ANN Optimization for Short Term Forecasting of Solar PV Power

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ABSTRACT
One of the renewable energy resources used worldwide is solar energy. Its availability varies from day to day and even within a day itself depending on season. Due to this variability, forecasting of solar PV power becomes necessary but also challenging. The reasonably accurate forecast is an important input to the state load dispatch centres for scheduling power generation by various sources of energy. Artificial Neural Network (ANN) is widely used for such forecasting which involves training of the ANN using Bayesian Regularization and Levenberg-Marquardt algorithms. The forecasting approaches endeavour to minimize the error. In this paper, ANN based short term PV power forecasting algorithm is used to forecast solar PV power 6 hour ahead using trial and error approach and to compare different training approaches to reach at an optimized ANN solution.

Keywords: Solar PV forecasting, Artificial Neural Network, Bayesian Regularization, Levenberg-Marquardt algorithm

I INTRODUCTION

A renewable energy source for power generation helps to reduce greenhouse gases and protects environment [1]. Globally the installed power capacity of renewable energy based sources is rapidly increasing [2]. With the use of solar and wind energy, India is steadily moving towards renewable power target of 175 GW by 2022. National Institute of Wind energy (NIWE) is an Autonomous Research & Development Institution under the Ministry of New and Renewable Energy (MNRE), Government of India that provides high quality various services including forecasting of wind and solar resources [3]. MNRE launched a Solar Radiation resource assessment (SRRA) project in the year 2011 in India aiming for large scale utilization of solar energy [4].

Sun is a clean and renewable energy source available in plenty in the form of light and heat. The DC voltage obtained from the solar PV system can be enhanced using boost converter [5]. The forecasting of wind and solar energy for power generation is very difficult due to their variable nature unlike coal, nuclear or hydropower plants [6]. Forecasting of solar PV power facilitates the state load dispatch centre to schedule the generation of various power plants. A converter based photovoltaic (PV) module is simulated using mathematical modelling. Data of solar power is collected for the purpose of forecasting [7].

Forecasting methods utilize solar resource data from satellite and weather station, output from numerical weather prediction (NWP) model besides solar PV system data. Forecasting of solar energy is generally based on physical and statistical approaches. Physical approach utilizes PV modules to forecast solar power. With the help of available software tools, necessary forecast results can be obtained by simulation in statistical approach [8].

Requirement of forecasting energy depends on different time horizon. On the basis of various time horizons, solar forecasting can be classified into very short term or now-casting (2 to 3 hours ahead), short term (for next few days) and long term (monthly to yearly basis) [9][10].

The rapid change in solar irradiance on the day of forecasting leads to wide variation in power generation and results in higher forecasting error. Higher accuracy in forecasting helps in proper generation scheduling and thus in making optimum utilization natural resource. Forecasting accuracy helps to ease price risks associated with the power exchange and thereby evading economic penalties on the balancing market [11]. Power can be planned to consumers only when their demand pattern is known. Hourly load data of consumers were used in neural network model to forecast future values of load data trained by LM algorithm [12].

A forecasting model for a solar power plant was developed using LM optimization approach. For multi-layered feed forward network architecture, LM approach helped to choose the best training rate through back propagation method [13][14][15]. To achieve better accuracy in forecasting, optimization of LM algorithm along with a recurrent neural network (RNN) model helps to forecast solar power generation in very short intervals [16].

In this paper Section II deals with various steps in methodology for forecasting are elaborated. Section III deals with the application of ANN to forecast solar PV power 6 hour ahead for Bhilai, C.G. (India). The results and discussion are provided in Section IV. Finally, the conclusions drawn from the work is discussed.

II METHODOLOGY

The purpose of this work is to simulate a Short Term PV Power Forecasting with the help of Artificial Neural Networks which can forecast solar PV power 6 hour ahead. A Multi Layered Back Propagation Neural Network is used for achieving this. Trial and error approach was utilized to obtain the optimized network for the application.

