Implementation of DWT and Regression Learning Based ANN for Forecast of Solar PV Output

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Abstract: - The intermittent nature of PV generation makes it difficult to plan load dispatch from grids which have PV integration. One of the most effective ways to predict PV power is to estimate the solar irradiation on the PV cells which typically vary to month, day, time, temperature and other variables. The sporadic nature of the irradiation on PV cells males it extremely challenging to prediction of short term and long-term PV outputs. The proposed work presents a DWT-regression learning based neuro network predictor for solar PV generation output for both short- and long-term conditions. The performance of the system has been evaluated based on the mean absolute error, number of iterations and the regression curves. It can be observed from the results that the proposed system attains extremely low mean absolute error for the PV output thereby rendering high accuracy to the micro/smart grids with PV integration.

Keywords: - Photovoltaic (PV) output Prediction, Neuro-Network Predictor, Mean Absolute Error, and Regression Learning

1. Introduction

Solar PV outputs are high solar irradiation dependent and intermittent in nature. Hence it becomes challenging to predict solar PV outputs. The figure below shows the solar radiation spectrum. The spectrum comprises of the infrared, visible and ultra violet regions of the spectrum. In the proposed work, a system is put forward that can accurately determine the maximum power point tracking of solar PV Cells by proper and accurate prediction of the solar irradiance.

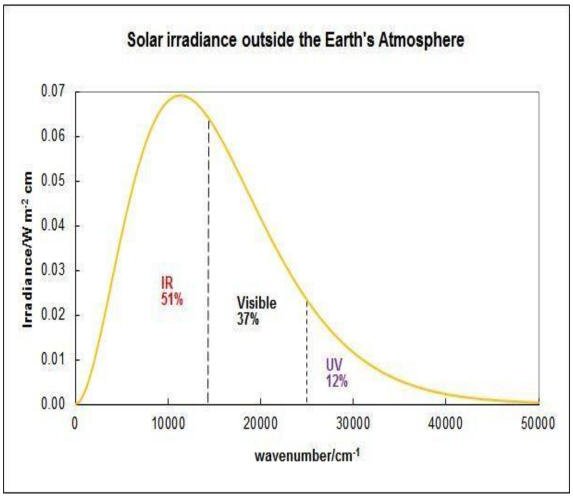


Fig.1 Solar Irradiation Spectrum

The two main challenges to high penetration rates of PV systems are variability and uncertainty, i.e. the fact that PV output exhibits variability at all timescales (from seconds to years) and the fact that this variability itself is difficult to predict. The proposed work addresses the second issue, uncertainty, and the method used to address it: photovoltaic forecasting.

2. PV Forecasting and its Link to Solar Irradiation

The different uses of PV forecasts require different types of forecasts. Forecasts may apply to a single PV system, or refer to the aggregation of large numbers of systems spread over an extended geographic area. Forecasts may focus on the output power of systems or on its rate of change (also known as the ramp rate).

Accordingly, different forecasting methods are used. Forecasting methods also depend on the tools and information available to forecasters, such as data from weather stations and satellites, PV system data and outputs from numerical weather prediction (NWP) models.

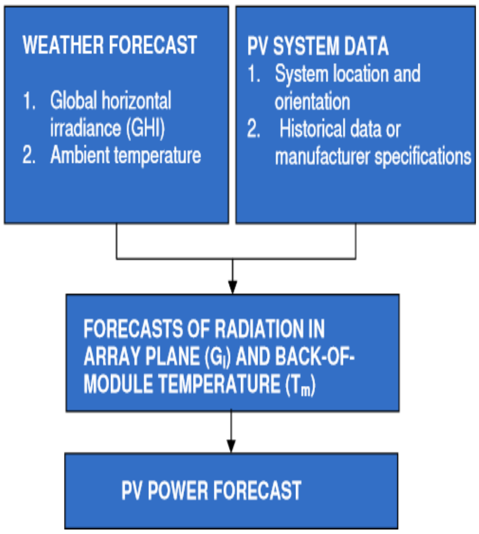


Fig.2 Model for PV Forecasting

Forecasting methods can be broadly characterized as physical or statistical. The physical approach uses solar and PV models to generate PV forecasts, whereas the statistical approach relies primarily on past data to train models, with little or no reliance on solar and PV models. The PV forecast is typically a function of relevant weather variables and PV system characteristics. The main variables influencing PV output power are the irradiance in the plane of the PV array and the temperature at the back of the PV modules or cells.

