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Short-Term Power Production Forecasting in Smart Grid Based on Solar Power Plants

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Abstract— **Since the world is moving towards the modernization so the smart grid idea is one of the smart idea leads to the modernization. One of the most important factors for the smart grid is the optimal production-commutation balance. Due to the lacking capabilities of accomplishing the increasing needs of the power with normal procedures, the world is moving towards the power production from the renewable energy sources. To get the efficient power production, the world is making the grids which generate power from the renewable sources, smart. Since solar is one of the important renewable energy sources, hence the changing climatic conditions affect heavily the ratio of power production from the solar sources. In this research, some of these climatic factors are considered to predict the solar power production by using the real-time data of a solar power plant located at Konya, Turkey. The inputs factors in consideration are on the daily basis which includes the average humidity, the minimum, average and the maximum temperatures, the solar irradiance, average and the maximum wind speed and the power generation values. The behavior of this solar power plant along with the prediction of the power production is carried out by using an Artificial Neural Network (ANN) in Matrix Laboratory (MATLAB) software's built-in toolbox named as Neural Net Fitting toolbox. In ANNs, three different built-in learning algorithms in this toolbox named as Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient are used to compare the prediction results, finally to get good and accurate results.**

Index Terms— **Artificial neural network in MATLAB, forecasting of energy production from renewable energy source, neural net fitting toolbox, solar power production.**

I. INTRODUCTION

Renewable energy nowadays, is prominent technology to fulfill the desired power consumption needs. As the countries are devolving day by day, the power requirements are also increasing. Power production as required, is the most important factor in the smart grids based on solar power plants. Solar power plant gives power production based on the intensity of solar radiation, which depends on the daily weather conditions. There are so many factors of weather which affect the power production from solar power plants. Therefore, it is highly required to know possible power production depending on weather factors somewhat earlier so that load needs can be satisfied. The prediction of power production can be carried out by using different methodologies varying from numerical to artificial neural and fuzzy models considering the affecting factors and the time intervals for forecasting. Affecting factors include the intensity of solar radiation, wind speed, humidity, temperature, etc. Time intervals are described on the basis of time duration; hence the forecasting can be short-term, mid-term and long-term.

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II. LITERATURE REVIEW

Many types of research have been carried out by using a variety of databases and different models are presented in these years to forecast the load or power production of solar power plants to match the requirements. One of the researcher modeled a variety of solar-based applications through Artificial Neural Network (ANN) [1] whereas another researcher provided a comparative survey on several predicting models[2]. Other researchers discussed the short, long and medium-term behavior of the smart grid respectively [3], [4]. Researchers also presented different types of solar and Photovoltaic (PV) forecasting models [5]–[10].

Most of the researchers used an ANN to forecast the solar energy potential in different areas of Turkey, Italy, Nigeria, California, Kuwait, Queensland, and Australia respectively [11]–[17]. Some of the researchers forecasted the effect of the solar power on islands[18]–[20]. Others, predicted the solar production of a laboratory-level micro-grid and real-time micro-grid using many ANN respectively [21], [22]. Other than that, researchers forecasted the power production by using ANN in Matrix Laboratory's (MATLAB) built-in toolboxes over the datasets of Nigeria and India respectively [23], [24].

One of the researcher provided an online forecasting two-stage method for a small village in Denmark [25] whereas another predicted short-term load requirements [26]. Other researcher designed a NARX based forecasting model [27] whereas one gave a solar forecasting model which gets the input from sensors [28]. Many other researcher used machine learning algorithms for the solar forecasting [29]–[31].

One of the scientist gave a solar power forecasting model used an ANN tuning technique developed for acoustic signal classification and image edge detection to improve the accuracy [32]. To gain higher accuracy, one of the scientist combined the ANN with wavelet analysis [33], another combined Machine Learning with ANN [34], other combined an ANN with Analog Ensemble (AnEn) technique [35] and other than that, one combined the spatial modeling with ANNs [36].

In this research, the forecasting of the power production of a solar power plant located in Konya, Turkey will be carried out for a short time interval through the ANN.

III. METHODOLOGY

ANN model can be designed by following the number of steps, the description of these steps are given below. A flow chart for designing an ANN is shown in figure 1[37].