The steps for designing the neural networks for solar power forecasting are given below:

(a) Data collection: (Data can be collected from Photovoltaic Geographical Information System (PVGIS), NASA, local meteorological station etc.)
(b) Creating the Neural Network: (The input values to be assigned to the network are fixed).
(c) Configuration of the Network: (The data to be used for Training, Validation and Testing and the number of hidden neurons are to be fixed)
(d) Initializing the weights and biases for the network: (This is done automatically by the Neural Network using software program)
(e) Training the Network: (An appropriate method to train the Neural Network has to be selected. The available optimization methods are Levenberg-Marquardt, Bayesian Regularization, Scaled Conjugate Gradient etc.)
(f) Validating the–results: (Analysing the values of errors, regression plots and comparing forecasted and actual values)
(g) Using the network for an application: (The developed neural network can be used for the application for which it was created)

Coding for forecasting can be done in R, Scilab, Python, MATLAB etc.

III APPLICATION OF DEVELOPED METHODOLOGY

The Neural Network based PV forecasting method is applied on Bhilai, Chattisgarh, India (Latitude - 21.220 N, Longitude- 81.380 E). The Input Data were collected online from Photovoltaic Geographical Information System (PVGIS), an official website of European Union that provides free and open access to full time series of hourly data solar radiation data. For obtaining the Short Term PV Power Forecasting, MATLAB 2016a is used which provides a multi paradigm numerical computing environment and a proprietary programming language developed by Math Works. Coding is done using Command Window and Script Editor. Neural Network toolbox available in MATLAB is used to simulate the required network.

Two inputs i.e. temperature and irradiance are given to the neural network. Output of the neural network is PV power. There are 256 hidden layers in the network. The optimum value 256 for hidden layers was reached by trial and error. Any deviation from the value 256 increases the error. The forecasted results are monitored looking at the values of error and regression plots. The Neural Networks structure is shown in Fig No.1.

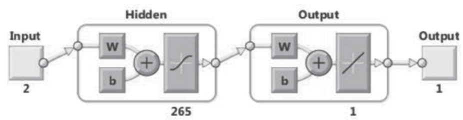

Fig.1: Neural Network structure for Short Term PV Power Forecasting

The training of neural network was first done using Levenberg-Marquardt algorithm. While training the error values using Levenberg-Marquardt optimization were very large and the forecasted value had large error and was not accurate. Hence, Bayesian Regularization was used which minimised the error and improved the forecast accuracy. But time required for training was more. The Fig No.2 shows the Neural Network Training status.

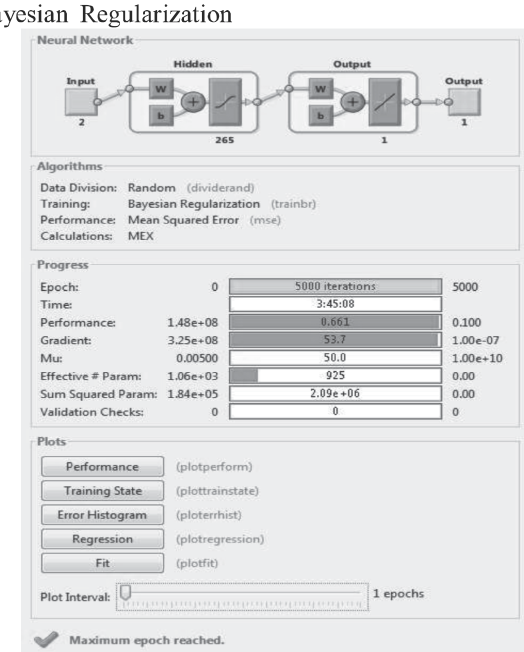

Fig.2: Neural Network Training Status

Data Division is done using "divider and" to separate the data into three sets of values, viz. training, validation and testing. By default 70% of values are allocated for training and 15% each for validation and testing.

Training is done using the functions "trainlm" and "trainbr". Here, "trainlm" is a network training function in which the weights and bias are updated using Levenberg-Marquardt optimization. This is normally the first choice and the fastest back propagation algorithm. The network training function for Bayesian Regularization is "trainbr" that updates weights and bias using Levenberg-Marquardt optimization. But here it minimizes a combination of weights and squared errors and determines the combination to produce a well generalized network.

