411.32
Saturday	29.11.2003	402.05	417.85
Sunday	30.11.2003	350.61	402.99

Continued of Table 5.7.

Day	Date	Actual Load (kW)	Prediction Load (kW)
Thursday	25.12.2003	396.73	396.73
Friday	26.12.2003	433.72	444.39
Saturday	27.12.2003	447.88	454.21
Sunday	28.12.2003	417.12	444.92
Monday	29.12.2003	424.52	421.22
Tuesday	30.12.2003	468.32	411.94
Wednesday	31.12.2003	442.64	442.64

5.2. MEAN ABSOLUTE DEVIATION (MAD) AND MEAN ABSOLUTE PERCENT ERROR (MAPE)

The calculation of the MAD and MAPE for the load of Table 5.1. Prediction Load with Neural Networks Model on January 2003 would look as follows:

$$\textbf{MAD} = \frac{\sum |forecast\ error|}{no.of\ forecasts}$$

$$= \frac{\sum \left| y_t - \hat{y}_t \right|}{n} = \frac{\sum |e_t|}{n}$$

The error of the forecast for day 25 is : $443.42 - 479.00 = -35.58$

The absolute value of $-35.58 = |-35.58| = 35.58$

The error of the forecast for day 26 is : $399.70 - 399.70 = 0$

The error of the forecast for day 27 is : 407.26 – 356.42 = 50.84

The error of the forecast for day 28 is : 459.08 – 451.94 = 7.14

The error of the forecast for day 29 is : 397.58 – 391.93 = 5.65

The error of the forecast for day 30 is : 433.43 – 451.52 = -18.09

The absolute value of – 18.09 = $|-18.09| = 18.09$

The error of the forecast for day 31 is : 415.50 – 422.25 = -6.75

The absolute value of – 6.75 = $|-6.75| = 6.75$

Total error of the forecast is :

35.58 + 0 + 50.84 + 7.14 + 5.65 + 18.09 + 6.75 = 124.05

Number of forecasts is 7

$$\mathbf{MAD} = \frac{124.05}{7} = 17.72$$

$$\mathbf{MAPE} = \frac{\sum \left| \textit{forecast error} \middle/ \textit{actual value} \right|}{\textit{no.of forecasts}} = \frac{\sum \left| e_t \middle/ y_t \right|}{n} \cdot 100\ \%$$

The forecast error / actual value for day 25 is : 35.58 / +479.00 = 0.08

The forecast error / actual value for day 26 is : 0 / 399.70 = 0

The forecast error / actual value for day 27 is : 50.84 / 407.26 = 0.12

The forecast error / actual value for day 28 is : 7.14 / 459.08 = 0.02

The forecast error / actual value for day 29 is : 5.65 / 397.58 = 0.01

The forecast error / actual value for day 30 is : 18.09 / 433.43 = 0.04

The forecast error / actual value for day 31 is : 6.75 / 415.50 = 0.02

Total the forecast error / actual value is :

$0.08 + 0 + 0.12 + 0.02 + 0.01 + 0.04 + 0.02 = 0.29$

$$\textbf{MAPE} = \frac{0.29}{7} \times 100\,\% = 4.18\,\%$$

With same way, We get MAD and MAPE for each forecasting model month, is shown in Table 5.8. MAD and MAPE in Neural Networks Model.

Comparison MAD and MAPE in Neural Networks Model with Time Series and Regression Analysis is shown in Table 5.9.

Table 5.1. Daily Average Temperature in Roorkee During 2003

Day	Jan (C)	Feb (C)	March (C)	April (C)	May (C)	June (C)	July (C)	Aug (C)	Sept (C)	Oct (C)	Nov (C)	Dec (C)
1	9.55	12.25	21.00	23.50	29.05	33.40	29.60	25.50	27.70	26.50	22.70	15.55
2	13.15	13.00	17.50	24.50	30.75	33.50	30.50	28.65	29.15	24.25	21.90	15.85
3	12.00	15.20	21.90	25.45	28.75	33.20	30.25	28.75	27.75	24.30	22.10	16.00
4	14.45	15.85	17.15	28.00	27.50	34.80	32.25	28.35	26.60	25.80	21.70	15.75
5	9.75	15.00	13.05	26.50	24.75	33.25	30.00	29.45	26.15	25.65	22.30	16.00
6	10.65	14.95	14.75	25.00	26.70	33.25	28.70	31.80	29.45	26.15	22.30	17.00
7	8.60	16.25	16.75	24.65	27.75	32.35	28.40	30.90	29.05	26.00	21.60	16.55
8	11.65	16.40	17.05	24.35	27.25	31.95	31.00	31.90	26.85	25.90	22.00	16.50
9	8.30	16.10	17.90	25.00	27.90	29.60	30.60	30.65	29.40	25.65	21.20	17.50
10	7.65	15.60	19.30	26.30	28.50	32.70	29.20	29.00	28.20	25.15	21.20	17.00
11	10.25	15.50	19.50	27.70	29.75	33.50	25.30	29.15	26.50	24.50	19.20	17.55
12	7.40	15.65	20.55	28.00	30.50	33.95	23.65	28.65	27.35	23.30	19.10	18.15
13	7.55	15.95	21.50	27.75	28.65	33.00	26.95	29.15	27.35	23.10	20.30	20.00
14	6.80	16.00	20.40	28.80	27.50	33.50	28.50	28.75	29.70	23.70	20.90	15.20
15	7.25	16.00	20.35	28.65	28.60	33.90	30.25	27.75	29.30	23.50	18.50	21.00
16	10.25	18.05	20.50	30.00	29.20	33.05	30.50	26.85	27.10	24.65	19.80	18.35
17	10.25	18.60	22.25	26.80	29.05	33.00	30.75	29.40	26.25	25.40	15.90	17.30
18	13.25	19.05	23.20	26.75	30.25	28.10	30.85	30.65	27.85	25.75	18.00	16.90
19	12.50	16.45	22.30	28.25	30.75	26.00	29.90	30.10	28.45	24.20	19.40	14.40
20	9.75	13.25	21.50	28.80	32.95	29.70	30.25	26.95	29.70	23.00	19.20	13.55
21	11.00	15.30	21.10	28.65	32.00	29.45	29.60	28.20	29.85	23.05	17.00	15.15
22	7.20	16.10	22.50	27.50	33.40	30.25	26.60	28.40	30.25	23.75	16.30	14.50
23	9.75	17.60	22.25	28.20	29.00	30.75	30.65	30.65	27.80	24.45	16.30	13.85
24	11.35	19.25	22.95	28.95	27.50	29.00	30.90	29.75	25.75	24.15	16.90	13.35
25	12.50	19.25	24.25	30.20	28.25	30.90	32.15	30.10	26.60	23.50	17.60	14.25
26	13.25	20.25	23.45	31.00	29.25	30.85	31.55	29.75	26.60	23.10	15.50	9.25
27	16.90	20.30	23.40	29.25	29.90	30.45	31.40	29.75	27.25	21.60	16.30	11.30
28	17.35	21.90	24.25	29.30	32.00	28.05	32.00	30.60	27.20	22.60	16.50	10.65
29	15.00	-	25.25	26.40	32.75	30.75	30.00	30.35	27.65	23.15	16.60	10.45
30	15.80	-	25.70	28.40	30.65	29.55	29.30	27.60	25.70	23.10	15.90	9.40
31	13.55	-	23.45	-	31.50	-	29.10	27.65	-	22.70	-	9.25

