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# Short Term Load Forecasting Methods

**Avijit Awasthi**
Department of Electrical and Electronics Engineering
*Galgotias College of Engineering and Technology,*
Greater Noida, India
avijit.awasthi@gmail.com

**Charchil Gupta**
Department of Electrical and Electronics Engineering
*Galgotias College of Engineering and Technology,*
Greater Noida, India
gcharchil@gmail.com

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**Abstract:**

This paper, presents the basic concepts and techniques of short term load forecasting. The factors influencing the forecasting results have conjointly been mentioned. The various applications are found at the generation end of the electricity. Scheduling of maintenance and reducing the generation cost are the main applications. The purpose of paper is focusing on the different methods of short term load forecasting and the factors influencing them as well as comparing the ARIMA model with Artificial Neural Network (ANN).

***Keywords:** Load forecasting, classical methods, parametric methods, fuzzy logic, artificial intelligence, neural network, genetic algorithm.*

## I. Introduction

As we know that electricity cannot be generated and stored in any device because of its sinusoidal wave property. Because of this reason the load forecasting have a huge significance in the power industry. The accurate load forecasting results into the better plant management as well as the better financial condition. [1] The load forecasting has been divided into three different methods. These three methods are Short-Term Load Forecasting, Medium-Term Load Forecasting, and Long-Term Load Forecasting. At this point of time, there are several methods available to forecast the load data. To forecast the load accurately, various predictors like Temperature, Time, and Weather etc. Short term forecasting sometimes refers for the one hour to one week. For a specific region, there is a chance to forecast the load with 2-4% accuracy.

In the first step different techniques for short term load forecasting is discussed. After that, the results have been found out while testing a PV connected DC Microgrid data.

## II. Factors' Influencing Load Forecasting

There are numerous factors that have an impact on the demand for load significantly. We have to study these factors to develop a correct load forecasting model. Factors such as Temperature, Humidity, Time, and Cost of the electricity play a huge role in the consumption of electricity by customer. The various factors which affects the consumption as well as the forecasting of electricity are shown in fig.1 [7]:

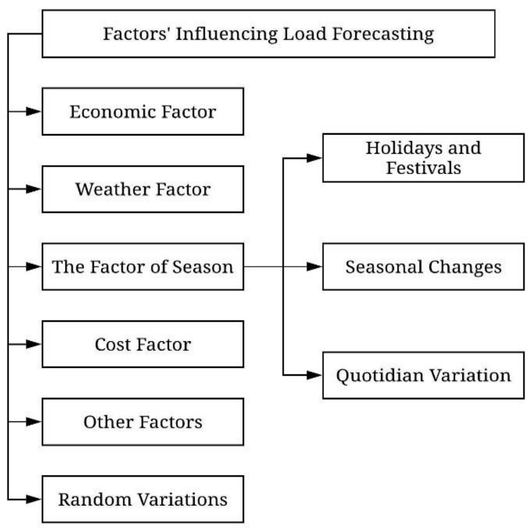


*Fig. 1 Load Forecasting Influencing factors*

## III. Methods for Short Term Load Forecasting

For the forecasting, there are several methods which have been used for a long time. These include the statistical techniques, various regression methods; Artificial intelligence-based system, daily approach, and expert system, etc. short term load forecasting techniques are classified into four

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classes. Several techniques for short term load forecasting are shown in Fig. 2.

### A. Classical Models

This technique needs a particular mathematical model. This model provides the relation between load and several input factors. There are numerous classical models, which are applied for the forecasting of the load, are given below:

#### 1) Multiple Regression Analysis

Multiple regression analysis is the most commonly used technique of mathematical statistic. From this analysis, we are able to calculate the connection between the entire load and therefore the atmospheric phenomena.This technique relies on the technique of weighted least square estimation. In this methodology, we have to calculate the regression coefficient by victimization historical information in the equitably or exponentially weighted least-squares estimation. The formula employed in this analysis is given below [2].

