



PV POWER FORECASTING USING ARTIFICIAL NEURAL NETWORKS

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Abstract

Solar Energy is inconsistent in nature as it depends on factors like the position of the sun, time of the day, atmospheric conditions, season, characteristics of solar plant etc. Critics of solar energy claim that it is unreliable in nature. It becomes necessary to forecast solar power generation for the efficient usage of Solar Energy, and for the accurate management of loads in combination with a grid. With the help of solar forecasting the unreliability of solar power can be reduced to some extent and it can be used extensively. In this paper we are designing an ANN based short term PV power forecasting algorithm using trial and error approach and comparing different training approaches to reach at an optimized ANN which can forecast hourly PV power. PV system combined with this forecasting approach will be useful in improving the penetration of solar energy to rural areas. This approach will also find application in setting up a standalone off grid system.

1. Introduction

Renewable energy is the type of energy generated from inexhaustible natural resources since it is always regenerated after use. Usage of sources of renewable energy for electricity production helps to reduce greenhouse gases generated by non-renewable energy sources and it also helps to protect environment by conserving conventional energy sources and renewable sources are economical as they are available in plenty. Forecasting can be defined as the process of making predictions or estimations for the future based on the past as well as present data or by studying the trends. Or in

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other words it can be defined as a technique which uses historical data to make well trained estimates for future trends.

Some papers were gone through to know what all progress has been made in the field of forecasting and also to get an idea about the implementation of training algorithms. Based on that some of the key points identified are as listed below:

Sempe Lehole et al. [1] implemented a training function to forecast daily average solar irradiance (DASI) using the learning rule of Levenberg Marquardt (LM) algorithm for a feed forward network with a structural design of back propagation. Shahid M. Awan et al. [2] proposed a recurrent neural network model for forecasting generation of solar power. Levenberg Marquardt (LM) algorithm is used to optimize the network model in order to achieve improved forecasting accuracy.

Musaed Alrashidi et al. [3] estimated a short term forecasting model to forecast output power of a photovoltaic (PV) system using support vector regression (SVR). Anil Patel et al. [4] proposed a mathematical model using nonlinear autoregressive with external input (NARX model) trained by Levenberg Marquardt (LM) algorithm to forecast electrical output power from a converter based photovoltaic (PV) module in MATLAB Simulink environment.

D. A. Snegirev et al. [5] presented a short term forecast model to forecast generation capacity of a solar power along with mathematical equations of the model. Short term forecasting of the plant helps to evaluate mean hourly value of generation capacity of the. A. Ghanbarzadeh et al. [6] proposed a model to forecast global solar radiation (GSR) on the daily basis by training a neural network using Levenberg Marquadt (LM) algorithm.

2. Methodology

The objective of this paper is to design and implement an Artificial Neural Network which can forecast hourly PV Power values with accuracy and minimal error values while training the neural network and to get an optimized neural network by using trial and error approach. For implementation of the Short Term PV Power Forecasting, MATLAB is used [7] [8].

The standard steps for designing the neural networks to solve a given problem are as shown below:

1. Collect Input Data and Target Data: (Photovoltaic Geographical Information System (PVGIS) provides free and open access to hourly data of solar radiation and PV performance over a long period of time.
2. Creating the Neural Network: (The Input Values and the Target Values to be given to the network are fixed)
3. Configuration of the Network: (The amount of data to be used for Training, Validation and Testing and the number of hidden neurons has to be fixed)
4. Initializing the weights and biases for the network: (This is done automatically by the Neural Network Toolbox in MATLAB)
5. Training the Network. (Some method to train the Neural Network has to be defined example-Levenberg-Marquardt optimization, Bayesian Regularization etc.)
6. Validating the network. (Looking at the values of error and regression plots)
7. Using the network for an application: (The designed neural network can be used for the application for which it was created).

The Neural Network designed in our study has 2 inputs (temperature and Irradiance), 256 hidden layers and 1 output (PV power), the value 256 of hidden layers was reached using trial and error it is seen that decreasing or increasing the value beyond 256, error is increased. The Neural Networks structure is as shown below:

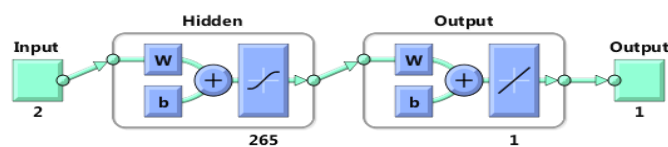


Figure 1. Neural Network structure for Short Term PV Power Forecasting.

