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SOLAR PHOTOVOLTAIC OUTPUT POWER FORECASTING USING BACK PROPAGATION NEURAL NETWORK

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Abstract

Solar Energy is an important renewable and unlimited source of energy. Solar photovoltaic power forecasting, is an estimation of the expected power production, that help the grid operators to better manage the electric balance between power demand and supply. Neural network is a computational model that can predict new outcomes from past trends. The artificial neural network is used for photovoltaic plant energy forecasting. The output power for solar photovoltaic cell is predicted on hourly basis. In historical dataset collection process, two dataset was collected and used for analysis. The dataset was provided with three independent attributes and one dependent attributes. The implementation of Artificial Neural Network structure is done by Multilayer Perceptron (MLP) and training procedure for neural network is done by error Back Propagation (BP). In order to train and test the neural network, the datasets are divided in the ratio 70:30. The accuracy of prediction can be done by using various error measurement criteria and the performance of neural network is to be noted.

Keywords:

Energy Forecasting, Error Back Propagation (BP)

1. INTRODUCTION

Solar photovoltaic systems transform solar energy into electric power. The power output depends on the incoming radiation and on the solar panel characteristics. Photovoltaic power production is increasing nowadays.

In recent years, photovoltaic (PV) technology has been rapidly developed due to the maintenance free, long lasting, and environment friendly nature of PV as well as government's support. However, power output of PV system is a non-stationary random process because of the variability of solar irradiation and environmental factors.

Any grid-connected PV system in the public power grid, is regarded as a non-controlled, non-scheduling unit, its power output fluctuations will affect the stability of power system. As the use of large-scale grid-connected PV system is increasing, it's important to strengthen the prediction of PV system power output, which can help the dispatching department to make overall arrangements for conventional power and photovoltaic power coordination, scheduling adjustment, operation mode planning

Solar Photovoltaic power forecasting information is essential for an efficient use, the management of the electricity grid and for solar energy trading.

The interest in solar energy is continuously increasing due to environmental concerns and reduced technology costs.

Due to meteorological uncertainty, photovoltaic energy is difficult to predict [9]. Weather variables such as temperature, global solar irradiation, sunshine duration, wind speed, relative humidity, cloudiness or sky cover, dew point and precipitation are used as inputs for solar power forecasting models.

2. SOLAR PHOTOVOLTAIC FORECASTING METHOD

Solar Photovoltaic forecasting methods can be broadly characterized as physical or statistical [11], [15]. Physical models are based on mathematical equations which describe the ability of PV systems to convert the introduced meteorological resources into electrical power [4]. These models can be very simple, if based only to the global solar radiation, or more complicated if they include additional parameters. As a matter of fact, it is not easy to predict PV module energy production since it depends on several parameters.

Nowadays the most applied techniques to model is the stochastic nature of solar irradiance at the ground level and thus the power output of PV installations are the statistical methods; in particular regression methods are often employed to describe complex nonlinear atmospheric phenomenon that includes the Auto-Regressive Moving Averages (ARMAs) method, as well as its variations, such as the Auto-Regressive Integrated Moving Averages (ARIMAs) method [8]. The performance of these models is very good for few-minutes to few-hours ahead of forecasting. Nonlinear methods, such as wavelet-based methods [18], [21] have been shown superior to linear models.

Nowadays the most common way to forecast the future values of a time series [8] is the use of machine learning methods, PSO method [2], [7], genetic algorithm [10] , Adaptive Neuro Fuzzy Inference system (ANFIS) [20] and ANN. Reviewed literature shows that ANN methods have been successfully applied for forecasting.

Soft computing techniques based on ANN are used for few-hours power output forecast. Thus in statistical approach of forecasting process, artificial neural network plays an important role photovoltaic energy forecasting. In order to define the accuracy of the prediction, some error indexes are introduced to evaluate the performances of the forecasting models. The analysis is based on the experimental activities carried out by real photovoltaic plant from which the dataset has been collected.

3. ARTIFICIAL NEURAL NETWORKS

Neural networks, more accurately called artificial neural networks are computational model that consists of a number of simple processing units. These processing unit, communicate by sending signals to one another over a large number of weighted connections. The topologies of neural network is depends on the way of operation they perform in the network [17].

3.1 FEEDFORWARD NETWORK

The feedforward neural network was the first and arguably simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. There are no cycles or loops in the network. The data processing can extend over multiple units, but no feedback connections are present, that is, connections extending from outputs of units to inputs of units in the same layer or previous layers [16].