$$Y_t = v_t \alpha_t + \varepsilon_t \tag{1}$$

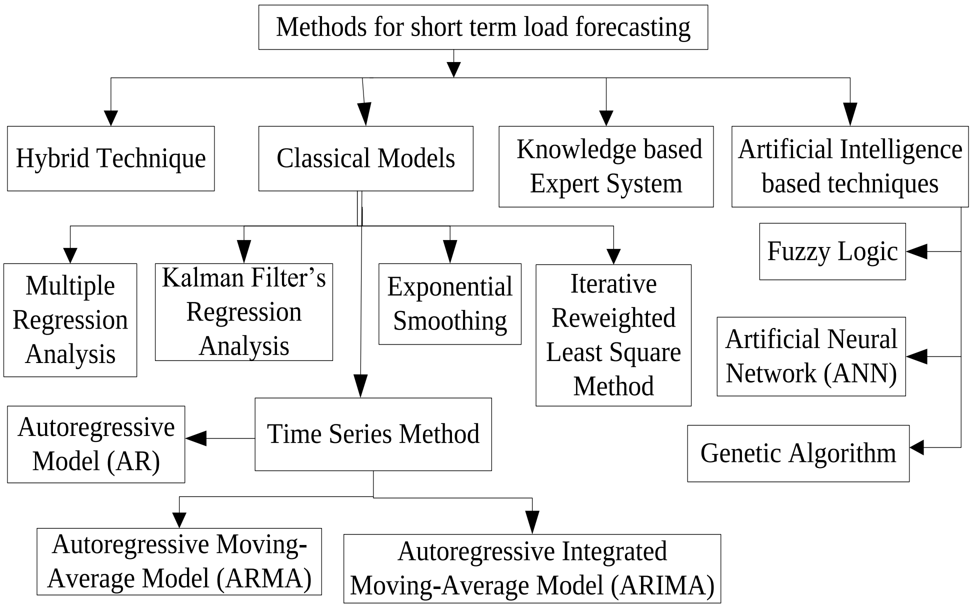


*Fig.2 Different methods of short term load forecasting*

Where, $Y_t$ is the total measured system's load, $v_t$ is modified variables' vector like time, humidity, light strength, sort of the day, temperature, etc., $\alpha_t$ is transposed vector of the regression coefficient, and $\varepsilon_t$ is error at time t.

In this method of load forecasting, we can vary the polynomial degree of influence from one to five. If we need to point out the error factors, this method is able to describe the relationship between variables. So the application of this methodology is fairly extensive [3].

In Eq. 1, the value of $\varepsilon_t$ is as given below:

$$\varepsilon_i = Y_t - \hat{Y} \tag{2}$$

Where, $Y_i$ is new total measured the load of the system [4].

#### 2) Exponential Smoothing

Exponential technique, first off models the load supported the previous information then use this model to predict the longer term load. This technique isn't solely used for short term load forecasting however additionally used for medium-term and long term load forecasting technique. The accuracy of this model depends upon the smoothing constant α. The method that used for the determining of α are optimum seeking approach and expertise estimation technique. According to the basic principle of exponential smoothing methodology, the essential formula of exponential smoothing coefficient is cited below:

$$Y_t = \alpha x_t + (1-\alpha) Y_{t-1} \tag{3}$$

Where, $Y_t$ = Load value at time t, $x_t$ = Actual inspected value at time t, $Y_{t-1}$ = Load value at time t-1, α = Smoothing coefficient. (Domain value 0 to 1). Given Eq. 2 can also be rewritten as:

$$Y_t = Y_{t-1} + \alpha (x_t - Y_{t-1}) \tag{4}$$

As we can see from Eq. (4), that new value of the load is equal to the addition of α times error in previously predicted value [5].