Error is checked using "mse" function. It is a network performance function which measures the error of a neural network based on the mean of squared errors.

The Neural Network stops the training when any of following conditions is met:

(a) Maximum number of iterations as defined is reached.
(b) Maximum execution time is reached.
(c) Error is minimized within specified limit.
(d) Minimum error gradient value is reached (1e-7 in case of Bayesian Regularization and Levenberg-Marquardt optimization).
(e) Maximum value for "mu" function to control weight of neuron updation process during training is reached (1e10 in case of Bayesian Regularization, and Levenberg-Marquardt optimization)

This Condition given below holds true only for Levenberg-Marquardt optimization:

(f) The validation has deteriorated even after 6 times validation failures (system built in)

IV RESULTS AND DISCUSSION

The Neural Network was simulated and run successfully for Short Term PV Power Forecasting using Back propagation ANN trained with Bayesian Regularization & Levenberg-Marquardt algorithm.

Here 8762 data (i.e., hourly data of a year) were used for training the neural network. The graph of Actual PV Power vs. Forecasted PV Power obtained from Levenberg-Marquardt optimization is shown in Fig No.3. A small portion of graph in Fig No.3 has been zoomed and shown in Fig No. 4 to have a clear view of the superimposition of actual PV power plot on the forecasted PV plot. It can be seen that the forecasted values have low accuracy as the training could not be fully completed.

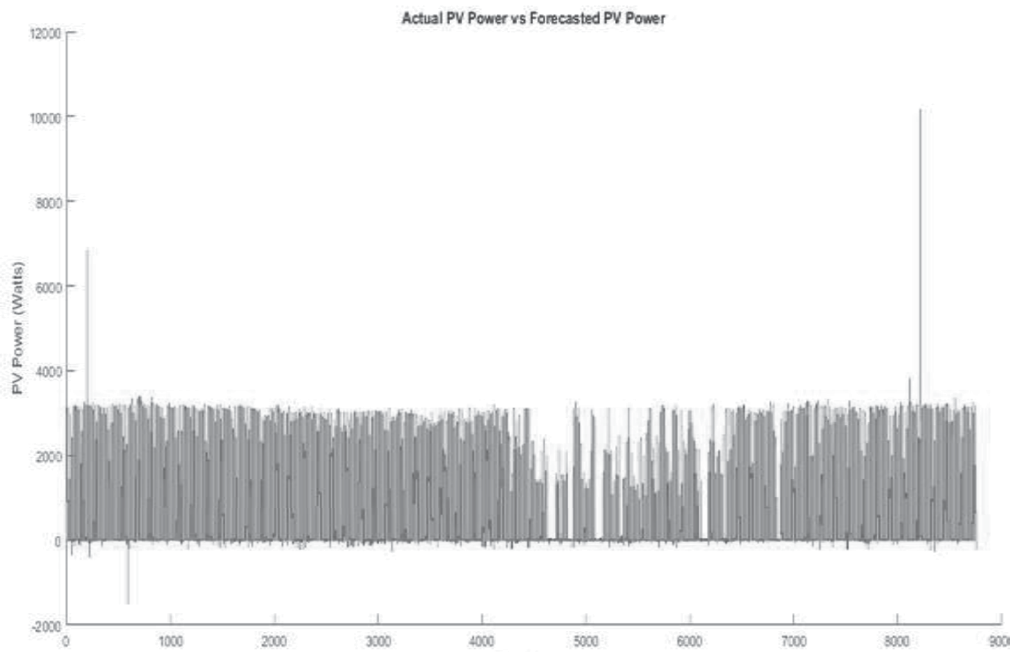

Fig.3: Actual PV power vs. Forecasted PV Power produced using Levenberg-Marquardt optimization