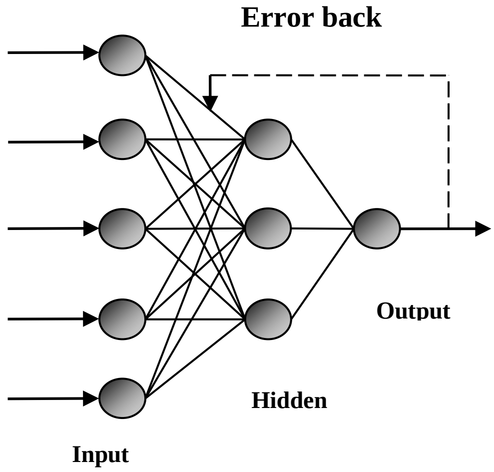

Fig.1. Feedforward network

Feed-forward ANNs allow signals to travel one way only, from input to output as specified in Fig.1. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs.

3.2 MULTILAYER PERCEPTRON

The most popular form of feed forward neural network is multilayer perceptron (MLP) [1]. A multilayer perceptron network has any number of inputs. This has one or more hidden layers with any number of units. They use linear combination function in the input layers and are generally sigmoid activation in the hidden layers. They had any number of outputs with any activation function. Then they had connections between the input layer and first hidden layer, between the last hidden layer and output layer.

By providing enough data, enough hidden units, and enough training time, an MLP with just one hidden layer can learn to approximate virtually any function to any degree of accuracy. Although one hidden layer is always sufficiently provided with enough data and there are situation where a network with two or more hidden layers may require fewer hidden units and weights than a network with one hidden layer, so extra hidden layers sometimes can improve generalization [6].

Consider a neural network with input signal X_i to the neuron in hidden layer. Each neuron in the hidden layer sum ups its input signal after weighting them with the strengths of respective connections W_{ij} from the input layer and computes its output Y_j as a function f of the sum.

$$Y_j = f\sum_{i=1}^{n} W_{ij} X_i \tag{1}$$

where, f can be a simple threshold functions. The output of the neuron in the output layer is computed similarly.

4. DATA DESCRIPTION

Solar photovoltaic historical dataset is collected from the photovoltaic (PV) panel which is installed in certain location. The data are collected from the atmosphere for the production of solar power from the solar irradiation. Radiation will be depends only on the environmental condition. The solar power collected will be greater, when the atmospherical conditions are good.

The PV panel will collect certain parameter such as humidity average, wing speed average, amount of solar radiation, temperature of the day, cloud coverage, output AC power and output DC power etc. Thus the data are collected for time interval. The time intervals are determined by the setting in PV panel. Thus the dataset may collect for one minute time interval or 15 minutes time interval based on the PV panel setting. The first dataset was collected from 50KW DC ground mount installation located in Rutland, for every 15 minutes time interval and the second dataset was collected from GECAD Photovoltaic system, for every 5 minutes time interval. The preprocessing and data validation can be done by the collection of historical dataset.

After data collection, data preprocessing procedure are conducted to train the ANN more efficiently. The procedure is to normalize the dataset. Then finally randomize the data in the dataset. Before any other step, historically measured data must be always validated, since unreliable data increase the odds of higher errors in the forecast. The preprocessing block initially includes the control of the coherence among the main variables measured in the PV plant, such as the solar radiation and the PV output power.

4.1 RUTLAND DATASET

The dataset which was collected for this project is from 50KW DC ground mount installation located in Rutland. The dataset was collected for each fifteen minutes time interval. This dataset contains about 1248 data. The dataset contains six parameters:

- Ambient temperature average
- Panel temperature average
- Transformer temperature average
- Solar irradiance
- Wind speed
- Power output

The dataset was collected from 19th January 2010 to 31st January 2010. This was obtained by daily observation of solar irradiance, temperature, humidity and generated power by photovoltaic installation which is located in particular location.

4.2 GECAD PHOTOVOLTAIC SYSTEM DATASET

This data is obtained from GECAD photovoltaic system. The capacity of one photovoltaic panel is 200W. This dataset was collected for each and every five minutes time interval. This dataset was collected for one month, that is, from 1st May 2015 to 31st May 2015.The parameter of the dataset can be as follows,

- Actual solar radiation
- Sensor usage
- Ambient temperature
- Module temperature
- Total amount of energy

There is about 8451 data contained in the respective dataset collected from GECAD photovoltaic system. Thus the dataset contains the solar radiation average which is the amount of daily irradiance from the sun.