Table 5.2. Daily Relative Humidity in Roorkee During 2003

Day	Jan (%)	Feb (%)	March (%)	April (%)	May (%)	June (%)	July (%)	Aug (%)	Sept (%)	Oct (%)	Nov (%)	Dec (%)
1	95.00	96.00	84.00	73.00	48.00	36.00	73.00	90.00	86.00	86.00	83.00	95.00
2	95.00	94.00	89.00	67.00	54.00	40.00	89.00	95.00	85.00	77.00	79.00	91.00
3	97.00	96.00	84.00	65.00	49.00	44.00	75.00	85.00	96.00	74.00	90.00	97.00
4	96.00	95.00	81.00	72.00	56.00	53.00	71.00	83.00	90.00	82.00	90.00	92.00
5	98.00	97.00	78.00	68.00	50.00	44.00	100.00	76.00	80.00	78.00	92.00	89.00
6	96.00	97.00	80.00	70.00	45.00	51.00	97.00	86.00	85.00	71.00	83.00	88.00
7	96.00	86.00	75.00	65.00	40.00	48.00	73.00	79.00	90.00	75.00	68.00	88.00
8	94.00	87.00	75.00	60.00	38.00	54.00	70.00	79.00	83.00	80.00	76.00	93.00
9	94.00	90.00	83.00	58.00	0.00	76.00	76.00	98.00	85.00	80.00	69.00	94.00
10	97.00	84.00	67.00	63.00	40.00	75.00	90.00	90.00	92.00	73.00	64.00	95.00
11	97.00	90.00	70.00	60.00	36.00	75.00	100.00	82.00	84.00	78.00	85.00	95.00
12	98.00	96.00	84.00	56.00	48.00	49.00	98.00	93.00	83.00	64.00	87.00	91.00
13	98.00	78.00	90.00	56.00	56.00	47.00	96.00	92.00	83.00	66.00	87.00	93.00
14	98.00	81.00	82.00	58.00	48.00	45.00	78.00	90.00	85.00	74.00	89.00	80.00
15	94.00	83.00	81.00	58.00	45.00	48.00	75.00	94.00	88.00	74.00	83.00	89.00
16	90.00	73.00	83.00	62.00	40.00	54.00	94.00	92.00	93.00	75.00	82.00	93.00
17	95.00	89.00	56.00	58.00	42.00	57.00	82.00	86.00	87.00	74.00	80.00	93.00
18	97.00	73.00	60.00	56.00	39.00	98.00	73.00	84.00	75.00	74.00	81.00	90.00
19	98.00	92.00	65.00	58.00	44.00	72.00	90.00	89.00	77.00	82.00	71.00	95.00
20	97.00	80.00	71.00	54.00	46.00	77.00	83.00	92.00	76.00	71.00	86.00	92.00
21	97.00	80.00	73.00	55.00	44.00	68.00	92.00	92.00	86.00	76.00	85.00	88.00
22	98.00	91.00	72.00	54.00	48.00	75.00	83.00	81.00	81.00	74.00	81.00	95.00
23	100.00	86.00	70.00	53.00	77.00	79.00	83.00	78.00	95.00	78.00	92.00	92.00
24	97.00	71.00	65.00	52.00	65.00	71.00	80.00	79.00	82.00	77.00	86.00	94.00
25	92.00	95.00	76.00	51.00	56.00	80.00	80.00	67.00	88.00	74.00	73.00	94.00
26	92.00	85.00	75.00	53.00	48.00	73.00	86.00	86.00	78.00	77.00	81.00	88.00
27	88.00	78.00	71.00	60.00	44.00	87.00	87.00	76.00	80.00	61.00	95.00	97.00
28	82.00	72.00	64.00	65.00	34.00	84.00	69.00	80.00	76.00	72.00	89.00	97.00
29	87.00	-	70.00	50.00	45.00	79.00	97.00	84.00	77.00	80.00	90.00	91.00
30	95.00	-	71.00	62.00	41.00	89.00	80.00	96.00	77.00	78.00	83.00	93.00
31	93.00	-	85.00	-	38.00	-	86.00	98.00	-	82.00	-	83.00

Table 5.3. Daily Average Wind Velocity in Roorkee During 2003

Day	Jan (Km/hr)	Feb (Km/hr)	March (Km/hr)	April (Km/hr)	May (Km/hr)	June (Km/hr)	July (Km/hr)	Aug (Km/hr)	Sept (Km/hr)	Oct (Km/hr)	Nov (Km/hr)	Dec (Km/hr)
1	0.90	0.80	2.10	2.70	1.70	1.40	1.50	2.30	0.70	0.60	0.30	0.40
2	0.50	0.50	2.30	3.00	2.80	1.30	1.50	2.00	2.00	0.75	0.30	0.40
3	0.70	0.40	2.90	1.90	1.80	1.90	1.50	2.10	1.70	0.50	0.30	0.20
4	0.50	0.80	2.30	0.90	2.60	2.00	2.30	2.80	1.00	0.60	0.50	0.25
5	1.20	0.80	4.00	1.30	2.00	3.00	4.00	1.00	0.70	0.40	0.50	0.50
6	0.40	0.60	2.50	1.40	1.40	2.30	1.60	1.10	1.00	0.80	0.30	0.80
7	0.60	0.30	2.50	1.20	1.60	1.90	1.20	1.00	1.10	0.30	0.30	0.60
8	0.70	0.60	0.00	1.20	1.00	1.80	0.90	1.40	1.00	0.75	0.30	0.30
9	0.50	0.40	1.50	0.80	0.00	3.00	1.40	1.80	0.90	0.75	0.30	0.40
10	0.70	0.50	1.70	1.00	1.30	2.10	1.80	1.10	0.80	0.80	0.50	0.80
11	1.50	0.40	1.60	1.40	2.00	2.00	3.00	1.90	1.00	1.25	0.90	0.60
12	0.50	0.40	0.93	1.30	1.70	1.30	2.00	1.25	1.00	0.75	0.50	0.30
13	0.50	0.80	1.10	1.20	2.80	1.70	1.80	1.30	1.00	0.75	0.30	0.60
14	0.40	1.30	1.20	1.30	2.30	1.60	1.60	1.30	1.00	0.90	0.30	1.00
15	0.50	1.42	1.64	1.40	1.80	2.00	1.50	1.30	1.00	0.75	0.30	0.70
16	0.00	2.20	0.95	5.70	2.00	1.30	1.70	0.80	1.20	0.30	0.40	1.25
17	0.40	0.50	1.30	0.40	2.10	4.00	1.60	0.90	0.90	0.30	0.70	0.80
18	0.30	2.00	0.75	0.40	1.70	2.30	2.00	0.60	1.00	0.60	0.60	1.30
19	0.00	8.30	1.30	1.00	1.50	1.60	1.20	2.00	0.60	0.30	0.40	0.40
20	0.30	1.02	1.20	1.30	1.50	1.40	1.40	1.30	0.80	0.50	0.70	1.00
21	0.75	1.70	2.60	1.40	0.70	1.30	2.00	1.00	0.90	0.80	1.70	1.30
22	0.25	2.70	1.20	2.30	2.00	1.60	1.40	1.20	0.60	0.40	0.80	0.60
23	0.30	1.03	1.00	1.00	4.00	1.40	0.70	1.00	1.00	0.40	0.30	0.70
24	0.20	1.12	1.00	1.80	1.30	1.00	0.90	1.60	0.80	0.40	0.30	0.90
25	0.60	1.90	1.30	3.10	1.80	1.70	1.00	1.50	1.40	0.40	0.50	1.00
26	0.70	1.70	1.70	1.80	1.20	1.40	2.10	1.80	1.00	0.40	1.00	0.40
27	0.30	1.20	1.30	1.90	2.40	1.80	1.50	1.30	1.30	0.50	0.40	0.40
28	0.30	2.20	1.50	2.10	2.75	1.30	1.50	1.25	1.00	0.30	0.30	1.50
29	1.10	-	1.30	1.00	1.40	0.90	2.25	1.40	1.00	0.50	0.40	1.00
30	1.00	-	1.30	1.30	2.00	1.00	2.90	1.50	0.80	0.40	0.30	0.70
31	0.40	-	1.60	-	1.30	-	3.00	1.60	-	0.80	-	0.40