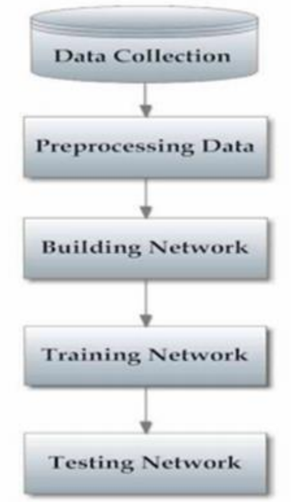


Fig.1: Steps to Design an ANN

A. *Collection of Data*

The first step needed to design an ANN is the collection of the data. The data used in this research is a real-time data, collected from the Supervisory Control and Data Acquisition (SCADA) center for the solar power plant located in Konya, Turkey.

B. *Pre-Processing of Data*

The next step after collection of the data is to the fill the places of missing data. The missing data in this research are filled by following the method of linear regression. Also, the normalization of data is good practice, if required to convert the large values of data in the range of 0 to 1. In this research, we used data with and without normalization to compare the results. The sampled data set is shown in fig.2. In fig.2, the columns start from A to H identifying the inputs factors which are the daily basis average humidity, minimum, average and maximum temperatures, average and maximum wind, solar irradiance, and power generation values respectively

Next, the whole data set is divided into the training and testing portions. The toolbox automatically divides the data into training, testing and validation data sets but, we require another set of data for further testing. In this research, we used 10 months data for training and 1-month data for further testing.

	A	B	C	D	E	F	G	H
7	53.6	9.6	16.7	23.4	1.6	10.2	6131.41	3482.4
8	52.6	11.1	16.6	22.1	2.1	9.2	6160.9	2615.28
9	45.4	12	16.9	22.1	3	11.3	5203.91	3753.04
10	41.4	11	17	22.4	2.6	12.3	6228.37	3726.44
11	54.5	9.3	15.6	21.6	1.9	11.3	5861.59	3684.47
12	67.9	6.6	14	20.3	1.1	10.2	4276.81	1285.39
13	68.8	10.5	14.2	20.5	1.2	13.3	6082.53	782.27
14	78	6.9	12.6	18.9	0.3	12.3	4071.06	2875.62
15	76.5	10.8	13.1	17.9	0.6	7.7	6508.69	3741.19
16	81.5	6	12.4	19.1	0.9	8.2	6437.44	1280.28
17	86.8	10	11.9	15.7	1.4	13.8	4189.02	3540.88
18	81.3	8.3	12.5	20.1	2	15.9	2853.31	3976.23
19	59.8	7.2	8.7	12.2	3.6	16.4	6363.52	2200.31
20	61.3	0.9	5.3	10.6	2.3	11.3	6237.98	1818.33
21	52.8	-1.4	8	16.9	0.8	4.6	6183.71	144.24

Fig.2: Input Data Set

C. *Building the Network*

During this stage of design, the architecture of the ANN, number of neurons, number of layers, activation functions and learning algorithms are decided. In this research, since we used toolbox so we can only choose the type of the toolbox depending on the application and then it automatically creates the network. We only changed the number of neurons that is, in this research we used 100 hidden neurons.

D. *Training the Network*

At this stage of designing, a designer needs to give the input data as well as the target data and the network then adjusts the weight biases by itself so that it can learn to match the targets with actual outputs. Also, the learning algorithms are to be selected.

E. *Testing the Network*

Finally, in this stage, the learning of the network is to be tested on the testing data set which is not exposed to the network at first. To analyze the performance of the network root mean square error (RMSE) and the mean bias error (MBE) is checked. RMSE is the information of the short-term performance that is a measure of the variation of forecasted values from the measured data while MBE gives the information of the long-term performance of the model, it is an indication of the average deviation of the forecasted values from the corresponding measured data. If the results are satisfied then the network is ready otherwise the network is to be retrained and re-tested.

IV. RESULTS

Since we discussed the designing of the ANN in neural net fitting toolbox earlier, now we discuss the results got by using 3 techniques available in toolbox.

A. *Training through Scaled Conjugate Gradient*

Through the training of the network by using Bayesian Regularization, the network is trained in 56 iterations. The performance or mean squared error (MSE) of the network is $2.24e^{06}$. The gradient of the network is $4.07e^{07}$. The Table I shows the sample values along with MSE and the Regression values for training, testing and validation data.

Table I MSE and the Regression values for training, testing and validation data.