This may vary due to different climate condition. Thus the temperature of the atmosphere may change. The environment may produce different climate. Due to change in climate, the parameter of the dataset may vary widely. The dataset was collected for twenty four hours where the initial reading may contains zero value because the reading will be started only after the sunrise. Thus the amount of power produced in each and every solar photovoltaic plant may vary due to variation in the solar radiation from the sun. If there is good radiation in sun, that is, during summer climate the dataset will contains the perfect values which are used for photovoltaic forecasting in this paper.

5. NEURAL NETWORK IN PHOTOVOLTAIC FORECASTING

5.1 IMPLEMENTATION OF NEURAL NETWORK

At this stage, the neural network was designed by specifying the number of hidden layers, number of neuron and number of output layer. Thus the following steps are carried out for the process of implementation of neural network with the corresponding dataset.

- In this project the total number of input to be considered is five. Thus the number of neuron in input layer is five.
- Then the number of hidden layer is one and number of neuron in hidden layer is 8 (considered).
- The output of the network is one, so number of neuron in output layer is one.
- The weight of the neural network is fixed randomly. Thus the neural network which was designed for forecasting the solar photovoltaic power can be specified in Fig.2. In this work multilayer perceptron network is used.

Initially the neural network implementation was done for the first dataset which is collected from the Rutland. Here there are six parameters in this dataset. Five parameters is considered as input, and one parameter is considered as output.

Thus the input layer of the neural network contains five neurons, and output layer is provided with one neuron. As specified in the coding the neural network was provided with 8 neurons in the hidden layer which can be specified in Fig.2.

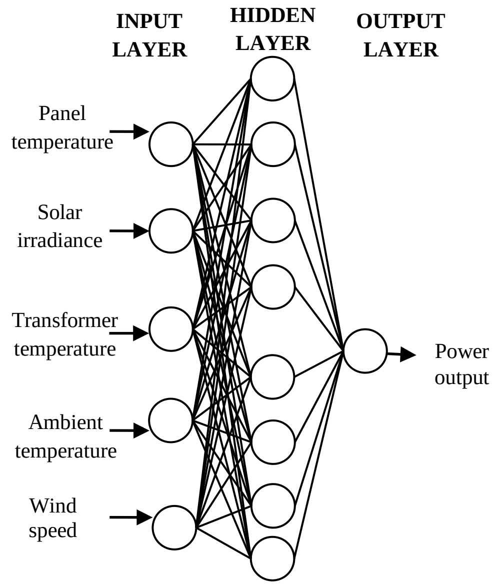

Fig.2. Implementation of neural network for Rutland Dataset

Now the neural network implementation was done for the second dataset which is collected from the GECAD photovoltaic system. Here there are five parameters in this dataset. Four parameters are considered as input, and one parameter is considered as output.

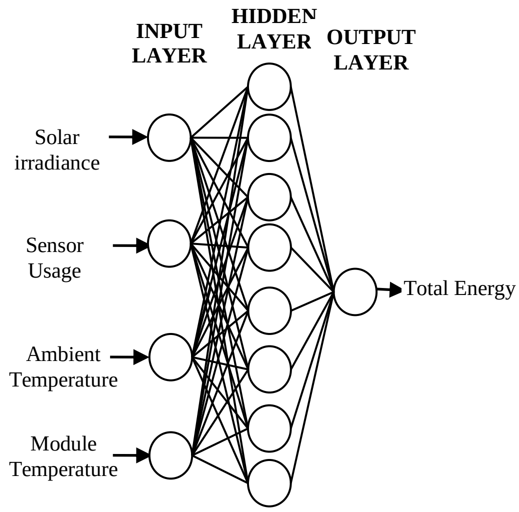

Fig.3. Implementation of neural network for GECAD dataset

Thus the input layer of the neural network contains four neurons, and output layer is provided with one neuron. As specified in the coding the neural network was provided with 8 neurons in the hidden layer which can be specified in Fig.3.

5.2 TRAINING AND TESTING OF NEURAL NETWORK

The neural network training was carried out by “Error Back Propagation algorithm”. The MATLAB code for the EBP is written by providing the dataset as input and target. Different activation functions are used during network training.

5.2.1 Error Back Propagation Algorithm

The back propagation algorithm [19] uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated.

The idea of the back propagation algorithm [1], [5] is to reduce this error, until the ANN learns the training data. The back propagation algorithm helps train the ANN to recognize similar data. In the back propagation concept, information flows in one direction between the neurons (nodes) and the errors back propagate in the opposite direction, changing the strength (weights) of the synapses (links) between the nodes while attempting to minimize the errors by using an appropriate optimization technique such as the gradient descent method.

