NEURAL NETWORKS FORECASTING MODEL FOR MONTHLY ELECTRICITY LOAD IN ANDHRA PRADESH

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Abstract: In this paper, forecasting of monthly electricity load using Box-Jenkins methodology and feed forward neural networks is discussed. This study investigates application of neural networks models and the results of neural networks will be compared with those obtained by Box-Jenkins method.

Keywords: Box-Jenkins methodology, Electricity load, Neural networks.

1. Introduction

The electric power production is planned using a long term production program, based on forecasts of future power load. To plan the production in the power generation plants, it is therefore very important to have accurate forecasts of the power consumption. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Load forecasts are extremely important for energy suppliers, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets.

The data used in this paper is collected from Andhra Pradesh Transmission Company (APTRANSCO), Hyderabad, India. The data set contains monthly electricity load in Andhra Pradesh from April 01, 2005 to March 31, 2010 consisting of 60 observations, in which 54 monthly observations used for estimation purpose (in-sample) and the remaining 6 monthly observations left for forecast evaluation (out- of-sample).

Table 1.Average Monthly Electricity Load

Month	January	February	March	April	May	June
Average Load	5362.22	5234.15	5788.20	5109.22	4940.16	4676.84
Month	July	August	September	October	November	December
Average Load	5004.24	5253.69	5028.97	5266.20	4660.20	4963.18

The Box-Jenkins method is one of the most widely used time series forecasting methods in practice. It is also one of the most popular models in traditional time series forecasting and is often used as a benchmark model for comparison with any other forecasting method. The recent upsurge in research activities into artificial neural networks (ANNs) has proven that neural networks have powerful pattern classification and prediction capabilities. One of the major application areas of ANNs is forecasting. ANNs are data-driven non-parametric methods that do not require many restrictive assumptions on the underlying process from which data are generated. As such, they are less susceptible to the model misspecification problem than parametric methods. This "learn from data or experience" feature of ANNs is highly desirable in various forecasting situations where data are usually easy to collect, but the underlying data-generating mechanism is not known or pre-specifiable. Neural networks have been mathematically shown to have the universal functional approximating capability in that they can accurately approximate many types of complex functional relationships. This is an important and powerful characteristic, as any forecasting model aims to accurately capture the functional relationship between the variable to be predicted and other relevant factors or variables. The combination of the above-mentioned characteristics makes ANNs a very general and flexible modeling tool for forecasting.

Box et. al. (1994) presents the Box-Jenkins methodology for time series forecasting. Ljung and Box (1978) present the test for adequacy of a time series model. De Gooijer and Hyndman (2006) discuss the developments in time series forecasting methods in the last 25 years. Hippert et. al. (2001) reviewed the methodology for forecasting short-term load using neural networks. Haykin (1999) presents the neural networks modeling and its applications. Tang et.al. (1991) discussed time series forecasting using Box-Jenkins methodology and neural networks. Myint Myint Yi, et.al. (2008) studied on short term load forecast in the electricity load using neural network, time series and wavelet transform. Paras Mandal et.al. (2005) studied on a several – hour – ahead electric load forecasting using similar days approach in neural nerworks. Pituk Bunnoon, et.al. (2010) studied for midterm load forecasting using neural networks and time series. Ismail et.al. (2009) studied for forecasting peak load electricity demand using time series and Zhang et. al. (1998) presents the review of forecasting models using neural networks. R. Ramakrishna et.al. (2011) presents modeling of daily electricity load in Andhra Pradesh using neural networks. There are many authors studied on modeling of electricity load and time series prediction using neural networks.

In this paper, forecasting of monthly electricity load using Box-Jenkins methodology and feedforward neural networks is discussed. In section 2, we present the modeling using Box-Jenkins methodology. In section 3, building feedforward neural networks model is discussed. Final results are given in section 4.

