Application of Artificial Neural Networks for Solar Photovoltaic Power Forecasting

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Abstract**—**This paper presents multi-layer feed-forward artificial neural network based forecast model for predicting solar photovoltaic power generation. The application of this method has been doing well in various fields of power system engineering also admired intended for handling different problems like control, forecasting, planning, scheduling etc. Power forecasting is used to decrease some of the difficulties, which comes from the unpredictability in the resource. Due to the growing of energy demands, generation of electricity through solar energy is most reliable, feasible and reasonable solution. It is the goal of the Indian government to achieve more saturation levels of renewable power sources into the electric grid. ANN based forecast model has given more accurate and better results. The developed forecast model is trained by historical data. Here solar PV generation power is forecasted through the back propagation training algorithms. The simulation model is designed in MATLAB to assessment the system performance.

Keywords—*Artificial Neural Network, PV Power, Solar Energy, Forecasting.*

I. INTRODUCTION

Now a day, research in solar system are determined on developing more accurate solar forecasting with research on new techniques, which will give better preparation, performance and operation in order to manage the fluctuation in the output of solar photovoltaic system. Global horizontal irradiation (GHI) forecasting is the basic process in the solar power prediction devices.

Solar photovoltaic system use PV cells so as to convert sun radiation into electric energy. It is the most encouraging source for generating electricity for residential, industrial and commercial application. More energy is produced by tracking the solar panel to remain aligned to the sun at a right angle to the rays of light. Developed Forecasting models are incessantly being improved to performing high accurate prediction of solar power.

In previous years researches have projected several forecasting methods some of regression based such as AutoRegression (AR), MovingAverage (MA), and combined of them well-known as Auto Regressive Moving Average (ARMA) and Auto Regression Integrated Moving Average (ARIMA), both are advanced regression models used as stationary time series and others are Artificial Intelligence based techniques they are: Artificial Neural Network (ANN), fuzzy logic, Adaptive Neuro-Fuzzy Inference System (ANFIS), Genetic algorithm, Generalized Neural network (GNN), expert system model. An ANN consists of inputs, weighted connection of nodes and network topology.

Neural networks have been trained to perform complex function in several areas these are pattern recognition, categorization, identification, and vision, speech, and control systems. The back- propagation algorithm helps to train the ANN model in similar pattern. With the help of applied calculation, the back-propagation concept is to flow information in single direction between neurons and error, which is back propagating in the opposite direction. With the help of gradient decent method, changing the weight of synapses between the neurons (node) to optimize the minimum error after the sufficient training result adjustment until the correct response will come.

The forecasting with developed model validate access, robust and fast performed that permits investors to trade on power sector, provide funds, research and new development in the field. ANN is primarily used to predict the solar PV power consists diverse weather variable such as temperature, sun radiation, humidity, wind speed, wind direction etc. A simulation model of proposed system is developed in MATLAB/ SIMULINK to estimate the system performance.

II. MULTILAYER FEEDFORWARD ANN

It consist multiple no. of layers of computational components that are generally interconnected in a feed-forward direction. Each neuron in one layer has directly connected to the neurons of the next layer. In various applications, the components of these networks apply in a sigmoid transfer function (i.e. an activation function).

Multi-layer feed forward networks employ learning techniques. The most popular algorithm is back- propagation. The outputs are compared for calculating some predefined error function. The error is fed by the network. Through this, the algorithm adjusted the weights of each links in order to mitigate the substance of error function. After that recurring this process for a large number of training steps, the network will have combine to some unit where the error is low.

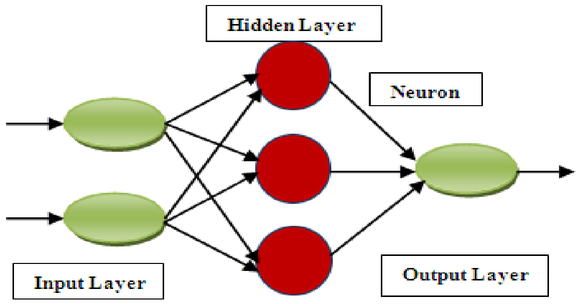

Figure1: Typical feed forward neural network comprised of three layers.