The steps involved in training a neural network by error back propagation algorithm involves the following steps,

- Present a training sample to the neural network.
- Compare the network's output to the desired output from that sample. Calculate the error in each output neuron.
- For each neuron, calculate what the output should have been, and a scaling factor, how much lower or higher the output must be adjusted to match the desired output. This is the local error.
- Adjust the weights of each neuron to lower the local error.

Here 1248 data is divided in the ratio 70:30, where 70% of the data i.e. 874 data is used for training the neural network and remaining 30% of data i.e. 374 data is used for testing the neural network.

The neural network training was carried out by “Error Back Propagation algorithm”. The MATLAB code for the EBP is written by providing the dataset as input and target. Different activation functions are used during network training.

The second dataset which is collected from 1st May to 31st May 2015 contains about 8451 data. This data is divided in the same ratio 70:30, where 6330 data is used for training the neural network and remaining 2121 data is used for testing the neural network. During the training process, the weights are adjusted in order to make the actual outputs which are the predicted output close to the target or measured outputs of the neural network. The first dataset which is collected from 19th January to 31st January 2010 contains about 1248 data.

6. EVALUATION CRITERIA

To test the performance of the developed model and to correctly define the accuracy of the prediction and to relate error, it is necessary to define the indices that can be used to evaluate the performance of the forecast model.

Hourly error (e_h) is defined as the difference between the average power produced (measured) $p_{m,h}$ and the given prediction $p_{p,h}$ provided by the forecasting model [12].

$$e_h = p_{m,h} - p_{p,h} \tag{2}$$

Absolute hourly error ($e_{h,abs}$), which is the absolute value of hourly error which is used to calculate the performance.

$$e_{h,abs} = |e_h| \tag{3}$$

Hourly error percentage ($e\%,_p$) based on hourly expected power output $p_{p,h}$.

$$e\%,_p = \frac{|e_h|}{p_{p,h}} \cdot 100 \tag{4}$$

Hourly error percentage ($e\%,_p$) based on hourly measured power output $p_{m,h}$.

$$e\%,_m = \frac{|e_h|}{p_{m,h}} \cdot 100 \tag{5}$$

Normalised Mean Absolute Error (NMAE %) based on net capacity of the photovoltaic panel from which the dataset is collected, C [3], [15].

$$\text{NMAE\%} = \frac{1}{N} \sum_{h=1}^{N} \frac{|p_{m,h} - p_{p,h}|}{C} \cdot 100 \tag{6}$$

where, N represents the number of samples (i.e.) 874 for training the neural network and 374 for testing the neural network.

Weighted Mean Absolute Error (WMAE %) based on total energy production [3]

$$\text{WMAE\%} = \frac{\sum_{h=1}^{N} |p_{m,h} - p_{p,h}|}{\sum_{h=1}^{N} p_{m,h}} \cdot 100 \tag{7}$$

The normalised Root Mean Square Error (nRMSE %) based on the maximum observed power output $p_{m,h}$

$$\text{nRMSE\%} = \frac{\sqrt{\sum_{h=1}^{N} |p_{m,h} - p_{p,h}|}}{N} \cdot 100 \tag{8}$$

The most commonly used errors in predictive models are Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

Mean Absolute Error (MAE) can be expressed as,

$$\text{MAE} = \frac{1}{2} \sum_{i=1}^{n} |p_{m,h} - p_{p,h}| \tag{9}$$

Root Mean Square Error (RMSE) which can be root value of mean square error and can be expressed [13], [14] as,

$$\text{RMSE} = \frac{1}{n} \sum_{i=1}^{n} \left(p_{m,h} - p_{p,h}\right)^2 \tag{10}$$

These are parameter to evaluate the accuracy of prediction. All the error assessment is carried out for both Rutland and GECAD Photovoltaic dataset.

7. RESULTS

The MATLAB code for error Back Propagation (BP) algorithm with Rutland dataset (5 inputs) and GECAD photovoltaic system dataset (4 inputs) for Photovoltaic output power forecasting is executed and the predicted power output is compared with measured output power.

The implementation of network can be done by considering eight neurons in the hidden layer and one neuron in output layer.