3. The Neuro-Network Predictor

Due to the complexity and size of the data, off late machine leaning or AI based techniques are being used for time series data analysis such as Solar PV output prediction.

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. Other advantages include:

- **Adaptive learning:** An ability to learn how to do tasks based on the data given for training or initial experience.

- **Self-Organization:** An ANN can create its own organization or representation of the information it receives during learning time.

- **Real Time Operation:** ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.

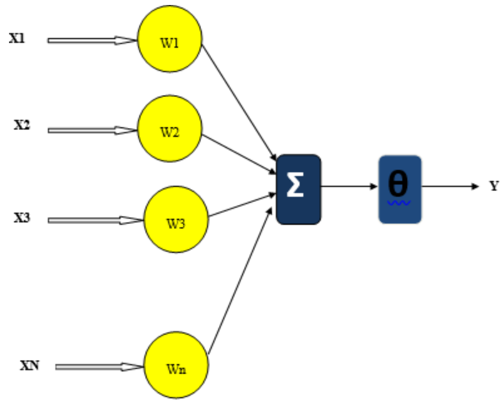


Fig.3 Mathematical Model of Neural Network

The output of the neural network is given by:

$$\sum_{i+1}^{n} XiWi + \theta \qquad (1)$$

Where,

Xi represents the signals arriving through various paths,
Wi represents the weight corresponding to the various paths and ϴ is the bias. It can be seen those various signals traversing different paths have been assigned names X and each path has been assigned a weight W.

The signal traversing a particular path gets multiplied by a corresponding weight W and finally the overall summation of the signals multiplied by the corresponding path weights reaches the neuron which reacts to it according to the bias ϴ. Finally, it's the bias that decides the activation function that is responsible for the decision taken upon by the neural network. The activation function φ is used to decide upon the final output. The learning capability of the ANN structure is based on the temporal learning capability governed by the relation:

$$w\ i = f\ (i, e) \qquad (2)$$

Here,
w (i) represents the instantaneous weights
i is the iteration

e is the prediction error

The weight changes dynamically and is given by:

$$\boldsymbol{W_k} \quad \boldsymbol{e,i} \quad \boldsymbol{W_{k+1}} \qquad \textbf{(3)}$$

Here,
W_k is the weight of the current iteration.
W_{k+1} is the weight of the subsequent iteration.

3.1 Regression Learning Model

Regression learning has found several applications in supervised learning algorithms where the regression analysis among dependent and independent variables is needed. Different regression models differ based on the kind of relationship between dependent and independent variables, they are considering and the number of independent variables being used. Regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a relationship between x (input) and y(output). Mathematically,

$$\boldsymbol{y} = \boldsymbol{\theta_1} + \boldsymbol{\theta_2 x} \qquad \textbf{(4)}$$

Here,
x represents the state vector of input variables
y represents the state vector of output variable or variables.
Θ1 and Θ2 are the co-efficient which try to fit the regression learning models output vector to the input vector.

By achieving the best-fit regression line, the model aims to predict y value such that the error difference between predicted value and true value is minimum. So, it is very important to update the θ1 and θ2 values, to reach the best value that minimize the error between predicted y value (pred) and true y value (y). The cost function J is mathematically defined as:

$$\boldsymbol{J} = \frac{1}{n}\sum_{i=1}^{n} (\boldsymbol{pred_1} - \boldsymbol{y_i}) \qquad (5)$$

Here,
n is the number of samples
y is the target
pred is the actual output.

3.2 Gradient Descent in Regression Learning

To update θ1 and θ2 values in order to reduce Cost function (minimizing MSE value) and achieving the best fit line the model uses Gradient Descent. The idea is to start with random θ1 and θ2 values and then iteratively updating the values, reaching minimum cost. The main aim is to minimize the cost function J.