The first layer is identified as the input layer, the target is called the output layer and hidden layer are between them. Each neuron in a separate layer is associated with all neurons in the next layer. The link between the i^{th} and j^{th} neuron is categorized through the weight coefficient (w_{ij}) and i^{th} neurons with the aid of threshold coefficient V_i. In the neural network, the weight coefficient returns to the degree of consequence of the given connection. The output power of the i^{th} neuron x_i is resolved by Equation (1) and (2). It shows that:

$$Xi = f(\xi i) \tag{1}$$

$$\xi i = Vi + \sum_{j=\Gamma i}^{n} W_{ij} X_i \tag{2}$$

Where,

ξi = the potential of the i^{th} neuron

$f(\xi i)$ = the so-called transfer function

Γ = the mapping function

The suitable notation has been used in the two-layer 'tansig' or 'purelin' networks. These networks could be use as a universal function approximation. It can approximate any function with a limited number of discontinuities illogically well that is provided adequate neurons in the hidden layer.

III. SOLAR SYSTEM PV ARCHITECTURE

The concept of solar photovoltaic system architecture is explained through the block diagram in figure 2. It consists photovoltaic modules, charge controller, battery storage system, PV component mounting system, and inverter, battery discharger. Solar panels are the spirit or the main part of the system and are generally called the energy generation of the system. One would also have mounting structure to which PV modules have to preset and focused towards the sun. Power storage is required when PV system have to run during the bad weather condition or at night. The batteries are required for electrical energy storage. The output power of a solar photovoltaic module depends on intensity of sun isolation and temperature of the cell. Therefore, components that smoothen the direct current output and provide it to batteries, grid and load, that are essential for function of the given system.

A forecasts model that produced generation power from renewable sources. Our aim is to improve hourly and daily average prediction of generation so as to mitigate the costs associated with the differences between target and actual production. The consequence training model will consist of methodology. The algorithms designed for data mining that we build up and validate which is based on data derived from testing set units where the architecture system will be developed.

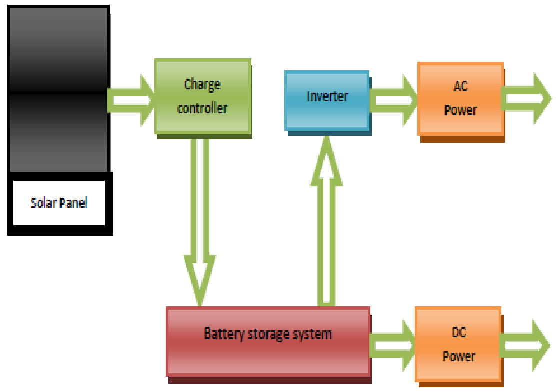

Figure2: Solar PV system architecture.

IV. SOLAR FORECASTING MODELING

The main aim of this fragment is to construct a neural networks base model for photovoltaic power generation. This will be followed in following steps:

A. *Data Sets*

In this paper, 5 atmospheric parameters namely; Surface Temperature(°C), Global Horizontal Insolation (KW-hr/m^2/day), Wind Speed(km/h), Wind Pressure (mbar), Relative Humidity(%) are considered as input variables toward train the developed model. The aim is to establish the solar PV power forecasts in daily steps through a month of estimated horizon. The historical data for solar PV power generation (in MW) that is acquired from the Elia, Belgium's electricity transmission system and the world weather and climate information Brussels, Balgium. The location is at the Latitude of 50.8503 and Longitude is 4.3517. The target data is measured as based on average daily solar power output of the whole month.

B. *Data Preprocessing*

The data normalization is vital step for using the data to be prepared for the performance and modeling steps. Data pre-processing technique is to handle diverse varieties of input variables. The min-max Normalization method offers superior results with maximum accuracy. The flowchart diagram of the solar PV power forecasting modeling is shown from fig. 3.

Figure 3: Flowchart diagram of the solar PV forecast modeling

C. The model building

The complexity and the non-linear of the problem can easily switch with an ANN. The ANN performed feedback from history data. The following steps, which has pursued for development of the neural network based model:

- Selection of input parameters
- Selection of neural network
- Selection of perfect training algorithm
- Selection of training parameter.

The mathematical model of an artificial neural network is obscured in below fig.4. It is a feed-forward curve fitting kind model. It performed healthy when it is not required to use the previous delayed value of the output and also some accessible inputs have been applied to attain a better regression.