7.1 TRAINING A NEURAL NETWORK BY BP ALGORITHM

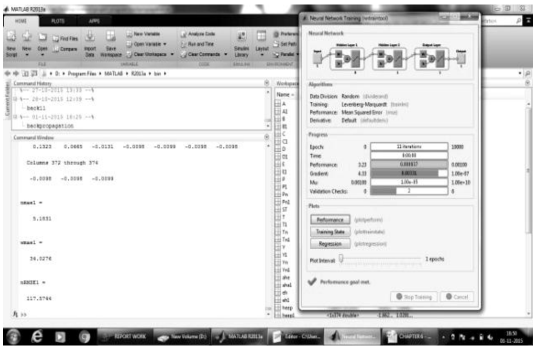

Fig.4. Neural Network training by BP

The above output Fig.4 was obtained by computing, error Back Propagation (BP) by providing the input data (5 input) and target data (1 output) from dataset 1 collected from Rutland and the input data (4 input) and target data (1 output) from dataset 2 collected from GECAD photovoltaic system.

7.2 EVALUATION CRITERIA

In order to find the accuracy of prediction, certain errors are calculated with two dataset. Errors are hourly error which is difference between the predicted output power and measured output power, absolute hourly error, absolute hourly error based on predicted output power and measured output power, NMAE (Normalised Mean Absolute Error) which is depend on the net capacity of the PV plant from which the datasets are collected, WMAE (Weighted Mean Absolute Error) and nRMSE (normalised Root Mean Square Error).

7.2.1 Normalised Mean Absolute Error (NMAE)

Normalised Mean Absolute Error (NMAE) is based on net capacity of plant from which dataset is collected. When NMAE value is lower, then accuracy of prediction will be greater. The NMAE for Rutland dataset is 0.872 for training and 1.59 for testing, similarly the NMAE for GECAD dataset is 24.31 for training and 22.38 for testing. The result of NMAE is given in Table.1.

Table.1. NMAE for different dataset

Different dataset	**NMAE (Normalised Mean Absolute Error)**	
	Training	**Testing**
Rutland data	0.8723	1.5935
GECAD data	24.3166	22.3855

7.2.2 Weighted Mean Absolute Error (WMAE)

Weighted Mean Absolute Error (WMAE) is greater when NMAE is used (during unstable days) and can be calculated by the Eq.(7).

The WMAE for Rutland dataset is 11.79 for training and 20.44 for testing. Similarly the WMAE for GECAD dataset is 4.15 for training and 3.43 for testing. The result of WMAE is given in Table.2.

Table.2. WMAE for different dataset

Different dataset	**WMAE (Weighted Mean Absolute Error)**	
	Training	**Testing**
Rutland data	11.7925	20.4437
GECAD data	4.1576	3.4382

7.2.3 normalised Root Mean Square Error(nRMSE)

Normalised Root Mean Square Error (nRMSE) - measures the average magnitude of absolute hour error. It gives higher weights to larger error. The nRMSE for Rutland dataset is 28.46 for training and 76.70 for testing, similarly the nRMSE for GECAD dataset is 132.66 for training and 83.95 for testing. The result of nRMSE is given in Table.3.

Table.3. nRMSE for different dataset

Different dataset	**nRMSE (normalised Root Mean Square error)**	
	Training	Testing
Rutland data	28.468	76.7015
GECAD data	132.6648	83.9534

7.2.4 Mean Absolute Error (MAE)

The MAE is calculated by the Eq.(9) which is specified in section 6. Mean Absolute Error (MAE) percentage for Rutland dataset is 4.24 during training and 9.92 during testing. Similarly MAE percentage for GECAD dataset is 0.31 for training and 0.94 for testing the neural network. The result of MAE is given in Table.4.

Table.4. MAE for different dataset

Different dataset	**MAE% (Mean Absolute error percentage)**	
	Training	**Testing**
Rutland data	4.24	9.92
GECAD data	0.31	0.94

7.2.5 Root Mean Square Error (RMSE)

The RMSE is calculated by the Eq.(10) which is specified in section 6.

Root Mean Square Error (RMSE) percentage for Rutland dataset is 3.45 during training and 5.28 during testing, similarly RMSE percentage for GECAD dataset is 2.11 during training and 3.66 for testing the neural network. The result of RMSE is given in Table.5.

