Comparision of Regression and Neural Network for Demand Forecasting

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Abstract— Forecasting of power consumption and planning of the balances of electric power maybe said to be main objective of management. The amount of energy consumption defines the structure of generating equipment electric network configuration, the production of electric and thermal energy, use of energy resources, reliability of power supply ,the quality of electric power .the planning accuracy is an actual task and it depends upon calculation method. This work shows a comparative analysis of regressive and neural network model for the solution of a problem of forecasting of daily power consumption. The result shows that NN provide accurate prediction outperforming three state of the art approaches and a number of base line. NN is also more accurate and efficient than a non-iterative version approach (regression method).

Key words: Forecasting of energy consumption, Neural Networks, Regression Analysis, Forecasting Model, Prediction Error

I. INTRODUCTION

Load forecasting problem is receiving vast and growing thought as being an important and primary apparatus in power system planning control and operation. Importance of load forecasting becomes more significant in developing countries. In power system the term load forecasting of power consumption is connected with term planning all the participants of the power resources market need to calculate the amount of power consummation accurately. Generation companies can supply electricity in amount of consumer need and stick the optimal load curve and prevent overloading of generating equipment. The main problem in getting the reliable forecast of electrical energy consumption for all time ranges is to choose a model of forecast which presents the initial data in the most accurate way.

This paper mainly divided into two section,

1. Artificial intelligence (AI)
2. Time series model/Regression Model

The forecast methodology of electric load curve for the short planning technologies [1] Regulate the following forecasting mathematical model:-

Regression dependences, a model represent by Fourier series and additive model [16].

However a choice of the final forecasting model for specific task should take into consideration the analysis of obtain result. It is possible to use a neural network as an alternative model [5].

The greatest influence on the reliability of the result is provided by following states:-

1. Initial data processing. It is necessary to identity unfaithful value on the stage of initial data prediction excludes them from the following analysis or replaces them for the model parameter.
2. Introducing correction for independent variable in basic mathematical model.

Independent /irregular effect, which are often natural lead to deviation of actual value of power consumption from the trend line such independent variable are: - temperature, light, humidity, prediction, wind velocity, system frequency and energy loss caused by transient etc.

To assess the possibilities of using various forecasting method it’s necessary to set the lead time. The period of year was chosen as an interval for such load time As for forecasting needs proportion of the load and retrospective times to be at least one or three so daily consumption data over three year were taken for the retrospective time series since 2016 to 2019.

Owing to the importance of load forecasting various models have been proposed, such as regression based model, time series approaches, neural network model and fuzzy-Neural network model for short term forecasting [9].

The second kind of predication is known as medium term forecasting. There is several method of medium term forecasting such as time series approach, neural network model and Fourier series approach presented a pragmatic methodology than be used a a guide to construct electric power load forecasting model. Some result can be reported to guide forecasting future need of this network.

The third of predication is known as long term forecasting. The major methods for long term load forecasting are time series approach, intelligence method, and neuro fuzzy approach dynamic simulation theory and support vector machine. Their result demonstrated the effectiveness of methodology handling this type of problem.

In paper we compare the iterative neural network approach with regression approach. The regression model uses a separate NN for each hour in forecasting horizon.

II. REGRESSION MODEL

Regression analysis is most popular method among a number of probabilistic static methods used in forecasting of power consumption. This method used widely because of two reasons:

1. Description of dependency between variable allow identifying causality.
2. Using regression equation it’s possible to forecast the value of dependent variable basing on the value of independent ones.

Regression analysis include two main task

1. Choosing the form of the function for regression equation and determining the most important independent variables.
2. Fourier series expansion, which approximation the actual distribution was used as a regression model of the load curve and since the power consumption

has trend showing stable systematic change of load curve it is necessary to take into consideration such behavior when creating model by summarizing the trend with periodic function.

For this source data the trend function is

$$Y_t = 2.06548x + 45278$$

Fourier series function is:

$$Y_{11} = 102017 \cdot \left(\sin\left(\frac{x+73}{56.4}\right)\right) + 4258 \cdot \left(\sin\left(\frac{x+41}{56.4}\right)\right)$$

These are (Y_t, Y_{11}) are trend function respectively.

Fig. 1 shows that changing the average annual of energy consumption is not so significant.