4. Proposed Methodology

The wavelet transform can be crudely seen as a tool for the smoothening of local disturbances in the data set and is widely used as a data pre-processing tool. The mathematical formulation for the wavelet transform is given by the scaling and shifting approach of the wavelet function.

The scaling, shifting dependence can be defined as:

$$\mathbf{W\Psi\ (sc, sh) = \text{₩}(\{x,t\})} \qquad \textbf{(6)}$$

Here,
x is the space variable t is the time variable
₩ is the transform
sc is the scaling factor
sh is the shifting factor

Thus, the wavelet transform can be considered to be a shifted-scaled version of wavelet family functions.
There are several wavelet families such as haar, Mexican hat, morlet etc. The base functions differ from conventional sine/cosine functions exhibiting smoothness in the period of definition. The proposed approach uses the wavelet transform on the independent variables and then trains the neural network with the values.
The algorithm is based on the concept of feeding back the errors to the neural network i.e., back propagation. The salient feature of the algorithm is its relatively low time complexity and accuracy. The reason for the mentioned phenomena is the fact that the algorithm searches for the direction for the steepest direction right from the first iteration. Mathematically,

$$\boldsymbol{p_0} = -\boldsymbol{g_0} \qquad \textbf{(7)}$$

p_0 is the negative of the gradient vector g_0
For the k[th] iteration

$$p_k = -g_k + \Theta_k p_{k-1} \qquad (8)$$

It is worth noting that the in addition to the weights, the search vector also keeps updating with the iterations.

The overall training rule for algorithm can be mathematically expressed as:

$$w_{k+1} = w_k + \beta_k p_k \qquad (9)$$

The essence of the algorithm can be summarized in the following points:

- The algorithm starts a search for the steepest descent vector right from the first iteration of training
- The steepest descent ensures fast training
- Step 2 ensures lower time complexity for the algorithm
- In addition to the update of weights, the steepest descent vector is also updated with the number of iterations.
- The algorithm is in general requires low memory space for execution. This is particularly useful for large data sets and low memory applications.

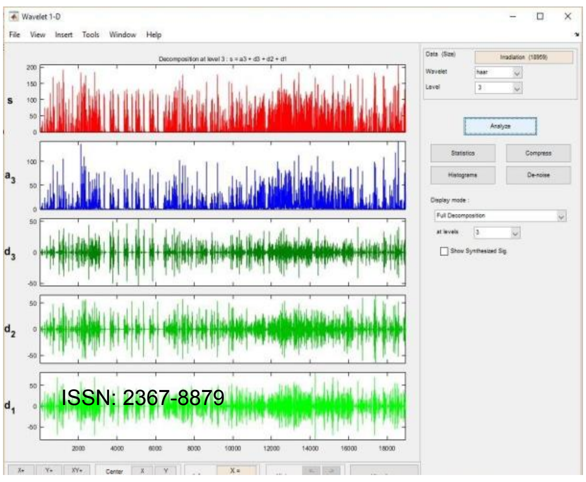
4.1 Evaluation of Parameters:

After the testing process is over, the following parameters are computed to evaluate the performance of the proposed approach:

- Mean Absolute Error
- Number of Iterations
- Regression

5. RESULTS AND DISCUSSIONS

The system has been simulated on Matlab 2018a



Before the data is applied to the neural network for pattern analysis, it is decomposed into approximate and detailed co-efficients using the Discrete Wavelet Transform which acts as a filtering tool.