Table 5.4. Daily Evaporation in Roorkee During 2003

Day	Jan (mm)	Feb (mm)	March (mm)	April (mm)	May (mm)	June (mm)	July (mm)	Aug (mm)	Sept (mm)	Oct (mm)	Nov (mm)	Dec (mm)
1	0.30	0.00	1.60	4.50	6.00	9.00	3.80	1.00	0.60	4.00	2.00	1.10
2	0.20	0.20	1.30	6.00	6.50	9.20	4.20	0.60	0.40	3.00	0.00	1.20
3	0.20	0.40	1.40	6.00	7.00	9.00	4.00	1.00	0.00	2.90	0.00	1.00
4	0.30	1.00	2.50	5.40	6.50	9.00	6.00	1.00	0.40	3.00	1.40	0.80
5	0.20	0.60	3.00	5.80	6.60	7.80	2.30	4.00	1.00	2.70	1.60	1.00
6	0.20	1.00	3.00	5.40	7.00	8.00	1.00	4.50	2.60	3.00	1.30	1.00
7	0.40	1.20	3.00	5.50	6.50	8.50	1.30	5.60	1.80	3.50	1.40	0.90
8	0.60	1.20	0.00	6.00	6.50	8.00	3.20	5.00	2.70	3.00	1.50	0.80
9	0.60	1.00	2.20	5.40	0.00	7.00	4.00	1.60	4.00	2.80	1.60	1.00
10	0.50	1.30	2.50	5.00	7.00	6.80	3.20	0.80	2.90	2.30	1.40	0.60
11	0.80	1.60	2.30	6.20	6.80	7.00	2.10	1.30	0.80	2.80	1.80	0.90
12	0.20	1.60	2.70	6.00	6.80	7.00	0.00	0.60	1.80	2.80	1.00	1.00
13	0.20	1.80	2.20	6.50	6.20	7.00	1.00	1.00	2.80	2.80	1.10	0.80
14	0.20	1.50	2.15	6.30	6.70	7.80	2.40	1.80	3.00	2.70	1.10	0.20
15	0.30	1.90	2.30	6.50	6.80	8.00	5.40	0.60	2.40	2.60	1.00	1.10
16	0.00	2.00	1.05	5.80	7.00	7.00	4.60	1.60	0.60	2.30	0.90	0.60
17	0.50	1.40	2.20	4.50	7.40	7.40	6.00	1.80	0.40	2.60	0.60	0.70
18	1.30	0.20	2.90	5.60	7.80	6.80	5.00	2.80	2.00	2.40	0.50	0.90
19	0.00	3.40	4.00	6.00	7.80	4.50	3.00	1.30	2.30	2.10	0.80	0.60
20	0.40	1.05	3.80	6.30	6.60	5.00	3.40	0.80	2.50	2.30	0.80	0.60
21	0.40	2.80	4.00	6.50	6.10	7.60	1.60	0.60	3.00	2.20	1.40	0.50
22	0.20	2.30	3.80	6.00	6.90	6.80	1.00	2.40	3.00	2.10	1.60	0.60
23	0.30	2.10	3.50	6.50	5.90	6.00	3.50	3.20	0.70	2.00	1.40	0.60
24	0.20	1.80	3.00	7.00	7.40	4.50	3.00	3.50	0.80	2.00	1.20	0.50
25	0.80	2.00	3.60	6.80	7.00	6.00	4.00	3.70	2.30	2.00	1.10	0.70
26	0.80	2.10	3.50	7.00	7.00	5.90	4.00	4.20	2.30	2.00	1.20	0.40
27	1.50	2.30	4.00	6.80	4.50	5.80	4.50	4.20	2.60	2.00	1.10	0.30
28	0.20	2.50	4.00	5.60	8.30	6.00	4.80	3.80	2.80	1.80	1.10	0.00
29	0.30	-	4.20	6.00	8.60	3.60	5.00	5.00	2.80	1.40	1.20	0.20
30	1.30	-	4.10	5.50	9.50	3.70	2.00	0.80	3.60	2.00	1.10	0.20
31	1.00	-	5.00	-	9.00	-	0.80	0.00	-	2.00	-	0.10

Table 5.5. Daily Rainfall in Roorkee During 2003

Day	Jan (mm)	Feb (mm)	March (mm)	April (mm)	May (mm)	June (mm)	July (mm)	Aug (mm)	Sept (mm)	Oct (mm)	Nov (mm)	Dec (mm)
1	1.80	49.80	5.40	0.00	0.00	0.00	0.20	21.80	0.40	0.00	0.00	0.00
2	0.00	0.00	11.00	0.00	0.00	0.00	3.00	1.20	2.60	0.00	0.00	0.00
3	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.60	69.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	3.60	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	88.80	0.00	0.40	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	7.20	0.00	10.60	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	4.60	1.80	0.40	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.40	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.40	18.60	0.00	0.00	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	8.20	66.20	0.00	0.00	0.00	0.00
11	0.00	0.00	0.00	0.00	0.00	0.00	14.20	0.00	0.60	0.00	0.00	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	26.00	10.60	0.00	0.00	0.00	0.00
13	0.00	0.00	0.00	0.00	9.20	0.00	20.40	10.80	0.00	0.00	0.00	4.80
14	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	16.20	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	1.20	0.00	0.00	1.20	7.00	34.20	0.00	0.00	9.40
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	17.00	0.00	2.20	0.00
18	0.00	1.40	0.00	0.00	0.00	23.60	0.00	0.00	0.00	0.00	0.40	0.00
19	0.00	48.10	0.00	0.00	0.00	4.20	2.80	1.20	0.00	0.00	0.00	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	36.40	0.00	0.00	0.00	0.00
21	0.00	0.00	0.00	0.00	0.00	0.00	30.80	30.20	0.00	0.00	0.00	0.00
22	0.00	0.00	0.00	0.00	0.40	0.00	9.00	0.00	0.00	0.00	0.00	0.40
23	0.00	0.00	0.00	0.00	4.80	8.00	0.00	0.00	56.80	0.00	0.00	0.00
24	0.00	0.20	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00
25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
26	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.20	0.00	0.00	0.00	0.00
27	0.00	0.00	0.00	0.00	0.00	5.20	0.00	0.20	0.00	0.00	0.00	0.00
28	1.40	0.00	0.00	3.40	0.00	8.40	0.00	0.20	0.00	0.00	0.00	5.80
29	5.40	-	0.00	0.00	0.00	2.40	4.00	11.80	0.00	0.00	0.00	0.00
30	0.00	-	0.00	0.00	0.00	5.60	0.40	72.20	0.00	0.00	0.00	0.00
31	6.00	-	0.00	-	0.00	-	1.20	2.20	-	0.00	-	0.00

Table 5.6. Indian National Holiday 2003

DATE	DAY OF THE WEEK	NATIONAL HOLIDAY
January 1st	Wednesday	New Years Day
January 13th	Monday	Lohri
January 14th	Tuesday	Makar Sankranti
January 26th	Sunday	Republic Day
February 6th	Thursday	Basant Panchami
February 13th	Thursday	Id-ul-Zuha
February 16th	Sunday	G. Ravidas Jayanti
March 1st	Saturday	Shiv Ratri
March 15th	Saturday	Moharram
March 17th	Monday	Holi March
March 18th	Tuesday	Dhulendi
April 11th	Friday	Ram Navmi
April 13th	Sunday	Baisakhi
April 15th	Tuesday	Mahavir Jayanti
April 18th	Friday	Good Friday
May 15th	Thursday	Milad-ul-Nabi
May 16th	Friday	Budha Poornima
August 12th	Tuesday	Raksha Bandhan
August 15th	Friday	Independence Day
August 20th	Wednesday	Srikrishna Janmanshtmi
September 9th	Tuesday	Anant Chaudas
October 2nd	Thursday	Mahatma Gandhi Jayanti
October 5th	Sunday	Dushera
October 10th	Friday	Balmiki Jayanti
October 25th	Saturday	Deepawali
October 26th	Sunday	Govardhan Pooja
November 9th	Sunday	Guru Nanak Birthday
November 26th	Wednesday	Id-ul-Fittr
December 25th	Thursday	Christmas Day
December 31st	Wednesday	G Govind S Birthday