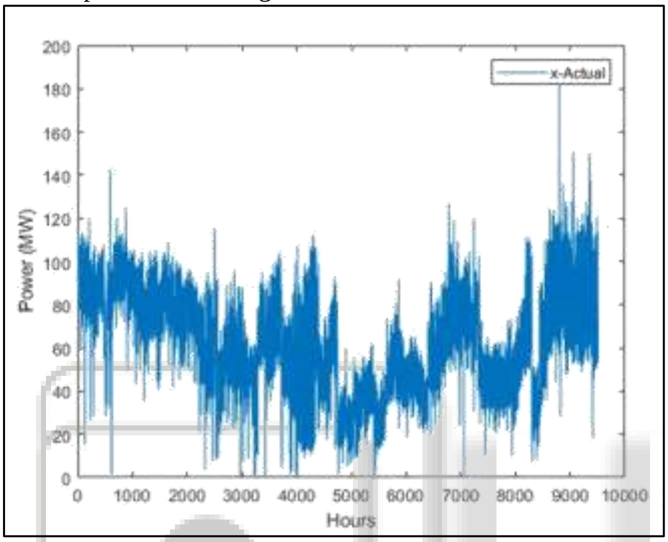

Fig. 1: Annul consumption of Power

In this paper on average relative error on whole amount of data fetch e was used as model error assessment

$$\sum_{t=1}^{N} \frac{(Actual_t - Forecast_t)}{Actual_t} * 100\%$$

The procedure of linear regression work could be summarized as follow

1) A linear regression model is derived for all cases (one day, one week, one month, and one year). An example for the estimated maximum, minimum and average value.

2) Then the electric load was calculated as the predicted shifted by the predication average value figure 2 shown a graph user interface used to predict electric load.

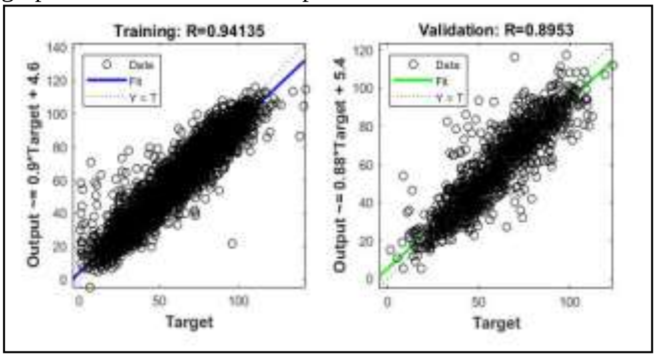

Fig. 2: Interface used to predict

III. Neural Network

An artificial neural network (ANN) is a computational algorithmic model that attempts to account for the parallel nature of human brain. Specifically, it is a network of highly interconnecting processing element (Neurons) operating in parallel. An ANN can be used to solve problem involving complex relationship between variable. The particular type of ANN used in this study is a supervised one, wherein the target observation is specified, and the ANN is trained to minimize the error between the ANN output and the intention, resulting in an most favorable solution. ANN was selected for this study owing to their ability to model non liner relationship between the input and output parameter in this study is highly non liner.

Model of artificial neural network have a number of advantages, which can be widely used for analysis and forecasting they are:

1. No need to build a mathematical model of the process analyzed.
2. Ability to recover non linear functional relationship between the studied parameter

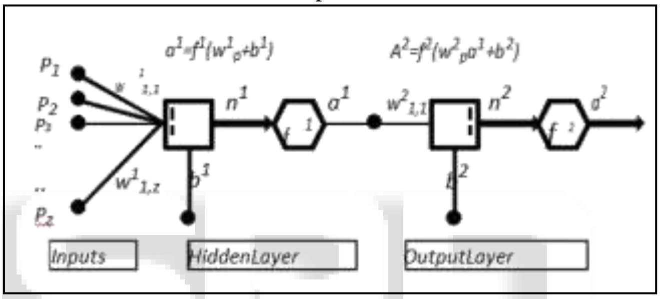

Fig. 3: Neural network Block Diagram

The neural network arthritically made on basis of a multilayer perception was used to forecast time series. This network can simulate function of almost any complex city. The advantage of using this architecture unlike the radial basis function network is that it better catches the trend component of the time series. To initialize the network and to work with the original training subsample “static” software package was used.

It should be noted that it is not possible to achieve a significant reduction in the prediction error, by choosing the linear variation function of neuron in that layer. The same is seen in the choice of activation function. This leads to concludes that the increase of the number of neuron in the hidden layer does not entail the increase of the forecast quality.

After the visual estimation of the obtained forecast of each network, the best option was chosen the possibility of which will be further compared the possibility of regression approach [19]. Finally the network is selected with following configuration.

365-5-1 where 365 is number of input, 5 is number of neuron hidden klayer, 1 is number of output. Fig. 3 show a comparison of actual time series and the forecast of network for the lead time period (2019).