2. SARIMA Model

In this Section, we discuss the modeling of monthly electricity load in Andhra Pradesh using Box-Jenkins methodology. As we have earlier stated that development of seasonal autoregressive integrated moving average (SARIMA) model for any variable involves mainly four steps: Identification, Estimation, Diagnostic checking and Forecasting.

Model Identification:

Time plot of the monthly electricity load in Andhra Pradesh (figure 1) reveals that the data is seasonal and non stationary.

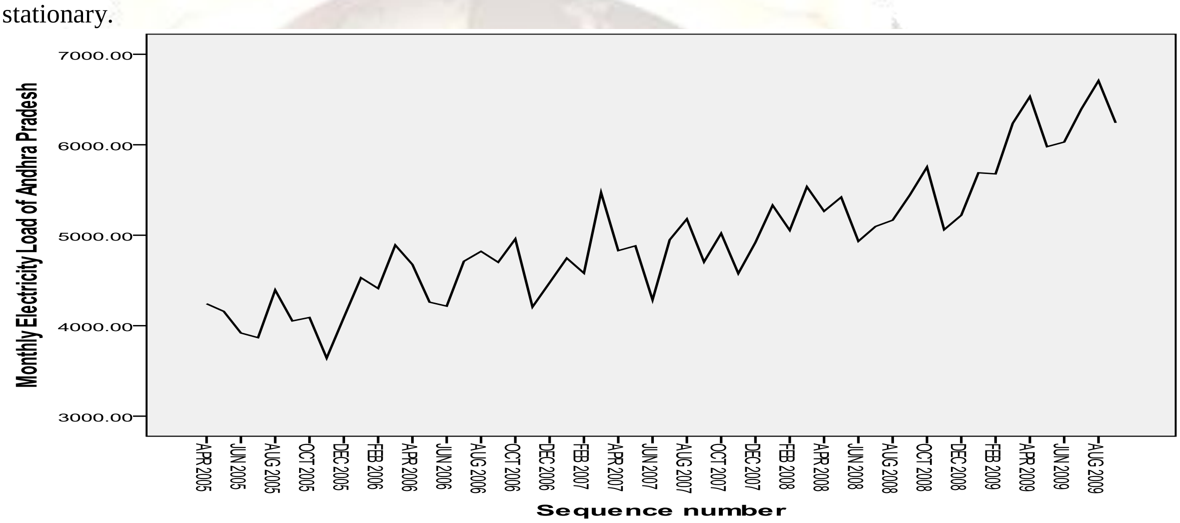

Figure 1. Time plot of monthly electricity load

The sample autocorrelation function (ACF) for the monthly electricity load in Andhra Pradesh is given below.

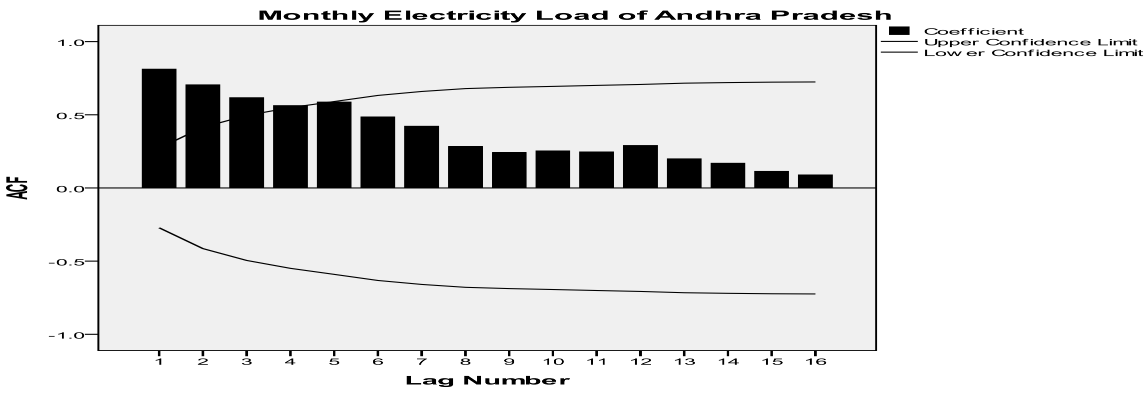

Figure 2. Sample ACF for the monthly electricity load

From the above time plot and ACF plot, one can observe that the given electricity load is seasonal and a SARIMA model can fit the given data well. First we apply the seasonal difference to the given electricity load and observed the following ACF and partial autocorrelation function (PACF) plots of monthly electricity load in Andhra Pradesh.