Table 5.8. MAD and MAPE in Neural Networks Model

FORECASTING MODEL	Jan '03		Feb '03		March '03		April '03		May '03		June '03	
	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)
Neural Network	17.72	4.18	43.51	13.18	13.47	3.64	13.67	3.42	15.29	3.16	25.60	5.40

FORECASTING MODEL	July '03		Aug '03		Sept '03		Oct '03		Nov '03		Dec '03	
	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)
Neural Network	40.29	7.19	27.28	5.95	29.49	7.34	23.18	5.63	26.57	6.28	14.93	3.34

Table 5.9. Comparison MAD and MAPE in Neural Networks with Time Series and Regression Analysis Model

FORECASTING MODEL	Jan ' 03		Feb '03		March '03		April '03		May '03		June '03	
	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)
Moving Average	26.04	6.14	24.60	7.30	23.24	6.23	25.29	6.42	28.54	5.96	32.39	6.80
Exponential Smoothing	54.58	13.22	31.94	9.53	26.50	7.05	28.76	7.45	34.98	7.22	38.01	8.02
ARIMA	39.73	9.55	37.27	11.40	17.11	4.55	38.87	10.14	40.31	8.54	34.81	6.98
Simple Linear Regression	74.81	18.03	34.43	10.90	25.93	6.94	37.70	9.99	35.00	7.12	59.75	12.10
Neural Network	17.72	4.18	43.51	13.18	13.47	3.64	13.67	3.42	15.29	3.16	25.60	5.40

FORECASTING MODEL	July '03		Aug '03		Sept '03		Oct '03		Nov '03		Dec '03	
	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)	MAD	MAPE (%)
Moving Average	47.60	9.10	49.15	10.25	26.35	5.98	30.24	6.76	35.06	8.74	19.50	4.49
Exponential Smoothing	65.46	12.12	63.92	12.68	51.31	10.65	54.11	12.80	39.18	9.49	42.72	9.76
ARIMA	42.67	7.54	60.16	12.55	54.43	12.48	52.39	11.86	37.21	8.73	24.61	5.50
Simple Linear Regression	86.91	15.38	43.09	8.90	36.26	8.14	44.30	9.66	33.30	8.00	35.18	7.91
Neural Network	40.29	7.19	27.28	5.95	29.49	7.34	23.18	5.63	26.57	6.28	14.93	3.34

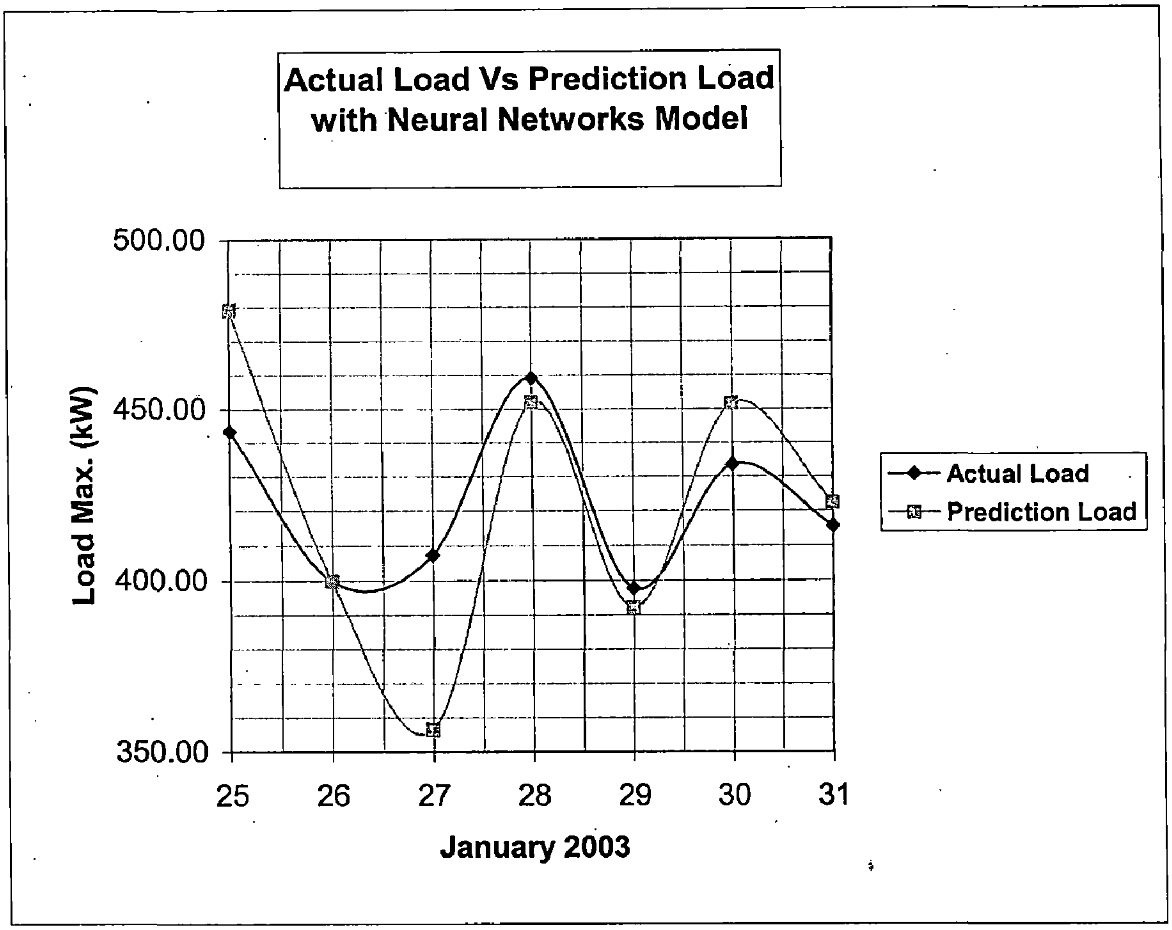


Figure 5.1. Actual Load Versus Prediction Load with Neural Networks Model on January 2003