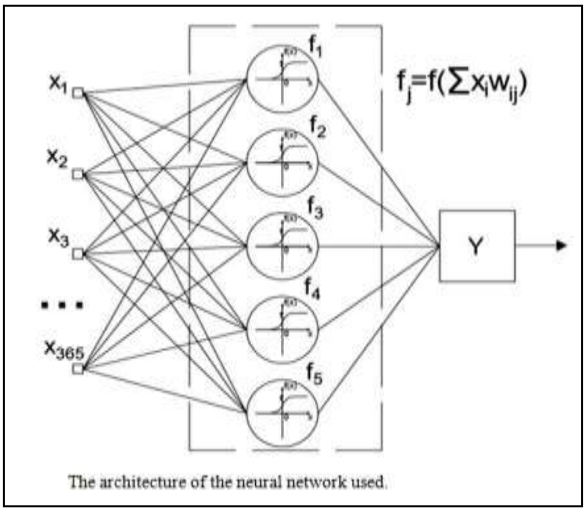

Fig. 4: Architecture of Neural Network

The correlation index is 0.6 or more (between 06-1) it is quite high to enough the confirm that the network capture the law of time series. The relative forecast error is -3.38% which also satisfy the technical management requirement.

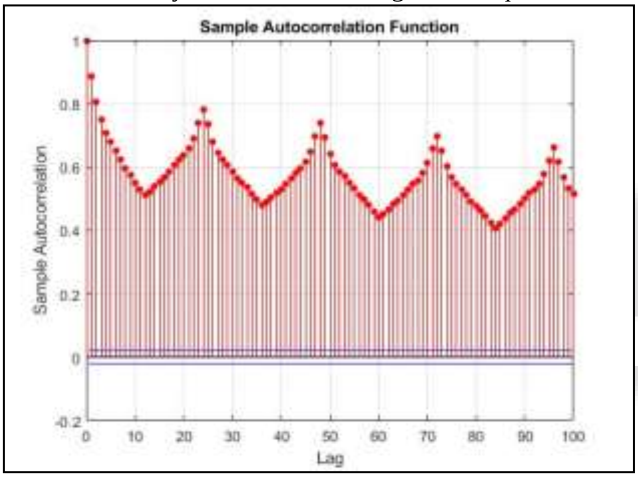

Fig. 5: Sample Auto correlation function

IV. Data Preparation

Successful operation of load forecast using ANN requires an appropriate training data set and training algorithm. The training data set should over all range of input pattern sufficiently to provide the network knowledge recognize and generalize the relationship among the variables in the problem. In this work, a historical data from the Dahibana substation from 2016 to 2019 were used.

V. Analysis Method

For comparing accuracy of results of two forecasting methods, first of all it's necessary to assess visually the similitude of the diagrams obtained by simulation, with the actual load curve. For example, the regression model captures well the General character of the changes of electricity consumption during the year, and the neural network model seeks to identify some regularity in ramp changes of the system [3]. For quantitative assessment of these models it is convenient to use the relative errors, which were found previously. Their average values are presented in the table I. If you compare these errors, you can see that the regression model more accurately reproduces the behavior of the actual curve than the neural network.

The histogram shows that two distributions are close to normal function, but have a certain asymmetry, which may affect the average value. Therefore, the median estimates of the distributions of the errors were used as an extra criterion for the comparison.

Option	Types of Model	
	Regression	Neural
The Avg value of error, %	2.35	3.38
Median of error, %	1.99	2.84

Table.1: Model wise parameter

The results from the table. 1 confirm that the neural is superior to the network regression model in the context of this experiment.

VI. Results

The aim of this paper is to compare two forecasting method of daily power consumption and assessment of their application adequacy. Every model has both advantage and disadvantage. For example the regression model unlike the neural network has less forecasting error at once according to criteria i.e. Average module of relative error and median module of relative error.

A. *Result for regression method (Week wise)*

Before ACF		
	MAPE	RMSE
1st week	0.118028	115.01442
2nd week	0.07273	9.80974
3rd week	0.055339	6.391987
4th week	0.090355	10.2691
Whole Month	0.084717	10.76463

Table. 2: Regression Result before ACF

After ACF		
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Table. 3: Regression Result after ACF