Levenberg-Marquardt optimization and Bayesian Regularization were used to train the neural network, while training the error values using

Levenberg-Marquardt optimization was very large and the forecasted value was not accurate, hence Bayesian Regularization was used which minimised the error and the forecast accuracy, but time required for training was more. The figure 2 shows the Neural Network Training status.

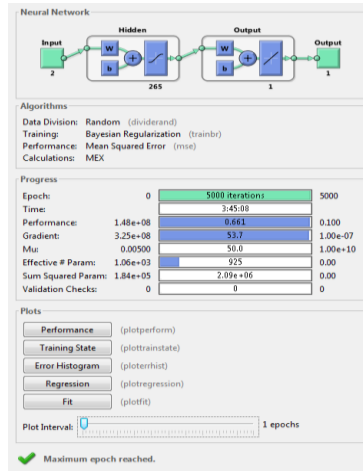


Figure 2. Neural Network Training Status.

In the training algorithms we have used certain techniques, they are as described below:

Data Division is done using “dividerand”, this is used to separate the target values into three sets of training, validation and testing. By default 70% of values are allocated for training and 15% each for validation and testing.

Training is done using “trainlm” and “trainbr”, trainlm is a network training function that uses Levenberg-Marquardt optimization to update the weights and bias, normally the first choice and the fastest back propagation algorithm; trainbr means Bayesian Regularization, it is also a network training function which also updates weights and bias are optimised using Levenberg-Marquardt optimization, however here it minimises a blend of weights and squared errors before deciding the best combination to create a well-generalized network.

Performance is checked using “mse”, it is a system performance function that evaluates a neural network’s performance using the mean of squared errors.

The Neural Network stops when any of the following circumstances are satisfied, the training is terminated:

- Defined maximum number of iterations has been attained.
- Time Limit has exceeded.
- As defined Performance or Error is minimized.
- The performance of gradient's value has been attained ($1e-7$ in case of Bayesian Regularization and Levenberg-Marquardt optimization).
- Maximum value for μ is reached ($1e10$ in case of Bayesian Regularization, and Levenberg-Marquardt optimization)

This Condition holds true only for Levenberg-Marquardt optimization. Since the last time it decreased, validation performance has increased more than maximum validation failures (6 times).

3. Results and Discussion

The Neural Network was designed and run successfully for Short Term PV Power Forecasting using Back propagation ANN trained with Bayesian Regularization and Levenberg-Marquardt optimization. Here 8762 data (i.e., hourly data of a year) were used for training the neural network.

Actual PV Power vs. Forecasted PV Power graph produced using Levenberg-Marquardt optimization and Bayesian Regularization is as shown in Figure 3(a) and 3(b). It is zoomed to show the overlapping between the actual PV values and the forecasted PV values. In figure 4(a) it can be seen that the forecasted values are not that accurate while in figure 4(b), it can be seen that the forecasted values are accurate. The Neural Networks Regression plots using both the training methods are shown in Figure 5(a) and 5(b).

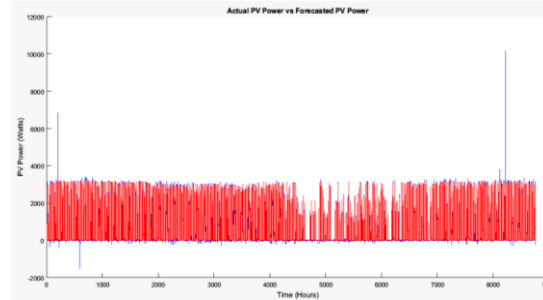


Figure 3(a). Actual PV power vs. Forecasted PV Power produced using Levenberg-Marquardt optimization.

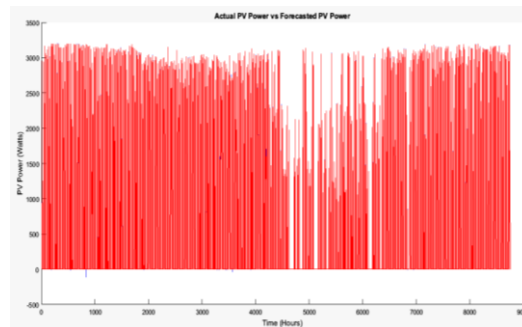


Figure 3(b). Actual PV power vs. Forecasted PV Power produced using Bayesian Regularization.



Figure 4(a). Actual PV power vs. Forecasted PV Power produced using Levenberg-Marquardt optimization.