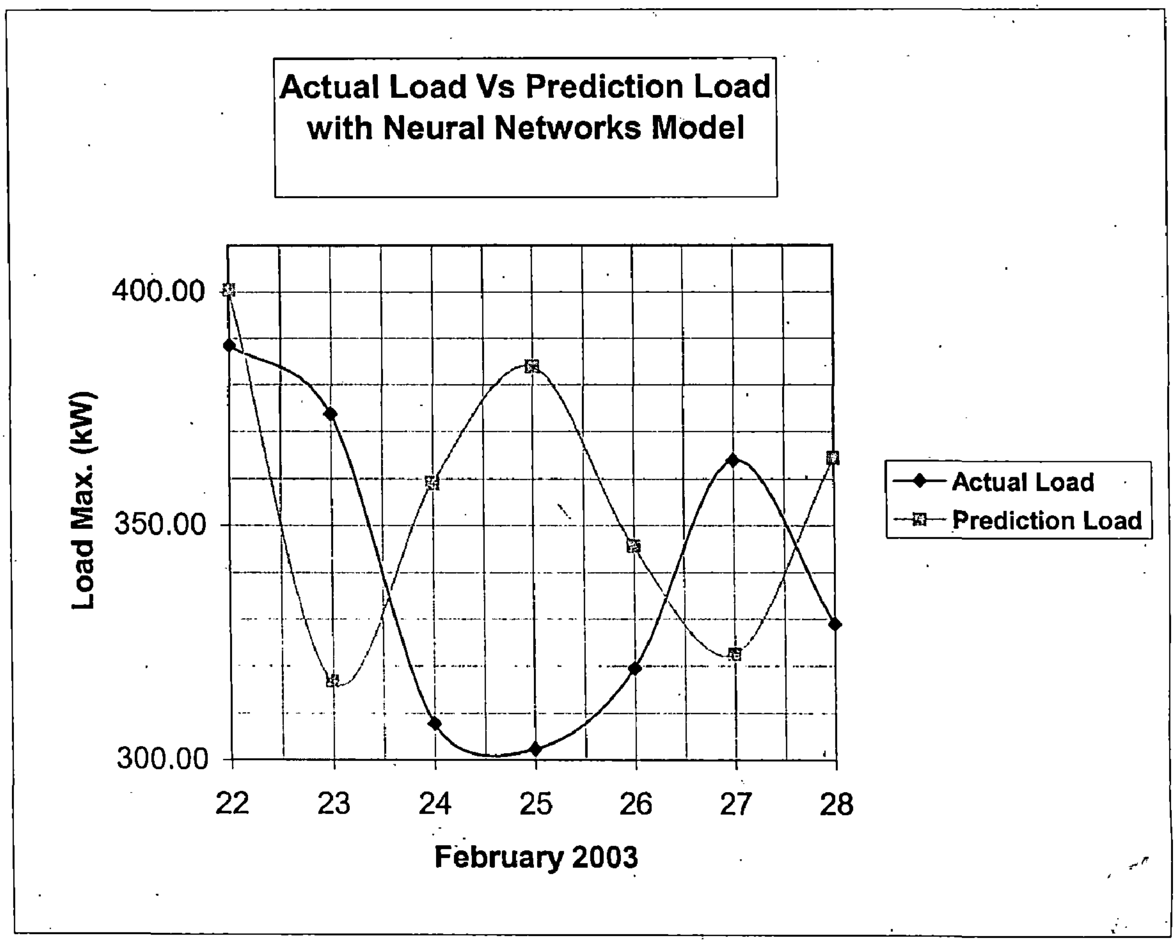


Figure 5.2. Actual Load Versus Prediction Load with Neural Networks Model on February 2003

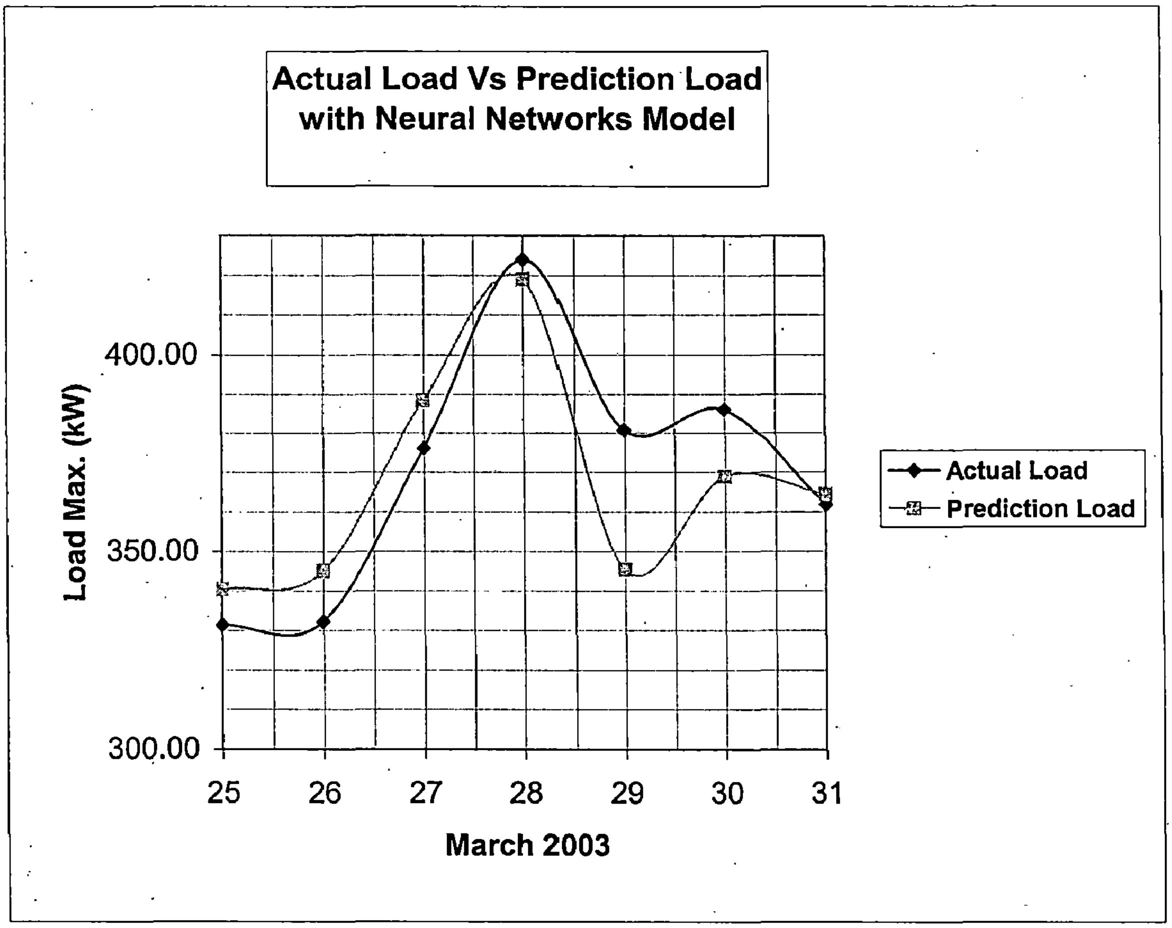


Figure 5.3. Actual Load Versus Prediction Load with Neural Networks Model on March 2003