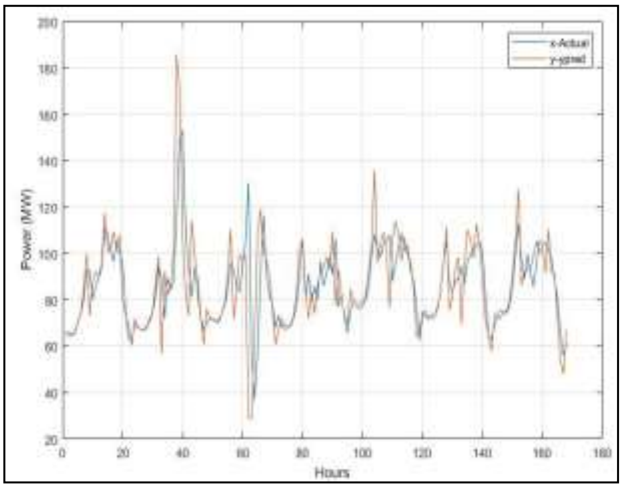

Fig 6: Actual vs. predict 1st week without ACF

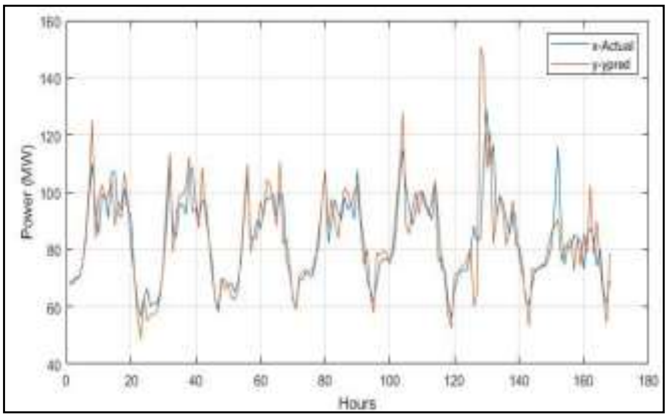

Fig. 7: Actual vs. predict 2nd week without ACF

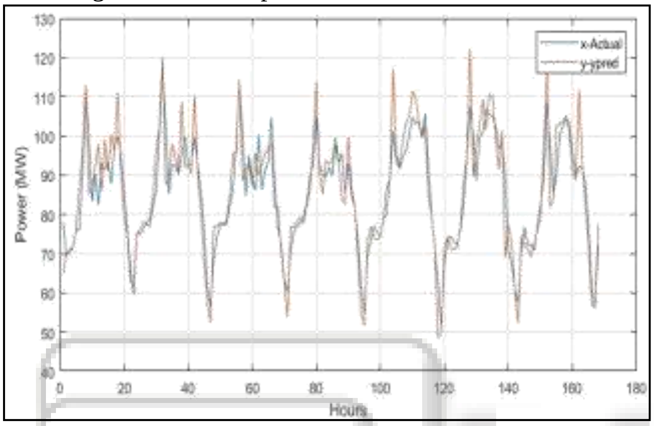

Fig. 8: Actual vs. predict 3rd week without ACF

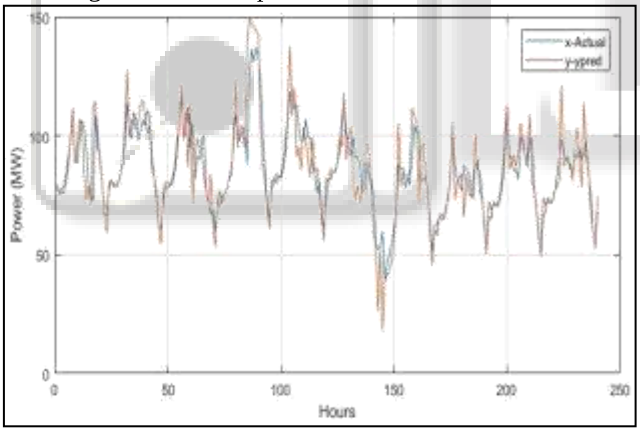

Fig. 9: Actual vs. predict 4th week without ACF

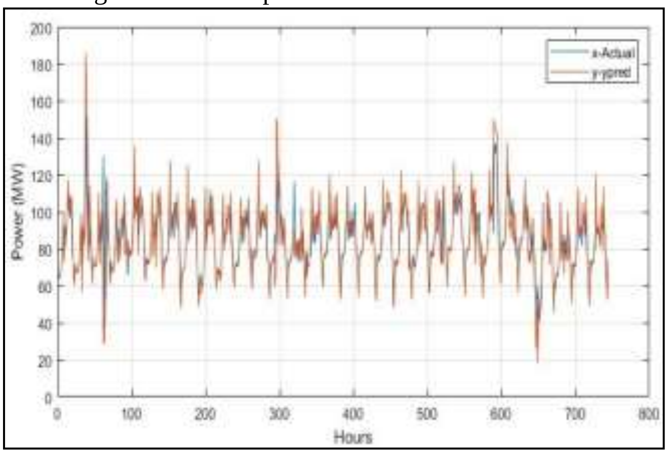

Fig. 10: Actual vs. predict monthly without ACF

1) After Autocorrelation

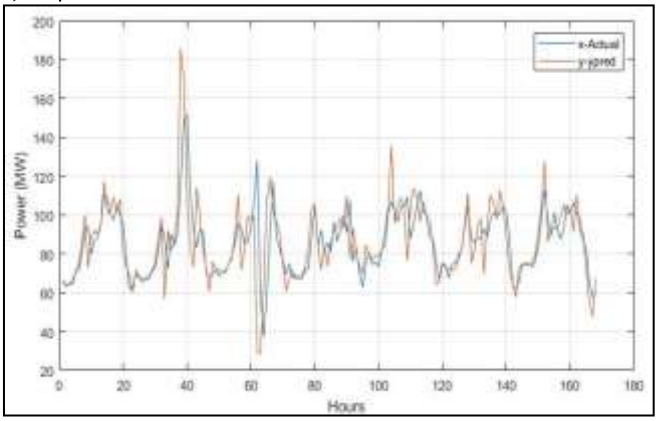

Fig. 11: Actual vs. predict 1st week with ACF