Non stationarity in variance is corrected through square root transformation and non stationarity in mean is corrected through appropriate differencing of the data. In this case, non seasonal difference of order 1 (i.e. d=1) and seasonal difference of order 1 (i.e. D=1) is sufficient to achieve stationary in mean and variance. The newly constructed variable $W_t = \nabla^1 \nabla_{12}^1 Z_t$ can now be examined for stationarity.

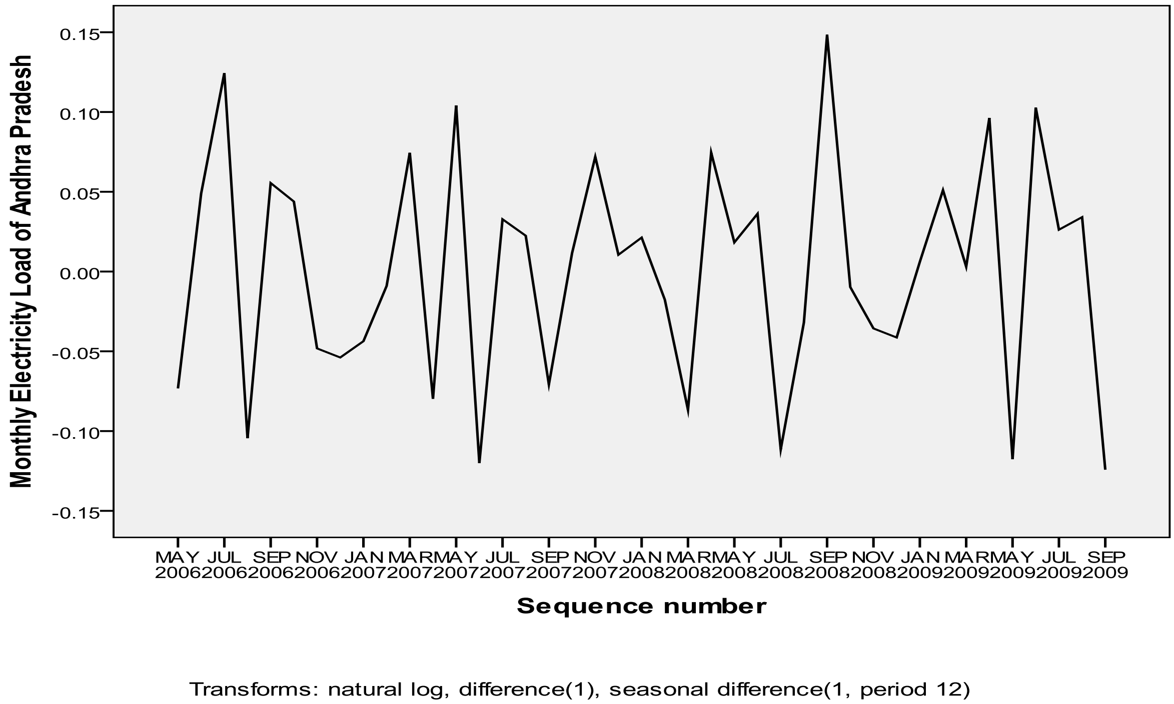

Figure 3. Time plot of log transformed monthly electricity load

The graph (figure 3) of W_t is stationary in mean and variance. The next step is to identify the values of p, q, P and Q. Autocorrelations and partial autocorrelations for 16 lags of W_t are computed for the identification of the parameters of SARIMA model.