*3) Iterative Reweighted Least Square Method*

In this technique, we have to use an operator that controls one variable at a time. Let's think about the classical parameter drawbacks encompassing the measurement equation:

$$Y = X\beta + \varepsilon \tag{5}$$

Where, $Y$ = n×l observational vector; $X$ = n×p known coefficient's matrix (Old load data); $\beta$ = p×l unknown parameters' vector; $\varepsilon$ = n×l unknown errors' matrix

The weighted least square estimation for β, minimizes as:

$$\sum_{i=1}^{n} \frac{(Y_i - X_i\beta)^2}{\sigma} \tag{6}$$

Where, σ = Estimated scale parameter

Robust estimation for β and , reduces a more problematic expression, as given below:

$$\sum_{i=1}^{n} \rho\left(\frac{Y_i - X_i\beta}{\sigma}\right) \tag{7}$$

Where, $\rho$ = Robust loss function, $X_i$ = Design matrix's $i^{th}$ row, $\sigma$ = Estimated scale parameter

The requisite conditions for minimization of Eq. (6) and Eq. (7) needs that their various respective derivatives with respect to β scale backs to zero. The weighted least squares problem reduces to a standard least square once the loss function becomes quadratic, that is $\rho(r) = r^2$. When the error distribution is non-gaussian then the strong estimation issues results become powerful [6].

*4) Kalman Filter's Regression Analysis*

The Kalman Filter estimate subsequent state vector by using the current prediction error and current weather knowledge however additionally the state vector is determined by analyzing the overall historical knowledge. In this method, we can switch in between the multiple regression analysis and the adoptive regression analysis. In this model, we use the same model which we have already used in multiple regression analysis [2]. As described in Eq. (8):

$$Y = v_t \alpha_t + \varepsilon_t \tag{8}$$

*5) Time Series Method*

The methods of time series method are one in every of the foremost, well-liked ways among the opposite ways of prognostication. In these methods, a model is developed which is based on the previous information and prognosticates based on the methodology of the model. These methods are so well liked, although these methods have several drawbacks and complicated to use. It needs longer time and historical data for the accurate prediction. Time series method principally used for the short term load forecasting. These models, which are used for load forecasting has been given below [7]:

a) Autoregressive Model(AR)
b) Autoregressive Moving-Average Model(ARMA)
c) Autoregressive Integrated Moving-Average Model (ARIMA)

*a) Autoregressive Model*

Autoregressive model uses in several fields like Statistics, Econometrics, and Signal Processing, etc. There are various orders of the autoregressive model based on the order of the model. Mostly the autoregressive model of order p is denoted as AR(p).The Autoregressive model of order p [AR(p)] is represented as [8]:

$$Y_t = \sum_{i=1}^{r} \Psi_i Y_{t-1} + \varepsilon_t + c \tag{9}$$

Where, $\Psi_i$ = Parameter of the model; $Y_t$ = load at time t;$Y_{t-1}$ = load at time t-1; $\varepsilon_t$ = Noise or Error; $c$ = Constant.

Autoregressive models are considered as the output of the all-pole infinite impulse filter with the input of noise [8]. The first order of the autoregressive model is not stationary. So, to keep Autoregressive model stationary, the roots of the polynomial should lie within the unit circle. There is an instantaneous relationship between these parameters and therefore the variance function of the method. This relationship may be inverted to work out the autocorrelation function. This may be completed with the assistance of Yule-Walker's equations, which is given below:

$$\Upsilon_m = \sum_{k=1}^{r} \psi_k \Upsilon_{m-k} + \rho_\varepsilon^2 \delta_{m,0} \tag{10}$$

Where, $m$ = Total number of the equation; $\Upsilon_m$= Autocorrelated function of $Y$, $\rho_\varepsilon$= input noise's Standard deviation, $\delta_{m,0}$ = Kronecker delta function. Eq. 10 generally solved as a matrix for $m$>0

*b) Autoregressive Moving Average Model*

The general form of the Autoregressive moving average model is given below: [9].

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$$X(t) = Y_p(t) + Y(t) \qquad (11)$$

Where, $Y_p(t)$ = A element which depends on time and also the weather of the day; $Y(t)$ = Additive load residual term that depends on the weather pattern $Y_p(t)$ (in Eq. 11) may be described as a periodic time function is given below:

$$z(t) = \sum_{i=1}^{N} \alpha_i k_i(t) + v(t) \qquad (12)$$

Where, z(t) = Load at t time; $k_i(t)$ = Sum of a finite number of explicit time function; $v(t)$ = Modeling errors; $\alpha_i$ = Time-varying constant .