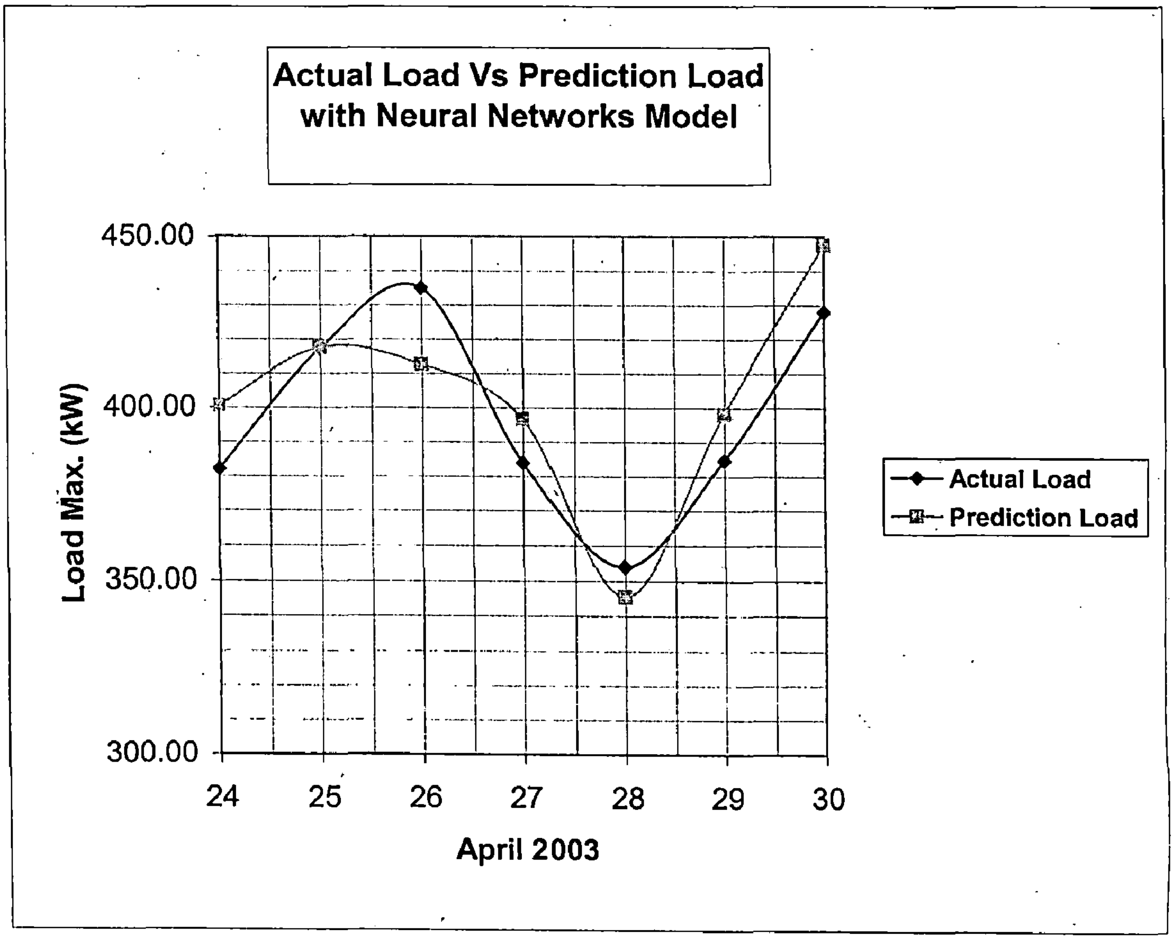


Figure 5.4. Actual Load Versus Prediction Load with Neural Networks Model on April 2003

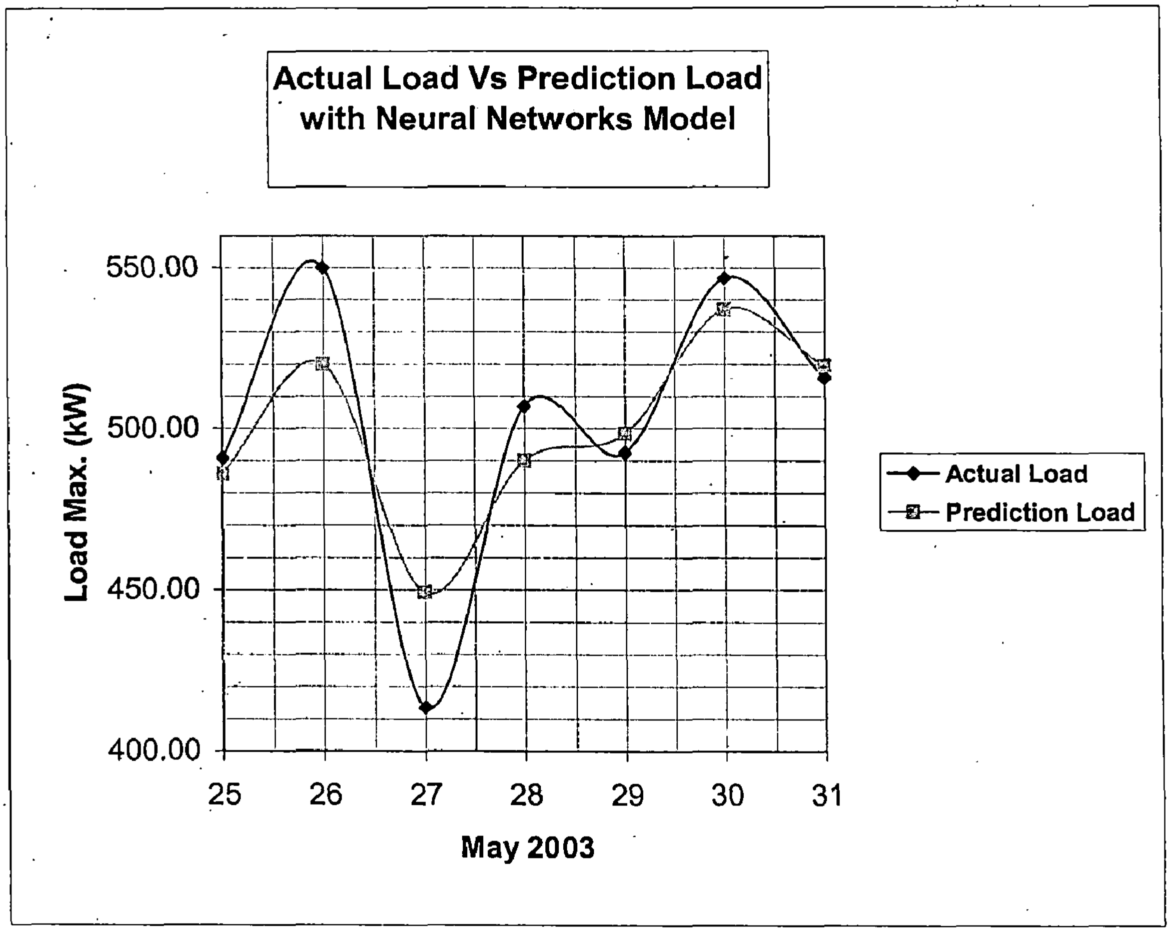


Figure 5.5. Actual Load Versus Prediction Load with Neural Networks Model on May 2003

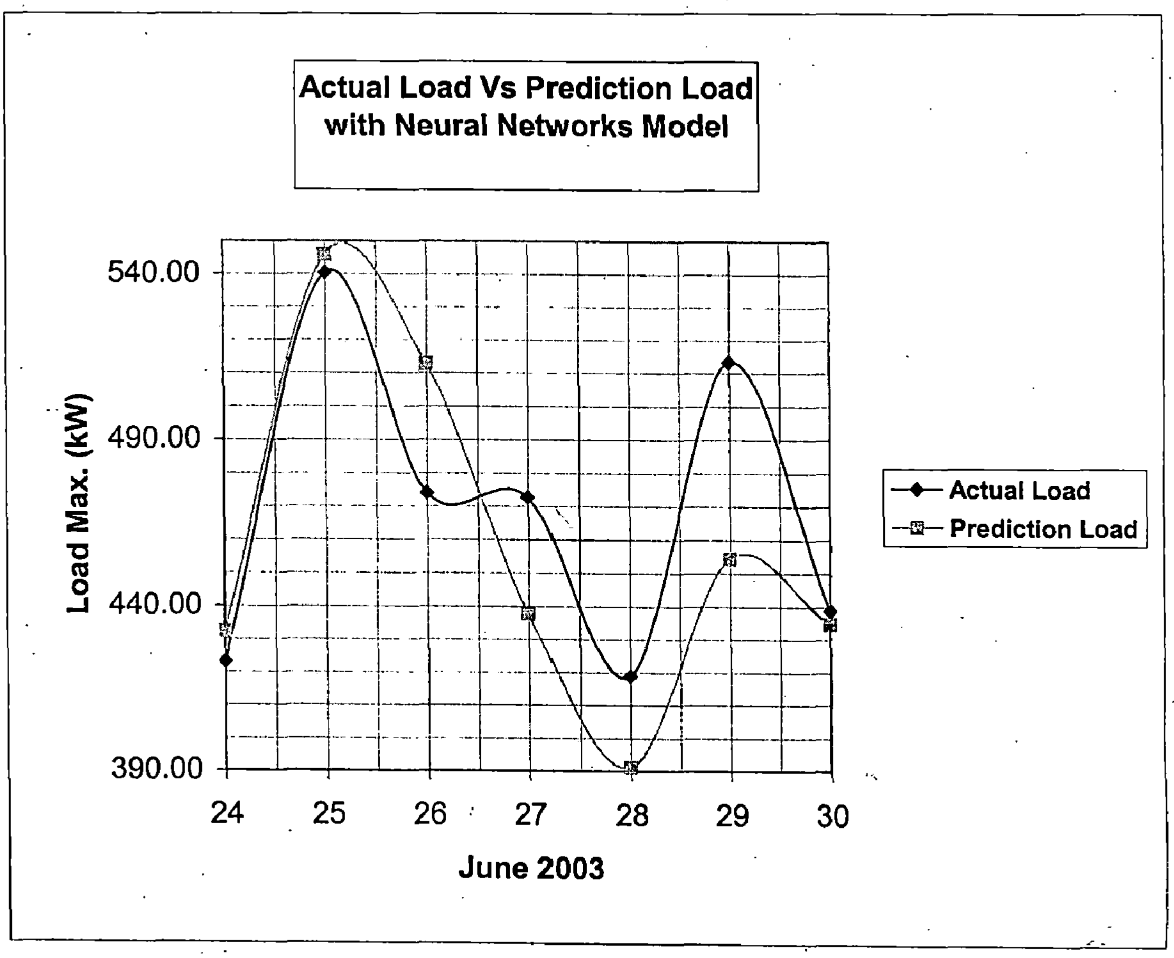


Figure 5.6. Actual Load Versus Prediction Load with Neural Networks Model on June 2003