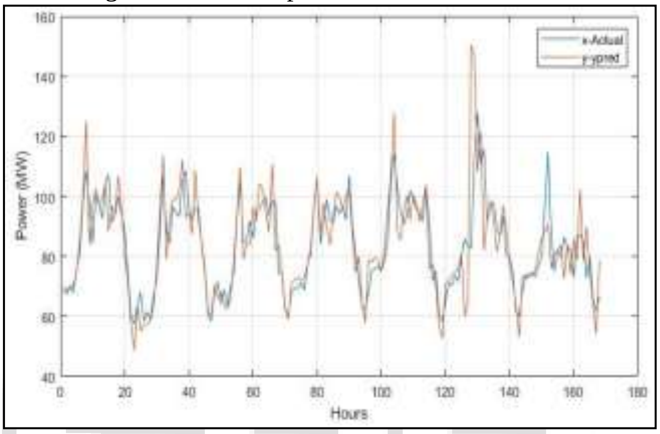

Fig. 12: Actual vs. predict 2nd week with ACF

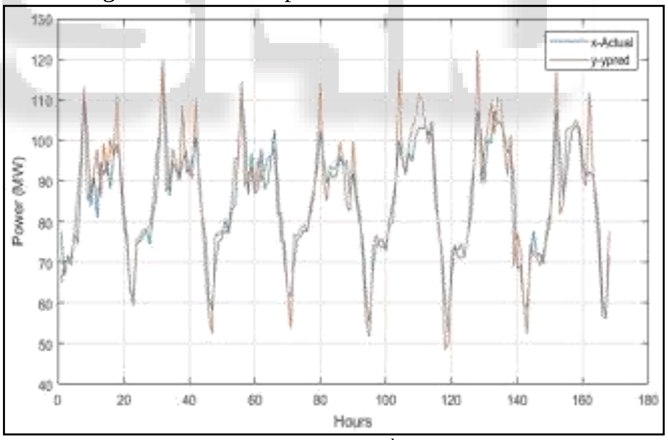

Fig. 13: Actual vs. predict 3rd week with ACF

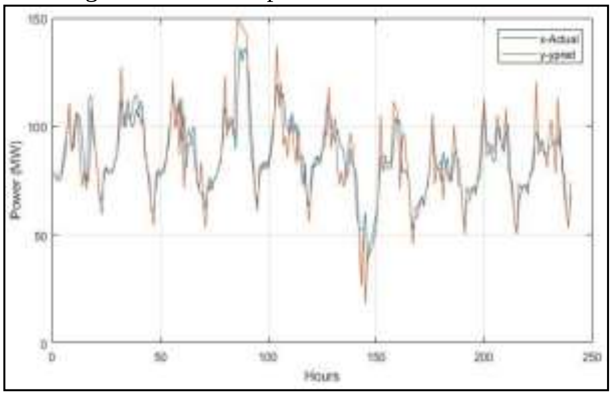

Fig. 14: Actual vs. predict 4th week with ACF

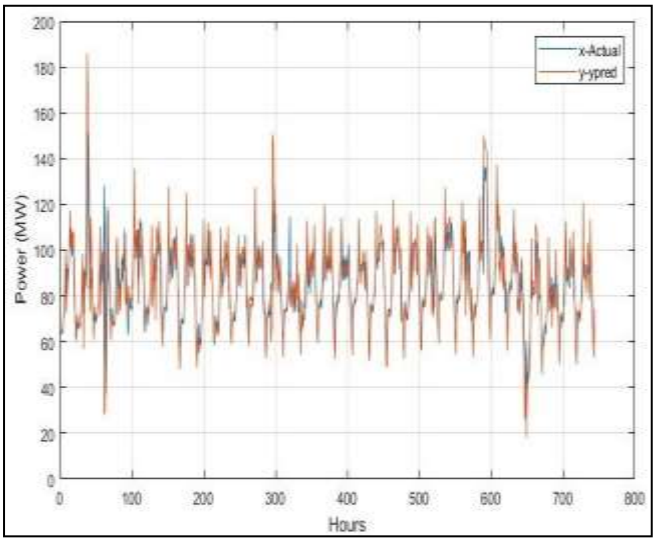

Fig. 15: Actual vs. predict monthly with ACF

B. Neural network:

Before ACF		
	MAPE	RMSE
1st week	0.14853	17.76706
2nd week	0.091524	11.79763
3rd week	0.085386	10.82108
4th week	09.123429	12.85723
Whole Month	0.093763	17.3653