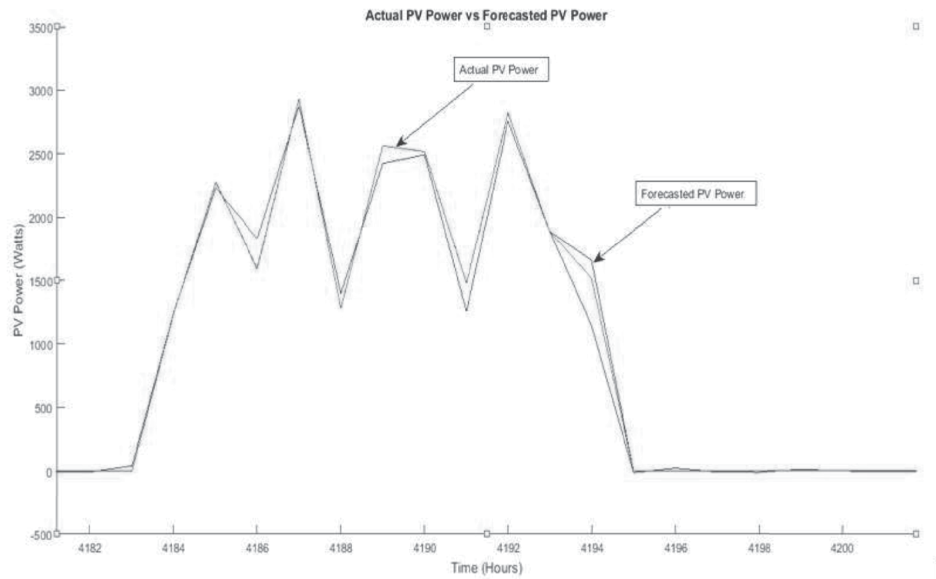

Fig. 4: Actual PV power vs. Forecasted PV Power produced using Levenberg-Marquardt optimization

The graph of Actual PV Power vs. Forecasted PV Power produced using Bayesian Regularization is shown in Fig No. 5. A small portion of graph in Fig No.5 has been zoomed and shown in Fig No. 6 for clarity. The forecasted results were found have an average accuracy of 99.3%.

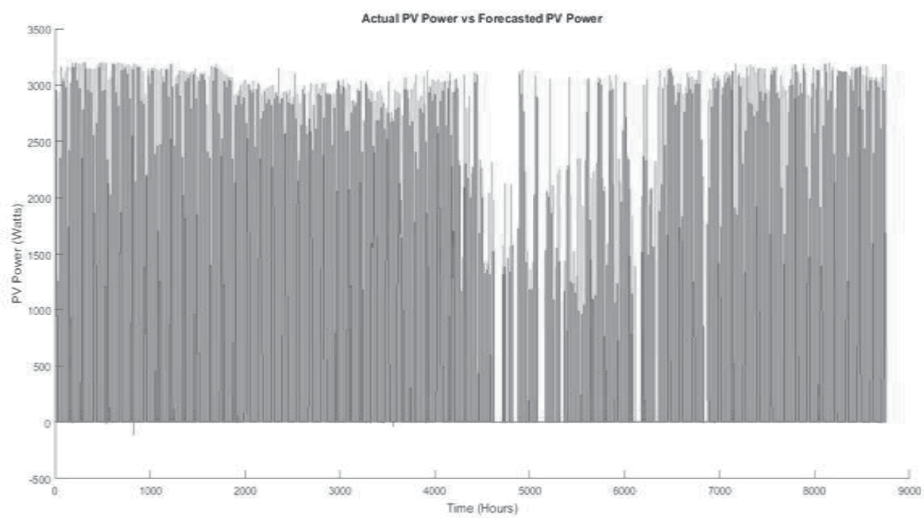

Fig. 5: Actual PV power vs. Forecasted PV Power produced using Bayesian Regularization