Table.5. RMSE for different dataset

Different dataset	**RMSE%(Root Mean Square Error percentage)**	
	Training	**Testing**
Rutland data	3.45	5.28
GECAD data	2.11	3.66

7.3 ANALYSIS OF DATASET

The Rutland dataset and GECAD PV dataset are used for analysis. The input and target output are fed to the neural network and it is trained using Back Propagation algorithm. By analysing Rutland dataset the following error graphs are obtained. First the graph is plotted against the target output (T) and measured output (Y) of the solar photovoltaic dataset during training the neural network. In Rutland dataset from 1248 data only 70%, that is about 874 data is used for training the neural network. In GECAD photovoltaic system dataset from 8451 data only 6330, that is, about 70% of dataset is used for training the neural network.

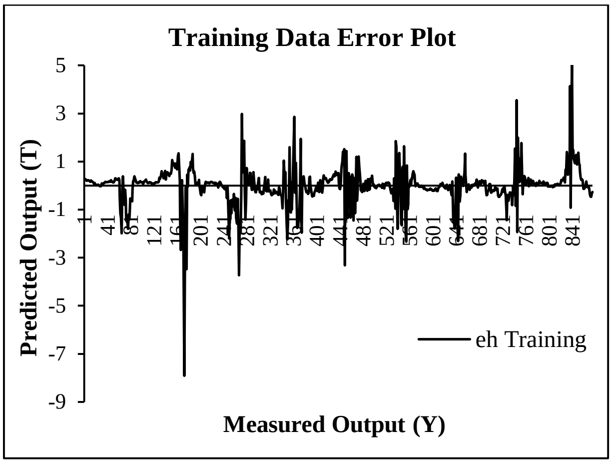

Fig.5. Training data error plot

The Fig.5 is the error obtained as the difference between the measured output (Y) and target output (T). The difference between the actual output and network output is given.

Next the graph can be plotted against the measured power output (Y1) predicted power output which target output (T1) during prediction process. The amount of data used for testing the neural network is only 30% of the dataset which is used for prediction.

- In Rutland dataset from 1248 data only 30%, that is about 374 data is used for testing the neural network.
- In GECAD photovoltaic system dataset from 8451 data only 2121, that is about 30% of dataset is used for testing the neural network.

Next the error analysis was done by introduction of certain error definition in the coding in order to plot the error obtained during the processes of testing the neural network.

The Fig.6 is the graph plotted during testing the neural network. This plot is also called as error plot obtained by the difference the actual output and network's output. The error of projects output power prediction is shown in the plot.

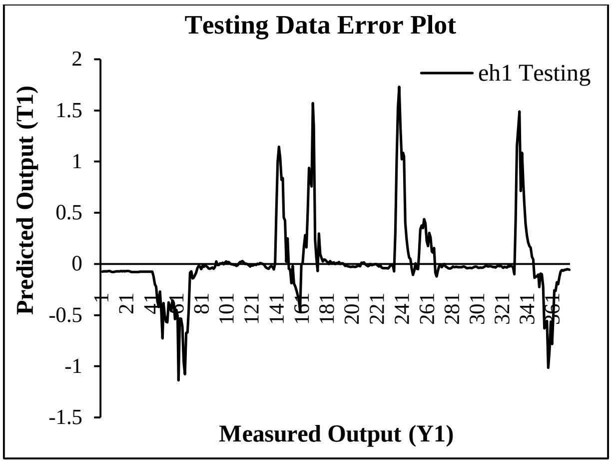

Fig.6. Testing data error plot

7.4 ANALYSIS OF ahe, heep, hemp OF RUTLAND DATASET

The analysis of absolute hourly error, hourly error based on measured power and expected power can be done in order to predict the accurate value of prediction. The absolute hourly error, hourly error percentage based on expected output and hourly error percentage based on measured output are calculated, which was then tabulated. The obtained readings are plotted for analysis.

This analysis of absolute value of errors are done for the dataset which is obtained from Rutland for about 1248 dataset, which is divided for training and testing process.

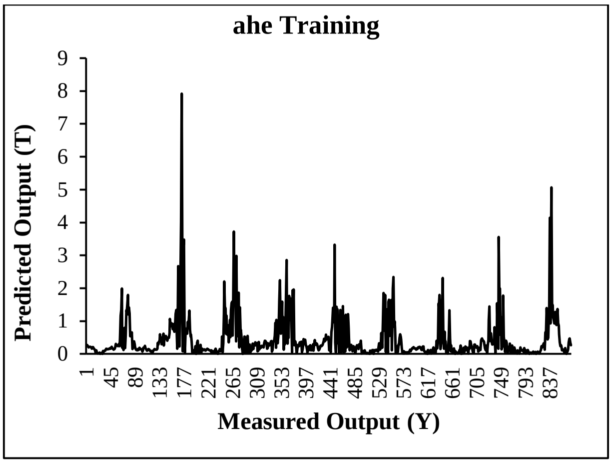

Fig.7. Training Absolute error plot

The Fig.7 is the graph obtained by calculating absolute hourly error (ahe) i.e. the error calculated by difference between the absolute value of measured output (Y) and absolute value of expected output power (T). This error plot is obtained during the training of neural network using Rutland dataset.