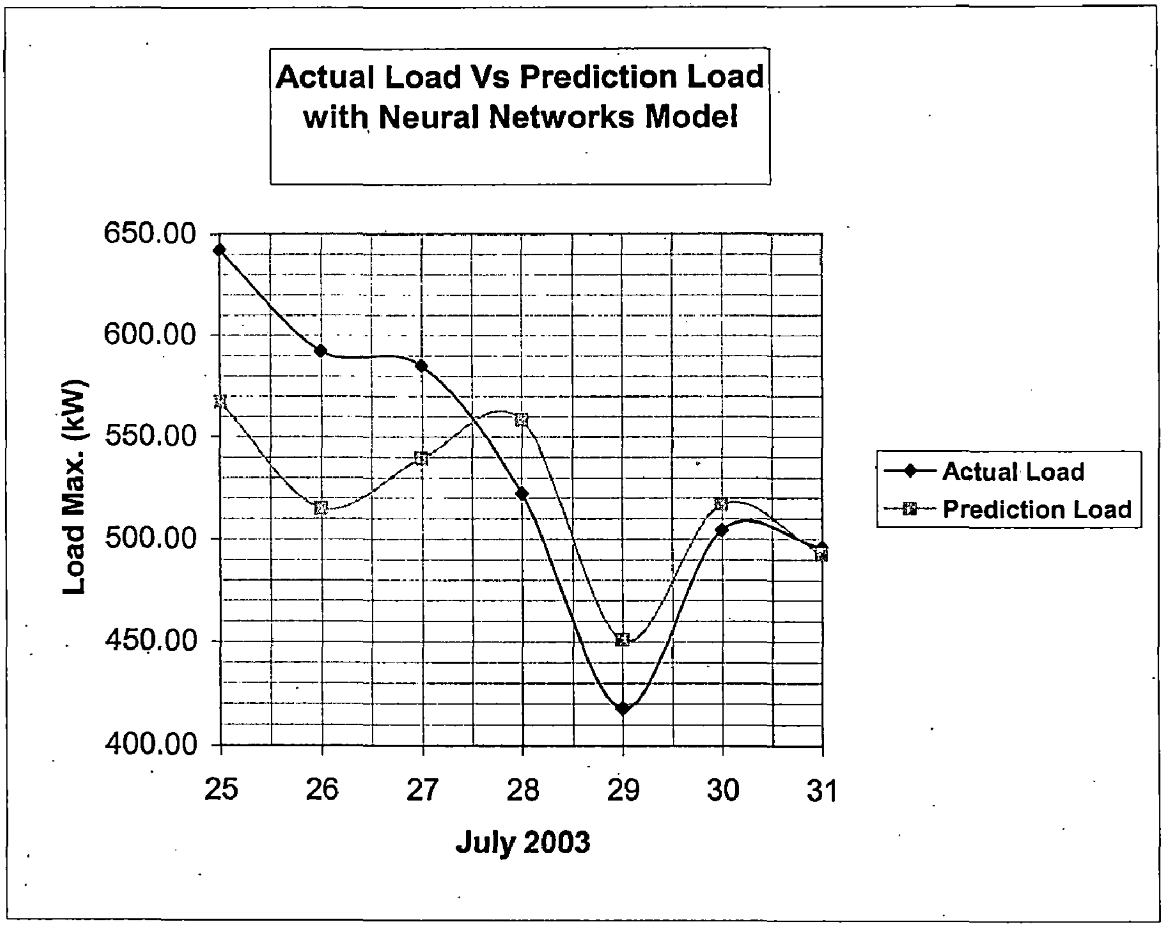


Figure 5.7. Actual Load Versus Prediction Load with Neural Networks Model on July 2003

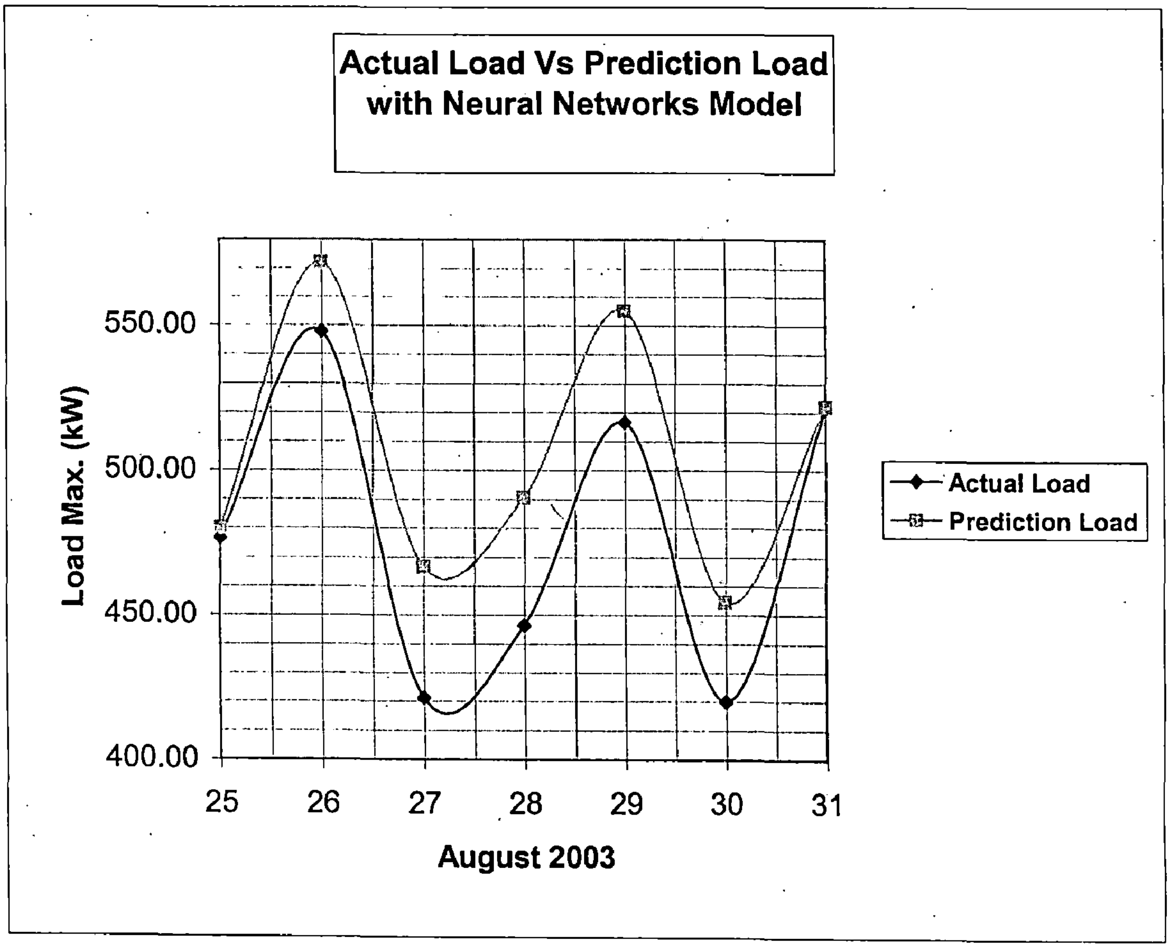


Figure 5.8. Actual Load Versus Prediction Load with Neural Networks Model on August 2003