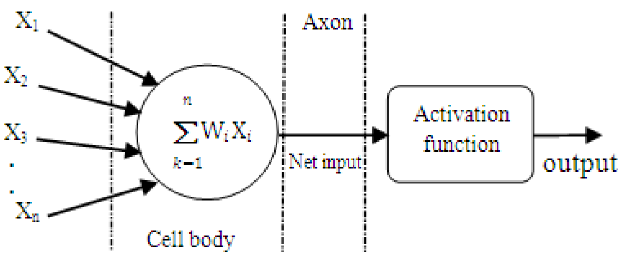

Figure 4: Mathematical modeling of Neural Network.

The developed model has an input layer, an output layer and a hidden layer. The hidden layer has considered 10 nodes further the bias node. This bias node is feeding into each node of the hidden output layers. The bias node has been shifted through the activation function (right or left). Because a short time variation in the weights is not sufficient to minimized the errors and enhance the performance of the model. The input parameters of the model are tracked for training, validation and testing.

Fig.5: Flowchart diagram for developing the ANN model

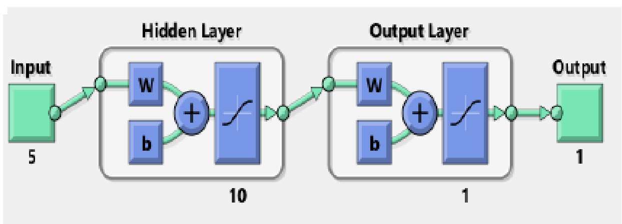

Figure 6: Structure model of ANN

The neural network-fitting tool has been helped for selecting data, create and train the network, and estimate its performance using mean square error. Hidden and output neurons might well with multi- dimensional mapping problems randomly. The network will be train with Levenberg-Marquardt back- propagation algorithm; Back propagation training algorithm can frankly help in adjustment of the weight (w_{ij}) and threshold coefficients (v_i). Fig.1 shows the signal flow through input variables toward hidden layer and output layer. The net activation at hidden layer to output layer has been written in Equation (3).

$$net_{ij}^{d} = \sum_{k=i}^{j} W_{ij} X_i^{d} \quad (3)$$

Where,

Xi = Input pair, d= Number of net, j= Hidden unit

Here, in the multilayered feed forward neural network log-sigmoid, transfer function is normally used. The back propagation algorithm trains it, because this function is differentiable and it generates output between 0 and 1. The transfer function is defined by eq. 4-5, and shown in fig. 7.

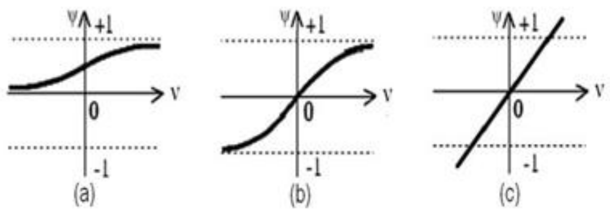

Figure 7: Log-Sigmoid Transfer Function [2]

Where,

$$a = f(net_j) = logsig(n) \quad (4)$$

$$a = f(net_j) = \frac{1}{1+e{-n}} \quad (5)$$

The back-propagation learning algorithm may achieve with one of two fundamental ways, i.e. pattern method and batch method. In the pattern method, after the exhibit of each training pattern is performed weight updating. In the batch mode, weight updating is performed after the exhibit of all the training examples that is after the total epoch. Back-propagation learning algorithm includes the utilize of learning rate and momentum factor. The rate of learning (η) established the scaling of the slope of the error surface, while momentum part offers stability to the learning process. The weight adjustment equation has shown in back propagation algorithm as in equation (6).

$$W_{net} = W_{old} + \Delta W \quad (6)$$

When error of validation set, achieve minimum then network training stops [5]. It will exhibit in validation. samples with increase in the mean square error. The training set start with random values of the weights. They could be arbitrary numbers and proceeds receptively. Each repetition of the complete training set is called an epoch, in each epoch the model adjusts the weights in the error direction. As the monotonous process of incremental adjustment continues, the weights will gradually junction to the optimal place of value. Several epochs are normally required before training has completed. At Validation and Testing set, the original data at each dataset is 15%. The input and target variables will have randomly separated into three sets as follows:

- 15% of samples are used for validate the network and before over fitting, it will be stop training.
- 70% of samples are used for training.
- The last 15% of samples are used for completely independent testing of network generalization