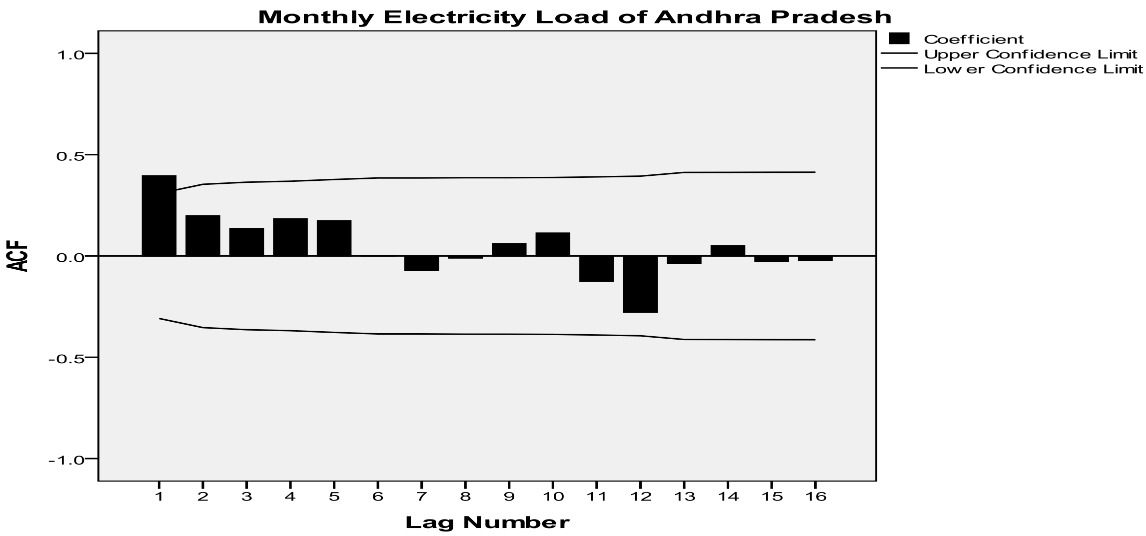

Figure 4. Sample ACF with with d=1, D=1 and period 12.

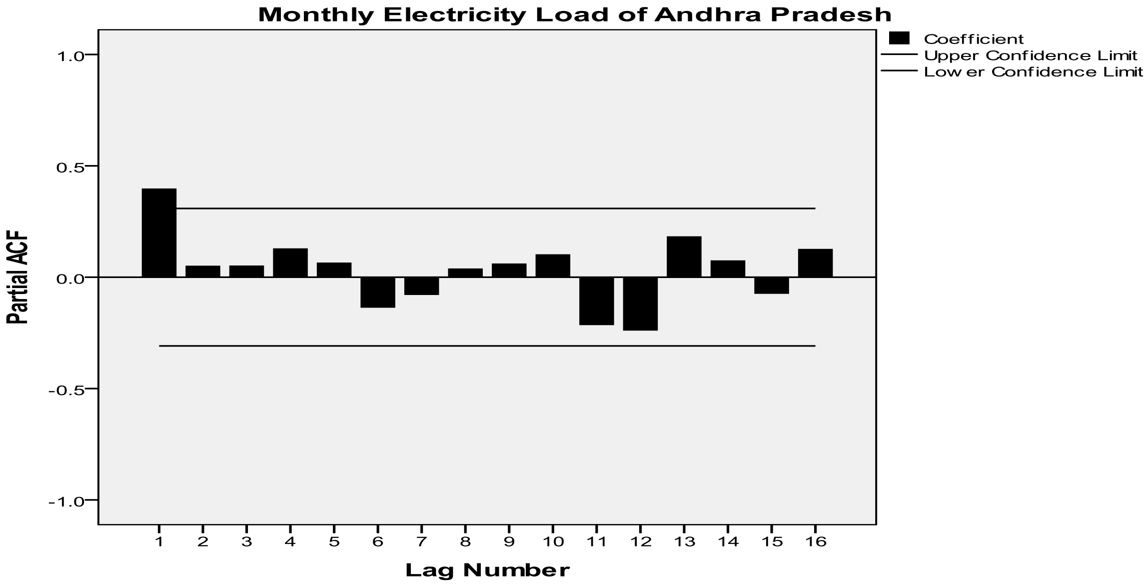

Figure 5. Sample PACF with d=1, D=1 and period 12.