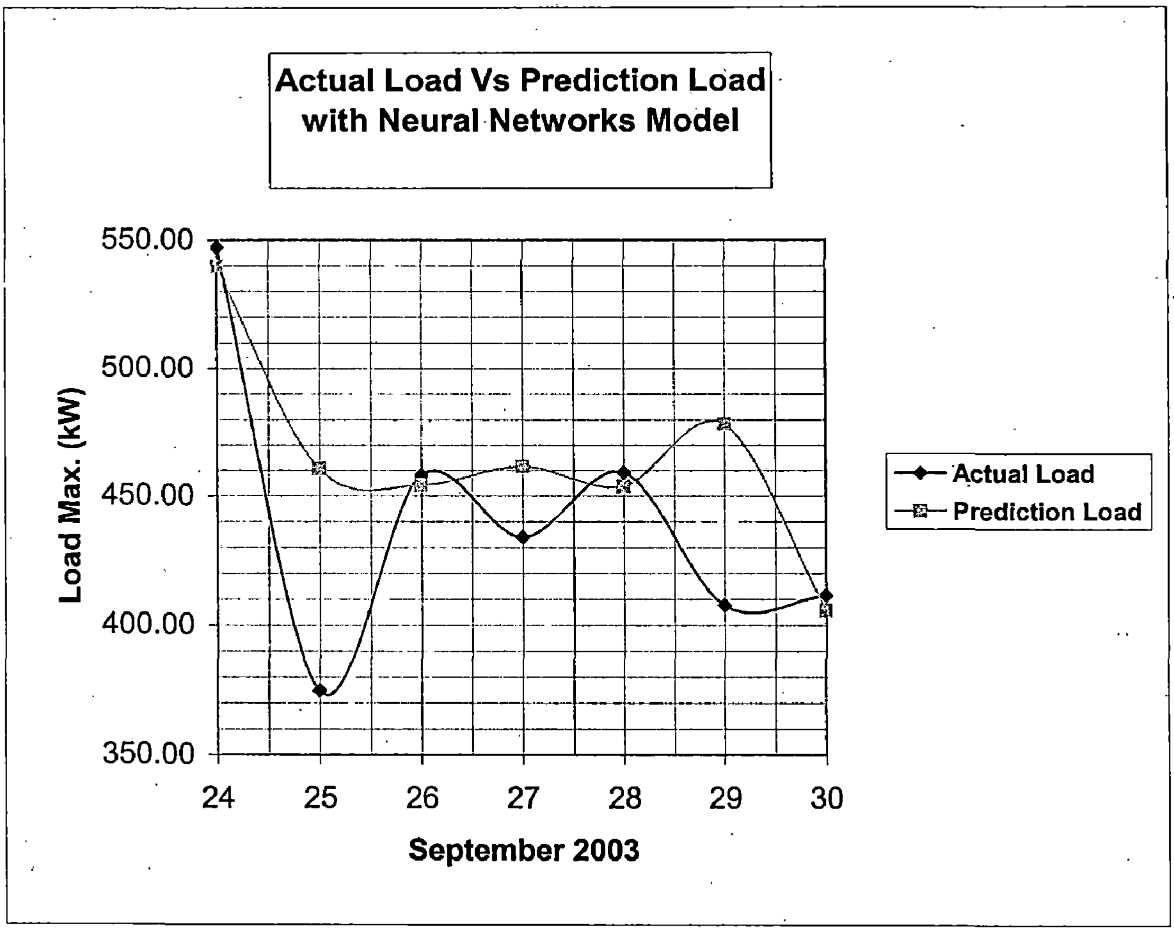


Figure 5.9. Actual Load Versus Prediction Load with Neural Networks Model on September 2003

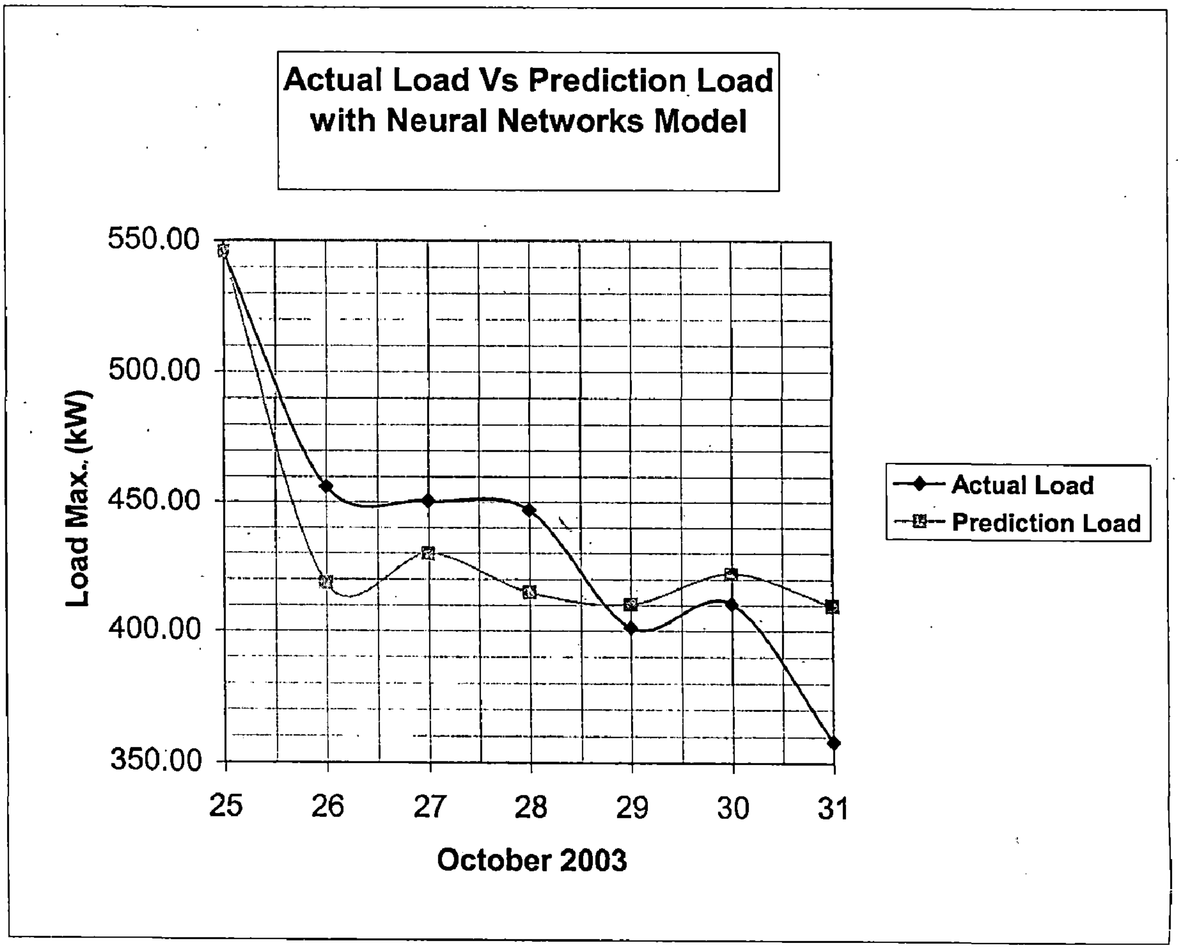


Figure 5.10. Actual Load Versus Prediction Load with Neural Networks Model on October 2003