The residual term y(t) (as in Eq. 11) can be represented by the ARMA model:

$$y(t) = \sum_{i=1}^{n} a_i y(t-i) + \sum_{k=1}^{n_u} \sum_{j_k=0}^{m_k} b_{ik} u_k(t-i_k) + \sum_{h=1}^{H} C_h w(t-h) \qquad (13)$$

According to Durbin's methodology of Autoregressive moving average (ARMA), A statistic model will be conferred by the filter linear distinction equation of complicated coefficients:

$$\begin{aligned} y(n) &= -\sum_{k=1}^{p} a_p(k) y(n-c) + \sum_{k=0}^{q} b_q(c) u(n-c) \\ &= \sum_{k=0}^{\infty} h(c) x(n-c) \end{aligned} \qquad (14)$$

Where, $y(n)$ = Causal filter's output; $x(n)$ = White noise sequence driven by input; Eq. 14 represents the Autoregressive Moving Average Model for the $y(n)$ time series [10].

*c) Auto progressive Integrated Moving Average Model*

ARIMA model has been used widely to prognosticate the future load in Short term load forecasting. This model is usually referred as Box Jenkins' model. In this model the worth of a variable forecasted by a linear combination of errors and past values. Equation of the ARIMA model is given below: [11]

$$x = \theta_0 + \Psi_1 x_{t-1} + \ldots + \Psi_p x_{t-p} + e_t - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q} \qquad (15)$$

Where, $x_t$ = Value of load at time t; $\theta, \psi$ = Coefficients; $p$ = Autoregressive (AR)'s order; $q$ = Moving average (MA)'s order; $e_t$ = Error.

The main advantage of this methodology is that it solelyneeds the previous data of a time series for the generalization of the forecast. So, by keeping the amount of parameters minimum, it may increase the accuracy of foretelling.

*B. Artificial Intelligence(AI) Based Techniques*

This approach relatively new in the comparison of other old methods. There are huge chances of mistakes in non-adoptive features of statistical load forecasting. Beside of that applied mathematical techniques conjointly rely upon human intervention to enhance their accuracies through planned adjustment and verifications. Artificial Intelligence technique has incontestable the potential of learning the advanced non-linear relationships [12]. In Artificial Intelligence-based strategies, mainly there are three fields of Machine Intelligence, which are given below:

1. Artificial Neural Network(ANN)
2. Fuzzy Logic
3. Genetic Algorithm

*1) Artificial Neural Network (ANN)*

Artificial Neural Network (ANN) is one among the foremost used AI ways of load forecasting. It's based on the model of a biological neural system. As data flows across the network, it affects the total network of the ANN structure. As a result of it, the supported input and output of the system make it act like a biological neural network. This function will absolutely match the curves on nonlinear complex patterns through the mathematical models. A typical ANN structure is shown in the given Fig. 3.

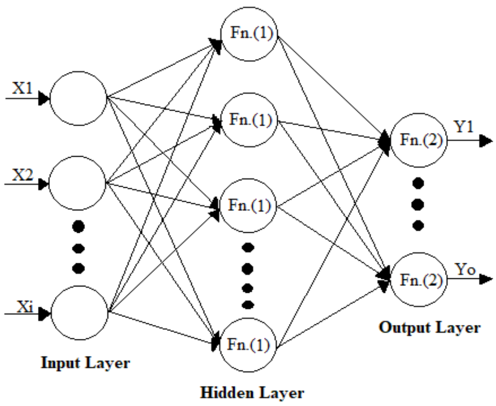


*Fig. 3 Neural Network Structure*

The above normal architecture of the neural network, is a three layered network. These three layers are Input layer, hidden layer, and output layer. Hidden layer is the layer in which the different calculations related to the predictors and variables occurs. The mathematical form of the ANN model can be described as given below:

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$$y_i = f_i \sum_{i=1}^{n} \left( X_i w_{ij} + b_j \right) \qquad (16)$$

Where, $Y_i$ = Output variables; $X_i$ = Input variables; $f_i$ = Activation function; w = Weights

### 2) *Genetic Algorithm*

The design methodology of the Genetic Algorithm supported Dholland's notion of schemata. That states that schemata are sets of string that have additional feature in common. The mechanism of Genetic Algorithm based supported the action, within which the stronger people are seemingly to be the winner in a very competitor surroundings. It presumes the potential answer of a retardant as personal and represents by a collection of parameters [14]. It understands improvement disadvantage by reflecting the norms of natural advancement, again and again changing an open of individual spotlights using principles showed on quality mixes in natural multiplication [15]. Throughout the genetic evolution, a work body has the probability to yield sensible quality off-spring, means that a more robust answer to the matter.