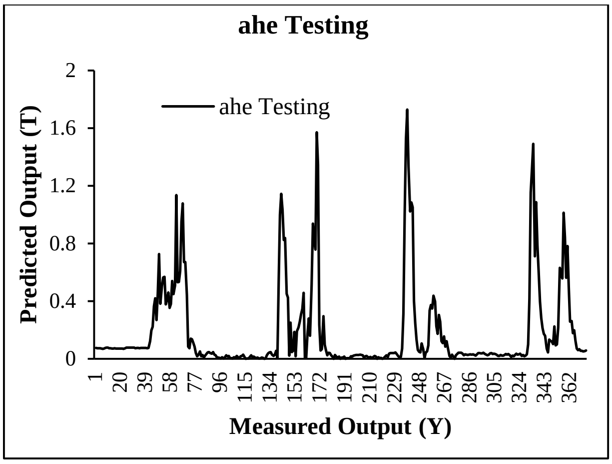

Fig.8. Testing Absolute error plot

The Fig.8 is the graph which is the plot of absolute value of error (e_h) and the calculation of absolute hourly error (ahe).The above values which was plotted are calculated by the Eq.(3).

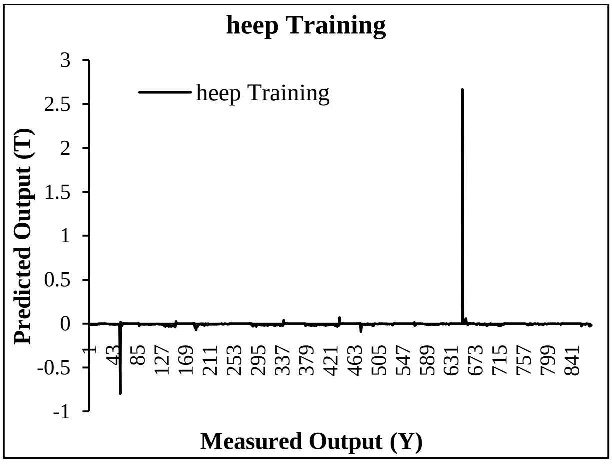

Fig.9. Training Hourly error based on expected output power

The Fig.9 is the graph which is obtained in order to show the hourly error percentage based on expected output power (heep) obtained during training of neural network in photovoltaic forecasting of output power which is obtained by substituting the error values obtained during testing in Eq.(3).

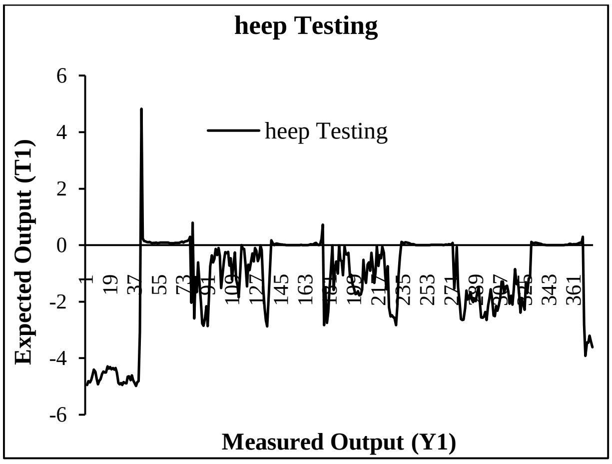

Fig.10. Testing Hourly error based on expected output power

The Fig.10 is the graph which is obtained by calculating hourly error percentage for expected power output (heep) during network testing.

The value of hourly error which is based on expected output power was calculated by the Eq.(4). The same analysis can be performed for training and testing hourly error which is based on the measured output power.

Hourly error percentage based on predicted power ($e\%_{,p}$) is generally smaller than measured power.