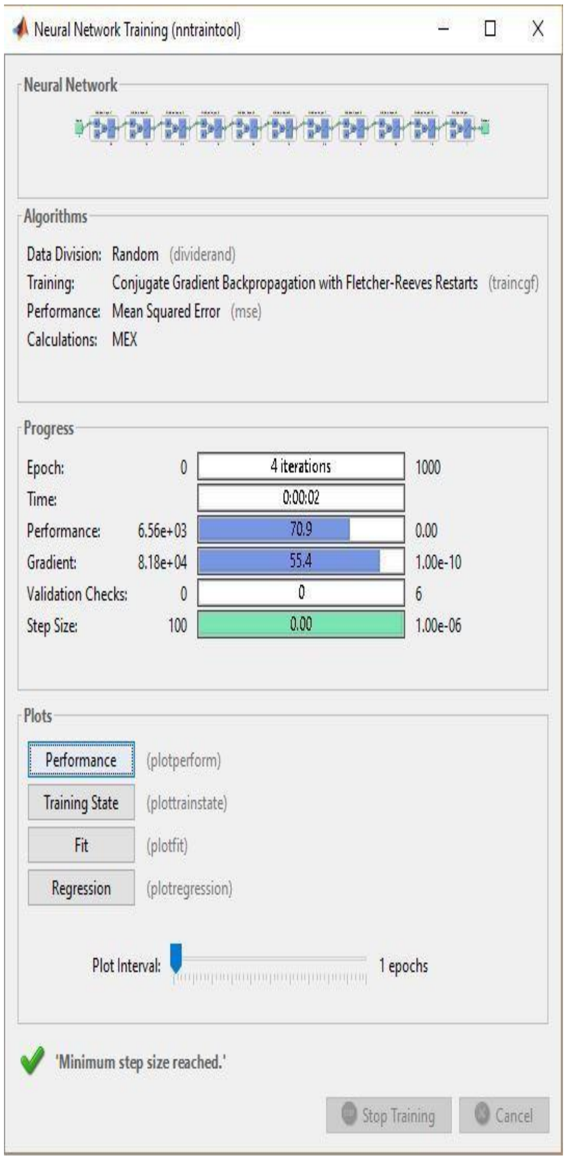


Fig.5 Training the Neural Network

The DWT is used to decompose the data into approximate and detailed co-efficents. The approximate co-efficents contain the maximum information and the detailed co-efficients contain the additional details.
Discarding the detailed co-efficents helps to smoothen out the data and remove local

disturbances and fluctuations in the data .
A third level decomposition has been done in this case. Increasing the levels above 3 does not increase the accuracy much but increases the system complexity.

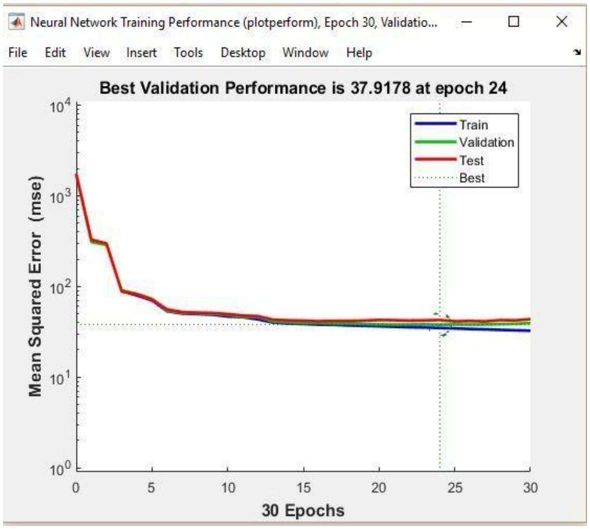


Fig. 6 MSE variation as a function of time

The training and the performance metrics of the proposed model is shown in the figure above.

In above graph depicts the variation of MSE w.r.t. epochs.

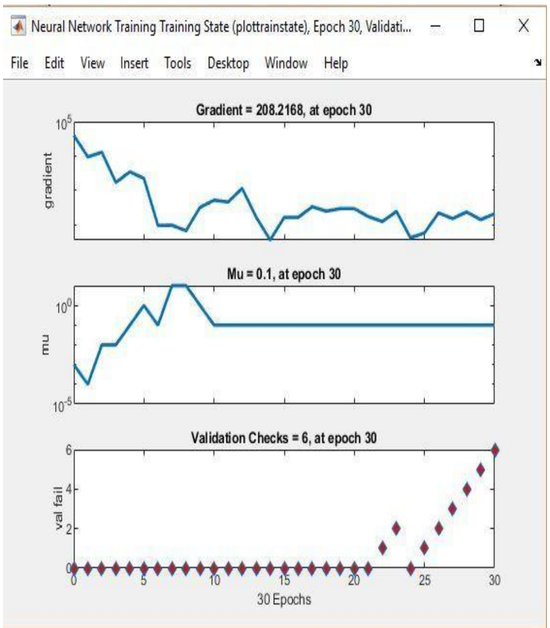


Fig. 7 Variation of Training Parameters

In above graph depicts the variation of training parameters as training states.