### 3) *Fuzzy Logic*

Fuzzy Logic may be a reasoning methodology that resembles human reasoning. The main aim of this technique is to commonly replace a talented human operator with a fuzzy rule-based system. It works on the amount of potentialities of input to realize a definite output. The control systems of the fuzzy network are a rule-based system during which a collection of rules called fuzzy rules represents an effect call mechanism. Fig. 4 represents the essential configuration of a fuzzy system, during which a fuzzification, Expert knowledge able content, fuzzy interface, and a defuzzification consists [13].

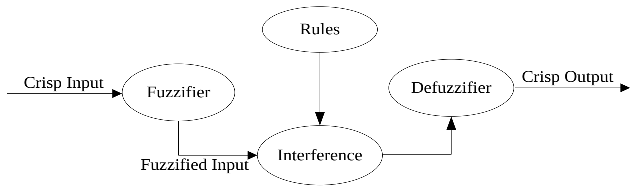


*Fig. 4Graphical Representation of Fuzzy System*

The Fuzzifier has a major role in fuzzy Logic Control because it converts the crisp input into the fuzzy input sets. Inference means the predefined rules, according to the use of control system by the experts. Defuzzifier transforms the fuzzy output set to the crisp output.

### C. *Knowledge-Based Expert System*

A Knowledge-Based Expert System for Short Term Load Forecasting implies it can give reasons and clarifications to its very own choices. In this framework, the specialists' learning stacked as information or guidelines. These information and principles approached when the master framework need them to take care of the issue. The calculation of this standard based framework comprises of the accompanying:

a) The change in burden, normal factors, and constrained components.
b) The grammatical and coherent connection among climate and burden shape changes.

All the principles are written as IF… THEN and scientific expression [16].

### D. *Hybrid Techniques*

These are the most common approach now-a-days. Generally, in these types of approaches, two or more than two different techniques merge to reduce the chances of mistakes. Mostly, there are combinations of AI-based techniques with classical techniques.

## IV. RESULTS

The methods have been tested for the PV connected DC microgrid data. Fig. 5 to fig. 7 showing the results obtained in the forecasting of the load for 24 hours with ARIMA model. Fig. 5 showing the comparison plot between forecasted and test load. The graph is plotted between the Load and the Time. The error distribution is shown in the graph in Fig.6. For showing error distribution, ARIMA model is used. The fitting for this ARIMA model is shown in Fig. 7.

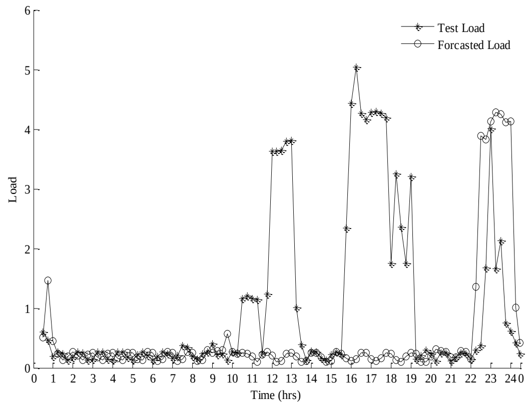

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*Fig. 5 One day load forecasting using ARIMA model*