	Samples	MSE	Regression
Training	307	2485724.43296 e^{-0}	9.48068 e^{-1}
Validation	17	4197884.36314 e^{-0}	8.87526 e^{-1}
Testing	17	2923919.16154 e^{-0}	9.42175 e^{-1}

Fig.3 shows the error histogram and the regression analysis of the trained network. İn fig.3a, there is a graph which identifies the instances in which error (errors = target - output) occurs that is where the output misses the target. İt also shows the zero error margin. In this result, many values almost missed the targets and are away from that zero margin means the performance of the network is bad. İn fig.3b, there is analysis which basically shows how the output data fit to the target data. The closer the regression value is to 1 that means the relationship between the output and the target is good. So in this result, almost all the values are 0.9 except the validation; hence this means the relationship is not bad between the targets and outputs in this trained network.

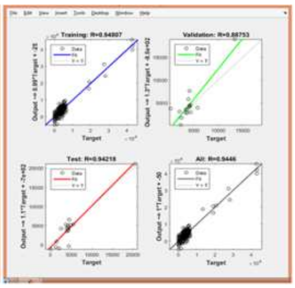


Fig.3a: Error Histogram for Training Data
Fig.3b: Regression Analysis for Training Data

B. Testing through Scaled Conjugate Gradient

Next, the performance of the trained network is tested by providing it new samples which were not given to the network during training process. The MSE and Regression values for testing data samples are 2357036.87842e^{-0} and 6.74205e^{-1} respectively.

Fig.4 shows the error histogram and the regression analysis of the trained network on the testing data sample. İn fig.4a, there is a graph which results that many values almost missed the targets and are away from the zero margin which means the performance of this network is bad. İn fig.4b, not many output values fit to the target values as the regression value is 0.67, this means the relationship is bad between the targets and outputs in this trained network.

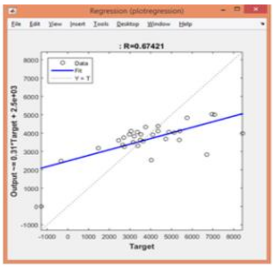


Fig.4a: Error Histogram for Testing Data
Fig.4b: Regression Analysis for Testing Data

C. Training through Levenberg-Marquardt

Through the training of the network by using Levenberg-Marquardt, the network is 10 iterations. The performance or MSE of the network is 3.56e^{-22}. The gradient of the network is 8.27e^{-08}. The Table II below shows the sample values along with MSE and Regression values for training, testing and validation data.

Table II MSE and the Regression values for training, testing and validation data.

	Samples	MSE	Regression
Training	307	908.80788e^{-0}	9.99981e^{-1}
Validation	17	973.00195e^{-0}	9.99980e^{-1}
Testing	17	1777.00699e^{-0}	9.99639e^{-1}

Fig.5 shows the error histogram and the regression analysis of the trained network İn fig.5a, there is a graph which results that almost all the values of output which missed the targets are close to that zero margin means the performance of this network is good. İn fig.5b, almost all the values are 0.99; hence this means the relationship is good between the targets and outputs in this trained network.

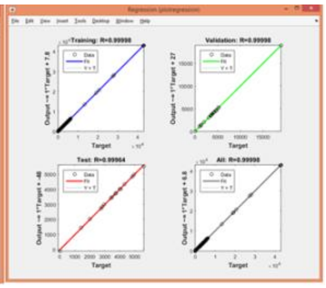
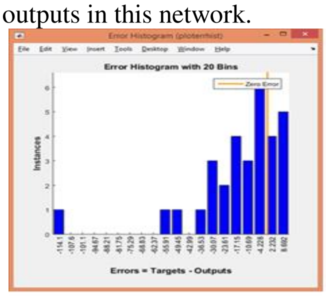


Fig.5a: Error Histogram for Training Data
Fig.5b: Regression Analysis for Training Data

D. Testing through Levenberg-Marquardt

Now the trained network is tested on the new samples which were not given to the network during training process. The MSE and Regression values for testing data samples are 869.15896e^{-0} and 9.99642e^{-1} respectively.

Fig.6 shows the error histogram and the regression analysis of the trained network on the testing data sample. İn fig.6a, there is a graph which results that almost all the values of output which missed the targets are close to that zero margin except only one which means the performance of the network is good on the unseen data. İn fig.6b, almost all the output values fit to the target values and the regression value is 0.99, this means the relationship is good between the targets and outputs in this network.