The overall regression is 0.63 due to the sporadic

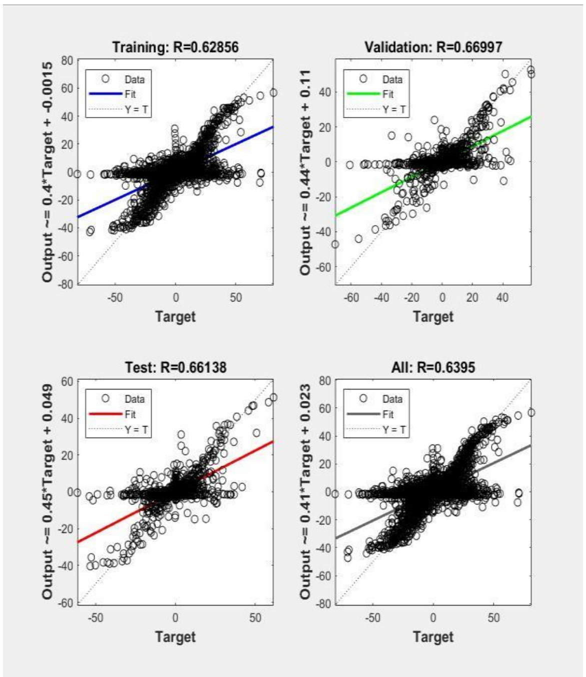


Fig. 8 Regression analysis

and intermittent nature of the PV outputs.

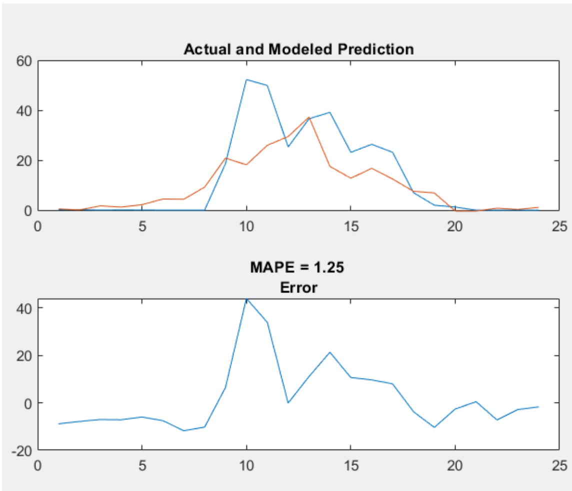


Fig. 9. Forecasted Values, Actual Values and MAPE w.r.t. time

The figure above depicts the accuracy with which the neural network is capable to predict future values. The relation which related the MAPE and accuracy is given by:
Accuracy (%) =100-error (%)
The MAPE is 1.27,
Hence the accuracy is 98.75%.
The number of iterations is 4.
The previous work attained a normalized MAE of 3.6% but the proposed work attains an MAE of 1.25% only thereby outperforming the previous approach.

6. Conclusion:

Predicting Solar PV output has been shown to be extremely complex due to the nature of the irradiation. As it has been pointed out earlier, PV output prediction can be challenging because of the wide range variation of the parameters affecting irradiation on the PV cells. Any neural network system can find it difficult to follow the pattern of solar irradiation owing to the fact that solar irradiation varies significantly and some may even become zero during nights. This discontinuity causes even more problems. Hence a two-fold approach has been used for solar irradiation prediction which can be summarized as:

1) Using the wavelet transform as a data processing tool for all the relevant parameters.

2) Using the processed data to train a neural network.

From the results shown, it can be clearly observed that the proposed technique performs better than the previous work [1].

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