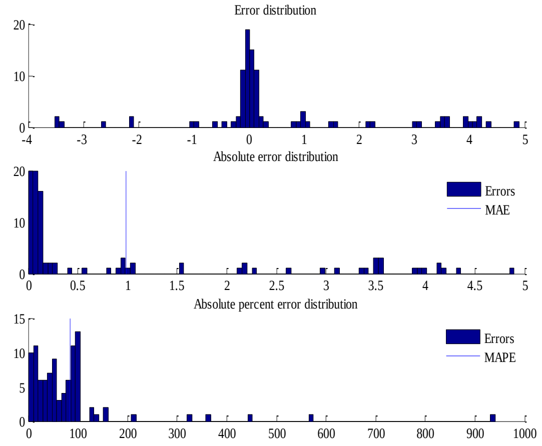


*Fig. 6 Error distribution using ARIMA model*

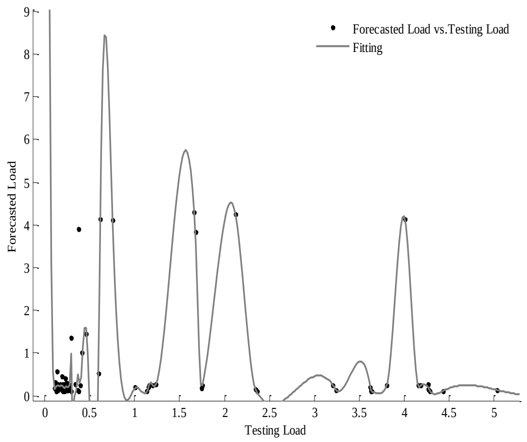


*Fig.7fitting for the ARIMA model*

Fig.8 to fig. 13 showing the results obtained in the forecasting of the load of 24 hrs from the ANN's Levenberg Marquardt algorithm. Fig. 8is showing the comparison plot between forecasted and test load. The error, which is taken at x-axis, is the difference between the Target data and the output. The graph between error and time is shown in fig.9. The mean square error is calculated and plotted with respect to epochs. It is shown in Fig. 10. The epochs refer to the number of passes completed through the total set of data. For this plot,the number of epochs taken are 10 for simplicity of analysis. Fig. 12 represents the Fitting regression analysis. The three of the four plots show the training, validation and testing process. The fourth plot is the combination of all the other three plots.

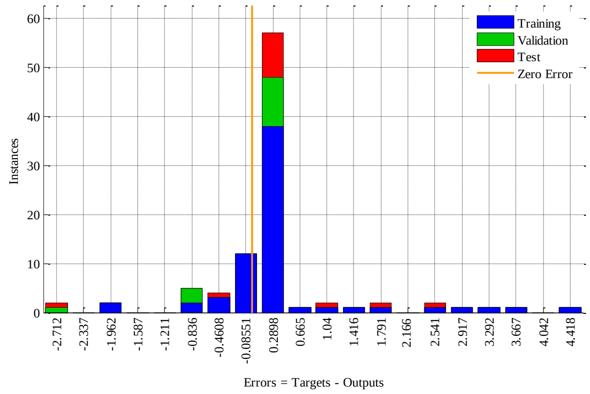


*Fig. 8 Error histogram (20 bins) while training using Levenberg-Marquardt training method*

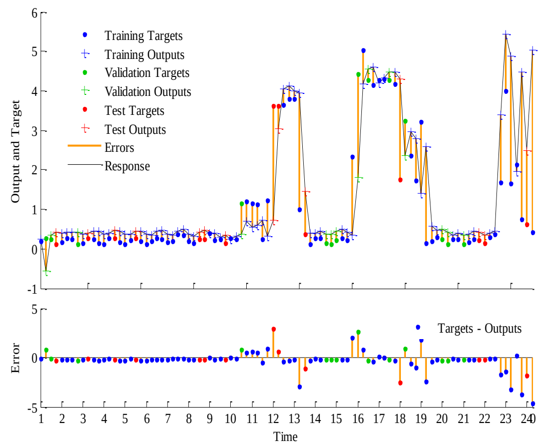


*Fig.9 Response of output for time series*

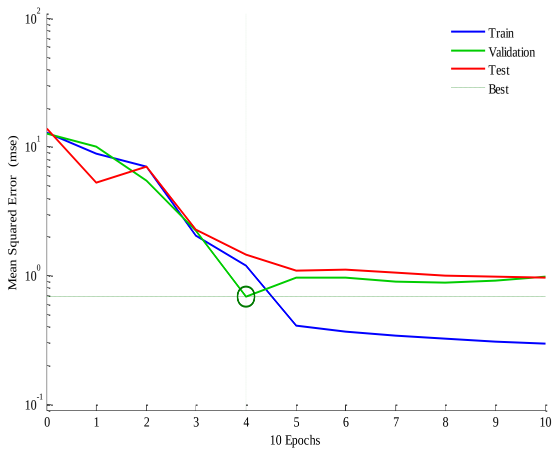


*Fig. 10 Mean square error in respect to epochs (best validation performance is 0.68137 at epoch 4)*