Table. 4: NN before ACF

After ACF		
	MAPE	RMSE
1st week	0.0834	10.55
2nd week	0.0746	8.5749
3rd week	0.0798	8.7149
4th week	0.1091	11.958
Whole Month	0.084717	10.55

Table. 5: NN after ACF

1) Before auto correlation:

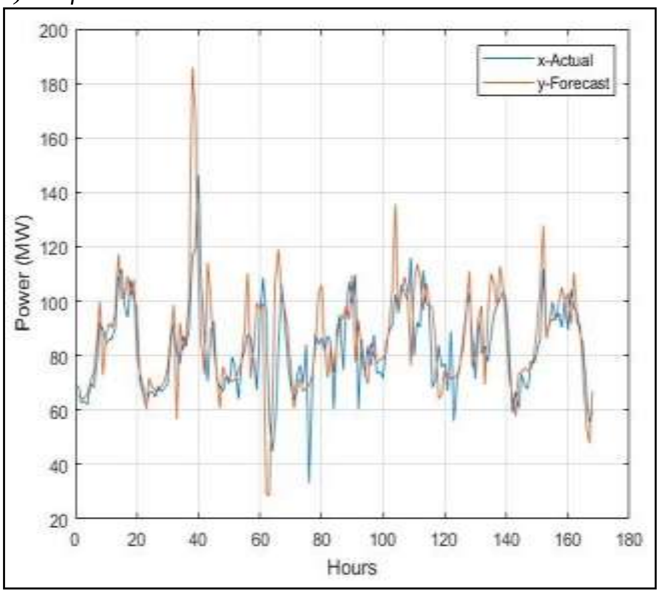

Fig. 16: Actual vs. predict 1st week without ACF

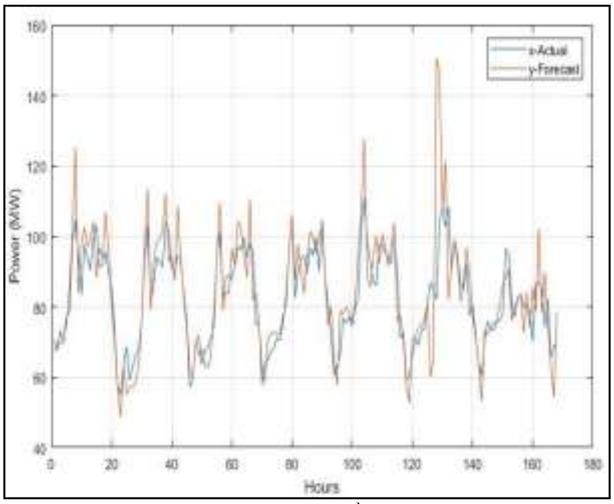

Fig. 17: Actual vs. predict 2nd week without ACF

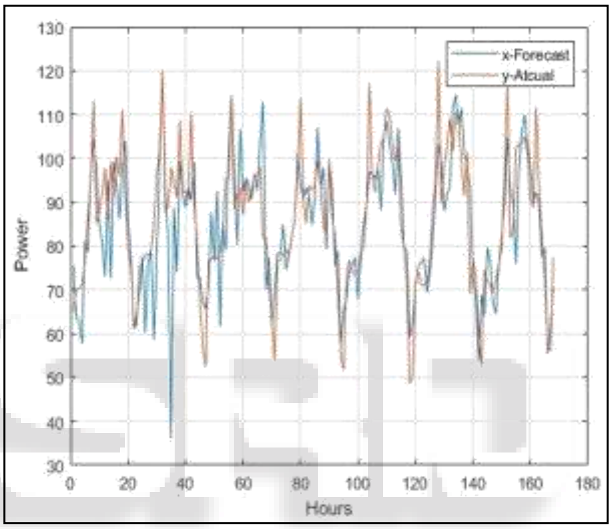

Fig. 18: Actual vs. predict 3rd week without ACF

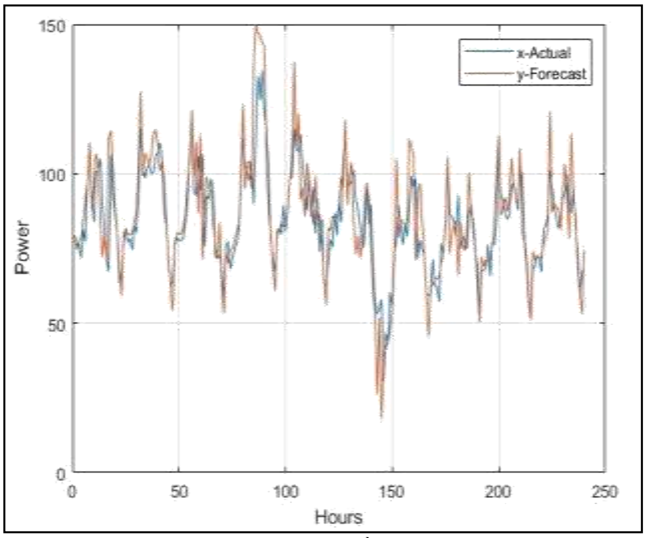

Fig. 19: Actual vs. predict 4th week without ACF

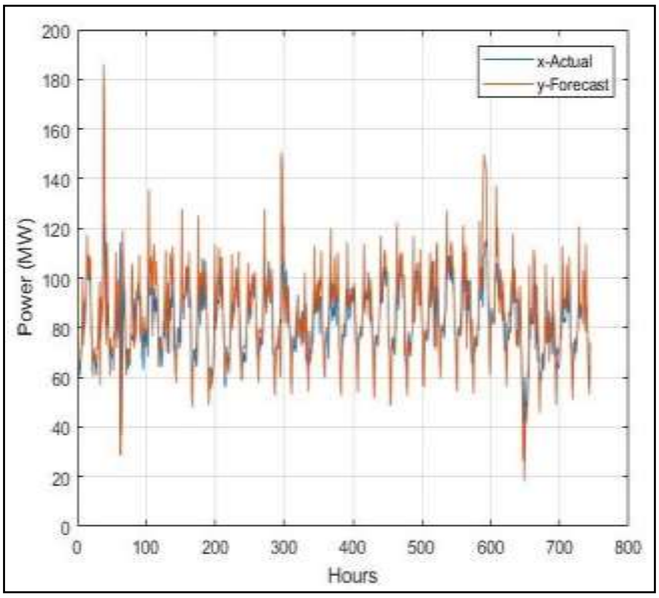

Fig. 20: Actual vs. predict monthly without ACF

2) *After Auto Correlation:*

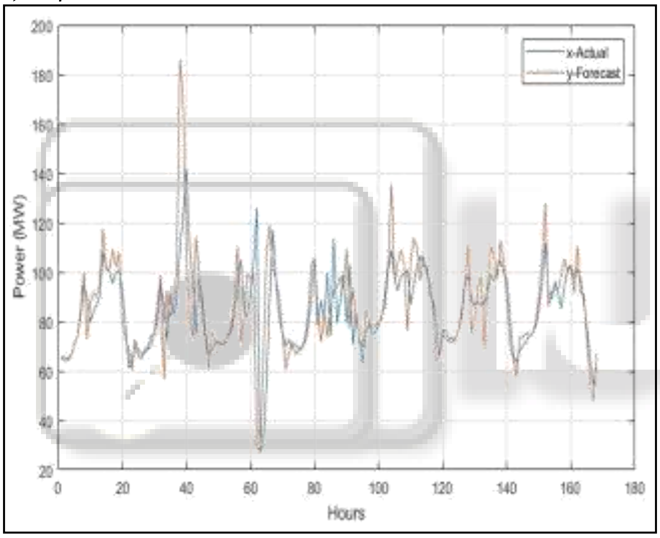