V. RESULT AND EVALUATION

In this work daily averaged pre-processed data of the PV power plant is considered. The RMSE method is used to evaluate the accurateness of the forecasts output and model performance, which has shown in graphs, RMSE, and the correlation coefficient (R) between the actual measure and forecasts solar PV power. The model was trained with the help of MATLAB NN toolbox. It helps for selecting data, create, and train the network. After train the NN each network was simulated, and their performance has been observed. The average square error between the net output data and the target data is defined as:

$$\text{Error} = \frac{F_t - A_t}{A_t}$$

$$\text{RMSE} = \sqrt{\frac{\Sigma F_t^2 - \Sigma A_t^2}{\Sigma A_t^2}}$$

Where,

F_t = Forecasts power, A_t = Actual power

The lesser values of MSE will better and zero means no error. The correlation coefficient (R) approaches 1 and mean square error approach 0. This indicates the explanation of the problem obtain the most accurate solution. The developed model consists of an input layer, an output layer and 10 hidden layer neurons have designed. This ANN model has selected after the huge testing of different possible architecture. The performance is tested by predicting months of 2018 i.e. May. The Levenberg-Marquardt back-propagation learning algorithm that was tested, to give the best performance the MSE value for May month of 0.002 and the R is 0.99. The result graphs are shown in following figures:

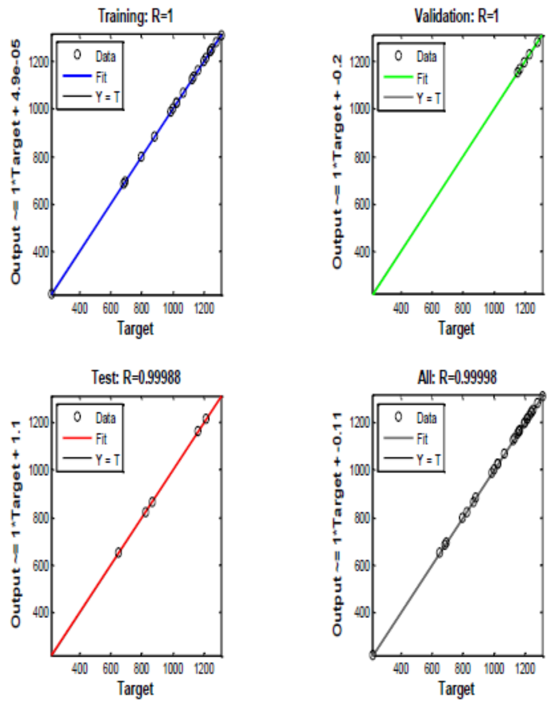

Figure 8: Neural Network Training Regression Coefficient R for PV Power

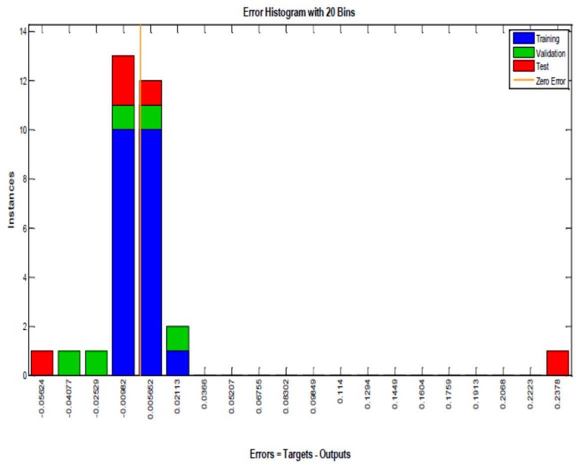

Figure 9: Neural Network Training Error distribution Graph

We can see that most of errors drown between -0.01 to 0.022 these outliers/deviation are visible on testing regression plot. The Neural Network Training performance graph for solar PV power plant, displayed in fig.9, validation reached maximum Epoch. The best validation performance is 0.00058 at Epoch 952. The training set continued processed for 6 iterations before the training stopped.