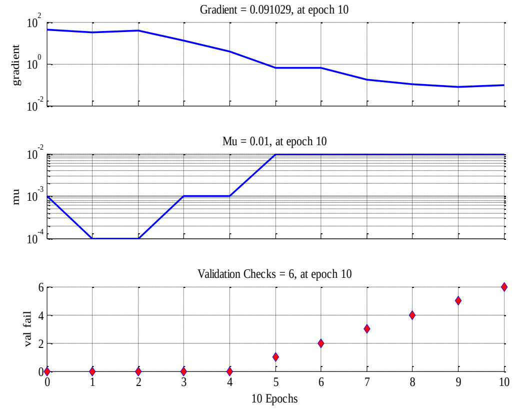


*Fig. 11 Gradient, mu and validation check*

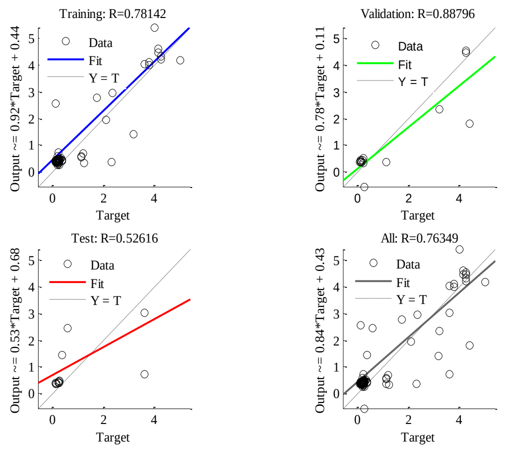


*Fig. 12Fitting regression*

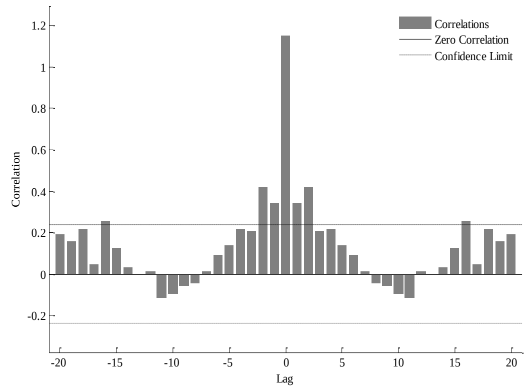


*Fig. 13 Autocorrelation of error*

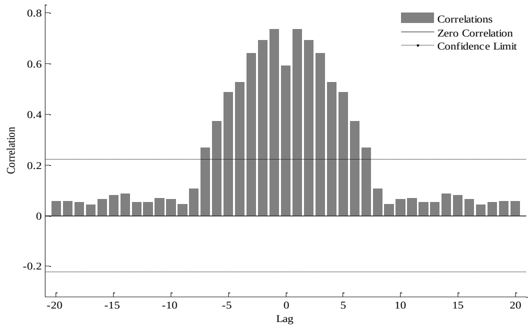


Fig. 14 Correlation between Input and Error

## V. CONCLUSION

Approaches for short term load forecasting have been reviewed and two of them is being analyzed for the data of PV connected DC microgrid in this paper. Despite the fact that the time series method is still generally utilized, more up to date methods offer a ton of guarantee for this creating and quickly evolving field. The quickly expanding intensity of the computers is making it conceivable to apply increasingly confused arrangement strategies. New load forecasting strategies dependent on artificial intelligence based methods offer new trusts toward this path of research. In the course of the most recent couple of years, the most dynamic research region has been neural system based load forecasting.

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