From the above sample ACF and PACF, it is observed that the order of p, d and q is at most 1 and the order of P is at most 2, D is at most 1 and Q is zero. We entertained the following tentative SARIMA models and chosen that the model, which has minimum Baysian information criterion (BIC) value. We considered the residual analysis of each model by computing mean absolute percentage error (MAPE), root mean squared error (RMSE), mean absolute error (MAE), Box-Ljung Q-Statistic and its significant probability for 16 lags are used to identifying a suitable model for the given time series on monthly electricity load in Andhra Pradesh

Table 2. Tentative adequate SARIMA Models for forecasting monthly electricity load.

SARIMA(p, d, q)X(P,D,Q)$_{12}$ Model	BIC	MAPE	RMSE	MAE
SARIMA(0,1,1)X(0,1,0)$_{12}$	11.632	5.193	320.801	273.186
SARIMA(0,1,1)X(1,1,0)$_{12}$	11.527	4.410	290.882	229.004
SARIMA(0,1,1)X(2,1,0)$_{12}$	11.492	4.141	273.211	213.348

So the most suitable model is SARIMA (0, 1, 1) X (2, 1, 0)$_{12}$ as this model has the lowest BIC and RMSE values.

Model Estimation:

Model parameters (without constant term in the model) are estimated using PASW18 for selected model. Results of estimation of parameters are given below.

Table 3. Model Parameters of the SARIMA (0, 1, 1) X (2, 1, 0)$_{12}$ Model

Parameters	B	S.E.(B)	T-Ratio	Prob.
MA1	0.661	0.124	5.346	0.000
SAR1	-0.762	0.200	-3.804	0.001
SAR2	-0.475	0.216	-2.194	0.034

From the above table it is observed that all the parameters are significant at 5% level. So the fitted model for the monthly electricity load in Andhra Pradesh is

$$(1+0.762B^{12}+0.475B^{24})\nabla^1\nabla_{12}^1\widetilde{Z}_t=(1+0.661B)a_t.$$

Diagnostic Checking:

Diagnostic checking is done through examining the autocorrelations and partial autocorrelations of the residuals of various orders.