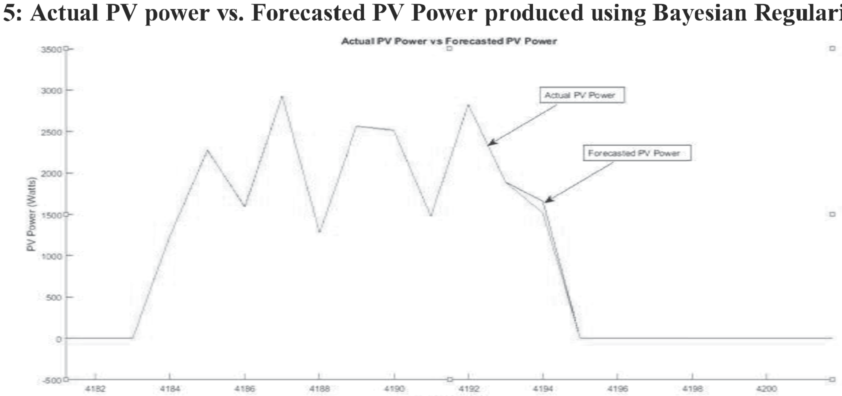

Fig. 6: Actual PV power vs. Forecasted PV Power produced using Bayesian Regularization

The Regression plots for the Neural Network using both the training methods are shown in Fig No. 7a and Fig No. 7b. The regression plot displays the output of the network with respect to the data for training, validation, and test sets. For a perfect fit, the data should fall along a 45 degree line, where the network outputs match with the targets.

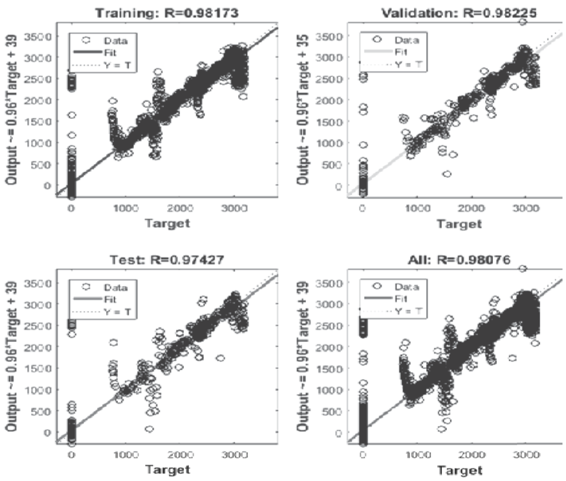

Fig. 7a: Regression Plot for Levenberg-Marquardt optimization

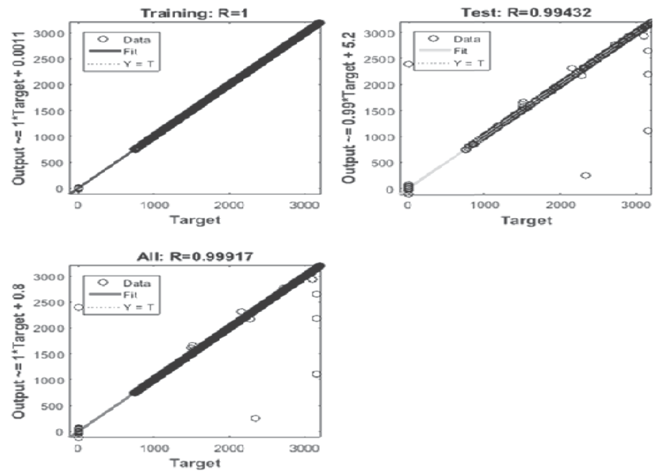

Fig.7b: Regression Plot for Bayesian Regularization

It is seen from Fig. 7a that there is large deviation from the target whereas in Fig. No. 7b a good matching well within a narrow band resulting in high accuracy in forecasting.

V CONCLUSION

The simulation for ANN based optimized short term PV power to forecast 6 hour ahead was simulated successfully for Bhilai, Chhattisgarh. Here both Levenberg-Marquardt optimization and Bayesian Regularization training methods were used. It was observed that Levenberg-Marquardt optimization takes less time (36 iterations) to train neural network but it results in very high error (MSE=3.7443e+04) i.e. poor accuracy which makes it unsuitable for very large number of inputs. By Bayesian Regularization, the error was MSE=0.6610 i.e. high accuracy of 99.3% (after 5000 iterations) was obtained but it took more time to train the neural network. Thus, ANN trained by Bayesian Regularization performs better for the short term PV power forecasting.

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