Fig. 21: Actual vs. predict 1st week with ACF

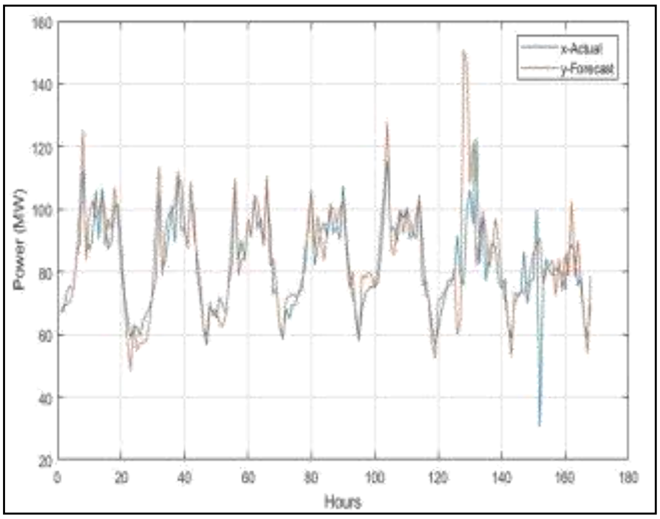

Fig. 22: Actual vs. predict 2nd week with ACF

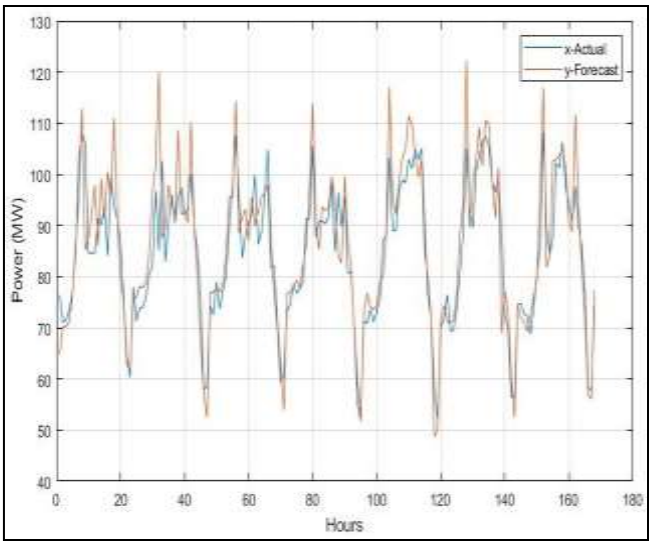

Fig. 23: Actual vs. predict 3rd w eek with ACF

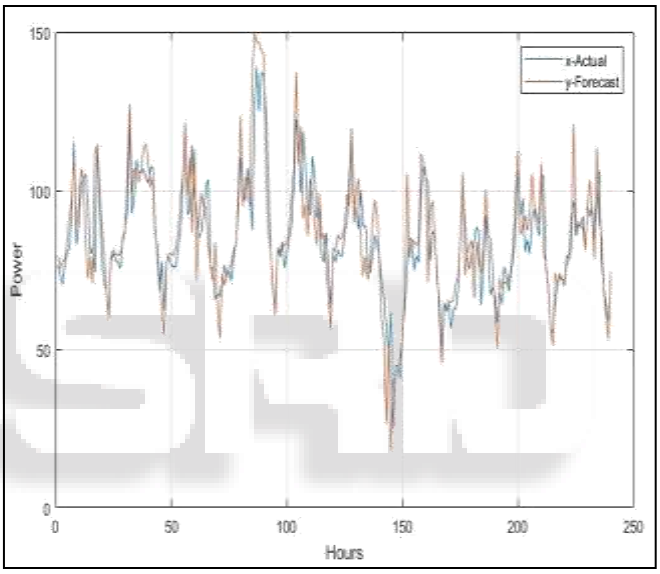

Fig. 24: Actual vs. predict 4th week with ACF

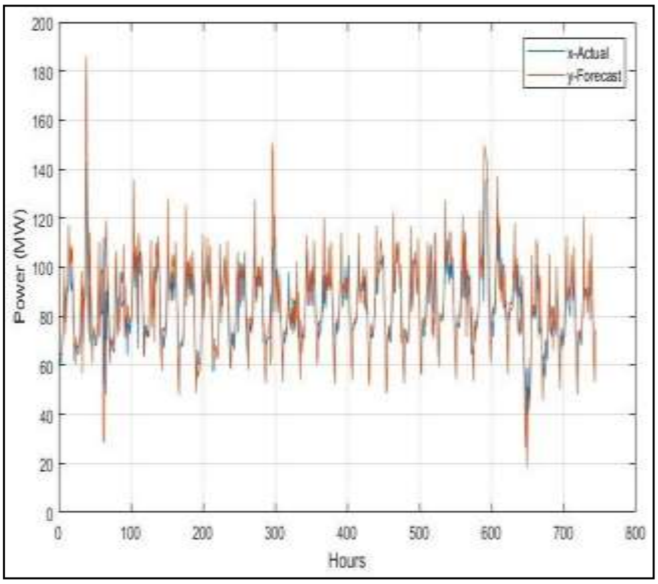

Fig. 25: Actual vs. predict 4th week with ACF

VII. Conclusion

We considered the task of predicating the hour's electricity load profile for the next day, from a time series of previous hour electricity load. We developed ANN and regression approach that combines an efficient MI feature selection of model.

We also conducted the comparison of NN and Regression approach. Where a separate NN is used to predict the load for each hour of the forecasting horizon. The regression approach was not only more computationally efficient but it also out formed the non-iterative approach in the term of predictive accuracy the improvement was from 24% to 40% in MAPE.

Therefore, we conclude that proposed NN approach is viable option for forecasting the hourly electricity load profile it provides high accuracy and low computational requirement. It also shows excellent result. In future work we plan investigate the effectiveness of NN for forecasting of other energy time series e.g. solar and wind power and electricity prices. We will also study the performance of NN for forecasting horizons longer than 24 hours.

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