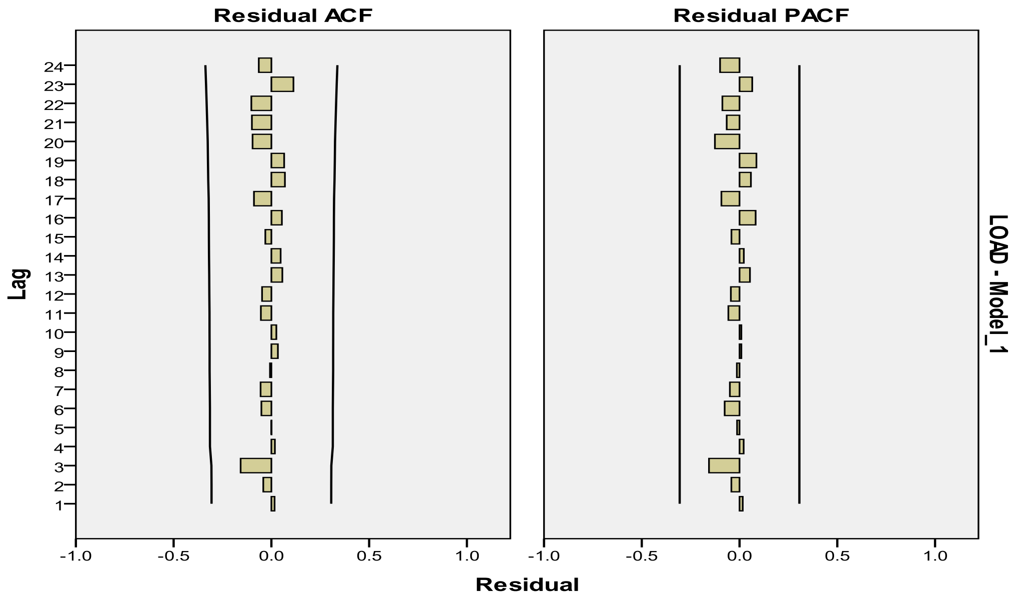

Figure 6. Residual ACF and PACF up to the 25 lags.

As the results indicate, none of these autocorrelations is significantly different from zero at 5% level. This proves that the model is an appropriate model.

Portmanteau Test:

For this purpose, the various autocorrelations of residuals for 25 lags are computed and the same along with their significance which is tested by Box-Ljung Q- test statistic. Let the hypothesis on the model is

H_o: The selected model is adequate.

H_1: The selected model is inadequate.

Table 4. Portmanteau Test

Ljung-Box Q-Test		
Statistics	DF	Sig.
3.516	15	0.999

Since the probability corresponding to Box-Ljung Q-statistic is greater than 0.05, therefore, we accept H_o and we may conclude that the selected seasonal autoregressive integrated moving average model is an adequate model for the given time series on monthly electricity load in Andhra Pradesh.

One can forecast the future monthly electricity load in Andhra Pradesh by the equation (fitted model) by minimum mean square error method. We have forecasted the monthly electricity load in Andhra Pradesh (in GW) for the out-of-sample set(October, 2009 - March, 2010) using the selected SARIMA(0,1,1)X(2,1,0)$_{12}$ model is tabulated in Section 4.

3. FFNN Forecasting Model

In this Section, we develop a Feed forward neural networks (FFNN) model for forecasting of monthly electricity load (GW) in Andhra Pradesh State. PASW 18 software is used to build a feed forward neural network for the forecasting of electricity load in Andhra Pradesh State.

Scale-dependent variables and covariates are rescaled to improve network training. In the present study, we use adjusted normalized method to rescale the variables. The adjusted normalized values fall between -1 and +1. The given data is partitioned into three samples namely training, testing and hold out samples. The training sample comprises the data records used to train the neural networks; the testing sample is an independent set of data records used to track errors during training in order to prevent over training. The hold out sample is another independent set of data records used to assess the final neural network; the error for the hold out sample gives an honest estimate of the predictive ability of the model because the hold out cases are not used to build the model.

We have considered the following partitions of the data for searching of an optimal FFNN model.

Table 5. Partitions of the time series data

Partition	Partition-I	Partition-II	Partition-III	Partition-IV
Training (%)	85	80	75	70
Testing (%)	5	10	15	20
Hold-out (%)	10	10	10	10
Total (%)	100	100	100	100

The model is a three layer feed forward neural network and it consists of an input layer, a hidden layer and an output layer. Total number of input neurons needed in this model is two, each representing the values of lag_1 (previous month in the same year) and lag_{12} (same month in the previous year).

In this model only one output unit is needed and it indicates the forecasts of monthly electricity load. There is no easy way to determine the optimum number of hidden units without training and testing. The best approach to find the optimal number of hidden units is trial and error. In practice, we can use either the forward selection or backward selection to determine the hidden layer units. We apply forward selection method, in which we select a small number of hidden neurons then record the network performance by computing the RMSE, MAE and MAPE. Next increase the hidden neurons one by one, train and test until the error is acceptably small or no significant improvement is noted. It is noted that the optimum network is 2-3-1 and optimum number of hidden neurons are three in the hidden layer and the best partition is given below for which the error measures are minimum.