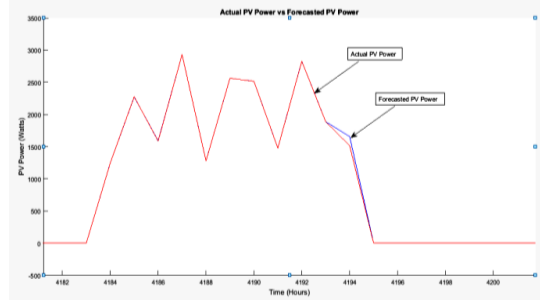


Figure 4(b). Actual PV power vs. Forecasted PV Power produced using Bayesian Regularization.

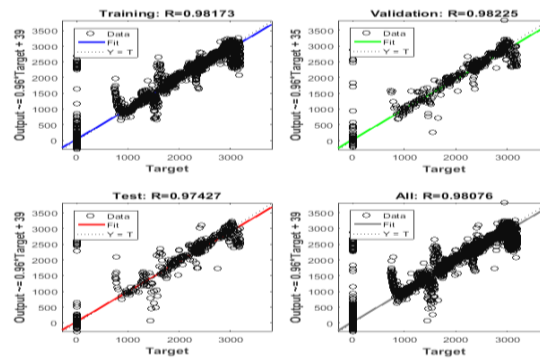


Figure 5(a). Regression Plot for Levenberg-Marquardt optimization.

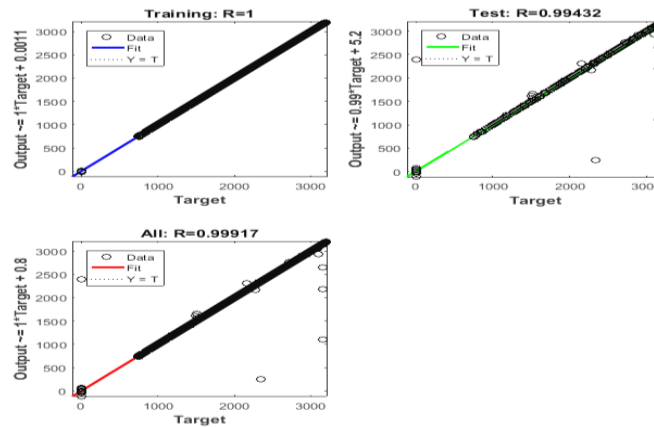


Figure 5(b). Regression Plot for Bayesian Regularization.

The regression plot displays the output of the network in regards to the

training, validation, and test sets have goals. The data should fall along a 45-degree line, with the network outputs equal to the targets, for a perfect match. For forecasting the next interval values we have fed 7 inputs and got the next 5 intervals Forecasted PV power values in Figure 6 using the designed ANN.

The Mean Square Error Value for Levenberg-Marquardt optimization is $3.7443e+04$ and the Mean Square Error Value for Bayesian Regularization is 0.6610, which shows that ANN trained using Bayesian Regularization performs better for the proposed Short Term PV Power Forecasting application.

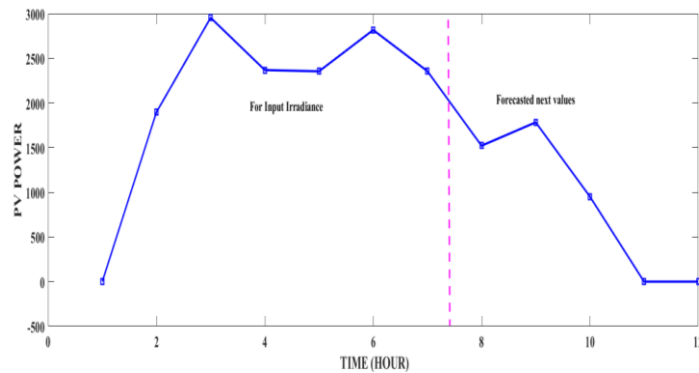


Figure 6. Forecasted Hourly value for Next 5 Hours.

4. Conclusion

Based on the simulation done it can be said that an ANN based optimized Short Term PV Power Forecasting was designed and implemented successfully. Here we have used both Levenberg-Marquardt optimization and Bayesian Regularization training methods, based on the study it can be said that Levenberg-Marquardt optimization takes less time to train but its error values are very high ($MSE=3.7443e+04$) and it does not give accurate results. By Bayesian Regularization the error values are less ($MSE=0.6610$) and we get accurate results, but it takes more time to train the neural network. Also we were able to forecast hourly PV power for the upcoming 5 hour period as well.

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