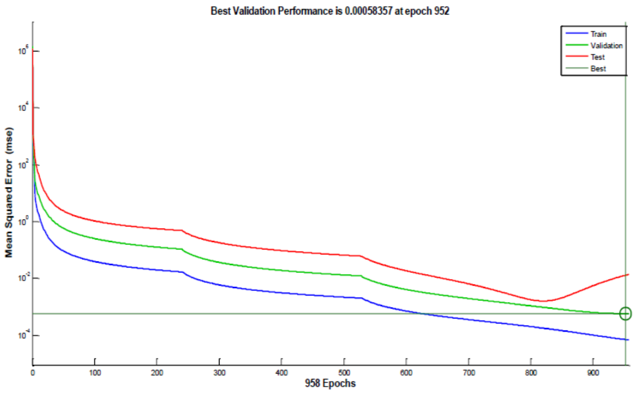

Figure 10: Neural Network Training performance graph at maximum epoch

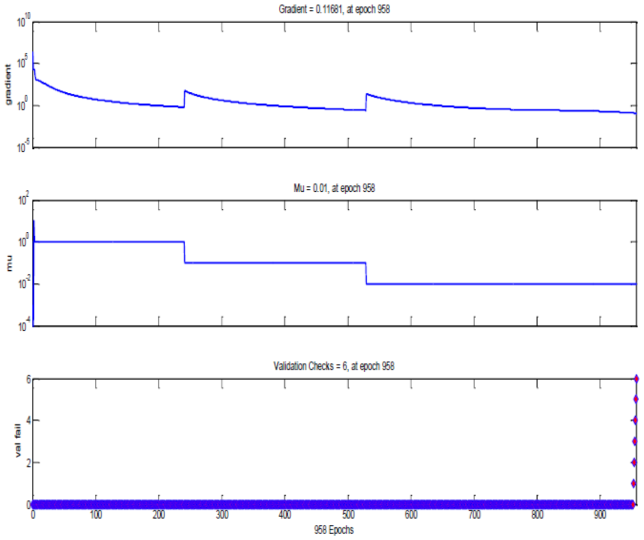

Figure 11: Neural Network Training State analysis graph

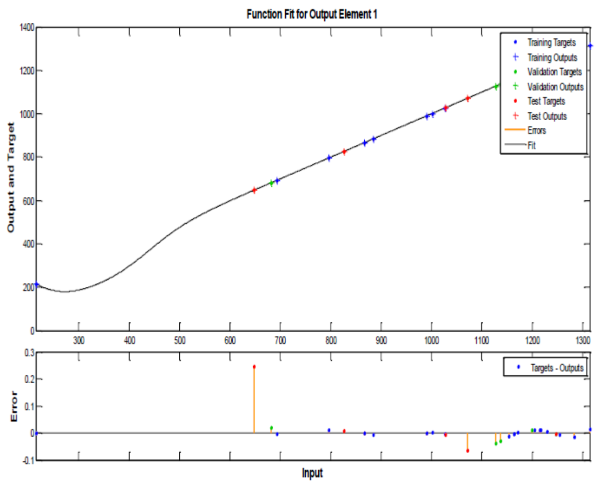

Figure 12: Neural Network Training Fit Graph at maximum epoch reached

The forecasted data using ANN model, compared to actual data of May month, which has plotted in MATLAB software as show in fig.12. It shows a small difference between actual data corresponding to forecasted data.

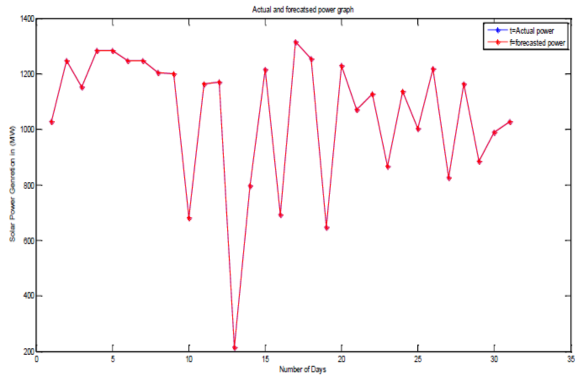

Figure 13: Actual and Forecasted Solar PV Power Generation graph of a Month

TABLE I. THE SUMMARY OF FORECASTED POWER FOR A TEST MONTH

Model	**Performance phase**	**May 2018**		
		Sample	***RMSE***	***R***
ANN	Trainig	21	0.0134	0.9999
	Validation	5	0.0218	0.9999
	Testing	5	0.0199	0.9999

VI. CONCLUSION

In this paper a new topology of ANN with multi- layer feed-forward network is presented for forecasting solar PV power. The performance of the developed model is based on how well it is trained, and also depends up on the quality of historical data that is used as pre-processing input-output. It has determined through an error investigating metric that is MSE the result obtained by developed model is accurate. The ANN model is trained by past data, so we use the more accurate weather data, the more accurate PV of solar power will be produced. The forecasting with ANN model validate access, robust and fast performed that permits investors to trade on energy market, provide funds, research and new development in the field. For future aspect optimization technique can be used for better performance and an accurate assessment, also comparative analysis can do with other models.

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