Table 6. Optimum partition data for the FFNN (2-3-1) model

partition	Percentage of data set	Number of observations
Training Set	80%	48
Testing Set	10%	06
Hold-out Set	10%	06
Total	100%	60

A feed forward neural network consists with one input layer, one hidden layer and one output layer. An input layer consists of two neurons representing the lag_1 and lag_{12} of the electricity load, hidden layer consists of three neurons and output layer consisting of one neuron representing the forecast value of the monthly electricity load. We apply the backpropogation algorithm to train the FFNN with the following parameters.
Learning method: Supervised Learning method
Training Criteria: Mini-Batch
Optimization Algorithm: Gradient descent
Initial learning rate: 0.3
Lower boundary of learning rate: 0.001
Momentum: 0.0001
Learning rate reduction, in Epochs: 10
Interval center: 0
Interval offset: ± 0.5.
Stopping rule used: 10,000 epochs.

The below table displays the coefficient estimates that show the relationship between the units in a given layer to the units in the following layer. The synaptic weights are based on the training sample even if the active data set is portioned into training, testing and holdout data. Note that the number of synaptic weights can become rather large and these weights are generally not used for interpreting network results.

Table 7. Parameter Estimates

Predictor		Predicted			
		Hidden Layer 1			Output Layer
		H(1:1)	H(1:2)	H(1:3)	Monthly Load
Input Layer	(Bias)	0.395	-0.594	0.578	
	lag1	-0.511	1.753	0.241	
	lag12	0.659	1.139	1.279	
Hidden Layer 1	(Bias)				0.055
	H(1:1)				0.614
	H(1:2)				0.916
	H(1:3)				0.747

Hidden activations:

$h_1 = \tanh(0.395 - 0.511\tilde{Z}_{t-1} - 0.659\tilde{Z}_{t-12})$, $h_2 = \tanh(-0.594 + 1.753\tilde{Z}_{t-1} + 1.139\tilde{Z}_{t-12})$,

$h_3 = \tanh(0.578 + 0.241\tilde{Z}_{t-1} + 1.279\tilde{Z}_{t-12})$ where $\tilde{Z}_{t-k}$ is the rescaled variable at lag k.

Neural networks model: $\tilde{Z}_t = I(0.055 + 0.614h_1 + 0.916h_2 + 0.747h_3)$ where I(.) is the activation function, that converts the rescaled data into the original series. The selected FFNN model is used to forecast the future monthly electricity load and the forecasts are presented in Section 4.

4. Conclusion

The forecasts obtained using two models presented in the following table.

Table 8. Forecasts of Electricity Load (in GW) using SARIMA and FFNN models

Month	Original Load	SARIMA Forecasts	FFNN Forecasts
Oct-09	6507.79	6730.48	6563.75
Nov-09	5812.5	5880.96	6242.49
Dec-09	6108.52	6230.14	6072.29
Jan-10	6512.99	6691.68	6524.75
Feb-10	6445.64	6477.4	6532.46
Mar-10	6806.84	6397.93	6695.44

Here the results obtained by SARIMA and Neural networks forecasting models for monthly electricity load in Andhra Pradesh State, are compared with respect to MAPE, RMSE and MAE.

Table 9. Performance of the SARIMA and FFNN models

Forecasting Model	Error Measures	In-Sample Set	Out-of-Sample Set
SARIMA Model	MAPE	4.14	2.64
	RMSE	273.21	211.82
	MAE	213.35	172.02
FFNN Model	MAPE	3.78	2.00
	RMSE	231.71	186.82
	MAE	192.33	122.03

From the above table 9, it is clear that neural networks model is the best to forecast the future values, because it has minimum measures of forecasting errors such as MAPE, RMSE and MAE. Therefore we can conclude that the forecasting of monthly electricity load with feed forward neural networks is more efficient than the Box-Jenkins methods.

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