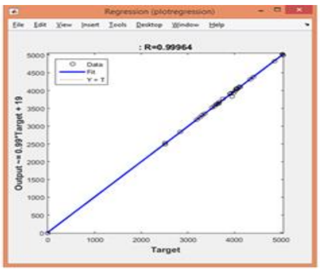


Fig.6a: Error Histogram for Testing Data
Fig.6b: Regression Analysis for Testing Data

E. Training through Bayesian Regularization

Through the training of the network by using Bayesian Regularization, the network is trained in 1000 iterations. The performance or MSE of the network is 0.0664. The gradient of the network is 419.The Table III below shows the sample values along with MSE and Regression values for training, testing and validation data.

Table III MSE and the Regression values for training, testing and validation data.

	Samples	MSE	Regression
Training	307	6.63709e^{-2}	9.999999 e^{-1}
Validation	17	0.000 e^{-0}	0.000e^{-0}
Testing	17	8.74735e^{-2}	9.99999e^{-1}

Fig.7 shows the error histogram and the regression analysis of the network. İn fig.7a, there is a graph which results that almost all the values of output which missed the targets are close to that zero margin means the performance of this network is good. İn fig.7b, almost all the values are 1; hence this means the relationship is very good between the targets and outputs in this network.

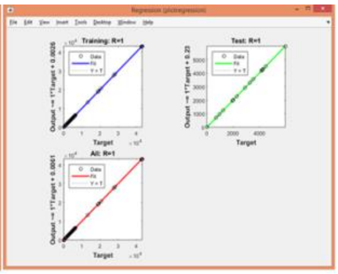
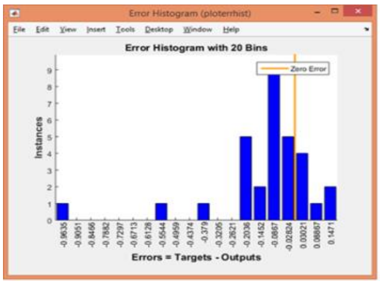


Fig.7a: Error Histogram for Training Data
Fig.7b: Regression Analysis for Training Data

F. *Testing through Bayesian Regularization*

Next, the trained network is tested on the new samples which were not given to the network during training process. The MSE and Regression values for testing data samples are $5.89484e^{-2}$ and $9.99999e^{-1}$ respectively.

Fig.8 shows the error histogram and the regression analysis of this network on the testing data sample. İn fig.8a, there is a graph which results that almost all the values of output which missed the targets are close to that zero margin except only one which means the performance of the network is good on the unseen data. İn fig.8b, almost all the output values fit to the target values and the regression value is 1, this means the relationship is good between the targets and outputs in this trained network.



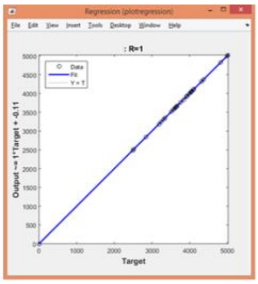


Fig.8a: Error Histogram for Testing Data
Fig.8b: Regression Analysis for Testing Data

G. *Comparison*

The compariosn between all three traning algorithms used to train an ANN is shown in Table IV.

Table IV Comparison between all three Traning algorithms.

S. No	Scaled Conjugate Gradient	Levenberg-Marquardt	Bayesian Regularization
1	The network is trained in 56 iterations.	The network is trained in 10 iterations.	The network is trained in 1000 iterations.
2	MSE is very high.	MSE is acceptable.	MSE is very low.
3	Regression values are low.	Regression values are acceptable.	Regression values are good.
4	The gradient is very high.	The gradient is good.	The gradient is acceptable.
5	The Performance Parameter is very high.	The Performance Parameter is good.	The Performance Parameter is acceptable.
6	Error histogram is bad.	Error histogram is acceptable.	Error histogram is good.

I. CONCLUSION

Forecasting is an important task for power system management. There are many researches in literature for more accurate and easy solutions to forecast power and energy.

This research presented an easy and time-saving method by using the MATLAB's built-in toolbox to predict the short-term production by the solar power plant as it does not require any complicate modeling or heavy mathematical calculations. Through this method, the production of any solar power plant can be predicted by using an appropriate database of that power plant.

According to the results of this research, error rates, gradient and regression values of Levenberg-Marquardt and Bayesian Regularization are very close to each other. But, it can be concluded that Bayesian Regularization gave better results as compared to other two algorithms by considering all the factors.

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