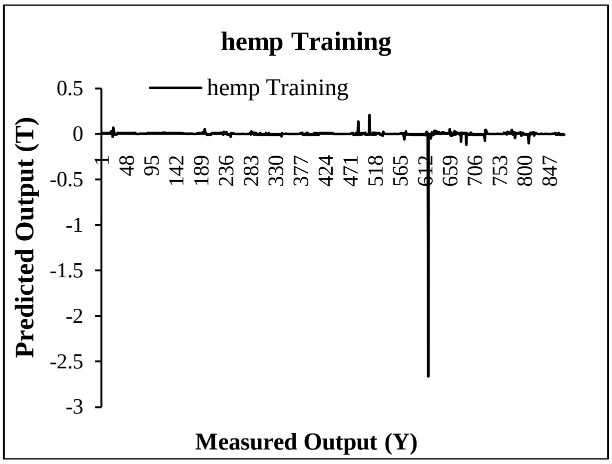

Fig.11. Training Hourly error based on measured output power

This Fig.11 is the graph obtained during the training operation of neural network and the hourly error based on measured output (Y) during training.

Among 1248 dataset only 70%, that is about 674 dataset are used in this training of neural networks.

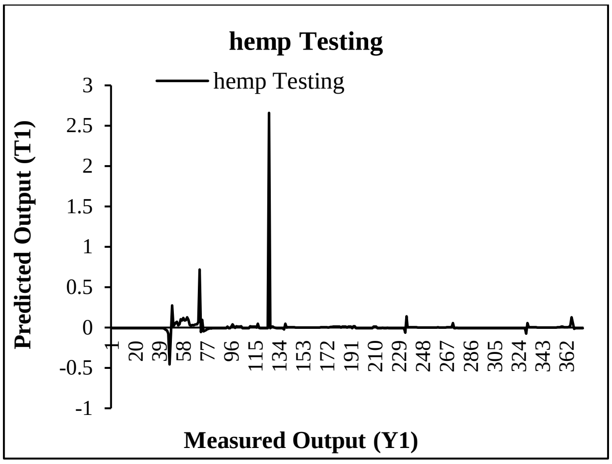

Fig.12. Testing Hourly error based on measured output power

The Fig.12 is the graph plotted to explain the hourly error based on measured output power during testing of neural network for photovoltaic forecasting of output power. The graph is plotted against measured output power (Y1) during testing and predicted output power (T1) during testing. Thus among 1248 dataset only 30%, that is about 374 dataset are used in this testing of neural networks.

These are the errors which are calculated during the photovoltaic output power forecasting using artificial neural network.

7.5 COMPARISION WITH EXISTING METHOD

Back Propagation (BP) algorithm is used as existing method in this paper. The performance evaluation has been done to calculate the values of error. In [15], the WMAE calculated during network training is 30.7, NMAE is 8.3, by using BP algorithm. In this proposed method the result obtained for WMAE is 11.7 for Rutland dataset and 4.15 for GECAD dataset. Then NMAE values are 0.87 for Rutland dataset. These comparative results are tabulated in Table.6. Thus the error value is reduced showing that the performance of the method has been improved.

Table.6. NMAE and WMAE result comparison

Errors	Proposed method results		Existing results
	Rutland data	GECAD data	
WMAE	11.7	4.15	30.7
NMAE	0.87	24.3	8.3

Next in reference [22], RMSE% is 9.3 and 9.8 for training and testing respectively. MAE% is 4.9 and 5.05 for training and testing the network. But in this paper RMSE% obtained during network training is 2.11 and 3.45 for GECAD and Rutland dataset respectively. Error obtained during network testing is 3.6 for GECAD dataset and 5.2 for Rutland dataset. Then MAE% obtained for GECAD dataset is 0.31, Rutland dataset is 4.24 for network training and 0.94 for GECAD dataset for network testing, showing that the error values has been decreased comparatively with the values obtained by [22] which has been specified in Table.7.

Table.7. RMSE and MAE result comparison

Error	Proposed method results				Existing results	
	Training		Testing		Train	Test
	Rutland	Gecad	Rutland	Gecad		
RMSE	3.45	2.11	5.2	3.6	9.3	9.8
MAE	4.24	0.31	9.9	0.94	4.9	5.05

Thus by lowering the values of error it can be proved that the accuracy of prediction is high.

8. CONCLUSION

Photovoltaic forecasting method based on Artificial Neural Network (ANN) using error Back Propagation (BP) algorithm was done. Here two types dataset is used for analysis, Rutland dataset and GECAD PV dataset.

The training and testing of both datasets was done with back propagation algorithm using MATLAB code and the obtained training and testing output power is tabulated and plotted.

The tabulated values are compared with the results obtained in [15] and [22]. Comparative result shows that the values of error in existing paper have reduced widely. Thus by lowering the error it is highlighted that the accuracy of prediction becomes high.

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